REVISTA INVECOM
ISSN en línea: 2739-0063

Information Technologies applied to probabilistic simulation of geotechnical stability using Python

Tecnologías de la Información aplicadas a la simulación probabilística de estabilidad geotécnica mediante Python

Received: 15/04/2026 - **Accepted:** 10/07/2026

Jesus Kliver Anchiraico Alderete
https://orcid.org/0009-0003-6434-0151
janchiraico@uncp.edu.pe
Universidad Nacional del Centro del Perú. Huancayo, Peru

Eugenio Emilio Orellana Mendoza
https://orcid.org/0000-0002-8302-378X
eeorellana@uncp.edu.pe
Universidad Nacional del Centro del Perú. Huancayo, Peru

Vilma Ayre Balbin
https://orcid.org/0009-0005-1580-3935
vayre@uncp.edu.pe
Universidad Nacional del Centro del Perú. Huancayo, Peru

César Roberto Toykin Mucha
https://orcid.org/0009-0004-7050-907X
ctoykin@uncp.edu.pe
Universidad Nacional del Centro del Perú. Huancayo, Peru

Abstract

Information Technology (IT) has transformed geotechnical engineering by enabling the development of computational simulations that overcome the limitations of traditional deterministic methods. In this context, the objective of this study was to design a probabilistic geotechnical stability simulation tool implemented in Python, integrating Monte Carlo simulation (50,000 iterations) and Rosenblueth point estimation (32 combinations) to quantify the uncertainty of the Safety Factor (SF) in underground excavations. Methodologically, the approach is quantitative and projective; the scientific libraries NumPy, SciPy, and Matplotlib were used, defining truncated statistical distributions for the input geomechanical parameters. The results showed that the developed digital tool yields an average SF of 3.602 (σ = 0.577), a reliability index β = 4.512, and a failure probability P (FS<1) ≈ 0.00%, with full agreement between the two methods (discrepancy < 1.5%) and a computation time of just 0.12 seconds. The Kolmogorov-Smirnov test validated the log-normal distribution as the functional fit model (KS = 0.0073). It is concluded that the application of information technology using Python constitutes an effective and accessible digital tool for geotechnical risk management, which optimizes support design without compromising safety.

Keywords: probabilistic simulation, geotechnical stability, Python.

Resumen

Las Tecnologías de la Información (TI) han transformado la ingeniería geotécnica al permitir el desarrollo de simulaciones computacionales que superan las limitaciones de los métodos determinísticos tradicionales. En este contexto, el presente estudio tuvo como objetivo diseñar una herramienta de simulación probabilística de estabilidad geotécnica implementada en Python, integrando las tecnologías de simulación Monte Carlo (50.000 iteraciones) y estimación puntual de Rosenblueth (32 combinaciones) para cuantificar la incertidumbre del Factor de Seguridad (FS) en excavaciones subterráneas. Metodológicamente, el enfoque es cuantitativo de tipo

proyectivo; se emplearon las bibliotecas científicas NumPy, SciPy y Matplotlib, definiendo distribuciones estadísticas truncadas para los parámetros geomecánicos de entrada. Los resultados mostraron que la herramienta digital desarrollada obtiene un FS medio de 3,602 (σ = 0,577), un índice de confiabilidad β = 4,512 y una probabilidad de falla P(FS<1) ≈ 0,00%, con plena concordancia entre ambos métodos (discrepancia < 1,5%) y un tiempo de cómputo de apenas 0,12 segundos. La prueba de Kolmogorov-Smirnov validó la distribución lognormal como modelo de ajuste funcional (KS = 0,0073). Se concluye que la aplicación de Tecnologías de la Información mediante Python constituye una herramienta digital eficaz y accesible para la gestión de riesgos geotécnicos, que optimiza el diseño del sostenimiento sin comprometer la seguridad.

Palabras clave: simulación probabilística, estabilidad geotécnica, Python.

