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A comparative study of the bivariate statistical methods and the Analytical Hierarchical Process for the assessment of mass movement susceptibility. A case study: The LM-116 Road - Peru

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Abstract

It has been long observed that the Peruvian Central Highway (PE-22) and the LM-116 road are among the roads most affected by mass movements (MM) in Peru, frequently exposed to the occurrence of rockfalls, debris flow and landslides; both roads represent an important connection alternative between Lima with towns, cities and mining centers located in the Central Mountain Range of the Andes. In this research, firstly, a point density analysis was performed using Geographic Information Systems (GIS) considering the road network of all of Peru (composed of 144,499 km) and the inventory of geological hazards (GEOCATMIN) prepared by the Geological, Mining and Metallurgical Institute of Peru **INGEMMET (2000-2018)**. Subsequently, the evaluation of the mass movement susceptibility on the LM-116 road has been carried out using free access data reported by Peruvian institutions (INGEMMET, MTC, MINAM) from which it was possible to elaborate thematic maps, including the most relevant factors in the occurrence of mass movements, like a slope, lithology, geomorphology, land use, drainage density, and the distance from tectonic structures. Finally, for the mass movement susceptibility analysis, three methods have been considered: the Analytic Hierarchical Process (AHP), the Statistical Index (Wi) and the Weights of Evidence (WoE). The results were validated using the area under the curve criteria (AUC). Both bivariate statistical methods (Wi and WoE) presented a prediction rate above 78%, with a higher rate for the WoE method. On the other hand, the semi-quantitative method (AHP) obtained values in the order of 69%. Therefore, it is concluded that the maps elaborated with the statistical methods presented a better approximation concerning the database of geological hazards reported by GEOCATMIN.

Keywords:
Mass movement susceptibility; linear projects; Weights of Evidence; statistical index

1. Introduction

Linear projects, such as highways, aqueducts, and gas pipelines, are constantly affected by external geodynamic phenomena, such as landslides, floods, and earthquakes, which can cause considerable impacts, generating the loss of human lives and financial damage. According to the data recorded by the Ministry of Transport and Communications of Peru (**MTC, 2016**), Peru has a road network of 144,499 km, of which 26,706 km correspond to the national road network, 4,406 correspond to the departmental road network, and 113,387 km belong to the local road network. In the last 19 years, according to the Inventory of the Mining Geographic and Cadastral Information System of Peru (GEOCATMIN), more than 25,000 mass movements have been recorded throughout the country. Many of these events have directly affected the highways, highlighting that only during the "El Niño Costero" phenomenon in 2017, approximately 18,089 km of roads were destroyed or affected (**INDECI, 2017**).

An important approach for understanding and reducing losses due to mass movements is the susceptibility zoning of the territory (**Mezughi et al., 2012**). These susceptibility maps spatially predict landslides considering the causes of previous events (**Guzzetti et al., 1999**). There are different methods for mass movement susceptibility analysis, whose application depends on the type of mass movement, the size of the study area, the information available, the research scale and the knowledge of the experts who perform the studies (**Van Westen et al., 2008**). Among the most widely used methodologies to perform susceptibility models are semi-quantitative methodologies like the Analytical Hierarchical Process (AHP) and statistical methods, such as the Statistical Index (Wi) and Weights of Evidence (WoE) (**Khali et al., 2022**).

The Analysis Hierarchy (AHP) method has been successfully applied to landslide susceptibility mapping

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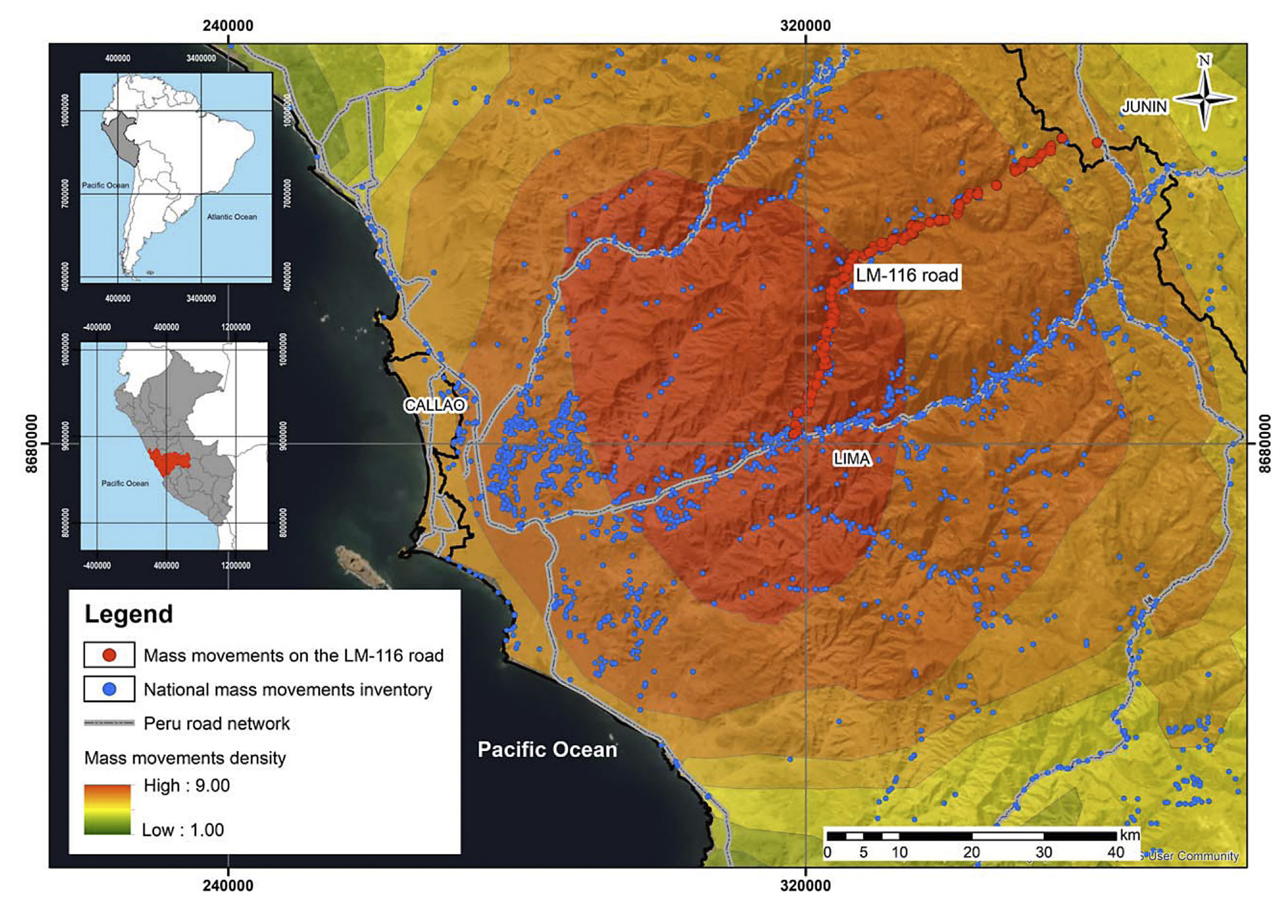

Figure 1: Point density analysis of all mass movement data from GEOCATMIN (2000-2018).

(**e.g. Ahmed, 2014; Ruff et al., 2008; Meena et al., 2019; Es-smari et al., 2021 and Shahabi et al., 2014**). On the other hand, the Statistical Index (Wi) was considered in the analysis reported by **He et al.** (**2008**), **Saenkang et al.** (**2022**) and **Qi et al.** (**2017**). Finally, the Weights of Evidence (WoE) methodology has been widely developed by **Van Westen et al.** (**2002**) and applied by **Riaz et al.** (**2018**), **Arifianti et al.** (**2020**), **Sadisun et al.** (**2021**), **Rohan et al.** (**2020**) **and Galindo et al.** (**2015**), who mainly applied this methodology to assess the susceptibility to mass movements in areas with road infrastructure.

In Perú INGEMMET has developed susceptibility maps at regional scales (1:50,000 - 1:100,000), using bivariate-heuristic methods, e.g. "The Susceptibility Map of Mass Movements in Peru" (**Villacorta et al., 2012**) or "The Susceptibility Map of Mass Movements in Piura" at a scale of 1:100,000 (**Vilchez et al., 2012**). Additionally, **CENEPRED (2014)** suggested that susceptibility zoning is essential in obtaining natural hazard levels in a study area. Although several studies of susceptibility to MM have been carried out at regional scales, few investigations have implemented methodologies for zoning susceptibility to roads in Peru.

