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A review of the satellite remote sensing techniques for assessment of runoff and sediment in soil erosion

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Abstract: Soil erosion monitoring is essential for the ecological evaluation and dynamic monitoring of land resources via remote sensing technology. In this paper, we provide new insights into the existing problems and development directions of traditional models, which are supported by new technologies. An important role is played by remote sensing information acquisition technology in the qualitative and quantitative evaluation of soil erosion, and the data and technical support provided are systematically reviewed. We provide a detailed overview of the research progress associated with empirical statistical models and physically driven process models of soil erosion, and the limitations of their application are also summarized. The preliminary integration of remote sensing data sources with high spatial and temporal resolution and new technologies for soil erosion monitoring enables the high-precision quantitative estimation of sediment transport trajectories, the watershed river network density, and the terrain slope, enhancing the accuracy of erosion factor identification, such as spectral feature recognition from erosion information, gully erosion feature extraction, and vegetation coverage estimation. However, the current erosion models, driven by algorithms and models, are not comprehensive enough, particularly in terms of the spatial feature extraction of erosion information, and there are limitations in the applicability and accurate estimation of such models.

Keywords: Remote sensing; Soil erosion; Qualitative monitoring; Quantitative model; Research progress.

1 INTRODUCTION

Soil erosion is the process of the transportation, stripping, and deposition of soil and parent material under specific spatial and temporal conditions by external forces, such as hydraulics, wind, freezing and thawing, and gravity (Niu, 2015). Widely acknowledged as a global ecological concern, soil erosion requires thorough investigation and assessment to formulate scientifically informed preventive measures. Monitoring and evaluating erosion in real time through soil erosion prediction has thus become indispensable in mitigating erosion risks (Wang et al., 2022). At present, the continuous development and enhancement of remote sensing platforms and data sources has allowed us to fully leverage the characteristics of remote sensing technologies, such as its multi-platform, multi-type, multi-period, and multi-band features. Thus, aspects such as soil erosion monitoring at the macro-scale, erosion index extraction, and image processing have been improved, overcoming the limitations of the traditional static research focused on erosion points and linear features (Xue and Yang, 2004).

Early studies on erosion mechanisms relied on the establishment of monitoring stations to obtain real-time monitoring data from hillslopes or runoff areas. However, this approach was primarily limited to the characterization of the surface and the qualitative description of soil properties (Cai et al., 2002), and the erosion parameters obtained were insufficient due to the geographical complexity and labor costs. The results of field observation are highly uncertain due to the field conditions, such as the rainfall intensity, subsurface soil conditions, and terrain factors. Moreover, it is unclear to what extent the individual soil erosion forces contribute to composite erosion. Therefore, this method is not suitable for the monitoring and evaluation of large-scale regions. With the quantification of soil erosion, quantitative modelling techniques have emerged that can be applied to soil erosion under different external forces. They can be combined with large-scale repeated observations, spatial analysis, and dynamic monitoring (Li et al., 2003). Leveraging the capabilities of remote sensing and GIS technology, soil erosion models have undergone a transformation, enabling the comprehensive identification of erosion and deposition processes on the surface and in the watershed. It is also helpful to obtain the time series changes in the soil erosion degree. These developments have promoted the diversification and multi-form development of qualitative judgment and quantitative calculation methods (Guohong and Dongwei, 2010) for soil erosion. With the high resolution and high effectiveness of remote sensing data sources and with new technologies entering the practical application stage, linear relationships can be established, which is helpful in the development of erosion models and in clarifying the mechanisms

behind erosion factors and erosion parameters. For instance, Sahour and others used three machine learning algorithms, Regression Tree, Deep Learning, and Multiple Linear Regression, to identify the relationship between soil erosion rates and control erosion variables, in order to estimate the soil erosion rate in a large area (Sahour et al., 2021).Shi and others quantified the explanatory power of the erosion rate and runoff volume by simulating rainfall experiments and employing multiple linear regression, aiming to establish a bidirectional interaction between all factors and sheet erosion and runoff rates (Shi et al., 2024). Due to the nonlinear structure between the inputs and outputs of the erosion process, soil erosion susceptibility modelling is now widely used, which helps to identify the environmental relationships between spatial and temporal scales, enhances the accuracy of erosion assessment for predictable and unpredictable patterns, and mitigates the uncertainty in the estimation (Khosravi et al., 2023). Although a large number of machine models have been widely used in model construction and erosion evaluation, most of the existing models are still unable to accurately select the optimal erosion parameters values and erosion factor weights in the practical application stage. The output parameters, on the other hand, are susceptible to interference from the soil characteristics and environmental features. Therefore, deep learning algorithms, with greater flexibility and predictive performance, combined with evaluation techniques integrating empirical statistical models and physical process models, can compensate for the existing deficiencies in this area and have been validated through preliminary testing (Avand et al., 2023). Meanwhile, the gully erosion susceptibility (GES) prediction module in the erosion model also incorporates various machine learning models. The soil erosion susceptibility prediction system developed by Moayedi et al. (2024), based on the principles of artificial neural networks, optimizes various geological environmental parameters involved in gully erosion. It enhances the efficiency and accuracy in identifying high-risk erosion areas and greatly improves the accuracy of spectral feature identification, gully feature extraction, and vegetation fraction estimation using erosion information (Moayedi et al., 2024; Wang et al., 2023). Flood modelling and landslide susceptibility assessment, coupled with CNN (Convolutional Neural Networks) at an initial stage, enable high-precision simulations of sediment transport pathways, the watershed river network density, and the terrain slope (Patil et al., 2015). To address highly stochastic compound erosion processes, researchers have defined compound erosion prediction models based on artificial neural networks, revealing the quantitative mechanisms of multiple forces interacting in soil erosion (Yang et al., 2023). This also lays the foundation for the more accurate quantification of compound erosion processes in the future; meanwhile, remote sensing data and technology have already become an important source of support for the evaluation of erosion.

In this paper, we comprehensively describe the role of remote sensing technology in erosion monitoring applications through the use of remote sensing data-driven soil erosion monitoring methods. Additionally, we summarize the shortcomings of the remote sensing investigation of soil erosion. Moreover, the development trends of soil erosion are considered. The insights described in this paper provide ideas for the further exploration of remote sensing monitoring technology in soil erosion.

2 REMOTE SENSING AND SOIL EROSION MONITORING

2.1 Extraction of Erosion Indicators Supported by Multi-Source Remote Sensing Data

Soil erosion involves the combined influence of various erosion factors, leading to spatial and temporal variations in action modes, resulting in the dependence on remote sensing data at different spatial and temporal scales (Fu et al., 2006). Currently, due to the lack of reliable technical methods, the assessment of soil degradation by erosion is achieved mainly based on local scale of observation data. Therefore, remote sensing technologies, which provide rapid access to high spatial resolution data over large-scale areas, have become an effective approach to addressing erosion assessment on regional or global scales (Vrieling, 2006). In the current stage of the remote sensing monitoring of soil erosion, as shown in Figure 1, the support of multi-level remote sensing data sources is indispensable in both qualitative and quantitative erosion research.

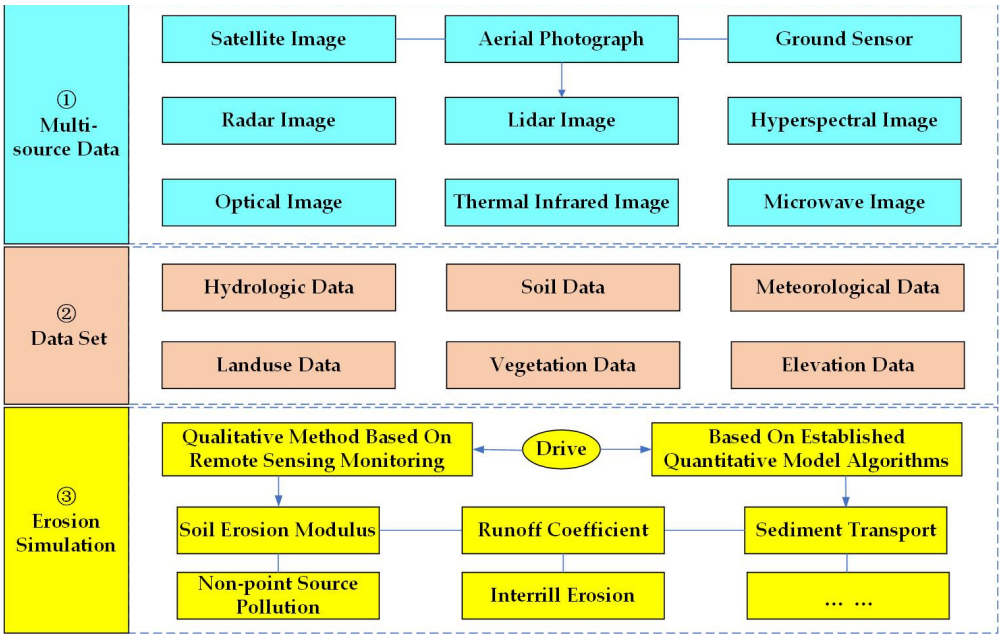


Fig. 1. Soil erosion assessment driven by remote sensing data.

