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Coupling Benefit of Land Use, Land Cover Change and Soil Erosion Under Algorithmic Optimization Model

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Abstract

INTRODUCTION: Technology realizes the quantitative and positioning acquisition of soil erosion and land use information, grasps the relationship between the two from space, and provides theoretical reference and scientific basis for local ecological environment construction and soil and water conservation work.
OBJECTIVES: This paper uses remote sensing images in my country in 2020 and 2021 as the data source and obtains land use data in four periods, respectively. The experimental results show that the land use structure in my country underwent great changes in 2020, and the land use type gradually changed from a structure dominated by cultivated land, grassland, and unused land to grassland, forest land, and cultivated land.
METHODS: The economic and financial effects of the Belt and Road policy can provide a more comprehensive understanding of the significance of the Belt and Road Initiative, which positively enhances economic development. The other four types of land use area have increased to varying degrees; the unused land has decreased significantly, and the grassland and forest land have increased considerably; there are differences in the changes in the degree of land use in each study period, and the overall level of land use has developed phase by phase toward higher levels
RESULTS: This paper also studies the clustering algorithm in machine learning and proposes an improved interpolation algorithm for completing the original rainfall data.
CONCLUSION: This algorithm can also be applied to the calculation process of rainfall erosion factors, which realizes the automatic calculation system of soil erosion model factors, realizes real-time calculation and monitoring of soil erosion in the form of calculation tasks, and solving the problem that manual calculation consumes manpower and material resources.

Keywords: improved interpolation; land cover; soil erosion.

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1. Introduction

The spatial structure and character characteristics of the land will reduce the land area and quality, resulting in the loss of land resources; the change of land use cover changes the original surface runoff, vegetation phenology and soil microscopic physical and chemical properties, which become the factors affecting soil encroachment [1-2]. Unsustainable land use, such as deforestation, intensive agriculture, and urbanization, hastens soil erosion, compromising soil health, biodiversity, and water quality. Effective land use management and control are critical for maintaining ecosystem services and promoting sustainable agriculture.

In recent years, the negative impact of global land degradation, environmental quality and human and animal health due to soil erosion has become increasingly serious, causing serious economic and environmental problems in many countries. Cover cropping, crop rotation, conservation tillage, buffer zones, agroforestry, and reforestation are examples of land management methods that can help to preserve soil quality throughout land use changes. These measures help to prevent erosion, maintain nutrient balance, minimize compaction, stabilize soil,

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increase organic matter content, and avoid degradation caused by urbanization or agricultural intensification. Reasonable land use and cover changes can effectively improve the natural environment factors such as soil, runoff, and climate so that soil encroachment can be controlled and the ecological environment can be effectively managed and restored. Reforestation, erosion control structures, bioremediation techniques, controlled grazing practices, and the establishment of protected areas can all help to restore ecological balance in places prone to soil invasion. These techniques improve soil stability, restore habitat, and prevent further invasion by minimizing compaction and overgrazing. The first is theoretical significance. Although soil erosion is a long-standing phenomenon, it is limited to the degree of understanding of natural processes and the restriction of research methods. The systematic study of soil erosion has been a matter of recent decades since the 1990s. Community involvement in restoration approaches adapts to local conditions, educating communities about soil, weather patterns, and erosion control methods. This promotes long-term project sustainability, ownership, and culturally relevant approaches, hence increasing community support and engagement in conservation initiatives. The research on the relationship between land use cover change and soil encroachment has become an important topic in environmental research, especially since the application of technology has realized the location and acquisition of soil encroachment and land use information, making the research on land use cover change and soil encroachment closer. Understanding how land use changes affect soil encroachment aids in the identification of crucial conservation zones, such as deforestation or urbanization, and focused interventions, such as reforestation and soil conservation techniques. This provides policymakers with information about sustainable land management strategies that balance development and environmental preservation. The four main drivers influencing land use intensity are population increases, urban expansion, agricultural intensification, economic development policies, climate variability, and ecological conservation efforts. Population growth and urbanization lower plant cover, whilst intensive farming techniques intensify land usage, affecting erosion rates and soil stability.

