SAINS TANAH – Journal of Soil Science and Agroclimatology

Journal homepage: http://jurnal.uns.ac.id/tanah

A systematic review of artificial intelligence approaches for sedimentation modeling in hydrological systems

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ARTICLE INFO

Keywords:
Artificial intelligence
Google Earth Engine
Reservoir siltation
Sedimentation modeling
Soil erosion

Article history
Submitted: 2025-06-12
Revised: 2025-12-23
Accepted: 2026-01-08
Available online: 2026-06-30
Published regularly:
June 2026

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ABSTRACT

Soil erosion and sedimentation are important environmental challenges, particularly within data-scarce and climate-sensitive regions. Accurate sediment yield prediction is essential for mitigating reservoir siltation and supporting sustainable land and water management. This study systematically reviews and synthesizes recent applications of Artificial Intelligence (AI) in sedimentation modeling, clearly outlining its objectives, screening scope, key findings, and novelty. From 277 screened publications, 16 studies were selected following the PRISMA 2020 guidelines. The results show that hybrid AI models, which integrate physical process-based equations with data-driven algorithms (ANN and LSTM), consistently outperform traditional and standalone machine learning approaches, improving R^2 by up to 15% and reducing the RMSE by 25-40%. The integration of Google Earth Engine (GEE) enables multi-source remote sensing, climatic, and hydrological data fusion, enhancing spatiotemporal sediment monitoring and reproducibility. Despite these advances, challenges remain regarding data quality, computational cost, and model transferability. This review contributes a standardized and reproducible framework to assess AI-based sedimentation models and to outline future research directions towards scalable, interpretable, and climate-resilient sediment management.

How to Cite: Bassairate, O., Chikhaoui, M., Naimi, M., & Bokoye, A. I. (2026). A systematic review of artificial intelligence approaches for sedimentation modeling in hydrological systems. Sains Tanah Journal of Soil Science and Agroclimatology, 23(1), 101-119. https://doi.org/10.20961/stjssa.v23i1.92633

1. INTRODUCTION

Sedimentation in reservoirs and watersheds is a critical global issue that threatens water resource sustainability, ecosystem integrity, and economic stability. Sediment accumulation reduces reservoir capacity, degrades water quality, alters aquatic habitats, and increases maintenance costs through dredging and infrastructure repair (Lee et al., 2022; Wang et al., 2018). These impacts are further exacerbated by human-induced pressures, including deforestation, high-input agriculture, urban expansion, and mining, which intensify soil erosion and increase sediment delivery to rivers and reservoirs, thereby complicating sediment management strategies (Borrelli et al., 2020; Trinugroho et al., 2022; Xiong & Leng, 2024). Furthermore, climate-driven variability in precipitation intensity and spatiotemporal patterns exerts a strong control on sediment dynamics by affecting erosion mechanisms and sediment transport pathways, thereby complicating watershed and reservoir management (Panagos & De Rosa, 2023; Trinugroho et al., 2022).

Traditional sedimentation models, including the Revised Universal Soil Loss Equation (RUSLE), coupled with Sediment Delivery Ratios (SDR), have long provided foundational frameworks for estimating soil erosion and sediment fluxes at the plot and watershed levels (Ahmad et al., 2022; Bassairate et al., 2021; Gourfi et al., 2018; Kanito et al., 2023). However, these empirical and semi-empirical approaches frequently rely on simplified assumptions that inadequately capture the nonlinear and complex interactions governing sediment generation and deposition across diverse landscapes under evolving climatic conditions (Heckmann et al., 2018; Yan et al., 2022). This limitation is particularly evident when scaling predictions for large, heterogeneous watersheds that are experiencing rapid changes in land use and climate (Andualem et al., 2023; Hajigholizadeh et al., 2018). In this

STJSSA, p-ISSN 1412-3606 e-ISSN 2356-1424
http://dx.doi.org/10.20961/stjssa.v23i1.92633

context, nature-based solutions, such as agroforestry, vegetative buffer strips, and terracing, have shown promising results in reducing surface runoff and soil erosion while providing economic co-benefits to local communities. Studies have demonstrated that integrating these measures, particularly on steep and very steep slopes, reduces sediment yield and enhances agricultural productivity and long-term land resilience (Karyati et al., 2021; Koch et al., 2019).

Artificial intelligence (AI) offers powerful alternatives for modeling nonlinear sedimentation. Methods like Artificial Neural Networks (ANN), Support Vector Machines (SVM), Random Forests, Long Short-Term Memory (LSTM) networks, and hybrid frameworks capture complex relationships that are often missed by conventional models (Meshram et al., 2020). For instance, ANN architectures have successfully predicted sediment yields in data-scarce Himalayan basins with significantly greater accuracy than RUSLE-SDR approaches (Sarkar et al., 2017), whereas SVM integrations have reduced uncertainty in sediment load forecasts during Mediterranean flash floods (Asaly et al., 2023). Furthermore, the integration of AI with advanced geospatial analysis platforms, including Google Earth Engine (GEE), enables highly detailed, long-term monitoring of sediment dynamics using satellite-derived indices, including the Normalized Difference Vegetation Index (NDVI) and Modified Normalized Difference Water Index (MNDWI) (Jha et al., 2024; Yang et al., 2022). This powerful combination allows for the continuous identification of erosion hotspots, mapping of sediment sources and sinks, and early detection of landscape changes across continental scales, fundamentally transforming watershed diagnostics and management (Bezak et al., 2024; Uroš et al., 2024).

This review synthesizes insights from 16 key studies selected from a comprehensive pool of 277 peer-reviewed publications, focusing on AI-driven sedimentation modeling, enhanced by satellite remote sensing and high-resolution climate data. Unlike previous reviews that have primarily emphasized algorithmic performance or theoretical development, this synthesis critically evaluates how AI methods, particularly hybrid models that integrate physical sedimentation principles using machine learning algorithms, advance the prediction of sediment yield, timing of sediment mobilization, and spatiotemporal dynamics under changing environmental conditions. Our analysis reveals that these integrated approaches consistently outperform standalone empirical and physically based models, with reported increases in prediction accuracy ranging from 25 to 45 percent, as supported by several quantitative assessments (e.g., Allawi et al., 2023; El Bilali et al., 2020; Meshram et al., 2020; Yadav et al., 2022). These studies indicate that hybrid AI-physical frameworks, such as ANN-GA, LSTM-CEEMDAN, and MUSLE-ANN, reduce the RMSE values by 25-40% and increase R^2 by up to 15% compared to standalone Machine learning models. Additionally, this review highlights the importance of the operational scalability and transferability of AI techniques across diverse geographic, climatic, and socio-economic contexts, an aspect that has often been underexplored in earlier syntheses.

Although promising advances have been made, several challenges remain. Key issues include inconsistencies in data quality and availability, high computational resource demands, the need for large and diverse training datasets, and limitations in model transferability across different environmental settings (Zhao et al., 2024). These challenges can be addressed by developing standardized validation protocols and modular frameworks that enable the efficient integration of diverse datasets (e.g., climate projections, land-use maps, and soil data), and improved transparency in model architecture and parameterization (Batista et al., 2021). Moreover, incorporating stakeholder engagement and local knowledge into AI model development and validation processes can enhance their relevance, social acceptance, and practical applicability.

While several reviews have examined AI applications in hydrology, few have specifically focused on sedimentation processes by integrating physical, empirical, and hybrid AI models into a unified analytical framework. Existing reviews often emphasize either algorithmic performance or erosion mapping but rarely analyze how AI-driven hybrid frameworks (e.g., ANN-MUSLE and LSTM-SWAT) contribute to improving sediment yield prediction, physical interpretability, and large-scale operational transferability of the models. Therefore, this review fills a clear research gap by providing the first systematic synthesis linking AI-based sedimentation modeling with remote sensing, climate data, and process-based approaches. Its novelty lies in assessing not only the predictive accuracy but also the balance between data-driven performance and physical understanding, an aspect essential for developing robust and transferable sediment management models in data-scarce and climate-sensitive regions.

This review addresses the critical gaps in the literature and offers a comprehensive evaluation of the role of AI in advancing sedimentation science and sediment management. It provides quantifiable benchmarks of model performance across various environmental and operational contexts and identifies future research priorities essential for developing scalable, robust, and climate-resilient sediment management strategies. Ultimately, integrating AI-driven approaches with high-resolution environmental datasets, nature-based solutions, and participatory frameworks holds the potential to support sustainable watershed and reservoir management. This would provide long-term security for water supplies and ensure the health of ecosystems in the face of accelerating global environmental change.

This review bridges a clear gap in the existing literature by explicitly integrating artificial intelligence (AI) models with cloud-based geospatial analysis platforms, particularly Google Earth Engine (GEE), for sedimentation modeling under climate variability. Unlike previous reviews that mainly focused on algorithmic performance, this study introduced a categorical framework that organizes AI-based sedimentation research into four dimensions: occurrence, severity, period, and spatial distribution, providing a more systematic and interpretable overview of the sediment dynamics. Furthermore, it uniquely combines the hybrid AI–physical modeling perspective (e.g., ANN-MUSLE and SWAT-LSTM) with a climate change lens, highlighting how data-driven models can support adaptive and sustainable sediment management. By addressing these conceptual and methodological gaps, this review advances existing syntheses through a standardized and reproducible evaluation of model performance, scalability, and transferability across different environmental contexts.

Accordingly, the main objective of this review is to provide a thorough and organized summary of AI-based approaches to sedimentation modeling, emphasizing their methodological innovations, integration with remote sensing data, and potential contributions to the management of climate-resilient watersheds and reservoirs.

2. Methodology

2.1. Review structure

This review employed a structured methodology to identify and analyze studies on AI-based sediment-yield prediction. A focused research question guided the selection process, followed by a comprehensive literature search using predefined inclusion and exclusion criteria to determine each study's relevance. The following step involved data extraction from the selected studies, focusing on the key variables and methodological aspects. Finally, the findings were synthesized to highlight the contributions, limitations, and trends of AI applications in sediment modeling. In line with this methodology, we examine the specific AI techniques used, along with their performance and limitations. Figure 1 illustrates the overall review process, from formulating the research question to synthesizing the findings to be discussed.

This workflow followed the PRISMA 2020 guidelines to ensure transparent and reproducible screening and selection of studies. Each step is numerically reported in the corresponding flowchart (Fig. 1).

2.2. Identifying relevant studies

To identify relevant research articles, a systematic review was conducted using two databases: Google Scholar and Scopus, over an eight-month period from February to October 2024. A comprehensive set of search terms (Fig. 2) was employed to ensure inclusion of all pertinent resources. These terms were initially chosen based on the authors' expertise and subsequently refined by incorporating keywords extracted from relevant studies.

The research methodology was systematic, and targeted searches were performed using keywords that comprised three or four terms. The study began with a thorough analysis of various studies on modeling and forecasting sedimentation in reservoirs and watersheds, with a particular focus on approaches that utilize artificial intelligence (AI). This approach is more sophisticated than simple sediment yield estimation and encompasses various methodologies, including artificial neural networks (ANN), support vector machines (SVM), and random forests (RF) (Jooshaki et al., 2021).

