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OCENA PODATNOŚCI NA OSUWISKA NA ODCINKU DROGI CHILLANES–SAN PABLO DE ATENAS (PROWINCJA BOLÍVAR, EKWADOR)

ASSESSMENT OF LANDSLIDE SUSCEPTIBILITY ON THE CHILLANES–SAN PABLO DE ATENAS ROAD (BOLÍVAR, ECUADOR)

Introduction

Landslides are a frequent and destructive geodynamic hazard, especially in mountainous areas with steep slopes and heavy rainfall. Fidan et al. (2024) found that over 69% of global landslide-related deaths happen in mountainous regions. Additionally, Duan et al. (2025) estimated that about 13% of the Earth's surface is highly prone to slope failures. Global studies have used factors like rock type, slope angle, soil moisture, and rainfall in susceptibility modeling, which has improved how geomorphological hazards are represented (Jiang et al. 2025). Ecuador is particularly vulnerable to landslides due to its steep Andean terrain, heavy rainfall, and road networks built on unstable geological formations.

The Secretaría Nacional de Gestión de Riesgos (SNGR 2025) reported 1,143 rainfall-induced incidents from January to March 2025, with landslides constituting 42.4% of these events, affecting 23 provinces. Within this nationwide framework, the Chillanes–San Pablo de Atenas Road in Bolívar Province represents a vital route frequently subject to slope instability. A rotational landslide at kilometer 13 in 2020, for instance, displaced more than 76,500 m^3 of material, completely obstructing the road (Ministerio de Infraestructura y Transporte (MIT), 2025). Conversely, despite the frequency of such events, landslide susceptibility assessments in Ecuador have largely focused on urban Andean environments and the Amazon region, resulting in a relative lack of analysis of rural road corridors characterized by complex geological conditions.

Existing evaluations are constrained using low-resolution geospatial data and incomplete cartographic resources, which impedes the precise identification of vulnerable segments within the Chillanes–San Pablo corridor. Consequently, this deficiency diminishes the efficacy of preventative planning efforts and complicates the prioritization of slope stabilization measures. To address these shortcomings, this research formulates a landslide susceptibility model for the Chillanes–San Pablo de Atenas Road, employing AHP–GIS integration. The objective is to pinpoint the most unstable segments of the corridor and facilitate risk-informed decision-making regarding infrastructure management within Bolívar Province.

Area of study

The Chillanes–San Pablo de Atenas Road corridor, situated within the Bolívar Province of Ecuador's inter-Andean region, served as the study area (see Fig. 1). This route, extending roughly 21 kilometers, traverses a challenging mountainous landscape distinguished by steep inclines surpassing 35°, deeply carved ravines, and constricted valleys. Elevations within the corridor fluctuate between 520 and 2.480 meters above sea level, thereby establishing a pronounced altitude that significantly affects slope instability. Furthermore, annual precipitation fluctuates between 1.800 and 2.200 mm, with the most intense rainfall occurring from January to April, these conditions exacerbate soil saturation and infiltration. Consequently, the combination of altered volcanic materials, substantial rainfall, and steep topography renders the corridor especially vulnerable to mass movements.

Materials and methods

The research is based on the integration of Geographic Information Systems (GIS) and the Analytic Hierarchy Process (AHP), which have received wide recognition for their effectiveness in spatially assessing the propensity to landslides (Saaty 1977; Reichenbach et al. 2018). This integration makes it possible to convert geomorphological, geological, and hydrometeorological criteria into quantitative susceptibility maps through weighted comparisons. The steps that make up the sequence of methods, shown in Fig. 5, are: (i) compile and homogenize spatial data; (ii) establish standard criteria on a scale of 1 to 9; (iii) carry out an AHP analysis to determine the weights of each element; (iv) overlay GIS in a weighted manner; and (v) confirm using the ROC curves and the AUC coefficient. Recent studies in road corridors in the Andes support the robustness of the approach, demonstrating accuracy levels above 0.85 and consistency values below 0.1 (Cargua et al. 2024; Zhang et al. 2024).