Considering the highly complex situation related to the effects of geodynamic processes and the need for analysis that specifically consider the particularities of linear projects, this research proposes to analyze the susceptibility to mass movements on the LM - 116 (Santa Eulalia - Marcapomacocha). The choice of the study area was defined through a point density analysis in the Geographic Information System (GIS), considering the inventory of mass movements as input data **GEOCATMIN (2000-2018)** and the data corresponding to the National and Departmental Road Network (**MTC, 2016**). The result indicated that the majority of occurrences are concentrated in the roads that connect Lima with the central Andean zone of Peru (see **Figure 1**), known as PE-22C ("Carretera Central") and the LM-116 road. The analysis also shows that the LM-116 presents the highest concentration of occurrences along its 85.26 km. For this reason, LM-116 was chosen as a suitable area for the investigation.

In this study, the principal objective is to compare the results of three widely used methodologies to develop susceptibility maps, such as the AHP semi-quantitative method and bivariate statistical methods (Wi and WoE), and subsequently define which model has a better fit according to the area under the curve criterion (AUC).

The hypothesis of this research states that the susceptibility maps of the LM-116 road developed with semi-quantitative methods (AHP) can improve their level of

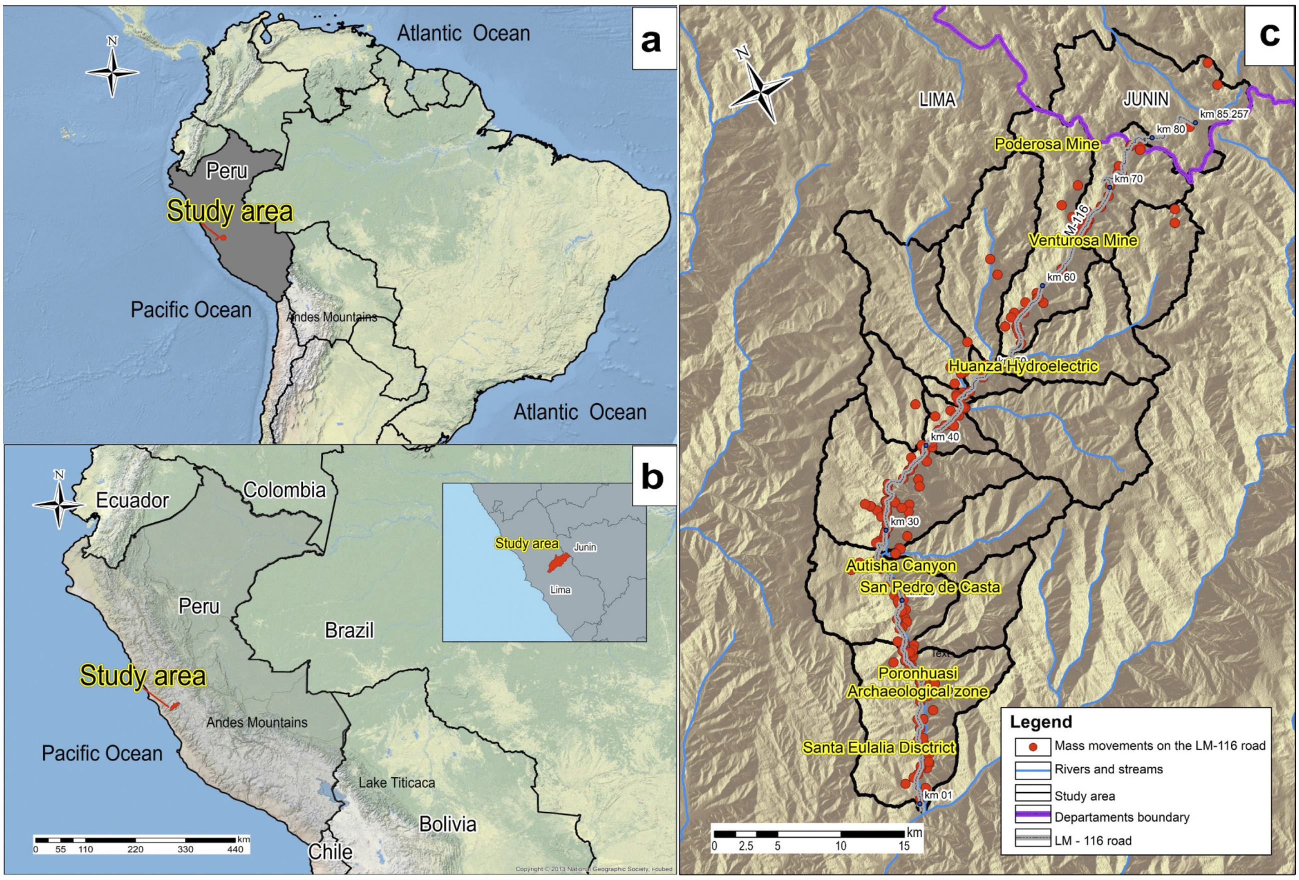

Figure 2: Geographic location of the study area: (a) Peru; (b) central zone of Peru; (c) inventory of mass movements in the study area.

prediction using statistical methodologies (Wi and WoE). This idea concords with previous research published by **Yalcin et al.** (**2011**) and **Meena et al.** (**2019**), who demonstrated that statistical methods have a more excellent approximation than semi-quantitative methods.

The present investigation is relevant because for the first time, the susceptibility to MM in one of the most affected roads by geological hazards in Peru (LM-116) is analyzed comparatively considering semi-quantitative and bivariate statistical methods. The adequate performance of the models implemented in this study will serve as valuable information to define critical sectors on other different linear projects in Peru.

2. Study area

To accomplish the comparative study of the three previously mentioned methodologies, the LM-116 road has been considered, which connects Santa Eulalia (Lima) and Marcapomacocha (Junín), located on the western flank of the Peruvian Andes (see **Figure 2**). The road belongs to one of the 29 routes of the department of Lima, which is classified as a departmental road network and has a length of 85.26 km. The study area is located within the Santa Eulalia Sub-basin, with average temperatures between 11°C and 25°C and annual rainfall between 60-800 mm with peaks between December and March.

The regional geology is presented in sheets 24j and 24k published by INGEMMET (**Palacios et al., 1992**) at a scale of 1:100. The study area is composed of a varied lithology spanning ages from the Cretaceous to the Quaternary. Sequences of tuffs in massive banks, tuffaceous breccias, and fractured andesitic lavas represent the oldest units. Sedimentary rocks correspond to the lithology of the Santa Eulalia River Basin and are characterized by intercalations of siltstones, calcareous mudstones, tuffaceous sandstones, and some levels of limestone (**Palacios et al., 1992**). Intrusive rocks are located to the southeast and at the end of the road; they are composed of tonalite and diorite corresponding to the Coastal Batholith of Peru.

Geomorphologically, the area corresponds to mountainous reliefs and hills molded in volcanic and volcano-sedimentary rocks affected by faults, folding and superficial fractures of ages between the Cretaceous and the Tertiary, which contrast with smooth reliefs in the bottom of the valley associated with Quaternary deposits (**Palacios et al., 1982; Salazar, 1983**).

The delimitation of the study area regards the micro-basins as borders; it has allowed the evaluation of the characteristics of the terrain considering the morpho-

