

Article

Estimating the Soil Erosion Response to Land-Use Change Using GIS-Based RUSLE and Remote Sensing: A Case Study of Heilongjiang Province, China

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Abstract: Understanding soil erosion in the northeastern area of China with black soil is vital for protecting the natural environment and preserving food security. Although spatial and temporal studies of soil erosion have been conducted, further research is needed on the correlation between soil erosion and land use type changes. In this study, the soil erosion modulus is computed using RUSLE. The model that is most suitable to the research area was produced by contrasting three different approaches to estimating the rainfall erosion factor. The RUSLE based on the multi-year continuous high-density hourly average precipitation had the best performance of the bunch, with a MAPE of 15.49%, RMSPE of 7.99%, and R^2 of 0.99. Based on this model, simulated soil erosion trends in the study region from 1980 to 2020 were examined, along with the link between soil erosion and land use change. The results showed that 40.47% of the overall erosion area is made up of cultivated land, and 97.83% of it is low erosion. The most severe soil erosion occurred on unused land, with moderate and above soil erosion occupying 48.93%. Since 2000, there has been an increase in the erosion of soil in the study region, which is primarily spatially represented in the rise in the soil erosion of forests in the central and northern mountainous areas. The study's findings serve as a guide for land planning and the development of sustainable agriculture.

Keywords: black soil of northeast China; soil erosion; RUSLE; R factor; land use change



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1. Introduction

As the source of all things and the root of life, soil carries the important task of promoting the growth and prosperity of all things and is one of the natural resources that cannot be renewed to promote scientific and technological progress and human development [1]. However, owing to long-term over-cultivation and use, fast population expansion accompanied by the accelerated industrial revolution, gentrification, long-term over-cultivation and utilization, climate change, and other factors, soil degradation has brought challenges to sustainable human development [2]. One of the most prevalent types of soil degradation is soil erosion, which is a natural process where the topsoil is stripped from its original location, exposing the subsoil. Moreover, transporting and depositing the stripped dirt to the most distant location causes deposition issues in water bodies [3–5]. Soil erosion is a major environmental issue on a worldwide scale. It has a number of detrimental effects, including reducing the quality of water, eroding soil fertility, and jeopardizing food security [6–9]. Furthermore, soil erosion is a key problem resulting in land degradation [10]. Boasting a soil erosion area of 2.67 million km², or 27.76% of the country's total surface area, China has one of the greatest rates of soil erosion in the entire world [11]. The substantial threat that soil erosion poses to the availability of food, water supplies, the natural world, and ecological integrity has garnered the attention of many governments and academics [12,13].

The Soil Carbon Initiative, which aims to align soil security policy with those on the protection of water and food, was started by a global coalition of scientists [14]. In order to preserve soil, provide food security, and manage water resources sustainably, it is crucial to investigate and evaluate soil erosion.

Since the 21st century, research on soil erosion at home and abroad has often integrated multiple methods for more accurate estimation, with outdoor runoff plot monitoring, indoor model estimation, the stylus method, fixed-point observation, laser scanning, and isotope tracing, as well as other methodological techniques being very widely used [8,15–18]. Although there are various methods to study soil erosion, these methods are generally costly and time-consuming to conduct on a large scale. Soil erosion models typically comprise both experiential and physical models that can accurately assess soil and water erosion. Physical models, e.g., the water erosion prediction project (WEPP) and pan-European soil erosion risk assessment (PESERA), are more complex, the measurements are more difficult to obtain, and they are not suitable for large area soil evaluations [15–17]. The flexibility of the empirical model in areas of data scarcity enhances its reception and application. Among them, the revised universal soil loss equation (RUSLE) model has been widely recognized and applied in the field of soil erosion worldwide because of its extensive use of data, high data accessibility, sufficient information basis, and wide area coverage [19–23].

The rainfall erosion rate can be determined from rainfall observation data and is a measure of the capacity of rainfall to produce soil erosion. It is a key input parameter to soil erosion models and is currently widely used in the RUSLE [24,25]. The erosive power of a rainfall event is measured as the product of the total storm energy (E) and the maximum 30 min intensity (I_{30}) of the event (EI_{30}) [26]. The rainfall erosivity indicator needs to be calculated using the information on the intensity of rainfall at breakpoints or equal interval rainfall processes with observation intervals less than or equal to 5 min. However, the relevant data mentioned above are difficult to obtain. It has been found through numerous experimental studies that rainfall erosivity indicators can be calculated from conventional rainfall data. For example, daily, monthly, and annual rainfall statistics. The basic method is to calculate the rainfall erosivity using the stations for which rainfall information has been obtained and to obtain the rainfall erosivity indicator of the area by analyzing the correlation of rainfall erosivity with the distance decay between stations, performing spatial interpolation, and drawing the spatial distribution of rainfall erosivity [24,27,28]. Different regions need to use different precipitation data with different accuracies and calculation methods to achieve the best forecast due to their different climate, altitude, and topography.

Black soil is one of the most valuable resources in the world, a unique treasure that was given to mankind by nature. Black soil has good properties and high fertility, making it an ideal soil for plant growth [29]. One of the three main regions with black soil in the world is northeast China. Here, between 1996 and 2019, 11.6 million hectares of land were converted to agricultural land, diminishing the interconnection and integrity of the ecosystems as well as the habitat offered by wetlands. It has resulted in more than 19% of agricultural soils failing to meet relevant quality standards. Additionally, due to its high organic matter content and loose structure, black soil is delicate and prone to erosion [30]. In 2022, the total grain output of Heilongjiang Province was 7.76 million tons; it was the first in the country for thirteen consecutive years and is an important grain base in China [31]. However, to maintain food security, steps must be made to promote land fertility recovery [30,32]. Thus, the (draft) law for the conservation of black soil was released by the Chinese National People's Congress in December 2021. Through small-scale field experiments and the use of models, several authors have evaluated soil erosion in the study region [33–36]. Accuracy validation was achieved by comparing the results with previous studies (runoff maps, ^{137}Cs tracing techniques, and model measurements) [18]. However, most studies were conducted in small areas. In Heilongjiang Province, there has not been much extensive, long-term soil erosion research and it is unclear how the changing land use over the past 40 years has affected soil erosion. Therefore, this study uses Heilongjiang Province as the study area. Meteorological data from 1951 to 2020, land use data from 1980 to 2020, soil

data, and DEM were used to assess soil erosion in Heilongjiang Province using the RUSLE. In addition, the soil and water conservation bulletin of Heilongjiang Province was used as the validation data to analyze and compare three methods of calculating rainfall erosivity factors. The aim was to develop the most applicable model for the study area and increase the reliability of the forecast for soil erosion while revealing the contribution of land use change to soil erosion.

2. Materials and Methods

2.1. Study Area

Heilongjiang Province ($43^{\circ}26'–53^{\circ}33' \text{ N}$, $121^{\circ}11'–135^{\circ}05' \text{ E}$) is located in northeastern China, with a total area of about $47.3 \times 10^4 \text{ km}^2$ (Gagadchi district was not included in this study) (Figure 1). The north borders Russia, the south borders Jilin Province, and the west is adjacent to Inner Mongolia. The topography of the province is complex, with the Songnen Plain in the west, the Sanjiang Plain in the northeast, and the mountains in the north and southeast, with an elevation ranging from 23 to 1694 m.

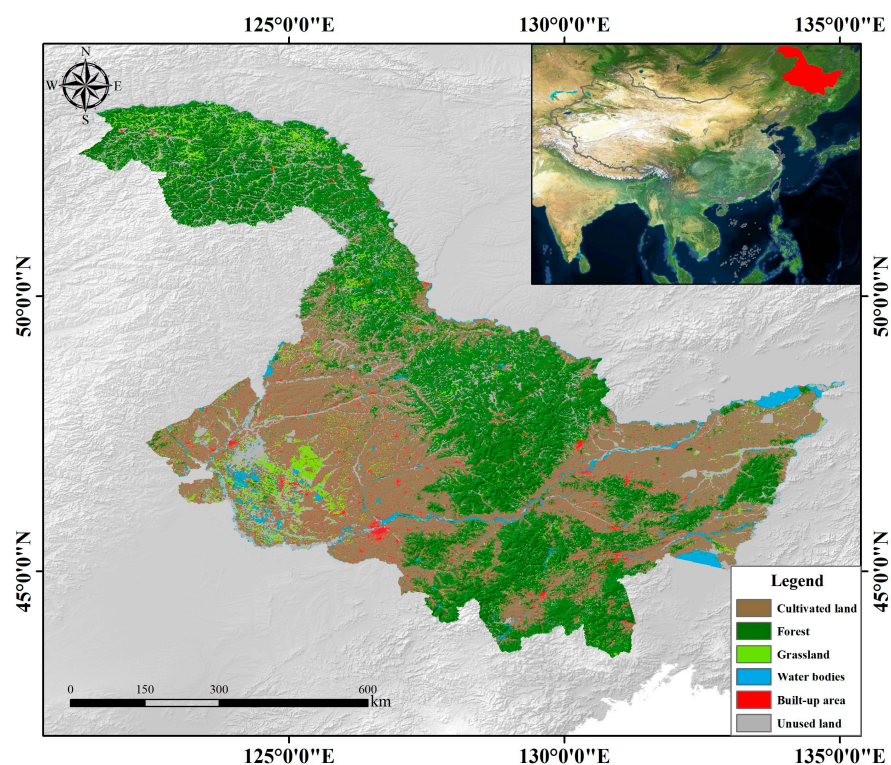


Figure 1. Study area locations. Land use maps of Heilongjiang Province (2020).