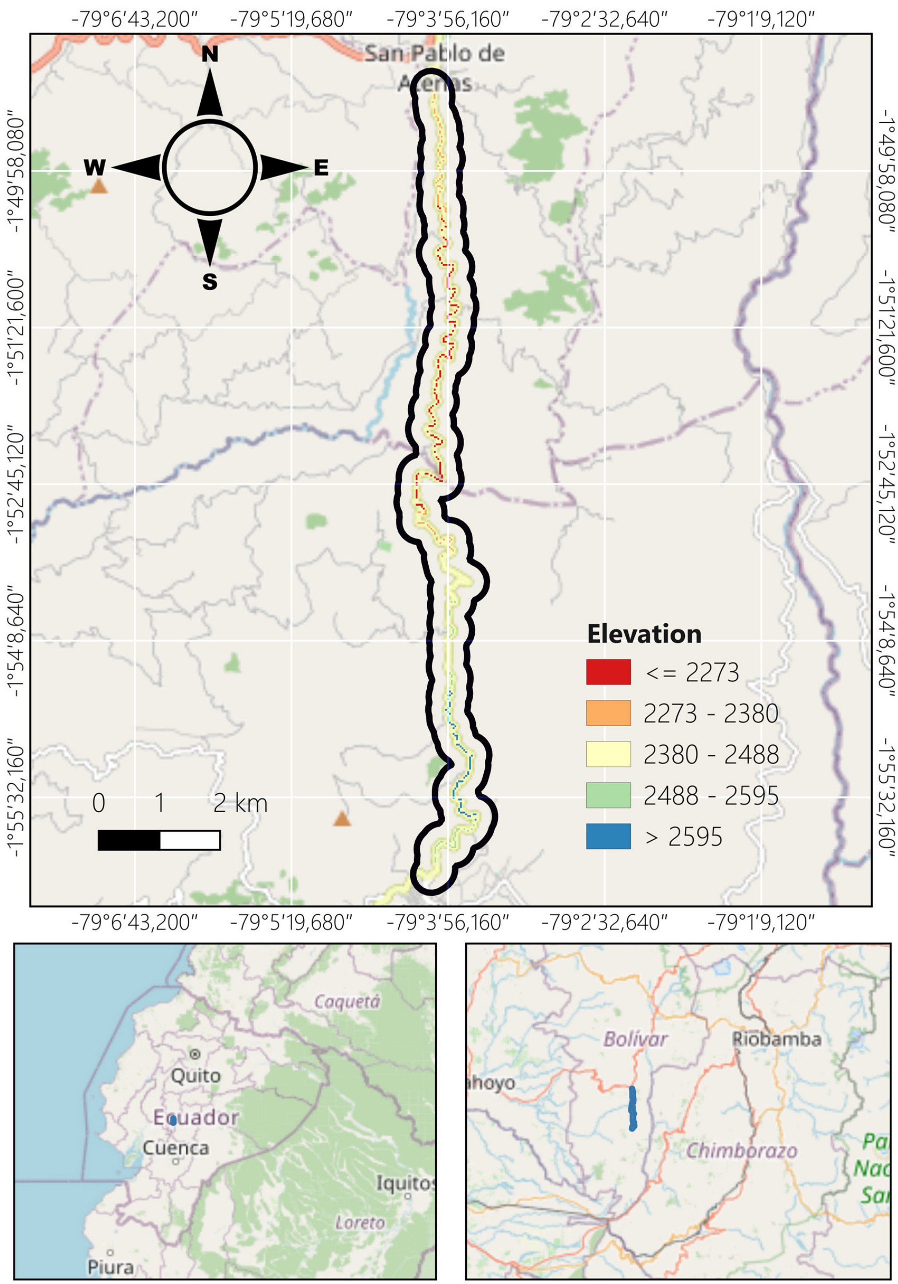

Fig. 1. Section via San Pablo de Atenas–Chillanes.

Landslide inventory

Liu et al. (2018) posits that a landslide inventory is crucial for determining the spatial and temporal characteristics of mass movements, encompassing their location, extent, and classification. A validated and representative inventory is indispensable for any evaluation of susceptibility or risk.

In the Chillanes–San Pablo de Atenas corridor, a geospatial reconnaissance survey was undertaken along the principal roadway, covering 21 km, and an additional 4 km along the San Pablo side route. Each identified instability point was subsequently georeferenced and categorized based on lithology and the specific type of movement observed (Table 1).

Table 1. Inventory of the most relevant landslides in recent years.

Figure	Longitude (°)	Latitude (°)	Sector	Geological formation	Type of landslide
2	−79.06730	−1.8750	km 3 (San Pablo–Chillanes section)	Modified colluvial deposits	Rotational slide
4	−79.06345	−1.8940	km 14 (Perezán)	Fractured andesite	Mixed fall
3	−79.06380	−1.8935	km 13 (Perezán)	Fractured andesite	Large-scale landslide

Source: Prepared by the authors based on the review of road report bulletins (MIT 2025). To confirm the accuracy of the locations, we compared satellite images, official bulletins from the Ministry of Infrastructure and Transport (MIT), Ecuador, and field observations. Only landslides with clear boundaries and a spatial accuracy matching the 12.5 m Digital Elevation Model (DEM) resolution were included. This verified inventory was then used to calibrate and validate the susceptibility model.

Sliding variables (layers)

Official and academic sources, in particular the National Institute of Meteorology and Hydrology (INAMHI), the Institute of Geological and Energy Research (IIGE), the SNGR and the MTOP, are the ones that provide all the data used to carry out this research. Table 2 summarizes the information used. For the study of susceptibility to mass movements, slope, lithology, and distances to roads were established as essential variables. Both geospatial observations and the availability of official thematic cartography supported the choice of these three variables and their categories.

The interaction between morphostructural conditions, hydrological elements, and changes made by humans has been proven to significantly explain the spatial distribution of landslides, according to several international studies (Reichenbach et al. 2018). Specifically, lithology and slope are recognized as the most influential factors, while distance

Fig. 2. Landslide at km 3.

Fig. 3. Landslide at km 13.

Fig. 4. Landslide at km 14.

from rivers and roads has a secondary triggering effect by altering the local stability of the slope (Li et al. 2024). Finally, the variables were transformed into raster thematic layers, which were the initial resources to develop the cartographic model of susceptibility through AHP and GIS. Although the AHP method is widely used and conceptually sound, it has documented constraints, mostly related to the subjectivity of expert judgment, the sensitivity of the model to small changes in weights, and the possibility of inconsistencies in large matrices. These limitations have encouraged the advancement of hybrid versions (AHP-RF, AHP-SVM), which allow for better prediction and less bias. To frame the scope of the results achieved, it is essential that these limitations are recognized.

Table 2. Data sources used for the study
(source: authors' elaboration based on literature research).

Data	Description	Source
Photographic images	Event-related photographs	https://www.mit.gob.ec/?s=San+Pablo+-+Chillanes
Digital Elevation Model (DEM) (12.5 m resolution)	Model describing terrain elevation	ASF, https://search.asf.alaska.edu/#/
DEM derivative	DEM-derived layer	DEM 12.5 m
Roads	Information on the local road network	IGM, http://www.geoportaligm.gob.ec/portal/
Lithology	Mineralogical classification (composition, texture, origin)	MAGAP, http://geoportal.agricultura.gob.ec/

Information from official IIGE mapping and the ALOS PALSAR digital elevation model were used to rasterize all thematic layers with a spatial resolution of 12.5 m per pixel. The weights assigned to the three variables (slope, distance from roads and lithology) were determined based on the cartography analyses and the verifications carried out in QGIS. Each variable was recoded into subcategories according to its specific ranges or values. In a multi-criteria environment, the method (AHP) was applied to integrate the raster layers and (WLC) to combine them. This is a hybrid quantitative-qualitative approach that allows spatial susceptibility to be assessed (Li et al. 2023). Finally, the susceptibility model was achieved by applying the weighted superposition of the layers in raster format. This methodology has been successfully tested in Andean areas with similar geographical characteristics and allowed the generation of a landslide susceptibility map due to mass movements along the Chillanes–San Pablo de Atenas Road (see Fig. 9).

All vector thematic layers were raster with a pixel resolution of 12.5 meters by 12.5 meters. Thanks to rasterization, it was possible to merge the three thematic layers to create a single raster layer. A pixel resolution of 12.5 m was chosen, as that spatial resolution was used in the DEM file. The process for each variable is described below.

