



# OPEN Exploring the driving mechanism path of ecosystem service relationships based on the social-ecological system framework

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Understanding the driving mechanisms behind ecosystem service (ES) trade-offs and synergies is crucial for sustainable ecosystem management. This study integrates the Social-Ecological System Framework (SESF) with path analysis to explore the relationships among crop production (CP), water retention (WR), and soil conservation (SC) in Shanxi Province, China. We identified six key driving factors—annual mean temperature (Tem), total annual precipitation (Pre), Net Primary Productivity (NPP), per capita GDP (GDP), agricultural, forestry, and water fiscal expenditure (Exp), and urban and rural per capita disposable income (Inc)—to analyze their direct and indirect influences on ES interactions over the years 2000, 2010, and 2020. Results show that CP and WR exhibit a persistent trade-off, while CP and SC maintain a synergistic relationship. WR and SC display a trade-off in static time points but shift towards synergy in long-term changes. Path analysis confirms that natural factors (Tem, Pre, and NPP) dominate short-term ES dynamics, whereas socio-economic variables (GDP, Exp, and Inc) play a greater role in long-term ES changes. Mediation analysis reveals that NPP partially mediates climate effects on ESs, while Inc mediates the influence of GDP on ESs. However, Exp does not significantly affect ESs through Inc, likely due to policy implementation delays and regional economic priorities. Findings suggest that spatially targeted policies should be implemented to optimize ES relationships. Long-term ES governance should integrate ecological restoration strategies with socio-economic incentives to enhance ES sustainability.

**Keywords** Ecosystem service, Ecosystem service relationships, Driving mechanism path, Social-ecological system frame, Path analysis

Effective policy management is essential for achieving sustainable ecosystem services (ESs) supply, and a comprehensive understanding of the relationships and underlying mechanisms among ES is fundamental to this goal<sup>1,2</sup>. These relationships are shaped by a combination of natural and social factors, which influence ES dynamics at various spatial and temporal scales<sup>3</sup>. Natural factors directly regulate ES patterns by determining ecosystem functions and processes<sup>4</sup>. Social factors, modify ES through land-use changes, resource management, and policy interventions<sup>5,6</sup>. For instance, climate change-induced temperature increases in northern coniferous forests have led to reduced soil nitrogen cycling rates, which in turn affect carbon storage and soil fertility maintenance, demonstrating how biophysical processes serve as mechanisms driving ES relationships<sup>7,8</sup>. Similarly, policy decisions that alter land-use patterns can significantly modify ES trade-offs and synergies. Given the complex interplay of these factors, identifying the key drivers of ES and their mechanistic pathways is crucial for understanding ES trade-offs and informing sustainable management strategies.

Bennett et al.<sup>5</sup> highlighted that trade-offs/synergies relationships among ES depend on the driving factors and their mechanistic pathways. The same two ES may exhibit completely different relationships in different regions or under varying driving factors<sup>9</sup>. This is because driving factors have different transmission elements and relationships, leading to diverse mutual relationships between the ESs. Bennett's research categorizes the

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driving factors of ES relationships into two types: shared driving factors, which affect both ES simultaneously, and independent driving factors, which affect only one ES. Identifying these driving factors and exploring their mechanistic pathways can help clarify key nodes in the cause-and-effect chain of ES changes, enabling effective policy management with minimal inputs for sustainable benefits.

Numerous studies have analyzed how driving factors affect the relationship between ESs. Existing research has primarily focused on quantifying trade-offs/synergies between ESs, identifying key driving factors, and exploring their potential interactions<sup>10</sup>. However, these studies often lack a comprehensive framework that integrates these aspects into a unified analytical approach. The identification of ES relationships has been largely reliant on correlation analysis and geographically weighted regression (GWR), which are commonly used to measure spatially explicit trade-offs/synergies<sup>11,12</sup>. While these methods provide useful spatial insights, they fail to establish causal mechanisms linking ES interactions to their underlying drivers. To determine the impact of driving factors on ES relationships, various methods have been employed. Principal component analysis (PCA) and regression analysis have been widely used to identify key socio-economic and biophysical factors affecting ES dynamics<sup>13,14</sup>. Additionally, redundancy analysis (RDA) has facilitated the quantification of the relative importance of multiple influencing factors in shaping ES trade-offs/synergies<sup>15,16</sup>. Some studies have applied geographical detector models to assess spatial heterogeneity and non-linear relationships between ES and their drivers<sup>17,18</sup>, while others have used GWR to address spatial non-stationarity in ES-driving factor interactions<sup>19,20</sup>. Although these methods have contributed significantly to understanding ES relationships, they exhibit certain limitations. First, existing studies often focus on either ES trade-offs/synergies or driving factor analysis, but rarely integrate these components within a cohesive analytical framework, leading to fragmentation in research approaches<sup>21</sup>. Second, ES relationship formation mechanisms are frequently inferred through correlation-based methods, which lack a robust causal inference foundation, resulting in subjectivity and uncertainty in findings. Third, the separation of driving factor selection, ES relationship quantification, and driver identification has led to inconsistencies between studies, limiting their comparability and applicability across different spatial and temporal scales.

