Journal of Cleaner Production 485 (2024) 144405

Contents lists available at ScienceDirect

Journal of Cleaner Production

journal homepage: www.elsevier.com/locate/jclepro

Soil erosion drivers in Chinese croplands

Ran Wo [a,b], Delin Fang [a,b,*], Sijing Ye [a,b], Yakov Kuzyakov [c,d,e]

[a] State Key Laboratory of Earth Surface Processes and Resource Ecology, Beijing Normal University, Beijing, 100875, China
[b] Faculty of Geographical Science, Beijing Normal University, Beijing, 100875, China
[c] Department of Soil Science of Temperate Ecosystems, Department of Agricultural Soil Science, University of Goettingen, 37077, Göttingen, Germany
[d] Peoples Friendship University of Russia (RUDN University), 117198, Moscow, Russia
[e] Institute of Environmental Sciences, Kazan Federal University, 420049, Kazan, Russia

A R T I C L E I N F O

Handling Editor: Xin Tong

Keywords:
Cropland soil erosion
Multi-regional input-output model
Structural decomposition analysis

A B S T R A C T

Soil erosion in croplands poses a strong threat to food security and environmental sustainability. A comprehensive understanding of the driving forces and their contributions to changes in cropland soil erosion provides solutions for effective mitigation strategies. The factors of embodied soil erosion changes have rarely been systematically described on the regional scale. We combined the Modified Universal Soil Loss Equation (RUSLE) with the multi-regional input-output (MRIO) model in the first step to analyze the flow of embodied cropland soil erosion in the trade network. The structural decomposition analysis (SDA) model was used to decompose the embodied cropland soil erosion into six driving factors: natural factor, human factor, and socio-economic activities. The SDA results reflect that the nature factor (8.0 % and 6.0 % in two periods from 2012 to 2017) and the final demand factor (17.3 % and 9.9 % in two periods from 2012 to 2017) facilitated the national cropland soil erosion increasing. The human factor and the economic production structure factor always reduced the growth of cropland soil erosion. This study contributes to understanding erosion drivers at provincial and national levels in China, and guides the policy interventions for sustainable soil and water management.

1. Introduction

Soil is one of the most important natural resources, serving as a crucial environmental element that provides humanity with food, resources and ecosystem services. The topic of food security, which is often assessed on the basis of whether food production is high enough to meet human consumption, has received high attention as populations grow and the need for high quality dietary conditions increases (Jiang et al., 2024). However, the nutrient losses from topsoil and the decline in soil fertility due to erosion have serious implications for food, water and livelihood security, and have attracted worldwide attention (Sartori et al., 2019).

Although cropland area occupies only 11% of the total global land area, it contributes nearly 50% of the estimated soil erosion globally (Borrelli et al., 2017). While threatening food security, soil erosion also affects the achievement of SDG 2.4 (Sustainable Food Production and Resilient Agricultural Practices) and SDG 15.3 (End Desertification and Restore Degraded Land). "The State of the World's Land and Water Resources for Food and Agriculture – Systems at breaking point" (FAO, 2021) presented by the FAO points out that human pressures on land, soil and freshwater systems are increasing, while the impact of climate change is already outweighing the environmental consequences of decades of unsustainable use. Land, soil and water management need to find better synergies to change pre-existing irrational water and land use patterns, the exacerbation of resource scarcity by irrational transboundary trade activities, and the environmental impacts to keep the systems functioning.

China, as one of the most populated countries, has always been under great pressure in terms of food production. The main data of the 3rd National Land Resource Survey shows that China's cropland area is 127.58 million ha. China is one of the countries with the most serious soil erosion in the world. Although China's cropland area is huge, accounting for half of the total land area, the per capita arable land area is far below the world average. The extensive development and management of arable land aimed at feeding a 1.4 billion population have led to serious soil erosion and degradation (Du et al., 2024). Many studies have calculated the soil erosion volume. Fu et al. (2010) analyzed the coupling mechanisms between landscape pattern and soil and water resources. The soil erosion model (Revised Universal Soil Loss Equation, RUSLE) can effectively account for the soil loss depending on time and

* Corresponding author. No. 19, Xinjiekouwai St., Beijing, 100875, China.
E-mail address: fangd@bnu.edu.cn (D. Fang).

https://doi.org/10.1016/j.jclepro.2024.144405
Received 24 September 2024; Received in revised form 4 November 2024; Accepted 4 December 2024
Available online 5 December 2024

space, providing effective suggestions for soil and water conservation work to achieve optimal utilization of soil and water resources.

The mastery of the dynamic law governing soil erosion and the analysis of its underlying driving factors are essential tasks for achieving comprehensive erosion control and formulating effective policies for soil and water conservation. Most attribution analysis of soil erosion is discussed through correlation analysis and spatial analysis (Kun et al., 2022; Mirchooli et al., 2023; Sahour et al., 2021; Wen et al., 2023). These studies have primarily focused on exploring the main causes and contributions of soil erosion from a production perspective, predominantly emphasizing natural factors while giving less consideration to the role of social and economic factors. The soil erosion associated with agricultural activities represent strong environmental impact resulting from both human actions and the natural environment. Therefore, it is essential to integrate both natural and human factors when considering driving forces.

In the socio-economic-ecosystem, the resource flows are highly intricate due to specifics in natural resource endowment and economic development levels across regions. The rise of urbanization and the northward shift of the grain production center in China (from "sending grain from the South to the North" in to "sending grain from the North to the South") (Sun et al., 2020) have increased in inter-regional trade, resulting not only in the exchange of products and services but also implicit transfers of resources and environmental impacts. Interregional trade can either raise regional specialization for resource utilization efficiency (Costello et al., 2011) or exacerbate regional resource scarcity. Regions act as "producers" or "consumers" within the trade network. For example, the economic level of the southeast coastal areas of China is high, and the cultivated land is under great pressure from urban expansion. At the same time, the higher population density is accompanied by higher food demand. Therefore, the agricultural provinces with higher output export grain to the southeast coastal provinces. However, large agricultural exports may come at a cost of internal water and soil resources consumption and soil loss, leading to regional development inequality that hinders harmonious development and social stability. The problem of spatial transfer of resource utilization based on footprint flow is one of the current research hot topics.

Input-output analysis, as the typical top-down approach, can provide a comprehensive description of the supply chain (Guo et al., 2025; Jin et al., 2024; Zhong et al., 2021). Multiregional input-output modeling integrates interregional trade linkages across regions and sectors, and is an important tool for cross-regional resource and environmental studies. Currently, some studies that combine RUSLE and top-down MRIO models to calculate indirect soil erosion driven by final demand, using data from each region as a satellite account. Fang et al. (2022) explored water-land nexus while considering soil erosion in a trade network constructed from MRIO tables in Heihe River Basin. Xie et al. (2024) established a virtual land flow network for 13 cities in China with MRIO table to understand urban land use metabolism. Wang et al. (2021) quantified the contribution of soil erosion in various sectors and provinces on the consumption side with the combination of the RUSLE and MRIO models. Cui et al. (2022) estimated global cropland soil erosion footprint and allocated it to broad range of crops. Therefore, our study calculates embodied soil erosion by using the multi-regional input–output model (MRIO) to reveal the total cropland soil erosion hidden behind regional trade in the economic network according to previous studies (Guo and Wang, 2023).

Decomposition analysis is an approach widely used to study the causes of changes in economic indicators during a certain period. Its fundamental concept is rooted in comparative static analysis, whereby the alteration of an economic indicator is decomposed into several factors to analyze their respective contributions. There are two prevalent decomposition methods: index decomposition method (IDA) and structural decomposition method (SDA). Presently, SDA has gradually emerged as an essential empirical tool for input-output technology both at regional, national and continental levels, with its meticulous analytical process and comprehensive data collection practices (Bai et al., 2024; Liu et al., 2022; Wang et al., 2017; Yu et al., 2019).

At present, SDA is mainly used in the research of driving factors of carbon emission and water resource use change (Cai et al., 2019; Franco-Solís and Montanía, 2021; Liang et al., 2021; Wang et al., 2024; Wo et al., 2023; Yu et al., 2023). The use of SDA to quantify resources' footprints and their drivers provides an important reference for alleviating resource and ecological pressures (Bai et al., 2024). Changes in soil erosion have rarely been systematically described. In addition, since SDA is decomposed directly from the input-output table, most of the analyses only consider the contribution of the changes in the technology used by production processes and the contribution of the economic cycle (final demand change) to explain the changes in greenhouse gas emissions or resource consumption. However, soil erosion is caused by the joint influence of human activities and natural environment. Traditional decomposition methods can not accurately identify the main attributes of soil erosion changes.

This paper first construct time-series (2012–2017) estimates of China's provincial soil erosion inventory based on the RUSLE model, then uses the MRIO tables to analyze the flows and inter-annual changes in the trade network. With these estimates, we can further investigate the drivers behind the changes in soil erosion using the SDA. To the best of our knowledge, this is the first study distinguishing contributions between natural and human factors of these changes.

