Exploring topographic variables in gully erosion susceptibility mapping in Central Brazil

Explorando variables topográficas en el mapeo de susceptibilidad a la erosión en cárcavas en el centro de Brasil

Laudier Lopes **Abreu**[1], Alessandra Cristina **Pereira**[1], Fabio Corrêa **Alves**[2], Max Well de Oliveira **Rabelo**[1], Elizon Dias **Nunes**[3], Édipo Henrique **Cremon**[1,4,*]

[1] Instituto Federal de Goiás, Campus Goiânia. Rua 75, 46 Centro, 74055-110, Goiânia, Brazil.

[2] Universidade Federal do Oeste da Bahia, Centro das Humanidades. Rua da Prainha 1326, Morada Nobre, CEP 47810-047, Barreiras, Brazil.

[3] Universidade Federal de Goiás, Instituto de Estudos Socioambientais. Av. Esperança, s/n Samambaia, 74001-970, Goiânia, Brazil.

[4] Instituto Nacional de Pesquisas Espaciais, Divisão de Observação da Terra e Geoinformatica. Avenida dos Astronautas, 1.758, 12227-010, São José dos Campos, Brazil.

* Corresponding author:
(E.H. Cremon) *edipo.cremon@inpe.br*

How to cite this article:
Abreu, L.L., Pereira, A.C., Alves, F.C., Oliveira-Rabelo de, M., Dias-Nunes, E., Cremon, E.H., 2025, Exploring topographic variables in gully erosion susceptibility mapping in Central Brazil: Boletín de la Sociedad Geológica Mexicana, 77(3), A121025. http://dx.doi.org/10.18268/BSGM2025v77n3a121025

Manuscript received: December 6, 2024.
Corrected manuscript received: May 21, 2025.
Manuscript accepted: August 1, 2025.

Peer Reviewing under the responsibility of Universidad Nacional Autónoma de México.

ABSTRACT

This study investigates gully erosion susceptibility in southwestern Goiás State, Central Brazil, where extensive gully erosion affects the landscape. The primary objective was to evaluate the predictive power of less commonly analyzed topographic variables, derived from Digital Elevation Models, in comparison with traditional predictors. A total of 5 660 gully samples were mapped, with gully heads selected as the main modeling target due to their geomorphological relevance. The methodology integrated topographic, hydrological, lithological, pedological, and anthropogenic factors. Advanced variable selection methods, including the Recursive Feature Elimination (RFE) algorithm and Variance Inflation Factor (VIF), were employed to enhance model accuracy and eliminate multicollinearity. The Random Forest algorithm was implemented for modeling, calibrated through cross-validation and tested independently using the Area Under the Curve (AUC) metric. Results demonstrated that incorporating unconventional topographic variables, such as multiscale roughness and terrain surface texture, significantly improved predictive performance. The RFE-based model achieved the highest AUC value (0.9459), underscoring the effectiveness of this approach in identifying critical predictors. Gully erosion susceptibility mapping was primarily associated with land use, drainage density, and specific terrain characteristics. The findings emphasize the value of integrating advanced geomorphometric analyses with machine learning to better understand and predict gully erosion processes, such as gullies in southwestern Goiás, Central Brazil.

Keywords: soil erosion modeling, digital elevation models, machine learning applications.

RESUMEN

Este estudio investiga la susceptibilidad a la erosión en cárcavas en el suroeste del estado de Goiás, Brasil Central, una región significativamente afectada por este fenómeno. El objetivo principal es evaluar la capacidad predictiva de variables topográficas menos analizadas, derivadas de Modelos Digitales de Elevación (MDE), en comparación con variables tradicionales. Se cartografiaron 5 660 cárcavas; sus cabezas se identificaron como el foco principal del modelado debido a su relevancia geomorfológica. La metodología integró factores topográficos, hidrológicos, litológicos, pedológicos y antropogénicos. Se aplicaron métodos avanzados de selección de variables, como el algoritmo de Eliminación Recursiva de Características (RFE) y el Factor de Inflación de Varianza (VIF), para optimizar la precisión del modelo y eliminar la multicolinealidad. Se implementó el algoritmo Random Forest para el modelado, calibrado mediante validación cruzada y evaluado independientemente con la métrica de Área Bajo la Curva (AUC). Los resultados demostraron que la inclusión de variables topográficas no convencionales, como la rugosidad multiescala y la textura de la superficie del terreno, mejoró considerablemente el rendimiento predictivo. El modelo basado en RFE obtuvo el valor más alto de AUC (0.9459), lo que resalta la eficacia de este enfoque para identificar predictores clave. La cartografía de la susceptibilidad a la erosión en cárcavas se asoció principalmente con el uso del suelo, la densidad de drenaje y características específicas del terreno. Los resultados subrayan la importancia de integrar análisis geomorfométricos avanzados con aprendizaje automático para comprender y predecir los procesos de erosión, como las cárcavas, en el suroeste del estado de Goiás, Brasil Central.

Palabras clave: modelado de erosión del suelo, modelos digitales de elevación, aplicaciones de aprendizaje automático.

http://dx.doi.org/10.18268/BSGM2025v77n3a121025

1. Introduction

Gully erosion is a significant cause of soil degradation, reducing the quality and availability of arable land in both developed and developing countries (Valentin *et al.*, 2005; Boardman *et al.*, 2003). According to FAO (2015), soil erosion results in the annual loss of 25 to 40 billion tons of soil, diminishing agricultural productivity, compromises food security, and reduces the soil's capacity to retain water and nutrients.

In this study, gully erosion refers to channels exceeding the dimensions of rills (depth >0.3 m), including both ephemeral gullies (temporary features erased by tillage) and permanent gullies (deep, persistent incisions into subsoil). The latter represent the most severe form of linear erosion, requiring distinct mitigation strategies due to their irreversibility under conventional land management (Poesen *et al.*, 2003; Valentin *et al.*, 2005).

This phenomenon negatively affects several United Nations (UN) Sustainable Development Goals (SDGs), including Zero Hunger and Sustainable Agriculture, Life on Land, and Sustainable Cities and Communities. In this context, gully erosion susceptibility mapping is a valuable tool for identifying vulnerable areas, guiding conservation strategies, controlling erosion, and supporting sustainable soil management. These maps help mitigate erosion impacts and contribute to achieving sustainable development objectives.

Recent advances in machine learning have enabled algorithms to identify patterns in large datasets (Zhang and Tsai, 2006). In gully erosion susceptibility mapping, methods such as Random Forest (RF), Support Vector Machine (SVM), Logistic Regression (LR), Multilayer Perceptron (MLP) and Extreme Gradient Boosting (XGBoost) have been increasingly employed. These models effectively capture complex environmental relationships and process large geospatial datasets. RF, in particular, has been widely utilized due to its high predictive accuracy (Mohebzadeh *et al.*, 2022).

In South America, particularly in Brazil, regional-scale studies have tested multiple algorithms, with RF typically achieving superior performance (Lana *et al.*, 2022; Bouramtane *et al.*, 2022; Marques Filho *et al.*, 2024; Pereira *et al.*, 2025). Globally, recent research confirms the efficacy of RF and XGBoost across diverse environments, including highly dissected terrains (Yang *et al.*, 2021), semi-arid basins (Hasanuzzaman and Shit, 2025), and regions under land-use pressure (Arabameri *et al.*, 2020b). These findings highlight their adaptability for erosion modeling under varying conditions.

The integration of machine learning with remote sensing, geographic data, and Geographic Information System (GIS) enables researchers to evaluate multiple conditioning factors simultaneously, improving the accuracy of gully erosion predictions (Arabameri *et al.*, 2019; Arabameri *et al.*, 2020a). Key geo-environmental factors affecting gully erosion encompass geomorphological (topographic), hydrological, lithological, pedological, and anthropogenic characteristics (Arabameri *et al.*, 2020a). These variables influence water-flow dynamics and erosive processes, underscoring their importance in developing effective soil and water conservation strategies (Shit *et al.*, 2015).

Geomorphological factors, derived from Digital Elevation Models (DEMs) using GIS software, are represented by topographic variables such as slope, aspect, curvature, and the topographic position index. These variables, also referred to as topographic attributes, terrain attributes, or geomorphometric attributes (Pike *et al.*, 2009; Florinsky, 2016), provide quantitative information about the Earth's surface.

Although commonly used topographic variables are frequently applied in erosion studies, exploring less commonly analyzed variables may reveal additional patterns and enhance model performance. Evaluating these lesser-known topographic variables and comparing their predictive value with established ones addresses an important gap in the literature. Expanding the range of conditioning factors can improve predictive accuracy and deepen understanding of gully erosion processes.

This study investigates the role of less-conventional topographic variables derived from DEMs in gully erosion susceptibility mapping. It compares their predictive value to that of widely used variables to determine their contribution to improving model outcomes and understanding erosion dynamics.

2. Study area

The study area is located in the southwestern region of Goiás State, Central Brazil, covering 12 002.35 km² and including the municipalities of Mineiros, Santa Rita do Araguaia, Perolândia, and Portelândia (Figure 1). This region exhibits a high density of gullies, previously examined from multiple perspectives (Marinho *et al.*, 2006; Nunes and Castro, 2015; Nunes and Castro, 2023; Carvalho and Castro, 2023; Pereira *et al.*, 2025). However, the relative contribution of variables commonly used in gully erosion susceptibility models has not yet been systematically evaluated.

