



1 **Modelling the effects of 300-year cropland expansion on soil erosion in** 2 **Northeast China**

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4 Authors: Gefei Tan ^{a,b}, Haiyan Fang ^{a,b,*}

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6 Affiliation:

7 ^a Key Laboratory of Water Cycle and Related Land Surface Processes, Institute of Geographic Sciences and Natural
8 Resources Research, Chinese Academy of Sciences, Beijing 100101, China

9 ^b College of Resources and Environment, University of Chinese Academy of Sciences, Beijing 100049, China

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16 ***Corresponding author:** Haiyan Fang (fanghy@igsnr.ac.cn)

17 **Address:** Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, 11A, Datun
18 Road, Chaoyang District, Beijing, 100101, China.



23 Abstract

24 Historic soil erosion induced by long-term croplands' expansion is less reported, which greatly inhibits understanding
25 long-term soil erosion process and soil erosion conservation. In the present study, the reconstructed historical cropland and
26 the RUSLE model was integrated to assess potential erosion changes during 1700 to 2020 in the black soil region, Northeast
27 China (NEC). During the past over 300 years, cropland expanded from near zero to 0.07 million km² by 1900 and further
28 to 0.35 million km² in 2020 from flat or gentle areas to steeper slopes. Affected by expanded croplands, soil erosion was
29 intensified markedly over 300 years, with mean erosion rates increasing from 1.24 to 2.81 t ha⁻¹ yr⁻¹ and total soil loss
30 rising from 0.15 to 0.35 Gt yr⁻¹. Cropland accounted for 78% of the areas and soil erosion exceeded the tolerable value
31 (i.e., 2 t ha⁻¹ yr⁻¹) in 2020. Cumulative erosion depth averaged 3.7 cm across the whole croplands and reached 9.13 cm in
32 areas with > 120-year cultivated period. The land cultivation history as well as its induced soil erosion exhibited distinct
33 latitudinal pattern characteristics. These results highlight the importance of the effect of long-term land cultivation history
34 on the cumulative impacts of soil erosion, and provide a scientific basis for sustainable management for the black soil
35 region, NEC and similar regions in the world.

36 **Keywords.** Black soil region; Soil loss; Cropland expansion; Reclamation history; Cumulative effects

37



38 1. Introduction

39 Soil erosion is one of the most widespread forms of land degradation globally, negatively affecting soil productivity,
40 ecosystem stability, and global biogeochemical cycles (Berhe et al., 2018; Tan et al., 2020; Carr et al., 2021; Xiong and
41 Leng, 2024). Although it occurs naturally, it is often intensified by anthropogenic activities, particularly agricultural
42 expansion (Jenny et al., 2019). The conversion of natural vegetation cover to cropland alters landscape structure and
43 increases soil susceptibility to erosion (Potapov et al., 2022; Chen et al., 2025; Wang et al., 2025). Understanding how
44 cropland expansion shapes erosion risk is therefore critical for sustainable land management.

45 Land use and cultivation date back thousands of years, and cropland expansion in many regions peaked centuries ago
46 (Vanwalleggem et al., 2017). Numerous regional and global studies have examined soil erosion responses to land use
47 change, especially agricultural land expansion (Fang, 2017; Golosov et al., 2018; Xiong and Leng, 2024; Vangeli et al.,
48 2025). However, due to limited data availability, most quantitative assessments focus on the post-1980 period, leaving
49 long-term historical soil erosion research underdeveloped. Using sediments as information carriers, scholars have applied
50 radionuclide tracing (Meliho et al., 2019; Zhai et al., 2026), radiocarbon dating (Zhang et al., 2020), and pollen analysis
51 (Zhao et al., 2022) to reconstruct historical sediment yield changes. However, these methods only reflect erosion history
52 indirectly and fail to capture its temporal dynamics.

53 The Northeast China (NEC) provides an ideal case for investigating long-term anthropogenic impacts on soil erosion.
54 As one of the four major black soil regions worldwide, NEC is not only a key grain production base of China, but also one
55 of the most intensively reclaimed agricultural frontiers globally (Xu et al., 2020; Tong et al., 2024). Since the eighteenth
56 century (i.e., mainly from the year of 1860), large-scale cropland expansion has rapidly transformed natural landscapes
57 into agricultural systems (Ye et al., 2009). Despite its relatively short history of large-scale agricultural reclamation, severe
58 soil erosion has already led to substantial degradation of the fertile black soil layer (Li et al., 2021; Tan and Fang, 2026a).
59 Previous studies have investigated longer time-period soil erosion in this region using a range of approaches. Fallout
60 radionuclide techniques, particularly ^{137}Cs tracing, have been widely applied to estimate around 60-year average erosion



61 rates at plot and small watershed scales (Wang et al., 2022; Shen et al., 2023; Xie et al., 2023). In addition, historical soil
62 erosion estimates integrating county-level cropland data with empirical models have yielded important regional-scale
63 insights (Xie et al., 2019). However, it is constrained by limited temporal detail or coarse spatial resolution. This makes it
64 difficult to capture the accurate spatiotemporal erosion dynamics during historical periods. A major existed bottleneck is
65 the lack of long-term, spatially explicit cropland datasets. With recent advances in high-resolution cropland reconstruction
66 (Tan and Fang, 2026b), it is now possible to conduct more detailed assessments of soil erosion over long timescales, i.e.,
67 300 years.

68 The change of soil erosion rates, typically expressed as mass loss per unit area (i.e., $\text{t ha}^{-1} \text{yr}^{-1}$), has been widely used
69 as a standard indicator to characterize erosion processes (Borrelli et al., 2017; Wuepper et al., 2020; Yan et al., 2025).
70 However, such mass-based indicators do not directly reflect soil degradation severity and surface lowering. Previous studies
71 have indicated that the impacts of cropland expansion accumulate over decades to centuries, leading to substantial soil loss
72 and persistent topsoil depletion (Mieth and Bork, 2005; Montgomery, 2007; Yu et al., 2017). Therefore, converting soil
73 loss into erosion depth provides a more intuitive representation of cumulative soil removal (Xu et al., 2025). This is
74 particularly relevant in NEC, where black soils are thinning or even completely loss (Xie et al., 2020; Wang et al., 2022)
75 due to its relatively shallow topsoil layers and severe soil erosion (Xie et al., 2020; Li et al., 2021; Song et al., 2025). Soil
76 thinning is closely associated with the degradation of soil physical structure and the loss of organic matter and essential
77 nutrients, thereby constraining crop productivity (Zhang et al., 2021; Liu et al., 2024a; Xie et al., 2026). The estimation of
78 erosion depth over time is essential for revealing legacy effects of cropland expansion and assessing potential hazard.

79 Soil erosion models provide essential tools for quantifying erosion processes across spatial and temporal scales (Li et
80 al., 2017; Borrelli et al., 2021). Among them, the Revised Universal Soil Loss Equation (RUSLE) has been widely applied
81 due to its simple structure, modest data requirements, and strong adaptability (Cao et al., 2023b; Chakraborty et al., 2025;
82 Yan et al., 2025). Although RUSLE is an empirical model, its parameterization has been continuously refined and localized



83 (Naipal et al., 2015; Zhang et al., 2019; Kaffas et al., 2021), making it particularly suitable for long-term regional
84 assessments.

85 Therefore, the aims of the present study were to (i) reconstruct the spatiotemporal characteristics of erosion rates in
86 the NEC since 1700, (ii) quantify the cumulative effects of cropland expansion on soil loss, and (iii) examine the
87 relationship between cultivation duration and soil erosion dynamics. The findings of this study are expected to provide
88 insights for developing soil conservation measures, while take into account both erosion rates and cumulative erosion.

89 **2. Materials and methods**

90 *2.1. Study area*

91 The NEC is located between approximately 38 °–54 °N and 115 °–135 °E (Fig. 1a), covering a total area of about 1.24
92 million km². The region includes Heilongjiang, Jilin, and Liaoning Provinces, as well as four cities in Inner Mongolia. The
93 terrain is characterized by a pattern of plains surrounded by mountains, including the Songnen Plain, Sanjiang Plain, and
94 Liaohe Plain, and the Greater Khingan, Lesser Khingan, and Changbai Mountains.

95 The NEC has a temperate continental monsoon climate. Mean annual precipitation ranges from approximately 400 to
96 800 mm, with the majority occurring during the summer months. The natural vegetation shows a clear zonal pattern from
97 southeast to northwest, transitioning from deciduous broadleaf forest to mixed forest, coniferous forest, and grassland.
98 Correspondingly, the soil types are multiple, varying from brown soils and dark brown forest soils in the southeast to black
99 soils, gray forest soils, chernozems, and chestnut soils toward the northwest (Liu et al., 2021a). Over the past 300 years,
100 extensive agricultural reclamation has transformed most plains, gentle slopes, and low hilly areas into cropland (Fig. 1b–
101 e). The main crops are maize, soybean, and rice.

