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Evaluating the EROSION-3D model for soil degradation assessment in the Myjava Region, Slovakia

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ABSTRACT

The Myjava region in western Slovakia is a hilly landscape characterized by rapid runoff responses and a high susceptibility to soil degradation. Historically, this area has undergone significant anthropogenic transformation including large-scale agricultural collectivization which has exacerbated soil erosion and led to frequent "muddy floods". This study focuses on two specific catchments, Svacenicky Creek and Turá Lúka, to evaluate degradation processes under diverse climatic scenarios, ranging from short-term intense rainfall to long-term continuous precipitation. While physically-based models offer a process-oriented alternative to empirical methods, their application in degradation-prone areas is often hindered by extreme model complexity and the difficulty of obtaining high-quality on-site parameters. A critical unresolved issue is the "skin factor" a parameter representing soil crusting and biological activity which is nearly impossible to measure directly and requires extensive, site-specific calibration to ensure model relevance. Furthermore, current models often treat soil as a homogeneous, rigid element, failing to fully capture the natural variability and complexity of infiltration processes. The application of the EROSION-3D model revealed that land management is the primary driver of soil stability in the region. Winter wheat emerged as the most effective conservation practice, reducing surface runoff by 73% and net erosion by 76% compared to fallow land. Conversely, fallow land was the most vulnerable, yielding a mean net erosion of 7 tons per hectare. Sensitivity analyses identified initial soil moisture as a critical factor, showing a strong correlation (>0.70) with runoff and sediment volume across all soil types. To overcome current data limitations and reduce over prediction or underestimation, this study proposes a technical transition toward hybrid modeling. By integrating remote sensing for real-time parameter estimation and machine learning (e.g., ensemble models and deep learning) to analyze complex erosion factors, the predictive accuracy and robustness of the EROSION-3D model can be significantly enhanced.

Keywords: EROSION-3D Model, Myjava Hills, soil degradation, land management, skin factor.

INTRODUCTION

In the Slovak Republic, soil degradation primarily water-driven erosion represents a critical challenge to the stability of agricultural ecosystems, particularly in the hilly terrains of the Myjava region. Soil erosion and the degradation of agricultural land are among the most critical challenges (Gholami et al., 2024; Fatima et al., 2025) the humanity is facing and will face in the coming decades (Das et al., 2024; Xiong, Leng, 2024). The gradual loss of soil is a part of large global environmental challenge (Salma et al., 2024), threatening agricultural productivity, water quality, and ecosystem stability (Firoozi, Firoozi, 2024; Brecheisen, Richter, 2021). Soil erosion contribute to a decreasing in soil quality and thanks to sedimentation and eutrophication deteriorates aquatic ecosystems (Rendana et al., 2024). Approximately 80% of the land suitable for cultivation worldwide experiences moderate to severe erosion (Tang et., 2025). Additionally, the soil erosion can contribute to increase other processes such as floods, mudslides, landslides or deteriorate soil quality (Tanner et al., 2023).

To address these threats, researchers utilize a range of modeling approaches with distinct advantages and limitations. Traditional empirical models like the USLE (Universal Soil Loss Equation) and its revised versions (RUSLE) remain popular due to their simple data requirements and ease of integration with Geographic Information Systems (GIS) (Abdulkareem et al. 2019). However, these models are based on statistical observations and often lack the capacity to simulate the dynamics of single, high-intensity rainfall events (Alewell et al., 2019). In contrast, physically-based models such as WEPP (Water Erosion Prediction Project) and SHETRAN offer process-oriented simulations of hydrological and sediment transport mechanisms, though they are frequently hindered by high data demands and the complexity of on-site parameterization (Mohammed, 2025).

The EROSION-3D model was selected for this study as it represents a robust physically-based framework that balances mathematical complexity with practical application (Schmidt, 1991, 1997). Unlike empirical methods, EROSION-3D simulates the three-stage erosion cycle surface runoff generation, particle detachment, and sediment transport using momentum-based equations (Németová et al., 2020). Despite its established history, the model's effectiveness is often sensitive to local parameters like the "skin factor" (representing soil crusting and biological activity), which requires rigorous site-specific calibration against observed data (Koch et al., 2024; Németová, 2020). The physically-based EROSION-3D model has been applied in numerous studies across diverse locations in Slovakia, Czech Republic and Poland characterized by varying soil conditions (Honek et al., 2018), (Németová, Kohnová, 2022; Németová, 2020). These studies commonly focused on the areas vulnerable to degradation processes, with a specific emphasis on simulating the impact of precipitation events (long term continuous events or short intense events).

Effective soil management in the Myjava Hills requires a transition from static monitoring to dynamic modeling. Current research indicates that approximately 80% of the land suitable for cultivation worldwide experiences moderate to severe erosion (Tang et al., 2025). By evaluating the EROSION-3D model's performance against different land management strategies such as winter wheat, which can reduce net erosion by up to 76% and sediment transport by 91% compared to fallow land this study clarifies the model's reliability and explores its future enhancement through the integration of remote sensing and machine learning (Németová et al., 2018; Németová and Kohnová, 2022).

The study aims to evaluate the application of physically-based EROSION-3D model for assessing soil erosion and other degradation processes under different condition, identify and discuss the challenges encountered in calibrating, validating, and applying these physically-based methods, particularly in areas prone to degradation, emphasize the importance of high-quality input data and effective parameterization techniques in improving the accuracy of these models, explore the integration of advanced technologies such as remote sensing, GIS, and machine learning into physically-based models to enhance their predictive capabilities and monitoring potential, highlight the ongoing uncertainties and limitations in current modeling approaches, including data limitations, scale dependencies, and the complexity of natural processes. Through this comprehensive evaluation, the overall objective is to contribute to the advancement of soil degradation assessment methodologies, with a focus on physically-based approaches, to better understand and address this critical environmental issue.

MATERIALS AND METHODS

EROSION-3D model: A physically-based soil erosion model

In this study, a physically-based modelling approach EROSION-3D was employed to analyse erosion processes and assess its applicability to the research location. When selecting the most appropriate modelling approach, it is essential to consider the characteristics of the study area. Accurate identification of site-specific features is crucial for making informed decisions regarding the feasibility and effectiveness of using the model. The EROSION-3D model is a physically-based, spatially distributed soil erosion model developed by Jürgen Schmidt in the early 1990s (Schmidt, 1991; Schmidt, 1997). The model simulates water erosion processes on agricultural land by integrating hydrological, sediment transport, and deposition mechanisms. The EROSION-3D model has been widely applied in various agricultural landscapes to assess erosion risk, evaluate land management practices, and predict the impact of both single rainfall events and long-term erosion trends. This model is particularly useful for event-based soil erosion modeling and is capable of capturing short-term, high-intensity erosion events caused by heavy rainfall, as well as simulating long-term erosion through iterative calculations. It utilizes high-resolution digital elevation models (DEMs) and detailed soil and land-use data, making it suitable for both small scale and large scale erosion studies in agricultural settings.