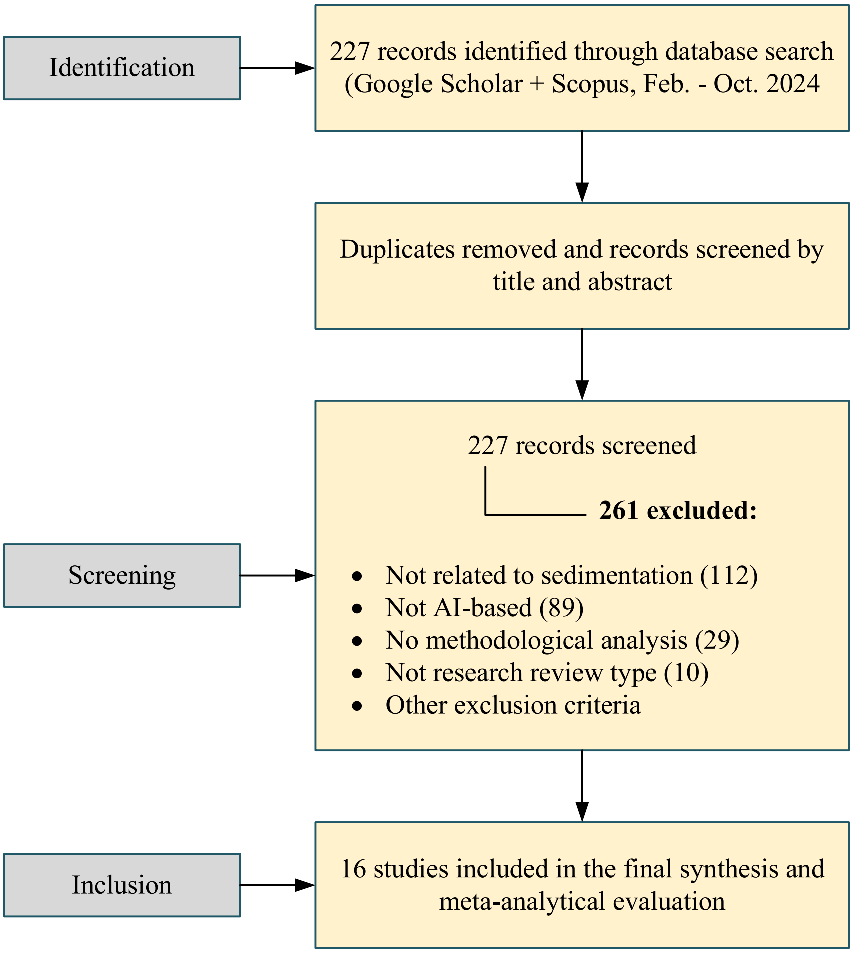

Figure 1. Systematic Review Workflow

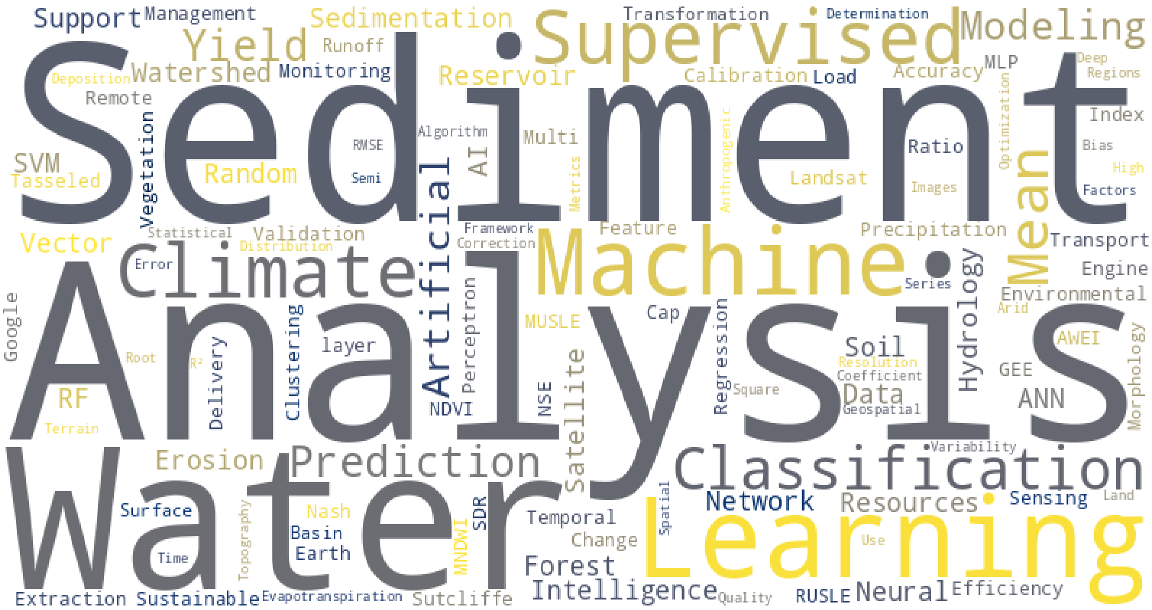

Figure 2. Keyword Cloud Highlighting Dominant AI and Sedimentation Modeling Themes

The primary objective was to ensure that all AI-based methods used to model sediment dynamics, hydrological and climatic impacts, and water resource management were included in the systematic review. Articles examining the correlations among precipitation, soil erosion, and discharge variations were also included. These factors are directly linked to sediment modeling because they influence key phenomena, such as the transport and deposition of solid particles.

Furthermore, the consideration of spectral indices such as NDVI, MNDWI, and AWEI, combined with the use of geospatial tools like Google Earth Engine (GEE), provides a more comprehensive representation of the input data used in the models. The integration of these environmental variables with clustering approaches (e.g., k-means clustering) and temporal analysis offers a valuable framework for understanding the complex dynamics of hydrological systems.

The initial search yielded 277 publications, which were subsequently screened for evaluation purposes. A comprehensive review of the reference lists of the selected publications was then conducted. The reviewed documents included journal articles, conference proceedings, books, review papers, theses, and online databases. This approach ensured that the analysis was based on a comprehensive and diverse range of sources.

2.3. Screening criteria

The adopted strategy was designed to ensure the reproducibility and transparency of the results. Exact search strings and combinations were documented and consistently applied across both databases to minimize bias. Specifically, the search in Scopus was conducted using the following query:

TITLE-ABS-KEY (("sediment yield" OR "sediment load" OR "reservoir siltation") AND ("artificial intelligence" OR "machine learning" OR "deep learning" OR "neural network" OR "hybrid model") AND ("watershed" OR "reservoir" OR "catchment")), while the same Boolean operators were used in Google Scholar searches. Duplicate records were automatically removed through metadata matching (title, DOI, and year) prior to manual screening.

The screening and selection processes followed the PRISMA 2020 framework. Figure 1 presents a PRISMA-style flow diagram summarizing the number of records identified, screened, excluded, and retained. At each stage, the number of studies was reported as follows: 277 records were initially identified, 45 duplicates were removed, 232 records were screened based on titles and abstracts, 53 were excluded due to irrelevance, and 179 full-text articles were assessed for eligibility. Finally, 16 research papers met all inclusion criteria and were retained for synthesis. This transparent workflow ensures that each exclusion step can be replicated using the same criteria.

Table 1 summarizes the exclusion criteria applied during the study selection process, which ensured the inclusion of only AI-based sedimentation studies.

Following a rigorous selection process, 16 articles were retained for analysis. These included original research or systematic reviews covering various approaches, such as the use of satellite data (NDVI, MNDWI) and cloud-based geospatial processing platforms such as Google Earth Engine (GEE), to advanced modeling techniques, including artificial neural networks (ANN), support vector machines (SVM), and random forest (RF). This selection provides a comprehensive framework for analyzing the contributions and trends of sedimentation forecasting and management.

Table 2 summarizes the selected studies by outlining their study areas, study types, key findings, and data sources.

2.4. Data extraction

In accordance with PRISMA 2020 guidelines, screening and data extraction were performed to ensure methodological transparency and reproducibility. Consistent inclusion and exclusion criteria were applied throughout the process, focusing on studies that utilized artificial intelligence–based approaches for sedimentation modeling.

Table 1. Summary of Exclusion Criteria

Criteria	Description	Excluded by this criterion
AI-based modeling methods applied to sedimentation	The article must include modeling or prediction aspects related to sedimentation (production, transport, or deposition).	112
AI-based modeling methods applied to sedimentation	The article must use at least one AI method (ANN, SVM, RF, LSTM, etc.) or provide a review of AI methods applied to sedimentation.	89
In-depth methodological analysis	The studies must include a detailed assessment of data, variables, and environmental factors influencing sedimentary processes.	29
Type of study	Must be original research or a systematic review.	10
Type of publication	Must be a journal article, conference communication, thesis, or book chapter.	14
Language of publication	Must be written in English.	7

Table 2. Selected Studies

Title	Study Area (Countries)	Type	Source
Reservoir Sedimentation Estimation Using an Artificial Neural Network	India	Research article	Jothiprakash and Garg (2009)
Comparison of a data-based model and a soil erosion model coupled with multiple linear regression for the prediction of reservoir sedimentation in a semi-arid environment	Morocco	Research article	El Bilali et al. (2020)
Neural Network Prediction of Reservoir Sedimentation	India	Research article	Froehlich and Giri (2019)
Suspended sediment flux modeling with artificial neural network: An example of the Long Chuan Jiang River in the Upper Yangtze Catchment, China	China	Research article	Zhu et al. (2007))
Capability and Robustness of Novel Hybridized Artificial Intelligence Technique for Sediment Yield Modeling in Godavari River, India	India	Research article	Yadav et al. (2022)
Estimating Sediment Discharge Using Sediment Rating Curves and Artificial Neural Networks in the Shiwen River, Taiwan	Taiwan	Research article	Tfwala and Wang (2016)
A New Clustering Method to Generate Training Samples for Supervised Monitoring of Long-Term Water Surface Dynamics Using Landsat Data through Google Earth Engine	Iran	Research article	Taheri Dehkordi et al. (2022))
Comparison of the soil and water assessment tool (SWAT) and multilayer perceptron (MLP) artificial neural network for predicting sediment yield in the Nagwa agricultural watershed in Jharkhand, India	India	Research article	Singh et al. (2012)
Estimation of Sediment Yield for the Dasu Hydropower Project Using Artificial Neural Networks	Pakistan	Research article	Rehman et al. (2016)
Application of Artificial Neural Networks, Support Vector Machine, and Multiple Model-ANN to Sediment Yield Prediction	India	Research article	Meshram et al. (2020)
Predicting reservoir volume reduction using an artificial neural network	Iran	Research article	Iraji et al. (2020)
Sediment load estimation by MLR, ANN, NF, and Sediment Rating Curve (SRC) in the Rio Chama River	USA	Research article	Ghorbani et al. (2013)
Hybrid Machine Learning Approach for Gully Erosion Mapping Susceptibility at a Watershed Scale	Morocco	Research article	Hitouri et al. (2022)
Prediction of current and future gully erosion susceptibility in the Oued Zat watershed in the High Atlas region of Morocco using an SVM-based machine learning approach	Morocco	Research article	Dallahi et al. (2025)
Suspended sediment load prediction modeling based on artificial intelligence methods: The tropical region as a case study	Malaysia	Research article	Allawi et al. (2023)
Daily Sediment Yield Modeling with Artificial Neural Network using 10-fold Cross Validation Method: A small agricultural watershed, Kapgari, India	India	Research article	Singh and Panda (2011)

Data were extracted from 16 studies meeting the inclusion criteria for this review, covering key aspects of sedimentation modeling and prediction, including publication year, study site or watershed, and principal research objectives. The extracted information also included the artificial intelligence methods applied—such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), Random Forests (RF), and Long Short-Term Memory (LSTM)—along with the model architectures developed, data preprocessing techniques (including the use of spectral indices such as NDVI, MNDWI, and AWEI), model inputs (e.g., precipitation, NDVI, and streamflow), and model outputs (such as sediment production in tons). In addition, the time periods covered by the datasets, the limitations identified in each study, and the data sources used, including Landsat satellite imagery, climate databases, and watershed data, were systematically recorded to provide a comprehensive synthesis of the selected studies.