Normative scientific, and systematic development. The second is practical significance. In the middle of the 20th century, the area of wind, water erosion and desertification in my country increased, the three large sand belts in the territory gradually expanded, and the ecological environment was seriously damaged. In China, various environmental environment governance projects have been implemented successively, such as managing Beijing-Tianjin sandstorm sources, environmental migration, and returning farmland to forests and grasslands. In recent years, the desertification area has been significantly reduced, the forest land has increased in large areas, and the sand and dust weather has been effectively controlled [4]. The analysis emphasizes China's Belt and Road Initiative's concerns in balancing economic development and environmental protection, citing greater land disturbance, deforestation, and soil erosion threats. It proposes strong governance, multinational collaboration, and regulatory measures to address these concerns.

In monitoring soil erosion, geographic researchers usually use the real-time rainfall data collected by rainfall stations as the original data for calculation. However, rainfall data differs from common data, which is spatial [5]. Model performance feedback can help discover data gaps, improve data quality checks, adjust validation processes, and determine the need for additional monitoring stations or sensors. Incorporating input into data collection promotes continual improvement and future data that meets model precision criteria. Due to the limitations of manpower, material resources, terrain and other factors, researchers can only reasonably distribute rainfall stations in the observation area as the observation points of rainfall [6]. Rainfall data collected by interpolation is critical for soil erosion models because it improves forecasts of erosion rates owing to rainfall variability. This data is also useful in assessing erosion risk, allowing for more effective soil conservation techniques and better land management practices. Based on this situation, researchers will use an appropriate interpolation algorithm to obtain the rainfall at any other location based on the rainfall data at the location of the rainfall station, that is, to realize the expansion of rainfall calculation from point to surface. In addition, the rainfall data is collected through physical devices, and the rainfall data needs to be transmitted through the network, which will inevitably lead to data loss due to device damage, network blockage and other reasons. To reduce data loss, use redundant transmission systems, real-time data backup, planned automated synchronization, data compression, and efficient encoding methods. These techniques ensure data can reach the database even if one system fails, reducing data gaps and improving transmission reliability. Therefore, a calculation method is needed to compensate for the lost rainfall data. [7]. The research and improvement of the interpolation algorithm are of great significance to the scientific research work of geographic researchers. An effective rainfall interpolation algorithm should be adaptive, resistant to outliers, able to integrate numerous data sources, and computationally efficient for real-time applications, providing realistic rainfall variance across landscapes and time frames. In the national soil and water loss monitoring work, researchers take the Chinese soil loss equation as the core to predict and analyze the soil and water erosion in the area of interest, realize real-time erosion monitoring and calculation, and support the spatial calculation of soil and water conservation data. Provide better information support. Therefore, an automated computing system can save a lot of manpower, material resources, and time costs, and it can positively affect the country's soil and water conservation work [8]. To sum up, this topic's three main content relationships are shown in Figure 1.

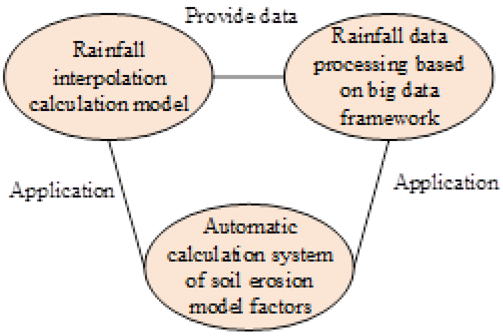

Figure 1. Research content relationship diagram

To sum up, the improved interpolation algorithm can improve interpolation accuracy to predict rainfall at any location in the area. This block can be directly applied to the automatic calculation system of soil erosion model factors. The big data framework processes rainfall data, provides basic data for predicting rainfall at any region location, and improves the data processing performance.

