sustainability

MDPI

Article

Assessing Soil Erosion Susceptibility in a Tropical Landscape: Insights from a Brazilian Case Study

João Vitor Roque Guerrero [1,*], Elton Vicente Escobar-Silva [2], Cláudia Maria de Almeida [3], Cintia Campos [4], José Augusto Di Lollo [5], Alberto Gomes [6] and Fabrizia Gioppo Nunes [1]

[1] Institute of Socio-Environmental Studies, Federal University of Goiás (UFG), Goiânia 74690-900, GO, Brazil; fabrizia@ufg.br
[2] National Center for Monitoring and Early Warning of Natural Disasters (Cemaden), São José dos Campos 12247-016, SP, Brazil; eltescobar@gmail.com
[3] Earth Observation and Geoinformatics Division, National Institute for Space Research (INPE), São José dos Campos 12227-010, SP, Brazil; claudia.almeida@inpe.br
[4] Faculty of Science and Technology, Federal University of Goiás (UFG), Goiânia 74971-451, GO, Brazil; cintiacampos@ufg.br
[5] Ilha Solteira College of Engineering, São Paulo State University, Ilha Solteira 15385-000, SP, Brazil; jose.lollo@unesp.br
[6] CEGOT—Centre of Studies in Geography and Spatial Planning, Faculty of Arts and Humanities of Porto, University of Porto, Via Panorâmica s/n, 4150-564 Porto, Portugal; atgomes@letras.up.pt
* Correspondence: jvguerrero2@gmail.com

Abstract

Soil is a strategic resource essential for maintaining ecosystem services, an initiative closely linked to a country's stage of development. In this sense, urgent strategies are required to mitigate the impacts of climate change on soil systems. This study aimed to assess the susceptibility to soil erosion as a means to support sustainable land-use planning in the municipality of Anápolis, presenting a highly disturbed landscape in Brazil. To achieve this, we applied the Information Value (IV) technique—a Bayesian statistical method based on frequency analysis—which quantifies the influence of various geoenvironmental factors on the probability of erosion occurrence by statistically evaluating their relationship with past erosion events. The results showed that approximately 50% of the municipality is highly susceptible to erosion, and for this reason, these areas should be prioritized by public authorities. The proposed geoenvironmental model demonstrated a satisfactory accuracy (~80%), confirming its effectiveness as a tool to enhance soil resilience.

Keywords: soil erosion; information value; susceptibility; landscape planning; GIS

Check for updates

Academic Editors: Slobodan B. Mickovski, Olavo F. Santos, Jr., Alejandro Gonzalez-Ollauri and Jovan Br. Papić

Received: 15 September 2025
Revised: 22 January 2026
Accepted: 4 February 2026
Published: 12 February 2026

1. Introduction

Growing global pressures from climate change and unsustainable land-use changes have heightened concerns about soil degradation, underscoring soil's role as one of the most critical natural resources supporting human activities [1]. Among the various forms of land degradation, soil erosion stands out as a major environmental threat, resulting in severe impacts such as the loss of arable land, disruption of ecosystem services, and severe socio-economic damages [2,3]. This process directly compromises the ability of ecosystems to provide essential services, including food production, regulation of water and carbon cycles, and biodiversity conservation, ultimately jeopardizing long-term sustainability efforts [4].

Soil erosion results from an imbalance in the interactions between climate, soil properties, and land use, leading to the progressive removal of soil layers [5]. Although erosion is a natural process, human activities substantially accelerate its rate, rendering landscapes increasingly vulnerable to degradation [2]. Projections suggest that global soil erosion rates will continue to rise due to climate change, particularly in response to more intense precipitation events associated with the intensification of the hydrological cycle in a warming atmosphere [6,7]. Recognizing the urgency of addressing soil erosion, the United Nations has included combating land degradation and promoting sustainable land use in Sustainable Development Goal 15 of the 2030 Agenda [8]. Target 3 of this goal has as its aims to combat desertification, restore degraded land and soil, including land affected by desertification, drought and floods, and strive to achieve a land degradation-neutral world by 2030, focusing on ending desertification and restoring degraded lands to achieve a balanced world regarding land use.

The impacts of climate change on soil erosion affect both terrestrial and aquatic ecosystems [9]. In the case of the former ones, impacts regard the enhancement of drought risks, leading to further erosion and desertification, as well as habitat disruption and biodiversity loss, which causes the destruction of micro-organisms that are vital for nutrient cycling and soil health. As to aquatic ecosystems, the threats to be mentioned are sediment pollution, habitat smothering, eutrophication, chemical contamination, and increased flood risk [10]. At a higher scale level, soil erosion can cause air pollution, given that suspended fine soil particles in the air may create dust storms [11], and also impacts the carbon cycle, for a healthy soil is a massive carbon sink [12].

Brazil is particularly vulnerable to soil erosion impacts. The country's trade balance strongly relies on agricultural exports, a fact that keeps pushing forward agricultural frontiers into previously forested areas [13]. Nowadays, the current rate of such expansion contributes to an estimated 800 million tons of annual soil loss, a figure likely to increase if deforestation-driven agricultural activities continue in sensitive biomes such as the Cerrado and the Amazon [14]. This scenario emphasizes the importance of adopting technical and scientific approaches to enhance soil resilience and assessing soil susceptibility to erosion, while preserving essential ecosystem services. These can be categorized into: (i) provisioning services, which assure food production, forage for livestock, freshwater supply, and the protection of biomass/genetic resources; (ii) regulating services, which promote flood control, water quality, and climate regulation, this latter through carbon sequestration; (iii) cultural services, that protect aesthetic values of landscapes as well as heritage sites and assets, and finally (iv) supporting services, that prevent soil loss, maintain nutrient cycling, sustain primary production, and preserve below-ground biodiversity [4,15].

According to [16], soil resilience is defined as the ability of this resource to tolerate disturbances without changing to an alternative configuration. This is important for maintaining desired ecosystem functions, especially in a scenario where climate variability and land use practices impose frequent and sudden threats. From a geoscientific perspective, effective territorial management relies on systematic analyses and the integration of environmental and socio-economic data to support sustainable landscape planning [17] primarily through the assessment of the landscape's susceptibility to erosion. Recent advances in geospatial technologies have considerably improved the ability to assess environmental hazards, with Geographic Information Systems (GIS) playing a significant role in processing multi-source geographic data and integrating mathematical models for geoenvironmental analyses [18–22].

Several works in the literature are committed to producing erosion susceptibility maps with varied approaches, ranging from simple maps algebra and multicriteria evaluation

https://doi.org/10.3390/su18041878

analyses to machine and deep learning (ML/DL) algorithms. These studies encompass diverse sets of input factors and were accomplished throughout the world, in regions belonging to Europe, Middle East, Asia, and North and South America, and the set of critical variables greatly differ from one another [23–29]. A couple of studies leveraged the parameters of the Universal Soil Loss Equation (USLE) and its variations for identifying erosion-prone areas [26,30–33]. The USLE parameters have been explored either independently, as in [31], or integrated with other geoenvironmental variables [26,32,33]. Physical and climatic characteristics, like soil texture, elevation, slope, lithology, the Normalized Difference Vegetation Index (NDVI), and the average and cumulative annual precipitation, were also considered in the study of [32].

In Brazil, studies dedicated to investigating erosion susceptibility rely on distinct methods and were applied to different regions [34]. Some of them made use of simple though effective approaches, like multicriteria evaluation (MCE) [35,36]. In the latter work, the authors sought to understand how climate change and land use have affected susceptibility to erosion in the central-eastern region of São Paulo State, southeastern Brazil, over the past few decades. They concluded that slope and soil types were the most sensitive factors; however, changes in land use, in particular, increased land cultivation and its expansion showed to be highly susceptible to erosion.

Among the various modeling techniques used for susceptibility mapping, the Information Value (IV) is to be mentioned for it has gained prominence due to its efficiency, ease of application, besides its capability to produce reliable results [37,38]. The IV method assigns statistical weights to explanatory variables based on the spatial distribution of known erosion events, enabling the identification of erosion-prone areas through the integration of key conditioning factors, including soil type, slope, land use, and topographic patterns [14,39]. This method was thus chosen for its capacity to deliver systematic and reproducible susceptibility assessments while minimizing subjectivity in the analysis.

In most of the previously reported cases in the literature, the methods tend to be conceptually complex and data-intensive, sometimes demanding data not easily accessible or readily available for driving an analysis in a GIS. This paper is committed to introducing instead an operational method relying on open-access data and free software, aimed to assess soil erosion susceptibility to gullies and, consequently, provide subsidies for future investigations of soil resilience to climate change within a highly disturbed environment. By integrating GIS and statistical modeling, this study contributes to the development of spatially explicit tools to support sustainable land management and erosion mitigation strategies.

2. Materials and Method

2.1. Study Area

The municipality of Anápolis is located in the Brazilian Cerrado, a biome originally vulnerable with respect to climatic conditions, regardless of climate change, in face of its well-defined seasons, marked by intense droughts during the dry season and heavy rainfalls during the rainy season [40].

Anápolis is a central-western Brazilian municipality, located 60 km away from Goiânia (the capital of Goiás State) and 154 km away from Brasília, the national capital, situated within the Federal District (Distrito Federal—DF) (Figure 1). It shelters a population of 398,869 inhabitants and extends over a surface of 935.672 km^2, of which 103.35 km^2 are urbanized—being ranked as the 41st municipality with the largest urbanized area in Brazil [41]. The municipality, according to the Köppen-Geiger climate classification, has a tropical savanna climate, type 'Aw'—tropical with a dry season in winter, with an average annual temperature of 22.5 °C, with average minimum and maximum temperature oscillating between 18 °C and 28 °C, and average annual rainfall of 1553 mm [41].