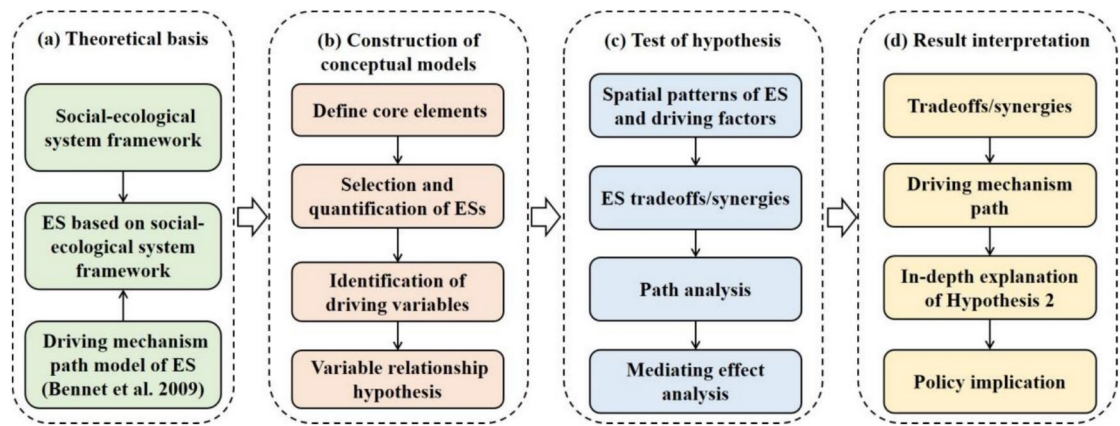
Given these challenges, there is a growing need for an integrated methodological approach to systematically analyze ES relationships, their driving factors, and the mechanisms that shape them. The Social-Ecological System framework (SESF) provides a structured approach to selecting ES drivers while considering the complex interplay between ecological and social factors<sup>22</sup>. Moreover, path analysis serves as a valuable tool to quantify the influence and directionality of driving factors on ES relationships, allowing for a more rigorous evaluation of causal mechanisms<sup>23</sup>. This methodological integration has demonstrated significant advantages in recent studies<sup>24</sup>. It facilitates the systematic selection and categorization of ES drivers, enables a unified analysis of ES interrelationships and their drivers, and quantifies the causal influences of driving factors, reducing uncertainty in ES relationship assessments. By incorporating both SESF and path analysis, this study offers a comprehensive and structured approach to understanding the mechanisms driving ES interactions, thus enhancing the robustness and applicability of ES research.

Based on the path conceptual model of ES driving mechanisms proposed by Bennett et al.<sup>5</sup>, this study employs the SESF to systematically define ES co-production, its driving factors, and their interrelationships. To analyze these interactions, a structural equation modeling (SEM) approach with path analysis is applied, allowing for the identification of direct and indirect influences as well as dominant and secondary driving factors that shape ES trade-offs/synergies relationships. The primary objective of this study is to examine the mechanisms underlying ES trade-offs and synergies by integrating the SESF and path analysis, thereby identifying key leverage points for ecosystem management and decision-making. Specifically, this study tests three hypotheses: (H1) Resource systems, resource units, governance systems, and stakeholders directly influence ESs. (H2) Resource units mediate the relationship between resource systems and ESs, while stakeholders mediate the relationship between governance systems and ESs. (H3) The dominant factors influencing ESs at a single time point are natural and ecological variables, whereas long-term ecosystem service changes are primarily driven by governance systems and stakeholder factors.

