

Article

Scale-Dependent Controls on Landslide Susceptibility in Angra dos Reis (Brazil) Revealed by Spatial Regression and Autocorrelation Analyses

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Abstract

Landslides are a persistent and destructive hazard in Angra dos Reis, located in the highlands of Rio de Janeiro State, southeastern Brazil, where steep slopes, intense orographic rainfall, and unregulated urban expansion converge to trigger recurrent mass movements. In this study, we applied Multiscale Geographically Weighted Regression (MGWR) to examine the spatially varying relationships between landslide occurrence and topographic, hydrological, geological, and anthropogenic factors. A detailed inventory of 319 landslides was compiled using high-resolution PlanetScope imagery after the December 2023 rainfall event. Following multicollinearity testing and variable selection, thirteen predictors were retained, including slope, rainfall, lithology, NDVI, forest loss, and distance to roads. The MGWR achieved strong performance ($R^2 = 0.94$; AICc = 134.99; AUC = 0.99) and demonstrated that each factor operates at a distinct spatial scale. Slope, rainfall, and lithology exerted broad-scale controls, while road proximity had a consistent global effect. In contrast, forest loss and land use showed localized significance. These findings indicate that landslide susceptibility in Angra dos Reis is primarily driven by the interaction of orographic rainfall, steep terrain, and geological substrate, intensified by human disturbances such as road infrastructure and vegetation removal. The study underscores the need for targeted adaptation strategies, including slope stabilization, restrictions on road expansion, and vegetation conservation in steep, rainfall-prone sectors.

Keywords: spatial non-stationarity; orographic rainfall; terrain instability; urban expansion; risk modeling



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1. Introduction

Landslides are a recurrent and devastating natural hazard in Brazil, especially in the southeastern coastal regions where rugged topography, intense orographic precipitation,

and unregulated land occupation converge [1–4]. The municipality of Angra dos Reis, in the state of Rio de Janeiro, is emblematic of this problem. The city has a high incidence of geological disasters, especially associated with heavy rains in densely populated areas [5]. Over the past decades, the city has experienced numerous fatal landslides, notably during 2002 and 2010 events, when torrential rainfall triggered large-scale slope failures, causing dozens of deaths and the collapse of critical infrastructure, including roadways and housing units and leaving dozens of deaths. The combination of steep slopes, weathered lithology, and rapid urbanization in geomorphologically fragile areas has made Angra dos Reis one of the most landslide-prone areas along Brazil’s southeastern seaboard [6].

Physically based models require detailed geotechnical and hydrological data that are rarely available at municipal scales. Under these constraints, statistical and machine learning models such as logistic regression and random forests have become popular for integrating multiple environmental variables and producing continuous susceptibility maps. However, these approaches generally assume spatial stationarity, which is inadequate in highly heterogeneous settings like Angra dos Reis, where slope, geology, land cover, and anthropogenic pressure vary considerably over short distances [7–10].

To address the issue of spatial non-stationarity, geographically weighted regression (GWR) has been proposed as a local modeling technique that allows regression coefficients to vary spatially [11]. GWR has been successfully applied in landslide studies to capture the localized effects of terrain and land use on slope instability [12,13]. However, one major limitation of GWR is that it operates on a single spatial scale: all variables are modeled using the same bandwidth, even though different conditioning factors may influence landslides at distinct spatial extents. For example, slope and aspect may exert highly localized effects, whereas precipitation accumulation or land cover patterns may influence susceptibility over broader areas. MGWR has emerged as a methodological advance that addresses this limitation [14]. By allowing each explanatory variable to operate at its optimal spatial scale, MGWR provides a flexible and spatially nuanced framework for modeling complex environmental phenomena. For landslide susceptibility, it allows for the detection of multiscale interactions between physical and anthropogenic variables and improves both interpretability and prediction accuracy [12,15]. In this study, we applied MGWR to model landslide susceptibility in Angra dos Reis, incorporating a range of conditioning factors including slope, curvature, lithology, soil type, land use/land cover, vegetation indices (NDVI), drainage density, and elevation. Angra dos Reis was chosen as the study area because of its recurrent landslide disasters, steep topography, intense orographic rainfall, and rapid urban expansion, which together create a critical setting for testing susceptibility models. To minimize redundancy and address multicollinearity among predictors, we implemented a combination of Pearson’s Correlation, Variance Inflation Factor (VIF) analysis and feature importance ranking derived from ensemble learning techniques. These procedures aim to ensure that only the most relevant and independent variables are retained for modeling, enhancing the robustness of spatial inference [16].

The hypothesis underlying this study is that landslide susceptibility in Angra dos Reis is controlled by spatially heterogeneous and multiscale interactions between environmental and anthropogenic factors, which are inadequately represented by global or single-scale models. By allowing each explanatory variable to operate at its own optimal spatial scale, the Multiscale Geographically Weighted Regression (MGWR) framework enables a more accurate and interpretable assessment of susceptibility patterns in complex terrains. This hypothesis is supported by international literature demonstrating the superiority of MGWR over traditional regression techniques in capturing spatial non-stationarity in geomorphologically dynamic regions [17,18].

The objectives of this study are (1) to develop a high-resolution landslide susceptibility map of Angra dos Reis using Multiscale Geographically Weighted Regression (MGWR); (2) to evaluate the spatial variability in the influence of topographic, hydrological, geological, and anthropogenic conditioning factors; and (3) to identify statistically significant spatial patterns in landslide susceptibility across the study area. This approach aims to advance the spatial modeling of landslide processes in tropical mountainous environments by incorporating local-scale variations in explanatory variables, improving the forecast of risk of geological disasters.

This study advances landslide susceptibility modeling by employing MGWR to explicitly capture multiscale, spatially varying relationships between topographic, climatic, and anthropogenic drivers in a tropical coastal environment—an innovation that enhances both the explanatory power of the analysis and its practical relevance for local risk management.

2. Materials and Methods

The methodological approach adopted in this study integrates remote sensing, geospatial analysis, and spatial statistical modeling to generate landslide susceptibility maps for the municipality of Angra dos Reis, Rio de Janeiro (Figure 1). Beginning the process with the definition of the study area (Angra dos Reis, RJ) and the compilation of a detailed landslide inventory using high-resolution PlanetScope imagery, subsequent steps include raster data preprocessing, multicollinearity assessment conducted in Python version 3, spatial sampling of predictor variables, spatial autocorrelation analysis using Local Indicators of Spatial Association (LISA) in GeoDa, MGWR modeling performed in ArcGIS Pro, and the final production and interpretation of landslide susceptibility maps. A set of geomorphological, hydrological, geological, and land cover predictor variables was then prepared. Multicollinearity analysis was conducted in Python to ensure the independence of explanatory variables. This multiscale modeling approach allowed for the identification of local variations in the relationship between predictor variables and landslide occurrence, ultimately resulting in the production of spatially explicit susceptibility maps.

2.1. Study Site

Angra dos Reis is a coastal municipality located in the southern part of the state of Rio de Janeiro, southeastern Brazil (latitude $\sim 23^{\circ}00' S$, longitude $\sim 44^{\circ}19' W$) (Figure 2). The city occupies an area of approximately 825 km² and includes both mainland and 365 offshore islands, the largest of which is Ilha Grande. It is bounded by the Atlantic Ocean to the south and the rugged Serra do Mar escarpment to the north, forming a highly dissected landscape characterized by steep slopes, dense Atlantic Forest remnants, and short but high-gradient drainage basins [19].

The main panel displays land use and land cover (LULC) classes derived from thematic mapping of MabBiomass Project, overlaid with recorded landslide rupture points (red dots). Major roads (BR-101 and RJ-155) and hydrographic features are also shown. The inset at the top right locates the study area within Brazil and South America. The lower right inset shows a kernel density surface representing the spatial intensity of landslide occurrences, highlighting the concentration of events in steep terrain near urbanized zones. The figure also delineates protected areas, including Ilha Grande State Park and Ilha Grande Bay.

The region's geomorphology, shaped by ancient Precambrian crystalline rocks, combined with high annual rainfall totals—ranging 1500–2000 mm per year, with some areas receiving more than 2500 mm—makes it particularly prone to gravitational mass movements. Angra dos Reis has a wet season from October to March and a dry season from April to September. The region receives most of its rainfall during the summer months. Orographic effects from the Serra do Mar intensify convective storms, particularly during

the austral summer months, when rainfall is more frequent and intense. These factors contribute to a dynamic and unstable terrain that becomes hazardous when combined with anthropogenic pressures [20].

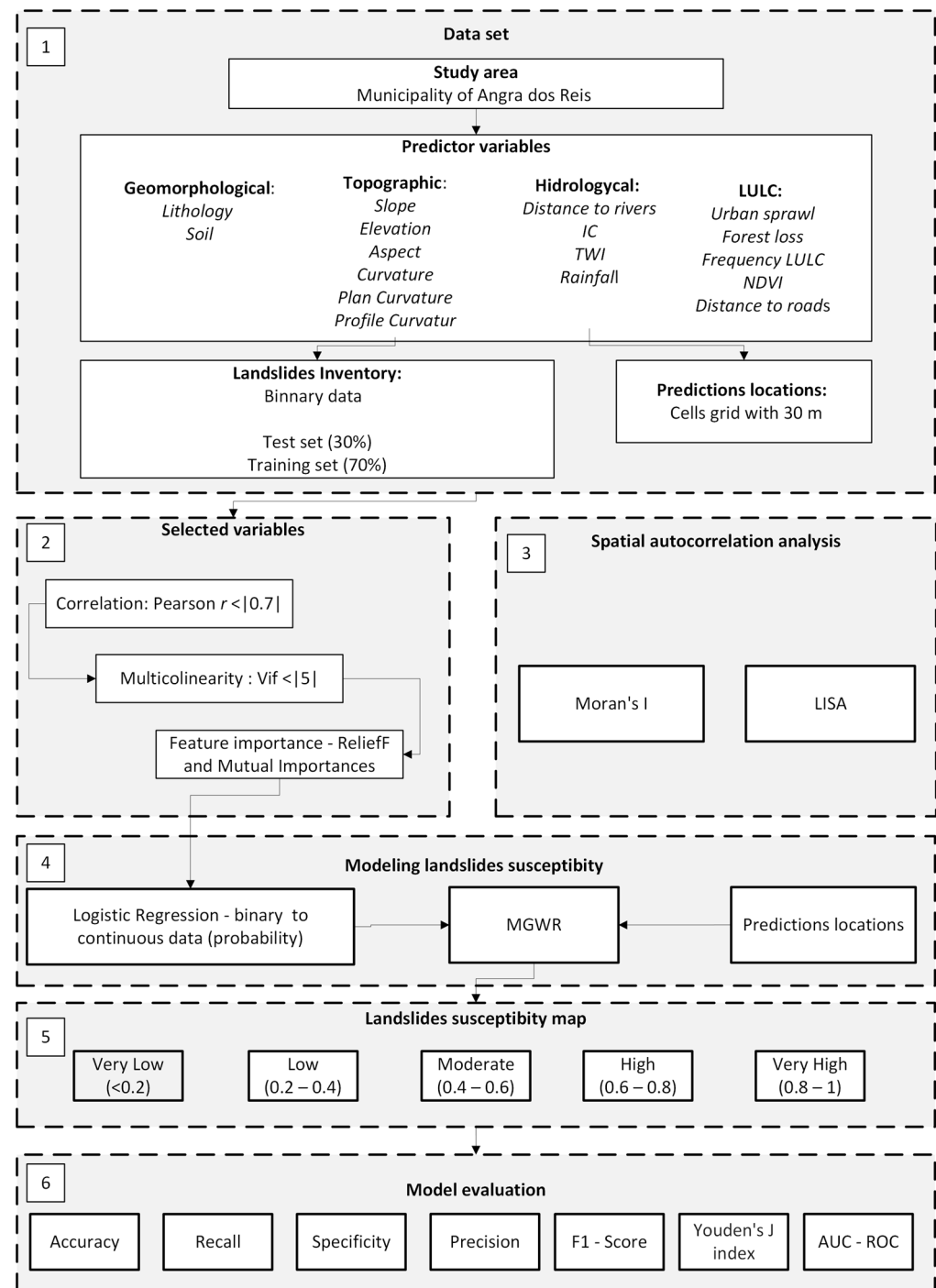


Figure 1. Workflow diagram illustrating the methodological framework employed in this study.

