

ASSESSING THE IMPACT OF LAND USE, SOIL, AND SLOPE ON SEDIMENT PRODUCTION RATES USING HYDROSEDIMENTOLOGICAL MODELING AND ARTIFICIAL NEURAL NETWORKS

AVALIAÇÃO DO IMPACTO DO USO DA TERRA, SOLO E DECLIVE NAS TAXAS DE PRODUÇÃO DE SEDIMENTOS USANDO MODELAGEM HIDROSEDIMENTOLÓGICA E REDES NEURAIS ARTIFICIAIS

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Submetido: 17/06/2025 / Aprovado: 07/09/2026 / Publicado: 27/09/2026.

Abstract

Understanding the impacts of land use, soil type, and slope on sediment production is vital for water resource management and environmental conservation. This study uses hydrosedimentological modeling and Artificial Neural Networks (ANNs) to evaluate these relationships. The SWAT model was employed to simulate sediment production rates in Brazilian basins, considering hydrological, climatic, and topographic variables. ANN techniques were integrated to analyze the importance of land use, soil type, and slope. The results show that agriculture had the greatest impact on sedimentation rates (36.32%), followed by pastures (29.73%), non-vegetated areas (21.61%), and natural vegetation (12.34%). Soil types such as Neosol and Gleysol were the most influential (23.56% and 22.88%), while Latosol and Nitosol had the least impact (9.15% and 11.15%). Higher slopes (>45%) had a greater influence (29.32%) on sediment production. The model performance was evaluated by Kling-Gupta efficiency (KGE), percentage bias (PBIAS) and Pearson correlation coefficient (r), indicating satisfactory accuracy. The findings highlight the relevance of land use, soil and slope in sediment dynamics, providing support for sediment management and environmental conservation strategies.

Keywords: Sensitivity of soil slope and land use. Sediment production rate. Modeling with SWAT.

Resumo

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DOI: <http://dx.doi.org/10.24021/raac.v23i1.8492>

V. 23, N. 1 (2026)



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Entender os impactos do uso da terra, tipo de solo e declive na produção de sedimentos é vital para o gerenciamento de recursos hídricos e a conservação ambiental. Este estudo utiliza modelagem hidrossedimentológica e Redes Neurais Artificiais (RNAs) para avaliar essas relações. O modelo SWAT foi empregado para simular taxas de produção de sedimentos em bacias brasileiras, considerando variáveis hidrológicas, climáticas e topográficas. Técnicas de RNA foram integradas para analisar a importância do uso da terra, tipos de solo e declive. Os resultados mostram que a agricultura teve o maior impacto nas taxas de sedimentação (36,32%), seguida por pastagens (29,73%), áreas não vegetadas (21,61%) e vegetação natural (12,34%). Tipos de solo como Neossolo e Gleissolo foram os mais influentes (23,56% e 22,88%), enquanto Latossolo e Nitossolo tiveram menor impacto (9,15% e 11,15%). Declives maiores (>45%) apresentaram maior influência (29,32%) na produção de sedimentos. O desempenho do modelo foi avaliado pela eficiência de Kling-Gupta (KGE), porcentagem de viés (PBIAS) e coeficiente de correlação de Pearson (r), indicando precisão satisfatória. As descobertas destacam a relevância do uso da terra, solo e declive na dinâmica de sedimentos, oferecendo subsídios para estratégias de gerenciamento de sedimentos e conservação ambiental.

Palavras-chave: Sensibilidade da declividade do solo e uso da terra. Taxa de produção de sedimentos. Modelagem com SWAT.

1. INTRODUCTION

The hydrosedimentological processes are very important in the environmental context and discussed by different authors, as Fernandes *et al.* (2024), Comerlato, Lamour and Silveira (2023), Costa *et al.* (2023), Cabral and Castro (2022), Oliveira *et al.* (2018). The interaction between land use and cover dynamics, soil characteristics, and topography is crucial in regulating hydrosedimentological processes within river basins (Lambin; Geist; Rindfuss, 2008; Kayitesi; Guzha; Mariethoz, 2022; Branco *et al.*, 2023; Maltauro *et al.*, 2024; Rautela *et al.*, 2024). Understanding how these factors affect sediment production and transport rates is essential for effective and sustainable water resources management and mitigating environmental impacts throughout river basins.

The topography of a river basin significantly influences sedimentological processes. Mountainous basins, typically smaller, often have limited depositional areas and exhibit higher specific sediment supply (Magalhães Júnior; Barros, 2020). In contrast, larger basins tend to be less sloped on average, promoting sediment deposition before it reaches surface water systems (Magalhães Júnior; Barros, 2020). Physical and chemical characteristics affect soil moisture and play a critical role in sedimentological processes (Singh *et al.*, 2008). Additionally, various studies highlight the effect of climate and land cover changes on water availability (Prado; Tarso; Oliveira, 2022) and soil loss in water basins (Dos Santos *et al.*, 2023; Anley; Minale, 2024). These studies underscore the significant impact of land use and cover on sedimentological processes. In mountainous and cryospheric-fed basins such as the Himalayan Teesta River Basin, SWAT-based hydrosedimentological modelling under CMIP6 climate projections has shown that sediment yield may rise by up to 91% under high-emission scenarios, illustrating how climate-driven changes in precipitation and temperature can compound the effects of land use and topography on sediment dynamics (Lepcha *et al.*, 2026).

