Geospatial assessment of landslide susceptibility in the district of Mananjary, Madagascar: A logistic regression modeling approach

Hobiniaina Anthonio Rakotoarison, Natacha Rakotondratrimo, Raymond Rakotondrazafy

Abstract — **This article explores landslide susceptibility mapping in the district of Mananjary, Madagascar, through the application of a logistic regression modeling approach. Through geospatial data, including climate, environment, geology and topography, a comprehensive model is constructed to assess and map landslide susceptibility. Logistic regression was used to quantify the interdependencies between these variables and landslide occurrences, enabling the identification of susceptible areas. The study enhances comprehension of spatial landslide distribution in the district, offering valuable insights for proactive risk management and better decision-making. It exemplifies the integration of geospatial technologies and statistical modeling for accurate and applicable landslide susceptibility mapping, offering a foundation for future research in similar regions facing georisks. Findings reveal the key factors influencing landslide occurrence and model validation showed satisfactory prediction with an AUC of 81 %, providing valuable insights for policymakers and local communities to formulate effective mitigation strategies.**

Keywords — **geospatial assessment, landslide susceptibility, logistic regression, Mananjary district, Modeling**

I. Introduction

Natural disasters, such as cyclones, often leave a trail of devastation in their wake, significantly impacting the physical and environmental landscape [1]. Among the various consequences, landslides represent a critical geohazard that poses substantial threats to human lives, infrastructure, and the overall stability of affected regions [2]. The district of Mananjary, located in the southeastern part of Madagascar, faced the powerful impacts of the Chezda cyclone in 2015, heightening the district's susceptibility to landslide occurrences.

Landslide susceptibility mapping has emerged as a crucial tool in disaster risk management and reduction providing valuable insights into the area's most susceptible to landslides [3]–[5]. The aftermath of the Chezda cyclone in this district has underscored the need to study the interplay of environmental factors that contribute to landslide susceptibility in a post-cyclonic landscape. In this context, we present a comprehensive investigation using logistic regression modeling as a robust analytical framework to assess and map landslide susceptibility in the region.

The objectives of this study include the identification of the key factors influencing landslide susceptibility, the development of a reliable predictive model, and the generation of susceptibility maps to assist local authorities and stakeholders in making informed decisions for disaster management.

Through this research, we aspire to contribute to the expanding corpus of knowledge on landslide susceptibility mapping and to provide valuable insights that can enhance the resilience of communities facing the imminent threat of landslides in similar geographical settings.

II. Materials and Methods

II.1. Study area

Belonging to Vatovavy region, the district of Mananjary is situated in the southeastern part of Madagascar. Bordered to the north and south respectively by the districts of Nosy-Varika and Manakara, to the west by the district of Ifanadiana, and to the east by the Indian Ocean, it comprises 29 communes. It covers an area of approximately 5,450 km². The altitude in the district of Mananjary varies from -8 m to 682 m (Figure 1).

Climate

The climate in the district of Mananjary is hot and humid tropical. Despite the rains persisting almost all year long, a less humid season is observed from April to August, when drizzle replaces the heavy thunderous downpours from November to March. There is a brief dry season in September to October. The average annual rainfall is 1,500 mm, but can exceed 3 meters. The average temperature ranges between 27°C in the hot season and 19°C in the cool season.

Hydrology

The hydrographic network of the district of Mananjary is oriented towards the Indian Ocean, to which it is tributary. It is shaped by the orogenic curvature of the area, highlighted by the Mananjary River. The course of this major river generally runs parallel to the schistosity lines of the crystalline schists on which it flows. Mananjary River has several tributaries such as Sahanofa, Ivoana, Ampasary, etc. The entire water system of the district includes numerous sections with many rapids.

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Population and Infrastructure

The population of the district of Mananjary is unevenly distributed, with an estimated density of 51 people/km² in 2018 [6]. It is significant in towns, particularly the main municipal centers, and is lower in the rest of the district. Roads constitute the primary physical infrastructure in the district of Mananjary. The road network of the district consists of four national roads (RN11, RN12, RN24, and RN25) and several secondary roads. The Canal des Pangalanes, located in the far east of the district and bordering the Indian Ocean, is a significant infrastructure that connects the cities of Toamasina and Farafangana, passing through Mananjary. It represents a crucial economic artery for this area.