2. Materials and methods

2.1. Soil erosion model

The soil erosion on cropland was calculated by the model of Revised Universal Soil Loss Equation (RUSLE) and the RUSLE '*Soil loss refers to the amount of sediment that reaches the end of a specified area on a hillslope that is experiencing net loss of soil by water erosion*'(Nearing et al., 2017). The evaluation equation is described as following:

$$W = R \times K \times LS \times C \times P \tag{1}$$

Table 1
Crop types and their corresponding base C_{crop} values.

Crop Type		C_{crop}
Cereal grains	Rice	0.15
	Maize	0.38
	Various	0.20
Root and tuber crops	Tuber crops	0.34
	Sugar crops	0.34
Fibre crops	Cotton	0.40
	Hemp	0.28
Tobacco		0.50
Leafy vegetables		0.25
Shrubs herbs		0.15
Green fodder		0.10
Oilseed group		0.25
Legumes		0.32
Other crops		0.15

where W is the yearly soil erosion rate of at each cell (t •ha^{-1}· year^{-1}); R is the rainfall erosivity factor on year basis (MJ • mm • ha^{-1} • h^{-1} • year^{-1}); K is the soil erodibility factor (t • ha • h • ha^{-1} • MJ^{-1} • mm^{-1}). LS is the slope length-steepness factor (dimensionless); C is the cover management factor (dimensionless); and P is the erosion control (conservation support) practices factor (dimensionless).

Using Borrelli's (2017) method for calculating the C factor of cropland (C_{crop} values for various crop types are shown in Table 1).

The study used the main crop types and sown areas of arable land in each province published by the National Bureau of Statistics (NBS) and referred to the study of Li et al. (2020) to categorize the published crops into 10 groups, and calculated the C factor of cropland in 2012, 2015, and 2017 by using the following formula:

$$C = \sum_{n=1}^{10} C_{crop} \times \%\, Region_{Crop} \tag{2}$$

where C_{crop} is C factor of crop n, $\%\, Region_{Crop}$ is the proportion of the sown area of crop n to the total cropland area of each province.

2.2. Environmentally extended MRIO analysis

The basic linear equation of the MRIO model is:

$$X = (I - A)^{-1} \times Y = LY \tag{3}$$

where X denotes the total output matrix, I is the unit matrix; A is the technical coefficient sub-matrix and a_{ij}^{rs} is given by $a_{ij}^{rs} = z_{ij}^{rs} / x_j^s$ ($j = 1, 2, \ldots, n$), in which z_{ij}^{rs} is the intersectoral monetary flows from sector i in region r to sector j in region s, and x_j^s is the total output of sector j in region s; $L = (I - A)^{-1}$ is the Leontief inverse matrix which captures both direct and indirect inputs to satisfy one unit of final demand in monetary value; Y is the final demand matrix.

Embodied soil erosion refers to the total erosion produced throughout the entire process. When calculated from the consumption side, we discuss the erosion generated by the products and services necessary to support economic development. To calculate the environmental impact, the soil erosion intensity needs to be incorporated to calculate the embodied soil erosion. Soil erosion intensity is direct soil per unit of product or service, the total soil erosion can be expressed as follows:

$$W = \widehat{E} \times L \times Y \tag{4}$$

where W is the embodied soil erosion matrix; $\widehat{E}$ is a diagonal matrix where the diagonal elements are the soil erosion per unit output in each sector (10^{-4} tonnes •US\$$^{-1}$).

2.3. Structural decomposition analysis

SDA has been widely used to estimate the drivers of changes in greenhouse gas emissions and resources consumption based on the MRIO table (Cai et al., 2019; Feng et al., 2015, 2017; Wei et al., 2017). According to Eq. ($W = \widehat{E} \times L \times Y$) and Eq. ($W = R \times K \times LS \times C \times P$), the total soil erosion associated with the final demand in MRIO can be decomposed into six drivers (i.e., M (intensity of heterogeneity in the spatial distribution of soil erosion), Q (area of cropland soil erosion occupied per unit of agricultural economic output), $\overline{N}$ (nature factor), $\overline{H}$ (human factor), L (economic production structure) and Y (final demand)):

$$\begin{aligned} W = \widehat{E} \times (I - A)^{-1} \times Y &= \frac{\sum_{n=1}^{S} (R \times K \times LS) \times (C \times P)}{Total\ output} \times L \times Y \\ &= \frac{\sum_{n=1}^{S} (R \times K \times LS) \times (C \times P)}{S} \times \frac{S}{Total\ output} \times L \\ &\quad \times Y \\ &= \frac{\sum_{n=1}^{S} (R \times K \times LS) \times (C \times P)}{\overline{N} * \overline{H} * S} \times \frac{S}{Total\ output} \times \overline{N} \\ &\quad \times \overline{H} \times L \times Y \\ &= M \times Q \times \overline{N} \times \overline{H} \times L \times Y \end{aligned} \tag{5}$$

where S is the area of cropland soil erosion in each province; $\overline{N}$ is the regional mean of the product of the R, LS, and K values for each province, which stands for the nature factor; $\overline{H}$ is the regional mean of the product of the C and P values for each province, which stands for the human factor; M factor ($M = \frac{\sum_{n=1}^{S} (R \times K \times LS) \times (C \times P)}{\overline{N} * \overline{H} * S}$) represents the intensity of heterogeneity in the spatial distribution of soil erosion; Q factor ($Q = \frac{S}{Total\ output}$) stands for the area of cropland soil erosion occupied per unit of agricultural economic output.

Over the given period of 2012–2015 and 2015–2017, the changes in cropland soil erosion embodied in trade can be decomposed as:

$$\begin{aligned} \Delta W = {} & \Delta M Q \overline{N} \overline{H} L Y + M \Delta Q \overline{N} \overline{H} L Y + M Q \Delta \overline{N} \overline{H} L Y + M Q \overline{N} \Delta \overline{H} L Y \\ & + M Q \overline{N} \overline{H} \Delta L Y + M Q \overline{N} \overline{H} L \Delta Y \end{aligned} \tag{6}$$

where Δ represents the change in a factor. Each of the six terms in Eq. (6) denotes the contributions to soil erosion changes, which are triggered by one driving force if other variables are kept constant.

In the sixth terms in Eq. (6), $\Delta Y = Y_t - Y_{t-1}$ is the change in the final demand from the base year to the target year, where t is the target year and t-1 is the base year. Put the variable of each item on the right and the other constants on the left in the equation, and extract the constant in each item. Eq. (6) can be written as:

$$\Delta W = d^M \Delta M + d^Q \Delta Q + d^{\overline{N}} \Delta \overline{N} + d^{\overline{H}} \Delta \overline{H} + d^L \Delta L + d^Y \Delta Y \tag{7}$$

where d^M, d^Q, $d^{\overline{N}}$, $d^{\overline{H}}$, d^L, and d^Y are the coefficients for each Δ factor. According to the order of six factors, Eq. (6) is one of 720 ($6! = 720$) decomposition equations. Although each decomposition equation produced the same results for Δ W, De Haan (2001) found that the coefficient for each Δ factor depends on the used equations. The method of Dietzenbacher and Los (1998) was used in this study which takes the average of all the decompositions (Table S1).

To be expressed in such a form, the 720 equations need to be arranged in a standard order and the Δ factor is places in turn from "M" to "Y". For example, in the sixth terms in Eq. (7), the coefficient $M_{t-1} Q_{t-1} \overline{N}_{t-1} \overline{H}_{t-1} L_{t-1}$ appears 120 times, and same as the coefficient $M_t Q_t \overline{N}_t \overline{H}_t L_t$. Each term in the equation always has $2^{(6\text{-}1)} = 32$ different coefficients attached to the Δ factor. The weight of the coefficient $M_{t-1} Q_{t-1} \overline{N}_{t-1} \overline{H}_{t-1} L_{t-1}$ is 120 for it appeared 120 times (Feng et al., 2015). And each item in Eq. (7) can be present, for example, the contribution of the population to the changes in the total cropland soil erosion can be expressed as:

$$
\begin{aligned}
d^{Y}\Delta Y = \frac{1}{720}(&120M_{t-1}Q_{t-1}\overline{N}_{t-1}\overline{H}_{t-1}L_{t-1}\Delta Y + 24M_{t}Q_{t-1}\overline{N}_{t-1}\overline{H}_{t-1}L_{t-1}\Delta Y + 24M_{t-1}Q_{t}\overline{N}_{t-1}\overline{H}_{t-1}L_{t-1}\Delta Y + 24M_{t-1}Q_{t-1}\overline{N}_{t}\overline{H}_{t-1}L_{t-1}\Delta Y \\
&+ 24M_{t-1}Q_{t-1}\overline{N}_{t-1}\overline{H}_{t}L_{t-1}\Delta Y + 24M_{t-1}Q_{t-1}\overline{N}_{t-1}\overline{H}_{t-1}L_{t}\Delta Y + 12M_{t}Q_{t}\overline{N}_{t-1}\overline{H}_{t-1}L_{t-1}\Delta Y + 12M_{t}Q_{t-1}\overline{N}_{t}\overline{H}_{t-1}L_{t-1}\Delta Y + \ldots 12M_{t-1}Q_{t}\overline{N}_{t-1}\overline{H}_{t}L_{t}\Delta Y \\
&+ 12M_{t-1}Q_{t-1}\overline{N}_{t}\overline{H}_{t}L_{t}\Delta Y + 24M_{t}Q_{t}\overline{N}_{t}\overline{H}_{t}L_{t-1}\Delta Y + 24M_{t}Q_{t}\overline{N}_{t}\overline{H}_{t-1}L_{t}\Delta Y + 24M_{t}Q_{t}\overline{N}_{t-1}\overline{H}_{t}L_{t}\Delta Y + 24M_{t}Q_{t-1}\overline{N}_{t}\overline{H}_{t}L_{t}\Delta Y + 24M_{t-1}Q_{t}\overline{N}_{t}\overline{H}_{t}L_{t}\Delta Y \\
&+ 120M_{t}Q_{t}\overline{N}_{t}\overline{H}_{t}L_{t}\Delta Y)
\end{aligned}
\tag{8}
$$