It is reasonable to anticipate increased sediment production rates in sloped areas. An analysis of sediment transport capacity in agricultural areas in the Loess Plateau, China, revealed an exponential rise in sedimentation rates as the slope increased (Zhu *et al.*, 2024). Another study assessed the impact of sediment particle size on rill erosion in reforested areas using an

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V. 23, N. 1 (2026)



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experimental flume with varying flow rates and bed slopes. Sediments over 1 mm exhibited significantly higher rill erosion capacity than smaller soil fractions. This difference arises from the combined effects of flow energy, turbulence, particle size, and surface area. Additionally, bed slope had a more pronounced effect on rill erosion capacity than water depth (Parhizkar *et al.*, 2021).

Water erosion is a major consequence of rain acting on soil (Marzen *et al.*, 2017). Soil susceptibility to erosion depends on factors like structure, clay type and amount, permeability, depth, and the presence of impermeable layers. While it takes hundreds to thousands of years for soil to develop 1 cm, it can be lost rapidly due to poor management, sometimes even in a single harvest (Crepani *et al.*, 2001).

A hydrological model simulates water movement within a river basin, enabling predictions of conditions beyond those currently observed. Its effectiveness depends on the quality of available data, the discretization approach, the properties of the elements, the processes involved, and the specific objectives of the model. Hydrological models are utilized for various purposes, including forecasting events, informing decision-making, understanding basin comportment, predicting future conditions, assessing environmental impacts, identifying extreme events, extracting valuable information, and reducing uncertainties. These models are instrumental in water resource management and analyzing water body changes (Tucci, 2005).

Hydrological models offer several key benefits, including the ability to anticipate events for more accurate and timely decision-making (Clark; Kavetski; Fenicia, 2011). They provide insights into river basin behavior, enabling predictions of conditions beyond current observations (Blöschl *et al.*, 2017). These models are also valuable for analyzing the impacts of changes in water bodies due to land use and climate variations through detailed simulations (Hrachowitz *et al.*, 2013). They help identify statistically probable extreme events, such as floods and droughts, aiding in disaster preparedness and mitigation. Additionally, hydrological models enhance the measurement of hydrological parameters, reducing uncertainties associated with these processes (Gupta *et al.*, 2012). Advanced techniques improve data extraction, such as precipitation and flow information.

The SWAT (Soil and Water Assessment Tool) model is widely used for simulating hydrological flow and sedimentation processes in river basins (Arnold *et al.*, 2012a). It accounts for variables like land use and cover, soil type, and terrain slope, which are crucial for hydrosedimentological modeling (Oliveira *et al.*, 2024). SWAT also modeling water quality, evaluates agricultural practices, assesses climate change impacts, manages water resources, and tracks pollutant transport (Arnold *et al.*, 1998; Gassman *et al.*, 2007; Ficklin *et al.*, 2009; Arnold *et al.*, 2012b; Srinivasan; Zhang; Arnold, 2010). It incorporates precipitation rate, terrain topography, soil type, and vegetation cover, helping identify erosion-prone areas and estimate soil loss and sediment transport (Dos Santos *et al.*, 2023).

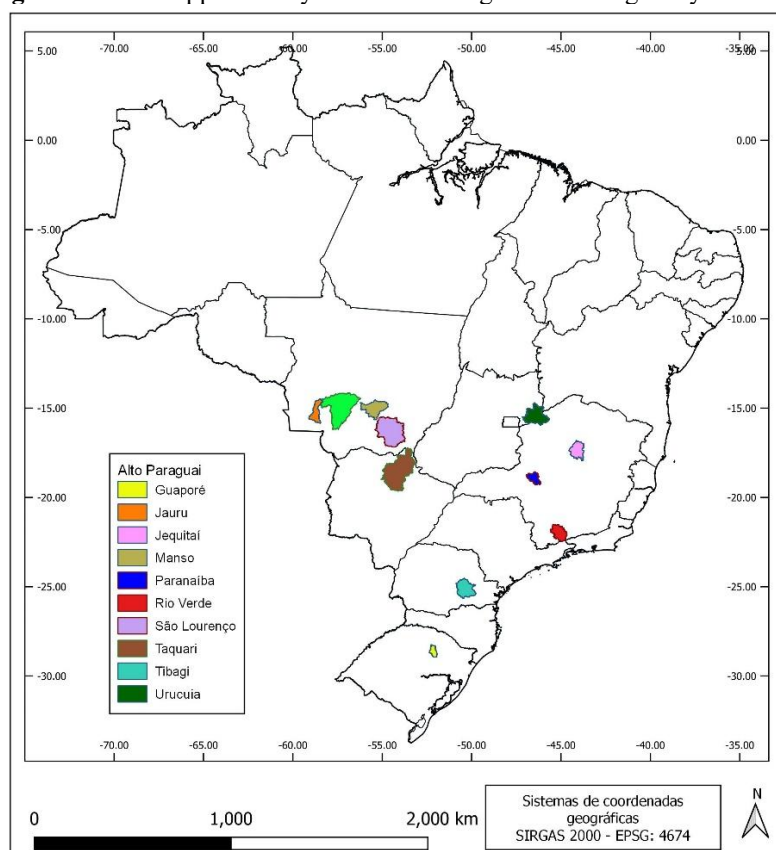
Artificial Neural Networks (ANNs) are empirical models that use observed data to adjust weights and functions, estimate response variables, and compare them to observed values (Kerem Cigizoglu; Kisi, 2006). Thus, ANNs can identify patterns between observed values and basin characteristics to estimate hydrological indices (Booker; Woods, 2014). In this context, this study aims to employ ANNs to assess the impact and contribution of land use and cover, soil types, and terrain slopes on sediment production rates within a set of Central-South Brazilian large basins, using SWAT for hydrosedimentological modeling.

