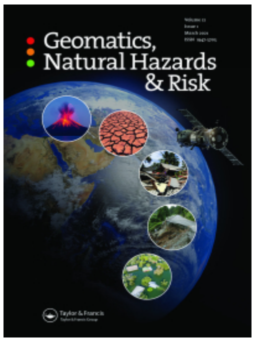

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Insights into landslide susceptibility: a comparative evaluation of multi-criteria analysis and machine learning techniques

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ABSTRACT

Landslides threaten communities worldwide, resulting in financial, environmental, and human losses. Although some studies have employed machine learning (ML) algorithms and multi-criteria analysis (MCA) for landslide susceptibility mapping (LSM), comparative evaluations of these methods remain scarce, particularly regarding predictor importance, performance metrics, and hyperparameter optimization. This research addresses these gaps by comparing logistic regression (LR), random forest (RF), support vector machines (SVM), and MCA, focusing on landslide susceptibility in Petrópolis, Brazil. The ML models used 29 influencing factors, encompassing geographic, geological, climatic, and anthropogenic variables, where feature importance analysis and hyperparameter tuning were applied to identify the most significant predictors. RF achieved the highest performance, with an accuracy of 0.94, ROC AUC of 0.98, and F1 score of 0.94. SVM and LR also performed well, with ROC AUCs of 0.96 and 0.95 and F1 scores of 0.92 and 0.89, respectively. Conversely, MCA showed lower results, with an accuracy of 0.41, ROC AUC of 0.41, and F1 score of 0.55. We attribute RF's robustness to its adaptability to diverse variable types, reduced overfitting risk, and high predictive accuracy. These findings underscore RF's strength in LSM and highlight ML's potential to support urban planning and mitigate risks in landslide-prone areas.

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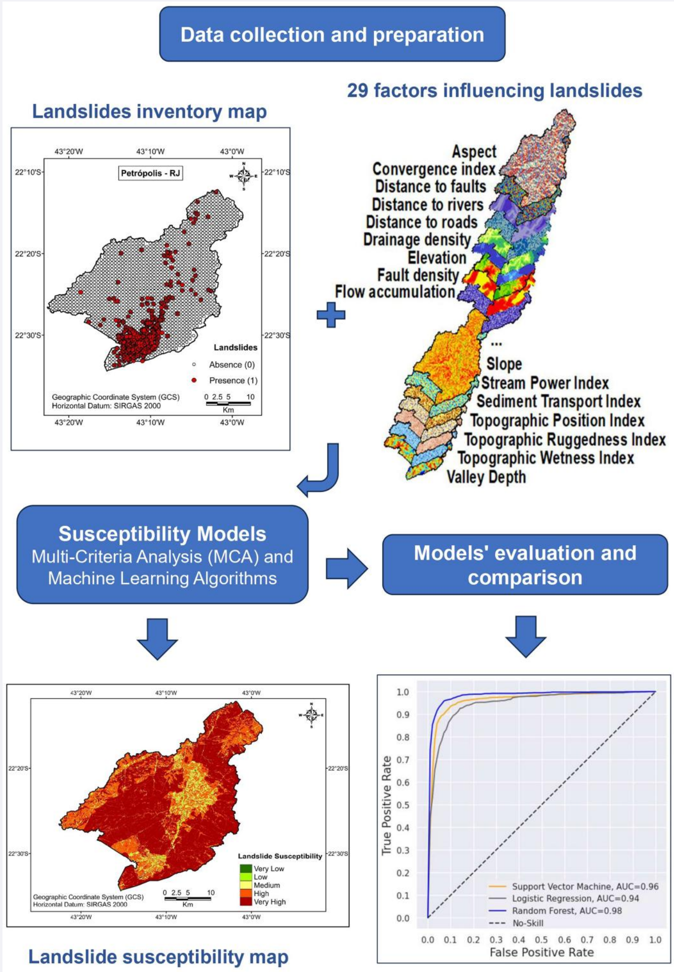
GRAPHICAL ABSTRACT



HIGHLIGHTS

- Effective landslide susceptibility analysis is essential for anticipating and mitigating risks.
- MCA failed to identify non-landslide areas, highlighting its limitations.
- ML overcomes traditional MCA in landslide susceptibility mapping.
- RF achieved the highest prediction accuracy for landslide susceptibility, outperforming other methods.
- ML-based landslide susceptibility mapping ranks susceptibility factors more effectively.

1. Introduction

A landslide refers to the downward displacement of soils, rocks, and organic materials caused by the effect of gravity (Highland and Bobrowsky 2008). This phenomenon ranks among the most devastating natural disasters, as it can damage natural and artificial structures and significantly change landscape morphology (Kavzoglu et al. 2014). When favourable factors such as topography, climate, soil types, vegetation, and human influences combine with agents like intense precipitation or earthquakes, landslides can occur on both natural and anthropogenic slopes (Das et al. 2010). Furthermore, changes in land use are considered a significant factor affecting both erosive processes and landslides (Glade 2003; Reichenbach et al. 2014; Modernel et al. 2016; Senanayake et al. 2020).

It is important to emphasize that Brazil's complex geophysical and climatic conditions significantly contribute to the occurrence of landslides, raising serious concerns for civil society and government authorities (IBGE 2019). In response, federal organizations have implemented proactive measures, while numerous studies have been conducted (Marcelino et al. 2009; Vieira et al. 2010; Listo and Vieira 2012; Barella et al. 2019; Oliveira et al. 2019; Canavesi et al. 2020; Dias et al. 2021). The Brazilian Institute of Geography and Statistics (*Instituto Brasileiro de Geografia e Estatística – IBGE*) offers nationwide data regarding landslide susceptibility, whilst entities such as the Technological Research Institute of São Paulo (IPT) and the Laboratory of Cartography at the Federal University of Rio de Janeiro (GEOCART/UFRJ) engage in the documentation and recording landslide occurrences.

From January 1995 to December 2014, 3,876 landslides worldwide were associated with 163,658 fatalities and 11,689 injuries (Haque et al. 2019). According to Macedo and Sandre (2022), landslides caused 4,146 deaths between 1988 and 2022 across 269 municipalities in 16 Brazilian states. The most affected cities are primarily located in the mountainous region of Rio de Janeiro, specifically Petrópolis, Teresópolis, and Nova Friburgo, an area renowned for its lush landscapes and heavy rainfall (Macedo and Sandre 2022). On 15 February 2022, Petrópolis experienced an unprecedented rainfall accumulation of 258 millimetres within 3 hours, culminating in the deadliest landslide disaster ever recorded in the region (Alcântara et al. 2023). On 24 December 2001, this city recorded 190 millimetres of precipitation in just 12 hours, resulting in devastating events such as landslides and floods (Camarinha and Seki 2024). Research indicates that Petrópolis often experiences landslides when cumulative rainfall exceeds certain thresholds since daily rainfall thresholds exceeding 100–150 millimetres are commonly associated with shallow landslides (Alcântara et al. 2023). Monsieurs et al. (2019) emphasized that landslides triggered by rainfall often occur in areas where cumulative antecedents (7–15 days) and peak daily rainfall exceed thresholds established for specific regions. In Petrópolis, the rainfall thresholds for initiating landslides range from 200 to 300 millimetres of cumulative rain over 5 days, depending on the soil type and slope conditions (Alcântara et al. 2023).

In recent decades, advancements in computational capabilities, geographic information systems (GIS), and remote sensing technologies have significantly enhanced the efficacy of risk assessments (Erener and Düzgün 2012; Zhao and Lu 2018; Nhu et al. 2020; Kontoes et al. 2021). Machine learning (ML) and deep learning (DL) methodologies have been utilized due to their capacity to discern relationships between events and socio-environmental characteristics, as well as to recognize intricate patterns (Merghadi et al. 2020; Wei et al. 2022; Saha et al. 2023). Although the results of DL models are promising, particularly in managing complex and high-dimensional data, ML models remain relevant due to their interpretability, ease of implementation, and favourable balance between performance and computational efficiency (Saha et al. 2023; Huang et al. 2024). Worldwide studies have applied these techniques in landslide susceptibility mapping (LSM) (Pham et al. 2017; Chen et al. 2018; Jaafari et al. 2019; Pham et al. 2019; Bui et al. 2020; Chen and Chen 2021; Xu et al. 2022). At the national level, studies mapped landslides using random forest (RF) algorithms (Oliveira et al. 2019; Canavesi et al. 2020; Lucchese et al. 2022), logistic regression (LR) (Barella et al. 2019; Riegel et al. 2020), and support vector machines (SVM) (Uehara et al. 2020; Dias et al. 2021). Nevertheless, there is a lack of evidence of studies comparing these three ML algorithms with multi-criteria analysis (MCA), predictor importance analysis, performance comparison evaluation, and hyperparameter optimization. Moreover, our study replicates the MCA methodology developed by the IBGE (2019), which served as the foundational basis for Brazil's first national landslide susceptibility map. This reference dataset is a well-established resource that utilizes the MCA framework alongside carefully selected factors, including geology, geomorphology, land use/land cover (LULC), pedology, rainfall, and slope. By adhering to the IBGE's standardized criteria, our study aligns with a recognized national model, enhancing the credibility and consistency of our weighting choices and ensuring that our findings are comparable to national-level assessments.