This area was selected due to the detailed mapping of soils and erosion features by Nunes and Castro (2015, 2023), who classified soils at the third hierarchical level of the Brazilian Soil Classification System (SiBCS; Santos *et al.*, 2018) at a 1:50,000 scale. Dominant soil types include Oxisols (Latossolos), Ultisols (Argissolos), and Quartzarenic Neosols (Neossolos Quartzarênicos), with smaller areas of Litholic Neosols (Neossolos Litólicos), Cambisols (Cambissolos), and Gleysols (Gleissolos).

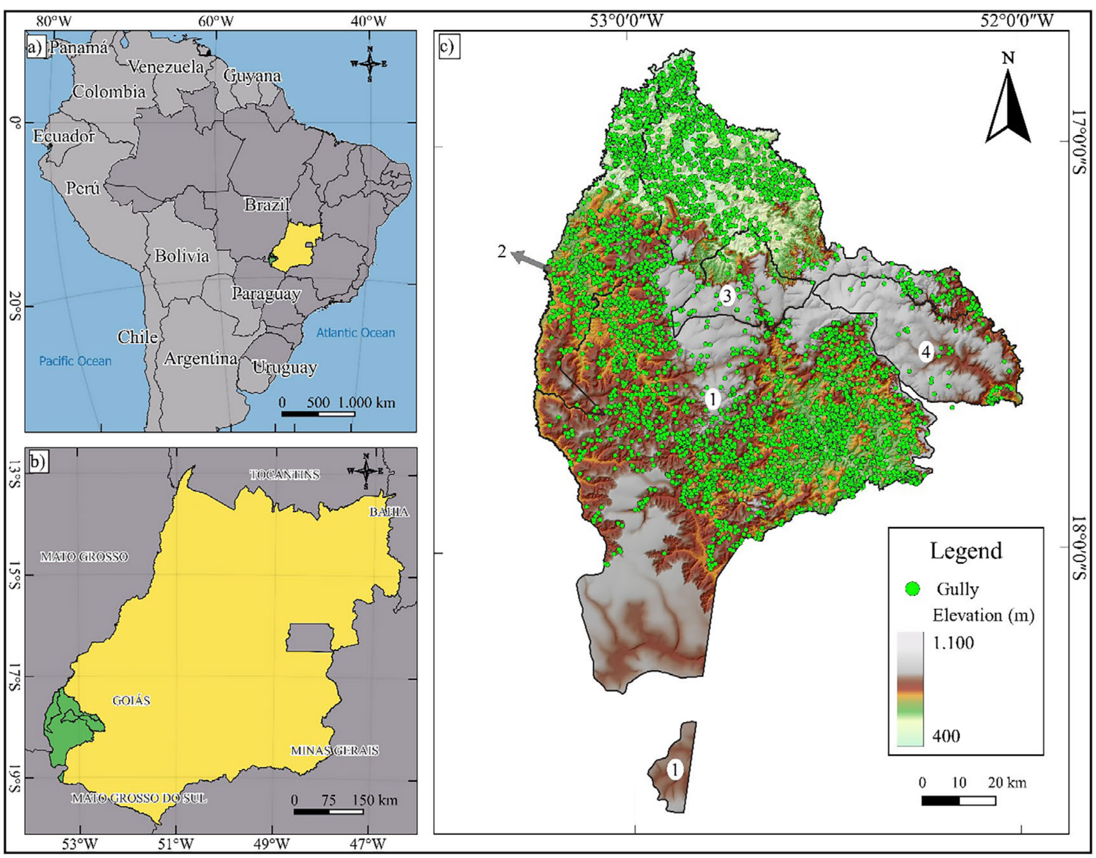

Figure 1 Study area in the southwestern region of Goiás State, Brazil, characterized by widespread gully erosion, varied geology, and diverse soil types. The area includes the municipalities of 1-Mineiros, 2-Santa Rita do Araguaia, 3-Portelândia, and 4-Perolândia.

The terrain is mostly flat, with slopes ranging from 3.45% to 8.84%, although isolated areas exceed 45%. The geology is composed of sedimentary rocks (IBGE, 2023), mainly sandstones and basic intrusives, creating a stepped relief.

In the north, Phanerozoic sedimentary deposits prevail, including sandstones, shales, and siltstones from the Aquidauana Formation, with elevations reaching up to 590 m. Narrow sandstone and siltstone bands from the Corumbataí Formation occur near watercourses, where Neosols are present. Red Ultisols occupy middle slopes, and Red-Yellow Oxisols occur near drainage divides. In the south, basaltic rocks of the Serra Geral Formation and shales from the Irati Formation are associated with steeper, rugged terrain dominated by Litholic Neosols. Interspersed areas contain sandstones and siltstones of the Corumbataí Formation.

The central region features eolian sandstones of the Botucatu Formation, with elevations between 500 and 1 000 m. Quartzarenic Neosols are widespread, and Red and Red-Yellow Oxisols dominate the western portion. In the central-eastern and southern zones, Phanerozoic deposits from the Cachoeirinha Formation, composed of clays, sandstones, and sandy materials, are prevalent. These gently sloping areas are mainly covered by Red Oxisols, with Haplic Gleysols near drainage lines (Cremon *et al.*, 2021).

3. Methodology

3.1. ACQUISITION OF GULLY EROSION SAMPLES

A total of 5 660 gully erosion features were mapped as polygons through visual interpretation of high-resolution remote sensing imagery from 2018 (Nunes and Castro, 2023), representing areas affected by erosion in the study region.

In susceptibility mapping, gully heads are emphasized due to their geomorphological and hydrological relevance, marking the initiation of erosion (Valentin *et al.*, 2005). These points concentrate key triggering factors—soil properties, topography, and runoff—and reflect the interaction between land use and natural conditions, making them highly sensitive to environmental and anthropogenic changes.

Although gullies often exhibit multiple active incision points, including lateral branches, the uppermost head cut with the greatest up slope contributing area generally represents the primary zone of initiation. Using this point as a proxy for gully occurrence is supported by geomorphological and hydrological principles, particularly the well-established relationship between slope (*S*) and drainage area (*A*) as a threshold for gully initiation (Torri and Poesen, 2014). This strategy allows for consistent extraction of key conditioning factors and has been widely adopted in recent susceptibility studies using statistical and machine learning approaches (*e.g.*, Hosseinalizadeh *et al.*, 2019; Arabameri *et al.*, 2021; De Geeter *et al.*, 2023).

To identify gully heads, mapped polygons were geometrically corrected, and their vertices extracted. The vertex with the highest elevation and flow accumulation was designated as the gully head (Figure 2). This was determined using the D8 algorithm, which assigns flow direction based on the steepest downslope path in the DEM (O'Callaghan and Mark, 1984).

Based on the gully presence points, absence points were defined as areas assumed to be non-gullied. To ensure spatial independence and minimize environmental overlap, absence points were randomly selected under the condition that they were located at least 1 000 meters away from any gully presence point. This minimum distance was defined through preliminary sensitivity tests to balance representativeness and spatial separation. A total of 5 660 absence points were generated—matching the number of gully presence points—to maintain a balanced dataset for binary classification. Presence and absence points were labeled as '1' and '0', respectively, and used for binary classification modeling.

3.2. ACQUISITION AND PROCESSING OF VARIABLES

The study employed a broad set of topographic variables as independent predictors to identify areas susceptible to gully formation. These variables were derived from the Forest and Building Removed Copernicus Digital Elevation Model (FABDEM) (Hawker *et al.*, 2022), a Digital Terrain Model (DTM) in geographic coordinates, based on the Copernicus DSM, with WGS-84 datum and 1 arc-second resolution. FABDEM provides the most accurate freely available elevation data for the study area (Cremon *et al.*, 2022; Bielski *et al.*, 2024).

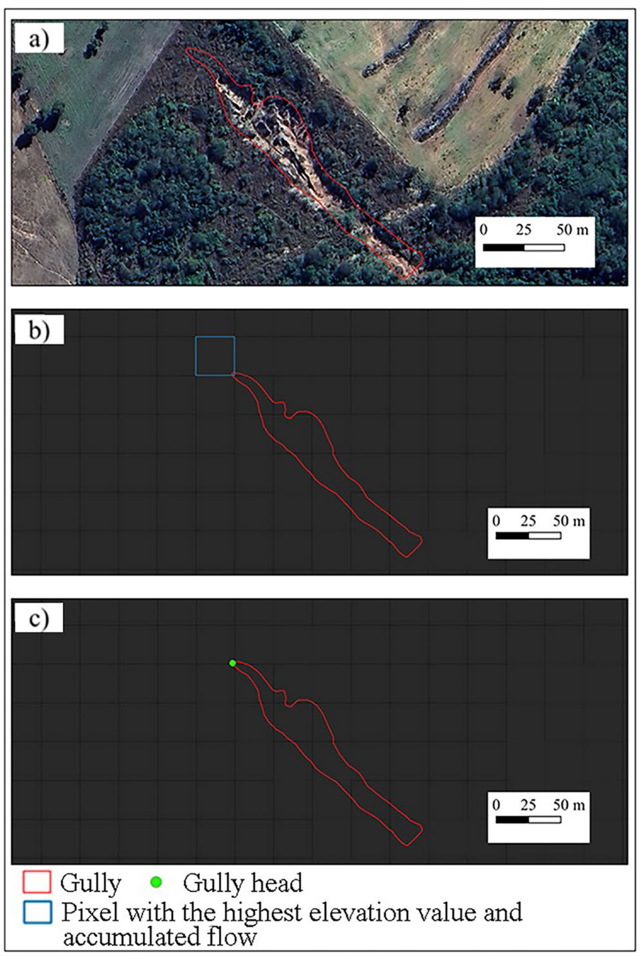

Figure 2 **Workflow for identifying gully heads. (a) Polygon delineating the erosion area; (b) Automatic identification of the pixel with the highest elevation and flow accumulation; (c) Final determination of the gully head.**

The dataset was reprojected to UTM Zone 22 South, SIRGAS2000 datum, with 30-meter resolution. Cubic spline resampling was applied using QGIS (QGIS Development Team, 2024), following the recommendations of Purinton and Bookhagen (2021).