Slope

The slope variable was obtained from the DEM, with a spatial resolution of 12.5 meters per pixel, using the GDALDEM tool of the QGIS 3.4 program. This variable is a main determining element for mass movements to occur, since the increase in the angle of in-

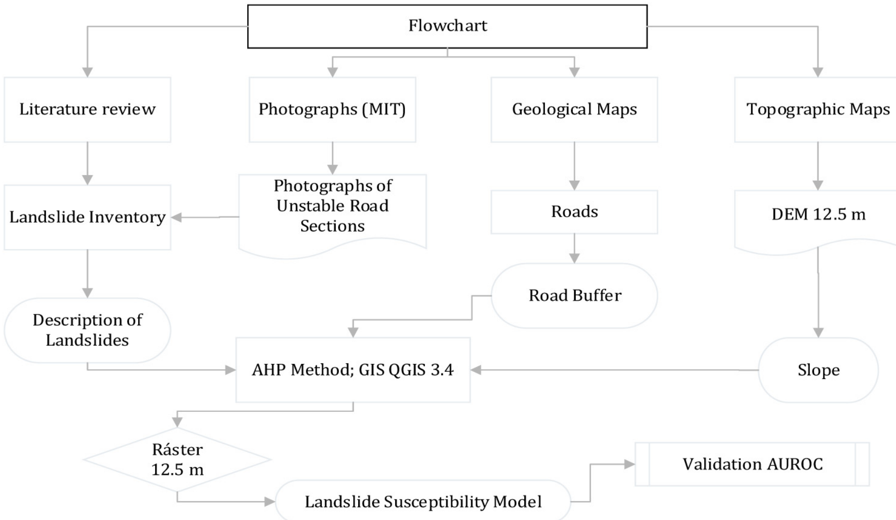

Fig. 5. Study flowchart.

clination of the terrain decreases the stability of the materials and the resistance to shear, which causes the slopes to become unstable (Li et al. 2023; Wang et al. 2023). The slope values in the Chillanes–San Pablo de Atenas Road corridor range between 0° and 50.06°, which shows that there are areas with moderate slopes and others with marked slopes, related to the cutting slopes and lateral erosion zones. Following the intervals obtained from the statistical analysis of the raster and the methodology suggested by Aceves et al. (2016), the thematic reclassification of the layer into six groups was carried out, with the following categories: < 5° (very low), 5 to 10° (low), 10 to 20° (moderate), 20 to 30° (high), 30 to 40° (very high), and more than 40° (critical) (see Fig. 6).

Lithology

Lithology is one of the most influential variables in the stability of slopes, since the structure, composition, and level of fracture of the rocks directly affect both the resistance that the ground offers to shear and its reaction to weathering (Corominas et al. 2023; Wang et al. 2023). Three fundamental units were found on the road: colluvial deposits, fractured or altered diorite, and diorite (massive intrusive rock) (see Fig. 7). These findings confirm the direct connection between lithological features and soil instability in mountain road corridors.

Distance to roads

The stability of the terrain is greatly affected by roads that are in hillside areas, due to the fact that urbanization processes, the opening of slopes and infrastructure works alter the natural balance of the slopes, which increases the probability of landslides (Igwe et al. 2020). It was found that, in the sector of the Chillanes-San Pablo de Atenas Road, the areas adjacent to the highway have significant human intervention related to local deforestation, soil displacement and the expansion of secondary roads. This creates circumstances conducive to instabilities. The spatial analysis revealed that the areas with indications of mass removal and impacted outcrops are mainly located less than 600 m from the road axis, which confirms the direct impact of the infrastructure on hillside processes. For this reason, the thematic layer of distance to road was categorized into five ranges: 0-145 m; 145-290 m; 290-435 m; 435-580 m; and more than 580 m (see Fig. 8). The highest susceptibility values are observed in the areas that are closest to the road, which demonstrates the impact of slope cutting and the accumulation of surface drainage at the edge of the road.

Susceptibility mapping

An intentional sample of experts was carried out to build the paired comparison matrix, which was composed of three professionals with experience in GIS, geotechnics and slope instability analysis. The selection that was made was based on years of technical experience and specific knowledge of the road corridor, which made it possible to ensure the validity of the judgments used to weigh the variables of the AHP model.

Likewise, the variables that are considered in the research to apply the AHP method must be weighted. For spatial processing, QGIS was used and for mathematical calculations to define the values of each step of the AHP, RStudio software was used. The following are the phases that were implemented: a) development of the hierarchical structure of the variables; b) elaboration of a comparative matrix by pairs (Table 3), with the fundamental scale proposed by Saaty (1977), to establish the order of priority between them; (c) synthesis of comparative judgements and calculation of standardised weights; d) evaluation of the judgment in terms of consistency, with the aim of verifying the coherence between the comparisons made; e) integration of the thematic layers by means of the Weighted Linear Combination (WLC), to obtain the cartographic model corresponding to susceptibility; and f) reclassification of the final model according to levels of susceptibility, in order to facilitate a clearer spatial interpretation.