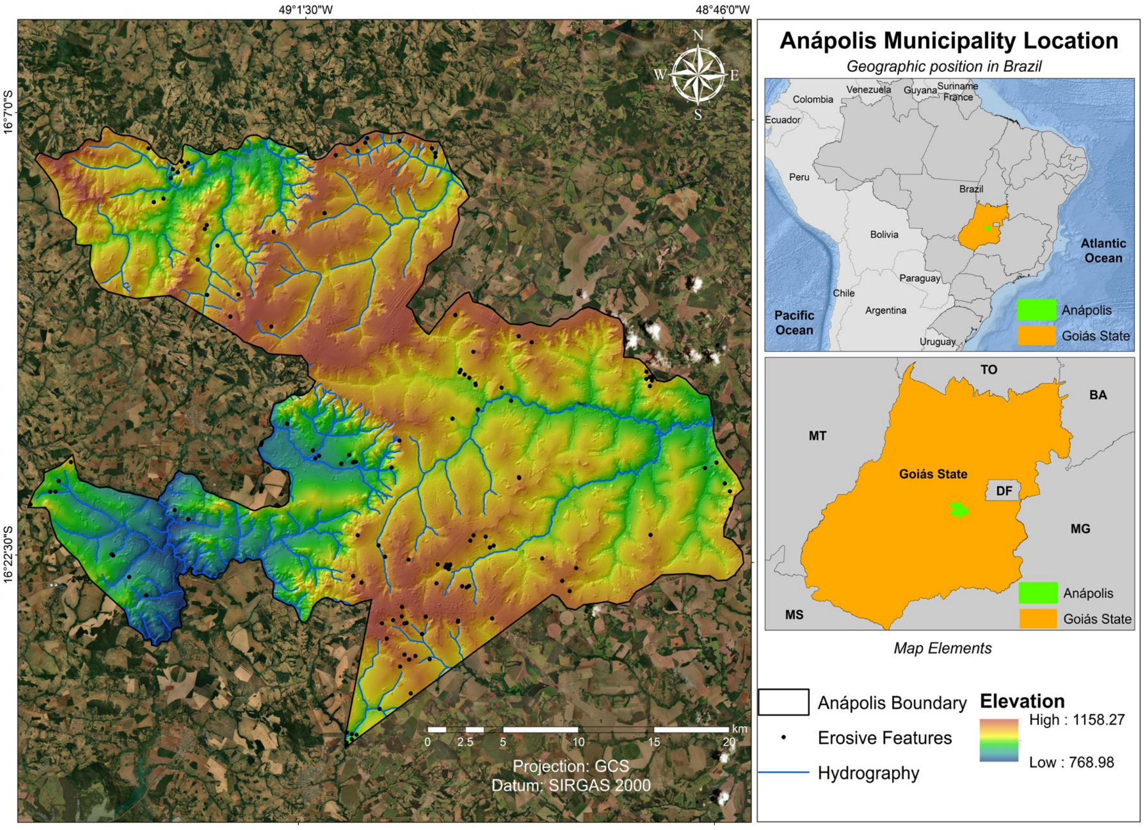

Figure 1. Location of the study area: the municipality of Anápolis, GO, Brazil. Source: Adapted from [42].

At a geomorphological macroscale, the municipality is found in the morphostructural domain of the Neoproterozoic Mobile Belts, characterized by extensive areas represented by plateaus, mountain alignments, and interplateau depressions developed in folded and faulted terrains, mainly comprising metamorphic rocks and associated granitoids [43]. The geological substrate of Anápolis is primarily composed of Neosols and Latosols, reflecting both the relief and underlying geology of the region. Metasedimentary and sedimentary rocks are predominant throughout the area. On a more localized scale, the relief is marked by plateaus and broad valleys, along with lower, flatter areas resembling river terraces [44], with elevations ranging from 722 m to 1153 m.

The data produced and made available by [45] demonstrate that 65% of the territory of Anápolis is covered by agricultural activities, mainly related to soybean cultivation and pastures, while only 21% of the territory is composed of forests. According to [46], the central plateau region of Brazil has undergone an intensive process of agricultural mechanization, often without consideration for the soil's susceptibility to erosion. As a result of unplanned land occupation, areas such as Anápolis have experienced severe soil erosion over the past two decades. This degradation is particularly evident in the northern and western sectors, where the edges of the plateaus are being heavily eroded due to the pronounced headward retreat of watercourse springs (Figure 1).

The municipality of Anápolis was selected due to its local and national peculiarities. At a local level, it is characterized by an intrinsic climate vulnerability as previously exposed, a fact that is aggravated by the considerable pressure exerted by agricultural activities on its landscapes. At a national level, it is worth mentioning its inclusion in the monitoring network of the National Center for Monitoring and Early Warning of Natural Disasters (Cemaden), under the National Plan for Risk Management and Disaster Response. This is due to the presence of areas at risk for both hydrological and geological hazards [47]. Furthermore, Anápolis is located within the Cerrado Biome, which is in absolute terms the most deforested Brazilian ecosystem, and has contributed substantially to climate change and reduced biodiversity, consequently threatening soil stability and fertility [48].

2.2. Methodological Development

The methodological procedures of this study were divided into three main stages: (i) the inventory of erosive processes; (ii) the acquisition of geoenvironmental data; and (iii) the mapping of vulnerability to soil erosion, using the IV method (Figure 2).

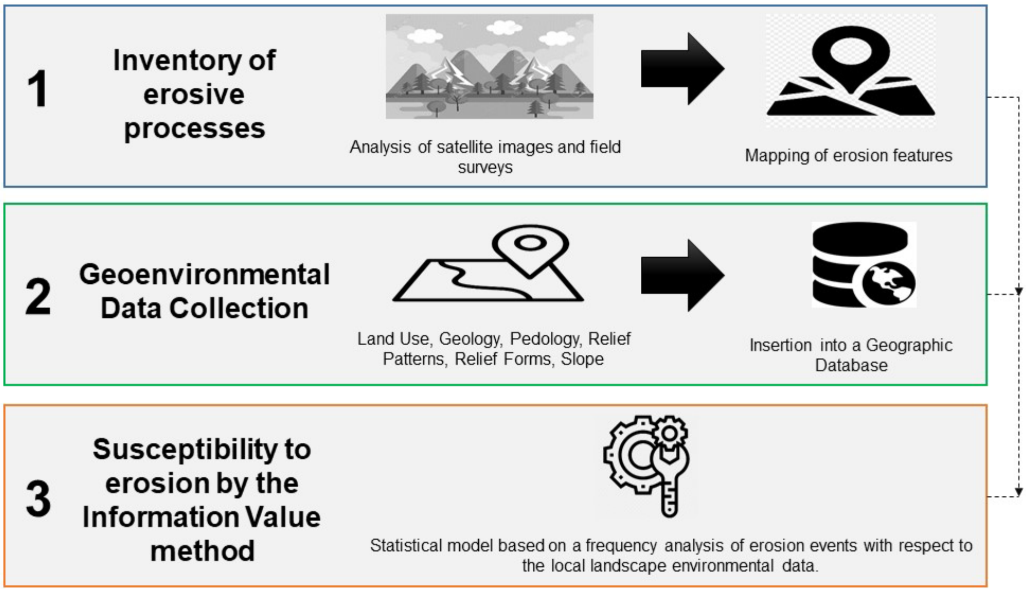

Figure 2. Methodological procedures applied in this study.

2.2.1. Inventory of Erosive Processes

The IV method used to analyze susceptibility to soil erosion in this study is based on the occurrence frequency of such phenomenon. Erosion features (gullies, ravines, and rills) were mapped through the interpretation of remote sensing data, using high spatial resolution images from [42], complemented by qualitative field inspection. A total of 190 erosion events were assessed. Figure 3 illustrates some examples of the identified soil erosion features.

2.2.2. Geoenvironmental Data Collection

To identify the most relevant factors favoring the occurrence of erosion processes in landscapes with geographic physiognomies similar to those of the study area, a bibliographic review was conducted. Based on the studies of [49–53], five key factors were identified as most decisive in triggering erosion: terrain forms, relief patterns, pedology, slope, and land use. Accordingly, these variables were selected to compose the geoenvironmental dataset, as detailed in Table 1, along with their respective sources and acquisition dates.

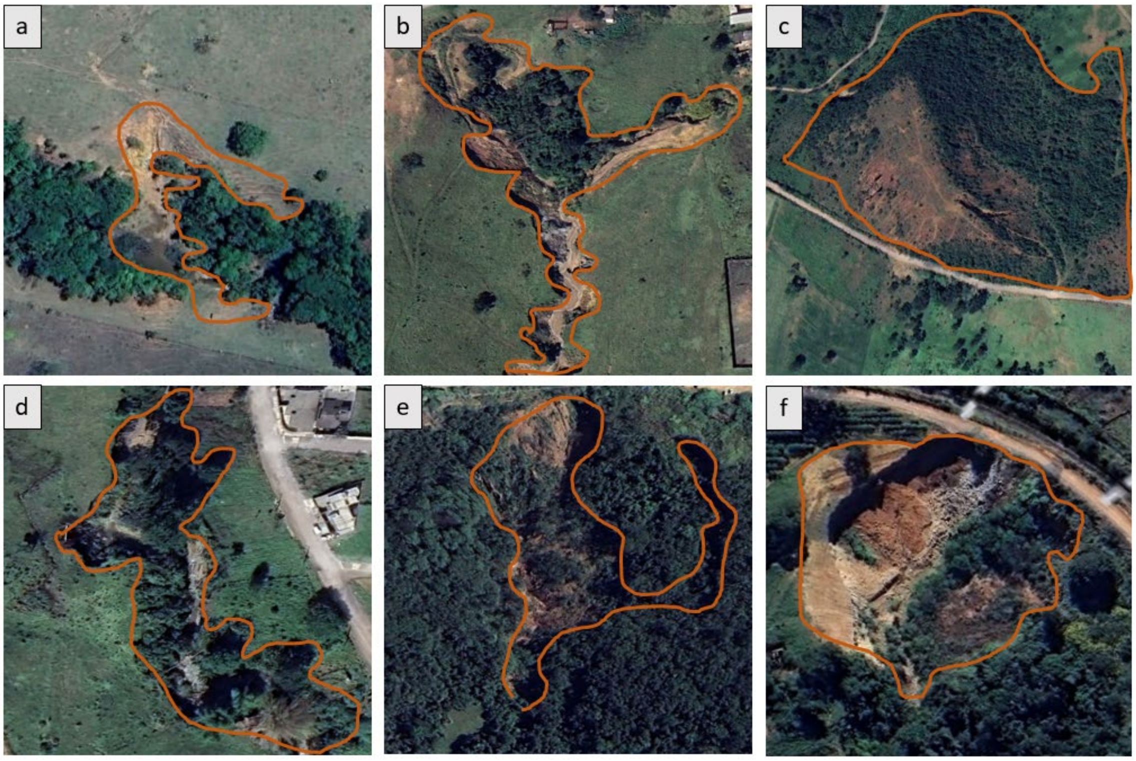

Figure 3. Examples of soil erosion features in the study area, with borders highlighted in orange. (**a**) Furrow next to a river; (**b**) Gully in a drainage head; (**c**) Furrow and ravine near a road; (**d**) Gully in an urban area; (**e**) Gully of large proportions on a steep slope; (**f**) Gully in a rural property. Some vegetated areas were subject to subsidence, and hence, are included within the erosion processes boundaries. Source: Adapted from [42].

Table 1. Dates and sources of the dataset used in this study.

Data	Source	Spatial Resolution (m)	Year
Terrain Forms	[54]	30	2008
Relief Patterns	[44]	30	2024
Pedology	[55]	30	2023
Slope (from SRTM DEM) *	[56]	30	2011
Land Use	[45]	30	2024

* Shuttle Radar Toography Mission Digital Elevation Model.

2.2.3. Susceptibility to Soil Erosion Assessed by the Information Value (IV) Method

Susceptibility is the spatial probability of occurrence of a certain phenomenon in a given area, considering the conditioning factors existing in the territory [37]. Thus, mapping susceptibility to gully erosion corresponds to a spatial delimitation of areas with the greatest probability of soil loss by gully erosion [57].