As of the 2022 national census estimates, Angra dos Reis has a population of approximately 200,000 residents, a significant portion of whom live in densely populated hillside neighborhoods or precariously settled areas. Economic activity in the municipality is heavily influenced by the presence of the Angra 1 and Angra 2 nuclear power plants, as well as port logistics, tourism and naval installations. However, the city's rapid and unregulated urban growth, particularly from the 1970s onwards, has resulted in the occupation of geologically unstable slopes, often by low-income families lacking access to basic

infrastructure and secure housing. The urban dynamic has intensified land conflicts and further marginalized lower-income communities, who are often forced to settle in high-risk areas, such as steep hillsides susceptible to landslides. This situation is compounded by the area's rugged topography, intense summer rains, and the widespread disregard for environmental and climatic constraints in urban development, resulting in a particularly high incidence of rainfall-induced landslides. Nearly 60% of the population lives on or near steep slopes, with over 25% residing in officially classified high-risk landslide zones [21–23].

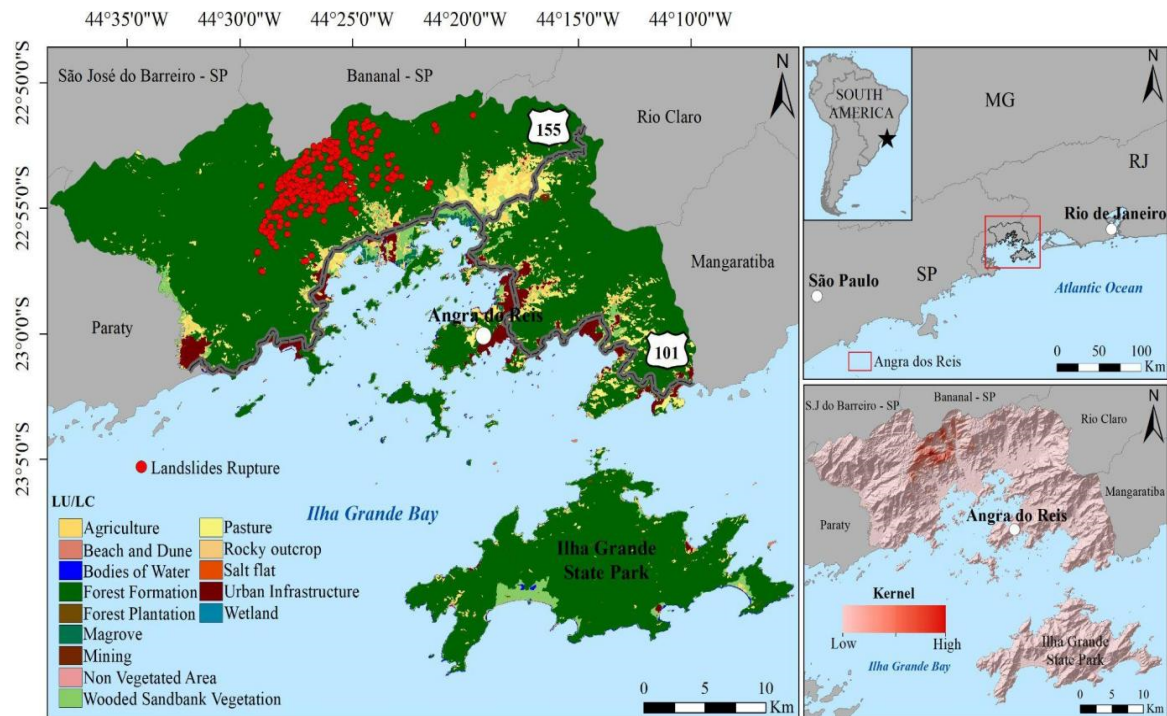


Figure 2. Location map of the study area in Angra dos Reis, Rio de Janeiro State, southeastern Brazil.

One of the earliest and most dramatic landslide disasters in the region occurred in 1985, when a translational slide at Praia da Piraquara displaced nearly 2.8 million cubic meters of earth, blocking the BR-101 highway and generating destructive tidal waves. A deadly episode followed in December 2002, when over 240 mm of rainfall within 24 h triggered debris flows in Areal and Frade neighborhoods, resulting in 42 fatalities. The most catastrophic landslide event in Angra's recent history occurred during the New Year's period of 2009–2010, when 440 mm of rainfall fell within 36 h, causing slope failures in Ilha Grande that destroyed residences and led to at least 53 deaths, prompting the declaration of a state of public calamity by local authorities [24,25]. In April 2022, another extreme rainfall episode again overwhelmed the region, with nearly 800 mm of precipitation in 48 h, producing widespread slope failures and infrastructural collapse. The city experienced further disasters in late 2023, including floods and smaller landslides, reflecting a pattern of compounding hydroclimatic extremes intensified by climate variability.

Beyond the physical hazards, social vulnerability plays a critical role. As shown in a study by [25], residents in previously affected areas reported high risk awareness, yet continued exposure due to economic constraints and limited resettlement options. The lack of coordinated urban policies and delayed implementation of structural mitigation further entrench this risk. Combined, these elements form a risk landscape in which landslides are not solely the result of natural phenomena but emerge from socio-environmental configurations that reinforce exposure and limit resilience.

2.2. Landslide Inventory and Prediction Locations

Following moderate to heavy rainfall on 8 December 2023, numerous mass movement events—including shallow landslides and debris flows—were triggered across multiple catchments in the municipality of Angra dos Reis, Rio de Janeiro. The most affected river basins were Ambrósio, Grataú, Bracui, and Florestão. These processes were systematically mapped at a detailed scale of 1:4000 using high-resolution PlanetScope satellite imagery, accessed through the Brasil Mais Platform. The resulting landslide inventory was compiled and made publicly available by [26], who published the dataset in Zenodo. The inventory served as the ground-truth reference for this study’s modeling efforts. A total of 319 landslide points were mapped across the study area.

To generate non-landslide samples, circular buffers with a 500 m radius were created around each landslide location, from which an equal number of random points were extracted. For modeling purposes, landslide occurrences were labeled as class “1” and non-landslide points as class “0”. This landslide inventory dataset was then randomly partitioned into two subsets: 70% for training the model and 30% for validating its performance [11,16]. To map landslide susceptibility across the entire study area, the Angra polygon was divided into a 30 m grid using the Grid Index Features tool in ArcGIS Pro. The variables selected through multicollinearity analysis and feature importance ranking were extracted for each grid cell using the same method applied to the landslide inventory.

2.3. Pre-Selected Predictor Variables

Eighteen variables were evaluated for potential use in the model. These factors were derived from multiple geospatial sources and preprocessed using GIS-based techniques to ensure spatial consistency across the study area. The respective data sources and processing platforms used for generating each factor are detailed in Table 1.

Table 1. All Variables used for investigating landslide susceptibility analysis and their respective data sources.

Factors	Variable	Description	Resolution	Source
Geological	Lithology	Frequency ratio of lithotypes, indicating which rock types are more prone to landslides relative to their extent in the study area.	1:100,000	[24]
	Soil	Frequency ratio of soil types, identifying which soil types are more susceptible to landslides.		
Topographic	Slope	Slope gradient, where steeper slopes are more prone to landslides due to gravitational forces acting on the soil and rock.	10 m	Sentinel-1 SAR (ESA)
	Elevation	Height above sea level, influencing microclimatic conditions, vegetation cover, and erosion processes that affect slope stability.		
	Aspect	Frequency ratio for slope aspect, indicating the orientation’s relative landslide occurrence, evaluating how aspect influences landslide risk.		
	Curvature	Overall curvature of the terrain, affecting water flow concentration. Concave areas are more susceptible to landslides [27].		
	Plan curvature	Horizontal curvature, indicating the potential for water convergence or divergence on slopes, impacting erosion rates.		
	Profile curvature	Vertical curvature, reflecting changes in slope that influence water velocity and erosion potential along the slope [28].		

Table 1. *Cont.*

Factors	Variable	Description	Resolution	Source
Hydrological	Distance to rivers	Euclidean distance to the nearest river, where proximity may increase saturation and instability of slopes during heavy rainfall.	10 m	Sentinel-1 SAR (ESA)
	IC	The Index of Connectivity (IC) quantifies the potential for sediment transfer from slopes to drainage networks, improving spatial risk assessments by identifying areas where mobilized material is more likely to reach streams [29].	10 m	[30]
	TWI	Topographic Wetness Index, representing areas with higher potential for water accumulation, which can reduce slope stability [16,31].	10 m	(Sentinel-1 SAR (ESA)
	Rainfall	Annual total precipitation in wet days, with higher values indicating increased water input that can saturate soils and trigger landslides.	0.05°	CHIRPS (Climate Engine)
Land use and land cover	Urban Sprawl	Percentage increase in urban sprawl from the previous year, which can disturb natural drainage and slope conditions, enhancing landslide risk [32].	30 m	MapBiomas Project
	Forest loss	Percentage of forest loss compared to the previous year, where deforestation can reduce slope stability and increase erosion potential [33].		
	LULC	Frequency ratio for different land use and land cover types, revealing how certain land cover types might contribute to or mitigate landslide occurrences [34].		
	NDVI	Normalized Difference Vegetation Index, indicating vegetation health and density, which contributes to slope stabilization and protection against erosion [33].	30 m	Google Earth Engine
	Distance to roads	Euclidean distance to the nearest road, where proximity may increase saturation and instability of slopes [35].	30 m	Open Street Map
	Distance to buildings	Euclidean distance to buildings, relevant for representing urban occupation within potential landslide impact zones [36].	30 m	Open Street Map

2.4. Multicollinearity and Feature Selection

To prevent model overfitting and ensure the interpretability of spatial regression outputs, multicollinearity among predictor variables was first evaluated using the Variance Inflation Factor (VIF) and Pearson’s correlation coefficient (r). Variables exhibiting VIF values above 5 or pairwise correlation coefficients exceeding $|0.7|$ were considered redundant and excluded from further analysis, following established recommendations in geostatistical modeling [37].