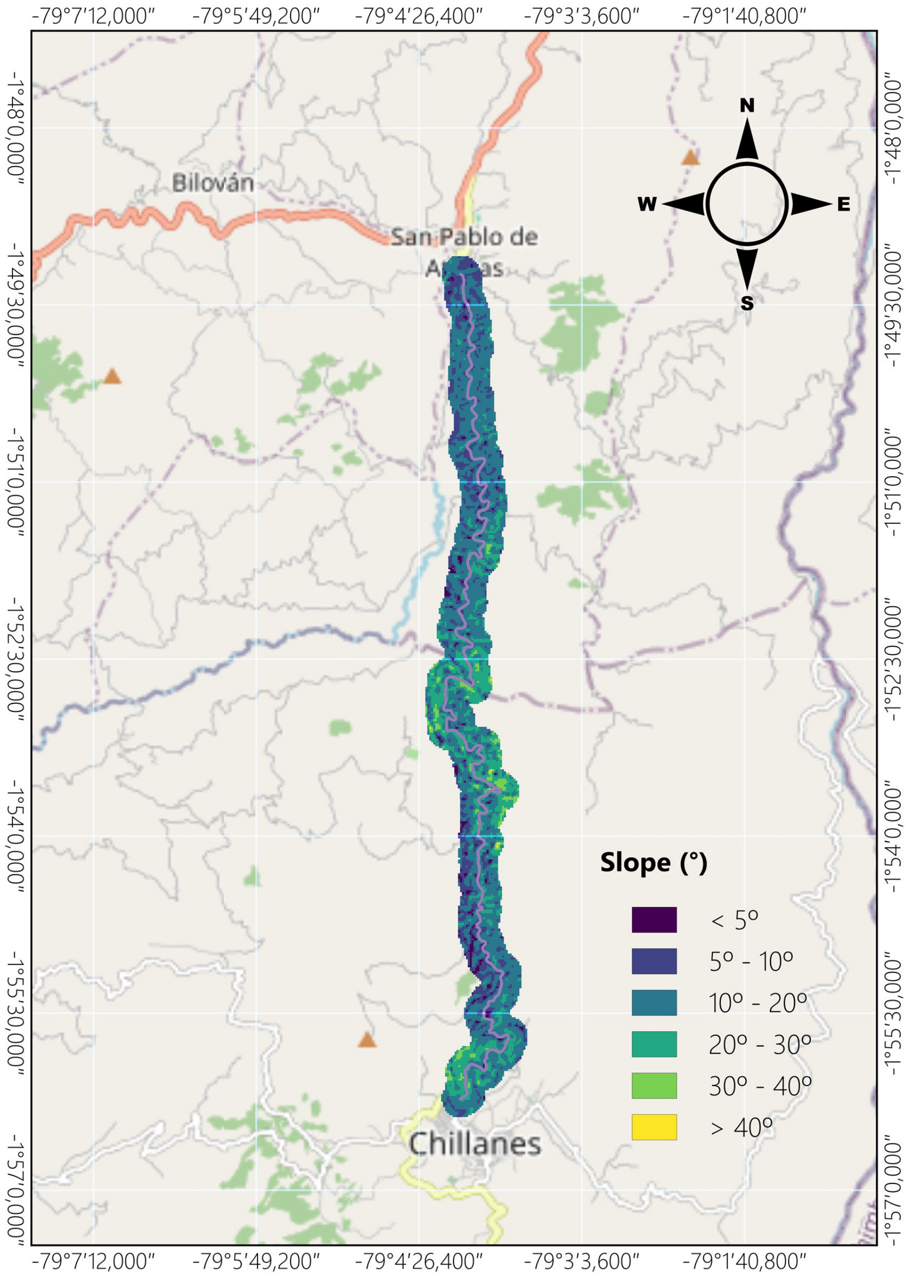

Fig. 6. Slope map.

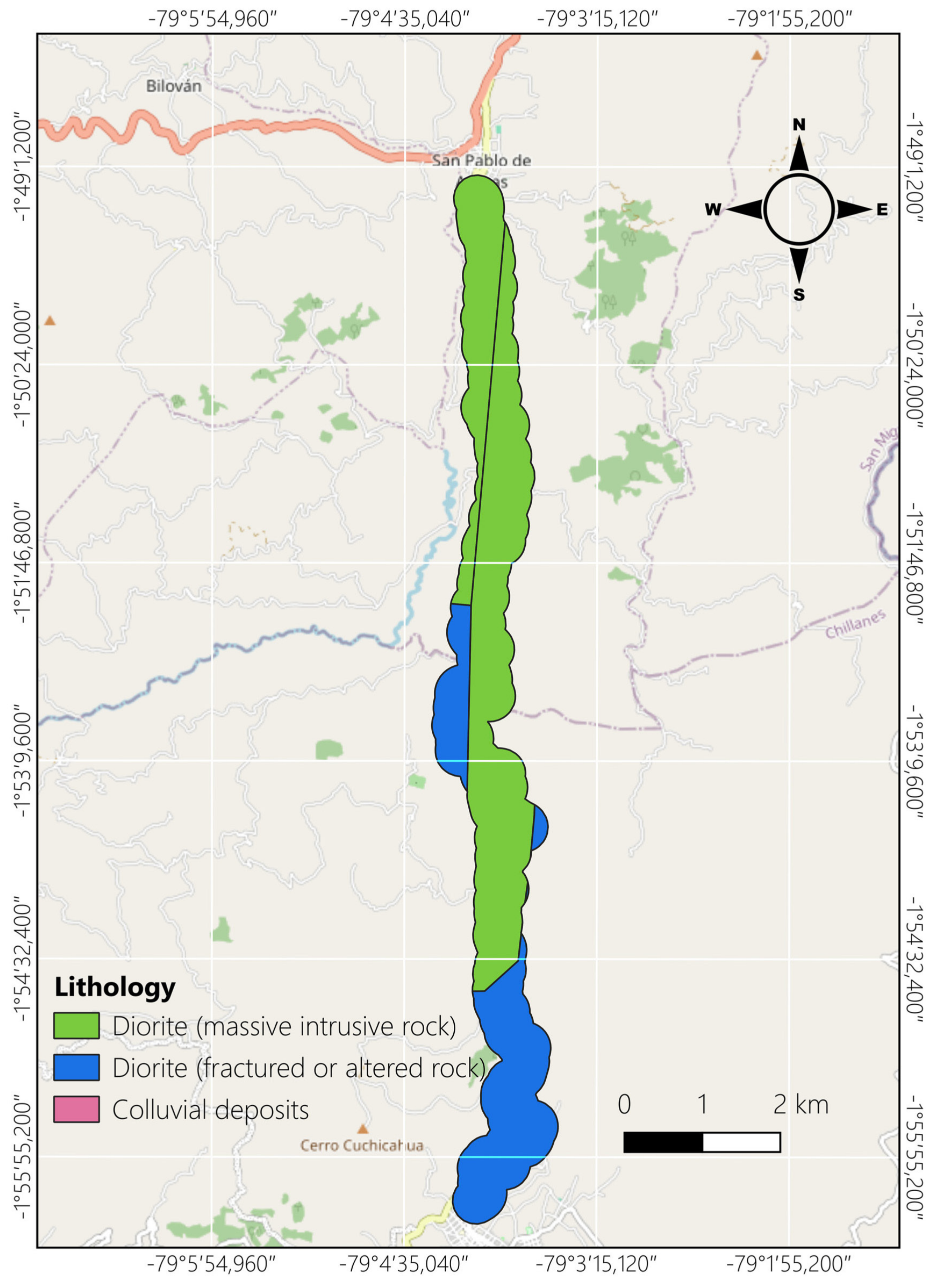

Fig. 7. Lithological map.