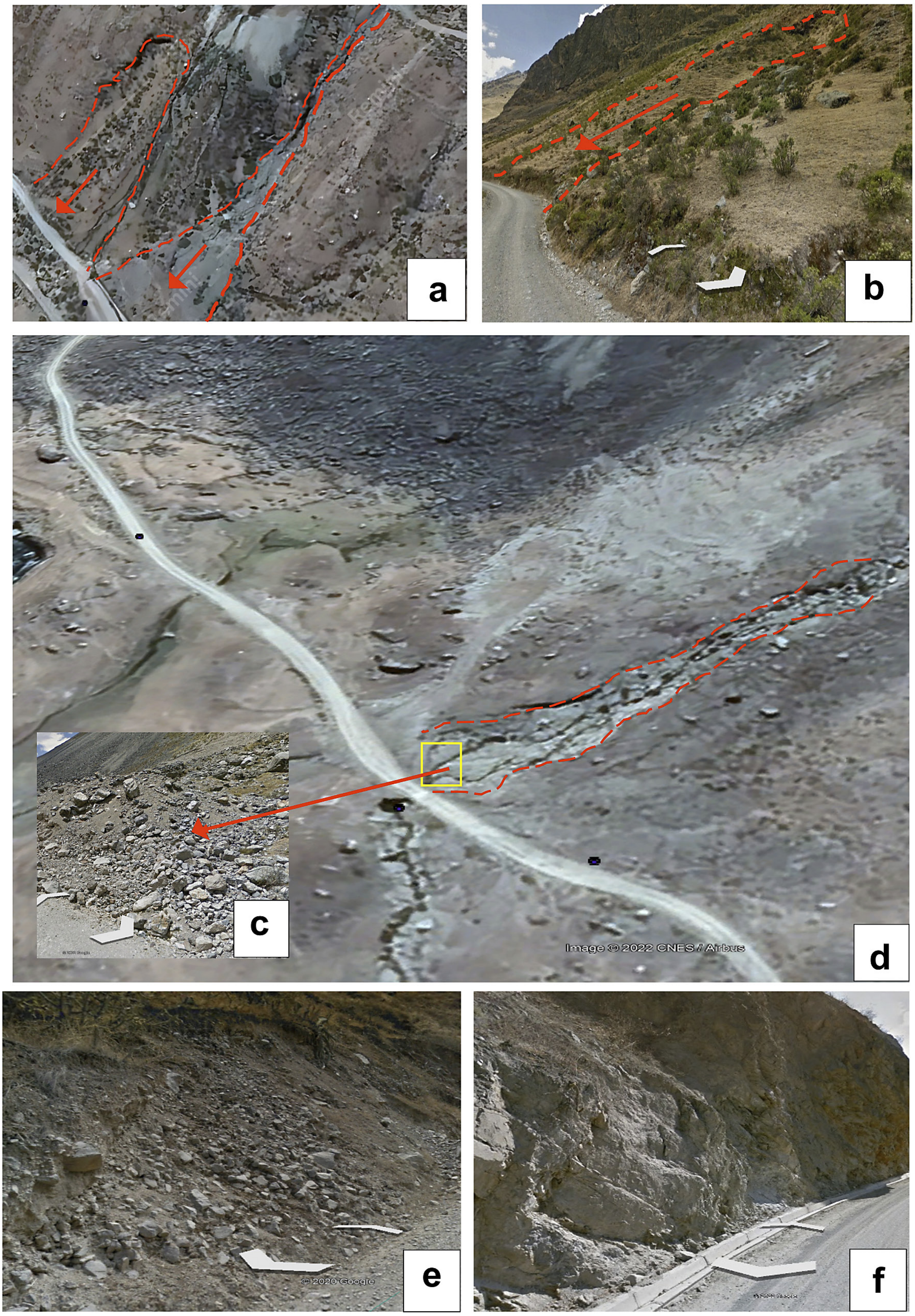

Figure 3: Images of some MM occurred in the study area. (a) Translational landslide and debris flow at km 13+250, (b) translational landslide at km 18+250. Figures (c) and (d) show a debris flow affecting the road. Figures (e) and (f) show rockfalls at km 30+000 (**Google Earth, 2022**).

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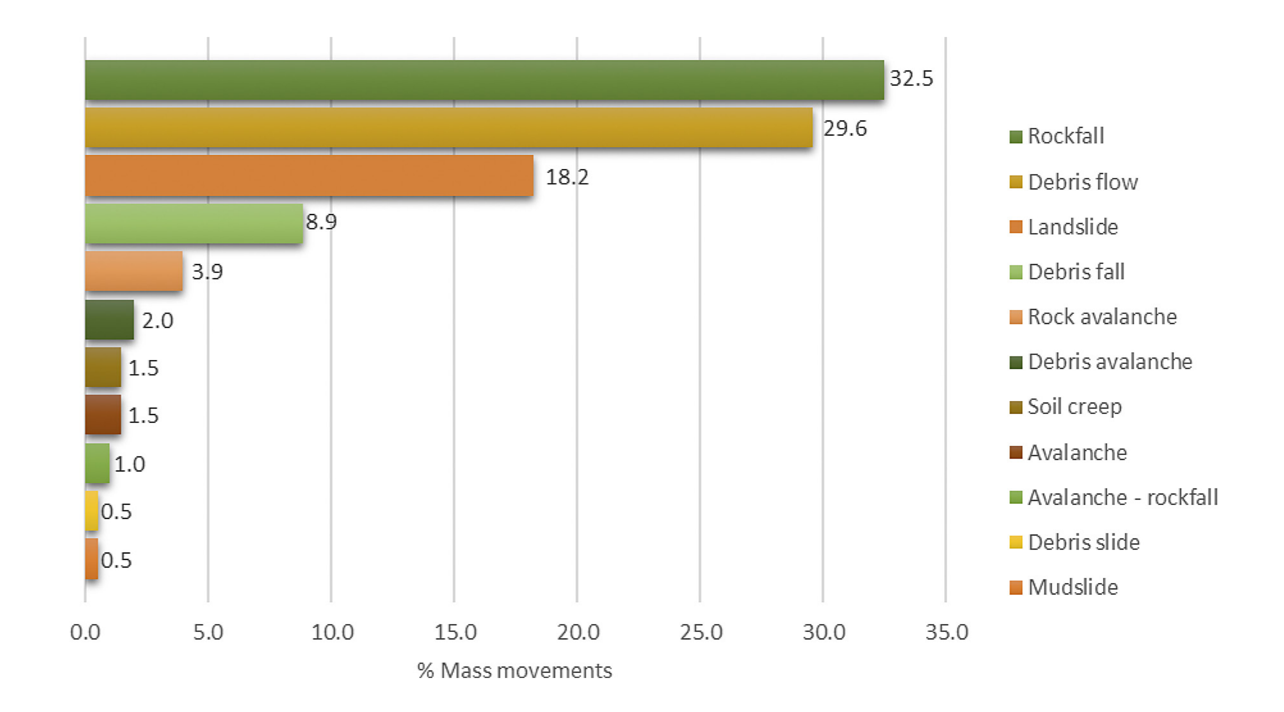

Figure 4: The mass movement inventory includes 200 mass movements of which 32.5% correspond to rock falls, 29.6% to debris flow, 18.2% to landslides and 19.7% to another type of process.

metric attributes of the Santa Eulalia River Sub-basin, which is part of the Rimac River Basin. The Rimac River Basin is one of the most important on the Peruvian coast. It allows the construction of various hydroelectric plants and the use of its waters for domestic consumption, especially in Lima. The Rimac River Basin is located in an area of high seismic activity, as part of the Pacific Ring of Fire and the activity of the South American Plate and the Nazca Plate. Deep earthquakes have been recorded that could cause rock falls and affect the structures in the basin (**Palacios et al., 1992**).

3. Database

Mass movement inventories are considered the first approach to susceptibility and threat maps since they strengthen the spatial distribution of mass movements that have occurred in the past (**Mendoza, 2017**). Thus, the first step to developing a susceptibility map is to build a spatial database including the most relevant factors in landslide occurrences (**Arsyad et al., 2019; Sinčić et al., 2021**).

Initially, the inventory of mass movements used in this research consists of 200 georeferenced points that belong to the compilation of geological processes that have occurred and are documented in the central studies of geodynamics and geological hazards compiled by **INGEMMET** (**2000 – 2018**) and registered in the GEOCATMIN database. Subsequently, all the MM were delimited with polygons considering a visual inspection using an orthophoto as a layout with a spatial resolution of 0.5 according to **Salas** (**2018**), who consider morphological criteria, such as slope change, land use, among others.

3.1. Mass movements description

A total of 200 mass movements were identified along the LM-116 road, covering an area of 21.53 km², representing 2.04% of the study area (1,054.13 km²). This research considered the classification of MM used in the Guide for the Evaluation of Threats of the Andean Multinational Project (**PMA, 2007**). This document is based on the classification of **Cruden and Varnes** (**1996**) and considers the characteristics of MM observed in the Andes Mountains.

The mass movements in the study area are varied, and composed mainly of rockfalls, debris flows and landslides (see **Figure 3**). The rockfalls represent 32.5% of the total registered movements and their occurrence is related to the alternation of competent rocks with weathered or highly fractured and altered rocks.

Debris flow constitutes 29.6% of the total registered movements. They are composed of thick material saturated with water activated by occasional or exceptional high-intensity rainfall and transport materials accumulated in the streambeds and the course of the Santa Eulalia River. Many of these do not present recent activity. However, this does not mean that the materials accumulated in their channels cannot generate debris flows in the future.

The landslides represent 18.2% of the total movements, compromising superficial formations and even