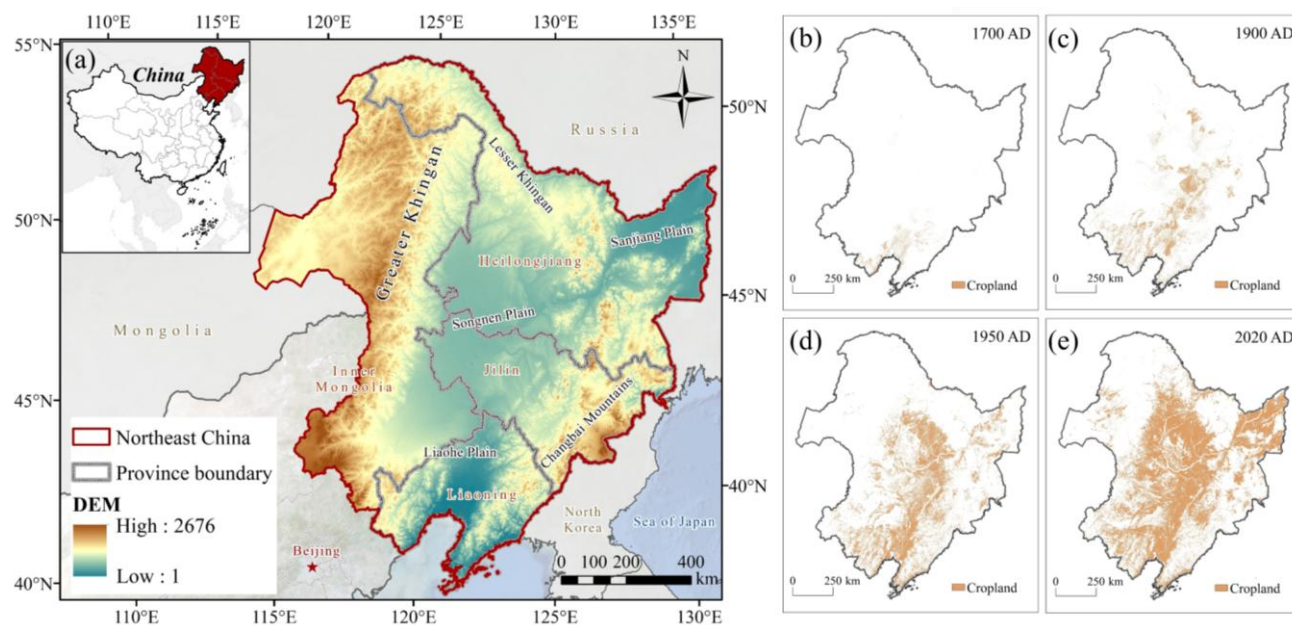


Fig. 1. Study area and reconstructed cropland distribution. (a) Location and topography of the NEC; (b–e) The exampled cropland distribution in 1700, 1900, 1950, and 2020, respectively. Cropland data are derived from Tan and Fang (2026b). All spatial data are projected in the Krasovsky 1940 coordinate system.

2.2. Data source

The historical cropland dataset was obtained from Tan and Fang (2026b), which reconstructed cropland distribution in Northeast China at a spatial resolution of 30 m for 1700–2020 (Table 1). This dataset was reconstructed through using county-level cropland fraction data (Jia et al., 2024) and a suitability-based allocation framework. It provides a spatially explicit representation of cropland expansion over the past three centuries. For this study, historical time slices were selected at 50-year intervals from 1700 to 1900 and at 10-year intervals thereafter. These maps provided the spatial and temporal framework for estimating erosion associated with cropland expansion and identifying areas with different reclamation histories.

The other datasets used in this study were summarized in Table 1. Rainfall erosivity data covering 1951–2018 were obtained from (Yue et al., 2022) to specify the baseline R-factor and assess sensitivity to changing rainfall erosivity. Soil



property data from (Shi et al., 2025a) were used to calculate soil erodibility and convert soil loss into equivalent erosion depth. The LS-factor was obtained from (Sun et al., 2024), while elevation data from the Resource and Environmental Science Data Center (RESDC, www.resdc.cn) were used to characterize terrain and derive slope classes. Potential natural vegetation data from (Hengl et al., 2018) informed the representation of background vegetation. Land-cover, Normalized Difference Vegetation Index (NDVI), and crop-type data supported the assignment of C-factors to cropland and non-cropland areas.

All spatial datasets were registered to a unified 30-meter grid based on the WGS 84 geodetic datum. The modelling period and historical time slices followed the selected cropland reconstruction maps for 1700–2020.

Table 1 The datasets used in this study.

Dataset description	Spatial resolution	Temporal period	Source
Historical cropland	30 m	1700–2020	(Tan and Fang, 2026b)
R-factor	0.01 °	1951–2018	(Yue et al., 2022)
Soil properties	90 m	1980	(Shi et al., 2025a)
LS-factor	1 arc-sec	2010	(Sun et al., 2024)
Elevation	30 m	2010	www.resdc.cn
potential natural vegetation	1 km	/	(Hengl et al., 2018)
Land cover	30 m	2020	www.resdc.cn
NDVI	30 m	2020	www.resdc.cn
Main crop types	30 m	2021	www.geodata.cn

2.3. *RUSLE model*

The *RUSLE* is widely applied for quantifying average annual soil loss at regional scales (Borrelli et al., 2021). The model is expressed as:



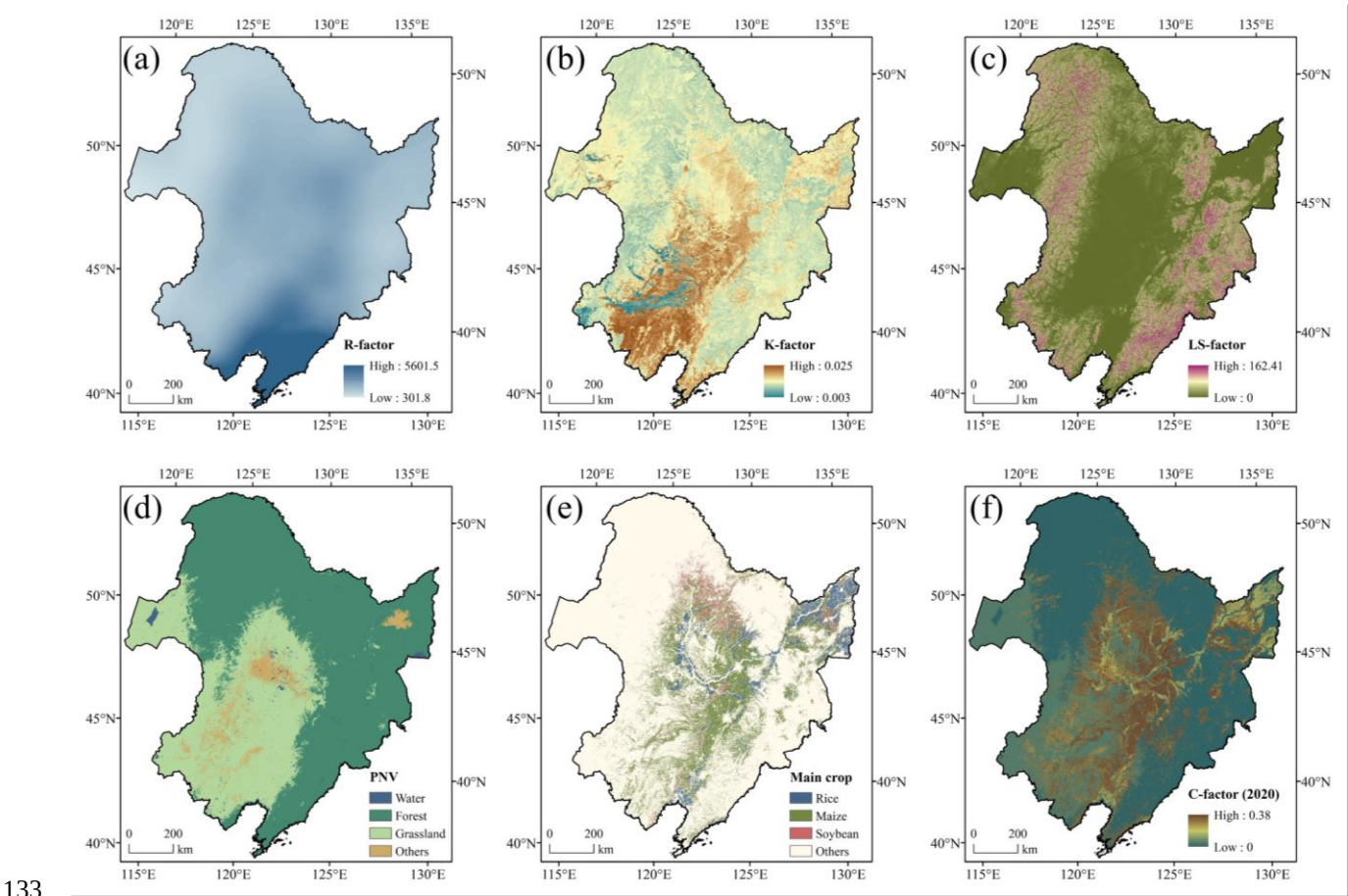
128
$$A = R \times K \times LS \times C \times P \quad (1)$$

129 where A is the annual soil erosion rate ($\text{t ha}^{-1} \text{yr}^{-1}$); R is the rainfall erosivity factor ($\text{MJ mm h}^{-1} \text{ha}^{-1} \text{yr}^{-1}$); K is the soil

130 erodibility factor ($\text{t ha h MJ}^{-1} \text{mm}^{-1}$); LS is the topographic factor (dimensionless) representing slope length and steepness;

131 C is the land cover and management factor (dimensionless); and P is the erosion-control practice factor (dimensionless).

