

Article

A Hierarchical Modular Fuzzy Model for Instability Susceptibility Assessment and Stabilization Decision Support in Rock Slopes

Marsella Gissel Rodríguez-Servín ¹, José Eleazar Arreygue-Rocha ¹, Mariana Lobato-Báez ²,
Juan Carlos López-Pimentel ³, José Manuel Díaz-Barriga ¹ and Luis Alberto Morales-Rosales ^{1,4,*}

¹ Facultad de Ingeniería Civil, Universidad Michoacana de San Nicolás de Hidalgo, Morelia 58030, Michoacán, Mexico; marsella.gissel.rodriguez@umich.mx (M.G.R.-S.); eleazar.arreygue@umich.mx (J.E.A.-R.); 1116803h@umich.mx (J.M.D.-B.)

² Tecnológico Nacional de México (TECNM), Instituto Tecnológico Superior de Libres, Puebla 73780, Puebla, Mexico; mariana.lb@libres.tecnm.mx

³ Facultad de Ingeniería, Universidad Panamericana, Álvaro del Portillo 49, Zapopan 45010, Jalisco, Mexico; clopezp@up.edu.mx

⁴ Secretaría de Ciencia, Humanidades, Tecnología e Innovación (SECIHTI), Insurgentes Sur 1582, Colonia Crédito Constructor Demarcación Territorial Benito Juárez, Ciudad de Mexico 03940, Mexico

* Correspondence: lamorales@conacyt.mx or lamorales@secihtl.mx

Abstract

Traditional rock mass evaluation methods have three main limitations: (1) their application depends largely on specialist judgment; (2) their discrete classification approach, such as RMR (Rock Mass Rating) and SMR (Slope Mass Rating), leads to abrupt transitions between categories; and (3) the interaction among geomechanical parameters is limited; these aspects reduce their ability to represent slope behavior in a gradual manner. The main objective of this research was to develop a model capable of representing gradual transitions between geomechanical conditions and the interaction among parameters related to susceptibility to instability. The model uses a hierarchical modular framework based on the Mamdani fuzzy inference mechanism, allowing the incorporation of expert knowledge through linguistic rules. It is implemented in a graphical environment that allows users to directly use geomechanical parameters obtained through conventional characterization or from three-dimensional digital models derived from UAV (Unmanned Aerial Vehicle) photogrammetry. Model consistency was evaluated through a sensitivity analysis, which verified the model's response coherence across variations in input parameters. The graphical evaluation tool was then applied to three real case studies with different geomechanical configurations, and the results were compared with those from traditional methods (RMR and SMR). The results showed differences between traditional and fuzzy approaches, as our proposal links recommendations to specific geomechanical conditions across different evaluation levels, identifying conditions for potential intervention measures. In addition, the model enables the zonification of instability susceptibility, facilitating its use in future risk analyses. Our model is intended for application under normal slope conditions, without accounting for extreme events or external dynamic loads, such as seismic activity, groundwater level variations, infiltration, or high-mountain conditions.

Keywords: instability susceptibility; fuzzy logic; rock slopes; hierarchical modular model; UAV photogrammetry; geomechanical characterization



Academic Editor: Penghai Zhang

Received: 2 July 2026

Revised: 22 July 2026

Accepted: 29 July 2026

Published: 3 August 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article

distributed under the terms and

conditions of the [Creative Commons](#)

[Attribution \(CC BY\)](#) license.

1. Introduction

Rock slope instability susceptibility assessment is often a critical issue in civil and geotechnical engineering, particularly in the development and operation of transportation infrastructure, as slope failures may lead to severe consequences, including loss of life, economic losses, and social impacts. Instability susceptibility refers to the degree to which a slope presents geomechanical conditions favorable for the development of movements, regardless of the presence of a specific failure mechanism. Therefore, its assessment allows potentially critical areas to be identified and stabilization and intervention measures to be proposed within geotechnical analysis and risk management.

However, instability susceptibility assessment is a complex process due to the heterogeneity of rock masses and the interactions among multiple geomechanical parameters. Susceptibility does not depend on a single parameter, but rather on the combined influence of rock mass properties, the discontinuity system, slope geometry, and physical conditions [1,2]. This complexity introduces uncertainty and subjectivity into data interpretation, leading to a strong reliance on expert judgment. In practice, the quality of the assessment may vary significantly with the engineer's experience, which can be an important limitation to the replicability and consistency of geotechnical analyses.

Rock slope susceptibility assessment has traditionally been addressed through geomechanical classification systems such as Rock Mass Rating RMR [3] and Slope Mass Rating (SMR) [4]. In the case of RMR, several geomechanical parameters are assigned to specific classes with corresponding ratings, which are subsequently accumulated to estimate the overall quality of the rock mass. On the other hand, SMR is an extension of the RMR method, using the basic classification as a starting point and applying correction factors related to the failure mechanism and the geometric relationships between discontinuities and slope orientation to evaluate slope stability conditions.

These methods present complementary approaches, where RMR is focused on determining rock mass quality and SMR on slope stability assessment. However, both methods represent geomechanical information in discrete classes and ranges and assume that the parameters behave independently [1]. As a consequence, the interaction among rock mass properties, discontinuity characteristics, and slope geometry is not explicitly represented, even though these conditions may be highly variable. Furthermore, discretizing parameters into predefined ranges produces abrupt transitions between classification categories, so even very small variations in input values can lead to differences in the final classification and limit the ability of these methods to represent the uncertainty associated with rock masses. Particularly, this type of representation restrains the ability to describe the gradual evolution of the conditions that favor instability susceptibility.

These limitations pose a significant problem because instability susceptibility corresponds to a condition in which several geomechanical factors interact simultaneously, progressively modifying the susceptibility of the slope to instability. For example, parameters such as roughness, degree of weathering, and moisture conditions correspond to characteristics that evolve progressively and therefore influence slope instability susceptibility [5]. This shows that the representation of rock mass behavior through discrete methods is inherently limited. Consequently, representing susceptibility through rigid categories makes it difficult to adequately describe the natural variability of geomechanical behavior.

The evaluation of instability susceptibility has been widely studied in the literature through different approaches, including multi-criteria methods, statistical models, and machine learning techniques, which aim to identify potentially unstable areas based on conditioning factors [1,2]. In general, susceptibility is defined as the propensity of a terrain to develop movements based on its intrinsic conditions, without explicitly considering the time of occurrence of the event [5].

Furthermore, the literature distinguishes between slope stability assessment and landslide susceptibility evaluation, which are typically addressed using different methodological approaches [6]. While stability analysis is focused on evaluating specific failure mechanisms or safety factors, susceptibility approaches aim to identify conditions that may favor the occurrence of instability.

Several studies have implemented fuzzy models for stability and instability susceptibility assessment. For example, fuzzy expert systems have been developed for the assessment of toppling failure mechanisms in rock slopes [7], as well as approaches for stability analysis under sliding conditions through the identification of critical blocks [8], Mamdani-type models for rock slope risk assessment [9], and hybrid models combining fuzzy and machine learning for early risk evaluation [10].

Despite these advances, several fuzzy models [7–9] for rock slope stability assessment integrate all geomechanical information into a single inference system, which complicates their interpretation and calibration [8,9]. Consequently, the influence of each group of geomechanical parameters on slope behavior cannot be clearly identified. In addition, a large proportion of existing approaches do not explicitly address the generation of geotechnical recommendations, focusing only on determining stability class or rating. In practice, however, it is necessary not only to assess the geomechanical conditions, but also to identify the factors that favor instability susceptibility and to establish intervention measures based on the site's specific conditions.

These differences highlight the need to develop evaluation tools capable of adequately representing the interaction among the geomechanical conditions that control instability susceptibility. In this sense, it is necessary to adopt approaches that not only consider the influence of multiple parameters, but also allow modeling the gradual transitions of geomechanical conditions, avoiding the limitation associated with discrete classifications.

The present work proposes an evaluation tool based on Mamdani-type fuzzy logic, structured through a hierarchical modular model. This approach integrates different geomechanical parameters through progressive evaluation levels, combining the geometric stability of the slope and its physical conditions to determine the system's overall condition. This condition is interpreted as a continuous instability susceptibility index, allowing the identification of the conditions that favor the occurrence of slope movements. Furthermore, the proposed model enables the zonation of slope susceptibility to instability, particularly in road infrastructure, facilitating risk management strategies and maintenance planning.

External dynamic factors such as groundwater level variation, rainfall-related infiltration processes, and seismic effects are not explicitly considered, as the model focuses on the evaluation of instability susceptibility based on the geomechanical conditions of the rock mass and the slope geometry. Furthermore, the approach is oriented toward identifying potential instability conditions, with the aim of supporting the zoning of road sections for their conservation and maintenance.

As part of our research, we developed an assessment tool based on a Mamdani-type fuzzy inference mechanism through a hierarchical modular model. Each module represents a specific geotechnical condition defined by the interaction of two or more geomechanical parameters, whose output used as input to the subsequent evaluation level. The structure allows gradual transitions among different groups of geomechanical variables related to instability susceptibility. In addition, the assessment tool can use information from both traditional field surveys and digital characterization techniques.

The main contributions of this research are summarized as follows:

1. A hierarchical modular fuzzy model was developed to assess susceptibility to instability in rock slopes, based on fuzzy logic, in which different geotechnical parameters are interconnected through modules that represent specific geotechnical conditions. This

enables the interpretation of intermediate evaluation states, facilitating the identification of conditions that favor instability susceptibility.

2. A graphical evaluation tool was developed based on the proposed model, in which the input data are entered in their original measured form, while the environment internally automates variable normalization, execution of the fuzzy inference systems, and result generation, facilitating its practical application using real geomechanical data. The code is located in <https://marsella94.github.io/FISlope/> (accessed on 7 July 2026).
3. A recommendation activation scheme was integrated into the model, in which stabilization measures are associated with the geotechnical conditions identified during the final stage of the evaluation process. This allows recommendations to be linked to the factors that favor instability susceptibility, rather than relying solely on a final classification.
4. The model was validated using real-world case studies and compared with the results obtained from traditional geomechanical classification systems (RMR and SMR), as well as through a sensitivity analysis that allowed the evaluation of the consistency of the model response and the identification of the most influential parameters.

Our work aims to contribute to the development of evaluation tools that support decision-making in the stabilization of rock slopes through systems capable of representing the interaction among different geomechanical parameters and the gradual transition associated with rock mass behavior, with the goal of improving the assessment of instability susceptibility

2. Related Work on Rock Slope Stability Assessment

Slope stability assessment has traditionally been addressed using analytical and numerical methods, including limit-equilibrium methods, kinematic analyses, and finite- or discrete-element methods. These techniques estimate slope behavior based on geotechnical or geomechanical parameters, providing indicators such as the factor of safety and the probability of specific failure mechanisms. However, their application is often affected by the uncertainty associated with rock mass characterization, material heterogeneity, and the complexity of geological conditions encountered in the field [11,12].

In parallel, advances in digital photogrammetry, LiDAR, and unmanned aerial vehicles have advanced methodologies for the remote characterization of rock masses. Several authors have proposed techniques for the automatic identification of discontinuities, the determination of orientations, spacings, and persistence, and the generation of three-dimensional models for geomechanical analysis [13–15]. These tools have improved data acquisition in inaccessible slopes while reducing personnel exposure during fieldwork. Nevertheless, most studies focus on the extraction and characterization of geomechanical parameters without directly addressing their integration into models for stability assessment or movement susceptibility evaluation.

Over the last decade, artificial intelligence techniques have gained increasing relevance in slope stability analysis. Several studies have employed machine learning algorithms, including Support Vector Machine (SVM), Random Forest (RF), Artificial Neural Networks (ANN), and hybrid models optimized through evolutionary algorithms to predict stability indices, factors of safety, or levels of movement susceptibility [11,12,16,17]. These approaches have demonstrated a high predictive capability by identifying complex relationships among multiple geotechnical variables. However, many of these models prioritize predictive performance over interpretability, making it difficult to understand the individual influence of geomechanical parameters and limiting their use as decision-support tools in engineering practice [11,12,17].

In the evaluation of slope susceptibility using machine learning techniques and remote sensing studies such as [2] have combined deformation monitoring through SBAS-InSAR, a satellite-based interferometric technique that allows the analysis of ground displacement with high precision using time series, with Support Vector Machine algorithms to assess slope hazard susceptibility, demonstrating the capabilities of hybrid approaches.

Similarly, recent studies such as [6] have applied methodologies for stability assessment and susceptibility mapping in the development of predictive models in complex geological areas. However, these approaches are mainly oriented toward prediction, and therefore their geotechnical interpretation is not direct, which limits their use as decision-support tools in engineering.

On the other hand, fuzzy logic has been widely adopted as an alternative framework for representing the uncertainty inherent in geological material and geotechnical assessment processes. Unlike methods based on discrete classifications, fuzzy systems incorporate expert knowledge through linguistic rules and membership functions, allowing gradual transitions between different stability conditions. Several studies have applied this methodology to rock slope stability assessment, geomechanical classification, and geotechnical risk evaluation [7,8,10,18–20].

Specifically in the field of rock slope stability, refs. [7,8] developed fuzzy models to evaluate specific failure mechanisms, including planar sliding, wedge failures, and block toppling. Similarly, ref. [18] proposed a fuzzy logic-based methodology for stability assessment using the Q-Slope system. In addition, ref. [10] developed a fuzzy neural network approach for early risk warning of highway soft-rock slope groups, showing the potential of combining fuzzy reasoning and machine learning for risk identification under uncertain geotechnical conditions. These studies demonstrate the capability of fuzzy-based systems to incorporate uncertainty and support geotechnical decision-making.

However, a large proportion of the fuzzy models reported in the literature integrate all input parameters within a single inference stage or are coupled with data-driven learning structures. As a consequence, the number of required rules may increase considerably as new variables are incorporated, while the physical interpretation of the contribution of each geomechanical parameter can become more difficult [10,18]. Furthermore, many of these approaches are oriented towards evaluating specific failure mechanisms, risk levels, or stability indices, thereby limiting independent analysis of different groups of geomechanical parameters and their influence on the overall behavior of the slope.

In addition, several studies have explored the application of artificial intelligence techniques to complement or automate widely used rock mass classification systems such as RMR, GSI, and Q-System [11,16]. Although these approaches help improve rock mass characterization procedures, they generally focus on obtaining geomechanical indices and do not establish an explicit relationship among rock mass quality, slope movement susceptibility, and the definition of mitigation measures for risk management.

Table 1 summarizes some of the main approaches in the literature regarding digital rock mass characterization, artificial intelligence, and fuzzy logic applied to geomechanical classification and slope stability problems.

