Sediment Yield Simulation using the SWAT Model: A Systematic Review and Meta-Analysis of Calibration and Validation Approaches

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Abstract: - Determining sediment yield is essential for successful watershed management, as it affects reservoir capacity, water quality, and environmental sustainability. The Soil and Water Assessment Tool (SWAT) ranks among the most commonly used hydrological modeling systems for simulating sediment dynamics across various climate zones and geographical regions. This comprehensive review analyzes 200 studies collected from Google Scholar and Scopus published between 2014 and 2024. Following rigorous inclusion and exclusion criteria, 143 studies were chosen for comprehensive review. Studies that clearly documented calibration and validation methods were prioritized, along with those reporting key statistical metrics including Nash-Sutcliffe Efficiency (NSE), Coefficient of Determination (R^2), Percent Bias (PBIAS), and Root Mean Standard Deviation Ratio (RSR). Findings indicate that SWAT delivers reliable and satisfactory performance when forecasting sediment yield at the watershed scale, showing consistent results across both calibration and validation stages. A comprehensive analysis of the chosen studies emphasizes prevailing methods in calibration and validation, reveals parameter sensitivities, and highlights issues concerning data limitations, low spatial resolution, and input data quality. The review concludes by identifying significant research gaps and suggesting ways to improve the accuracy and regional adaptation of SWAT applications for modeling sediment yield.

Key-Words: - SWAT model, sediment yield, hydrological modelling, model validation, model calibration, sensitivity analysis.

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1 Introduction

Ongoing global warming and climate-related changes have led to a noticeable increase in the frequency and intensity of extreme hydrological events, which in turn have amplified surface runoff and soil erosion across many watersheds, [1]. As a result, systematic assessment and continuous monitoring of sediment yield have become increasingly important for the development and implementation of effective and sustainable watershed management strategies. Sediment transport directly affects water reservoir storage capacity, water quality, aquatic ecosystems, and agricultural productivity, [2]. Sediments generated from erosion processes are transported to rivers through surface runoff and constitute the majority of riverine sediment loads, contributing substantially to sediment deposition in water reservoirs and dams, [3]. Consequently, controlling sediment yield is essential for effective watershed management, particularly given that the implementation of mitigation measures often requires substantial financial and institutional resources, [4].

The SWAT model, developed by the USDA Agricultural Research Service [5], is a continuous, semi-distributed, process-based tool designed to simulate and assess soil and water resources at the watershed to river basin scale, [6]. It was designed to simulate how land management practices affect water flow, sediment transport, and agricultural chemical outputs in large and complex watersheds, characterized by diverse soil properties, land uses, and management strategies over extended time periods, [7]. The Soil and Water Assessment Tool is one of the most widely used models internationally for eco-hydrological modelling, as evidenced by previous review studies and a rich body of literature that now includes more than 5,000 publications, [8], [9]. This review aims to critically evaluate the application of the SWAT in estimating sediment yield, with a particular focus on the modelling methodologies employed, the model's predictive performance, and its inherent limitations. The review examines how various studies have approached model calibration and validation, the effectiveness of different statistical performance indicators—such as R^2, NSE, and PBIAS—and the sensitivity of the model to input parameters and environmental variability.

Previous SWAT-related studies have widely applied indicators such as NSE, R^2, and PBIAS to evaluate sediment yield performance. However, studies that systematically summarise how these indicators are used across different hydrological and geographical conditions remain limited. In particular, a dedicated review focusing exclusively on SWAT applications for sediment yield prediction is still lacking in the existing literature.

Although SWAT has been widely applied for modelling a variety of watershed processes, its specific use is for enhancing understanding of the reliability, limitations, and regional adaptability of SWAT in assessing sediment dynamics at different spatial and temporal scales. Sediment yield estimation remains fragmented and dispersed throughout the literature, without an integrated analysis of modelling strategies, the quality and sources of input data, calibration and validation practices, and reported performance metrics.

This review focuses on the application of the SWAT model in sediment yield estimation and attempts to address certain key problems. One of the objectives is to review the use of the model throughout the last decade and to identify the main trends documented in the literature. Another goal is to study the methods used for calibration, validation and model evaluation, including the use of indicators such as NSE, R^2, PBIAS and RSR. Furthermore, the paper also addresses the constraints which have been faced in the past research and points out the areas which need more research to increase the dependability of predictions of sediment output.