Continual innovation of measurement techniques, image processing algorithms, development of computation models, new sensors and new remote sensing satellites have brought new data and methods to evaluating soil erosion (Žížala et al., 2017). Satellite data and aerial images can be directly employed for soil erosion and sedimentation monitoring based on remote sensing techniques. General analysis of soil spectral characteristics has an excellent potential for soil erosion assessment, as the hyperspectral data, thanks to their high spectral resolution, allows for more efficient quantification of spectral features (Ben-Dor et al., 2009; Ben-Dor and Demattê, 2015). Although the method is mainly used for soil erosion evaluation in semi-arid conditions, Lin et al. (2013, 2014) have analysed the spectral response of hyperspectral data to different eroded soils under laboratory conditions. They compared direct and indirect identification of erosion stages, and found that the latter performs better due to mixing and crossover effect among erosion properties. The various types and wavelengths of remotely sensed data have different degrees of sensitivity to the surface erosion characteristics. Landsat and SPOT satellite imagery data are suitable for the investigation of seasonal changes in land use and vegetation in large mesoscale watersheds. However, when detecting the subtle erosion of shallow gullies in river basins, their efficiency is reduced (Zhai et al., 2014). High-resolution digital elevation models with different time scales are helpful to investigate the long time series of surface sediments. The IKONOS and Quick Bird satellites are advantageous for the high-precision extraction of gully area, perimeter, and proximity information (Wang et al., 2004). On the other hand, ASTER imagery is constrained by noise issues in plain areas but proves useful for gully shape analysis and recognition (El Haj Tahir et al., 2010). Karale et al. (Vrieling, 2006) through comparatively analysing the performance of TM images and aerial photos in erosion parameter extraction, found that aerial photos had more obvious advantages in estimating the gully erosion development rate. Feng et al. (2022) utilized multi-source remote sensing data, including GF-6 WFV, and employed the random forest algorithm for the rapid and automated extraction of terraces. They applied the CSLE model to quantitatively assess soil erosion on cultivated land in mountainous areas. Additionally, spatial autocorrelation analysis was employed to unveil the characteristics of the spatial distribution of soil erosion. Furthermore, certain erosion features present obvious spectral reflectance differences in the different bands of remote sensing images. High-resolution panchromatic images focus on detecting microscopic surface erosion information, while the visible and near-infrared bands of TM images are suitable for the calculation of vegetation cover and the identification of erosion features in forested land (Ni, 2003). The mid-infrared band is suitable for the detection of rock structures, and microwaves are expected to play a role in the study of the surface texture, surface crust, etc. For the correlation analysis of the soil surface characteristics and sediment deposition affecting watershed outlets, the different states of sediments can be determined by identifying the reflection changes in the water body through the near-infrared bands. In recent years, 3D laser scanner technology can realistically represent the surface morphology under the impact of multiple forces, which has been widely used in soil erosion monitoring. The amount of soil erosion can be quantified by scanning the slope morphology, this technique facilitates the revelation of the mechanism of the influence of multiple force superposition on soil slope erosion (Fawzy et al., 2020). The remote sensing monitoring of soil erosion not only benefits from the support of large-scale remote sensing data sources, but GIS also provides great advantages for the overlay analysis of spatial entity data.

2.2 Remote sensing technology support for soil erosion monitoring

The establishment of an erosion inversion framework driven by data and models is a crucial aspect in the integration of quantitative remote sensing and erosion monitoring, as shown in Figure 2. Remote sensing technology plays an indispensable driving role in soil erosion remote sensing monitoring. The qualitative detection of soil erosion based on remote sensing compensates for the deficiencies in erosion information acquisition, regional dynamic monitoring, and erosion index inversion links. These methods realize the visual analysis of the spatial distribution and changes in soil erosion characteristics. Meanwhile, remote sensing technologies, such as linear regression, ensemble learning, machine learning, and deep learning, provide promising results in surface feature classification and quantitative erosion retrieval (Lee et al., 2019; Wang et al., 2019).

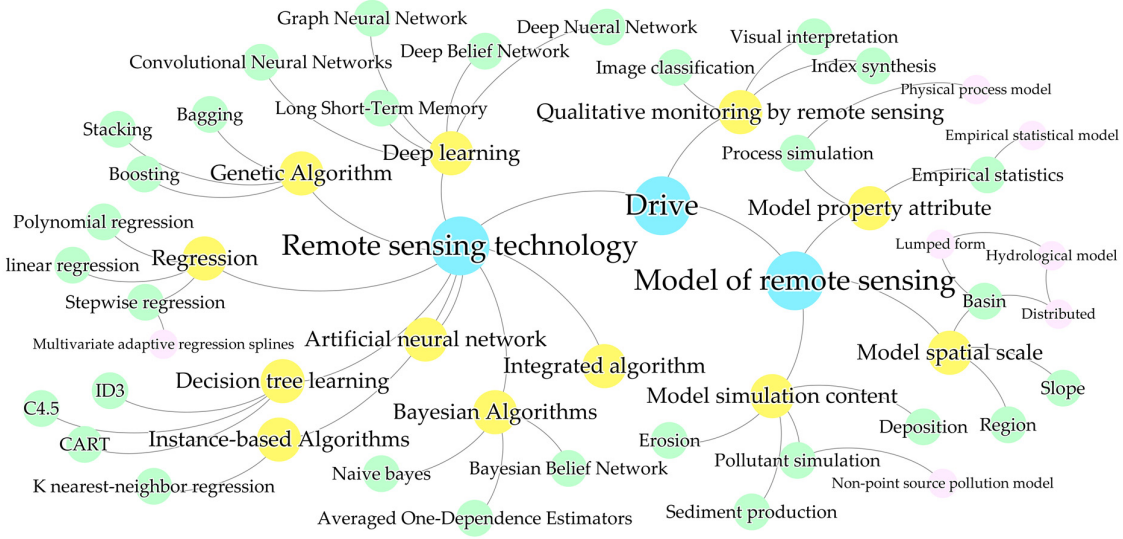


Fig. 2. Soil erosion inversion model based on remote sensing technology.

The empirical statistical model is grounded in the multiple regression relationship between erosion factors and soil loss, enabling the conversion from remote sensing data to target parameters. For example, Mohammed et al. (Mohammed et al., 2020) used a generalized linear model (GLM) to track soil erosion and runoff after a rainstorm under three different soil cover types. Physical process modelling focuses on the erosion and sediment yield mechanism, with some erosion parameters not directly obtainable, thus requiring the support of diversified remote sensing quantitative inversion techniques (Brazier et al., 2001). In addition to the traditional qualitative monitoring techniques of remote sensing, Wei et al. (2017) applied an instance-based K-nearest neighbour regression algorithm to invert the plant leaf area index and biological richness index. Elnaggar and Noller (2010) used the decision tree algorithm to optimize the feature characteristics used for vegetation and soil classification. Guo et al. (2013) implemented a three-layer grid structure based on a back-propagation neural network to simulate the soil erosion and sediment yield on slope surfaces with different cultivation measures. Watershed erosion models predict the runoff and sediment yield by considering soil erosion in slope and watershed sediment transport processes. The lumped watershed model describes the overall or average erosion modulus of the entire watershed by accounting for the spatial heterogeneity of equal area point parameters within the watershed. Distributed models divide the watershed into multiple grids, calculate the runoff and sediment yield for each grid by simulating the spatiotemporal variations in erosion factors, and ultimately approximate the natural erosion conditions of the river network. With the spatial and temporal heterogeneity and parameter complexity of watershed erosion simulation, multivariate adaptive regression splines (Vu et al., 2020) can achieve better results based on the concept of stepwise regression. Huang et al. (2020) exploited the interpretability of the MARS algorithm for the concentration inversion of a river network's compartmentalized units. Islam et al. (2015) combined the MARS algorithm and microwave remote sensing data to effectively invert rainfall data. Furthermore, by using image fusion technology to construct a fusion prediction image from sensors, the acquisition of erosion information can be enhanced, and image feature recognition is highlighted. In turn, this facilitates the automatic extraction of erosion areas through remote sensing technology. Liu et al. (2018) achieved the automatic extraction of disturbed patches using the fusion results of principal component analysis and the Gram–Schmidt algorithm.

