Modeling Soil Futures: Integrating Classic and Emerging Approaches to Water Erosion

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Abstract: Soil erosion by water remains one of the most pressing forms of land degradation, undermining agricultural productivity, ecosystem services, and global food security. Over the past decades, diverse modeling approaches have been developed to quantify and predict soil erosion, ranging from classical empirical models to advanced machine learning and hybrid frameworks. This review synthesizes the evolution of erosion modeling, highlighting both the historical foundations and emerging directions. Empirical models such as USLE and RUSLE provided the first standardized and widely adopted methods, while process-based models like WEPP and EUROSEM advanced mechanistic understanding but faced limitations due to extensive data demands. The integration of Geographic Information Systems (GIS) and Remote Sensing (RS) transformed erosion modeling by enabling spatially explicit risk assessments at watershed and regional scales. More recently, machine learning algorithms—including Random Forests, Support Vector Machines, and deep learning architectures—have demonstrated superior predictive power, although challenges of interpretability, transferability, and data dependency remain unresolved. Hybrid and integrated models now represent the state-of-the-art frontier, combining empirical transparency, process-based rigor, and AI-driven adaptability. Future-oriented perspectives, including GeoAI, digital twins, cloud-based platforms, and participatory modeling approaches, offer transformative potential. These innovations are particularly critical under non-stationary conditions driven by climate change and land-use transformations, which demand dynamic, probabilistic, and stakeholder-inclusive frameworks. The review concludes that no single paradigm is sufficient to capture the complexity of water erosion. The way forward lies in integrated, multi-scale, and uncertainty-aware modeling systems that bridge scientific precision with policy relevance, supporting sustainable land management and climate adaptation in the coming decades.

Keywords: Water erosion, Soil erosion modeling, RUSLE, WEPP, GIS, Remote Sensing, Machine Learning, GeoAI, Hybrid models, Digital twins.

INTRODUCTION

Soil erosion by water is one of the most widespread forms of land degradation, threatening agricultural productivity, water quality, and ecosystem services across the globe. The removal of fertile topsoil not only reduces crop yields but also alters hydrological cycles, increases sedimentation in rivers and reservoirs, and accelerates land degradation processes that undermine sustainable development. According to recent estimates by the Food and Agriculture Organization (FAO) and the Intergovernmental Panel on Climate Change (IPCC), more than 24 billion tons of fertile soil are lost annually worldwide, with water erosion accounting for the majority of this degradation [1-3]. This phenomenon is particularly critical in regions experiencing intense rainfall events, steep topography, and fragile soils, but it is also increasingly relevant in temperate landscapes where land-use intensification and climate change are altering erosion dynamics [4]. In Mediterranean regions, for example, the combination of seasonal rainfall variability, olive monocultures, and overgrazing has produced severe erosion hotspots. In tropical and subtropical areas, deforestation and unsustainable agricultural practices exacerbate erosion rates, while in arid and semi-arid regions, water erosion interacts with desertification processes [5-8], creating compounded challenges for land managers. Water erosion is thus not only a local agronomic concern but also a global environmental issue. Its impacts extend into socio-economic domains, including food security, rural livelihoods, and infrastructure stability [9]. Reservoir sedimentation, for instance, reduces the lifespan of hydropower dams and irrigation systems, creating long-term economic costs. Additionally, soil erosion releases stored carbon into the atmosphere, linking erosion processes with broader debates on climate change mitigation and adaptation [10]. The urgency of addressing water erosion is therefore clear, and modeling has become a central tool in understanding, predicting, and managing its impacts [11, 12]. The modeling of water erosion has a long history, beginning with empirical formulations derived from plot-scale experiments in the mid-twentieth century. The Universal Soil Loss Equation (USLE), later revised as RUSLE, provided the first standardized framework for predicting average annual soil loss based on rainfall erosivity, soil erodibility, topography, cover-management, and conservation practices. These models, though empirical in nature, achieved widespread adoption because of their simplicity, transparency, and policy relevance [13]. The 1980s and 1990s saw the rise of process-based models, such as the Water Erosion Prediction Project (WEPP) and the European Soil Erosion Model (EUROSEM). These models aimed to simulate the physical processes of rainfall impact, infiltration, surface runoff, detachment,