Hydrological correction of the DTM was performed using the TerraHidro package (Rosim *et al.*, 2011), which applies flat-carving algorithms and the Priority-First Search (PFS) method (Jones, 2002), preserving terrain features and ensuring drainage continuity in flat or depressed areas.

A total of 64 topographic variables were derived using GRASS GIS (GRASS Development Team, 2024), SAGA-GIS (Conrad *et al.*, 2015), QGIS (QGIS Development Team, 2024), and Whitebox (Lindsay, 2016), as well as the TAK toolbox for MATLAB (Forte and Whipple, 2019), SurfRough (Trevisani *et al.*, 2023), and the terra package for R (Hijmans, 2024).

For interpretability, variables were grouped into categories based on primary characteristics: morphology (geometric terrain properties), roughness (surface complexity), relative topographic position (elevation relative to surroundings), and hydrological/combined variables, which integrate terrain attributes with hydrological processes. Some variables span multiple categories due to overlapping functions (Figure 3).

Given the large number of variables tested for gully erosion susceptibility mapping, two selection methods were used: Variance Inflation Factor (VIF) and Recursive Feature Elimination (RFE). VIF was initially applied to identify and remove highly collinear variables. Variables with VIF values above 10 were iteratively removed to retain only independent predictors, enhancing model reliability and interpretability. Logistic regression was used to fit the initial model, and VIF values were recalculated at each step until all retained variables had VIF values below 10, eliminating multicollinearity.

http://dx.doi.org/10.18268/BSGM2025v77n3a121025

In parallel, RFE was used to identify the most relevant predictors. This backward selection algorithm determines the optimal subset of variables for regression or classification tasks (Kuhn and Johnson, 2013). In this study, RFE was implemented with Random Forest, iteratively removing less informative variables and retaining those with higher predictive power. Using 10-fold cross-validation, the final subset of predictors was defined. The combined use of VIF and RFE reduced redundancy while improving model relevance.

For variables requiring a defined filter size, a 21-pixel window (630 m) was applied, based on the 30 m DEM resolution. This value reflects the average spatial dependency range of the topographic data (Figure 4), as determined by variogram analysis (Cremon *et al.*, 2021).

Mohebzadeh *et al.* (2022) reviewed the most frequently used variables in gully erosion susceptibility studies. Among topographic predictors, 14 key variables were identified, including elevation and aspect. Other key variables were slope and the LS Factor, defined as the

Variables associated with morphology	**Variables associated with roughness**	**Variables associated with relative topographic position**	**Hydrological and/or combined variables**
Aspect [WB]	Average Normal Vector Angular Deviation [WB]	Deviation from mean elevation (21) [WB]	Average Upslope Flowpath Length [WB]
Aspect (Post-processing of the Topodata method) [SG]	Circular Variance of Aspect [WB]	Difference from mean elevation (21) [WB]	Catchment area / Flow accumulation [SG]
Convergence index [SG]	Edge density (21) [WB]	Elevation	Chi (χ) [TAK]
Convergence index (21) [SG]	Entropy (21) [GR]	Elevation percentile (21) [WB]	Downslope Distance [SG]
Gaussian curvature [WB]	Max. anisotropy in elevation deviation (ML) [WB]	Local relief (21) [GR]	Downslope Index [WB]
Geomorphons [GR]	Multiscale Roughness (21) [WB]	Max Difference From Mean (ML) [WB]	Index for Lowlands (TCI Low) [SG]
Maximal curvature [WB]	Multiscale Std Dev Normals (ML) [WB]	Max Downslope Elev Change [WB]	Ksn [TAK]
Mean curvature [WB]	Roughness Concentration Index (RCI) (21) [QG]	Max Elevation Deviation (ML) [WB]	LS fator [SG]
Minimal curvature [WB]	Radial Roughness Index (RRI) (21) [R]	Max Upslope Elev Change [WB]	Max Branch Length[WB]
Multiresolution index of the ridge top flatness (ML) [SG]	Spherical Std Dev Of Normals (21) [WB]	Mid Slope Positon [SG]	Max upslope flowpath length [WB]
Multiresolution Index of Valley Bottom Flatness (ML) [SG]	Standard Deviation Of Slope (21) [WB]	Min Downslope Elev Change [WB]	SAGA TWI [SG]
Negative Openness [SG]	Terrain Ruggedness Index (TRI) (21) [WB]	Multiscale Elevation Percentile (ML) [WB]	Stream Power Index[SG]
Plan Curvature [WB]	Terrain Surface Texture (21) [SG]	Slope Height [SG]	TWI [SG]
Plan Curvature (Post-processing of the Topodata method) [SG]	Topographic coherence (21) [R]	Topographic Position Index (TPI) (21) [SG]	
Positive Openness [SG]	Vector Ruggedness Measure (VRM) (21) [SG]	Valley Depth [SG]	
Profile Curvature [SG]		Vertical Distance to Channel Network (VDCN) [SG]	
Profile Curvature (Post-processing of the Topodata method) [SG]			
Slope [WB]			
Tangential curvature [WB]			

Processed in:

[SG] SAGA GIS
[WB] WhiboxTools
[GR] GRASS GIS
QGIS [QG] QGIS
TAK for TopoToolbox [TAK] Topographic Analysis Kit (TAK) for TopoToolbox
[R] R

(21) based on a 21-pixel filter, i.e., 630m
(MS) based on a multiscale algorithm

Figure 3 Categories of topographic variables used and associated processing software.

product of slope and contributing area, commonly used in the Universal Soil Loss Equation (USLE).

Additional variables included flow accumulation, curvature, plan curvature (horizontal), profile curvature (vertical), and convergence index, which aid in assessing flow paths and water accumulation. Topographic indices such as the stream power index and topographic wetness index (TWI) were also emphasized for their relevance to erosion and flow concentration. Terrain roughness index and topographic position index (TPI) contribute to understanding surface complexity and erosion potential, making them widely applied in susceptibility modeling (Mohebzadeh *et al.*, 2022).

Beyond topography, the study incorporated hydrological, lithological, pedological, environmental, and anthropogenic factors:

- **Hydrological variables:** Rainfall erosivity (R Factor in USLE; Panagos *et al.*, 2017) and drainage density were included. Drainage density was derived from IBGE's hydrographic network, refined at 1:50 000 scale, and calculated within a 1 km radius.
- **Lithological variables:** Based on the 1:250,000 geological map (IBGE, 2023), lithology was treated as a categorical variable. Euclidean distance rasters were generated for lithological boundaries and morphostructural lineaments.
- **Pedological variables:** A 1:50,000 scale soil map (Nunes and Castro, 2015; Cremon *et al.*, 2021) was used, with erodibility values (K Factor in USLE) assigned to each class (Nunes and Castro, 2023).
- **Environmental and anthropogenic variables:** Land use and land cover (LULC) data were obtained from the 2018 mapping of MapBiomas Collection 9. NDVI and road proximity rasters were also included. NDVI was calculated using a temporal median of Landsat-8 OLI images from 2018, matching the gully inventory year, and processed via Google Earth Engine. Road data were sourced from IBGE and OpenStreetMap (OSM).

All datasets were standardized to the same grid size and reference coordinate system. The methodological flowchart is presented in Figure 5.

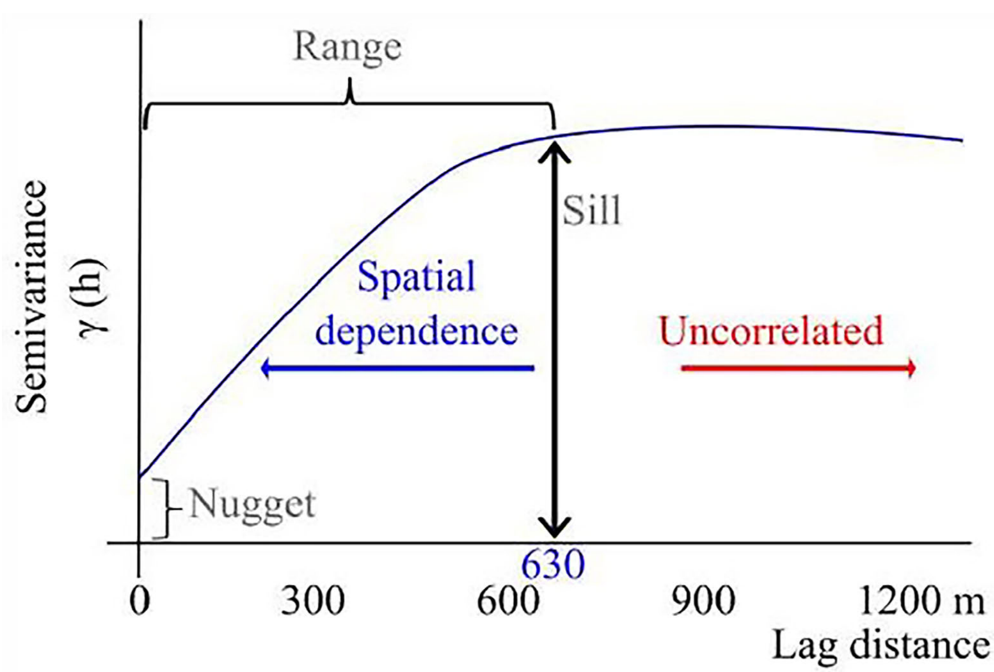

Figure 4 Semivariogram example used to define the spatial dependency of elevation data for selecting topographic variable filter size.