Beyond statistical redundancy, feature relevance was assessed through a hybrid approach combining the ReliefF algorithm and Mutual Information (MI) analysis. The ReliefF method ranks features based on their ability to distinguish between near-hit and near-miss instances, while MI quantifies the amount of information shared between each predictor and the target variable. This dual strategy allowed the selection of the most informative and non-redundant variables, thereby enhancing model robustness and generalizability prior to MGWR implementation.

2.5. Selected Predictor Variables

Geomorphological variables (e.g., slope, aspect, curvature, TWI) were derived from the DEM, whereas geological variables (lithology and soils) were obtained from national databases, ensuring no overlap between the two groups of predictors. Figure 3 illustrates the spatial distribution of the 12 explanatory variables retained after the application of the multicollinearity criterion, capturing the environmental and anthropogenic heterogeneity across the study area. Elevation exhibits a strong altitudinal gradient, with the highest terrains located in the northern and central-western regions, reaching values above 1600 m. In contrast, the southern and eastern portions are characterized by low-lying areas. This topographic variability is a key factor influencing gravitational processes and slope instability. The spatial pattern of forest loss reveals localized disturbances, with higher values concentrated in the northern portions of the region, indicating zones of recent or intense deforestation. These areas are particularly susceptible to landslides due to the reduction in root cohesion and increased surface runoff following vegetation removal.

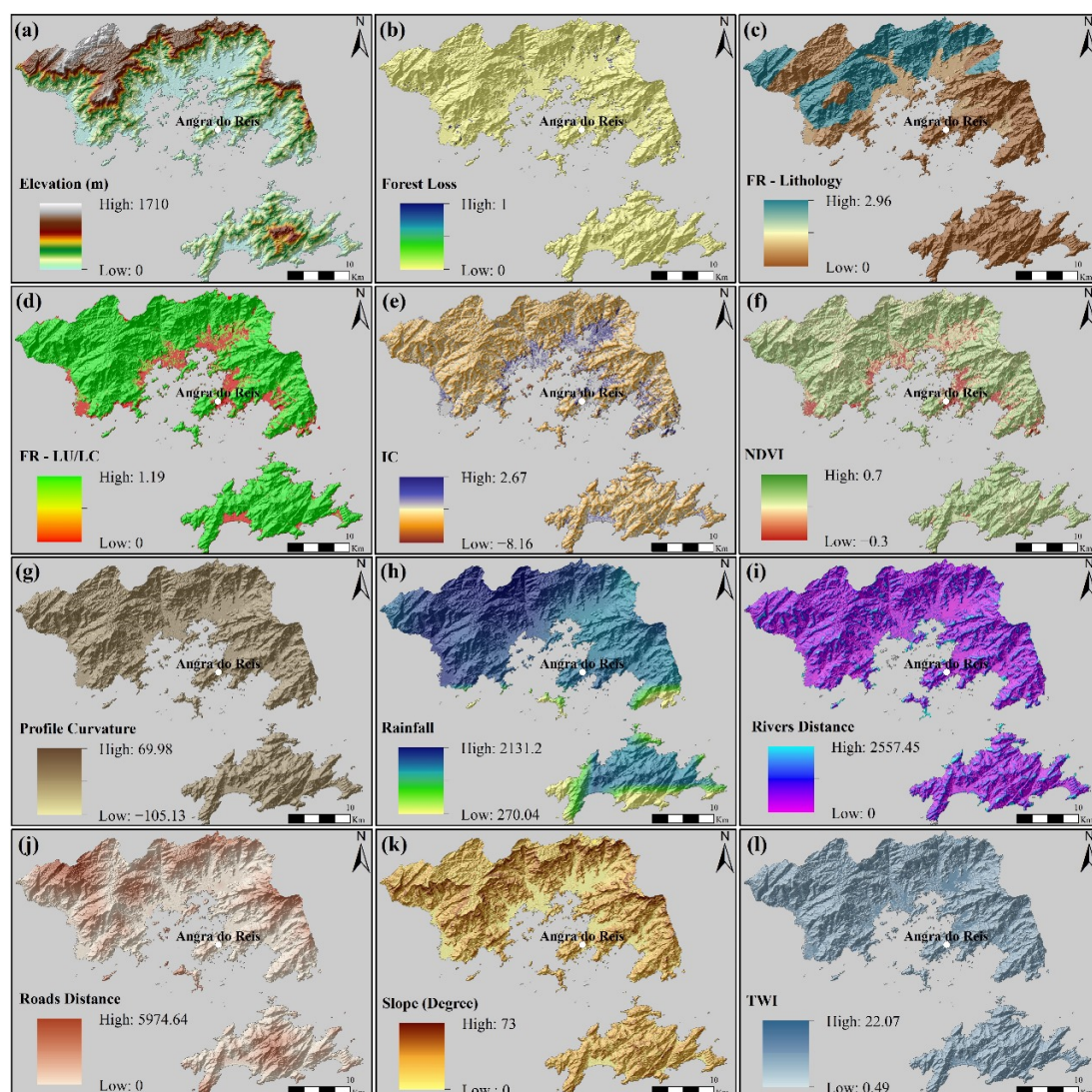


Figure 3. Spatial distribution of the conditioning factors used for landslide susceptibility modeling in Angra dos Reis, Brazil. The maps include: (a) Elevation, (b) Forest loss, (c) Frequency Ratio (FR) for Lithology, (d) FR for Land Use and Land Cover (LULC), (e) Connectivity Index (IC), (f) Normalized Difference Vegetation Index (NDVI), (g) Profile curvature, (h) Precipitation (mm), (i) Distance to rivers, (j) Distance to roads, (k) Slope (degrees), and (l) Topographic Wetness Index (TWI).

The FR-Lithology variable highlights discrete lithological units distributed across the landscape, reflecting the geomechanical contrasts in bedrock composition that affect slope resistance and weathering processes. Conversely, the FR-LULC layer is dominated by a single land use category throughout most of the study area, with only minor local variation. This homogeneity limits the explanatory capacity of land use in the model, as also evidenced by its low statistical significance.

The Connectivity Index (IC) was calculated in SAGA GIS through a sequence of integrated geoprocessing steps based on methodology proposed by [30]. The process began with the preparation of input data, starting from a hydrologically corrected Digital Elevation Model (DEM), free of sinks and projected in meters. From this DEM, the slope map was generated, while flow accumulation was calculated using the Top-Down method. The drainage network was then extracted, and the distance to the nearest drainage channel was obtained using the previously defined channel network as input. To incorporate land cover characteristics into the model, the Cover Management Factor (C) was prepared by reclassifying a land use/land cover raster based on standard C-factor values. The resulting raster was resampled to ensure spatial consistency with the other layers, using the “Nearest Neighbour” method. With the necessary layers harmonized, the upstream and downstream components of the IC were computed, and the index itself was finally derived as the logarithmic ratio between these two components.

The IC variable displays a complex and finely structured spatial pattern. Higher contiguity values are associated with more compact and spatially cohesive land cover patches, which are predominantly found in the northern and central zones. These areas tend to reflect lower degrees of landscape fragmentation and may influence landslide dynamics by altering surface connectivity and runoff concentration pathways. NDVI values range from approximately -0.2 to 0.6 , with higher values indicating dense vegetation cover concentrated in the southern and central regions. Lower NDVI values, typical of anthropogenically altered zones such as deforested or urbanized areas, are primarily found in the northeastern portion of the study area.

Profile curvature is distributed in a heterogeneous manner, with positive values identifying convex slopes and negative values identifying concave terrain. These microtopographic features affect local water accumulation, infiltration, and slope convergence, all of which play important roles in slope stability. The spatial distribution of rainfall reveals a clear gradient from north to south, with precipitation exceeding 2000 mm annually in the northernmost sectors and decreasing to below 1000 mm in the southernmost areas. This climatic gradient constitutes significant control on landslide triggering conditions.

Distance to rivers highlights the fluvial network structure, with low values near main drainage axes and increasing values toward interfluves. Areas closer to rivers are often more susceptible to erosion and hydrological saturation. Distance to roads exhibits strong spatial variability, with shorter distances observed in valley bottoms and urban corridors, whereas mountainous regions remain less accessible. This variable is indicative of anthropogenic influence, as road construction is a known destabilizing factor in steep terrain.

Slope presents a broad range of values, with the steepest areas ($>60^\circ$) concentrated in the northern and central mountainous sectors. These steep gradients are closely associated with higher landslide susceptibility due to the increased influence of gravitational forces. Lastly, the Topographic Wetness Index (TWI), the most commonly used hydrologically based topographic index, describes the tendency of a cell to accumulate water and highlights potential zones of moisture accumulation—particularly in convergent and low-lying areas where water tends to concentrate and reduce soil shear strength [31]. High TWI values are associated with increased saturation, which reduces soil cohesion and raises the

risk of landslides. Therefore, TWI is a valuable tool for predictive susceptibility modeling, planning field sampling in unmapped areas, and complementing soil attribute data.

The Topographic Wetness Index (TWI) was calculated in SAGA GIS, using a Digital Elevation Model (DEM), following a multi-step process based on the methodology proposed by [31]. Initially, depressions in the DEM were filled using algorithm to ensure continuous flow routing. Flow accumulation was then computed using a top-down algorithm, from which flow width and specific catchment area were derived. Slope was calculated in radians, and together with the specific catchment area, used to compute the TWI [38].

The variables lithology, soils, LULC, and aspect are categorical and were transformed using the Frequency Ratio (FR) method (Table 2). FR quantifies the relative influence of each class on landslide occurrence as the ratio between the proportion of landslides in the class and the proportion of the class in the study area [39]. An FR value of 1 indicates average correlation, values > 1 denote positive association with landslides, and values <1 denote negative association [40].

Table 2. Frequency Ratio for lithology, soils, LULC, and aspect variables (with non-zero frequency ratios).

Variable	Class	Frequency Ratio
Lithology	Sand, Clay, Silt	0.6109
	Mylonitic Gneiss, Metamark, Gneissic Granite	2.9622
	Granite	0.2794
Soil Type	Cambisol—CX	0.4401
	Red-yellow Latosol—LVA	0.1082
	Litholic Neosol—RL	4.7201
LULC	Forest	1.1962
	Mosaic	0.3827
	North	0.9779
	Northeast	1.3216
	East	1.6917
Aspect Orientation	Southeast	1.5569
	South	1.0262
	Southwest	0.2500
	West	0.3270
	Northwest	0.4725
	Flat/no defined aspect	1.8093

These predictor variables were incorporated into the attribute tables of both the landslide dataset and the prediction grid using the Add Multiple Values to Points tool in ArcGIS Pro, in order to prepare the data for subsequent analyses using the MGWR model.