Our research aims to evaluate and compare the predictive accuracy of LR, RF, SVM, and MCA for LSM. Specifically, the study seeks to determine whether ML algorithms provide advantages over MCA regarding predictive performance and selecting predictor factors. Furthermore, it examines the applicability, strengths, and limitations of the ML and MCA approaches, investigating whether ML models can provide more comprehensive insights into feature importance than MCA. The research hypothesis is that ML may surpass MCA's traditional approach to assessing landslide susceptibility. By overcoming MCA's subjectivity in determining the influencing factors and their respective weights, ML may provide more accurate, reliable, and efficient outcomes in predicting landslides.

Petrópolis, Brazil, was selected as a study area due to its notable vulnerability to destructive landslides. The region's steep topography and distinct orographic conditions contribute to concentrated rainfall, establishing an environment prone to landslides. Unplanned urban development on unstable slopes further aggravates this issue, heightening the susceptibility to large-scale mass movements (Guerra et al. 2007; Neves 2017; Fernandes et al. 2020). Besides, rapid urban development and informal settlements on steep slopes heighten the risks of landslides. These settlements often lack proper infrastructure or adherence to zoning regulations, further amplifying their vulnerability. In this context, Petrópolis exemplifies the critical interactions between natural and human factors in landslide susceptibility, making it an ideal area to analyse and test predictive models. We expect that our findings will enhance the understanding of applying these techniques for landslide assessments in other regions with similar conditions and aid in developing mitigation plans. This research serves as a tool to improve community safety in landslide-prone areas and to reduce disaster impacts, aligning with related targets of the United Nations Sustainable Development Goals (U.N 2017).

2. Data and methods

2.1. Data

2.1.1. Study area

Petrópolis is situated in Rio de Janeiro, Brazil, encompassing an area of 791.14 square kilometres and is home to a population of 278,881 people (IBGE 2023a) (Figure 1). The region's main physical characteristics are steep slopes, faulted and fractured rocks, deep soil profiles, and heavy rainfall, predominantly between December and March (Guerra 1995). With elevations ranging from around 100 metres in valley areas to over 2,000 metres in mountainous regions, this steep topography creates gravitational stress on the soil, making the slopes highly susceptible to landslides, especially during heavy rainfall. The region is characterized by a tropical climate with a distinctive rainy summer season that can exceed 200 millimetres in a single day during storms (Alcântara et al. 2023). Such events saturate the soil and increase the pore water pressure, weakening slope stability, particularly on deforested slopes or areas with loose surface material (Guerra et al. 2007). The soils vary across the landscape but generally include weathered materials, such as clayey or sandy soils, derived from the bedrock geology, primarily composed of granite and gneiss. These rock types are susceptible to weathering, developing loose, unstable surface layers that can easily detach under stress. Slopes exposed to bedrock due to soil erosion or construction can experience rockslides, especially during or after heavy rainfall.

The original vegetation, characterized by tropical rainforest *(Mata Atlântica)*, has progressively receded due to agricultural expansion and urban development and is

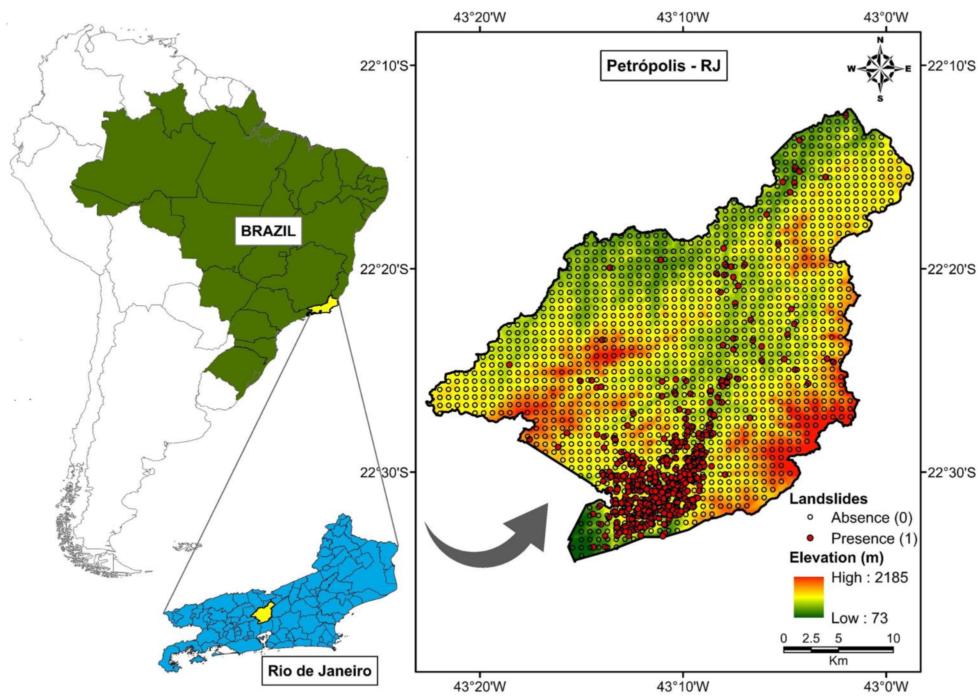


Figure 1. Study area with landslide occurrences from 1933 to 2015 (Neves 2017). Digital elevation model (DEM) from IBGE (2023b).

now restricted to specific areas within Conservation Units (Guerra 1995; Guerra et al. 2007). Rapid urbanization in the city has led to the expansion of settlements on steep, unstable slopes, often disregarding formal construction guidelines. This urban expansion into marginal lands has reduced natural vegetation cover, increased surface runoff, and altered drainage patterns, further destabilizing slopes and leading to a higher frequency of landslides and floods in the Municipality of Petrópolis (Fernandes et al. 2020). The most destructive and lethal events occurred in 1966, 1979, 1988, 2011, and 2022, when 80, 87, 171, 73, and 241 deaths were recorded, respectively (Kobiyama 2022; Blaudt et al. 2023). Figure 2 shows a landslide that took place in Petrópolis on 15 February 2022, destroying 54 houses and causing 93 deaths.

2.1.2. Landslide inventory map

The landslide inventory includes over 80 years of records, with 1,401 historical events data registered in the Municipality of Petrópolis. These occurrences were collected and reported by the Technological Research Institute of São Paulo (IPT) and the Cartography Laboratory of the Federal University of Rio de Janeiro (GEOCART/UFRJ) from 1933 to 2015 (Neves 2017) (Figure 1). The inventory consists of 1,310 general slides (93.5%), 43 rockfalls (3.1%), 42 heterogeneous (3.0%), and 6 mudflows (0.4%). The frequently adopted ratio between data representing the presence and absence of landslides in the training dataset is 1:1 (Hong et al. 2019). Therefore, to prevent bias in the sampling procedure, we generated representative points for the

Figure 2. An area with unplanned occupation in Petrópolis that experienced a mass movement in 2022.

landslide absence class in the same proportion as the presence points (Dai and Lee 2002; Yesilnacar and Topal 2005; Bui et al. 2011), resulting in 2,802 sampling points (1,401 presence and 1,401 absence) (Figure 1).

2.1.3. Independent variables

Reviewing 87 studies that used ML to map landslide susceptibility from 2015 to 2021 led to identifying 29 variables (Appendix A). Appendix B presents more details about the literature review process. Table 1 lists these 29 factors considered as predictors of landslide susceptibility.

Some datasets, such as geology, landform, pedology, geomorphology, LULC, and digital elevation model (DEM), were ready to use. However, other data were produced and derived from DEM through ArcGIS Pro software, including aspect, convergence index, flow accumulation, curvature (general, plan, and profile), relief amplitude, slope, sediment transport index (STI), stream power index (SPI), topographic position index (TPI), topographic wetness index (TWI), and topographic ruggedness index (TRI). Slope length, length-slope factor (LS-Factor), and valley depth were additionally generated from DEM through SAGA software (Conrad et al. 2015). Distances to roads, faults, and rivers were calculated using the Euclidean Distance tool, while road density, drainage density, and fault density were computed using the Line Density tool in ArcGIS Pro.

