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Linking landscape dynamics to the relationship between water purification and soil retention

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ABSTRACT

Landscape pattern is vital for supplying ecosystem services, and demonstrating the interactions among landscape dynamics and multiple ecosystem services is a key scientific basis for ecosystem management. As a typical ecologically vulnerable region in China, the Three Gorges Reservoir Area (TGRA) suffers from both severe soil loss and non-point pollution. Although many ecological restoration projects have been implemented to control sediment and pollutants into the reservoir, it is still unclear whether and how reforestation improves both soil retention and water quality. Therefore, we proposed a conceptual framework to couple landscape dynamics and multiple ecosystem services, in which drivers could directly affect two ecosystem services or indirectly affect them by affecting landscape dynamics. Ecological models were applied to assess water purification and soil retention, and spatial analysis tools were adopted to demonstrate their spatial relationship. Structural equation model documented the effect values of the conceptual framework, meanwhile, relative importance analysis reported the contributions of drivers to forest cover, water purification and soil retention. Our results showed that nitrogen loss and soil loss of the TGRA both decreased from 2001 to 2015, indicating an improvement in both water purification and soil retention. However, correlation analysis revealed significant spatial heterogeneity in their relationship, which may partly be explained by the district and county differences in human activities and development policies. Structural equation model documented the correlation coefficient between nitrogen loss and soil retention was −0.71. Relative importance of forest cover to the nitrogen loss was more than 50%, indicating that water purification could mainly be explained by the effect of forest cover on nitrogen loss. Annual precipitation contributed 26.9% to soil retention, and the overall contribution of climate conditions was 52.1%, which indicated the direct and indirect effects of climate conditions are both important for soil retention. Moreover, the landscape plannings of vegetation restoration were suggested for these key ecological zones in the TGRA to synergistically improve two ecosystem services.

1. Introduction

Two-thirds of ecosystem services have declined over the past half-century, with serious negative impacts on human well-being (Jiang et al., 2018). Many scholars (such as Bao et al., 2018; Bai et al., 2019; Li et al., 2021a) have demonstrated that landscape dynamics significantly altered ecosystem service. It could affect the composition and configuration of ecosystems, and ultimately their ability to provide ecosystem services (Bai et al., 2019). In this context, many ecological projects aiming to recover vegetation coverage have been implemented for reducing environmental risks (Strehmel et al., 2016; Singh et al., 2019). These ecological projects not only increased the vegetation cover in the project areas (Qi et al., 2019), but also gradually restored the damaged ecosystems and enhanced multiple ecosystem services such as promoting regional water cycling, controlling land desertification and improving soil retention (Teng et al., 2019; Huang et al., 2020; Li et al., 2021b). Although landscape regulation and management could contribute to enhancing multiple ecosystem services (Gao et al., 2017; Feng et al., 2020; Gou et al., 2021), it is still unclear whether and how landscape dynamics alter these ecosystem services simultaneously.

Meanwhile, it is vital to demonstrate the relationship among multiple ecosystem services for managing regional ecosystems and

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maintaining the long-term supply of ecosystem services (Jiang et al., 2018). Relationships between two ecosystem services were defined and classified as synergy and trade-off in many previous studies (Wang et al., 2019; Feng et al., 2020; Gou et al., 2021). The former refers to two services both increase or decrease (Wang et al., 2019), and the trade-off occurs when one service is enhanced at the expense of reducing another service (Gou et al., 2021). In recent years, trade-offs and synergies of multiple ecosystem services were reported in different regions (Qiu, 2019), but their driving mechanisms are still unclear, and the current knowledge is insufficient to allow us to properly balance the various ecosystem services (Feng et al., 2020). Bennett et al. (2009) suggested that the generation mechanisms of relationships among ecosystem services may include interactions between services and potential co-influencing factors. Ecosystem responses to different drivers often occur at different spatial and temporal scales, resulting in trade-offs or synergies in ecosystem services (Qiu, 2019). In addition, landscape dynamics is the response of human activities to the natural environment, which often affects ecological processes and, in turn, the provisions of ecosystem services (Li et al., 2021a). Changing landscape patterns could affect multiple ecosystem services simultaneously, leading to trade-offs or synergistic effects (Qiu, 2019). Being aware of this, many scholars (e.g., Wei et al., 2020; Yohannes et al., 2021) have attempted to explore how and when the landscape composition and configuration affect ecosystem services and their interactions in recent years. Therefore, it is necessary to clarify the intrinsic linkages between landscape dynamics and multiple ecosystem services (Li et al., 2021a), and identify the important co-influencers to characterize trade-offs (Wang et al., 2019), so as to reduce or even eliminate trade-offs and achieve a win–win situation for economic construction and ecosystem service maintenance.

Currently, many methods such as descriptive methods, correlation analysis, regression analysis, and radar plot analysis have been applied to identify relationships among multiple ecosystem services (Malinga et al., 2015; Chen et al., 2019; Wu and Li, 2019). Among them, correlation analysis is most commonly used to determine the overall direction and magnitude of trade-offs and synergies (Jiang et al., 2018), as it does not ignore no-effect relationships. In addition, several sophisticated models for estimating and assessing trade-offs of ecosystem services have been developed (Xu et al., 2018), including the Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) model, the Artificial Intelligence for Ecosystem Services (ARIES) model and the Social Value of Ecosystem Services (SolVES) model. Among them, the InVEST model is an open-source modeling environment, which has been widely adopted to estimate and map multiple ecosystem services at different spatial scales (Singh et al., 2019). The nutrient delivery ratio (NDR) module of the InVEST model combines the strengths of nutrient transport models (e.g., SWAT and RHESSys) to assess the water purification services based on the mechanisms of vegetation and soil removing or reducing nutrients in runoff through storage and transformation (Redhead et al., 2018). Compared to process-based models (e.g., SWAT), the InVEST model is relatively simple, with relatively low data requirements (Vigerstol and Aukema, 2011; Dennedy-Frank et al., 2016). Meanwhile, being more applicable to larger data scales than SWAT, InVEST facilitates the assessment of the impact of landscape dynamics on multiple ecosystem services within a relatively large watershed (Bagstad et al., 2013). The Revised Universal Soil Loss Equation (RUSLE) is commonly used to estimate regional soil erosion due to its simple model form and high accuracy and applicability (Tian et al., 2021). Nowadays, the InVEST and RUSLE models have been widely used to estimate regional nutrient loss and soil erosion (Singh et al., 2019; Mohammed et al., 2020), providing guidelines for developing conservation plans and controlling water pollution and soil erosion under different land cover conditions. Consequently, we also utilized these two models to assess water purification and soil retention services, and then to explore their relationship.

The Three Gorges Reservoir Area (TGRA) is an important ecological functional area for soil and water conservation in China, and plays an important role in the ecological security of the middle and lower reaches of the Yangtze River. *China's Ecological Security Strategy* states a comprehensive technical support model for enhancing multiple ecosystem services in the TGRA. Strategic emphasis of ecological restoration of the TGRA is to control sediment entering the reservoir and improve water quality. In recent years, China has implemented many ecological restoration projects, leading to significant landscape dynamics. Many scholars (e.g., Shao et al., 2013; Xiao et al., 2020; Xu et al., 2022) have studied the ecological and environmental impacts of landscape dynamics in the TGRA. For example, Shao et al. (2013) and Strehmel et al. (2016) studied the spatio-temporal characteristics of landscape structure and function in the TGRA, and concluded that the construction of the Three Gorges project, population growth, socio-economic development and national macro policies were the driving forces for the landscape pattern evolution. Huang et al. (2019) also studied landscape pattern changes in the TGRA after water storage and its response to natural environmental factors. However, the responses of multiple ecosystem services on landscape dynamics are still unclear, and how to comprehensively improve the water purification and soil retention services still is a challenge for the TGRA. Therefore, researching the landscape dynamics and spatio-temporal evolution of key ecosystem services in the TGRA can help to optimize landscape patterns and synergistically enhance multiple ecosystem services.

Here, we proposed a conceptual framework to couple landscape dynamics and multiple ecosystem services for the TGRA. In this framework, drivers could directly affect two ecosystem services or indirectly affect them by affecting landscape dynamics. The InVEST and RUSLE models were applied to assess water purification and soil retention, while spatial analysis tools were adopted to demonstrate their spatial relationship. Structural equation model was used to explore the effect values of the conceptual framework, while relative importance analysis was applied to reflect the contributions of drivers to forest cover, water purification and soil retention. Our objectives are (1) to reveal the spatial and temporal characteristics of water purification and soil retention services in the TGRA, (2) to demonstrate the interactions among landscape dynamics and multiple ecosystem services, (3) to propose a landscape planning for enhancing water purification and soil retention synergistically, and provide a scientific basis for ecological security and regional landscape management for the TGRA.

2. Material and methods

2.1. The study area

The TGRA is located in the middle and upper reaches of the Yangtze River (Fig. 1), between 28°31′–31°44′N and 105°50′–111°40′E. It includes 20 cities and counties of Chongqing and Hubei Province, with a total area of 57802 km^2, directly affected by the construction of the Three Gorges Dam (TGD), the world's largest dam. The TGRA has a high population density, but the limited farmlands and high proportion of sloping land lead to a serious land conflict between development and protection. In addition, the natural environment is complex and the main landscapes are mountains, low hills and river plains in the TGRA. Whereas more than 74 % of the region's landform is mountainous, 21.7 % is low hills, and only 4.3 % is a small plain next to river valleys. It has a humid subtropical monsoon climate characterized by variable weather in spring, hot and humid in summer, dry in autumn, and cold in winter (Xiao et al., 2017). Average annual precipitation is 1250 mm, mainly from June to September. Average annual temperature is 17 ℃–19 ℃. Soil type of TGRA at altitudes below 800 m is purple soil, at altitudes from 2000 to 2700 m is brown soil, and above 2700 m is mainly yellow–brown loam (Gou et al., 2021).

The TGD construction and impoundment have brought some new environmental problems, which produced significant socio-economic impacts. Due to the combing effect of climate changes and human activities, soil erosion and non-point source pollution have become the

Fig. 1. Location of the Three Gorges Reservoir Area (TGRA) in China.

most important ecological risks in the TGRA (Teng et al., 2019). Firstly, soil erosion may decrease land productivity and sediment accumulation in water bodies, and increase the frequency of floods and droughts. Secondly, the excessive discharge of domestic sewage, industrial waste, pesticides and fertilizers has brought serious water pollution to the TGRA (Xiao et al., 2017). To alleviate these problems, the Chinese government has adopted a series of regional-scale ecological restoration projects, such as the Return of Cultivated Land to Forests project, the Yangtze River Protected Forest Project, the Natural Forest Protection Project, and forestry projects along the Yangtze River (Huang et al., 2019; Teng et al., 2019).

2.2. Data source and preprocessing

2.2.1. Data sources

The study data include land use, topographic, climate, soil and socio-economic data (Table 1). Land use data were derived from Landsat TM/ETM+/OLI images with a resolution of 30 m. We used supervised classification and artificial neural network methods to obtain land use maps for the TGRA in 2001, 2005, 2010 and 2015 (Huang et al., 2020). The overall classification accuracy of all periods was above 85 % (Huang et al., 2019), which met the needs of this study.

The DEM data with 30 m resolution were derived from ASTER Global Digital Elevation Model V002 (http://www.gscloud.cn/). It is a key parameter of ecological model for assessing ecosystem services, and could be used to calculate the required topographical parameters including elevation, slope and surface height fluctuation in the ArcGIS.

Climate data include annual precipitation (mm), monthly average temperature (°C) and annual radiation (MJ/m^2), obtaining from our previous studies (Huang et al., 2019, Huang et al., 2020). Considering the tremendous effect of topography on climate, the 30 m resolution precipitation and temperature maps were interpolated by using the co-kriging method (Salhi, 2022) based on the observation data of 29 meteorological stations in or near the TGRA and DEM data. And 30 m

Table 1
The description and data source in this study.