Based on the reviewed literature, there remains a need for methodologies capable of integrating multiple geomechanical parameters within structured and interpretable models that explicitly represent the interaction among rock mass quality. Furthermore, a limited number of studies have focused specifically on evaluating slope movement susceptibility as an integrated geomechanical system and on generating intervention recommendations directly derived from the assessment process [10,12,16,18].

Table 1. Representative studies on digital characterization, artificial intelligence, and fuzzy logic applied to rock slope assessment.

Reference	Category	Contribution
[15]	Digital characterization	Review of automated discontinuity extraction techniques from 3D models.
[13]	Digital characterization	Automatic discontinuity identification from point clouds.
[14]	Digital characterization	UAV-based discontinuity interpretation and rockfall identification.
[12]	Artificial intelligence	Review of machine learning applications for slope stability prediction.
[16]	Artificial intelligence	AI-based rock mass classification systems.
[8]	Fuzzy logic	Fuzzy assessment of planar and wedge failures.
[7]	Fuzzy logic	Fuzzy evaluation of block toppling susceptibility.
[18]	Fuzzy logic	Stability assessment based on a fuzzy Q-Slope approach.
[10]	Fuzzy logic	Early warning of highway soft-rock slopes using fuzzy neural networks.
[19]	Fuzzy logic	Fuzzy-based geotechnical stability assessment.
[20]	Fuzzy logic	Fuzzy cognitive maps for uncertainty analysis.
This study	Fuzzy logic	Hierarchical modular assessment of movement susceptibility and intervention recommendations.

To address these limitations, this research proposes a hierarchical, modular Mamdani-type fuzzy inference system to assess the susceptibility of rock slopes to movement. The proposed framework integrates commonly used geomechanical parameters via interconnected modules that represent different aspects of rock mass behavior. This organization preserves the interpretability of the assessment process, explicitly incorporates the uncertainty associated with geomechanical information, and enables the analysis of the influence of different groups of variables on the overall response of the system.

3. Materials and Methods

The methodology presented in this research consists of obtaining geomechanical information from the rock slope using conventional characterization techniques and three-dimensional digital models, from which the geomechanical parameters required by the hierarchical fuzzy model are extracted to derive instability susceptibility indices and stabilization recommendations. In the following subsections, we describe this process in detail.

3.1. Data Collection and Geomechanical Characterization from Photogrammetric Products

The geomechanical information used by the model can be obtained through conventional field surveys or digital characterization techniques, such as photogrammetry using Unmanned Aerial Vehicles (UAVs). This technique allows the generation of detailed digital models of the rock slope, enabling specialists to identify, measure, and interpret both quantitative and qualitative geomechanical parameters remotely. In a previous work [21], a methodology is presented for generating three-dimensional digital models via UAV photogrammetry, which can be used to derive geomechanical parameters related to discontinuities and slope geometry. The parameters obtained can be used for geomechanical characterization and slope stability analysis.

UAV photogrammetry involves acquiring overlapping images from different positions and observation angles of the slope face, considering factors such as georeferencing, environmental conditions, and flight parameters. Subsequently, the captured images are processed using algorithms such as Structure-from-Motion (SfM), which reconstructs a digital model by identifying point correspondences through overlap between photographs. This process generates several digital products, including point clouds, triangular meshes, and textured models, which provide a more detailed representation of the slope surface, geometry, and surface conditions.

One of the main products of photogrammetry is the three-dimensional point cloud, which can be processed with clustering algorithms to identify discontinuity sets. This facilitates analysis of the discontinuity system's influence on the slope's orientation and dip.

Likewise, products such as meshes and textured models allow specialists to perform digital measurements to obtain geomechanical parameters such as persistence, spacing, aperture, and Rock Quality Designation (RQD). In addition, Digital Elevation Models (DEMs) can be used to estimate Joint Roughness Coefficient (JRC) values as part of the surface characterization of discontinuities.

Furthermore, the use of multi-spectral cameras enables the generation of spectral indices, such as the Normalized Difference Water Index (NDWI), for detecting moisture.

The extracted geomechanical parameters serve as input variables for the modular hierarchical model, enabling the integration of information on rock mass quality, the geometric and physical properties of discontinuities, and slope geometry.

To ensure the reliability of the information obtained from the photogrammetric products, key factors influencing the quality of the generated digital models were considered, such as ground resolution (GSD), point cloud density, and the presence of vegetation. These factors allow for sufficient detail to identify and interpret geomechanical parameters and surface conditions.

The dense point cloud constitutes the main product of the photogrammetric process and was subjected to a preprocessing stage that included manual and semi-automated cleaning of elements not belonging to the slope, as well as vegetation removal. In addition, a controlled reduction of the point cloud density was carried out in order to adequately represent the rock mass without affecting the quality required for the semi-automated identification and extraction of discontinuity properties.

Regarding georeferencing, different reference methods were used, such as Post-Processed Kinematic (PPK) and ground control points (GCP's), which allowed achieving an adequate level of accuracy for the geomechanical characterization purposes of this study.

On the other hand, the normalized difference water index (NDWI) was used as a complementary indicator for the identification of surface moisture conditions. For its interpretation, ranges reported in the literature [22] were taken as reference. However, these were not used as strict classification thresholds, but rather as supporting criteria within the analysis.

3.2. General Description and Model Approach

Rock slope stability assessment requires consideration of multiple geomechanical parameters, including rock mass quality, discontinuity characteristics, slope geometry, and surface conditions. In this work, a model based on a Mandani-type fuzzy inference system is proposed to integrate these conditions within a continuous geotechnical evaluation framework.

The information used by the model can be obtained through conventional field surveys, digital interpretation of three-dimensional models, or photogrammetric acquisition techniques previously developed in [21]. These methodologies enable characterization of geometric and surface condition parameters of the rock mass, which serve as input variables for the system.

The evaluation is developed through a hierarchical, modular process that relates the geometric and physical conditions of the rock mass to derive a continuous slope-stability index. This approach allows the behavior of the rock mass to be analyzed by considering the combined influence of the different parameters involved in instability susceptibility.

Slope evaluation is performed by identifying and classifying geomechanical parameters observed directly in the field or through digital interpretation of the rock mass. The operator must evaluate variables related to rock mass quality, discontinuity system geometry, surface condition, and slope geometric configuration, which are entered into the evaluation environment developed for the fuzzy system. This procedure allows geomechanical site information to be organized in a structured manner and partially reduces the subjectivity associated with conventional analysis.

3.3. Hierarchical Modular Fuzzy Model

The proposed model is structured as a Mamdani-type fuzzy inference system organized under a hierarchical modular approach. The architecture comprises eleven interconnected inference modules that decompose the stability evaluation process into multiple levels of analysis, facilitating the progressive integration of geomechanical information.

Each module receives normalized geomechanical variables in the range 0 to 1, as well as intermediate outputs from other modules. The normalization process provides a common basis for comparison, since, depending on the nature of each parameter, values close to 1 may indicate either favorable or unfavorable conditions.

The model structure is defined by the following modules:

- Rock mass quality: evaluates the mechanical properties and overall quality of the rock mass based on parameters such as strength and degree of fracturing (RQD).
- Structural definition: evaluates discontinuity system characteristics, such as spacing and persistence, to represent block configuration within the rock mass.
- Discontinuity geometric condition: considers the orientation of discontinuities relative to slope geometry, evaluating their influence on slope stability.
- Discontinuity contact: analyzes the interaction between surfaces, considering variables such as aperture and roughness.
- Contact quality: evaluates the influence of infilling material on the shear strength of discontinuities.
- Surface condition: evaluates weathering and moisture conditions of discontinuities, reflecting environmental effects on stability.
- Physical condition: represents the overall physical state of the discontinuity system by integrating contact quality and surface conditions.
- Slope geometric condition: considers slope geometry, such as height and inclination, as factors influencing geometric stability.
- Block hazard: evaluates the presence and size of potentially unstable rock blocks.
- Geometric stability: integrates conditions related to discontinuity geometry, slope geometry, and block hazard.
- Global stability: represents the final output of the model, integrating all evaluated conditions to generate a continuous slope stability index.

Each module produces intermediate outputs that are progressively integrated until a global stability index is obtained, expressed as a continuous value in the range [0, 1].

The hierarchical relationship among modules and the information flow within the system are shown in Figure 1, which illustrates the model's organization and the interactions among different levels of analysis.

This structure reduces model complexity, facilitates calibration, and improves the interpretation of results by explicitly identifying each group of variables' contribution to the final stability assessment.

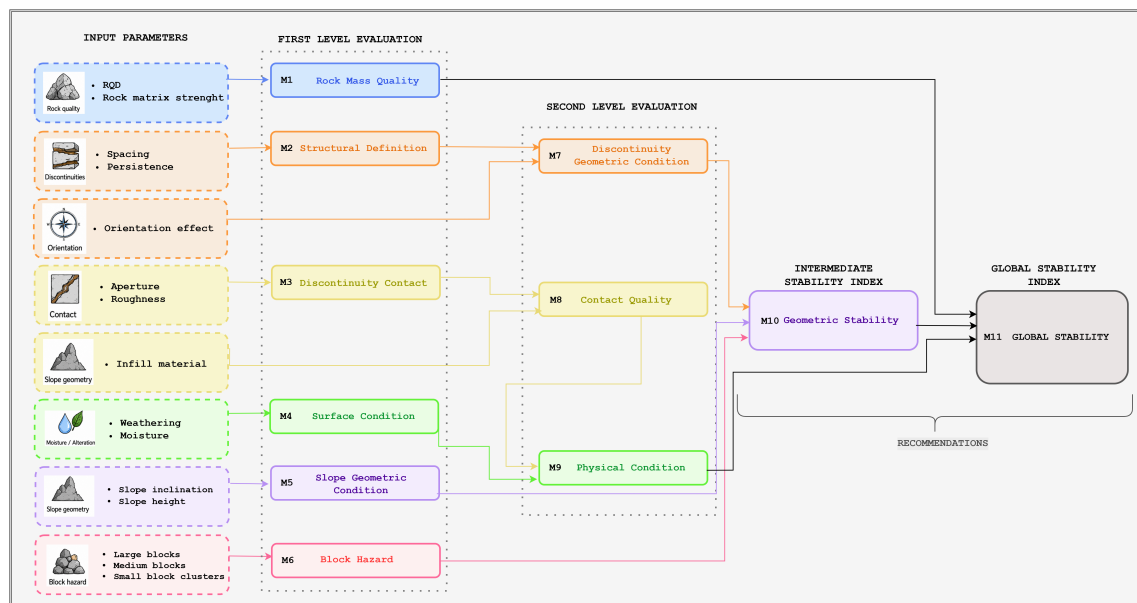


Figure 1. Hierarchical modular architecture of the proposed Mamdani fuzzy inference model for rock slope stability assessment.

3.3.1. Fuzzy Membership Functions

The model's input and output variables are represented by fuzzy membership functions defined over the normalized range [0, 1], enabling modeling of the progressive transition between different stability states.

The selection of the membership function type was based on each parameter's expected behavior and its influence on slope stability. For this purpose, different types of functions were employed, including sigmoidal, S-shaped, and Z-shaped functions, as well as Gaussian, generalized bell-shaped, and trapezoidal functions, in order to adequately represent both gradual transitions and intermediate states, as well as the extreme conditions of each parameter.

Each variable was defined using five linguistic terms, allowing a detailed representation of intermediate system conditions. However, for variables associated with block presence, only three membership functions were used, as their characterization is based on practical classification criteria commonly used in geomechanical field assessments.

For the definition of the linguistic labels and their corresponding ranges, the most commonly used geomechanical classification systems, such as RMR [3] and SMR [4], were used as reference. We used their variables as reference thresholds adapted to normalized ranges of [0, 1], maintaining consistency between the proposed model and engineering practice.

On the other hand, the overlap between membership functions was intentionally defined to represent the gradual transition between geomechanical conditions, in order to avoid abrupt changes in the evaluation results and to more realistically represent the granularity of conditions where the boundaries between states are not clearly defined.

For model implementation, the input variables were normalized within a range of 0 to 1 using a min-max normalization scheme, defined as:

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}}$$

where x is the original value of the variable, and x_{min} and x_{max} correspond to the minimum and maximum values defined for each parameter. This normalization allows all variables to be expressed within the same domain, facilitating the construction of the membership functions.

An example is presented using the variable RQD, which has an original range from 0 to 100 according to the RMR classification. This range was transformed into the normalized interval $[0, 1]$. Based on this transformation, the membership functions corresponding to the linguistic labels *Very Poor*, *Poor*, *Fair*, *Good* and *Excellent* were defined, using S-shaped and Z-shaped functions at the extremes and bell-shaped functions for the intermediate classes, as shown in Figure 2.

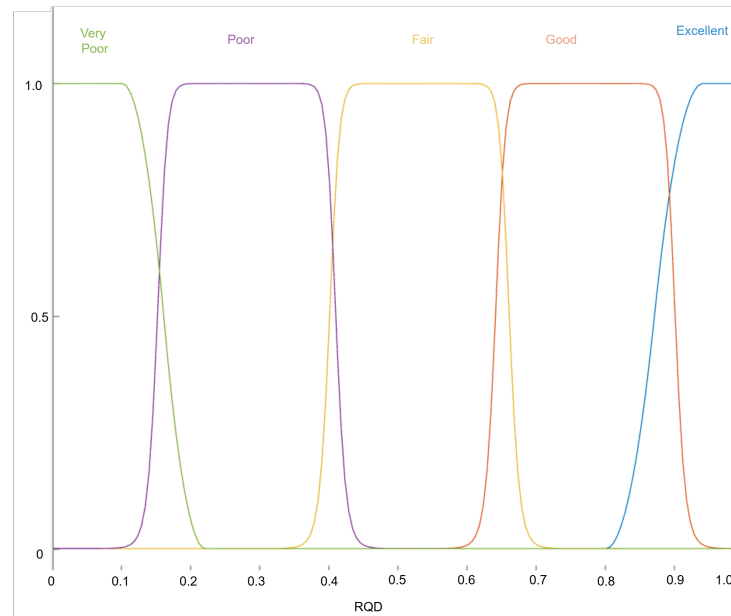


Figure 2. Membership functions defined for the RQD variable in the normalized range $[0, 1]$. Five linguistic labels (*Very Poor*, *Poor*, *Fair*, *Good*, and *Excellent*) are represented using S-shaped and Z-shaped functions at the extremes and bell-shaped functions for intermediate classes.

Additionally, the gradual overlap between classes can be observed, which allows the representation of uncertainty between categories in traditional classifications. The parameters of the membership functions were defined according to the expected geomechanical behavior.

This procedure is applied to the rest of the input variables, adjusting the parameters of the membership functions according to the nature, significance, and behavior of each variable.