1.1 Area of study



The study areas were selected to represent a range of hydrological and climatological characteristics. The initial selection was based on the availability of sedimentological monitoring data disposal by the Brazilian Geological Survey (CPRM - Companhia de Pesquisa de Recursos Minerais in Portuguese). Eleven large basins across Central-south Brazil were selected for modeling: Urucuia, Jequitaiá, Paranaíba, and Rio Verde (Minas Gerais); Tibagi (Paraná); Guaporé (Rio Grande do Sul); Jauru, Alto Paraguai, Manso, and São Lourenço (Mato Grosso); and Taquari (Mato Grosso do Sul) (Figure 1). Detailed information on each basin can be found in the supplementary materials.

Figure 1. Basins applied in hydrosedimentological modeling study.



Source: the authors (2024).

2. MATERIAL AND METHODS

2.1. Hydrosedimentological modeling

The SWAT (Soil and Water Assessment Tool) model (Arnold *et al.*, 2012c) was used to simulate hydrosedimentological processes and to calculate sediment production rates. SWAT model was designed to predict the impact of soil management practices on water resources. Since its launch in the 1990s, SWAT has evolved through multiple versions and extensive research (https://www.card.iastate.edu/swat_articles/).

The calibration process involves setting parameters that influence the modeled hydrological processes. These parameters are organized by file type within SWAT, with values processed by sub-basins or Hydrologic Response Units (HRUs). An HRU combines land use and cover classes, soil type, and slope categories, defined through a layer overlay process that

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V. 23, N. 1 (2026)



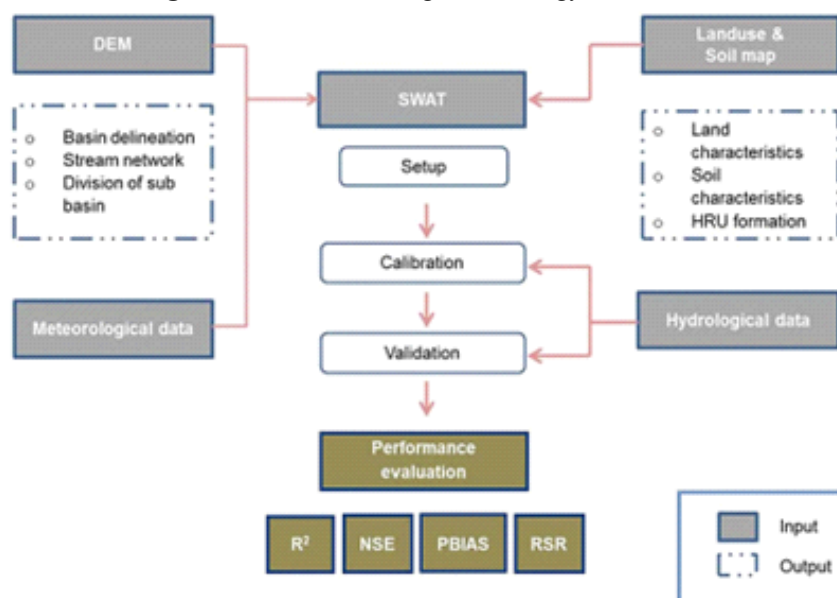
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maintains spatially distributed parameters and homogeneous characteristics within each sub-basin (Ueslei; Oliveira, 2020).

To define HRUs, sub-basins were determined from a digital elevation model (DEM) and a threshold value specifying the minimum number of cells (or area) required for a catchment to be considered a sub-basin. This threshold affects model spatial resolution and differs by basin in this study: Jauru = 10, Manso and Guaporé = 20, Alto Paraguai, Taquari, and Jequitáí = 30, São Lourenço = 40, Paranaíba = 70, Tibagi and Rio Verde = 100, Urucuia = 226. After delineating sub-basins, categorical maps of land use and cover, soil, and terrain slope were combined to create HRUs. A 100% threshold was set for the tree layers within a sub-basin to ensure comprehensive HRU definition without overloading computational resources (Supplementary Material 1).

Model calibration occurred in two phases. First, an automated process randomly adjusted parameter values within SWAT's standard limits using custom management computer routines developed by this study (Supplementary Material 2). This process continued until a minimum efficiency coefficient (KGE) of 0.60 was achieved or 50 iterations were completed. In the second phase, the most efficient parameter set was manually fine-tuned until a performance coefficient above 0.50 was reached. Model performance was evaluated using Kling-Gupta Efficiency (KGE), Pearson correlation (r), and Percentage of Bias (PBias), following established methodologies (Arnold *et al.*, 2012c; Gupta *et al.*, 2009). Validation involved applying the calibrated parameters to a different data period and verifying that they fit the same values used in calibration. SWAT model structure integrates input, processing, and output data (Figure 2).

Figure 2. SWAT modeling methodology framework.