2.4. Data sources

MRIO tables were obtained from the Carbon Emission Accounts and Datasets (CEADs, https://www.ceads.net). These tables consist of 31 provinces and 42 sectors. To describe the flows of cropland soil erosion, the sectors of agriculture, forestry, animal husbandry, and fishery were disaggregated into two new sectors, agriculture and forestry, animal husbandry and fishery using the methodology of Lindner et al. (2013). To eliminate the effects of price, Chinese Yuan was converted into US dollars based on Purchasing Power Parity as published by the Organization for Economic Co-operation and Development (OECD, https://www.oecd.org/). The 2015 and 2017 MRIO tables were converted to 2012 constant prices by the price index deflation method (Liu and Peng (2010); Zhu et al. (2018)). The price indexes were obtained from the China Statistical Yearbook (National Bureau of Statistics of China, 2018).

The annual cropland dataset of China from 2012 to 2017 were obtained from Tu et al. (2023). The *R* and *P* factor (Li et al., 2023) was collected from the Science Data Bank (https://cstr.cn/31253.11.sciencedb.07135) with spatial resolution of 1 km × 1 km. The annual *K* factor was collected from the study of Yue et al. (2022), which was calculated based on the physical and chemical analysis data from the Second national Soil Survey of China with spatial resolution of 30 m × 30 m. The *LS* factor (Tang et al., 2019) was obtained from the National Earth System Science Data Center with spatial resolution of 1 km × 1 km (https://www.geodata.cn). All data were resampled to the same spatial resolution of 1 km × 1 km. The areas of various types of crops and the Gross Regional Product (GRP) data were obtained from NBS Database (https://data.stats.gov.cn/).

3. Results

3.1. Soil erosion on croplands

The spatial distribution of soil erosion in croplands had a heterogeneity (Fig. 1(a–c)), which was similar in the three years. In 2012, 2015 and 2017, the estimated erosion summed to 1359 Mt, 1379 Mt, and 1445 Mt in China (except Hong Kong, Macau and Taiwan). The national average soil erosion rate in 2012 was 8.2 t hm^{-2} a^{-1}, 8.5 t hm^{-2} a^{-1} in

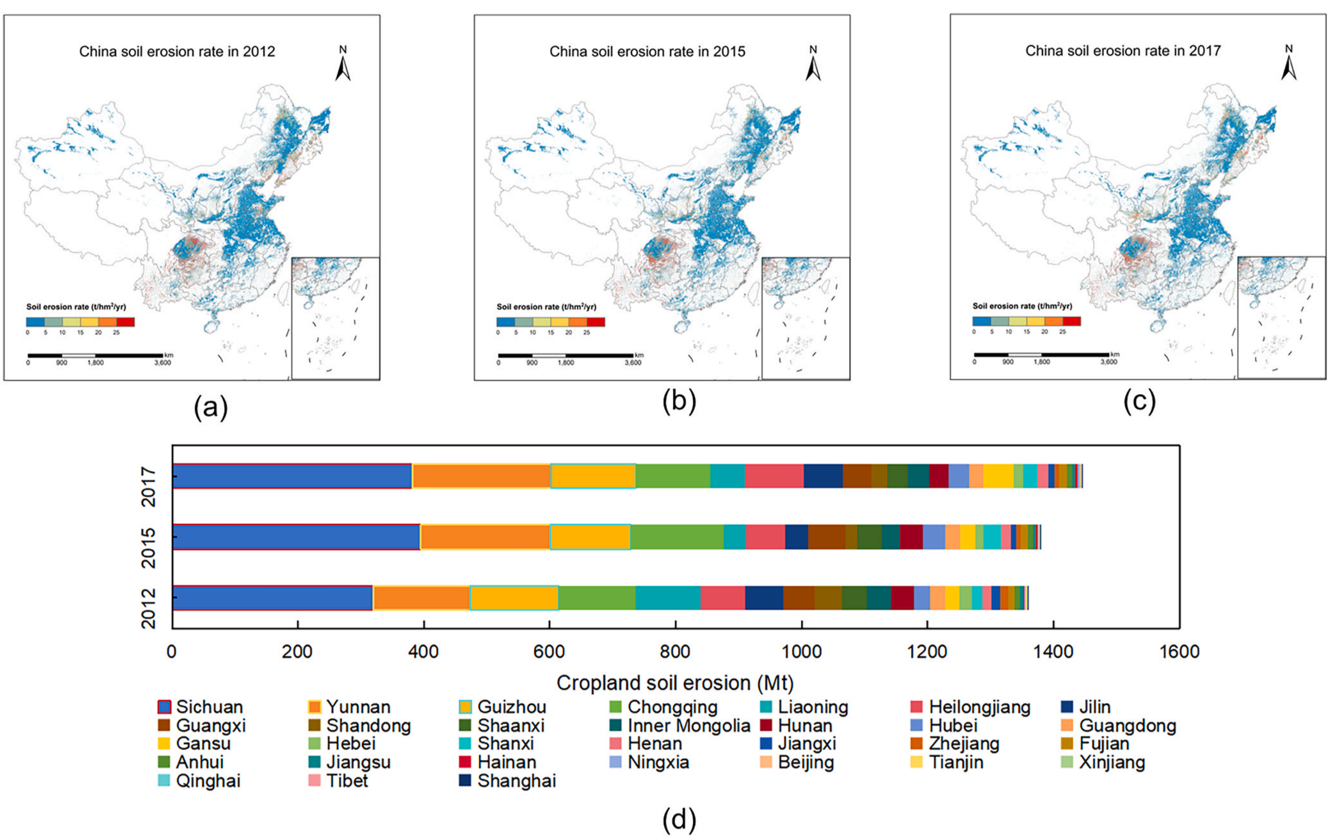

Fig. 1. Soil erosion rate in (a) 2012, (b) 2015, and (c) 2017, and (d) provincial soil erosion depending on years.

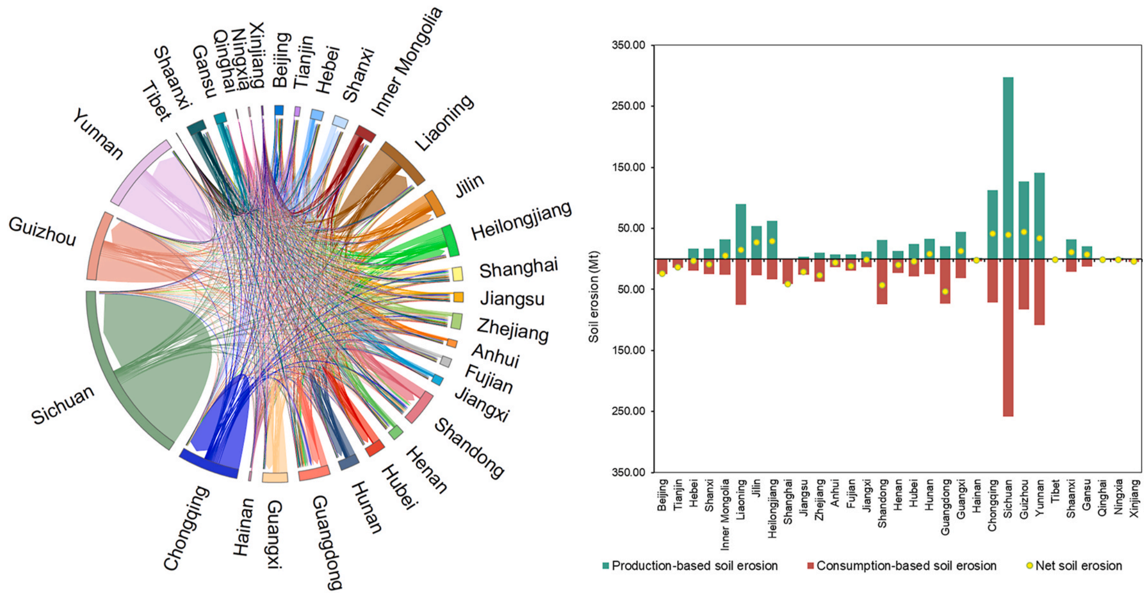

Fig. 2. (a) Cropland soil erosion transfer patterns in 2012, (b) Production-based and consumption-based soil erosion in 2012 (Mt) (*Note: in Fig. 2(a), the outer circle represents the total volume of imports and exports and the width of the flow between two provinces is determined by the soil erosion trade volume*).