Key components and processes in EROSION-3D and input parameters

The EROSION-3D model decomposes the soil erosion process into three interconnected components, each representing a critical step in the overall erosion cycle. These components capture the generation of surface runoff, the detachment of soil particles, and the transport and eventual deposition of eroded sediment. The effectiveness of the modeling framework relies on the accurate parameterization and representation of each of these fundamental processes, which are described as follows:

- Surface runoff generation: Infiltration is calculated using the Green-Ampt model to determine the partitioning between soil water storage and overland flow. This process is characterized by the momentum of the flux exerted by overland flow and includes both gravitational and matrix components (Schmidt, 1991; Németová et al., 2020).
- Soil detachment processes: This component simulates the separation of soil particles through two primary mechanisms: raindrop impact (splash erosion) and flow-driven detachment (rill and interrill erosion). The detachment rate depends on rainfall intensity, soil cohesion, and surface resistance (Schmidt, 1996; Németová et al., 2020).
- Sediment transport and deposition: Transport capacity is determined using stream power equations. Deposition is simulated to occur when the sediment load exceeds the calculated transport capacity of the surface flow (Schmidt, 1991; Németová et al., 2020).

The effectiveness of the EROSION-3D framework relies on a complete set of nine input parameters. These specific parameters were selected because they represent the fundamental physical properties required to solve the model's core governing equations. For example, parameters such as bulk density, organic carbon, and initial soil moisture are essential for calculating the gravitational and matrix components of the Green-Ampt infiltration model. Similarly, erosion resistance and surface roughness are required to define the critical shear stress and hydraulic friction necessary for simulating soil detachment and transport capacity. While these nine inputs are the only primary data required, they are not the only variables used in the final evaluation. The model utilizes these inputs to calculate various derived parameters through physical interactions. These derived parameters – such as time-varying infiltration rates, critical shear velocity, and transport capacity – are integral to the results section as they provide a higher-resolution understanding of how specific land management practices influence the stability of the soil surface. To ensure international comparability and address variations in national standards, the input parameters in Table 1 are defined according to standardized soil science protocols.

Study area

The modeling of degradation processes was conducted at multiple locations, including Svacenicky Creek and Turá Lúka catchments (approximate coordinates: 48°45' N, 17°34' E), located in the Myjava region in western Slovakia

Table 1. Overview of EROSION-3D model´s input parameters

Input parameters	Unit	Definition and Standard Reference
Altitude (DEM)	[m]	Digital Elevation Model representing relief characteristics
Rainfall intensity per time step	[mm/min]	Precipitation volume per time step
Bulk density	[kg/m^3]	The dry mass of soil per unit volume
Organic carbon content	[%]	Percentage of organic carbon, influencing water retention and stability
Grain size distribution	[%]	Mass percentages of sand, silt, and clay fractions (e.g., ISO 11277)
Skin factor	[–]	Correction factor for surface crusting, compaction, and biological activity (Schmidt, 1991)
Surface roughness	[s/m$^{1/3}$]	Manning's coefficient representing hydraulic resistance (Engman 1986)
Initial soil moisture	[%]	Volumetric water content at the start of a rainfall event
Erosion resistance	[N/m^2]	Critical shear stress required for soil particle detachment (Schmidt 1996)

(Figure 1), under a range of conditions: short and intense rainfall events, saturated soils, dry soils, continuous rainfall without intensity peaks, and continuous rainfall combined with intense rainfall. These scenarios were simulated repeatedly to evaluate the model's response and generate forecasts with practical applications. This region is characterized by hilly terrain with rapid runoff responses and high erosion risk, especially on arable land. The relief is characterized by a dissected hilly landscape with slopes ranging from 7° to 15°, reaching up to 27° in concentrated flow channels. The region belongs to a moderately warm and humid climatic zone. The mean annual temperature is 8.5 °C, and average annual precipitation is approximately 650 mm. The precipitation distribution is seasonally skewed, with over 60% occurring during the growing season (April – September), often as high-intensity convective storms exceeding 1.0 mm/min. These events drive the transformation of soil moisture into surface runoff, especially when antecedent moisture levels exceed 70% of field capacity. The experiments in the Myjava area concentrated on mitigating muddy floods and soil erosion resulting from steep slopes and prevailing agricultural management. The soil cover is dominated by Haplic Luvisols and Eutric Cambisols developed on flysch substrates. According to the USDA soil textural triangle, these are classified into three primary groups: Clay, Silty-Clay, and Silty-Clay Loam (Table 2). The crop structure within the soil–crop system is dominated by winter wheat (35%), silage corn (25%), and oilseed rape (15%), interspersed with periods of black fallow. The Myjava Hills have experienced significant anthropogenic changes in form of deforestation during medieval settlement periods and large-scale agricultural collectivization after 1949, both of which have exacerbated erosion processes and contributed to frequent muddy floods with high sediment concentrations (Honek et al. 2018; Stankoviansky 1997). Further, crop management strategies were tested to assess their effectiveness in reducing runoff and sediment transport. Special attention was given to the influence of soil moisture scenarios, as initial moisture is a critical driver of both runoff and erosion risk.

Calibration of the EROSION-3D model for Slovak conditions required detailed parameter catalogues and adaptation of soil textural classification systems. Overall, the region serves as a representative example of central European hilly landscapes susceptible to soil and water degradation due to land use practices and climate extremes (Németová, 2020; Németová et al., 2020; Németová, Kohnová, 2022).

The implementation and evaluation of the EROSION-3D model were conducted in two distinct temporal blocks to assess different agricultural management impacts:

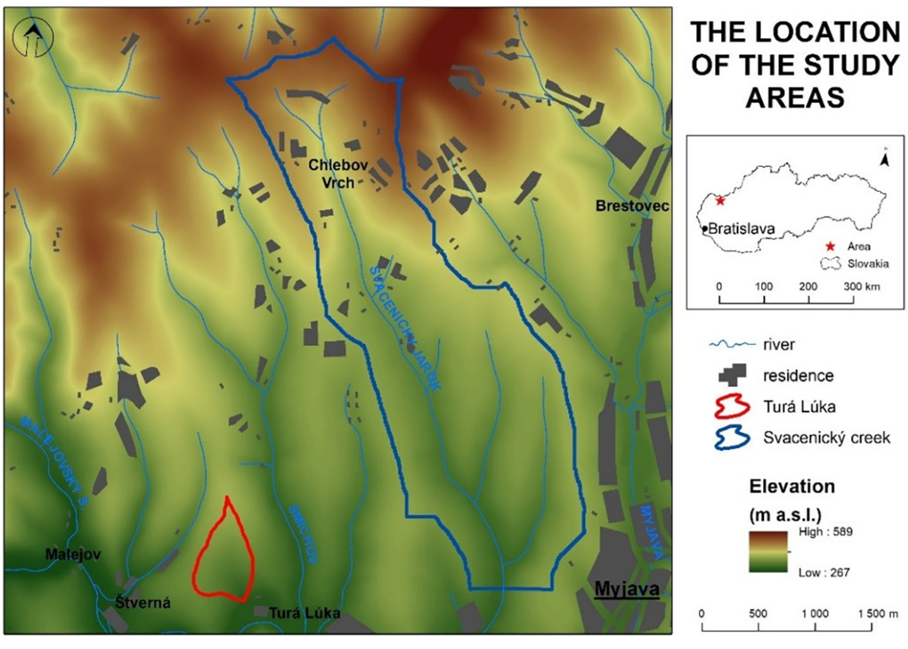


Figure 1. Location of Svacenicky Creek Catchment and Digital elevation model of researched catchment area

- Period I (2015–2016): Focused on the evaluation of soil protection under winter wheat management, characterized by higher intensity but fewer rainfall events.
- Period II (2016–2017): Focused on the implementation of silage corn management, which experienced more frequent, lower-intensity rainfall events

To ensure the model's parameters accurately reflect the field conditions, soil sampling was conducted following a systematic grid format (50 x 50). A density of 4 samples per hectare was utilized to capture the high spatial variability of soil texture and moisture across different topographical positions (summit, backslope, and footslope). Samples were processed according to ISO 10381 (Sampling) and ISO 11277 (Determination of particle size distribution). This density was chosen to minimize the "pixel-scale uncertainty" inherent in raster-based modeling, ensuring that the input grid accurately reflects the heterogeneous nature of the Myjava flysch substrate. 42 rainfall events were selected for simulation. Short-term events (e.g., 22.5 mm / 50 min) were used to test peak detachment rates, while continuous long-term series were used to assess cumulative soil profile thinning.