Data Category	Definition and description	Data Source
Land use data	30 m resolution land use maps in 2001, 2005, 2010 and 2015.	Derived from the previous study (Huang et al., 2020)
Topographical data	30 m resolution elevation map 30 m resolution slope map 30 m resolution surface height fluctuation map	Derived from ASTER Global Digital Elevation Model V002 (http://www.gscloud.cn/)
Soil data	30 arc-second resolution soil bulk density map 30 arc-second resolution soil total nitrogen map 30 arc-second resolution soil organic matter map	Derived from Cold and Arid Regions Sciences Data Center at Lanzhou (https://westdc.westgis.ac.cn/)
Climate data	30 m resolution annual/monthly precipitation maps from 2001 to 2015 30 m resolution monthly average temperature maps from 2001 to 2015 30 m resolution annual radiation maps from 2001 to 2015	Derived from the previous studies (Huang et al., 2019, 2020)
Socio-economic data	Total population at the county level from 2001 to 2015 GDP at the county level from 2001 to 2015 Grain yield at the county level from 2001 to 2015 Social investment at the county level from 2001 to 2015 Social consumption at the county level from 2001 to 2015 Resident deposit at the county level from 2001 to 2015 Per capita net income of farmers at the county level from 2001 to 2015	Derived from statistical yearbooks of Hubei and Chongqing from 2001 to 2015

resolution radiation maps were interpolated by using the ordinary kriging method to the radiation observation data of other 22 meteorological stations (Liao et al., 2020).

We collected soil data including bulk density (g/cm^3), soil total nitrogen (mg/kg) and soil organic matter (g/kg) from the China Dataset of Soil Properties for Land Surface Modeling provided by Cold and Arid Regions Sciences Data Center at Lanzhou (https://westdc.westgis.ac.cn/). It is a comprehensive 30 arc-second resolution gridded soil data (Wei et al., 2013), including physical and chemical attributes of soils derived from 8979 soil profiles and the Soil Map of China (1:1,000,000).

Meanwhile, socio-economic data at the county level from 2001 to 2015 were collected from statistical yearbooks. These data include total population (thousand person), GDP (billion yuan), grain yield (thousand tons), social investment (billion yuan), social consumption (billion yuan), resident deposit (billion yuan) and per capita net income of farmers (yuan).

2.2.2. *Study flowchart*

Our purpose is to demonstrate the relationship between water purification and soil retention of the TGRA (Fig. 2). The InVESET model was used to assess the nitrogen (N) loss rate, a negative indicator to reflect the water purification. Specifically, the lower the N loss rate, the higher the water purification, and vice versa. The RUSLE model was used to assess the actual and potential soil loss to generate soil retention. Meanwhile, the spatial variations of two ecosystem services in the TGRA were then analyzed by using the spatial analysis tool of ArcGIS software version 10.2. Finally, we used a structural equation model to quantify the effect values of various factors on landscape dynamics, water purification and soil retention.

2.2.3. *Conceptual framework*

We construct a conceptual framework to link landscape dynamics to the relationship between water purification and soil retention (Fig. 3a). In this conceptual framework, 16 drivers (Table 2, Figs. S1–S4) were selected, which could directly affect two ecosystem services or indirectly affect them by affecting landscape dynamics. Due to a large number of drivers and their possible collinearity, the principal component analysis was used to reduce the dimensionality of the data, and we modified this conceptual framework to Fig. 3b.

2.3. *Ecosystem service assessment*

2.3.1. *Water purification*

The TGRA is a relatively large scale and the data collection is difficult, limiting the process-based model usage. Therefore, we used the NDR module of the InVEST model to estimate the N loss rate. This model could describe the movement of nutrients in space, representing the long-term, steady-state flow of nutrients (Redhead et al., 2018). Specifically, nutrient sources across the landscape are derived from land-use change-specific nutrient loading rates and are primarily based on empirical data. It simulated the N flow through the grid cells in the simulation domain according to the mass balance equation, and the nutrient loads and nutrient transport were estimated. Where nutrient load indicates the source of nutrients across the landscape is determined by the land use map and associated loading rates (Redhead et al., 2018). In contrast, nutrient transport is calculated as a factor for each pixel based on the properties of the pixels belonging to the same flow path (Han et al., 2021). In this paper, pixel-scale N loss is characterized by the nutrient load and the nutrient delivery ratio (Eq. (1)), and N loss at the watershed scale is the sum of pixel-scale N losses (Eq. (2)).

$$N\_loss_{pixel} = load_i \times NDR_i\left(D_{up},\ D_{dn}, eff_{dn}\right) \tag{1}$$

$$N\_loss_{watershed} = \sum_{watershed} N\_loss_{pixel} \tag{2}$$

where N_{pixel} and $N_{watershed}$ are the nitrogen loss (kg/year) at the pixel and watershed scales, respectively. The $load_i$ is the N load (kg/year) for the *i-th* pixel. The NDR_i is the nutrient delivery ratio of N for the *i-th* pixel, and is a function decided by the upslope area parameter (D_{up}), the downslope flow path parameter (D_{dn}), and the retention efficiency of land use type on the downslope flow path (eff_{dn}).

The input data required for the NDR model include DEM, land use data, nutrient runoff proxy raster data and watershed boundary vector data. DEM and watershed boundary vector data are static, while precipitation data varied from 2001 to 2015 as the nutrient runoff proxy. Because regional land use would not change drastically in a short period and we do not have access to annual land use maps, land use maps of 2001, 2005, 2010 and 2015 are used to determine the N load in 2001–2003, 2004–2008, 2009–2012, and 2013–2015. In addition, a biophysical table and some parameters are the key inputs in this model (Han et al., 2021). We have used this model to explore the spatio-temporal variation of the N loss in the TGRA in the previous study (Huang et al., 2022), and the model description and these parameters settings are detailly described in the Annex (Appendix).

2.3.2. *Soil retention*

The RUSLE is commonly used to estimate annual soil loss rates for

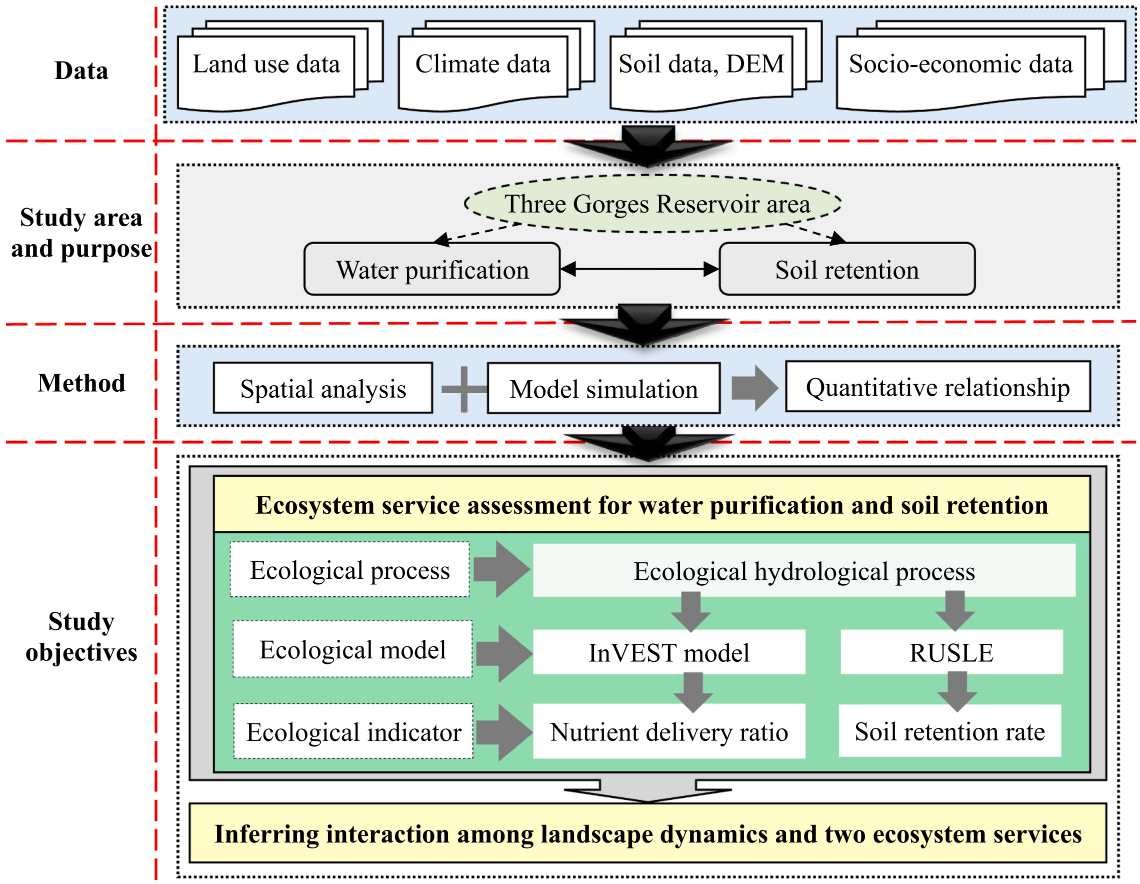

Fig. 2. Data processing flowchart of our study.

sheet and hilly erosion (Tian et al., 2021). Soil loss of the TGRA is assessed by this model as Eq. (3) at the pixel scale and regional scale, which is a negative indicator for soil retention. Soil erosion control service in ecosystems is expressed by soil retention here. Referring to Fu et al. (2011), soil retention (Eq. (5)) is calculated as soil loss without vegetation cover and soil retention practice minus the actual soil loss (Eq. (4)).

$$A_0 = R \times K \times L \times S \times C \times P \tag{3}$$

$$A_p = R \times K \times L \times S \tag{4}$$

$$\Delta A = A_p - A_0 = R \times K \times L \times S \times (1 - C \times P \tag{5}$$

where A_0 and A_p are annual soil loss rates (t ha^{-1} yr^{-1}) for actual soil loss and potential soil loss (without vegetation cover and soil erosion control practice); ΔA is soil retention (t ha^{-1} yr^{-1}); R is rainfall erosivity factor (MJ mm ha^{-1} h^{-1} yr^{-1}); K refers to soil erodibility factor (t h MJ^{-1} mm^{-1}); L and S are slope-length factor and slope factor, respectively; C is vegetation cover factor; P is soil retention practice factor.

This model has been used to explore the effects of climate, land use changes on soil loss in the TGRA in our previous studies (Teng et al., 2019; Huang et al., 2020), and the six factors of this model are detailly described in the Annex (Appendix).

2.4. Statistical analysis

2.4.1. Trend analysis

The least-square linear regression model (Eq. (6)) was used to analyze the temporal variation, and the change trend was described by the modelled slope. Meanwhile, the t statistic was applied to test the significance of the modelled slope, and the significance was documented by the p-value.

$$y = ax + b \tag{6}$$

where y is the ecological indicators, and x is the time (year). The a is the modeled slope, which could reflect the change trend of the ecological indicators. And the b is the intercept of the regression model.

2.4.2. Spearman's rank correlation

Spearman's rank correlation was used to identify the association among 16 drivers at the county scale. There was a significant correlation among 16 drivers (Fig. S5). Among topographical factors, elevation and slope were significantly correlated with a coefficient of 0.91. Among soil factors, soil total nitrogen and soil organic matter were significantly correlated with a coefficient of 0.94. Among climate factors, annual precipitation and annual radiation were significantly negatively correlated with a coefficient of −0.95. Meanwhile, there were significant co-linearity problems among 7 socio-economic factors compared to other drivers.