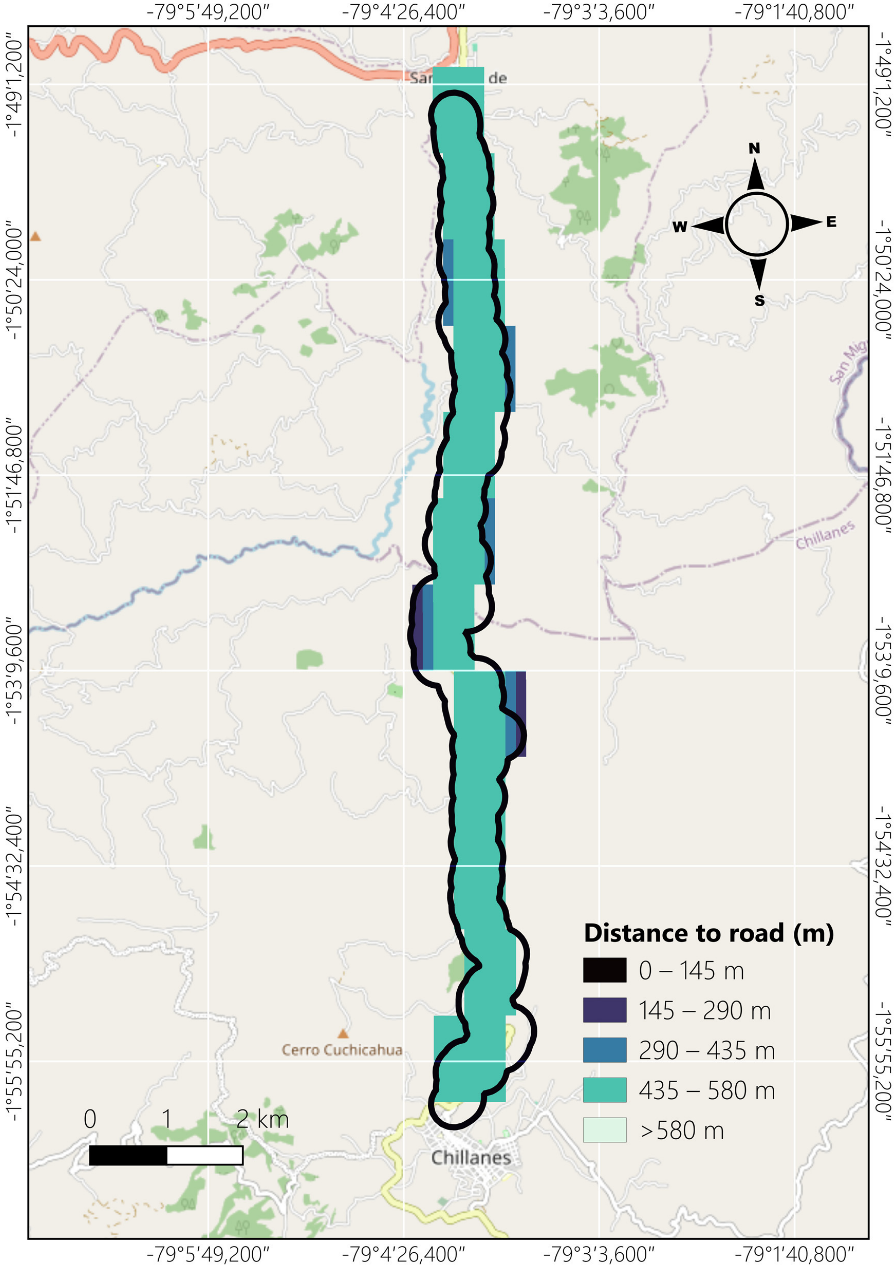

Fig. 8. Distance from the road (m).

Table 3. Saaty's fundamental 1-9 scale used in pairwise comparisons (Saaty 1977).

Value	Definition	Explanation
1	Equally important	Both decision elements have equal influence
3	Moderately more important	One decision element is moderately more influential than the other
5	Strongly more important	One element has a significantly greater influence than the other
7	Very strongly more important	One element has much greater influence than the other
9	Extremely important	One element has exceptionally greater influence than the other
2, 4, 6, 8	Intermediate values	Comparative judgments: moderately, strongly, and extremely

Using the values of the judgment matrix, equation (1) was applied to determine the final priority of each variable, normalizing the values to determine the final weight of each variable. This phase makes it possible to calculate the influence that each variable has on the general propensity to slippage.

$$CR = \frac{RI}{CI} \tag{1}$$

where *RI* (Table 4) is the random consistency index and *CI* is the consistency index, which is determined by the following equation (2):

$$CI = \frac{\lambda_{max} - n}{n - 1} \tag{2}$$

where is the highest value obtained from the eigenvector of the pairwise comparison matrix and $\lambda_{max} - n$ represents the number of variables in the study. The coherence relationship should, in accordance with Saaty and Vargas (2012), be equal to or less than 10% or have an inaccuracy of less than 10%. The principle is based on comparing judgments by randomly selecting elements. Finally, the weights unified various classes of causes into a single index of propensity to slip, *LSI*, using equation (3):

$$LSI = \textstyle\sum_{i=l}^{n} R_i W_i \tag{3}$$

where the classification classes of each variable are represented and the weights assigned to each variable are. As a result, a map is obtained that classifies the susceptibility to landslides into five levels: very high, high, moderate, low and very low. The quantile method is used to determine these categories, distributing the pixel values of the final cartographic model of susceptibility according to the established classes $R_i W_i$.

Checking the mapping model

The validation of the final cartographic model, which was built using the AHP method, was carried out by comparing the susceptibility results with the inventory of documented landslides in the road segment under study. This procedure makes it possible to evaluate the predictive ability of the model and establish its level of reliability (Tikuye et al. 2025). To balance the proportion between stable and unstable areas, non-event points were generated through stratified random sampling for this validation, leaving out a radius of 100 meters around the inventoried landslides. Likewise, the evaluation was applied by means of the ROC curve method, which is commonly used in research on susceptibility and prediction of mass movements (Zhang et al. 2024). This ROC curve is a graphical method that shows the relationship between the rates of true positives and false positives, which makes it possible to evaluate the model's discriminatory capacity. The predictive capacity of the cartographic model is measured through the area under the curve (AUC). If the value is close to 1.0, the predictive capacity is high; if, on the other hand, the value is close to 0.5, it means that the prediction is random and therefore the reliability decreases (Sharir et al. 2022).

A total of 3 inventoried landslide events were used as presence points for the ROC analysis. To ensure representation of stable areas, 46 non-event points were generated through stratified random sampling outside a 100 m buffer around the inventoried landslides, resulting in 49 validation points in total. The validation was internal, as the same inventory employed for model construction was used for performance assessment. Given the limited number of documented landslide events in the study corridor, the results should be interpreted with caution, and future research should incorporate larger independent inventories to strengthen predictive reliability.

Table 4. Random Consistency Index (source: Saat, Vargas 2012).

n	1	2	3	4	5	6	7	8	9	10
RI	0	0	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49

Results

Analytic hierarchy process

The evolution of the process of hierarchization and comparison of pairs made it possible to recognize the level of impact that the variables analyzed have on the occurrence of mass movements along the Chillanes–San Pablo de Atenas Road (Table 5). Slope,

Table 5. Hierarchy matrix and comparison of variables
(source: authors' elaboration based on the results of RStudio).