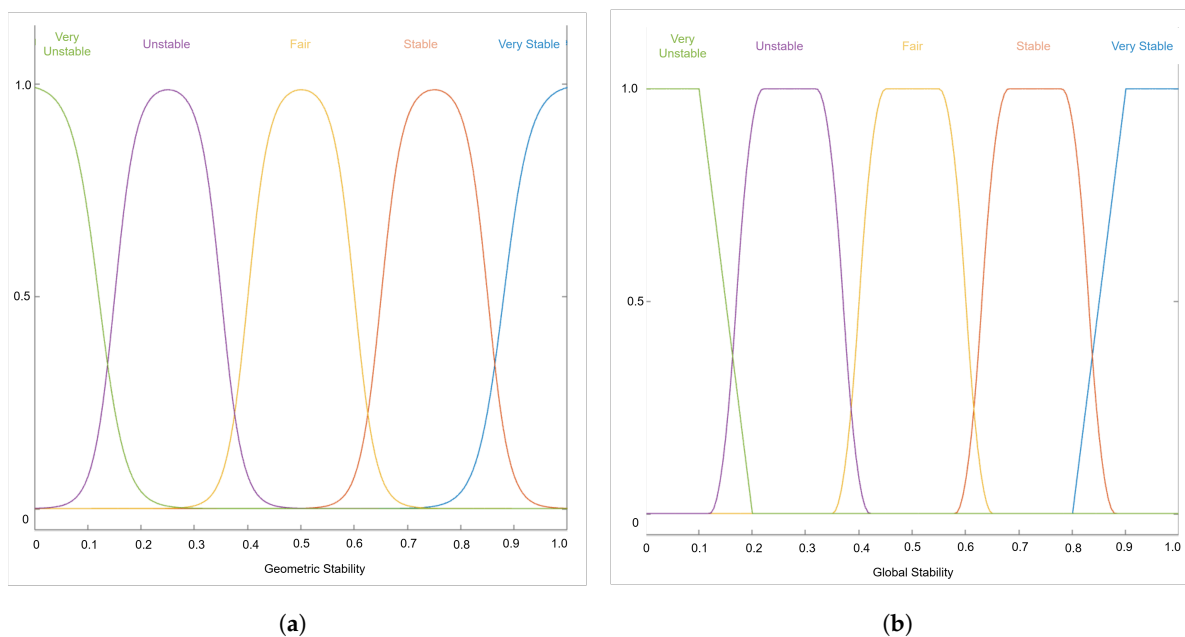
Table 2 shows the types of membership functions assigned to each input parameter of the fuzzy inference system. Additionally, an appropriate overlap between membership functions was defined to avoid abrupt transitions and to ensure a more robust inference within the system.

The membership functions defined for the output variables of the model are shown in Figure 3. These correspond to the geometric stability (a) and global stability (b) modules, where five linguistic terms are used to represent the transition between different stability conditions, taking as reference the RMR and SMR classification methods, adapting them to a normalized range of 0 to 1.

The configuration of these functions allows the obtained values to be directly related to defined stability states, showing intermediate conditions between them, which facilitates the interpretation of the model results based on the evaluated geomechanical conditions, without relying on abrupt changes between categories.

Table 2. Membership functions and linguistic labels used for the input variables of the proposed fuzzy inference model.

Parameter	Membership Function	Linguistic Labels
RQD	S-shape/Generalized bell/Z-shape	Excellent/Good/Fair/Poor/Very Poor
Strength	S-shape/Difference of sigmoids/Z-shape	Very Good/Good/Fair/Poor/Very Poor
Spacing	Sigmoid/Difference of sigmoids	Very Wide/Wide/Moderate/Close/Very Close
Persistence	Sigmoid/Difference of sigmoids	Not Persistent/Low Persistence/Moderate Persistence/Persistent/Very Persistent
Orientation effect	Sigmoid/Pi-shaped	None/Low/Moderate/High/Very High
Aperture	Sigmoid/Difference of sigmoids	None/Slightly Open/Moderately Open/Open/Very Open
Roughness (JRC)	Linear S-shape/Difference of sigmoids/Linear Z-shape	Very Rough/Rough/Slightly Rough/Undulating/Smooth
Infilling material	Sigmoid/Generalized bell	None/Hard infill < 5 mm/Hard infill > 5 mm/Soft infill < 5 mm/Soft infill > 5 mm
Weathering	Trapezoidal/Gaussian	Fresh/Slightly Weathered/Moderately Weathered/Highly Weathered/Decomposed
Moisture condition	Sigmoid/Gaussian	Dry/Slightly Moist/Moist/Dripping/Flowing Water
Slope inclination	Sigmoid/Generalized bell	Gentle/Moderately Inclined/Steep/Very Steep/Subvertical
Slope height	Sigmoid/Difference of sigmoids	Very Low/Low/Moderate/High/Very High
Large blocks	Sigmoid/Gaussian	Lower Third/Middle Third/Upper Third
Medium blocks	Sigmoid/Gaussian	Lower Third/Middle Third/Upper Third
Small blocks	Sigmoid/Gaussian	Lower Third/Middle Third/Upper Third

**Figure 3.** Membership functions for the output variables of the fuzzy model: (a) geometric stability and (b) global stability, defined in the normalized range [0, 1] using five linguistic labels (Very Unstable, Unstable, Fair, Stable, Very Stable).

3.3.2. Fuzzy Model Rules

The relationships between the model's input and output variables are defined by a set of fuzzy if-then rules that establish logical connections between geomechanical parameters and slope stability conditions.

The hierarchical modular structure allowed the problem to be decomposed into less complex inference systems, facilitating the engineering approach to generate the rules according to the specific geotechnical conditions they represent. Therefore, the rules base

was developed considering the interaction between geomechanical parameters, with the objective of representing characteristic conditions of rock slope behavior. The rules were not defined arbitrarily. We first generated the rules by considering all possible combinations, then we eliminated those that do not represent real geomechanical scenarios.

Hence, the number of rules for each module is determined by the specific combinations of real geotechnical conditions, responding to the need to adequately represent the relevant interactions among geomechanical parameters.

Likewise, the hierarchical modular structure allows the rule base to be distributed into simpler inference subsystems, avoiding the generation of excessively large sets of rules in a single system, thus reducing redundancy without affecting the consistency of the system response.

Based on this approach, the rule base was structured according to geomechanical principles and expert judgment, considering the influence of each parameter on the rock mass's mechanical behavior. In this sense, the rules represent known relationships, such as the effect of discontinuity orientation relative to the slope, the influence of surface conditions and infilling material on shear strength, and the role of block size and distribution in potential instability mechanisms.

Each rule was constructed by combining input variables using fuzzy logical operators. The AND operator represents the intersection of simultaneous conditions, enabling the evaluation of scenarios in which multiple factors jointly influence slope stability. On the other hand, the OR operator is used in unitary rules or when a single condition is sufficient to activate a system response, representing situations in which a single parameter can significantly influence stability.

Accordingly, each inference module has its own set of rules, which operate on specific groups of variables. These sets generate intermediate outputs that are progressively integrated at higher levels of the system until the geometric stability and global stability indices are obtained. In Appendix A we describe the rules of the geometric stability and global stability.

Furthermore, the rule base was designed to represent both favorable and unfavorable conditions, enabling evaluation of different stability scenarios across a wide range of geomechanical configurations.

Table 3 presents the number of rules defined for each inference module, as well as the total number of rules used in the model.

Table 3. Number of fuzzy rules defined for each inference module.

Inference Module	Number of Rules
M1. Rock mass quality	26
M2. Structural definition	25
M7. Discontinuity geometric condition	25
M3. Discontinuity contact	27
M8. Contact quality	26
M4. Surface condition	26
M9. Physical condition	27
M5. Slope geometric condition	28
M6. Block hazard	32
M10. Geometric stability	80
M11. Global stability	125
Total	447

3.3.3. Inference Mechanism and Defuzzification

Based on the previously defined rule base, the model evaluates interactions among input variables through a fuzzy inference process that integrates the slope's different geomechanical conditions.

The inference process is carried out by evaluating the fuzzy rules using the minimum operator to represent the intersection of conditions (AND) and the maximum operator to aggregate the outputs of the activated rules. This approach allows the integration of multiple conditions and the representation of parameters for slope stability.

Once the aggregated fuzzy output is obtained, defuzzification is applied to convert it into a continuous numerical value. For this purpose, the centroid method is used to compute the representative value of the resulting fuzzy set.

The model's final output is a continuous stability index in the range $[0, 1]$, where values close to 1 indicate more favorable stability conditions and values close to 0 indicate less favorable conditions.

This approach enables continuous, consistent evaluation of slope conditions by integrating information from multiple parameters within a unified analytical framework.

The proposed model was implemented using a first-order Mamdani-type fuzzy inference system, as it allows the representation of expert knowledge through linguistic rules, which is appropriate in the geotechnical context, since it enables the establishment of direct relationships between input parameters and stability conditions in linguistic terms.

Although other approaches exist, such as Sugeno-type systems, which use mathematically defined output functions, this makes their interpretation in linguistic terms more difficult and limits their direct association with specific geotechnical conditions. In addition, this type of system is commonly used in industrial process control, where computational efficiency and mathematical optimization are prioritized. Therefore, the Mamdani approach is more suitable for representing the uncertainty associated with the qualitative interpretation of geomechanical parameters.

While Sugeno-type systems may offer advantages in terms of computational efficiency, their use is less appropriate in problems where interpretability and linguistic representation are essential, such as in the geomechanical characterization of slopes, where both qualitative and quantitative parameters are involved.

On the other hand, type-2 fuzzy systems are capable of representing higher levels of uncertainty; however, they require greater computational complexity and calibration effort.

3.4. Fuzzy Model Response Analysis

The response surfaces for geometric stability and global stability modules were evaluated to analyze the behavior of the fuzzy inference mechanism and the interactions among different groups of geomechanical parameters. These surfaces allow visualization of the relationship between the rock mass's geometric and physical conditions, as well as their combined influence on slope stability.

The response surfaces reflect gradual transitions between stability stages, allowing continuous representation of variation in slope-stability behavior. This behavior is primarily associated with the system's modular and hierarchical structure.

Unlike traditional discrete approaches, surfaces generated using fuzzy logic can represent intermediate scenarios and nonlinear relationships among geomechanical variables, avoiding abrupt changes in system response due to small variations in input parameters.

3.4.1. Geometric Stability

Geometric stability integrates the influence of the geometric conditions of discontinuities, the geometric condition of the slope, and the hazard associated with potentially

unstable blocks. The geometric condition of discontinuities describes the relationship between the structural configuration of the rock mass and the orientation of discontinuities relative to the slope geometry, whereas the geometric condition of the slope considers parameters related to slope inclination and height. In turn, the block hazard module evaluates the presence and distribution of blocks susceptible to detachment within the rock mass.

Figure 4 presents the response surfaces corresponding to the geometric stability module. Surface (a) reflects the interaction between the geometric condition of discontinuities and the hazard associated with potentially unstable blocks, where geometric stability increases as the structural configuration of the rock mass improves, and the hazard related to detachable blocks decreases.

On the other hand, surface (b) shows the relationship between the geometric condition of discontinuities and the geometric condition of the slope, evidencing that unfavorable slope geometric conditions can progressively reduce geometric stability, even when the discontinuity system presents relatively favorable configurations.

Finally, surface (c) indicates that geometric stability does not depend solely on the orientation of discontinuities or on slope geometry individually, but rather on the combined interaction between these conditions and the presence of potentially unstable blocks. This behavior enables the representation of intermediate scenarios and nonlinear relationships among geomechanical variables within a continuous evaluation framework.

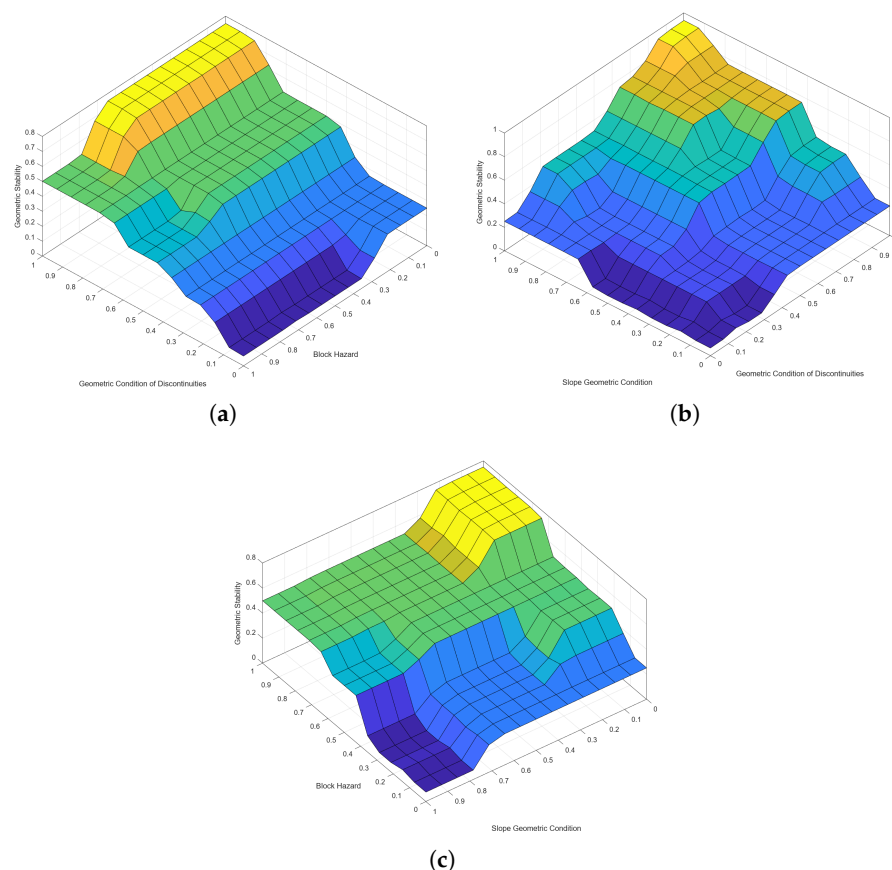


Figure 4. Response surfaces associated with the geometric stability module: (a) discontinuity geometric condition versus block hazard, (b) discontinuity geometric condition versus slope geometric condition, and (c) slope geometric condition versus block hazard.

3.4.2. Global Stability

Global stability represents the final output of the fuzzy inference system, integrating the influence of rock mass quality, the physical condition of discontinuities, and the geometric stability of the slope. Rock mass quality considers parameters related to the RQD

index and intact rock strength, while the physical condition encompasses aspects related to surface condition, infill presence, roughness, and moisture within the discontinuities.