2.4.3. Principal component analysis

Due to the serious co-linearity problems among 16 drivers, principal component analysis was used to reduce the dimensionality (Muhsina et al., 2020), and convert the 16 drivers into a set of uncorrelated variables. The cumulative variance of first principal components of topographic, soil, climate, and socioeconomic factors were 64.80 % (Table A2), 64.12 % (Table A3), 73.28 % (Table A4) and 83.07 %, respectively (Table A5), which met our study requirement. Therefore, the first principal components of topographic, soil, climate, and socio-economic factors were extracted and named as *Ft*, *Fs*, *Fc*, and *Fse*, respectively. Where the loading rates of *Ft* on elevation, slope and

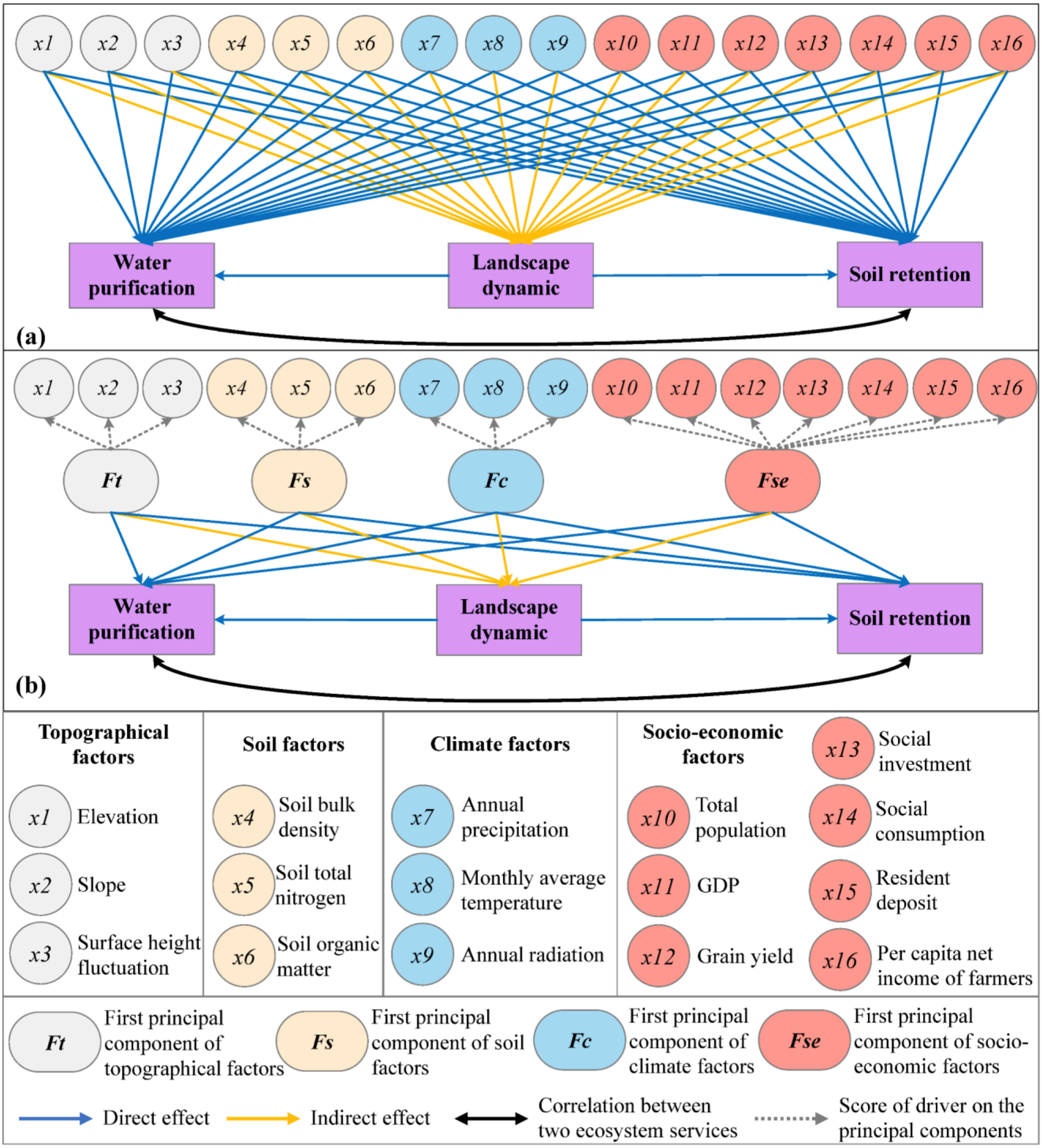

Fig. 3. The conceptual framework (a) and modified conceptual framework (b) of linking landscape dynamics to two ecosystem services. Note: The driver can directly affect ecosystem service by the blue single arrow line, and also could affect landscape dynamic by the yellow single arrow line and then indirectly affect ecosystem service by the blue single arrow line between landscape dynamic and ecosystem service. The black double arrow line indicates the correlation between water purification and soil retention. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

surface height fluctuation were 0.50, 0.50 and −0.12, respectively (Table A6). The loading rates of *Fs* on soil bulk density, soil total nitrogen and soil organic matter were 0.10, 0.51 and 0.50, respectively (Table A7). The *Fc* loadings on annual precipitation, monthly average temperature and annual radiation were 0.95, 0.59 and −0.98, respectively (Table A8). The *Fse* had a loading rate of 0.16 for total population, 0.17 for the variation of GDP, social investment, social consumption, resident deposit and per capita net income of farmers, and −0.03 for grain yield (Table A9).

2.4.4. *Structural equation model*

Structural equation model is a statistical technique for explaining complex multivariate relationships. It compares a priori theoretical model with the data to derive a structural equation that represents the statistical dependence or association between the variables (Capmourteres and Anand, 2016). The model could include observed variables that we did not measure directly, as well as theoretical structures, which can reveal not only the relationship between explicit and latent variables, but also the relationship between all latent variables (Felipe-Lucia et al., 2015; Capmourteres and Anand, 2016). Therefore, we used it to

Table 2
The description and spatial map of the 16 drivers at the county scale.

Variable Category	Variable	Definition and description	Spatial map
Topographical factor	*x1*	Elevation (m)	Fig. S1
	x2	Slope (°)	
	x3	Surface height fluctuation	
Soil factor	*x4*	Soil bulk density (g/cm^3)	Fig. S2
	x5	Soil total nitrogen (mg/kg)	
	x6	Soil organic matter (g/kg)	
Climate factor	*x7*	Annual precipitation (mm) in 2015	Fig. S3
	x8	Monthly average temperature (°C) in 2015	
	x9	Annual radiation (MJ/m^2) in 2015	
Socio-economic factor	*x10*	Total population (thousand person) in 2015	Fig. S4
	x11	GDP (billion yuan) in 2015	
	x12	Grain yield (thousand tons) in 2015	
	x13	Social investment (billion yuan) in 2015	
	x14	Social consumption (billion yuan) in 2015	
	x15	Resident deposit (billion yuan) in 2015	
	x16	Per capita net income of farmers (yuan) in 2015	

reveal the intrinsic linkage between the latent variables such as forest cover, water purification and soil retention services, and the explicit variables such as topographical, soil, climate and socio-economic factors. Each latent variable has a linear function and a residual with its explicit variable, which were used to infer causal links between the variables in the conceptual model and interpret the results, thereby identifying the driving mechanisms among the ecosystem services.

2.4.5. Relative important analysis

The relative important analysis was performed by the R package of "relaimpo" (https://cran.r-project.org/web/packages/relaimpo/index.html) to identify the relative contributions of 16 drivers to two ecosystem services. First, the generalized linear model (GLM) was used to fit the ecosystem service and 17 independent variables (16 drivers and the forest cover). Then we selected the metric of "lmg" (R^2 partitioned by averaging over orders) to quantify the contribution of the independent variables to dependent variable in the relative important analysis. In the same way, we fitted the GLM and assessed the relative importance of 16 drivers on forest cover.

In the conceptual framework, we hypothesized that 16 drivers could indirectly affect ecosystem service by altering the forest cover. Consequently, the overall contribution of drivers consists of the direct and indirect contributions, and the sum of the indirect contributions of all drivers equals the contribution of forest cover. Therefore, we used the following equations to decouple the indirect contributions to 16 drivers from the effect of forest cover.

$$e = de_{x1} + de_{x2} + de_{x3} + \cdots + de_{xi} + \cdots + de_{x16} + e_{fc} \quad (7)$$

$$e_{fc} = ie_{x1} + ie_{x2} + ie_{x3} + \cdots + ie_{xi} + \cdots + ie_{x16} \quad (8)$$

$$e_{xi} = de_{xi} + ie_{xi} \quad (9)$$

where, e is the contribution of all independent variables on dependent variable (the N loss or soil retention), which is equal to the R^2 of the fitted regression model. The de_{xi} and ie_{xi} are the direct and indirect contributions of xi on the dependent variable, respectively. The e_{fc} is the contribution of forest cover on the dependent variable, while the e_{xi} is the overall contribution of xi on the dependent variable.

3. Results

3.1. Temporal variations of N loss and soil retention during 2001–2015

The estimated results of InVEST model showed that the N loss of the TGRA decreased from 8.72×10^6 kg in 2001 to 6.32×10^6 kg in 2015, with a change rate of -0.19×10^6 kg/yr (Fig. 4a), indicating a significant improvement of water purification service. The highest N loss occurred in 2003 with 8.83×10^6 kg and the lowest N loss occurred in 2015 with 6.32×10^6 kg. In addition, the N loss over the past 15 years could be divided into four phases, namely, 2001–2003, 2004–2007, 2008–2011 and 2012–2015.

Actual and potential soil loss rates of the TGRA from 2001 to 2015 were estimated by the Eqs. (3) and (4), presenting a decreasing trend (Fig. S5a) and an increasing trend (Fig. S5b), respectively. Then, we used the Eq. (5) to obtain the temporal variation of soil retention of TGRA (Fig. 4b), which showed an overall increasing trend with a change rate of 0.22×10^{11} kg/yr. Soil retention was highest in 2007 with 26.48×10^{11} kg, followed by 22.62×10^{11} kg in 2003. In contrast, soil loss was lowest in 2006 with 10.63×10^{11} kg, followed by 11.63×10^{11} kg in 2011. In terms of changes in each phase, the most significant changes were observed during 2005–2006 and 2006–2007.

3.2. Spatial variations of N loss and soil retention in the TGRA

The N loss exhibited a significant spatial heterogeneity in the TGRA (Fig. 5a1). Based on the trend analysis of the N loss rate from 2001 to 2015, the middle regions had the highest N loss rate of 462 kg km^{-2} yr^{-1}, but had the larger annual change rate (Fig. 5a2). The N loss rate was relatively high in the southwestern regions such as Chongqing, Yubei, Banan and Jiangjin. The other areas performed best in terms of water purification services, as their N loss rates were essentially 0. Moreover, 84.5 % of the TGRA had no change in N loss over the past 15 years (Fig. 5a3), which was mainly found in the southwestern and eastern regions. The N loss was significantly reduced in 15.1 % of the TGRA, which was concentrated in the middle regions with an annual change rate of −38.32 (kg km^{-2} yr^{-1})/yr. In contrast, the area with a significant increasing trend of N loss was only 0.4 %. The increasing areas were mainly located in Jiangjin, with a maximum growth rate of 34.83 (kg km^{-2} yr^{-1})/yr.

Similarly, the variations of soil retention also exhibited a significant spatial heterogeneity (Fig. 5b1). The middle regions had the highest soil retention and the largest change rate with 12.73(t ha^{-1} yr^{-1})/yr (Fig. 5b2). Soil retention was unchanged during 2001–2015 in 89.8 % of the TGRA (Fig. 5b3), mainly located in the southwestern and eastern parts. 7.6 % of the TGRA was increasing in soil retention, while only 2.6 % of the TGRA had a significant decrease in soil retention. In terms of soil erosion control, the southwestern regions and the eastern part of Yiling County performed the best. Most of the soil loss rates in these areas were slight (<5 t ha^{-1} yr^{-1}) and low (5–25 t ha^{-1} yr^{-1}) (Fig. S6a). In contrast, the middle of the TGRA experienced the most severe soil erosion, with most classes being high (50–80 t ha^{-1} yr^{-1}), very high (80–150 t ha^{-1} yr^{-1}), and severe (>150 t ha^{-1} yr^{-1}). Meanwhile, the spatial variation of soil loss is similar to the soil retention (Fig. S6b).