3 QUALITATIVE REMOTE SENSING MONITORING FOR SOIL EROSION

Qualitative remote sensing methods do not require erosion parameters as evaluation criteria; rather, they can provide erosion risk probabilities that change with the stage of erosion (Zhang et al., 2010). This approach offers significant flexibility and is primarily represented by methods such as visual interpretation, integrated indicators, and image classification for erosion evaluation (Li et al., 2008).

Visual interpretation involves visually analysing the erosion factors in remote sensing images by leveraging the accumulated expertise and knowledge of the investigated area. It entails marking the attributes of corresponding patches in the remote sensing image based on this visual analysis (Yang, 2011). Its essence lies in the collaborative human–computer process of reasoning and judgment, utilizing the remote sensing image storage capacity of the computer and the prior knowledge of experts to interpret the features, thereby achieving the identification of these features (Yang and Zhu, 2000). In China, the Ministry of Water Resources conducted the first, second, and third national soil erosion remote sensing surveys based on MSS images, TM images, and digital remote sensing images in 1985, 1999, and 2001, respectively (Xie et al., 2002). This method fully capitalizes on human perception to recognize the structures of remote sensing images and determine the judgment criteria for soil erosion. It helps to avoid the challenges associated with the complete numerical interpretation of multi-spectral data by computers. At the same time, a hybrid approach combining automated processing of satellite data and visual interpretation is commonly used to monitor forest areas and its change over time (De Sy et al., 2015; Pengra et al., 2015). In the absence of field data, visual interpretation of satellite imagery is often used to create training data for assessing forest structure and biomass estimation (Schepaschenko et al., 2019). Examples include studies on forest species classification, tree crown identification and biomass estimation (Bilous et al., 2017; Hussin et al., 2014; Karlson et al., 2014). However, there are certain limitations. Due to the lack of uniform judgement rules and the different levels of complexity of remote sensing image interpretation, the accuracy of the expert's recognition will also change, increasing the errors caused by human subjectivity. Meanwhile, with the continuous advancements of remote sensing technology, the semi-automatic interpretation of remote sensing information can be achieved with the assistance of image processing software. However, a complete quantitative description, integrated with RS and GIS, is still not fully achievable. Due to the large volume of remote sensing images, inevitable issues of low efficiency arise. Therefore, visual interpretation methods are suitable for scenarios involving limited data volumes that require precise classification. Additionally, they are not restricted to a single remote sensing image and are often regarded as benchmarks for comparison against other classification methods.

Soil erosion surveys often extract the required erosion indicators from remote sensing images. These indicators can be associated with corresponding erosion classes based on decision rules or applied to various types of quantitative erosion models. Among these, the vegetation index is the most direct indicator of information reflecting surface erosion features. It is a physical parameter extracted from the multispectral vegetation data acquired by remote sensing sensors through linear or nonlinear combinations (Zhao, 2013). The extraction of vegetation indices with different response effects based on different combinations of infrared and near-infrared bands has made it possible to monitor vegetation cover over large areas. However, the extraction of senescent and dry vegetation is less effective. Using the red and near-infrared bands of images and different combinations, various vegetation indices with different response effects can be calculated (Zhang and Bian, 2007). Vegetation index extraction directly reflects the surface vegetation information of each pixel among the image's spectral features, enabling large-scale vegetation coverage monitoring. However, it may not perform well in extracting aged or withered vegetation. For instance, Huang et al. (2001) conducted the graded calibration of vegetation cover factors and determined the soil erosion intensity class based on the soil erosion factor score. The remote sensing index can reflect the spatial and temporal variability under the combined influence of multiple factors, making it suitable to obtain the surface erosion conditions of relatively large regions (Zhou and Wu, 2011). However, considering the differences in the spatial and temporal scales of different regions, the evaluation accuracy of the erosion index can change. Qualitative erosion assessment models generally

adopt the form of factor grading, which is beneficial for the rapid evaluation of the erosion risk and the monitoring of soil erosion, but the selection of factors and the determination of weights will have an impact on the results of the assessment. Moreover, regarding the remote sensing data source, a higher data resolution does not necessarily result in higher evaluation accuracy. Instead, the accuracy of the evaluation results increases with the compatibility between the data resolution and the scale of application of the qualitative model.

Image classification is a technique used in the remote sensing evaluation of erosion that identifies the spectral features of the surface recorded in a remote sensing image, in order to distinguish the degree of soil erosion on the surface and assess its spatial distribution. Wei et al. (2000) determined the surface vegetation cover and material composition of Xinjiang based on the colour shade, texture, and soil data interpretation of TM images. Whether it is based on direct or indirect surface spectral analysis, the spectral information about soil properties is often masked by the soil surface information. The current remote sensing detectors face challenges in capturing microscopic elements reflecting soil erosion information, such as the soil hue, texture, and spectral features. Consequently, image classification is often constrained to high-quality remotely sensed imagery and regions characterized by arid or semi-arid conditions, where noticeable differences in surface feature coverage exist. Meanwhile, optical remote sensing data involving high latitudes are exceptionally difficult to store and process, and the lack of large public erosion-affected datasets indirectly leads to the deep learning classification method being applicable only to scenarios whereby the sample set is suitable for training (Ke et al., 2021). Although the neural network method is more widely used in the field of image recognition, its accuracy is also highly dependent on the number of neural network layers and the number of training samples. Existing classification algorithms are primarily constructed based on the data requirements and practical applications, often neglecting the geographic interpretation and significance of image classification. Addressing this gap is crucial for the development of image classification methodologies.

4 QUANTITATIVE REMOTE SENSING MONITORING FOR SOIL EROSION

The quantitative remote sensing monitoring of erosion relies on erosion modelling, driven by both traditional and emerging remote sensing information acquisition techniques. The methods applied to obtain the erosion parameters involve completing the inversion and extrapolation of surface erosion information through mathematical algorithms and physical models. This approach aims to determine the degree of regional erosion or the risk of erosion through spatial superposition analysis (Hu et al., 2015). The development of erosion modelling research began with the qualitative description of the natural factors affecting soil erosion. It involves the quantitative calculation of comprehensive erosion factors, and various quantitative models have been proposed that are applicable to different spatial and temporal scales, as shown in Figure 3. The application of quantitative models reduces the cost of soil erosion surveys while ensuring the accuracy required for erosion evaluation, but they ignore the spatial variability in the model parameters. The integration of geographic information systems (GIS) and remote sensing (RS) with erosion models addresses the research challenges associated with spatial data collection, classification, management, and analysis. RS and GIS both deal with spatial entities as their research objects. RS focuses on spatial data acquisition and classification, serving as an important source of information for GIS. Meanwhile, GIS focus on the management and analysis of spatial data, proving to be a crucial means of extracting and analysing RS information (Song, 2006). For instance, Islam et al. (2022) evaluated the relationships between erosion variables using WOE, FR, and IV models based on the integration of GIS and RS. They produced soil erosion susceptibility maps and identified the distinct zones susceptible to soil erosion in Murree, Pakistan.