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and sediment transport, offering a more mechanistic understanding of erosion dynamics. While powerful, these models also revealed the challenges of high data requirements and calibration difficulties, particularly in data-scarce regions of the Global South. In parallel, the integration of Geographic Information Systems (GIS) and Remote Sensing (RS) expanded the spatial scope of erosion modeling [14]. By transforming model parameters into geospatial layers, GIS-based approaches enabled the mapping of erosion risks at watershed, regional, and national scales. Remote sensing technologies, ranging from Landsat to Sentinel and UAV platforms, provided unprecedented access to vegetation indices, land-use dynamics, and digital elevation models, which significantly enriched the parameterization of erosion models [15]. The twenty-first century has witnessed a surge in data availability, computational capacity, and methodological innovation. Machine learning and artificial intelligence have emerged as transformative tools, capable of uncovering nonlinear relationships between environmental drivers and erosion processes [16-18]. Random Forests, Support Vector Machines, and deep learning architectures have achieved remarkable predictive performance, particularly when combined with remote sensing datasets. Yet, persistent challenges remain [19, 20]. Data scarcity continues to limit model applicability in many parts of the world. High-resolution rainfall records, soil hydraulic properties, and long-term field measurements are often unavailable, constraining the calibration and validation of both process-based and ML-driven models [21]. Uncertainty quantification is another pressing issue: few models rigorously propagate uncertainties from input datasets through to final predictions, leading to risks in policy applications. Transferability across regions is also limited, as models calibrated in one watershed often fail when applied to others with different climatic or geomorphic conditions. Computational complexity further complicates the use of advanced models, particularly in developing regions where resources are scarce. Moreover, many erosion models remain designed primarily for scientists, with interfaces and outputs poorly aligned with the needs of policymakers, land managers, and local communities. Bridging this gap requires not only technical improvements but also institutional and participatory innovations. Given these limitations, the field is moving toward a new paradigm that emphasizes integration, adaptability, and inclusivity. Future-oriented perspectives include the development of GeoAI, which merges geospatial data with artificial intelligence to provide real-time erosion predictions; digital twins of watersheds, which create continuously updated virtual replicas capable of scenario testing; and cloud-based platforms, which democratize access to big data and advanced modeling tools. Equally important is the integration of climate change scenarios into erosion modeling [22-24]. Non-stationary conditions demand probabilistic frameworks that can represent ranges of possible futures, rather than single deterministic predictions. Participatory approaches, such as participatory GIS and interactive decision-support systems, are also gaining momentum, ensuring that erosion models are not only scientifically rigorous but also socially relevant. This evolution suggests that the future of water erosion modeling will not be defined by the dominance of any single paradigm but by the integration of multiple approaches—empirical, process-based, GIS/RS, machine learning, and hybrid systems—within flexible, multi-scale, and uncertainty-aware frameworks [25, 26]. Against this backdrop, the aim of this review is to provide a comprehensive synthesis of the current state of water erosion modeling, critically evaluating the strengths and limitations of different approaches, and identifying emerging opportunities and challenges. By systematically examining empirical, process-based, GIS/RS, machine learning, hybrid, and future-oriented frameworks, this article seeks to clarify how erosion modeling can evolve into a more robust, adaptive, and policy-relevant tool. Ultimately, the paper aims to highlight pathways toward integrated and participatory modeling systems capable of supporting sustainable land management and climate adaptation strategies in the decades to come. While several reviews have addressed erosion modeling from specific angles, few have provided a unified cross-paradigm synthesis linking classical models with AI-driven and GeoAI frameworks. The novelty of this review lies in bridging these traditionally separate domains to propose an integrative perspective that connects scientific modeling with real-world engineering and policy applications.

MATERIALS AND METHODS

This study adopts a systematic review and conceptual framework approach to explore the future of water erosion modeling, its challenges, and emerging methodologies. The research design consisted of the following steps:

1 Literature Collection

- A comprehensive search of peer-reviewed articles, reports, and book chapters published between 2000 and 2025 was conducted using databases such as *Web of Science, Scopus, and Google Scholar*.
- Keywords included combinations of: *soil erosion, water erosion modeling, future perspectives, climate change impacts,*

remote sensing, machine learning, process-based models, RUSLE, WEPP, GeoAI.

2 **Inclusion and Exclusion Criteria**

- Studies were included if they addressed (i) modeling of soil erosion caused by water, (ii) advancements in simulation approaches, or (iii) challenges under future climate and land-use scenarios.