In this study, the mapping of susceptibility to erosion was executed with the IV method, originally proposed by [58] to evaluate susceptibility to landslides. This method refers to a Bayesian statistical approach based on frequency analysis, where a score is assigned to each independent variable (classes of conditioning factors relevant to the erosive process) as a function of the dependent variable (samples of erosive processes mapped according to an inventory). IV was chosen in view of its benefits, like the fact that it relies on historical evidence rather than expert opinion, eliminating human bias; it is easier to compute and interpret compared to complex machine learning “black boxes”; handles well heterogeneous data, allowing to easily compare the influence of a discrete factor (e.g., lithology) with a continuous one (e.g., slope) on the same numerical scale;

works well for regional assessments where detailed physical parameters (like soil cohesion) are unavailable; besides being resilient to messy or missing real-world data.

The occurrence frequency of erosion processes in each class defines the relative importance of each independent variable. Thus, for each of the classes of each variable, the respective IV is determined based on the elaboration of binary matrices that reflect the spatial correlation between the classes of variables of interest and 130 erosion samples used in the analysis, according to Equation (1):

$$l_i = log\,\frac{S_i/N_i}{S/N}, \tag{1}$$

where l_i is the IV of variable i, S_i represents the number of terrain units with movements of type y and with the presence of the variable X_i, N_i is the number of land units with the presence of the variable X_i, S is the total number of terrain units with y-type movements, and N is the total number of land units.

The total IV of the analyzed area is determined by the sum of the IV of the independent variables, according to Equation (2).

$$total\ l_i = \sum_{t=1}^{m} X_{ji}\ l_i, \tag{2}$$

where m is the number of variables, X_{ji} is equal to 0 or 1 whether the variable is present or not in pixel j, respectively.

When the value of l_i is negative, the analyzed variable is not decisive for erosion. On the other hand, positive values reveal a decisive relationship between the variable and the occurrence of erosive processes, where the more critical the instability, the greater the resulting value. Thus, the susceptibility to erosion varies directly on the basis of the respective total IV (l_i) [59]. The IV method relies on some assumptions. Initially, the model assumes that the target variable is binary (e.g., classes like "events" and "non-events"), and all continuous variables must be discretized. Each variable range must have non-zero counts for both "events" (class 1) and "non-events" (class 0) of the dependent variable. It also assumes that each predictor variable's relationship with the outcome is independent of other variables, allowing for the isolation of their effect [60].

Another important aspect of IV concerns the fact that it is calculated on a variable-by-variable basis. In other words, it assesses the strength of each individual feature in predicting the target without considering its correlation or interaction with other predictor variables. A monotonic relationship between the predictor variables and the probability of the outcome is as well assumed, meaning as the value of the predictor increases, the probability of the outcome either consistently increases or decreases. Finally, a sufficient amount of data is necessary for reliable estimation of IV to ensure accurate evaluation of the variables predictive power [61].

The study by [37] states that the class division method that obtains the best results for creating the final erosion susceptibility map is based on the geometry breaks applied to the success curve. After obtaining the range of IVs for the entire study area, we validated the model using the area under the curve (AUC) method, considering both the success and prediction curves [62], a statistical technique widely used in geosciences, mainly to evaluate the accuracy of predictive models for the occurrence of geological events. This approach aims not only to verify the quality of the model but also to analyze the success curve geometry breaks and support class division for the final map.

The success curve is based on the spatial comparison between the susceptibility classes and the 130 erosion samples used to generate the susceptibility map, and represents the model's internal efficiency rate. Based on the analysis of the success curve, the AUC method [62,63] aims to characterize the model's ability to correctly anticipate the occurrence of predefined events, as indicated in Equation (3).

$$\sum_{i=1}^{n} (l_{si} - l_i) \times \frac{a_i + b_{i,}}{2} \tag{3}$$

where $l_{si} - l_i$ is the class amplitude, a_i is the value of the corresponding ordinate (l_i), and b_i is the value of the ordinate corresponding to l_{si}.

In addition to the success curve, we constructed a prediction curve to evaluate the model's predictive capability using an independent dataset. For this end, 60 erosion samples were separated prior to the modeling process and were not used in the computation of the information value (IV). The prediction curve is obtained by comparing these independent occurrences with the susceptibility classes, following the same cumulative logic applied in the success curve. This procedure allows assessing the model's generalization capacity, that is, its effectiveness in identifying erosion-prone areas not previously used in calibration. Higher AUC values in the prediction curve indicate a stronger correspondence between predicted susceptibility levels and independently observed erosion features. Together, the success and prediction curves provide complementary insights, allowing the evaluation of both internal consistency and external predictive performance of the susceptibility model.

3. Results

3.1. Accuracy Performance

The AUC analysis for the success curve (Figure 4) indicated that the success rate obtained by the model was 0.79, a value that indicates that the model is reliable for analyzing susceptibility to erosion, mainly because we have worked with coarse data, within the 30-m spatial resolution range.

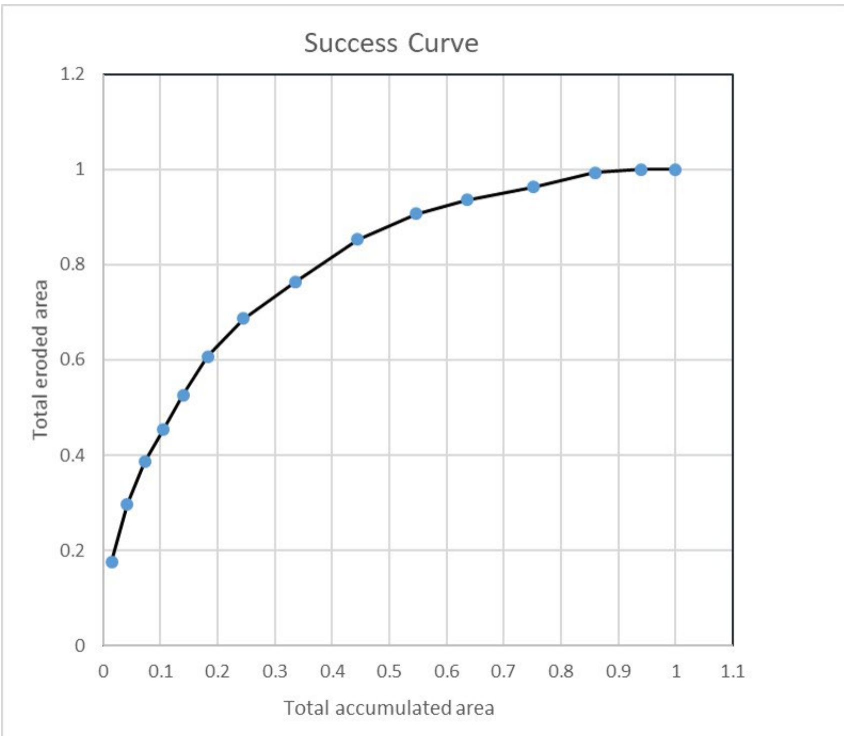

Figure 4. The success curve for the results generated in this work (AUC = 0.79).

In addition to the success curve, the prediction curve was generated using the 60 independent erosion samples reserved exclusively for validation (Figure 5). The curve shows a clear positive relationship between the accumulated susceptible area and the proportion of correctly predicted erosion occurrences. Hence, the model rapidly captures a substantial share of the independent erosion features within the lower susceptibility classes, indicating that the model effectively prioritized the most erosion-prone areas.

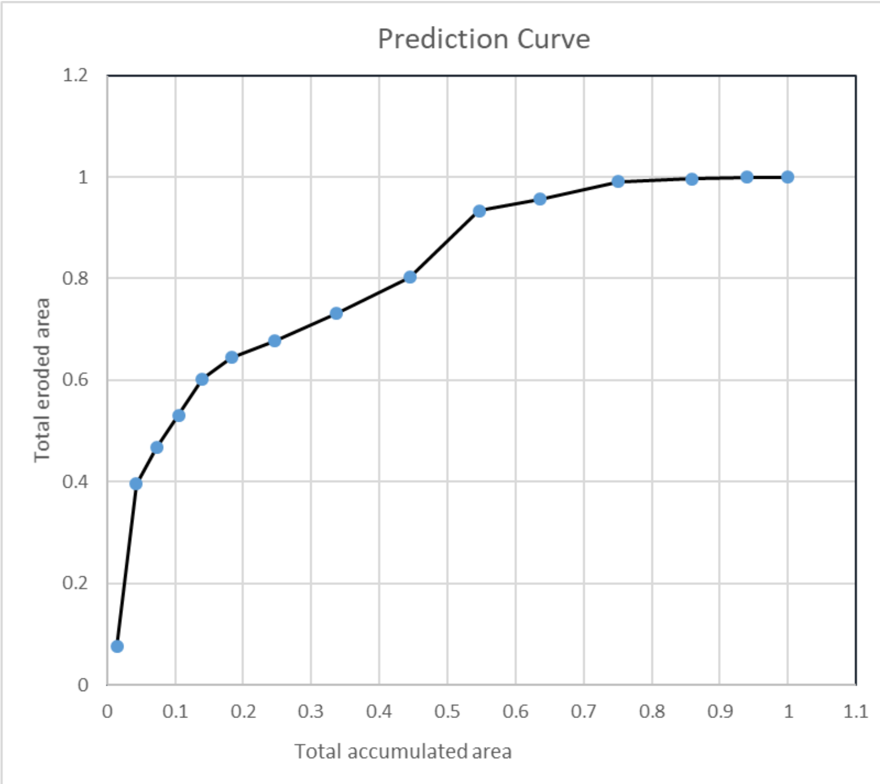

Figure 5. The prediction curve for the results generated in this work.

The prediction curve approaches the upper asymptote gradually, reaching approximately 0.95 of the cumulative eroded area at around 0.70 of the accumulated map area, and stabilizing near 1.0 in the final portion of the curve. This behavior demonstrates that the model maintains good predictive consistency. Although the prediction curve tends to be more conservative than the success curve—as expected when independent samples are used—the model still shows a satisfactory predictive performance.

Overall, the prediction curve confirms that the susceptibility map exhibits a robust capacity to generalize erosion occurrence beyond the training dataset. This reinforces the reliability of the final susceptibility classes for supporting territorial management and identifying priority areas for erosion prevention and monitoring.

3.2. Information Value (IV) and Soil Erosion Susceptibility Map

The application of univariate statistics produced IV for each independent variable, which reveals the role of each class in causing erosion, as shown in Table 2. Negative values are the least contributory to this process, while the highest positive values are the most decisive ones [59].

Figure 6 spatially demonstrates the IVs distribution for each independent variable, diagnosed throughout the analyzed study area.

Table 2. Information Value (IV) results. * Slope classes were defined according to [64].