Source: Arnold *et al.* (2012c)

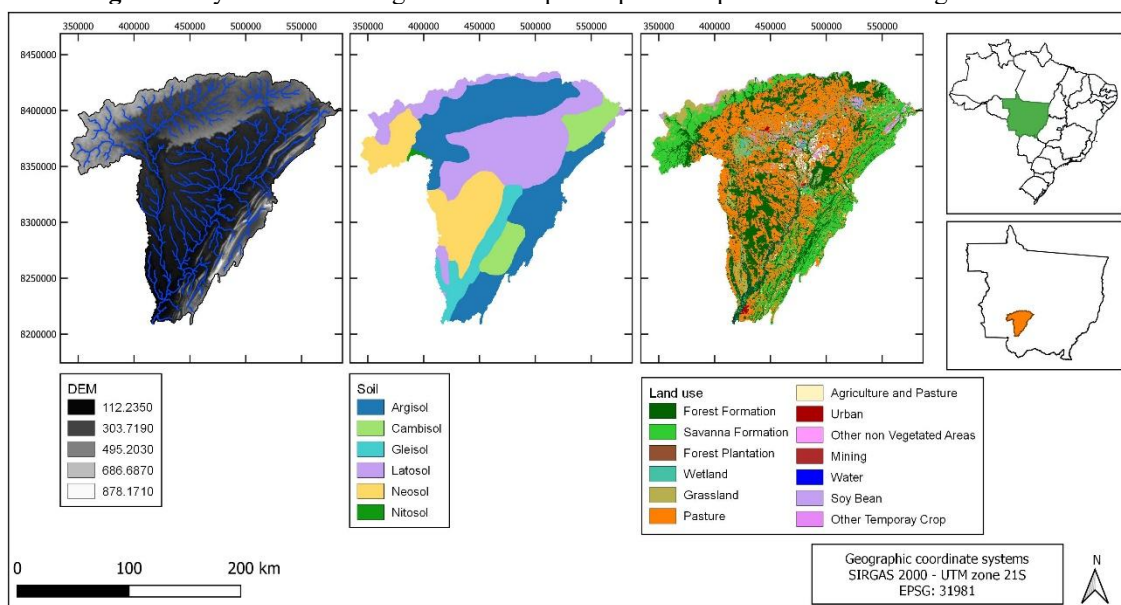
The data used for modeling included the digital elevation model (SRTM 30 m), land use and cover map (Mapbiomas, 2020), soil map (EMBRAPA, 2011), and we used these maps to create sub-basins and their HRUs as described.

The next step in the modeling involved integrating climate data, including precipitation, temperature, solar radiation, relative humidity, and wind speed. Precipitation data were collected from the rainfall monitoring station available in Hidroweb system of the National Water and Sanitation Agency (ANA, 2023). Temperature, radiation, humidity, and wind speed data were

obtained from the National Centers for Environmental Prediction (NCEP) Climate Forecast System Reanalysis (CFSR), which provides a 36-year dataset (1979–2014). The CFSR offers high-resolution global climate data with a 0.3° (~335 km) grid spacing. These data are available daily in SWAT file format for specified locations and periods (CFSR, 2021). Data points closest to the precipitation station coordinates were used for temperature, radiation, humidity, and wind speed. Details of the precipitation stations are provided in Supplementary Material 3

The parameter calibration began once the HRU structure was established and climate data incorporated. Model performance was evaluated with KGE, pBias, and Pearson efficiency indices. Figure 3 displays the Alto Paraguai basin as an example; other basins are shown in Supplementary Material 4. The hydrosedimentological simulations used calibration and validation periods, flow and sediment stations and their geographic locations (Table 1).

Figure 3. Hydrosedimentological model input maps. Example for the Alto Paraguai basin.



Source: the authors (2024)

Table 1. Flow and sediment stations and modeling period.

Basin	Flow and sediment station	Latitude	Longitude	Calibration period	Validation period
Jauru	66071400	-15.8500	-58.4600	1997-2006	2007-2013
Alto Paraguai	66070004	-16.0761	-57.7022	1994-2006	2007-2013
Manso	66122000	-14.8100	-55.2761	2007-2010	2011-2013
São Lourenço	66460000	-15.9980	-55.9217	2009-2009	2010-2012
Taquari	66850000	-18.7244	-54.5297	2004-2007	2008-2010
Jequitai	42145498	-17.2097	-44.4603	2001-2006	2006-2008
Urucuia	43429998	-15.9178	-46.1192	1993-1995	1994-1996
Paranaíba	60011000	-18.6017	-46.5394	1985-1988	1988-1990
Rio Verde	61537000	-21.6108	-45.4889	2004-2008	2009-2012

Guaporé	86560000	-28.9122	-51.9531	2010-2012	2012-2013
Tibagi	64465000	-24.5094	-50.4097	2008-2011	2011-2013

Source: the authors (2024).

Flow data are monitored daily, whereas sediment data are collected only about three times a year. To fill the gaps in the sediment data, we estimated that no data was collected through interpolation procedures, using the regression model between observed flow and sediment levels. We applied either exponential or linear regression methods, depending on which provided the best fit, to estimate the missing sediment data (Supplementary Material 5).

2.2. The Relative importance of land use and cover classes, soil types and slope terrain categories

The relative importance of the classes was assessed using Artificial Neural Networks (ANNs) based on sediment production rates from hydrosedimentological modeling. Sediment production rates were tabulated for each HRU, expressed in tons per hectare per year. Each HRU combines land use and cover, soil type, and slope categories listed in separate columns. Since the tree layer data are categorical, we converted them into a dummy format (presence/absence) to allow the ANN algorithm to compute relative importance based on sediment production rates. The dummy format converts alphanumeric data into numeric, with 0 indicating absence and 1 indicating presence. Table 2 shows the dummy format data structure. This transformation allowed the ANN model to use land use and cover, soil type, terrain slope categories as explanatory variables and sediment production rate as the response variable.

Table 2. Table structure in dummy format for use in ANN.

HRU	Natural cover	Pasture	Agriculture	Non vegetated area	Sediment rate
1	1	0	0	0	Value 1
2	0	1	0	0	Value 2
3	0	0	1	0	Value 2
4	0	0	0	1	Value 4
...	...	...	...	...	...