132 The P factor is not considered in this study due to not availability in the large area of NEC over the past 300 years.



134 **Fig. 2. Spatial distribution of factors used in the RUSLE model.** (a) Rainfall erosivity factor (R); (b) soil erodibility factor (K); (c)

135 slope length and steepness factor (LS); (d) potential natural vegetation (PNV); (e) main crop types; and (f) cover and management factor

136 (C) in 2020.



Detailed descriptions of each factor are provided in the following sections, and a summary of all input datasets is given in Table 1. All factors were projected into the Krasovsky 1940 coordinate system, and the spatial resolution was resampled to 30 m (Fig. 2).

2.3.1. The R factor

The R factor is traditionally calculated from the rainfall energy and its maximum 30-min intensity (EI_{30}) (Wischmeier and Smith, 1978). The EI_{30} method typically requires high-resolution rainfall intensity observations, which are generally available only for recent decades (Li et al., 2022). Thus, the applicability of EI_{30} data in long-term reconstructions is constrained. Moreover, the precipitation regimes have undergone dramatic changes in recent decades (Ipcc, 2023). It may lead to biases if EI_{30} -derived R factor is directly extrapolated to earlier periods.

In this study, R-factor dataset calculated from hourly precipitation data (Yue et al., 2022) was applied. It enables the extension of R-factor estimation back to the 1950s, offering a more robust temporal basis. To isolate the long-term effects of cropland expansion on soil erosion, the annual average R factor during 1951–2018 (Fig. 2a) was applied uniformly in the 1700–2020 simulation.

2.3.2. The K factor

The K factor reflects the inherent sensitivity of soil to erosion (Wischmeier and Smith, 1978; Yang et al., 2024). It is determined by its physical and chemical properties, such as texture, structure, and organic matter content. In this study, the K factor (Fig. 2b) was estimated using the improved method proposed by Zhang et al. (2019). It is modified based on the K_{epic} method to improve its applicability in Chinese agricultural soils. The equation is as follows:

$$K_{epic} = \left\{ 0.2 + 0.3 \exp \left[-0.0256 SAN \left(1 - \frac{SIL}{100} \right) \right] \right\} \left(\frac{SIL}{CLA + SIL} \right)^{0.3} \left[1 - \frac{0.25 OC}{OC + \exp(3.72 - 2.95 OC)} \right] \left[1 - \frac{0.7 SN1}{SN1 + \exp(-5.51 + 22.9 SN1)} \right] \quad (2)$$

$$SN1 = 1 - \frac{SAN}{100} \quad (3)$$

$$K = (-0.01383 + 0.51575 K_{epic}) \times 0.1317 \quad (4)$$



158 Where SAN, SIL, and CLA are the percentages (%) of sand, silt, and clay, respectively; OC is the soil organic carbon
159 content (%); SN1 is the complement of sand content. All soil property data were obtained from Shi et al. (2025a), and
160 resampled from 90 m resolution to 30 m.

161 2.3.3. The LS-factor

162 The LS factor accounts for the effects of slope length (L) and slope steepness (S) on soil erosion. In this study, the LS
163 factor (Fig. 2c) was obtained from Sun et al. (2024), which was calculated as follows:

$$164 \quad S = \begin{cases} 10.8 \sin \theta + 0.03 & \theta < 5^\circ \\ 16.8 \sin \theta - 0.05 & 5^\circ \leq \theta < 10^\circ \\ 21.91 \sin \theta - 0.96 & \theta \geq 10^\circ \end{cases} \quad (5)$$

$$165 \quad L = \begin{cases} \frac{\lambda_{out}^{m+1} - \lambda_{in}^{m+1}}{(\lambda_{out} - \lambda_{in})(22.13)^m} & \lambda_{out} - \lambda_{in} > 0 \\ \left(\frac{\lambda_{out}}{22.13}\right)^m & \lambda_{out} - \lambda_{in} \leq 0 \end{cases} \quad (6)$$

$$166 \quad m = \begin{cases} 0.2 & \theta < 0.5^\circ \\ 0.3 & 0.5^\circ \leq \theta < 1.5^\circ \\ 0.4 & 1.5^\circ \leq \theta < 3^\circ \\ 0.5 & \theta \geq 3^\circ \end{cases} \quad (7)$$

167 Where θ is the slope steepness ($^\circ$), S is the slope steepness factor, λ_{in} is the slope length at the inlet, λ_{out} is the slope
168 length at the outlet, m is a variable length-slope exponent, and L is the slope length factor.

169 2.3.4. The C-factor

170 The C-factor represents the effect of vegetation cover and land management on soil erosion by reducing raindrop
171 impact and surface runoff (Wischmeier and Smith, 1978). In this study, the historical land use in the NEC was reconstructed
172 for each time slice based on the combination of historical cropland distribution (Tan and Fang, 2026b), main crop types
173 (Table 1; Fig. 2e) and potential natural vegetation (Hengl et al., 2018). Potential natural vegetation represents the vegetation
174 distribution that would exist under natural environmental conditions in the absence of human activities. The potential
175 natural vegetation data is derived by machine learning models, with a spatial resolution of 1 km. Land use was classified
176 into five categories: water, forest, grassland, cropland and others, and cropland was divided into rice, maize, and soybean.



Table 2 C-factor value and reference range of non-cropland.

Class	Land-cover type	C-factor value	Reference range	Sources
1	Forest	0.0008	0.0001 ~ 0.003	
2	Grassland	0.044	0.01 ~ 0.1	(Borrelli et al., 2017)
3	Others	0.274	0.1 ~ 0.5	
4	Cropland	Rice	0.15	/
		Maize	0.38	
		Soybean	0.32	
		Others	0.30	
5	Water	0	/	(Panagos et al., 2015b)

For non-cropland, C values were estimated based on the present-day land cover conditions. The landsat 8 imagery derived land cover and NDVI data were downloaded from the Resource and Environmental Sciences, Chinese Academy of Sciences (Table. 1). The C values of non-cropland were calculated by (Panagos et al., 2015a; Borrelli et al., 2017; Li et al., 2023):

$$F_{cover} = \frac{NDVI_i - \min(NDVI)}{\max(NDVI) - \min(NDVI)} \quad (8)$$

$$C_{ni} = \min(R_n) + [\max(R_n) - \min(R_n)] \times (1 - F_{cover}) \quad (9)$$

$$C_n = \overline{C_{ni}} \quad (10)$$

Where F_{cover} is the vegetation coverage, $NDVI_i$ is the NDVI at grid cell i , $\max(NDVI)$ and $\min(NDVI)$ represent the maximum and minimum values of the NDVI; C_{ni} is the C value in grid cell i of land cover type n , $\max(R_n)$ and $\min(R_n)$ represent the maximum and minimum values of the reference values of the C-factor in land cover type n (Table 2); C_n is the C values of land cover type n .

For cropland, crop-specific C values were therefore assigned based on the distribution of major crops (Table 2), with the values referencing to Panagos et al. (2015a), which were used in research both globally (Xiong and Leng, 2024) and in China (Li et al., 2023). Based on the data of major crop types in NEC (Table 1), the main crops are divided into rice, maize, soybeans, and others.



2.4. Soil erosion effects of cropland expansion

The soil erosion effects of cropland expansion were quantified using the increment in cumulative soil erosion depth relative to a fixed baseline. Annual soil erosion depth (ED , mm yr^{-1}) was calculated based on soil erosion rate and soil bulk density:

$$ED_i = \frac{A_i}{BD \times 10} \quad (11)$$

Where ED_i is soil erosion depth in year i (mm yr^{-1}); A_i is soil erosion rate in year i ($\text{t ha}^{-1} \text{yr}^{-1}$); BD is soil bulk density (g cm^{-3}), the data source is contemporary soil properties dataset (Table 1; Shi et al. (2025a)).

The total cumulative soil erosion depth (ED_T , mm) over the study period (1700–2020) was estimated using a trapezoidal integration scheme based on discrete time slices:

$$ED_T = \sum_{i=1}^{n-1} \frac{(ED_i + ED_{i+1})}{2} \cdot \Delta t_i \quad (12)$$

where ED_i and ED_{i+1} are erosion depths at consecutive time points, Δt_i is the time interval between them (i.e., 50 or 10 years depending on the period).

To quantify the baseline cumulative erosion depth (ED_B , mm), land-use condition in 1700 were assumed to remain unchanged throughout the study period:

$$ED_B = ED_{1700} \times (2020 - 1700) \quad (13)$$

The soil erosion effect of cropland expansion was then expressed as the increment in cumulative erosion depth relative to this baseline (ED_E , mm):

$$ED_E = ED_T - ED_B \quad (14)$$

To further assess the erosion increment per year of cropland presence, the mean annual excess erosion depth ($\overline{ED}_E$) was computed as:

$$\overline{ED}_E = \frac{ED_E}{CD} \quad (15)$$



214 Where CD is the cumulative duration of cropland presence (years), derived by integrating cropland presence over
 215 time. This metric was calculated only where (CD>0).