	Class	N.° of Pixels in Each Class	Eroded Pixels	IV
Slope *	<5%	262,010	350	−0.719
	5.1–10%	388,646	903	−0.165
	10.1–15%	197,992	629	0.147
	15.1–20%	124,781	626	0.604
	20.1–25%	22,358	223	1.291
Land Use	Forest	103,035	60	−1.470
	Savannah, Wetland, Grassland, Water	54,711	422	1.100
	Silviculture, Coffee	39,182	97	−0.030
	Pasture, Mosaic of Uses	586,249	1664	0.100
	Sugarcane, Soy, Other Temporary Crops	128,406	51	−1.860
	Urban	120,443	112	−1.010
	Bare Soil, Mining	32,942	316	1.320
Relief	Hills	55,254	49	−1.098
	Isolated Ridges and Low Mountain Ranges	35,548	333	1.259
	Technogenic Deposits (Landfills)	523	0	-
	Degraded Cliffs, Structural Steps, and Erosive Ledges	92,165	795	1.177
	Karst Features	419	0	-
	Technogenic Formations	312	89	4.675
	Waterbody	2051	0	-
	High Hills	44,031	124	0.057
	Low Hills	53,358	118	−0.184
	Plateaus	74,986	66	−1.106
	Dissected Plateaus	422,584	782	−0.362
	Floodplains	108,915	147	−0.678
	Alluvium-Colluvium Ramps	8493	36	0.466
	Degraded Planed Surfaces	134,706	161	−0.800
Terrain Forms	Convex-Divergent	131,055	498	0.360
	Rectilinear-Divergent	170,834	703	0.440
	Concave-Divergent	24,689	145	0.796
	Concave-Planar	34,801	77	−0.181
	Rectilinear-Planar	202,026	460	−0.152
	Convex-Planar	25,776	110	0.476
	Convex-Convergent	33,099	101	0.141
	Rectilinear-Convergent	323,153	341	−0.921
	Concave-Convergent	91,662	314	0.256
Soils	CXbd—Haplic Inceptsols Tb Dystrophic	4828	0	-
	LVd—Dystrophic Red Oxisol	62,565	59	−1.03
	LVw—Acric Red Oxisol	742,040	1941	−0.01
	PVAd—Dystrophic Red-Yellow Ultisol	16,210	22	−0.67
	PVAe—Eutrophic Red-Yellow Ultisol	105,425	565	0.70
	Urban Area	106,134	170	−0.50

The erosion susceptibility map (Figure 7) originally had IVs oscillating between −5.64 and 6.43. Following the methodological proposition, these values were reclassified into four susceptibility classes based on the geometric breaks: (i) low (<−2.14); (ii) moderate to low (−2.14 to −1.02); (iii) moderate to high (−1.02 to 0.04); and (iv) high (>0.04). The proportions of area and sample points used both to generate and validate the model for the different erosion susceptibility classes are shown in Table 3. This statistics-based mapping reveals that the most susceptible areas in the geographic context of the municipality of Anápolis are mainly related to slopes greater than 15%, presence of Savannah (*Cerrado*), pastures and bare soil, isolated ridges and low mountain ranges, degraded cliffs, structural steps, and erosive ledges and technogenic formations, besides concave-convergent, concave-divergent, rectilinear-divergent, and convex-divergent landforms and eutrophic red-yellow ultisol soils.

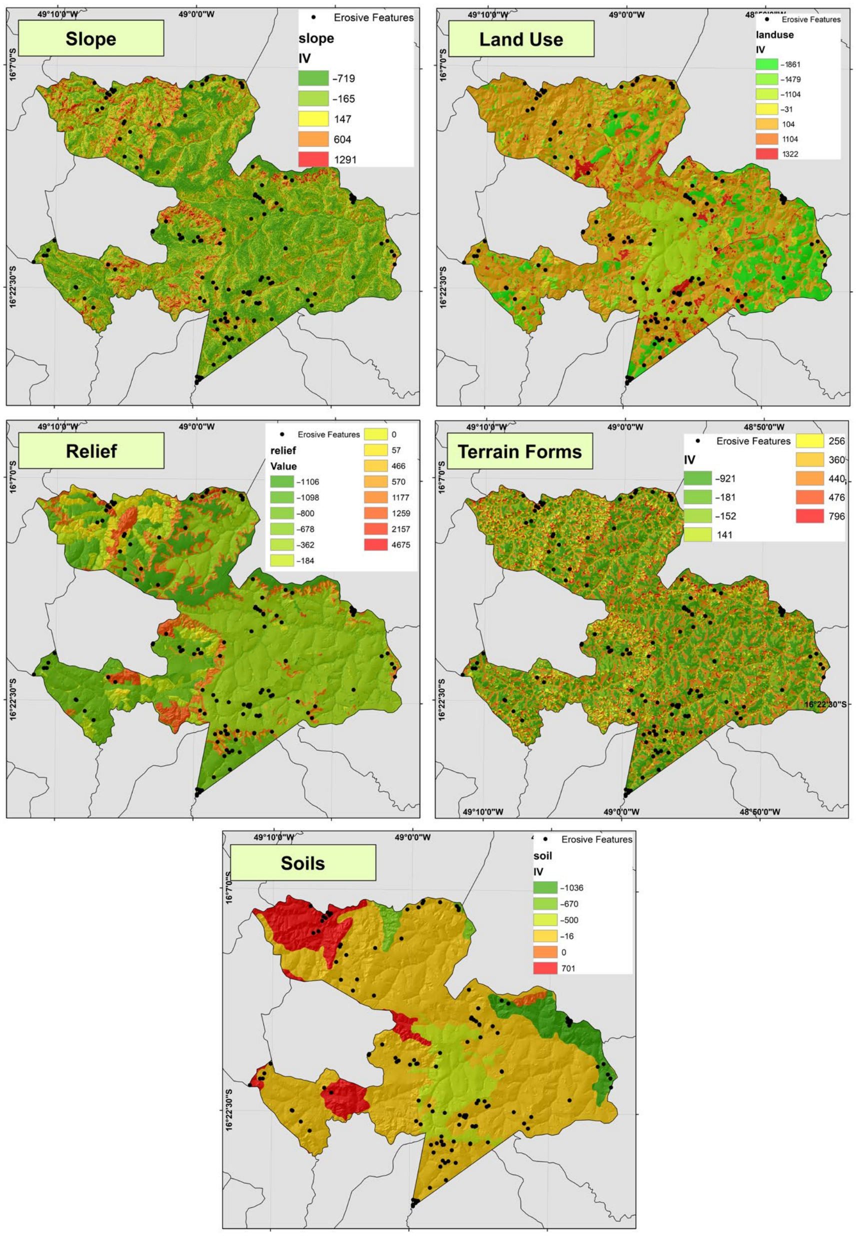

Figure 6. Spatial distribution of IVs related to each independent variable.

Table 3. Proportions of area and sample points used both to generate and validate the model for the different erosion susceptibility classes.

Susceptibility Class	Area (ha) of the Erosion Samples Used to Generate the Model	% of the Erosion Samples Used to Generate the Model	Area (ha) of the Erosion Samples Used to Validate the Model	% of the Erosion Samples Used to Validate the Model
Low	8.87	3	1.2	1
Moderate to Low	20.01	8	10.5	11.5
Moderate to High	46.6	20	28.5	31.5
High	169.99	69	51.2	56

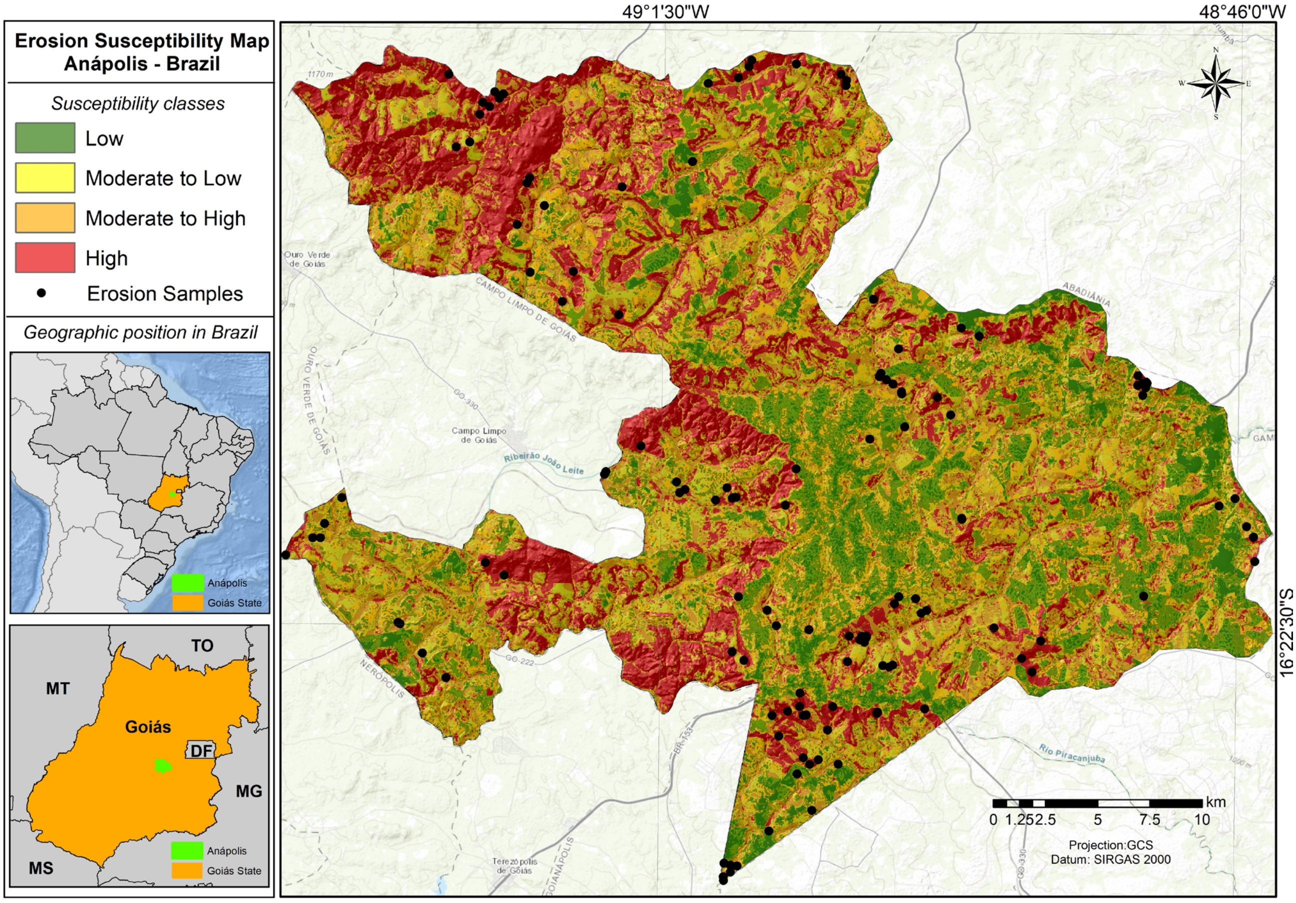

Figure 7. The soil erosion susceptibility map, indicating the erosion samples (black circles) extracted from [42].