4.1 Materials and methods

By collecting the relevant literature on erosion models and summarizing their construction principles and applicability, it

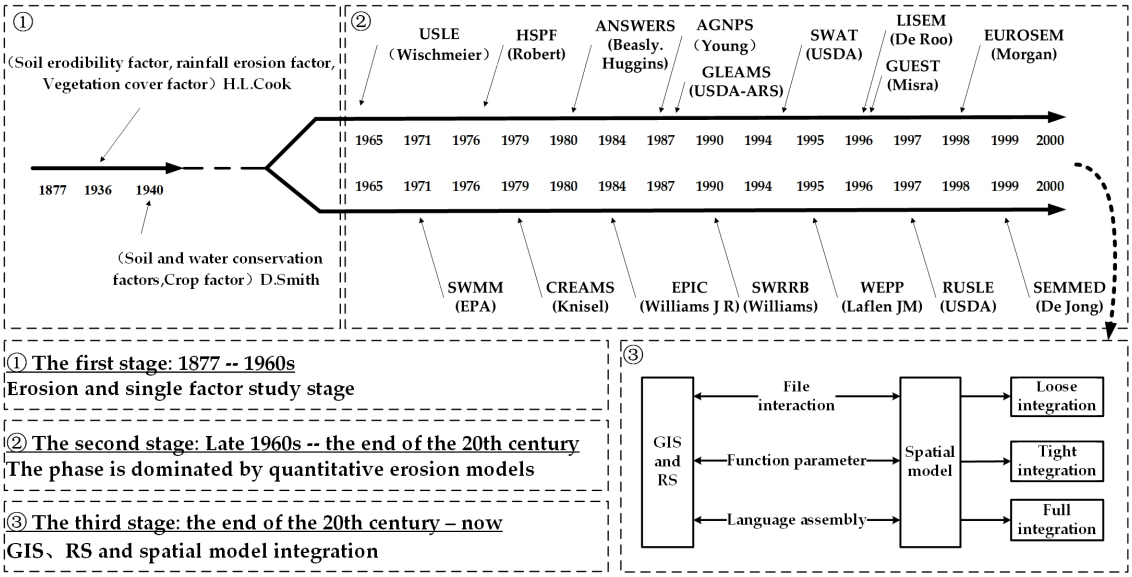


Fig. 3. Development process of quantitative soil erosion models.

was found that the existing empirical statistical models and physical process models primarily focus on regional erosion, hillslope erosion, and watershed erosion processes. The soil erosion process can be represented as a complete system, starting with raindrop splash erosion, where the disrupted soil texture is separated by an overland flow. Soil detachment occurs after soil runoff, leading to sheet erosion, followed by rill and gully erosion, and potentially leading to gravitational erosion and piping. When gully erosion occurs after a storm flow event, sediment transport and migration occur as the channel enters the watershed. Erosion models primarily rely on empirical data and statistical methods to describe the relationships between erosion and the influencing factors. Among them, the most representative factor analysis model is the Revised Universal Soil Loss Equation (RUSLE) (Renard et al., 1991). This model quantitatively calculates soil erosion by using factors such as the rainfall erosivity, soil erodibility, slope length and steepness, land cover, and conservation practices. It is used to estimate the average annual soil loss and evaluate the spatial distribution characteristics of soil erosion. Alternatively, erosion and sediment transport laws have been elucidated mechanistically, based on soil erosion processes and mathematical analysis, to derive erosion process models at the hillslope and watershed scales.

4.1.1 Slope erosion simulation

Rill erosion and interrill erosion play significant roles in the sediment yields on hillslopes. Interrill erosion refers to the complex process of soil detachment and transport by raindrop splash and overland flow processes on hillslopes. Under the impact of raindrops and slope water flows, soil particles undergo erosion through detachment and transport. In contrast, rill erosion refers to the process of soil detachment, transport, and deposition within rills. Hillslope erosion models, represented by the Water Erosion Prediction Project (WEPP) model (Flanagan et al., 2012), describe the soil detachment and deposition between rills through water erosion processes, simulate climatic erosion, and calculate surface runoff. They utilize the steady-state sediment continuity equation to predict the dynamic changes in sediment transport on any hillslope under rainfall conditions. The steady-state sediment continuity equation describing sediment movement is as follows:

$$\begin{cases} D_i = K_i \cdot I_e^2 \cdot G_e \cdot C_e \cdot S_f \\ D_r = K_r \cdot (\tau_1 - \tau_2) \\ \dfrac{dG}{dX} = D_i + D_r \end{cases} \tag{1}$$

where D_i is the rate of sediment transport from interrill areas to rills ($kg \cdot s^{-1} \cdot m^{-2}$), K_i is the erodibility of interrill soil, I_e^2 is the effective rainfall intensity, G_e is the canopy cover adjustment factor, C_e is the canopy layer adjustment coefficient, S_f is the slope adjustment factor, D_r is the rate of sediment transport from interrill areas to rills ($kg \cdot s^{-1} \cdot m^{-2}$), K_r is the rill erosion rate ($s \cdot m^{-1}$), τ_1 is the shear stress of the water flow, τ_2 is the critical shear stress of the soil, G is the sediment yield ($kg \cdot s^{-1} \cdot m^{-1}$), and X represents the distance along the downslope direction at a certain point (m).

In the process of sediment erosion, the transport and erosion rates of sediment in interrill areas and rills are influenced by various factors, including the soil properties, meteorological conditions, vegetation status, and terrain characteristics. Therefore, under different environmental conditions, the soil erosion rates in rills exhibit different trends.

When the shear force of water exceeds the critical shear force of the soil, and the sediment transport rate is less than the sediment transport capacity, the predominant process in the rill is transportation with the following equation:

$$\begin{aligned} D_r &= D_c \left(1 - \frac{G}{T_c}\right) \\ D_c &= K_r \left(\tau_f - \tau_c\right) \end{aligned} \tag{2}$$

where τ_f represents the critical shear stress of the water flow (Pa), and τ_c denotes the critical shear stress for soil erosion in the rill (Pa). The remaining parameters are the same as in Equation (1).

When the sediment transport rate exceeds the sediment transport capacity, the sedimentation process predominates with the following equation:

$$\begin{aligned} D_r &= \frac{\beta V_f}{q}\left(T_c - G\right) \\ T_c &= \mathrm{k}_t \tau_f^{\frac{3}{2}} \end{aligned} \tag{3}$$

where β is the raindrop splash turbulent coefficient, V_f is the effective sediment settling velocity ($m \cdot s^{-1}$), q is the unit width of runoff discharge ($m^2 \cdot s^{-1}$)), and k_t is the sediment deposition coefficient.

4.1.2 Hydrological erosion simulation

The process of water cycling on the surface is known as the land surface water cycle, which mainly includes evaporation, precipitation, runoff, and plant transpiration. In estimating daily rainfall and surface runoff hydrological processes, most models employ the SCS-CN equation in their hydrological modules (Mishra and Singh, 2003). This equation considers various factors, such as land use, the soil type, and the antecedent moisture conditions, to estimate the runoff volume more accurately. Meanwhile, distributed hydrological models, such as the Soil and Water Assessment Tool (SWAT) (Arnold, 1990), use the Modified Universal Soil Loss Equation (MUSLE) (Sadeghi et al., 2014) to estimate the soil loss for each Hydrological Response Unit (HRU). This approach allows for the comprehensive consideration of the erosive effects of land use and the soil type. The cycling of water in this model is represented by the water balance equation:

$$SW_t = SW_0 + \sum_{i=1}^{t}\left(R_{day} - Q_{surf} - E_a - W_{seep} - Q_{gw}\right) \tag{4}$$

where SW_t is the final soil moisture content (mm), SW_0 is the initial soil moisture content (mm), t is the simulation time (d), R_{day} is the daily precipitation (mm), Q_{surf} is the daily surface runoff (mm), E_a is the daily evapotranspiration (mm), W_{seep} is the amount of water entering the vadose zone from the soil profile on a given date (mm), and Q_{gw} is the baseflow on a given date (mm).