Baseline indicators for model sensitivity, such as the mean skin factor for different tillage stages and critical shear stress values, were adopted from multi-year field rainfall simulations previously conducted in the region (Németová et al., 2020; Németová and Kohnová, 2022). This integration allows for a more robust evaluation of the model's effectiveness across varying climatic cycles.

All data processing was automated using the EROSION-3D sensitivity tool and post-processed using R Statistics (v4.2.1). Pearson's correlation coefficients (r) were used to quantify the relationship between moisture regimes and sediment yield. All statistical tests were conducted at a significance level of $\alpha = 0.05$. Confidence intervals (95%) and root mean square error (RMSE) were calculated to determine the reliability of the model's predictive output compared to measured erosion plots.

RESULTS

The model results cover a number of outputs that the model can generate along with graphical maps, which gives the model added value. On those maps displayed, it is possible to clearly observe areas prone to erosion, and relatively quickly identify places where eroded material will collect, or even the routes of surface runoff (based on erosion grooves) (Figures 4–5). In this study, the Svacenicky Creek catchment is analyzed as a one of the experimental catchments where the EROSION-3D model was applied. The results are divided into two parts, i.e., the first results datasets demonstrate the effect of the three intense and short rainfall events against the three land management practices (Figure 4 A–C), (Tables 8–9). The results display net erosion values in tons per hectare (Figure 4 A–C). The second results datasets contain evaluation of 42 continuous rainfall events for two period analyzed, i.e., Period A (Silage corn) (Figure 5 A) and Period B (Winter wheat), (Figure 5 B). The sensitivity analyses of EROSION-3D model (Figures 2–3) was performed for three soil types, i.e., clay soil, silt-clay soil and silt-clay-loam and for all soil parameters (Table 1) by changing individual input parameters by 10% against the reference value. The soil parameters of EROSION-3D model are listed in Table 1. The tables 4–7 shows statistical interpretation covering mean, median, standard deviation, minimum, maximum, and coefficient of determination for surface runoff measurements and sediment volume (in m^3) for clay soil, silty-clay soil, and silty-clay loam. The negative coefficient of determination within the Organic Carbon Content (Table 4–5) implies that soils with higher organic carbon content tend to exhibit lower runoff and sediment volume due to improved water retention, enhanced infiltration, and greater soil stability. However, the relationship isn't always perfectly linear in real-world scenarios (as indicated by the weaker correlations in soil type Silt-Clay), but the general trend is that increasing organic carbon leads to

Table 2. Soil textural groups and grain size distribution

Soil textural group	Sand (2.0–0.05 mm) [%]	Silt (0.05–0.002 mm) [%]	Clay (< 0.002 mm) [%]
Clay soil	12.4	32.1	55.5
Silty-clay soil	8.2	46.8	45.0
Silty-clay loam	14.5	52.3	33.2

a reduction in these two factors. The coefficient of determination values for soil initial moisture (>0.70) indicate the statistical strength of the relationship between initial soil moisture content and the surface runoff and sediment volumes and confirms the assumption that initial soil moisture content strongly influences surface runoff and sediment volumes in all soil types.

The coefficient of determination (R^2) across all soil groups ranges from 0.44 to 0.62 (Table 3), confirming that initial soil moisture is a primary driver of erosion variance within the model. The Silty-Clay soil exhibited the highest Standard Error (*SE*), particularly in sediment volume prediction (±2105.6 m^3), which highlights the increased sensitivity and lower predictability of this soil type under high-intensity rainfall scenarios compared to the more stable Silty-Clay Loam.

The results datasets (Svacenicky Creek catchment, Slovakia) (Figure 4 A–C), (Tables 8–9) show the fallow land is most vulnerable to net erosion, with the highest mean net erosion value of 7 tons per hectare. The moderate mean erosion value belongs to silage corn (4.58 tons per hectare), while winter wheat demonstrates the smallest amount of net erosion (1.65 tons per hectare). According to the standard deviations the erosion values are more consistent for silage corn and winter wheat compared to fallow land. These results can be very helpful for those who implements management strategies and conversation practices of agricultural land.

The calculations were performed for three storm rainfall events, which were the most extreme rainfall events occurring during the time period of 1995–2017. The two rainfall events were from 2008 and one from 1999. The first rainfall scenario occurred on 15.8.2008 with a total rainfall amount of 22.5 mm and duration of 50 minutes. The second rainfall scenario occurred on the same day with a rainfall amount of 16.3 mm for 20 minutes, and the third rainfall scenario one on 8.6.1999 was an 80 minutes rainfall event with 18 mm of rain.

When compared the individual crops, the land without cover, i.e., fallow land has the highest mean and median erosion values, determining

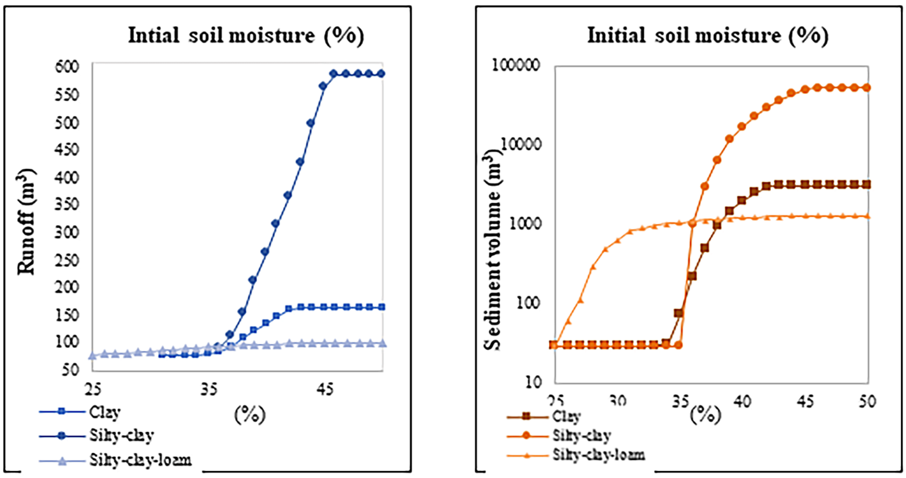
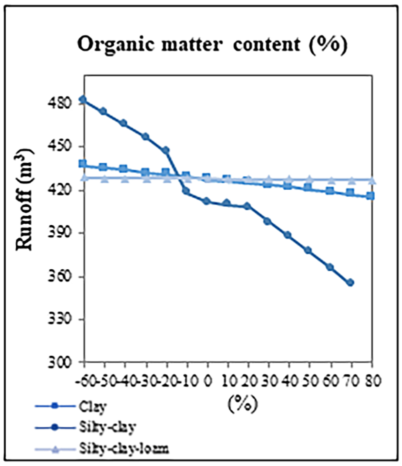