Introduction

Information Technologies (IT) have made decisive inroads into engineering disciplines that historically depended on manual calculations or costly commercial software. In the field of geotechnical engineering, this digital transition manifests in the adoption of open-source programming languages, especially Python, and specialized scientific libraries that enable the implementation of complex numerical simulations with unprecedented accessibility (Harris et al., 2020; Virtanen et al., 2020). The capacity to execute tens of thousands of iterations in fractions of a second transforms how engineers approach the uncertainty inherent in soil and rock parameters.

In underground excavation engineering, support design in rock masses has traditionally relied on deterministic approaches based on average values of geomechanical parameters. However, these methods present significant limitations by failing to account for the inherent variability of discontinuities, which can lead to inaccurate estimates of the Safety Factor (SF) and to support designs that are either overdimensioned or unsafe. In this context, contemporary geotechnical research shows a clear shift toward probabilistic and reliability-based approaches that incorporate uncertainty into the analysis and improve design precision (Qin et al., 2024).

The principal challenge in probabilistic slope stability analyses lies in the inherent uncertainty of soil parameters, whose values exhibit considerable spatial and statistical variability (Chuaiwate et al., 2022; Kar & Roy, 2022). IT tools, particularly scientific programming environments, offer a solution to this limitation by enabling the automation of thousands of calculation scenarios, the visualization of probability distributions, and the statistical validation of models within a single digital workflow.

Several recent investigations confirm this methodological evolution driven by IT. For instance, Qin et al. (2024) highlight the growth of data-driven models in tunnel reliability analysis, while Pandit and Sivakumar Babu (2021) demonstrate that the spatial variability of geomechanical parameters significantly modifies the response of the tunnel-support system. Complementarily, Nguyen et al. (2024) show that rock mass anisotropy directly influences failure probability, and Man et al. (2024) propose advanced metamodels that reduce computational cost without compromising analysis accuracy.

A critical aspect in the implementation of these methods is precisely the computational efficiency afforded by IT tools. Although Monte Carlo simulation is considered one of the most reliable techniques for geotechnical reliability analysis, it requires a large number of simulations. The Python environment, thanks to its vectorized computation libraries, allows 50,000 simulations to be executed in tenths of a second (Rana et al., 2023). In response to the demand for greater efficiency, the Rosenblueth point estimation method constitutes a digitally implementable alternative that yields results comparable to Monte Carlo at a fraction of the computational cost (Renaud & Al Heib, 2024).

Given this context, the objective of the present study was to design a probabilistic geotechnical stability simulation tool implemented through Information Technologies, specifically the Python language and its scientific libraries, based on the Monte Carlo and Rosenblueth methods. The relevance of this digital tool lies in its capacity to address the key question facing the excavation engineer: How much support is necessary to guarantee safety without compromising the budget, considering the inherent uncertainty of the terrain? Furthermore, the difference between actual ground behavior and that predicted by numerical models constitutes an important source of uncertainty that IT helps to quantify in a systematic and reproducible manner (Low & Boon, 2024; Nguyen & Marciniak, 2024).

SciELO Venezuela latindex LatinREV CC BY

Methodology

The study adopted a quantitative approach and a projective research type, defined by Hurtado (2000) as that which consists of developing a proposal, plan, program, or model as a solution to a problem or need within a specific area of knowledge. The central product is a digital tool implemented in Python through Information Technologies.

The tool was developed using the Python programming language, selected for being an open-source information technology widely adopted by the scientific community. The following specialized IT libraries were used: NumPy (Harris et al., 2020), which provides high-performance vectorized computation for matrix and statistical operations; SciPy (Virtanen et al., 2020), which offers algorithms for statistics, probability distributions, and goodness-of-fit tests; and Matplotlib (Hunter, 2007), which enables scientific graphical visualization of results. The combination of these technologies constitutes an integrated digital ecosystem for geotechnical reliability analysis.