2 Framework for Sediment Yield Modelling using SWAT

The SWAT model operates on a diverse set of input datasets, encompassing the digital elevation model (DEM), soil characteristics, land use and land cover (LULC), along with meteorological information, [10]. The simulation of watershed hydrology is carried out in two distinct components: The first is the land phase of the hydrological cycle, which governs the quantity of water, sediments, nutrients, and pesticides that are delivered to the main channel within each sub-basin, [11]. The second component is the routing phase of the hydrological cycle, which is defined as the movement of water, sediments, nutrients, and organic chemicals through the watershed's channel network toward the outlet, [11]. In the land phase of the hydrological cycle, SWAT simulates the hydrological cycle based on the water balance [12] equation as presented in Equation (1):

$$SW_t = SW_0 + \sum_{i=1}^{t}(R_{day} - Q_{surf} - E_a - W_{seep} - Q_{qw}) \tag{1}$$

SW_t denotes the soil water content at the end of the simulation period, SW_0 represents the initial soil water content on day i, while t denotes the time step under consideration, R_{day} corresponds to the daily precipitation input, Q_{surf} refers to the surface runoff depth generated on day i, E_a captures the evapotranspiration losses, W_{seep} accounts for the water percolating into the unsaturated zone from the soil profile, Q_{qw} represents the contribution of groundwater return flow, all expressed in millimeters of water.

The SWAT model quantifies soil erosion and sediment yield through the application of the Modified Universal Soil Loss Equation (2) (MUSLE), originally developed by [13]. In the SWAT model, the watershed is initially partitioned into multiple sub-watersheds, each of which is further divided into Hydrologic Response Units (HRUs). These HRUs represent spatial units with uniform characteristics in terms of land use, management practices, topography, and soil properties, [14].

$$S_y = 11.8(Q_s \times q_p \times area_{hru})^{0.56} \times K_{USLE} \times C_{USLE} \times P_{USLE} \times LS_{USLE} \times CFRG \tag{2}$$

In this equation, S_y represents the sediment yield for a specific day (in metric tons), while Q_s refers to the surface runoff volume (expressed in mm/ha), q_p denotes the peak runoff rate (measured in m³/s), and $area_{hru}$ is the land area of the hydrologic response unit (in hectares). The K_{USLE} factor accounts for soil erodibility. Additionally, C_{USLE} and P_{USLE} represent the cover-management and support practice factors, respectively. The equation also includes the LS_{USLE} topographic factor and CFRG, which adjusts for the influence of coarse soil fragments, [12].

Before implementation, it is essential to establish the reliability and accuracy of the SWAT model. This requires a comprehensive hydrological assessment and systematic model testing to confirm that the model can effectively replicate watershed dynamics and thereby provide a sound basis for scenario analysis [9]. Sensitivity analysis and calibration represent critical, interrelated components in the application of SWAT and comparable hydrological models, [15]. The extensive body of literature on SWAT highlights the use of sensitivity analysis to identify the parameters exerting the greatest influence on model outputs, offering valuable guidance for calibration strategies. Both sensitivity analysis and calibration may be conducted through manual or automated approaches, employing a variety of graphical and statistical techniques, [15]. Figure 1 depicts the conceptual framework of the calibration–validation procedure applied in the SWAT model. The evaluation of SWAT's hydrological performance is typically undertaken using established statistical indicators. Among the most widely applied are R^2, NSE, PBIAS and RSR. According to the evaluation framework proposed by [16], these indicators collectively provide a robust and comprehensive basis for assessing the accuracy and efficiency of model simulations. For sediment yield modelling, model performance is generally considered acceptable when the statistical evaluation criteria meet the following thresholds: the coefficient of determination exceeds 0.40, the Nash–Sutcliffe Efficiency is greater than 0.35, and the Percent Bias falls within ±30%, and 0.6< RSR ≤ 0.7. These benchmarks provide a balanced framework for assessing the accuracy and reliability of hydrological model predictions in capturing sediment yield dynamics, [17]. The coefficient of determination indicates the level of agreement and linear relationship between the simulated and observed data. It ranges from 0 to 1, where a value of 0 indicates no correlation, while a value of 1 signifies a perfect match in variability between the simulated and observed results, [16], [18], [19], [20], [21]. Equation (3) presents the coefficient of determination employed to assess model performance:

$$R^2 = [\frac{\sum_{i=1}^{n}(Y_i-\bar{Y}_{obs})(\hat{Y}_i-\bar{Y}_{sim})}{\sum_{i=1}^{n}(Y_i-\bar{Y}_{obs})^2 \sum_{i=1}^{n}(\hat{Y}_i-\bar{Y}_{sim})^2}]^2 \quad (3)$$