For this study, three scenarios were analyzed (Figure 5). In the first scenario, the analysis included the most commonly used topographic and environmental variables for gully erosion susceptibility studies, as identified by Mohebzadeh *et al.* (2022). The following variables were considered: Aspect, Catchment area, Convergence Index, Drainage density, K Factor, Rainfall erosivity (R Factor), LS Factor, Distance to the road network, Plan Curvature, Profile Curvature, Slope, Stream Power Index (SPI), Topographic Position Index (TPI), Topographic Wetness Index (TWI), Terrain Ruggedness Index (TRI), Lithology map, LULC, and NDVI.

In the second scenario, less commonly used topographic variables were evaluated, and variable selection was performed using the Variance Inflation Factor (VIF) method. In the third scenario, the same set of less conventional variables was analyzed using the Recursive Feature Elimination (RFE) method. For both scenarios 2 and 3, conventional variables were included in the selection process to ensure a comprehensive evaluation of predictors.

Gully erosion susceptibility was modeled using the RF algorithm implemented via the caret package (Kuhn and Johnson, 2013) in R, using the RStudio interface. RF was chosen for its efficiency

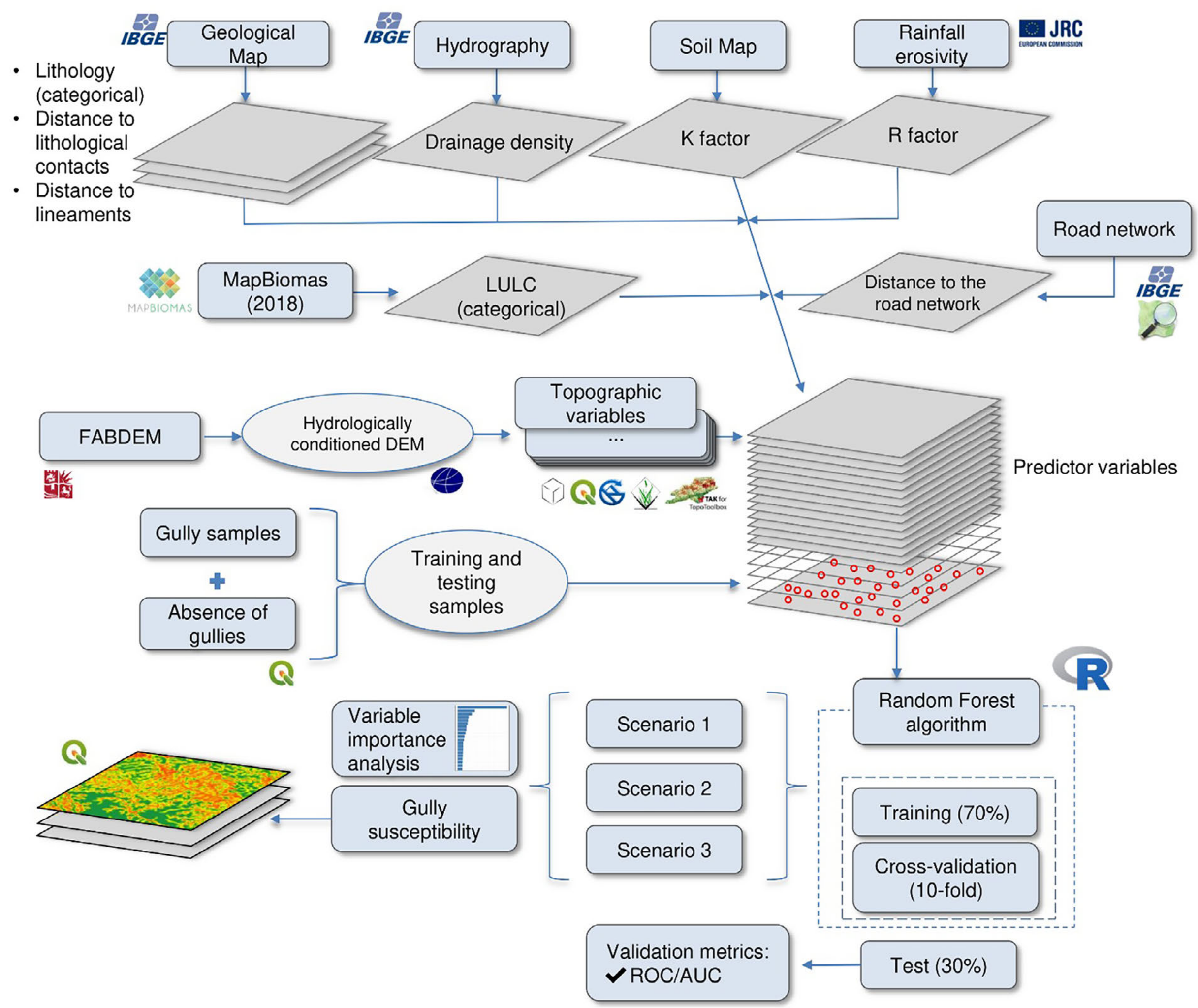

Figure 5 **Methodological workflow for generating a gully erosion susceptibility map.**

http://dx.doi.org/10.18268/BSGM2025v77n3a121025

and strong performance in this modeling context (Mohebzadeh *et al.*, 2022).

Model training and calibration were performed using 10-fold cross-validation, with evaluation based on the Receiver Operating Characteristic (ROC) curve. Hyperparameters were tuned by testing 10 values to identify optimal settings. 70% of samples were used for training, and the remaining 30% for independent testing, with model performance assessed by the Area Under the ROC Curve (AUC; Kuhn and Johnson, 2013).

Variable importance was evaluated using the varImp function, based on the Gini importance metric (Breiman, 2001). Results were presented graphically for the 20 most influential variables in predicting gully occurrence.

4. Results

4.1. VARIABLE SELECTION PERFORMANCE

The analysis of RF models was conducted across three scenarios, each applying different strategies for variable selection and hyperparameter tuning. In scenario 1, which included traditional variables, the optimal number of predictors per tree split was set to 10. In scenario 2, where variable selection was based on the VIF method, the optimal number of predictors per tree split was adjusted to 13. In scenario 3, where variables were selected using the RFE method, the optimal number of predictors per tree split was reduced to 6.

The models were validated using an independent test dataset, and the AUC values obtained were 0.9344 for scenario 1, 0.9396 for scenario 2, and 0.9459 for scenario 3. The results indicate an improvement in model performance as variable selection and hyperparameter tuning were refined, with scenario 3 achieving the highest predictive accuracy, as demonstrated by the highest AUC value (Figure 6).

The findings suggest that incorporating less conventional topographic variables improved the predictive capacity of the models for gully erosion susceptibility. The scenario utilizing variables selected through the RFE method achieved the highest AUC, indicating superior predictive performance compared to the scenarios with traditional variables and those selected using the VIF method. These results highlight that, in addition to exploring less commonly used variables, the RFE approach was more effective in identifying the most relevant predictors for modeling gully erosion susceptibility.

Following the evaluation of validation metrics, the best-performing model was applied to generate a susceptibility map for gully formation in the study area. The resulting raster dataset ranges from 0 to 1, indicating areas with the lowest and highest susceptibility to gully formation, respectively (Figure 7).

Regions with lower susceptibility to gully erosion are typically associated with flat terrain and the presence of vegetation, which mitigates the impact of rainfall and reduces surface runoff.

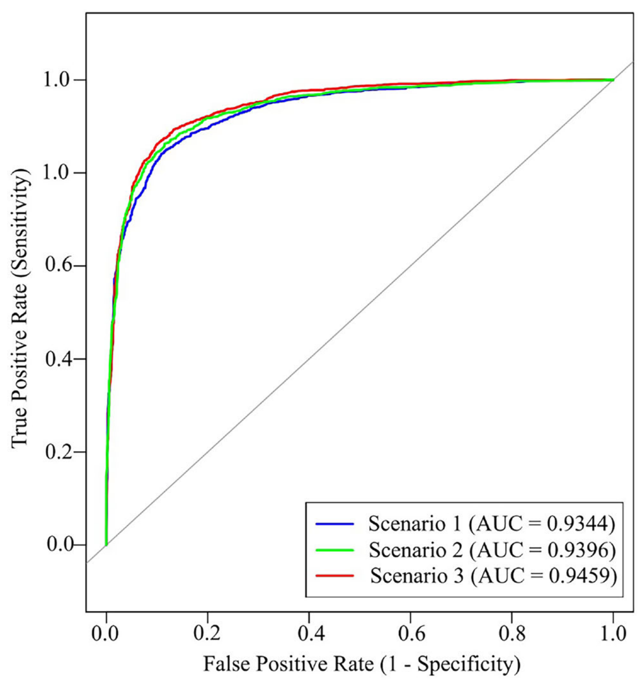

Figure 6 ROC curves for the three analyzed scenarios (1, 2 and 3). The curves illustrate the relationship between the true positive rate (sensitivity) and the false positive rate (1-specificity) across different classification thresholds.

In some agricultural areas, such as those used for soybean cultivation under appropriate management practices, the occurrence of gullies is also minimized. In contrast, areas with higher susceptibility to gully formation are predominantly located near drainage headwaters. These regions are characterized by factors such as high terrain roughness, erosion-prone soils, water flow convergence, proximity to the water table, and insufficient implementation of conservation practices. Pasturelands, in particular, often lack effective management strategies, contributing to the development of intense erosive processes (Figure 7).