2.6. Spatial Autocorrelation Analysis (LISA)

To assess the spatial structure and clustering of landslide susceptibility, a spatial autocorrelation analysis was performed using both Global Moran's I and Local Indicators of Spatial Association (LISA), as proposed by [41]. The analysis was applied to the Frequency Ratio (FR) values calculated for each spatial unit, enabling the detection of spatial dependence in landslide susceptibility patterns. Global Moran's I was used to evaluate whether high or low FR values exhibited significant clustering or spatial randomness. A positive Moran's I indicates spatial clustering of similar values, while a value near zero suggests randomness. LISA was then applied to identify localized patterns of spatial association, classifying each unit into High-High, Low-Low, High-Low, Low-High, or non-significant categories. The statistical significance of these local clusters was assessed via 999 Monte Carlo permutations, using significance thresholds of $p < 0.05$, $p < 0.01$, and

$p < 0.001$. The analysis was conducted using GeoDa software (version 1.20) with queen contiguity spatial weights. LISA Cluster and Significance Maps were subsequently interpreted to reveal persistent instability zones, stable sectors, and potential spatial outliers in landslide susceptibility.

2.7. MGWR Modeling

Multiscale Geographically Weighted Regression (MGWR) was applied using the Geographically Weighted Regression toolset available in ArcGIS Pro, with adaptive kernel weighting and individual bandwidth calibration enabled to capture variable-specific spatial scales. This multiscale approach allows each predictor to exert influence over different geographic extents, offering a refined representation of the spatial heterogeneity underlying landslide susceptibility.

All input rasters—representing the predictor variables and the landslide inventory—were resampled to a common spatial resolution of 10 m and projected to SIRGAS 2000/UTM Zone 23S. Using ArcGIS’s “Extract Multi Values to Points” tools, each raster was converted to a point dataset with attribute values extracted per pixel. The landslide inventory, derived from high-resolution imagery and field-confirmed events, was used as the dependent variable (1 = presence, 0 = absence).

Prior to running the MGWR model, multicollinearity diagnostics were conducted in Python 3.11 using the pandas, statsmodels, and scikit-learn libraries (code available at: https://github.com/CheilaBaiao/Landslide_Angira). Pearson correlation coefficients were computed to identify pairs of highly correlated variables ($|r| > 0.7$), and the Variance Inflation Factor (VIF) was calculated for all predictors. Variables with $VIF > 5$ were excluded to ensure statistical robustness and avoid redundancy in spatial regression. Subsequently, binary variables were transformed into continuous format through logistic regression to allow their use in the MGWR model. The logistic regression was implemented using the LogisticRegression function from the scikit-learn library. Selected predictor variables were retained in the final model to ensure interpretability and relevance.

After fitting the model, predicted probabilities were computed and used as continuous representations of landslide susceptibility. Additionally, standard errors of the coefficients were estimated from the observed Fisher information matrix, derived from the predicted probabilities and the design matrix. Based on these estimates, z -values and two-tailed p -values were calculated to assess the statistical contribution of each coefficient. Odds ratios were obtained by exponentiating the coefficients, providing insight into the relative influence of each predictor. All analyses were performed in Python 3.11 using the NumPy, SciPy, and scikit-learn libraries.

The Multiscale Geographically Weighted Regression (MGWR) model is designed to investigate spatially varying relationships between conditioning factors and landslide susceptibility by accounting for different spatial scales of influence. One of its key advantages is the ability to assign an individual bandwidth to each explanatory variable, allowing the model to reflect distinct spatial processes across the study area [42], as represented in Equation (1):

$$y_i = \beta_0(u_i, v_i) + \sum_{j=1}^m \beta_j(u_i, v_i) x_{ij} + \varepsilon_i \quad (1)$$

In this equation, y_i represents the probability at location i , (u_i, v_i) represents the coordinates of sampling point i , $\beta_0(u_i, v_i)$ represents the intercept at location i , β_{bwj} refers the adjustment of the j th bandwidth, m is the number of sampling points, x_{ij} represents the value of independent variable x_j at point i , ε_i is the error term of the model.

MGWR has become widely adopted in environmental modeling and risk assessment, including studies focused on landslide susceptibility [11,15,17,42,43]. The MGWR model

was executed in ArcGIS Pro using an adaptive Gaussian kernel, with optimal bandwidths determined via corrected Akaike Information Criterion (AICc). By enabling variable-specific bandwidth optimization, the model estimated local coefficients that reflect the spatially varying influence of each explanatory factor. Output layers included local R^2 , parameter estimates, residuals, and diagnostics that were mapped and interpreted to assess the spatial dynamics of landslide drivers across Angra dos Reis. This methodology enabled the identification of regions where specific variables—such as slope angle, lithology, drainage density, or vegetation cover—exert stronger or weaker influence on landslide susceptibility, thereby supporting more targeted mitigation strategies.

2.8. Model Validation and Performance Metrics

To rigorously evaluate the predictive capacity of the MGWR model in discriminating landslide-prone areas, a series of standard classification metrics were employed, based on the comparison between observed landslide presence (binary inventory) and predicted susceptibility values reclassified using a threshold optimization approach. The binary classification performance was assessed using Accuracy, Precision, Recall, F1-score, and Area Under the Receiver Operating Characteristic Curve (ROC-AUC). From the confusion matrix, the following metrics were derived:

The confusion matrix, also referred to as the error matrix, was used to evaluate the performance of the binary classification. It provides a summary of prediction results by comparing the model's outputs with the actual observed values [44]. The matrix is composed of four components: True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN). These elements help determine the model's classification accuracy. TP represents correctly identified positive cases, while TN refers to correctly identified negative cases. FP corresponds to negative instances incorrectly labeled as positive, and FN denotes positive instances mistakenly classified as negative [45].

Accuracy (Equation (2)) indicates how well the model performs in correctly identifying the true classes, calculated as the proportion of correct predictions to the total number of instances [45]. It is widely applied in landslide susceptibility mapping [46].

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (2)$$

Precision, also known as Positive Predictive Value (Equation (3)), refers to the proportion of the number of correctly classified positive examples divided by all samples labeled by the system as positive [47]. High precision indicates that the model is effective at accurately labeling positive cases [45].

$$Precision = \frac{TP}{TP + FP} \quad (3)$$

Sensitivity, also known as True Positive Rate (TPR) or Recall (Equation (4)), reflects the model's capacity to correctly identify actual positive instances within each class. In landslide susceptibility mapping, this metric is particularly important, as it helps avoid misclassifying areas vulnerable to landslides as safe, which is essential for effective risk management [48]. It is calculated as the proportion of correctly predicted positive cases to the total number of actual positive cases.

$$Recall = \frac{TP}{TP + FN} \quad (4)$$

The reliability of the model's results can be assessed using the F1-score, a widely adopted metric in machine learning that has also been applied in landslide susceptibility

studies. It is calculated as the harmonic mean of precision and recall, providing a balanced measure of both (Equation (5)). The F1-score ranges from 0 to 1, where higher values indicate stronger model performance. In the context of landslides, a high F1-score reflects the model's ability to effectively detect vulnerable areas while minimizing false alarms [45,49].

$$F1\text{-Score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \quad (5)$$

The ROC curve represents a graph of the True Positive Rate (TPR) versus the False Positive Rate (FPR) across different classification thresholds. The Area Under the Curve (AUC) is calculated by integrating the ROC curve and reflects the model's ability to distinguish between classes [50]. AUC values range from 0 to 1, where 1 indicates perfect classification performance and 0.5 corresponds to random guessing. Regarding classification accuracy, the scale proposed by Hosmer and Lemeshow, classifies AUC values as follows: 0.90–1.00 (excellent), 0.80–0.90 (good), 0.70–0.80 (fair), 0.60–0.70 (poor), and 0.50–0.60 (fail). In general, an AUC value greater than 0.8 suggests that the model has excellent performance [49].

The Youden index (Y), also referred to as informedness, is one of the most widely used methods for determining a binary classification threshold in ROC analysis. In this study, different probability cut-off values derived from MGWR outputs were tested as thresholds. Mathematically, it is designed to maximize the overall correct classification rate while minimizing misclassifications, by identifying the optimal cut-off point (where the difference between the True Positive Rate and the False Positive Rate is greatest, or where sensitivity and specificity reach their highest combined values). The index assigns equal importance to false positives and false negatives (Equation (6)), but it can be generalized by applying different weights. This flexibility makes the Youden index particularly useful in contexts such as landslide susceptibility assessment, where the relative importance or weight of sensitivity and specificity may vary [51].

$$\text{Youden Index } (J) = \text{Sensitivity } (TPR) + \text{Specificity } (TNR) - 1 \quad (6)$$

All evaluations were conducted on an independent test set comprising 30% of the total sample, selected via stratified random sampling to maintain the proportion of landslide presence and absence. The results provide a robust and interpretable basis for assessing the spatial predictive quality of the MGWR model.

Figure 4 presents the spatial distribution of landslide samples used for training and validation of the susceptibility model in Angra dos Reis. The dataset was randomly divided into two subsets: 70% of the samples (green dots) were used for model training, while the remaining 30% (magenta dots) were reserved for independent validation. This spatial arrangement ensures comprehensive geographic coverage across diverse topographic and land use conditions within the study area. The clear dispersion of both training and validation points helps reduce spatial bias and supports the robustness and generalizability of the model, particularly in capturing localized patterns of landslide occurrence.

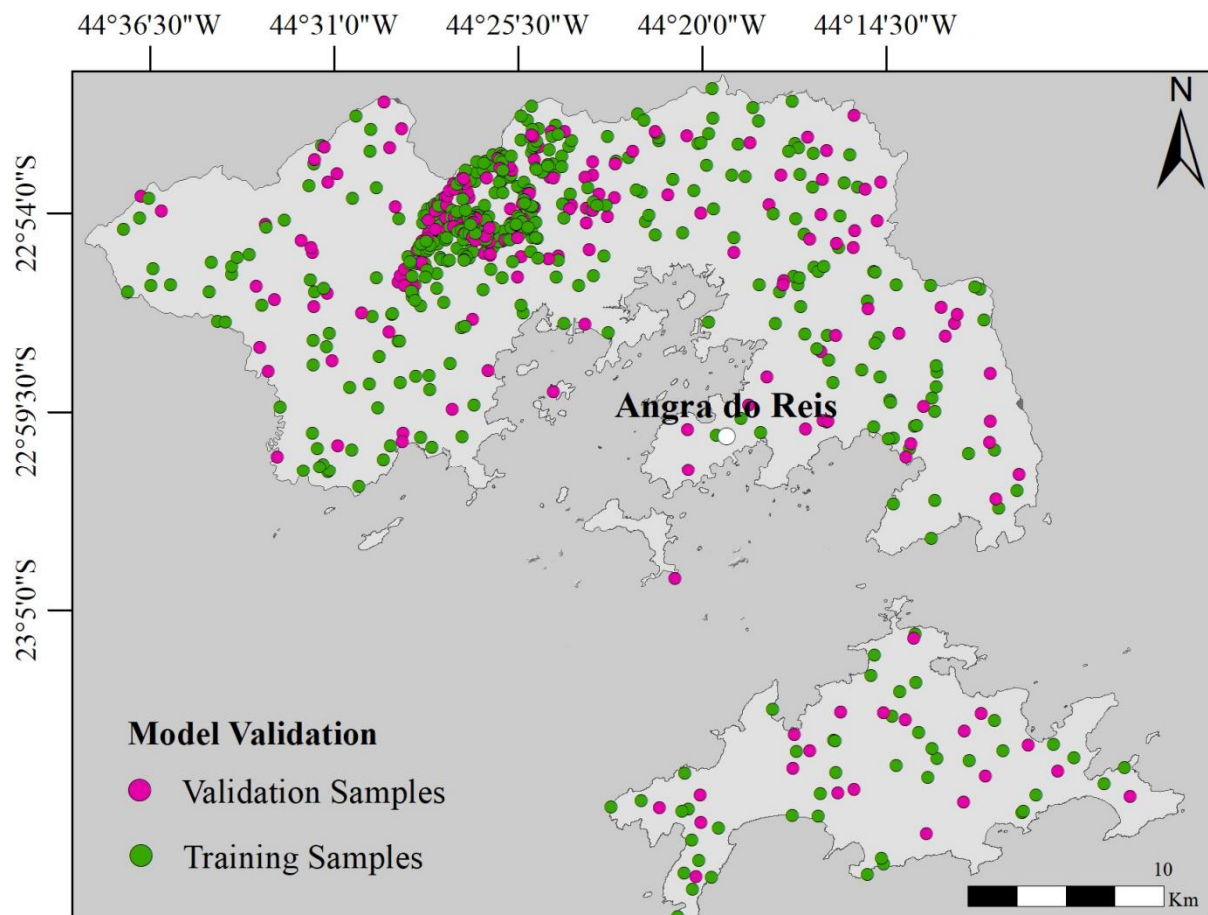


Figure 4. Spatial distribution of landslide samples used for model development and validation in Angra dos Reis. Green dots represent training samples, while magenta dots indicate validation samples. The geographic spread highlights coverage across the municipality, ensuring representativeness of the spatial modeling process.