Table 3 summarizes the main objectives, methodologies, and key results of selected studies. Overall, hybrid and deep learning models exhibited the strongest predictive capabilities, followed by ensemble and classical ML algorithms. Specifically, physically coupled hybrid frameworks (e.g., SWAT-LSTM and MUSLE-ANN) achieved the highest average R^2 values (≈0.94-0.97) and the lowest RMSE (<0.12), highlighting their robustness in modeling complex sediment processes. Ensemble models (e.g., RF–bagging and stacking) also demonstrated high accuracy and stability across various climates.

In contrast, classical models, such as ANN and SVM, although widely applied, exhibited lower stability under heterogeneous hydrological conditions. To streamline the results, only the aggregated performance metrics are discussed below, and detailed numerical values are reported in Table 4. Table 4 summarizes the hierarchy of model performance, ordering the algorithms from most to least accurate and grouping them by environmental context to provide a concise comparative overview.

These results highlight that although ANN remains widely applied, hybrid and LSTM-based models deliver the highest accuracy and stability, particularly in complex or data-scarce hydrological environments. Comprehensive data extraction provided a complete overview of the scope of application of AI-based methods in sediment management and hydrological processes in the field. Furthermore, it assists in assessing the various methodologies, model performance, and remaining gaps in this field of study. Figure 3 illustrates the number of studies conducted for each model used in sedimentation modeling, showing the distribution across various AI methods.

3. Framework for sedimentation study categories

Artificial intelligence (AI) methods provide a robust means of analyzing various aspects related to sedimentation processes in reservoirs and watersheds (Tao et al., 2021). The data extracted during the systematic review were used to categorize the selected studies into four categories: occurrence, severity, period, and spatial distribution. These categories facilitate the organization and analysis of the collected data related to sedimentation modeling and prediction.

3.1. Occurrence

The occurrence category is related to the frequency and patterns of sedimentation events. Sedimentation events are influenced by several factors, including precipitation intensity, soil type, vegetation cover, and topography. Most studies analyzed defined occurrences in a binary manner (yes/no), linking them to critical conditions, such as intense runoff episodes or specific land-use practices. These analyses are essential for identifying areas at high risk of sediment accumulation and for developing appropriate management strategies, such as soil conservation measures.

3.2. Severity

Severity analysis enables a more comprehensive assessment of the magnitude and effects of sedimentation relative to the occurrence category. AI-based approaches, including artificial neural networks (ANNs) and support vector machines (SVMs) (Jooshaki et al., 2021), have been employed to assess maximum sediment loads, deposition rates, and reductions in reservoir capacity. The key variables were the maximum sediment load (tons), sediment deposition rate, and the impact on the capacity of the hydraulic infrastructure. This information is crucial for planning dredging operations and assessing the economic and environmental consequences of sedimentation.

3.3. Period

This period category is concerned with forecasting the likelihood of significant sedimentation events at specific times. This includes forecasting seasonal periods of high sediment discharge or peaks associated with major climatic events. Models based on LSTM networks and time series have proven effective in predicting these periods using historical precipitation and flow data. Such forecasts enable proactive management, including the preparation of reservoirs for significant sediment input and the initiation of impact-reducing interventions.

3.4. Spatial distribution

The objective of the spatial distribution category was to identify areas within a watershed or reservoir where sediment deposition is most likely to occur. A combination of AI methods with geospatial data (NDVI, MNDWI, the AWEI indices, and digital elevation models) was employed to map erosive zones and sediment deposition areas. These studies employed platforms including Google Earth Engine (GEE) and geographic information systems (GIS) to integrate data on land use, topography, and hydrology. Table 5 categorizes the methodologies applied to address different sedimentation themes, such as sediment yield prediction, erosion mapping, and reservoir volume-loss estimation. The results are presented in the form of detailed maps that highlight priority areas for targeted interventions, such as reforestation or the construction of control dams.

Table 3. Selected Studies: Main Objectives, Methodologies, and Key Results

Title	Main Objective	Methodology Used	Key Results
Reservoir Sedimentation Estimation Using an Artificial Neural Network	To estimate reservoir sedimentation using ANN techniques.	MLP with 3-5-1 architecture, analyzing rainfall and inflow data.	ANN outperformed traditional regression, achieving R^2 of 0.97.
Comparison of a data-based model and a soil erosion model coupled with multiple linear regression for the prediction of reservoir sedimentation in a semi-arid environment	Comparison of ANN and MLR for predicting reservoir sedimentation.	Coupling MUSLE with MLR and using ANN for comparison.	ANN was significantly more accurate with R^2 of 0.911 compared to 0.820 for MUSLE-MLR.
Neural Network Prediction of Reservoir Sedimentation	To develop an ANN model for predicting sedimentation in reservoirs.	ANN was trained on a time series of reservoir sedimentation data.	The ANN model achieved a regression accuracy of 0.96 with an NSE of 0.989.
Suspended sediment flux modeling with artificial neural network: An example of the Long Chuan Jiang River in the Upper Yangtze Catchment, China	To predict suspended sediment flux using ANN.	Feedforward ANN trained on river flow and sediment data.	Successfully modeled sediment flux with RMSE of 0.12.
Capability and Robustness of Novel Hybridized Artificial Intelligence Technique for Sediment Yield Modeling in Godavari River, India	To evaluate hybrid AI models for sediment yield prediction.	Hybrid models combining ANN and genetic algorithms.	Hybrid models significantly improved prediction accuracy compared to ANN alone.
Estimating Sediment Discharge Using Sediment Rating Curves and Artificial Neural Networks in the Shiwen River, Taiwan	To compare SRC with ANN for sediment discharge assessment.	MLP and SRC models trained on sediment and flow data.	ANN outperformed SRC with R^2 of 0.903 compared to 0.765.
A New Clustering Method to Generate Training Samples for Supervised Monitoring of Long-Term Water Surface Dynamics Using Landsat Data through Google Earth Engine	To develop a clustering method for training sample generation.	Iterative K-means clustering combined with GEE.	Enhanced classification accuracy for water surface monitoring.
Comparison of soil and water assessment tool (SWAT) and multilayer perceptron (MLP) artificial neural network for predicting sediment yield in the Nagwa agricultural watershed in Jharkhand, India	To evaluate SWAT and MLP for sediment yield prediction.	Comparison of SWAT model and MLP neural networks.	MLP achieved higher accuracy in calibration and validation.
Estimation of Sediment Yield for Dasu Hydropower Project Using Artificial Neural Networks	To estimate sediment yield for the Dasu Hydropower Project.	MLP neural networks trained on hydrological data.	Improved sediment yield predictions with R^2 of 0.92.
Application of Artificial Neural Networks, Support Vector Machine and Multiple Model-ANN to Sediment Yield Prediction	To compare ANN, SVM, and hybrid models for sediment prediction.	Hybrid ANN models trained on multiple datasets.	Hybrid ANN achieved the highest accuracy among tested models.
Predicting reservoir volume reduction using artificial neural network	To predict reservoir volume reduction due to sedimentation.	ANN trained on sedimentation and volume reduction data.	Accurate predictions of sedimentation rates and operational lifespan.
Sediment load estimation by MLR, ANN, NF and Sediment Rating Curve (SRC) in Rio Chama River	To evaluate multiple models for sediment load estimation.	MLR, ANN, neuro-fuzzy models, and SRC.	ANN provided the most reliable predictions compared to other methods.
Hybrid Machine Learning Approach for Gully Erosion Mapping Susceptibility at a Watershed Scale	To map gully erosion susceptibility using hybrid ML models.	RF, SVM, and Naive Bayes combined with frequency ratio.	RF-FR achieved the highest AUC of 0.91.
Prediction of current and future gully erosion susceptibility in the Oued Zat watershed in the High Atlas region of Morocco using an SVM-based machine learning approach	To predict gully erosion under current and future climate scenarios.	SVM trained on environmental and geospatial datasets.	AUC of 0.92 for current predictions, with future susceptibility areas identified.
Suspended sediment load prediction modelling based on artificial intelligence methods: The tropical region as a case study	To model sediment load in a tropical river using AI methods.	ANN and LSTM models trained on hydrological datasets.	LSTM outperformed ANN with RMSE of 148.4 and R^2 of 0.97.
Daily Sediment Yield Modeling with Artificial Neural Network using 10-fold Cross Validation Method: A small agricultural watershed, Kapgari, India	To predict daily sediment yield using ANN with cross-validation.	ANN with 10-fold cross-validation.	Reliable predictions with improved generalization.

Table 4. Meta-Analytical Synthesis of Model Performance According to Algorithm Type and Environmental Context

Algorithm Type	Example Models	Mean R^2 Range	RMSE Range	Mean NSE Range	Typical Watershed Scale	Predominant Climate	Representative References
ANN	ANN, MLP	0.82-0.91	0.04-0.12	0.80-0.92	Small-medium	Semi-arid, tropical	Jothiprakash and Garg (2009); Singh and Panda (2011)
SVM / RF	SVM, RF	0.83-0.92	0.03-0.09	0.85-0.93	Medium-large	Mediterranean, tropical	Jooshaki et al. (2021); Dallahi et al. (2025)
Hybrid AI	ANN-GA, MUSLE-ANN, LSTM-CEEMDAN	0.90-0.97	0.02-0.07	0.93-0.97	Variable	Humid, tropical	Yadav et al. (2022); Meshram et al. (2020); Allawi et al. (2023)
Ensemble Models	RF-Bagging, Model Stacking	0.88-0.95	0.03-0.08	0.90-0.96	Medium-large	Humid	Bezak et al. (2024); Hitouri et al. (2022)
Physically Coupled AI	SWAT-LSTM, MUSLE-ANN	0.91-0.96	0.02-0.06	0.93-0.97	Large	Semi-arid, tropical	El Bilali et al. (2020); Rehman et al. (2016)

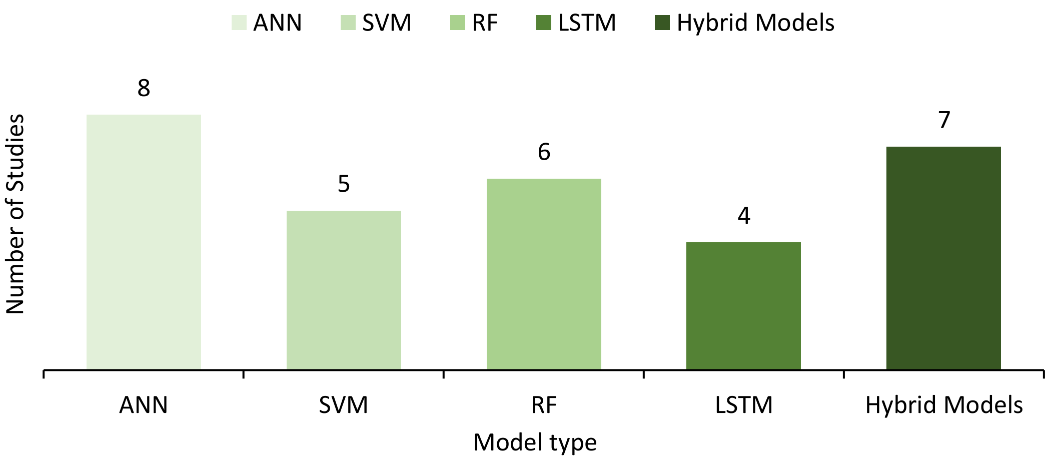

Figure 3. Distribution of AI Methods and Environmental Data Used in Reviewed Studies

3.5. Evolution of sedimentation research categories

Figure 4 illustrates the evolution of research priorities within these categories. Initially, studies focused on the occurrence and severity of sedimentation. However, since 2010, there has been growing interest in the period category, driven by the availability of high-resolution temporal data and advanced AI models.