Variables	Categories	Value	Category	Variable weight	*CR* variable
Slope (°)	<5°	1	0.04	0.724	0.026
	5-10°	2	0.08		
	10-20°	4	0.15		
	20-30°	5	0.19		
	30-40°	8	0.31		
	>40°	6	0.23		
Lithology	Massive diorite	3	0.21	0.193	0.046
	Fractured diorite	5	0.33		
	Colluvial deposits	7	0.46		
Distance to roads (m)	0-145 m	7	0.41	0.083	0.013
	145-290 m	5	0.29		
	290-435 m	3	0.17		
	435-580 m	2	0.09		
	>580 m	1	0.04		

Table 6. Peer Comparison Matrix.

	Slope	Lithology	Distance to roads	Final weighting	*CR* final
Slope	1.00	0.20	0.14	0.724	0.096
Lithology	-	1.00	0.33	0.193	
Distance to roads	-	-	1.00	0.083	

Note. The consistency value (*CR* = 0.096) indicates
satisfactory consistency in comparisons (Saaty 1977).

lithology and distance to roads are the conditioning factors influencing slope instability, with slope showing the highest weight.

The validity of the comparative judgments was corroborated by the analysis of the consistency index (*CR* = 0.096), since it remained below the limit value of 0.10 proposed by Saaty (1977). This result shows that the weights given to the three variables are consistent and that the AHP process was carried out correctly. After the hierarchy and the evaluation of consistency, the final matrix of weights was generated. This matrix was used as a basis to build the slippage susceptibility model (Table 6).

The final susceptibility model was divided into five categories: very low, low, moderate, high, and very high (see Fig. 9). Most of the corridor exhibits moderate susceptibility, as evidenced by this spatial pattern; however, there are critical areas where the concentration of high instability is notable. The spatial analysis allowed the identification of 49 sections of the road with high and very high susceptibility levels, distributed discontinuously along the corridor (Table 7). These areas are mainly located between km 13 and 14 of the Perezán sector and in the surroundings of the Bilován and Hualicunhuaycu streams, areas that have historically been affected by mass removal phenomena (MIT 2025).

Cartographic model validation

The ROCR package was used to validate the model for mapping landslide susceptibility, and the statistical analysis of the ROC curve was performed in RStudio. Using the inventoried landslides along the study corridor as reference data, the predictive capability of the model was evaluated by comparing true positive and false positive rates (Agboola et al. 2024). The results yielded an Area Under the Curve (AUC) value of 0.885 (see Fig. 10), indicating high discriminatory performance. According to the classification proposed by Çorbacıoğlu and Aksel (2023), this value corresponds to a very good performance category, demonstrating that the model has strong ability to distinguish between stable and unstable areas.

Discussion

The AHP method, which is incorporated into a GIS environment, made it possible to detect areas with high landslide susceptibility on the Chillanes–San Pablo de Atenas Road. Significant differences were observed in the influence of the analyzed variables on slope instability (slope, lithology, and distance to roads). According to the results of the hierarchical analysis, slope was identified as the most significant variable, followed by lithology, whereas distance to roads showed a comparatively lower influence. This model is consistent with the findings reported by Reichenbach et al. (2018) and Corominas et al. (2023), which emphasize that geological and geomorphological factors are primary determinants of slope stability in Andean environments.

The consistency ratio remained below the threshold of 0.1 set by Saaty (1977), which confirms the internal consistency of the pairwise comparisons. This supports consistency within the AHP matrix and the reliability of the weights that are assigned, in line with

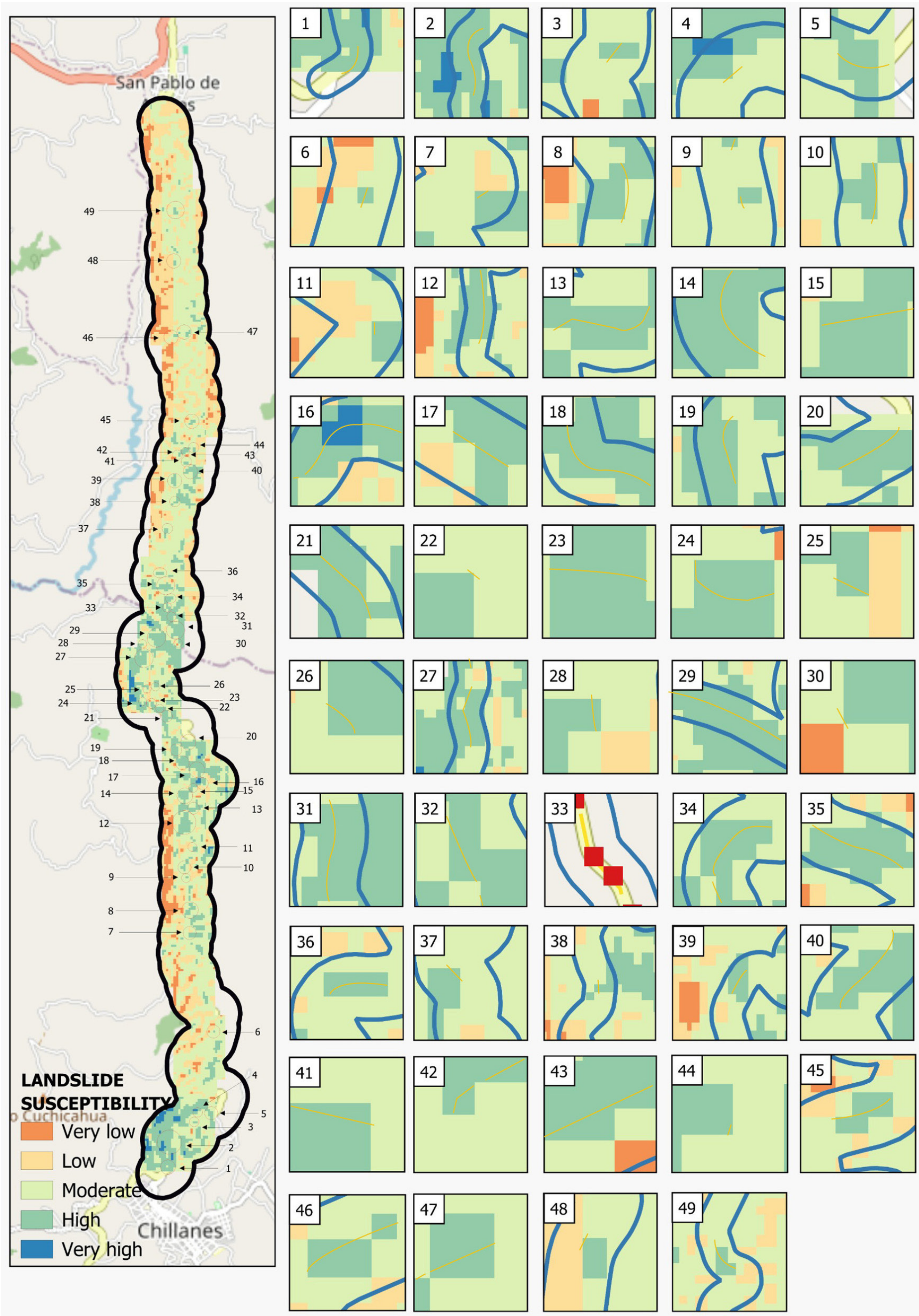

Fig. 9. LSI Susceptibility mapping model.