Figure 5 presents the response surfaces corresponding to the global stability module. In general, the surfaces indicate that slope stability increases progressively as the rock mass exhibits more favorable structural, physical, and geometric conditions. Likewise, gradual transition zones between stability states can be observed, allowing intermediate scenarios to be represented within the evaluation process.

Surface (a) shows the interaction between rock mass quality and the physical condition of discontinuities. It is observed that scenarios involving poor rock mass quality and unfavorable physical conditions of discontinuities tend to lead to more critical stability states. In particular, the presence of moisture, infill, and altered surfaces progressively reduces the slope's global stability. In contrast, as the structural and physical conditions of the rock mass improve, global stability increases continuously throughout the evaluation process.

On the other hand, surface (b) reflects the relationship between rock mass quality and geometric stability. It is observed that even when the rock mass exhibits favorable quality, unfavorable geometric conditions may limit the slope's global stability. This evidence shows that stability depends not only on the structural quality of the rock mass but also on the geometric configuration and conditions associated with susceptibility to instability.

Finally, surface (c) shows the interaction between geometric stability and the physical condition of discontinuities, indicating that global stability does not depend exclusively on geometric or physical conditions evaluated in isolation, but rather on their combined interaction. This behavior allows nonlinear relationships and intermediate scenarios to be represented within the fuzzy evaluation framework.

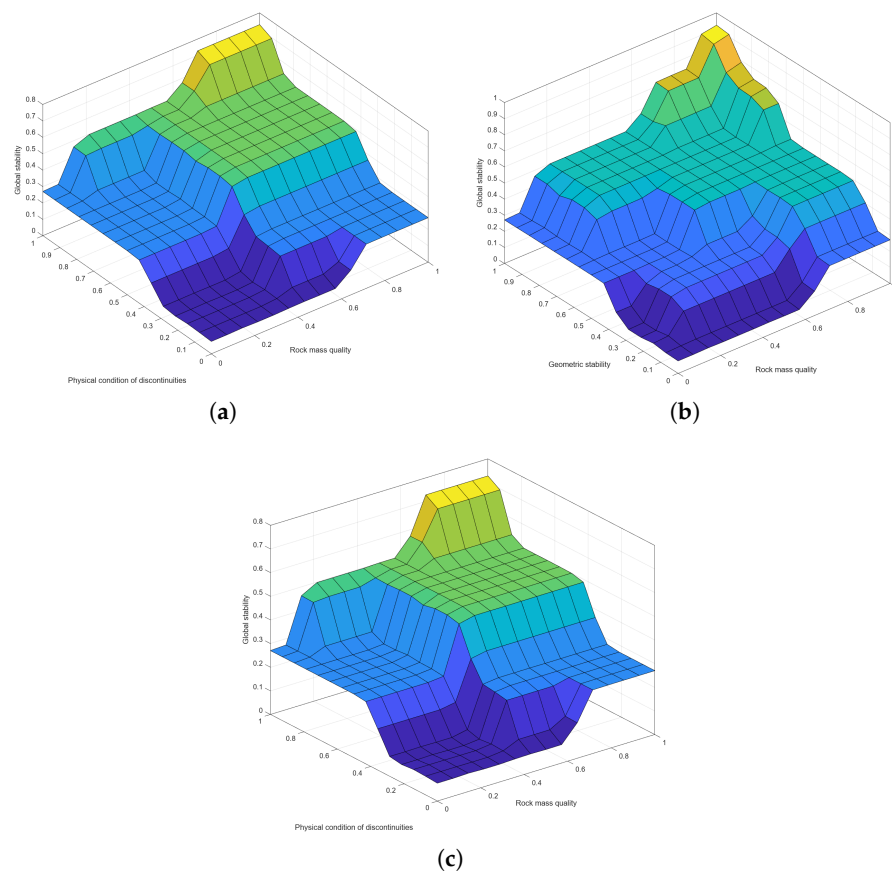


Figure 5. Response surfaces associated with the global stability module: (a) rock mass quality versus physical condition of discontinuities, (b) rock mass quality versus geometric stability, and (c) geometric stability versus physical condition of discontinuities.

3.5. Sensitivity Analysis and Sampling Strategy

A sensitivity analysis was conducted in order to evaluate the influence of the input variables on the response of the proposed model. For this purpose, a sampling scheme based on Monte Carlo simulations was employed, in which the geomechanical variables were represented using probability distributions of the normal, lognormal, beta, and uniform types; these distributions were assigned according to the nature of each geomechanical variable. From these distributions, independent random samples were generated for each variable, constructing input vectors that represent different combinations of geomechanical conditions.

Each simulation is represented by an input vector of the form:

$$\mathbf{x}^{(k)} = [x_1^{(k)}, x_2^{(k)}, \dots, x_{15}^{(k)}] \quad (1)$$

where each variable $x_i^{(k)}$ is sampled from a probability distribution $f_i(\theta_i)$, i.e:

$$x_i^{(k)} \sim f_i(\theta_i) \quad (2)$$

Two analysis approaches were considered: (1) 5000 random samples were generated, considering five conditioned scenarios associated with the five labels of the final model output (Very Stable, Stable, Fair, Unstable, Very Unstable); (2) 10,000 unconditioned random samples were generated.

The number of samples for each approach was defined based on a 95% confidence level, using the following expression for the sample size:

$$n = \left(\frac{Z \cdot \sigma}{E} \right)^2 \quad (3)$$

where n is the number of samples, Z is the value associated with the confidence level ($Z = 1.96$ for 95%), σ is the standard deviation, and E is the allowable error.

The confidence level is related to the confidence interval defined as:

$$CI = \bar{x} \pm Z \cdot \frac{\sigma}{\sqrt{n}} \quad (4)$$

Each set of samples was evaluated using the proposed hierarchical fuzzy model, obtaining as output the geometric stability and global stability indices.

Subsequently, the influence of the input variables on the model output was quantified using the Spearman rank correlation coefficient, defined as

$$\rho = 1 - \frac{6 \sum d_i^2}{n(n^2 - 1)} \quad (5)$$

where d_i represents the difference between the ranks of the input variable and the model output. The magnitude of ρ was used to interpret the level of influence, where values close to 0 indicate low influence and values close to 1 indicate high influence.

4. Results

The results presented in this section are organized into three parts. The first part presents the results obtained from extracting geomechanical parameters using UAV photogrammetry. The second part applies the proposed model to three real case studies with different geomechanical conditions. Finally, the third part presents a comparison of the results obtained with the proposed model and those from traditional geomechanical classi-

fication systems. In general, the purpose is to analyze the model's behavior, the consistency of the results, and the coherence of the recommendations with respect to the geomechanical conditions identified during the evaluation process.

The three case studies correspond to road rock slopes located in the state of Michoacán, México. Table 4 summarizes the geographic location of each case study using UTM coordinates. Cases 2 and 3 are located along the same road corridor, whereas the first case was previously characterized in earlier work [21].

Table 4. Geographic location of the three case studies using UTM coordinates.

Case	Road Section	UTM Easting (m)	UTM Northing (m)	UTM Zone
Case 1	Former State Highway No. 171, Morelia–Pátzcuaro	262,935.56	2,171,905.92	14 N
Case 2	Cuitzeo–Pátzcuaro toll highway, km 12+200–13+000	260,819.90	2,194,426.54	14 N
Case 3	Cuitzeo–Pátzcuaro toll highway, km 12+600–12+800	260,831.11	2,194,258.75	14 N

The case studies correspond to road slopes located in a region classified as seismic zone C (moderate) according to the national regionalization [23]. The proposed model focuses on analyzing instability susceptibility based on observable geomechanical conditions. In this sense, the study is oriented toward its application in road slopes under representative service conditions, rather than in extreme scenarios such as high mountain environments or regions with intense seismic activity.

Therefore, the model should be interpreted as a tool for geomechanical susceptibility assessment and not as a slope stability analysis under dynamic conditions.

To provide spatial and visual context for the analyzed cases, Figure 6 presents the location of the three slopes along with their corresponding field views. These images allow the identification of slope geometry and features that show material accumulation at the slope toe.

As shown in Figure 6, different conditions can be observed among the analyzed cases. In Case 1, discontinuities with apertures are identified, indicating a reduction in the degree of contact between discontinuity planes. In Cases 2 and 3, accumulation of detached material and blocks is observed at the slope toe, indicating the presence of block instability conditions. These observations are consistent with the approach of this work, which is based on the evaluation of instability susceptibility through the interaction of geomechanical conditions.

To demonstrate the quality of the photogrammetric models used in this work, Table 5 presents the main characteristics of the models generated for each case study, including ground resolution (GSD), the quality of the generated point clouds, the georeferencing method used, and the reprojection error.

Table 5. Main characteristics of the photogrammetric models generated for each case study.

Case	GSD (cm/Pixel)	Point Cloud Quality	Georeferencing	Reprojection Error (px)
Case 1	0.23	High	GCPs + total station	0.68
Case 2	1.24	High	PPK + GCPs	0.86
Case 3	1.24	High	PPK + GCPs	0.86

As shown in Table 5, the models present sufficient resolution for the geomechanical characterization of the analyzed slopes, as the GSD values allow the identification of discontinuities and surface conditions. The quality of the point clouds was high in all cases, allowing an adequate representation of the rock mass for analysis.

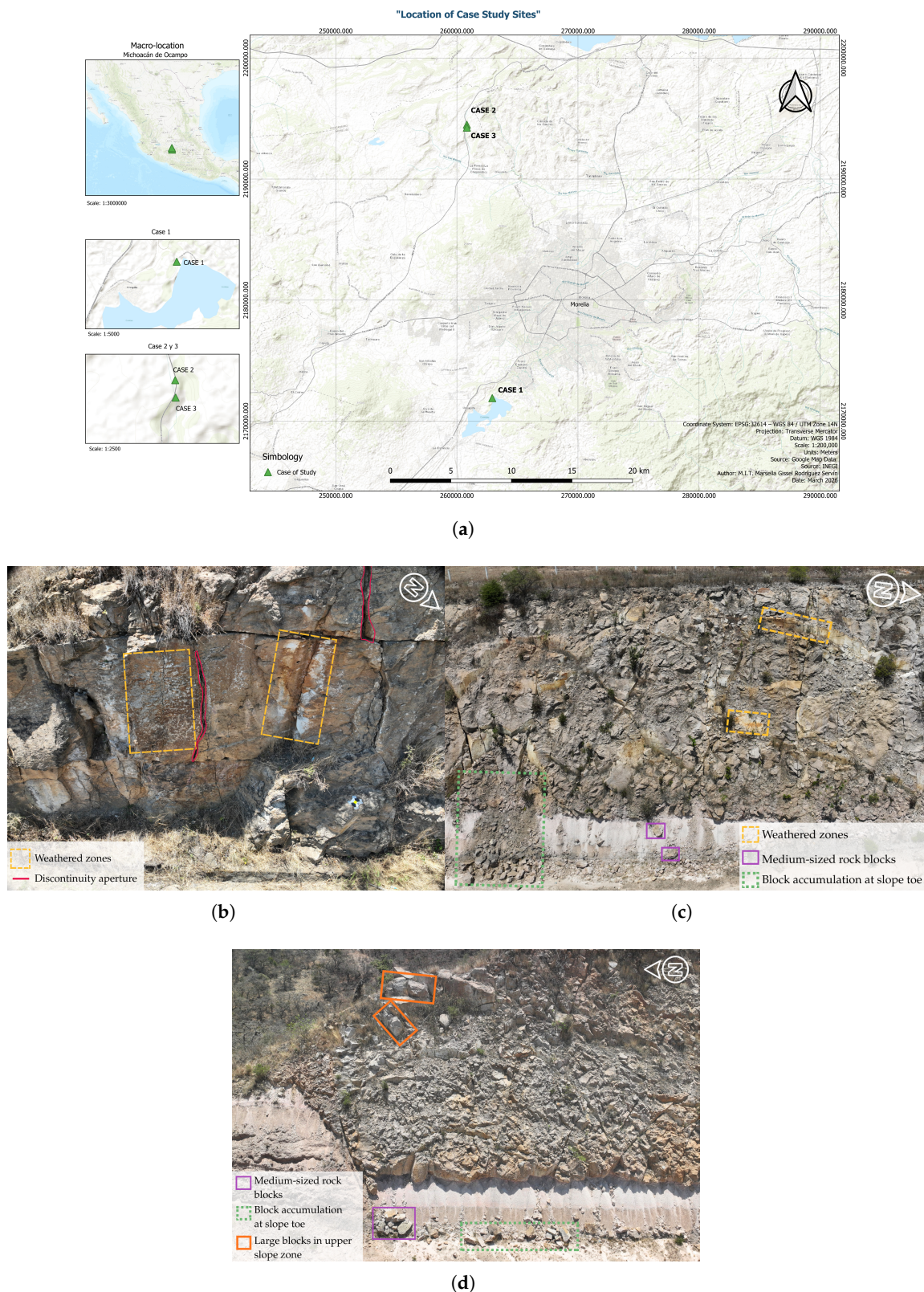


Figure 6. Location of the analyzed slopes and corresponding field views. (a) Map showing the spatial distribution of the three case studies. (b) Field views of Case 1, highlighting fracture apertures (red) and weathered zones (yellow). (c) Field view of Case 2, showing weathered zones (yellow), medium-sized rock blocks (purple), and block accumulation at the slope toe (green dashed area). (d) Field view of Case 3, illustrating large blocks in the upper slope (orange), medium-sized rock blocks (purple), and block accumulation at the slope toe (green dashed area), reflecting conditions associated with instability susceptibility and material transport toward the slope base.

For georeferencing, different methods were used according to the survey conditions, including the use of ground control points (GCPs) and PPK positioning, obtaining low reprojection error suitable for geomechanical characterization.

In Cases 2 and 3, these were processed as part of the same photogrammetric model due to their proximity, which explains the identical values of resolution and reprojection error.

Case 1 corresponds to a rock slope located along the former State Highway N° 171 between Morelia and Pátzcuaro, in the state of Michoacán, México. The slope has an approximate length of 100 m and a maximum height of about 14 m.

Case 2 corresponds to a rock slope located along the Cuitzeo-Pátzcuaro toll highway in the state of Michoacán, México, between km 12+200 and km 13+000. The slope has an approximate length of 700 m and a maximum height of about 25 m. Due to its dimensions, the geomechanical characterization was carried out using a representative analysis window approximately 100 m long. During the field inspection, no significant variations in lithology or geomechanical characteristics of the rock mass were identified; therefore, the selected window was considered representative of the predominant conditions at the site.

Case 3 corresponds to a rock slope located along the Cuitzeo-Pátzcuaro toll highway in the state of Michoacán, México, between km 12+600 and km 12+800. The slope has an approximate length of 200 m and a maximum height of about 20 m.