Source: the authors (2024).

The ANN method was applied using R software and the H2O library, specifically with the `h2o.deeplearning` function (Script 1 in Supplementary Material 6). The process involved varying the number of neuron layers and epochs. The input layer of neurons handles the explanatory variables for the ANN, while the epochs determine the number of cycles the ANN performs to adjust and validate against the sediment production rate. Model performance and variable importance were assessed using the `h2o.performance` function. Each model run with the configurations detailed in Table 3 produced results showing the relative importance of variables and the mean squared error to evaluate performance, with a 5% error threshold applied (Maier; Dandy, 2000). The model was executed multiple times to find the best performance. A routine was created in R to run the model 50 times, selecting the top three models and averaging their results.

Table 3. ANN settings for identifying the relative importance of classes.

DOI: <http://dx.doi.org/10.24021/raac.v23i1.8492>

V. 23, N. 1 (2026)



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Model settings	Land use and cover	Soil	Slope
Neuron layers	3	2	3
Number of neurons by layers	5, 10 and 15	6 and 12	5, 10 and 12
Number cycles for each model (epochs)	30,000	30,000	30,000

Source: the authors (2024).

3. RESULTS AND DISCUSSION

3.1 Hydrosedimentological modeling

The calibration and validation of the models resulted in a set of parameters that ensured high simulation performance (Table 4). The "Arq. SWAT" column in the table indicates the type of file organizing these parameters, providing an initial view of their performance. Table 4 represents the Alto Paraguai basin highlighted in the body of the article, with the other basins presented in supplementary material 7.

Table 4. Calibrated parameters in the model. Example for the Alto Paraguai basin.

SWAT file	Parameters	Calibrated value	SWAT file	Parameters	Calibrated value
GW	ALPHA_BF	0,7	GW	GWQMN	1000
GW	ALPHA_BF_D	0,5	SOL	Ksat	0,1
RTE	ALPHA_BNK	0	HRU	LAT_SED	100
SOL	ANION_EXCL	0,6	HRU	LAT_TTIME	55
HRU	CANMX	85	HRU	OV_N	50
RTE	CH_ERODMO	0	GW	RCHRG_DP	1
RTE	CH_K2	30	GW	REVAPMN	100
RTE	CH_N2	0.02	HRU	SED_CON	300
MGT	CN2	35	HRU	SLSOIL	100
HRU	DIS_STREAM	30000	SOL	SOL_AWC	0
HRU	EPCO	0,6	SOL	SOL_BDI	0,15
HRU	ESCO	0,02	SOL	SOL_CRK	0,7
HRU	EVPOT	0,8	SOL	SOL_K1	0,12
GW	GW_DELAY	500	HRU	SURLAG	2
GW	GW_REVAP	0,2	SOL	USLE_K	0,7

Source: the authors (2024).

After calibrating and validating all basins, efficiency metrics for flow (Table 5) and sediment (Table 6) rates were generated. Hydrographs and sedimentograms showing observation and simulation curves are presented for the Alto Paraguay basin (Figures 4 and 5). Curves for other basins are available in Supplementary Material 8.

Table 5. Hydrosedimentological model performance data - Flow rate.

Basins	Calibration period				Validation period			
	Period	KGE	pBias	r	Period	KGE	pBias	r

Jauru	1997-2006	0.69	0.03	0.76	2007-2013	0.65	0.13	0.74
Alto Paraguai	1994-2006	0.69	0.08	0.87	2007-2013	0.62	0.12	0.78
Manso	2007-2010	0.75	0.02	0.76	2011-2013	0.71	0.11	0.70
São Lourenço	2006-2009	0.78	0.14	0.79	2010-2012	0.71	0.16	0.77
Taquari	2004-2007	0.64	0.19	0.67	2008-2010	0.61	0.17	0.67
Jequitaí	2001-2006	0.63	-0.01	0.78	2006-2008	0.62	-0.05	0.77
Urucuia	1993-1995	0.75	0.09	0.76	1994-1996	0.71	0.11	0.73
Paranaíba	1985-1988	0.73	-0.01	0.81	1988-1990	0.68	-0.04	0.77
Rio Verde	2004-2008	0.67	-0.08	0.76	2009-2012	0.63	0.06	0.72
Guaporé	2010-2012	0.65	-0.11	0.88	2012-2013	0.61	-0.11	0.81
Tibagi	2008-2011	0.66	0.12	0.85	2011-2013	0.64	0.07	0.82

Source: the authors (2024).

Table 6. Hydrosedimentological model performance data – Sediment rate.