Core simulation formula

The main equation of the tool represents the Safety Factor (SF) against planar sliding based on the Mohr-Coulomb strength criterion (Hoek & Bray, 1981):

$$SF = [c \cdot A + (W \cdot \cos \psi - U) \cdot \tan \varphi] / [W \cdot \sin \psi]$$

Where: c = cohesion of the failure plane (kPa); A = area of the failure plane (m²); W = weight of the rock block (kN); ψ = dip angle of the failure plane (°); U = water pressure force (kN); φ = internal friction angle (°).

Phases of IT tool development

The digital implementation was structured into the following phases.

- **Phase 1 – Initialization and parameter loading:** The algorithm defines the input geotechnical properties (cohesion, friction angle, dip, block weight, and water pressure) with their respective means and standard deviations, along with the fixed area of the failure surface (A = 25 m²).
- **Phase 2 – Sampling configuration:** N = 50,000 simulations are established for the Monte Carlo branch.
- **Phase 3 – Bifurcated processing:** The tool executes two algorithmic branches in parallel. In the Monte Carlo branch, the IT tool generates 50,000 random values for each variable using truncated statistical distributions, ensuring realistic physical bounds (no negative cohesion or friction values). It then evaluates the SF vectorially across the 50,000 scenarios and extracts key indicators: mean SF, standard deviation (σ), Coefficient of Variation (COV), reliability index (β), and failure probability (Pf). In the Rosenblueth branch, the tool optimizes computation by generating exactly $2^5 = 32$ fixed combinations (μ ± σ) for the five input variables, evaluating the SF at those 32 points, and analytically calculating the probabilistic moments with a weight factor p = 1/32.
- **Phase 4 – Statistical fitting and validation:** The tool fits a lognormal distribution to the Monte Carlo results and validates the fit using the Kolmogorov-Smirnov (KS) test.
- **Phase 5 – Graphical rendering:** The tool automatically generates and exports a PNG image (300 dpi) that overlays the empirical Monte Carlo histogram with the theoretical lognormal curve, visually marking the SF = 1 threshold and the mean SF.

Once the five processing phases are completed, the IT tool automatically consolidates the geotechnical reliability indicators (mean SF, standard deviation, coefficient of variation, β index, and failure probability) along with the statistical validation graph exported in PNG format. This integrated digital workflow, which articulates probabilistic computation with visualization and goodness-of-fit diagnostics, forms the basis upon which the findings presented in the following results section are grounded.

SciELO Venezuela latindex LatinREV CC BY

Results

This section presents the findings derived from the execution of the digital tool, organized into two complementary components: first, the geotechnical reliability statistical indicators obtained through the Monte Carlo and Rosenblueth methods; second, the graphical representation of the processing flow and the probabilistic distribution of the Safety Factor. Each result is accompanied by its respective technical interpretation.

The IT tool developed in Python produced the following execution results, as shown in Table 1:

Table 1

Probabilistic simulation results obtained through the Python digital tool

Indicator	**Monte Carlo**	**Rosenblueth**
Mean SF	3,602	3,598
Standard deviation (σ)	0,577	0,567
Coefficient of Variation (COV)	0,160	—
Reliability index (β)	4,512	4,582
Failure probability P(SF<1)	0,00%	—
Computation time	0,1202 s	< 0,001 s
KS / p-value	0,0073 / 0,0094	—