2015, and 8.8 t hm^{-2} a^{-1} in 2017. From a spatial point of view, soil erosion is especially intensive on the Loess Plateau and the areas south of the Qinling-Huaihe River line, especially in northeast, North and southwest China. The four provinces with the highest soil erosion intensity in the three years are Chongqing, Sichuan, Yunnan, and Guizhou amounting in 2012 for 36 t hm^{-2} a^{-1}, 29 t hm^{-2} a^{-1}, 29 t hm^{-2} a^{-1}, and 29 t hm^{-2} a^{-1}, respectively. The provinces in northeast China, especially Liaoning, also had a high rate of soil erosion. The areas with high erosion rate are mainly distributed in the vicinity of the Lesser Khingan Mountains, Changbai Mountains and the Greater Khingan Mountains. The areas with high soil erosion rate in North China are mainly distributed in the Shandong Peninsula and the mountainous and hilly areas of south-central Shandong Province. In Southwest China, the areas with high soil erosion rate are mainly distributed in karst areas. Both the national average soil erosion rate and the amount of soil erosion increased year by year, especially 2017, which increased by 66 Mt compared with 2015 (Fig. 1(d)). Heilongjiang, Jilin, Liaoning, as the main contributors to the major soil erosion, showed a strong increase in soil erosion from 2015 to 2017, while the provinces in the southwest region showed a decrease, such as Chongqing, Guangxi, and Sichuan.

3.2. Embodied cropland soil erosion characteristics

Fig. 2(a), Fig. S1(a), and Fig. S2(a) show the soil erosion flows between provinces in 2012, 2015, and 2017. The most provinces were remarkably dependent on the products and services from their own region. The domestic demand erosion of these provinces was the main component for both the direct and embodied cropland soil erosion. Taking Sichuan, Yunnan, and Guizhou as an example, these provinces were among the areas with the most serious erosion in croplands over the three years. In 2012, the soil erosion caused by their own final demand accounted for 62%, 71% and 84% of the all respectively, with similar proportions in 2015 and 2017. These provinces need to take responsibility for their soil erosion.

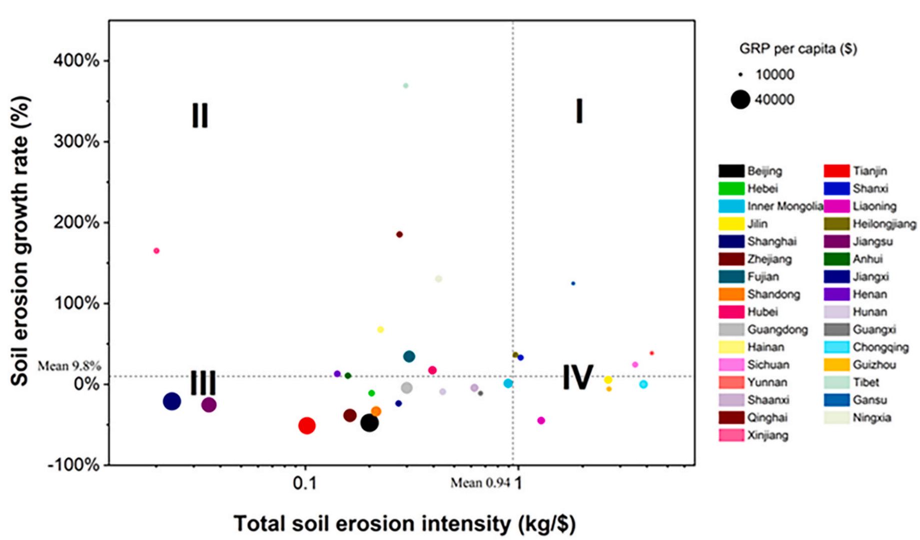

Fig. 3. Classification of provinces based on soil erosion growth rate and total soil erosion intensity in croplands in 2017 (**I** High intensity–High growth rate, **II** Low intensity–High growth rate, **III** Low intensity–Low growth rate、**IV** High intensity–Low growth rate).

Table 2
Classification of provinces based on soil erosion growth rate and total soil erosion intensity in croplands in 2017.

	Low intensity (lower than 0.94 kg/$)	High intensity (larger than 0.94 kg/$)
High growth rate (faster than 9.8%)	Group 2 Tibet, Qinghai, Xinjiang, Ningxia, Hainan, Fujian, Hubei, Henan, and Anhui	Group 1 Gansu, Yunnan, Heilongjiang, Shanxi, and Sichuan
Low growth rate (lower than 9.8%)	Group 3 Inner Mongolia, Shaanxi, Guangdong, Hunan, Hebei, Guangxi, Shanghai, Jiangxi, Jiangsu, Shandong, Zhejiang, Beijing, and Tianjin	Group 4 Jilin, Chongqing, Guizhou, and Liaoning

According to the net soil erosion (Fig. 2 (b), Fig. S1(b), Fig. S2(b)), namely the difference between production and consumption sides, there were 19 net importers in 2012 and 2015. Shannxi changed from net soil erosion exporter to net importer in 2017. The amounts of net imports more than net exports provinces. Guizhou, Chongqing, Sichuan, Yunnan, Heilongjiang, Jilin, and Liaoning, which are major soil erosion provinces and also major net exporters. Among them, Yunnan and Heilongjiang bore increased soil losses pressure from 2012 to 2017. It can be seen that Yunnan and Heilongjiang's net soil erosion exports have increased by 133% (from 33 Mt to 77 Mt) and 67% (from 30 Mt to 50 Mt) in 2017. This pressure may further increase in the future. The net importers with the developed economy such as Guangdong, Shanghai, Zhejiang, and Beijing have a very small amount of production-based soil erosion. The total amount of soil eroded in these provinces in 2012, 2015, and 2017 was 31 Mt, 27 Mt, and 26 Mt, respectively, which accounted for only 2.6%, 2.1%, and 2.0% of the total eroded amount in the country. Most of this erosion was triggered by their own demand. As can be seen from Fig. 2(a), Fig. S1(a), and Fig. S2(a), the consumption soil erosion in these provinces mainly source from Heilongjiang, Jilin, Liaoning, Yunnan, Guizhou, Sichuan, and Chongqing. Some provinces, such as Tibet, Qinghai, Ningxia, Xinjiang and Hainan, have very little soil erosion on both the production and consumption sides.

3.3. *Classification of all provinces based on soil erosion intensity and growth rate*

To gain deeper insights into the primary contributors to soil erosion and anticipate the future trends across various provinces, the combined erosion intensity for the year 2017 and its growth rate spanning from 2012 to 2017 across all provinces are shown in Fig. 3. The intensity serves as an indicator for erosion reduction potential, while the growth rate offers insights for the persistence of erosion patterns. As a result, provinces can be classified into four distinct groups based on China's average soil erosion intensity and growth rate (Table 2).

The five provinces in Group 1 have higher erosion intensity than the national average, indicating a more severe requirement of erosion per unit of agricultural output value, lower efficiency in land resource utilization. There is a considerable increase from 2012 to 2017. These provinces have a relatively close per capita GRP ranging from 10658 $ to 15399 $, which is lower than China's per capita GDP of 16764 $ in 2017, suggesting a low level of economic development.

The provinces in the Group 2 are characterized by low soil erosion intensity primarily due to minimal erosion (Tibet, Qinghai, Xinjiang, Ningxia, and Hainan) or owing to high land use efficiency (e.g., Hubei), but the amount of soil erosion has increased greatly.

Like the Group 2, the intensity of soil erosion in Group 3 was also low, with little or even decreasing fluctuations in erosion between 2012 and 2017. This Group has the largest number of provinces. The provinces may have minimal soil erosion or high land use efficiency, and at the same time their trade pattern change little from 2012 to 2017 or become more environmentally friendly (the supply of products and services in the agricultural sector decreased). In this Group, Shanghai, Beijing, and Tianjin stand out with much higher per capita GRP compared to the China's per capita GDP. The provinces with better economic development level in Group 2 and Group 3 and the provinces with less economic development level in the Group 1 can show that soil erosion and economic level are not synergistic.

The soil erosion changes of the four provinces in Group 4 are decreased, but these provinces have a serious soil erosion per unit of agricultural output, indicating a low efficiency in land resource utilization.

3.4. *Drivers of soil erosion in croplands*

The reasons for the increase of soil erosion can be attributed to natural and human factors, including increase of precipitation, change of land use cover and the change of grain crop types and sown area. From a trade perspective, there are impacts from both local and external demands that increase pressure on agricultural production in the province, along with changes in economic production structure. To further clarify the segmentation reasons for soil erosion in both the production and consumption ends at the national and provincial levels, this study utilized SDA to decompose soil erosion.