3. Results

3.1. Rainfall Patterns

Precipitation in Angra dos Reis exhibits a clear seasonal pattern, with markedly higher rainfall during the austral summer (December to March) and reduced totals during the winter months (June to August). From January to March, monthly accumulated precipitation typically ranges from 200 to over 400 mm, with frequent extreme events reaching above 600 mm and occasional outliers exceeding 800 mm (Figure 5). This reflects the influence of intense convective systems and orographic enhancement due to the Serra do Mar. In addition, the occurrence of the South Atlantic Convergence Zone (ZCAS), the main mechanism responsible for prolonged rainfall events, is more frequent between October and March, further intensifying the wet season and increasing the risk of hydrogeomorphological disasters in the region [20].

April and November represent transitional periods, with moderate rainfall but still significant variability. Between May and September, precipitation decreases substantially, with median values around or below 150 mm, and reduced interquartile ranges indicating less variability. The lowest rainfall is observed from June to August, consistent with the dominance of subtropical high-pressure systems and reduced atmospheric moisture transport from tropical regions during the dry season in southeastern Brazil. Overall, the distribution reflects a humid tropical regime, where precipitation is both abundant and

highly concentrated in the summer months, posing increased hydrological and geohazard risks, particularly in steep, urbanized regions like Angra dos Reis.

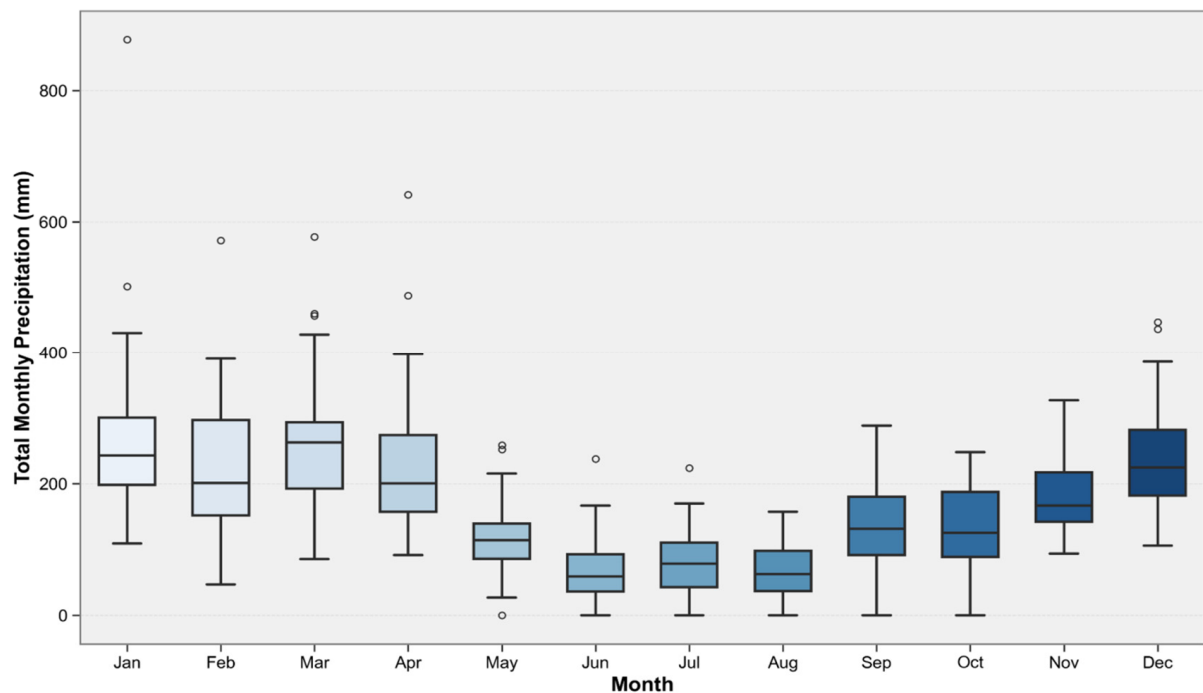


Figure 5. Boxplot showing the monthly distribution of daily precipitation in Angra dos Reis (CHIRPS dataset, 1981–2024).

3.2. Multivariate Analysis of Explanatory Variables

To ensure the robustness and stability of the landslide susceptibility model, a multivariate analysis was conducted to assess relationships, redundancies, and the predictive relevance of the variables considered. From an initial set of 18 explanatory variables, only 12 variables were retained after applying the correlation and multicollinearity criteria. Specifically, variables with a Pearson correlation coefficient above $|0.7|$ or a Variance Inflation Factor (VIF) above 5 were excluded. The removed variables also exhibited the lowest importance scores based on feature selection algorithms.

Figure 6 summarizes the results of this multivariate evaluation using the 12 retained variables. The Pearson correlation matrix (Figure 6a) confirmed that no pair of variables showed strong linear correlation ($|r| < 0.7$). The VIF values (Figure 6b) further indicated no significant multicollinearity, with all values below the commonly accepted threshold of 5.

To assess the individual relevance of each variable, two feature importance methods were applied. The ReliefF algorithm (Figure 6c) ranked variables based on their ability to distinguish between landslide and non-landslide conditions in local neighborhoods. The highest-scoring predictors included lithology, rainfall, and elevation. Similarly, the Mutual Information approach (Figure 6d) measured the nonlinear dependence between each variable and the landslide class, reinforcing the importance of rainfall, lithology, and slope.

3.3. Spatial Autocorrelation of Landslide Frequency Ratio

To evaluate the spatial dependence of landslide occurrence, Moran's I statistic and Local Indicators of Spatial Association (LISA) were applied to the Frequency Ratio (FR) of Landslides (Figure 7). The Global Moran's I value was 0.534, indicating a strong and statistically significant positive spatial autocorrelation. This suggests that areas with

high (or low) landslide susceptibility tend to be geographically clustered rather than randomly distributed.

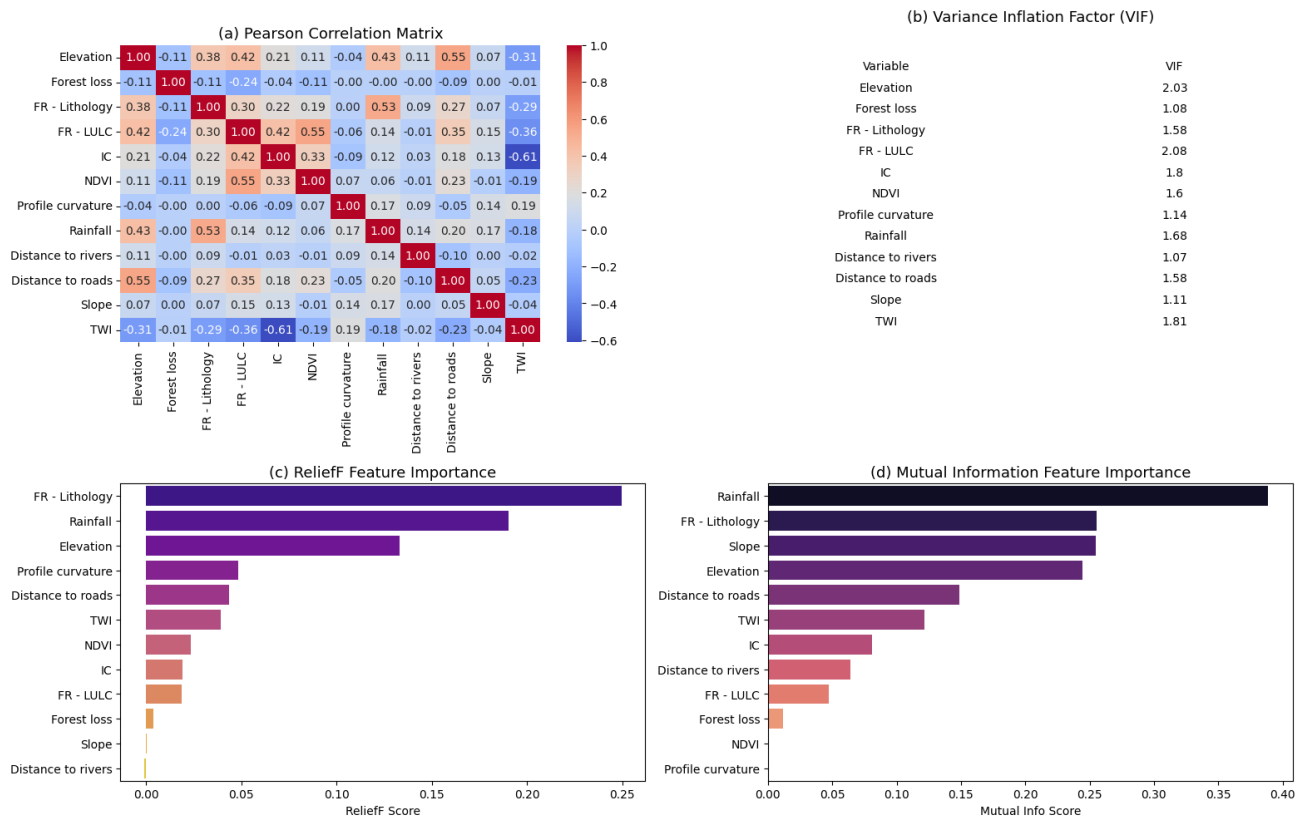


Figure 6. Multivariate analysis for selection and evaluation of explanatory variables used in landslide susceptibility modeling. (a) Pearson correlation matrix among the 12 explanatory variables ($r < |0.7|$); (b) Variance Inflation Factor (VIF) values indicating no multicollinearity ($VIF < |0.5|$); (c) Variable importance estimated using the ReliefF algorithm and (d) Variable importance based on the Mutual Information criterion. These analyses were used to identify and retain the most relevant and stable predictors for logistic regression and MGWR models.