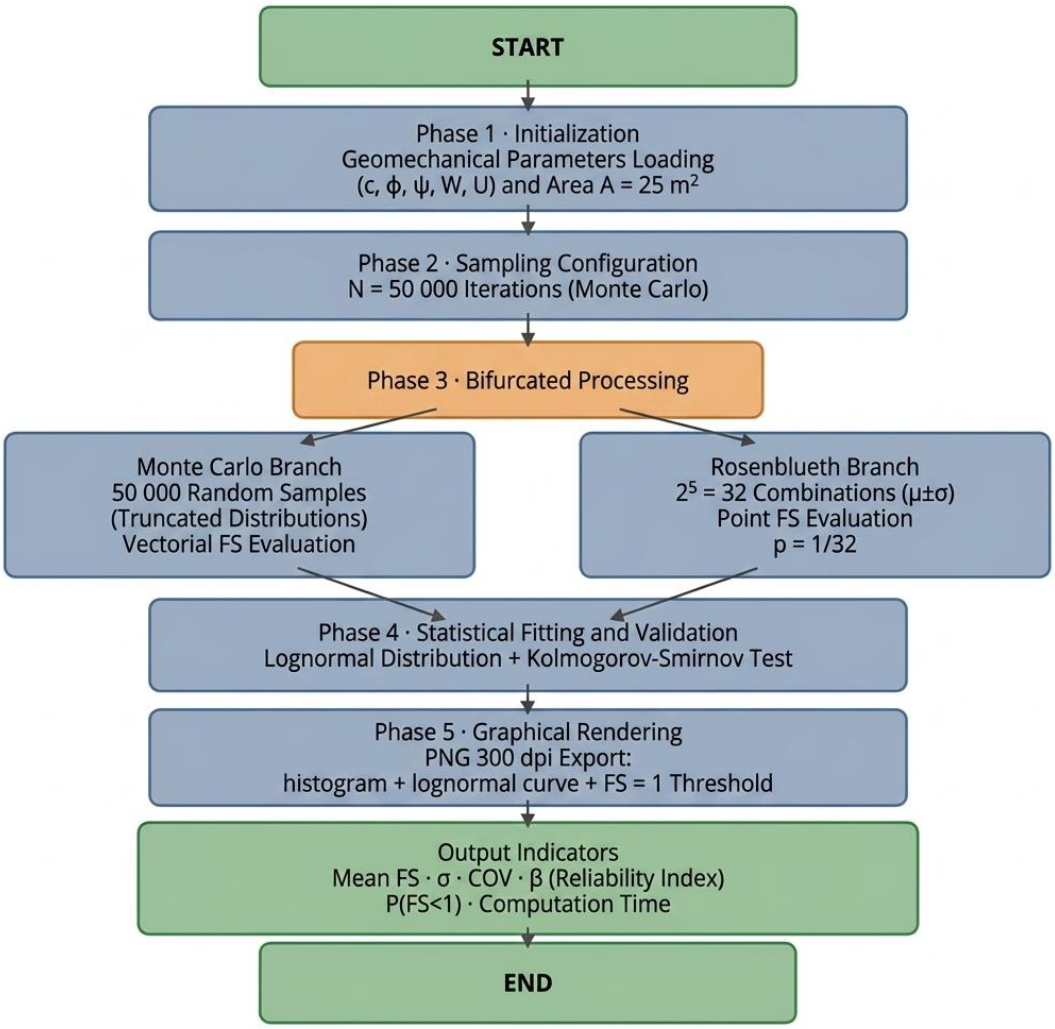
Note. Authors' own elaboration using the Python digital tool

The results in Table 1 reveal a high degree of agreement between both probabilistic methods: the relative discrepancy between the reliability indices β obtained by Monte Carlo (4.512) and Rosenblueth (4.582) is less than 1.5%, confirming the internal robustness of the IT tool and the functional equivalence of both calculation paths. In practical terms, the mean SF exceeding 3.5 and the virtually nil failure probability (0.00%) indicate that the analyzed support design possesses a considerably wide safety margin relative to the critical threshold (SF = 1). Likewise, the difference of more than three orders of magnitude in computation time (0.1202 s versus less than 0.001 s) highlights the computational advantage of the Rosenblueth method when rapid or iterative design evaluations are required.

Figure 1 shows the flowchart of the developed IT tool, which synthesizes the five phases of the computational process, from parameter initialization to graphical rendering of results.

SciELO Venezuela latindex LatinREV CC BY

Figure 1
Flowchart of the IT tool for probabilistic geotechnical stability simulation in Python.