The Nash–Sutcliffe Efficiency ranges from negative infinity to 1 and is used to evaluate how closely the simulated data align with the observed values along the ideal 1:1 line. An NSE value of 1 indicates a perfect agreement between simulated and observed data, whereas a value of 0 or lower suggests that the mean of the observed data provides a more accurate estimate than the model's predictions, [22], [23]. The Nash–Sutcliffe efficiency is expressed in Equation (4):

$$NSE = 1 - \frac{\sum_{i=1}^{n}(Y_i-\hat{Y}_i)^2}{\sum_{i=1}^{n}(Y-\bar{Y}_{obs})^2} \quad (4)$$

Percent Bias serves as a key statistical indicator for evaluating model performance by quantifying the average tendency of simulated values to deviate from their corresponding observed data. The optimal benchmark for PBIAS is 0.0, which reflects a perfect alignment between simulated and observed outcomes. Low-magnitude values are generally interpreted as evidence of accurate model simulations. Positive PBIAS values indicate that the model systematically underestimates the observed results, whereas negative values denote an overestimation bias in the simulations, [17]. Equation (5) defines the PBIAS.

$$PBIAS = \frac{\sum_{i=1}^{n}(Y_i-\hat{Y}_i)\times 100}{\sum_{i=1}^{n}Y_i} \quad (5)$$

where:

Y_i-ith observed value,

$\hat{Y}_i$-with simulated value,

$\bar{Y}_{obs}$- mean observed value over the study period,

$\bar{Y}_{sim}$ -mean simulated value over the study period,

N- total number of observations.

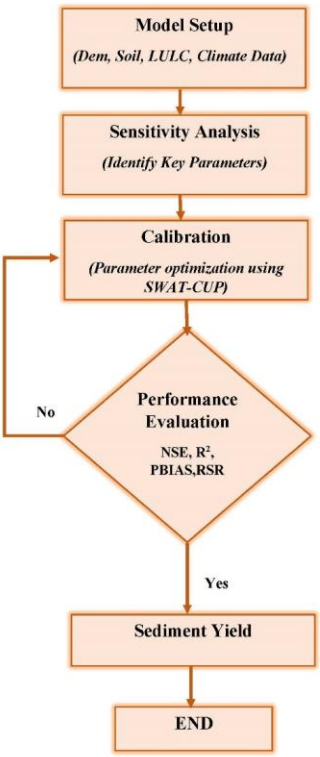

Fig. 1: Conceptual Framework of Calibration–Validation Procedure in SWAT
Source: created by the authors

3 Review Methodology

The review involved a systematic search of scientific literature using databases such as Scopus and Google Scholar. Keywords used included "SWAT model," "sediment yield," and "erosion modelling". Studies published between 2014 and 2024 were reviewed, with particular emphasis on those that explicitly reported calibration and validation procedures for sediment simulations. From this body of literature, 143 studies were ultimately retained, based on their scientific relevance, geographical coverage, and availability of required data.

3.1 Establishment of Eligibility Criteria

3.1.1 Inclusion Criteria

i**.** Studies that used monthly time series data and the SWAT model to model sediment yield and erosion processes.
ii. Articles that clearly described the model's calibration and validation stages and included the relevant statistical performance metrics (e.g., NSE, R^2, PBIAS, RSR).
iii. Works published in peer-reviewed journals from 2014 to 2024, guaranteeing coverage of methodological advancements and contemporary breakthroughs.
iv. Research that provided a thorough and understandable explanation of the modeling framework, including the calibration method and input datasets, including soil characteristics, land use, and climate.
v. Articles presenting original empirical contributions, including watershed-scale case studies or simulation experiments with sediment as a primary output.