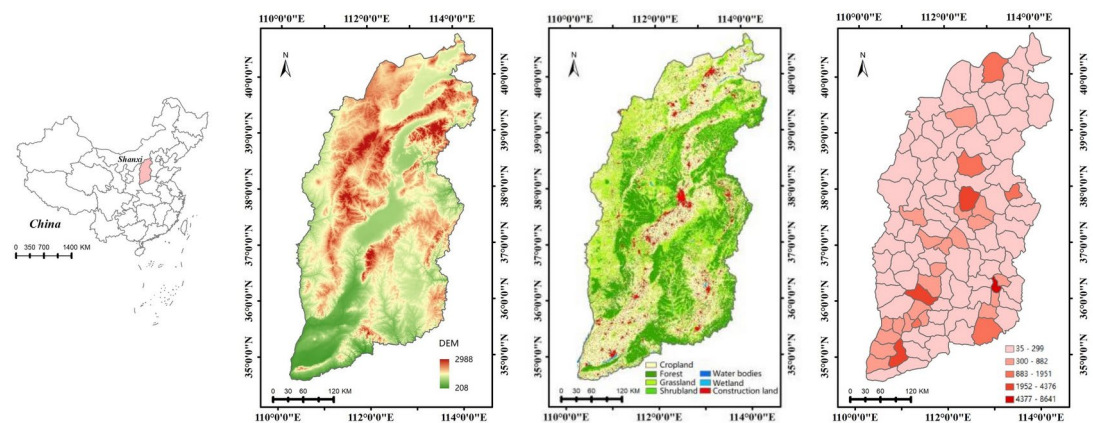
By integrating the SESF with a robust path analysis approach, this study offers a comprehensive perspective on ES relationships and enables a deeper understanding of the mechanistic pathways governing ES relationships. Using Shanxi Province, China, as a case study, we aim to provide empirical insights that contribute to a more balanced approach between social development and ecological restoration at the provincial management level, and facilitate more effective decision-making for sustainable ES governance.

## Materials and methods

County boundaries were used to delineate the spatial units in this study because they were the most effective administrative boundaries for social governance<sup>12</sup>. Additionally, these boundaries can reflect the social processes that influence the production and consumption of ESs in the study area<sup>25</sup>. Importantly, they provide the optimal spatial unit for which social and economic census data are available. This study investigated the driving mechanisms of ES relationships at three static time points: 2000, 2010, and 2020. We also examined two change periods: 2000–2010 and 2010–2020, comparing ES trade-offs, driving factors, and mechanisms between these single time points and change periods. The years 2000, 2010, and 2020 were selected as the static time points for analysis based on the following factors: (1) these three years encompass significant ecological and socio-economic transitions in Shanxi Province and China, including economic reforms and major environmental policy implementations; (2) these years provide comprehensive and high-resolution official statistical data, ensuring reliability and comparability; (3) the past two decades have witnessed major ecological restoration programs, and these time points allow us to assess their impact on ESs; and (4) these time points enable an examination of long-term ES trends, contributing to better-informed conservation and resource management



**Fig. 1.** Methodological framework for analyzing driving mechanism path of ES trade-offs/synergies.



**Fig. 2.** Study area location in China (A) elevation, (B) land use type (C) and population density (D) of Shanxi Province.

strategies. Detailed explanations of each step in the methods and materials are provided in the subsequent sections (Fig. 1).

### Study area

Shanxi Province, located in northern China (110°14'–114°33' E, 34°34'–40°44' N), covers an area of 156,700 square kilometers, accounting for 1.6% of China's total land area (Fig. 2). The region features the complex and diverse topography of the Loess Plateau, including mountains, hills, plateaus, basins, and platforms. The Taihang Mountains dominate the east, the Luliang Mountains dominate the west, and the central area is characterized by basins, forming the topographical features of "two mountains and one river," with elevations ranging from 208 to 2988 m. Shanxi Province falls within the temperate continental monsoon climate zone. The area north of the Inner Great Wall experiences a temperate semi-arid climate, while the area between the Inner Great Wall and the Yangquan-Taiyue Mountain-Hejin line has a warm temperate semi-arid climate. South of this line, the climate is warm temperate semi-humid. The province's average annual temperature ranges from 4.2 to 14.2°C, and the average annual rainfall is 468 mm. The vegetation varies from warm temperate deciduous broad-leaf forests and coniferous forests in the south to deciduous broad-leaf forests, temperate zones, and warm temperate steppes in the north.

Approximately 53% of Shanxi Province's surface is covered by primary or secondary loess, making it one of the provinces most severely affected by soil erosion in China<sup>26</sup>. Over-exploitation of coal and mineral resources, excessive groundwater extraction, rapid urbanization, and accelerated development of soil and water resources have rendered the ecosystem in Shanxi Province extremely fragile<sup>27</sup>. However, extensive ecological protection and restoration policies implemented over the past 20 years have led to significant progress. Ecological engineering projects in Shanxi Province have started to yield positive results, promoting the restoration of ecosystem functions at various scales.