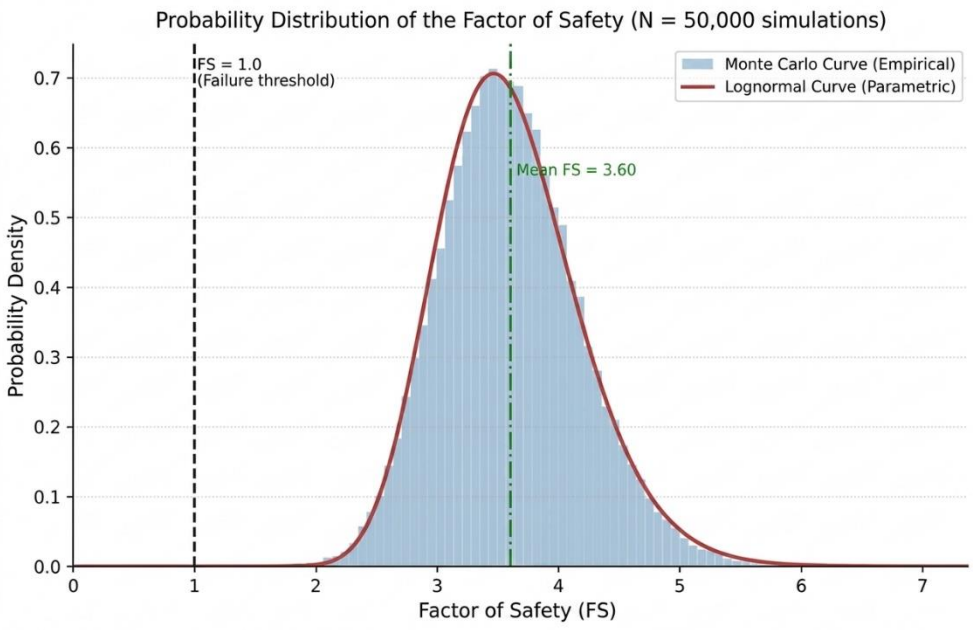


Source: Authors' own elaboration

As can be observed in Figure 1, the flow bifurcates into two parallel calculation routes, Monte Carlo and Rosenblueth, which reconverge in the statistical fitting phase, evidencing the modular design of the digital tool. Each branch can be executed independently depending on the level of precision or computational efficiency required by the user, and both feed into a single validation and graphical rendering process. This bifurcated architecture constitutes, in itself, a relevant methodological contribution to the automation of probabilistic analyses in geotechnical engineering.

Regarding Figure 2, it presents the graph automatically generated by the algorithm, which overlays the empirical Monte Carlo histogram with the fitted lognormal distribution curve.

Figure 2
Probabilistic planar sliding analysis generated by the digital tool.



Source: Authors' own elaboration

The X-axis represents the Safety Factor (SF) as the output random variable; the Y-axis represents probability density. The Monte Carlo (empirical) curve corresponds to the smoothed histogram obtained after the 50,000 digital simulations; the lognormal (parametric) curve represents the theoretical fit, which is physically consistent given that SF is a ratio of positive variables exhibiting positive skewness. The Vertical Line SF = 1.0 marks the failure threshold (the area to its left equals Pf); the Mean SF = 3.60 line indicates the central value of the distribution. Together, both curves exhibit virtually complete overlap, visually supporting the quality of the lognormal fit despite the marginal discrepancies detected by the Kolmogorov-Smirnov test.

Discussion

The results obtained through the IT tool, developed in Python, demonstrate that Information Technologies constitute an effective means of overcoming the limitations of deterministic methods in geotechnical analysis. Beyond the quantitative description of the findings, the following subsections critically interpret their implications, contrast them with previous literature, evaluating both convergences and divergences, and weigh the methodological limitations that condition their scope.