The province experiences a continental monsoon climate, with four distinct seasons including hot, wet summers and cold, dry winters. A total of 723.1 mm of precipitation falls each year, with more precipitation in the central mountainous area, followed by the eastern part; the western and northern parts have less rainfall and an average annual water resource of $772 \times 10^8 \text{ m}^3$ [37]. Rich in forest and mineral resources, the vegetation landscape is composed of forests centered on the Daxinganling, Xiaoxinganling, and southeastern mountains, grasslands centered on the Songnen Plain, and wetlands centered on the Sanjiang Plain. The three vegetation zones are mainly temperate grasslands, temperate mixed coniferous forests, and cold temperate coniferous forests.

Heilongjiang Province has many types of soils, mainly black soil, dark brown soil, meadow soil, white pulp soil, black calcium soil, and chestnut calcium soil, and is the Chinese province with the highest proportion of black soil; it is also a largely agricultural province [38]. However, with the accelerated industrialization and urbanization of China and the increasing demand for food, a substantial portion of land has been turned into crop-

land, and the high-intensity arable land use pattern has become a common phenomenon. However, the farmed land in the black soil region has a diminished capacity to hold water and fertilizer, which worsens soil erosion. This, the black soil layer's thickness diminishes, the soil's physical characteristics deteriorate, the texture becomes loose, and the resistance to erosion is impaired [39–41].

2.2. Data and Materials

In this study, the main data used are meteorological data, digital elevation model data (DEM), and land use data.

Land use data were obtained from the data center of the Institute of Resources and Environment, Chinese Academy of Sciences [42]. It was generated by manual visual interpretation based on Landsat TM imagery from the USA. It is a raster dataset with a spatial resolution of 1 km, and its overall accuracy is greater than 92% after field survey data and peer validation [43].

Meteorological data were obtained from the National Climate Center of China [44]. The following criteria were used to handle missing values: a missing day is one with at least four hours missing, a missing month is one with at least six days missing, and a missing year is one with at least one month missing during the wet season. Missing years were removed. The missing period was followed by a non-zero record, and each missing hour and the next non-zero hour were assigned the mean value of the non-zero record in these hours. If the period following the missing period was zero, the hours were entered as a value of zero [45].

Soil data came from the Harmonized World Soil Database version 1.1. The National Tibetan Plateau/Third Pole Environment Data Center provided the information [46]. It is a raster dataset with a spatial resolution of 1 km. By comparison with the land use data, it was found that the areas missing values were water bodies so the default soil erosion for water bodies in this study was zero. A missing value was input as a zero value.

The DEM, which has a resolution of around 90 m, was made available via the Geospatial Data Cloud [47].

2.3. Methods

Soil erosion is controlled by many site conditions, and RUSLE is a linear equation that can simplify a complex system into a fairly simple system that integrates five variables, involving rainfall erosion, erodibility of soil, slope length and gradient, cover management, and strategies to conserve water and soil, for use in predicting the long-term soil erosion of vast areas. It has been demonstrated to be appropriate for the northeast Chinese area with black soil [48–51].

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

where K is the erodibility factor of soil ($\text{ton} \times \text{ha} \times \text{h} \times \text{ha}^{-1} \times \text{MJ}^{-1} \times \text{mm}^{-1}$), A is the soil erosion rate ($\text{ton} \times \text{ha}^{-1} \times \text{a}^{-1}$), R is the rainfall erosion factor ($\text{MJ} \times \text{mm} \times \text{ha}^{-1} \times \text{h}^{-1} \times \text{a}^{-1}$), L and S are the slope length and gradient factors, C is the cover management factor, and P represents strategies to conserve water and soil factors.

The runoff rate and volume directly related to a precipitation event are forecasted by the rainfall erosivity factor (R), which evaluates the influence of rainfall effects in the form of kinetic energy. Different types of precipitation data provide different levels of information richness. The various approaches for calculating rainfall erosivity result in naturally varying degrees of accuracy. Three precipitation erosion rate algorithms to be applied to the northeastern Chinese region of “black soil” are proposed in conjunction with the literature and are analyzed and compared to determine the best algorithm [39,45,49].

The following definitions describe the basic algorithmic methodology for predicting rainfall erosivity based on monthly average precipitation [39]:

$$R = \sum_i^{12} [1.735 \times 10^{(1.5 \times \lg \frac{P_i^2}{P} - 0.8188)}] \quad (2)$$

where P is the yearly precipitation (mm), P_i is the precipitation in the given month (mm), and R is the rainfall erosivity factor ($\text{MJ} \times \text{mm} \times \text{ha}^{-1} \times \text{h}^{-1} \times \text{a}^{-1}$).

The following definitions describe the basic algorithmic methodology for predicting rainfall erosivity based on daily precipitation [49]:

$$R_i = \alpha \sum_{j=1}^i (D_j)^\beta \quad (3)$$

$$\beta = 0.8363 + \frac{18.144}{P_{d12}} + \frac{24.455}{P_{y12}} \quad (4)$$

$$\alpha = 21.586 \times \beta^{-7.1891} \quad (5)$$

where R_i indicates a half-month R ($\text{MJ} \times \text{mm} \times \text{ha}^{-1} \times \text{h}^{-1} \times \text{a}^{-1}$); i represents how many days are in a half-month, and D_j is the damaging downpour on day j . The average daily and yearly rainfall totals of more than 12 mm (mm) are expressed as P_{d12} and P_{y12} , respectively. D_j is equal to the actual amount of rain when it exceeds 12 mm; else, it is 0.

The following definitions describe the basic algorithmic methodology for predicting rainfall erosivity based on the multi-year continuous average high-density hourly precipitation [45]:

$$R = \frac{1}{N} \sum_{i=1}^N \sum_{j=1}^m (EI_{30})_{ij} \quad (6)$$

$$E = \sum_{r=1}^I (\theta_r \times P_r) \quad (7)$$

$$\theta_r = 0.29 \times \left[1 - 0.72 \times e^{-0.082i_r} \right] \quad (8)$$

where EI_{30} (event rainfall erosivity, $\text{MJ} \times \text{mm} \times \text{ha}^{-1} \times \text{h}^{-1}$) is the result of the total storm energy E ($\text{MJ} \times \text{ha}^{-1}$) and the maximum 30 min intensity I_{30} ($\text{mm} \times \text{h}^{-1}$); $j = 1, 2, \dots, m$ denotes that there are m erosive storm occurrences in the i th year, and $i = 1, 2, \dots, N$ is the number of effective years. According to the temporal precision of the rainfall data, the amount of rainfall for each storm event is separated into I time periods. The sum of the energies for each time period r makes up the overall storm energy, E . The energy unit is er (energy per millimeter of rainfall, $\text{MJ} \times \text{ha}^{-1} \times \text{mm}^{-1}$) times the volume of precipitation P_r (mm) for each period of time. Finally, i_r ($\text{mm} \times \text{h}^{-1}$) is the intensity of the r th interval. The I_{30} was taken into account for hourly data as being equivalent to the maximum 1 h intensity.

An essential variable influencing the RUSLE soil erosion estimate model is the soil erodibility factor (K) which describes the viscosity of the soil under the action of raindrops and storm runoff. The type of soil and surface geological components, such as its parent rock, form, and structure, have an impact on how easily soil erodes [52]. Using EPIC to calculate K , the method has been successfully applied to the northeastern Chinese area of “black soil” [39,48,49].

$$K = 0.2 + 0.3e^{[-0.0256sand(1 - \frac{silt}{100})]} \times \left(\frac{silt}{clay + silt} \right)^{0.3} \times \left[1 - \frac{0.25soc}{soc + e^{(3.27 - 2.95soc)}} \right] \times \left[1 - \frac{0.72san}{SN + e^{(22.9san - 5.51)}} \right] \quad (9)$$

where $sand$ is the percentage of sand, $silt$ is the percentage of silt, $clay$ is the percentage of clay, soc is the percentage of soil organic carbon, and san is equal to $1 - sand/100$.

Indicating how topography affects soil erosion, the slope length and slope gradient factor (LS) combines the effects of slope length (L) and slope gradient (S) [53]. The algorithmic model for calculating the LS factor is as follows [48]:

$$\left\{ \begin{array}{l} LS = L \times S \\ L = (\lambda / 22.13)^m \\ m = \begin{cases} 0.5, \theta \geq 5\% \\ 0.4, 3\% < \theta < 5\% \\ 0.3, 1\% < \theta < 3\% \\ 0.2, \theta < 1\% \end{cases} \\ S = \begin{cases} 10.8\sin\theta + 0.03, \theta \leq 5^\circ \\ 16.8\sin\theta - 0.50, 5^\circ < \theta < 14^\circ \\ 21.9\sin\theta - 0.96, \theta \geq 14^\circ \end{cases} \end{array} \right. \quad (10)$$

where L and S indicate the slope length and slope gradient factors, λ is cumulative slope length (m), θ is the slope gradient in degrees, and m is the slope length and gradient index.

The cover management factor (C) indicates that vegetation cover prevents raindrops from impacting the soil surface and dissipates raindrop energy before it reaches the soil surface. The strategies to conserve water and soil factor (P) indicates that the implementation measures will reduce the rate and amount of runoff and thus the amount and rate of soil erosion. The type of land use is strongly connected to C and P . Considering the purpose of this study, we referred to some studies in the northeastern Chinese area of “black soil” and obtained the corresponding C and P values with the actual conditions in the study area [48,54,55]. Table 1 displays the C and P values.

Table 1. The study’s weighted C and P factor values.