Table 7. Main regions of the Chillanes–San Pablo highway with high and very high susceptibility to landslides (source: authors' elaboration based on the results of QGIS).

Region	Km_start	Long_start	Lat_start	Km_end	Long_end	Lat_end
1	0.103	-79.067695	-1.936739	0.103	-79.067262	-1.936039
2	0.103	-79.067052	-1.934151	0.332	-79.067092	-1.932691
3	0.332	-79.064608	-1.931473	0.361	-79.064532	-1.931263
4	0.361	-79.064296	-1.930458	0.392	-79.064079	-1.930283
5	0.392	-79.060328	-1.930317	0.469	-79.062385	-1.930456
6	0.479	-79.064273	-1.921404	0.493	-79.062404	-1.921194
7	0.493	-79.065188	-1.910396	0.507	-79.065075	-1.910335
8	0.507	-79.065184	-1.908411	0.597	-79.065061	-1.907629
9	0.597	-79.065503	-1.904347	0.608	-79.065529	-1.90425
10	0.608	-79.065656	-1.903551	0.696	-79.065631	-1.902769
11	0.696	-79.064742	-1.900936	0.705	-79.064742	-1.900858
12	0.705	-79.065578	-1.899263	0.959	-79.065537	-1.896999
13	0.959	-79.057593	-1.899263	1.083	-79.057593	-1.896547
14	1.083	-79.061587	-1.894595	1.203	-79.065325	-1.894638
15	1.203	-79.061587	-1.894406	1.252	-79.047771	-1.894323
16	1.252	-79.064672	-1.894823	1.445	-79.063304	-1.893687
17	1.445	-79.063648	-1.892739	1.519	-79.064147	-1.89239
18	1.519	-79.064839	-1.892146	1.731	-79.066217	-1.891129
19	1.731	-79.063331	-1.890675	1.837	-79.066366	-1.889774
20	1.837	-79.065767	-1.889778	1.954	-79.064679	-1.8892
21	1.954	-79.067443	-1.886716	2.151	-79.068563	-1.885368
22	2.151	-79.0681	-1.885157	2.154	-79.068324	-1.885139
23	2.154	-79.06903	-1.885069	2.192	-79.069369	-1.885028
24	2.192	-79.069586	-1.885307	2.272	-79.070136	-1.884806
25	2.272	-79.069285	-1.883322	2.299	-79.069599	-1.883416
26	2.299	-79.068848	-1.883216	2.33	-79.069033	-1.883019
27	2.33	-79.070188	-1.880715	2.509	-79.070208	-1.87915
28	2.509	-79.070178	-1.878582	2.534	-79.070204	-1.878359
29	2.534	-79.06961	-1.87751	2.901	-79.066576	-1.878709
30	2.901	-79.06632	-1.873772	2.907	-79.066342	-1.873824
31	2.907	-79.06676	-1.877559	3.059	-79.06674	-1.876213
32	3.059	-79.06691	-1.875719	3.198	-79.06741	-1.874636
33	3.198	-79.067502	-1.874514	3.251	-79.067693	-1.874077

Region	Km_start	Long_start	Lat_start	Km_end	Long_end	Lat_end
34	3.251	-79.06707	-1.87374	3.381	-79.06812	-1.873298
35	3.381	-79.067165	-1.873236	3.533	-79.0684	-1.8718
36	3.533	-79.06782	-1.870676	3.625	-79.070329	-1.870637
37	3.625	-79.06777	-1.865767	3.651	-79.067629	-1.865583
38	3.651	-79.06677	-1.862872	3.677	-79.06674	-1.862641
39	3.677	-79.06657	-1.860722	3.755	-79.066592	-1.860118
40	3.755	-79.065433	-1.859566	3.892	-79.06478	-1.858582
41	3.892	-79.065239	-1.858434	3.948	-79.065374	-1.858326
42	3.948	-79.066293	-1.85767	3.974	-79.066145	-1.857497
43	3.974	-79.066056	-1.857445	4.075	-79.065242	-1.857046
44	4.075	-79.06503	-1.856889	4.08	-79.065019	-1.856849
45	4.08	-79.065239	-1.854032	4.173	-79.06446	-1.853752
46	4.173	-79.066944	-1.844422	4.244	-79.066397	-1.844109
47	4.244	-79.066377	-1.8441	4.271	–79.066158	-1.844001
48	4.271	-79.066948	-1.836141	4.291	-79.066883	-1.83597
49	4.291	-79.066381	-1.830733	4.389	-79.06692	-1.8301

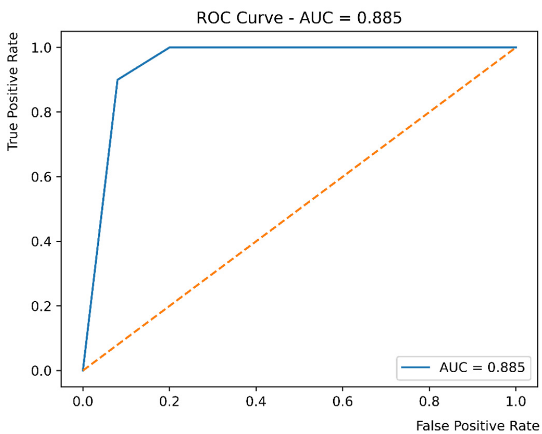

Fig. 10. ROC curve cartographic model.

what Shabbir et al. (2025) point out: that an appropriate normalization of factors makes the mathematical stability of multicriteria models better.

The model falls within the "very good" performance category, as defined by Çorbacıoğlu and Aksel (2023), which validates the effectiveness of the AHP-WLC approach. This value falls within the range reported by Agboola et al. (2024), who achieved an AUC of approximately 0.85 in similar susceptibility models applied to tropical highway corridors and is close to those achieved by Zhang et al. (2024) by combining AHP with AI techniques for mountain areas (AUC > 0.90). However, the model does not outperform machine learning approaches such as random forests, SVMs, or hybrid models. If these methods were included, it would be possible to assess the stability and robustness of the weights acquired through AHP.