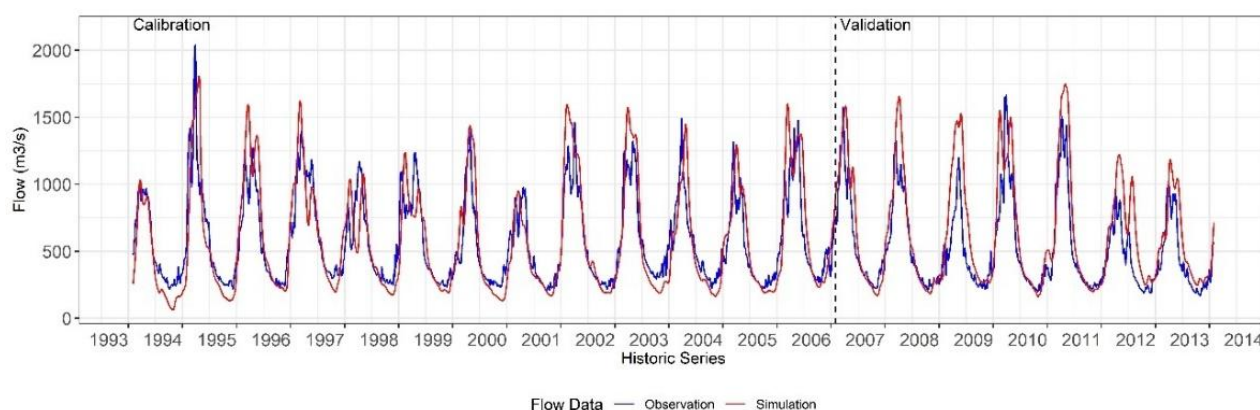
Basins	Calibration period				Validation period			
	Period	KGE	pBias	r	Period	KGE	pBias	r
Jauru	1997-2006	0.61	0.03	0.67	2007-2013	0.60	0.13	0.65
Alto Paraguai	1994-2006	0.63	0.08	0.70	2007-2013	0.61	0.12	0.68
Manso	2007-2010	0.60	0.02	0.72	2011-2013	0.59	0.11	0.70
São Lourenço	2006-2009	0.66	0.14	0.81	2010-2012	0.66	0.16	0.80
Taquari	2004-2007	0.58	0.19	0.67	2008-2010	0.59	0.17	0.67
Jequitaí	2001-2006	0.62	-0.01	0.72	2006-2008	0.62	-0.05	0.75
Urucuia	1993-1995	0.74	0.09	0.89	1994-1996	0.75	0.11	0.81
Paranaíba	1985-1988	0.73	-0.01	0.81	1988-1990	0.71	-0.04	0.82
Rio Verde	2004-2008	0.67	-0.08	0.60	2009-2012	0.63	0.06	0.72
Guaporé	2010-2012	0.61	-0.11	0.66	2012-2013	0.62	-0.11	0.72
Tibagi	2008-2011	0.64	0.12	0.75	2011-2013	0.63	0.07	0.77

Source: the authors (2024).

The model performance values (Table 6) are considered good (Arnold *et al.*, 2012c; Gupta *et al.*, 2009). However, performance evaluation depends on project objectives and input data quality. The results are satisfactory for this research, which focuses on measuring sediment production and assessing the impact of land use and cover, soil, and slope classes.

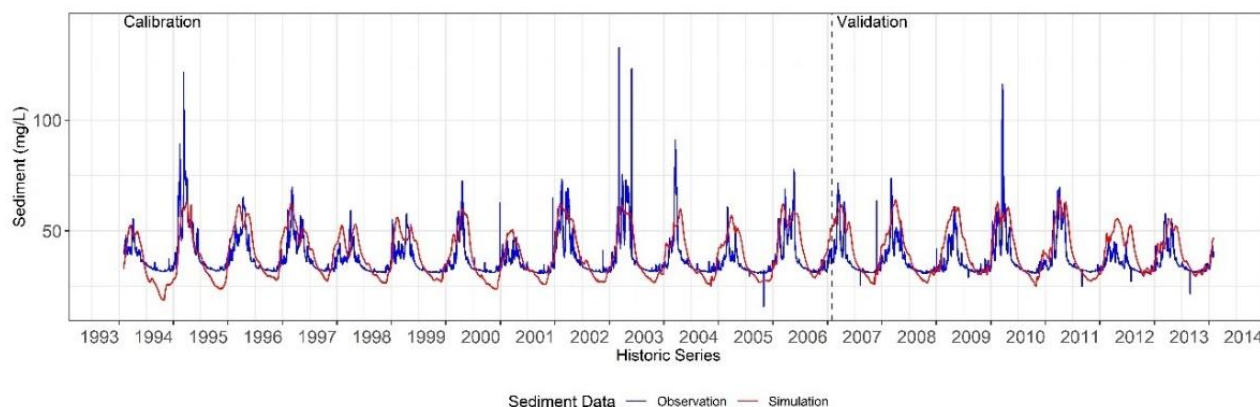
Figure 4. Simulation of hydrosedimentological modeling – Flow rate. Example for Alto Paraguai basin.





Source: the authors (2024).

Figure 5. Simulation of hydrosedimentological modeling – Sediment rate. Example for Alto Paraguai basin.

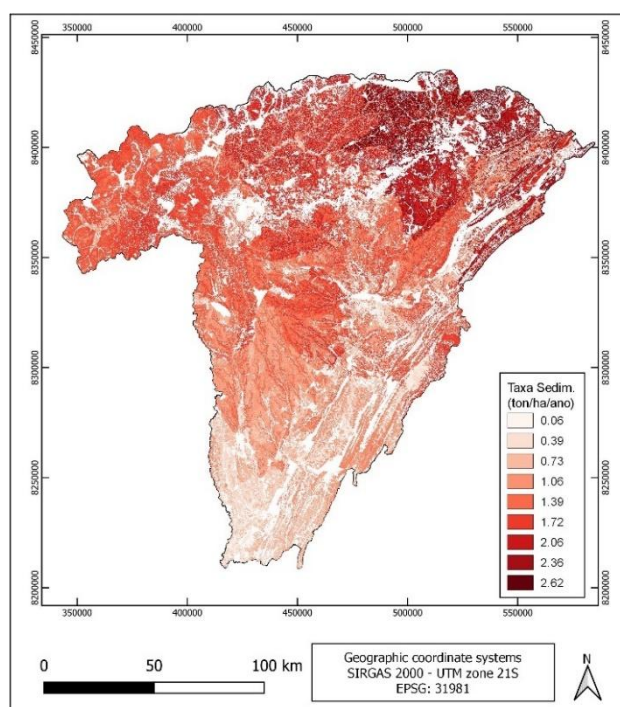


Source: the authors (2024).