The entire land surface water cycle in the watershed follows the law of the water balance equation, in which the Manning equation is used to calculate the river flow and velocity, expressed as follows:

$$\begin{cases} \mathrm{q} = \dfrac{A \cdot R^{2/3} \cdot SLP^{1/2}}{n} \\ v = \dfrac{R^{2/3} \cdot slp^{1/2}}{n} \end{cases} \quad (5)$$

where q represents the channel flow rate ($m^3 \cdot s^{-1}$), A denotes the cross-sectional area of water passage (m^2), R represents the hydraulic radius (m), SLP represents the bottom slope, n signifies the Manning coefficient of the channel, and v denotes the flow velocity ($m \cdot s^{-1}$). The hydraulic processes of water flow in the channel are simulated using the Manning formula, expressed as follows:

$$\begin{cases} V = K \cdot \left[X \cdot q_{in} + (1 - X) \cdot q_{out} \right] \\ K = \dfrac{600 \cdot L_{ch}}{v} \end{cases} \quad (6)$$

where V represents the volume of water in the channel (m^3), q_{in} denotes the upstream flow rate ($m^3 \cdot s^{-1}$), q_{out} signifies the downstream flow rate ($m^3 \cdot s^{-1}$), K denotes the channel residence time (s), X is the weight factor measuring the relationship between the outflow and inflow in the channel segment, L_{cn} represents the length of the channel (km), and v denotes the flow velocity ($m \cdot s^{-1}$).

The soil erosion and sediment transport generated by rainfall and surface runoff are predicted using the MUSLE with the following equation:

$$sed = 11.8\left(Q \times q_{peq} \times area_{hru}\right)^{0.56} \cdot K \cdot C \cdot P \cdot LS \cdot CFRG \quad (7)$$

where sed represents the soil loss (tons), q_{pea} denotes the peak flow rate ($m^3 \cdot s^{-1}$), $area_{hru}$ denotes the area of HRU (ha), and K, C, P, and LS represent the soil erodibility, vegetation cover and management, conservation practices, and terrain factors, respectively. $CFRG$ is the roughness factor.

4.2 Empirical statistical models

The Universal Soil Loss Equation (USLE) (Wischmeier and Smith, 1978) is a simple and widely available erosion prediction equation based on long-term observations of runoff plots, quantitatively inverted by soil erosion factors. However, due to the equation's yearly time step, the prediction of soil erosion with rainfall cannot be realized. To address this limitation, the United States Department of Agriculture has modified the definition and algorithm of each factor by using a computer model and proposed the RUSLE, based on the USLE. The basic data of the USLE are taken from a section of easy grading in the eastern part of the United States, which has significant uncertainty and limitations in promotion and outreach in other experimental areas. Many researchers have modified the soil loss equation based on extensive experimental results and the specific conditions of various regions. For example, Liu et al. (2002) directly modified the erosion factors based on the Chinese context, and they constructed the CSLE model, which was superior to the traditional soil loss assessment methods for hillside farmland. However, this model ignored the effects of soil erodibility, erosion furrows, and water conservation measures. The most common modified USLE models are summarized in Table 1.

An empirical watershed model has been developed by establishing the empirical relationship among the erosion factors in the basin. This model is utilized to determine the runoff and sediment erosion on the slope and gully of the basin. The Agricultural Non-Point Source (AGNPS) model was established by Young et al. (1989). It discretizes the watershed into physically homogenous grid cells to solve the spatial heterogeneity problem. However, it is limited to a single rainfall simulation and cannot evaluate the long-term impact of non-point-source pollution in the basin. The Annualized Agricultural Non-Point Source (AnnAGNPS) model (Tamanna et al., 2020) is based on this model and can be employed to evaluate surface runoff, sediment erosion, and nitrogen and phosphorus loss in the basin. This model is capable of simulating both the long-term runoff and sediment quantity of the basin and the runoff and sediment transport process within the watershed at multiple scales. The Erosion-Productivity Impact Calculator (EPIC) model, developed by Williams et al. (Williams et al., 1984), can sustainably simulate the impact of management strategy changes in agricultural production on soil erosion and soil productivity at the field scale. This model reflects the erosion sensitivity in terms of crop yields, soil erosion, and climate change. However, it exhibits lower sensitivity to climatic factors under the influence of extreme weather.

Table 1. The common USLE modified models.

Researcher	Model expression	Application area
Liu et al. (Liu et al., 2002)	$A = R \cdot K \cdot L \cdot S \cdot B \cdot E \cdot T$	Standard plots
Xin et al. (Xin and Xia, 2020)	$A = R \cdot K \cdot L \cdot S \cdot C \cdot W$	Hydro-fluctuation belts of the reservoirs
Kinnell (Kinnell, 2016)	$A_e = Q_R\, EI_{30}\, K_{UM}\, LS\, C_{UM}\, P_{UM}$	Event plot soil loss
Pampalone (Bagarello et al., 2018)	$A_e = \left(Q_R\, EI_{30}\right)^{b_1} K_{UM}\, LS\, C_{UM}\, P_{UM}$	Event plot soil loss
Pampalone (Pampalone et al., 2023)	$A_e = Q_R^{b1}\, EI_{30}\, K_{MB}\, L_{MB}\, S_{MB}\, C_{MB}\, P_{MB}$	Rill and interrill events

* A is the annual soil erosion modulus/($t \cdot hm^{-2} \cdot a^{-1}$) ; A_e is the event soil loss per unit area/ ($Mg \cdot ha^{-1}$) ; R is the rainfall erosivity factor/($MJ \cdot mm \cdot hm^{-2} \cdot h^{-1} \cdot a^{-1}$) ; K is the soil erodibility factor/($t \cdot h \cdot MJ^{-1} \cdot mm^{-1}$) ; L and S are slope and slope length factor; C is the vegetation cover management factor; P is the soil and water conservation measure factor; B is the biological measure factor; Q_R is the event runoff coefficient; E is the event kinetic energy/($MJ \cdot ha^{-1}$) ; I_{30} is the maximum 30-min rainfall intensity observed during the event/($mm \cdot hr^{-1}$) ; K_{UM} is the soil erodibility factor/($\mathrm{Mg} \cdot \mathrm{ha} \cdot \mathrm{hr} \cdot \mathrm{ha}^{-1} \cdot MJ^{-1} \cdot mm^{-1}$) , C_{UM} is the cover and management factor, and P_{UM} is the support practice factor; L_{MB} and S_{MB} are the plot length and steepness factors, respectively.

4.3 Physical process models

Physical process models focus on quantitatively describing the runoff and sediment erosion caused by the spatial heterogeneity of rainfall and underlying surfaces with mathematical methods. These models predict the amount of soil erosion under different spatial and temporal distributions through process simulation (Zhang et al., 2009), but the accuracy is limited by the complexity of the regional topography. Compared to the research in some countries focusing on watershed runoff and sediment yields, the global research on water erosion, rainfall splashing, shallow gully erosion, and nutrient transport involved in the erosion process is more developed.