Validity of the digital model and statistical dispersion

The mean SF of 3.602 (Monte Carlo) and the coefficient of variation (COV) of 16% are statistically consistent with the typical ranges reported in the literature for geotechnical parameters (cohesion typically exhibits a COV of 0.20–0.30, and internal friction angle, 0.10–0.15). For clarity, the COV expresses the ratio between the standard deviation and the mean of a variable, such that higher values reflect greater relative dispersion and, therefore, greater uncertainty associated with the analyzed parameter. In this case, a moderate COV indicates that, although inherent variability exists in the input geomechanical parameters, it remains within reasonable margins and does not compromise the numerical stability of the model, suggesting that the IT tool is correctly parameterized and realistically reproduces the stochastic behavior expected for fractured rock masses (Chuaiwate et al., 2022; Kar & Roy, 2022). Nevertheless, this consistency depends directly on the quality of the input data: in scenarios with

scarce or poorly representative geotechnical information for the specific site, the model would inherit such uncertainty without the ability to internally correct it, which constitutes a limitation to be considered in its practical application.

Failure probability and digital risk management

A reliability index β = 4.512 corresponds, in the standard normal distribution, to a failure probability of 3.2×10^{-6} (0.00032%), which when rounded to two decimal places is reported as 0.00%. In simple terms, the β index quantifies how many standard deviations separate the expected value of the Safety Factor from the critical threshold (SF = 1); the higher the β, the lower the probability of system failure. From a normative standpoint (Eurocode 7, AASHTO LRFD), a target β between 3.0 and 4.0 is typically required for ductile failure modes; the value of 4.5 obtained in this study indicates that the evaluated support design is overdimensioned relative to the minimum normative requirement. This critical reading is relevant because it shows that the IT tool not only confirms the safety of the design but also allows the identification of a technical and economic margin susceptible to optimization without compromising minimum structural reliability levels. This capacity to translate probabilistic results into concrete engineering decisions (reducing support, reallocating resources, prioritizing critical sectors) is ultimately the added value that IT brings to the decision-making process (Rusydy et al., 2024). It should be noted, however, that this conclusion assumes that the input geomechanical parameters faithfully represent the actual conditions of the rock mass; insufficient geotechnical characterization could underestimate the real variability and, consequently, overestimate the calculated reliability.

Kolmogorov-Smirnov test and fitting limitations

The p-value of 0.0094, being less than the conventional significance level of 0.05, implies that, in a strict statistical sense, the lognormal distribution does not constitute a perfect fit for the simulated data. For readers unfamiliar with goodness-of-fit tests, it is worth clarifying that the Kolmogorov-Smirnov (KS) test measures the maximum distance between the empirical cumulative distribution function of the data and the proposed theoretical cumulative distribution function; low p-values indicate that this distance is statistically significant. However, this result must be interpreted with caution, as it constitutes an expected effect in massive samples: with N = 50,000 observations, the KS test acquires very high statistical power, capable of detecting minimal differences, even in the tails of the distribution, that lack practical relevance and are not visually perceptible in the histogram. From an engineering perspective, it is more relevant to evaluate the agreement between statistical moments (mean and variance) and the area under the left tail of the distribution, which is precisely what determines the failure probability (Pf). In this regard, the discrepancy of barely 1.5% in the β index between both methods supports the functional robustness of the digital tool, even when the distributional fit is not mathematically exact (Low & Boon, 2024). This distinction between statistical significance and practical relevance constitutes a conceptual limitation that should be considered when interpreting goodness-of-fit tests in studies with large sample sizes.

Computational efficiency of the IT tool

The tool based on the Rosenblueth method, requiring only 32 evaluations compared to the 50,000 needed for Monte Carlo, demonstrates that Information Technologies can be designed at multiple efficiency levels depending on the computational complexity of the problem at hand. This difference is particularly relevant in scenarios where each individual evaluation of the geotechnical model is computationally expensive, as occurs in three-dimensional finite element models, where a single run can take hours; in such cases, executing 50,000 Monte Carlo iterations would be computationally unfeasible, whereas the 32 evaluations required by Rosenblueth constitute a practical and accessible alternative. This capacity to scale computational efficiency according to the problem context represents a strategic advantage of IT tools in contemporary engineering (Man et al., 2024; Pandit & Sivakumar Babu, 2021). Nevertheless, it is important to recognize that such efficiency carries a conceptual cost: the Rosenblueth method is based on a second-order statistical moment approximation, so its accuracy may degrade in distributions with high skewness or in the presence of complex correlations between variables, a limitation that does not affect the Monte Carlo method in the same way.