- Papers focused exclusively on wind erosion or non-hydrological processes were excluded.

3 **Thematic Categorization**

- Selected studies were categorized into thematic areas:

a. Traditional and Process-Based Models (*e.g.*, RUSLE, WEPP, EUROSEM)
b. GIS and Remote Sensing-Based Approaches
c. Machine Learning and Data-Driven Models
d. Hybrid and Integrated Models (coupling physical and AI-based approaches)
e. Future-Oriented Perspectives (climate change, big data, policy integration).

4 **Comparative Analysis**

- Each category was analyzed with respect to input data requirements, spatial and temporal resolution, computational complexity, scalability, and capacity for integration with new technologies.

- Special attention was given to recent innovations, including *GeoAI, cloud computing, digital twins, and Earth observation datasets*.

5 **Expert Consultation**

- To validate the framework, expert opinions were synthesized from existing review papers and technical reports published by organizations such as the *FAO, European Commission, and USDA*.

6 **Framework for Future Directions**

- Based on the synthesis, a conceptual framework was developed highlighting major challenges (data availability, model transferability, uncertainty quantification) and innovative pathways (AI integration, multi-scale modeling, participatory approaches).

RESULTS

3.1. Conventional and Process-Based Models

Empirical and process-based models form the historical backbone of water erosion research, and despite the emergence of more advanced approaches, they continue to play a fundamental role. Among them, the Universal Soil Loss Equation (USLE) and its subsequent revision (RUSLE) remain the most widely implemented due to their simplicity and adaptability across diverse geographic contexts. The general formulation of RUSLE is expressed in Equation (1) [27-30]:

$$A = R \cdot K \cdot LS \cdot C \cdot P \quad (1)$$

where *A* represents the mean annual soil loss, and the multiplicative factors account for rainfall erosivity (*R*), soil erodibility (*K*), slope length and steepness (*LS*), cover-management (*C*), and conservation practices (*P*). RUSLE has become popular largely because of its ease of application and transparency, making it a preferred tool in policy-oriented studies and land management planning. However, it remains limited to long-term average soil loss estimates and does not capture short-term variability, sediment deposition, or gully formation.

Building upon RUSLE, the Modified Universal Soil Loss Equation (MUSLE) introduced a refinement by replacing the rainfall factor with runoff volume and peak discharge, thereby enabling predictions at the event scale. This adjustment, shown in Equation (2):

$$Sed = 11.8 \cdot (Q \cdot q_p)^{0.56} \cdot K \cdot C \cdot P \cdot LS \quad (2)$$

demonstrates the evolution from purely empirical relationships toward a closer connection with hydrological processes. MUSLE has been especially useful in linking erosion modeling with watershed hydrology, yet it still inherits some of the constraints of empirical approaches, particularly the need for regional calibration of input parameters. In parallel, process-based models such as the Water Erosion Prediction Project (WEPP), the European Soil Erosion Model (EUROSEM), and the Limburg Soil Erosion Model (LISEM) have sought to simulate erosion by explicitly representing the physical processes of rainfall impact, infiltration, surface runoff, detachment, transport, and deposition. Unlike the empirical formulations of RUSLE or MUSLE, these models operate at finer temporal resolutions and can provide event-based predictions. For example, WEPP can simulate continuous hydrological and erosion processes, producing not only soil loss estimates but also runoff volumes, sediment size distributions, and spatial patterns of erosion across a watershed. EUROSEM and LISEM, in contrast, are typically applied to individual storm events and emphasize the spatial distribution of erosion within catchments, drawing heavily on DEMs and land use data. The advantages of process-based models are clear: they provide mechanistic insights, allow scenario testing for different land management practices, and are more responsive to climate and land-use changes. Nevertheless, these strengths come at the cost of demanding high-resolution input data and significant calibration effort, often making them impractical for regions with limited monitoring infrastructure. Empirical models, by contrast, while less precise in process representation, remain accessible and cost-effective tools that continue to dominate large-scale erosion risk assessments. Thus, conventional and process-based models should not be regarded as competing paradigms but rather as complementary tools. Empirical models such as RUSLE are effective in producing rapid, large-area erosion estimates suitable for policy and land management, while process-based models like WEPP or EUROSEM are indispensable for research that requires detailed understanding of event-driven erosion dynamics. The continued relevance of these models lies not only in their historical legacy but also in their ability to serve as benchmarks and foundations for hybrid and next-generation modeling frameworks.