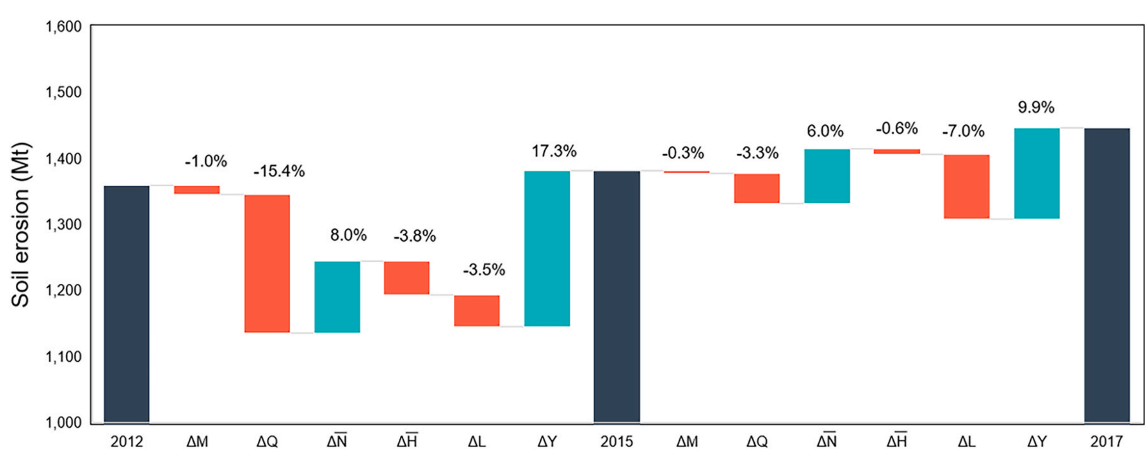

Fig. 4. Contribution of driving factors to the changes for soil erosion in China from 2012 to 2017. *M*-intensity of heterogeneity in the spatial distribution of soil erosion, *Q*-area of cropland soil erosion occupied per unit of agricultural economic output, $\overline{N}$-nature factor, $\overline{H}$-human factor, *L*-economic production structure, and *Y*-final demand, columns with negative numbers in orange and positive numbers in green. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

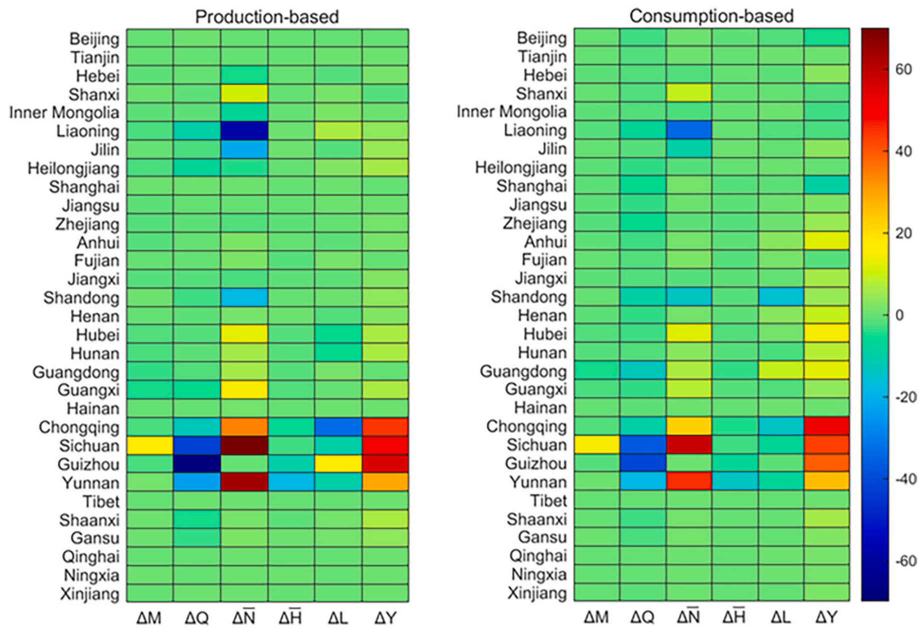

Fig. 5. Contribution of several driving factors to the changes for soil erosion in provinces from 2012 to 2015 (unit: Mt). (*M*-intensity of heterogeneity in the spatial distribution of soil erosion, *Q*-area of cropland soil erosion occupied per unit of agricultural economic output, $\overline{N}$-nature factor, $\overline{H}$-human factor, *L*-economic production structure, and *Y*-final demand, columns with negative numbers in orange and positive numbers in green.). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

China's soil erosion has increased by 1.6% from 2012 to 2015, and increased by 4.7% in 2017 (Fig. 4). The six factors played the same role in two time periods that only factor *Y* and factor $\overline{N}$ accelerated erosion in China, the other four factors always contributed to the erosion decrease. From 2012 to 2015, factor *Y* and factor $\overline{N}$ contributed to the erosion increase by 17.3% and 8%, respectively. The *Q* factor greatly promoted the reduction of soil erosion by 15.4%. The factor $\overline{H}$, *L, and M* drove the soil erosion decreased by 3.8%, 3.5%, and 1.0% in 2015, respectively. In 2017, the Y factor change, as the largest contributor, drove the soil erosion increased by 9.9% compared with 2015. And factor $\overline{N}$ promoted the soil erosion increased by 6.0%. The L (7.0%) and *Q* (3.3%) factors, jointly drove the total soil erosion decreased by 10.3%.

Driving factors on the change of total soil erosion from 2012 to 2017 (Fig. 4) are consistent from the production side and the consumption side, and there are differences only in provinces. At provincial level, the *M* factor contributed to the reduction of production-based soil erosion for most of the provinces from 2012 to 2015 (Fig. 5), especially in Guangxi and Guangdong. This revealed that the planting structure in all regions has changed over time. The effect of factor *M* to provinces was very low, the highest was not more than 4.5 Mt (inhibition). It is worth

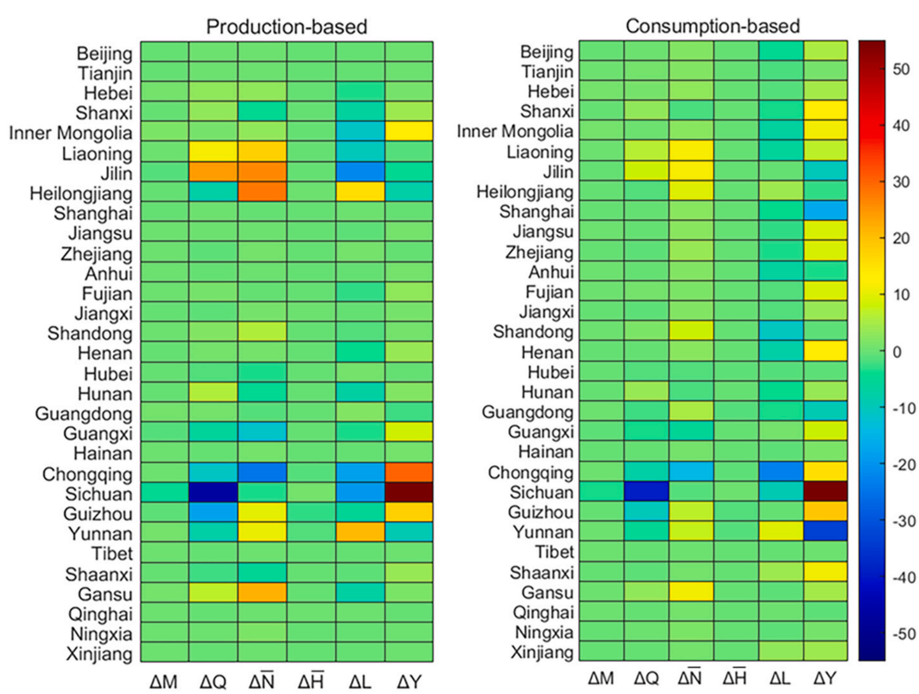

Fig. 6. Contribution of several driving factors to the changes for soil erosion in provinces from 2015 to 2017 (unit: Mt).

noting that Sichuan's erosion increased by 17.3 Mt under the effect of factor *M*. *Q* factor only contributed to a small increase in production-based soil erosion of Beijing, Shanghai, Xinjiang and Tibet, and was an inhibiting factor for other provinces. It is worth noting that this factor greatly drove down the soil erosion of Guizhou, Sichuan, and Yunnan by 68%, 42%, and 24%, respectively. $\overline{N}$ factor was a highly influential factor, and its effect regionally specific. The decrease of soil erosion in several provinces such as Liaoning (58 Mt), Jilin (22 Mt), and Shandong (18 Mt), were induced by 64%, 40%, and 57% under the change of $\overline{N}$ factor. And the $\overline{N}$ factor greatly promoted the soil erosion increased by 23%, 45%, and 30% for Sichuan (69.5 Mt), Yunnan (63.6 Mt), and Chongqing (34 Mt), respectively. Consistent with *M* factor, $\overline{H}$ factor inhibited most of provinces' soil erosion, and its effect ranges from −18.1 Mt to 0.5 Mt. The L factor promoted or inhibited provinces' soil erosion in a relatively balanced manner that half of provinces' erosion reduced under the *L* factor, and the other half increased. It greatly promoted the soil erosion decreased by 29% in Chongqing (33 Mt), and increased by 13% in Guizhou (17 Mt). *Y* factor was the largest contributor to the increase of production-based soil erosion from 2012 to 2015, especially for Guizhou, Sichuan, Chongqing, and Yunnan, which was responsible for the increase of 44%, 17%, 39%, and 21% of their production-based soil erosions, respectively.