Figure 2. The effect of initial soil moisture on model outputs of runoff and sediment quantity for three soil types

Table 3. Regression equations and statistical indicators for initial moisture (2015–2017)

Soil type	Output parameter (*y*)	Regression Equation (*y* = *mx* + *c*)	R^2
Clay	Runoff [m³]	$y = 0.788x – 20.88$	0.62
	Sediment [m³]	$y = 10.91x – 289.17$	0.62
Silty-clay	Runoff [m³]	$y = 0.665x – 68.44$	0.44
	Sediment [m³]	$y = 47.92x – 3972.85$	0.44
Silty-clay loam	Runoff [m³]	$y = 0.760x – 19.65$	0.58
	Sediment [m³]	$y = 4.05x – 104.51$	0.58



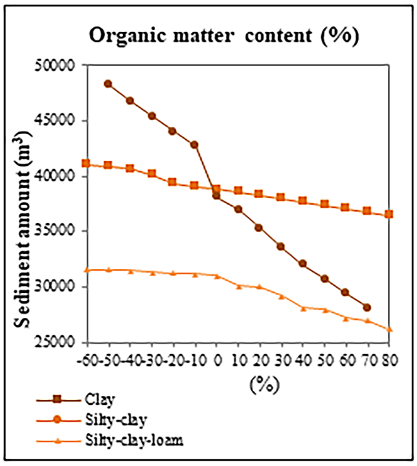


Figure 3. The influence of organic matter content on model results of runoff and sediment quantity for three soil types

Table 4. Statistical characteristics for soil organic matter (m^3/m^3) content and surface runoff (m^3) of research period (2015 – 2017) based on reference value of soil parameters

Soil type	Mean	Median	Std Dev	Min	Max	Coefficient (R^2)
Clay soil	400.6	404.0	16.5	379	430	-0.774
Silty-clay soil	369.5	395.0	99.9	150	480	-0.040
Silty-clay loam	423.1	423.5	4.7	416	430	-0.866

Note: (α = 0.05 significance level).

Table 5. Statistical characteristics for soil organic matter (m^3/m^3) content and sediment volume (m^3) of research period (2015 – 2017) changed 10% against the reference value

Soil Type	Mean	Median	Std Dev	Min	Max	Coefficient (R^2)
Clay soil	40193.1	40000	1229.8	37000	42000	-0.780
Silty-clay soil	37034.4	35530	6505.6	27000	48000	-0.032
Silty-clay loam	29591.6	30000	2139.6	26544	32000	-0.718

Note: (α = 0.05 significance level).

Table 6. Statistical characteristics for soil initial moisture (m^3/m^3) and surface runoff (m^3) of research period (2015 – 2017) based on reference value of soil parameters

Soil Type / Statistic	Mean	Median	Standard Deviation	Minimum	Maximum	Coefficient (R^2)
Clay soil	98.5	80.0	30.8	75.0	150.0	0.788
Silty-clay soil	204.3	93.0	190.7	75.0	580.0	0.665
Silty-clay loam	81.9	81.0	4.6	75.0	89.0	0.760

Note: (α = 0.05 significance level).

it is most susceptible to erosion processes compared to the other two crops, following by the silage corn with the intermediate mean and median erosion values, indicating a moderate level of erosion. The lowest mean and median erosion values are expected to winter wheat which assume the minimal probability of erosion processes. The respond of model to fallow land (bare soil) consistently shows the highest values for surface runoff, net erosion, erosion/deposition, and amounts of sediments across all rainfall events, which makes it most vulnerable to those processes. Net erosion rates are remarkably variable within fallow land signaling sensitivity to rainfall

Table 7. Statistical characteristics for soil initial moisture (m³/m³) and sediment volume (m³) of research period (2015 – 2017) changed 10% against the reference value

Soil type / Statistic	Mean	Median	Standard deviation	Minimum	Maximum	Coefficient (R^2)
Clay soil	1363.8	40.0	1926.0	40.0	4991.0	0.788
Silty-clay soil	13762.9	40.0	27105.3	40.0	80003.0	0.665
Silty-clay loam	436.2	44.0	322.2	38.0	1000.0	0.760

Note: (α = 0.05 significance level).

intensity and duration. Silage corn indicates moderate levels of runoff, soil loss and erosion with its outputs it falls between fallow land and winter wheat which documents the lowest values for all measured parameters and based on that the winter wheat provides the best solution for agricultural land in critical condition in terms of potential soil erosion processes and when choosing the suitable land management practices.

The statistical results listed in the Table 8 shows there are significant differences between land management practices. Winter wheat lowers surface runoff by 73%, net erosion by 76%, erosion/deposition by 82% and sediment transport by 91% compared to Fallow land. Silage corn results in reduction of net erosion by 35% compared to fallow land but still triggers significant sediments. Surface runoff showed a high F-statistic (32.22) compared to p-value (0.0006), which can be translated as a significant impact of land management practices to runoff. Similarly, it is also in the case of erosion/deposition, amounts of

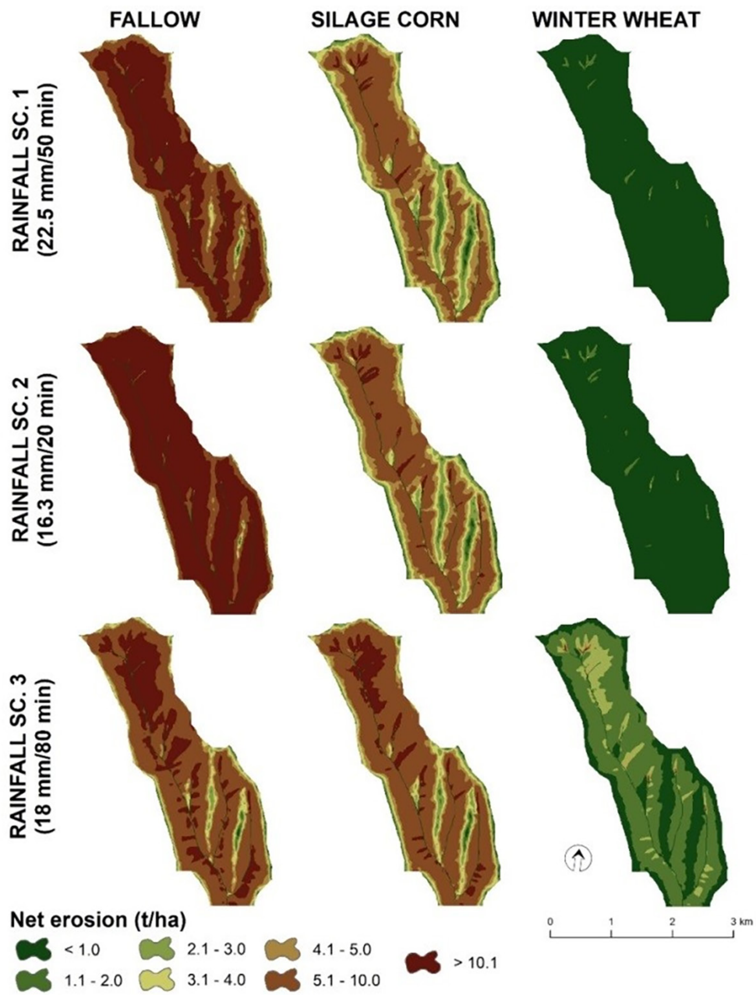


Figure 4. The graphical model´s output (Svacenicky creek catchment) (Net erosion t/ha) A) Rainfall event scenario 1, B) Rainfall event scenario 2, C) Rainfall event scenario 3

sediments (Table 8), which highlights the critical role of vegetation cover in soil conservation, land management practices and soil stabilizing.