The high susceptibility class expands over a surface of 229 km^2 and is recognized as a critical area due to its steep slopes, dissected terrains, presence of pastures, thin grass, bare soil, abandoned mining deposits, essentially convergent landforms that increase surface runoff, and sandy soils. Thus, this class refers to the portion where soils have the least resilience to the impacts of climate change, being strongly sensitive to changes in the volume, energy, and intensity of rainfall, which potentially lead to an increase in weathering and erosion rates, in addition to secondary impacts. Precipitation becomes the most important climatic factor among those that promote water-driven erosion; thus, the intensity of soil erosion is directly connected to local edaphoclimatic characteristics and their possible changes related to climate change [65].

The moderate to high class on the map accounts for areas of steep slope with high surface runoff and several thalwegs with river erosion. It is also noted that many areas of this class correspond to permanent preservation areas—a category within the Brazilian legal framework that requires the preservation of territories with critical environmental functions [66]—which makes it mandatory by law that degraded areas be recovered and those still vegetated be maintained.

In our mapping, the moderate to low susceptibility class indicates that, despite requiring careful management of land use, this is a zone of landscape resilience in terms of erosion caused by the increasing impacts of climate change in the Brazilian *Cerrado*. This refers to regions with slopes of less than 10% (and in many locations, they are spatially corresponding to the catchment areas of drainage networks), with divergent landforms that disperse surface runoff, and with more mature and structured soils.

Lastly, the low erosion susceptibility class indicates the locations with greater resilience to erosion in the municipality of Anápolis. These are places presenting the lowest slope values (less than 5%), soils with a higher clay content, essentially flat and divergent landforms (which dissipate surface runoff along the slopes), and land uses that tend to protect the local soil, such as forests, the Savannah biome (*Cerrado*), wetlands, and grasslands.

4. Discussion

In its onset in geosciences applications, the IV technique aimed to contribute essentially to the identification of areas susceptible to the occurrence of landslides [67–69]. However, in recent years, several studies have applied it to soil erosion investigations [38,70], corroborating the methodological application carried out in this study.

The advantages of the IV approach concern its methodological straightforwardness, for it is a univariate probabilistic method. In this sense, it assesses the occurrence of a phenomenon (erosion susceptibility) in relation to each class of the explaining variables in an independent way by means of the natural logarithm of the ratio of the phenomenon occurrence density in a given class to the average density of this occurrence throughout the study area. It offers a direct interpretability of results, handles well scarce and low-to-medium resolution data, is easily implemented in GIS environments, and presents a low computational cost. Nonetheless, the IV method presents some disadvantages, like the loss of information through the categorization of continuous variables, the sensitivity to zero frequencies; the lack of multivariate perspective; the risk of overfitting; besides the sample size sensitivity and the binary limitation.

When compared to other statistical and machine learning methods, IV does not depend on experts' judgments, as in the AHP method, and does not require previous distribution assumptions or multicollinearity assessments either. In view of its simplicity, it is suitable for being explored by local practitioners due to its intuitive character.

The application of the IV technique proved to be a robust methodological approach, achieving an accuracy of nearly 80%. This good level of predictive performance validates its utility for identifying areas at risk and guiding mitigation efforts. The satisfactory correlation between past erosion occurrences and geoenvironmental factors such as slope gradient, relief forms, relief patterns, land use, and soil type reaffirms the role of these elements as key drivers of erosion processes in the study area. Alike works in the literature attained AUC values ranging from 0.512 to 0.927. Ref. [26] conducted several experiments, diversifying the set of input variables, and the authors concluded that the different combinations of variables subsets impact the AUC values, which extended from 0.512 to 0.630. In general, the tangential curvature, stream power index (SPI), and plan curvature showed high predictive skills.

In the study of [25], who followed the same line of research of [26], the authors adopted the Maxent model and different combinations of topography, pedology, land cover, and meteorological variables, and the 21 generated models had AUC values oscillating from 0.753 to 0.828, indicating slope, land cover, organic matter, seasonal leaf area index (LAI), and maximum daily precipitation as the most contributing environmental factors for gully erosion susceptibility. Ref. [28] explored random forest (RF), support vector machine (SVM, and logistic regression (LR) driven by topographic, geomorphological, environmental, and hydrologic factors, with AUCs respectively attaining 0.890, 0.87, and 0.87, revealing NDVI), lithology, drainage density, and distance to rivers as the most influential factors. In the work of [34], the LR AUC reached 0.888, mainly pushed by NDVI, erosivity and land surface temperature.

Higher AUC values were reported by [23], who achieved 0.916 using a stacking model, combining RF and gradient boosting machine (GBM) as base models with LR as the meta-learner. Slope, vertical curvature, LAI, and yearly precipitation emerged as the most important variables. An AUC of 0.921 was obtained by [33] relying on memetic programming (MP) taking into account elevation, slope, distance from river, TWI, and SPI, although slope and land cover showed to be the most decisive factors for erosion susceptibility. Ref. [24] attained an AUC of 0.927 using RF and concluded that elevation, fractional vegetation cover, rainfall erosivity, lithology, and TWI acted as the most impactful variables. In our work, in its turn, slope, relief forms, and land use had crucial roles for assessing erosion-prone areas. None of the works consulted in the literature explored IV for erosion susceptibility, but the AUC we obtained lies within the AUC values spectrum range found in the literature.

According to [5], the most susceptible areas to erosion result from environmental degradation caused by the transformation of territories without soil protection mechanisms, which raises the need for territorial planning actions, meant to organize the landscape occupation so that the land use respects local potentialities and vulnerabilities [71]. Notably, the results indicate that erosion susceptibility is not uniformly distributed across the municipality. Areas with steep slopes, degraded or rugged landforms, unconsolidated soil formations, and intensive land use changes exhibit higher vulnerability, also reported in studies worldwide [23,25,27,29,30,33]. These findings are consistent with previous studies on soil erosion in tropical environments, which emphasize the combined effects of natural terrain characteristics and anthropogenic activities in exacerbating erosion processes [36]. Reinforcing this argument, ref. [72] identified in the southwest of Anápolis the relationship between linear erosion features in relief form units with slopes greater than 10%, covered by Latosols and Cambisols, developed from rocks of the Anápolis-Itauçu Granulitic complex and the Araxá Sul de Goiás Group, and with land deprived of conservation practices.

The high susceptibility diagnosed in this study poses a crucial challenge in the context of climate change impacts. According to [73], the main impacts of climate change related to soil erosion will be derived from extreme precipitation, making the unrestrained increase in surface runoff on slopes a factor of extreme concern, especially in tropical environments with high rainfall rates, like Brazil [71,74]. The Brazilian *Cerrado* region (a Savannah-like biome where the study area is located) has future predictions of an increase in average temperatures and long periods of drought as a reflection of climate change, according to [75]. In these places with lower amounts of rainfall, there is a global tendency for infrastructure to be less prepared for extreme rainfall events. This fact raises great concern as the impacts caused by human activities on a local scale, combined with climate impacts on a global scale, tend to also increasingly cause extreme events, even in dry regions [76].

Therefore, Anápolis, as a vulnerable area in the Brazilian *Cerrado*, cannot underestimate the occurrence and consequences of such events, which can further aggravate local erosion processes, focusing efforts on their mapping and implementing mitigating actions in the most vulnerable regions. Thus, our results aimed to guide the process of occupying the territory in a sustainable way, avoiding proposing total conservation scenarios, but rather indicating the least vulnerable portions of the land for human use.

For sustainable territorial planning, given the imminent impacts of climate change in the Brazilian *Cerrado*, the areas with greater susceptibility to erosion should be considered as total conservation zones, with restrictions on human activities and with urgent adoption of soil erosion control techniques for already eroded areas, as well as prevention initiatives and reforestation projects to inhibit/slow down new erosion processes. Considering that the municipality of Anápolis heavily depends on farming—mainly livestock and soybeans—[77], it is imperative that land use planning stop the advancement of the agricultural frontiers into the conservation and recovery zones.

As further recommendations, it is as well suggested to allow human activities in the moderate to low susceptibility areas, as long as they respect the carrying capacity of the area, that is, activities with reduced impact on the soil. Given its characteristics, this portion of the territory can be considered as a consolidation area, which is also in accordance with what is stated by [78], where it is recommended that studies be implemented on soil loss tolerance thresholds, aiming to identify the maximum rate of erosion that allows the maintenance of high productivity and thus guides mitigating actions and anthropogenic use [79].

The low erosion class can be considered an expansion class, mainly due to its greater environmental carrying capacity, being ideal for the expansion of human activities in the municipality. As to flat areas with lower surface runoff rates and more structured soils, ref. [80] claim that they are suitable for agricultural production, which is one of the main economic activities in the municipality of Anápolis [41]. Thus, the areas less susceptible to erosion (and consequently with greater resilience to the impacts of climate change)—moderate to low and low classes—should, according to [78], be the only places intended for the expansion of the municipality's productive potential.

In this context, analyzing and identifying susceptibility to erosion is a fundamental tool for territorial planning aimed at combating climate change, mainly because it contributes to the mitigation of serious social, economic, and environmental problems, such as the degradation of landscapes, loss of arable land, risks of disasters, and degradation of urban environments, being fundamental for the development of countries like Brazil. Similarly, delimiting the expansion zone in the municipality of Anápolis is a strategic tool to achieve the goals set in SDG 15, especially in topic 15.3, which aims to effectively contribute to a neutral world in terms of soil degradation [79]. Given that erosion-prone areas require immediate attention, policy makers and local authorities should prioritize interventions in highly susceptible zones. For areas where erosion processes already occurred, ref. [81] recommended control techniques, such as runoff diversion, gully reshaping, check dams, and revegetation, mainly in a scenario of evolving loss of native vegetation in the Cerrado biome, as proven by [14,45,82].

More specifically, considering that the land use that most impacts erosion in Anápolis is bare soil, refs. [83,84] indicate that vegetation recovery techniques, such as cover crops, reforestation, and mulching, are particularly suitable, resulting in a reduction of up to 90% in erosion and runoff rates. For regions where erosion occurs on steep slopes, isolated ridges, landfills, degraded cliffs, structural steps/erosive edges, and technogenic formations, ref. [85] highlight the effectiveness of implementing structural measures, such as terraces, trenches, and bunds, which promote up to 87% erosion reduction in areas of severe risk. In concrete terms, incorporating nature-based solutions, such as reforestation and agroforestry systems, could play a key role in mitigating erosion risks while simultaneously promoting biodiversity conservation and sustainable livelihoods [81,86,87].