The *M* factor drove down the consumption-based erosion in most of provinces from 2012 to 2015 to a small extent. Only Sichuan experienced a large increase in soil loss under the influence of *M* factor (14 Mt). Soil loss was reduced in all provinces driven by *Q* factor, which greatly drove down the erosion in Guizhou, Sichuan, and Yunnan for the value of 41 Mt, 37 Mt, and 18 Mt, respectively. The $\overline{N}$ factor exhibited promotion for more provinces in consumption side than production side. Same as the production side, Sichuan, Yunnan, and Chongqing's erosion was greatly promoted, Liaoning, Shandong, and Jilin's consumption-based erosion was inhibited under the effect of $\overline{N}$ factor. The $\overline{H}$ factor promotes an decrease in all provinces except for slightly increase in Jilin. The L factor promoted (Guangdong, Henan, etc.) and inhibit (Shandong, Chongqing, Yunnan, etc.) provinces' consumption-based soil erosion in a relatively balanced manner. The *Y* factor was still the most important contributor to the increase of consumption-based erosion, which was responsible for the increase of 73%, 17%, 47% and 24% of the change for Chongqing, Sichuan, Guizhou, and Yunnan, respectively.

From 2015 to 2017 (Fig. 6), the effect of *M* factor was weak from both production-based and consumption-based erosion. From the perspective of production side, the *M* factor promoted the growth of erosion in 17 provinces, and the effect range was between −4.6 Mt and 1.5 Mt. The *Q* factor was still an important contributor to inhibiting the increase of erosion at the production and consumption sides in Sichuan Province, which inhibits the increase of 12% and 12% respectively. In addition, the growth of Jilin's soil erosion at production and consumption sides was also greatly driven down by *Q* factor. The production-based erosion of Jilin increased by 73%, and the consumption side increased by 43% from 2015 to 2017 under the effect of factor *Q*, respectively. The $\overline{N}$ factor was the important contributor to the increase of erosion from 2015 to 2017, and only Chongqing and Guangxi had a greater decrease due to the influence of the $\overline{N}$ factor. At the production side, affected by $\overline{N}$ factor, soil erosion increased sharply in Heilongjiang (27 Mt), Jilin (26 Mt), Gansu (22 Mt), and Liaoning (18 Mt), increasing by 47%, 77%, 97%, and 57%, respectively. From the consumption side, the soil erosion in Liaoning and Jilin increased by 43% and 61% respectively. Consistent with 2012–2015, $\overline{H}$ factor promoted the growth of erosion in almost all provinces from both production and consumption sides. From the perspective of production side, the effect range was between −2.7 Mt and 0.6 Mt. From the perspective of consumption side, the effect range was between −1.6 Mt and 0.4 Mt. The L factor was the most important factor to reduce erosion from 2015 to 2017, which drove the production side of Jilin, Sichuan, and Chongqing decreased by 65%, 5%, and 13%, respectively. The consumption-based erosion in Chongqing, Shandong, and Sichuan was reduced by 20%, 27%, and 3%, respectively, under the effect of the *L* factor. Yunnan and Heilongjiang's erosion increased sharply both at production (11% and 28%) and consumption (7% and 15%) side under the influence of the *L* factor. The *Y* factor still drove the increase of soil erosion in general in 2015–2017, not as strong as in 2012–2015. From 2015 to 2017, the production side increased by 17%, 22%, and 15% in Sichuan, Chongqing, and Guizhou, respectively, and the consumption-based erosion increased by 17%, 26%, and 13% in Sichuan, Guizhou, and Chongqing, respectively. The consumption-based erosion in Yunnan, Shanghai, and Jilin decreased by 24%, 87%, and 52%, respectively, driven by *Y* factor.

4. Discussion

The agricultural products produced from cropland not only guarantee the food security, but also serve as an important raw material for industry production from the perspective of the whole industrial chain. Soil erosion is highly likely to occur during agricultural production. The total erosion value of 2012 (Fig. 1) was close to the result of Li et al. (2022)' s observation of 2010. The value of 2015 was consistent with the finding of Wang et al. (2021)' s. The spatial distribution of soil erosion in China is consistent with the findings of other scholars (Li et al., 2020) that the cropland soil erosion hotspots are concentrated in southwest, northwest and northeast China. The unstable soil characteristics and the transition between natural and semi-natural vegetation and cultivated land, which may be one of the reasons for the considerable erosion in provinces such as the northeastern provinces. The first reason for the relatively large erosion in the southwestern region is that it is the main distribution area of karst landform with high altitude and large slope, and the second reason is the higher precipitation levels.

With the rapid development of industrialization and urbanization, the center of grain production in China has shifted northward. The interregional cropland soil erosion flow analysis showed that the amount of net importer increased, and the major net exporter (including most of the northern provinces, Yunnan, Guizhou, and Sichuan) exported more erosion from 2012 to 2017. These provinces need to increase the degree of agricultural mechanization and enhance the specialization of agricultural production. In addition, rationally arranging the planting structure according to their own climatic conditions and resource endowment is necessary. In addition, it is necessary for government departments to guide the layout of large-scale planting to save resources. These measures can reduce erosion intensities, maximize agricultural output, and improve the efficiency of cropland use while minimizing erosion. Beijing, Shanghai, Jiangsu, Zhejiang and Guangdong provinces account for the highest proportion of tertiary industries in China, indicating that their industrial structure is service-dominated. These provinces import agricultural products and services from economically undeveloped regions to meet their own demands, and embodied cropland erosion transferred, too. Under the protection system for permanent basic farmland, crops with comparative advantages can be selected for planting. Urban agriculture and other types of agriculture with economic, social, ecological, educational and other integrated functions can be vigorously developed to serve the diversified needs of these developed regions.

The result of grouping provinces that the regions with high GRP are concentrated in the Group 2 and Group 3 (the erosion intensity is lower than the national level) confirms the conclusion of previous studies that erosion is not beneficial to the growth of real gross domestic product (GDP) (Sartori et al., 2019). In addition, another conclusion can be inferred from Inner Mongolia that there is no strong relationship between the area of cropland and erosion amount. As the most important pastoral region in China, Inner Mongolia is fast becoming an agricultural province, ranking second in the country's cropland, after Heilongjiang. Inner Mongolia ranked among the top 10 in terms of grain production from 2012 to 2017, much higher than Sichuan (NBS, https://www.stats.

gov.cn/). However, the amount of soil erosion is much lower than that of Sichuan, which was 8.9% of that of Sichuan Province in 2017. In the third part of this study, Inner Mongolia was divided into the Group 3, with lower erosion intensity and growth rate.

Overall, from the national driving factors' perspective, it is necessary to optimize the national agricultural production layout, especially the planting structure in provinces with intensive cropland soil erosion, while safeguarding grain production and ecological environment. At the same time, environmentally beneficial provinces should be encouraged to increase economic and technical support to net soil erosion exporters. $\overline{N}$ factor is one of the decisive factors that dominate the change of cropland soil erosion. Since erodibility factor and slope length-steepness factor were assumed to be constant from 2012 to 2017 in this study, $\overline{N}$ factor actually characterized the influence of rainfall. Spatially, the national soil erosion in 2015 was gently increased by the $\overline{N}$ factor. According to China Climate Bulletin (China Meteorological Administration, 2016), the national average precipitation in 2015 was 650 mm, 3% more than that of the usual year, but the spatial-temporal distribution of precipitation was uneven, with more precipitation in South China. Precipitation is less in North China. From the provincial driving factors' perspective, the results showed that the $\overline{N}$ factor was the main driver for the increase of erosion in most southern provinces (e.g., Sichuan, Yunnan, Chongqing), while it contributed to the decrease in northern provinces (e.g., Liaoning, Jilin, Shandong). Y factor is the most decisive factor that dominate the growth of soil erosion in both periods, indicating that the demand for soil erosion increased with the development of economy. At present, many countries advocate residents to change their eating habits, such as reducing foods with high virtual water content, such as meat and dairy products, to improve water utilization. Similarly, the government should encourage the internalization of soil erosion as well as other environmental costs into the product prices. This can not only reduce the environmental impact of the industrial sector, which is highly dependent on agricultural products, but also guide more families to change their consumption habits through the help of the market to reduce soil erosion from the perspective of supply chain (Wang et al., 2021). $\overline{H}$ factor drove the decrease of national soil erosion in both time periods. Since the erosion control practices factor was assumed to be constant from 2012 to 2017 in this study, $\overline{H}$ factor actually characterized the influence of the planting structure. However, the cropland area with soil erosion decreased from 2012 to 2015, and increased from 2015 to 2017. It can be inferred that the planting structure changed that from 2015 to 2017 the proportion of crops with lower value of C_{crop} increased. The L factor is an important driving factor that can lead to a decrease in soil erosion. This result suggests the proportion of agricultural products in the economic production structure was decreasing, and the demand inputs for the soil erosion from upstream supply chain was reduced. The Q factor played a substantial role in inhibiting the increase of soil loss. This indicates an enhancement in the land use efficiency of agricultural production across the majority of provinces, leading to a reduction in the area of cropland occupied per unit of agricultural economic output.