Table 1. Factors influencing landslide susceptibility: 29 predictors covering geographic, geologic, climatic, and anthropogenic variables included in this analysis.

Factor	Range value	Data source	Data type	Scale
Rainfall (mm)	1,089.45 – 2,560.11	ANA (2023)	Point	–
Distance to faults (m)	0–18,451.34	CPRM (2023)	Line	1:100,000
Fault density	0–2.13	CPRM (2023)	Line	1:100,000
Geology	Categorical	CPRM (2023)	Polygon	1:100,000
Landform	Categorical	CPRM (2023)	Polygon	1:100,000
Pedology	Categorical	CPRM (2023)	Polygon	1:100,000
Geomorphology	Categorical	IBGE (2023c)	Polygon	1:250,000
Elevation (m) (DEM)	73.00–2,185.00	IBGE (2023b)	Raster	1:25,000
Aspect	−1–360	IBGE (2023b)	Raster	1:25,000
Convergence index	−100.00–100.00	IBGE (2023b)	Raster	1:25,000
Flow accumulation	0–22,880.00	IBGE (2023b)	Raster	1:25,000
General curvature	−85.25–58.75	IBGE (2023b)	Raster	1:25,000
LS-Factor	0–314.33	IBGE (2023b)	Raster	1:25,000
Plan curvature	−49.99–29.40	IBGE (2023b)	Raster	1:25,000
Profile curvature	−46.49–47.61	IBGE (2023b)	Raster	1:25,000
Relief amplitude	0–238.00	IBGE (2023b)	Raster	1:25,000
Slope (%)	0–258.30	IBGE (2023b)	Raster	1:25,000
Slope length	0–3,045.93	IBGE (2023b)	Raster	1:25,000
SPI	−13.81–8.60	IBGE (2023b)	Raster	1:25,000
STI	0–317.59	IBGE (2023b)	Raster	1:25,000
TPI	−91.67–62.55	IBGE (2023b)	Raster	1:25,000
TRI	0–330.93	IBGE (2023b)	Raster	1:25,000
TWI	1.66–23.89	IBGE (2023b)	Raster	1:25,000
Valley Depth	−209.03–756.69	IBGE (2023b)	Raster	1:25,000
Distance to rivers (m)	0–17,876.76	IBGE (2023b)	Line	1:25,000
Distance to roads (m)	0–18,059.95	IBGE (2023b)	Line	1:25,000
Drainage density	0–5.39	IBGE (2023b)	Line	1:25,000
Road density	0–5.77	IBGE (2023b)	Line	1:25,000
LULC	Categorical	INEA (2023)	Polygon	1:25,000
Landslide inventory	Categorical	Neves (2017)	Point	–

2.2. Methods

2.2.1. Multi-criteria analysis

The MCA conducted in this study followed the methodology developed by the IBGE (2019) to produce the national dataset, which serves as an essential reference in disseminating information about landslide susceptibility and guiding specific actions to minimize their impacts. Accordingly, the IBGE/MCA model included six factors: geology, geomorphology, LULC, pedology, rainfall, and slope. In this type of analysis, experts may assign weights to each factor considered in calculating 'degrees of landslide potential' (Chakhar and Mousseau 2008), which refers to subjective values on a scale from 1 to 10 adopted to measure the potential of each class regarding landslide occurrence, where 1 means very low, and 10 indicates very high susceptibility (IBGE 2019). We assigned the weights and the degrees of landslide potential to each factor and its respective classes according to IBGE (2019) (Table 2).

2.2.2. Machine learning algorithms

The choice of SVM, RF, and LR as the core algorithms for this study was based on a comprehensive review of 87 journal articles focused on machine learning applications in LSM from 2015 to 2021 in the Scopus database (Appendix B). We selected these 87 articles from a total of 117 studies due to their scientific relevance in the field. We did not find any papers in the aforementioned database prior to 2015 (Appendix A). This review emphasized that SVM, RF, and LR are the most widely applied techniques, appearing in 35 (40%), 27 (31%), and 20 (23%) studies, respectively. This highlights their strong track record and effectiveness in the field (see more details in Appendix B). Additionally, recent studies have used RF, SVM, and LR to predict landslide occurrences and as benchmarks to evaluate their performance against a single ML or hybridized model (Chen et al. 2023; Chen and Fan 2023; He et al. 2023; Trinh et al. 2023; Chowdhury et al. 2024; Zhang, Zhao, et al. 2024). These comparisons underscore the robustness and adaptability of these algorithms, whether used independently or in conjunction with other methods, to assess landslide susceptibility across varied geographical contexts. These comparative studies have consistently shown RF, SVM, and LR as reliable and interpretable methods, further validating our selection of these algorithms to assess and compare landslide susceptibility in our study. Furthermore, the robust performance and interpretability of these algorithms, which range from linear (LR) to non-linear (RF and SVM), have led to their extensive use in this domain (Chang et al. 2019; Akinci and Zeybek 2021). This diversity in model complexities allows the study to compare how well each model captures the drivers and contributes to classifying landslide susceptibility.

The SVM algorithm (Boser et al. 1992) is popular because of its resilience, accuracy, and adaptability for minimal training data (Shao and Lunetta 2012). Due to its more significant generalization potential, SVM may outperform with imbalanced data, even when dealing with limited training sample sizes (Tarantino et al. 2021). This method classifies data by identifying the optimal hyperplane to separate training data into a predefined number of classes (Thanh Noi and Kappas 2018). The SVM decision function can be expressed as follows:

$$f(X) = \text{sign}(Xw^T + b)$$

Table 2. Degrees of potentiality to landslides assigned to each factor (adapted from IBGE 2019).

Factor/type	Weight (%)	Classes	Degrees of landslide potential
Slope (%) (Continuous)	35	0–3	1
		3–8	3
		8 – 20	5
		20 – 45	8
		45–75	9
		>75	10
Geomorphology (Categorical)	20	Geomorphol_1: Structural dissection of convex hilltop (DEc35)	10
		Geomorphol_2: Structural dissection of convex hilltop (DEc42)	7
		Geomorphol_3: Structural dissection of convex hilltop (DEc43)	7
		Geomorphol_4: Structural dissection of convex hilltop (DEc44)	9
		Geomorphol_5: Homogeneous dissection of convex hilltop (Dc43)	7
		Geomorphol_6: Homogeneous dissection of sharp hilltop (Da43)	7
		Geomorphol_7: Homogeneous dissection of convex hilltop (Dc52)	7
		Geomorphol_8: Structural dissection of sharp hilltop (Dea35)	10
		Geomorphol_9: Homogeneous dissection of convex hilltop (Dc42)	7
Geology (Categorical)	15	Geology_1: Diorite, Gabbro, Gneiss and Tonalite	3
		Geology_2: Granite	1
		Geology_3: Orthogneiss	3
		Geology_4: Gneiss and Migmatite	3
		Geology_5: Gneiss	3
		Geology_6: Alluvial and colluvial sediments	8
		Geology_7: Gneiss, quartzite, meta-ultramafic rocks and gondite	4
Pedology* (Categorical)	15	Pedology_1: Water body**	–
		Pedology_2: Acrisols	7
		Pedology_3: Cambisols	8
		Pedology_4: Ferralsols (red/yellow)	3
		Pedology_5: Ferralsols (red)	3
		Pedology_6: Rocky outcrops	10
		Pedology_7: Urban Area	1
		Pedology_8: Leptosols	10
		Pedology_9: Fluvisols	10
LULC (Categorical)	10	LULC_1: Forestry	4
		LULC_2: Non-forest natural area	5
		LULC_3: Water body**	–
		LULC_4: Forest Vegetation	1
		LULC_5: Agricultural area	9
		LULC_6: Artificial area	10
		LULC_7: Mosaic of anthropic areas in forest remnants	6
Rainfall (mm) (Continuous)	5	400–1,000	4
		1,000–1,500	6
		1,500–2,000	8
		2,000–2,500	9
		2,500–4,300	10
Total	**100**%		

*Soil classes at a categorical level in the World Reference Base for Soil Resources (FAO 2015; EMBRAPA 2023).
**Water body classes were excluded in LULC and Pedology analyses following the methodology of IBGE (2019).

where w^T is the transpose weight vector, X is the input feature vector, and b is the bias term. The optimal hyperplane is found by solving the following optimization problem:

$$\min_{w,b}\frac{1}{2}\ ||w||^2 \text{ subject to } \ y_i\left(X_i w^T + b\right) \geq 1 \text{ for all } i$$

This approach is rooted in the concept of structural risk minimization for addressing overfitting (Wang et al. 2021). However, SVM takes longer to execute on large datasets (Khwarahm 2021). RF is an ensemble learning method created to improve the classification and regression trees (CART) method (Breiman 1984) by simultaneously building numerous decision trees. As a meta-estimator, RF utilizes averaging to enhance predictive accuracy and mitigate overfitting by fitting several decision tree classifiers on various subsamples of a dataset (Breiman 2001). RF classifies *via* bootstrap aggregation, generating many training subsets and trees, each yielding a classification result (Hunter et al. 2020). It uses out-of-bag sampling with a replacement method to handle dimensionality, multicollinearity, outliers and noise, and sample inadequacy (Hudak et al. 2020). The advantages of using RF instead of CART are the predictors' value range and their tolerance to overfitting (Wall et al. 2021).