To evaluate non-point-source pollution under the influence of a single storm and to achieve long-term managerial measurement within a field management unit, Knisel and Douglas-Mankin (2012) developed the Field Scale Model for Chemical, Runoff, and Erosion from Agricultural Management Systems (CREAMS). However, its applicability is limited by the larger scale of regional evaluation. Building upon CREAMS, Williams et al. (1985) developed the Simulator for Soil and Water Resources in Rural Basins (SWRRB) model, which operates at a daily scale. This model takes into account the relevant factors involved in the water cycle, and it was used to predict the watershed hydrology, sediment transport, and nutrient migration under continuous changes in geographical factors and climatic conditions. However, the outlet of the basin is taken as the cross-point of runoff and sediments in the branch basin. Channel flood routing should be realized by connecting the operation results of small basins based on the roto model. Due to the cumbersome calculation process, Arnold et al. (Arnold et al., 1990) developed the Soil and Water Assessment Tool (SWAT) based on the SWRRB model and GIS technology. This model was used to simulate the impacts of long-term land management measures on the water quality, sediment, and agrochemicals in large and medium-sized watersheds. This model calculated the hydrological balance of the river basin based on the Hydrologic Research Unit and the flow and sediment transport at the outlet cross-section, but the sensitivity of the basin sediment yield results to the HRU was weak and it was limited to the simulation of short-duration floods for a single event. Meanwhile, to compensate for the shortcomings of the USLE in predicting the spatial and temporal distribution of erosion, the U.S. Department of Agriculture developed the Water Erosion Prediction Project (WEPP) model to simulate the sediment yield from single or continuous rainfall events on slopes and watersheds (Flanagan et al., 2012). The model is based on relevant physical processes that described soil detachment and sediment deposition in interrill areas. It simulates climatic erosion, calculates the surface runoff, and replicates the essential natural processes causing erosion through watershed slopes, canals, and retaining facilities. However, it cannot simulate the dynamic transport of sediment in the watershed segment and may produce slight deviations in predicting the transport of surface runoff from steep slopes. The Griffith University Erosion System Template (GUEST) model, which was designed to be applied in bare ground runoff plots, was established by Misra and Rose (1996) in Australia. It was based on the theory of slope flow erosion and rainfall splash erosion, analysing the secondary separation, dispersion, and transport of rainfall and runoff on a new silt layer. However, the transport processes of runoff and sediment at the hillslope outlet section need to be clarified. The Area Nonpoint Source Watershed Environment Response Simulation (ANSWERS) model was developed by Beasley et al. (1980) to forecast the surface runoff, soil erosion, and pollutant loss during a single rainfall event in a typical agricultural watershed. It establishes local watershed units based on differences in soil texture and vegetation cover, studying the hydrological processes of soil erosion under the influence of changes in land use and the best management practices. The model primarily analyses the hydrological characteristics of small watersheds in flat areas during and after rainstorms. It is highly sensitive to errors in the physical and infiltration parameters of the soil and does not consider interflow and groundwater in watersheds with a relatively strong base flow. In (De Roo et al., 1996), the Limburg Soil Erosion Model (LISEM) was developed to model the effects of protection measures such as grass planting on soil erosion in the Netherlands. This model primarily simulates the hydrological and sediment transport processes in small watersheds after a single rainfall event. It is integrated with GIS and RS to analyse the spatial and temporal dynamics of soil erosion. Although it performs effectively in simulating the effects of land use changes, the parameters must be obtained through the regression inversion of measured data. The European soil erosion model (EUROSEM) is a distributed rainfall erosion model established by Morgan et al. (1998) to predict the field and watershed. It is particularly accurate in calculating the runoff and sediment between rills and interrill areas. While considering the effect of plant interception on the infiltration and rainfall energy, it also incorporates factors such as infiltration, the flow velocity, and splash erosion under the cover of surface rock fragments. However, the description of erosion physical processes is relatively simple, and it may not be suitable for regions with complex soil conservation measures. The Storm Water Management Model (SWMM) is a comprehensive mathematical model developed for the design and management of urban stormwater and is widely used in urban storm runoff simulation and forecasting (Gironás et al., 2010). Using the calculation module for runoff, transport, extended transport, and storage treatment, the spatial structures of drainage networks and ditches in the watershed can be quickly constructed. This enables a comprehensive simulation of the process of urban rainfall runoff and pollutant transport. However, challenges arise in meeting the conditions for the construction of the database and interoperation with data sharing between different regions. The Hydrological Simulation Program Fortran (HSPF) is a semi-distributed comprehensive model developed by Johanson et al. (1980) and based on the SWMM model. It can simulate long-term hydrological changes within the watershed and has a significant effect on point source pollution and non-point-source pollution in the watershed. The model provides detailed simulations of the hydrological changes resulting from changes in land management measures, predicting runoff, sediment, and pollutant transport on the soil surface and in the river course. However, meeting the time span conditions of the simulated monitoring data proves challenging due to a lack of internal algorithmic considerations. The Soil Erosion Model for Mediterranean Regions (SEMMED) is a regionally distributed erosion forecasting model developed by De et al. (De Jong et al., 1999). It is designed for the assessment of soil erosion in Mediterranean areas and synthesizes various data resources to spatially analyse the ability of soil grains to be dispersed and spattered particles to be transported. However, it does not consider the impact of overland flows on soil grain detachment and the soil crust.

4.4 Non-point-source pollution model

Due to the substantial influx of nutrients, pesticides, and other

inorganic pollutants from non-point-source pollution into water bodies, which disrupts the ecological functioning and environment in aquatic ecosystems, non-point-source pollution has become the largest source of water pollution (Shou et al., 2019). Recently, through quantitative research on non-point-source pollution, Chinese scholars have established a mathematical model of non-point-source pollution, which is used to reflect the spatial and temporal variations in nutrients and other substances. The most widely used models are summarized in Table 2.

For instance, utilizing satellite images and field surveys of the Caohai River watershed, Zhou et al. (2019) applied the SWAT model to simulate surface source pollution from farmland, forest land, grassland, water areas, construction land, and unused land in the watershed. The study analysed in detail the runoff, sediment, and nitrogen and phosphorus levels of non-point-source pollution. In order to monitor the non-point-source pollution loads under a simulation scenario in the Jiujiang River Basin, Hong et al. (2005) investigated the dynamic changes in the percentages of nitrogen, phosphorus, and soluble nitrogen and phosphorus content based on the AnnAGNPS model. To compare the erosion effects under different soil and water management measures, Sun and Hao (2004) used the SWAT model to simulate the runoff, sediment, and pollution load in the Guanting Reservoir and the Lushi watershed of the Yellow River. Based on a model that coupled SWAT and dVine Copula, Ding et al. (2023) conducted a multivariate analysis of the reduction effect of BMPs. They considered the randomness caused by hydro-meteorological variability, along with the correlations among different indicators. The study evaluated the multi-indicator effect of individual BMPs in the watershed and the combined effects of various BMPs. Moreover, Li et al. (2023) predicted land use patterns and effectively simulated the spatial and temporal dynamics of specific pollutants, such as ammonia nitrogen and total phosphorus, in the northern reaches of the Jiulong River Basin in 2040 by coupling the SWAT model with the GeoSOS-FLUS model.

5 UNCERTAINTY IN REMOTE SENSING MONITORING OF SOIL EROSION

5.1 Uncertainty in qualitative remote sensing monitoring

Although remote sensing technology has enabled the qualitative remote sensing monitoring of soil erosion in various forms, its performance is still subject to significant limitations. The current stage of remote sensing image recognition overly relies on the spectral characteristics, colour tone, and textures of the remote sensing data, which leads to limitations in the estimation of vegetation types and cover. Moreover, the detection of the surface lithology, roughness, texture, and crust and the identification of various spatial characteristics of the image and other attributes of the feature are not fully considered (Luo, 2000). Qualitative remote sensing monitoring primarily employs visual interpretation and index extraction methods, contributing to remote sensing's application in erosion information processing. However, there still exists subjectivity and a lack of quantifiability during the image interpretation phase. Monitoring methods that combine knowledge bases and spatial information can directly extract surface erosion features, overcoming the inherent subjectivity in the process of interpretation through human–machine interaction. This approach is beneficial in reducing the random errors associated with remote sensing monitoring. However, it requires the induction and summarization of prior knowledge to establish a regional erosion knowledge base (Zhang et al., 2017). The regional remote sensing monitoring of soil erosion from a macro perspective aims to reflect the overall erosion level. However, it tends to be insufficient for refined detailed erosion assessments within small units, leading to relatively low overall assessment accuracy. The limitations on the resolution of RS images and the complexity and instability of ground conditions result in differences in the amount of soil erosion obtained between images and field data (Elyagoubi and Mezrhab, 2022). Based on the fusion of multi-source remote sensing data, it can compensate for the shortcomings of the single type of data on temporal resolution, spatial resolution or spectral resolution, and realize cyclical sequence monitoring of rapid changes in the ecological environment (Li et al., 2020).

5.2 Uncertainty in quantitative remote sensing inversion

Due to the complexity of the soil erosion process, the influence of different factors is considered in the construction of soil erosion models. Different soil models are established based on various foundational theories, simulation methods, and simulation processes. Therefore, in terms of the continuous development of erosion models, the complexity of the simulation processes of erosion models, the limitations of research methods, and the constraints of model functionality have introduced uncertainties in their practical application.

5.3 Temporal and spatial scale differences

The assessment of the applicability of erosion models involves a comprehensive evaluation of the simulation accuracy, process simulation capacity, selection of temporal and spatial scales, and operational complexity (De Vente et al., 2013). With regard to temporal and spatial scales, the establishment of models on different scales results in variations in the dominant erosion processes, leading to significant differences in the erosion models. Short time scales are suitable for low-frequency, high-intensity erosion simulations, while long time scales can be used to perform high-frequency, low-intensity erosion simulations. However, longer time scales may neglect the details of the simulation process, resulting in the accumulation of errors. Additionally, as the spatial scale increases, the required temporal scale for research also increases, as shown in Table 3, which details the temporal differences in erosion models.