2. Related works

At the end of this century, influenced by Western science and technology development, my country began to study soil erosion science. [10] According to the observation data of hydrology and sediment in the small watersheds of northern Shaanxi, western Shanxi and southeastern Long Dong, a statistical model for estimating sediment yield in the sub-rainfall watershed was established. [11] According to the observation data of the Chaba watershed in Zizou, northern Shaanxi, the estimated small watershed was established using empirical formulas for forecasting sub-flood and annual sediment yield. In the mid-20th century, some researchers began to study conceptual models based on the physical processes of erosion and sediment production [12]. Sreekar looks into using K-means clustering in cloud computing to analyze Gaussian data. The results reveal that cluster sizes considerably impact computation speed and accuracy, resulting in cost savings. The study emphasizes the value of intelligent resource management and selecting the ideal beginning points for optimal clustering performance [13]. Rajya offers an improved version of the Variational Autoencoder Generative Adversarial Network (VAEGAN) for detecting credit card fraud, which is widespread when shopping online. The method generates diverse minority class data using a new oversampling strategy and a Convolutional Neural Network (CNN), enhancing fraud detection accuracy. The model beats current techniques regarding accuracy, precision, recall, and F1 score [14]. Physical erosion models like WEPP and RUSLE use sophisticated equations but require much field data. Machine learning clustering methods such as K-means can generate reliable erosion forecasts from current data without requiring high physical parameter precision. The two major units of beam slope and ditch slope are summarized, and from the dynamic point of view, using bed and suspended sediment transport formulas, the estimation of sediment production in small watersheds is established. The mathematical model of the quantity [15]. According to the mechanism of watershed runoff formation and erosion and sediment production, using the basic theory of hydrology and sediment movement mechanics, a small watershed sediment production dynamic model with a strong physical origin was constructed [16]. The Chengdu Institute of Mountain Hazards and Beijing Forestry University have conducted remote sensing application experiments and research, covering the whole country, large rivers, key soil erosion areas and small watersheds. Land use data is collected using remote sensing techniques such as high-resolution satellite images, multispectral and hyperspectral imaging, and lidar. These methodologies allow for precise classification of land use types, vegetation health, land cover changes, and surface composition, which is critical for soil erosion modelling. Conduct remote sensing surveys and monitoring and compile many remote sensing images [17]. Using the artificial visual interpretation of the latest satellite photos, a map of the current situation of soil erosion in various provinces across the country was drawn.

The predicted values have gradually become more and more accurate. They used WLSTM, CLSTM, multilayer perceptron and LSTM for rainfall forecasting, and the results showed that the LSTM method is a better choice for time series forecasting. A precipitation prediction model based on random forest was established based on the measured rainfall data of Liangshan Hydrological Station. By comparing with the traditional rainfall forecasting model, it is concluded that the rainfall forecasting model based on random forest has high forecasting accuracy and can avoid the phenomenon of overfitting. A precipitation budget model combining a support vector machine and particle swarm optimization algorithm was pioneered. Machine learning clustering methods, such as K-means, strike a compromise between interpretability, computational economy, and effectiveness, making them ideal for large-scale environmental data analysis. Deep learning methods like CNNs can capture complicated spatial patterns, potentially enhancing prediction accuracy while needing more computer resources.

The above studies are based on collecting local historical geological data and using machine learning or deep learning methods to predict soil erosion. This also provides a broad idea for the research on the calculation model of land cover change and soil erosion. The study proposes a method for improving land use data collection and analysis using remote sensing images, including an improved interpolation algorithm for rainfall data, machine learning techniques like K-means for erosion forecasts, and an automated computing system for real-time soil erosion monitoring, incorporating feedback for continuous improvement.