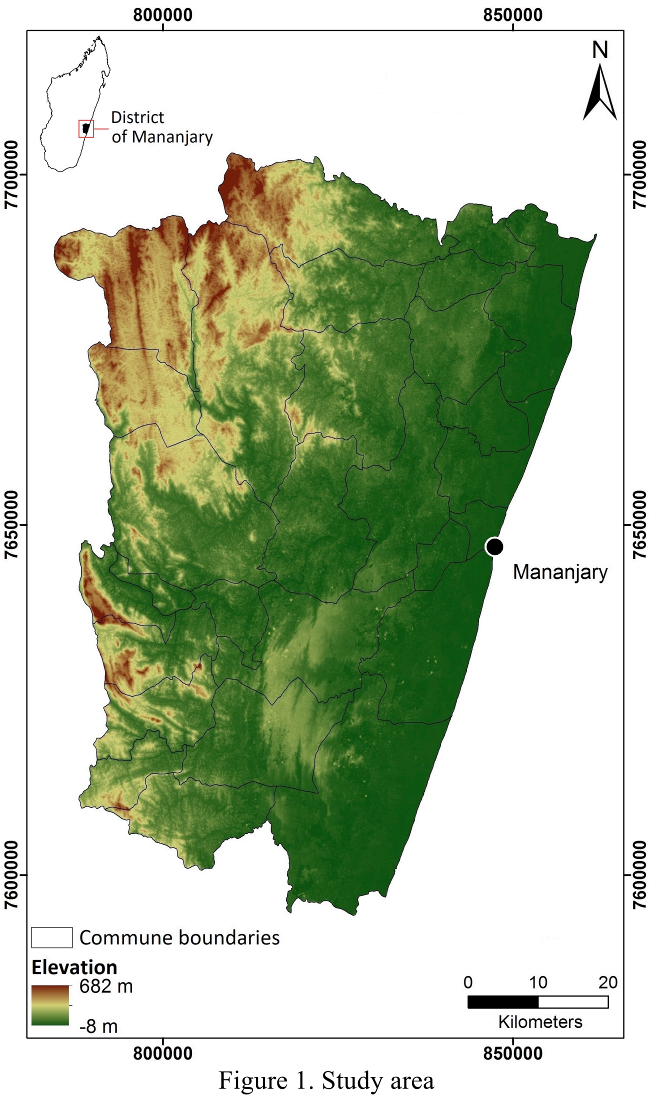

Figure 1. Study area

Geology

The Precambrian shield of Madagascar is divided into six geodynamic domains (Bemarivo, Antongil-Masora, Antananarivo, Ikalamavony, Anosyen-Androyen, and Vohibory) with a subdivision into sub-domains of two domains. The Antongil-Masora domain has been subdivided into the Antongil sub-domain and the Masora sub-domain, while the Anosyen-Androyen domain has been split into the Anosyen sub-domain and the Androyen sub-domain [7].

The district of Mananjary is characterized by two distinct domains and Cretaceous volcanism. Its northwest part corresponds to the southern section of the Masora sub-domain. This area is defined by the Vohilava-Nosivolo group and the Maha group. It is primarily composed of undifferentiated schists, pelitic schist, and amphibolite [7]. This northwest part of the district is also characterized by the Nosy Boraha suite of the Mesoarchean, primarily consisting of migmatitic orthogneiss of Befody [7]. The southwest sector of the district of Mananjary belongs to the Antananarivo domain and is characterized by formations of the Manampotsy group [7]. It mainly comprises Ampasary paragneiss with relics of ultrabasic rocks, schist, and quartzite. Additionally, there are granite, monzonite, undifferentiated syenite, and stratoïd syenite rocks in the area [7], [8]. In its eastern part, the district of Mananjary is formed by Cretaceous volcanic formations about twenty kilometers wide, creating a band parallel to the coast. Various petrographic varieties are found here, including basalts, basanites, and a small proportion of rhyolite, trachyte, and phonolite [8].

II.2. Data used

The study utilized various data sources (Table 1) to conduct a comprehensive analysis of landslide susceptibility.