4.1. Geomechanical Characterization from Photogrammetric Products

The photogrammetric products enabled the extraction of the geomechanical parameters required to implement the proposed model. To achieve this, the methodology proposed in a previous work [21] for extracting geomechanical parameters from three-dimensional digital models was followed, enabling the extraction of information on the discontinuity system, slope geometry, and surface conditions.

For the three case studies, photogrammetric products were generated from images acquired with a DJI Mavic 3M UAV to obtain both general information about the study site and detailed information from the slope face. Two types of flights were carried out: (1) a programmed double-grid flight aimed at capturing general information about the site, and (2) a detailed manual flight over the slope surface. During image acquisition, environmental conditions suitable for flight operations were considered, along with flight parameters such as flight altitude, camera inclination angle, GSD, and image overlap percentage.

The acquired images were processed to generate photogrammetric products, including point clouds, triangular meshes, and textured models, for each case study. These products formed the basis for extracting the geomechanical parameters required for the evaluation.

For point clouds, a preprocessing stage was performed in which the slope surface area was delineated, vegetation was filtered, and point cloud density was reduced before processing with DSE. This tool employs clustering algorithms to identify the main discontinuity sets, enabling analysis of the discontinuity system's influence on slope geometry.

Furthermore, products such as triangular meshes and textured models enabled digital measurements to obtain parameters such as persistence, spacing, aperture, slope height, and slope dip. Likewise, they facilitated the identification of potentially unstable blocks and surface alteration. In addition, Digital Elevation Models (DEMs) were used to estimate the average Joint Roughness Coefficient (JRC) of the rock surface.

The multispectral images enabled the generation of spectral indices. In this study, the NDWI (Normalized Difference Water Index) was employed, and its results were interpreted using the ranges established by [22] for classifying moisture conditions, thereby identifying the site's moisture condition. With these elements, the geomechanical parameters required to implement the proposed model were finalized.

From the photogrammetric products, it was possible to identify the main discontinuity sets and determine their dip direction and dip orientation, information that forms part of the geomechanical characterization of the three case studies, which also allowed the analysis of their behavior.

Additionally, a kinematic analysis of the slope was performed based on the identified discontinuity sets, with the objective of identifying potential failure mechanisms. This analysis was used as a complementary reference for the application of the SMR classification and for developing the comparison between methods.

In contrast, the proposed model considers qualitative variables related to the interaction between the overall slope geometry and the discontinuity system, which allows the evaluation of instability susceptibility.

The three case studies correspond to road rock slopes developed in ignimbrite. Although they share the same lithology, they exhibit different dip directions and dip orientations of the main discontinuity sets. These differences constitute one of the main factors influencing susceptibility to instability and justify evaluating the proposed model under different geomechanical scenarios.

Table 6 summarizes the dip direction and dip orientation of the main discontinuity sets identified in each case study, together with a general description of the configuration observed at each site.

Table 6. Main discontinuity sets identified in the three case studies.

Case	Set	Dip Direction (°)	Dip (°)	General Configuration
Case 1 Slope 050°/74°	J1	51	76	Six discontinuity sets were identified, three of which exhibit orientations approximately parallel to the slope face toward the roadway, representing a potentially unfavorable geometric condition.
	J2	64	87	
	J3	39	83	
	J4	10	75	
	J5	243	89	
	J6	201	85	
Case 2 Slope 056°/54°	J1	079	36	Three discontinuity sets were identified, whose orientations are approximately parallel to the slope face, representing an unfavorable geometric condition.
	J2	080	82	
	J3	050	79	
Case 3 Slope 284°/48°	J1	279	37	Three discontinuity sets were identified, two of which exhibit orientations approximately parallel to the slope face, representing an unfavorable geometric condition.
	J2	295	87	
	J3	258	82	

The identification and interpretation of the main discontinuity sets enabled the determination of qualitative parameters, such as the orientation effect. In addition, the photogrammetric products enable the determination of geometric, physical, and geomechanical properties through digital measurements, observations, and interpretations, while the rock strength parameter was obtained from laboratory test. Together, these parameters are used as input variables for the fuzzy inference system.

Table 7 summarizes the geomechanical parameters obtained for each of the three case studies. These parameters correspond to the input values used during the evaluation process of the proposed model.

In general, the three case studies exhibit differences in geometric parameters, such as spacing, persistence, orientation effect, and block distribution, whereas parameters including aperture, roughness, infill type, weathering degree, and moisture condition present similar values. These differences represent different scenarios that were used to evaluate the performance of the proposed model.

Table 7. Geomechanical input parameters used for the evaluation of the three case studies.

Parameter	Case 1	Case 2	Case 3
RQD	67%	73%	72
Uniaxial compressive strength (MPa)	47	100	100
Spacing (m)	1.03	0.60	0.33
Persistence (m)	1.87	2.81	4.15
Orientation effect	Moderate	High	Moderate
Aperture (mm)	50	50	50
Roughness (JRC)	9	8	8
Infill	Hard < 5 mm	Hard < 5 mm	Hard < 5 mm
Weathering	Moderately weathered	Moderately weathered	Moderately weathered
Moisture	Dry	Dry	Dry
Slope inclination (°)	74	54	48
Slope height (m)	14.0	25	20
Large block (l/L)	0.00	0.00	–
Medium block (l/L)	0.00	0.00	0.80
Small block (l/L)	0.00	2.18	1.80

4.2. Application to Real Rock Slopes

To evaluate the performance of the proposed model under different geomechanical conditions, the fuzzy inference system was applied to three road rock-slope case studies. The first case corresponds to a slope previously characterized in earlier work [21], whereas the remaining two cases correspond to slopes located along the same road corridor. All three cases were characterized using UAV photogrammetry and digital visual inspection following the same methodology implemented in the previous study. Parameters related to the geometric configuration of the discontinuity, the physical conditions of the rock mass, and slope geometry were obtained and used as input for variables for the evaluation process.

The three case studies located within the Trans-Mexican Volcanic Belt correspond to rock slopes developed in ignimbrite volcanic deposits. This provides a common geological framework for evaluating the proposed model's performance under varying geomechanical conditions.

Due to the dimensions of the slopes corresponding to Cases 2 and 3, discontinuity characterization was performed using a representative analysis window. This approach allowed the predominant discontinuity sets to be identified and their geometric relationship with the slope orientation to be evaluated. The remaining geomechanical parameters were obtained based on the general conditions observed at each study site.

Subsequently, the obtained parameters were entered into the evaluation environment developed for the fuzzy inference system, which internally performs variable normalization to execute the fuzzy inference process. This facilitates the application of the model by allowing the user to directly use the real values of the geomechanical parameters, obtaining a stability index ranging from 0 to 1, as well as recommendations related to the geomechanical conditions identified at the final evaluation level. Table 8 summarizes the results for the three case studies and compares them with the traditional methods (RMR and SMR), providing an overall view of the evaluation before the individual analysis of each case study.

It is important to note that the comparison presented in Table 8 does not represent an equivalence between methods, as they evaluate different aspects of slope behavior. The RMR method focuses on defining a rock mass quality class, while SMR is used as a complement to RMR, evaluating slope stability based on specific failure mechanisms and

geometric relationships. In contrast, the proposed model evaluates instability susceptibility by considering the interaction of multiple geomechanical conditions.

Table 8. Comparison of results obtained using traditional methods and the proposed model.

Assessment Result	Case 1	Case 2	Case 3
Traditional methods			
RMR basic classification	Fair	Good	Fair
RMR corrected (slope)	Class IV—Poor	Class V—Very poor	Class IV—Poor
SMR classification	Class II—Good, Stable	Class III—Normal, Partially unstable	Class II—Good, Stable
Proposed model			
Geometric stability	Fair (0.4977)	Fair (0.4973)	Unstable (0.2584)
Global stability	Very unstable (0.0791)	Very unstable (0.1269)	Very unstable (0.0792)
Model recommendations	Comprehensive stabilization assessment, drainage control, and evaluation of geometric redesign	Shotcrete reinforced with steel mesh and anchors, drainage system, and evaluation of geometric redesign	Shotcrete reinforced with steel mesh and anchors, drainage system, and evaluation of geometric redesign

The results obtained from the model tend to be more conservative, as it integrates both geometric and physical conditions that influence slope behavior. The model considers elements such as the presence of detached blocks at the slope toe and discontinuities with visible apertures, which reveal conditions that are not fully captured by classification methods such as RMR or SMR.

Therefore, the variation observed between the results does not represent an inconsistency, but rather a difference in the evaluation approach, where the proposed model allows the identification of conditions that are susceptible to generating some type of movement within the slope.

4.2.1. Case 1

Figure 7 shows the three-dimensional model obtained through photogrammetry (a), together with the main discontinuity planes identified during the characterization process (b). These results enabled evaluation of the rock mass's structural configuration and provided the information required to assess stability using the proposed model.

The geomechanical parameters obtained during slope characterization are presented in Table 7. Moderate weathering conditions and low moisture presence were identified within the rock mass. Likewise, the orientation effect was classified as moderate because, although six discontinuity sets were identified, some exhibited orientations subparallel to the slope face and directed toward the roadway, increasing susceptibility to instability. In general, the slope exhibits moderate fracturing conditions, although slope geometry appears to be one of the main factors controlling geometric stability at this site.

The results obtained through the fuzzy inference system are presented in Table 8. The results for geometric and global stability indicate that geometric stability was classified as fair, whereas global stability was classified as very unstable.

This difference indicates that although the slope's geometric configuration exhibits intermediate stability, the overall system response is dominated by the combination of geometric conditions and the rock mass's physical condition. In this particular case, the presence of weathering, discontinuities with apertures on the order of 50 mm, infill material, and low intact rock strength values contributed to the progressive reduction of global slope stability.

These results are consistent with the characteristics observed during the geomechanical characterization, where several discontinuity families with potentially unfavorable orientations and evidence of surface degradation were identified. Consequently, the system

activated recommendations to improve rock mass conditions, control water infiltration, and evaluate possible modifications to the slope geometry.

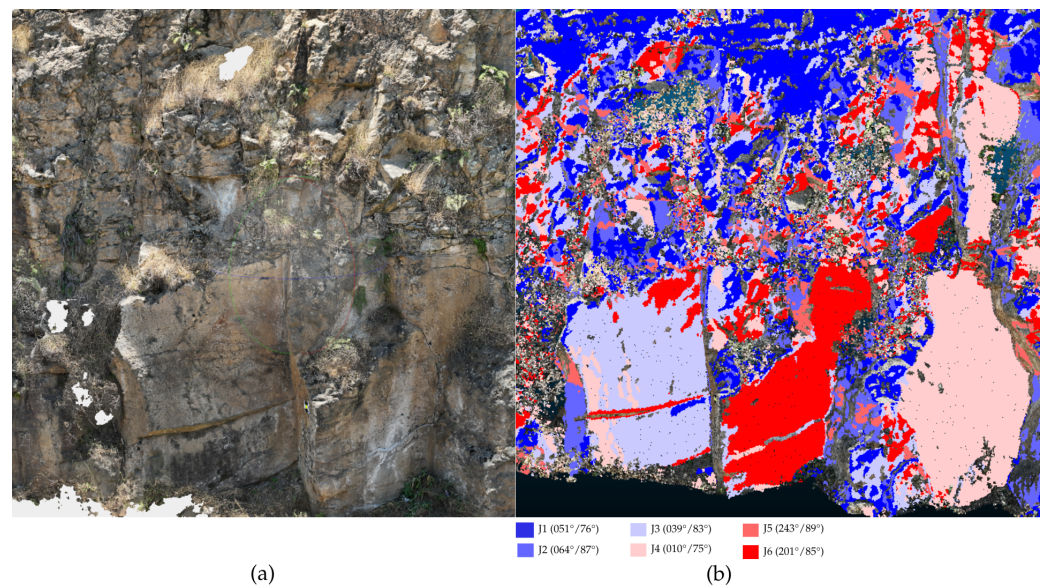


Figure 7. Structural characterization of case study 1: (a) photogrammetric model and (b) segmented point cloud showing the discontinuity sets identified during the structural analysis.

4.2.2. Case 2

Figure 8 shows the three-dimensional model obtained through photogrammetry (a), together with the main discontinuity planes identified during the characterization process (b). A volcanic ash layer is present at the toe of the slope, partially covering the rock mass. The digital model enabled the slope configuration to be analyzed, the predominant discontinuity sets to be identified, and the geomechanical parameters required for evaluation to be extracted using the fuzzy inference system.

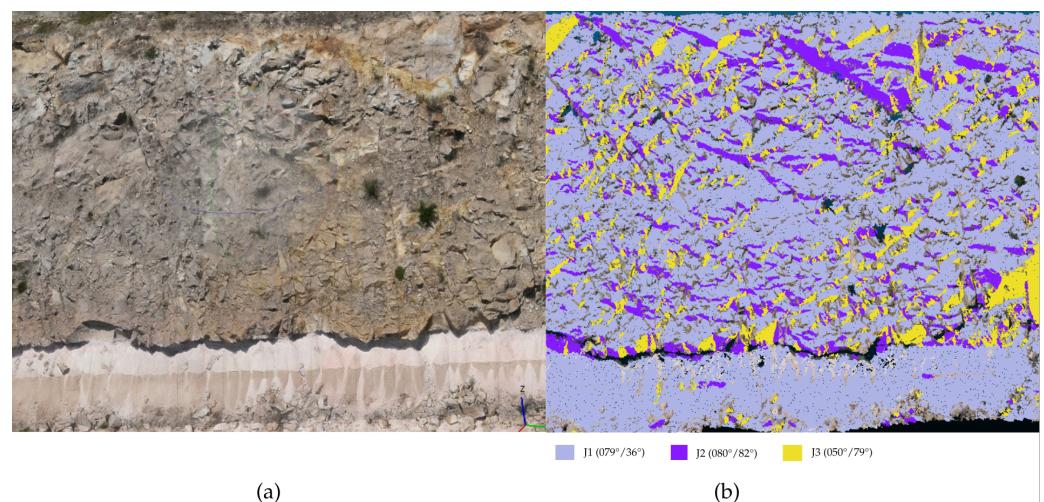


Figure 8. Structural characterization of case study 2: (a) photogrammetric model and (b) segmented point cloud showing the discontinuity sets identified during the structural analysis.

The geomechanical parameters obtained during the characterization are presented in Table 7. In general, the parameters indicate a moderately fractured and weathered geomechanical configuration. However, the orientation effect was classified as high due to the presence of discontinuity sets with directions similar to the slope orientation. Although

the dip angles differ from those of the slope face, the observed geometric relationship increases susceptibility to the development of instability mechanisms.