Land Use Type	Weighted C Factors	Weighted P Factors
Cultivated land	0.228	0.25
Forest	0.004	0.5
Grassland	0.043	0.2
Water bodies	0.006	0
Built-up area	0.03	0
Unused land	0.6	1

The soil erosion in the research area was rated according to the Chinese soil erosion classification standard [56], as indicated in Table 2. Analyses of the grading findings and comparisons with information from the Soil and Water Conservation Bulletin were conducted [57,58]. The performance of the model was evaluated by calculating three evaluation statistics, the Mean Absolute Percentage Error ($MAPE$), the Coefficient of Determination (R^2), and the Root Mean Square Percentage Error ($RMSPE$), to determine the most suitable RUSLE for the study area.

$$MAPE = \frac{1}{n} \sum_{i=1}^I \left| \frac{A_i - C_i}{A_i} \right| \quad (11)$$

$$RMSPE = \frac{1}{n} \sqrt{\sum_{i=1}^I \left(\frac{A_i - C_i}{A_i} \right)^2} \quad (12)$$

$$R^2 = 1 - \frac{\sqrt{\sum_{i=1}^I (A_i - C_i)^2}}{\sqrt{\sum_{i=1}^I (A_i - \bar{A})^2}} \quad (13)$$

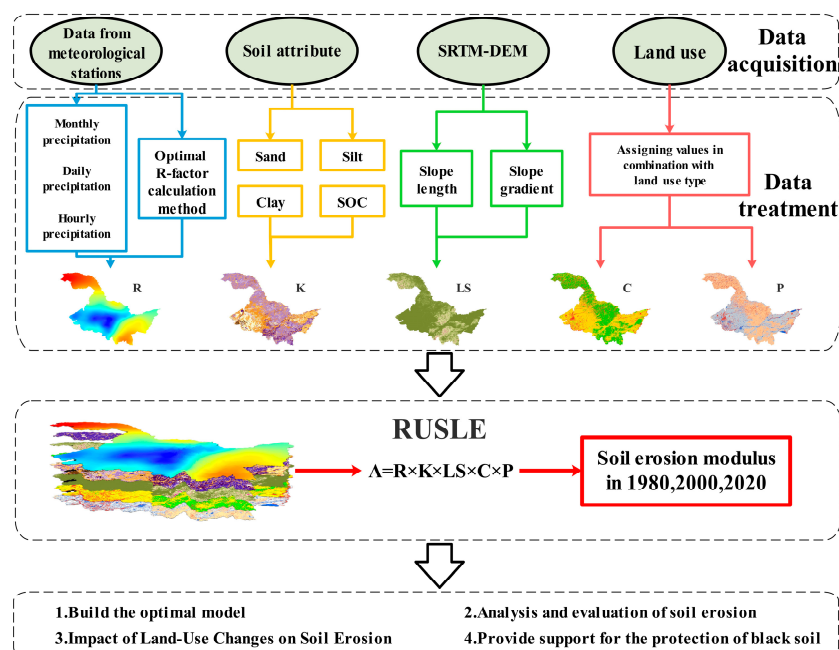
$$\bar{A} = \frac{1}{n} \sum_{i=1}^I A_i$$

where A is the actual value, C is the calculated value, $I = 1, 2, \dots, n$, and n is the sample size.

Table 2. Standards for grading and classifying soil erosion.

Soil Erosion Class	Mean Erosion Modulus ($t \times km^{-2} \times a^{-1}$)	Mean Loss Thickness ($mm \times a^{-1}$)
Very low	<200	<0.37
Low	200~2500	0.37~1.9
Moderate	2500~5000	1.9~3.7
High	5000~8000	3.7~5.9
Very high	8000~15,000	5.9~11.1
Critical	>15,000	>11.1

In this work, three RUSLEs based on different methods of calculating rainfall erosion rates were created using a combination of meteorological data, DEM data, and land use data. The model results were analyzed and compared to create the most suitable model for the study area and to reveal the contribution of land use change to soil erosion (Figure 2).

**Figure 2.** The study's main methodology.

3. Results

3.1. Land-Use Changes

Figures 3 and 4 depict the different land-use categories and how they have changed in the study region between 1980 and 2020, while Table 3 displays the data. The region's primary land use type has historically been forest, which makes up 45% of the entire area, and is primarily found in the northern, eastern, and central mountainous and hilly regions of the study area, with a slight degree of fragmentation. The next largest land use type is agriculture, which makes up 35% of the total area and is mostly found in the Songnen Plain in the study area's west and the Sanjiang Plain in its east. This area is the confluence of the Heilongjiang River, the Ussuri River, the Songhua River, and the Nenjiang River, with abundant water resources and flat terrain. These two types of land account for about 80% of the total area, while grassland, water bodies, built-up area, and unused land account for 7%, 3%, 2%, and 8% of the total area, respectively. The land use categories in the study region have dramatically altered during the last few decades. The proportion of cultivated land has continued to increase, from 29.51% in 1980 and 35.47% in 2000 to 38.29% in 2020, and the area has increased from 133,399 km² in 1980 to 173,297 km² in 2020, mainly from the reclamation of forest, grassland, and unused land. The proportion of forest continues to decrease, from

48.17% in 1980 and 45.95% in 2000 to 42.37% in 2020, decreasing in area from 217,747 km² in 1980 to 191,761 km² in 2020, including the return of cultivated land to forest, afforestation of grassland, harvesting, and the utilization and reclamation of forest land. The proportion of grassland continues to decrease, from 8.94% in 1980 and 7.04% in 2000 to 4.88% in 2020, and the area has decreased from 40,395 km² in 1980 to 22,097 km² in 2020, including grassland reclamation and grassland afforestation. The proportion of water bodies continues to decrease, from 3.28% in 1980 and 3.20% in 2000 to 2.56% in 2020, with an area of 14,826 km² in 1980 decreasing to 11,588 km² in 2020, mainly reclaimed as cropland. The proportion of built-up area continues to increase, from 1.77% in 1980 and 1.90% in 2000 to 2.41% in 2020, with an area increasing from 8009 km² in 1980 to 10,901 km² in 2020 reflecting the rapid economic development and urbanization in Heilongjiang Province. The proportion of unused land fluctuates and changes, from 8.33% in 1980 and 6.44% in 2000 to 9.48% in 2020, and the area fluctuates from 37,646 km² in 1980 to 42,920 km² in 2020, mainly due to land reclamation and abandonment, and the logging and utilization of forest land.

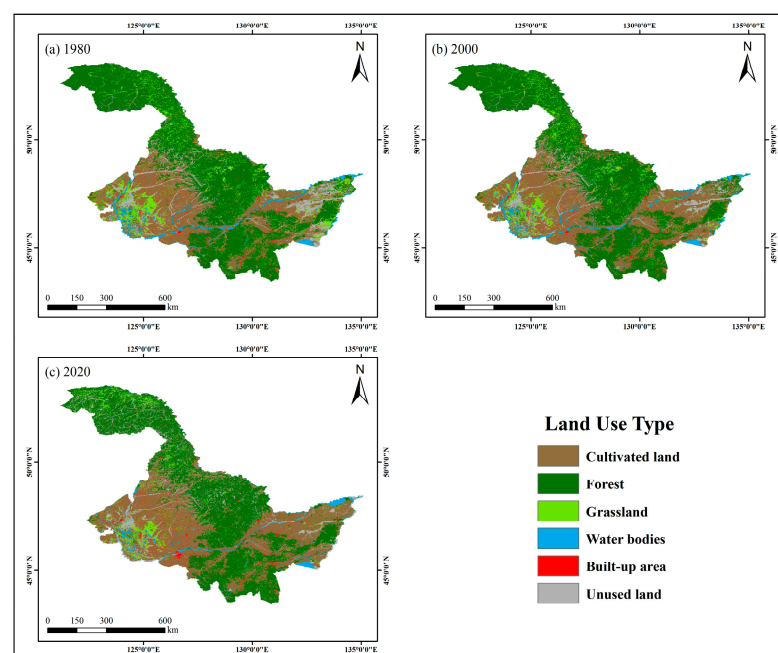


Figure 3. Land use maps of Heilongjiang Province: (a) 1980; (b) 2000; and (c) 2020.

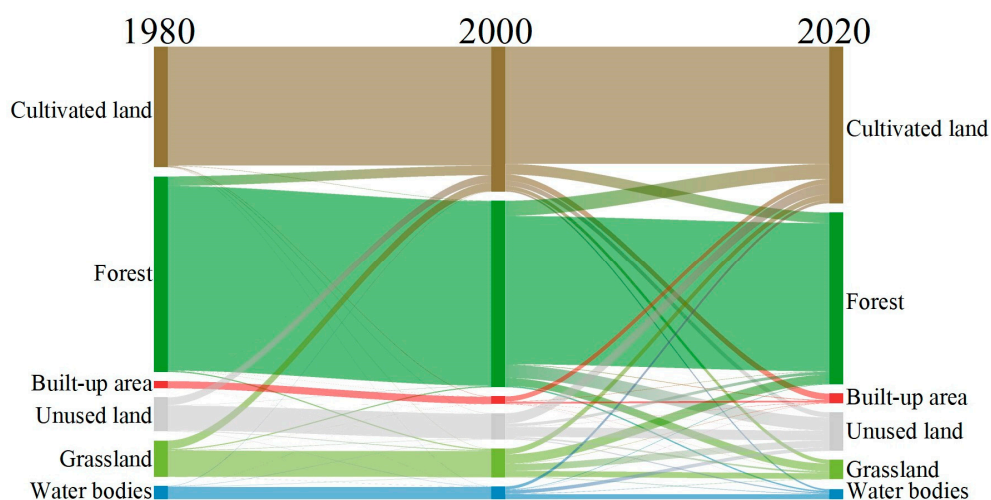


Figure 4. Land use changes and transfers from 1980 to 2020 in Heilongjiang Province.