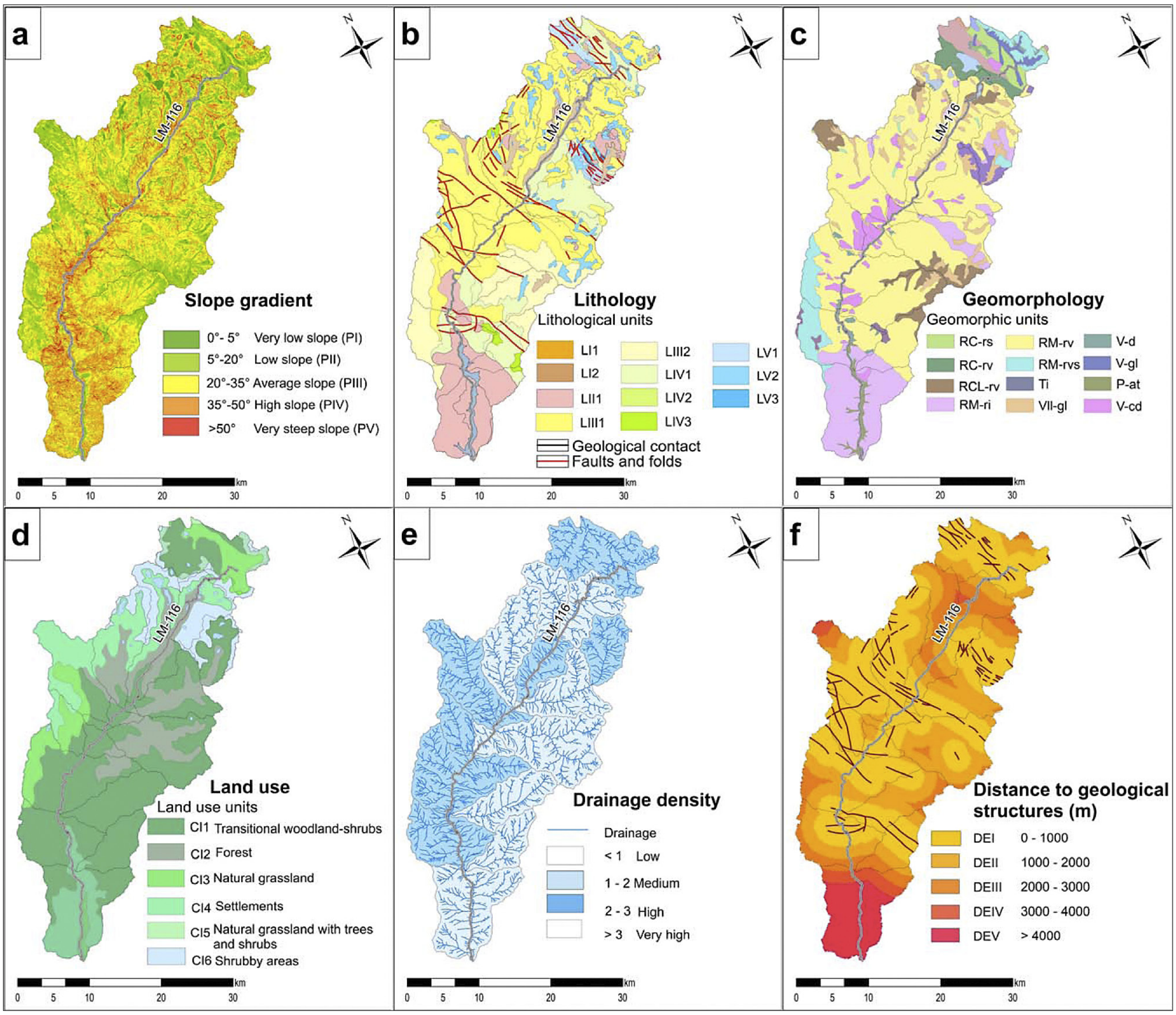

Figure 5: Mass movements conditioning factors: (a) slope gradient, (b) lithology, (c) geomorphology, (d) land use, (e) drainage density and (f) distance to geological structures.

substratum rocks. Most landslides are rotational, and they have active and old inactive scarps to the order of tens to hundreds of meters. In many cases, they have suffered reactivations due to slope cuts to construct roads. The complete mass movement inventory including all 200 events is presented in **Figure 4**.

3.2. *Conditioning factors*

Conditioning variables, intrinsic or predisposition variables, are used in elaborating mass movement susceptibility mapping. **Aristizabal et al.** (**2019**) indicate that the conditioning variables are the internal and inherent characteristics of the terrain that favor the occurrence of mass movements. These variables present slight temporal variation; for this reason, they are also called static or quasi-static variables. From the point of view of **Lee et al.** (**2008**), the set of conditioning variables that directly or indirectly influence the occurrence of MM differs depending on the scale of analysis, the characteristics of the study area and the type of mass movements.

The study area presents a set of variables that respond to the occurrence of mass movements, such as slope, lithology, geomorphology, land use, drainage density and distance to the tectonic structures, which are represented in thematic maps (see **Figure 5**).

3.2.1. Slope map

Slope is an important morphometric variable that affects slope stability at different scales (**Coco et al., 2015; Yalsin et al., 2011**). For the generation of the slope map, the digital elevation model (DEM) generated with ALOS PALSAR satellite images with a spatial resolution of 12.5 meters was used. These images were downloaded free of charge from Earth Science Data Systems (ESDS).

Once the slope raster was obtained, they were grouped into ranges between 0° and 80°; these values were reclassified into five categories from very low to very high slopes. Slope values were classified considering the ranges proposed by **Van Zuidam** (**1986**), which relate the slope inclination with the terrain characteristics.

3.2.2. Lithological map

Lithological maps are essential in heuristic and statistical methods in landslide susceptibility assessment. The information from these maps and their geological classification provides information on the rock composition and the rock mass strength (**Guzzetti et al., 1999**). For the preparation of the lithological map, geological sheets of Chosica (24-j) and Matucana (24-k) at 1:100,000 scale were considered (**Palacios et al., 1992**).

Initially, the geological units were divided into four groups: intrusive rocks, sedimentary rocks, volcanic rocks, and volcanic-sedimentary rocks. Subsequently, these units were reclassified into subunits based on the genesis and the degree of weathering. Finally, eleven different classes were considered (see **Table 1**).

3.2.3. Geomorphological map

The map of geomorphological units constitutes an essential input for the definition of potential hazard scenarios due to mass movements (**Rodríguez et al., 2017**). The external geodynamic processes that occurred in the past, as mass movements, are manifested through geomorphological footprints left by these phenomena in the past. The current configuration of the terrain reflected in the geomorphological units is a sample of the magnitude of these processes. In mass movement susceptibility modeling, geomorphology constitutes the most critical factor for the analysis of the evolution of the territory (**Van Westen et al., 2003**).

The characteristics of the geomorphological units are of interest for the mass movement analysis because they can be indicative of instability; for example, for rockfalls, the geoforms related to slopes and escarpments must be considered, while for flow analysis, it is advisable to consider geoforms whose origin is related to denudational or fluvial areas.

The information related to the geomorphological units was taken from the Geomorphological Map of Peru at a scale of 1: 100,000 prepared by **INGEMMET** (**2012**).

3.2.4. Land use map

Land use is generally considered a conditioning factor within susceptibility analyses. It can be included as an independent information layer representing current soil conditions in anthropic dynamics within the territory (**Van Westen et al., 2016**). Changes in land use have a significant influence on slope stability. It has been observed that the increase and conversion of secondary forests to grasslands and farmland lead to an increase in surface movements and that the abandonment of farmland induces a significant decrease in the frequency of landslides (**Reichenbach et al., 2014**).

The information corresponding to land use was obtained from the map prepared by the National Office for the Evaluation of Natural Resources of the Ministry of the Environment **(**ONERN-MINAM) at a scale of 1: 100,000.

3.2.5. Drain density map

The drainage density map was generated from the drainage network and hydrographic basins derived from the 12.5 m Alos Palsar DEM. The drainage density values corresponding to the 19 micro-watersheds in the study area range from 1.79 to 2.23. 53% of the micro-basins have moderate drainage density values and 47% have high values between 2.07 and 2.23. The drainage density map was classified into four categories considering the classification of **Delgadillo et al.** (**2008**).

3.2.6. Distance to geological structures map

Various studies, e.g. **Zare et al.** (**2014**), **Nohani et al.** (**2019**) and **Basharat et al.** (**2016**), include the distance to the tectonic structures (faults and folds) as a conditioning factor in the evaluation of mass movements susceptibility. This variable is associated with slope instability events because tectonic activity generates planes of weakness in the rock masses, which causes the material to weather and erode more quickly.

It is essential to mention that in the case of mass movements related to active faults, it is not enough to know only the distance to the rupture zone but also aspects such as the fault type, expected length of the rupture, depth of earthquakes, magnitude, among others (**Rodríguez et al., 2017**). The distance map to the tectonic structures was prepared based on Chosica (24-j) and Matucana (24-k) geological sheets, which indicates that the study area presents a fault system that crosses the Rimac River Valley with a NW-SE strike.

In this study, distances to the faults recommended by **Regmi et al.** (**2010**) were reclassified into ranges between 0 and 4,000 m, where lower values indicate greater susceptibility to mass movements.

4. Methodology

There are several approaches to generate susceptibility models. For example, semi-quantitative models are generally based on the weighting and qualification of the factors that condition the occurrence of landslides (**Ayalew, 2004**). One of the most widely used weighting methods is the Analysis Hierarchy (AHP) method, which has been successfully applied to landslide susceptibility mapping by researchers such as **Ahmed** (**2014**), **Ruff et al.** (**2008**), **Meena et al.** (**2019**), **Es-smari et al.** (**2021**) and **Shahabi et al.** (**2014**).