The results obtained through the fuzzy inference system are presented in Table 8. The geometric stability was classified as fair, whereas the global stability condition was classified as very unstable. The intermediate modules indicate that the physical condition of the rock mass was classified as very poor, primarily due to the quality of the discontinuity contacts. On the other hand, both the geometric condition of the discontinuities and the geometric condition of the slope were classified as fair, indicating that the geometric configuration of the site is not primarily controlled by the physical conditions associated with discontinuity contact.

Consequently, the system generated recommendations for a comprehensive intervention, including surface treatments with shotcrete reinforced with steel mesh and anchors, infiltration control through drainage systems, and evaluation of potential geometric modifications, subject to right-of-way availability.

4.2.3. Case 3

The Figure 9 shows the photogrammetric model (a) and the discontinuity analysis, in which several discontinuity sets with different orientations and dip angles were identified. The interaction among these sets favors instability mechanisms associated with block detachment and wedge formation. During the inspection, a significant accumulation of small and medium-sized rock fragments was observed at the toe of the slope, indicating rockfalls.

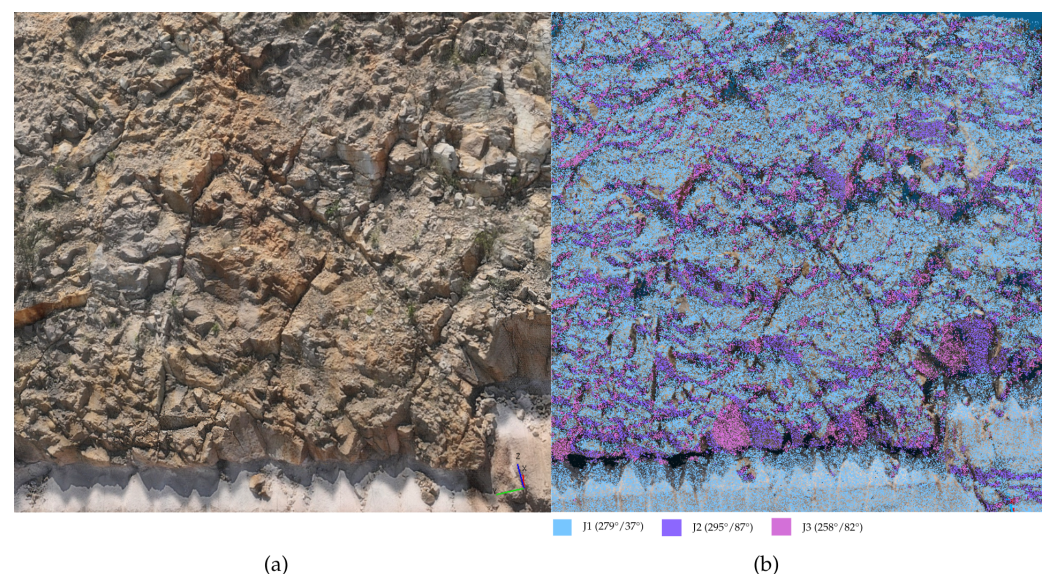


Figure 9. Structural characterization of case study 3: (a) photogrammetric model and (b) segmented point cloud showing the discontinuity sets identified during the structural analysis.

The geomechanical parameters obtained during characterization are presented in Table 7, which shows the presence of open and persistent discontinuities. Likewise, the geometric relationship between certain discontinuity sets and the slope orientation favors the development of, and susceptibility to, instability mechanisms associated with block detachment and wedge formation. Although the surface conditions of the rock mass do not indicate severe weathering, the observed geomechanical configuration increases the susceptibility to rockfalls.

The results of the evaluation process using the fuzzy inference system are presented in Table 8. Geometric stability was classified as unstable, while global stability was very unstable. The intermediate modules indicated that rock mass quality was classified as

fair, whereas structural definition and the geometric condition of discontinuities were classified as poor. Likewise, contact quality was very poor, resulting in a very poor physical condition of the slope. On the other hand, the geometric conditions of the slope were classified as good; however, the combined influence of the structural configuration on geometric stability resulted in an unstable condition.

Therefore, in this case, the low global stability is primarily controlled by the interaction between the physical condition and contact characteristics of the discontinuities rather than by the overall slope geometry. Consequently, the system activated recommendations for a comprehensive intervention, proposing surface treatments using shotcrete reinforced with mesh and anchors, drainage systems to control infiltration, and evaluation of potential geometric modifications contingent on right-of-way availability.

4.3. Comparison of Results Between Methods

In this comparison, it is important to note that the proposed model is not intended to replicate traditional classifications (RMR and SMR) through fuzzy inference; rather, the approach developed in this study focuses on evaluating instability susceptibility based on the interaction of multiple geomechanical conditions.

Although the model incorporates several of the geomechanical parameters and their corresponding ranges used in the RMR and SMR classifications, the way in which these are evaluated and interact within the system is what establishes the difference. Therefore, the comparison is presented as a general reference that allows contrasting the differences between discrete classification approaches and the proposed continuous susceptibility index, rather than as a direct validation of equivalence between methods.

For the three case studies, RMR and SMR classifications were performed to compare the results with those obtained using the proposed model. Table 7 presents the results of the three approaches using the same geomechanical information obtained during the characterization of each case study.

The RMR and SMR systems are based on discrete classification ranges, whereas the proposed model provides continuous stability indices that reflect the susceptibility to movement derived from the interaction of geomechanical parameters.

For the RMR system, both the basic classification (RMRb) and the corrected RMR were considered. The basic classification does not account for the influence of discontinuity orientation relative to the analyzed structure, whereas the corrected RMR incorporates the specific corrections used for slope assessment.

The results show that cases 1 and 3 maintained the same classification in both the basic and corrected RMR, although the final values decreased. In contrast, case 2 exhibited the greatest effect of the orientation correction, resulting in the most unfavorable classification among the three cases.

For the SMR system, it is important to note that it depends on the results of the basic RMR and requires correction factors for the geometric relationship between discontinuities and the slope, given the failure mechanism evaluated through kinematic analysis. The results show that condition, whereas case 2 was classified as Class III, corresponding to a normal and partially unstable condition.

However, the difference observed in case 2 was mainly due to a more unfavorable geometric condition for the failure mechanism under consideration, resulting in a greater penalty during the SMR correction process. In contrast, in cases 1 and 3, the correction factors had less influence on the final classification, allowing both slopes to remain stable.

On the other hand, the proposed model exhibited different behavior from the RMR and SMR classifications, as the global stability of all three case studies was classified as very unstable, even though the geometric stability conditions differed among the evaluated sites.

As shown in Table 8, cases 1 and 2 reached very similar geometric stability values, corresponding to a fair condition, whereas case 3 was classified as unstable. However, all three evaluations yielded a highly unstable global stability condition. This demonstrates that the final system response is not determined solely by slope geometry or discontinuity orientation, but also by the interaction of the different geomechanical parameters considered within the various evaluation levels of the proposed model.

Regarding intervention recommendations, differences were also observed between the evaluated methods. In the SMR method, recommendations are associated with specific classification ranges; therefore, Cases 1 and 3 yielded similar measures because they fell into the same stabilization category. In contrast, the proposed model generates recommendations based on the physical, geometric, and drainage conditions identified during the evaluation process.

In general, the results show that both stability classifications and recommendations may vary considerably depending on the approach employed, even when the same geomechanical information is used as the basis for the analysis. Likewise, the results indicate that susceptibility to instability depends not only on discontinuity orientation or slope geometry but also on interactions among the geomechanical factors considered in the evaluation process.

5. Discussion

5.1. Comparison of Traditional Classification Methods and the Proposed Model

Table 9 presents important differences between the traditional methods (RMR and SMR) and the proposed model. It can be observed that the RMR method is an empirical evaluation that assigns discrete values to geomechanical parameters related to discontinuity characteristics, degree of fracturing, intact rock strength, and moisture conditions. The sum of these ratings provides an overall rock mass quality value.

However, each parameter is evaluated independently and then incorporated additively, so the interaction among variables is not explicitly represented. This limits the method's applicability to situations in which multiple unfavorable conditions may occur simultaneously and influence the behavior of the rock mass. In addition, the use of discrete ranges generates abrupt transitions between classification categories, causing relatively small differences in parameter values to produce significant changes in the final classification.

The RMR and SMR methods are commonly used in a complementary manner, since SMR uses the classification obtained from basic RMR as its basis. Their main differences lie in the fact that SMR explicitly incorporates the influence of discontinuity orientation on the slope geometry through correction factors associated with the failure mechanism identified during the kinematic analysis.

On the other hand, the model developed in this work employs a hierarchical modular fuzzy inference system, in which each module represents a particular geotechnical concept based on the interaction of different geomechanical parameters. For example, the structural definition is determined by geometric parameters such as discontinuity spacing and persistence, constituting a first level of evaluation. Subsequently, the result of this evaluation is used as an input variable in successive evaluation modules until the global stability condition is obtained.

This allows the evaluation to go beyond a final stability classification and facilitates the interpretation of the factors that contribute to susceptibility to instability. In this way, it is possible to identify which groups of parameters exert the greatest influence on the resulting condition and to relate the obtained results to potential intervention measures.

On the other hand, the results reveal significant differences between the traditional methods and the proposed model. Our proposal is an assessment approach that integrates multiple geomechanical parameters to represent susceptibility to instability. This allows recommendations to be generated from different levels of evaluation, relating the identified conditions to potential intervention measures. However, to better understand the model's internal behavior and the influence of parameters during evaluation, it is necessary to analyze the sensitivity of its response.

Table 9. Methodological comparison between RMR, SMR, and the proposed model.

Aspect	RMR	SMR	Proposed Model
Method type	Empirical classification	Empirical classification with geometric correction	Hierarchical modular fuzzy inference system
Evaluation approach	Rock mass quality	Stability assessment based on kinematic analysis and rock mass quality	Stability assessment based on the susceptibility of conditioning factors
Variable integration	Sum of independent ratings	Basic RMR with correction factors	Integration through fuzzy rules
Variable interaction	Not explicitly considered	Partially considered	Explicitly represented through fuzzy inference
Variable representation	Discrete ranges	Discrete ranges and adjustment factors	Continuous membership functions
Output type	Rock mass quality class	Slope stability class for specific failure mechanisms	Continuous stability index
State transition	Abrupt	Abrupt	Gradual
Uncertainty handling	Limited	Limited	Explicitly represented through fuzzy logic
Intermediate evaluations	No	No	Yes
Interpretation of influential factors	Limited	Moderate	High
Consideration of slope orientation	Indirectly considered	Explicitly considered through correction factors	Integrated within the geometric assessment
Recommendation generation	Associated with classification ranges	Associated with failure mechanisms and classification ranges	Conditioned by the stability state and the evaluated parameters
Inspection coverage	Limited to accessible areas	Limited to accessible areas	Compatible with partial or complete slope coverage
Data acquisition method	Traditional field survey	Traditional field survey	Traditional field survey, digital inspection, or UAV-based photogrammetry
Dependence on evaluator judgment	Moderate	High	Moderate–Low
Automation potential	Low	Low	High

5.2. Sensitivity Analysis

A sensitivity analysis was conducted to assess the relative influence of the input parameters on the main outputs of the fuzzy inference system. The Spearman correlation coefficient was used to assess the relationship between the normalized geomechanical parameters and the model's stability responses.

In general, the results from the sensitivity analysis indicate that the model responds consistently to the geomechanical conditions represented at each evaluation level, allowing the identification of the groups of variables with the greatest influence within the fuzzy assessment tool.

In the case of geometric stability shown in Figure 10, the variables with the highest sensitivity mainly correspond to the discontinuity orientation effect, slope inclination, and slope height. Likewise, parameters such as discontinuity spacing and persistence also make important contributions to the system response. This indicates that geometric stability is primarily governed by the relationship between the rock mass's structural configuration and the slope geometry, consistent with geometric conditions associated with susceptibility to slope movement.

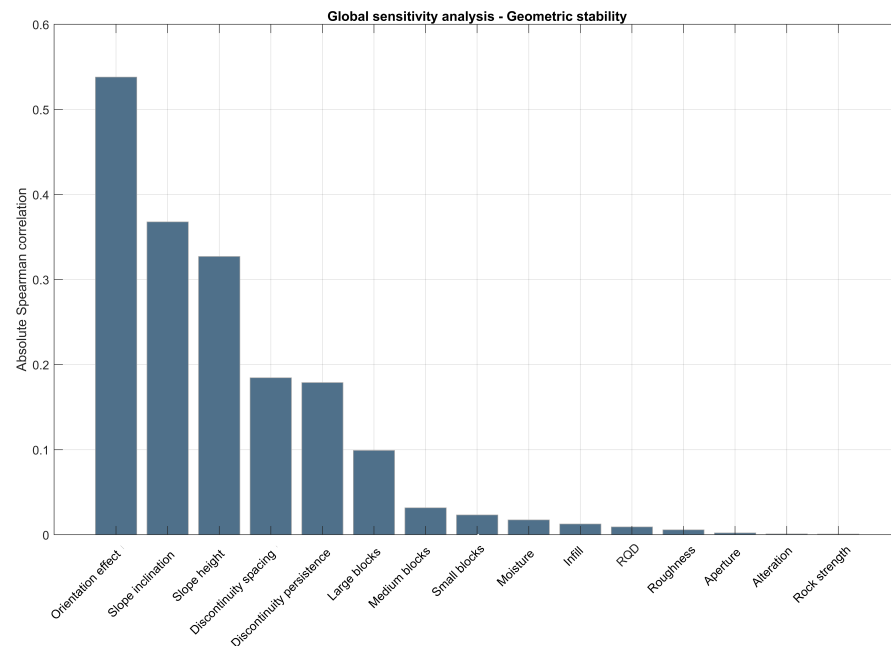


Figure 10. Global sensitivity analysis associated with the geometric stability module, showing the relative influence of geomechanical parameters on the system response.

On the other hand, parameters related to the physical conditions of discontinuities, such as alteration, moisture, infill, and roughness, show a much lower influence within this module. This is because geometric stability is primarily intended to represent the relationship between slope geometry and the configuration of the discontinuity system.

In contrast, the sensitivity corresponding to global stability shown in Figure 11 presents a different distribution of influence among variables. In this case, moisture, alteration, orientation effect, RQD, and the presence of infill material present the highest sensitivity values within the system response.

This behavior reflects that global stability depends on the combined integration of geometric, structural, and physical conditions of the rock mass. In particular, the high sensitivity to moisture and alteration indicates the influence of physical degradation processes on slope stability, while variables such as RQD and the orientation effect continue to make important contributions due to their relationships with the structural quality and geometric susceptibility of the rock mass.