3.1.2 Exclusion Criteria

i. Publications that did not incorporate the SWAT model for sediment yield assessment or omitted sediment as a target variable.
ii. Studies relying exclusively on alternative modelling or statistical approaches without integrating SWAT-based applications.
iii. Secondary literature, such as conceptual papers, editorials, conference abstracts, and book chapters that lacked primary data or calibration/validation evidence.
iv. Articles issued before 2014 were thereby excluded to ensure the focus remained on contemporary practices and innovations.
v. Publications not accessible in English, or those without sufficient methodological detail or performance evaluation results. Figure 2 depicts the PRISMA flow diagram outlining the study selection procedure.

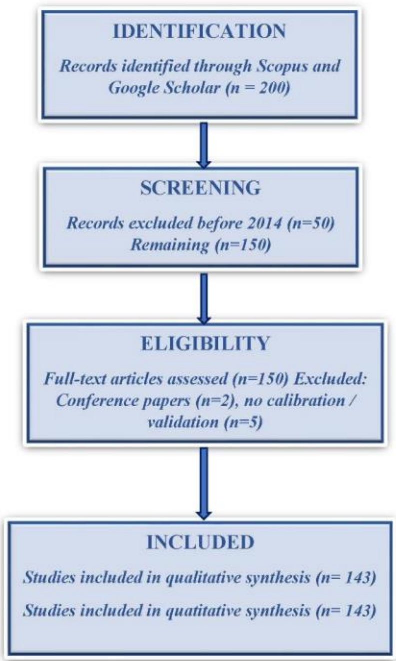

Fig. 2**:** PRISMA flow diagram illustrating the study selection process
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4 Results and Discussion

4.1 SWAT Studies on Soil Erosion and Sedimentation

This section focuses on the application of the Soil and Water Assessment Tool for sediment yield estimation, with particular emphasis on the statistical criteria commonly used to evaluate model performance during calibration and validation. Drawing on evidence reported in the existing literature, the analysis highlights how effectively SWAT represents sediment processes under a wide range of watershed conditions. Model performance is primarily assessed in terms of accuracy, reliability, and consistency across different spatial and temporal scales. Special attention is given to the most frequently reported performance indicators, including R^2, NSE, PBIAS, and RSR. These metrics are widely used to quantify the level of agreement between simulated and observed sediment data. Overall, the reviewed studies provide substantial support for the use of SWAT as a practical and dependable tool for simulating sediment transport and yield.

According to [24], the model showed satisfactory performance when evaluated using both visual inspection and statistical measures. The reported R^2 values, in particular, suggested a strong correspondence between simulated and observed streamflow and sediment yield at the monthly time scale.

Similarly, [25] applied the NSE, RSR, and PBIAS metrics to assess the applicability of the SWAT model in a semi-arid karst basin for predicting water discharge and sediment transport. Their findings indicated that the model produced good results for monthly streamflow and acceptable results for sediment yield. Moreover, the performance of these indices improved significantly at the annual time step, especially during the calibration phase.

The [26] performed a comprehensive study of the SWAT model in the upper North Bosque River watershed in north-central Texas. Their investigation found that the model produced an adequate agreement between projected and observed sediment losses at a monthly scale, but not at the daily one.

According to [9], SWAT is widely used in Mediterranean watersheds. The assessment showed that the model can reproduce hydrological responses and sediment output, but also highlighted persistent challenges related to limited data availability and variable input quality. The authors further noted that model robustness improves substantially when calibration and validation procedures are rigorously implemented, particularly through the use of performance indicators such as R^2, NSE, and PBIAS.

In Nigeria, [27], [28] and [19], [28] implemented SWAT to estimate sediment yield in the Kaduna and Chanchaga watersheds. Their models demonstrated satisfactory outcomes, with performance indices exceeding standard thresholds. Sensitivity analysis across both studies identified CN2, ALPHA_BF, and SOL_AWC as key contributors to model behavior.

The [11] employed SWAT-CUP (SWAT Calibration and Uncertainty Programs) with the Sequential Uncertainty Fitting (SUFI-2) algorithm in arid Iranian watersheds, underscoring the importance of uncertainty analysis. Their work reaffirmed the influence of CN2 and SOL_AWC on model accuracy. Similarly, [29] applied the MUSLE equation within a Geographic Information Systems (GIS) framework, reporting enhanced model performance post-calibration, with runoff energy and slope steepness emerging as the most sensitive inputs.

Additional insights from [10] focused on the role of input data resolution. Their review concluded that fine-resolution Digital Elevation Model , soil, and Land Use Land Cover data substantially improve model fidelity in simulating sediment yield. Complementary findings by [30] reiterated that integrating high-quality input datasets and calibration techniques is critical for improving SWAT performance and applicability.