The discrepancy in the temporal and spatial scales of a model formulation directly determines the direction of the model's application and its verification environment. Therefore, for most models, specific temporal and spatial scales for model verification are typically selected. By studying the erosion processes and controlling factors across different scales, the possibility of transitioning between multiple scales in models has been proposed (Yang et al., 2006). However, the current understanding of scale effects indicates that the optimal scale is often specific to a particular object, such as slopes (sheet, rill, ephemeral gully erosion) or runoff, rather than regional and watershed scales (Govers, 2010; Jetten et al., 2003; Merritt et al., 2003). Currently, the scale transformation method mainly relies on introducing parameters or combining slope models with RS techniques, but the error generally increases in the transformation process, and stepwise conversion between scales remains difficult to fully realize. Scale transformation is essential for the conversion and calibration of erosion models at different scales. Therefore, enhancing the mutual conversion of erosion processes between different scales is a challenge for future soil erosion research (Kandel et al., 2004).

Table 2. Common non-point source pollution models for various nutrients.

Model	Nutrients factors
SWAT	Nitrogen, phosphorus, pesticides, etc.
EPIC	
CREAMS	
GLEAMS	
ANSWERS	Nitrogen, phosphorus, etc.
AGNPS	Pesticides, nitrogen, phosphorus, and COD (Chemical Oxygen Demand)
STORM	Total nitrogen, total phosphorus, BOD (Biochemical Oxygen Demand), and Escherichia coli
SWMM	Total nitrogen, total phosphorus, COD, and BOD
HSPF	Nitrogen, phosphorus, COD, BOD, pesticides, etc.

Table 3. Temporal and spatial scale differences of erosion models.

	Scale	Model type	Model application
Time	Minutes/Hours	Flood model	Simulate the response of single flood
	Days	Daily model	Simulate the response to climate and land management over extended time periods
	Months/Years	Annual model	
Space	<0.1km^2	Hillslope model	Forecast erosion and sediment yield in slope plots
	<1000km^2	Small Watershed model	Predict hillslope, gully erosion, and watershed sediment yield.
	1000～10000 km^2	Large basin model	Model the dynamic runoff and erosion conditions in complex regions.

5.4 Variability in model applicability

The rapid development of erosion models has led to their gradual and widespread application, but this progress has also exposed inadequacies in various model algorithms and limitations in practical application scenarios. Meanwhile, it is relevant to remark that most of soil erosion models currently in use were developed initially for small-scale assessments or using data from small experimental plots (Borrelli et al., 2021). Hence, the functionality of these models need to be fully evaluated and tested (Alewell et al., 2019; Bezak et al., 2021). The characteristics of the soil erosion models are summarized in Table 4, and the hydrological simulation capabilities and comprehensive performance of the most common erosion models are summarized in Figure 4.

It is common to consider the data, model structure and parameters when analysing sources of uncertainty in model outputs and parameters (Jakeman et al., 2019). Overly complex models may introduce uncertainty, add unnecessary data collection and computational burden, and not provide more accurate outputs (Jetten et al., 2003). On the other hand, oversimplification of the modelling concepts can inadequately represent key processes, or lead to a large accumulation of errors (Wainwright et al., 2008). Therefore, an optimal balance between model complexity and data quality needs to be found.

As summarized in Table 4 and Figure 4, both the USLE and RUSLE models are characterized by low data requirements, a simple structure, and fast prediction speeds, but they also have the disadvantages of being unable to reflect the simulation process and requiring long time scales. Meanwhile, these models suffer from the same important limitations as most physical models, lacking detailed consideration of gully erosion, bank erosion and block movement processes (Vanmaercke et al., 2011). In contrast, physical process models, represented by WEPP, ANSWERS, and LISEM, are more detailed for the simulation of transport processes of hydrological components and sediment in the watershed. These models consider the slope erosion conditions of rills and inter-rills, which provides a more comprehensive depiction of the downslope erosion–transport–deposition processes in hillslopes and channels. This enables the better simulation of the sediment source and sink dynamics in the watershed. Nevertheless, the gravitational erosion of gullies in the process simulation is also neglected, resulting in the absence of the subprocess simulation of upslope runoff and sediment. The ability to predict sediment transport and nutrients is crucial when evaluating the comprehensive performance of erosion models. The CREAMS and WEPP, HSPF models facilitate prediction of soil loss due to ephemeral gully erosion. In contrast, the distributed hydrological models such as AnnAGNPS, SWAT, SWMM, and HSPF not only simulate the long-term impacts of changes in best management practices on the hydrological environment within a watershed but also incorporate predictions of nutrient transport alongside stream channels (Fu et al., 2019). However, the further the considerations of the same model are increased, the higher the accuracy of the simulation results will be and the more restrictive the model will be. To address the challenges and risks of applying models in such a situation, SWAT and HSPF modelling communities have invested in tools and data sets to support their application to data-sparse environments (Fu et al., 2019). With the increasing integration of models into interdisciplinary studies, models such as LISEM, SWAT, and AnnAGNPS show excellent compatibility with GIS. This facilitates the input and processing of model data, where the fusion effect is best with the LISEM model. Furthermore, research focused on models that are suitable only for specific erosion conditions, such as the ANSWERS model for the simulation of the characteristics of rainstorm and post-rainfall scenarios, should aim to reduce their limitations. Conversely, the extended application of a model under common conditions, data post-processing, graphic post-processing, and the user experience should be continuously strengthened. This may become the main direction for the development of erosion models in the future.

Table 4. Comprehensive evaluation of soil erosion models.

Models	Structure	Data requirement	Scale		Advantage	Disadvantage	Application
			Spatiality	Time			
USLE	Lumped	Low	Slope	Year	Simple structure and fast evaluation	Lack of erosion process simulation	Soil loss in Slope Surface
RUSLE	Lumped	Low	Slope	Year	Forecast of soil erosion in the single rainfall	Lack of erosion process simulation	Soil loss in Slope Surface
AGNPS	Distributed	High	Basin	Day	Using discrete parameter simulation methods	Unable to simulate long-term effects	Prediction of non-point source pollution
AnnAGNPS	Distributed	High	Basin	Day	Fast data extraction and suitable for various simulation	Default parameters affect the accuracy	Prediction on runoff, sediment, and nutrient loss in watershed
SWRRB	Distributed	High	Basin	Day	Simulate continuous changes in watershed hydrology over long periods of time	Lack of runoff and sediment	Runoff and sediment forecasting for management
SWAT	Distributed	High	Basin	Day	Simulate the long-term effect of soil management measures in large and medium-sized watershed	Limited to single flood process simulation	Climate change and land use scenario analysis
EPIC	Distributed	High	Cropland	Day	Evaluate the effect of changes in management strategies on soil erosion	Limited to areas with scarce resource data	Crop yield estimation
CREAMS	Lumped	Low	Cropland	Day	Forecast single storm and long-term precipitation	Calculation and prediction in a small range	Selecting optimal non-point source pollution management measures
WEPP	Distributed	High	Slope/ Basin	Day/ Flood	Simulate the sediment yield and sink in a watershed	Gravity erosion is not considered	Soil erosion on slopes and sediment yield in small watersheds
GUEST	Distributed	High	Basin	Day	Rill and no rill are considered	Only suitable for bare land runoff plot	Prediction of sediment yield by single rainfall
ANSWERS	Distributed	High	Basin	Day	Simulating the characteristics of a watershed during and after a rainstorm	Many sub-processes cannot be simulated without considering gully erosion	Prediction of hydrology and sediment transport in agricultural watersheds
LISEM	Distributed	High	Basin	Flood	Simulating the effect of land use changes in complex terrain	Limited to the prediction of erosion spatial distribution	Land use scenario analysis, determination of sediment and sink
EUROSEM	Distributed	High	Basin	Day/ Flood	Prediction of runoff yield under different environmental characteristics	Estimation of limited runoff and sediment yield	Simulation and prediction of soil and water loss on slopes and small watersheds
SWMM	Distributed	High	City	Day/ Flood	Detailed simulation of water flow on the surface and in pipes	Unable to simulate the transport process of specific pollutants	Estimate the surface runoff and pollution load of an urban rainstorm
HSPF	Semi- Distributed	High	Basin	Day	Detailed Simulation of continuous time step runoff formation	Lack of detailed spatial description	Water resources planning, design, and management
SEMMED	Distributed	High	Basin	Flood	Regional process simulation of all kinds of data	The effect of overland flow on soil was not considered	Predicting soil loss in the Mediterranean region