3.2. GIS- and Remote Sensing-Based Approaches

The integration of Geographic Information Systems (GIS) and Remote Sensing (RS) has fundamentally reshaped the way soil erosion is modeled and mapped. Unlike purely empirical formulations, which were initially developed at plot scale, GIS- and RS-based approaches allow the extrapolation of erosion processes across larger spatial domains by transforming model factors into geospatial layers [31]. A typical example is the spatial implementation of the RUSLE equation, where each factor is computed for individual grid cells rather than for an entire plot. The gridded formulation is expressed in Equation (3):

$$A(x,y) = R(x,y) \cdot K(x,y) \cdot LS(x,y) \cdot C(x,y) \cdot P(x,y) \tag{3}$$

Here, soil loss *A* is estimated at each cell *(x,y)*, making it possible to generate erosion risk maps at watershed, regional, or national levels. This capability to spatialize erosion predictions is one of the most important advantages brought by GIS technology. Remote sensing provides the observational backbone for parameterizing several of these factors. Rainfall erosivity (*R*) can be approximated using satellite-derived precipitation products such as TRMM or GPM; soil erodibility (*K*) can be mapped from global soil property databases; slope length and steepness (*LS*) are computed directly from digital elevation models (DEMs); and vegetation cover factors (*C*) are increasingly derived from indices such as NDVI or EVI obtained from multispectral sensors like Landsat or Sentinel-2. Conservation practices (*P*) can also be estimated indirectly using land management layers derived from classification of RS data. The main strength of GIS- and RS-based erosion modeling lies in its ability to provide consistent spatial coverage across large and heterogeneous landscapes [32, 33]. This allows not only identification of erosion hotspots but also monitoring of temporal dynamics when multi-temporal imagery is used. For instance, NDVI time series from MODIS have been widely applied to assess the seasonal variability of vegetation cover and its role in reducing erosion rates. Moreover, the increasing resolution of satellite platforms and the proliferation of UAV surveys have enabled more detailed assessments of rill and gully development, which were previously beyond the reach of coarse datasets. Nonetheless, several limitations persist. The accuracy of DEMs strongly influences the reliability of LS factor calculations, and coarse DEMs (*e.g.*, 30 m SRTM) may fail to capture micro-topographic features critical for gully initiation. Land cover classifications from RS imagery are also subject to errors, which propagate into C- and P-factor estimates. Furthermore, while RS data are temporally continuous, they do not always coincide with individual rainfall events, limiting their capacity to capture short-term erosion dynamics. Finally, most GIS/RS-based studies still require ground-based validation, which is often unavailable in data-scarce regions. Applications of GIS- and RS-based models are now widespread. In the Loess Plateau of China, RUSLE-GIS models integrated with MODIS NDVI data documented significant reductions in soil erosion following the “Grain for Green” reforestation program. In Mediterranean regions such as Spain and Italy, Sentinel-2 imagery has improved the estimation of vegetation cover factors, providing high-resolution erosion risk maps in olive-growing landscapes. In Ethiopia’s Upper Blue Nile Basin, DEM-based LS factors combined with rainfall erosivity maps have been used to identify priority sub-watersheds for soil conservation. In the United States, LiDAR-based DEMs have provided unprecedented detail for modeling gully initiation, outperforming traditional SRTM or ASTER products.

Recent advances further extend the capabilities of GIS/RS-based erosion modeling. One example is the use of the Unit Stream Power-based Erosion/Deposition (USPED) model, which estimates erosion and deposition patterns based on flow accumulation and slope derived from DEMs. The general formulation is shown in Equation (4):

$$E(x,y) = R(x,y) \cdot K(x,y) \cdot C(x,y) \cdot P(x,y) \cdot (LS(x,y))^m \cdot \sin(\beta(x,y))^n \quad (4)$$

where E represents net erosion or deposition at a given cell, β is slope angle, and m and n are empirical exponents controlling erosion–deposition dynamics. This formulation provides a more spatially nuanced view of sediment transport, moving beyond the uniform soil loss assumption of RUSLE.