Critical synthesis and study limitations

Overall, the discussed findings evidence that the developed IT tool not only reliably reproduces the results of two probabilistic methods widely validated in the literature but also allows such statistical information to be

SciELO Venezuela latindex LatinREV CC BY

translated into practical design and risk management criteria. However, the scope of these conclusions is conditioned by methodological limitations inherent to the study. First, the analysis is circumscribed to a planar failure mechanism with a fixed discontinuity area (A = 25 m²), so its extrapolation to more complex failure geometries (wedges, circular surfaces, or stratified slopes) would require additional developments. Second, the input parameters were defined from truncated statistical distributions without direct contrast with field data from a specific rock mass, which limits the empirical validation of results against actual site conditions. Future research should aim to validate the digital tool with documented historical cases and to incorporate the spatial variability of geomechanical parameters, thereby extending its applicability to more diverse geotechnical scenarios.

Conclusions

The execution of this study enabled the design and implementation of a digital tool for probabilistic geotechnical stability simulation using Information Technologies, specifically Python and its scientific libraries (NumPy, SciPy, and Matplotlib). This tool proved to be functional, efficient, and accessible for incorporating the uncertainty of geomechanical parameters into Safety Factor estimation.

It is worth noting that the developed IT tool achieved a mean Safety Factor of 3.602 (Monte Carlo) and a reliability index $\beta = 4.512$, with a virtually nil failure probability ($P(SF<1) \approx 0.00\%$). This level of over-safety, precisely quantified digitally, suggests a significant margin for economically optimizing support without compromising the minimum required safety, which translates into direct savings in excavation projects.

Furthermore, the comparison between the two methods implemented in the digital tool yielded a minimal discrepancy of 1.5% in the β index, validating that the Rosenblueth method, with only 32 evaluations, replicates Monte Carlo results in near-instantaneous fashion. This demonstrates that IT enables the design of scalable tools that are efficient for simple problems and strategically superior when the computational cost of Monte Carlo would be prohibitive (e.g., 3D finite element models).

Although the Kolmogorov-Smirnov test rejected the exact fit to the lognormal distribution ($KS = 0.0073$; $p = 0.0094$) due to high sample sensitivity, the fit is functionally excellent for estimating the mean, variance, and failure probability. This shows that in the context of IT tools for engineering, accuracy in statistical moments is more relevant for decision-making than perfect theoretical distribution fitting.

In synthesis, the application of Information Technologies through Python constitutes an accessible, reproducible, open-source digital tool for geotechnical risk management that allows engineers to quantify uncertainty, optimize design, and technically justify project decisions, advancing toward a more rational and efficient approach than traditional deterministic methods. It is recommended to extend the application of this tool to other types of geotechnical failure and to explore its integration with geospatial information platforms.

References

Chuaiwate, P., Jaritngam, S., Panedpojaman, P., & Konkong, N. (2022). Probabilistic analysis of slope against uncertain soil parameters. *Sustainability, 14*(21), 14530. https://doi.org/10.3390/su142114530

Harris, C. R., Millman, K. J., van der Walt, S. J., Gommers, R., Virtanen, P., Cournapeau, D., ... Oliphant, T. E. (2020). Array programming with NumPy. *Nature, 585*(7825), 357–362. https://doi.org/10.1038/s41586-020-2649-2

Hoek, E., & Bray, J. W. (1981). *Rock slope engineering* (3ra ed.). Institution of Mining and Metallurgy.

Hunter, J. D. (2007). Matplotlib: A 2D graphics environment. *Computing in Science & Engineering, 9*(3), 90–95. https://doi.org/10.1109/MCSE.2007.55

Hurtado, J. (2000). *Metodología de la investigación holística*. SYPAL.