216 This framework quantifies the incremental soil erosion effects associated with cropland expansion relative to the fixed
 217 1700 land-use baseline.

218 2.5. Sensitivity to rainfall erosivity and potential effects of conservation practices

219 Sensitivity analyses were conducted to evaluate the effects of R, and P factor parameterization on the estimated soil
 220 erosion patterns. In the baseline simulation (S0) for 1700–2020, R, K, and LS were held constant, and P was set to 1,
 221 allowing temporal changes in erosion to be associated with reconstructed land-use changes represented by C.

222 To evaluate sensitivity to the fixed-climate assumption, two R scenarios were established: S1, with both time-varying
 223 R and C; and S2, with time-varying R and C fixed at its 1980 spatial configuration:

$$224 A_{S1} = R_i \times K \times LS \times C_i \quad (16)$$

$$225 A_{S2} = R_i \times K \times LS \times C_{1980} \quad (17)$$

226 Here, R_i is the corresponding 30-year mean rainfall erosivity, and C_i represents the reconstructed C-factor
 227 distribution at time i . The R datasets for 1951–1980, 1961–1990, 1971–2000, 1981–2010, and 1991–2020 were assigned
 228 to the reference years 1980, 1990, 2000, 2010, and 2020, respectively. These combinations represent erosion under
 229 specified land-use configurations and 30-year climatic backgrounds. Comparisons between S1 and S0 quantified the
 230 influence of the fixed-R assumption on erosion estimates. To isolate the effect of R variation under a common land-use
 231 configuration, S2 was compared with the 1980 baseline estimate.

232 Sensitivity to the assumption $P = 1$ was evaluated for 2000, 2010, and 2020. Two support-practice scenarios were
 233 considered: slope-dependent contour ridge scenario (P1), and constant-parameter contour tillage scenario (P2). In P1,
 234 drylands (excluding cropland used for growing rice) with slopes of 2° – 15° was designated as the treatment area. The



relationship ($P = 0.45\theta$) reported by (Xin et al., 2019) was applied to slopes of 5° – 15° , where θ is slope steepness in degrees. For slopes of 2° – 5° , P was held at 0.225, the equation value at 5° , to avoid extrapolation towards near-zero values:

$$\begin{cases} P_1 = 0.225, & 2^\circ \leq \theta < 5^\circ \\ P_1 = 0.045\theta, & 5^\circ \leq \theta \leq 15^\circ \\ P_1 = 1, & \text{other areas} \end{cases} \quad (18)$$

In P2, P was set to 0.352 within the same treatment area, following the contour-tillage parameter used by (Fang and Sun, 2017), and remained 1 elsewhere. All P scenarios used the same fixed R , K , LS , and time-specific C factors. Regional erosion reduction was calculated as:

$$\Delta \text{Erosion} = \frac{\sum_i (A_{0,i} - A_{P,i}) S_i}{\sum_i A_{0,i} S_i} \times 100\% \quad (19)$$

where S_i is the area of grid cell i , $A_{0,i}$ is the erosion rate of grid cell i in baseline simulation, $A_{P,i}$ is the erosion rate of grid cell i in practice simulation. These comparisons evaluated the sensitivity of erosion magnitude and spatial patterns to the selected parameter assumptions.

3. Results

3.1. Cropland expansion characteristics

The cropland areas expanded markedly from near zero in 1700 to 0.07 million km^2 in 1900, and further to 0.35 million km^2 in 2020 (Fig. 3a). Cropland expansion was accompanied by a clear shift in slope distribution. Although cropland remained dominated by gentle slopes ($<2^\circ$), the area proportion showed a declining trend. In particular, the share of very gentle cropland ($<1^\circ$) reduced from 44% to 27%.

The spatial pattern of expansion exhibited a pronounced directional trend (Fig. 3b). Cropland showed a persistent southwest–northeast orientation throughout the study period. In 1700, the directional tendency was relatively weak, with an ellipse rotation angle of 15.32° . The orientation peaked in 2020 with a rotation angle of 37.7° ; the next highest was 33.9° in 1940. The dispersion of cropland distribution also changed over time. The ratio of the major to minor axis was 2.1 in



1700, indicating strong anisotropy. After 1900, this ratio gradually decreased, reaching 1.96 in 1900, 1.68 in 1940, 1.51 in 1980, and 1.46 in 2020.

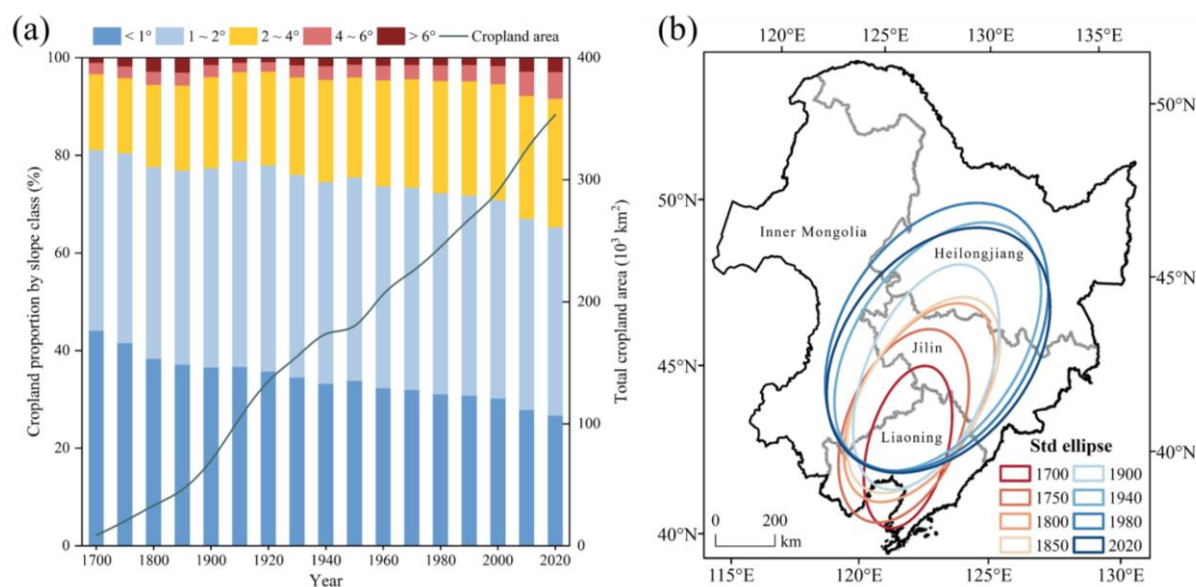


Fig. 3. Spatiotemporal characteristics of cropland expansion from 1700 to 2020. (a) Temporal changes in cropland area and the proportion of cropland across slope classes; (b) standard deviational ellipses of cropland distribution for example years.

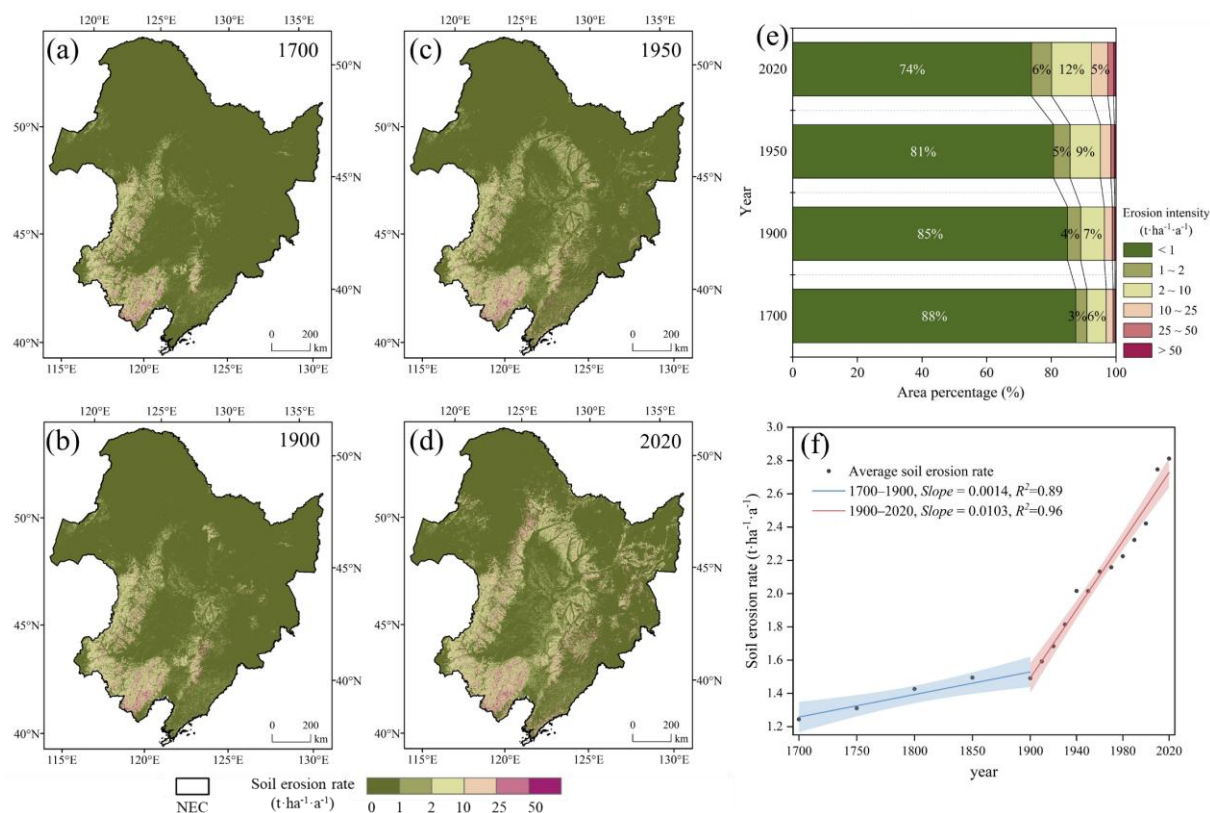
3.2. Spatiotemporal evolution of soil erosion