The prediction γ for an input feature vector X can be expressed as:

$$\gamma = \frac{1}{N}\sum\nolimits_{i=1}^{N} T_i(X)$$

where T_i represents the *i-th* decision tree in the forest and N is the total number of trees. RF reduces overfitting by averaging multiple trees' predictions. Each tree in the forest considers a random subset of features, which helps capture various patterns in the data.

ML algorithms like SVM and RF are non-parametric methods, meaning they do not assume a specific functional form for the relationship between the target and the independent variables. Instead, these methods use data-driven models to learn relationships and make predictions. Regression methods, such as LR (Hosmer and Lemeshow 2000), are parametric since they assume a specific functional form for the association between predictors and the dependent variable, make assumptions about the underlying data distribution, and estimate the parameters of that form using the data. LR entails predicting a dependent variable that takes the values 0 (representing non-landslide areas) or 1 (indicating landslide occurrence) based on the features' values. LR uses a logistic function (also known as the log odds-ratio link function) to model the relationship between the dependent and the independent variables (Hosmer and Lemeshow 2000). This logistic function transforms the linear combination of features into a value between 0 and 1, representing the probability of the target being 1. LR then uses these probabilities to make predictions based on the estimated relationships.

The LR is represented by the following equation:

$$P\left(y = 1|X\right) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n)}}$$

where $P(y = 1|X)$ is the probability of the occurrence of the event (landslide) given the predictor variables *X1, X2, … , Xn*. The coefficients *β0, β1, β2, … , βn* are estimated from the data and represent the influence of each predictor variable. A positive coefficient βi indicates that as the predictor Xi increases, the likelihood of a landslide increases.

Binary classification tasks were executed through an automated ML pipeline known as STREAMLINE (Urbanowicz et al. 2022). This pipeline is specifically crafted to assess performance across datasets and ML algorithms. STREAMLINE incorporates cross-validation partitioning, estimation and selection of feature importance, optimization of models' hyperparameters, and thorough performance evaluation. For validation and selection purposes, the software divided the data into seven distinct folds, encompassing three sets: a training set used to fit parameters and select the best hypothesis within each hypothesis class; a validation set employed to choose the best hypothesis class or model; and a test set utilized to estimate the true error of the final hypothesis. It is important to ensure that the splits maintain the dataset's statistical properties and avoid data leakage. The optimal model was determined through seven-fold cross-validation on the training set, employing stratified sampling. Assessing factors' importance yields valuable insights into understanding which features played a crucial role in making accurate predictions (Urbanowicz et al. 2018). STREAMLINE focuses on providing a pre-modelling estimation of feature importance and seeking to conservatively remove features that do not indicate informative value (Verma et al. 2018). It utilizes filter-based factor selection methods to examine the estimated feature importance, that is, mutual information (MI) (Peng et al. 2005) and MultiSURF (Urbanowicz et al. 2018). MI is proficient at evaluating univariate associations between a feature and an outcome, while MultiSURF has been demonstrated to be sensitive to not only univariate associations but also both two- and three-way feature interactions (even in the absence of univariate associations). If either MI or MultiSURF finds evidence that a feature may be informative, it is retained; otherwise, it is removed.

Most ML methods have several hyperparameters that affect how the algorithm runs and performs on a particular dataset (Wang et al. 2021). STREAMLINE identifies the whole set of critical hyperparameters for each algorithm and a wide range of possible configurations through the Optuna packages (Akiba et al. 2019). Optuna splits a given training dataset, using cross-validation folds to generate additional internal training and validation partitions to test possible hyperparameter combinations based on an automated Bayesian optimization (Urbanowicz et al. 2022). We use the evaluation metric-balanced accuracy to optimize hyperparameters, considering class imbalance and assigning equal weight to the accurate prediction of both class outcomes. Hyperparameter optimization overcomes biases when comparing ML algorithms, as most models are built with their default hyperparameter values. The optimization tool tried alternative hyperparameter values and kept those that produced the highest performance based on the balanced accuracy results.

2.2.3. Evaluation of model performance

We calculated seven metrics to assess prediction errors and evaluate model performance. Most functions adhere to the rule that a higher score corresponds to a more accurate prediction. The following measures were selected based on previous studies developing similar ML models (Kavzoglu et al. 2014; Dang et al. 2020; Nhu et al.

2020; Prakash et al. 2020; Zhu et al. 2020): sensitivity or recall or true positive rate (TPR) (1), specificity or true negative rate (TNR) (2), overall accuracy (ACC) (3), negative predictive value (NPV) (4), positive predictive value or precision (PPV) (5), Matthews correlation coefficient (MCC) (6), and F1 score (7).

$$\text{Sensitivity (TPR)} = \frac{TP}{TP + FN} \tag{1}$$

$$\text{Specificity (TNR)} = \frac{TN}{TN + FP} \tag{2}$$

$$\text{Accuracy (ACC)} = \frac{TP + TN}{TP + TN + FP + FN} \tag{3}$$

$$\text{Negative Predictive Value (NPV)} = \frac{TN}{TN + FN} \tag{4}$$

$$\text{Positive Predictive Value (PPV) or Precision} = \frac{TP}{TP + FP} \tag{5}$$

$$\text{Matthews correlation coefficient (MCC)} = \frac{TP * TN - FP * FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \tag{6}$$

$$F1 \text{ score} = \frac{2*TP}{2*TP + FP + FN} \tag{7}$$

Sensitivity reflects the model's ability to identify true positive occurrences, while specificity gauges the model's capacity to identify negative occurrences accurately (Carter et al. 2016). True positives (TP) indicate points correctly identified as landslide presence, while false positives (FP) represent the instances wrongly detected as landslide locations (Erener et al. 2016). Thus, sensitivity represents the fraction of pixels classified as landslide correctly, whereas specificity denotes the ratio of pixels classified as non-landslide accurately (Bui et al. 2016). Higher specificity and higher sensitivity indicate an enhanced predictive capacity of the model for identifying non-landslide and landslide pixels, respectively (Pham et al. 2016).

The overall accuracy quantifies the correct classification of both landslide occurrences and non-occurrences (Merghadi et al. 2020). Precision measures the correct classification of landslide pixels within the landslide category. In contrast, NPV represents the proportion of samples classified as negative that are truly negative or the portion of pixels correctly categorized as non-landslide pixels (Dung et al. 2021; Varoquaux and Colliot 2023). The PPV values range from 0 to 1, with a higher score indicating the model's proficiency in minimizing false positives and making accurate positive predictions (Ramos Filho et al. 2021; Singh 2022).

The F1 score is characterized by the harmonic mean of sensitivity and precision (PPV), with values varying between 0 and 1, where a higher value indicates a better model's function (Chicco and Jurman 2020; Al-Najjar et al. 2021; Liu, Khojandi, et al. 2021; Varoquaux and Colliot 2023).

The MCC evaluates the correlation between the observed binary landslide classification and the predicted landslide values, covering a scale from −1 to 1. A score of 1 signifies a flawless classification model, 0 indicates performance equivalent to random chance, and −1 suggests predictions entirely contrary to the true labels (Wang et al. 2019; Rong et al. 2020; Wang et al. 2020; Yuan and Chen 2022). The Area Under the Curve (AUC) measures the model's overall ability to distinguish classes. An AUC of 1 indicates perfect classification, while an AUC of 0.5 suggests random guessing. The Receiver Operating Characteristic (ROC) plots the true positive rate (sensitivity) against the false-positive rate (1 – specificity) at different threshold levels (Bui et al. 2016; Pham et al. 2016; Mouta et al. 2021).

3. Results

3.1. Multi-criteria analysis

Figure 3 shows the landslide susceptibility spatial distribution of Petrópolis obtained from the MCA. Around 90% of the area is considered to have high or very high susceptibility to landslides (Table 3). Conversely, 2% of the study area was classified as low or very low susceptibility, encompassing approximately 8% of landslide occurrences.