Table 3. Land use changes between 1980 and 2020. ($P = 100 \times (\text{area}_j + 1 - \text{area}_i) / \text{area}_i$; j stands for the year in various time frames. P1 (1980–2000), P2 (2000–2020)).

Land Use Type	1980		2000		2020		P1 (%)	P2 (%)
	(km ²)	(%)	(km ²)	(%)	(km ²)	(%)		
Cultivated land	133,399	29.51	160,344	35.47	173,297	38.29	20.20	8.08
Forest	217,747	48.17	207,695	45.95	191,761	42.37	−4.62	−7.67
Grassland	40,395	8.94	31,810	7.04	22,097	4.88	−21.25	−30.53
Water bodies	14,826	3.28	14,482	3.20	11,588	2.56	−2.32	−19.98
Built-up area	8009	1.77	8592	1.90	10,901	2.41	7.28	26.87
Unused land	37,646	8.33	29,099	6.44	42,920	9.48	−22.70	47.50

3.2. Model Performance

In this study, the performance of the RUSLE model was evaluated by comparing the soil erosion derived from the RUSLE with published soil and water conservation bulletins [57,58], and the R-factor algorithm was determined to create the most suitable model for the study area. Three models were obtained by changing the R-factor calculation method while the other factors of the model were calculated in the same way: the RUSLE based on the monthly average precipitation (R1), the RUSLE based on the daily precipitation (R2), and the RUSLE based on the multi-year continuous high-density hourly average precipitation (R3). Tables 4–6 and Figure 5 show that the R1 is smaller than the reported results, 2020MAPE of 89.25%, RMSPE of 40.11%, and R^2 of 0.21; 2018MAPE of 88.52%, RMSPE of 39.84%, and R^2 of 0.27. The R2 is larger than the reported results, with a 2020MAPE of 205.63%, RMSPE of 120.94%, and R^2 of 0.17; 2018MAPE of 181.13%, RMSPE of 91.38%, and R^2 of −1.73. R3 is generally consistent with the reported results, with a 2020MAPE of 25.65%, RMSPE of 15.69%, and R^2 of 0.99; 2018MAPE of 15.49%, RMSPE of 7.99%, and R^2 of 0.99. The soil erosion in 2000 and 1980 will be deduced from R3 in the next study.

Table 4. Soil erosion based on the monthly average precipitation (R1).

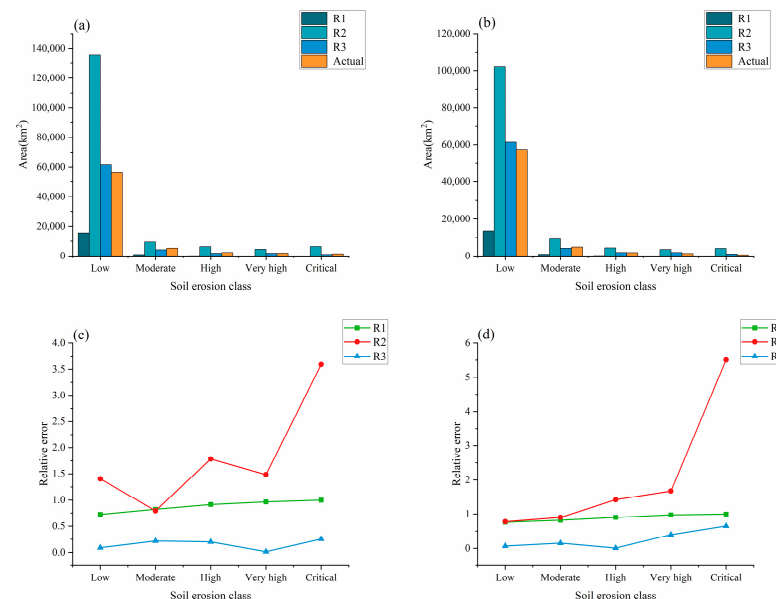
Soil Erosion Class	2018		2020	
	Calculated (km ²)	Actual (km ²)	Calculated (km ²)	Actual (km ²)
Low	15,608.70	56,488.95	13,544.32	57,431.40
Moderate	920.01	5231.35	862.88	4827.16
High	188.96	2235.20	172.26	1775.79
Very high	64.24	1814.16	32.97	1277.14
Critical	2.86	1383.23	0.07	622.92

Table 5. Soil erosion based on the daily precipitation (R2).

Soil Erosion Class	2018		2020	
	Calculated (km ²)	Actual (km ²)	Calculated (km ²)	Actual (km ²)
Low	135,823.64	56,488.95	102,108.70	57,431.40
Moderate	9383.34	5231.35	9191.14	4827.16
High	6222.40	2235.20	4298.46	1775.79
Very high	4507.91	1814.16	3411.96	1277.14
Critical	6348.71	1383.23	4053.51	622.92

Table 6. Soil erosion based on the multi-year continuous high-density hourly average precipitation (R3).

Soil Erosion Class	2018		2020	
	Calculated (km ²)	Actual (km ²)	Calculated (km ²)	Actual (km ²)
Low	61,512.84	56,488.95	61,397.19	57,431.40
Moderate	4094.00	5231.35	4090.04	4827.16
High	1789.58	2235.20	1788.49	1775.79
Very high	1788.29	1814.16	1787.40	1277.14
Critical	1031.52	1383.23	1030.30	622.92

**Figure 5.** Comparison of the soil erosion obtained by the three models with the real value: (a) 2018 and (b) 2020. Relative error of the calculated results of the three models: (c) 2018 and (d) 2020. R1: the RUSLE based on the monthly average precipitation; R2: the RUSLE based on the daily precipitation; and R3: the RUSLE based on the multi-year continuous high-density hourly average precipitation.

3.3. Changes in Soil Erosion

We determined the soil erosion classification and its distribution in the research region in 1980, 2000, and 2020 using the RUSLE soil erosion modulus calculation in combination with the Chinese soil erosion classification standard. These results are given in Figures 6 and 7. The predominant erosion class in the area, which makes up about 85% of the study area's total area, is very low erosion. The soil erosion modulus of very low erosion is less than the allowable loss in the northeastern Chinese area of "black soil" and is not considered soil erosion [56]. Soil erosion affects 15% of the land, with low erosion dominating 7% of the area. Moderate erosion, high erosion, very high erosion, and critical erosion each account for 4%, 2%, 1%, and 1%. Before 2000, soil erosion fluctuated less. The Songnun Plain in the west, the Sanjiang Plain in the east, and the mountainous regions in the center of the research area were the major locations of soil erosion. From 2000 to 2020, soil erosion increased, most noticeably in the northern mountainous areas.

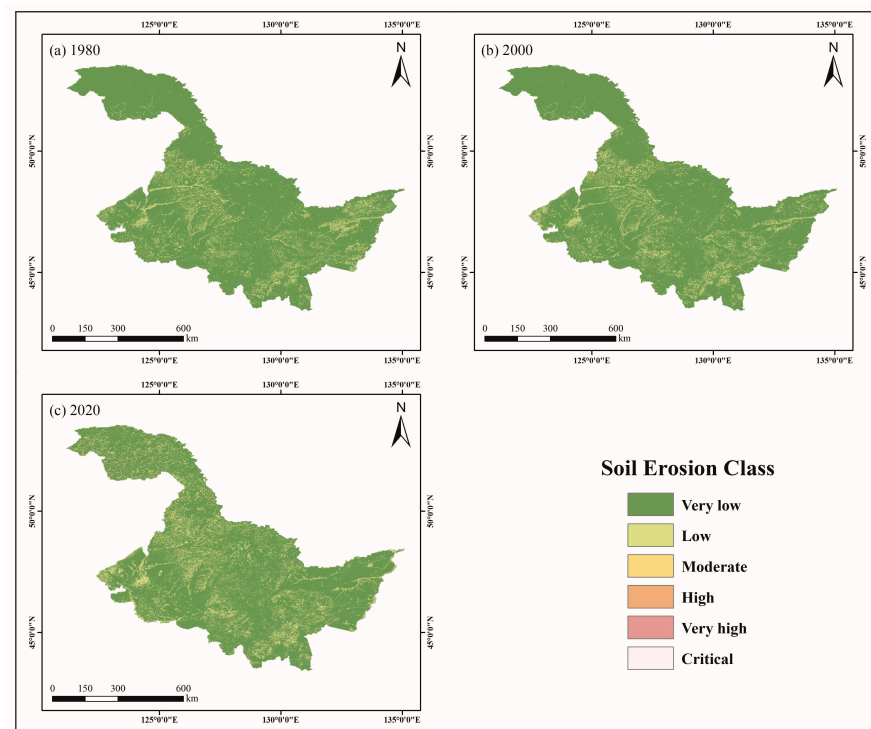


Figure 6. The spatial distribution characteristics of soil erosion in Heilongjiang Province: (a) 1980; (b) 2000; and (c) 2020.

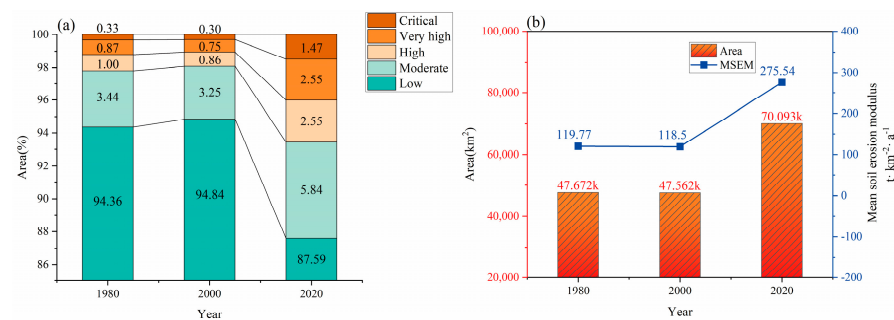


Figure 7. (a) Percentage of all levels of soil erosion in Heilongjiang Province (1980–2020); (b) Total soil erosion and mean soil erosion modulus in Heilongjiang Province (1980–2020).