Soil erosion in the NEC exhibited pronounced spatial heterogeneity and significant temporal changes over the past three centuries (Fig. 4a–d). In 1700, erosion rates were generally low across the region, only 9% of the area exceeded the tolerable soil loss threshold of $2 \text{ t ha}^{-1} \text{ yr}^{-1}$ (Fang, 2021b). Higher erosion was mainly confined to mountainous areas. By 1900, the overall spatial pattern remained similar, but localized increases in erosion emerged in lowland and transitional zones. This trend became more evident in 1950, with noticeable intensification of erosion in parts of the plains. By 2020, soil erosion rates further increased and expanded spatially, with about 20% of the area exceeding the tolerable erosion.

At the regional scale, the mean soil erosion rate shows an overall increasing trend from 1700 to 2020 (Fig. 4f). The mean erosion rate increased from $1.24 \text{ t ha}^{-1} \text{ yr}^{-1}$ in 1700 to 2.81 in 2020. The increase is relatively slow before 1900 but



269 accelerates afterward. After 1900, the regional mean erosion rate increased by $\sim 0.1 \text{ t ha}^{-1} \text{ yr}^{-1}$ per decade. Given the total
 270 area of 1.24 million km^2 , the annual soil loss increased from 0.15 Gt yr^{-1} in 1700 to 0.35 Gt yr^{-1} in 2020.



271
 272 **Fig. 4. Spatial patterns and temporal evolution of soil erosion in the NEC.** (a–d) Soil erosion rates in 1700, 1900, 1950, and 2020,
 273 respectively; (e) area proportions of different erosion intensity classes for the four selected years; (f) temporal trend of regional mean
 274 soil erosion rate during 1700–2020.

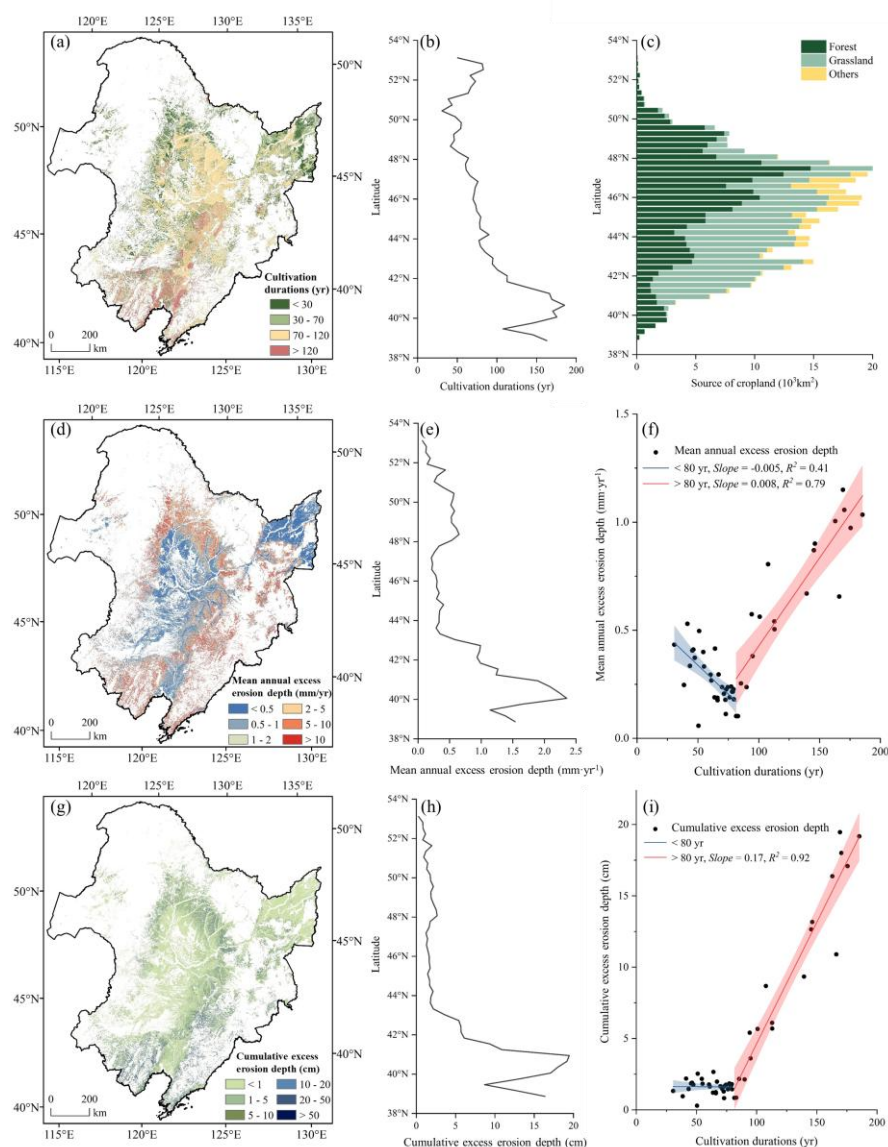
275 3.3. Latitudinal patterns of cultivation history and soil erosion effects

276 Cultivation duration exhibited a clear south–north gradient (Fig. 5a–b). Areas with cultivation durations exceeding
 277 120 years were concentrated in the southern plains, i.e., the Liaohe plain. Areas with intermediate durations of
 278 approximately 70–120 years occurred mainly in the Songnen Plain, whereas shorter cultivation durations were more



279 common in northern and peripheral regions. The sources of cropland also showed obvious latitudinal differences (Fig. 5c).

280 Cropland was primarily converted from grassland in the central plains and from forest in marginal areas.



281 **Fig. 5. Spatial and latitudinal patterns of cultivation history and soil erosion effects of cropland expansion.** (a) cultivation duration;
282 (b) latitudinal profile of cultivation duration; (c) latitudinal distribution of cropland sources in 2020 based on potential natural vegetation;
283



(d) mean annual excess erosion depth; (e) its latitudinal profile; (f) relationship between latitudinal-bin means of cultivation duration and mean annual excess erosion depth; (g) cumulative excess erosion depth; (h) its latitudinal profile; and (i) relationship between latitudinal-bin means of cultivation duration and cumulative excess erosion depth. (b), (e), and (h) show cropland means within 50 equal-width latitudinal bins, while (c) shows cropland areas within the same bins.

The erosion effects of cropland expansion were quantified as increments in erosion depth relative to the fixed 1700 baseline. Mean annual excess erosion depth showed a different spatial pattern (Fig. 5d–e). Higher values occurred in parts of the southern and northern regions, whereas lower values characterized much of the central plains. Across latitudinal bins, the relationship between mean cultivation duration and mean annual excess erosion depth exhibited a V-shaped pattern (Fig. 5f). The bins with a medium cultivation duration has the least erosion effect.

Compared to 1700, land cultivations had caused a mean cumulative excess erosion depth of 3.7 cm. Higher values were concentrated in long-term cultivated areas, particularly along the southern plain–hilly transition zone, where some locations exceeded 50 cm (Fig. 5g). In contrast, the central plains generally exhibited smaller increments (Fig. 5h). Cropland with cultivation durations exceeding 120 years had a mean cumulative excess erosion depth of 9.13 cm. Across latitudinal bins, longer mean cultivation durations generally coincided with greater cumulative increments, particularly among bins with mean durations exceeding approximately 80 years (Fig. 5f).

4. Discussion

4.1. Comparison with previous soil erosion estimates

Independent validation of regional soil erosion models remains challenging, particularly for long-term historical simulations. Comparison with previous estimates provides a useful reference for assessing the magnitude of modelled erosion. In this study, the simulated mean soil erosion rate for 2020 was $2.81 \text{ t ha}^{-1} \text{ yr}^{-1}$, close to the regional estimate of approximately $2.75 \text{ t ha}^{-1} \text{ yr}^{-1}$ from the global assessment (Borrelli et al., 2017). The estimate is higher than the values from China’s soil erosion datasets (Li et al., 2023; Yan et al., 2025), and lower than results from recent regional erosion



simulations (Fang, 2021c; Cao et al., 2023b; Tang et al., 2024). At the provincial scale, the estimates generally agree with previous studies in Heilongjiang and Jilin. However, relatively higher values are observed in Liaoning ($7.08 \text{ t ha}^{-1} \text{ yr}^{-1}$) and Inner Mongolia ($2.83 \text{ t ha}^{-1} \text{ yr}^{-1}$).