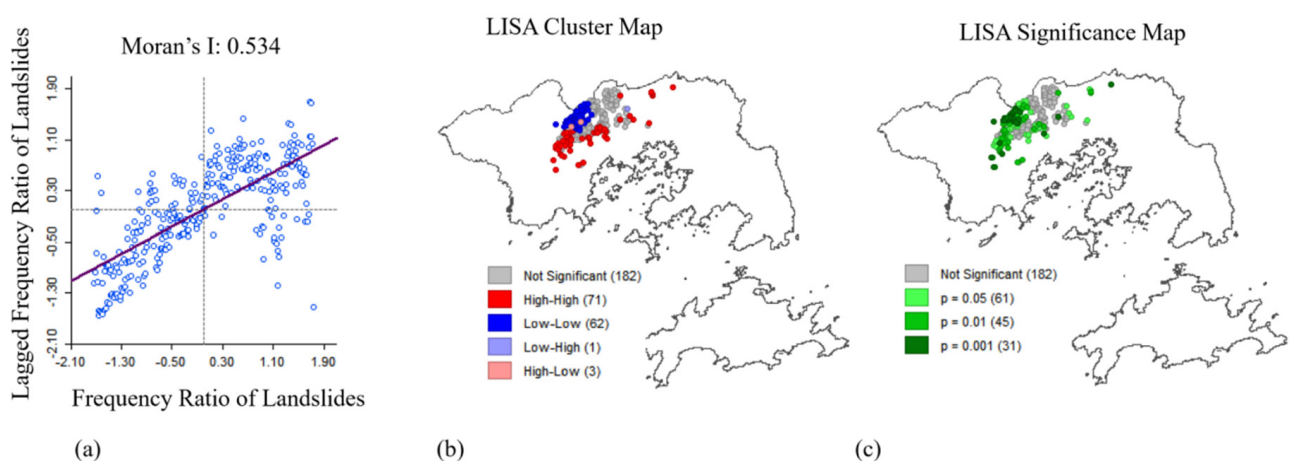


Figure 7. Spatial autocorrelation analysis of the Frequency Ratio of Landslides in Angra dos Reis. (a) Moran's I scatter plot shows a positive spatial autocorrelation with Moran's I = 0.534; (b) LISA Cluster Map identifies areas of local spatial association, including clusters with high and low values and spatial outliers; (c) LISA Significance Map indicates the statistical significance of local spatial autocorrelation at different confidence levels.

The LISA Cluster Map reveals two prominent types of spatial patterns: High-High clusters, concentrated primarily in the southern and southeastern parts of the study area, and Low-Low clusters in the northern and northeastern sectors. These spatial clusters highlight areas where local values are similar to their neighbors, reinforcing the significance of spatial context in landslide processes. In addition, a limited number of spatial outliers were identified, including three High-Low and one Low-High, which may represent local anomalies or transitional zones. The corresponding LISA Significance Map further supports these findings. Out of 319 polygons, 137 were statistically significant at confidence levels of $p = 0.05$ ($n = 61$), $p = 0.01$ ($n = 45$), and $p = 0.001$ ($n = 31$). These significant locations correspond closely to the High-High and Low-Low clusters, reinforcing the robustness of the observed spatial structures. These results emphasize the spatially structured nature of landslide susceptibility in Angra dos Reis, reinforcing the necessity of using spatial regression techniques like MGWR to appropriately model and interpret landslide risk in the region.

3.4. MGWR Model Diagnostics and Performance

The MGWR model demonstrated strong explanatory power, with an R-squared value of 0.9357 and an adjusted R-squared of 0.9289, indicating that the model accounts for approximately 93% of the spatial variability in the dependent variable (Table 3). The corrected Akaike Information Criterion (AICc) was 134.9961, supporting the model's adequacy and parsimony in relation to the number of parameters. The estimated variance (sigma-squared) was 0.0711, and the maximum likelihood estimate of sigma-squared was 0.0643, reflecting low residual variance. The effective degrees of freedom for the model was 390.47, suggesting a high level of spatial complexity and flexibility in capturing local variation across the study area. These diagnostics collectively indicate a well-performing spatially adaptive model capable of capturing multiscale spatial processes.

Table 3. Performance Metrics and Fit Diagnostics of the MGWR Model.

Statistic	MGWR
R-Squared	0.9357
Adjusted R-Squared	0.9289
AICc	134.9961
Sigma-Squared	0.0711
Sigma-Squared (MLE)	0.0643
Effective Degrees of Freedom	390.4722

Table 4 summarizes the spatial scale and statistical significance of each explanatory variable in the MGWR model. Most variables operated at a localized spatial scale, with an optimal bandwidth of 16,263.02 m, corresponding to 24.5% of the study area extent. Notably, 'Roads distance' exhibited a global spatial scale with an optimal bandwidth of 66,367.31 m (100% of the extent) and was statistically significant across the entire area (100%). Similarly, the 'Intercept' was significant throughout the region (100%), reflecting a strong and consistent baseline effect. Among the local-scale predictors, 'FR—Lithology', 'Rainfall' and 'Slope' showed high spatial significance, being significant in 97.92%, 82.87% and 75.93% of the area, respectively. 'NDVI' had a broader spatial influence (42.33% extent) and was significant across 78.94% of the area. In contrast, variables such as 'Rivers distance', 'TWI' and 'FR—LULC' showed either no significant effect or very limited spatial significance (0% and 0.69%, respectively), despite operating at local or regional scales. Due to the negligible spatial relevance of 'TWI' and 'Rivers distance', these variables were excluded from the final MGWR model. These results indicate the heterogeneous spatial

behavior of the predictors and highlight the importance of multiscale modeling in capturing complex spatial relationships driving landslide susceptibility.

Table 4. Spatial Scale and Significance of Explanatory Variables.

Explanatory Variable	Optimal Bandwidth (m)	% of Extent	% Significant
Intercept	16,263.02	24.50%	100.00%
Elevation	16,263.02	24.50%	16.20%
Forest loss	16,263.02	24.50%	13.66%
FR—Lithology	16,263.02	24.50%	97.92%
FR—LULC	16,263.02	24.50%	0.69%
IC	16,263.02	24.50%	45.83%
NDVI	28,091.04	42.33%	78.94%
Profile curvature	16,263.02	24.50%	54.40%
Rainfall	16,263.02	24.50%	82.87%
Rivers distance	32,608.94	49.13%	0.00%
Roads distance	66,367.31	100.00%	100.00%
Slope	23,861.64	35.95%	75.93%
TWI	47,229.17	71.16%	0.00%

Figure 8 presents the spatial variation in local regression coefficients obtained from the Multiscale Geographically Weighted Regression (MGWR) model applied to landslide susceptibility mapping in Angra dos Reis. As previously mentioned, the model demonstrated high performance ($R^2 = 0.9357$, AICc = 134.9961, and effective degrees of freedom = 390.47), indicating both strong explanatory performance and appropriate model complexity to account for spatial heterogeneity in the relationships between predictors and landslide occurrence.

The spatial distribution of the coefficients reveals pronounced local variability in the influence of each explanatory variable. Elevation displays a mixed pattern of influence, with positive coefficients dominating the northern and southeastern sectors, suggesting that higher terrain is associated with increased landslide susceptibility in these areas, likely due to gravitational instability and orographic rainfall. Forest loss shows distinct spatial contrasts: strong positive associations appear in the western part of the study area, consistent with slope destabilization following vegetation removal, while negative coefficients in the southeast suggest a reduced or context-dependent effect of deforestation.

The Frequency Ratio (FR) of lithology exhibits widespread positive coefficients across most of the territory, suggesting a stable and consistently strong influence of geological substrate on landslide dynamics, likely reflecting differences in rock weathering, permeability, and structural integrity. In contrast, the FR of land use/land cover (LULC) shows almost no spatial effect, with only a single weakly negative coefficient detected in the northwestern margin, corroborating its low significance in the MGWR output and suggesting limited land use variability in the region.

The Connectivity Index (IC), which quantifies spatial cohesion of landscape elements, shows localized positive effects in the northern zone. These results suggest that in areas with more spatially connected land cover patches—particularly where natural or semi-natural landscapes are preserved—there may be an increased or modulated risk of landslides due to enhanced hydrological connectivity and uninterrupted flow paths. NDVI displays predominantly negative coefficients in the northern and central regions, indicating that higher vegetation density tends to reduce landslide susceptibility by reinforcing slope stability through root cohesion and interception of rainfall.