3. Soil erosion model and interpolation calculation method

3.1. Soil erosion model

Soil erosion monitoring is important in our country's environmental protection work. In geographic ecological protection, the soil erosion calculation model is the simplest and most effective calculation method that has been researched. The K-means algorithm and interpolation method efficiently capture environmental variability by grouping comparable landscape elements. They are computationally efficient, appropriate for large-scale ecological research, and have excellent reproducibility and interpretability. They are useful for making environmental predictions, policy suggestions, and management decisions when dealing with enormous amounts of remote sensing data. Since the 1960s, geographic research experts from all over the world have developed many formulas related to soil erosion calculation to monitor the situation of land loss. Soil erosion prediction accuracy is improved by machine learning approaches such as Random Forest, Support Vector Machines, and Neural Networks, which analyze big datasets and uncover nonlinear correlations between parameters such as rainfall patterns, land cover, soil type, and topography. This real-time data integration and adaptive learning eliminate subjectivity, resulting in a more dynamic and data-driven approach to soil erosion modelling. Climate variables such as rainfall and temperature substantially impact soil erosion and land use change. Intense rainfall promotes soil separation, but extended dry times reduce vegetation cover. These changes frequently necessitate adjustments to land use or soil conservation strategies. However, these calculation formulas are built in different ways. We can divide them into empirical statistical models and physical cause models. Empirical statistical models, such as the USLE, employ observable data to connect erosion causes and rates, although they may be inaccurate in complicated situations. Physical cause models, such as the WEPP, mimic erosion through sediment separation, transport, and deposition, providing precise insights for dynamic or short-term erosion predictions. The empirical model is mainly aimed at the phenomenon of sediment production and runoff caused by rainfall scouring. Therefore, a few factors have been established: rainfall erosion, runoff sediment, plant coverage, land moisture content, soil water conservation measures, and land use methods. Relational expressions between factors. There are two main research objects for this type of model: sediment production and slope in small watersheds.

USLE allows the concept of soil loss to be expressed numerically using a multiplicative form of six factors. The Universal Soil Loss Equation (USLE) has six components: R (Rainfall Erosivity), K (Soil Erodibility), LS (Slope Length and Steepness), C (Cover and Management), P (Support Practice), and A (Predicted Soil Loss). These elements include environmental and land management aspects influencing erosion potential, resulting in a comprehensive model for assessing soil loss and guiding conservation strategies. The USLE model is recommended because of its simplicity, ease of application, and dependability in estimating erosion with limited data, making it appropriate for resource-constrained locations or areas lacking precise input. The specific situation of USLE is shown in the following Equation:

$$A = R * K * L * S * C * P \quad \text{Equation (1)}$$

Where is the rainfall erosivity factor. Rainfall erosivity generally expresses the ability of the soil structure to be damaged due to the falling and scouring of raindrops. It depends on the falling rate of raindrops during the rainfall process and some rainfall characteristics, such as the volume of raindrops. Soil erosion is caused by splashing raindrops and runoff from rainfall scouring, which causes soil particles to be separated and transported. Vegetation cover is an efficient natural defence against soil erosion. It absorbs kinetic energy, stops soil particles from being displaced, improves soil structure, increases water infiltration, and slows water movement. K-means Clustering is a basic and fast machine-learning approach that can be used in environmental studies, particularly to model soil erosion. It is quicker and easier to use than complicated models such as SVM or deep learning clustering, which demand a lot of computing power. However, neural networks may be more computationally costly and complex, rendering them unsuitable for soil erosion modelling. The effect of this rain damage depends not only on the structure of the land but also on some other properties of the soil, such as the slope of the land, whether there is sufficient vegetation protection on the surface, and what human protection measures are in place.

is the soil erodibility factor. Soil is the target of erosion, and after the soil has been washed, the soil will be mixed into the river to form sediment. The soil structure is different, resulting in different soils' resistance to external forces such as raindrops and water erosion. The K factor describes the ability of the land to respond to external effects such as raindrops and water erosion, and the magnitude of the value can reflect this ability. The smaller the K value, the weaker the induction ability, that is, the more difficult it is to be eroded; the larger the K value, the stronger the induction ability, and the easier the land is to be eroded.