Kar, S. S., & Roy, L. B. (2022). Probabilistic based reliability slope stability analysis using FOSM, FORM, and MCS. *Engineering, Technology & Applied Science Research, 12*(2), 8236–8240. https://doi.org/10.48084/etasr.4689

Low, B. K., & Boon, C. W. (2024). Probability-based design of reinforced rock slopes using coupled FORM and Monte Carlo methods. *Rock Mechanics and Rock Engineering*, *57*, 1195–1217. https://doi.org/10.1007/s00603-023-03607-6

Man, J., Zhang, T., Huang, H., & Dias, D. (2024). Probabilistic analysis of tunnel face seismic stability in layered rock masses using polynomial chaos Kriging metamodel. *Journal of Rock Mechanics and Geotechnical Engineering, 16*(7), 2678–2693. https://doi.org/10.1016/j.jrmge.2023.09.020

SciELO Venezuela latindex LatinREV CC BY

Nguyen, P. M. V., & Marciniak, M. (2024). Stochastic rock slope stability analysis: Open pit case study with adjacent block caving. *Geotechnical and Geological Engineering*, *42*, 5827–5845. https://doi.org/10.1007/s10706-024-02862-w

Nguyen, T. S., Tanapalungkorn, W., & Likitlersuang, S. (2024). Probabilistic analysis of dual circular tunnels in rock masses considering rotated anisotropic random fields. *Computers and Geotechnics*, *170*, 106319. https://doi.org/10.1016/j.compgeo.2024.106319

Pandit, B., & Sivakumar Babu, G. L. (2021). Probabilistic stability assessment of tunnel-support system considering spatial variability in weak rock mass. *Computers and Geotechnics*, *137*, 104242. https://doi.org/10.1016/j.compgeo.2021.104242

Qin, W., Chen, E. J., Wang, F., Liu, W., & Zhou, C. (2024). Data-driven models in reliability analysis for tunnel structure: A systematic review. *Tunnelling and Underground Space Technology*, *152*, 105928. https://doi.org/10.1016/j.tust.2024.105928

Rana, H., Pandit, B., & Sivakumar Babu, G. L. (2023). Estimation of uncertainties in soil using MCMC simulation and effect of model uncertainty. *Geotechnical and Geological Engineering, 41*, 6249–6266. https://doi.org/10.1007/s10706-023-02523-4

Renaud, V., & Al Heib, M. (2024). Probabilistic slope stability analysis: A novel distribution for soils exhibiting highly variable spatial properties. *Probabilistic Engineering Mechanics, 76*, 103586. https://doi.org/10.1016/j.probengmech.2024.103586

Rusydy, I., Canbulat, I., Zhang, C., Wei, C., & McQuillan, A. (2024). The development and implementation of design flowchart for probabilistic rock slope stability assessments: A review. *Geoenvironmental Disasters, 11*(28), 1–28. https://doi.org/10.1186/s40677-024-00290-9

Virtanen, P., Gommers, R., Oliphant, T. E., Haberland, M., Reddy, T., Cournapeau, D., ... van der Walt, S. J. (2020). SciPy 1.0: Fundamental algorithms for scientific computing in Python. *Nature Methods, 17*(3), 261–272. https://doi.org/10.1038/s41592-019-0686-2

AUTHORSHIP CONTRIBUTION

Jesus Kliver Anchiraico Alderete: Conceptualization, methodology, software, research, writing – original draft.
Eugenio Emilio Orellana Mendoza: Supervision, validation, writing – proofreading and editing.
Vilma Ayre Balbin: Data curation, visualization, formal analysis.
César Roberto Toykin Mucha: Research, resources, project administration.

STATEMENT ON THE USE OF ARTIFICIAL INTELLIGENCE (AI)

It is declared that the content of this article was not generated with the assistance of an artificial intelligence model. Likewise, the algorithm developed in Python is the product of the authors' intellectual design and constitutes the object of study of the research.

SciELO Venezuela latindex LatinREV CC BY