3.3. Machine Learning and Data-Driven Models

The rapid growth of Earth observation data, climate records, and in-situ monitoring has created fertile ground for the application of machine learning (ML) and artificial intelligence (AI) in erosion modeling [34]. Unlike empirical and process-based frameworks, which rely on predefined equations, ML models are data-driven: they infer patterns directly from observed relationships between environmental drivers and measured erosion responses. This shift marks a fundamental change in methodology, from deterministic formulations toward adaptive predictive systems. Among the most widely used algorithms are Random Forests (RF), Support Vector Machines (SVM), Artificial Neural Networks (ANNs), and Deep Learning (DL) architectures such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks [35]. RF and SVM have proven effective for susceptibility mapping, where the goal is to classify areas as erosion-prone or stable. ANNs are particularly suited to approximating highly nonlinear relationships, while deep learning excels in extracting spatial or temporal features from large, complex datasets [34].

The general principle of ML-based erosion modeling can be expressed in Equation (5):

$$E_{risk} = f(X_1, X_2, \dots, X_n) \quad (5)$$

where $E_{(risk)}$ represents erosion susceptibility or predicted soil loss, and $X_1 \dots X_n$ are predictor variables such as slope, rainfall, soil texture, vegetation indices, and land use. The function *f* is not specified a priori but is learned iteratively by the ML algorithm from training data [36].

For instance, in Random Forests, the predictive function *f* is the aggregated output of an ensemble of decision trees, formalized in Equation (6):

$$f(X) = \frac{1}{N}\sum_{i=1}^{N} T_i(X) \quad (6)$$

where N is the number of trees, and $T_i(X)$ is the prediction of the *i-th* decision tree. This ensemble structure allows RF to achieve high accuracy and robustness against overfitting.

The advantages of ML approaches are well documented. They are capable of capturing complex nonlinear relationships between multiple interacting variables, frequently achieving higher predictive performance than empirical models. They scale effectively with the size of the dataset, making them ideal for integrating multi-source information from DEMs, RS imagery, climate models, and soil databases. Furthermore, algorithms like RF provide variable importance measures, which can offer insight into the relative influence of factors such as slope, rainfall intensity, or vegetation cover. However, several limitations temper these strengths. Many ML algorithms are often criticized for their “black-box” nature, providing predictions without transparent explanations of underlying processes. Their performance is heavily dependent on the availability and quality of training datasets, which are scarce in many erosion-prone regions. Transferability across regions is also a challenge: models trained in one watershed may not generalize well to others with different geomorphic or climatic conditions. Deep learning models, although powerful, demand large computational resources and often require GPU-based infrastructure. Applications illustrate both the promise and the challenges of ML. In Iran’s Zagros Mountains, Random Forest models achieved an AUC exceeding 0.9 for erosion susceptibility mapping, clearly outperforming SVM classifiers. Yet, when applied to neighboring watersheds, predictive accuracy declined, highlighting the transferability problem. In the Loess Plateau of China, ANN-based models captured nonlinear terrain–climate–land cover interactions more effectively than statistical methods. CNNs applied to UAV orthophotos in Australia achieved more than 95% accuracy in detecting gully erosion features, while in Spain, LSTM networks successfully predicted event-driven sediment yield by combining rainfall time series with land surface parameters. Recent developments point toward a new generation of hybrid and explainable ML models. Hybridization allows physical understanding to complement predictive power, while Explainable AI (XAI) techniques such as SHAP (Shapley Additive Explanations) and LIME provide transparency by attributing predictions to specific input factors. Additionally, the use of transfer learning—adapting pre-trained CNN models to geospatial imagery—has reduced training data requirements, while cloud-based platforms like Google Earth Engine integrate ML tools with massive remote sensing archives to enable near real-time global erosion assessments.

3.4. Hybrid and Integrated Frameworks

The complexity of soil erosion processes has increasingly demonstrated the limitations of single-model approaches. Empirical models such as RUSLE offer simplicity and policy relevance but fail to capture short-term variability, while process-based models like WEPP provide mechanistic detail at the expense of high data requirements [37]. Machine learning approaches excel in predictive accuracy but suffer from interpretability and transferability issues. As a response, hybrid and integrated frameworks have emerged as the frontier of erosion modeling, combining the strengths of diverse paradigms to produce more robust, scalable, and future-oriented tools [38]. One common form of hybridization involves enhancing empirical models with machine learning. For instance, the cover-management (*C*) and support practice (*P*) factors in RUSLE, which traditionally require empirical calibration, can now be dynamically estimated from remote sensing data through algorithms such as Random Forests or ANNs. The resulting formulation, shown in Equation (7), extends the standard multiplicative form of RUSLE:

$$A_{hybrid} = R \cdot K \cdot LS \cdot C'(RS, ML) \cdot P'(RS, ML) \qquad (7)$$

Here, *C′* and *P′* are no longer static parameters but functions derived from remote sensing indices (*e.g.*, NDVI, EVI) and machine learning predictions, thereby reducing subjectivity and improving adaptability to temporal variability.