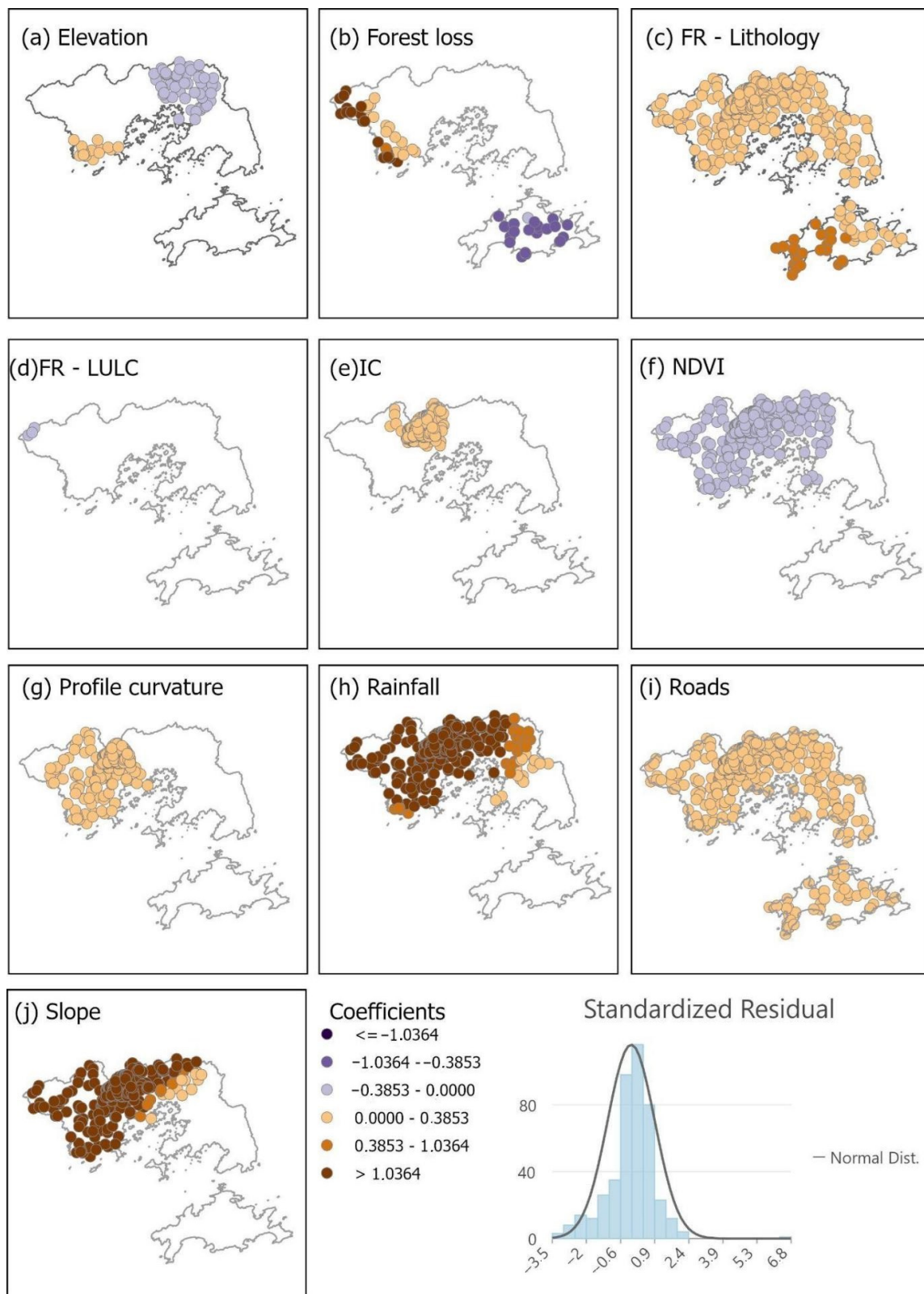


Figure 8. MGWR results for landslide susceptibility modeling in Angra dos Reis, with $R^2 = 0.9357$, $AICc = 134.9961$, and effective degrees of freedom = 390.47. Maps (a–j) illustrate the spatial variation in local regression coefficients for the variables Elevation, Forest Loss, Frequency Ratio (FR) of Lithology, FR of LULC, Connectivity Index (IC), NDVI, Profile Curvature, Rainfall, Distance to Roads, Profile Curvature, and Slope. The histogram in the bottom-right corner shows the distribution of standardized residuals, which closely approximates a normal distribution, thereby supporting the overall goodness-of-fit and reliability of the MGWR model.

Profile curvature presents clustered positive effects, particularly in the northern part of the study area. This suggests that convex landforms in this region may enhance surface runoff and reduce infiltration, favoring the initiation of shallow landslides. Rainfall emerges as one of the most spatially significant predictors, with uniformly high positive coefficients throughout much of the northern and central sectors. This pattern highlights the dominant role of intense and sustained precipitation in triggering slope failures, particularly in steep and convergent terrain.

Distance to roads is positively associated with landslide susceptibility across nearly the entire study area. This spatially consistent influence reinforces the well-documented role of road construction in altering slope stability by inducing cuts, modifying drainage patterns, and increasing surface runoff. Finally, slope angle displays a strongly positive influence in the central and northern mountainous regions, with dense clusters of high coefficients confirming the critical role of steep terrain in gravitational processes governing landslides.

The histogram of standardized residuals, shown in the lower-right panel, approximates a normal distribution centered around zero. This outcome confirms the adequacy of the MGWR model and indicates that residuals are randomly distributed without evidence of spatial autocorrelation or systematic bias. Notably, although the original landslide frequency ratio showed spatial autocorrelation (as confirmed by Moran's I and LISA cluster analysis), the MGWR framework effectively accounted for this structure. Altogether, the results highlight the value of the MGWR framework in capturing local-scale spatial variability and nonlinear interactions that govern landslide susceptibility across complex and heterogeneous landscapes.

The landslide susceptibility map reveals a heterogeneous spatial pattern across the municipality of Angra dos Reis, reflecting the influence of topographic, climatic, land use, and infrastructure-related variables (Figure 9). Areas classified as very high susceptibility are concentrated in the northwestern portion of the territory, particularly along steep slopes and regions with intense anthropogenic disturbance, including deforestation and proximity to roads. These zones align with known historical landslide clusters and are characterized by a convergence of multiple risk-enhancing factors.

High susceptibility areas form a continuous belt surrounding the very high zones and extend along mountainous regions with moderate to steep slopes. These areas are often located at the interface between natural vegetation and urban expansion, where slope modification and increased runoff contribute to instability. The high proportion of land under this classification underscores the potential for widespread hazard, especially under extreme rainfall events. Moderate susceptibility dominates much of the study area, particularly in the central and southern regions, where topographic gradients are less pronounced and vegetation cover is more continuous. While these areas are less prone to frequent landslides, they may still experience events under specific triggering conditions, such as prolonged rainfall or localized slope disturbance. Low and very low susceptibility zones are sparsely distributed, primarily confined to flat coastal plains, wetland areas, and regions with dense, undisturbed forest cover. These locations are generally stable due to favorable terrain and hydrological characteristics, as well as the absence of significant anthropogenic impact.

The MGWR model demonstrated outstanding predictive performance in classifying landslide susceptibility on the test dataset. The Area Under the Receiver Operating Characteristic Curve (AUC-ROC—Figure 10) reached 0.9904, indicating an excellent ability to discriminate between landslide and non-landslide occurrences. The model achieved an accuracy of 96.12%, a precision of 97.87%, and a recall (sensitivity) of 93.88%, reflecting a strong balance between false positives and false negatives. The specificity was 98.15%, confirming the model's robustness in correctly identifying stable areas. Additionally, the

F1 Score of 0.9583 and the Youden's J index of 0.9203 further emphasize the overall model quality. Notably, the optimal threshold for binarizing susceptibility values was determined to be 0.65, based on the maximum Youden index. Together, these metrics highlight the MGWR model's suitability for spatial prediction of landslide susceptibility, especially in heterogeneous and topographically complex regions such as Angra dos Reis.



Figure 9. Landslide susceptibility map for the municipality of Angra dos Reis, southeastern Brazil, generated using the MGWR model. The map classifies the territory into five susceptibility levels: Very Low, Low, Moderate, High, and Very High.

The proportional distribution of landslide susceptibility levels across Land Use and Land Cover (LULC) types in Angra dos Reis (Figure 11) reveals important interactions between land characteristics and geohazard risk. Classes such as *Urban Infrastructure*, *Districts*, and *Buildings* display a dominant proportion of pixels in the “Moderate” to “High” susceptibility ranges, with non-negligible contributions in the “Very High” category. This reflects the cumulative effect of anthropogenic disturbance, terrain modification, and increased runoff typical of urban areas. The MGWR model corroborates this spatial pattern by identifying distance to roads as a globally significant predictor, strongly associated with higher susceptibility values due to slope cuts and drainage alterations.

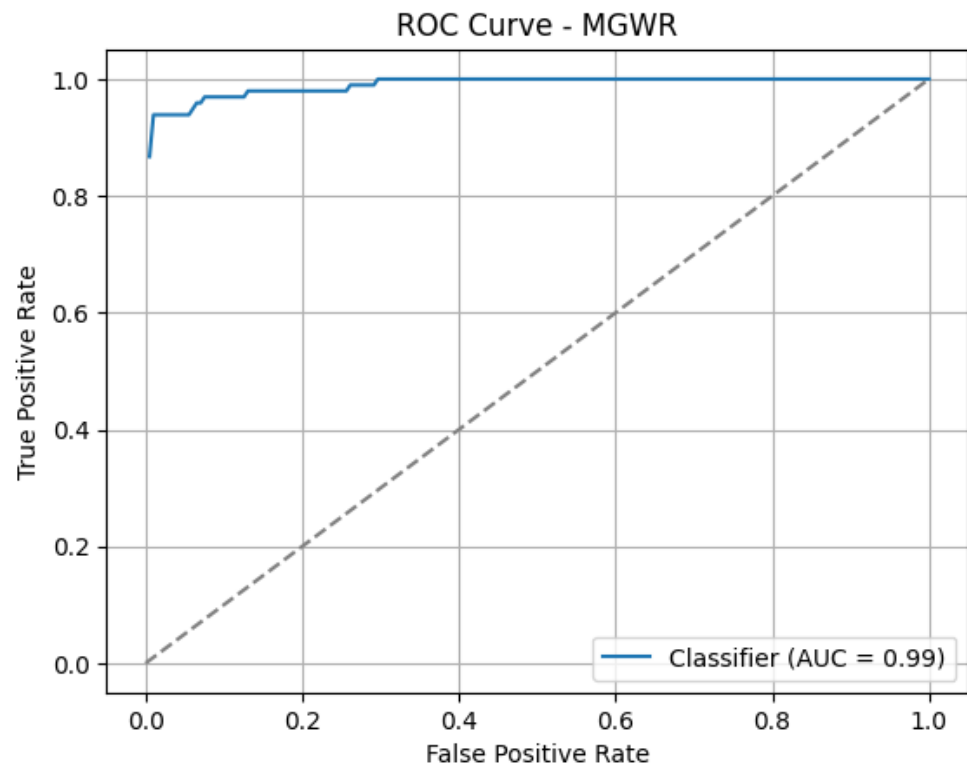


Figure 10. Receiver Operating Characteristic (ROC) curve of the MGWR model prediction. The model achieved excellent classification performance, with an Area Under the Curve (AUC) of 0.99, indicating high discriminatory power between landslide and non-landslide cases.

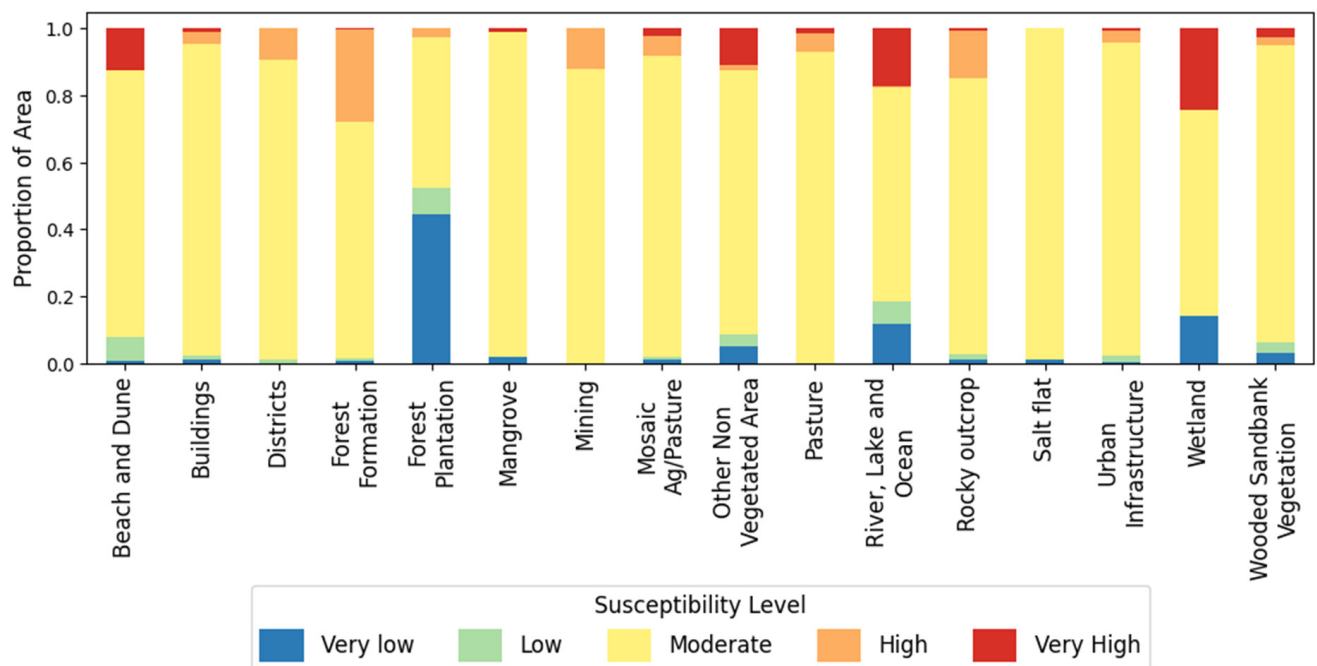


Figure 11. Proportional distribution of landslide susceptibility levels within each Land Use and Land Cover (LULC) class in Angra dos Reis. The stacked bar chart shows the relative frequency of five susceptibility levels—Very Low, Low, Moderate, High, and Very High—for each LULC type.