Table 1. Overview of the types and sources of data used in this study

Variable	Resolution (m) / Scale	Source
Elevation	30	SRTM 1 Arc-second https://earthexplorer.usgs.gov/
Slope	30	Derived from SRTM 1 Arc-second
Aspect	30	Derived from SRTM 1 Arc-second
Curvature	30	Derived from SRTM 1 Arc-second
NDVI	Multi: 10 Pan: 2.5	Derived from SPOT 5 images http://www.seas-oi.org
Distance from roads	-	OpenStreetMap https://www.openstreetmap.org/
Distance from rivers	-	OpenStreetMap https://www.openstreetmap.org/
Rainfall	-	http://iridl.ldeo.columbia.edu/
Lithology	1 : 500000	Malagasy geological service

Note: NDVI – Normalized Difference Vegetation Index, Multi – Multispectral bands, Pan – Panchromatic band

Landslide inventory

The landslide inventory serves as a crucial and fundamental foundation for the investigation of the correlation between landslides and influential factors, as well as for modeling. It is imperative not only for the creation of statistical models as an explanatory component but also for the validation stage. The landslide inventory database was created exclusively through field campaigns.

A field campaign that lasted for ten days took place in April 2015. The objective of the mission was to record landslides in the district of Mananjary, specifically along the national road axes (Figure 2). For model development, 80 % of collected data were used as the training dataset, while 20 % were reserved for the model validation.

Figure 2. Landslide on national roads #12 (a) and #25 (b)

Vegetation index

The NDVI (Normalized Difference Vegetation Index) is an important index for assessing landslide susceptibility, as it affects the stability of the terrain. It is an index derived from reflectance measurements in the red and near-infrared parts of the electromagnetic spectrum that describes the relative quantity of active green biomass present at the time of image capture [9].

The Spot 5 images were used to create the NDVI. The most common formula used to create NDVI is as follows:

$$NDVI = \frac{NIR - R}{NIR + R} \qquad \text{(Equation 1)}$$

where R and NIR are the spectral reflectance measurements acquired in the red and near-infrared bands, respectively. The value of the NDVI ranges from -1 to 1.

Elevation

Elevation significantly influences the occurrence of landslides due to its impact on the spatial variation of both hydrological conditions and slope stability [10]. Elevation data served as the basis for deriving thematic data layers which include slope, aspect and curvature.

The elevation in the district of Mananjary varies from -8 m to up to 650 m.

Slope angle

Slope angle is the most important variable in slope stability analysis [11]. The slope angle is the most important variable in slope stability analysis [11]. As the slope angle increases, the level of rupture stress induced by gravity in colluvium or residual soils also increases. Gentle slopes should exhibit a low frequency of mass movements due to the generally lower rupture stress associated with these mild gradients.

Slope aspect

The slope aspect displays the direction it is facing. It is also considered as an important factor in preparing landslide susceptibility maps [12]. The impact of aspect may be linked to its associated physical factors, including duration of sunlight, wind exposure which causes dryness, and direct sunlight itself. Generally, the slope aspect is categorized into nine classes: flat, north, northeast, east, southeast, south, southwest, west, and northwest [13].

Slope curvature

As a predisposing factor, curvature is a key factor in assessing landslide susceptibility. Topographical morphology is characterized by curvature values that play a significant role in water retention during rainfall. It is categorized into three classes, i.e., concave, flat and convex surfaces [14]. Concave areas, indicating a negative curvature, are more prone to landslide due to their higher water retention capacity. Conversely, surfaces with a positive curvature, known as convex areas, are less susceptible to such movements.

Lithology

Lithology plays a significant role in the assessment of landslide due to its various lithologic units having different degrees of susceptibility. It directly influences the rocks and soils strength and permeability and indirectly dictates the type and level of risk in a particular area. For instance, in the context of lavakas in Madagascar, the lithology is a controlling factor for ground movements [15].

Rainfall

Rainfall predisposes to and triggers landslides. Madagascar suffers from a scarcity of weather stations, with only 25 stations for the entire island (approximately 587,000 km^2), which significantly impacts the rainfall data's accuracy. To address this issue, substitute data obtained through remote sensing have been used in this study (Table 1).