3.2. Interpolation algorithm

Interpolation algorithms generally predict information at unknown points from known sample point information. The general idea includes artificially specifying the numerical relationship between the known sample point and the unknown point, adding an appropriate weight coefficient to the known point, and obtaining the value at the unknown point. Weight coefficients are optimized via interpolation algorithms using crossvalidation, machine learning techniques like gradient descent, and context-specific variables such as topography and distance to known points. These approaches repeatedly compare multiple weights on known data points to get the best values for predicting unknown points. The new interpolation approach increases rainfall data accuracy by addressing geographical variability, an important factor in soil erosion models. It combines spatial and temporal rainfall data from multiple sources to produce more precise and localized estimates. This level of accuracy is critical for soil erosion modelling, as it improves prediction dependability. Or fit a suitable function through the known points and then substitute the variables of the unknown points to calculate the predicted value. Common interpolation algorithms include reverse distance weight interpolation, kriging interpolation, nearest neighbour interpolation, etc.

Among them, the idea of the reverse distance weight interpolation algorithm is that in a search range, the observation point that is closer to the unknown point is more likely to affect the unknown point, and vice versa, with less impact. The enhanced interpolation approach enhances rainfall and soil erosion forecasts by capturing finer-scale geographical changes in rainfall data. It integrates multiple data sources to reduce mistakes in forecasting erosive force on various terrain types. This precision results in more accurate erosion estimates over numerous clusters. The inverse distance weight interpolation algorithm stipulates that its weight coefficient is represented by the power of the reciprocal distance, where the power value is a positive number, and its default value is 2. The number of sample points participating in the calculation can be artificially specified to avoid points with too low weights participating in the calculation process, resulting in unnecessary waste of computing resources. The specific calculation principle is shown in the Equation:

$$\mu_x = \sum_{i=1}^{N} \omega_i \, y_i \quad \text{Equation (2)}$$

$$\omega_i = \frac{d_{ix} - p}{\sum_{i=1}^{N} d_{ix}{}^{-p}} \quad \text{Equation (3)}$$

$$\sum_{i=1}^{N} \omega_i = 1 \quad \text{Equation (4)}$$

4. Methods

This chapter mainly proposes an optimized soil erosion interpolation calculation model to realize the estimation and prediction of soil erosion at a certain location. In the process of filling in the missing data of the rainfall station and calculating the soil erosion factor, we will use the interpolation method to obtain the rainfall and soil erosion at the predicted point. The soil erosion prediction model entails data collection, factor calculation, interpolation, model application, analysis and validation, and output interpretation. It collects information on rainfall, soil type, slope, land cover, and conservation strategies, then calculates factors, interpolates, and applies the model to estimate prospective soil erosion rates. The optimized soil erosion interpolation calculation model proposed in this chapter can improve the calculation accuracy of the predicted value. Land cover changes influence erosion projections by changing the soil's exposure to erosive forces. Vegetation cover protects the soil by minimizing raindrop impact, whereas barren terrain is more susceptible. The model uses land cover data and climate variables to forecast erosion vulnerability under specified conditions. Since the rainfall data is monitored by the rainfall station and transmitted into the database through the network, the phenomenon of data missing will inevitably occur. Therefore, it is necessary to conduct a data quality audit after the data is stored in the database. If data is found to be missing, it is necessary to take certain measures to make up for the missing data. In the previous topic, we directly filled the missing rainfall data as 0, which would cause the calculation results to deviate from the actual situation.

Based on the above analysis, we finally selected the K-means calculation method combined with the row algorithm as the model for soil erosion prediction. It uses K-means clustering and an enhanced interpolation approach to analyze erosion risk zones in various environmental data sets. This method simplifies segmentation and gives high-resolution rainfall estimates, addressing the limits of existing methods in complex terrains and improving the portrayal of soil erosion processes. In addition, we used the error between the predicted results of soil erosion and the actual soil erosion as the evaluation standard of calculation accuracy. In order to explore the relationship between the number of clusters and the prediction results of erosion, we also recorded the values of three evaluation indicators of clustering during the experiment: silhouette coefficient, CH, and DBI. Landscape heterogeneity, soil type variability, rainfall intensity distribution, land cover types, and topographic parameters were all examined to estimate the number of groups in the K-means clustering technique for forecasting soil erosion. Clustering accuracy was improved using the Elbow Method and the Silhouette Score. In this way, we can explore whether the quality of the clustering effect has an obvious relationship with the erosion prediction model proposed in this subject. The interpolation model combines climatic data, wind erosion data, soil nutrient levels, and vegetation characteristics to provide a comprehensive perspective of erosion hazards, allowing for accurate soil loss projections across a range of landscape circumstances while ensuring spatial and temporal continuity. Land use changes and soil erosion are analyzed using remote sensing technologies and rainfall data from 2020 and 2021. It uses interpolation methods, K-means clustering, and an optimized soil erosion prediction model. The model's accuracy is evaluated by comparing anticipated rates to actual data, and feedback mechanisms are provided to ensure ongoing development.