4.2. VARIABLE IMPORTANCE

The most relevant variables for predicting gully erosion susceptibility were evaluated for all three scenarios using the RF algorithm. In scenario 1, all traditional variables were included, regardless of potential informational redundancy. In scenario 2, variables with VIF values exceeding 10 were excluded, resulting in a more independent set of predictors. In scenario 3, the RFE algorithm combined with cross-validation was used to iteratively select the most informative variables, producing a subset with greater predictive power and improved model efficiency (Figure 8).

4.2.1. SCENARIO 1

In modeling gully erosion susceptibility in southwestern Goiás, the most relevant traditional variables were associated with physical characteristics and land use or land cover. Pasture emerged as the most important variable, followed by drainage density. The K Factor, representing soil erodibility, was also highly influential, along with the TWI and NDVI, which are proxies for soil moisture and vegetation cover, both critical for mitigating erosion. Other significant topographic variables, such as slope and the TRI, were also notable due to their impact on water flow dynamics and erosion potential.

Variables like the convergence index, profile curvature, plan curvature, and TPI, reflect terrain characteristics that influence surface runoff and water concentration; these variables ranked moderately important. The R Factor, which accounts for rainfall erosivity, contributed significantly to estimating erosion intensity.

Less influential variables included lithological classes such as the Botucatu Formation and the Neogene Detrital-Lateritic Cover. Proximity to the road network, though relevant, was less impactful than variables related to topography and land use or land cover. These results indicate that the interplay between physical factors, land use, and rainfall erosivity is a key determinant in modeling gully erosion susceptibility in the region.

4.2.2. SCENARIO 2

In the scenario using less conventional topographic variables selected via the VIF method, pasture remained the most significant variable, reaffirming its influence on gully erosion susceptibility. Drainage density was the second most significant variable, followed by multiscale roughness and terrain surface texture, which describe surface irregularity and variability, capturing interactions between terrain characteristics and erosive processes.

Other important variables included maximum downslope elevation change and average normal vector angular deviation, both of which influence water flow direction and velocity, contributing to erosion-prone areas. Variables such as valley depth and NDVI, representing valley morphology and vegetation cover, respectively, were also significant in reducing erosion susceptibility.

The roughness concentration index (RCI), linked to slope variability, and the vertical distance to channel network (VDCN), representing vertical proximity to drainage channels, were among the critical predictors. Variables derived from the TAK toolbox, such as ksn and χ (chi), ranked moderately in importance. Ksn quantifies the erosive power of fluvial systems based on slope

http://dx.doi.org/10.18268/BSGM2025v77n3a121025

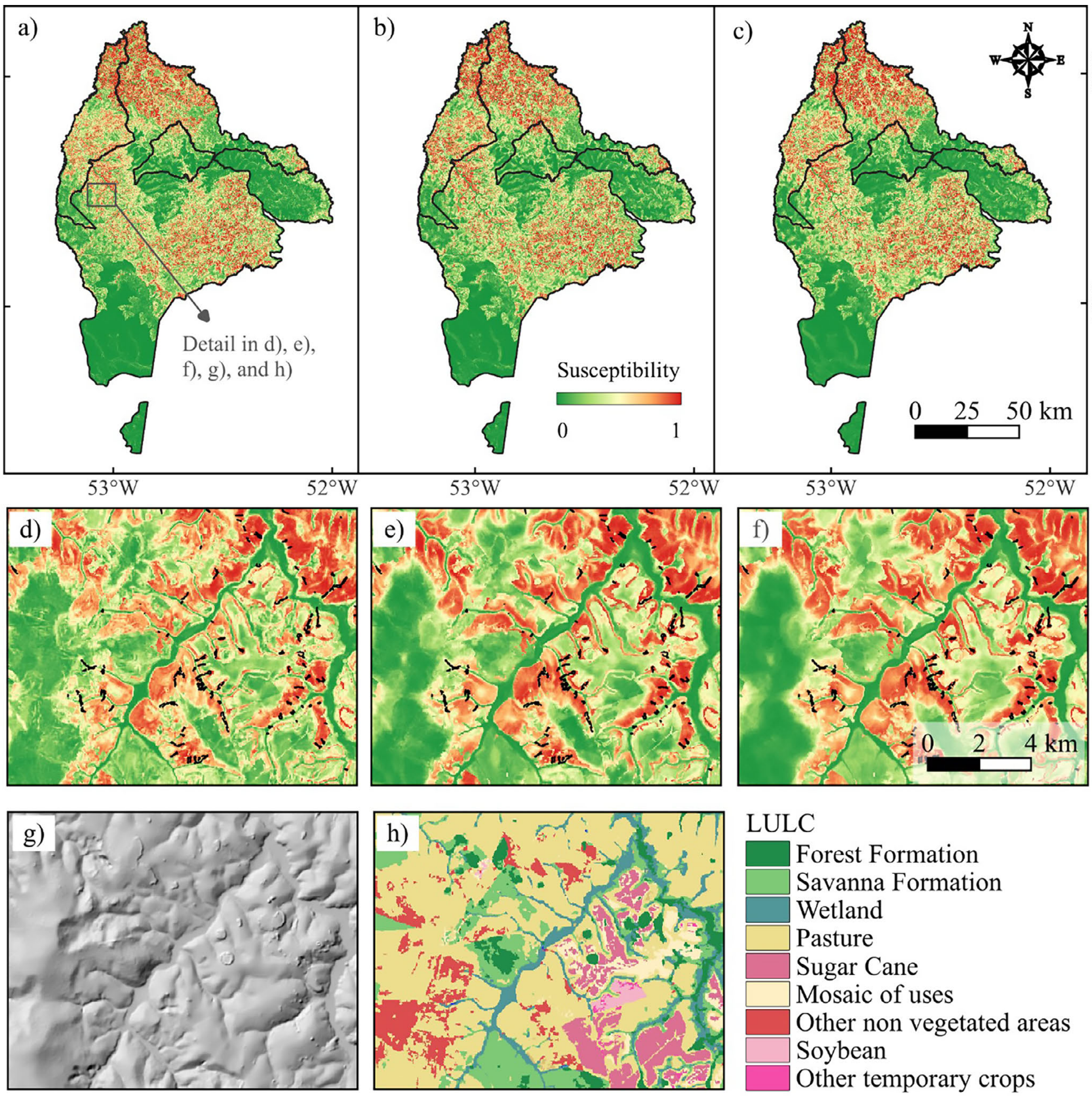

Figure 7 Gully erosion susceptibility mapping results for the study area. Panels (a), (b), and (c) show the susceptibility maps for scenarios 1, 2, and 3, respectively: scenario 1 includes traditional variables, scenario 2 applies variable selection using the VIF, and scenario 3 uses RFE. Panels (d), (e), and (f) present detailed views of the susceptibility maps for scenarios 1, 2, and 3, respectively. Black contours represent the mapped gully polygons. Panel (g) displays the hillshade derived from the DEM, and panel (h) shows the land use and land cover classification. Susceptibility values range from 0 (low) to 1 (high).

and contributing area, while χ (chi) measures the relative position of a point within the fluvial network, weighted by drainage area and erosion potential, offering valuable perspectives on geomorphic processes.

Additional variables, including topographic coherence, elevation entropy, and average normal vector angular deviation, captured terrain variability and played a significant role in modeling erosion processes. Proximity to the road network, convergence index, and profile curvature, derived from the Topodata method (Valeriano and Albuquerque, 2010), provided further insight into water flow direction and concentration, influencing susceptibility to erosion.

4.2.3. SCENARIO 3

In the scenario with less conventional topographic variables selected using the RFE method, pasture again emerged as the most important variable, highlighting its consistent role in determining erosion susceptibility. Similarly, drainage density was ranked as the second most significant variable, aligning with findings from the other scenarios.

Other significant variables included multiscale roughness and terrain surface texture, which describe terrain irregularity and variability. The K Factor, representing soil erodibility, emphasized the role of soil types in gully formation. Additionally, maximum downslope elevation change and average normal vector