In general, the results of the sensitivity analysis indicate the coherence of the model's hierarchical structure, as each module responds primarily to the parameters that should geotechnically influence its evaluation. This indicates the model's consistency with the specific representation defined for each evaluation level, enabling the identification of the groups of variables with the greatest influence within the fuzzy assessment tool.

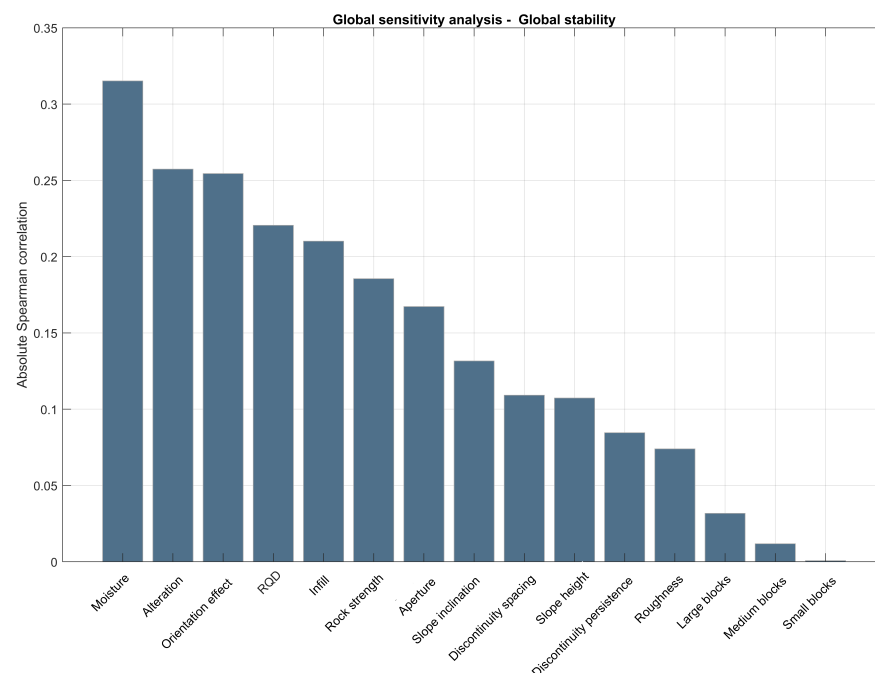


Figure 11. Global sensitivity analysis associated with the global stability module.

5.3. Comparison with Existing Fuzzy Logic Approaches

Fuzzy logic has been implemented in geotechnical engineering to represent uncertainty in evaluation and decision-making processes. Table 10 presents several studies focused on the application of fuzzy logic techniques to geotechnical stability problems, in contrast to the model proposed in this research.

Table 10. Comparison between selected fuzzy logic approaches for geotechnical stability assessment and the proposed model.

Characteristic	[7]	[24]	[20]	[25]	[18]	Proposed Model
Assessment approach	Mamdani fuzzy inference system for block-toppling assessment	Statistical and fuzzy logic approach for factor of safety (FOS) prediction	Fuzzy cognitive map (FCM) for rockburst susceptibility assessment	Improved intuitionistic fuzzy sets (UIFS) for rock slope stability assessment	Empirical Qslope classification integrated with fuzzy logic	Hierarchical modular fuzzy model for instability susceptibility assessment
Evaluation level	Specific	Global	Specific	Global	Global	Global
Output type	Toppling state	Factor of safety (FOS)	Critical factor prioritization	Stability category	Stability category	Susceptibility index
Hierarchical modular evaluation	No	No	No	No	No	Yes
Intermediate geotechnical interpretation	No	No	Partial	No	No	Yes
Integration of multiple geomechanical groups	Limited	Limited	Yes	Moderate	Moderate	Yes
Direct relationship with intervention measures	Limited	Limited	Moderate	Moderate	Limited	High

It can be observed that fuzzy logic has been applied through different approaches, ranging from the development of fuzzy inference systems for the evaluation of toppling failure mechanism [7], the prediction of Factors of Safety through the combination of statistical methods and fuzzy logic [24], the assessment of susceptibility related to rockburst phenomena using fuzzy cognitive maps [20], and the use of intuitionistic fuzzy sets for the global classification of slope stability [25], as well as empirical approaches such as Q-slope integrated with fuzzy logic [18]. Recent developments have explored the integration of fuzzy logic with data-driven approaches and remote sensing techniques [2], demonstrating

the evolution toward hybrid frameworks in geotechnical evaluation. In contrast, the proposed model is oriented toward assessing susceptibility to instability by integrating geometric, geomechanical, and physical parameters of the rock slope across different evaluation levels.

Some approaches focused on specific stability problems [7,20], whereas others perform global assessment [24,25] through indices, stability states, or classification categories. Although the proposed model also supports a global assessment, it differs in its hierarchical modular structure and the interconnections among parameters across evaluation levels. This, in turn, allows for a gradual interpretation of the conditions that influence susceptibility to instability, rather than limiting the analysis to a single final output.

This characteristic strengthens the decision-making process, since the reviewed studies primarily provide a classification, index, or level as the final result of the evaluation, which means that intervention measures may be limited [7,24] and, in other cases, moderate [20,25]. Similarly, empirical approaches such as Qslope-based methods [18] provide rapid stability classification but lack hierarchical interpretation and direct relation to intervention measures. In contrast, within the proposed model, recommendations are associated with the geotechnical conditions identified throughout the different evaluation levels.

On the other hand, despite the results obtained, the model presents some limitations that should be considered, which are described as follows:

- There is a dependence on the interpretation of qualitative parameters such as orientation effects, the degree of weathering, infilling characteristics, and moisture conditions when information derived from multispectral indices is not available. Although the evaluation environment provides criteria for assigning these parameters, the user's judgment may still influence the results, as in traditional methods.
- Several qualitative parameters still pose limitations to their automated calculation, as many require manual measurements from three-dimensional digital models (e.g., RQD and roughness), thereby increasing processing time and retaining a certain dependence on the specialist's experience.
- The membership functions and rule base were generated and adjusted considering the geomechanical conditions observed in the analyzed case studies, corresponding to ignimbrite slopes. Therefore, the model's behavior under other lithological types or geological conditions may require adjustments, additional calibration, or even modifications to certain inference rules.

6. Conclusions

The present study enabled the development and evaluation of a hierarchical modular model for assessing slope instability susceptibility. The structure integrates geometric, geomechanical, and physical parameters of discontinuities, as well as the geometric conditions of the slope, thereby enabling the representation of interactions among the factors that control stability. This approach facilitates the identification of the conditions that most influence susceptibility to instability and the corresponding recommendations based on the evaluation results.

The results obtained made it possible to verify the capabilities and limitations of the model, mainly through the following aspects:

- Slope evaluation is a complex problem in which traditional methods continue to be widely accepted, although there are present limitations in representing the interaction among multiple factors. The modular structure of the proposed model enabled the evaluation process to be organized into distinct geotechnical evaluation levels, thereby identifying the factors with the greatest influence on susceptibility to instability and facilitating interpretation of the results.

- The proposed model enabled the representation of gradual transitions between geomechanical conditions through a structure that incorporated rock mass quality, the physical and geometric conditions of discontinuities, and slope geometry, thereby avoiding abrupt changes associated with traditional methods based on discrete ranges.
- The different evaluation levels allowed recommendations to be related to specific geotechnical conditions, facilitating the activation of recommendations and stabilization measures tailored to the slope being evaluated.
- The analyzed case studies demonstrated the model's potential and overall consistency in assessing susceptibility to instability, as well as its applicability as a decision-support tool. This was complemented by a sensitivity analysis, which identified the parameters with the greatest influence on the evaluation process. In addition, the developed evaluation environment facilitated the practical implementation of the model with real data as input, automatically normalizing parameters.

The limitations of this work lie in the lack of explicit consideration of external dynamic factors, such as groundwater level variations, infiltration processes, high mountain conditions, or seismic activity, as the proposed model is focused on its application under representative service conditions, and the incorporation of these factors constitutes a line of future work toward its application in more complex scenarios.

As future work, it is intended to continue developing tools to automate the extraction of geomechanical parameters from three-dimensional digital models generated by digital photogrammetry, thereby reducing reliance on specialist interpretation through the use of artificial intelligence techniques. Likewise, it is necessary to evaluate the model's performance across different methodologies to assess its behavior in diverse lithological environments and to identify required modifications or adjustments.

Author Contributions: Conceptualization, M.G.R.-S., J.E.A.-R. and L.A.M.-R.; methodology, M.G.R.-S., J.E.A.-R. and L.A.M.-R.; software, M.G.R.-S., J.M.D.-B. and L.A.M.-R.; validation, J.E.A.-R., M.L.-B., J.C.L.-P., J.M.D.-B. and L.A.M.-R.; formal analysis, J.M.D.-B. and L.A.M.-R.; investigation, M.G.R.-S., M.L.-B., J.C.L.-P. and L.A.M.-R.; data curation, M.L.-B. and J.C.L.-P.; writing—original draft, M.G.R.-S., J.E.A.-R. and L.A.M.-R.; writing—review and editing, M.L.-B., J.C.L.-P. and J.M.D.-B.; visualization, M.L.-B., J.C.L.-P. and J.M.D.-B.; supervision, J.E.A.-R. and L.A.M.-R.; project administration, L.A.M.-R.; funding acquisition, J.E.A.-R. and L.A.M.-R. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by Secretaría de Ciencias, Humanidades, Tecnología e Innovación through the scholarship 1006917 and the project 613.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The code is located at <https://marsella94.github.io/FISlope/> (accessed on 7 July 2026).

Acknowledgments: During the preparation of this manuscript, the authors used Grammarly 14.1313.0 to review the English grammar and syntax. The authors have reviewed and edited the output and take full responsibility for the content of this publication.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

DEM	Digital Elevation Model
DSE	Discontinuity Set Extractor

FIS	Fuzzy Inference System
JRC	Joint Roughness Coefficient
NDWI	Normalized Difference Water Index
RMR	Rock Mass Rating
RQD	Rock Quality Designation
SfM	Structure from Motion
SMR	Slope Mass Rating
UAV	Unmanned Aerial Vehicle

Appendix A. Rule Base of the Geometric Stability Module

This appendix presents the rule base implemented for the Geometric Stability module, which consists of a total of 80 fuzzy inference rules. This information is provided to offer greater detail about the implemented inference process and to facilitate the reproducibility of the proposed model.

Table A1. Rule base of the Geometric Stability module (Rules 1–40).

Rule	Discontinuity Geometric Condition	Slope Geometric Condition	Block Hazard	Geometric Stability
1	Very Good	Very Good	Low	Very Stable
2	Very Good	Very Good	Moderate	Very Stable
3	Very Good	Very Good	High	Stable
4	Very Good	Good	Low	Very Stable
5	Very Good	Good	Moderate	Stable
6	Very Good	Good	High	Stable
7	Very Good	Fair	Low	Stable
8	Very Good	Fair	Moderate	Stable
9	Very Good	Fair	High	Fair
10	Very Good	Poor	Low	Fair
11	Very Good	Poor	Moderate	Fair
12	Very Good	Poor	High	Unstable
13	Very Good	Very Poor	Low	Fair
14	Very Good	Very Poor	Moderate	Unstable
15	Very Good	Very Poor	High	Unstable
16	Good	Very Good	Low	Stable
17	Good	Very Good	Moderate	Stable
18	Good	Very Good	High	Fair
19	Good	Good	Low	Stable
20	Good	Good	Moderate	Stable
21	Good	Good	High	Fair
22	Good	Fair	Low	Fair
23	Good	Fair	Moderate	Fair
24	Good	Fair	High	Fair
25	Good	Poor	Low	Unstable
26	Good	Poor	Moderate	Unstable
27	Good	Poor	High	Unstable
28	Good	Very Poor	Low	Unstable
29	Good	Very Poor	Moderate	Unstable
30	Good	Very Poor	High	Unstable
31	Fair	Very Good	Low	Stable
32	Fair	Very Good	Moderate	Fair
33	Fair	Very Good	High	Fair
34	Fair	Good	Low	Stable
35	Fair	Good	Moderate	Fair
36	Fair	Good	High	Fair
37	Fair	Fair	Low	Fair
38	Fair	Fair	Moderate	Fair
39	Fair	Fair	High	Unstable
40	Fair	Poor	Low	Fair

Table A2. Rule base of the Geometric Stability module (Rules 41–80).

Rule	Discontinuity Geometric Condition	Slope Geometric Condition	Block Hazard	Geometric Stability
41	Fair	Poor	Moderate	Unstable
42	Fair	Poor	High	Unstable
43	Fair	Very Poor	Low	Unstable
44	Fair	Very Poor	Moderate	Unstable
45	Fair	Very Poor	High	Unstable
46	Poor	Very Good	Low	Fair
47	Poor	Very Good	Moderate	Fair
48	Poor	Very Good	High	Unstable
49	Poor	Good	Low	Unstable
50	Poor	Good	Moderate	Unstable
51	Poor	Good	High	Unstable
52	Poor	Fair	Low	Unstable
53	Poor	Fair	Moderate	Unstable
54	Poor	Fair	High	Unstable
55	Poor	Poor	Low	Unstable
56	Poor	Poor	Moderate	Unstable
57	Poor	Poor	High	Unstable
58	Poor	Very Poor	Low	Unstable
59	Poor	Very Poor	Moderate	Unstable
60	Poor	Very Poor	High	Unstable
61	Very Poor	Very Good	Low	Fair
62	Very Poor	Very Good	Moderate	Unstable
63	Very Poor	Very Good	High	Unstable
64	Very Poor	Good	Low	Unstable
65	Very Poor	Good	Moderate	Unstable
66	Very Poor	Good	High	Unstable
67	Very Poor	Fair	Low	Unstable
68	Very Poor	Fair	Moderate	Unstable
69	Very Poor	Fair	High	Unstable
70	Very Poor	Poor	Low	Unstable
71	Very Poor	Poor	Moderate	Unstable
72	Very Poor	Poor	High	Unstable
73	Very Poor	Very Poor	Low	Unstable
74	Very Poor	Very Poor	Moderate	Unstable
75	Very Poor	Very Poor	High	Unstable
76	Very Poor	Very Poor	-	Unstable
77	Very Good	Very Good	-	Very Stable
78	Fair	Fair	-	Fair
79	Poor	Poor	-	Unstable
80	Very Poor	-	High	Unstable

Appendix B. Rule Base of the Global Stability Module

This appendix presents the rule base implemented for the Global Stability module, which consists of a total of 125 fuzzy inference rules. This information is provided to offer greater detail about the implemented inference process and to facilitate the reproducibility of the proposed model.

Table A3. Rule base of the Global Stability module (Rules 1–42).