Study [31] compared the performance of SWAT with a Radial Basis Neural Network (RBNN) model for sediment yield prediction in the Nagwa watershed, India. While SWAT achieved strong results during both calibration and validation, the RBNN model showed a slightly better ability to capture peak sediment loads. Based on these findings, the authors suggested that hybrid modelling approaches may offer improved simulation accuracy, particularly in complex terrain conditions.

In study [32], the impacts of land-use change on runoff and sediment yield were examined in the Da River Basin in Hoa Binh Province, north-western Vietnam. The SWAT model was used to simulate hydrological and sediment processes, and its performance was assessed through calibration and validation against observed streamflow and sediment data. The reported statistical indicators demonstrated satisfactory performance in both phases, supporting SWAT's capability to represent runoff and sediment dynamics under varying land-use scenarios.

Figure 3 illustrates the distribution of literature on sediment yield modelling using the SWAT model across different countries. Ethiopia represents the largest share of the studies, accounting for approximately 30–35% of the circle. This is expected, as Ethiopia faces significant challenges related to soil erosion and sediment management, which have made the application of SWAT highly prevalent in the region, [29], [33]. India and Iran also constitute a considerable portion of the literature, reflecting a strong research interest in sediment assessment within their basins, where climate variability and intensive land use have heightened concerns about land degradation and water management, [34]. Countries such as Nigeria, Morocco and Brazil are less commonly cited in the examined literature; yet, extant research highlight substantial uses of SWAT to tackle local sediment related problems. On the other hand, countries like Spain, Thailand and Tunisia are hardly mentioned, which points to a somewhat limited use of the SWAT model in these areas. In general, the geographic distribution of the studies reviewed shows a strong concentration of research activity in developing nations, especially in Africa and Asia, where soil erosion is still a major environmental problem.

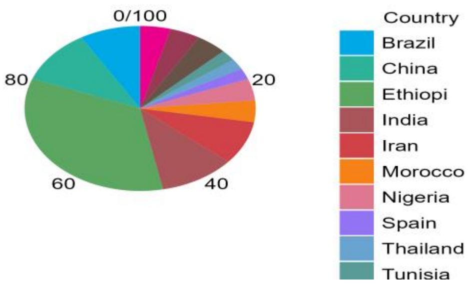

Fig. 3: Distribution of the literature on sediment yield modelling using the SWAT model across countries.
Source: created by the authors

The consolidation of this topic within the environmental and hydrological sciences is indicated by the apparent increase in publications from 2014 to 2024 that apply the SWAT model to sediment-yield assessment after 2016, (Figure 4). The years 2016–2020 in particular show a substantial increase in publications, indicating a rise in institutional and scientific understanding of soil erosion and sediment transport problems in watersheds. The number of studies seems to have stabilized after 2020, indicating that sediment modeling using SWAT has established itself as a reliable research method and has gained a steady place in the literature.

The global phenomena of land degradation and climate change, alongside the imperative for effective watershed management, have spurred considerable research into sediment yield across various regions. Concurrently, the development of tools such as SWAT-CUP, which facilitates advanced calibration and uncertainty assessment, has significantly contributed to the increased use of SWAT models in academic studies.

Over the last decade, the application of SWAT for modeling sediment yield has experienced consistent growth and solidification, positioning it as an essential instrument for hydrological research and environmental planning globally.

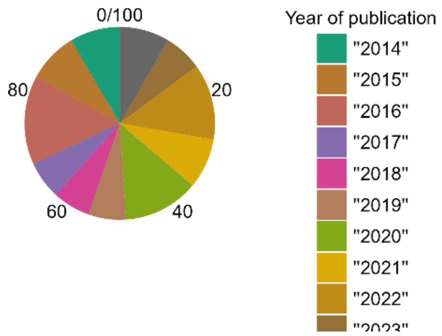

Fig. 4: Distribution of reviewed studies by year of publication (2014–2024)
Source: created by the authors

A raincloud plot, presented in Figure 5, depicts the range of Nash-Sutcliffe Efficiency values achieved during the calibration period. This visualization method integrates individual data points with summary statistics from a boxplot and the density representation of a violin plot to offer a comprehensive view of the model's performance.