3.3. Spatial relationship between water purification and soil retention

Correlation analysis was used to document the spatial relationship between water purification and soil retention at the pixel scale (Fig. 6a). In the eastern part of the TGRA, two ecosystem services mainly exhibited a synergistic relationship, with a maximum correlation coefficient of 0.99. Similarly, there was also a synergistic relationship between water purification and soil retention in Chongqing, Yubei, Banan, Wulong, Fengdu and Shizhu, but the correlation was weaker than that in the

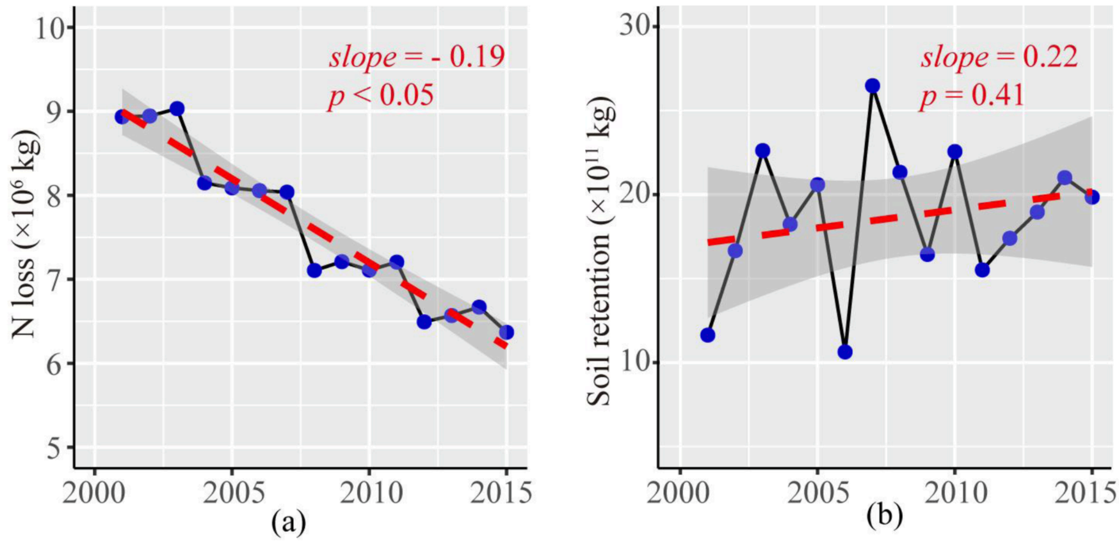

Fig. 4. Temporal variations of nitrogen (N) loss (a) and soil retention (b) of the TGRA from 2001 to 2015. Note: The least-square linear regression model was used to analyze the temporal variation, and the change trend is described by the modelled *slope*. Meanwhile, the *t* statistic was applied to test the significance of the modelled *slope*, and the *p* value was used to document the significance. The red line indicates the linear model fit, and the gray region is the 95% confidence intervals of the linear model. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

eastern part of the TGRA. However, there were also some areas (e.g., Wanzhou, Zhongxian and Changshou) with a strong trade-off relationship, whose correlation coefficient was −0.98.

There were 1091.02 km^2 of the TGRA with synergistic increases in water purification and soil retention (Fig. 6b), with only 9.89 km^2 where these services were synergistically decreasing. In contrast, the area within the TGRA where the two ecosystem services exhibited a trade-off relationship was only 183.76 km^2 (Fig. 6b). In addition, the pixels with a synergistic relationship between water purification and soil retention were highly clustered in the middle of TGRA (Fig. 6c), such as Fengjie, Yunyang, Wushan and Shizhu. And the pixels with a trade-off relationship between water purification and soil retention were scattered within each district and county, with Yiling, Zhongxian and Fuling the most obvious (Fig. 6d).

3.4. Driving mechanisms of water purification and soil retention

Effect values were illustrated by the structural equation model (Fig. 7). The residual errors of the partial least squares path models for forest cover, N loss and soil retention were 0.21, 0.41 and 0.22, respectively. The conceptual framework demonstrated that the four principal components could affect ecosystem services directly, or indirectly by affecting forest cover and thus affecting ecosystem services. Specifically, the effects of *Ft*, *Fs*, *Fc*, and *Fse* on forest cover were, 0.74, 0.70, −0.82 and −0.33, respectively. The effects of four principal components were −0.03, −0.09, −0.09 and −0.16 for N loss, while the effect of forest cover was −0.91. The effects of four principal components were 0.40, 0.10, −0.24 and −0.21 for soil retention, while the effect of forest cover was 0.70. Moreover, the correlation coefficient between the N loss and soil retention was −0.71.

Relative importance analysis documented that forest cover contributed about 51.3 % to controlling N loss (Fig. 8a) and 11.9 % to soil retention (Fig. 8b). Meanwhile, climate conditions (the sum of annual precipitation, monthly average temperature and annual radiation) have the greatest relative importance for soil retention. The relative importance of annual precipitation and monthly average temperature were 14.2 % and 8.5 % for controlling N loss, and 26.9 % and 17.0 % for soil retention.

Moreover, the relative importance analysis of forest cover (Fig. 8c) was conducted to decouple the contribution of forest cover into 16 drivers for controlling N loss (Fig. 8d) and soil retention (Fig. 8e) according to the Eqs. (7)–(9). Climatic conditions had the largest overall contribution to the two ecosystem services, with 40.1 % and 52.1 % relative importance for controlling N loss and soil retention, respectively.

4. Discussion

4.1. Spatio-temporal variations of two ecosystem services

4.1.1. N loss

N loss rate of the TGRA decreased from 154.49 kg/km^2 in 2001 to 108.81 kg/km^2 in 2015, presenting a significant downward trend (Fig. 4a). InVEST model was used to assess the non-point source pollution. Due to the complex composition of point source pollution such as industrial pollution and human domestic pollution, as well as the lack of accurate data, these pollutions were not considered. It is challenging to obtain the measured data of the N loss at the regional scale by field surveying, but the N loss change trend of the TGRA is supported by relevant studies (such as Liu et al., 2013; Zhong et al., 2020). Meanwhile, InVEST model parameters have been calibrated for the TGRA in our previous study (Huang et al., 2022), and scholars accept the estimated N loss by the InVEST model. Moreover, we compared the estimated results with annual agricultural N loss of the TGRA reported by the *Three Gorges Project Ecological and Environmental Monitoring Bulletin* (Table A10). Although our estimated results are smaller than the reported data, the change trends of N loss are same in the two data. Therefore, despite the lack of experimental validation, our estimated N loss is acceptable and its change trend is reliable, indicating that water purification service in this region has improved.

Due to the huge environmental differences in geology, geomorphology and human activities (Xiong et al., 2017; Xia et al., 2018), N loss exhibited a significant spatial heterogeneity. The middle of the TGRA (e.g., Kaixian and Yunyang) had the highest N loss, followed by the southwestern part of the TGRA (e.g., Chongqing, Yubei and Banan) (Fig. 5a1). This was mainly influenced by the topography and land use type in these areas. There are low hills and mountains, whose main land use types are agricultural land and artificial construction land with high intensity of human activities. The excessive application of fertilizers and the increase of pollutants and wastewater on impervious surfaces have exacerbated water quality deterioration and environmental pollution (Chen et al., 2019a; Zhang et al., 2020). Meanwhile, land use change

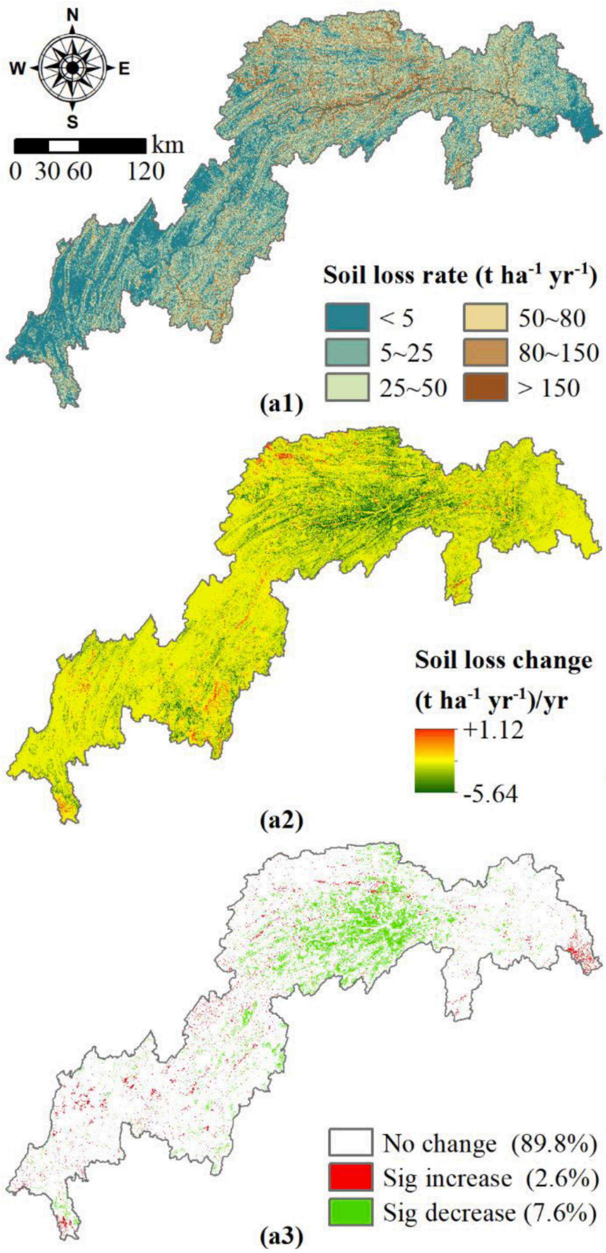

Fig. 5. Spatial variations of soil loss rate (a) and N loss rate (b) in the TGRA. Average (1), change trend (2) and change type (3) were calculated by the estimated results of N loss rate and soil loss rate from 2001 to 2015. Note: In the figure (a3) and (b3), No change documents that N loss rate or soil loss rate did significantly no change (the modeled slope is equal to 0 and $p < 0.05$) or changed but not significantly (the modeled slope is not equal to 0 and $p \geq 0.05$). Sig increase documents N loss rate or soil loss rate increased significantly (the modeled slope is greater than 0 and $p < 0.05$), while Sig decrease documents N loss rate or soil loss rate decreased significantly (the modeled slope is <0 and $p < 0.05$).

could partly explain the spatial heterogeneity of the N loss change. Cultivated land has a negative effect on N loss, while forestland has a positive effect on N loss (Hou et al., 2013). N loss decreased significantly in the middle of TGRA, which may be caused by the landscape dynamics such as afforestation and reforestation in sloping croplands (Xiong et al., 2017).

4.1.2. Soil retention

Soil retention of the TGRA increased from 11.63×10^{11} kg in 2001 to 19.85×10^{11} kg in 2015 (Fig. 4b). Meanwhile, the actual annual soil loss rate of the TGRA fluctuated between 24.10 t ha^{-1} yr^{-1} and 54.92 t ha^{-1} yr^{-1}, but presented a downward trend at a rate of $-$ 0.60 t ha^{-1} yr^{-1} (Fig. S6 a). It is difficult to validate the accuracy of soil retention, but our estimated results revealed that average soil loss rate and soil retention rate during 2001 $\sim$ 2015 are 38.07 t ha^{-1} yr^{-1} and 884.76 t ha^{-1} yr^{-1}, which are similar with other studies (Table A11). Moreover, the actual soil loss rate and its trend in our study is supported by other studies based on field experiments at a catchment scale (Shen et al., 2010; Fang et al., 2011; Tang et al., 2014; Liu et al., 2016; Bao et al., 2018), sediment discharge rate observed by the Huanglingmiao hydrological station (Teng et al., 2019) and ecological models at a regional scale (Wu et al., 2011; Xu et al., 2011). Meanwhile, many studies (such as Xiao et al., 2017; Teng et al., 2019; Huang et al., 2020) have demonstrated ecological restoration projects were effective in increasing forest cover, thus controlling soil erosion of the TGRA.