Step 1: Obtain the coordinate values of soil erosion in my country in the two-dimensional coordinate system.

Step 2: Integrate the rainfall data and the coordinate distribution data of the rainfall stations and select two data sets with 300 rainfall stations as unknown points. In one of the data sets, the rainfall at all stations is greater than 0, and this data is used to represent the dense rainfall. The file name is TEST.SCV; about 1/4 of the rainfall stations have a rainfall greater than 0, and the remaining rainfall stations are all 0. This data is used to represent the dry season with less rainfall.

Step 3: The prediction results are evaluated using the error sum of squares method, and the results are compared with the computational model without the clustering algorithm. K-means clustering is an important approach in soil erosion analysis because it groups similar locations according to erosion-influencing characteristics. This enables more specific research and projections, exposing high-risk locations. This granular modelling improves the model's capacity to precisely represent regional diversity in erosion risk, resulting in more precise soil erosion predictions. Its calculation formula is as Equation:

$$SSE = \sum_{i=1}^{N}(y_i - \hat{y}_l)^2 \quad \text{Equation (5)}$$

Its technical flow chart is shown in Figure 2:

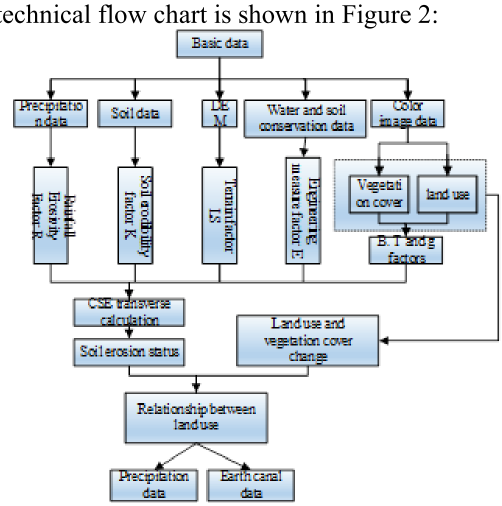

Figure 2. Flow chart of soil erosion factor calculation technology

In this calculation process, the main data sets involved are shown in Table 1:

Table 1. Data set field collation table

1. Climate data	Air temperature (minimum, maximum, average)
	temperature (min, max, average)
	Wind speed (max, average, wind direction)
2. Determination of wind erosion soil nutrients	Non-growing season: full carbon, full nitrogen, full hydrogen, carbon-nitrogen ratio, carbon-hydrogen ratio
	Growing season: full carbon, full nitrogen, full hydrogen, carbon to nitrogen ratio, carbon to hydrogen ratio
3. Surface vegetation characteristics	Vegetation height, coverage, existing stock
4. Determination of particle size of wind erosion soil	non-growing season
	growing season

The flow chart of the idea based on the calculation of terrain factors in this study is shown in Figure 3:

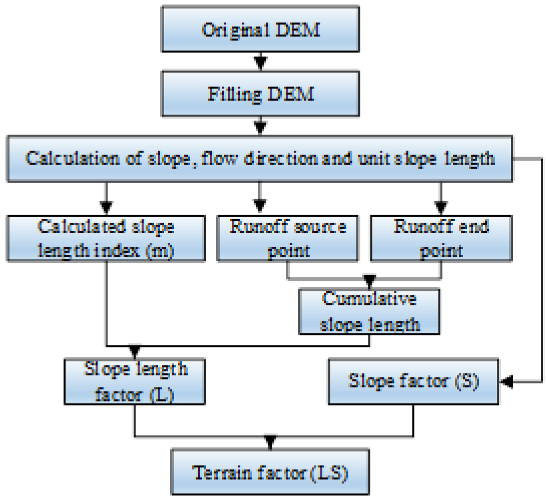

Figure 3. LS factor calculation flow chart

After that, using the contour map of 10m resolution in the spatial analysis module of ArcGIS9.3, the format DEM map of 30m resolution is generated. Its slope length factor algorithm is shown in the following Equation:

$$S = \begin{cases} 10.8\sin\theta + 0.03 & \theta < 5^{\circ} \\ 16.8\sin\theta - 0.5 & 5^{\circ} \leq \theta < 10^{\circ} \\ 21.9\sin\theta - 0.96 & \theta \geq 10^{\circ} \end{cases} \quad \text{Equation (6)}$$

The operation process is expressed as the function called first to fill the data; the slope factor extraction method is based on the slope value obtained by the maximum slope drop method, and the grid slope value is the height of the grid and the grid cell in the direction of the maximum slope drop. The difference is divided by the horizontal distance between the centres of the two grids. The slope algorithm is very mature. The functions and functions directly called extract the slope and the slope aspect and divide the slope segment according to the formula to obtain the slope factor value of the grid cell. The algorithm calculates the runoff flow direction to determine the slope length of the grid cell, finds the runoff source point and the runoff endpoint through the slope map, and takes the runoff source point as the starting point to calculate the maximum gradient direction accumulation about the grid cell. Slope length: Take the cumulative maximum value as the grid cell slope length and traverse it to calculate the slope length of each grid. Its topographic factor eigenvalues are shown in Table 2.

Table 2. Topographic factor characteristic value table

Topographic factor	Minimum value	Maximum	Average value	Standard deviation
L factor	0.55	8.72	4.63	0.42
S factor	0.31	16.15	8.23	1.61
LS factor	0.028	58.43	29.23	2.41

5. Case study

The experimental results show that in addition to meeting the functional requirements of users, the design of the erosion factor calculation system also needs to ensure some non-functional requirements, such as accuracy, maintainability, and integrity. The study used Geographic Information System (GIS) software, such as ArcGIS or QGIS, to analyze spatial data and generate erosion risk maps. The datasets were processed, and USLE factors were calculated using statistical analysis software such as R or Python. High-performance computers with plenty of RAM and storage were employed for efficient data processing and visualization.

5.1. Improve the accuracy of calculation results

The accuracy is reflected in the system's calculation results. For this system, calculation is the core function, and the result of system calculation will directly affect the user's judgment on regional soil erosion. To ensure the system's accuracy, we must first ensure the correctness and integrity of the calculation data and, secondly, ensure the correctness of the calculation formulas and methods in the system. Therefore, we need to ensure the correctness of the method realization link in the data preprocessing link, the basic data maintenance link, and the calculation formula and calculation.
Under the calculation of the optimized interpolation algorithm, the average temperature change is shown in Figure 4.

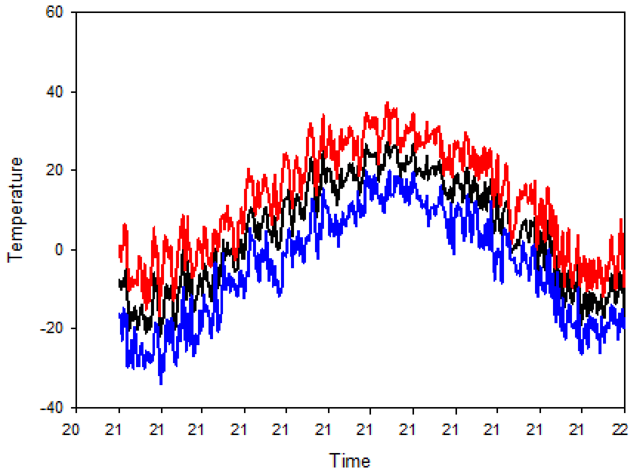

Figure 4. Schematic diagram of temperature changes in 2020-2021

Its humidity change is shown in Figure 5:

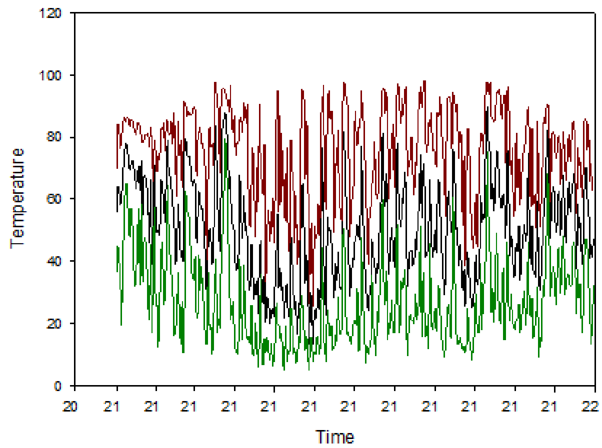

Figure 5. Schematic diagram of humidity changes in 2020-2021

The change in wind speed is shown in Figure 6:

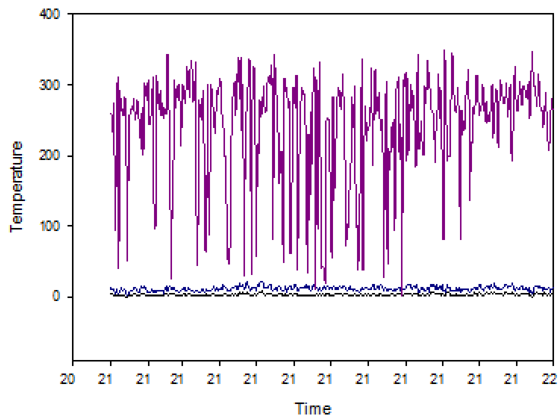

Figure 6. Schematic diagram of wind speed changes in 2020-2021

5.2. Algorithm maintainability and integrity improvement

The development and implementation of the system need to satisfy maintainability. The research and implementation of this system is mainly through the JAVA development language, through the construction of the SPRING BOOT development framework, combined with the SPRING JPA data persistence layer framework, to achieve the maintenance of the data in the database. Secondly, in the calculation part of geographic data, the GDAL class library in Java language is used to perform operations such as cropping and vector multiplication. Secondly, all the generated results in this system are in the form of files, and we have organized a set of file directory structures based on administrative divisions to store data. Therefore, the maintainability of the system is high. Integrity is reflected in the design level of the system architecture. The system is mainly composed of three modules. The processing and calculation module of rainfall data is responsible for verifying and calculating the system input data. The soil erosion model factor calculation module is accountable for realizing the factor calculation and obtaining the user's target result. The data storage and maintenance module is responsible for storing and maintaining system files.
The final soil erosion transfer matrix calculation results are shown in Table 3:

Table 3. Schematic diagram of calculation results of soil erosion transfer matrix

		1997						
1975year		Micro degree	Light	Moderate	Strength	Extremely strong 1	Extremely strong 2	Severe
Micro degree	Km^2%	994.39	343.29	105.14	32.03	8.27	1.25	0.68
		66.97	23.14	7.09	2.17	0.57	0.09	0.05
Light	Km^2%	166.78	389.79	538.49	205.82	33.61	15.43	18.32
		12.21	28.51	39.37	15.05	2.46	1.14	1.35
Moderate	Km^2%	76.28	189.9	472.48	555.35	490.68	128.39	27.22
		3.94	9.79	24.36	28.63	25.31	6.63	1.41
Strength	Km^2%	2.23	108.29	135.51	252.96	364.02	277.55	425.09

6. Conclusion

This paper mainly introduces the realization of the automatic calculation system of soil erosion model factors. Firstly, the realization goal of the system is outlined, and then the requirements of the system are analyzed from the functional and non-functional aspects. Then, the system's design is expounded, and the system is introduced mainly from system function and database design aspects. Finally, the system's detailed calculation process is introduced. The function and performance test of the system rainfall data processing module and soil erosion model factor calculation module are carried out.

Declarations

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