Table 1: The weight of each factor estimated by the Weights of Evidence methodology

	Factor map class	MM pixels	% MM	Pixels Class	% Class	Wi+	Wi-	Wf
Lithological units	Unconsolidated materials. Sand, silt, gravel (LI1)	54	0.160	17,177	1.018	-1.855	0.009	-1.864
	Unconsolidated deposits. Sand, silt, gravel and occasionally boulders (LI2)	1,127	3.346	21,847	1.294	0.996	-0.022	1.017
	Intrusive rocks. Tonalite, diorite, granodiorite and monzodiorite (LII1)	2,027	6.017	65,728	3.894	0.485	-0.024	0.510
	Basal conglomerate sequence, tuffs and andesites (LIII1)	1,734	5.148	97,550	5.779	-0.061	0.003	-0.064
	Sequence of tuffs, lavas and dacitic breccias (LIII2)	5,911	17.547	215,970	12.795	0.446	-0.074	0.520
	Rhyolites, limestones, and sandstones (LIV1)	2,828	8.395	276,603	16.387	-0.524	0.065	-0.589
	Volcanic agglomerates, limestone and shale (LIV2)	3,983	11.824	207,202	12.275	0.080	-0.010	0.090
	Rhyolitic tuffs, sandstones, and siltstones (LIV3)	0	0.000	1,580	0.094	0.000	0.001	-0.001
	Shales, limestones, and conglomerates (LV1)	34	0.101	14,357	0.851	-2.141	0.008	-2.148
	Volcanic agglomerates, limestone, and shale (LV2)	0	0.000	48,955	2.900	0.000	0.029	-0.029
	Sandstone and quartzite (LV3)	10,069	29.891	459,116	27.200	0.341	-0.116	0.458
Slope	0°-5° Very low slope (PI)	522	1.550	52,347	3.100	-0.673	0.015	-0.689
	5°-20° Low slope (PII)	8,130	24.140	547,287	32.45	-0.015	0.005	-0.020
	20°-35° Average slope (PIII)	16,172	48.010	743,063	44.05	0.459	-0.293	0.752
	35°-50° High slope (PIV)	7,914	23.500	311,144	18.450	0.420	-0.100	0.520
	>50° Very steep slope (PV)	946	2.810	32,854	1.950	0.395	-0.009	0.404
Geomorphological units	Sedimentary hill (RC-rs)	332	0.990	31,151	1.850	-0.618	0.009	-0.627
	Volcanic hill (RC-rv)	131	0.390	38,955	2.310	-1.774	0.019	-1.794
	Volcanic hill and volcanic knoll (RCL-rv)	215	0.640	84,433	5.000	-2.027	0.043	-2.070
	Intrusive mountain (RM-ri)	2,613	7.760	239,839	14.210	-0.479	0.053	-0.532
	Volcanic mountain (RM-rv)	15,602	46.320	878,623	52.050	0.307	-0.205	0.512
	Volcano-sedimentary mountain (RM-rvs)	2,664	7.910	97,318	5.770	0.381	-0.027	0.408
	Terrace (Ti)	2	0.010	834	0.050	-2.136	0.000	-2.137
	Glacial valley (VII-gl)	1,921	5.700	93,244	5.520	0.087	-0.005	0.092
	Colluvial slope (V-d)	382	1.130	14,469	0.860	0.295	-0.003	0.298
	Glacial or gelifraction slope (V-gl)	120	0.360	17,606	1.040	-1.077	0.007	-1.084
	Alluvium-torrential slope (P-at)	1,272	3.780	15,158	0.900	1.513	-0.030	1.543
	Colluvio-deluvial slope (V-cd)	8,404	24.950	81,067	4.800	1.785	-0.244	2.029
Land use	Transitional woodland-shrubs (CI1)	20,030	59.460	799,861	47.410	0.626	-0.520	1.147
	Forest (CI2)	3,694	10.970	242,468	14.370	-0.138	0.018	-0.157
	Natural grassland (CI3)	745	2.210	141,466	8.380	-1.265	0.059	-1.325
	Settlements (CI4)	980	2.910	207,482	12.300	-1.339	0.088	-1.427
	Natural grassland with trees and shrubs (CI5)	687	2.040	13,608	0.810	0.968	-0.013	0.980
	Shrubby areas (CI6)	2,684	7.970	115,863	6.870	0.220	-0.017	0.237

Table 1: Continued

	Factor map class	MM pixels	% MM	Pixels Class	% Class	Wi+	Wi-	Wf
Density of drains	Micro-basin_01 (Medium)	104	0.310	3,340	0.200	0.458	-0.001	0.459
	Micro-basin 02 (High)	693	2.060	7,231	0.430	1.654	-0.017	1.670
	Micro-basin 03 (High)	2,245	6.660	16,029	0.950	2.088	-0.061	2.149
	Micro-basin 04 (Medium)	2,788	8.280	27,147	1.610	1.742	-0.072	1.814
	Micro-basin 05 (High)	507	1.510	48,027	2.850	-0.618	0.013	-0.631
	Micro-basin 06 (Medium)	69	0.210	65,375	3.880	-2.920	0.037	-2.957
	Micro-basin 07 (High)	1,059	3.140	66,627	3.950	-0.193	0.007	-0.200
	Micro-basin 08 (Medium)	1,013	3.010	67,139	3.980	-0.245	0.009	-0.254
	Micro-basin 09 (High)	6,419	19.060	73,032	4.330	1.597	-0.172	1.769
	Micro-basin 10 (Medium)	1,331	3.950	85,931	5.090	-0.208	0.010	-0.217
	Micro-basin 11 (Medium)	602	1.790	94,094	5.580	-1.096	0.037	-1.133
	Micro-basin 12 (Medium)	0	0.000	98,774	5.850	0.000	0.058	-0.058
	Micro-basin 13 (High)	3,430	10.180	116,546	6.910	0.466	-0.041	0.507
	Micro-basin 14 (High)	1,281	3.800	122,854	7.280	-0.588	0.032	-0.620
	Micro-basin 15 (Medium)	1,300	3.860	126,432	7.490	-0.600	0.034	-0.633
	Micro-basin 16 (Medium)	65	0.190	159,441	9.450	-3.819	0.090	-3.909
	Micro-basin 17 (High)	3,062	9.090	164,341	9.740	0.024	-0.002	0.027
	Micro-basin 18 (High)	4,762	14.140	172,077	10.200	0.433	-0.056	0.490
	Micro-basin 19 (Medium)	2,956	8.780	172,816	10.240	-0.058	0.006	-0.064
Distance tectonic structures	0 – 1000 m (DEI)	222	0.660	21,116	1.250	-0.639	0.006	-0.645
	1000 – 2000 m (DEII)	362	1.070	36,083	2.140	-0.677	0.011	-0.688
	2,000 – 3,000 m (DEIII)	416	1.230	36,896	2.190	-0.559	0.009	-0.568
	3,000 – 4,000 m (DEIV)	432	1.280	37,001	2.190	-0.523	0.009	-0.532
	> 4000 m (DEV)	32,088	95.220	541,130	91.350	0.701	-2.402	3.103

Another of the widely used approaches is the bivariate statistical analysis, which includes methodologies that establish relationships between conditional factors (lithology, slope, land use, among others) and the current and past distribution of mass movements (**Aristizábal, 2019**). Some of the widely used statistical methodologies are the Radio Frequency (RF), used by **Chalkias et al.** (**2014**) and **Silalahi et al.** (**2019**), the Statistical Index (Wi) developed in the publications of **He et al.** (**2008**), **Saenkang et al.** (**2022**) and **Qi et al.** (**2017**). Regarding the Weights of Evidence (WoE) methodology, it has been widely developed by **Van Westen et al.** (**2002**) and applied by **Riaz et al.** (**2018**), **Arifianti et al.** (**2020**), **Sadisun et al.** (**2021**), **Rohan et al.** (**2020**) and **Galindo et al.** (**2015**), who mainly applied this methodology to assess the susceptibility to mass movements in areas with road infrastructure.

Considering the scope of this research and considering the characteristics of the study area and the cartographic information layers, three methodologies were developed and compared for the analysis of susceptibility to mass movements on the LM-116 road: the Hierarchical Analysis (AHP) and two bivariate statistical methods: the Statistical Index (Wi) and Weights of Evidence (WoE).

4.1. Multicriteria method (AHP)

The AHP method or Analysis Hierarchical Process consists of creating a decision hierarchy of priorities, where the different factors that influence decision-making are organized hierarchically and compared to each other through the organization of paired comparison matrices (**Saaty, 1987**). The basis of Saaty's methodology lies in that decision-makers can assign quantitative values for the evaluation, measuring how each element of the hierarchy contributes to the immediately superior level from which it emerges (**Toscano, 2005**). For these comparisons, ratio scales are used in preference, importance, or probability; based on a numerical scale proposed by Saaty, which ranges from 1 to 9.

To carry out the application of this analysis, an analytical ranking matrix was developed for each of the classes that make up the determining factors of the MM. This first analysis established a set of weights for each parameter and created thematic rasters: slope, lithological units, geomorphological units, land use, drainage density and distance to tectonic structures. After classifying the units of each information layer, mass movement conditioning factors were compared again using ranking matrices. This analysis provided the weighted weights for each parameter used in the algebra of maps.

4.2. Statistical Index method (Wi)

Statistical analyses of mass movement susceptibility combine factors that have generated MM in the past and that can be determined statistically. This way, quantitative predictions are made for areas free of mass movements where similar conditions exist (**González, 2015**).