Model	Hydrological modeling			Event modeling	Mixed land use simulation	Sediment simulation	Nutrient simulation	Evaluation of best management practices	GIS integration	Graphical user interface	Wide application	Domain interoperability
	Rainfall runoff	Sediment transport	Gully erosion									
USLE	×	×	×	×	×	×	×	○	○	×	●	◎
RUSLE	×	×	×	×	×	×	×	○	○	×	●	◎
AGNPS	◎	●	◎	●	○	●	◎	◎	◎	◎	◎	●
AnnAGNPS	●	●	◎	●	○	●	◎	◎	◎	◎	◎	●
SWRRB	◎	◎	×	●	○	◎	◎	◎	◎	●	●	◎
SWAT	●	●	×	◎	●	●	●	◎	◎	●	◎	◎
EPIC	◎	◎	×	×	×	×	×	×	×	×	×	×
CREAMS	◎	◎	◎	×	×	×	×	×	×	×	×	×
WEPP	◎	●	×	○	○	◎	×	◎	◎	◎	◎	●
GUEST	◎	◎	×	●	◎	◎	◎	○	◎	◎	◎	●
ANSWERS	◎	◎	×	●	◎	◎	◎	◎	◎	×	●	◎
LISEM	●	◎	×	●	●	●	◎	◎	●	●	◎	●
EUROSEM	◎	◎	◎	◎	◎	◎	◎	◎	◎	◎	○	●
SWMM	●	◎	◎	●	○	◎	◎	◎	◎	●	●	◎
HSPF	◎	●	●	●	●	●	●	◎	◎	◎	●	●
SEMMED	×	●	×	◎	◎	●	◎	◎	×	◎	○	○

NOTE: ○ — Low | ◎ — Middle | ● — High | × — Without

Fig. 4. Functions of soil erosion models.

6 PROBLEMS AND PROSPECTS

Recently, ecological monitoring and land evaluation have attracted significant attention, and the high-precision quantitative estimation of regional soil erosion can be realized by using remote sensing technology. However, the research on regional soil erosion is relatively weak at present, particularly in terms of the applicability and accurate estimation of the model.

6.1 Existing problems

1) Currently, remote sensing information extraction techniques are limited in terms of accurately extracting erosion indicators from remote sensing data sources, and the full potential of remote sensing technology has not been realized (Zhou and Wu, 2011). Research on erosion focuses on dynamic changes and management countermeasures, such as gully erosion extraction. Although progress has been made in improving the spatial resolution and basic performance of remotely sensed image data, the increase in spatial resolution also introduces more complex noise in the extraction of gully erosion information (Man et al., 2016). Additionally, there is currently relatively little research considering which type of imagery is most conducive to the extraction of gully erosion information. The extracted erosion information brings challenges in ensuring data reliability for surface erosion inversion. Shortcomings persist in the extraction of spatial characteristics and other attributes and features of erosion information. Moreover, the monitoring of temporal changes in the surface detected by remote sensing has certain limitations in the identification of vegetation, as well as in cover erosion research due to the influence of seasonal changes on remote sensing images.

2) At this stage, the erosion model covers a variety of erosion categories, with considerations for complex parameters and processes. However, the complexity of the model carries the risk of exceeding the data supply capacity. The mechanism analysis of the empirical model, such as research on slope erosion in the Loess Plateau, often overlooks a crucial factor triggering gully erosion—gravity erosion at the watershed scale. Most physical models focus primarily on slope and watershed erosion processes, neglecting the impact of gully erosion on water and sediment loss. This omission can result in the accumulation of errors during the simulation process (Batista et al., 2019). Meanwhile, the validation of the model is also limited to the regression analysis of the simulated and real values, ignoring the accuracy differences between different models within the same validation environment.

3) The spatial heterogeneity of erosion factors and the scale variability of soil erosion are essential pathways by which to improve the accuracy of runoff and sediment analysis in remote sensing erosion monitoring. However, most of the current models encounter challenges in describing the spatial variability of rainfall, surface features, and vegetation. For example, to describe the impact of the spatial characteristics of rainfall on the hydro-morphological system, it is necessary to obtain not only meteorological radar data at temporal or spatial scales matching the watershed, but also to compute hydrological response patterns at the watershed scale in the context of complex climatic patterns (Peleg et al., 2021). Most erosion models are limited in terms of underestimating large events and overestimating small events (Benavidez et al., 2018). If the spatial heterogeneity involved in the simulation of erosion elements or processes is completely ignored, it will reduce the predictive accuracy of the runoff and sediment process simulation, resulting in the accumulation of errors at different spatial scales. Historically, research on the dynamic changes of soil erosion has mainly focused on studying the effects of single factors or multiple factors on erosion evolution from a single spatial or temporal scale. However, regarding the comprehensive assessment of erosion over long sequences, under the interaction of multiple erosion factors, the research remains incomplete (Liang and Fang, 2021).

6.2 Prospects

The continuous advancements of remote sensing technology, the diversification of data sources, and the profound study of

remote sensing mechanisms in soil erosion provide support for the high-accuracy analysis of regional soil erosion. Considering the current research status and addressing the existing issues and development trends of soil erosion research, the following future directions are proposed.

1) Soil erosion research surveys based on remote sensing require upgraded data processing techniques and methods, and technologies such as 3D laser scanning, deep learning, and neural networks could enable the integration of remote sensing data with higher accuracy. The problem of long time series variations in remote sensing images has also been alleviated by the launch of experimental satellites focusing on the spatial and temporal distribution characteristics of rainfall. Synthetic aperture radar and LiDAR are proficient in acquiring high-precision vertical structural information unaffected by weather conditions, which is highly applicable for the estimation of non-photosynthetic vegetation cover. Based on LiDAR data and Landsat ETM+ data, Zhang et al. (2016) used multiple stepwise regression, random forest, and Cubist models to obtain the empirical relationship associated with temperate forest depression. This approach fully demonstrated the significant advantages of LiDAR in reflecting the erosion status of surface vegetation. Utilizing the spectral and spatial–temporal complementarity of multi-source data to improve the inversion accuracy is expected to facilitate the high-precision monitoring of non-photosynthetic vegetation cover and gully erosion extraction over long time series. For instance, Chen et al. (2024) developed an accurate and efficient LWG mapping method for the precise mapping of loess-water-eroded gully areas by integrating satellite images with DEM using deep learning techniques.

2) The practical application and accuracy of the model relies heavily on basic research, so it is necessary to strengthen the identification of fundamental concepts related to soil erosion. This involves promoting the collaborative development of theoretical and practical research in models and helping to develop erosion models with strong predictive abilities, minimal data requirements, and higher practicality by considering other disciplines. Additionally, remote sensing images reflect the comprehensive information of various natural features on the land surface. To enhance their monitoring and understanding, it is necessary not only to strengthen the coupling between data-driven and model-driven approaches but also to reinforce the need for comprehensive interpretation combined with non-remote-sensing information. The Iowa Daily Erosion Project (IDEP) is driven by soil, topographic, and crop management information provided by the United States Department of Agriculture, in conjunction with the WEPP model (Gelder et al., 2018). It also incorporates rainfall data obtained from weather radar, as well as detailed meteorological and hydrological data as a supplement to remotely sensed data, to generate daily assessments of soil erosion and runoff.

3) The capabilities of 3S technology are fully utilized through the integration of quantitative models with GIS. This not only enhances the spatial analysis capabilities of the model but also strengthens the spatiotemporal dynamic simulation of regional soil erosion. In research on the integrality of erosion models, the interoperability and general applicability among models should also be focused on. The combination of existing erosion models with deep learning and machine learning models has significantly improved the accuracy in predicting gully erosion in erosion-prone areas, laying the foundation for soil erosion modelling under subsequent multi-model integration (Saha et al., 2021).

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