As demonstrated, NSE values primarily fell between 0.4 and 0.9, with a median value of roughly 0.75, indicating generally strong calibration performance across the examined investigations.

Most values are concentrated within the 0.7–0.8 interval, indicating a good model fit according to widely accepted criteria in the literature, [35]. Nonetheless, the presence of relatively low values, in some cases close to 0.2, suggests that the model was not always able to accurately replicate the observed hydrological behaviour. Despite these deviations, the overall distribution of findings shows a largely consistent model performance over the calibration phase.

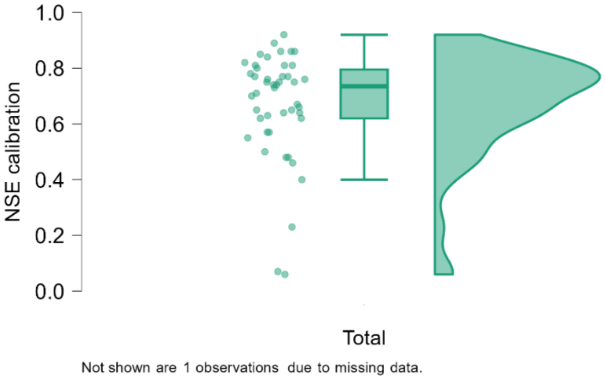

Fig. 5: Distribution of calibration NSE values for sediment yield modelling using the SWAT model across studies.
Source: created by the authors

The results synthesised from the literature (Table 1) demonstrate a consistent performance of the SWAT model in assessing sediment yield, both during calibration and validation. In terms of NSE, the mean values 0.669 for calibration and 0.689 for validation and median values above 0.70 indicate a satisfactory model fit, in line with the criteria proposed by [16]. This overall stability is also reflected in the coefficient of determination , which shows average values of about 0.71 during calibration and 0.74 during validation, pointing to a strong level of agreement between simulated and observed data. A similar pattern is observed for the RSR metric, with mean values of 0.614 in the calibration phase and 0.599 during validation. Both values fall within the commonly accepted performance threshold (≤ 0.7), further supporting the consistency of the model's performance across the two stages.

Overall, the statistical indicators highlight that SWAT achieves a satisfactory and robust performance in modelling sediment yield, with clear consistency between calibration and validation, although systematic bias, as reflected in PBIAS, remains a challenge. During the literature review on sediment yield modelling, it became evident that the reporting of the RSR indicator was, in many cases, absent. Since reliance on metrics like NSE, R^2, or PBIAS alone may miss significant aspects of predictive performance, evaluations of model efficiency remain incomplete in the absence of this indication. Additionally, the lack of RSR reduces the methodological transparency of calibration and validation processes and restricts comparability among research. Therefore, regular reporting of RSR together with other widely used performance metrics would help sediment yield modeling studies have more thorough assessments and better methodological coherence.

Table 1. Descriptive statistics

	NSE calibration	**R square calibration**	**PBIAS calibration**	**RSR calibration**
Mode	0.770	0.776	2.114	0.621
Median	0.735	0.760	0.960	0.626
Mean	0.669	0.710	1.835	0.614
Std. Deviation	0.192	0.156	15.35	0.187
25th percentile	0.620	0.645	-5.370	0.510
50th percentile	0.735	0.760	0.960	0.626
75th percentile	0.795	0.805	7.290	0.700
	NSE validation	**R-squared validation**	**PBIAS validation**	**RSR validation**
Mode	0.756	0.764	5.349	0.663
Median	0.720	0.740	6.800	0.650
Mean	0.689	1.741	11.92	0.599
Std. Deviation	0.163	6.382	16.05	0.225
25th percentile	0.615	0.610	1.750	0.468
50th percentile	0.720	0.740	6.800	0.650
75th percentile	0.795	0.810	17.40	0.685

Source: created by the authors

Figure 6 presents a comparison of NSE values during calibration, based on data collected from different studies employing various calibration algorithms (Manual, SUFI-2, and GLUE). This visualisation clearly illustrates the inter-study heterogeneity in the performance of the SWAT model:

Manual calibration shows relatively stable results, with the median concentrated around 0.70–0.75. Despite the absence of algorithmic sophistication, this approach appears to provide performance comparable to that of automated methods.