These results emphasize the winter wheat as the most effective crop for reducing soil erosion, sediments and runoff likely due to its dense ground cover and extensive root system which minimize soil disturbance. Silage corn represents moderate erosion control compared to fallow land but is less effective than winter wheat in reducing soil loss and sediment transport. Depending on the conditions of the specific area it may requires additional measures to minimize erosion.

In the context of second results datasets (Figure 5 A–B), (Tables 10–13), 42 rainfall events were analysed; Period I had total of 14 rainfall events (max: 26.11 mm) with higher intensity and Period II had more frequent but lower-intensity rainfall events with total of 28 events. Table 12 displays key differences between the two periods, showing changes in rainfall patterns, surface runoff, erosion/deposition, and sediment amounts. The data presents that Period A had higher average rainfall and erosion/deposition rates while Period B experienced higher average surface runoff despite lower rainfall. This may reflect the importance of the distribution of precipitation, the number of precipitation events, their amount and intensity within a single precipitation event. In this role, continuous long-lasting precipitation plays the most significant role compared to very intense but short-lasting precipitation, which was probably reflected in this case. The results datasets were also testing against the correlation

Table 8. Statistical overview of model results across three rainfall events

Land management	Statistic	Surface runoff (m^3)	Net erosion (t/ha) *	Erosion/Deposition (t/ha)	Amount of sediments (m^3)
Fallow	Mean	11.33	7.00	9.33	4.17
	Median	11.00	7.00	9.00	4.00
	St. Dev.	1.53	2.65	2.52	0.29
Corn	Mean	12.67	4.58	4.00	2.67
	Median	12.00	4.50	4.00	3.00
	St. Dev.	2.08	0.80	1.00	0.58
Winter wheat	Mean	3.00	1.65	1.67	0.36
	Median	3.00	1.40	1.00	0.07
	St. Dev.	1.00	0.74	1.15	0.55

Note: (α = 0.05 significance level).

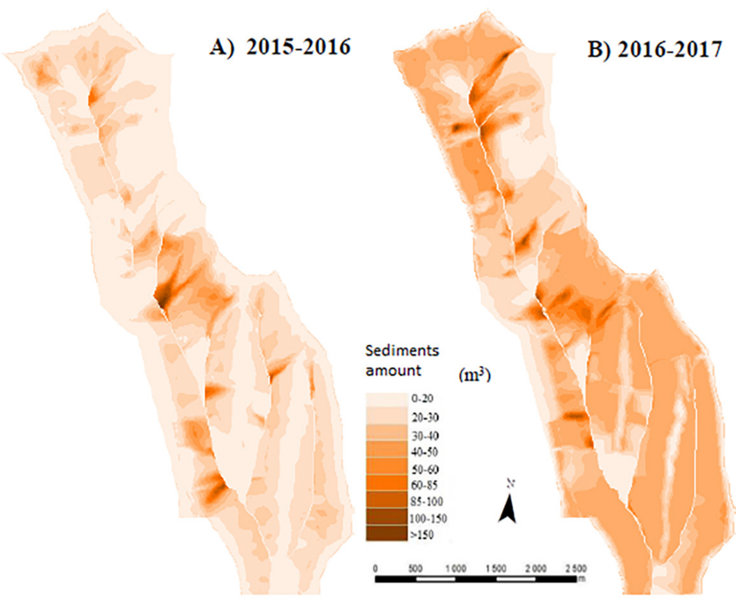


Figure 5. Erosion intensity A) Silage Corn 2015–2016, B) Winter Wheat 2016-2017 (Svacenicky Creek, Slovakia)

Table 9. Statistical interpretation of results for erosion parameters across various land management strategies

Variable	F-statistic	p-value	Interpretation
Surface runoff	32.22	0.0006	Highly significant differences between land management practices.
Net erosion	10.87	0.0101	Significant differences between practices.
Erosion/Deposition	16.04	0.0039	Significant differences between practices.
Amount of sediments	45.79	0.0002	Highly significant differences between practices.

Note: (α = 0.05 significance level).

Table 10. Statistics values for Period I Silage Corn (2015–2016)

Statistic	Rainfall (mm)	Runoff (m³)	Erosion (t/ha)	Sediments (m³)
Mean	7.13	2.68	0.26	11.58
Median	4.34	1.70	0.01	12.42
St. Dev.	7.12	3.08	0.72	5.08
Min	0.57	0.00	0.00	3.98
Max	26.11	10.20	2.75	18.55
Sum	99.82	37.53	3.57	162.08

Table 11. Statistics values for Period II Winter Wheat (2016–2017)

Statistic	Rainfall (mm)	Runoff (m³)	Erosion (t/ha)	Sediments (m³)
Mean	3.07	4.15	0.14	10.12
Median	2.77	3.15	0.14	7.99
St. Dev.	2.41	2.96	0.08	8.14
Min	0.48	0.00	0.00	1.20
Max	10.00	9.60	0.27	39.72
Sum	86.24	115.77	3.99	283.54

Table 12. The overview of both period analysed A) Silage Corn, B) Winter Wheat (Svacenicky Creek, Slovakia)

Characteristics variables	A Silage Corn (2015–2016)	B Winter Wheat (2016–2017)
Number of events	14	28
Average rainfall (mm)	7.13	3.07
Average surface runoff (m³)	2.68	4.15
Average erosion/deposition (t/ha)	0.26	0.14
Average amount of sediments (m³)	11.58	10.12
Maximum rainfall (mm)	26.11	10.00
Maximum surface runoff (m³)	10.20	9.60
Maximum erosion/deposition (t/ha)	2.75	0.27
Maximum amount of sediments (m³)	18.55	39.72

analyses (Table 13) and the strongest correlation (0.62) was found between rainfall and erosion/deposition, which means that higher rainfall result in more erosion. The weakest correlation (0.14) was identified between rainfall and amount of sediments, this may be explained by temporal disconnection between rainfall and measured sediment amounts, however rainfall events may trigger the sediments amount in most cases, the resulting sediments does not have to arrive at soil surface because of vegetation cover. The ANOVA results show a significant difference in

Table 13. Correlation analyses of output values (Svacenicky Creek, Slovakia)