Furthermore, around 2015, there was a notable shift towards emphasizing spatial distribution, highlighting the increasing role of geospatial approaches in sedimentation management. More recently, studies on sedimentation occurrence have resurged due to the heightened frequency of extreme climatic events and their associated impacts on watersheds and reservoir systems.

Figure 5 presents the conceptual structure linking the major components of AI-based sediment modeling. Input datasets, including climatic (precipitation and temperature), topographic (DEM and slope), and spectral indices (NDVI, MNDWI, and AWEI), were fed into three major AI model categories: (1) classical machine learning (e.g., ANN, SVM, RF), (2) hybrid physical-AI models (e.g., MUSLE-ANN, SWAT-LSTM), and (3) ensemble approaches (e.g., RF-bagging, stacking). These models generate diverse outputs, such as sediment yield (SY), spatial sediment deposition, and reservoir capacity loss, which inform management strategies and decision support systems.

4. Spatiotemporal monitoring of water reservoirs

Monitoring water reservoirs relies on reliable data and efficient tools for long-term spatiotemporal variation analysis (Kazemi Garajeh et al., 2024). This section highlights the data used and the analysis methods employed, as well as the key role of Google Earth Engine as a central platform in this methodology.

4.1. Key role of Google Earth Engine and satellite data utilization

Google Earth Engine (GEE) is a cloud-computing platform that offers an efficient environment for processing and integrating multi-source datasets, including Landsat, Sentinel, and climate archives. Rather than focusing on technical steps, this review emphasizes how GEE-enabled processing transforms sedimentation modeling through improved spatiotemporal scalability, reproducibility, and open-access integration (Amani et al., 2020; Kazemi Garajeh et al., 2024; Tamiminia et al., 2020).

Table 5. Methodology by Theme

Theme	Methodologies Used	Models Used	Key Variables
Sediment Yield Prediction	ANN, MUSLE-MLR	ANN, MUSLE	Rainfall, flow, basin area
Erosion Susceptibility Mapping	RF, SVM, NB, Hybrid	RF, SVM, NB	Slope, TWI, river distance, LULC
Sediment Transport	ANN, SVM, LSTM, Hybrid	ANN, LSTM, Hybrid	Flow, sediment concentration, temperature
Reservoir Volume Loss Prediction	ANN, SVM	ANN	Inflow/outflow, sediment volume

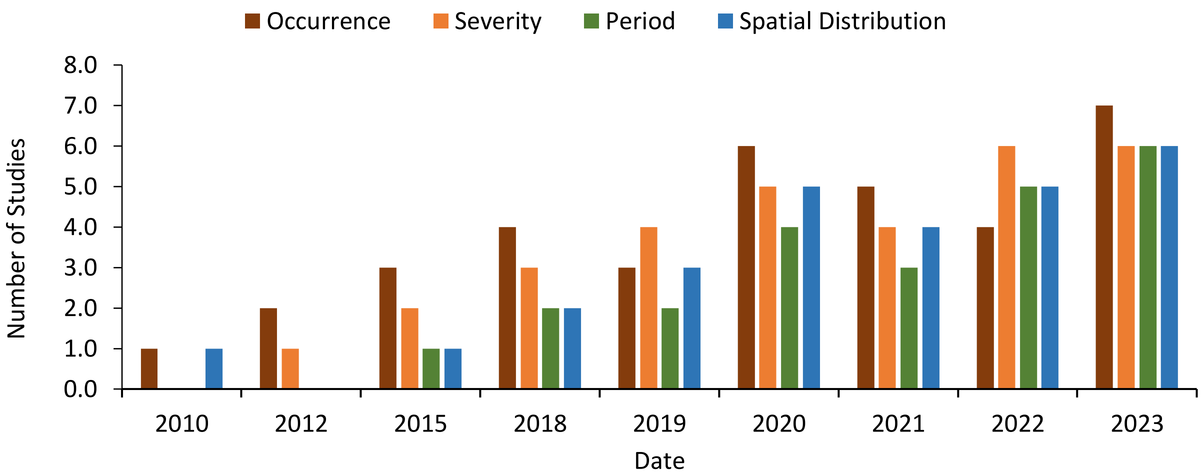

Figure 4. Temporal Trends in Sedimentation Research Categories (2005–2024)

GEE facilitates large-scale analysis by automating the preprocessing of satellite images (e.g., cloud masking and compositing) and generating environmental indices such as NDVI, MNDWI, and AWEI over multi-decadal periods. This capability ensures consistent and reproducible datasets that are comparable across different basins and timeframes (Chen et al., 2023; Pakdel-Khasmakhi et al., 2022).

Cloud-based computation allows near-real-time monitoring of reservoir dynamics, enabling the continuous detection of sedimentation trends and land-use changes without requiring high-performance local infrastructure. Researchers can reproduce analyses directly through shared scripts and datasets, promoting transparency and collaboration in science (Amani et al., 2020; Kazemi Garajeh et al., 2024).

In summary, GEE enhances sedimentation modeling by automating data preprocessing and spectral index generation, integrating climatic, hydrological, and topographic data across multiple spatial scales, improving spatiotemporal scalability and reproducibility, and supporting open-access, collaborative modeling frameworks.

Figure 6 illustrates the conceptual framework of the GEE workflow employed in sedimentation modeling. The Google Earth Engine (GEE) is the foundation of this methodology, offering a robust platform for processing, analyzing, and integrating satellite data from various sources (Tamiminia et al., 2020).

The key benefits of GEE include large-scale data processing, as it provides a comprehensive solution for managing and preprocessing vast volumes of satellite imagery, such as data from the Landsat 5, 7, and 8 missions covering the period from 1990 to 2021. Through automated procedures, GEE enhances imagery by removing artifacts such as clouds and shadows, thereby simplifying and streamlining complex preprocessing steps.

The platform enabled the rapid calculation of spectral indices, as GEE facilitates the efficient generation of essential indices for identifying and monitoring water surfaces (Chen et al., 2023). These include the Normalized Difference Vegetation Index (NDVI) for distinguishing vegetation from other land-cover types, the Modified Normalized Difference Water Index (MNDWI) for accurate water surface detection, and the Adjusted Water Index (AWEI) for reducing the effects of shadows and mixed pixels. The cloud-based computing capabilities of GEE ensure the consistent and rapid production of these indices, thereby supporting coherent spatiotemporal analyses over multiple decades.

Automated spatiotemporal analysis tools in Google Earth Engine (GEE) facilitate continuous observation of water surface dynamics, allowing the detection of trends and anomalies in reservoirs (Pakdel-Khasmakhi et al., 2022).

The generation of training samples for classification purposes was facilitated using GEE through the implementation of K-means clustering, which produced robust training samples subsequently used to train supervised models. These included Random Forest (RF) models, which effectively capture complex relationships between spectral indices and water surfaces, and Support Vector Machine (SVM) models, which are fully compatible with the platform and enable accurate classification of water areas. By leveraging the computational capabilities of GEE, this approach optimizes data processing while improving both efficiency and accuracy of the classification results.

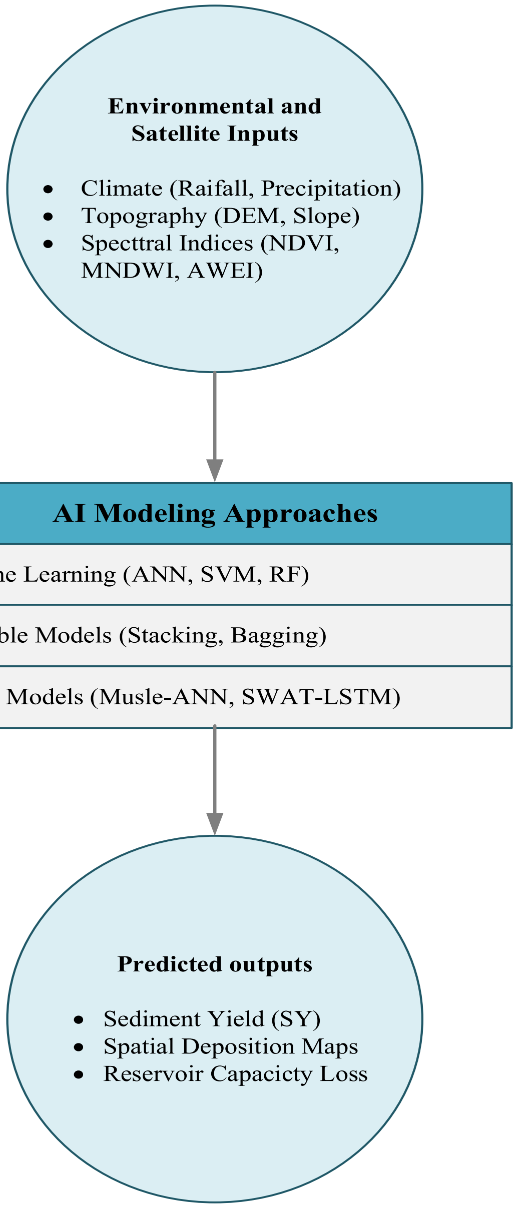

Figure 5. Conceptual Framework Linking Data Inputs, AI Model Categories, and Sedimentation Outputs

4.2. Climate and hydrological data

Furthermore, in addition to satellite data, climate and hydrological variables were integrated to enable a more comprehensive analysis of water reservoirs. These parameters included Mean Annual Precipitation (MAP), which directly influences reservoir inflow and sediment transport processes, and Mean Annual Temperature (MAT), which affects evaporation rates and overall hydrological variability. The GEE facilitates the integration of these data with generated spectral indices, thereby facilitating the analysis of complex interactions between climate, spatiotemporal trends, and water surface variations.

4.2.1. Databases on hydrological dynamics and surface variations of reservoirs

To effectively develop and validate hydrological models, it is essential to have comprehensive information on the spatiotemporal variations of reservoirs, including dates, locations, magnitudes of surface changes, and bathymetric data. The integration of these datasets with modern platforms, such as Google Earth Engine (GEE), enables a comprehensive and detailed analysis of large-scale water surface dynamics.

4.3. Satellite and geospatial databases

Satellite data, particularly from the Landsat missions, play a critical role in the long-term monitoring of water surface variations in reservoirs, as the Landsat archive available through Google Earth Engine (GEE) offers extensive spatiotemporal coverage over several decades. These data enable the production of accurate water surface maps and spectral indices, including the Normalized Difference Vegetation Index (NDVI) to monitor surrounding vegetation dynamics, the Modified Normalized Difference Water Index (MNDWI) for reliable identification of water surfaces, and the Adjusted Water Index (AWEI) to minimize interference from shadows and vegetation. Through GEE, these indices can be computed efficiently at large spatial and temporal scales, supporting precise temporal analyses of water surface variations.