Conversely, LULC types such as *Forest Plantation*, *Pasture*, and *Mosaic of Agriculture and Pasture* are predominantly associated with “Moderate” susceptibility levels. These areas tend to occupy transitional landscapes where vegetation cover is partial and topographic gradients are moderate. While not as destabilizing as urban infrastructure, these classes

may still contribute to susceptibility due to reduced root cohesion and increased exposure of soil layers—especially under intense or prolonged rainfall, as observed during the austral summer months influenced by the South Atlantic Convergence Zone (ZCAS).

Natural land cover types like *Wetland*, *River*, *Lake and Ocean*, and *Wooded Sandbank Vegetation* show higher proportions of “Very Low” and “Low” susceptibility. These results align with MGWR findings in which *NDVI* exhibited predominantly negative coefficients, indicating a protective role of dense vegetation in slope stability. Furthermore, wetlands and aquatic areas are typically located in flat, low-energy environments, where gravitational mass movement is naturally limited.

Interestingly, despite the limited spatial significance of forest loss in the MGWR results, the *Forest Formation* class shows a localized increase in “High” susceptibility in some areas. This supports the hypothesis that vegetation removal acts as a destabilizing factor, especially on steep slopes and in regions with high rainfall accumulation. In line with this, MGWR identified *Slope* and *Rainfall* as spatially significant in large portions of the municipality, reinforcing the interpretation that topography and hydrometeorological triggers are key drivers of landslide risk.

Overall, the stacked bar chart encapsulates the combined influence of biophysical and anthropogenic factors on landslide susceptibility. The results emphasize that land use planning and slope management must be prioritized in zones with rapid urban expansion, particularly in steep areas and those historically affected by intense rainfall. Integrating land cover data with spatial regression outputs and precipitation dynamics provides a comprehensive framework to inform territorial policies and disaster risk reduction strategies.

4. Discussion

4.1. Spatial Structure and Autocorrelation of Landslide Susceptibility

The application of global and local spatial autocorrelation techniques revealed a clear spatial structure in the Frequency Ratio (FR) of Landslides across Angra dos Reis. The Global Moran’s *I* value of 0.534 indicates a strong and statistically significant positive spatial autocorrelation, suggesting that similar susceptibility values tend to cluster geographically. This reinforces the notion that landslide susceptibility in tropical mountainous environments is not randomly distributed but instead exhibits marked spatial patterns shaped by terrain configuration, hydrological connectivity, and anthropogenic pressures.

The LISA analysis provided further insights into these spatial dynamics. High-High clusters were primarily located in the southern and southeastern sectors, corresponding to areas of steep slopes, high rainfall accumulation, and dense road networks—factors previously recognized as dominant controls on landslide occurrence. In contrast, Low-Low clusters were found in more stable zones in the northern portion of the study area, where topographic gradients are gentler and human disturbance is minimal. These findings align with the results reported by [52], who applied similar spatial statistical approaches to assess landslide patterns in Egypt. Their study emphasized that High-High clusters are often indicative of persistent physical conditions conducive to landslides, such as lithological weaknesses and hydrological concentration zones. Moreover, they highlighted the importance of LISA in identifying not only stable and unstable zones, but also spatial outliers—areas where local conditions diverge significantly from neighboring patterns.

In the present study, a few High-Low and Low-High outliers were detected, mostly located along transition zones between urbanized hillslopes and preserved forested regions. These outliers may indicate zones undergoing rapid land use change, drainage modification, or areas with residual instability not yet reflected in the surrounding landscape. Their identification is crucial for targeted field verification and localized mitigation efforts. Overall, the LISA results validate the spatially structured nature of landslide susceptibility

in Angra dos Reis and underscore the value of incorporating spatial autocorrelation into susceptibility assessments. The ability to distinguish between clustered and isolated risk areas enhances the effectiveness of planning strategies, particularly in data-scarce regions where environmental processes exhibit strong spatial dependency. As demonstrated both here and in other regional studies, spatial autocorrelation techniques serve not only as diagnostic tools but also as guides for refining spatially explicit models such as MGWR.

4.2. Influence of Topography and Rainfall on Landslide Susceptibility

The results reveal that topographic variables, particularly slope and elevation, play a predominant role in modulating landslide susceptibility in Angra dos Reis. These findings are consistent with multiple studies across the Serra do Mar and other humid mountainous regions in Brazil, where steep slopes are persistently associated with higher landslide density due to increased shear stress and gravitational forces acting on colluvial material [4,53]. The significant positive contribution of rainfall in our MGWR model reinforces its central role as a landslide trigger, corroborating regional studies that demonstrate a strong correlation between orographic precipitation and shallow landslides in southeastern Brazil [54,55]. Our results are also in line with [56], who demonstrated that in varied lithological and topographic settings, the spatial heterogeneity of strength and rainfall infiltration patterns leads to coalescent failures. In Angra dos Reis, this mechanism may be exacerbated by intense convective rainfall episodes combined with steep, deeply weathered slopes.

4.3. Spatial Non-Stationarity and the Role of MGWR

The application of MGWR allowed for the identification of spatial non-stationarity in the relationship between explanatory variables and landslide occurrence. Compared to global models, MGWR enhances interpretation by attributing different bandwidths to each variable, reflecting their localized or regional influence [57]. For instance, roads exhibit a global spatial scale (bandwidth > 66 km), suggesting a homogeneous influence across the municipality—likely due to widespread alteration of hillslope hydrology and toe-cutting by infrastructure. Conversely, variables such as forest loss and profile curvature operate at more localized scales, implying site-specific interactions with terrain morphology and root cohesion. These results echo recent literature emphasizing the importance of scale-specific analysis for hazard modeling [58,59], and demonstrate that ignoring spatial scale heterogeneity may mask critical landscape interactions responsible for landslide initiation.

4.4. Lithology, Land Use, and Connectivity Effects

The frequency ratio (FR) of lithology emerged as a highly significant driver in the model, consistent with previous studies in the Serra do Mar showing that geological substrates with low shear strength—especially highly fractured migmatites and gneisses—tend to concentrate landslide scars [11,55]. Although land use and land cover (LULC) showed low significance in our model, this might reflect the coarse temporal resolution of land use data relative to the recurrence of triggering events, or a reduced signal due to spatial averaging across slope units [60]. Similarly, the connectivity index (IC) demonstrated moderate significance, aligning with [56], who emphasized that hydrological connectivity across microtopographic depressions can determine the extent and coalescence of shallow failures.

4.5. Roads and Infrastructure as Persistent Triggers

The uniformly strong and positive contribution of road proximity suggests that anthropogenic disturbance remains a persistent destabilizing factor. Our results are supported by [61,62], who reported an overrepresentation of landslides along road cuts, associated with poor drainage and excavation at the base of slopes. The MGWR results confirm that such impacts are not spatially confined but widespread across the landscape, necessitat-

ing structural mitigation strategies and urban planning interventions that prioritize slope stabilization and drainage control.

4.6. Implications and Limitations

The findings highlight that landslide susceptibility in Angra dos Reis emerges from the combined influence of geomorphological, hydrological, and anthropogenic drivers, each operating at distinct spatial scales. The high adjusted R^2 (0.93) and low AICc values confirm the robustness and parsimony of the MGWR model in capturing spatial non-stationarity. Nevertheless, caution is needed when extrapolating these results beyond the spatial extent covered by the 2023 landslide inventory. As emphasized by [56,57], the reliability of spatial regression models depends strongly on the completeness of landslide records and the resolution and accuracy of environmental covariates. In addition, the static nature of our analysis does not incorporate temporal processes such as interannual rainfall variability, lagged vegetation recovery, or progressive anthropogenic disturbances—factors that can significantly modulate slope stability over time. Addressing these limitations will require the integration of multi-temporal inventories and temporally explicit covariates, paving the way for a “multi-temporal MGWR” framework capable of capturing both spatial and temporal heterogeneity in landslide susceptibility. These recommendations are consistent with the priorities of the Sendai Framework for Disaster Risk Reduction (2015–2030) and the United Nations Sustainable Development Goals, particularly SDG 11 (Sustainable Cities and Communities) and SDG 13 (Climate Action).

5. Conclusions

This study demonstrates that landslide susceptibility in Angra dos Reis is shaped by spatially heterogeneous interactions among topographic, hydrological, geological, and anthropogenic factors. Using Multiscale Geographically Weighted Regression (MGWR), it was determined that slope, rainfall, and lithology are the most influential and spatially stable predictors of landslide occurrence, while variables such as land use and forest loss exert more localized and context-specific effects. The proximity to roads emerged as a uniformly significant factor across the municipality, reinforcing the destabilizing role of linear infrastructure in steep and densely occupied areas.

The spatial bandwidths derived from the MGWR analysis revealed that each variable operates at a distinct geographic scale, confirming that susceptibility patterns in complex tropical terrains cannot be adequately captured by global or stationary models. Complementing these findings, the spatial autocorrelation analysis using Moran’s I and LISA confirmed that landslide susceptibility is not randomly distributed but rather exhibits significant spatial structuring. High-High clusters of landslide-prone areas were concentrated in southern sectors of the municipality, where topographic steepness, rainfall concentration, and human disturbance converge. These clusters reflect persistent conditions of instability, while identified outliers point to transitional zones or emerging hotspots of risk.

Together, the MGWR and LISA results reinforce that landslide susceptibility in Angra dos Reis is modulated by multiscale and spatially structured processes, including episodes of intense precipitation, particularly during the wet summer season. Natural predisposition and human interventions interact unevenly across space. These findings emphasize the importance of incorporating spatial non-stationarity and autocorrelation into susceptibility modeling and provide a robust scientific basis for designing spatially differentiated strategies for land use planning, infrastructure development, and disaster risk reduction in tropical and subtropical mountainous environments. In addition, these results can be used to improve landslide modeling and the forecast of risk of geological disasters, so alerts can be issued to the population and, therefore, save lives.

Climate change is expected to alter rainfall patterns in Angra dos Reis and the southeastern region of Brazil. Previous studies have indicated a positive trend in extreme rainfall events in southeastern Brazil over the past 50 years. Climate projections suggest that this trend will continue, which may result in an increase in the frequency and intensity of extreme weather events. If public policies do not address the exposure and vulnerability of cities like Angra dos Reis, heavy rainfall could lead to more frequent and deadly landslides.

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