Variables	Correlation coefficient (*r*)
Rainfall vs Surface runoff	0.41
Rainfall vs Erosion/deposition	0.62
Rainfall vs Amount of sediments	0.14
Surface runoff vs Erosion/deposition	0.22
Surface runoff vs Amount of sediments	0.31

rainfall events between the two periods (F = 7.28, p = 0.0101). This indicates that the rainfall patterns differed substantially between 2015-2016 and 2016-2017. Period II results in higher surface runoff (4.15 m^3) compared to Period I (2.68 m^3) even despite lower rainfall. This may be the consequences of different land management practices within the periods. Winter wheat in Period I provided better soil protection, reducing runoff by improving infiltration and stabilizing the soil while the Silage corn in Period II, being an erosion non-protective crop, likely reduced infiltration and increased overland flow. However, erosion rates were slightly higher in Period I (mean: 0.26 t/ha) compared to Period II (mean: 0.14 t/ha) most likely due to less intense rainfall trends. The critical sediment values occurred in Period II with high sediment amount of 39.72 m^3, far exceeding the average sediment transport for that period indicating localized erosion areas stimulated by land management practices in combination with intense rainfall event.

The significant difference in rainfall patterns between the two periods highlights how precipitation trends (distribution, frequency, intensity) influence surface runoff and additional erosion processes. The impact of land management practices can be declared by winter wheat in Period I which effectively reduced surface runoff and stabilized soils despite the higher-intensity rainfall events while the silage corn in Period II led to higher surface runoff, likely due to its poor soil protection ability. The result values demonstrate that certain areas within the study site are more susceptible to erosion under particular rainfall intensities or durations. These findings highlight the importance of identifying and managing these vulnerable areas to mitigate soil loss and improve overall land management practices. In the context of changing rainfall patterns, the careful crop selection and land strategies play a significant role especially in areas identified as prone to the development and occurrence of erosion.

DISCUSSION

Soil erosion is a serious environmental threat with devasting consequences to ecosystems, agriculture, and humans (Chandra Pal et al., 2021). The major effects of erosion lead to the loss of fertile topsoil which negatively impacts the agricultural productivity and declining agricultural production negatively affects food production. Unfortunately, that's not all, the eroded material has to end up somewhere, and in most cases it's rivers, basins, reservoirs, where not only does it silt up, but the risk of floods also increases along with the eroded material (Taloor et al., 2025).

Many studies use the well-known and well-established USLE and RUSLE methods and their modifications to local conditions (Delgado et al. 2025; Aldrees et al., 2024; Zhang et al., 2024; Alhasn et al., 2024; Helmi, 2023). The USLE and RUSLE are used with great popularity due to their easy applicability, data required are not too complicated and friendly with GIS (Abdulkareem et al. 2019). In the study of Shmilovitz et al. (2023) is implemented hybrid hydrological and erosional model (based on Kineros2) to simulate high erosive events with rainfall data from high-resolution meteorological radar. Cerretelli et al. (2023) applied RUSLE equation approach with GIS tools and remote sensing data to determine the soil erosion of the Costa Rican soil to protect and ensure production of coffee agroforestry systems.

While the empirical models work on the basis of statistical measurements and observations (Alewell et al., 2019), physically-based models use mathematical equation and relationship to describe the erosion processes. Using erosion models provide wide range of advantages not only for calculating soil loss but also for choosing the right land management, soil protection, designing various measures and evaluating their effectiveness or to develop strategies against soil erosion and subsequent environmental burdens (Koch et al., 2024).

In the regards of soil erosion, the validation of model´s results are quite complicated. Measuring the amount of soil loss on agricultural land tends to be practically unachievable. Therefore, reservoirs (or other sampling areas), where the amount of sediment can be regularly monitored by different and available methods are an effective method used for validation (Özşahin, 2023; Németová et al., 2020; Rompaey et al., 2003).

In general, soil erosion models are indispensable in solving various issues related to soil degradation, including the design of soil management practices. These models simplify the erosion processes and thus create an opportunity to evaluate areas to prone by degradation processes. However, these models usually demand a large amount of data (sometimes not available) and model´s outputs tend to overprediction or underestimation (Mohammed, 2025). In the EROSION-3D model nine input parameters are required, which represents a relatively small number of parameters. However, parameters such as skin factor (highly influence the model´s results) have to be calibrated to ensure the relevance of model results (Koch et al., 2024). In the context of case studies conducted in Slovakia, the parameter catalogue with soil input parameters reflected local conditions was created (Németová, Kohnová, 2022). The sensitivity analyses, parameterization, calibration and validation are an absolutely necessary step in applying the model. In the work of Sreedevi et al. (2022) was performed two stage sensitivity analyses the most significant input (flow parameters and erosion sediment transport parameters) in the SHETRAN model and the sensitivity of parameters was measured before the model calibration as was done also in the case of the EROSION 3D model (Honek et al. 2018). In the EROSION-3D model, the sensitivity of a model to parameter changes was tested by changing each input parameter and observing its impact on the final results. The similar principal of sensitivity analyses was done in many studies (Dimyati, 2023; Sreedevi et al. 2022). Sensitivity analysis is an effective precursor to model calibration and based on the results of the sensitivity analysis, it is possible to choose the appropriate calibration method (Duan et al., 2024). Currently, hybrid models are increasingly developed based on well-known and long-used models. Hybrid models of soil water erosion incorporate elements from both empirical and physically-based approaches to increase strength of both. These models point to provide more precise, accurate and adaptable predictions of degradation processes by integrating data-driven perception with process-based comprehension (Wang et al., 2024), (Hitouri et al., 2024). In the study of Barman et al. (2024) the empirical model ANN was incorporated into the physically-based model (SWATT) in order to provide the accuracy of simulations, and comprehensive interconnection between the hydrological processes within the catchment. Furthermore, machine learning is increasingly being used to model and predict soil erosion in order to enhances the accuracy of soil erosion predictions. Machine learning techniques engage the past measurements to produce prediction into the future while offering advanced and efficient analysis of complex data (Abouhalima et al., 2024) and shown capability and effectiveness for solving challenging soil science issues (Vu Dinh et al., 2021).

In the case of the EROSION 3D model, a comprehensive sensitivity analysis was performed and its confrontation with model results, multi-stage validation and calibration of the model, as well as comparison with other erosion models at different sites. Since the soil erosion research has recorded developments, within future direction incorporating remote sensing and machine learning into the EROSION-3D model would significantly enhance its predictive capabilities and accuracy in modeling soil erosion. Deep learning algorithms and hybrid models are the techniques that can enhance the erosion predictions (Liu et al., 2024). These techniques can improve the performance of EROSION-3D via enhancing parameter estimation and improving predictive accuracy. By complex analyzing relationships between erosion factors machine learning algorithms is capable to accurately predict soil erosion (Abouhalima et al., 2024; Dinh et al., 2021). The integration of machine learning to soil erosion research can fill the gaps and address current limitations in erosion modeling (Hitouri et al., 2024). Despite the many advantages of machine learning in relation to erosion modeling, it also faces some challenges has to be addressed, such as data quality issues and the need for multiple calibration (Alqadhi et al., 2023). According the Hitouri et al. (2024) future direction of erosion modelling can be focused on developing hybrid models which represent the combination of machine learning and physically-based or empirical approach (Tkeshelashvili et al., 2024).