In the bivariate statistical analysis, each conditioning factor (geology, geomorphology, slope, and land use, among others) is combined with the frequency of the MM, and weighted values of densities are calculated of the mass movements for each class. Therefore, a higher percentage of mass movements is found in a smaller accumulated susceptibility area (**Chalkias et al., 2014**).

For the Statistical Index method (Wi), the evaluation of susceptibility involves three steps: the inventory of mass movements, the recognition of the most significant parameters (conditioning factors) in the spatial distribution of the movements and the definition of the weights relative to each factor associated with the location of mass movements. The analysis compares the number of MM per area unit for each variable (class density) of the thematic maps concerning the number of all MM per area unit for the entire study area (total density). The result obtained is presented in terms of the natural logarithm of the said relationship. The comparison between the different variables is built according to equation (1), proposed by **Van Westen** (**1997**) and it was considered in further investigations by **Çevik et al.** (**2003**).

$$Wi = Ln\frac{DenClase}{DenMapa} = \frac{\acute{A}rea(Si)/\acute{A}rea(Ni)}{\sum \acute{A}rea(Si)/\sum \acute{A}rea(Ni)} \tag{1}$$

Where:

Wi – Calculated weight for each class of a factor,

Ln – Natural logarithm,

DenClase – Density of MM per class of a given variable,

DenMapa – Density of MM in the whole map,

Area (Si) – Area of the MM contained in a class for a given variable,

Area (Ni) – Total area of the class for a given variable.

4.3. Weights of Evidence (WoE) method

The bivariate statistical method (WoE) is based on Bayesian probability theory, where the relationship between two events is analyzed (**Sujatha et al., 2012**). In the case of models of mass movement susceptibility, the relationship between the areas affected by the MM and the spatial distribution of the conditioning factors is evaluated (**Van Westen et al., 2003**). This statistical method is oriented to the calculation of the weights of the classes that make up the conditioning variables; this weight indicates the presence and influence of the class as a parameter in the MM occurrence (**Lee et al., 2017**). The weights assigned to each class can be positive (W+) and negative (W-) weights. The positive weights (W+) indicate the presence of the class as a parameter that favors the MM, and its magnitude indicates its correlation. The negative weight (W-) indicates the absence of the class. If zero, the analyzed class is not of interest to the MM.

The Weight of Evidence method was developed by the Canadian Geological Survey (**Agterberg et al., 1990; Bonham-Carter et al., 1989**) used to calculate the weighting factors of the classes that make up the conditioning variables for the occurrence of landslides. Equations (2) and (3) are used to calculate the positive and negative weights, respectively. The final weight of evidence value, used for mass movement susceptibility analyses, is acquired using equation (4) (**Van Westen et al., 2002**).

$$W_i^+ = \ln\frac{\frac{Npix1}{Npix1 + Npix2}}{\frac{Npix3}{Npix3 + Npix4}} \tag{2}$$

$$W_i^+ = \ln\frac{\frac{Npix2}{Npix1 + Npix2}}{\frac{Npix4}{Npix3 + Npix4}} \tag{3}$$

Where:

Npix1 – Number of pixels with mass movements in the class,

Npix2 – Number of pixels with mass movements that are not present in the same category,

Npix3 – Number of pixels in the class where there are no mass movements,

Npix4 – Number of pixels in the class where there are no mass movements and that are not present in the same class.

The Weights of evidence Wi $^+$ and Wi $^-$ must be calculated for each variable, then, the Contrast Weight or Final Weight (Wf) is estimated with the following equation:

$$W_f = W_i^+ - W_i^- \tag{4}$$

Where:

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Table 2: Input used in each model

Map input data	Model 1 (AHP)	Model 2 (AHP)	Model 3 (Wi)	Model 4 (Wi)	Model 5 (WoE)	Model 6 (WoE)
Slope	X	X	X	X	X	X
Lithology	X	X	X	X	X	X
Geomorphology	X	X	X	X	X	X
Land use	X	X	X	X	X	X
Drain density		X		X		X
Distance to structures		X		X		X

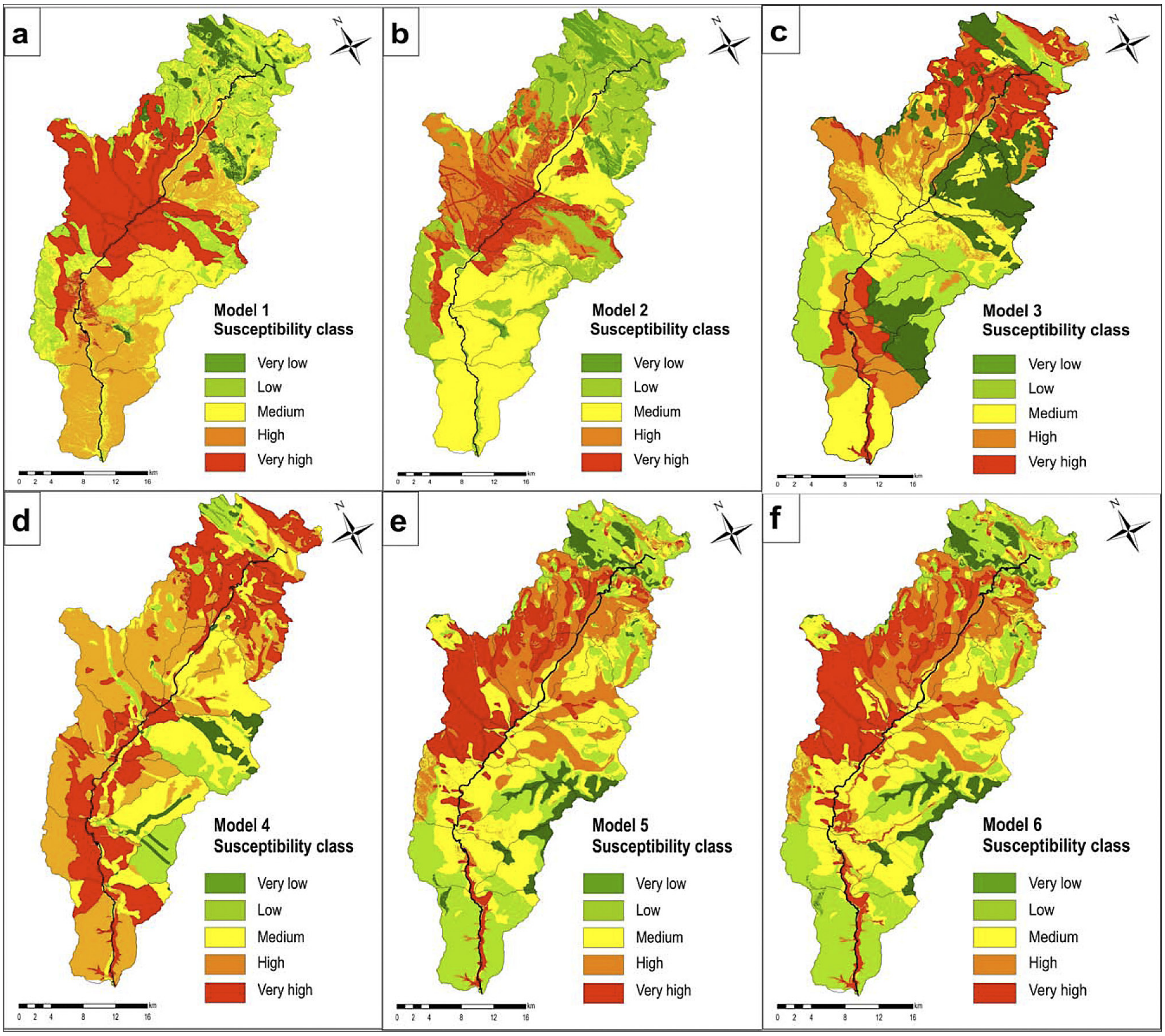

Figure 6: Comparison of the six mass movements susceptibility models obtained with the AHP, Wi and WoE methodologies. (a) Model 1 - AHP method, (b) Model 2 - AHP method, (c) Model 3 - Wi method, (d) Model 4 - Wi method, (e) Model 5 - WoE method and (f) Model 6 - WoE method.

W_i^+ – Positive weights (indicating the importance of the presence of the factor),

W_i^- – Negative weights (indicating the importance of the absence of the factor),

Wf – Weight of evidence value (weight factor).