Soil retention exhibited a distinct spatial heterogeneity according to the average soil retention rates during 2001–2015 (Fig. 5b1). The main reason is the differences in human activities such as population growth

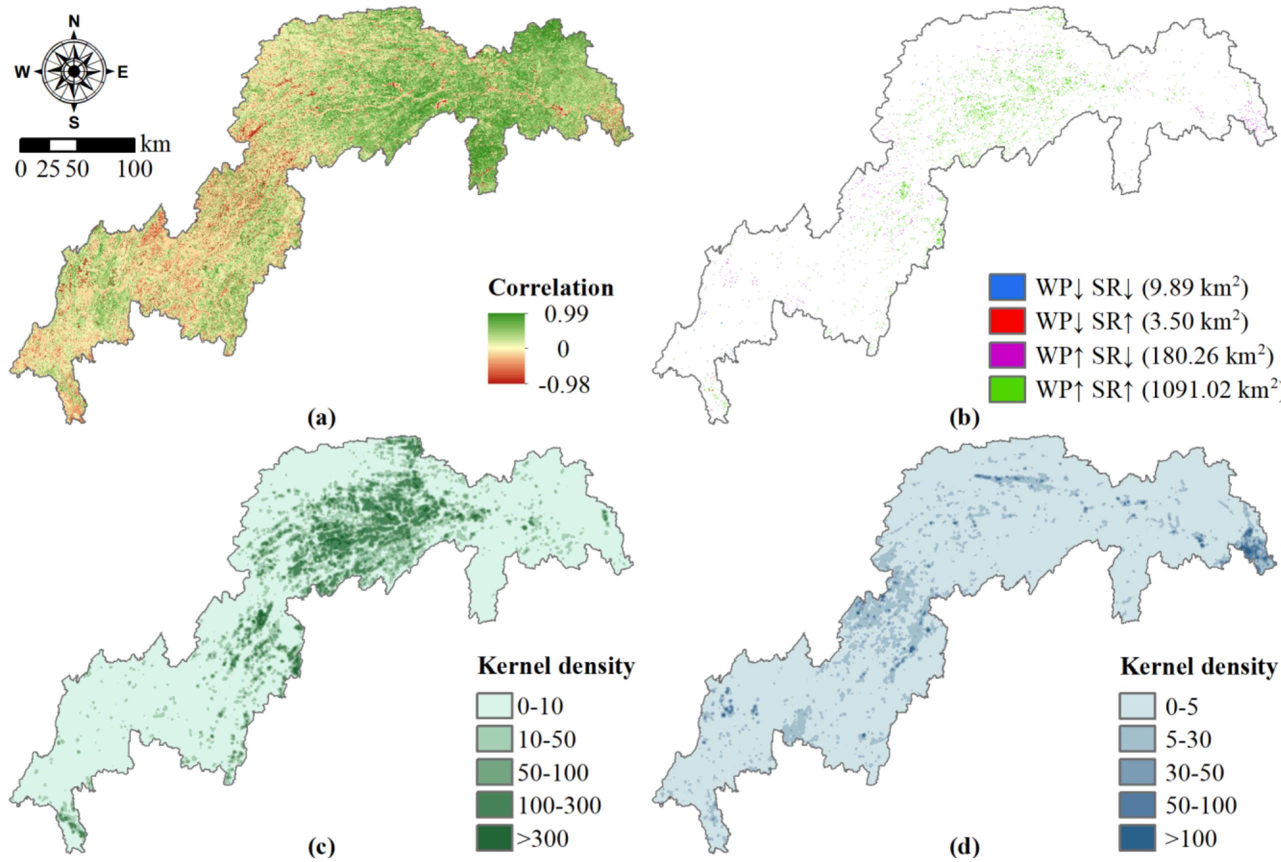

Fig. 6. Spatial relationship between water purification and soil retention. Figure (a) exhibited Spearman's rank correlation between water purification (indicated by the N loss rate with the negative direction) and soil retention (indicated by the soil retention rate) at the pixel scale. Figure (b) derived Fig. 5*a3* and Fig. 5*b3*. WP and SR are the abbreviations of water purification and soil retention, respectively. ↑ and ↓ indicate significant increase and significant decrease, respectively. Figure (c) exhibited the kernel density of grids with the significant synergy between two ecosystem services (the pixels of WP↑SR↑ and WP↓SR↓ in the Fig. 6*b*), while Figure (d) exhibited the kernel density of grids with the significant antagonism between two ecosystem services (the pixels of WP↑SR↓ and WP↓SR↑ in the Fig. 6*b*).

and land reclamation, as well as ecosystem types within each district and county (Xiong et al., 2017). Additionally, increased soil retention mainly occurred in the middle of the TGRA (Fig. 5b2), which is consistent with Xiao et al. (2020). The implementation of afforestation policies after 2000 returned cropland in the steeping slope regions to forests in the middle of the TGRA (Xiong et al., 2017), which contributed to improving soil retention service. Meanwhile, Wanzhou, Fengjie and Wushan in the eastern part of TGRA are mostly mountainous areas with dense natural forests and less human impact (Xiao et al., 2017; Xiao et al., 2019), so soil retention service is high, with insignificant change during 2001–2015. However, soil loss risk increased in some regions such as Yiling and Kai Counties, which might be attributed to the interaction among land use changes, climate changes, and human activities. Some forests planted through vegetation restoration and other measures are still in the young forest stage, with low vegetation cover and weak soil erosion control, which cannot offset the negative effects of other factors (Teng et al., 2019). Overall, the spatio-temporal variations soil retention is complicated by the ecological vulnerability of TGRA, but soil loss risk is effectively controlled in most regions.

4.1.3. Spatial relationship between water purification and soil retention

Soil retention and water purification services in the eastern regions have a clear synergistic growth relationship (Fig. 6). Xiao et al. (2017) demonstrated that the eastern part of the TGRA (e.g., Fengjie, Wushan, Zigui and Yiling) was mostly mountainous area with high density of forests and less affected by human activities. Forests are known to reduce soil loss by intercepting rainfall, reducing erosion, and promoting the restoration of ecosystem structure and function (Huang et al., 2020). And it can promote nutrient absorption in the soil, thus improving soil fertility and reducing nutrient loss. This means that forests have an important role in controlling soil erosion and N loss, and therefore biological projects (afforestation and reforestation) are considered as an effective method to synergistically reduce soil erosion and N loss, which is supported by other studies (Xiong et al., 2018; Wang et al., 2018). The restoration and reconstruction of forests not only increases ground cover and protects the soil from erosion and degradation, but also increases its root secretions and biomass, accumulating more organic carbon and nitrogen for the soil (Wang et al., 2018).

Water purification and soil retention in Chongqing, Yubei, Banan, Wulong, Fengdu and Shizhu also showed a synergistic relationship, but the main trend was a simultaneous decrease (Fig. 6). It may partly be explained by the high population density, frequent agricultural farming and rapid economic development (Xiao et al., 2017). On the one hand, rapid urbanization has led to vegetation degradation, which greatly counteracts the positive effects of ecological restoration (Gou et al., 2021). On the other hand, rapid economic development has resulted in huge pollution inputs to the major tributaries and large urban centers in the TGRA, which has a serious negative impact on water quality in the study area (Li et al., 2019). In this context, people often choose to increase the area of green space, whose function is similar to forests, in urban environments to mitigate the negative impact of economic construction on water purification and soil retention. It not only increases vegetation cover and reduces surface runoff and soil erosion, but also purifies suspended matter and impurities from stormwater runoff.

There were also some areas in the TGRA with a trade-offs relationship between soil retention and water purification, such as Wanzhou,

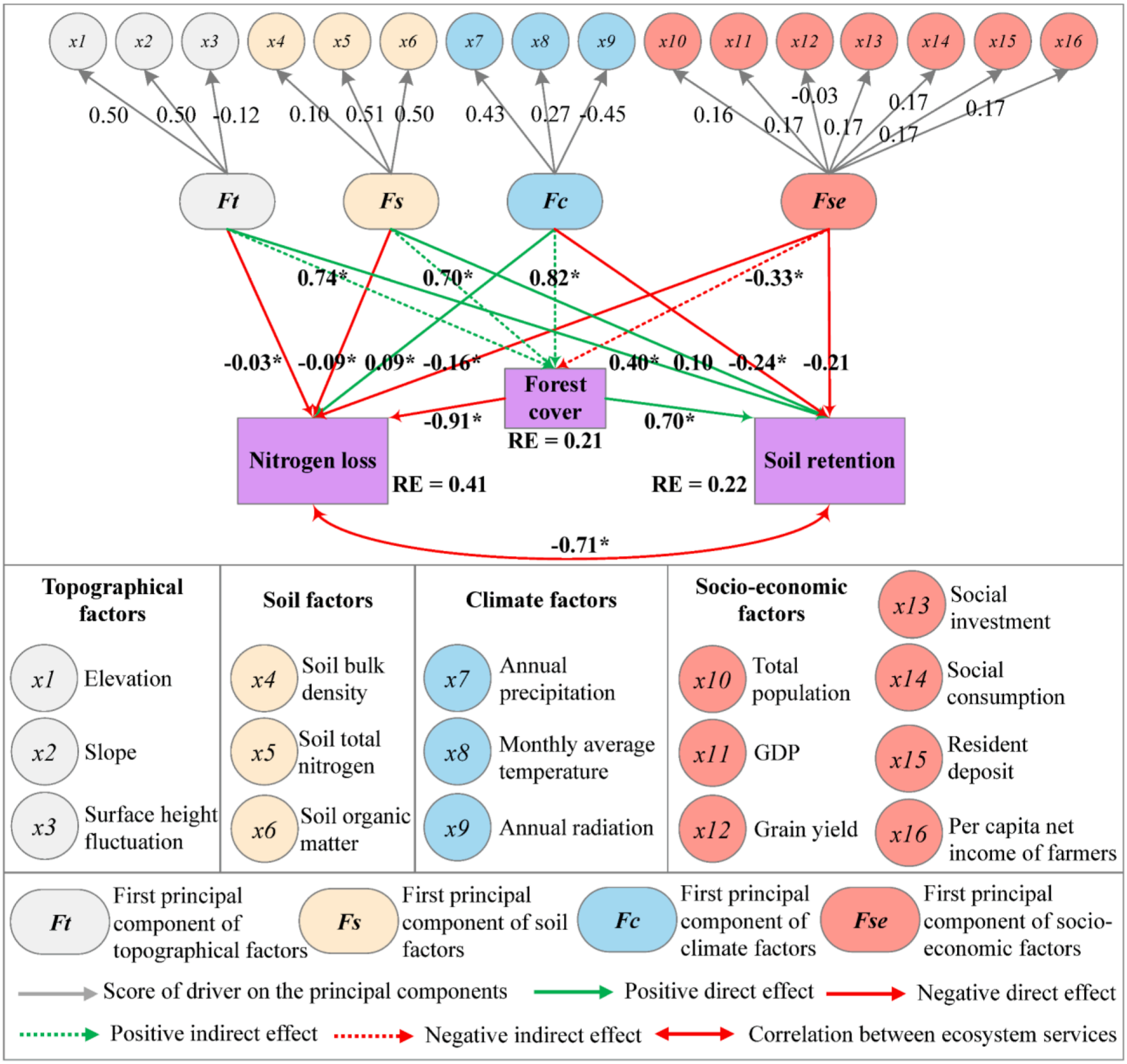

Fig. 7. Effects of independent variables (topographical, soil, climate, and socio-economic factors) on forest cover, N loss and soil retention were determined by partial least squares path modeling in the structural equation model. Note: The number around the line is the effect value, and "*" refers to the effect value is significant ($p < 0.05$). RE is the residual error of the path modeling. The sample size is 20 for statistical analysis ($N = 20$).

Zhongxian and Changshou (Fig. 6), where water purification increased while soil retention decreased. The likely reason is that most of these regions are rural. In recent years, the changes in agricultural production methods such as terracing, conservation tillage and balanced fertilization have effectively contributed to water purification service. Since the slope of terraced fields is reduced, the erosion effect of water is weakened (Arnáez et al., 2015). And the field ridge is slightly higher than the surface of terraced field, which can ensure that water and fertilizer do not easily flow out of the field and play a role in maintaining water and soil. Moreover, the terraces have better ventilation and light penetration conditions, which are conducive to crop growth and nutrient accumulation (Chen et al., 2021). Reducing fertilizer application, changing fertilizer application methods, and adopting agricultural tillage methods such as crop rotation and no-till can significantly reduce soil leachable nitrogen and increase the effective uptake of nitrogen by field crops (Dimkpa et al., 2020; Alghamdi and Cihacek, 2022). However, agricultural practices still can cause soil erosion and alter the carbon balance and feedback in the soil (Jiu et al., 2019).