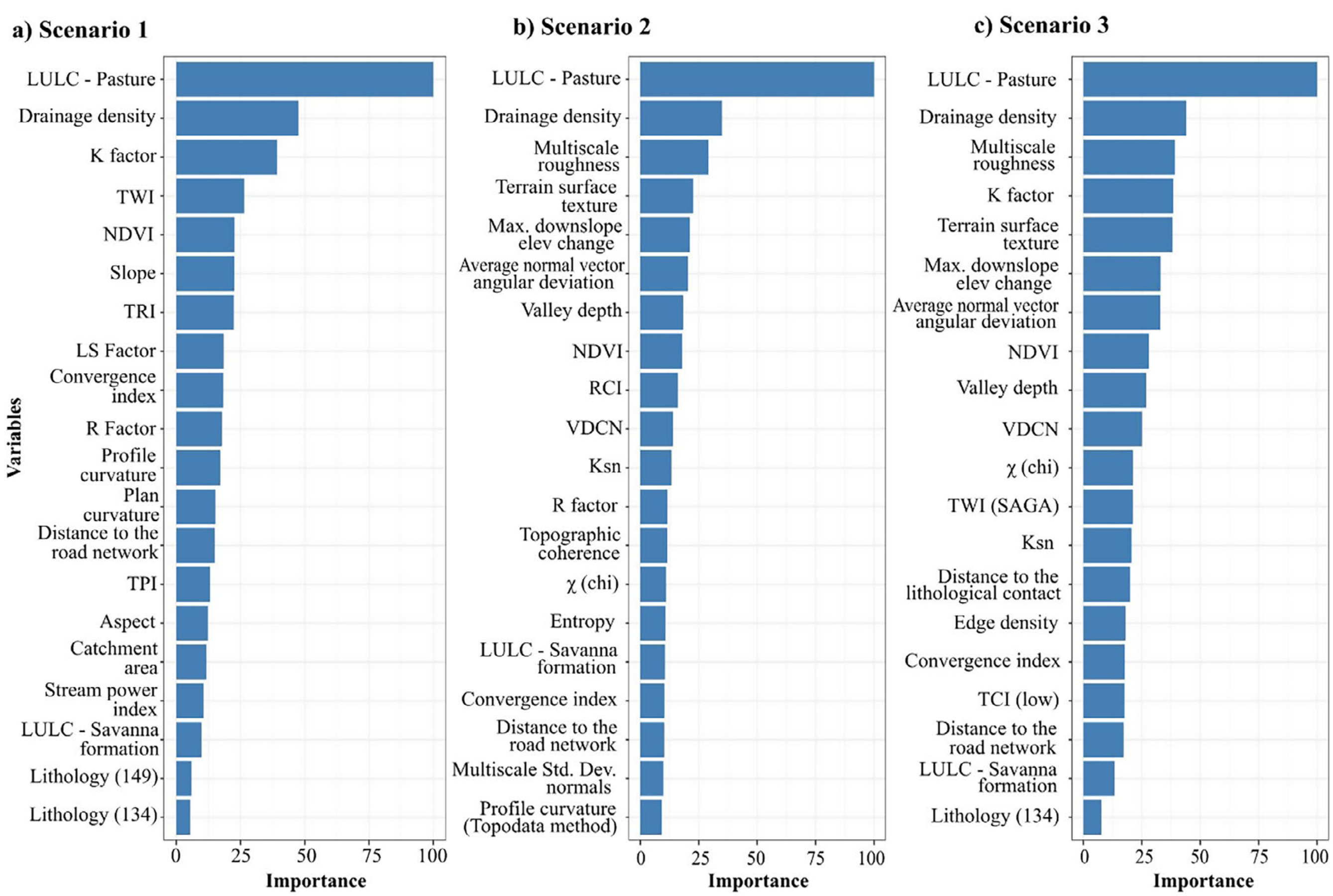

Figure 8 Variable importance for each scenario. Lithology (134) represents the Neogene Detrital-Lateritic Cover, while Lithology (149) corresponds to the Botucatu Formation, characterized primarily by sandstone composition.

angular deviation underscored the influence of slope and surface orientation on water dynamics and erosion.

Variables such as NDVI and valley depth captured vegetation cover and valley morphology, which are key factors in reducing erosion risk. The VDCN and geomorphic variables derived from the Topotoolbox, such as χ (chi) and ksn, ranked moderately in importance, reflecting the interactions between terrain features and the erosive capacity of fluvial systems.

Less impactful variables included the SAGA TWI and convergence index, which provide information on water concentration and slope saturation. Other variables, such as the terrain classification index for lowlands (TCI low) from SAGA GIS and edge density, represented surface morphology and roughness. Proximity to the road network and lithology, including savanna formations and the Neogene Detrital-Lateritic Cover, also contributed to the model, though their influence was relatively minor compared to topography and vegetation-related variables.

5. Discussion

Gully formation is a complex process influenced by various environmental, topographic, and hydrological factors that directly affect erosive potential. Conditioning variables such as topographic characteristics, hydrological features, climatic factors, land use and land cover, and soil properties are important for modeling susceptibility effectively. However, the selection of the most suitable variables lacks universal agreement, necessitating an evaluation of their relative importance within the specific context of the study area (Azareh *et al*., 2019). Machine learning models, including RF, have proven effective in identifying key variables and their interactions, enhancing the accuracy of susceptibility assessments.

Across the three evaluated scenarios—traditional variables in scenario 1, VIF-based variable selection in scenario 2, and RFE-based variable selection in scenario 3—the land use and land cover class “pasture” consistently ranked as the most significant predictor. This result likely reflects the impact of soil compaction and inadequate management practices, which increase erosion susceptibility (Galdino *et al*., 2016; Nunes and Castro, 2023; Pereira *et al*., 2025). In the study area, converted pastures often feature cattle trails and boundary fences that exacerbate erosive processes (Santana *et al*., 2007; Nunes and Castro, 2015; Pereira *et al*., 2025). Additionally, NDVI showed moderate importance in all scenarios, highlighting the role of vegetation cover in mitigating erosion. Dense and healthy vegetation reduces soil exposure to rainfall and surface runoff, limiting erosion.

Drainage density, defined as the ratio of total stream length to unit area, reflects the interplay between erosive forces and surface material resistance. Influenced by climate, vegetation, lithology, and soils (Huggett and Shuttleworth, 2022), this metric correlates with runoff capacity and directly impacts rock and soil erodibility (Gournellos *et al*., 2004). In the study area, drainage density was consistently ranked as a key predictor, being the second in the list (Figure 8). Regions with higher drainage density are often more susceptible to gully formation, especially in areas with poor soil management, such as degraded pastures.

The inclusion of less conventional topographic variables in scenarios 2 and 3 highlighted the significance of roughness-related metrics. In scenario 1, only one roughness variable was among the top 20 predictors, compared to seven in scenario 2 and four in scenario 3. Notable variables included multiscale roughness and terrain surface texture, which were highly predictive in both VIF- and RFE-based selection methods. Multiscale roughness adapts the level of detail based on the local topographic context of each DEM cell, enabling a nuanced understanding of roughness and its relationship with specific erosion patterns (Lindsay, 2023). Terrain surface texture, in contrast, uses a fixed filter radius to quantify the relative frequency of pits and peaks, delineating valleys and ridges. High-frequency cells indicate rougher terrain, while low-frequency cells suggest smoother surfaces (Iwahashi and Pike, 2007).

Additional roughness metrics, such as average normal vector angular deviation and edge density, provided additional perspectives under RFE selection. Average normal vector angular deviation quantifies angular variation in surface normal vectors, emphasizing topographic complexity (Ko *et al.*, 2016; Lindsay, 2023). Edge density measures the concentration of slope breaks, capturing abrupt changes in terrain (Lindsay, 2023). These variables enhance gully susceptibility modeling by identifying localized terrain variations that influence erosion processes. Among relative topographic position variables, max downslope elevation change, valley depth, and VDCN were highly significant. Max downslope elevation change identifies abrupt elevation variations, indicating areas with accelerated water flow and heightened erosion potential (Lindsay, 2023). Valley depth measures dissection relative to ridge cells, where concentrated water flow intensifies erosion. VDCN, widely used in gully susceptibility modeling, captures the relationship between groundwater emergence and surface processes. In areas where the water table is near the surface, exfiltration intensifies erosion, promoting gully development (Marinho *et al.*, 2006).

Combined topographic variables, such as the SAGA TWI and TCI low, were moderately significant in low-slope areas. SAGA TWI indicates moisture retention and saturation potential, with high values linked to soil instability and deep erosive processes (Valipour *et al.*, 2022; Wang *et al.*, 2021). TCI low integrates SAGA TWI and VDCN to identify low-slope, high-moisture areas conducive to gully formation (Bock *et al.*, 2007). The convergence index, which measures water flow concentration, was also important, amplifying erosion in susceptible areas (Chaplot, 2013).

Variables such as ksn, χ, and proximity to lithological boundaries exhibited intermediate importance. The ksn index reflects the erosive power of water, influenced by slope and contributing area, with higher values indicating greater susceptibility (Whipple *et al.*, 2022). The χ variable, used to analyze drainage divide mobility, highlighted areas with contrasting erosion rates, corresponding to boundaries of gully-prone regions (Willett *et al.*, 2014; Forte and Whipple, 2018). Proximity to lithological boundaries influences subsurface processes like piping, which destabilizes soil and promotes gully formation (Marinho *et al.*, 2006).

Proximity to road networks moderately influenced susceptibility, as poorly planned roads alter water dynamics and fragment landscapes, creating localized erosion conditions (Santana *et al.*, 2007). Lithological classes, such as the Neogene Detrital-Lateritic Cover, exhibited resistance to erosion due to their consolidated structures. Among land cover classes, savanna formations ranked within the top 20 variables, reflecting their ability to reduce runoff velocity and protect against direct rainfall impacts, mitigating initial erosive processes.

The consistent prominence of “pasture” as a predictor suggests the need for variable refinement. Current classifications may obscure internal variability, such as pasture age, degradation, and management practices, which affect soil structure and erosion. Incorporating descriptors like degradation indices or vegetation dynamics could improve model sensitivity.

Anthropogenic and microtopographic features—such as cattle paths, fences, and roadside ditches—can create preferential flow paths that influence gully initiation. However, the 30-meter DEM resolution used here precluded their explicit inclusion. Future studies should integrate high-resolution spatial data, including models derived from Unmanned Aerial Vehicles (UAVs) or manually mapped features, to better capture fine-scale flow dynamics critical to gully formation.

6. Conclusions

The results of this study confirm that incorporating less commonly explored topographic variables can enhance predictive models for gully erosion susceptibility. Variables such as multiscale roughness and terrain surface texture emerged as significant predictors, demonstrating the value of including more complex topographic characteristics in modeling erosive processes.

Among the variable selection methods evaluated, the RFE algorithm outperformed the VIF method. This is reflected in the relatively higher AUC values achieved and the identification of more relevant predictors. The RFE approach effectively captured interactions between variables while reducing redundancies, improving the efficiency and reliability of the generated models.

Surface roughness and terrain structure variables made substantial contributions to the models, highlighting the importance of surface variability in shaping erosive dynamics. The integration of data derived from DEMs with advanced machine learning methods was shown to be an effective strategy for mapping areas susceptible to gully formation.