To better understand the major soil erosion management regions in the study area, the soil erosion status in each of the study area's cities was counted independently. As shown in Table 7, only Heihe City had more serious soil erosion in 1980; the total soil erosion in Heihe City was 148.74×10^5 t, and the mean soil erosion modulus was $222.39 \text{ t} \times \text{km}^{-2} \times \text{a}^{-1}$. In 2000, soil erosion fluctuated with less change; Heihe City continued to be a more significant place for soil erosion, with a mean soil erosion modulus of $217.25 \text{ t} \times \text{km}^{-2} \times \text{a}^{-1}$ and total soil erosion of 145.3×10^5 t. In 2020, soil erosion increased. Soil erosion occurred in the Daxinganling area, Hegang City, Hehe City, Mudanjiang City, Qitaihe City, and Yichun City. The Daxinganling region had the highest level of soil erosion out of all of them, with a total soil erosion of 301.59×10^5 t and a mean soil erosion modulus of $465.52 \text{ t} \times \text{km}^{-2} \times \text{a}^{-1}$.

Table 7. Cities in Heilongjiang Province’s mean soil erosion modulus and overall soil erosion (1980–2020).

City	1980		2000		2020	
	Total (10^5 t)	Mean ($t \times km^{-2} \times a^{-1}$)	Total (10^5 t)	Mean ($t \times km^{-2} \times a^{-1}$)	Total (10^5 t)	Mean ($t \times km^{-2} \times a^{-1}$)
Daqing	16.43	77.51	18.59	87.70	26.98	127.26
Daxinganling	32.71	50.48	33.07	51.04	301.59	465.52
Harbin	58.41	110.06	70.51	132.86	85.56	161.21
Hegang	11.40	77.46	10.22	69.41	57.93	393.61
Heihe	148.74	222.39	145.30	217.25	244.62	365.75
Jixi	28.90	128.40	21.55	95.77	35.02	155.62
Jiamusi	34.19	105.01	28.64	87.96	46.35	142.35
Mudanjiang	59.54	153.34	61.24	157.73	141.97	365.66
Qitaihe	7.48	136.54	8.84	161.26	18.76	342.22
Qiqihar	45.85	108.51	45.48	107.63	63.98	151.42
Shuangyashan	26.63	116.30	23.11	100.93	34.38	150.13
Suihua	50.17	143.80	47.90	137.30	49.07	140.66
Yichun	25.08	76.38	25.56	77.84	124.78	380.07

The spatial and temporal characteristics of the severity of soil erosion in the 120 counties of the study area were plotted (Figure 8). In 1980, 11 counties had more severe soil erosion (an average of more than $200 t \times km^{-2} \times a^{-1}$). In 2000, 17 counties had more severe soil erosion. In 2020, 44 counties had more severe soil erosion. In 1980, the study area’s center saw the majority of the soil erosion. Both the southern and center regions of the study area experienced soil erosion in 2000. In the center and southern regions of the northern half of the research area in 2020, soil erosion is highly prevalent. Since the founding of the country, numerous individuals have moved into Heilongjiang Province from other provinces. People reclaimed land on a large scale, and the rough planting methods seriously damaged the soil’s physicochemical characteristics. People are mining a lot of minerals and cutting indiscriminately, severely damaging the vegetation. People’s awareness of protecting soil and water resources is not enough, the speed of treatment is slow, and the area of newly generated soil erosion is larger than the area of treatment, resulting in increased soil erosion. As a result of soil erosion, the black soil layer has thinned, soil fertility has decreased, and food production has declined. Vegetation is severely damaged, soil erosion is increasing, and erosion ditches are increasing and swallowing up the land. Furthermore, large amounts of sediment accumulate downstream, exacerbating flooding. The decline of the natural environment and the frequent occurrence of natural disasters create a vicious circle [59–61].

There are various vegetation kinds and levels of vegetation depending on the type of land usage, and there are also variations in the soil retention capacity [62]. In the study region, there are six different principal land use categories, and the soil erosion of each land use type is counted separately, as shown in Figure 9. In the plains to the west and east of the study area, the majority of the land is cultivated land, and although the soil erosion area is large, the erosion type is mainly low erosion, accounting for 98% of the erosion area. From 1980 to 2020, the soil erosion area increased from $16,838 km^2$ to $28,360 km^2$, the mean soil erosion modulus increased from $114 t \times km^{-2} \times a^{-1}$ to $139 t \times km^{-2} \times a^{-1}$, and the total soil erosion increased from $152 \times 10^5 t$ to $241 \times 10^5 t$. The study area’s northern and central mountainous regions are where the forest is primarily found. From 1980 to 2020, the area of forest decreased continuously, and the soil erosion increased from $6094 km^2$ to $12,418 km^2$, the mean soil erosion modulus increased from 112 to $341 t \times km^{-2} \times a^{-1}$, and the total soil erosion increased from $52 \times 10^5 t$ to $178 \times 10^5 t$; soil erosion increased continuously. Grassland covers a smaller area and from 1980 to 2020 the grassland area decreased, the soil erosion area change was about $2000 km^2$, the mean soil erosion modulus increased from 35 to $81 t \times km^{-2} \times a^{-1}$, and the total soil erosion increased from $14 \times 10^5 t$ to $18 \times 10^5 t$. Water bodies, specifically rivers, lakes, reservoirs, ditches, etc., had a modest soil erosion class size and soil erosion degree. The built-up area mainly includes land for settlements such as cities, villages, and towns, and land for public transportation such as railroads and roads. The built-up area is mainly low erosion, with a small degree of soil erosion. Unused land primarily is sandy, Gobi, saline, swampy, bare, etc., with little vegetation and no measures to conserve soil and water. This is the most serious land use type regarding soil

erosion, and it is mostly associated with moderate, high, very high, and critical erosion. From 1980 to 2020, the soil erosion area of unused land increased from 22,084 km² to 26,326 km², the mean soil erosion modulus increased from 613 to 1174 t × km⁻² × a⁻¹, and the total soil erosion increased from 230 × 10⁵ t to 504 × 10⁵ t; in summary, soil erosion keeps increasing.

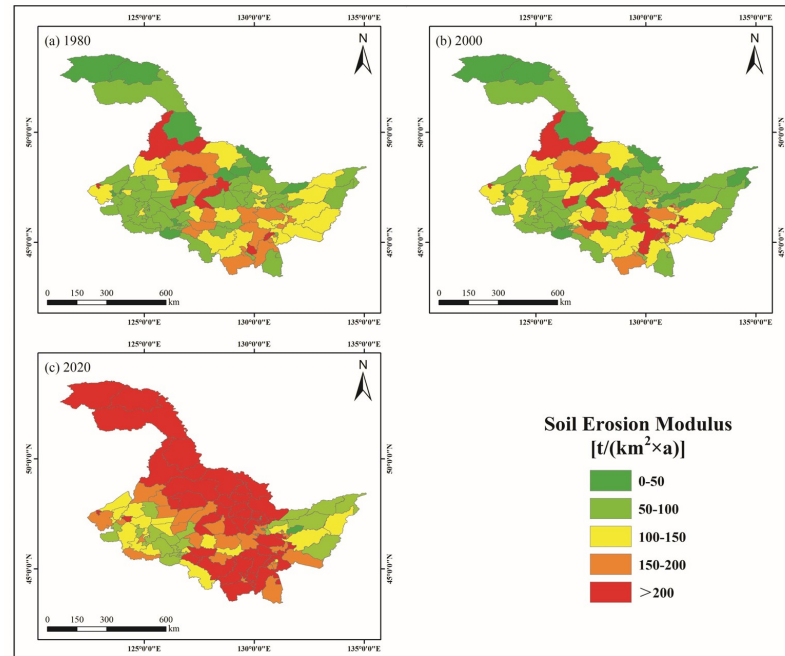


Figure 8. Grading chart of average soil erosion modulus by county soil in Heilongjiang Province: (a)1980; (b) 2000; and (c) 2020.

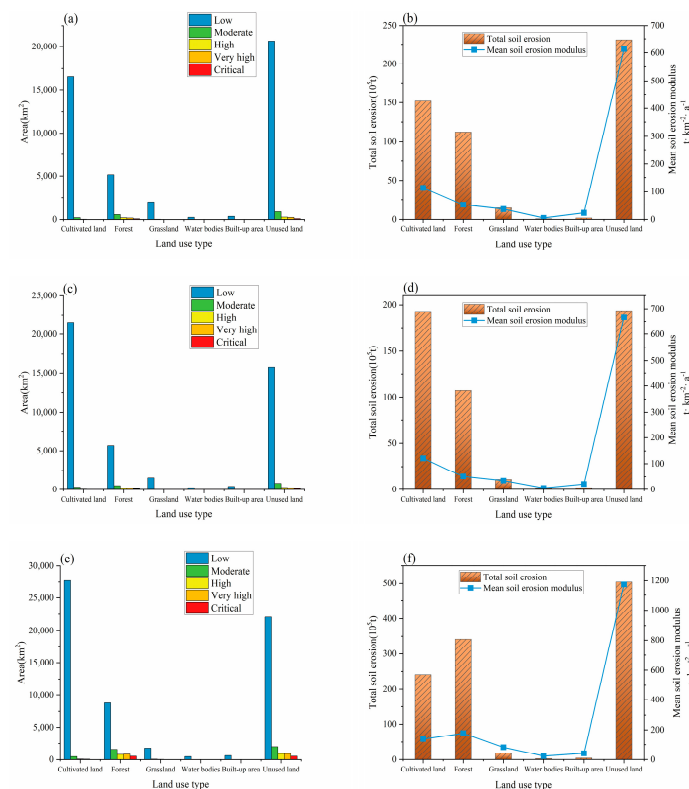


Figure 9. Areas of different levels of soil erosion in different land use patterns in Heilongjiang Province: (a)1980; (c) 2000; and (e) 2020. The total soil erosion and mean soil erosion modulus of different land use types in Heilongjiang Province: (b)1980; (d) 2000; and (f) 2020.