4.2. Conceptual framework analysis

Water purification and soil retention are significantly correlated (Fig. 7), which is consistent with other studies on the relationship between ecosystem services in the TGRA (Bao et al., 2018; Li et al., 2019). Soil retention can improve water quality because suspended sediment is an important nutrient source (Li et al., 2019), while soil erosion leads to agricultural productivity reduction and exacerbates the risks of floods and ecological disasters, leading to river sedimentation and water environment degradation (Jiu et al., 2019). The former focused on the role of soil and water conservation, while the latter mainly studied the effects of land use change on variations in these ecosystem services. Their relationship is more complex at the regional scale, which is also the reason for the significant spatial heterogeneity in the trade-off or synergistic relationship between water purification and soil retention in

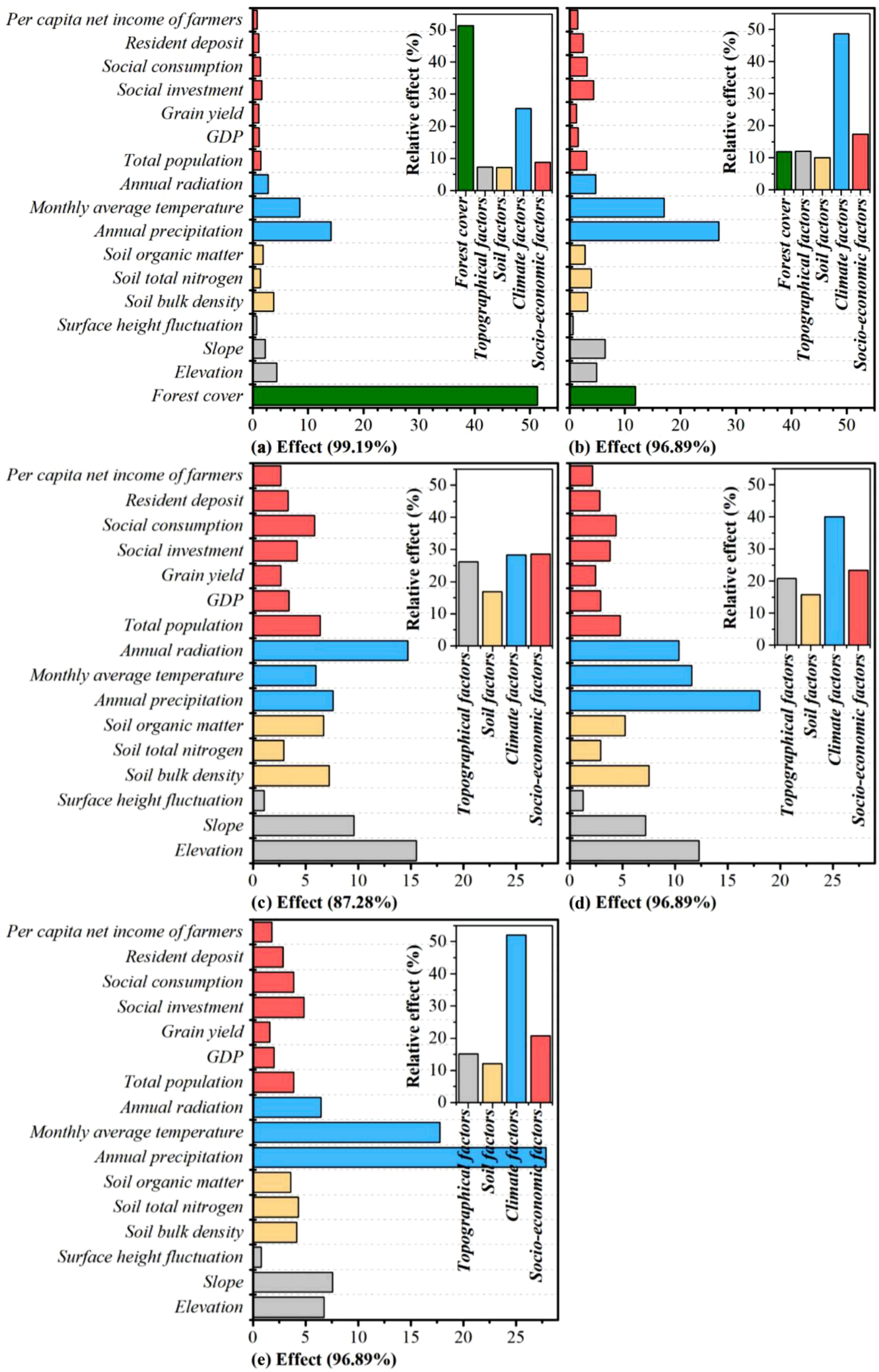

Fig. 8. Relative importance of 17 independent variables (16 drivers and the forest cover) on the N loss (a) and soil retention (b), and relative importance of 16 drivers on the forest cover (c), N loss (d) and soil retention (e) derived from the generalized linear regression analysis and the relative important analysis. Note: The metric of "lmg" (R^2 partitioned by averaging over orders) is used to quantify the contribution of the independent variables to the dependent variable. Effect is the R^2 of the generalized linear regression model. In the conceptual framework (Fig. 3), we hypothesized that the 16 drivers could indirectly affect the N loss or soil retention by altering the forest cover. Therefore, *Fig.*(d) was generated by combing *Fig.*(c) and *Fig.*(a) according to the Eqs. (7)–(9) for illustrating the overall contributions of 16 drivers on water purification. In the same way, *Fig.*(d) was generated by combing *Fig.*(c) and *Fig.*(b).

the TGRA (Fig. 6). Therefore, a conceptual framework was proposed to link forest cover to the relationship between water purification and soil retention (Fig. 3). We hypothesize that driver could directly affect the two ecosystem services and indirectly affect them by altering the forest cover, and the effect values in structural equation model (Fig. 7) and relative importance analysis (Fig. 8) both documented the significance of forest cover for two ecosystem services.

4.2.1. Driving mechanisms of forest cover

Effects of topographic, soil and climate principal components on forest cover are positive (Fig. 7). Forests are mainly distributed in high-altitude and steep-slope regions, which has been reported in many studies (such as Teng et al., 2019; Wang et al., 2021). Therefore, the forest cover is positively related to the elevation and slope. Meanwhile, forests have high soil organic matter and biological activity which would affect almost all soil properties (Bienes et al., 2016; Zarafshar et al., 2020). Ecological restoration projects in the TGRA have promoted a high accumulation of soil organic matter (Shao et al., 2019), which in turn promotes soil aggregation and prevents soil erosion. However, most of the population in the TGRA depends on agriculture, but the cultivated land in this region is dominated by purple soil and distributed in low-altitude and gentle-slope regions. Farming activities can accelerate the pollutants and nutrients such as organic N into water bodies (Chen et al., 2019a), resulting in non-point source pollution. Moreover, precipitation, temperature and radiation usually would promote vegetation growth (Ding et al., 2020), which supported the positive effect of climate principal component on forest cover (Fig. 7). However, socio-economic principal component had a negative impact on forest cover (Fig. 7), which may partly be explained by the rapid population growth and economic improvement leading to more and more land being used for food production (Gou et al., 2021). Meanwhile, continued population growth has increased the demand for built-up land. Urbanization destroys the natural vegetation, leading to a decrease in forest cover.

4.2.2. Driving mechanisms of N loss

Relative importance of forest cover for the N loss is more than 50 % (Fig. 8a), indicating that the indirect contributions of these drivers were more than their direct contributions. Meanwhile, most direct effect values are insignificant in the structural equation model (Fig. 7). Therefore, the indirect effect could be documented by how factor affects forest cover and then how forest cover affects N loss. Since how the driver affects forest cover has already been discussed above, driving mechanisms of N loss could mainly be explained by how forest cover affects N loss.

The control of N loss by forest cover is manifested in three main ways. First, forests are a key factor in reducing and controlling pollutants and sediments carried by surface runoff (Zhang et al., 2020). Vegetation stems and leaves can dissipate the kinetic energy of rainfall, reducing the surface runoff rate and increasing the evapotranspiration rate, thus leading to more water infiltration and lower surface runoff (Zhang et al., 2000; Chen et al., 2018). Meanwhile, its roots can bind the topsoil and improve soil erosion resistance (Bao et al., 2018). Additionally, ground cover close to the soil surface (such as grass and leaf litter) can be more effective in preventing raindrop splash, help to maintain soil absorption capacity, and act as a filter to capture sediments and pollutants to reduce non-point source pollution (Chen et al., 2018; Zhang et al., 2019). Second, plant diversity and vegetation distribution patterns are the main factors affecting N loss and its spatial distribution. Compared to single-species communities, diverse vegetation communities are more advantageous in reducing surface runoff (Chen et al., 2018). An appropriate species composition not only reduces competition with adjacent crops, but also maximizes the combined benefits of various vegetation types in reducing N losses (Chaves et al., 2021). Since there are obvious differences in the effects of various vegetation types on N loss, the differences in the distribution of various vegetation species are the main reason for the spatial heterogeneity of N loss. Third, forestland can absorb and assimilate N, thus creating an N sink, which helps to alleviate N loss (Yang *et al.*, 2013). In contrast, even though crop cultivation can also increase the corresponding vegetation cover, a large number of inefficient fertilizers and pesticides commonly used in agricultural production are the main source of N inputs (Xia et al., 2018). The resulting N losses are converted to pollutants and transported to water bodies through rainfall and irrigation, thus resulting in non-point source pollution (Xia et al., 2020). Therefore, the positive effect of forest cover on N loss was more significant than that of cropland. In general, areas with more forest cover have more forests and relatively less cropland. Combined with the above-mentioned role of forest cover on N loss, it can be concluded that the more vegetation there is, the less N loss there is.

4.2.3. Driving mechanisms of soil retention

Annual precipitation contributed 26.9 % for soil retention (Fig. 8 b), followed by temperature (14.2 %) and forest cover (11.9 %). Meanwhile, the overall contribution of climate conditions is 52.1 % (Fig. 8 e), which indicated the direct and indirect effects of climate conditions are both important for soil retention. Precipitation is the hydrological driving force and the main source of water supply for vegetation in mountainous areas (Rodriguez-Iturbe et al., 2001; Stumpf et al., 2017), and climate factors can dictate plant growth, and indirectly regulate soil retention service (Guo et al., 2019). Although precipitation could be pivotal in controlling plant physiological processes in water-limited environments (Rodriguez-Iturbe et al., 2001), it has a negligible effect on plant growth in the TGRA, where annual precipitation exceeds 1,000 mm. Consequently, precipitation contributes more to the physical process of soil loss, and has negative impacts on soil retention service, which could explain the largest relative importance in Fig. 8 b. Apart from precipitation, temperature and radiation could influence soil loss by contributing to the growth and development of plants (Mohammad and Adam, 2010).

Additionally, the direct effect of topographic principal component is 0.40 in the structural equation model (Fig. 7). On the one hand, terrain slope gradient could alter soil loss, which has been reported in many studies (Xiong et al., 2018; Zhang et al., 2018). On the other hand, soil conservation practice is enforced to implement on sloping croplands. Recently, soil and water conservation measures or conservation tillage systems promoted in the high-altitude and steep-slope regions, which have reduced runoff and sediment production on slopes by increasing ground cover, subsurface roughness and infiltration (Chen et al., 2020). Meanwhile, it adjusted the topography and stand structure to effectively maintain or increase soil stabilization (Arnáez et al., 2015).