Another approach integrates process-based simulations with data-driven methods. Outputs from WEPP [39], for example, can be used as training data for deep learning models that then predict sediment yield under future climate and land-use scenarios. This creates a hybrid predictive structure where process knowledge informs data-driven learning. The combination can be expressed in Equation (8):

$$Y_{hybrid} = \alpha \cdot Y_{WEPP} + (1 - \alpha) \cdot f_{ML}(X) \qquad (8)$$

where $Y_{(WEPP)}$ is sediment yield simulated by the WEPP model, $f_{(ML)}(X)$ is the machine learning prediction based on input variables *X*, and *α* is a weighting parameter optimized through calibration. Such formulations allow erosion predictions to balance mechanistic rigor with predictive flexibility.

Hybridization is not limited to pairwise model combinations. Increasingly, multi-model ensembles bring together empirical, process-based, and ML predictions within a single decision-support system. By averaging or probabilistically weighting outputs from different models, ensemble approaches reduce model-specific biases and provide uncertainty bounds, which are crucial for policy applications. The advantages of hybrid frameworks are evident. They consistently achieve higher predictive accuracy than stand-alone models and can be adapted to diverse data conditions. For example, in the Loess Plateau of China, a RUSLE-RF hybrid improved erosion risk mapping by refining *C* factor estimation with MODIS-derived vegetation indices [40]. In Mediterranean watersheds, WEPP was coupled with LSTM networks to better capture extreme-event sediment yields, offering valuable insights into climate change adaptation. In the United States, ensemble models integrating RUSLE, WEPP, and Random Forest reduced prediction errors by nearly one-third compared to individual models [41]. Similarly, in Australia, UAV-based CNN detections of gully erosion were merged with RUSLE-based soil loss estimates, producing high-resolution maps of both sheet and gully erosion. Despite these strengths, hybrid approaches present their own challenges. They are computationally demanding, often requiring high-performance infrastructure to run simulations and train ML models concurrently. Calibration and validation become more complex as multiple models must be tuned simultaneously, and expertise from multiple disciplines—hydrology, geomorphology, computer science—is necessary to ensure reliable implementation. Furthermore, while hybrid models improve transparency relative to black-box ML, they still increase system complexity, which can limit accessibility for policymakers and land managers. Nevertheless, the trajectory of erosion science suggests that hybridization is not a temporary trend but a structural evolution. By embedding empirical clarity, process-based rigor, and data-driven adaptability into a single framework, hybrid models are well positioned to address the dual needs of scientific precision and policy relevance. They also provide a bridge toward future-oriented paradigms such as GeoAI and digital twins, where integration across models and datasets becomes essential for real-time monitoring and decision support. A comparative summary of major modeling approaches, including their data requirements, spatial scales, advantages, and limitations, is presented in Table **1** to provide a structured overview of the methodologies discussed.

3.5. Future-Oriented Perspectives

The future of water erosion modeling is increasingly defined by the convergence of artificial intelligence, Earth observation, big data platforms, and participatory decision-making tools. Traditional approaches assumed stationarity in climate and land use, but emerging perspectives acknowledge that both are rapidly changing. As a result, models must be adaptive, dynamic, and capable of integrating multiple data

Table 1: Comparative Summary of Soil Erosion Modeling Approaches

Modeling Approach	Representative Models	Input Requirements	Spatial / Temporal Scale	Advantages	Limitations
Empirical	USLE, RUSLE, MUSLE	Rainfall, soil erodibility, slope, land cover	Plot to watershed; annual	Simple, transparent, easy to apply	Limited to average soil loss; lacks process detail
Process-based	WEPP, EUROSEM, LISEM	High-resolution rainfall, soil hydraulic, topography	Event to continuous; plot/watershed	Mechanistic understanding; scenario testing	Data-intensive; difficult calibration
GIS/RS-based	RUSLE-GIS, USPED	DEMs, NDVI, RS imagery, rainfall maps	Regional to national	Spatially explicit; integrates large datasets	DEM and RS errors; needs ground validation
Machine Learning	RF, SVM, ANN, CNN, LSTM	Environmental and climatic variables, RS indices	Watershed to continental	High predictive power; nonlinear learning	“Black-box” nature; low transferability
Hybrid / Integrated	RUSLE–RF, WEPP–LSTM, Ensemble Models	Multi-source inputs (empirical + ML + RS)	Multi-scale	Combines strengths of models; uncertainty reduction	Computationally demanding; complex calibration