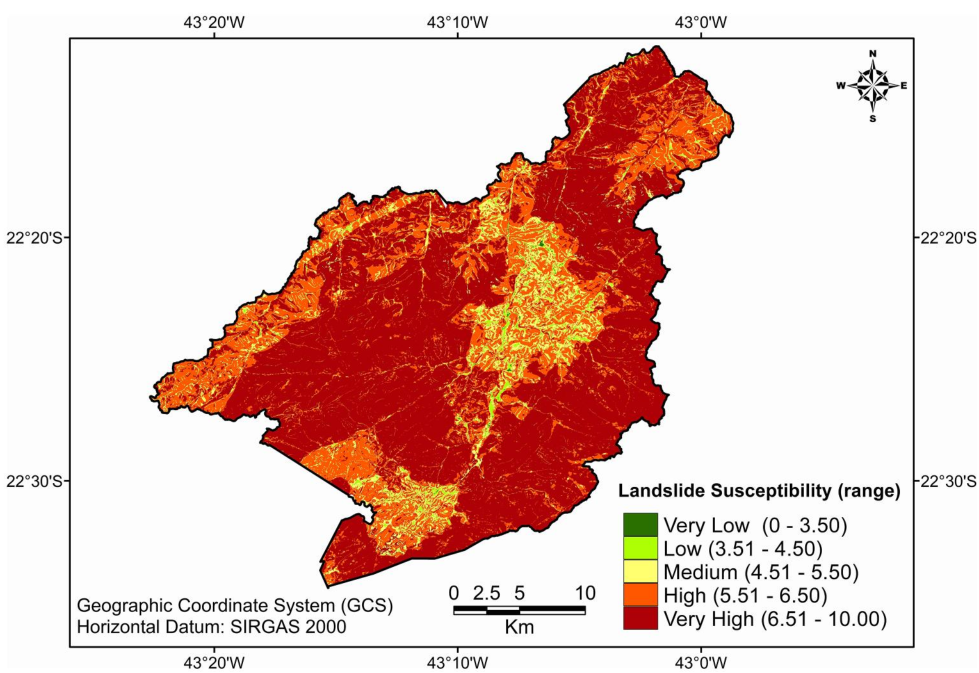


Figure 3. Spatial distribution of landslide susceptibility in Petrópolis generated using the MCA method.

Table 3. Landslide susceptibility spatial distribution in Petrópolis – Rio de Janeiro.

		Area		Presence points	
Class	Range	Km^2	%	Count	%
Very low	0–3 .50	1.26	0.16	2	0.14
Low	3.51–4.50	15.13	1.91	108	7.71
Medium	4.51–5.50	63.90	8.08	286	20.41
High	5.51–6.50	212.64	26.88	443	31.62
Very high	6.51–10.00	498.21	62.97	562	40.12
Total		**791.14**	**100.00**	**1401**	**100.00**

Table 4. Performance evaluation for MCA.

Model	TP	TN	FP	FN	Sensitivity	Specificity	Accuracy	PPV	NPV	F1	MCC	ROC AUC
MCA	1003	136	1265	398	0.72	0.10	0.41	0.44	0.25	0.55	−0.24	0.41

Table 3 illustrates that nearly 72% of presence points are located in high and very high landslide-susceptible areas. Besides, when the degree of landslide susceptibility increases, the frequency of landslide occurrences also increases, highlighting a clear positive correlation.

Table 4 illustrates the performance evaluation for MCA. This analysis showed a sensitivity of 0.72, a specificity of 0.10, and an overall accuracy of 0.41. MCA detected 1,003 true positives but had 398 false negatives, which means it failed to identify many landslide-prone areas. The low sensitivity (0.72) and specificity (0.10) suggest that MCA struggles with both identifying landslide-prone areas (true positives) and distinguishing stable zones (true negatives). This low performance likely reflects a low capacity to adapt to this dataset's complex interactions between variables.

3.2. ML models

3.2.1. Hyperparameter optimization settings

As most ML methods have several hyperparameters that affect algorithm performance, we used the capabilities of the STREAMLINE software to identify the critical hyperparameters and their best configurations. The optimal regularized LR model is deployed using the 'liblinear' solver and the inverse of regularization strength, C value (C: 0.32). The class weight is configured to the balanced option, automatically adjusting weights in inverse proportion to class frequencies in the input data based on y values. The maximum number of iterations for the solvers to converge is 152, and the penalty is l1, contingent on the chosen solver. In the RF algorithm, the number of trees in the forest is set to 863. The criterion function uses Gini impurity to assess the quality of a split. The maximum depth of the tree is 17. The minimum number of samples required to split an internal node is 16, and one is the minimum number of samples needed to be at a leaf node. The number of features considered when searching for the best split is implemented as log2, and bootstrap and out-of-bag options are set as true. The SVM algorithm was executed using the radial basis functions kernel type. The regularization parameter C (C: 13.59) is set to a strictly positive value. The class weight, set to balanced, automatically adjusts weights based on class frequencies in the input data. Appendix C depicts the best model's hyperparameters compared with the default values of each algorithm from the scikit-learn toolkit (Pedregosa et al. 2011).

3.2.2. Factors' importance and selection

Evaluating factors' importance and filtering is an opportunity to identify patterns in the data and address multidimensionality. Removing irrelevant or redundant factors improves the performance of ML algorithms. As such, STREAMLINE is conservative in selecting predictors and adopts a collective predictors selection step to avoid removing features with potentially small but meaningful effects. Figure 4 illustrates the importance of various factors derived from a sevenfold cross-validation on simulated landslide occurrence data. Figure 4(a) shows the MI scores, Figure 4(b) shows the MultiSURF scores, and Figure 4(c) lists the landslide influencing factors ranked by their cumulative mean importance. Table 1 provides more information on each score.

The top 10 important predictors of landslide susceptibility in Petrópolis are influenced by the region's unique geographic context. These predictors – drainage density, artificial areas (LULC_6), rainfall, elevation, urban areas (pedology_7), LS-Factor, slope length, distance to roads, distance to faults, and Topographic Position Index (TPI) – highlight the interplay between natural and anthropogenic factors. Drainage density, for instance, is a critical predictor as it reflects the movement of water through the landscape, affecting soil saturation and stability on the region's steep slopes. The impermeable surfaces associated with urban development (LULC_6 and pedology_7) further exacerbate water runoff, leading to increased landslide susceptibility. Rainfall, particularly in this orographic region, is a significant trigger for landslides. Heavy precipitation events saturate the soil and increase the likelihood of mass movements. Elevation is crucial, as higher altitudes correlate with steeper slopes that are more susceptible to landslide occurrences. The LS-Factor, which incorporates slope length and steepness, indicates that longer and steeper slopes influence soil loss, raising the chances of landslides. Additionally, the distance to roads and other infrastructure can destabilize slopes by altering natural drainage patterns. TPI and distance to faults are essential factors in assessing landslide susceptibility as they provide insights into the relative landscape positioning and potential instability of slopes. Considering these elements, we can better understand how geological structures and terrain variation influence landslide occurrence and susceptibility in the study area.

3.2.3. Accuracy assessment

Figure 5 depicts the comparison performance evaluation for LR, RF, and SVM models regarding landslide susceptibility prediction. The validation process was automatically conducted by STREAMLINE, which chooses the best model and estimates the true error of the final hypothesis. LR achieves a balanced sensitivity and specificity of 0.89, with an accuracy of 0.89 and a high AUC of 0.95, indicating good model performance. LR provides reliable performance across metrics, with all values (PPV, NPV, F1) at 0.89. While LR is effective, both RF and SVM outperform it, particularly in sensitivity and specificity, suggesting limitations in capturing more complex patterns. RF outperforms the other models with a sensitivity of 0.95, a specificity of 0.93,