4.3. Landscape regulating suggestions

Over the past 15 years, rapid population growth and economic development in the TGRA occurred under the interaction of various policies such as dam impoundment, ecological restoration and migration projects. It has been demonstrated that landscape dynamics such as hydropower construction and rapid urbanization have significantly altered the ecosystem structures and functions (Gou et al., 2021). Although reservoirs play an important role in water supply, flood control, navigation, fisheries and power generation, the operation of the Three Gorges Hydropower Project since 2003 can also pose new challenges in preventing sediment and pollutants from entering the reservoir (Teng et al., 2019; Li et al., 2019). Because the reservoir is located in a densely populated area of China, many towns and other settlements along the river were flooded, which required the Chinese government to relocate over hundreds and thousands of residents, thereby having a dramatic socio-economic impact on the region (Huang et al., 2022). To mitigate these negative impacts, the Chinese government has initiated and implemented many positive policies (e.g., the Return of Cropland to Forests program, the Yangtze River Protected Forest Project, and the Natural Forest Protection Program), facilitating forest cover and ecosystem restoration in the TGRA (Huang et al., 2019; Teng et al., 2019). The implementation of these ecological projects has initially established an ecological security system based on reforestation (Xiao et al., 2020), which effectively protects the soil around the reservoir from erosion and reduces reservoir siltation. However, there are still some regions that were subject to the Western Development Policy and the New Socialist Countryside Construction Program, which focused on accelerating economic development and urban expansion (Huang et al., 2020) thus posing regional ecological risks such as soil loss and water pollution. Topographical, soil and climate conditions are difficult to change in this region, but we can synergistically improve two ecosystem services by regulating landscape patterns and adjusting socio-economic conditions. Therefore, it is necessary to identify the key ecological zones to optimize landscapepatternsn. Meanwhile, it is also important to focus on achieving a win–win situation between ecological protection and economic development to ensure food security.

Based on the above objectives, we proposed a landscape planning of vegetation restoration by combining our results (Fig. S8). Key ecological zones were identified according to the *Technological Standard of Soil and Water Conservation* (SL190-2007, issued by the Ministry of Water Resources of China). Sloping farmland could be converted into terraces, economic forests or ecological forests. Sloping farmland $<15^{\circ}$ should be transformed into horizontal terraces. Soil conservation measures such as contour tillage, crop rotation, intercropping and hedging should be adopted to prevent soil erosion and water pollution. Farmland with a slope of 15-25° could be planted with economic forests, and configured with plant hedges to intercept the surface sediment, which would improve both economic and ecological benefits of soil and water conservation. Sloping farmland above 25° should be reforested to enhance ecosystem services. This will increase local incomes while controlling soil erosion. Meanwhile, riparian zone is another key ecological zone because the TGRA undergoes annual cyclic inundation and exposure. It frequently stops flowing during the rainy season and dries up completely during the dry season, with water levels fluctuating between 135 and 175 m (Huang et al., 2022). We suggest to plant vegetation buffer strips along the river banks to mitigate the negative effects of the surrounding farmland, and plant grass to reduce soil erosion (Gao et al., 2017). Meanwhile, methods such as building multi-level vertical structures or planting vegetation covers can be adopted to protect the soil, thereby controlling soil and nutrient losses. Although urbanization is an irreversible process of rapid population and economic growth, it is necessary to control the development intensity and agglomeration of urbanization and increase urban green spaces, thus mitigating the loss of ecosystem services (Gou et al., 2021).

5. Conclusions

Understanding the linkages among multiple ecosystem services is crucial for managing regional ecosystems and maintaining the long-term supply of ecosystem services, which can provide scientific reference and theoretical basis for optimizing landscape management models. Therefore, we constructed a conceptual framework to link landscape dynamics to the relationship between water purification and soil retention, then used the TGRA to verify the framework. The InVEST model and the RUSLE were adopted to assess the water purification and soil retention services in the TGRA. Meanwhile, spatial analysis demonstrated their spatial relationship, while statistical analysis documented the effect values of the conceptual framework. The results indicated that both water purification and soil retention services in the TGRA increased significantly during 2001–2015, which proved the effectiveness of the government's ecological projects in recent years. However, there were still some areas experiencing a decline in water purification service and soil retention service. In the conceptual framework, topographical, climate, soil and socio-economic drivers can not only directly affect two ecosystem services, but also indirectly affect them by influencing forest cover. The relative importance of forest cover to nitrogen loss is more than 50 %, indicating that water purification could mainly be explained by how forest cover affects nitrogen loss. Annual precipitation contributed 26.9 % for soil retention, and the overall contribution of climate conditions was 52.1 %, which indicated the direct and indirect effects of climate conditions are both important for soil retention. Moreover, structural equation model documented the correlation coefficient between nitrogen loss and soil retention was −0.71, indicating an obvious interaction between water purification and soil retention. However, there was obvious spatial heterogeneity in their trade-off and synergistic relationships, which is mainly due to significant differences in major human activities and drivers among districts and counties. Based on our quantified results, we proposed a landscape planning of vegetation restoration for these key ecological zones in the TGRA to synergistically improve two ecosystem services. On the one hand, vegetation restoration measures in sloping lands vary with terrain slope. On the other hand, vegetated buffer strips should be implemented in the riparian zone, which is a key ecological zone, since the TGRA undergoes annual cyclic inundation and exposure. Our findings could provide a scientific basis and reference for understanding the relationships among landscape dynamics and multiple ecosystem services, and provide decision support for ecological protection and sustainable development of ecologically fragile areas.

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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.

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecoser.2022.101498.

References

Alghamdi, R.S., Cihacek, L., 2022. Do post-harvest crop residues in no-till systems provide for nitrogen needs of following crops? Agron. J. 114, 835–852.
Arnáez, J., Lana-Renault, N., Lasanta, T., Ruiz-Flaño, P., Castroviejo, J., 2015. Effects of farming terraces on hydrological and geomorphological processes. A review. Catena 128, 122–134.
Bagstad, K.J., Semmens, D.J., Winthrop, R., 2013. Comparing approaches to spatially explicit ecosystem service modeling: A case study from the San Pedro River, Arizona. Ecosyst. Serv. 5, 40–50.
Bai, Y., Ochuodho, T.O., Yang, J., 2019. Impact of land use and climate change on water-related ecosystem services in Kentucky, USA. Ecol. Ind. 102, 51–64.
Bao, Y.H., He, X.B., Wen, A.B., Gao, P., Tang, Q., Yan, D.C., Long, Y., 2018. Dynamic changes of soil erosion in a typical disturbance zone of China's Three Gorges Reservoir. Catena 169, 128–139.
Bennett, E.M., Peterson, G.D., Gordon, L.J., 2009. Understanding relationships among multiple ecosystem services. Ecol. Lett. 12, 1394–1404.
Bienes, R., Marques, M.J., Sastre, B., Garcia-Diaz, A., Ruiz-Colmenero, M., 2016. Eleven years after shrub revegetation in semiarid eroded soils. Influence in soil properties. Geoderma 273, 106–114.
Capmourteres, V., Anand, M., 2016. Assessing ecological integrity: A multi-scale structural and functional approach using Structural Equation Modeling. Ecol. Ind. 71, 258–269.
Chaves, J.E., Aranibar, J.N., Gatica, G., 2021. Species and functional plant diversity enhance ecosystem functions in the central Monte desert. J. Veg. Sci. 32, e12952.
Chen, L., Chen, S.B., Li, S., Shen, Z.Y., 2019. Temporal and spatial scaling effects of parameter sensitivity in relation to non-point source pollution simulation. J. Hydrol. 571, 36–49.

Chen, X., Xu, G., Zhang, W., Peng, H., Xia, H., Zhang, X., Ke, Q., Wan, J., 2019a. Spatial Variation Pattern Analysis of Hydrologic Processes and Water Quality in Three Gorges Reservoir Area., Water.

Chen, X., Liang, Z., Zhang, Z., Zhang, L., 2020. Effects of soil and water conservation measures on runoff and sediment yield in red soil slope farmland under natural rainfall. Sustainability-BASEL 12, 3417.

Chen, D., Wei, W., Chen, L., 2021. Effects of terracing on soil properties in three key mountainous regions of China. Geogr. Sustain. 2, 195–206.

Chen, H., Zhang, X., Abla, M., Lü, D., Yan, R., Ren, Q., Ren, Z., Yang, Y., Zhao, W., Lin, P., Liu, B., Yang, X., 2018. Effects of vegetation and rainfall types on surface runoff and soil erosion on steep slopes on the Loess Plateau, China. Catena 170, 141–149.

Dennedy-Frank, P.J., Muenich, R.L., Chaubey, I., Ziv, G., 2016. Comparing two tools for ecosystem service assessments regarding water resources decisions. J. Environ. Manage. 177, 331–340.

Dimkpa, C.O., Fugice, J., Singh, U., Lewis, T.D., 2020. Development of fertilizers for enhanced nitrogen use efficiency – Trends and perspectives. Sci. Total Environ. 731, 139113.

Ding, Y., Li, Z., Peng, S., 2020. Global analysis of time-lag and-accumulation effects of climate on vegetation growth. Int. J. Appl. Earth Obs. Geoinf. 92, 102179.

Fang, N.F., Shi, Z.H., Li, L., Jiang, C., 2011. Rainfall, runoff, and suspended sediment delivery relationships in a small agricultural watershed of the Three Gorges area, China. Geomorphology 135 (1–2), 158–166.

Felipe-Lucia, M.R., Martín-López, B., Lavorel, S., Berraquero-Díaz, L., Escalera-Reyes, J., Comín, F.A., 2015. Ecosystem services flows: why stakeholders' power relationships matter. PLoS One 10 (7), e0132232.

Feng, Q., Zhao, W., Hu, X., Liu, Y., Daryanto, S., Cherubini, F., 2020. Trading-off ecosystem services for better ecological restoration: A case study in the Loess Plateau of China. J. Clean. Prod. 257, 120469.

Fu, B., Liu, Y., Lü, Y., He, C., Zeng, Y., Wu, B., 2011. Assessing the soil erosion control service of ecosystems change in the Loess Plateau of China. Ecol. Complex. 8 (4), 284–293.

Gao, J., Li, F., Gao, H., Zhou, C.B., Zhang, X.L., 2017. The impact of land-use change on water-related ecosystem services: a study of the Guishui River Basin, Beijing, China. J. Clean. Prod. 163, S148–S155.

Gou, M., Li, L., Ouyang, S., Wang, N., La, L., Liu, C., Xiao, W., 2021. Identifying and analyzing ecosystem service bundles and their socioecological drivers in the Three Gorges Reservoir Area. J. Clean. Prod. 307, 127208.

Guo, Y., Peng, C., Zhu, Q., Wang, M., Wang, H., Peng, S., He, H., 2019. Modelling the impacts of climate and land use changes on soil water erosion: Model applications, limitations and future challenges. J. Environ. Manage. 250, 109403.

Han, B., Reidy, A., Li, A., 2021. Modeling nutrient release with compiled data in a typical Midwest watershed. Ecol. Ind. 121, 107213.

Hou, W., Liao, X., Liu, X., Wang, H., 2013. Research Progress of non-point source pollution in three gorges reservoir area. J. Fujian Forest. Sci. Tech. 40, 208–218.

Huang, C., Huang, X., Peng, C., Zhou, Z., Teng, M., Wang, P., 2019. Land use/cover change in the Three Gorges Reservoir area, China: Reconciling the land use conflicts between development and protection. Catena 175, 388–399.

Huang, C., Zhou, Z., Teng, M., Wu, C., Wang, P., 2020. Effects of climate, land use and land cover changes on soil loss in the Three Gorges Reservoir area, China. Geogr. Sustain. 1, 200–208.

Huang, C., Zhao, D., Fan, X., Liu, C., Zhao, G., 2022. Landscape dynamics facilitated non-point source pollution control and regional water security of the Three Gorges Reservoir area, China. Environ. Impact Asses 92, 106696.

Jiang, C., Zhang, H., Zhang, Z., 2018. Spatially explicit assessment of ecosystem services in China's Loess Plateau: Patterns, interactions, drivers, and implications. Global Planet. Change 161, 41–52.

Jiu, J.Z., Wu, H.J., Li, S., 2019. The implication of land-use/land-cover change for the declining soil erosion risk in the three gorges reservoir region, China. Int. J. Env. Res. Pub. He. 16.

Li, C., Fu, B., Wang, S., Stringer, L.C., Wang, Y., Li, Z., Liu, Y., Zhou, W., 2021b. Drivers and impacts of changes in China's drylands. Nat. Rev. Earth Environ. 2, 858–873.

Li, Z., Ma, J.R., Guo, J.S., Paer, H.W., Brookes, J.D., Xiao, Y., Fang, F., Ouyang, W.J., Lu, L.H., 2019. Water quality trends in the Three Gorges Reservoir region before and after impoundment (1992–2016). Ecohydrol. Hydrobiol. 19, 317–327.