The reliability of EROSION-3D is fundamentally rooted in its momentum-based approach to sediment transport, which avoids the statistical "averaging" inherent in empirical models like USLE. By using the Green-Ampt infiltration model, EROSION 3D provides a mathematically sound representation of the partition between soil storage and surface runoff. Our analysis shows that the model is highly sensitive to initial soil moisture, with coefficients of determination (R^2) ranging from 0.44 to 0.62. This suggests that while the physical logic is sound, the model's reliability is strictly contingent upon the precision of antecedent moisture data. The EROSION 3D model is highly effective for targeted, site-specific soil conservation planning, but it is less efficient for broad, national-scale monitoring due to its heavy data requirements. While the results demonstrate the model's capacity to quantify soil loss, its overall efficiency must be viewed through a multidimensional lens.

CONCLUSIONS

This study demonstrates that the physically-based EROSION-3D model is a robust tool for identifying spatial degradation risks in hilly terrains like the Myjava region, provided site-specific calibration of complex parameters such as the skin factor is performed. Sensitivity analyses confirmed that initial soil moisture is a primary driver of erosion risk, maintaining a strong positive correlation (>0.70) with surface runoff and sediment volumes across all analyzed soil types (clay, silty-clay, and silty-clay loam). Conversely, soil organic matter exhibited a significant negative correlation (up to -0.86) with runoff, underscoring its role in enhancing infiltration and soil stability.

Statistical evaluation of land management strategies revealed that winter wheat is the most effective conservation practice, reducing surface runoff by 73%, net erosion by 76%, and sediment transport by 91% compared to fallow land. While silage corn provided a 35% reduction in net erosion over bare soil, it remained insufficient for preventing significant sediment yields during intense rainfall. To overcome the limitations of traditional field measurements and the ambiguity of local input parameters, future assessments should integrate remote sensing for high-resolution data acquisition and machine learning for developing hybrid models. These advancements will enable more accurate, real-time monitoring and support the implementation of targeted soil conservation strategies to mitigate global topsoil loss.

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REFERENCES

1. Abdulkareem, J. H., Pradhan, B., Sulaiman, W. N. A., Jamil, N. R. (2019). Prediction of spatial soil loss impacted by long-term land-use/land-cover change in a tropical watershed. *Geoscience Frontiers, 10*(2), 389–403, https://doi.org/10.1016/j.gsf.2017.10.010
2. Abouhalima, M., das Neves, L., Taveira-Pinto, F., Rosa-Santos, P. (2024). Machine learning in coastal engineering: Applications, challenges, and perspectives. *Journal of Marine Science and Engineering, 12*(4), 638. https://doi.org/10.3390/jmse12040638
3. Aldrees, A., El-Pateh, S. J., Dan'azumi, S., Abba, S. I. (2024). Spatio-temporal soil loss modelling using RUSLE and sediment delivery into a reservoir in a semi-arid region of northern Nigeria. *Heliyon, 10*(20). https://doi.org/10.1016/j.heliyon.2024.e38887
4. Alewell, C., Borrelli, P., Meusburger, K., Panagos, P. (2019). Using the USLE: Chances, challenges and limitations of soil erosion modelling. *International Soil and Water Conservation Research, 7*(3), 203–225, https://doi.org/10.1016/j.iswcr.2019.05.004
5. Al-hasn, R., Alghamaz, F., Dikkeh, M., Idriss, Y. (2024). Water soil erosion modeling with RUSLE, GIS & remote sensing: A case study of the AL-Sanaoubar River basin (Syria). *Journal of the Saudi Society of Agricultural Sciences, 23*(7), Pages 474–484, https://doi.org/10.1016/j.jssas.2024.05.004
6. Alqadhi S., Mallick J., Talukdar S., Alkahtani M.L. (2023). An artificial intelligence-based assessment of soil erosion probability indices and contributing factors in the Abha-Khamis watershed, Saudi Arabia. *Frontiers in Ecology and Evolution, 11*, https://doi.org/10.3389/fevo.2023.1189184
7. Barman, S., Singh, W. R., Tyagi, J., Sharma, S. K. (2024). A hybrid SWAT-ANN model approach for analysis of climate change impacts on sediment yield in an Eastern Himalayan sub-watershed of Brahmaputra. *Journal of Environmental Management, 365*, 121538, https://doi.org/10.1016/j.jenvman.2024.121538