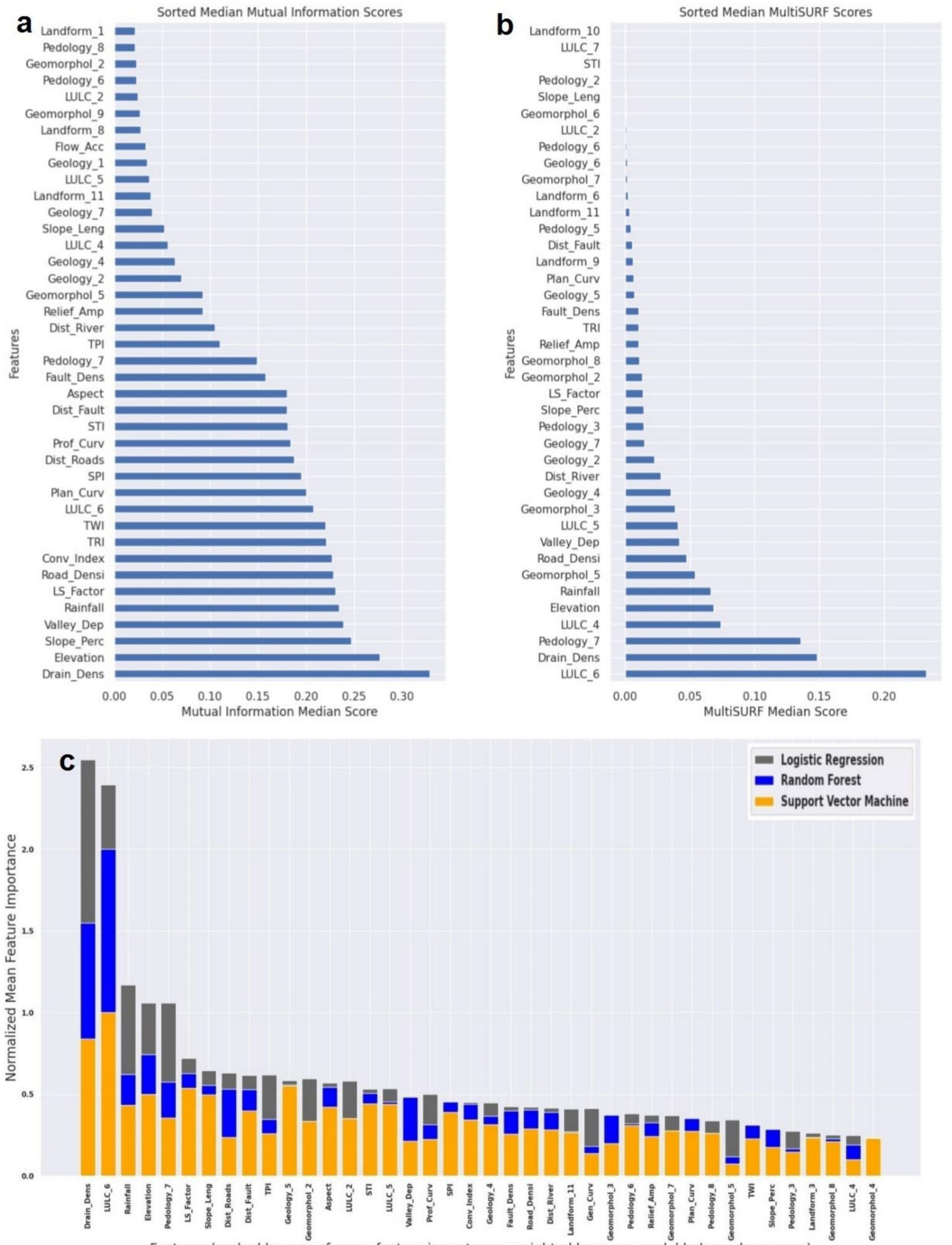


Figure 4. Factor importance results across sevenfold cross-validation on simulated landslide occurrences data: Mutual information (MI) scores (a); MultiSURF scores (b); and landslide influencing factors ranked by the sum of mean importance (c).

and an accuracy of 0.94. Its AUC of 0.98 highlights strong discriminatory power. RF's higher sensitivity and PPV indicate its superior ability to correctly identify landslides, making it ideal for applications where minimizing missed susceptible zones is critical. SVM performs comparably well, with sensitivity at 0.93, specificity at 0.91,

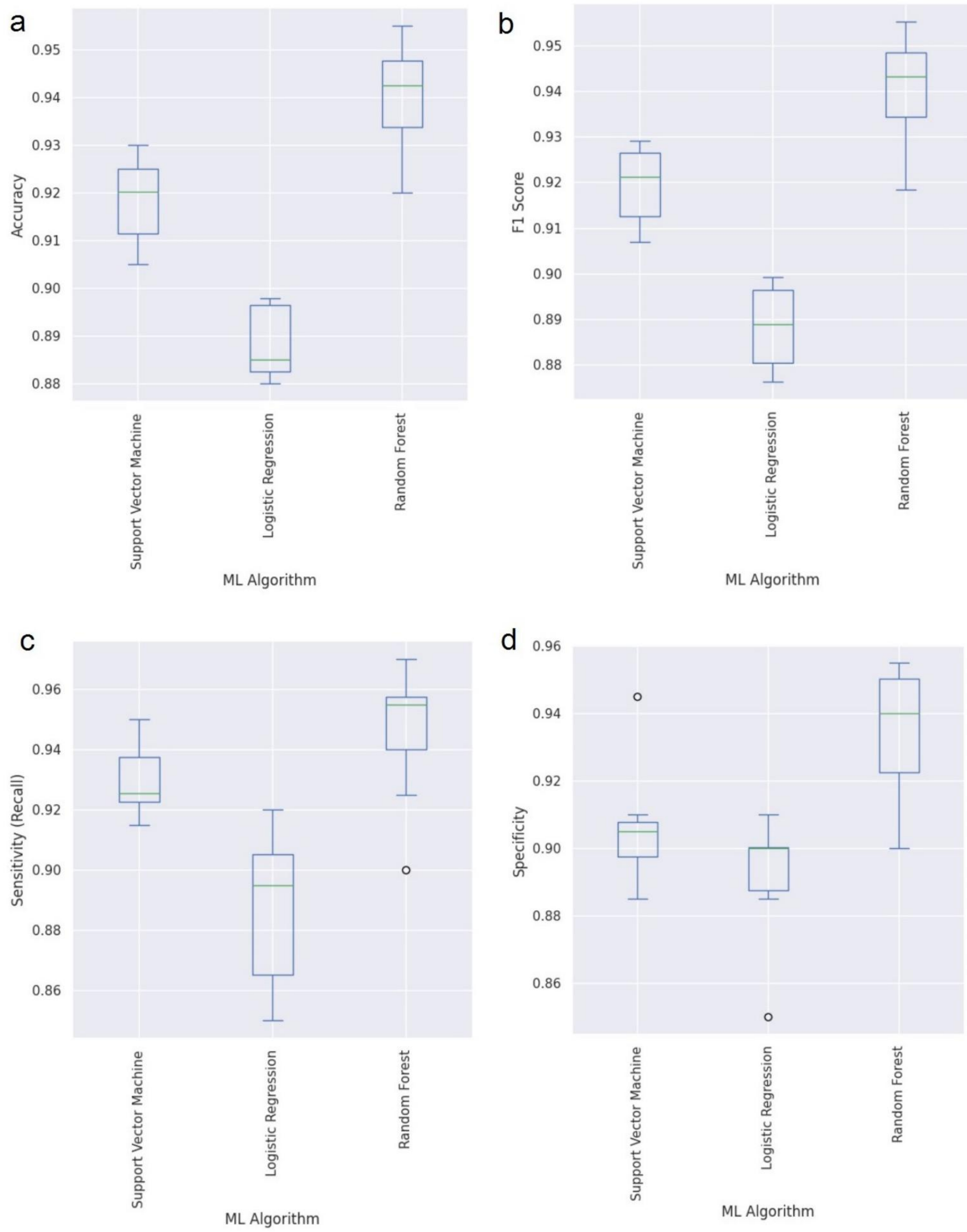


Figure 5. Metrics of the performance evaluation for ML models: accuracy (a); F1 score (b); sensitivity (recall) (c); and specificity (d).

and accuracy at 0.92. Its AUC of 0.96 also reflects strong discrimination. SVM balances LR and RF in terms of accuracy and complexity, achieving high sensitivity and specificity. However, SVM slightly underperforms compared to RF in sensitivity, which could be critical for applications focused on reducing false negatives.

The observation that RF shows superior performance is not universally guaranteed, as it can be influenced by several factors, such as data quality and sample size, input variables, and geographic variability. Missing values, noise, or biases in the dataset can lead to suboptimal results and inaccuracies in spatial data degrading model predictions. The choice and quality of input variables critically influence any ML performance. Excluding key predictors like rainfall or soil type could lead to over or underestimation, as landslide susceptibility is inherently location-specific. RF outperformance in Petrópolis results from the dataset scope and local conditions, which does not guarantee the model's generalizability in other regions with different environmental and socio-economic conditions. Further testing on external datasets, including sensitivity analysis, is recommended to assure its broader applicability.

4. Discussion

This research applied ML algorithms (LR, RF, and SVM) and MCA to assess landslide susceptibility in Petrópolis, Rio de Janeiro. It compared the applicability and effectiveness of these methods to provide a better understanding of landslide-influencing factors. The study advanced existing methodologies by comparing feature importance across ML models and MCA, highlighting key predictors and their influence on landslides. It also utilized modern hyperparameter optimization tools like Optuna, demonstrating a scalable and efficient workflow for tuning model parameters. Furthermore, the research evaluated each model's potential for integration into regional planning and disaster management, offering valuable insights to support informed landscape planning.