Analysis of the municipality's current land use patterns, an important tool that informs about the level of soil protection [46], indicates that only 9% of the territory is forested, a factor that demands attention considering that natural plant formations are decisive elements for controlling and preventing erosion [45]. In this context, several studies such as [88–90] reinforce the need to implement reforestation projects in territories sensitive to erosion. Furthermore, in other portions of the conservation zone, where erosion has not yet occurred, prevention techniques are recommended, such as land use control, soil and water conservation, maintenance of topsoil resistance, and the implementation of vegetation barriers [81].

From a planning perspective, the susceptibility map developed in this study can be directly integrated into local territorial management instruments. In the context of Anápolis, the map provides an evidence-based premise for zoning and defining priority areas for conservation, ecological restoration, and controlled land-use expansion, as recommended by [91].

Areas classified as highly susceptible should be incorporated into municipal environmental zoning as permanent preservation or restoration priority zones, guiding reforestation projects and limiting new urban or agricultural developments on steep slopes and erosion-prone soils. Conversely, areas with moderate to low susceptibility can be designated for productive uses, provided that sustainable soil management practices are adopted. Moreover, the susceptibility analysis outputs can support decision-making within the Municipal Master Plan [92] and the Environmental Regularization Program [93], ensuring that land-use policies align with the municipality's natural vulnerability and contribute to long-term climate adaptation strategies.

As a limitation of this work, we ought initially to mention statistical and conceptual constraints of the IV method. Since it is highly dependent on how continuous variables are discretized, different grouping strategies (equal width, equal frequency, or optimal binning) can yield wildly different IV scores for the same feature. Another problem is that IV ignores non-linearity, for its final score is a single scalar. It may aggregate a complex relationship into a medium importance score, missing the nuance of the susceptibility profile. Moreover, IV looks at each variable in isolation (univariate). It cannot detect if two variables are providing the same information, which may end up with a model full of redundant predictors.

Additionally, the IV method is designed specifically for binary outcomes (events versus non-events). This creates several conceptual bottlenecks, such as information loss, given that by forcing a problem into a binary (0 or 1) box, the richness of ordinal or continuous data is lost. A second bottleneck regards the probability disconnect, because IV measures the strength of a relationship but not the functional form of the probability, and hence, it will never inform how much the probability of the event changes with a unit change in the predictor. A third bottleneck is the binary target bias, which occurs when the target event is extremely rare (class imbalance problem), forcing manual smoothing that may introduce bias.

A critical issue in this method is also the lack of replication, a characteristic that imposes difficulty in maintaining the predictive power of IV-based groupings when applied to new, unseen data (out-of-time or out-of-sample). Because IV encourages fine-classing (creating many small ranges to maximize IV), it often captures noise specific to the training set. When the model is replicated on a new dataset, these specific ranges often fail to hold their predictive power. In sum, the method owns a static nature, missing a dynamic component in the sense that there is no built-in mechanism in the IV framework to update or replicate the logic as new data flows in, unlike other methods.

Still in methodological terms, another limitation of the present research concerns the fact that we worked with fixed training and validation datasets, as observed in the majority of the literature works. However, we consider applying resampling techniques, such as cross-validation or bootstrapping, to evaluate the stability of the model's performance in prospective studies. A further limitation we must report regards the use of input data at coarse scales. The best available soil map for Goiás State was originally produced at a 1:250,000 scale, and all remaining input data were released at a 1:50,000 scale. We ought to highlight that if the analysis were carried out with geoenvironmental data at more refined scales (1:10,000, for example), the results would be more significant, possibly achieving a higher accuracy rate for the model. However, Brazil, being a country of continental size, is still incipient in producing highly detailed geoenvironmental data. For this reason, we reinforce the need for geoscientists and related institutions in Brazil to produce detailed data for the entire country, which should be rendered available in open-access repositories of our National Geospatial Data Infrastructure. Dealing with such fine-scale input data is envisaged as a strategy for future works.

5. Conclusions

This study highlights the relevant susceptibility of the municipality of Anápolis to erosion, using the IV method and success curve analysis and emphasizing the necessity of targeted land management strategies to mitigate soil degradation. The use of the IV technique proved effective in assessing erosion risk, with an approximate 80% accuracy rate, reinforcing its applicability for similar climate-vulnerable landscapes.

The analysis identifies four classes that indicate the degree of soil resilience in a highly disturbed environment. The geoenvironmental characteristics of Anápolis municipality, combined with the lack of territorial planning, result in a high share of erosion-prone areas, a factor proven by the 190 erosion events mapped in different landscapes (urban areas, areas with natural vegetation, degraded pastures, agricultural areas, etc.). The use of the IV method (often applied to landslides) in the context of susceptibility to erosion proved to be efficient, even when applied at a cartographic planning scale (approximately 1:50,000), as it is an approach with a low implementation cost, with a satisfactory success rate and able to meaningfully reduce the subjectivity associated with heuristic models.

Finally, we hope that the proven effectiveness of this study will inspire similar works in other Brazilian regions that face erosion processes in a way to help pressing public managers to give greater importance to preventing and mitigating such environmental problem. Furthermore, based on the arguments that even in regions subject to long-lasting droughts there will be an increase in extreme rainfall events, it is important to raise awareness among Brazilian governmental decision makers so that they do not underestimate the occurrence of extreme rainfall events and their soil consequences even in drier regions.

Author Contributions: Conceptualization, J.V.R.G. and F.G.N.; methodology, J.V.R.G. and J.A.D.L.; formal analysis, J.V.R.G., E.V.E.-S., C.M.d.A., A.G., J.A.D.L., C.C. and F.G.N.; investigation, J.V.R.G., E.V.E.-S., C.M.d.A. and A.G. data curation, J.A.D.L. and J.V.R.G.; writing—original draft preparation, J.V.R.G., E.V.E.-S., C.M.d.A., A.G., J.A.D.L., C.C. and F.G.N.; writing—review and editing, J.V.R.G., E.V.E.-S., C.M.d.A., A.G., J.A.D.L., C.C. and F.G.N.; supervision, F.G.N.; project administration, F.G.N. All authors have read and agreed to the published version of the manuscript.

Funding: This study was funded by the São Paulo Research Foundation (FAPESP), No. 2024/02748-7 (E.V.E.-S.), and No. 2020/09215-3 (C.M.d.A.); by the Brazilian National Council for Scientific and Technological Development (CNPq), through grant No. 311324/2021-5 (C.M.d.A.); and the Brazilian Space Agency (AEB) (C.M.d.A.).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The raw data supporting the conclusions of this article will be made available by the authors on request.

Conflicts of Interest: Author Elton Vicente Escobar-Silva was employed by National Center for Monitoring and Early Warning of Natural Disasters (Cemaden). Author Cláudia Maria de Almeida was employed by Earth Observation and Geoinformatics Division, National Institute for Space Research (INPE). The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

References

1. Alewell, C.; Borrelli, P.; Meusburger, K.; Panagos, P. Using the USLE: Chances, Challenges and Limitations of Soil Erosion Modelling. *Int. Soil Water Conserv. Res.* **2019**, *7*, 203–225. [CrossRef]
2. Poesen, J. Soil Erosion in the Anthropocene: Research Needs. *Earth Surf. Process. Landf.* **2018**, *43*, 64–84. [CrossRef]
3. Pandey, S.; Kumar, P.; Zlatic, M.; Nautiyal, R.; Panwar, V.P. Recent Advances in Assessment of Soil Erosion Vulnerability in a Watershed. *Int. Soil Water Conserv. Res.* **2021**, *9*, 305–318. [CrossRef]
4. Lal, R. Managing Soils and Ecosystems for Mitigating Anthropogenic Carbon Emissions and Advancing Global Food Security. *Bioscience* **2010**, *60*, 708–721. [CrossRef]
5. Mafra, N.M.C. Erosion and Land Use Planification. In *Soil Erosion and Conservation*; Guerra, A.J.T., da Silva, A.S., Botelho, R.G.M., Eds.; Bertrand Brasil: Rio de Janeiro, Brazil, 2012; p. 340.
6. Eekhout, J.P.C.; de Vente, J. Global Impact of Climate Change on Soil Erosion and Potential for Adaptation through Soil Conservation. *Earth Sci. Rev.* **2022**, *226*, 103921. [CrossRef]
7. Trenberth, K. Changes in Precipitation with Climate Change. *Clim. Res.* **2011**, *47*, 123–138. [CrossRef]
8. UN—United Nations. *Human Development Report 2021/2022: Uncertain Times, Unsettled Lives: Shaping Our Future in a Transforming World*; United Nations Development Programme: New York, NY, USA, 2022.
9. Borrelli, P.; Robinson, D.A.; Panagos, P.; Lugato, E.; Yang, J.E.; Alewell, C.; Wuepper, D.; Montanarella, L.; Ballabio, C. Land Use and Climate Change Impacts on Global Soil Erosion by Water (2015–2070). *Proc. Natl. Acad. Sci. USA* **2020**, *117*, 21994–22001. [CrossRef]
10. Issaka, S.; Ashraf, M.A. Impact of Soil Erosion and Degradation on Water Quality: A Review. *Geol. Ecol. Landsc.* **2017**, *1*, 1–11. [CrossRef]
11. Katra, I. Soil Erosion by Wind and Dust Emission in Semi-Arid Soils Due to Agricultural Activities. *Agronomy* **2020**, *10*, 89. [CrossRef]
12. Lal, R. Accelerated Soil Erosion as a Source of Atmospheric CO_2. *Soil Tillage Res.* **2019**, *188*, 35–40. [CrossRef]
13. WBG—World Bank Group. *Publication: Brazil Country Climate and Development Report*; The World Bank Group: Washington, DC, USA, 2023; p. 74.
14. Merten, G.H.; Minella, J.P.G. The Expansion of Brazilian Agriculture: Soil Erosion Scenarios. *Int. Soil Water Conserv. Res.* **2013**, *1*, 37–48. [CrossRef]
15. de Groot, R.S.; Wilson, M.A.; Boumans, R.M.J. A Typology for the Classification, Description and Valuation of Ecosystem Functions, Goods and Services. *Ecol. Econ.* **2002**, *41*, 393–408. [CrossRef]
16. Todman, L.C.; Fraser, F.C.; Corstanje, R.; Deeks, L.K.; Harris, J.A.; Pawlett, M.; Ritz, K.; Whitmore, A.P. Defining and Quantifying the Resilience of Responses to Disturbance: A Conceptual and Modelling Approach from Soil Science. *Sci. Rep.* **2016**, *6*, 28426. [CrossRef] [PubMed]
17. Ross, J.L.S. *Ecogeografia Do Brasil: Subsídios Para Planejamento Ambiental*, 1st ed.; Oficina de Textos: São Paulo, Brazil, 2006.
18. Alanbagi, H.I.K. Using Geographic Information Systems (GIS) in Environmental Risk Analysis and Assessment: A Case Study on Baghdad City. *J. Eng.* **2025**, *31*, 51–64. [CrossRef]
19. Zumara, R.; Nasher, N.M.R. Soil Erodibility Mapping of Hilly Watershed Using Analytical Hierarchy Process and Geographical Information System: A Case of Chittagong Hill Tract, Bangladesh. *Heliyon* **2024**, *10*, e26728. [CrossRef]
20. Eminoğlu, Y.; Tarhan, Ç. Decadal Evolution of GIS in Disaster Management and Risk Assessment. *Int. J. Eng. Geosci.* **2025**, *10*, 173–196. [CrossRef]
21. Lu, Y.; Liu, Y.; Sun, Y.; Liu, C.; Li, X.; Wang, R.; Li, J.; Yao, K. A Novel Method for Analyzing the Spatial and Temporal Distribution of Freeze-Thaw Erosion Based on a Similar Information Value Model: A Case Study of the China-Mongolia-Russia Economic Corridor Region. *Geomat. Nat. Hazards Risk* **2023**, *14*. [CrossRef]
22. Alshehri, A.A. Utilizing Remote Sensing and GIS to Study Natural Disasters "Volcanoes" and Their Impact on Climate Change. *J. Environ. Earth Sci.* **2025**, *7*, 573–587. [CrossRef]
23. Han, J.; Guzman, J.A.; Chu, M.L. Prediction of Gully Erosion Susceptibility through the Lens of the SHapley Additive ExPlanations (SHAP) Method Using a Stacking Ensemble Model. *J. Environ. Manag.* **2025**, *383*, 125478. [CrossRef]
24. Ou, H.; Mu, X.; Yuan, Z.; Yang, X.; Liao, Y.; Nguyen, K.L.; Sombatpanit, S. Mapping Benggang Erosion Susceptibility: An Analysis of Environmental Influencing Factors Based on the Maxent Model. *Sustainability* **2024**, *16*, 7328. [CrossRef]
25. Han, J.; Guzman, J.A.; Chu, M.L. Gully Erosion Susceptibility Considering Spatiotemporal Environmental Variables: Midwest U.S. Region. *J. Hydrol. Reg. Stud.* **2022**, *43*, 101196. [CrossRef]
26. Conoscenti, C.; Agnesi, V.; Angileri, S.; Cappadonia, C.; Rotigliano, E.; Märker, M. A GIS-Based Approach for Gully Erosion Susceptibility Modelling: A Test in Sicily, Italy. *Environ. Earth Sci.* **2013**, *70*, 1179–1195. [CrossRef]
27. Momeni Damaneh, J.; Safdari, A.A.; Azarnejad, N.; Ghorbani, M.; Panahi, F.; Afzali, S.F.; Loppi, S. Modeling Soil Erosion Susceptibility Using Machine Learning Techniques: Rud-e-Faryab Basin, Iran. *Land Degrad. Dev.* **2025**, *36*, 6396–6409. [CrossRef]