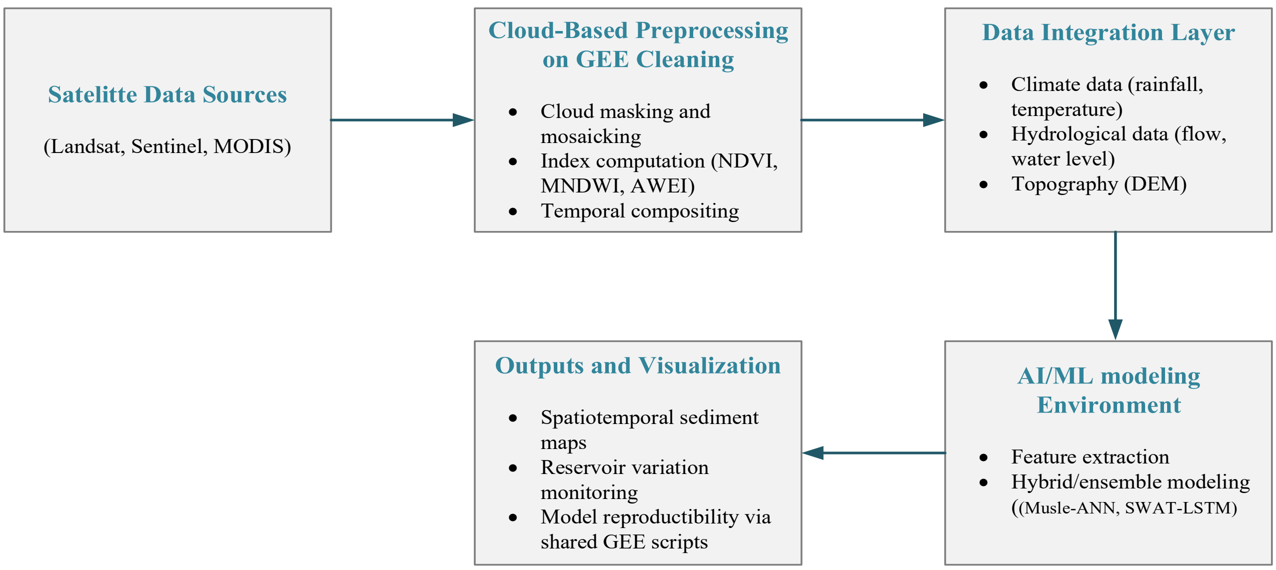

Figure 6. GEE-Enabled Cloud Workflow for Scalable and Reproducible Sedimentation Modeling

4.3.1. Bathymetric and hydrometric data

Bathymetric data, which measure the depth and shape of reservoir beds, are essential for assessing reservoir capacity and long-term evolution. These data are collected through sonar surveys and can be integrated into hydrological models to accurately estimate the remaining storage capacity and impact of sedimentation.

Local hydrometric data, including water level and flow rate, provide valuable complementary information when integrated with bathymetric data, as measurements from hydrometric stations are essential for modeling reservoir volume variations and overall dynamics. The parameters typically measured include inflow and outflow rates, reservoir water levels, and indicators of water quality and sedimentation, all of which can influence reservoir capacity over the long term.

4.3.2. Climate and hydrological data

The analysis of water reservoirs depends on climate data. Annual precipitation, average temperature, and other climatic parameters directly affect reservoir dynamics. Local hydrological data, such as tributary flow rates and water levels, allow us to model reservoir filling and draining, considering water inputs from rainfall and rivers.

4.3.3. Data integration and modeling via GEE

Google Earth Engine (GEE) provides a unified platform for integrating and visualizing data from diverse sources, including satellites, weather stations, bathymetric surveys, and hydrometric data. This cloud-based platform enables the processing of large datasets and facilitates spatiotemporal analyses over several decades (Pimple et al., 2018).

The key features of Google Earth Engine (GEE) include its cloud-based architecture, which enables the efficient processing of large volumes of data and supports spatiotemporal analyses spanning several decades (Amani et al., 2020). GEE facilitates the integration and visualization of satellite and climate datasets, the generation of interactive reservoir maps, the prediction of water surface dynamics, and the estimation of water volumes through the integration of bathymetric and hydrological information.

This multimodal approach enables the generation of predictive models that consider climatic factors, water input, and sedimentation. The resulting tools provide water resource management with the ability to optimize water usage. Climate data play a significant role in the analysis of water reservoirs. Annual precipitation, average temperature, and other climatic parameters directly influence reservoir dynamics. Local hydrological data, such as tributary flow rates and water levels, enable the modeling of reservoir filling and draining by considering water inputs from rainfall and rivers.

5. Input parameters for forecasting water reservoir dynamics

It is crucial to define the input parameters used in previous studies to predict the evolution of water reservoirs using artificial intelligence (AI) models to improve the accuracy and reliability of forecasting. Figure 5 illustrates the primary raw data most frequently employed in AI-based models for forecasting water reservoir dynamics. The main inputs for these models are precipitation, air temperature, and hydrometric parameters (such as discharge and water level). These parameters have a direct impact on reservoir dynamics, particularly with regard to water inflow and fluctuations in water levels.

5.1. Types of inputs used for predictive models

The inputs were classified into two main categories: raw data and derived data. Raw data consisted of fundamental datasets such as precipitation, air temperature, water level, and river discharge, while derived data included variables calculated from these primary datasets, notably vegetation and water indices obtained from satellite imagery.

5.2. Raw data for models

Several types of raw data are commonly used in water reservoir studies. Air temperature data are key inputs, as temperature variations directly influence evaporation rates and water inflow, particularly during dry seasons or snowmelt periods. Precipitation data collected from weather stations are essential for estimating the volume of water entering reservoirs, and climate models integrated within GEE use these data to better assess the impacts of climatic events on reservoir water management. In addition, discharge and water level data measured at hydrometric stations are used to estimate reservoir inflows and outflows, with discharge variability being a critical factor in reservoir management due to its direct effect on water availability.

5.3. Derived data and indices

The derived data obtained from the raw data include various indices that are essential for predictive models. These indices were calculated from parameters such as temperature, precipitation, and water level, providing valuable insights into the reservoir behavior.

The most commonly used indices include cumulative freeze degree days (AFDD) and thaw degree days (ATDD), which are derived from air temperature and are widely applied to assess ice and snow dynamics in watersheds, as these processes directly influence reservoir water levels during melting periods. Snowfall and Snow Water Equivalent (SWE), derived from precipitation data, are also key variables, particularly in regions where snowmelt contributes significantly to reservoir inflow. In addition, the Antecedent Precipitation Index (API), which represents cumulative rainfall prior to a given event and serves as a proxy for soil moisture conditions, is frequently used to forecast reservoir water levels by providing an effective measure of water accumulation before major hydrological events such as floods or abrupt water-level changes.

These indices are employed in AI models to forecast reservoir dynamics, particularly to identify periods of flooding or drought risk. By integrating these indices with satellite data in GEE, dynamic maps of reservoirs can be created, and their evolution can be simulated under various climate scenarios.

5.4. Bathymetric and elevation data

In addition to climatic and hydrological data, bathymetric data are essential for accurately predicting reservoir evolution. These data reveal the depth and shape of the reservoir's bottom, allowing the calculation of the water volume stored at any given time. Digital Elevation Models (DEMs) derived from these data were used to estimate water volumes in reservoirs and predict the impacts of sedimentation and topographic changes. Integrating these bathymetric data with climatic and hydrological data in GEE enables the simulation of long-term reservoir evolution and the prediction of scenarios under different climatic and hydrological conditions.

5.5. Input parameters for forecasting water reservoir dynamics

As illustrated in Figure 7, hydrometric parameters such as discharge, water level, and precipitation are the most commonly used raw inputs for modeling reservoir evolution. The introduction of climate data, such as air temperature and precipitation indices, has marked a significant shift in this field of study. These climate variables are crucial for assessing reservoir variations because of their direct impact on the filling and draining of reservoirs. Another significant development in reservoir dynamics modeling is the integration of bathymetric and watershed topography data using Digital Elevation Models (DEMs) and other geospatial variables, facilitated by software like the Google Earth Engine (GEE).

5.5.1. Input parameters for the intensity of reservoir variations

The intensity of reservoir fluctuations is typically estimated using the maximum water level and maximum daily discharge observed in reservoirs during flooding or drought events. These parameters are used as model outputs to quantify the intensity of events and are often associated with variables such as precipitation, runoff, and land-use changes. The raw parameters considered included runoff and water level, which are fundamental for modeling changes in reservoir volume, as well as air temperature and precipitation, especially in regions where variability in temperature and rainfall patterns strongly influences reservoir water levels. Furthermore, incorporating solar radiation or sunshine data into models enhances the forecasting of reservoir variations, particularly in areas where temperature patterns significantly affect water volume changes.

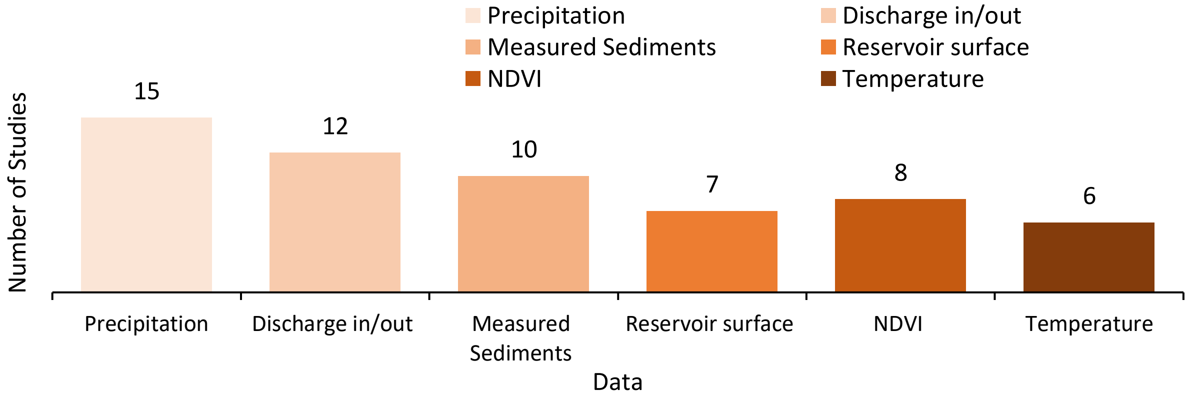

Figure 7. Main Input Parameters Used in AI-Based Reservoir and Sedimentation Forecasting

5.5.2. Input parameters for forecasting the timing of reservoir variations

Accurately forecasting the timing of reservoir variations is of utmost importance for effectively managing flood regimes and planning water demand. The most crucial raw parameters in this category include water level and discharge, which are essential for predicting flood and drought occurrences in reservoirs, as well as air temperature and precipitation, which are instrumental in identifying freeze–thaw periods that significantly influence reservoir dynamics. In addition, the use of digital elevation models and bathymetric data processed through GEE enhances these forecasts by enabling more accurate estimates of stored water volumes and reservoir absorption capacity.

6. Preprocessing of input data

It is essential to process the data used in AI-based models, particularly for water reservoir management and hydrological dynamics. The objective of this process was to prepare reliable, high-quality data for model training while enhancing performance and accuracy. The preprocessing stage comprises several key steps, including the selection of input variables, data normalization, detection of gaps and outliers, and assurance of data quality. It is important to ensure that all variables are considered during model training, which is why preprocessing steps are crucial in this study. AI-based models for water reservoir management often utilize sophisticated techniques to process vast quantities of climatic, hydrological, and satellite data.

6.1. Input data selection

The selection of input variables plays a critical role in AI models applied to water reservoir dynamics predictions. Many studies have used correlation coefficients to select input variables because of their simplicity and effectiveness. However, alternative approaches, such as regression methods, including stepwise and backward regression, are also commonly used to refine the selection of input variables. More recent strategies include techniques such as the two-step filter rapper (Chen & Chen, 2015) and the Weight of Evidence method, which incorporates geospatial approaches to further refine data selection, particularly for variables such as vegetation indices, air temperature, and water volume stored in reservoirs. These methods offer new ways to improve forecasts by combining historical and real-time satellite data.