This study still has some limitations. For example, in SDA analysis, it is assumed that all factors are independent. However, in most empirical cases, there is a mutual influence relationship between the factors (Dietzenbacher and Los, 2000). Some studies applied other methods to fill this gap, such as the Geo-detector tool (Jiang et al., 2018). Furthermore, the RUSLE model used in this study can only evaluated the erosion caused by the rainfall, while losses also comes from irrigation (McDermid et al., 2023) and is disregarded in this study. Due to the limitation of data acquisition in the input-output tables, the time series of this study from 2012 to 2017, which cannot reflect the latest state of soil erosion flow in the trade network. Nevertheless, the effects of human activities can be better reflected in the long time series (Xie et al., 2019). The following research would pay more attention to further discuss soil erosion in forest and grassland combination with cropland to analyze the transfer in trade networks over long time series.

5. Conclusions

China has a vast territory, and the agricultural planting structure of provinces depends on natural conditions, human influence and trade network, which leads to regionally specific contribution of driving factors to soil erosion. This study combined the grid layers of cropland soil erosion with MRIO table to evaluate the erosion from both production and consumption perspectives for 31 provinces of China. The change of soil erosion (2012–2017) decomposed for 6 natural and human factors to detect the driving forces by using the SDA method fills the gap where biophysical processes and socioeconomic impacts cannot be coupled in the previous studies. This study estimated that China's total erosion was about 1400 Mt from 2012 to 2017. The worst-hit areas of soil loss are Sichuan, Yunnan, Guizhou, Chongqing, Liaoning, Heilongjiang, and Jilin. Among them, Yunnan, Heilongjiang, and Sichuan are strongly in danger due to the high increase of soil loss and erosion intensity. The nature and the final demand factors are the dominant factors affecting the soil erosion increase in the whole, but the composition reasons of the erosion change exhibits distinguished features. For example, even though Heilongjiang, Jilin and Liaoning are also located in northeast China, the L factor greatly raised production-based erosion growth on Heilongjiang and Liaoning. However, it drove down Jilin's erosion. Therefore, all provinces need to formulate soil and water conservation policies according to their own positioning and needs.

CRediT authorship contribution statement

Ran Wo: Writing – original draft, Visualization, Methodology, Investigation, Data curation. **Delin Fang:** Writing – review & editing, Validation, Project administration, Funding acquisition, Conceptualization, Formal analysis, Supervision. **Sijing Ye:** Validation, Conceptualization. **Yakov Kuzyakov:** Validation, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement

This work was supported by the National Natural Science Foundation of China (No. 72174029, 42171250), the Fundamental Research Funds for the Central Universities, the RUDN University Strategic Academic Leadership Program, and the Strategic Academic Leadership Program "Priority 2030″ of the Kazan Federal University.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2024.144405.

Data availability

Data will be made available on request.

References

Bai, Y., Wang, Y., Xuan, X., Weng, C., Huang, X., Deng, X., 2024. Tele-connections, driving forces and scenario simulation of agricultural land, water use and carbon emissions in China's trade. Resour. Conserv. Recycl. 203, 107433. https://doi.org/10.1016/j.resconrec.2024.107433.

Borrelli, P., Robinson, D.A., Fleischer, L.R., Lugato, E., Ballabio, C., Alewell, C., Meusburger, K., Modugno, S., Schütt, B., Ferro, V., Bagarello, V., Oost, K.V., Montanarella, L., Panagos, P., 2017. An assessment of the global impact of 21st century land use change on soil erosion. Nat. Commun. 8, 2013. https://doi.org/10.1038/s41467-017-02142-7.

Cai, B., Zhang, W., Hubacek, K., Feng, K., Li, Z., Liu, Yawen, Liu, Yu, 2019. Drivers of virtual water flows on regional water scarcity in China. J. Clean. Prod. 207, 1112–1122. https://doi.org/10.1016/j.jclepro.2018.10.077.

China Meteorological Administration, 2016. China Climate Bulletin 2015. China Meteorological Administration,, Beijing, p. 11 (In Chinese).

Costello, C., Griffin, W.M., Matthews, H.S., Weber, C.L., 2011. Inventory development and input-output model of U.S. Land Use: relating land in production to consumption. Environ. Sci. Technol. 45, 4937–4943. https://doi.org/10.1021/es104245j.

Cui, H., Wang, Z., Yan, H., Li, C., Jiang, X., Wang, L., Liu, G., Hu, Y., Yu, S., Shi, Z., 2022. Production-based and consumption-based accounting of global cropland soil erosion. Environ. Sci. Technol. 56, 10465–10473. https://doi.org/10.1021/acs.est.2c01855.

De Haan, M., 2001. A structural decomposition analysis of pollution in The Netherlands. Econ. Syst. Res. 13, 181–196. https://doi.org/10.1080/09537320120052452.

Dietzenbacher, E., Los, B., 2000. Structural decomposition analyses with dependent determinants. Econ. Syst. Res. 12, 497–514. https://doi.org/10.1080/09535310020003793.

Dietzenbacher, E., Los, B., 1998. Structural decomposition techniques: sense and sensitivity. Econ. Syst. Res. 10, 307–324. https://doi.org/10.1080/09535319800000023.

Du, B., Ye, S., Gao, P., Ren, S., Liu, C., Song, C., 2024. Analyzing spatial patterns and driving factors of cropland change in China's National Protected Areas for sustainable management. Sci. Total Environ. 912, 169102. https://doi.org/10.1016/j.scitotenv.2023.169102.

Fang, D., Cai, Q., Wu, F., Chen, B., Zhang, L., 2022. Modified linkage analysis for water-land nexus driven by interregional trade. J. Clean. Prod. 353, 131547. https://doi.org/10.1016/j.jclepro.2022.131547.

FAO, 2021. The State of the World's Land and Water Resources for Food and Agriculture – Systems at Breaking Point (SOLAW 2021). FAO. https://doi.org/10.4060/cb7654en.

Feng, K., Davis, S.J., Sun, L., Hubacek, K., 2015. Drivers of the US CO_2 emissions 1997–2013. Nat. Commun. 6, 7714. https://doi.org/10.1038/ncomms8714.

Feng, L., Chen, B., Hayat, T., Alsaedi, A., Ahmad, B., 2017. The driving force of water footprint under the rapid urbanization process: a structural decomposition analysis for Zhangye city in China. J. Clean. Prod. 163, S322–S328. https://doi.org/10.1016/j.jclepro.2015.09.047.

Franco-Solís, A., Montanía, C.V., 2021. Dynamics of deforestation worldwide: a structural decomposition analysis of agricultural land use in South America. Land Use Pol. 109, 105619. https://doi.org/10.1016/j.landusepol.2021.105619.

Fu, B., Xu, Y., Lv, Y., 2010. Scale characteristics and coupling methods of landscape pattern and soil erosion. Adv. Earth Sci. 25, 673–681 (In Chinese).

Guo, S., Wang, Y., 2023. Spatial-temporal changes of land-use mercury emissions in China. Ecol. Indic. 146, 109430. https://doi.org/10.1016/j.ecolind.2022.109430.

Jiang, J., Ye, S., Sang, L., Gao, P., Song, C., 2024. Considering spatial heterogeneity of cultivation conditions can effectively improve the assessment of nitrogen use at the provincial scale in China. Ecol. Indic. 167, 112603. https://doi.org/10.1016/j.ecolind.2024.112603.

Guo, S., Zhao, Q., He, P., Wang, Y., Zhang, X., 2025. Embodied black carbon emission transfer within and across the Jing-Jin-Ji urban agglomeration. Environ. Impact Assess. Rev. 110, 107678. https://doi.org/10.1016/j.eiar.2024.107678.

Jiang, X., Wang, Q., Li, R., 2018. Investigating factors affecting carbon emission in China and the USA: a perspective of stratified heterogeneity. J. Clean. Prod. 199, 85–92. https://doi.org/10.1016/j.jclepro.2018.07.160.

Jin, X., Jiang, W., Fang, D., Wang, S., Chen, B., 2024. Evaluation and driving force analysis of the water-energy-carbon nexus in agricultural trade for RCEP countries. Appl. Energy 353, 122143. https://doi.org/10.1016/j.apenergy.2023.122143.