The hydrograph and sedimentogram curves show that simulations align closely with observed data, though differences exist among basins (supplementary material 8). Sediment simulation performance was lower than flow simulation, which was anticipated due to the interpolation of much of the observed sediment data (Moriassi *et al.*, 2007; Tuppad *et al.*, 2010; Gassman; Sadeghi; Srinivasan, 2014; Harmel *et al.*, 2006).

After completing the modeling, the SWAT model generates several output files, including the OUTPUT.STD file, which contains sediment production rate data for each HRU. We used this data to map algebra processes. Figure 6 displays the spatial distribution of sediment production rates for each HRU in the simulated basin. Table 7 shows a portion of the extracted data used for processing. Additional sediment production rate maps are available in Supplementary Material 9.

Figure 6. Spatial distribution of sediment production rate – Example for Alto Paraguai basin.



Source: the authors (2024).

Table 7. Data generated by SWAT modeling. Cutting of Alto Paraguai basin.

HRU	SUB	Land use and cover	Soil	Slope	Sediment rate
1095	274	Natural cover	Neosoil	a0-3.0	0.93
1494	377	Pasture	Oxisoil	a0-3.0	2.05
1242	313	Pasture	Neosoil	a0-3.0	1.15
1248	315	Pasture	Neosoil	a0-3.0	1.45
821	205	Pasture	Argisil	b3.0-8.0	2.08
1244	314	Natural cover	Neosoil	a0-3.0	0.86
1247	314	Pasture	Neosoil	a0-3.0	0.92
903	226	Natural cover	Argisil	b3.0-8.0	1.15
1693	430	Pasture	Argisil	b3.0-8.0	2.61
28	8	Natural cover	Gleysoil	a0-3.0	0.54

Source: the authors (2024).

3.2 The relative importance of classes

Relative importance indicates the percentage each class contributes to the sediment rate, reflecting its impact on the rate. For each variable—land use and cover (Figure 7), soil types (Figure 8), and slope categories (Figure 9)—the three best-performing ANN models were selected, as outlined in the methodology. The study revealed that agriculture had the most significant impact on sedimentation rates (36.32%), followed by pasture (29.73%), non-vegetated areas (21.61%), and natural vegetation (12.34%). Soil types such as Neosoil and Gleysoil were identified as the most influential on sediment production (23.56% and 22.88%, respectively). In comparison,

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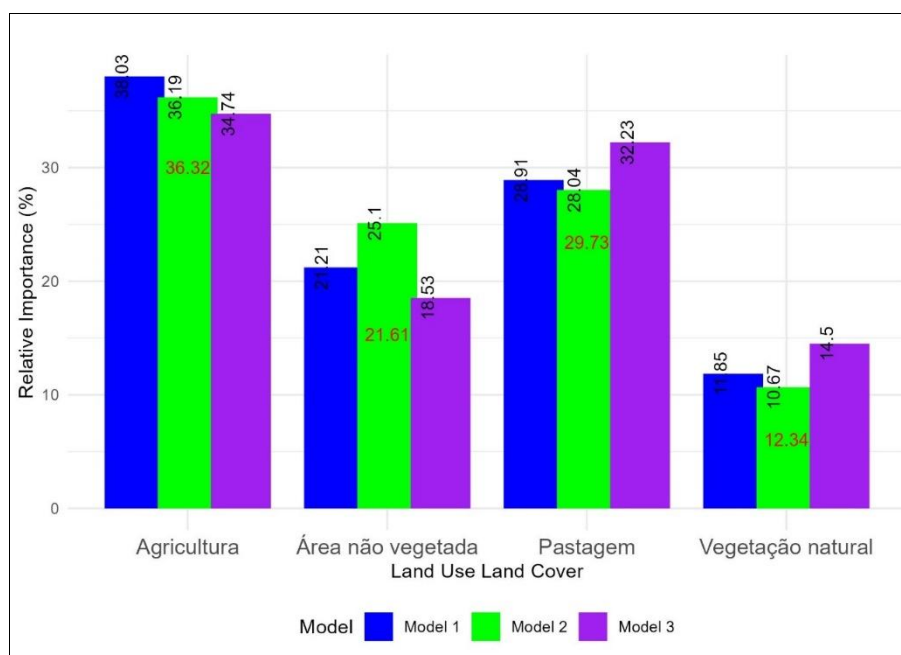
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oxisoils and nitisoils are less important (9.15% and 11.15%, respectively), consistent with their high vulnerability to erosion. Slope classes exhibited increasing influence on sediment production with progressively steeper gradients, ranging from 10.05% of importance for slope 0-3% to 29.32% for more sloped areas (>45%).