streams in near real time. These technological innovations are not only conceptual but increasingly operational. Real-time monitoring systems based on IoT sensors and satellite data streams now enable continuous tracking of rainfall, runoff, and soil loss dynamics. Digital twin platforms integrate these data with process-based and AI-driven models, allowing engineers to simulate, visualize, and optimize erosion control interventions before field implementation. Likewise, GeoAI applications provide automated detection of erosion hotspots from UAV or satellite imagery, supporting rapid response and adaptive management. Together, these technologies are transforming erosion modeling from a purely analytical tool into a practical decision-support system for environmental engineering and sustainable watershed management.

3.5.1. GeoAI and Next-Generation Artificial Intelligence

The integration of geospatial data with artificial intelligence, commonly termed **GeoAI**, represents a paradigm shift. Unlike conventional machine learning, which often ignores spatial dependencies, GeoAI explicitly incorporates spatial autocorrelation and neighborhood effects. Deep learning architectures such as Convolutional Neural Networks (CNNs) and Graph Neural Networks (GNNs) can recognize complex patterns in high-resolution satellite imagery or UAV orthophotos, capturing features like rills and gullies with unprecedented accuracy [42-44].

The general predictive structure of a GeoAI model can be expressed as Equation (9):

$$E_{GeoAI}(x,y,t) = f_{DL}(DEM(x,y), RS(x,y,t), Climate(t), Soil(x,y)) \quad (9)$$

where erosion risk $E_{(GeoAI)}$ is modeled as a function $f_{(DL)}$ learned by deep learning, integrating topography, time-varying remote sensing indices, climate inputs, and soil properties.

GeoAI’s promise lies in scalability and predictive performance, yet it is data-intensive and computationally demanding. Its current applications remain concentrated in research contexts, though pilot studies have shown significant accuracy gains in gully erosion detection and susceptibility mapping.

3.5.2. Digital Twins of Watersheds

The Digital Twin concept, already prominent in engineering and urban systems, is now emerging in hydrology and erosion research. A digital twin is a continuously updated virtual replica of a watershed that integrates process-based models with real-time data streams from satellites, climate models, and IoT sensors. Unlike static models, digital twins simulate ongoing system dynamics, enabling scenario testing and early-warning applications [45].

This can be represented schematically in Equation (10):

$$Twin_{state}(t) = f_{process}(Climate, Soil, LandUse) + f_{AI}(RS, IoT, DEM, \Delta t) \quad (10)$$

Here, the twin’s state at time t is jointly defined by process-based functions ($f_{(process)}$) and continuously updated AI-driven adjustments ($f_{(AI)}$). Digital twins enable “what-if” simulations that visualize the effects of extreme rainfall events, conservation interventions, or land-use changes. While the approach is still in its infancy for erosion, pilot projects under European Union Horizon programs have begun exploring soil erosion digital twins for policy integration.

3.5.3. Cloud Computing and Big Data Platforms

The explosion of Earth observation archives requires computational environments that can handle petabytes of data efficiently. Cloud platforms such as Google Earth Engine (GEE), Microsoft Planetary Computer, and ESA's DIAS offer scalable solutions by providing ready access to multi-decadal satellite datasets. Researchers can now run RUSLE-GIS or ML models at continental or even global scales without downloading raw imagery [46].

The general structure of cloud-based modeling can be formalized in Equation (11):

$$E_{cloud}(x,y,t) = f_{model}(RS_{archive}(x,y,t), DEM(x,y), Climate_{proj}(t)) \quad (11)$$

where $RS_{(archive)}$ provides the remote sensing time series, DEM contributes terrain structure, and $Climate_{(proj)}$ incorporates future rainfall projections. Such formulations illustrate how cloud systems act as integrative platforms for multi-source modeling. The advantage of cloud computing lies in scalability and reproducibility, though concerns remain about platform dependency and the reproducibility of workflows if APIs or data access policies change.