8. Cerretelli, S., Castellanos, E., González-Mollinedo, S., Lopez, E., Ospina, A., Haggar, J.. (2023). A scenario modelling approach to assess management impacts on soil erosion in coffee systems in Central America. *Catena, 228*, 107182, https://doi.org/10.1016/J.Catena.2023.107182
9. Das, S., Jain, M. K., Gupta, V. (2024). An assessment of anticipated future changes in water erosion dynamics under climate and land use change scenarios in South Asia. *Journal of Hydrology*, *637*, 131341. https://doi.org/10.1016/j.jhydrol.2024.131341
10. Delgado, D., Sadaoui, M., Ludwig, W., Méndez, W., Ortiz-Hernández, E., Farfán-Intriago, P. (2025). Assessment of soil erosion by RUSLE in the Ecuadorian basins (2001–2020) based on GIS and high-resolution satellite data: Main drivers and changes on soil erosion. *Geomorphology*, *469*, 109515, https://doi.org/10.1016/j.geomorph.2024.109515
11. Dimyati, M. (2023). Development, implementation and validation of Sediment Transport and Erosion Prediction (STEP) model. *Environmental Modelling & Software, 164*, 105686, https://doi.org/10.1016/j.envsoft.2023.105686
12. Duan, H., Zou, L., Cvetkovic, V. (2024). Sensitivity analysis of hydraulic erosion and calibration of the erosion coefficient. *Engineering Geology, 338*, 107624, https://doi.org/10.1016/j.enggeo.2024.107624
13. Engman, E. T. (1986). Roughness coefficients for routing surface runoff. *Journal of Irrigation and Drainage Engineering*, *112*(1), 39–53.
14. Fatima, B., Rachid, H., Abdeldjalil, B., Abdessalam, O., Mohamed, B., Alfagham, A.T., Tariq, A. (2025). Monitoring and forecasting water erosion in response to climate change effects using the integration of the global RUSLE/SDR model and predictive models. *Applied Soil Ecology, 206*, 105910.
15. Firoozi, A. AK., Firoozi, A. AS. (2024). Water erosion processes: Mechanisms, impact, and management strategies. *Results in Engineering, Volume 24*, 103237, https://doi.org/10.1016/j.rineng.2024.103237
16. Gholami, H., Jalali, M., Rezaei, M., Mohamadifar, A., Song, Y., Li, Y., Kaskaoutis, D. G. (2024). An explainable integrated machine learning model for mapping soil erosion by wind and water in a catchment with three desiccated lakes. *Aeolian Research, 67–69*, 100924, https://doi.org/10.1016/j.aeolia.2024.100924
17. Helmi, A.M. (2023). Quantifying catchments sediment release in arid regions using GIS-based Universal soil loss equation (USLE). *Ain Shams Engineering Journal, 14*(8), 102038, https://doi.org/10.1016/j.asej.2022.102038.
18. Hitouri, S., Meriame, M., Ajim, A. S., Pacheco, Q. R., Nguyen-Huy, T., Bao, P. Q., Varasano, A. (2024). Gully erosion mapping susceptibility in a Mediterranean environment: A hybrid decision-making model. *International Soil and Water Conservation Research, 12*(2), 279–297, https://doi.org/10.1016/j.iswcr.2023.09.008
19. Honek, D., Németová, Z., Kohnová, S., Šulc Michalková, M. (2018). The sensitivity analyses of soil parameters and their impact on runoff-erosion processes: the application of Erosion-3D model in small Slovak catchment. *Pollack Press*.
20. Igwe, P.U., Onuigbo, A.A., Chinedu, O.C., Ezeaku, I.I., Muoneke, M.M. (2017). Soil erosion: A review of models and applications. *International Journal of Advanced Engineering Research and Science (IJAERS), 4*(12), https://dx.doi.org/10.22161/ijaers.4.12.22
21. Koch, T., Aartsma, P., Deumlich, D., Chifflard, P., Panten, K. (2024). From field to model: Determining EROSION 3D model parameters for the emerging biomass plant *Silphium perfoliatum* L. to predict effects on water erosion processes. *Agronomy, 14*, 2097. https://doi.org/10.3390/agronomy14092097
22. Mohammed, S. (2025). Modeling current and future run-off and soil erosion dynamics in eastern mediterranean ecosystems using the WEPP model. *Energy Nexus, 100375*, https://doi.org/10.1016/j.nexus.2025.100375
23. Németová, Z., Kohnová, S. (2022). *Analysis of soil parameters for the application of physically based erosion models in the conditions of Slovak river basins. 1. Edition*. Bratislava: Spektrum STU, 84 s. Edition of scientific monographs.
24. Németová, Z. (2020). *Mathematical modeling of the intensity of erosion processes using a physically and empirically based model. 1. Edition*. Bratislava: Spektrum STU, 89 s. Edition of scientific papers 178.
25. Németová, Z., Honek, D., Kohnová, S., Hlavčová, K., Šulc Michalková, M, Sočuvka, V., Velísková, Y. (2020). Validation of the EROSION-3D model through measured bathymetric sediments. *Water, 12*(4), 1082.
26. Németová, Z., Honek, D., Látková, T., Šulc Michalková, M., Kohnová, S. (2018). An assessment of soil water erosion in the Myjava hill land: The application of a physically-based erosion model. *Pollack Periodica, 13*(3), 197–208.
27. Özşahin, E. (2023). Climate change effect on soil erosion using different erosion models: A case study in the Naip Dam basin, Türkiye. *Computers and Electronics in Agriculture, 207*, 107711, ISSN 0168-1699, https://doi.org/10.1016/j.compag.2023.107711.
28. Pal, S. C., Chakrabortty, R., Roy, P., Chowdhuri, I., Das, B., Saha, A., Shit, M. (2021). Changing climate and land use of 21st century influences soil erosion in India. *Gondwana Research*, *94*, 164–185, https://doi.org/10.1016/j.gr.2021.02.021
29. Rendana, M., Idris, W. M. R., Alia, F., Rahim, S.

E., Yamin, M., Izzudin, M. (2024). Relationship between drought and soil erosion based on the normalized differential water index (NDWI) and revised universal soil loss equation (RUSLE) model. *Regional Sustainability, 5*(4), 100183, https://doi.org/10.1016/j.regsus.2024.100183

30. Salma, K., Ahmed, A., Abdellah, A., Salma, E. (2024). Estimation and mapping of water erosion and soil loss: Application of Gavrilovic erosion potential model (EPM) using GIS and remote sensing in the Assif el mal Watershed, Western high Atlas. *China Geology, 7*(4), 672–685, https://doi.org/10.31035/cg2023058
31. Schmidt, J., Werner, M.V., Michael, A., Schmidt, W. (1997). *EROSION 2Dr3D—Ein Computermodell zur Simulation der Bodenerosion durch Wasser.* Sachsisches Landesamt fur Umwelt und Geologie, Sachsische Landesanstalt fur Landwirtschaft.
32. Schmidt, J. (1996). Development and Application of a Physically Established Simulation Model for the Erosion of Agricultural Areas. *Institute of Geographic Sciences: Berlin, Germany*, 148.
33. Schmidt, J. (1991). *EROSION 2Dr3D—Ein Computermodell zur Simulation der Bodenerosion durch Wasser.* Sachsisches Landesamt fur Umwelt und Geologie.
34. Shmilovitz, Y., Marra, F., Wei, H., Argaman, E., Goodrich, D., Assouline, S., Morin, E. (2023). Assessing the controlling factors on watershed soil erosion during intense rainstorm events using radar rainfall and process-based modeling. *Catena, 231*, 107282, https://doi.org/10.1016/j.catena.2023.107282
35. Sreedevi, S., Eldho, T.I., Jayasankar, T. (2022). Physically-based distributed modelling of the hydrology and soil erosion under changes in landuse and climate of a humid tropical river basin. *Catena, 217*, 106427, https://doi.org/10.1016/j.catena.2022.1064
36. Stankoviansky, M. (1997). Anthropogenic Transformations of Landscape in the Myjava Kopanitse. *Environment, 31*, 84–89.
37. Taloor, A. K., Khajuria, V., Parsad, G., Bandral, S., Mahajan, S., Singh, S., Kothyari, G. C. (2025). Geospatial assessment of soil erosion in the Basantar and Devak watersheds of the NW Himalaya: A study utilizing USLE and RUSLE models. *Geosystems and Geoenvironment, 4*(2) 100355, https://doi.org/10.1016/j.geogeo.2025.100355
38. Tang, J., Xie, Y., Cheng, H., Liu, G. (2025). Impact of farmland landscape characteristics on gully erosion in the black soil region of Northeast China. *CATENA, 249,* 108623, https://doi.org/10.1016/j.catena.2024.108623
39. Tanner, S., Ben-Hur, M., Argaman, E., Katra, I. (2023). The effects of soil properties and aggregation on sensitivity to erosion by water and wind in two Mediterranean soils. *CATENA, 221*, Part A, 106787, https://doi.org/10.1016/j.catena.2022.106787
40. Tkeshelashvili, N. (2024). Empirical and machine learning models for soil erosion risk assessment: A case study of Tsageri municipality, Georgia. *Journal of Geography, Environment and Earth Science International*, *28*(11), 148–162, https://doi.org/10.9734/jgeesi/2024/v28i11843.
41. Vu Dinh, T., Hoang, N. D., Tran, X. L. (2021). Evaluation of different machine learning models for predicting soil erosion in tropical sloping lands of Northeast Vietnam. *Applied and Environmental Soil Science, 6665485*, 14, https://doi.org/10.1155/2021/6665485
42. Wang, Q., Tang, B., Wang, K., Shi, J., Li, M. (2024). Evaluation of the gully erosion susceptibility by using UAV and hybrid models based on machine learning. *Soil and Tillage Research, 244*, 106218, https://doi.org/10.1016/j.still.2024.106218
43. Xiong, M., Leng, G. (2024). Global soil water erosion responses to climate and land use changes. *CATENA, 241*, 108043, https://doi.org/10.1016/j.catena.2024.108043