The MCA approach used in this study integrated LULC, geology, geomorphology, pedology, rainfall, and slope. We based on a nationally well-established methodology compiled from the IBGE (2019) to assign the weights for each factor. The MCA results showed that a significant portion of the municipality of Petrópolis is highly susceptible to landslides, with approximately 90% of this area classified as high and very high susceptibility classes. Moreover, the analysis of landslide susceptibility spatial distribution in Petrópolis (Table 3) shows that higher degrees of landslide susceptibility are associated with increased landslide occurrences, showing a clear positive correlation. This correlation aligns with previous findings reported by the IBGE (2019), which also stated a positive correlation between the number of landslide scars and the degrees of susceptibility to landslides. However, it is worth noting that MCA exhibited some limitations, particularly in terms of specificity, a metric that measures the ability to identify true negatives correctly. This model's tendency to generate false positives outweighed its capacity to correctly identify true positives, indicating that it may not be as effective in identifying non-landslide areas. This outcome is consistent with the results from Erener et al. (2016).

According to Zhu et al. (2018), landslide absence data is typically derived from areas without historical landslide occurrences, but these sampling methods have two significant limitations. Firstly, there is an ongoing debate about the appropriate buffer size for these strategies within specific regions, leading to uncertainty regarding the delimitation of areas free from landslides. Secondly, these areas believed to be free from landslides may encompass locations with high susceptibility to landslides but not have experienced events so far due to the absence of triggering elements (Zhu et al. 2018). In addition, neither subjective nor statistical testing can conclusively establish the absolute validity of a model because it represents an abstract and simplified version of the actual system (Qureshi et al. 1999).

The ML algorithms ranked the top 10 important predictors of landslide susceptibility as drainage density, LULC_6 (artificial area), rainfall, elevation, pedology_7 (urban area), LS-Factor, slope length, distance to roads, distance to faults, and TPI. The drainage density reflects water flow and soil saturation, directly impacting slope stability and landslide occurrence, as well as the presence of impermeable areas represented by (LULC_6 – Artificial Area) and soil characteristics often altered by human activities (Pedology_7 – Urban Area). The rainfall is also considered an important trigger for landslides. Higher elevations often correlate with steeper slopes, which are more prone to landslides. The LS-Factor combines slope length and steepness, with longer slopes accumulating more water and increasing the likelihood of landslides. Another factor is the distance to roads and other network infrastructures, which can destabilize slopes and change drainage patterns, lastly, the proximity to geological faults and the TPI, measuring the relative position within the landscape. Identifying and evaluating these top 10 factors provides a robust framework for understanding and mitigating risks to the population living in landslide-prone areas. Such advanced geohazard data-driven models contribute to the scientific literature and have real-world implications for improving resilience against natural hazards.

The spatial analysis of landslide susceptibility is critical for understanding geographic variation in risk across Petrópolis. The variability in slope angles across zones can significantly influence landslide occurrence patterns. Steeper rural areas may experience more natural landslides, while moderately steep urban zones are often more impacted by anthropogenic factors such as deforestation, slope cutting, poor land use planning, unregulated construction, and higher population density on vulnerable slopes (Ionita et al. 2024). The geographic, geologic, and climatic contexts of Petrópolis, characterized by steep slopes, fragile soil structures derived from a mix of granite and gneiss rock formations, and intense seasonal rainfall, help to explain these factors' importance. This complex topography exerts gravitational stress on the soil, rendering the slopes highly susceptible to landslides, especially during heavy rainfall, which often exceeds 200 mm in a single day during peak storms (Alcântara et al. 2023). The importance of factors related to human activities, such as land use and land cover changes, can be justified by the rapid urban expansion observed in the region. The informal, uncontrolled urban sprawl aggravates the situation by reducing natural forest cover, which is essential to help bind the soil and reduce runoff by enhancing infiltration. Artificial areas and network infrastructures also introduce changes in the local conditions by destabilizing slopes and disrupting their natural structure, further increasing landslide susceptibility.

The influence of drainage density, rainfall, and urbanization has been highlighted in studies conducted in Petrópolis (Oda et al. 2024), in the Himalayas (Nepal) (Acharya and Lee 2019), in the Sichuan region of China (Tang et al. 2019), and in central Italy (Catani et al. 2013). These studies similarly emphasize the role of these factors in driving landslide susceptibility. However, Petrópolis stands out due to its specific combination of steep topography and intense urban development, which makes it particularly vulnerable.

The assessment metrics applied in the comparison process among the MCA and ML algorithms included accuracy, specificity, sensitivity, NPV, PPV, MCC and F1 score, providing a comprehensive evaluation of the models' performance. We also employed the ROC AUC, a widely accepted metric for comparing ML model performance in landslide susceptibility analysis. RF outperformed the other methods in all parameters, including the ROC curve, which is generally applied to explore the balance between identifying real positives and avoiding false positives. As a result, models with these properties have a high accuracy and can reliably distinguish between landslide-prone and non-landslide-prone areas. The ROC curve provides a single measure of the model's performance. An AUC of 1 indicates a perfect model, while an AUC of 0.5 suggests a model with no discriminative power. RF often achieves higher AUC by aggregating the predictions of multiple trees and smoothing out the decision boundary, leading to a more robust model. In this study, there is a clear representation of its better performance, showing higher TPRs and lower FPRs across various thresholds. In addition, RF can handle imbalanced datasets more effectively by constructing trees that focus on minority classes, and averaging the results of multiple trees reduces the variance, leading to more stable and reliable predictions (Breiman 2001).

RF is often more accurate than other models like LR or SVM, as it can better capture complex interactions and non-linear relationships between features than linear models like LR. RF inherently performs feature selection by considering a random subset of features for each split in the trees, which helps reduce the impact of irrelevant features (Breiman 2001; Fawcett 2006; Hastie et al. 2009). The RF model achieved high scores across multiple metrics (accuracy of 0.94, ROC AUC of 0.98, and F1 score of 0.94), demonstrating its robust performance in identifying landslide and non-landslide areas. Its ability to handle complex interactions between variables and feature selection contributed to its success. SVM and LR also showed strong results (ROC AUCs of 0.96 and 0.95 and F1 scores of 0.92 and 0.89, respectively) but did not outperform the RF model.

These results align with findings that indicate RF models' superior accuracy over LR and SVM in predicting landslide susceptibility (He et al. 2023; Liu, Li, et al. 2021; Yuan et al. 2022; Zhang, Zhang, et al. 2024). For example, it has been observed that LR and SVM models tend to overestimate the proportions of high and very high susceptibility classes, underscoring RF's advanced capabilities in achieving higher accuracy and robustness, particularly in balancing susceptibility class distributions and accurately identifying high-susceptible areas (Zhang, Zhang, et al. 2024). The RF model's ability to assess the importance of conditioning factors using the mean decrease accuracy metric, which replaces individual variables with random values to evaluate their impact on model performance, underscores its superior analytical capabilities for landslide susceptibility prediction compared with LR and SVM models (Liu, Li, et al. 2021). Furthermore, the RF model's randomness is demonstrated through the variability in the training set and the selection of optimal attributes for node splitting, which helps prevent overfitting, improves the model's stability, and enhances its good anti-noise ability (Huang and Zhao 2018; Yuan et al. 2022). Regarding MCA, its results were significantly lower compared to those from ML models (accuracy 0.41, ROC AUC 0.41, F1 score 0.55).

Kavzoglu et al. (2014) have stated that MCA outperforms SVM and LR algorithms regarding overall accuracy. However, MCA showed the worst performance in this analysis compared to LR, RF, and SVM models, mainly regarding specificity, which measures the capacity to identify true negatives. This may be because assessing MCA involves a wide range of tasks to evaluate the model's overall reliability for its intended functions as its methods diverge from purely quantitative models like linear programming, where it is possible to compare the inputs and the outputs easily (Qureshi et al. 1999).

Traditional MCA methods rely heavily on expert judgment to select the landslide-influencing factors and assign their weights. This process, while intuitive, introduces subjectivity, which can lead to inconsistencies in the results. Different experts might assign divergent weights based on their experiences or biases, which may affect the reproducibility and reliability of the model. The subjectivity of MCA can lead to over-emphasis or underrepresentation of certain factors, especially when dealing with complex systems like landslide susceptibility. This lack of standardization may result in less accurate outcomes, especially when compared to data-driven ML models, which algorithmically determine optimal weights based on the underlying data.

Our findings show that ML models, especially RF, perform significantly better than MCA in terms of predictive accuracy. This is because ML algorithms learn from data and are more effective at dealing with complex interactions among variables, highlighting the strong potential of these models in landslide susceptibility analysis. To ensure the reliability of our findings, we employed various validation techniques, including cross-validation and performance metrics such as ROC AUC. This rigorous validation process underlines the effectiveness of ML in capturing the intricacies of landslide susceptibility, offering a better understanding of the influencing factors. Our research demonstrates the superiority of ML models, providing valuable insights for policy-makers since it enables them to make informed decisions based on reliable predictions, leading to better resource allocation and improved safety measures, thus protecting lives and property. Our work enriches the literature on the application of ML to geohazard assessment, emphasizing the potential of advanced analytical techniques to enhance the understanding and management of natural hazards.