Distance from rivers

The drainage of rivers or streams cans lead to banks failure due to the underestimation of slopes and the erosion of streams. Therefore, the proximity to rivers is considered as one of the key factors influencing slope stability. The degrees of water saturation in materials directly affect slope stability. Hence, the proximity of drainage structure to slopes is also an important factor in terms of stability [16].

Distance from roads

Several studies have shown the frequent occurrence of landslides in close proximity to roads [17], [18]. This is mainly due to the fact that most of the roads in the studied areas are bordered by slopes and ravines, coupled with inadequate drainage. The further away from the road, the less likely the terrain is to experience movement.

II.3. Logistic regression model

Input data

Logistic regression is a statistical technique used to model the nonlinear relationship between a binary dependent variable and a set of independent variables [19], [20].

In this study, the variable to be explained is derived from a landslide inventory and indicates the presence or absence of landslides (coded as 1 or 0, respectively). They include ground movements, rockfalls, block falls, or other types of soil displacement.

The explanatory variables, or covariates, are the factors being analyzed to understand their impact on the variable to be explain. In this study, these include vegetation index, elevation, slope angle, slope aspect, slope curvature, lithology, rainfall, distance from rivers and distance from roads.

Model construction

In the simplest form of logistic regression, the relationship between landslide frequency and explanatory variables can be expressed as follows:

$$P = \frac{1}{1 + e^{-(\alpha + \sum_{i=1}^{n} \beta_i X_i)}} \qquad \text{(Equation 2)}$$

where P represents the probability of a landslide occurrence, α denotes the model's intercept, n is the number of variables, β_i (i=1, 2, …, n) signifies the logic regression slope coefficient, and X_i (i=1, 2, …, n) represents the independent variables. The probability ranges between 0 and 1.

The logistic regression analysis was conducted using the open-source software "R". Stepwise regressions were undertaken. In the descending stepwise regression, all explanatory variables are included in the initial regression. Variables are then systematically eliminated until there is no longer a significant change in the regression. To do so, the p-value of each variable was determined. A $p\text{-value} \leq 0.01$ corresponds to very strong significance; $0.01 < p\text{-value} \leq 0.05$ indicates strong significance; $0.05 < p\text{-value} \leq 0.1$ signifies weak significance, and a $p\text{-value} > 0.1$ indicates lack of significance.

Validation of the model

The model of landslide susceptibility was validated using observational data. Model effectiveness was assessed through the computation of the Area Under Curve (AUC) derived from the Receiver Operating Characteristic (ROC) curve. A perfect model corresponds to an AUC of 1. Sensitivity and specificity of the models (Equations 3 and 4 respectively) were also determined, using optimal thresholds derived from the susceptibility classes of the model.

$$Sensitivity = \frac{TP}{TP + FN} \qquad \text{(Equation 3)}$$

$$Specificity = \frac{TN}{TN + FP} \qquad \text{(Equation 4)}$$

where TP (True Positives) and TN (True Negatives) represent the correctly classified landslide events, and FP (False Positives) and FN (False Negatives) denote the inaccurately classified landslide events.

III. Results

III.1. Landslide susceptibility map

Following the application of a stepwise descending method, the β coefficient for each conditioning factor is presented in table 2. The explanatory variables retained for the final model were rainfall, slope, distance from roads, elevation, NDVI, distance from rivers, and lithology (Table 2). Despite its lack of significance, the lithology variable was incorporated into the model, since it is a crucial factor in landslide occurrence. It was noted that elevation, slope, lithology, rainfall, and distance from roads significantly contribute to mapping susceptibility to landslides due to their positive β coefficients. On the other hand, variables with a negative β have an opposing effect.