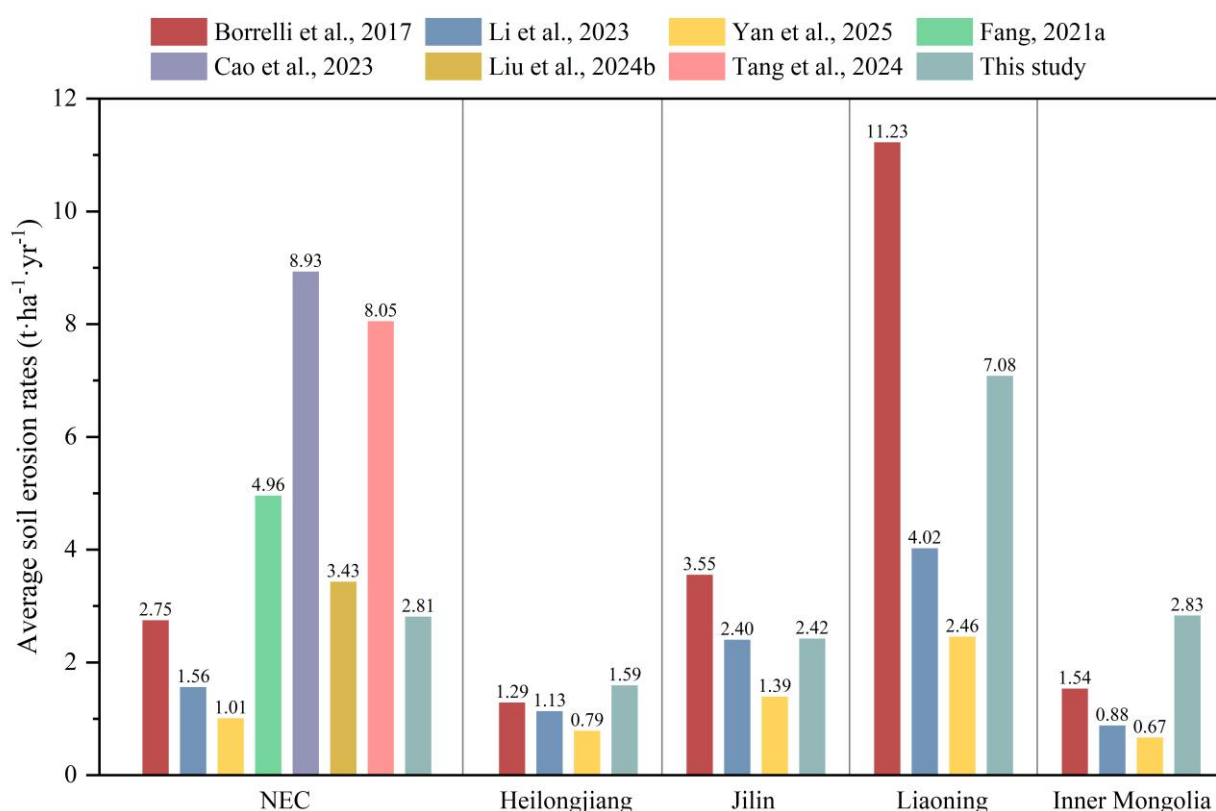


Fig. 6. Comparison of modelled soil erosion of other studies with our results. Notes: NEC (Northeast China), Inner Mongolia refers to the four cities located in the NEC. Data are derived from global datasets (Borrelli et al., 2017), national datasets of China (Li et al., 2023; Yan et al., 2025), and regional studies in NEC (Fang, 2021c; Cao et al., 2023b; Liu et al., 2024c; Tang et al., 2024).

These differences can be attributed to methodological factors. Relative to the studies by Li et al. (2023) and Yan et al. (2025), the higher estimates in the present study may stem primarily from the exclusion of the P-factor. Both previous studies included P factor parameterization, which significantly reduces estimated erosion rates. In particular, Yan et al. (2025) assigned a P value of 0.41 for grassland and as low as 0.49 for sloping cropland. In contrast, this study focused on



317 estimating potential soil erosion driven by cropland expansion under the absence of conservation practices. As a result,
318 erosion rates in regions with extensive sloping cropland, such as the Greater Khingan Mountains, are higher than those
319 reported in Li et al. (2023) and Yan et al. (2025).

320 Compared with the regional studies (Fang, 2021c; Cao et al., 2023b; Liu et al., 2024c; Tang et al., 2024), C-factor
321 parameterization is another possible source of discrepancies with regional studies. In this study, we assigned differentiated
322 C-value ranges to forest and grassland instead of a uniform NDVI-based empirical formula for both land cover. This
323 methodological difference is clearly reflected in the simulated erosion rates. For example, in the study of Tang et al. (2024),
324 the mean erosion rate was $12.57 \text{ t ha}^{-1} \text{ yr}^{-1}$ for forestland and $11.71 \text{ t ha}^{-1} \text{ yr}^{-1}$ for grassland. In our study, however, the
325 simulated rates were $0.14 \text{ t ha}^{-1} \text{ yr}^{-1}$ for forestland and $3.03 \text{ t ha}^{-1} \text{ yr}^{-1}$ for grassland in 2020. Such marked divergence
326 highlights how C-factor methodology can drive enormous variations in regional erosion estimates. Overall, the soil erosion
327 rate obtained in this study lies within a plausible range, supporting a reliable evaluation of regional soil erosion. Differences
328 in reference periods, spatial resolution, input data, and model assumptions limit comparability. To assess selected
329 assumptions more directly, we examined the sensitivity to rainfall erosivity and the potential effects of conservation
330 practices within the same modelling framework.

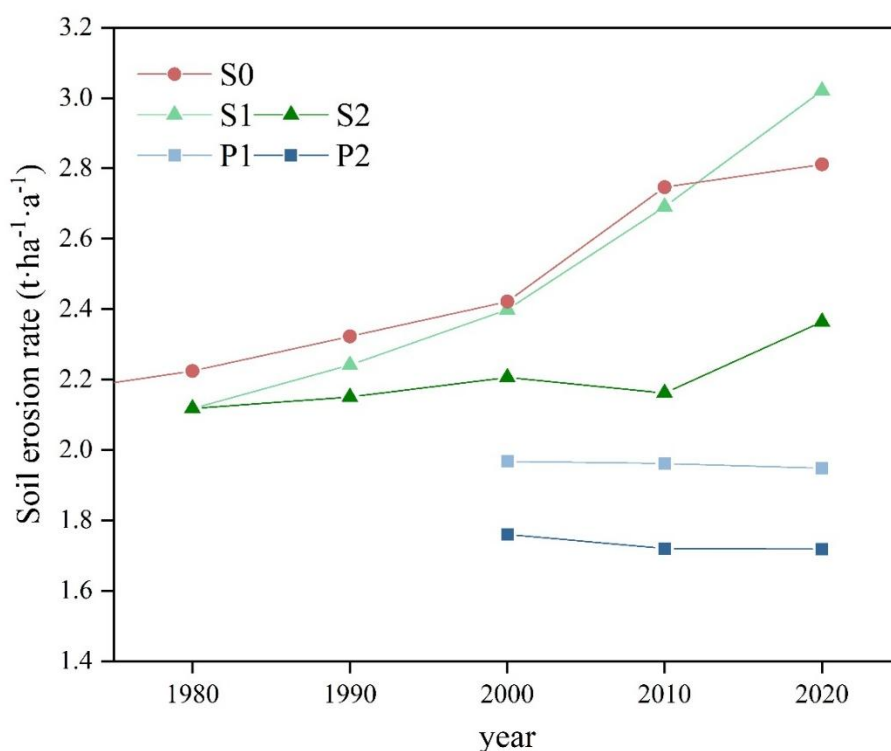
331 4.2. Erosion sensitivity to rainfall erosivity and conservation practices

332 Rainfall change and soil practice can greatly affect regional erosion (Eekhout and De Vente, 2022; Cao et al., 2023a).
333 In the baseline scenario, the constant R and P (i.e., it equals to unit) were used to estimate erosion changes in history. The
334 varying R and alternating P in the scenarios in Fig. 7 can thus quantified potential reductions under conservation practices.

335 In the NEC, soil erosion had a relatively limited sensitivity to regional changes of R (Fig. 7). The estimated erosion
336 changed only by from -4.80% to $+7.44\%$ across the five time slices when the fixed R was replaced by a time-varying one
337 in S1 scenario. The simulated erosion rate increased only slightly between the 1980 and 2010 time slices but rose markedly
338 in the 2020 time slice, reaching a value 11.6% higher than in 1980 in S2 scenario. The recent increase is consistent with



339 evidence from Cao et al. (2023a), which identified a pronounced increase in rainy-season erosivity in NEC after 2008,
 340 associated with changes in atmospheric circulation and ocean temperatures.