28. Aboutaib, F.; Krimissa, S.; Pradhan, B.; Elaloui, A.; Ismaili, M.; Abdelrahman, K.; Eloudi, H.; Ouayah, M.; Ourribane, M.; Namous, M. Evaluating the Effectiveness and Robustness of Machine Learning Models with Varied Geo-Environmental Factors for Determining Vulnerability to Water Flow-Induced Gully Erosion. *Front. Environ. Sci.* **2023**, *11*, 1207027. [CrossRef]
29. Bouramtane, T.; Hilal, H.; Rezende-Filho, A.T.; Bouramtane, K.; Barbiero, L.; Abraham, S.; Valles, V.; Kacimi, I.; Sanhaji, H.; Torres-Rondon, L.; et al. Mapping Gully Erosion Variability and Susceptibility Using Remote Sensing, Multivariate Statistical Analysis, and Machine Learning in South Mato Grosso, Brazil. *Geosciences* **2022**, *12*, 235. [CrossRef]
30. Adesina, E.A.; Ajayi, O.G.; Odumosu, J.O.; Kolade, T.S. Assessment of Soil Erosion Susceptibility Using Multi-Criteria Analysis. *Environ. Technol. Sci. J.* **2024**, *15*, 35–45. [CrossRef]
31. Weiler, E.B.; Tamiosso, M.F.; Cruz, J.C.; Reichert, J.M.; Schorr, L.P.B.; Mantovanelli, B.C.; Dos Santos, F.D.; Fantinel, R.A.; Baumhardt, E. Integrated Environmental Management and Planning Based on Soil Erosion Susceptibility Scenarios. *An. Acad. Bras. Cienc.* **2021**, *93*, e20191120. [CrossRef]
32. Salhi, A.; Benabdelouahab, S.; Heggy, E. Soil Erosion Susceptibility Maps and Raster Dataset for the Hydrological Basins of North Africa. *Sci. Data* **2025**, *12*, 65. [CrossRef]
33. Bouamrane, A.; Kantoush, S.A.; Dahri, N.; Bouamrane, A.; Saber, M.; Boutaghane, H.; Abida, H.; Sumi, T.; Sohei, K.; Mabrouk, E. Simulation of Erosion Susceptibility in the Medjerda Watershed under Different Climate Change Scenarios. *Georisk Assess. Manag. Risk Eng. Syst. Geohazards* **2025**, 1–24. [CrossRef]
34. Da Fonseca, E.L.; da Silva Filho, E.P. Binary Logistic Regression Applied to Erosion Susceptibility Mapping in the Southern Amazon. *Rev. Bras. Geomorfol.* **2023**, *24*. [CrossRef]
35. Nunes, M.C.M.; Neves, S.M.A.d.S.; Neves, R.J.; Kreitlow, J.P.; Chimello, A.M. Susceptibility to Water Erosion of Soils from the Municipality Salto Do Céu, SW Mato Grosso State, Brazil. *Geografia* **2013**, *38*, 191–203.
36. Bueno, L.O.; Anjinho, P.d.S.; Bolleli, T.d.M.; Barbosa, M.A.G.A.; Mauad, F.F. Erosion Susceptibility Mapping in the Central-Eastern Region of São Paulo in the Last Few Decades. *Environ. Monit. Assess.* **2022**, *194*, 927. [CrossRef] [PubMed]
37. Garcia, R.A.C.; Zêzere, J.L.; Oliveira, S. The Importance of the Data Classification Process in Cartography: An Example in Cartography of Susceptibility to Slope Movements. In *Geomorphological Dynamics. Methodologies. Application*; Pereira, A.R., Trindade, J., Garcia, R., de Oliveira, S.C., Paixão, R., Eds.; Oficina de Texto: São Paulo, Brazil, 2006; p. 354.
38. Fagbohun, B.J.; Aladejana, O.O.; Okonye, I.F.; Tobore, A.O. Assessing Gully Erosion Susceptibility Dynamics Using Information Value and Hazard Index Methods: A Case Study of Agulu-Nanka Watershed, Southeast Nigeria. *Catena* **2024**, *241*, 108070. [CrossRef]
39. Arabameri, A.; Chen, W.; Loche, M.; Zhao, X.; Li, Y.; Lombardo, L.; Cerda, A.; Pradhan, B.; Bui, D.T. Comparison of Machine Learning Models for Gully Erosion Susceptibility Mapping. *Geosci. Front.* **2020**, *11*, 1609–1620. [CrossRef]
40. Cattelan, L.G.; Mattos, C.R.C.; Pamplona, M.B.; Hirota, M. Mapping Climatic Regions of the Cerrado: General Patterns and Future Change. *Int. J. Climatol.* **2024**, *44*, 5857–5872. [CrossRef]
41. IBGE—Brazilian Institute of Geography and Statistics. Cities—Anápolis. Available online: https://cidades.ibge.gov.br/brasil/go/anapolis/panorama (accessed on 19 June 2025).
42. Google Inc. Google Earth. Available online: https://www.google.com.br/intl/pt-BR/earth/ (accessed on 23 June 2022).
43. Nunes, B.d.A. *Manual Técnico de Geomorfologia*; IBGE: Rio de Janeiro, Brazil, 2009.
44. Pinho, D.; Fernandes, R.L.G. *Susceptibility Chart to Gravitational Mass Movements and Flooding: Municipality of Anápolis—GO (Carta de Suscetibilidade a Movimentos Gravitacionais de Massa e Inundação: Município de Anápolis—GO)*; CPRM: Goiânia, Brazil, 2024.
45. Brazil. MapBiomas Project Brazilian Land Use Land Cover 2024. Available online: https://brasil.mapbiomas.org/ (accessed on 7 May 2025).
46. Baccaro, C.A.D. Processos Erosivos No Domínio Do Cerrado. In *Erosão e Conservação dos Solos*; Guerra, A.J.T., da Silva, A.S., Botelho, R.G.M., Eds.; Berttrand Brasil: Rio de Janeiro, Brazil, 2012; p. 339.
47. CEMADEN—National Center for Natural Disaster Monitoring and Alerts. Monitored Municipalities (Municípios Monitorados). Available online: http://www2.cemaden.gov.br/municipios-monitorados-2/ (accessed on 19 January 2025).
48. Ortega Adarme, M.; Queiroz Feitosa, R.; Nigri Happ, P.; Aparecido De Almeida, C.; Rodrigues Gomes, A. Evaluation of Deep Learning Techniques for Deforestation Detection in the Brazilian Amazon and Cerrado Biomes From Remote Sensing Imagery. *Remote Sens.* **2020**, *12*, 910. [CrossRef]
49. Campos, J.A.; da Silva, D.D.; Fernandes Filho, E.I.; Pires, G.F.; Amorim, R.S.S.; de Menezes Filho, F.C.M.; de Melo Ribeiro, C.B.; Uliana, E.M.; Aires, U.R.V. Environmental Vulnerability Assessment of the Doce River Basin, Southeastern Brazil. *Environ. Monit. Assess.* **2023**, *195*, 1119. [CrossRef]
50. Ouali, L.; Kabiri, L.; Essafraoui, B.; El Amaraoui, M.; El Ouali, M.; Kassou, A.; Ait Lahssaine, I.; Messaoudi, B.; Minoia, P. Spatial Modeling of Water Erosion Vulnerability and Mapping Potential Sites of Control Measures Using GIS and MCDM: A Case Study from the Drylands of Southeastern Morocco. *Model. Earth Syst. Environ.* **2023**, *9*, 3473–3482. [CrossRef]
51. Silva, J.P.O.; Silva, L.B.; da Silva, R.R.; Domingos, V.H. Potencial Erosivo de Um Solo Tropical Na Região de Anápolis-Go. *RECIEC—Rev. Científica Eng. Civ.* **2022**, *5*, 111–121.