6.2. Normalization

Data normalization is an important step in ensuring the stability and performance of AI models (Sujon et al., 2024). The most commonly used method is standard normalization, which converts data to a uniform scale, reduces redundancies and inconsistencies, and thus improves the accuracy of water reservoir dynamics forecasts. This technique is particularly useful in studies dealing with climate and hydrological data collected from different sources, such as satellites and weather stations. Normalization also reduces the impact of outliers, which can distort the data distribution and lead to errors in model predictions. Additional approaches, such as time-series normality and homogeneity methods, were used to ensure data quality and forecast robustness (Sujon et al., 2024).

6.3. Detecting gaps and outliers

Outliers and gaps in datasets are major challenges in data preprocessing, particularly when dealing with large climate and hydrological datasets. These anomalies can bias the model results and increase the prediction uncertainty. Several methods are used to detect these anomalies, such as box plots and the F-test, which help identify and deal with outliers. A more modern approach is to replace outliers with values calculated based on historical data to ensure data consistency, while minimizing bias. Various techniques have been developed to fill gaps in datasets, such as the use of the robust Kendall-Theil line, application of regularized expectation-maximization algorithms, and integration of remote sensing data from satellites, such as MODIS. Autoregressive algorithms and interpolation from other time series or neighboring station data are also used to deal with gaps, especially in areas where measurements are incomplete or missing.

6.4. Data quality verification

To ensure that the time series data were reliable and of high quality, additional tests were conducted to verify criteria such as normality, homogeneity, and independence of the data. These checks ensured that the data used to model the reservoir dynamics met the necessary standards for robust and reliable analysis.

7. Different AI-based approaches for predicting reservoir dynamics

Following the preparatory steps of input selection and post-processing, the next phase of the water reservoir management process involves selecting an AI-based model. A thorough literature review identified several AI models that can be used to predict reservoir dynamics, particularly with regard to aspects such as water-level fluctuations, sedimentation, and flood risk. These models can be classified into four main categories: machine learning, hybrid, ensemble, and framework. The advantages and limitations of each approach are detailed below.

7.1. Machine learning approaches

Machine learning (ML) is the most commonly used approach for predicting reservoir dynamics, particularly water levels, flow management, and sedimentation (Nourani, 2014). Popular machine-learning models include Artificial Neural Networks (ANN), Support Vector Machines (SVM), and algorithms (Jooshaki et al., 2021), such as k-nearest neighbors (KNN) and Adaptive Neuro-Fuzzy Inference Systems (ANFIS). These models can analyze complex time series and predict critical events for reservoir management by relying on historical data, meteorological measurements, and flow data. In particular, ANN can capture complex nonlinear relationships and has been used to estimate flooding and sedimentation events with high accuracy, as shown in recent studies on reservoir sediment yield prediction.

7.2. Hybrid approaches

Hybrid approaches use a combination of machine learning models and metaheuristic algorithms to create more robust and accurate models. These approaches are used particularly for complex tasks, such as predicting ice jam breakage in reservoirs and sedimentation. Particle Swarm Optimization (PSO) combined with ANN has achieved high predictive performance, with models reaching up to 95% accuracy in predicting flood events. For instance, while ANNs excel in handling nonlinear relationships in sediment yield prediction, hybrid approaches have been shown to be more effective in complex scenarios, achieving high accuracy. However, their computational requirements limit their scalability in data-scarce regions. Another interesting hybrid method is the combination of Long Short-Term Memory (LSTM) networks with Adaptive Signal Decomposition Techniques (CEEMDAN), which has shown significant improvements in modeling complex reservoir dynamics.

However, these hybrid models remain sensitive to data quality and availability, particularly in specific geographical or climatic contexts. Sites with low data availability or heterogeneous data can pose challenges in obtaining generalizable results, which remains a significant limitation of hybrid approaches.

7.3. Ensemble approaches

Ensemble approaches improve the overall accuracy and reduce errors by combining the predictions from multiple models. Random forests (RFs) and bagging are commonly used in this context and have shown good performance in predicting water levels and sedimentation in reservoirs. These models combine multiple decision trees into a random forest, allowing them to handle complex and nonlinear data that characterize reservoir hydrological dynamics. However, despite their power, ensemble approaches have limitations in predicting event locations, which remains a challenge for current models.

7.4. Framework approaches

Framework approaches integrate physical and AI models to improve reservoir forecasting, particularly in complex environments where hydrological and climatic data interact. For example, a hybrid model combining conceptual models with neural networks was used to assess the flows associated with ice jams and sedimentation. Recently, studies have combined Landsat and TIGGE data with hydraulic models, demonstrating improved capabilities for simulating flooding and sedimentation risks in reservoirs. However, these approaches are still under development and have not been widely applied to predict event occurrence or timing, which remains an area of exploration.

8. Discussion and research perspectives

Evaluating the strengths and weaknesses of prediction models is central to advancing sediment-yield forecasting and watershed management. Determining the best-performing approach is complex, particularly as hybrid and ensemble models are increasingly integrated with classical machine learning (ML) and physically based models. AI-based approaches, especially hybrid frameworks, have demonstrated remarkable success in capturing the nonlinear and dynamic nature of sedimentation processes; however, their practical and methodological implications warrant deeper analysis. An emerging trend from this review is that hybrid and ensemble models consistently outperform classical ML approaches in terms of accuracy, generalization, and stability. For instance, ANN-GA models (Yadav et al., 2022) and LSTM-CEEMDAN architectures (Allawi et al., 2023) achieved R^2 values between 0.90 and 0.97, surpassing standalone ANN or SVM models. Similarly, hybrid physical–AI frameworks such as MUSLE-ANN (El Bilali et al., 2020) and SWAT-LSTM (Singh et al., 2012) have been reported to reduce the RMSE by 25-40% compared to conventional empirical approaches. These improvements highlight how hybridization helps manage nonlinearities, temporal lags, and multiscale variability in sediment and hydrological data, which are often difficult to capture using classical models (Meshram et al., 2020).

Hybrid frameworks effectively handle strong nonlinear relationships, such as rainfall–runoff–erosion feedback, by embedding physical constraints or metaheuristic optimization techniques into the learning phase. They also capture temporal lags, as sediment responses do not necessarily coincide with the rainfall inputs. Methods such as LSTM-CEEMDAN decompose irregular time series into oscillatory components, allowing the network to learn both short-term and delayed hydrological signals. Furthermore, these frameworks represent multiscale variability by combining watershed-scale physical formulations, such as MUSLE, with local data-driven refinement using ANN or LSTM layers. This integration ensures physical interpretability while improving generalization across the heterogeneous basins. Ensemble models enhance robustness by integrating several base learners, reducing overfitting, and improving generalization across diverse environments.

From a practical standpoint, these advances have direct implications for watershed management, reservoir operations, and agricultural planning. Improved prediction of sediment yield timing enables more efficient dredging schedules and reservoir maintenance, while accurate spatial mapping identifies erosion-prone areas for implementing conservation practices, such as terracing, reforestation, and vegetative buffer strips. Furthermore, the integration of AI-based sediment models into watershed management frameworks provides decision-makers with tangible benefits. For example, predictive maps of erosion and deposition can inform land zoning, prioritize reforestation programs, and guide agricultural practices that minimize the loss of topsoil. In agricultural systems, improved sediment control reduces nutrient depletion and enhances soil productivity. From a policy perspective, incorporating AI-driven sediment forecasts into national water management plans can support early warning systems, optimize reservoir maintenance budgets, and strengthen resilience strategies against climate-induced hydrological extremes**.**

However, these accomplishments are not without challenges. Hybrid and ensemble models often require extensive computational resources, are sensitive to hyperparameter tuning, and rely on large and high-quality datasets. Their implementation in data-scarce regions remains limited, and the interpretability of AI-based models continues to lag behind that of physically based models. Integrating AI with process-based models (e.g., RUSLE, MUSLE, and SWAT) provides a way to balance empirical accuracy with physical transparency, which is a critical step towards developing models that are both robust and explainable. Although black-box AI models, such as ANN, SVM, and LSTM, exhibit strong predictive power, their lack of physical interpretability limits their scientific credibility and generalization capacity. In contrast, physics-guided or process-informed AI approaches embed physical laws and sediment transport principles within learning architectures, constraining model outputs to remain consistent with hydrological and geomorphic processes. Frameworks such as SWAT-LSTM and MUSLE-ANN integrate empirical learning with conservation equations, ensuring that predictions adhere to mass balance and sediment continuity principles. This paradigm, often termed physics-guided machine learning (PGML), enhances interpretability, reduces overfitting, and improves transferability across diverse watersheds. Incorporating domain knowledge, such as soil erodibility, runoff coefficients, or sediment delivery ratios, allows these models to explain not only what happens but also why it happens, thereby increasing their trustworthiness for decision-making.

However, a major limitation is the lack of comprehensive sediment and hydrological datasets, particularly in data-scarce or developing regions. In many watersheds, inconsistent monitoring and limited accessibility to remote sensing archives hinder the calibration and validation of models. This scarcity reduces model transferability because algorithms trained in data-rich environments may perform poorly under different climatic or geomorphological conditions. Therefore, future research should focus on developing data-efficient or transfer-learning models that can adapt to low-data contexts without sacrificing accuracy. Such approaches would greatly enhance the applicability of AI-driven sedimentation models in Africa, Latin America, and arid regions with similar monitoring gaps.

Figure 8 maps the geographical distribution of the reviewed studies, revealing a strong concentration in Asia (India, Iran, and China) and North Africa (Morocco). This regional bias highlights the areas where research and infrastructure for AI-based modeling are most developed. However, a significant regional gap persists in sub-Saharan Africa, Latin America, and the Mediterranean basins, where sedimentation problems are acute, but AI-based sedimentation studies remain limited. This imbalance primarily reflects the absence of long-term hydrological and sediment records, the scarcity of high-resolution remote sensing archives, and weak integration between research institutions and operational agencies. In many developing regions, sediment data collection is sporadic or inconsistent, which prevents model calibration and validation. In addition, limited computational infrastructure, insufficient expertise in data-driven modeling, and a lack of open-access databases hinder the broader application of AI tools. Consequently, most AI-based sedimentation studies originate from data-rich countries, raising concerns about the transferability of models to poorly monitored basins. Addressing this imbalance requires reinforcing institutional capacity, promoting data-sharing initiatives, and supporting collaborative regional networks to facilitate technology transfer and co-develop context-specific AI models. Enhancing data availability and expertise in underrepresented regions will ensure more equitable access to AI innovations and improve the global representativeness of sediment management research.