Li, J., Zhou, K., Xie, B., Xiao, J., 2021a. Impact of landscape pattern change on water-related ecosystem services: Comprehensive analysis based on heterogeneity perspective. Ecol. Ind. 133, 108372.

Liao, Q., Wang, Z., Huang, C., 2020. Green Infrastructure Offset the Negative Ecological Effects of Urbanization and Storing Water in the Three Gorges Reservoir Area, China., International Journal of Environmental Research and Public. Health.

Liu, Y.J., Hu, J.M., Wang, T.W., Cai, C.F., Li, Z.X., Zhang, Y., 2016. Effects of vegetation cover and road-concentrated flow on hillslope erosion in rainfall and scouring simulation tests in the Three Gorges Reservoir Area, China. Catena 136, 108–117.

Liu, R., Zhang, P., Wang, X., Chen, Y., Shen, Z., 2013. Assessment of effects of best management practices on agricultural non-point source pollution in Xiangxi River watershed. Agr. Water Manage 117, 9–18.

Malinga, R., Gordon, L.J., Jewitt, G., Lindborg, R., 2015. Mapping ecosystem services across scales and continents - A review. Ecosyst. Serv. 13, 57–63.

Mohammad, A., Adam, M., 2010. The impact of vegetative cover type on runoff and soil erosion under different land uses. Catena 81 (2), 97–103.

Mohammed, S., Alsafadi, K., Talukdar, S., Kiwan, S., Hennawi, S., Alshihabi, O., Sharaf, M., Harsanyie, E., 2020. Estimation of soil erosion risk in southern part of Syria by using RUSLE integrating geo informatics approach. Remote Sens. Appl.: Soc. Environ. 20, 100375.

Muhsina, A., Joseph, B., Kumar, V., 2020. Principal component analysis on soil fertility parameters of vegetable growing panchayats/ locations in Ernakulam District of Kerala. Int. Res. J. Pure Appl. Chem. 21, 58–65.

Qi, W., Li, H., Zhang, Q., Zhang, K., 2019. Forest restoration efforts drive changes in land-use/land-cover and water-related ecosystem services in China's Han River basin. Ecol. Eng. 126, 64–73.

Qiu, J., 2019. Effects of landscape pattern on pollination, pest control, water quality, flood regulation, and cultural ecosystem services: a literature review and future research prospects. Current Landscape Ecology Reports 4, 113–124.

Redhead, J.W., May, L., Oliver, T.H., Hamel, P., Sharp, R., Bullock, J.M., 2018. National scale evaluation of the InVEST nutrient retention model in the United Kingdom. Sci. Total Environ. 610–611, 666–677.

Rodriguez-Iturbe, I., Porporato, A., Laio, F., Ridolfi, L., 2001. Plants in water-controlled ecosystems: Active role in hydrologic processes and response to water stress: I. Scope and general outline. Adv. Water Resour. 24 (7), 695–705.

H. Salhi Evaluation of the Spatial Distribution of the Annual Extreme Precipitation Using Kriging and Co-Kriging Methods in Algeria Country . Dr. Tiefenbacher, J.P. Climate Issues in Asia and Africa - Examining Climate, Its Flux, the Consequences, and Society's Responses, IntechOpen 2022 Rijeka.

Shao, P., Liang, C., Lynch, L., Xie, H., Bao, X., 2019. Reforestation accelerates soil organic carbon accumulation: Evidence from microbial biomarkers. Soil Biol. Biochem. 131, 182–190.

Shao, J., Zhang, S., Wei, C., 2013. Remote sensing analysis of land use change in the Three Gorges Reservoir area, based on the construction phase of large-scale water conservancy project. Geogr. Res. 32 (12), 2189–2203.

Shen, Z., Gong, Y., Li, Y., Liu, R., 2010. Analysis and modeling of soil conservation measures in the Three Gorges Reservoir Area in China. Catena 81 (2), 104–112.

Singh, N.K., Gourevitch, J.D., Wemple, B.C., Watson, K.B., Rizzo, D.M., Polasky, S., Ricketts, T.H., 2019. Optimizing wetland restoration to improve water quality at a regional scale. Environ. Res. Lett. 14, 64006.

Strehmel, A., Schmalz, B., Fohrer, N., 2016. Evaluation of Land Use, Land Management and Soil retention Strategies to Reduce Non-Point Source Pollution Loads in the Three Gorges Region, China. Environ. Manag. 58, 906–921.

Stumpf, F., Goebes, P., Schmidt, K., Schindewolf, M., Schönbrodt-Stitt, S., Wadoux, A., Xiang, W., Scholten, T., 2017. Sediment reallocations due to erosive rainfall events in the Three Gorges Reservoir Area, Central China. Land Degrad. Dev. 28 (4), 1212–1227.

Tang, Q., Bao, Y.H., He, X.B., Zhou, H.D., Cao, Z.J., Gao, P., Zhong, R.H., Hu, Y.H., Zhang, X.B., 2014. Sedimentation and associated trace metal enrichment in the riparian zone of the three gorges reservoir, China. Sci. Total Environ. 479, 258–266.

Teng, M., Huang, C., Wang, P., Zeng, L., Zhou, Z., Xiao, W., Huang, Z., Liu, C., 2019. Impacts of forest restoration on soil erosion in the Three Gorges Reservoir area China. Sci. Total Environ. 697, 134164.

Tian, P., Zhu, Z., Yue, Q., He, Y., Zhang, Z., Hao, F., Guo, W., Chen, L., Liu, M., 2021. Soil erosion assessment by RUSLE with improved P factor and its validation: Case study on mountainous and hilly areas of Hubei Province, China. Int. Soil Water Conservation Res. 9, 433–444.

Vigerstol, K.L., Aukema, J.E., 2011. A comparison of tools for modeling freshwater ecosystem services. J. Environ. Manage. 92, 2403–2409.

Wang, Y., Ran, L., Fang, N., Shi, Z., 2018. Aggregate stability and associated organic carbon and nitrogen as affected by soil erosion and vegetation rehabilitation on the Loess Plateau. Catena 167, 257–265.

Wang, F., Yuan, X., Zhou, L., Liu, S., Zhang, M., Zhang, D., 2021. Detecting the Complex Relationships and Driving Mechanisms of Key Ecosystem Services in the Central Urban Area Chongqing Municipality, China., Remote Sensing.

Wang, L., Zheng, H., Wen, Z., Liu, L., Robinson, B.E., Li, R., Li, C., Kong, L., 2019. Ecosystem service synergies/trade-offs informing the supply-demand match of ecosystem services: Framework and application. Ecosyst. Serv. 37, 100939.

Wei, S., Dai, Y., Liu, B., Zhu, A., Duan, Q., Wu, L., Ji, D., Ye, A., Yuan, H., Zhang, Q., Chen, D., Chen, M., Chu, J., Dou, Y., Guo, J., Li, H., Li, J., Liang, L., Liang, X., Liu, H., Liu, S., Miao, C., Zhang, Y., 2013. A China data set of soil properties for land surface modeling. J. Adv. Model Earth Sytem. 5, 212–224.

Wei, L., Luo, Y., Wang, M., Su, S., Pi, J., Li, G., 2020. Essential fragmentation metrics for agricultural policies: Linking landscape pattern, ecosystem service and land use management in urbanizing China. Agr. Syst. 182, 102833.

Wu, S.Y., Li, S.C., 2019. Ecosystem service relationships: Formation and recommended approaches from a systematic review. Ecol. Ind. 99, 1–11.

Wu, C.G., Zhou, Z.X., Xiao, W.F., Wang, P.C., Teng, M.J., Huang, Z.J., 2011. Estimation of soil erosion in the Three Gorges Reservoir Area of China using RUSLE, remote sensing and GIS. J. Food Agric. Environ. 9 (2), 728–734.

Xia, J., Xu, G., Guo, P., Peng, H., Zhang, X., Wang, Y., Zhang, W., 2018. Tempo-Spatial Analysis of Water Quality in the Three Gorges Reservoir, China, after its 175-m Experimental Impoundment. Water Resour. Manag. 32, 2937–2954.

Xia, Y., Zhang, M., Tsang, D.C.W., Geng, N., Lu, D., Zhu, L., Igalavithana, A.D., Dissanayake, P.D., Rinklebe, J., Yang, X., Ok, Y.S., 2020. Recent advances in control technologies for non-point source pollution with nitrogen and phosphorous from agricultural runoff: current practices and future prospects. Appl. Biol. Chem. 63, 8.

Xiao, Q., Hu, D., Xiao, Y., 2017. Assessing changes in soil retention ecosystem services and causal factors in the Three Gorges Reservoir region of China. J. Clean. Prod. 163, S172–S180.

Xiao, Q., Xiao, Y., Tan, H., 2019. Changes to soil retention in the Three Gorges Reservoir Area between 1982 and 2015. Environ. Monit. Assess. 192, 44.

Xiao, Y., Xiao, Q., Xiong, Q., Yang, Z., 2020. Effects of Ecological Restoration Measures on Soil Erosion Risk in the Three Gorges Reservoir Area Since the 1980s. GeoHealth 4, e2020G–e2274.

Xiong, M., Sun, R., Chen, L., 2018. Effects of soil conservation techniques on water erosion control: A global analysis. Sci. Total Environ. 645, 753–760.

Xiong, Q., Xiao, Y., Ouyang, Z., Pan, K., Zhang, L., He, X., Zheng, H., Sun, X., Wu, X., Tariq, A., Li, L., 2017. Bright side? The impacts of Three Gorges Reservoir on local ecological service of soil retention in southwestern China. Environ. Earth Sci. 76, 323.

Xu, X.B., Tan, Y., Yang, G.S., Li, H.P., Su, W.Z., 2011. Soil erosion in the Three Gorges Reservoir area. Soil Res. 49 (3), 212–222.

Xu, X., Yang, G., Tan, Y., Liu, J., Hu, H., 2018. Ecosystem services trade-offs and determinants in China's Yangtze River Economic Belt from 2000 to 2015. Sci. Total Environ. 634, 1601–1614.

Xu, J.Y., Zhang, Y.Y., Huang, C.B., Zeng, L.X., Teng, M.J., Wang, P.C., Xiao, W.F., 2022. Forest restoration shows uneven impacts on soil erosion, net primary productivity and livelihoods of local households. Ecol. Ind. 134.

Yohannes, H., Soromessa, T., Argaw, M., Dewan, A., 2021. Impact of landscape pattern changes on hydrological ecosystem services in the Beressa watershed of the Blue Nile Basin in Ethiopia. Sci. Total Environ. 793, 148559.

Zarafshar, M., Bazot, S., Matinizadeh, M., Bordbar, S.K., Rousta, M.J., Kooch, Y., Enayati, K., Abbasi, A., Negahdarsaber, M., 2020. Do tree plantations or cultivated fields have the same ability to maintain soil quality as natural forests? Appl. Soil Ecol. 151, 103536.

Zhang, X., Shao, M., Huang, Z., Lu, Z., 2000. An experimental research on soil erosion and nitrogen loss under different vegetation cover. Acta Ecol. Sin. 2000, 1038–1044.

Zhang, X., Hu, M., Guo, X., Yang, H., Zhang, Z., Zhang, K., 2018. Effects of topographic factors on runoff and soil loss in Southwest China. Catena 160, 394–402.

Zhang, J., Li, S., Jiang, C., 2020. Effects of land use on water quality in a River Basin (Daning) of the Three Gorges Reservoir Area, China: Watershed versus riparian zone. Ecol. Ind. 113, 106226.

Zhang, Y., Xu, X., Li, Z., Liu, M., Xu, C., Zhang, R., Luo, W., 2019. Effects of vegetation restoration on soil quality in degraded karst landscapes of southwest China. Sci. Total Environ. 650, 2657–2665.

Zhong, S., Chen, F., Xie, D., Shao, J., Yong, Y., Zhang, S., Zhang, Q., Wei, C., Yang, Q., Ni, J., 2020. A three-dimensional and multi-source integrated technology system for controlling rural non-point source pollution in the Three Gorges Reservoir Area, China. J. Clean. Prod. 272, 122579.