The relationship of the historical mass movements records for each lithological unit suggests that the unconsolidated deposits, conformed by sand, silt and gravel (Wf=1.017), as well as the volcanic sedimentary rocks composed of tuff sequences, lavas and breccias with a

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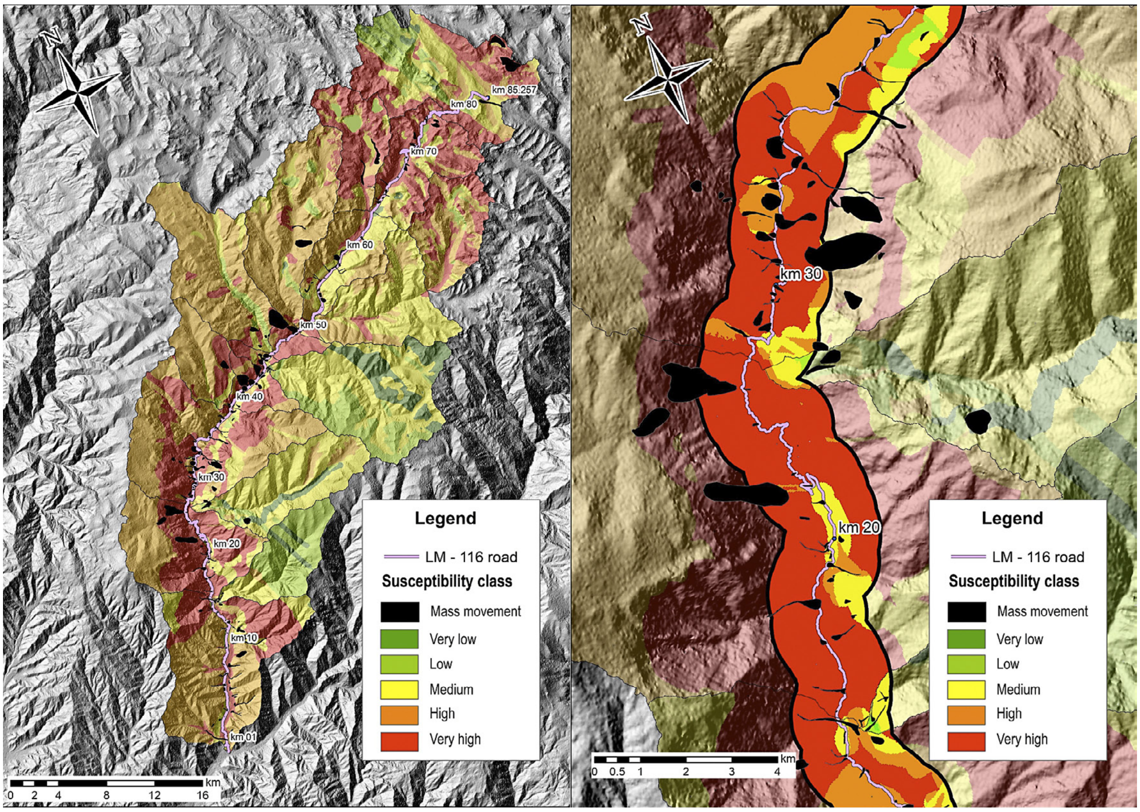

Figure 7: Approximation to the mass movements susceptibility Model 4 (Wi methodology). It is observed that the sector located between km 14+000 - km 36+000 presents areas of very high susceptibility.

high degree of erosion (Wf= 0.520), have a greater predisposition for the occurrence of MM, likewise slopes with inclination between 20º and 35° present a major occurrence of mass movements, which is reflected in the positive value of Wf equal to 0.752. In the case of geomorphological units, the class corresponding to the colluvio-diluvial slopes and foothills shows a greater predisposition to the occurrence of MM; the calculations carried out show a value of Wf equal to 2.029.

Table 1 presents the calculations corresponding to the WoE methodology. This table lists the data obtained from the superposition of the MM with each class of the conditioning factors, the positive and negative weights, and the final contrast weights.

5. Results

5.1. Mass movement susceptibility models

Landslide susceptibility maps are presented in **Figure 6**. Susceptibility values obtained with AHP, Wi, and WoE methods were classified into five categories ranging from very low susceptibility to very high susceptibility.

The six susceptibility models obtained used conditioning factors as input data distributed as follows: Model 1 was prepared with the AHP methodology included conditioning factors such as slope, lithology, geomorphology, and land use. The second model reorganized the thematic map analysis and added variables such as drainage density and distance to geological structures. This procedure was replicated with models 3 and 4 (Wi) and models 5 and 6 (WoE) (see **Table 2**).

In general, the distribution of susceptible areas varies according to the methodology used in each model; however, one aspect in common is that the sectors with very high and high susceptibility are located in the western area of the LM-116 road. On the other hand, the models elaborated with the AHP methodology show a greater extension of low susceptibility sectors.

5.2. Critical sectors on the LM-116 road

The development of susceptibility maps in road infrastructure projects allows considering the limitations of the territory and the identification of the most critical sectors that require special attention during the useful life of the project.

The susceptibility analysis along the LM-116 road has allowed to recognize critical sectors in three very well differentiated sections that correspond to the kilometer markers: km 14+000 - km 36+000, km 39+000 - km 51+000 and km 66+ 000 and km 80+000 (see **Figure 7**).

5.3. Validation of susceptibility maps

To measure the goodness of representation of the mass movements maps susceptibility, the success rate

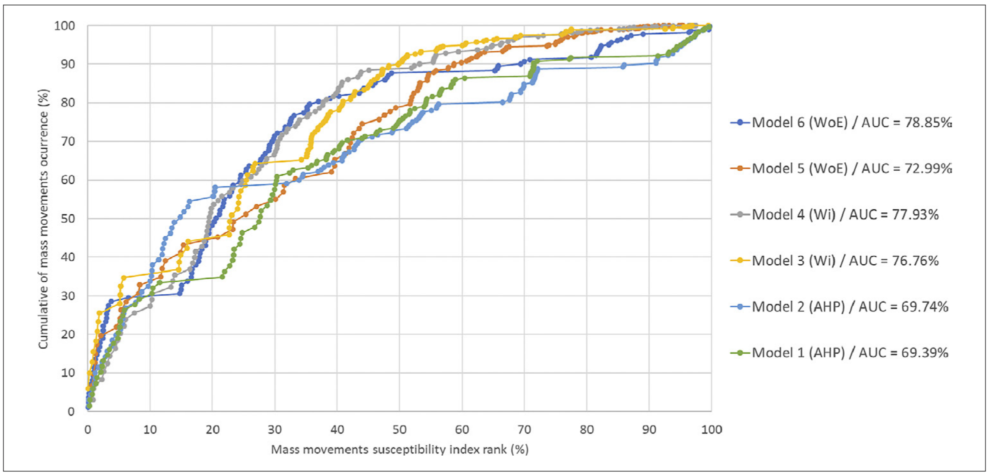

Figure 8: Success rate curves of all obtained susceptibility mass movements models

curves were constructed for each model (see **Figure 8**), these curves relate to the percentage of accumulated pixels of MM concerning the accumulated percentage of the values of the susceptibility index (SI) in the study area. The success rate curves measure the goodness of fit of the susceptibility function to the inventoried MM. For their construction, the SI values must be arranged in descending order and divided into percentiles of 100 categories (**Dahal et al., 2008**).

These curves were constructed in terms of the total area of the study and the total area of the mass movements considered. Once the curve was built, the area under the curve (AUC) was evaluated to establish the quality of data fit; the steeper the initial part of the curve and the larger the AUC, the better the ability of the function to describe the distribution of the MM. An acceptable adjustment percentage should be greater than 70% (**Rodríguez et al., 2017**). This analysis indicates that the models with a higher percentage of AUC were the susceptibility models developed with bivariate statistical methodologies: the AUC corresponding to model 4 (Wi methodology) was 77.93% and the AUC of model 6 developed with the WoE methodology was 78.85%.

6. Discussion

The discussion involves evaluating the quality of landslide susceptibility maps, considering possible biases and other errors. First, this section describes the limitations of the input data and then compares the results obtained with different methods applied in the susceptibility models.

6.1. Input data limitations

The mass movement inventory constitutes one of the essential input data for susceptibility mapping (**Herrera et al., 2021**). The completeness, precision and quality of the inventory data can significantly influence the susceptibility analysis, generating distortions.

The inventory used in this investigation (**GEOCATMIN, 2000-2018**) documents 200 MM composed mainly of rockfalls, debris flows and landslides that affect the road, however the type of sample corresponding to landslides is located in specific sectors of the highway and is a part of only the 18.2% of the entire inventory, so it was not considered a representative sample of the total data that does represent a more excellent distribution and diversity along the LM-116 road. This problem was addressed by combining different types of movements in mass in a single set to counteract the bias of landslides and include information from other sectors of the road, however the most realistic approach is to elaborate a susceptibility map for each type of phenomenon, this is because rockfalls, landslides and debris flows are mass movements generated by different mechanisms on slopes.

On the other hand, the elaboration of susceptibility maps including input data with different types of landslides is widely covered in various studies (**e.g. Abad et al., 2022; He and Zhang., 2022; Ndonbou et al., 2021; Mastere et al., 2015; Jemmah and Brahim., 2018; Elmoulat et al., 2021; Emami et al., 2020; Zorn et al., 2012**).