341
 342 **Fig. 7. Regional mean soil erosion rates under rainfall erosivity and conservation practice scenarios.** S0 combines fixed R, time-
 343 varying C, and P = 1; S1 combines time-varying R and C with P = 1; S2 combines time-varying R with C fixed at its 1980 configuration
 344 and P = 1. P1 and P2 retain the fixed R and time-varying C of S0 but apply slope-dependent and constant contour tillage P values,
 345 respectively.

346 The conservation measures in the NEC can substantially reduce soil erosion (Fang, 2021b; Zhang et al., 2023), .
 347 Compared to no practices (i.e., P = 1), the slope-dependent and constant-P scenarios reduced regional soil loss by 18.7%
 348 and 27.3%, respectively, in 2000, increasing to 30.7% and 38.9% in 2020 (Fig. 7). This erosion-reduction potential is also
 349 supported by runoff-plot observations at the hillslope scale (Xin et al., 2019). Both scenarios indicate considerable potential
 350 for erosion reduction, although the estimated magnitude depends on P-factor parameterization.



However, applications of specific P values throughout the whole NEC may overstate realized benefits. Wen et al. (2023) reported an average preservation rate of only 56.51% for slope-treatment measures in surveyed conservation projects in the northeastern black-soil region. Our estimates therefore represent an optimistic implementation scenario rather than actual regional conservation outcomes. More realistic assessments require information on the distribution, adoption, and condition of conservation practices, in addition to their plot-scale effectiveness. Moreover, under unfavourable slope and rainfall conditions, contour ridges may lose their function and even transport additional sediment (Zhang et al., 2023; Shi et al., 2026). The estimated reductions should therefore be interpreted as optimistic conservation potential rather than realized regional benefits.

4.3. Historical cropland expansion and its effect to soil erosion

The spatial expansion of cropland in NEC was closely associated with changes in settlement policies, population, and agricultural development. From 1700 to the mid-19th century, cropland was highly concentrated in southern Liaoning, with small, compact ellipses indicating limited spatial extent and weak dispersion (Fig. 3b). This pattern corresponds to the long-standing Qing policy of restricting Han migration into Manchuria (the “Willow Palisade” system) (Ye et al., 2009). During this period, the population of the NEC accounted for less than 1% of the national total (Xie et al., 2019). From the late 19th to the early 20th century, cropland expansion accelerated alongside the large-scale “Chuang Guandong” migration (Ye et al., 2012). During this period, cropland expanded northward, with limited lateral expansion (Fig. 3b).

Expansion slowed during the 1940s, consistent with wartime disruption reported by Tan and Fang (2026b). After 1949, state-led reclamation and the establishment of large state-owned farms facilitated further agricultural expansion (Ye and Fang, 2012). After 1980, the northeastward shift was associated with the development of the Sanjiang Plain (Ning et al., 2024). During this period, large-scale mechanized agriculture and land consolidation became dominant (Li et al., 2024), while overall spatial growth became limited. In recent years, the Grain-for-Green Program and basic farmland protection policies have continued to reshape the composition of land use (Fang, 2021c; Yu et al., 2024). However, this has not been fully reflected in this study.

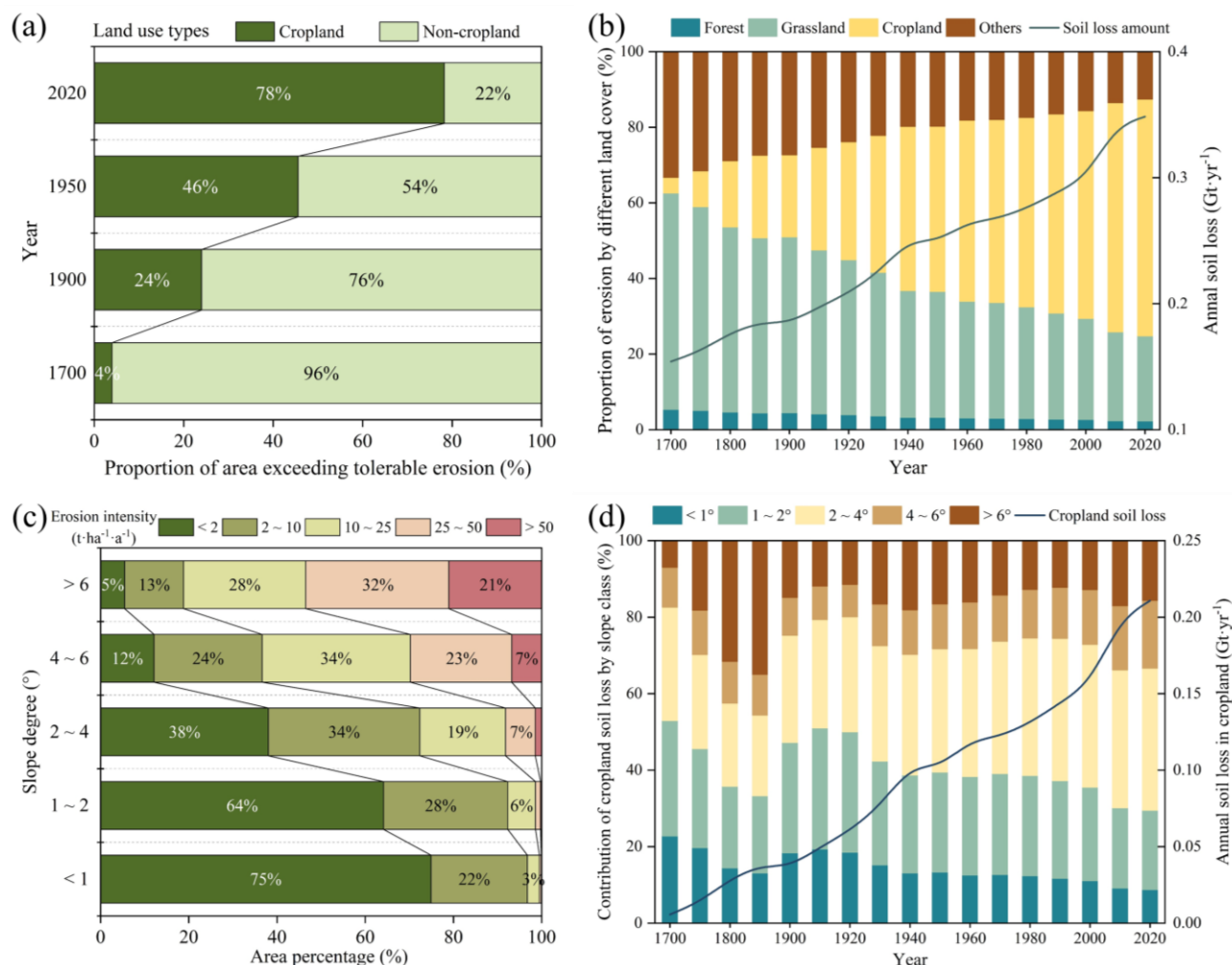


Fig. 8. Contribution of cropland expansion to soil erosion in Northeast China from 1700 to 2020. (a) Proportion of cropland and non-cropland within areas exceeding tolerable erosion ($2 \text{ t ha}^{-1} \text{ yr}^{-1}$) in 1700, 1900, 1950, and 2020; (b) changes in the annual soil loss amount and contribution of different land cover type; (c) distribution of cropland area across erosion-intensity classes by slope class in 2020; (d) changes in the annual soil loss amount from cropland and the proportion by slope degree class.

This expansion was accompanied by a substantial increase in the contribution of cropland to regional erosion (Fig. 8a and b). Cropland accounted for only 4% of the area exceeding the adopted tolerable erosion threshold in 1700, but this proportion increased to 24% in 1900, 46% in 1950, and 78% in 2020. By 2020, cropland occupied approximately 28% of



the study area but contributed 62.6% of simulated annual soil loss, reaching 0.22 Gt yr⁻¹. Over the study period, cropland expansion caused a net increase of about 0.19 Gt yr⁻¹ in regional potential annual soil loss. This shift reveals the profound and irreversible impact of three centuries of continuous cropland expansion on regional soil degradation. This is consistent with previous studies, which indicate that agricultural land conversion is a primary driver of accelerated soil erosion (Nearing et al., 2017; Potapov et al., 2022). Estimates from Borrelli et al. (2017) revealed that expansion of merely 0.22 million km² of cropland between 2001 and 2012 triggered a pronounced increase in soil erosion of 0.69 Pg yr⁻¹.