Rule	Rock Mass Quality	Physical Condition	Geometric Stability	Global Stability
1	Very Good	Very Good	Very Stable	Very Stable
2	Very Good	Very Good	Stable	Very Stable
3	Very Good	Very Good	Fair	Stable
4	Very Good	Very Good	Unstable	Unstable

Table A3. Cont.

Rule	Rock Mass Quality	Physical Condition	Geometric Stability	Global Stability
5	Very Good	Very Good	Very Unstable	Fair
6	Very Good	Good	Very Stable	Very Stable
7	Very Good	Good	Stable	Very Stable
8	Very Good	Good	Fair	Fair
9	Very Good	Good	Unstable	Fair
10	Very Good	Good	Very Unstable	Fair
11	Very Good	Fair	Very Stable	Very Stable
12	Very Good	Fair	Stable	Stable
13	Very Good	Fair	Fair	Fair
14	Very Good	Fair	Unstable	Fair
15	Very Good	Fair	Very Unstable	Unstable
16	Very Good	Poor	Very Stable	Fair
17	Very Good	Poor	Stable	Fair
18	Very Good	Poor	Fair	Unstable
19	Very Good	Poor	Unstable	Unstable
20	Very Good	Poor	Very Unstable	Very Unstable
21	Very Good	Very Poor	Very Stable	Stable
22	Very Good	Very Poor	Stable	Stable
23	Very Good	Very Poor	Fair	Unstable
24	Very Good	Very Poor	Unstable	Unstable
25	Very Good	Very Poor	Very Unstable	Very Unstable
26	Good	Very Good	Very Stable	Very Stable
27	Good	Very Good	Stable	Stable
28	Good	Very Good	Fair	Stable
29	Good	Very Good	Unstable	Fair
30	Good	Very Good	Very Unstable	Fair
31	Good	Good	Very Stable	Stable
32	Good	Good	Stable	Stable
33	Good	Good	Fair	Fair
34	Good	Good	Unstable	Fair
35	Good	Good	Very Unstable	Unstable
36	Good	Fair	Very Stable	Stable
37	Good	Fair	Stable	Fair
38	Good	Fair	Fair	Fair
39	Good	Fair	Unstable	Fair
40	Good	Fair	Very Unstable	Unstable
41	Good	Poor	Very Stable	Fair
42	Good	Poor	Stable	Fair

Table A4. Rule base of the Global Stability module (Rules 43–84).

Rule	Rock Mass Quality	Physical Condition	Geometric Stability	Global Stability
43	Good	Poor	Fair	Unstable
44	Good	Poor	Unstable	Unstable
45	Good	Poor	Very Unstable	Very Unstable
46	Good	Very Poor	Very Stable	Fair
47	Good	Very Poor	Stable	Unstable
48	Good	Very Poor	Fair	Unstable
49	Good	Very Poor	Unstable	Very Unstable
50	Good	Very Poor	Very Unstable	Very Unstable
51	Fair	Very Good	Very Stable	Stable
52	Fair	Very Good	Stable	Stable
53	Fair	Very Good	Fair	Fair
54	Fair	Very Good	Unstable	Fair
55	Fair	Very Good	Very Unstable	Fair
56	Fair	Good	Very Stable	Stable
57	Fair	Good	Stable	Stable

Table A4. *Cont.*

Rule	Rock Mass Quality	Physical Condition	Geometric Stability	Global Stability
58	Fair	Good	Stable	Stable
59	Fair	Good	Fair	Fair
60	Fair	Good	Very Unstable	Unstable
61	Fair	Fair	Very Stable	Fair
62	Fair	Fair	Stable	Fair
63	Fair	Fair	Fair	Fair
64	Fair	Fair	Unstable	Unstable
65	Fair	Fair	Very Unstable	Very Unstable
66	Fair	Poor	Very Stable	Unstable
67	Fair	Poor	Stable	Unstable
68	Fair	Poor	Fair	Unstable
69	Fair	Poor	Unstable	Very Unstable
70	Fair	Poor	Very Unstable	Very Unstable
71	Fair	Very Poor	Very Stable	Unstable
72	Fair	Very Poor	Stable	Unstable
73	Fair	Very Poor	Fair	Very Unstable
74	Fair	Very Poor	Unstable	Very Unstable
75	Fair	Very Poor	Very Unstable	Very Unstable
76	Poor	Very Good	Very Stable	Stable
77	Poor	Very Good	Stable	Fair
78	Poor	Very Good	Fair	Fair
79	Poor	Very Good	Unstable	Fair
80	Poor	Very Good	Very Unstable	Unstable
81	Poor	Good	Very Stable	Stable
82	Poor	Good	Stable	Fair
83	Poor	Good	Fair	Unstable
84	Poor	Good	Unstable	Unstable

Table A5. Rule base of the Global Stability module (Rules 85–125).

Rule	Rock Mass Quality	Physical Condition	Geometric Stability	Global Stability
85	Poor	Good	Very Unstable	Unstable
86	Poor	Fair	Very Stable	Fair
87	Poor	Fair	Stable	Fair
88	Poor	Fair	Fair	Unstable
89	Poor	Fair	Unstable	Unstable
90	Poor	Fair	Very Unstable	Very Unstable
91	Poor	Poor	Very Stable	Unstable
92	Poor	Poor	Stable	Unstable
93	Poor	Poor	Fair	Very Unstable
94	Poor	Poor	Unstable	Very Unstable
95	Poor	Poor	Very Unstable	Very Unstable
96	Poor	Very Poor	Very Stable	Unstable
97	Poor	Very Poor	Stable	Unstable
98	Poor	Very Poor	Fair	Very Unstable
99	Poor	Very Poor	Unstable	Very Unstable
100	Poor	Very Poor	Very Unstable	Very Unstable
101	Very Poor	Very Good	Very Stable	Stable
102	Very Poor	Very Good	Stable	Unstable
103	Very Poor	Very Good	Fair	Unstable
104	Very Poor	Very Good	Unstable	Unstable
105	Very Poor	Very Good	Very Unstable	Unstable
106	Very Poor	Good	Very Stable	Fair
107	Very Poor	Good	Stable	Fair
108	Very Poor	Good	Fair	Unstable
109	Very Poor	Good	Unstable	Unstable
110	Very Poor	Good	Very Unstable	Unstable

Table A5. Cont.

Rule	Rock Mass Quality	Physical Condition	Geometric Stability	Global Stability
111	Very Poor	Fair	Very Stable	Unstable
112	Very Poor	Fair	Stable	Unstable
113	Very Poor	Fair	Fair	Unstable
114	Very Poor	Fair	Unstable	Very Unstable
115	Very Poor	Fair	Very Unstable	Very Unstable
116	Very Poor	Poor	Very Stable	Fair
117	Very Poor	Poor	Stable	Fair
118	Very Poor	Poor	Fair	Very Unstable
119	Very Poor	Poor	Unstable	Very Unstable
120	Very Poor	Poor	Very Unstable	Very Unstable
121	Very Poor	Very Poor	Very Stable	Fair
122	Very Poor	Very Poor	Stable	Unstable
123	Very Poor	Very Poor	Fair	Very Unstable
124	Very Poor	Very Poor	Unstable	Very Unstable
125	Very Poor	Very Poor	Very Unstable	Very Unstable

References

- Moragues, S.; Lenzano, M.G.; Lanfri, M.; Moreiras, S.; Lannutti, E.; Lenzano, L. Analytic hierarchy process applied to landslide susceptibility mapping of the North Branch of Argentino Lake, Argentina. *Nat. Hazards* **2021**, *105*, 915–941. [\[CrossRef\]](#)
- Yu, Y.; Zhu, C.; Gulayozov, M.; Li, J.; Chen, B.; Shen, Q.; Zhou, H.; Xiao, W.; Niyazov, J.; Gulakhmadov, A. Monitoring and Assessment of Slope Hazards Susceptibility Around Sarez Lake in the Pamir by Integrating Small Baseline Subset InSAR with an Improved SVM Algorithm. *Remote Sens.* **2025**, *17*, 2300. [\[CrossRef\]](#)
- Bieniawski, Z. Classification of rock masses for engineering: The RMR system and future trends. In *Rock Testing and Site Characterization*; Elsevier: Amsterdam, The Netherlands, 1993; pp. 553–573.
- Romana, M.R. A Geomechanical Classification for Slopes: Slope Mass Rating. In *Rock Testing and Site Characterization*; Hudson, J., Ed.; Elsevier: Amsterdam, The Netherlands, 1993; pp. 575–600.
- Zêzere, J.L. Landslide susceptibility assessment considering landslide typology. A case study in the area north of Lisbon (Portugal). *Nat. Hazards Earth Syst. Sci.* **2002**, *2*, 73–82. [\[CrossRef\]](#)
- Mandal, S.; Mani, A.; Lall, A.R.; Kumar, D. Slope stability assessment and landslide susceptibility mapping in the Lesser Himalaya, Mussoorie, Uttarakhand. *Discov. Geosci.* **2024**, *2*, 51. [\[CrossRef\]](#)
- Azarafza, M.; Asghari-Kaljahi, E.; Ghazifard, A.; Akgün, H. Application of fuzzy expert decision-making system for rock slope block-toppling modeling and assessment: A case study. *Model. Earth Syst. Environ.* **2021**, *7*, 159–168.
- Azarafza, M.; Akgün, H.; Feizi-Derakhshi, M.R.; Azarafza, M.; Rahnamarad, J.; Derakhshani, R. Discontinuous rock slope stability analysis under blocky structural sliding by fuzzy key-block analysis method. *Heliyon* **2020**, *6*, e03907. [\[CrossRef\]](#) [\[PubMed\]](#)
- Matos, Y.M.P.d.; Dantas, S.A.; Barreto, G.d.A. Risk assessment in a rock slope stability analysis using a Mamdani fuzzy controller. *REM-Int. Eng. J.* **2023**, *76*, 313–320. [\[CrossRef\]](#)
- Zhou, C.; Ouyang, J.; Liu, Z.; Zhang, L. Early risk warning of highway soft rock slope group using fuzzy-based machine learning. *Sustainability* **2022**, *14*, 3367. [\[CrossRef\]](#)
- Battulwar, R.; Emami, E.; Zare, M.; Battulwar, K.; Shahsavari, M.; Moniri-Morad, A.; Sattarvand, J. Utilizing Deep Learning for the Automated Extraction of Rock Mass Features from Point Clouds. *Geotech. Geol. Eng.* **2024**, *42*, 6179–6194. [\[CrossRef\]](#)
- Gao, W.; Ge, S. A comprehensive review of slope stability analysis based on artificial intelligence methods. *Expert Syst. Appl.* **2024**, *239*, 122400. [\[CrossRef\]](#)
- Kong, D.; Wu, F.; Saroglou, C. Automatic identification and characterization of discontinuities in rock masses from 3D point clouds. *Eng. Geol.* **2020**, *265*, 105442. [\[CrossRef\]](#)
- Wang, W.; Zhao, W.; Chai, B.; Du, J.; Tang, L.; Yi, X. Discontinuity interpretation and identification of potential rockfalls for high-steep slopes based on UAV nap-of-the-object photogrammetry. *Comput. Geosci.* **2022**, *166*, 105191. [\[CrossRef\]](#)
- Battulwar, R.; Zare-Naghadehi, M.; Emami, E.; Sattarvand, J. A state-of-the-art review of automated extraction of rock mass discontinuity characteristics using three-dimensional surface models. *J. Rock Mech. Geotech. Eng.* **2021**, *13*, 920–936. [\[CrossRef\]](#)
- Saadati, G.; Javankhoshdel, S.; Mohebbi Najm Abad, J.; Mett, M.; Kontrus, H.; Schneider-Muntau, B. AI-Powered Geotechnics: Enhancing Rock Mass Classification for Safer Engineering Practices. *Rock Mech. Rock Eng.* **2025**, *58*, 11319–11349. [\[CrossRef\]](#)
- Pu, C.; Zhan, J.; Zhang, W.; Peng, J. Characterization and clustering of rock discontinuity sets: A review. *J. Rock Mech. Geotech. Eng.* **2024**, *17*, 1240–1262. [\[CrossRef\]](#)

18. Mao, Y.; Chen, L.; Nanekharan, Y.A.; Azarafza, M.; Derakhshani, R. Fuzzy-Based Intelligent Model for Rapid Rock Slope Stability Analysis Using Qslope. *Water* **2023**, *15*, 2949. [[CrossRef](#)]
19. Falamaki, A.; Shafiee, A.H.; Esfandiyari, M. Feasibility study of fuzzy method in slope stability analysis of earth dams with respect to the uncertainty of geotechnical parameters. *J. Hydraul. Struct.* **2024**, *10*, 34–50.
20. Hosseini, S.; Armaghani, D.J.; He, X.; Pradhan, B.; Zhou, J.; Sheng, D. Fuzzy Cognitive Map for Evaluating Critical Factors Causing Rockbursts in Underground Construction: A Fundamental Study. *Rock Mech. Rock Eng.* **2024**, *57*, 9713–9738. [[CrossRef](#)]
21. Rodríguez-Servín, M.G.; Arreygue-Rocha, J.E.; Rodríguez-Rangel, H.; Lobato-Báez, M.; Díaz-Barriga, J.M.; Morales-Rosales, L.A. Comparative Analysis of Rock Mass Characterization Techniques to Recommend Geomechanical Prevention Mechanisms Using UAV Photogrammetry. *Appl. Sci.* **2025**, *15*, 11388. [[CrossRef](#)]
22. Ismail, A.; Rashid, A.S.A.; Sa'ari, R.; Mustaffar, M.; Abdullah, R.A.; Kassim, A.; Yusof, N.M.; Abd Rahaman, N.; Apandi, N.M.; Kalatehjari, R.; et al. Application of UAV-based photogrammetry and normalised water index (NDWI) to estimate the rock mass rating (RMR): A case study. *Phys. Chem. Earth Parts A/B/C* **2022**, *127*, 103161. [[CrossRef](#)]
23. Comisión Federal de Electricidad. *Capítulo de Diseño por Sismo. Manual de Diseño de Obras Cíviles*; Comisión Federal de Electricidad (CFE): Mexico City, Mexico, 2015; Versión 2015.
24. Chakraborty, A.; Goswami, A. The Application of Statistics and Fuzzy Logic in Predicting Slope Stability. In *Proceedings of the Recent Advances in Civil Engineering*; Kumar, P.G., Subramaniam, K.V.L., Santhakumar, S.M., Satyam D.N., Eds.; Springer Nature: Singapore, 2022; pp. 137–147.
25. Wu, S.; Dong, C.; Zhang, T.; Huo, L. Evaluation of Rock Slope Stability Based on Improved Intuitionistic Fuzzy Sets. *Geol. J.* **2026**, 1–13. [[CrossRef](#)]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.