This study emphasizes the importance of incorporating less conventional topographic variables in future research, particularly in tropical and subtropical regions where terrain and hydrological processes are highly heterogeneous. This approach enhances the accuracy of susceptibility predictions and contributes to a more in-depth understanding of the mechanisms underlying gully initiation and development.

Contributions of authors

(1) Conceptualization: LLA, ÉHC; (2) Analysis or data acquisition: LLA, FCA, ÉHC, EDN, ACP; (3) Methodologic/technical development: LLA, ACP, ÉHC; (4) Writing of the original manuscript: LLA, ÉHC, FCA; (5) Writing of the corrected and edited manuscript: LLA, ÉHC, FCA; (6) Financing: ÉHC; (7) Software: LLA, ÉHC, ACP; (8) Supervision and resources, EDN, ÉHC.

Financing

This research has not received any external funding.

Acknowledgements

ÉHC is research fellow of Brazilian National Council for Scientific and Technological Development -CNPq/Brazil (#310198/2022-4).

Conflicts of interest

The authors declare not having any conflict of interest.

Handling editor

Grace Bungenstab Alves.

References

Arabameri, A., Chen, W., Loche, M., Zhao, X., Li, Y., Lombardo, L., Cerda, A., Pradhan, B., Bui, D.T., 2020a, Comparison of machine learning models for gully erosion susceptibility mapping: Geoscience Frontiers, 11, 1609–1620. https://doi.org/10.1016/j.gsf.2019.11.009

Arabameri, A., Pradhan, B., Bui, D.T., 2020b, Spatial modelling of gully erosion in the Ardib River watershed using three statistical-based techniques: Catena, 190, 104545. https://doi.org/10.1016/j.catena.2020.104545

Arabameri, A., Pradhan, B., Rezaei, K., 2019, Gully erosion zonation mapping using integrated geographically weighted regression with certainty factor and random forest models in GIS: Journal of Environmental Management, 232, 928–942. https://doi.org/10.1016/j.jenvman.2018.11.110

Arabameri, A., Chandra-Pal, S., Costache, R., Saha, A., Rezaie, F., Seyed-Danesh, A., Pradhanh, B., Lee, S., Hoang, N.D., 2021, Prediction of gully erosion susceptibility mapping using novel ensemble machine learning algorithms: Geomatics, Natural Hazards and Risk, 12, 469–498. https://doi.org/10.1080/19475705.2021.1880977

Azareh, A., Rahmati, O., Rafiei-Sardooei, E., Sankey, J.B., Lee, S., Shahabi, H., Ahmad, B.B., 2019, Modelling gully-erosion susceptibility in a semi-arid region, Iran: Investigation of applicability of certainty factor and maximum entropy models: Science of the Total Environment, 655, 684–696. https://doi.org/10.1016/j.scitotenv.2018.11.235

Bielski, C., López-Vázquez, C., Grohmann, C.H., Guth, P.L., Hawker, L., Gesch, D., Trevisani, S., Herrera-Cruz, V., Riazanoff, S., Corseaux, A., Reuter, H.I., Strobl, P., 2024, Novel approach for ranking DEMs: Copernicus DEM improves one arc second open global topography: IEEE Transactions on Geoscience and Remote Sensing, 62, 1–22. https://doi.org/10.1109/TGRS.2024.3368015

Boardman, J., Parsons, A. J., Holland, R., Holmes, P. J., Washington, R., 2003, Development of badlands and gullies in the Sneeuberg, Great Karoo, South Africa: Catena, 50, 165–184 . https://doi.org/10.1016/S0341-8162(02)00144-3

Bock, M., Boehner, J., Conrad, O., Koethe, R., Ringeler, A., 2007, Methods for creating functional soil databases and applying digital soil mapping with SAGA GIS, in Hengl, T., Panagos, P., Jones, A., Toth, G. (eds.), Status and prospect of soil information in South-Eastern Europe: Soil databases, projects and applications: Luxembourg, Office for Official Publications of the European Communities, 149–162.

Bouramtane, T., Hilal, H., Rezende-Filho, A.T., Bouramtane, K., Barbiero, L., Abraham, S., Valles, V., Kacimi, I., Sanhaji, H., Torres-Rondon, L., de Castro, D.D., Vieira Santos, J.d.C., Ouardi, J., Beqqali, O.E., Kassou, N., Morarech, M., 2022, Mapping gully erosion variability and susceptibility using remote sensing, multivariate statistical analysis, and machine learning in South Mato Grosso, Brazil: Geosciences, 12, 235. https://doi.org/10.3390/geosciences12060235

Breiman, L., 2001, Random forests: Machine Learning, 45, 5–32. https://doi.org/10.1023/A:1010933404324

Carvalho, H.S.M., Castro, S.S., 2023, Mapeamento e identificação de áreas críticas à erosão hídrica linear: O exemplo do bioma Cerrado no estado de Goiás, Brasil: Revista Brasileira de Geomorfologia, 24(00), 1–30. https://doi.org/10.20502/rbgeomorfologia.v24i00.2373

Chaplot, V., 2013, Impact of terrain attributes, parent material and soil types on gully erosion: Geomorphology, 186, 1–11. https://doi.org/10.1016/j.geomorph.2012.10.031

Conrad, O., Bechtel, B., Bock, M., Dietrich, H., Fischer, E., Gerlitz, L., Wehberg, J., Wichmann, V., Böhner, J., 2015, System for automated geoscientific analyses (SAGA) v. 2.1.4: Geoscientific Model Development, 8, 1991–2007. https://doi.org/10.5194/gmd-8-1991-2015

Cremon, É.H., Bettiol, G.M., Júnior, J.P.M., Macedo, F.C., 2022, Avaliação da altimetria do MDE COP-30 no Centro-Oeste do Brasil: Revista Brasileira de Cartografia, 74, 536–546. https://doi.org/10.14393/rbcv74n3-60846

Cremon, É.H., Pereira, A.C., Paula, L.D.L., Nunes, E.D., 2021, Geological and terrain attributes for predicting soil classes using pixel- and geographic object-based image analysis in the Brazilian Cerrado: Geoderma, 401, 115315. https://doi.org/10.1016/j.geoderma.2021.115315

De-Geeter, S., Verstraeten, G., Poesen, J., Campforts, B., Vanmaercke, M., 2023, A data driven gully head susceptibility map of Africa at 30 m resolution: Environmental

Research, 224, 115573. https://doi.org/10.1016/j.envres.2023.115573

Food and Agriculture Organization (FAO), 2015, Status of the World's Soil Resources: Rome, ITPSIntergovernmental Technical Panel on Soils, 650 p.

Florinsky, I., 2016, Digital Terrain Analysis in Soil Science and Geology: San Diego, Academic Press, 379 p. https://doi.org/10.1016/C2010-0-65718-X

Forte, A.M., Whipple, K.X., 2018, Criteria and tools for determining drainage divide stability: Earth and Planetary Science Letters, 493, 102–117. https://doi.org/10.1016/j.epsl.2018.04.026

Forte, A.M., Whipple, K.X., 2019, The topographic analysis kit (TAK) for TopoToolbox: Earth Surface Dynamics, 7, 1, 87–95. https://doi.org/10.5194/esurf-7-87-2019

Galdino, S., Sano, E.E., Andrade, R.G., Grego, C.R., Nogueira, S.F., Bragantini, C., Flosi, A. H.G., 2016, Large-scale modeling of soil erosion with RUSLE for conservationist planning of degraded cultivated Brazilian pastures: Land Degradation & Development, 27, 3, 773–784. https://doi.org/10.1002/ldr.2414

Gournellos, T., Evelpidou, N., Vassilopoulos, A., 2004, Developing an erosion risk map using soft computing methods (case study at Sifnos Island): Natural Hazards, 31, 63–83. https://doi.org/10.1023/B:NHAZ.0000020277.28291.06

GRASS Development Team, 2024, Geographic Resources Analysis Support System (GRASS GIS) Software, Version 8.4., available at <https://grass.osgeo.org>.

Hasanuzzaman, M., Shit, P., 2025, Assessment of gully erosion susceptibility using four data-driven models AHP, FR, RF and XGBoosting machine learning algorithms: Natural Hazards Research, 1, 36–47. https://doi.org/10.1016/j.nhres.2024.05.001

Hawker, L., Uhe, P., Paulo, L., Sosa, J., Savage, J., Sampson, C., Neal, J., 2022, A 30 m global map of elevation with forests and buildings removed: Environmental Research Letters, 17, 2, 024016. https://doi.org/10.1088/1748-9326/ac4d4f

Hijmans, R.J., 2024, Terra: Spatial Data Analysis. R package version 1.8-2, available at <https://github.com/rspatial/terra> accessed on November 28, 2024.

Hosseinalizadeh, M., Kariminejad, N., Chen, W., Pourghasemi, H.R., Alinejad, M., Behbahani, A.M., Tiefenbacher, J.P., 2019, Gully headcut susceptibility modeling using functional trees, naïve Bayes tree, and random forest models: Geoderma, 342, 1–11. https://doi.org/10.1016/j.geoderma.2019.01.050

Huggett, R., Shuttleworth, E., 2022, Fundamentals of geomorphology: London, Routledge, 538 p. https://doi.org/10.4324/9781003251156

Instituto Brasileiro de Geografia e Estatística (IBGE), 2023, Banco de Dados e Informações Ambientais (BDiA): Mapeamento de Recursos Naturais (MRN), escala 1:250,000: Rio de Janeiro, IBGE, nota metodológica, 64 p.