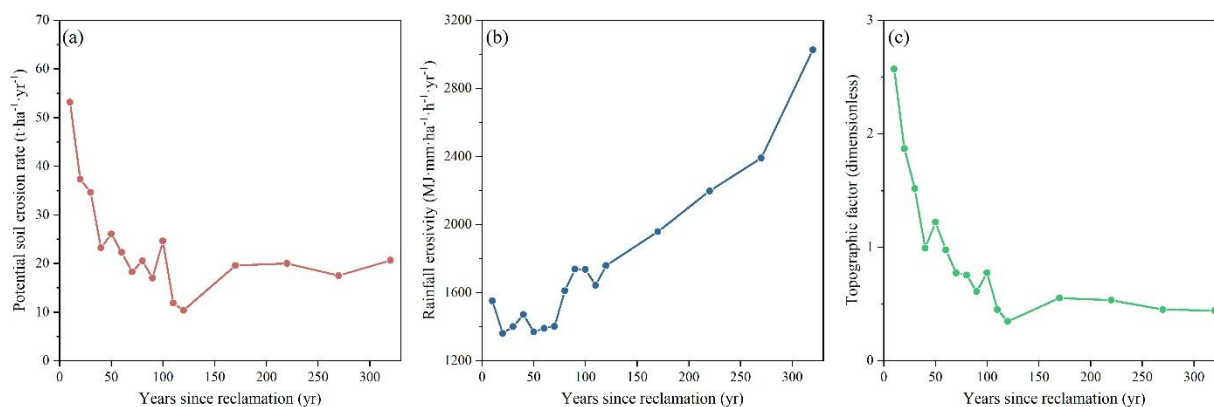
The erosion consequences of expansion also depended on its topographic distribution (Fig. 8c and d). Although gentle slopes continued to dominate the cropland area, the proportion on slopes below 1 ° declined from 44% to 27% (Fig. 3a) (Xie et al., 2019). In 2020, 64%–75% of cropland on slopes below 2 ° experienced only slight erosions (<2 t ha⁻¹ yr⁻¹). Moderate to severe erosion became much more common on steeper slopes (Fig. 8c). This contrast is consistent with the slope dependence reported in regional studies (Fang, 2021a; Liu et al., 2024b; Wang et al., 2026). Runoff velocity and sediment production are primarily controlled by slope gradient, while interrill erosion exhibits a power-function increase with rising slope gradients (Wu et al., 2021). In this study, the average erosion rate was 2.68 t ha⁻¹ yr⁻¹ for cropland with slopes <2 ° and 12.26 t ha⁻¹ yr⁻¹ for slopes >2 °. Even small-scale reclamation on steep slopes could markedly amplify regional soil loss.

4.4. Cultivation history and potential erosion risks

A long-term soil erosion associated with cropland expansion since 1700 in the NEC is investigated in this study. It agrees with previous study results that land cultivation land and human disturbance greatly affect regional soil erosion (Borrelli et al., 2017; Fang, 2021c; Cao et al., 2023b). Furthermore, spatial contrasts in over 300-year of cultivation history and its erosion effects was further revealed by the V-shaped association of cultivation duration and annual excess erosion depth along the latitudinal gradient (Fig. 5i).



To investigate the relationship between land reclamation time and erosion environment, the potential erosion risks yielded by the multiplications of R, K, and LS factors for different land reclamation age groups (Fig. 9). Earlier-reclaimed cropland with cultivation durations of 170–320 years had relatively high R values but low LS values, yielding moderate erosion risks. In croplands reclaimed approx. 110–120 years ago, the R was lower with values around $1700 \text{ MJ mm ha}^{-1} \text{ h}^{-1} \text{ yr}^{-1}$, while LS reached 0.35–0.45. Potential erosion risks were lowest in these groups. However, LS and potential erosion risk generally increased for the subsequently reclaimed groups, although with fluctuations. Cropland reclaimed within the most recent 10–30 years had substantially higher LS values and the highest potential erosion rates of $35\text{--}53 \text{ t ha}^{-1} \text{ yr}^{-1}$.



410

411 **Fig. 9. Mean potential erosion risk and environmental factors across cropland reclamation-age groups:** (a) potential soil erosion
412 risk (RKLS); (b) rainfall erosivity (R); and (c) topographic factor (LS).

The cropland expansion from southern to northern NEC (Tan and Fang, 2026b) and different combinations of R and terrain conditions can thus explain the changing erosion risks for those lands with cultivation years. Across historical periods, changes in land use policies and the availability of arable land directed cropland expansion into areas with different erosion environments. Due to restrictive ban policies, early cultivation was concentrated in southern regions (Jia et al., 2024), where higher rainfall erosivity and more dissected terrain. After 1900, large-scale reclamation shifted to the central plains, i.e., Songnen Plain, which has lower rainfall erosivity, flat terrain, and naturally covered with grassland (Ye et al., 2009). After 1980, as suitable flat land became exhausted, cultivation increasingly encroached upon surrounding upland

419



420 and marginal areas (Xie et al., 2019). This transition significantly enhanced erosion due to the strong topographic control
421 on soil loss processes (Fang, 2021a; Cao et al., 2023b; Liu et al., 2024b). This has led to the renewed increase in erosion
422 rates observed in recently cultivated cropland. Overall, the observed nonlinear relationship reflected the interaction of
423 cultivation duration, historical reclamation pathways, climatic gradients, topographic conditions, and land surface
424 properties.

425 4.5. Limitations and implications

426 Despite the integration of long-term cropland reconstruction and RUSLE, several limitations should be acknowledged.
427 Uncertainty in cropland reconstruction remains an important source of error in the long-term erosion estimates. Although
428 multiple data sources were integrated, spatial allocation becomes increasingly uncertain backward in time. The
429 representation of land surface conditions is also simplified. A fixed crop structure is assumed throughout the study period.
430 But the cropping systems in NEC have changed substantially under climate warming and agricultural intensification (Liu
431 et al., 2021b; Liang et al., 2025; Lu et al., 2025). In addition, forest and grassland dynamics are not explicitly reconstructed.
432 Changes in these land covers are implicitly attributed to cropland expansion, which may overestimate the contribution of
433 cultivation (Liu and Tian, 2010; Yang et al., 2018). The R and P scenarios address selected assumptions but do not fully
434 quantify historical uncertainty. Nevertheless, this study has reconstructed the history of cropland expansion to the extent
435 possible and isolated its effects on soil erosion. The results can be considered a reasonable estimate.

436 The contrasting patterns of cumulative excess erosion and potential erosion risk may carry important implications for
437 land management. Regions characterized by high cumulative erosion, particularly areas with a long cultivation duration,
438 should be prioritized for soil restoration and fertility recovery. Measures such as crop rotation, fallow management, and
439 organic amendment application are essential to reverse soil degradation and improve soil structure (Shen et al., 2019;
440 Iheshiulo et al., 2023). By contrast, areas with high erosion rates, especially sloping cropland, demand practices that directly
441 control runoff and sediment delivery (Fang and Sun, 2017). Contour tillage, terracing, and strip cropping can effectively
442 slow overland flow and reduce slope erosion (Jia et al., 2020; Fang, 2021a; Shi et al., 2025b). Their implementation in the



field requires further consideration of site conditions, extreme events, and maintenance. Such differentiated strategies may improve the efficiency of soil conservation.

5. Conclusions

This study assessed the potential soil erosion changes associated with cropland expansion in NEC during an over 300-year history by combining historical cropland datasets with RUSLE. It is the first time to use high-resolution land cultivation data to evaluate spatial soil erosion patterns in such a long history.

In the NEC, the cropland area increased from near zero to 0.07 million km² by 1900 and further to 0.35 million km² by 2020. Most of cropland was distributed on gentle slopes of less than 2°, but its proportion decreases with expansion. Expansion maintained a southwest–northeast orientation, while the spatial distribution became increasingly dispersed after 1900.

With cropland expansion, the mean erosion rate increased from 1.24 to 2.81 t ha⁻¹ yr⁻¹, and total soil loss rose from 0.15 to 0.35 Gt yr⁻¹. Cropland accounted for merely 4% of the area exceeding the tolerable erosion in 1700, yet its share increased substantially to 78% in 2020. Cropland accounted for 28% of the total area in 2020 but contributing 62.6% of total soil loss. Expansion toward steeper slopes significantly increased erosion rates. Cropland with slopes >2° exhibited erosion rates (12.26 t ha⁻¹ yr⁻¹) nearly five times higher than those on gentle slopes (<2°, 2.68 t ha⁻¹ yr⁻¹).

Cumulative erosion showed strong dependence on cultivation duration. The mean cumulative excess erosion depth reached 3.7 cm across cropland and 9.13 cm in areas cultivated for more than 120 years. Larger accumulated increments were concentrated in long-cultivated southern areas, particularly the plain–hilly transition zone. Mean annual excess erosion depth followed a V-shaped relationship with cultivation duration, which reflects spatial contrasts in cultivation history and erosion environments. The fixed-RKLS analysis further showed that recently reclaimed cropland had higher potential erosion risk associated with higher LS values.



464 These results indicate that cropland expansion has fundamentally reshaped erosion patterns through its spatial
465 pathways and long-term accumulation effects. Soil erosion in the NEC is strongly influenced by land-use history, with
466 important implications for understanding cumulative black soil degradation and promoting sustainable land management.

467 **CRediT authorship contribution statement**

468 **Gefei Tan:** Writing – original draft, Conceptualization, Data curation, Formal analysis, Methodology, Software,
469 Visualization, Validation. **Haiyan Fang:** Writing – review and editing, Conceptualization, Funding acquisition, Project
470 administration, Resources, Supervision.

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473 42277334).

474 **Data availability**

475 Data will be made available on request.



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