Kun, Y., Bing, Z., Lei, H., Bin, L., Han, L., Dunlong, L., Yuxia, L., 2022. Changes in soil erosion in the upper reaches of the minjiang river based on geo-detector. Res. Soil Water Conserv. 29, 85–91.

Li, J., He, H., Zeng, Q., Chen, L., Sun, R., 2023. A Chinese soil conservation dataset preventing soil water erosion from 1992 to 2019. Sci. Data 10, 319. https://doi.org/10.1038/s41597-023-02246-4.

Li, J., Sun, R., Xiong, M., Yang, G., 2020. Estimation of soil erosion based on the RUSLE model in China. Acta Ecol. Sin. 40. https://doi.org/10.5846/stxb201903290610.

Li, K., Wang, L., Wang, Z., Hu, Y., Zeng, Y., Yan, H., Xu, B., Li, C., Cui, H., Yu, S., Shi, Z., 2022. Multiple perspective accountings of cropland soil erosion in China reveal its complex connection with socioeconomic activities. Agric. Ecosyst. Environ. 337, 108083. https://doi.org/10.1016/j.agee.2022.108083.

Liang, Y., Liang, S., Li, K., Qi, J., Feng, C., Xu, L., Yang, Z., 2021. Socioeconomic determinants for the changing food-related scarce water uses in Chinese regions. J. Clean. Prod. 316, 128190. https://doi.org/10.1016/j.jclepro.2021.128190.

Lindner, S., Legault, J., Guan, D., 2013. Disaggregating the electricity sector of China's input–output table for improved environmental life-cycle assessment. Econ. Syst. Res. 25, 300–320. https://doi.org/10.1080/09535314.2012.746646.

Liu, M., Wen, J., Meng, Y., Yang, X., Wang, J., Wu, J., Chen, H., 2022. Carbon emission structure decomposition analysis of manufacturing industry from the perspective of input-output subsystem: a case study of China. Environ. Sci. Pollut. Res. https://doi.org/10.1007/s11356-022-23334-9.

Liu, Q., Peng, Z., 2010. China 1992–2005 Comparable Price Input-Output Series Tables and Analysis. China Statistics Press.

McDermid, S., Nocco, M., Lawston-Parker, P., Keune, J., Pokhrel, Y., Jain, M., Jägermeyr, J., Brocca, L., Massari, C., Jones, A.D., Vahmani, P., Thiery, W., Yao, Y., Bell, A., Chen, L., Dorigo, W., Hanasaki, N., Jasechko, S., Lo, M.-H., Mahmood, R., Mishra, V., Mueller, N.D., Niyogi, D., Rabin, S.S., Sloat, L., Wada, Y., Zappa, L., Chen, F., Cook, B.I., Kim, H., Lombardozzi, D., Polcher, J., Ryu, D., Santanello, J., Satoh, Y., Seneviratne, S., Singh, D., Yokohata, T., 2023. Irrigation in the Earth system. Nat. Rev. Earth Environ. 4, 435–453. https://doi.org/10.1038/s43017-023-00438-5.

Mirchooli, F., Mohammadi, M., Sadeghi, S.H., 2023. Spatial modeling of relationship between soil erosion factors and land-use changes at sub-watershed scale for the Talar watershed, Iran. Nat. Hazards 116, 3703–3723. https://doi.org/10.1007/s11069-023-05832-2.

National Bureau of Statistics of China, 2018. China Statistical Yearbook 2018. China Statistics Press, Beijing.

Nearing, M.A., Yin, S., Borrelli, P., Polyakov, V.O., 2017. Rainfall erosivity: an historical review. Catena 157, 357–362. https://doi.org/10.1016/j.catena.2017.06.004.

Sahour, H., Gholami, V., Vazifedan, M., Saeedi, S., 2021. Machine learning applications for water-induced soil erosion modeling and mapping. Soil Tillage Res. 211, 105032. https://doi.org/10.1016/j.still.2021.105032.

Sartori, M., Philippidis, G., Ferrari, E., Borrelli, P., Lugato, E., Montanarella, L., Panagos, P., 2019. A linkage between the biophysical and the economic: assessing the global market impacts of soil erosion. Land Use Pol. 86, 299–312. https://doi.org/10.1016/j.landusepol.2019.05.014.

Sun, M., Chou, J., Xu, Y., Yang, F., Li, J., 2020. Study on the thresholds of grain production risk from climate change in China's main grain-producing areas. Phys. Chem. Earth, Parts A/B/C 116, 102837. https://doi.org/10.1016/j.pce.2020.102837.

Tang, Y., Shao, Q., Liu, J., Zhang, H., Yang, F., Cao, W., Wu, D., Gong, G., 2019. Did ecological restoration hit its mark? Monitoring and assessing ecological changes in the grain for green Program region using multi-source satellite images. Remote Sens 11, 358. https://doi.org/10.3390/rs11030358.

Tu, Y., Wu, S., Chen, B., Weng, Q., Bai, Y., Yang, J., Yu, L., Xu, B., 2023. A 30 m annual cropland dataset of China from 1986 to 2021. https://doi.org/10.5281/zenodo.7936885.

Wang, H., Ang, B.W., Su, B., 2017. Assessing drivers of economy-wide energy use and emissions: IDA versus SDA. Energy Pol. 107, 585–599. https://doi.org/10.1016/j.enpol.2017.05.034.

Wang, Y., Bai, Y., Hu, Y., Deng, X., Weng, C., Shu, J., Wang, C., 2024. Tele-connecting local consumption to cultivated land use and hidden drivers in China. Sci. Total Environ. 912, 169523. https://doi.org/10.1016/j.scitotenv.2023.169523.

Wang, Z., Zeng, Y., Li, C., Yan, H., Yu, S., Wang, L., Shi, Z., 2021. Telecoupling cropland soil erosion with distant drivers within China. J. Environ. Manage. 288, 112395. https://doi.org/10.1016/j.jenvman.2021.112395.

Wei, J., Huang, K., Yang, S., Li, Y., Hu, T., Zhang, Y., 2017. Driving forces analysis of energy-related carbon dioxide (CO_2) emissions in Beijing: an input–output structural decomposition analysis. J. Clean. Prod. 163, 58–68. https://doi.org/10.1016/j.jclepro.2016.05.086.

Wen, L., Peng, Y., Zhou, Y., Cai, G., Lin, Y., Li, B., 2023. Study on soil erosion and its driving factors from the perspective of landscape in Xiushui watershed, China. Sci. Rep. 13, 8182. https://doi.org/10.1038/s41598-023-35451-7.

Wo, R., Fang, D., Song, D., Chen, B., 2023. Analysis of embodied carbon emissions and carbon sequestration in Tibetan Plateau-Case study of Tibet and Qinghai. Appl. Energy 347, 121449. https://doi.org/10.1016/j.apenergy.2023.121449.

Xie, W., Yang, X., Han, Z., Sun, M., Li, Y., Xie, H., Yu, H., Chen, B., Fath, B., Wang, Y., 2024. Urban sector land use metabolism reveals inequalities across cities and inverse virtual land flows. Resour. Conserv. Recycl. 202, 107394. https://doi.org/10.1016/j.resconrec.2023.107394.

Xie, Y., Lin, H., Ye, Y., Ren, X., 2019. Changes in soil erosion in cropland in northeastern China over the past 300 years. Catena 176, 410–418. https://doi.org/10.1016/j.catena.2019.01.026.

Yu, F., Wang, Y., Liu, X., Yu, J., Zhao, D., Deng, H., Guo, B., Shi, R., Wu, B., Chen, H., 2023. Driving forces and variation in water footprint before and after the COVID-19 lockdown in Fujian Province of China. J. Clean. Prod. 402, 136696. https://doi.org/10.1016/j.jclepro.2023.136696.

Yu, Y., Liang, S., Zhou, W., Ren, H., Kharrazi, A., Zhu, B., 2019. A two-tiered attribution structural decomposition analysis to reveal drivers at both sub-regional and sectoral levels: a case study of energy consumption in the Jing-Jin-Ji region. J. Clean. Prod. 213, 165–175. https://doi.org/10.1016/j.jclepro.2018.12.167.

Yue, T., Yin, S., Xie, Y., Yu, B., Liu, B., 2022. Rainfall erosivity mapping over mainland China based on high-density hourly rainfall records. Earth Syst. Sci. Data 14, 665–682. https://doi.org/10.5194/essd-14-665-2022.

Zhong, H., Feng, K., Sun, L., Tian, Z., Fischer, G., Cheng, L., Munoz Castillo, R., 2021. Water-land tradeoffs to meet future demands for sugar crops in Latin America and the Caribbean: a bio-physical and socio-economic nexus perspective. Resour. Conserv. Recycl. 169, 105510. https://doi.org/10.1016/j.resconrec.2021.105510.

Zhu, B., Su, B., Li, Y., 2018. Input-output and structural decomposition analysis of India's carbon emissions and intensity, 2007/08 – 2013/14. Appl. Energy 230, 1545–1556. https://doi.org/10.1016/j.apenergy.2018.09.026.