Iwahashi, J., Pike, R.J., 2007, Automated classifications of topography from DEMs by an unsupervised nested-means algorithm and a three-part geometric signature: Geomorphology, 86, 409–440. https://doi.org/10.1016/j.geomorph.2006.09.012

Jones, R., 2002, Algorithms for using a DEM for mapping catchment areas of stream sediment samples: Computers & Geosciences, 28, 9, 1051–1060. https://doi.org/10.1016/S0098-3004(02)00022-5

Ko, M., Kang, H., Kim, J.U., Lee, Y., Hwang, J.E., 2016, How to measure quality of affordable 3D printing: Cultivating quantitative index in the user community, in Stephanidis, C. (ed.), HCI International 2016 – Posters' Extended Abstracts: Cham, Springer International Publishing, 116–121. https://doi.org/10.1007/978-3-319-40548-3_19

Kuhn, M., Johnson, K., 2013, Applied Predictive Modeling: New York, Springer, 600 p. https://doi.org/10.1007/978-1-4614-6849-3

http://dx.doi.org/10.18268/BSGM2025v77n3a121025

Lana, J.C., Castro, P.D.T.A., Lana, C.E., 2022, Assessing gully erosion susceptibility and its conditioning factors in southeastern Brazil using machine learning algorithms and bivariate statistical methods: A regional approach: Geomorphology, 402, 108159. https://doi.org/10.1016/j.geomorph.2022.108159

Lindsay, J.B., 2016, Whitebox GAT: A case study in geomorphometric analysis: Computers & Geosciences, 95, 75–84. https://doi.org/10.1016/j.cageo.2016.07.003

Lindsay, J.B., 2023, WhiteboxTools User Manual: Guelph, Canada, Whitebox Geospatial Inc.: Guelph, Canada, University of Guelph, available at <https://www.whiteboxgeo.com/manual/wbt_book/>, accessed on November 28, 2024.

Marinho, G.V., Castro, S.S., Campos, A.B., 2006, Hydrology and gully processes in the upper Araguaia River Basin, Central Brazil: Zeitschrift für Geomorphologie, 145, 119–145.

Marques-Filho, J.d.P., TexGuerra, A.J.T., Cruz, C.B.M., Jorge, M.D.C.O., Booth, C.A., 2024, Machine learning models for the spatial prediction of gully erosion susceptibility in the Piraí Drainage Basin, Paraíba Do Sul Middle Valley, Southeast Brazil: Land, 13, 10, 1665. https://doi.org/10.3390/land13101665

Mohebzadeh, H., Biswas, A., Rudra, R., Daggupati, P., 2022, Machine learning techniques for gully erosion susceptibility mapping: A review: Geosciences, 12(12), 429. https://doi.org/10.3390/geosciences12120429

Nunes, E.D., Castro, S.S., 2015, Compartimentação morfopedológica aplicada à distribuição de padrões espaciais de processos erosivos em solos frágeis – município de Mineiros, GO, in Castro, S.S., Hernani, L.C. (eds.), Solos frágeis: Caracterização, manejo e sustentabilidade: Brasília, Embrapa, 293–324.

Nunes, E.D., Castro, S.S., 2023, Análise multiescalar aplicada à avaliação de erosão hídrica linear para área tropical subúmida situada na região sudoeste do estado de Goiás-Brasil: Revista Brasileira de Geomorfologia, 24(00). https://doi.org/10.20502/rbgeomorfologia.v24i00.2368

O'Callaghan, J.F., Mark, D. M., 1984, The extraction of drainage networks from digital elevation data: Computer Vision, Graphics, and Image Processing, 28(3), 323–344. https://doi.org/10.1016/S0734-189X(84)80011-0

Panagos, P., Borrelli, P., Meusburger, K., Yu, B., Klik, A., Lim, K.J., Yang, J.E., Ni, J., Miao, C., Chattopadhyay, N., Sadeghi, S.H., Hazbavi, Z., Zabihi, M., Larionov, G.A., Krasnov, S.F, Gorobets, A.V., Levi, Y., Erpul, G., Birkel, C., Hoyos, N., Naipal, V., Oliveira, T.S., Bonilla, C.A., Meddi, M., Nel, W., Al-Dashti, H., Boni, M., Diodato, N., Van-Oost, K., Nearing, M., Ballabio, C., 2017, Global rainfall erosivity assessment based on high-temporal resolution rainfall records: Scientific Reports, 7, 4175. https://doi.org/10.1038/s41598-017-04282-8

Pereira, A.C., Cremon, É.H., Abreu, L.L., Carvalho, H.S.M., 2025, Avaliação de variáveis críticas para a ocorrência de erosões lineares utilizando algoritmos de aprendizado de máquina, in Gomes, R.A., Mendes, T.A., Oliveira, S.B. (eds.), Inovação e Sustentabilidade em Goiás: Perspectivas Interdisciplinares: Curitiba, Editora CRV, 29–46. https://doi.org/10.24824/978652517324.5

Pike, R.J., Evans, I.S., Hengl, T., 2009, Geomorphometry: A Brief Guide, in Hengl, T., Reuter, H.I. (eds.), Geomorphometry: Concepts, Software, Applications: Amsterdam, Elsevier, 3–30. https://doi.org/10.1016/S0166-2481(08)00001-9

Poesen, J., Nachtergaele, J., Verstraeten, G., Valentin, C., 2003, Gully erosion and environmental change: importance and research needs: Catena, 50, 91–133. https://doi.org/10.1016/S0341-8162(02)00143-1

Purinton, B., Bookhagen, B., 2021, Beyond vertical point accuracy: Assessing inter-pixel consistency in 30 m global DEMs for the arid Central Andes: Frontiers in Earth Science, 9, 758606. https://doi.org/10.3389/feart.2021.758606

QGIS Development Team, 2024, QGIS Geographic Information System: Open Source Geospatial Foundation Project, available at <https://qgis.org>, accessed on November 28, 2024.

Rosim, S., Monteiro, A.M.V., Rennó, C.D., Oliveira, J.R.F., 2011, Terrahydro – A distributed hydrological system using graph structure for unified water flow representation, in IEEE International Geoscience and Remote Sensing Symposium: Vancouver, Canada, IEEE,. 4192–4195. https://doi.org/10.1109/IGARSS.2011.6050154

Santana, N.M.P., Castro, S.S., Stone, L.F., Silva, S.C., 2007, Chuvas, erosividade, erodibilidade, uso do solo e suas relações com focos erosivos lineares na alta bacia do rio Araguaia: Sociedade & Natureza, 19, 103–121. https://doi.org/10.1590/S1982-45132007000200007

Santos, H.G., Jacomine, P.K.T., Anjos, L.H.C., Oliveira, V.A., Lumbreras, J F., Coelho, M.R., Almeida, J.A., Filho, J.C.A., Oliveira, J.B., Cunha, T.J.F., 2018, Brazilian Soil Classification System: Brasília, Embrapa, 356 p.

Shit, P.K., Paira, R., Bhunia, G., Maiti, R., 2015, Modeling of potential gully erosion hazard using geo-spatial technology at Garbheta Block, West Bengal in India: Modeling Earth Systems and Environment, 1, 1–16. https://doi.org/10.1007/s40808-015-0001-x

Torri, D., Poesen, J., 2014, A review of topographic threshold conditions for gully head development in different environments: Earth-Science Reviews, 130, 73–85. https://doi.org/10.1016/j.earscirev.2013.12.006

Trevisani, S., Teza, G., Guth, P.L., 2023, Hacking the topographic ruggedness index: Geomorphology, 439, 108838. https://doi.org/10.1016/j.geomorph.2023.108838

Valentin, C., Poesen, J., Li, Y., 2005, Gully erosion: Impacts, factors, and control: Catena, 63, , 132–153. https://doi.org/10.1016/j.catena.2005.06.001

Valeriano, M.M., Albuquerque, P.C.G., 2010, TOPODATA: Processamento dos dados SRTM: São José dos Campos, Instituto Nacional de Pesquisas Espaciais (INPE), 79 p., available at <http://urlib.net/ibi/8JMKD3MGP7W/37FCH9B>, accessed on November 28, 2024.

Valipour, M., Mohseni, N., Hosseinzadeh, S.R., 2022, Factors affecting topographic thresholds in gully erosion occurrence and its management using predictive machine learning models: Earth Sciences Research Journal, 25, 423–432. https://doi.org/10.15446/esrj.v25n4.95748

Wang, F., Sahana, M., Pahlevanzadeh, B., Pal, S.C., Shit, P.K., Piran, M.J., Janizadeh, S., Band, S.S., Mosavi, A., 2021, Applying different resampling strategies in machine learning models to predict head-cut gully erosion susceptibility: Alexandria Engineering Journal, 60, 5813–5829. https://doi.org/10.1016/j.aej.2021.04.026

Whipple, K.X., DiBiase, R.A., Crosby, B., Johnson, J.P.L., 2022, Bedrock rivers, in Shroder, J.F. (ed.), Treatise on Geomorphology (Second edition): Oxford, Academic Press, 865–903. https://doi.org/10.1016/B978-0-12-818234-5.00101-2

Willett, S.D., McCoy, S.W., Perron, J.T., Goren, L., Chen, C.-Y., 2014, Dynamic reorganization of river basins: Science, 343, 1248765. https://doi.org/10.1126/science.1248765

Yang, A., Wang, C., Pang, G., Long, Y., Wang, L., Cruse, R.M., Yang, Q., 2021, Gully erosion susceptibility mapping in highly complex terrain using machine learning models: ISPRS International Journal of Geo-Information, 10, 680. https://doi.org/10.3390/ijgi10100680

Zhang, D., Tsai, J.J.P., 2006, Advances in machine learning applications in software engineering: Hershey, IGI Global Scientific Publishing, 350 p. https://doi.org/10.4018/978-1-59140-941-0