The Sequential Uncertainty Fitting Version 2 (SUFI-2) approach displays a broader distribution of results, with the majority of values concentrated between 0.65 and 0.75. This wider spread reflects its more frequent application in the reviewed literature, allowing for a more comprehensive assessment of its performance. In contrast, Generalized Likelihood Uncertainty Estimation (GLUE) is represented by a smaller number of studies and exhibits a lower median, approximately in the range of 0.55 to 0.60, which points to comparatively weaker performance than the other calibration approaches.

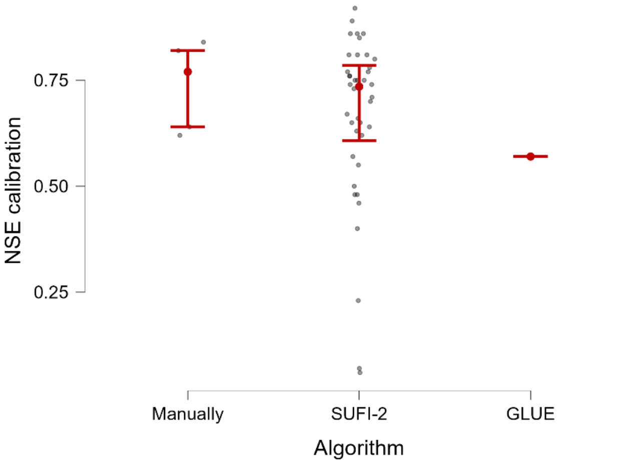

Fig. 6: NSE calibration values of the SWAT model under different algorithms
Source: created by the authors

A paired-samples t-test was carried out to compare NSE values obtained during calibration and validation (Table 2). The analysis showed no statistically significant difference between the two phases (p = 0.719). Similar NSE values were observed in both datasets, suggesting that the SWAT model produced relatively stable results during model evaluation.

The reviewed studies also showed that, in many cases, SWAT was able to reproduce sediment yield behaviour not only for calibration data, but also when applied to validation datasets. Some variation between studies was observed, which may be related to differences in watershed characteristics, input data, and environmental conditions across the analysed case studies.

Table 2. Paired Samples T-Test

Measure 1		Measure 2	t	p
NSE calibration	-	NSE validation	0.363	.719

Note. Student's t-test.
Source: created by the authors

5 Conclusion

It is well known that the Soil and Water Assessment Tool is a dependable and adaptable model for simulating erosion processes and sediment output. This systematic analysis is based on 200 research articles from 2014 to 2024 that were found using Google Scholar and Scopus. Publications that specifically detailed calibration and validation processes and reported statistical performance indicators, including NSE, R^2, PBIAS, and RSR, are given special attention in the study. After applying strict inclusion and exclusion criteria, 143 studies were included for further analysis. Results indicate that SWAT performs satisfactorily at a watershed scale for sediment yield modelling with similar results obtained during the calibration and validation periods. Furthermore, the studies on temporal and geographical dispersion reveal the importance of the model in addressing the sediment problems, especially in areas with high environmental stresses. Overall, the evidence suggests that SWAT is a robust and reliable tool for sediment yield modelling, with performance levels consistent with widely accepted benchmarks reported in the literature. Regarding calibration methods, SUFI-2 is the most established and most commonly used method. GLUE is less commonly used and seems to be less efficient. The geographic and temporal patterns observed also indicate a strong research focus on areas and periods affected by pronounced environmental challenges, reinforcing the position of SWAT as a key tool for watershed management and sediment assessment.

Nevertheless, a critical observation concerns the fact that the RSR indicator is often not reported in the literature, which restricts the ability to perform harmonised and comparable evaluations of model performance. Given that RSR combines the interpretive clarity of RMSE with normalisation against the variability of observed data [16], its omission creates methodological gaps and reduces the transparency of results. This situation underscores the need for future studies to standardise reporting practices by incorporating a comprehensive set of indicators, including RSR, to ensure greater comparability and methodological rigour in subsequent meta-analyses.

5.1 Future Research

Future studies that employ the SWAT model to analyze sediment yield should focus further on enhancing model accuracy through the incorporation of high-resolution soil, land use, and climate datasets. To guarantee dependability in a variety of watershed scenarios, calibration and validation processes must be improved under the direction of strong statistical performance metrics. To improve predictive performance, it is also advised to use machine learning techniques with data from remote sensing. Lastly, to increase methodological rigor, cross-study comparability, and general transparency, future research should routinely disclose a wider range of performance metrics, especially RSR.

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