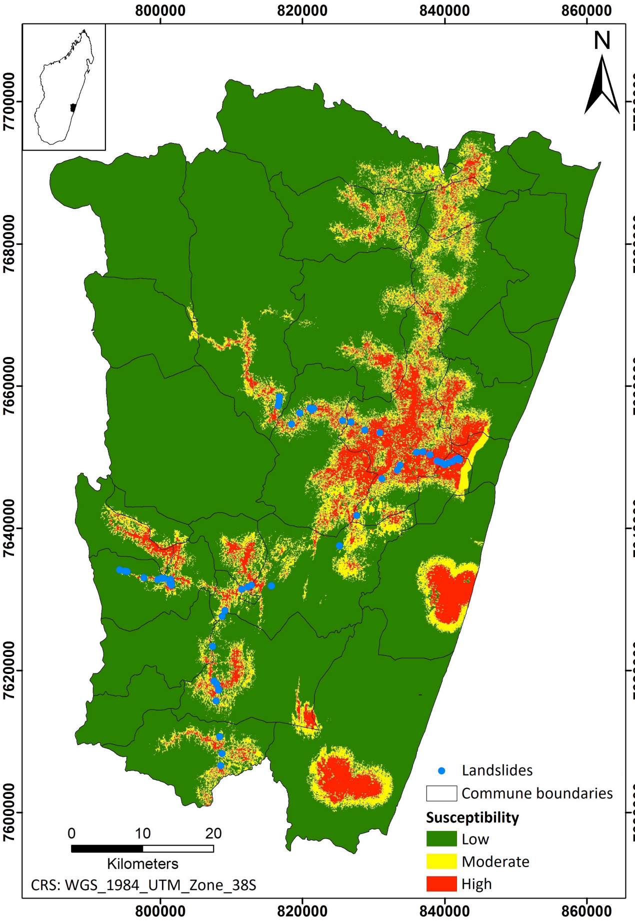

Figure 3. Landslide susceptibility map of the district of Mananjary

The generated landslide susceptibility map is depicted in figure 3. These susceptibilities were computed based on equation 2. The distribution of susceptibility classes is defined as follows: 85% for low susceptibility, 9% for moderate susceptibility, and 6% for high susceptibility. According to figure 3, areas intersected by the road network exhibit a high susceptibility to landslides. This network primarily comprises national roads #11, 12, 24, and 25. The central-eastern part of the district of Mananjary is characterized by a predominance of high susceptibility to landslides.

Table 2. Regression coefficient and p-value

Predictors	Coefficients	p-value

NDVI	-9.82E-04	0.000408
elevation	3.75E-02	0.000176
Slope angle	1.36E-01	1.39E-05
Curvature	-	-
Aspect	-	-
Lithology	1.26E+00	0.064674
Rainfall	9.84E+01	4.58E-06
Distance from rivers	-5.06E-04	0.064474
Distance from roads	1.38E-03	0.000141
Constant	-4.52E+01	0.000538

Note: p-value in bold correspond to the most significant variables (with a significance level of 0.05). Variables without values represent non-significant explanatory variables and are excluded from the final models.

III.2.Model validation

The susceptibility model validation outcome reveals a satisfactory performance [21], with an AUC of 0.811 (Figure 4). The model exhibits a sensitivity of 91.1% and specificity of 67.9% (Table 3). Given its higher sensitivity compared to specificity, the model effectively identifies areas prone to landslides.

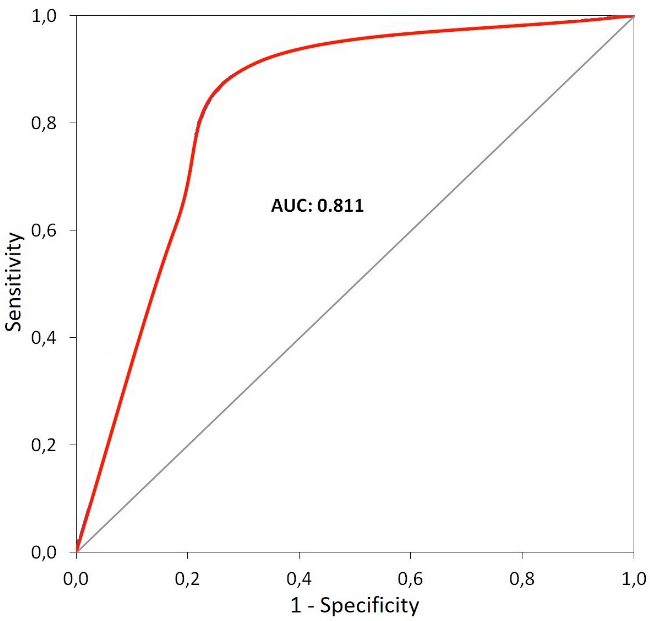

Figure 4. ROC curve of the model

Table 3. ROC analysis result

	Observations	
Susceptibility model	**Present**	**Absent**
High	TP: 51	FP: 18
Low	FN: 5	TN: 38
Accuracy	79.464 %	
Sensitivity	0.911	
Specificity	0.679	