The final susceptibility model (LSI) indicates that about 17.8% (1.49 km²) of the studied area has a high and very high susceptibility, especially between kilometers 13 and 14 of the Perezán area, as well as in the vicinity of the Bilován and Hualicunhuaycu streams. The coincidence of these areas with the historical landslides recorded corroborates the spatial correspondence between the observed events and the areas classified as more unstable. On the contrary, the categories of low and very low susceptibility comprise 32.5% of the corridor, areas that are characterized by gentle slopes and dense vegetation, which decreases the probability of the terrain sliding (Table 8).

The uncertainty inherent in the expert judgment used in the AHP is a key part of the analysis, as it can impact on the model's sensitivity and the weight's stability. This dependence on qualitative criteria, from an epistemological perspective, highlights the importance of incorporating additional validations and comparative models to strengthen the inferences that are made. Identifying and managing this uncertainty is an essential element for the progression towards more comprehensive assessments of geotechnical risk.

Table 8. Areas of susceptibility to landslides
(source: authors' elaboration based on the results of RStudio).

Category	Area (km²)	Area (%)
Very low	0.550	6.56
Low	2.177	25.93
Moderate	4.172	49.73
High	1.411	16.82
Very high	0.082	0.98
Total	8.392	100

Conclusion

The susceptibility model developed through the integration of the Analytic Hierarchy Process (AHP) and Geographic Information Systems (GIS) effectively identified areas most prone to landslides along the Chillanes–San Pablo de Atenas highway. The multi-criteria analysis, based on slope, lithology, and distance to roads, achieved high spatial accuracy in mountainous terrain with limited geotechnical data. Slope and lithology were the dominant conditioning factors, with weights of 0.724 and 0.193, respectively, while distance to roads had a secondary influence (0.083).

Model validation using the ROC curve (AUC = 0.885) confirmed an excellent predictive performance and demonstrated the robustness of the weighting structure. Approximately 17.8% of the study area exhibited high or very high susceptibility, mainly between kilometers 13 and 14 of the Perezán sector and in the surroundings of the Bilován and Hualicunhuaycu streams. These zones coincide with historical mass movements, reinforcing the reliability of the model.

The susceptibility map serves as a valuable instrument for managing road-related risks. It can assist organizations like the SNGR and MIT in determining priorities for slope stabilization, preventive maintenance, and the implementation of early warning systems. Furthermore, the methodological approach is adaptable for use in other Andean corridors, thereby facilitating improved planning and a reduction in exposure to natural hazards.

A primary constraint lies in the reliance on expert judgment during the AHP weighting process, which could potentially compromise the stability of the outcomes. Subsequent research should mitigate this by integrating hybrid methodologies (AHP–RF, AHP–SVM) to augment predictive capabilities and diminish subjectivity. Moreover, incorporating exposure and vulnerability analyses would contribute to the development of a more comprehensive risk assessment model for Ecuadorian road infrastructure.

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Streszczenie

Autostrada Chillanes-San Pablo de Atenas w Bolívar jest bardzo podatna na ruchy masy ze względu na swoje cechy geomorfologiczne, geologiczne i hydrometeorologiczne. Ten problem spowodował powtarzające się uszkodzenia infrastruktury drogowej, takie jak osuwiska o dużej skali, jak to, które miało miejsce na kilometrze 13 w 2020 roku. Celem tych badań było stworzenie kartograficznego modelu podatności na osuwiska za pomocą AHP-GIS, aby zidentyfikować obszary krytyczne i przyczynić się do zarządzania ryzykiem drogowym na drodze Chillanes-San Pablo de Atenas. Rozważano trzy główne zmienne: nachylenie, litologię oraz bliskość dróg, które ważono przez porównania parowe i nakładano na siebie przez ważone wagi liniowe. Ostateczny model został przeklasyfikowany na pięć klas podatności: bardzo niska, niska, umiarkowana, wysoka i bardzo wysoka. Wyniki wykazały, że obszary o wysokiej i bardzo wysokiej podatności, położone głównie między 13 a 14 kilometrami sektora Perezán, stanowią 17,8% wszystkich analizowanych obszarów. Łącznie wykryto 49 krytycznych segmentów o wysokim ryzyku osuwisk. Model został zweryfikowany na podstawie krzywej ROC i uzyskano wartość pola poniżej krzywej (AUC) 0,885, co oznacza, że jego wydajność jest bardzo dobra, jeśli uwzględnić międzynarodowy standard. Model kartograficzny jest użytecznym narzędziem technicznym do zapobiegawczego zarządzania ryzykiem geologicznym, ponieważ umożliwia ustalanie priorytetów interwencji, planowanie utrzymania dróg oraz ograniczanie wpływu przyszłych wydarzeń na pobliskie społeczności i budynki. Wyniki te są cennym narzędziem w zarządzaniu drogami, ponieważ sprzyjają priorytetowemu traktowaniu interwencji stabilizacyjnych, poprawiają planowanie konserwacji zapobiegawczej oraz zmniejszają podatność infrastruktury i społeczności na przyszłe osuwiska.

Słowa kluczowe: ruchy masowe; podatność na osuwiska; metoda analitycznego procesu hierarchicznego (AHP); krzywa ROC; model GIS.

Summary

The Chillanes-San Pablo de Atenas highway, in Bolívar, is highly susceptible to mass movements due to its geomorphological, geological and hydrometeorological characteristics. This problem has caused repetitive damage to road infrastructure, such as large-scale landslides, including the event that occurred at km 13 in 2020. The purpose of this research was to generate a cartographic model of susceptibility to landslides using AHP-GIS to identify critical areas and contribute to road risk management on the Chillanes-San Pablo de Atenas Road. Three main variables were considered: slope, lithology and proximity to roads, which were weighted by paired comparison and overlapped by weighted linear weighting. The final model was reclassified into five susceptibility classes: very low, low, moderate, high, and very high. The findings showed that the areas of high and very high susceptibility, located mainly between kilometers 13 and 14 of the Perezán sector, represent 17.8% of the total analyzed. In total, 49 critical segments with a high risk of landslides were detected. The model was validated with the ROC curve and an area under the curve (AUC) value of 0.885 was obtained, which means that its performance is very good if the international standard is considered. The cartographic model is a useful technical tool for the preventive management of geological risk, since it makes it possible to establish priorities for intervention, plan the maintenance of roads and reduce the effect of future events on nearby communities and structures. The results are a valuable tool for road management, as they favor the prioritization of stabilization interventions, improve preventive maintenance planning and reduce the susceptibility of infrastructures and communities to future landslides.

Keywords: landslides; landslide susceptibility; Analytic Hierarchy Process (AHP); ROC curve; GIS model.