3.5.4. Climate Change and Scenario-Based Modeling

Perhaps the most critical dimension of future erosion modeling is its explicit integration with climate change scenarios. Climate change alters rainfall intensity, storm frequency, and vegetation cover, all of which directly influence erosion rates [47]. Traditional deterministic models are ill-suited for non-stationary conditions. Scenario-based approaches now incorporate downscaled climate projections (*e.g.*, CMIP6 datasets) into erosion simulations. Instead of producing single deterministic estimates, probabilistic frameworks generate ranges of possible erosion outcomes, allowing stakeholders to prepare for multiple futures.

Formally, this can be represented as Equation (12):

$$P(E \mid Scenario_i) = \int f_{model}(X, Climate_i)\, dX \quad (12)$$

where $P(E \mid Scenario_i)$ denotes the probability distribution of erosion under a given climate scenario *i*. This probabilistic framing is essential for risk management and adaptation planning.

3.5.5. Participatory and Policy-Oriented Modeling

The final trend shaping future erosion modeling is the move toward participatory decision support. Models are increasingly being co-designed with farmers, watershed managers, and policymakers to ensure usability. Tools such as Participatory GIS (PGIS), interactive dashboards, and even VR-based watershed visualizations allow non-experts to explore the implications of conservation practices in accessible ways [48]. Digital twins, for example, can be integrated with visualization interfaces that show how soil loss changes under alternative land-use scenarios, making them powerful communication tools. This shift is not only technical but also epistemological: models are no longer just for scientists, but for a broader community of decision-makers.

CONCLUSION

The trajectory of water erosion modeling over the past decades demonstrates both significant advances and persistent challenges. Empirical approaches such as RUSLE and MUSLE provided the first widely applicable tools for assessing soil loss, and despite their simplicity, they remain indispensable as baseline frameworks. Process-based models like WEPP and EUROSEM advanced the field by incorporating hydrological and sediment transport processes, thereby offering mechanistic insights into event-driven erosion. However, their extensive data demands and calibration requirements limit their use outside well-monitored regions. The integration of GIS and remote sensing has marked a turning point by enabling spatially explicit risk assessments across large areas, supported by increasingly accessible satellite imagery and digital elevation models. These approaches, however, remain constrained by input data quality and the necessity of ground validation. Machine learning and deep learning methods have introduced unprecedented predictive power, capturing complex nonlinear relationships and leveraging big data. Yet, their limited interpretability and transferability across regions highlight the need for frameworks that combine predictive accuracy with explanatory depth. Hybrid and integrated models represent the current frontier, synthesizing the clarity of empirical approaches, the rigor of process-based models, and the adaptability of AI. Case studies across diverse environments consistently demonstrate that hybrid systems outperform stand-alone methods in terms of accuracy and robustness, though they also require advanced expertise and computational resources. Looking forward, future-oriented perspectives such as GeoAI, digital twins, cloud-based platforms, and participatory decision-support systems hold transformative potential. These innovations move erosion modeling beyond static assessment toward dynamic, probabilistic, and stakeholder-inclusive frameworks capable of addressing the uncertainties of climate change and land-use transformation. From an environmental engineering perspective, the outcomes of erosion modeling directly inform the design and optimization of soil and water conservation structures—such as terraces, check dams, vegetative buffer strips, and contour bunds—by identifying erosion hotspots and sediment transport pathways. Moreover, model-based assessments support watershed engineering and land management planning by prioritizing critical sub-basins for intervention, estimating sediment yield reduction under alternative conservation scenarios, and evaluating the cost-effectiveness of mitigation strategies. Integrating these insights into policy tools enables adaptive management practices that enhance soil resilience, water quality, and infrastructure stability. Strengthening the connection between erosion modeling, climate change adaptation, and sustainable land-use planning is essential to achieving long-term soil resilience. By integrating erosion risk predictions with spatial planning frameworks and adaptation policies, model-based insights can guide decisions on reforestation, crop rotation, and conservation structure placement under future climate scenarios. This cross-disciplinary linkage positions erosion modeling as a key instrument in advancing sustainability goals, supporting both environmental protection and socio-economic stability in vulnerable regions.

COMPETING INTERESTS STATEMENT

The authors declare that they have no competing interests.

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