Note: TP (True Positives), TN (True Negatives), FP (False Positives), FN (False Negatives),
Accuracy = (TN+TP)/(TN+TP+FN+FP),
Sensitivity = Equation 3, Specificity = Equation 4

IV. Discussion

In landslide modeling process, the quality of models relies significantly on the relevance, the quality, and the reliability of the chosen conditioning factors, along with their input data, and the applied methodology [22]. Therefore, the careful selection of conditioning factors is pivotal for achieving accurate outcomes. This study has specifically concentrated on primary geo-environmental and climatic factors. Secondary factors, such as roughness index and topographic position index, were not taken into account. Moreover, the choice of conditioning factors is also contingent upon data availability. For instance, in our case, data pertaining to distances from faults were not accessible.

The susceptibility to landslide can be mapped using various methods, depending on the available data [23]. However, no consensus has yet been reached on the optimal method for generating maps of landslide susceptibility [24]. Compiling data on terrain movements is particularly challenging due to the often-restricted availability of datasets, especially in Madagascar. Conducting field surveys represents the most accurate method for assessing susceptibility to terrain movements. However, analyzing the potential for movements across an extensive area is highly challenging and entails significant time and financial costs. This is particularly true in developing countries, such as Madagascar, where on-site observation is prohibitively expensive, and most areas are inaccessible. [25] and [26] have suggested that not only, generating reliable susceptibility maps should be feasible but may also be more accurate. In many countries, remote sensing data may be the sole possible source available for such studies. The available satellite data can offer valuable and accurate insights into the surface characteristics of the Earth and the dynamic processes involved in the occurrence of landslides.

GIS became a highly valued tool for evaluating landslide as they enable the analysis of a large quantity of information from various sources and at various scales over a relatively short period. Logistic regression models have been widely applied in landslide mapping [27], [28]. Thus, the logistic regression model could be applied for predicting future susceptibility to landslides in Madagascar. In this study, all coefficients, except those related to NDVI and distance from rivers for study district, are positive. This suggests a positive association with the probability of landslides. Rainfall, elevation, lithology, and slope angle appear to be more strongly associated with landslides than the other factors. [20] developed a logistic regression model for the Hendek region in Turkey, incorporating 14 factors that highlighted the significance of geology (lithology), land use/cover, elevation, slope, and distance from streams. [12] applied the logistic regression model to assess terrain susceptibility in Trabzon, Northeast Turkey. Their findings indicated positive associations between geology, slope, and aspect with terrain movement occurrence. Conversely, land use, distance from the stream, elevation, and distance from road seemed to have a negative association with the presence of movement in their study area.

The model outlined in this study not only delineates the locations of documented landslides but also provides a susceptibility index for the entire study area. The derived susceptibility map can be overlaid with land use, geological/geomorphological, and development maps for decision-making purposes. This map can serve as a broad reference for risk and disaster management authorities, such as the Malagasy BNGRC. However, it's important to note that the map generated in this study lacks details on the rupture period, rupture type, or volume of materials. Consequently, it should not be viewed as a substitute for site-specific scientific investigations or the professional guidance of qualified geologists, geotechnicians, and planners but rather as a supporting document.

V. Conclusion

In conclusion, this study successfully applied logistic regression to assess landslide susceptibility in the district of Mananjary. To our best knowledge, it has resulted in the first landslide susceptibility map in this district. The findings highlight the significance of elevation, slope, lithology, rainfall, and distance from roads in determining landslide-prone areas. The developed model demonstrated robust predictive capabilities, offering a reliable tool for decision-makers to prioritize vulnerable zones for preventive measures. This study thus makes a substantial contribution to the understanding of landslide and lays the groundwork for developing targeted strategies to mitigate the impact of landslides in the studied district, thereby advancing promoting sustainable development and community resilience.

Availability of data and materials

The datasets used during the current study are available from the corresponding author on reasonable request.

Competing interests

The authors declare that they have no competing interests.

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