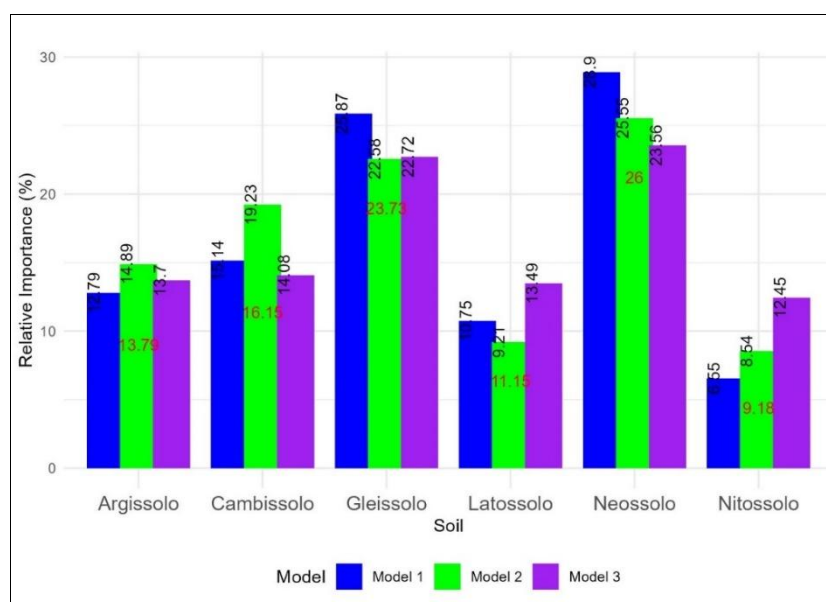
Figure 7. Relative importance of land use and cover classes



Source: the authors (2024).

Analysis of the top three ANN models for land use and cover shows that agriculture has the greatest impact on sedimentation, followed by pasture, non-vegetated areas, and natural vegetation, with respective influences of 36.32%, 29.73%, 21.61%, and 12.34% (see Figure 7). This reflects the high susceptibility of cultivated areas to surface runoff and sediment transport, especially in areas lacking vegetation (Kenea *et al.*, 2021). A simulation experiment on vegetated slopes showed increased sediment production from downstream to upstream, with more upstream vegetation and bare areas producing more sediment than vegetation closer to runoff points (Chen; Zhang, 2022). This confirms the ANN analysis, indicating vegetation has a relatively smaller effect on sediment production.

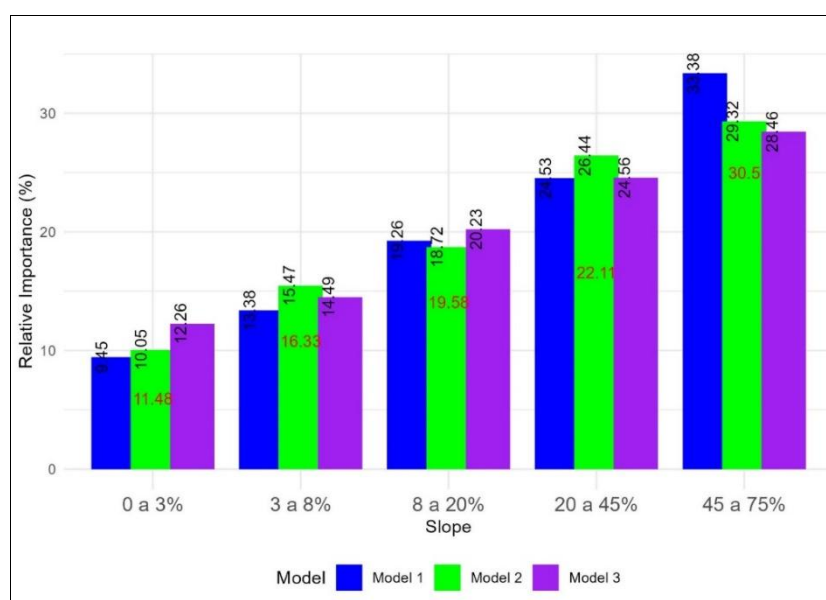
Figure 8. Relative importance of soil classes



Source: the authors (2024).

The findings on soil types align with the vulnerability scale proposed by Crepani *et al.* (2008), where Neosoil and Gleysoil are most vulnerable (3), Cambisol is moderately vulnerable (2.5), Acrisoil is less vulnerable (2), and Oxisol and Nitisol are least vulnerable (1). Neosoil and Cambisol, identified as highly vulnerable, were also significant sediment producers in the Santa Maria Stream basin, northwest Rio de Janeiro (Marchioro *et al.*, 2011; Zhu *et al.*, 2024; Parhizkar *et al.*, 2021). Although soil maps in Brazil are deficient (Almeida *et al.*, 2023), this study was conducted in large basins, which helps to minimize this issue.

Figure 9. Relative importance of slope classes



Source: the authors (2024).

These results have practical applications for understanding sediment dynamics, including sediment connectivity, terrain roughness adjustment in calculations, surface runoff models, soil erosion studies, and land use planning for environmental conservation.

4. FINAL CONSIDERATIONS

The diversity in hydrological, climatic, topography, and landscape characteristics was crucial in validating our results. The primary database, derived from hydrosedimentological modeling influenced by these factors, underpins the main objectives. While previous studies have examined land use and cover, soil, and terrain slope as factors affecting sediment production rates, they did not quantify their degree of influence, mainly in tropical areas. In this study, agriculture, pasture, non-vegetated areas, and natural vegetation were found to have the greatest impacts on sediment production. The variability in soil classes is notable, as it is rare to find all soil types within a single region. Thus, weighting soil types requires careful consideration. The results aligned with water vulnerability patterns, with Neosol, Gleysoil, and Cambisol showing the highest influence on sediment production. For slope classes, influence weights increased progressively with slope. These results were obtained through empirical methods that adjust values based on observed data and functions not directly tied to physical processes. However, they can still provide valuable insights when combined with physical process analyses and other research methods.

5. ACKNOWLEDGEMENTS

The lead author would like to thank Fundação de Amparo à Pesquisa do Estado de Minas Gerais - FAPEMIG (Agreement for PD&I Scholarship Quota nº 5.18/2022) for granting the doctoral scholarship during the period of this study.

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