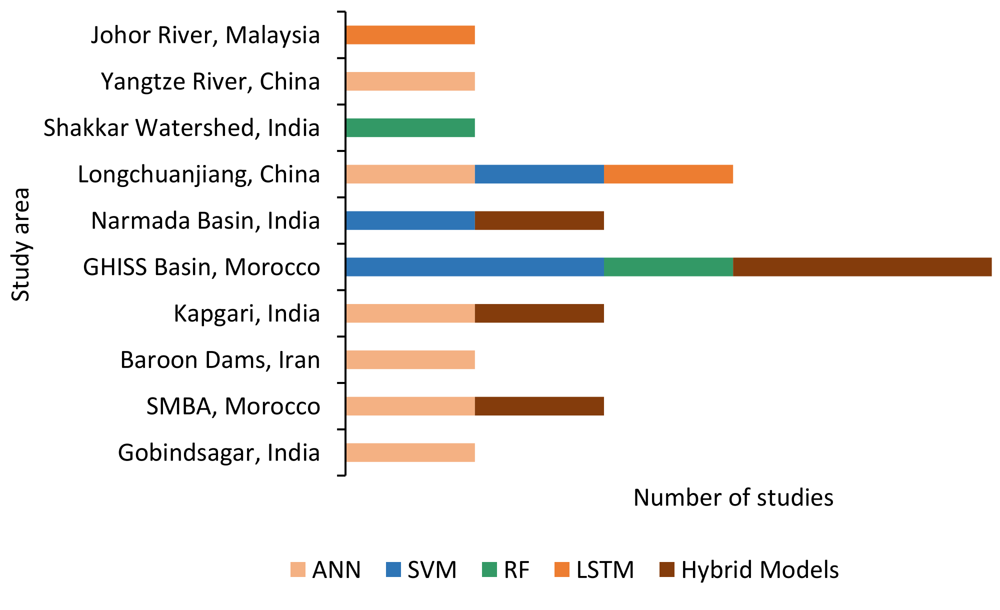

Figure 8. Geographical Distribution of the Reviewed Studies by Region and Country

Table 6. Limitations and Perspectives

Theme	Main Limitations	Perspectives
Sediment Modeling	Difficulty incorporating physical factors	Combine physical (e.g., MUSLE) and AI approaches
Sediment Prediction	Dependence on low-resolution data	Use Sentinel-2 satellite data for higher resolution
Hybrid Modeling	Complexity in model adjustments	Develop a more robust hybrid mode

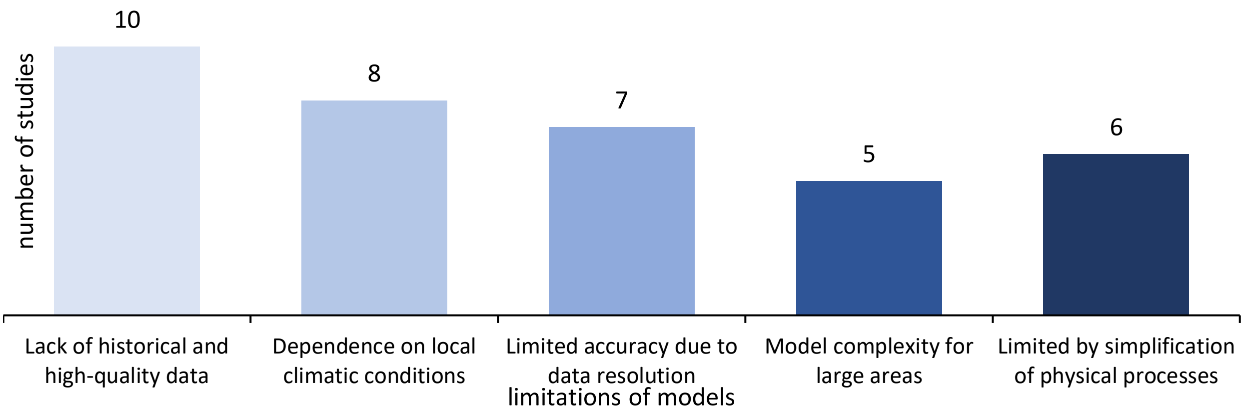

Figure 9. Main Limitations and Future Perspectives of AI-based Sedimentation Models

This review also emphasizes the need for standardized comparative frameworks to objectively assess model performance. Developing benchmark datasets and harmonized evaluation metrics (e.g., R^2, RMSE, NSE, and MAE) would enhance reproducibility and facilitate meta-analyses across watersheds. Additionally, model comparison protocols should incorporate uncertainty quantification and sensitivity analyses to evaluate the robustness of predictions under varying climatic and land-use scenarios.

To maintain clarity, the discussion below emphasizes only the most critical gaps rather than repeating all the entries from Table 6. This review highlights three key research weaknesses: the limited integration of physical processes, dependence on low-resolution data, and complexity of hybrid model calibration.

Table 6 condenses these aspects into a concise summary of limitations and forward-looking perspectives, avoiding redundancy with the main text.

Firstly, rigorous comparative studies are needed to evaluate the performance of various AI-based models. To ensure objective comparisons between different approaches, it is recommended that a standardized test case be developed on a well-documented reservoir management site with defined input parameters and target outputs.

Figure 9 illustrates the main limitations of AI-based sedimentation models, emphasizing the issues associated with data quality, model complexity, and scalability

Finally, integrating physics-based models with AI and gridded remote sensing data (e.g., Sentinel-2, ERA5) represents a promising research avenue. Such integration can improve long-term predictions by linking climate projections with sediment yields and reservoir evolution. Embedding physical constraints into AI architecture enhances both empirical performance and mechanistic understanding, allowing for more accurate and policy-relevant sediment management. Ultimately, AI-driven hybrid frameworks offer a pathway towards data-informed, interpretable, and scalable solutions for sustainable watershed and reservoir management in the face of climate change challenges.

9. CONCLUSIONS

This systematic review synthesizes the most recent advances in the use of artificial intelligence (AI) in sedimentation modeling. The main findings indicate that hybrid and deep learning architectures, particularly those integrating physical process equations, consistently outperform conventional empirical models in terms of accuracy, transferability, and adaptability. Physics-guided frameworks that combine AI algorithms with hydrological principles provide a balanced approach that enhances both predictive skill and interpretability. In practical terms, integrating AI with remote sensing platforms such as Google Earth Engine (GEE) enables large-scale, reproducible, and near-real-time monitoring of sediment dynamics. Such frameworks can directly support watershed and reservoir management by identifying erosion hotspots, optimizing sediment control strategies, and improving long-term soil and water conservation planning. Future studies should prioritize three aspects: (i) developing transferable, data-efficient, and explainable AI models for data-scarce environments; (ii) standardizing validation protocols, performance metrics, and open-access datasets to ensure methodological comparability; and (iii) strengthening multi-source data integration by coupling satellite, climatic, and hydrological information within unified AI platforms. Addressing these priorities will facilitate the integration of AI innovations into practical sediment management, thereby contributing to adaptive, transparent, and climate-resilient watershed systems.

Acknowledgments

The authors express their sincere gratitude to all contributors and collaborators whose support was invaluable to this study. They also wish to acknowledge the Hassan II

Institute of Agronomy and Veterinary Medicine and the Hassan II Academy of Science and Technology for their generous support through the GISEC project.

Declaration of Competing Interest

The authors declare that no competing financial or personal interests may appear to influence the work reported in this paper.

References

Ahmad, W. S., Jamal, S., Taqi, M., El-Hamid, H. T. A., & Norboo, J. (2022). Estimation of soil erosion and sediment yield concentrations in Dudhganga watershed of Kashmir Valley using RUSLE & SDR model. *Environment, Development and Sustainability*, *26*(1), 215-238. https://doi.org/10.1007/s10668-022-02705-9

Allawi, M. F., Sulaiman, S. O., Sayl, K. N., Sherif, M., & El-Shafie, A. (2023). Suspended sediment load prediction modelling based on artificial intelligence methods: The tropical region as a case study. *Heliyon*, *9*(8). https://doi.org/10.1016/j.heliyon.2023.e18506

Amani, M., Ghorbanian, A., Ahmadi, S. A., Kakooei, M., Moghimi, A., Mirmazloumi, S. M.,…Brisco, B. (2020). Google Earth Engine Cloud Computing Platform for Remote Sensing Big Data Applications: A Comprehensive Review. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *13*, 5326-5350. https://doi.org/10.1109/JSTARS.2020.3021052

Andualem, T. G., Hewa, G. A., Myers, B. R., Peters, S., & Boland, J. (2023). Erosion and Sediment Transport Modeling: A Systematic Review. *Land*, *12*(7), 1396. https://doi.org/10.3390/land12071396

Asaly, S., Gottlieb, L.-A., Yair, Y., Price, C., & Reuveni, Y. (2023). Predicting Eastern Mediterranean Flash Floods Using Support Vector Machines with Precipitable Water Vapor, Pressure, and Lightning Data. *Remote Sensing*, *15*(11), 2916. https://doi.org/10.3390/rs15112916

Bassairate, O., Chikhaoui, M., Naimi, M., & Sabir, M. (2021). Effets de la dynamique de la végétation sur le rythme d'envasement et la disponibilité de l'eau dans le barrage Makhazine (Maroc) [Effects of vegetation dynamics on the rate of siltation and water availability in the Makhazine Dam (Morocco)]. *Revue Marocaine des Sciences Agronomiques et Vétérinaires*, *9*(4), 553-561. https://www.agrimaroc.org/index.php/Actes_IAVH2/article/view/1037

Batista, P. V. G., Laceby, J. P., Davies, J., Carvalho, T. S., Tassinari, D., Silva, M. L. N.,…Quinton, J. N. (2021). A framework for testing large-scale distributed soil erosion and sediment delivery models: Dealing with uncertainty in models and the observational data. *Environmental Modelling & Software*, *137*, 104961. https://doi.org/10.1016/j.envsoft.2021.104961

Bezak, N., Borrelli, P., Mikoš, M., Jemec Auflič, M., & Panagos, P. (2024). Towards multi-model soil erosion modelling: An evaluation of the erosion potential method (EPM) for global soil erosion assessments. *CATENA*, *234*, 107596. https://doi.org/10.1016/j.catena.2023.107596

Borrelli, P., Robinson, D. A., Panagos, P., Lugato, E., Yang, J. E., Alewell, C.,…Ballabio, C. (2020). Land use and climate change impacts on global soil erosion by water (2015-2070). *Proceedings of the National Academy of Sciences*, *117*(36), 21994-22001. https://doi.org/10.1073/pnas.2001403117

Chen, G., & Chen, J. (2015). A novel wrapper method for feature selection and its applications. *Neurocomputing*, *159*, 219-226. https://doi.org/10.1016/j.neucom.2015.01.070

Chen, H., Yang, L., & Wu, Q. (2023). Enhancing Land Cover Mapping and Monitoring: An Interactive and Explainable Machine Learning Approach Using Google Earth Engine. *Remote Sensing*, *15*(18), 4585. https://doi.org/10.3390/rs15184585

Dallahi, Y., Malaainine, M. E. I., Dansou, C., Hbiak, I., Boujraf, A., & Orlando, C. A. (2025). Prediction of current and future gully erosion susceptibility in the Oued Zat watershed in the High Atlas region of Morocco using an SVM-based machine learning approach. *Arid Land Research and Management*, *39*(2), 151-179. https://doi.org/10.1080/15324982.2024.2390477

El Bilali, A., Taleb, A., El Idrissi, B., Brouziyne, Y., & Mazigh, N. (2020). Comparison of a data-based model and a soil erosion model coupled with multiple linear regression for the prediction of reservoir sedimentation in a semi-arid environment. *Euro-Mediterranean Journal for Environmental Integration*, *5*(3), 64. https://doi.org/10.1007/s41207-020-00205-8

Froehlich, D., & Giri, S. (2019). *Neural Network Prediction of Reservoir Sedimentation*. https://doi.org/10.13140/RG.2.2.17962.77764

Ghorbani, M. A., Hosseini, S. H., Fazelifard, M. H., & Abbasi, H. (2013). Sediment load estimation by MLR, ANN, NF and sediment rating curve (SRC) in Rio Chama river. *Journal of Civil Engineering and Urbanism*, *3*(4), 136-141. https://www.ojceu.com/main/attachments/article/26/J.%20Civil%20Eng.%20Urban.,22-136-141.pdf