The quality of mass movement inventories depends on several factors, as the procedure for collecting information on landslides (**Herrera et al., 2021**). Initially, all the freely accessible data was based on georeferenced points, so that the analysis was more exhaustive, a complete inventory comprised by polygons was created. In order to identify the MM in the study area in an orderly and systematic manner, a visual interpretation was performed taking the initial points as a reference.

The image used in this process was downloaded with the free software SAS Planet, which is characterized by collecting high-resolution images from different servers. The orthophoto is from the year 2020 with a spatial resolution of 0.5 m, 3 bands (RGB) and a size of 15,000 pixels by 10,000 pixels.

The data of the conditioning factors was based on the information available in shape formats of the maps of lithological units, geomorphological units and land use, the scale of the three maps is 1:100,000.

The slope and drainage density maps were obtained from the digital elevation model; however, it must be considered that these maps depend to a great extent on the quality of the DEM since any errors present in this data set will be reflected in susceptibility models.

The different spatial resolutions used in the input maps may present biases and generalizations of specific areas, this must be considered when interpreting the resulting susceptibility maps. It is important to note that these data are mapped at a scale of 1:100,000, which compared to the pixel size of susceptibility maps (25 m) may be too different. However, these data are available for the study area, so they were used, despite their limitations.

6.2. Comparison of susceptibility methods

A comparison of the models elaborated with three different methodologies shows that statistical methods (Wi and WoE) have satisfactory levels of precision, compared to the models elaborated with the AHP methodology.

Maps of susceptibility to landslides generated with bivariate statistical methods show similar patterns in specific areas of high and very high susceptibility. This is expected because these models take the mass movement inventory as input data.

The models developed with the WoE method have the advantage of evaluating the association patterns between conditioning factors and unstable areas by means of weights. Being developed with objective methods, the subjectivity of choosing the weights of the factors was avoided, as was done with model 1 and model 2 developed with the AHP semiquantitative method. The advantages of statistical methods over semiquantitative methods have been identified in different publications, such as **Yalcin et al.** (**2011**) where MM susceptibility models were produced and compared using various statistical approaches and the AHP methodology. The authors highlight a considerable spatial concordance between the susceptibility maps created by different statistical methods. On the other hand, **Barella et al.** (**2018**) also showed satisfactory results in the areas under the curve for the susceptibility maps developed with statistical methods.

Based on the values obtained with the area under the curve (AUC), it was determined that model 6, developed with the WoE methodology, is the most suitable for the zoning of areas susceptible to MM because it obtained the best adjustment concerning the other maps.

Analyzing comparatively, it has been observed that the results in the success rate curves (model 4 and model 6) about the models that had lower percentages (model 1 and model 2), it is evident that the methodologies used to elaborate mass movements susceptibility maps conditioner the results of the values of the susceptibility indices.

In the case of models, 1 and 2 (AHP methodology) obtained values of less than 70% in the area under the curve, indicating that methods based on expert opinions could have subjective criteria.

When verifying the results obtained in this research with the results obtained in different publications where mass movements susceptibility methodologies are also compared, several points in common are observed, for example, in the publications of **Guzzetti et al.** (**1999**) and **Lee et al.** (**2008**), it is concluded that the statistical methods have a better performance compared to the AHP methodology because the statistical analysis allows for the establishment of cause and effect relationships between the selected conditioning variables and the occurrence of MM, allowing to identify which are those natural conditions of the land that favor the occurrence of mass movements.

The distribution of susceptibility classes was analyzed in the two models with the highest fit. In this analysis, it was observed that 22% of the total area of model 6 represents the areas that are highly susceptible to MM, unlike model 4, where 11% of the evaluated area is highly susceptible. On the other hand, in model 6 40% of the MM are located in areas of very high susceptibility and 47% of the MM are located in areas of high susceptibility. According to the **Van Westen** (**2016**) criteria, these percentages are good indicators, which indicate that the high and very high susceptibility categories should have the largest accumulated area of mass movements.

In general, model 6 presents slightly better results for the evaluation of the precision of the susceptibility models, this shows that although the different evaluation methods use the same input data, they may differ in precision. On the other hand, in the models with the highest precision (models 4 and 6), more significant concordance patterns are observed, regardless of the conditioning factors used as input data and the statistical technique used. The cartographic representation of MM in the form of polygons tends to generate more constant models, regardless of the statistical technique used during the analysis. In this context, the use of polygons allows a better spatial analysis of susceptibility to MM.

It is very important to consider that the validation of susceptibility maps from data analysis cannot be taken as absolute and requires careful review by experts who know the study area. Those areas where the susceptibility classification does not explain the results or are inconsistent, should be analyzed and discussed by the experts, in order to establish the reason for the incorrect classifications **Rodriguez et al.** (**2017**).

7. Conclusions

Landslide susceptibility models are powerful tools to present information about areas predisposed to slope instability. Decision makers at the engineering level can use this information to better plan the construction and maintenance of roads in susceptible areas.

In this research, three widely known methods were used in the evaluation and zoning of mass movements susceptibility: multicriteria evaluation called the Analysis Hierarchical Process (AHP) and two bivariate statistical methods: the Statistical Index (Wi) and Weights of Evidence (WoE). These methods were implemented through geomatics tools, allowing us to analyze the direct relationship between the conditioning factors and the MM.

The methodologies that best fit the evaluation of susceptibility to MM are the statistical approaches; these proved to be efficient and achieved a good performance in the success rate curves compared to the multicriteria method (AHP).

The percentages achieved in the area under the curve by the Statistical Index (Wi) and Weights of Evidence (WoE) methodologies exceeded 70%. This confirms that bivariate statistical methods represent an adequate tool for evaluating mass movement susceptibility, providing objective and quantitative procedures.

The application of the AHP, Wi and WoE susceptibility methods in the study area raised methodological problems that required different ways of handling the mass movement inventory data, specifically in the combined use of different classes of mass movements in one single data set, considering that each type of mass movement has a different origin mechanism.

The results reveal some challenges in modeling susceptibility to landslides. First, the input data (conditioning factors and inventories of mass removal phenomena) may not be of sufficient quality for the analysis.

Second, different susceptibility mapping methods can lead to different results, demonstrating the need for field validation to assess the applicability of the results.

It is concluded that the models developed with statistical methodologies have a prediction accuracy greater than 70%. However, field validation is necessary as these models may differ on a finer scale.

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SAŽETAK

Usporedba metoda bivarijatne statistike i analitičkoga hijerarhijskog procesa u procjeni podložnosti pokreta na padini, studija slučaja: cesta LM-116 – Peru

Peruanska središnja autocesta (PE-22) i cesta LM-116 već su duže pogođene pokretima na padinama u Peruu te su često izložene pojavi odrona stijene, tečenju debrita i klizištima. Obje ceste predstavljaju važnu alternativnu vezu između Lime, manjih gradova i rudarskih središta smještenih u središnjemu planinskom lancu Anda. U ovome istraživanju prvo je provedena analiza gustoće točaka korištenjem Geografskoga informacijskog sustava (GIS) uzimajući u obzir cestovnu mrežu cijeloga Perua (sastavljenu od 144 499 km) i inventara geoloških hazarda (GEOCATMIN) koji je pripremio Geološki, rudarski i metalurški institut Perua INGEMMET (2000. – 2018.). Naknadno je provedena procjena podložnosti na pokrete na padinama na cesti LM-116 korištenjem dostupnih podataka peruanskih institucija (INGEMMET, MTC, MINAM), iz kojih je bilo moguće izraditi tematske karte koje uključuju najrelevantnije preduvjete u pojavi pokreta na padinama, poput nagiba padina, litologije, geomorfologije, korištenja zemljišta, gustoće drenažne mreže i udaljenosti od tektonskih struktura. Na kraju, za analizu podložnosti na pokrete na padinama razmatrane su tri metode: analitički hijerarhijski proces (AHP), statistički indeks (Wi) i metoda *Weights of Evidence* (WoE). Rezultati su validirani korištenjem kriterija površine ispod krivulje (AUC). Obje bivarijatne statističke metode (Wi i WoE) pokazale su stopu predviđanja iznad 78 %, s višom stopom za WoE metodu. S druge strane, korištenje polukvantitativne (AHP) metode rezultiralo je vrijednošću od otprilike 69 %. S obzirom na navedeno zaključeno je da su karte izrađene statističkim metodama dale bolju aproksimaciju u odnosu na bazu podataka o geološkim hazardima koje je objavio GEOCATMIN.

Ključne riječi:
podložnost pokreta na padini, linijski projekti, *Weights of Evidence*, statistički indeks

Author contribution

This publication was prepared as part of the research of the master's thesis of **Jenny Vásquez** (Master in Disaster Risk Management of the Faculty of Civil Engineering of the National University of Engineering), who prepared the input data, performed the multicriteria and statistical analyses, prepared the maps and interpreted the results. **Miguel Estrada** (Associate Professor at the National University of Engineering, Principal Investigator at the Japanese Peruvian Center for Seismic Research and Disaster Mitigation - CISMID) made a critical and comprehensive review of the article.