4. Discussion

4.1. Building the Optimal Model

Three models were created for this investigation based on various R-factor calculation techniques. In general, we discovered that the model's output was better the greater the temporal resolution of the input rainfall data. The RUSLE based on the monthly average precipitation was smaller than the real value, the RUSLE based on the daily precipitation was larger than the real value, and the RUSLE based on the multi-year continuous high-density hourly average precipitation was substantially the most accurate. It was also found that the results obtained by the multi-year average precipitation were closer to reality, i.e., if each year's data is used to independently predict soil erosion for that year, the error will be larger. This is mainly reflected in the fact that it is greatly influenced by the precipitation of the year, and soil erosion changes drastically from years of drought and little rainfall to years of high rainfall. Moreover, soil erosion is a continuous process and generally does not change suddenly and drastically. Therefore, the RUSLE based on continuous high-density hourly average precipitation for many years is a more suitable model for the northeastern Chinese area of "black soil".

Table 8 shows the results of the RUSLE-derived soil erosion modulus in this study compared with published data. The unit $\text{mm} \times \text{a}^{-1}$ was converted to unit $\text{t} \times \text{km}^{-2} \times \text{a}^{-1}$ using the average bulk density of $1.3 \text{ g} \times \text{cm}^{-3}$ [63]. According to this study's RUSLE model, the soil erosion modulus is lower than the numbers that were previously reported. This difference may stem from two aspects. On the one hand, the time period between the current study and the literature study is different. On the other hand, the present study has a large spatial scale. The spatial resolution of the data is small. The soil erosion modulus of the first validation site in Table 8 is zero mainly because the spatial resolution of the land use data is 1 km, which is not accurate enough in a small area, resulting in the misjudgment of the validation site land type as a built-up area. The default soil erosion for a built-up area is 0. The comparative analysis with published data reveals that the RUSLE based on the multi-year continuous high-density hourly average precipitation performs better in a large spatial range, with a MAPE of 15.49%, RMSPE of 7.99%, and R^2 of 0.99. There is also the problem of inaccurate calculations in small ranges due to insufficient spatial resolution of the data.

Table 8. Results of prior studies in Heilongjiang Province.

Longitude	Latitude	Time	Method	Soil Erosion ($\text{mm} \times \text{a}^{-1}$)	Soil Erosion Modulus ($\text{t} \times \text{km}^{-2} \times \text{a}^{-1}$)	Current Study ($\text{t} \times \text{km}^{-2} \times \text{a}^{-1}$)	Reference
126°05'56"	47°35'45"	1980–1985	Monitoring	0.456	59.28	0	[49]
125°53'13"	48°02'16"	1985–1990	¹³⁷ Cs tracer	1.97	256.1	189.07	[36]
127°27'44"	45°44'04"	1985–1990	¹³⁷ Cs tracer	3.31	430.3	353.82	[36]
125°13'19"	48°58'16"	2003–2004	¹³⁷ Cs tracer	1.12	145.6	83.71	[18]

4.2. Impact of Land-Use Changes on Soil Erosion

The influence on soil erosion modification is mostly achieved through altering the plant cover, which is considered a typical human activity. A reduction in vegetation cover can significantly alter albedo, exacerbate climate change, and accelerate the rate of soil degradation and erosion [64–66]. This study shows that the biggest area of soil erosion is on cultivated land, which accounts for 40.47% of all erosion areas, and is mainly low erosion; the most catastrophic soil erosion occurs on unused land, with moderate and above soil erosion occupying 48.93% of the area. Since 2000, the study area's soil erosion has become more severe, which is mainly spatially reflected in the increased soil erosion of the forest in the northern mountains; the soil erosion of grassland, water bodies, and built-up areas is lower. Globally, soil erosion on cultivated land is generally high [67], and soil erosion on bare land is the most severe [68]. On forested land, soil erosion is exacerbated by the loss of vegetation cover brought on by overexploitation, and the lower the vegetation cover the more likely soil erosion is to occur [6]. The primary cause of the rise in soil erosion in the study region is that forest, grassland, and

water bodies have been reclaimed for cultivated land, and that overexploitation degrades the area to unusable land, such as sand and salty land, destroying the vegetation on the surface and loosening the soil, worsening soil erosion. In recent decades, ecological issues have gradually attracted attention and many ecological policies have been developed to protect and restore natural ecosystems. China started large-scale ecological restoration programs, such as the Sloping Land Conversion Program (SLCP) and the Natural Forest Conservation Program (NFCP), in 2000 to enhance forest cover and decrease soil erosion [69]. Crop rotation, straw mulching, terracing, the creation of windbreak woods, and monoculture are a few examples of soil and water conservation techniques that have been widely used [70]. In addition, the Ministry of Natural Resources has held yearly land change surveys since the Third National Land Survey was finished in order to continually update the results and maintain the survey data. The Black Earth Protection Law (draft) was also issued by the Chinese National People's Congress in December 2021 [30]. A series of policies is necessary to provide strong support for territorial spatial planning, protection of black soil land, and guarantee national food security.

4.3. Limitations and Future Research

Hydraulic erosion is the activity of water forces (precipitation, surface runoff, and subsurface runoff) removing, transporting, and accumulating soil and its parent material, rocks, etc. on the earth's land surface [71]. The RUSLE calculates the soil erosion modulus mainly for hydraulic erosion, which is the most dominant form of soil erosion in Heilongjiang Province, accounting for 89% of the erosion area [58], and is the best technique for evaluating soil erosion. However, the research region also has erosion caused by wind and freeze–thaw, and the absence of these two factors in the RUSLE leads to a possible underestimation of soil erosion. Dengfeng Tuo et al. (2018) evaluated the proportional role that hydraulic erosion plays in the overall soil loss on China's Loess Plateau slopes. The overall erosion was calculated using the ^{137}Cs tracer method, and the hydraulic erosion was calculated using the RUSLE model. The results show that hydraulic erosion using the RUSLE model accounts for 60.3% of the total erosion [72]. Thus, the RUSLE lacks consideration of other soil erosion types, leading to a possible underestimation of the extent of soil erosion. The next step could be to introduce the freeze–thaw factor into the model and further improve the model by fitting the calculation equation with a large amount of data. At the same time, with the Revised Wind Erosion Equation (RWEQ), wind erosion could be calculated to achieve an accurate calculation of soil erosion in the study area. In this work, the RUSLE based on the multi-year continuous high-density hourly average precipitation was determined to be the best model, and the results obtained from the multi-year average precipitation were considered to be closer to reality. What time scale should be selected as the average data and how to determine the proportion of data in each year within the specified time scale are the directions for further research. Furthermore, the study area is large, the spatial resolution of the data is small, and the model is not accurate enough to calculate in a small area. In the next step, we can explore the optimal spatial resolution of the data by analyzing the calculation results of data with different spatial resolutions. The K-factor in the model is mainly calculated from the data of the second national soil census, and there is no data on large soil areas after the second national soil census data (1979–1985). Because the spatial scale of the study area is large, we consider that the variation in the spatial distribution of soil physicochemical properties is negligible [49,73,74]. However, this reduces the extent to which soil erosion varies in time and space. The third national soil census is underway and is expected to end in 2025. We can use the soil data (sand, silt, clay, and SOC) obtained from the third national soil census to update the K-factors in the model and achieve further optimization.

5. Conclusions

In this study, the performance of three models was analyzed and evaluated, and the RUSLE based on the multi-year continuous high-density hourly average precipitation was determined to be the most suitable algorithm for the northeastern black soil region.

Using this method, soil erosion and its variation pattern with land use type in Heilongjiang Province from 1980 to 2020 were studied at provincial, municipal, and county scales. Temporally, the soil erosion modulus fluctuated between 1980 and 2000 and went up between 2010 and 2020. Spatially, the research area's center was where soil erosion was more intense from 1980 to 2000, and from 2010 to 2020 soil erosion increased and spread to the north. The significant expansion of the cultivated land area, reduction in natural vegetation, and reduction in understory vegetation cover are the main reasons for the increase in soil erosion. In addition, the most dangerous land use type for soil erosion was found to be unused land with little to no vegetation cover and no water or soil conservation measures. The significance of environmentally sound soil management is shown by this study. Policymakers can control soil erosion through improved ecosystem management and policies, strengthen initiatives to save water and soil on sloping agricultural land and in erosion ditches; strengthen field improvement, reasonably divide suitable fields for cultivation and repair damaged arable land; and plant trees, protect water resources, reduce the amount of unused land, and increase the plant cover. Implementing these measures would thus reduce soil erosion, protect the northeastern Chinese area of "black soil", and guarantee national food security.