Gourfi, A., Daoudi, L., & Shi, Z. (2018). The assessment of soil erosion risk, sediment yield and their controlling factors on a large scale: Example of Morocco. *Journal of African Earth Sciences*, *147*, 281-299. https://doi.org/10.1016/j.jafrearsci.2018.06.028

Hajigholizadeh, M., Melesse, A. M., & Fuentes, H. R. (2018). Erosion and Sediment Transport Modelling in Shallow Waters: A Review on Approaches, Models and Applications. *International Journal of Environmental Research and Public Health*, *15*(3), 518. https://www.mdpi.com/1660-4601/15/3/518

Heckmann, T., Cavalli, M., Cerdan, O., Foerster, S., Javaux, M., Lode, E.,…Brardinoni, F. (2018). Indices of sediment connectivity: opportunities, challenges and limitations. *Earth-Science Reviews*, *187*, 77-108. https://doi.org/10.1016/j.earscirev.2018.08.004

Hitouri, S., Varasano, A., Mohajane, M., Ijlil, S., Essahlaoui, N., Ali, S. A.,…Teodoro, A. C. (2022). Hybrid Machine

Learning Approach for Gully Erosion Mapping Susceptibility at a Watershed Scale. *ISPRS International Journal of Geo-Information*, *11*(7), 401. https://www.mdpi.com/2220-9964/11/7/401

Iraji, H., Mohammadi, M., Shakouri, B., & Meshram, S. G. (2020). Predicting reservoir volume reduction using artificial neural network. *Arabian Journal of Geosciences*, *13*(17), 835. https://doi.org/10.1007/s12517-020-05772-2

Jha, S., Dixit, S., Mehta, D., Verma, S., Shaikh, M. M., & Patel, P. (2024). Assessment of Reservoir Sedimentation Using Geospatial Tools: A Case Study of Kadana Reservoir. *Journal of Environmental Informatics Letters*, 93-100. https://doi.org/10.3808/jeil.202400129

Jooshaki, M., Nad, A., & Michaux, S. (2021). A Systematic Review on the Application of Machine Learning in Exploiting Mineralogical Data in Mining and Mineral Industry. *Minerals*, *11*(8), 816. https://doi.org/10.3390/min11080816

Jothiprakash, V., & Garg, V. (2009). Reservoir Sedimentation Estimation Using Artificial Neural Network. *Journal of Hydrologic Engineering*, *14*(9), 1035-1040. https://doi.org/10.1061/(ASCE)HE.1943-5584.0000075

Kanito, D., Bedadi, B., & Feyissa, S. (2023). Sediment yield estimation in GIS environment using RUSLE and SDR model in Southern Ethiopia. *Geomatics, Natural Hazards and Risk*, *14*(1), 2167614. https://doi.org/10.1080/19475705.2023.2167614

Karyati, K., Sarminah, S., Karmini, K., Akbar, A. M., & Hermansyah, R. (2021). Conservation and economic aspects of a combination of forestry-agricultural crops (Neolamarckia cadamba-Phaseolus vulgaris) and terrace systems in different slope classes. *Sains Tanah Journal of Soil Science and Agroclimatology*, *18*(1), 9. https://doi.org/10.20961/stjssa.v18i1.47708

Kazemi Garajeh, M., Haji, F., Tohidfar, M., Sadeqi, A., Ahmadi, R., & Kariminejad, N. (2024). Spatiotemporal monitoring of climate change impacts on water resources using an integrated approach of remote sensing and Google Earth Engine. *Scientific Reports*, *14*(1), 5469. https://doi.org/10.1038/s41598-024-56160-9

Koch, N., zu Ermgassen, E. K. H. J., Wehkamp, J., Oliveira Filho, F. J. B., & Schwerhoff, G. (2019). Agricultural Productivity and Forest Conservation: Evidence from the Brazilian Amazon. *American Journal of Agricultural Economics*, *101*(3), 919-940. https://doi.org/10.1093/ajae/aay110

Lee, F.-Z., Lai, J.-S., & Sumi, T. (2022). Reservoir Sediment Management and Downstream River Impacts for Sustainable Water Resources—Case Study of Shihmen Reservoir. *Water*, *14*(3), 479. https://doi.org/10.3390/w14030479

Meshram, S. G., Singh, V. P., Kisi, O., Karimi, V., & Meshram, C. (2020). Application of Artificial Neural Networks, Support Vector Machine and Multiple Model-ANN to Sediment Yield Prediction. *Water Resources Management*, *34*(15), 4561-4575. https://doi.org/10.1007/s11269-020-02672-8

Nourani, V. (2014). A review on applications of artificial intelligence-based models to estimate suspended sediment load. *International Journal of Soft Computing and Engineering*, *3*(6), 121-127. https://www.ijsce.org/portfolio-item/F2009013614/

Pakdel-Khasmakhi, H., Vazifedoust, M., Paudyal, D. R., Chadalavada, S., & Alam, M. J. (2022). Google Earth Engine as Multi-Sensor Open-Source Tool for Monitoring Stream Flow in the Transboundary River Basin: Doosti River Dam. *ISPRS International Journal of Geo-Information*, *11*(11), 535. https://www.mdpi.com/2220-9964/11/11/535

Panagos, P., & De Rosa, D. (2023). *Indicators to support the soil perspectives of the Common Agricultural Policy (CAP)*. Publications Office of the European Union. https://doi.org/10.2760/235604

Pimple, U., Simonetti, D., Sitthi, A., Pungkul, S., Leadprathom, K., Skupek, H.,…Towprayoon, S. (2018). Google earth engine based three decadal landsat imagery analysis for mapping of mangrove forests and its surroundings in the trat province of Thailand. *Journal of Computer and Communications*, *6*(01), 247-264. https://doi.org/10.4236/jcc.2018.61025

Rehman, S. A. U., Bui, M. D., Riaz, Z., & Rutschmann, P. (2016). *Estimation of Sediment Yield for Dasu Hydropower Project Using Artificial Neural Networks* Conference: 18. Wasserbau-Symposium 2016At: Wallgau Germany, https://www.cee.ed.tum.de/fileadmin/w00cbe/wb/freunde/Symposium_2016/Beitraege_Wallgau2016/32_-_Rehman.pdf

Sarkar, A., Sharma, N., & Singh, R. D. (2017). Sediment Runoff Modelling Using ANNs in an Eastern Himalayan Basin, India. In N. Sharma (Ed.), *River System Analysis and Management* (pp. 73-82). Springer Singapore. https://doi.org/10.1007/978-981-10-1472-7_5

Singh, A., Imtiyaz, M., Isaac, R. K., & Denis, D. M. (2012). Comparison of soil and water assessment tool (SWAT) and multilayer perceptron (MLP) artificial neural network for predicting sediment yield in the Nagwa agricultural watershed in Jharkhand, India. *Agricultural Water Management*, *104*, 113-120. https://doi.org/10.1016/j.agwat.2011.12.005

Singh, G., & Panda, R. K. (2011). Daily sediment yield modeling with artificial neural network using 10-fold cross validation method: a small agricultural watershed, Kapgari, India. *International Journal of Earth Sciences and Engineering*, *4*(6), 443-450. https://www.researchgate.net/profile/Gurjeet-Singh-8/publication/265988179

Sujon, K. M., Hassan, R. B., Towshi, Z. T., Othman, M. A., Samad, M. A., & Choi, K. (2024). When to Use Standardization and Normalization: Empirical Evidence From Machine Learning Models and XAI. *IEEE Access*, *12*, 135300-135314. https://doi.org/10.1109/ACCESS.2024.3462434

Taheri Dehkordi, A., Valadan Zoej, M. J., Ghasemi, H., Ghaderpour, E., & Hassan, Q. K. (2022). A New Clustering Method to Generate Training Samples for Supervised Monitoring of Long-Term Water Surface Dynamics Using Landsat Data through Google Earth Engine. *Sustainability*, *14*(13), 8046. https://doi.org/10.3390/su14138046

Tamiminia, H., Salehi, B., Mahdianpari, M., Quackenbush, L., Adeli, S., & Brisco, B. (2020). Google Earth Engine for geo-big data applications: A meta-analysis and systematic review. *ISPRS Journal of Photogrammetry and Remote Sensing*, *164*, 152-170. https://doi.org/10.1016/j.isprsjprs.2020.04.001

Tao, H., Al-Khafaji, Z. S., Qi, C., Zounemat-Kermani, M., Kisi, O., Tiyasha, T.,…Yaseen, Z. M. (2021). Artificial intelligence models for suspended river sediment prediction: state-of-the art, modeling framework appraisal, and proposed future research directions. *Engineering Applications of Computational Fluid Mechanics*, *15*(1), 1585-1612. https://doi.org/10.1080/19942060.2021.1984992

Tfwala, S. S., & Wang, Y.-M. (2016). Estimating Sediment Discharge Using Sediment Rating Curves and Artificial Neural Networks in the Shiwen River, Taiwan. *Water*, *8*(2), 53. https://doi.org/10.3390/w8020053

Trinugroho, M. W., Arif, S. S., Susanto, S., Nugroho, B. D. A., & Prabowo, A. (2022). Changes in Rainfall Pattern in Bengawan Solo Sub-Watershed. *Sains Tanah Journal of Soil Science and Agroclimatology*, *19*(2), 12. https://doi.org/10.20961/stjssa.v19i2.61640

Uroš, D., Tara, O., Aleksandar, K., & Marija, P. (2024). Zaštita prirode life and nature primena GIS-a i ERM modela u proceni intenziteta erozije zemljišta u slivu reke Lugomir [Application of GIS and EPM model in assessment of soil erosion intensity in the Lugomir river basin]. *Zaštita prirode*, *74*(1), 1-11. https://doi.org/10.5937/ZasPri2401001D

Wang, H.-W., Kondolf, M., Tullos, D., & Kuo, W.-C. (2018). Sediment Management in Taiwan's Reservoirs and Barriers to Implementation. *Water*, *10*(8), 1034. https://doi.org/10.3390/w10081034

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

Yadav, A., Joshi, D., Kumar, V., Mohapatra, H., Iwendi, C., & Gadekallu, T. R. (2022). Capability and Robustness of Novel Hybridized Artificial Intelligence Technique for Sediment Yield Modeling in Godavari River, India. *Water*, *14*(12), 1917. https://doi.org/10.3390/w14121917

Yan, X.-q., Jiao, J.-y., Tang, B.-z., Liang, Y., & Wang, Z.-j. (2022). Assessing sediment connectivity and its spatial response on land use using two flow direction algorithms in the catchment on the Chinese Loess Plateau. *Journal of Mountain Science*, *19*(4), 1119-1138. https://doi.org/10.1007/s11629-021-6936-7

Yang, L., Driscol, J., Sarigai, S., Wu, Q., Chen, H., & Lippitt, C. D. (2022). Google Earth Engine and Artificial Intelligence (AI): A Comprehensive Review. *Remote Sensing*, *14*(14), 3253. https://doi.org/10.3390/rs14143253

Zhao, T., Wang, S., Ouyang, C., Chen, M., Liu, C., Zhang, J.,…Wang, L. (2024). Artificial intelligence for geoscience: Progress, challenges, and perspectives. *The Innovation*, *5*(5), 100691. https://doi.org/10.1016/j.xinn.2024.100691

Zhu, Y.-M., Lu, X. X., & Zhou, Y. (2007). Suspended sediment flux modeling with artificial neural network: An example of the Longchuanjiang River in the Upper Yangtze Catchment, China. *Geomorphology*, *84*(1), 111-125. https://doi.org/10.1016/j.geomorph.2006.07.010