52. Santos, R.C.N.d.O. Analysis of the Erodibility Potential of the Soil in Anápolis—GO Through Environmental Fragility. 2022. Available online: https://repositorio.ifg.edu.br/handle/prefix/1304/ (accessed on 12 June 2025).
53. De Jesus, A.S. Multidisciplinary Investigation of Linear Erosion Processes: Case Study of the City of Anápolis. Ph.D. Thesis, University of Brasilia, Brasilia, Brazil, 2013; p. 340.
54. INPE—National Institute for Space Research. TOPODATA: Brazilian Geomorphometric Database. Available online: http://www.dsr.inpe.br/topodata/index.php (accessed on 13 May 2025).
55. IBGE—Brazilian Institute of Geography and Statistics. Pedology 1:250.000. Available online: https://geoftp.ibge.gov.br/informacoes_ambientais/pedologia/mapas/ (accessed on 4 May 2025).
56. Watkins, D. 30-Meter SRTM Tile Downloader. Available online: https://dwtkns.com/srtm30m/ (accessed on 13 May 2025).
57. Arabameri, A.; Pradhan, B.; Rezaei, K.; Conoscenti, C. Gully Erosion Susceptibility Mapping Using GIS-Based Multi-Criteria Decision Analysis Techniques. *Catena* **2019**, *180*, 282–297. [CrossRef]
58. Yin, K.; Yan, T. Statistical Prediction Models for Slope Instability of Metamorphosed Rocks. In Proceedings of the Fifth International Symposium on Landslides, Lausanne, Switzerland, 10–15 July 1988; pp. 1268–1272.
59. Zêzere, J.L. *Distribution and Rhythm of Slope Movements in the Region North of Lisbon*; Universidade de Lisboa—Centro de Estudos Geográficos: Lisbon, Portugal, 2001; p. 167.
60. Howard, R. Information Value Theory. *IEEE Trans. Syst. Sci. Cybern.* **1966**, *2*, 22–26. [CrossRef]
61. Wang, Z.; Badiu, M.-A.; Coon, J.P. Relationship between Age and Value of Information for a Noisy Ornstein–Uhlenbeck Process. *Entropy* **2021**, *23*, 940. [CrossRef] [PubMed]
62. Yesilnacar, E.; Topal, T. Landslide Susceptibility Mapping: A Comparison of Logistic Regression and Neural Networks Methods in a Medium Scale Study, Hendek Region (Turkey). *Eng. Geol.* **2005**, *79*, 251–266. [CrossRef]
63. Swets, J.A. Measuring the Accuracy of Diagnostic Systems. *Science* **1988**, *240*, 1285–1293. [CrossRef]
64. Lepsch, I.F.; Espindola, C.R.; Vischi Filho, O.J.; Hernani, L.C.; Siqueira, D.S. (Eds.) *Manual Para Levantamento Utilitário e Classificação de Terras No Sistema de Capacidade de Uso*; Embrapa Solos: Viçosa, Brazil, 2015.
65. Castagna, D.; Pacheco de Souza, A.; Gonçalves Vendrusculo, L.; Zolin, C.A. Rainfall Erosivity in Municipalities of the Brazilian Cerrado Biome. *Nativa* **2022**, *10*, 373–386. [CrossRef]
66. Brazil. What Are Permanent Preservation Areas? Available online: https://www12.senado.leg.br/noticias/materias/2009/04/29/o-que-sao-as-areas-de-preservacao-permanente (accessed on 7 March 2025).
67. Wubalem, A.; Meten, M. Landslide Susceptibility Mapping Using Information Value and Logistic Regression Models in Goncha Siso Eneses Area, Northwestern Ethiopia. *SN Appl. Sci.* **2020**, *2*, 807. [CrossRef]
68. Ji, J.; Zhou, Y.; Cheng, Q.; Jiang, S.; Liu, S. Landslide Susceptibility Mapping Based on Deep Learning Algorithms Using Information Value Analysis Optimization. *Land* **2023**, *12*, 1125. [CrossRef]
69. El Abidine, R.Z.; Abdelmansour, N. Landslide Susceptibility Mapping Using Information Value and Frequency Ratio for the Arzew Sector (North-Western of Algeria). *Bull. Miner. Res. Explor.* **2018**, *160*, 197–211. [CrossRef]
70. Hembram, T.K.; Paul, G.C.; Saha, S. Spatial Prediction of Susceptibility to Gully Erosion in Jainti River Basin, Eastern India: A Comparison of Information Value and Logistic Regression Models. *Model. Earth Syst. Environ.* **2019**, *5*, 689–708. [CrossRef]
71. Gouveia, I.C.M.-C.; Ross, J.L.S. Fragilidade Ambiental: Uma Proposta de Aplicação de Geomorphons Para a Variável Relevo. *Geogr. Dep. Univ. Sao Paulo* **2019**, *37*, 123–136. [CrossRef]
72. Teixeira, L.L.F.M.; Romão, P.D.A. Análise Integrada Do Meio Físico Como Subsídio Ao Diagnóstico de Processos Erosivos Na Bacia Do Ribeirão Extrema Em Anápolis (GO). *Bol. Goiano Geogr.* **2010**, *29*, 127–142. [CrossRef]
73. Nearing, M.A.; Pruski, F.F.; O'Neal, M.R. Expected Climate Change Impacts on Soilerosion Rates: A Review. *J. Soil Water Conserv.* **2004**, *59*, 43–50. [CrossRef]
74. Roque Guerrero, J.V.; De Lollo, J.A.; Lorandi, R. Cartografia Geoambiental Como Base Para Planejamento Territorial Na Bacia Do Rio Clarinho, SP. *Rev. Bras. Cartogr.* **2016**, *68*. [CrossRef]
75. Hofmann, G.S.; Cardoso, M.F.; Alves, R.J.V.; Weber, E.J.; Barbosa, A.A.; de Toledo, P.M.; Pontual, F.B.; Salles, L.d.O.; Hasenack, H.; Cordeiro, J.L.P.; et al. The Brazilian Cerrado Is Becoming Hotter and Drier. *Glob. Change Biol.* **2021**, *27*, 4060–4073. [CrossRef] [PubMed]
76. Donat, M.G.; Lowry, A.L.; Alexander, L.V.; O'Gorman, P.A.; Maher, N. More Extreme Precipitation in the World's Dry and Wet Regions. *Nat. Clim. Change* **2016**, *6*, 508–513. [CrossRef]
77. IBGE—Brazilian Institute of Geography and Statistics. Environmental Information: Soils. Available online: https://www.ibge.gov.br/geociencias/downloads-geociencias.html (accessed on 7 December 2024).
78. Becker, B.; Egler, C.A. *Detalhamento Da Metodologia Para Execução Do Zoneamento Ecológico-Econômico Pelos Estados Da Amazônia Legal*; EMBRAPA: Rio de Janeiro, Brazil, 1996.
79. Guerra, A.J.T.; Cunha, S.B. (Eds.) Processos Erosivos Nas Encostas. In *Geomorfologia Uma Atualização de Bases e Conceitos*; Beertrand Brasil: Rio de Janeiro, Brazil, 2007; pp. 149–209.

80. Viana, J.S.; Goncalves, E.P.; Silva, A.C.; Matos, V.P. Climatic Conditions and Production of Soybean in Northeastern Brazil. In *A Comprehensive Survey of International Soybean Research—Genetics, Physiology, Agronomy and Nitrogen Relationships*; InTech: Vienna, Austria, 2013.
81. Frankl, A.; Nyssen, J.; Vanmaercke, M.; Poesen, J. Gully Prevention and Control: Techniques, Failures and Effectiveness. *Earth Surf. Process. Landf.* **2021**, *46*, 220–238. [CrossRef]
82. Falcão, K.d.S.; Panachuki, E.; Monteiro, F.d.N.; da Silva Menezes, R.; Rodrigues, D.B.B.; Sone, J.S.; Oliveira, P.T.S. Surface Runoff and Soil Erosion in a Natural Regeneration Area of the Brazilian Cerrado. *Int. Soil Water Conserv. Res.* **2020**, *8*, 124–130. [CrossRef]
83. Du, X.; Jian, J.; Du, C.; Stewart, R.D. Conservation Management Decreases Surface Runoff and Soil Erosion. *Int. Soil Water Conserv. Res.* **2022**, *10*, 188–196. [CrossRef]
84. Martínez-Mena, M.; Carrillo-López, E.; Boix-Fayos, C.; Almagro, M.; García Franco, N.; Díaz-Pereira, E.; Montoya, I.; de Vente, J. Long-Term Effectiveness of Sustainable Land Management Practices to Control Runoff, Soil Erosion, and Nutrient Loss and the Role of Rainfall Intensity in Mediterranean Rainfed Agroecosystems. *Catena* **2020**, *187*, 104352. [CrossRef]
85. Ame, M.A.; Wei, W.; Zhang, S.; Liu, W.; Chen, L. The Effects of Rainfall and Terracing–Mulch Combinations on Soil Erosion in a Loess Hilly Area, China: Insights from Plot Simulations and WEPP Modeling. *Land* **2025**, *14*, 432. [CrossRef]
86. Apollonio, C.; Petroselli, A.; Tauro, F.; Cecconi, M.; Biscarini, C.; Zarotti, C.; Grimaldi, S. Hillslope Erosion Mitigation: An Experimental Proof of a Nature-Based Solution. *Sustainability* **2021**, *13*, 6058. [CrossRef]
87. Vanacker, V.; Molina, A.; Rosas, M.A.; Bonnesoeur, V.; Román-Dañobeytia, F.; Ochoa-Tocachi, B.F.; Buytaert, W. The Effect of Natural Infrastructure on Water Erosion Mitigation in the Andes. *Soil* **2022**, *8*, 133–147. [CrossRef]
88. Yao, X.; Yu, K.; Wang, G.; Deng, Y.; Lai, Z.; Chen, Y.; Jiang, Y.; Liu, J. Effects of Soil Erosion and Reforestation on Soil Respiration, Organic Carbon and Nitrogen Stocks in an Eroded Area of Southern China. *Sci. Total Environ.* **2019**, *683*, 98–108. [CrossRef]
89. Veldkamp, E.; Schmidt, M.; Powers, J.S.; Corre, M.D. Deforestation and Reforestation Impacts on Soils in the Tropics. *Nat. Rev. Earth Environ.* **2020**, *1*, 590–605. [CrossRef]
90. Ricci, G.F.; Jeong, J.; De Girolamo, A.M.; Gentile, F. Effectiveness and Feasibility of Different Management Practices to Reduce Soil Erosion in an Agricultural Watershed. *Land Use Policy* **2020**, *90*, 104306. [CrossRef]
91. Dos Santos, R.F. *Planejamento Ambiental: Teoria e Prática*; Oficina de Textos: São Paulo, Brazil, 2007.
92. Anápolis Municipality Anápolis Municipal Master Plan. 2016. Available online: https://leismunicipais.com.br/plano-diretor-anapolis-go (accessed on 31 July 2025).
93. SEMAD. Environmental Regulation. State Secretariat for Environment and Sustainable Development (Secretaria de Estado de Meio Ambiente e Desenvolvimento Sustentável—SEMAD). Available online: https://goias.gov.br/meioambiente/regularizacao-ambiental/ (accessed on 4 November 2025).

https://doi.org/10.3390/su18041878