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References

1. Luca, M. Agricultural policy: Govern our soils. *Nature* **2015**, *528*, 32–33. [\[CrossRef\]](#)
2. Ulain, Q.; Ali, S.M.; Shah, A.A.; Iqbal, K.M.J.; Ullah, W.; Tariq, M.A.U.R. Identification of Soil Erosion-Based Degraded Land Areas by Employing a Geographic Information System—A Case Study of Pakistan for 1990–2020. *Sustainability* **2022**, *14*, 11888. [\[CrossRef\]](#)
3. Panditharathne, D.L.D.; Abeysingha, N.S.; Nirmanee, K.G.S.; Mallawatantri, A. Application of Revised Universal Soil Loss Equation (Rusle) Model to Assess Soil Erosion in "Kalu Ganga" River Basin in Sri Lanka. *App. Environ. Soil Sci.* **2019**, *2019*, 4037379. [\[CrossRef\]](#)
4. Kastridis, A.; Kamperidou, V. Influence of land use changes on alleviation of Volvi Lake wetland (North Greece). *Soil Water Res.* **2015**, *10*, 121–129. [\[CrossRef\]](#)
5. Degife, A.; Worku, H.; Gizaw, S. Environmental implications of soil erosion and sediment yield in Lake Hawassa watershed, south-central Ethiopia. *Environ. Syst. Res.* **2021**, *10*, 28. [\[CrossRef\]](#)
6. Wang, X.; Zhao, X.; Zhang, Z.; Yi, L.; Zuo, L.; Wen, Q.; Liu, F.; Xu, J.; Hu, S.; Liu, B. Assessment of soil erosion change and its relationships with land use/cover change in China from the end of the 1980s to 2010. *Catena* **2016**, *137*, 256–268. [\[CrossRef\]](#)
7. Deng, Z.-Q.; Lima, J.L.M.P.d.; Jung, H.-S. Sediment transport rate-based model for rainfall-induced soil erosion. *Catena* **2008**, *76*, 54–62. [\[CrossRef\]](#)
8. Margiourou, S.; Kastridis, A.; Sapountzis, M. Pre/Post-Fire Soil Erosion and Evaluation of Check-Dams Effectiveness in Mediterranean Suburban Catchments Based on Field Measurements and Modeling. *Land* **2022**, *11*, 1705. [\[CrossRef\]](#)
9. Cerdan, O.; Govers, G.; Le Bissonnais, Y.; Van Oost, K.; Poesen, J.; Saby, N.; Gobin, A.; Vacca, A.; Quinton, J.; Auerswald, K.; et al. Rates and spatial variations of soil erosion in Europe: A study based on erosion plot data. *Geomorphology* **2010**, *122*, 167–177. [\[CrossRef\]](#)

10. Wuepper, D.; Borrelli, P.; Finger, R. Countries and the global rate of soil erosion. *Nat. Sustain.* **2020**, *3*, 51–55. [\[CrossRef\]](#)
11. Ministry of Water Resources of the People's Republic of China. *China Soil and Water Conservation Bulletin*; Ministry of Water Resources of the People's Republic of China: Beijing, China, 2021.
12. Mukanov, Y.; Chen, Y.; Baisholanov, S.; Amanambu, A.; Issanova, G.; Abenova, A.; Fang, G.; Abayev, N. Estimation of annual average soil loss using the Revised Universal Soil Loss Equation (RUSLE) integrated in a Geographical Information System (GIS) of the Esil River basin (ERB), Kazakhstan. *Acta Geophys.* **2019**, *67*, 921–938. [\[CrossRef\]](#)
13. Chen, T.; Niu, R.; Li, P.; Zhang, L.; Du, B. Regional soil erosion risk mapping using RUSLE, GIS, and remote sensing: A case study in Miyun Watershed, North China. *Environ. Earth Sci.* **2011**, *63*, 533–541. [\[CrossRef\]](#)
14. Koch, A.; McBratney, A.; Lal, R. Global soil week: Put soil security on the global agenda. *Nature* **2012**, *492*, 186. [\[CrossRef\]](#) [\[PubMed\]](#)
15. Su, Z.-A.; Zhou, T.; Zhang, X.-B.; Wang, X.-Y.; Wang, J.-J.; Zhou, M.-H.; Zhang, J.-H.; He, Z.-Y.; Zhang, R.-C. A Preliminary Study of the Impacts of Shelter Forest on Soil Erosion in Cultivated Land: Evidence from integrated ¹³⁷Cs and ²¹⁰Pbex Measurements. *Soil Tillage Res.* **2021**, *206*, 104843. [\[CrossRef\]](#)
16. Zhou, R.P.; Qu, L.Q.; Zhao, Y.; Du, P.F.; Chen, Y.; Ding, D.H. Soil erosion survey system in the United States and its evolution characteristics. *Sci. Soil Water Conserv.* **2022**, *20*, 139–150. [\[CrossRef\]](#)
17. Marondedze, A.K.; Schütt, B. Predicting the Impact of Future Land Use and Climate Change on Potential Soil Erosion Risk in an Urban District of the Harare Metropolitan Province, Zimbabwe. *Remote Sens.* **2021**, *13*, 4360. [\[CrossRef\]](#)
18. Liu, B.Y.; Yan, B.X.; Shen, B.; Wang, Z.Q.; Wei, X. Current status and comprehensive control strategies of soil erosion for cultivated land in the Northeastern black soil area of China. *Sci. Soil Water Conserv.* **2008**, *6*, 1–8. [\[CrossRef\]](#)
19. Mithlesh, K.; Prasad, S.A.; Narayan, S.; Sandeep, D.S.; Kumar, R.S.; Balram, P. Global-scale application of the RUSLE model: A comprehensive review. *Hydrol. Sci. J.* **2022**, *67*, 806–830. [\[CrossRef\]](#)
20. Othman, A.A.; Ali, S.S.; Salar, S.G.; Obaid, A.K.; Al-Kakey, O.; Liesenberg, V. Insights for Estimating and Predicting Reservoir Sedimentation Using the RUSLE-SDR Approach: A Case of Darbandikhan Lake Basin, Iraq–Iran. *Remote Sens.* **2023**, *15*, 697. [\[CrossRef\]](#)
21. Kanito, D.; Bedadi, B.; Feyissa, S. Sediment yield estimation in GIS environment using RUSLE and SDR model in Southern Ethiopia. *Geomat. Nat. Hazards Risk* **2023**, *14*, 2167614. [\[CrossRef\]](#)
22. Egbueri, J.C.; Igwe, O.; Ifediegwu, S.I. Erosion risk mapping of Anambra State in southeastern Nigeria: Soil loss estimation by RUSLE model and geoinformatics. *Bull. Eng. Geol. Environ.* **2022**, *81*, 91. [\[CrossRef\]](#)
23. Bircher, P.; Liniger, H.P.; Prasuhn, V. Comparison of long-term field-measured and RUSLE-based modelled soil loss in Switzerland. *Geoderma Reg.* **2022**, *31*, e00595. [\[CrossRef\]](#)
24. Yin, S.; Xie, Y.; Liu, B.; Nearing, M.A. Rainfall erosivity estimation based on rainfall data collected over a range of temporal resolutions. *Hydrol. Earth Syst. Sci.* **2015**, *19*, 4113–4126. [\[CrossRef\]](#)
25. Renard, K.G.; Foster, G.R.; Weesies, G.A.; McCool, D.K.; Yoder, D.C. *Predicting Soil Erosion by Water: A Guide to Conservation Planning with the Revised Universal Soil Loss Equation (RUSLE)*; U.S. Government Printing Office: Washington, DC, USA, 1997.
26. Wischmeier, W.H. A Rainfall Erosion Index for a Universal Soil-Loss Equation. *Soil Sci. Soc. Am. J.* **1959**, *23*, 246–249. [\[CrossRef\]](#)
27. Zhang, W.B.; Fu, J.S. Rainfall erosivity estimation under different rainfall amount. *Resour. Sci.* **2003**, *25*, 35–41. [\[CrossRef\]](#)
28. Zhang, W.B.; Xie, Y.; Liu, B.Y. Rainfall erosivity estimation using daily rainfall amounts. *Sci. Geogr. Sin.* **2002**, *22*, 705–711. [\[CrossRef\]](#)
29. Lei, G.P.; Dai, L.; Song, G. Evaluation of soil ecological environment quality of typical black soils in Heilongjiang Province. *Trans. Chin. Soc. Agric. Eng.* **2009**, *25*, 243–248. [\[CrossRef\]](#)
30. Deyi, H. China: Protect black soil for biodiversity. *Nature* **2022**, *604*, 40. [\[CrossRef\]](#)
31. Chen, Q. *Vigorously Improve Food Production Capacity and Quality as a Good Food Security “Ballast”*; College of Agriculture, Tohoku University of Agriculture: Sendai, Japan, 2023; pp. 34–36. [\[CrossRef\]](#)
32. Ding, X.; Liu, W. Black land protection legislation: Protect the “pandas of arable land”. In Proceedings of the China National People's Congress, Beijing, China, 5 March 2022; p. 42.
33. Zhou, N.; Li, C.; Ju, C.Y.; Ma, Y.B. Analysis of characteristics of soil erodibility K-value in Heilongjiang province. *Trans. Chin. Soc. Agric. Eng.* **2015**, *31*, 182–189. [\[CrossRef\]](#)
34. Zhang, J.; Zheng, F.; Li, Z.; Feng, Z. A novel optimal data set approach for erosion-impacted soil quality assessments—A case-study of an agricultural catchment in the Chernozem region of Northeast China. *Land Degrad. Dev.* **2022**, *33*, 1062–1075. [\[CrossRef\]](#)
35. Dai, T.Y.; Wang, L.Q.; Li, T.A.; Qiu, P.P.; Wang, J. Study on the Characteristics of Soil Erosion in the Black Soil Area of Northeast China under Natural Rainfall Conditions: The Case of Sunjiagou Small Watershed. *Sustainability* **2022**, *14*, 8284. [\[CrossRef\]](#)
36. Zhang, X.K.; Xu, J.H.; Xu, X.Q.; Deng, Y.J.; Gao, D.W. A Study on the Soil Loss Equation in Heilongjiang Province. *Bull. Soil Water Conserv.* **1992**, *12*, 1–9+18. [\[CrossRef\]](#)
37. Jiang, N.; Fu, Q. Spatial matching analysis of Heilongjiang Province's water resource based on Gini coefficient. *J. Northeast Agric. Univ.* **2010**, *41*, 5. [\[CrossRef\]](#)
38. Liu, Y.N.; Wu, K.N.; Li, X.L.; Li, X. Classification of land types at provincial level based on the goal of black land protection: A case study of Heilongjiang Province. *Sci. Geogr. Sin.* **2022**, *42*, 1348–1359. [\[CrossRef\]](#)