The susceptibility maps provide fundamental insights that guide urban planners in identifying safe zones for urban expansion. Thus, this research's results underscore the critical role ML models, like RF, SVM, and LR, can play in guiding urban planning and policy decisions in landslide-prone regions. In this sense, policy-makers can leverage this information to enforce construction standards and allocate resources more effectively. This is particularly crucial for regions undergoing rapid urbanization, where informal settlements often emerge in hazardous zones. In Petrópolis, for instance, the combination of steep slopes, intense rainfall, and swift urban growth increases the risks of landslide events. By identifying high-susceptibility zones, these models provide data-driven evidence to support the development of zoning regulations and land use policies to curb the development of new settlements in hazardous areas, thereby potentially mitigating the risks associated with uncontrolled urban sprawl. Our findings can also be used in early warning systems to present a proactive approach to disaster management, offering the authorities information to improve evacuation planning, strategically optimize resource allocation during emergencies, and develop awareness programmes for the community living in landslide high-susceptibility zones, reducing financial and human losses.

A limitation of statistical and ML models is the inherent uncertainty in every process, which persists despite the existence of several methodologies, such as ROC AUC, to assess the reliability and effectiveness of these techniques (Di Napoli et al. 2020; Achu et al. 2023). Another restriction is that the RF algorithm rules used to split the data into subsets are unknown (Fitts et al. 2021). Nonetheless, given the known instability of traditional recursive partitioning techniques, RF offers a great alternative to LSM and better insight into variable interactions than traditional logistic regression since RF can detect interactions among variables, adding predictive value to these classification tasks.

The MCA's subjectivity is also a limitation since decision-makers choose the influence factors, considering one criterion more important than another and assigning relative importance to different criteria (Chakhar and Mousseau 2008). Therefore, decision-makers define the influencing factors and weights based on their expertise, which may not ensure an impartial or objective assessment and might introduce biases into the analysis process. In this context, a direct comparison between the results of the MCA and ML is challenging due to the differing sets of influencing factors selected by each method since the factors included in the MCA did not align precisely with those identified and used by the ML algorithms.

The adequacy of data spatial resolution in the LSM may also influence the model's accuracy and predictive capability. The impact of raster resolution on LSM is primarily attributed to its influence on deriving landform parameters (Tian et al. 2008). In fact, morphology at a mesoscale influences landslides since this scale more accurately reflects slope features and related processes (Chang et al. 2019). In contrast, high-resolution DEMs capture micro-scale topographic details that are likely not significantly related to mesoscale processes (Chang et al. 2019). However, some factors, such as geology and human activities, are substantially less affected by the data resolution (Tian et al. 2008). Though higher-resolution DEMs are expected to be considered more suitable for LSM as they allow for the capture of detailed topography data, several parameters are more relevant at coarser scales, such as curvature and topographic indices (like SPI and TWI), suggesting that finer-scale variations in these parameters may not accurately represent the physical processes that trigger landslides (Paudel et al. 2016).

The quality of the selected DEM influences LSM outputs; however, using a finer raster resolution does not substantially improve the model's predictive accuracy (Chang et al. 2019). In this sense, LSM at scales between 1:10,000 and 1:50,000 is generally preferred for planning and engineering purposes, as DEM derivative data with medium scales (1:25,000 – 1:50,000) is suitable for quantitative methods (van Westen et al. 2008; Hearn and Hart 2019). High-resolution DEMs are more likely to introduce noise, which can result in a model with suboptimal performance (Chang et al. 2019). Conversely, models generated from topographic data at coarser resolutions often demonstrate relatively high accuracy when identifying extensive zones with high or very high landslide susceptibility (Gaidzik and Ramírez-Herrera 2021). In addition, curvature and slope inconsistencies obtained from a fine-resolution DEM are higher than those from lower-resolution ones, which may increase false positive rates (Chang et al. 2019).

In this study, most factors (22 out of 29) were derived from data at a 1:25,000 scale. Five influencing factors related to geologic conditions were based on datasets at a 1:100,000 scale, and one factor (geomorphology) was derived from a dataset at a 1:250,000 scale. Although some datasets are coarser than 1:25,000, they still offer sufficient detail for LSM studies, as geologic and geomorphologic factors tend to change more gradually over space, making this resolution suitable for capturing their impact on landslide susceptibility (Tian et al. 2008; Chang et al. 2019; Gaidzik and Ramírez-Herrera 2021). Thus, future studies may investigate the impact of spatial resolution on LSM, particularly in the context of ML algorithms and MCA. Specifically, the research could explore how different DEM resolutions influence the ML models' predictive accuracy and feature importance and whether finer resolutions provide significant advantages over coarser data. Additionally, further investigations could examine landslide temporal analysis, focusing on environmental modifications over time to uncover the direct impacts of climate and land use changes. A promising avenue for future research is the integration of ML and MCA, combining expert knowledge from MCA with data-driven insights from ML to create a more comprehensive framework for landslide susceptibility assessments. Moreover, future studies could explore how socio-environmental variables influence landslide susceptibility in different regions and assess the temporal accuracy of models within the study area or in similar regions.

5. Conclusion

Landslide susceptibility analysis provides essential insights for decision-makers and researchers involved in geohazard risk management. The primary objectives of this approach were to assess and compare the effectiveness of different modelling techniques – LR, RF, SVM, and MCA – in predicting landslide susceptibility and to enhance the understanding of the factors that most influence landslide occurrences. Our study aimed to identify the strengths and limitations of each method and determine the most robust model for landslide susceptibility prediction by conducting a detailed analysis of predictor importance, model performance, and hyperparameter optimization.

Our main findings demonstrated that RF outperforms other models in predictive accuracy (0.94), ROC AUC (0.98), and F1 score (0.94), highlighting its robustness for landslide prediction. SVM and LR also showed strong results, while MCA performed significantly lower. These insights reveal the potential of ML techniques, mainly RF, to provide reliable landslide susceptibility assessments. Our results proved that ML algorithms outperform MCA in terms of accuracy and reliability, providing more precise predictions by capturing complex relationships between landslide occurrences and environmental factors. These outcomes underscore the importance of ongoing research and refinement of landslide susceptibility models to enhance the understanding of these hazards and reduce risks to people living in landslide-prone areas, particularly in vulnerable regions such as Petrópolis.

This study underscores the potential of ML models, especially RF, as a crucial resource to support urban planning and disaster risk management, where accurate susceptibility assessments are essential for developing effective mitigation strategies. Thus, this research demonstrated the effectiveness of ML techniques in enhancing landslide susceptibility assessments, highlighting their value in guiding better-informed decisions about mitigating geotechnical hazards in landslide-prone areas. Nevertheless, it is necessary to recognize the inherent constraints of these models, including the challenges associated with defining landslide-free regions and the need for validation measures that consider the complex nature of landslide events. The potential of ML is promising; however, it requires evaluation for applicability to different geographic regions and datasets. RF proves advantageous in landslide susceptibility analysis by overcoming the instability associated with traditional recursive partitioning, but its main limitation lies in the unknown split rules.

The MCA approach demonstrated difficulties in accurately identifying areas without landslides since it presented a relatively high number of false-positive points. Moreover, the subjectivity inherent in MCA poses a challenge, as the judgements of decision-makers directly influence factor selection and weighting. In addition, comparisons between MCA and ML detected discrepancies in the included influencing factors, complicating direct result interpretation but unveiling the potential of data-driven models to landslide susceptibility predictions.

More research is required to enhance landslide prediction models' accuracy and reliability and ensure their effective contribution to disaster risk management. Future research should focus on refining landslide susceptibility models by improving their accuracy and specificity. This may involve developing advanced ML techniques and enhancing the MCA approach. Research should also address regional adaptation, real-time monitoring, risk mitigation strategies, interdisciplinary collaboration, climate change impact, and improving data accessibility to provide more comprehensive and effective disaster management and risk reduction solutions.

Author contributions

Z. Ferreira and B. Almeida contributed to conceptualization, methodology, validation, formal analysis, investigation, writing – original draft, review, and editing. A. C. Costa and P. Cabral contributed to conceptualization, methodology, validation, formal analysis, writing – original draft, and review, editing – and supervision. M. C. Fernandes contributed to resources, review, and editing.

Disclosure statement

No potential conflict of interest was reported by the authors.

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Data availability statement

The data that support the findings of this study are available from the corresponding author, Z. Ferreira, upon reasonable request.

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