39. Wan, W.; Liu, Z.; Li, B.G.; Fang, H.Y.; Wu, H.Q.; Yang, H.Y. Evaluating soil erosion by introducing crop residue cover and anthropogenic disturbance intensity into cropland C-factor calculation: Novel estimations from a cropland-dominant region of Northeast China. *Soil Tillage Res.* **2022**, *219*, 105343. [CrossRef]
40. Han, X.Z.; Zou, W.X. Research Perspectives and Footprint of Utilization and Protection of Black Soil in Northeast China. *Acta Pedol. Sin.* **2021**, *58*, 1341–1358. [CrossRef]
41. Wang, J.K.; Xu, X.R.; Pei, J.B.; Li, S.Y. Current Situations of Black Soil Quality and Facing Opportunities and Challenges in Northeast China. *Chin. J. Soil Sci.* **2021**, *52*, 695–701. [CrossRef]
42. Xu, X.L.; Liu, J.Y.; Zhang, S.W.; Li, R.D.; Yan, C.Z.; Wu, S.X. Multi-Period Land Use Remote Sensing Monitoring Dataset in China. Resource and Environmental Science Data Registration and Publication System. 2018. Available online: <http://www.resdc.cn/> (accessed on 25 January 2023).
43. Fang, H. Impact of Land Use Change and Dam Construction on Soil Erosion and Sediment Yield in the Black Soil Region, Northeastern China. *Land Degrad. Dev.* **2017**, *28*, 1482–1492. [CrossRef]
44. National, M. Data Set of Basic Meteorological Elements from National Ground Weather Stations in China. Available online: <http://data.cma.cn/> (accessed on 15 January 2023).
45. Yue, T.Y.; Yin, S.Q.; Xie, Y.; Yu, B.F.; Liu, B.Y. Rainfall Erosivity Mapping over Mainland China Based High-Density Hourly Rainfall Records. *Earth Syst. Sci. Data* **2022**, *14*, 665–682. [CrossRef]
46. Food and Agriculture Organization of the United Nations (FAO). China Soil Map Based Harmonized World Soil Database (HWSD) (v1.1). National Tibetan Plateau/Third Pole Environment Data Center. 2009. Available online: <https://data.tpdc.ac.cn/> (accessed on 16 January 2023).
47. Digital Elevation Model. Geospatial Data Cloud. Available online: <https://www.gscloud.cn/> (accessed on 15 January 2023).
48. Ma, S.; Wang, L.J.; Wang, H.Y.; Zhao, Y.G.; Jiang, J. Impacts of land use/land cover and soil property changes on soil erosion in the black soil region, China. *J. Environ. Manag.* **2023**, *328*, 117024. [CrossRef]
49. Fang, H.; Fan, Z. Assessment of Soil Erosion at Multiple Spatial Scales Following Land Use Changes in 1980–2017 in the Black Soil Region, (NE) China. *Int. J. Environ. Res. Public Health* **2020**, *17*, 7378. [CrossRef] [PubMed]
50. Wang, R.; Zhang, S.; Yang, J.; Pu, L.; Yang, C.; Yu, L.; Chang, L.; Bu, K. Integrated Use of GCM, RS, and GIS for the Assessment of Hillslope and Gully Erosion in the Mushi River Sub-Catchment, Northeast China. *Sustainability* **2016**, *8*, 317. [CrossRef]
51. Yang, X.; Zhang, X.; Deng, W.; Fang, H. Black soil degradation by rainfall erosion in Jilin, China. *Land Degrad. Dev.* **2003**, *14*, 409–420. [CrossRef]
52. USDA. Soil Survey Manual. In *Soil Conservation Service. U.S. Department of Agriculture Handbook No. 18*; USDA: Washington DC, USA, 1951; p. 503.
53. Ghosal, K.; Bhattacharya, S.D. A Review of RUSLE Model. *J. Indian Soc. Remote Sens.* **2020**, *48*, 689–707. [CrossRef]
54. Li, J.L.; Sun, R.H.; Xiong, M.Q.; Yang, G.C. Estimation of soil erosion based on the RUSLE model in China. *Acta Ecol. Sin.* **2020**, *40*, 3473–3485. [CrossRef]
55. Yang, J.J.; Bai, L.; Wu, S. Study on the erosion in typical black soil areas of Heilongjiang Province by remote sensing monitoring technology. *Geol. Resour.* **2019**, *28*, 193–199+183. [CrossRef]
56. Ministry of Water Resources of the People's Republic of China. *Standards for Classification and Gradation of Soil Erosion, SL190-2007*; Ministry of Water Resources of the People's Republic of China: Beijing, China, 2008; p. 8.
57. Heilongjiang Provincial Department of Water Resources. *Heilongjiang Province Soil and Water Conservation Bulletin (2018)*; Heilongjiang Provincial Department of Water Resources: Harbin, China, 2018.
58. Heilongjiang Provincial Department of Water Resources. *Heilongjiang Province Soil and Water Conservation Bulletin (2020)*; Heilongjiang Provincial Department of Water Resources: Harbin, China, 2020.
59. Li, W.; Fan, W.; Mao, X.; Wang, X. Dynamic Study of Soil Erosion in Greater Khingan Forest. *Adv. J. Food Sci. Technol.* **2015**, *7*, 864–871. [CrossRef]
60. Wang, J.; Liu, X.; Zhang, L. Study on soil erosion situation and counter measures in Heilongjiang Province. *J. Northeast Agric. Univ.* **2009**, *40*, 131–135. [CrossRef]
61. Lin, C. Soil erosion control measures and benefit analysis. *Water Ecol.* **2011**, 48–49. [CrossRef]
62. Li, P.; Zang, Y.; Ma, D.; Yao, W.; Holden, J.; Irvine, B.; Zhao, G. Soil erosion rates assessed by RUSLE and PESERA for a Chinese Loess Plateau catchment under land-cover changes. *Earth Surf. Process. Landf.* **2020**, *45*, 707–722. [CrossRef]
63. Xie, Y.; Lin, H.; Ye, Y.; Ren, X. Changes in soil erosion in cropland in northeastern China over the past 300 years. *Catena* **2019**, *176*, 410–418. [CrossRef]
64. Leh, M.; Bajwa, S.; Chaubey, I. Impact of Land Use Change on Erosion Risk: An Integrated Remote Sensing, Geographic Information System and Modeling Methodology. *Land Degrad. Dev.* **2013**, *24*, 409–421. [CrossRef]
65. Green, R.E.; Cornell, S.J.; Scharlemann, J.P.; Balmford, A. Farming and the Fate of Wild Nature. *Science* **2005**, *307*, 550–555. [CrossRef]
66. Montgomery, D.R. Soil erosion and agricultural sustainability. *Proc. Natl. Acad. Sci. USA* **2007**, *104*, 13268–13272. [CrossRef] [PubMed]
67. García-Ruiz, J.M.; Beguería, S.; Nadal-Romero, E.; González-Hidalgo, J.C.; Lana-Renault, N.; Sanjuán, Y. A meta-analysis of soil erosion rates across the world. *Geomorphology* **2015**, *239*, 160–173. [CrossRef]

68. Jia, C.; Zhongwu, L.; Haibing, X.; Ke, N.; Chongjun, T. Effects of land use and land cover on soil erosion control in southern China: Implications from a systematic quantitative review. *J. Environ. Manag.* **2021**, *282*, 111924. [[CrossRef](#)]
69. Ouyang, Z.; Zheng, H.; Xiao, Y.; Polasky, S.; Liu, J.; Xu, W.; Wang, Q.; Zhang, L.; Xiao, Y.; Rao, E.; et al. Improvements in ecosystem services from investments in natural capital. *Science* **2016**, *352*, 1455–1459. [[CrossRef](#)] [[PubMed](#)]
70. Xu, X.; Zheng, F.; Wilson, G.V.; He, C.; Lu, J.; Bian, F. Comparison of runoff and soil loss in different tillage systems in the Mollisol region of Northeast China. *Soil Tillage Res.* **2018**, *177*, 1–11. [[CrossRef](#)]
71. Yi, L. Studying on the Soil Erosion Risk by Water in China. Ph.D. Thesis, Institute of Remote Sensing and Digital Earth Chinese Academy of Sciences, Beijing, China, 2017.
72. Tuo, D.; Xu, M.; Gao, G. Relative contributions of wind and water erosion to total soil loss and its effect on soil properties in sloping croplands of the Chinese Loess Plateau. *Sci. Total Environ.* **2018**, *633*, 1032–1040. [[CrossRef](#)]
73. Fang, G.; Yuan, T.; Zhang, Y.; Wen, X.; Lin, R. Integrated study on soil erosion using RUSLE and GIS in Yangtze River Basin of Jiangsu Province (China). *Arab. J. Geosci.* **2019**, *12*, 173. [[CrossRef](#)]
74. Zhu, X.; Zhang, R.; Sun, X. Spatiotemporal dynamics of soil erosion in the ecotone between the Loess Plateau and Western Qinling Mountains based on RUSLE modeling, GIS, and remote sensing. *Arab. J. Geosci.* **2021**, *14*, 33. [[CrossRef](#)]

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