Dataset	Data Type	Spatial Resolution	Data Source
Land use/land cover	Raster	30 m	National Geomatics Center of China ( <a href="http://www.globallandcover.com/GLC30Download/index.aspx">http://www.globallandcover.com/GLC30Download/index.aspx</a> , accessed on 11 December 2020)
NDVI	Raster	250 m	National Aeronautics and Space Administration and United States Geological Survey ( <a href="http://e4ftl01.cr.usgs.gov/MOLT/MOD13Q1.006/">http://e4ftl01.cr.usgs.gov/MOLT/MOD13Q1.006/</a> , accessed on 7 December 2020)
DEM	Raster	90 m	Geospatial Data Cloud ( <a href="https://www.gscloud.cn/#page">https://www.gscloud.cn/#page</a> 1, accessed on 20 December 2020)
Meteorological data	Text	Sites	China Meteorological Data Sharing Service System ( <a href="http://www.esi.cn/metadata/page/index.html">http://www.esi.cn/metadata/page/index.html</a> , accessed on 5 November 2020)
Soil database	Raster	30 arc-second	Harmonized World Soil Database ( <a href="http://www.fao.org/soils-portal/soil-survey/soil-maps-and-databases/harmonized-world-soil-database-v12/en/">http://www.fao.org/soils-portal/soil-survey/soil-maps-and-databases/harmonized-world-soil-database-v12/en/</a> , accessed on 1 December 2020)
Administrative map	Vector	County	National Geomatics Center of China ( <a href="http://ngcc.sbsm.gov.cn/ngcc/">http://ngcc.sbsm.gov.cn/ngcc/</a> , accessed on 11 December 2020)
Crop yield, GDP and population	Numeric	County	China County (city) Social and Economic Statistical Yearbook (2001, 2011, 2021)
Public expenditure for agriculture, forestry and water (yuan)	Numeric	County	Statistical Yearbook
Per capita disposable income (yuan)	Numeric	County	Statistical Yearbook

Table 1. Datasets used in the study.

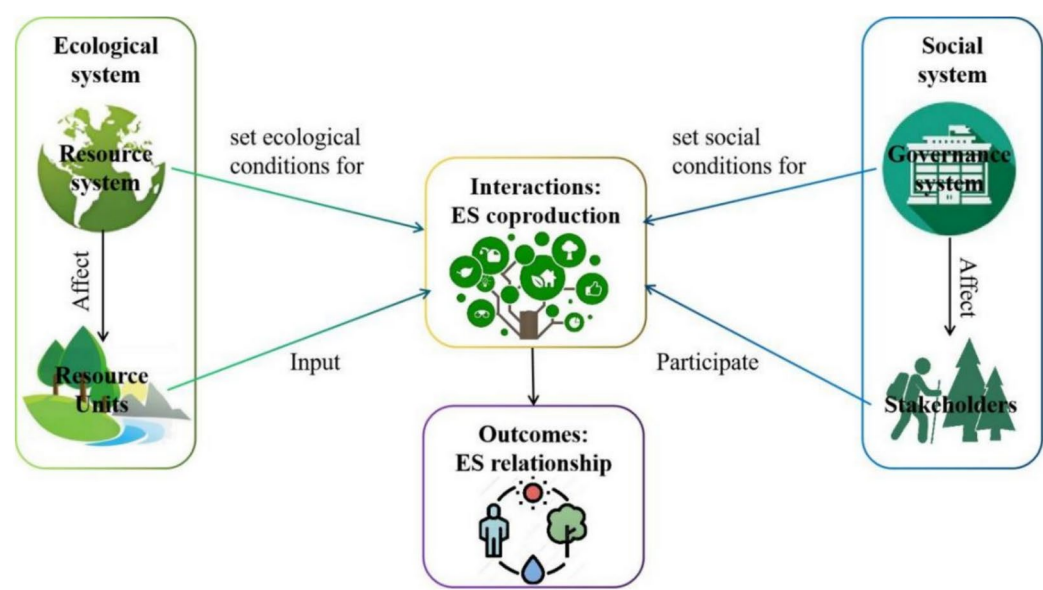


Fig. 3. ES relationships and influencing factors based on the SESF.

Data collection and processing

In this study, we collected representative data for the years 2000, 2010, and 2020. We chose publicly available data to ensure that our methods and results can be easily transferred and compared with other studies. The data sources include three main types: spatial data, text data, and statistical data (Table 1). We employed different aggregation methods based on data type and research needs to ensure accuracy and scientific validity at the county scale. Specifically, (1) land use/land cover, NDVI, and DEM data were aggregated using a pixel-weighted averaging method to preserve spatial characteristics; (2) meteorological data were obtained from 69 meteorological stations in and around Shanxi Province. We applied Kriging interpolation to generate continuous climate distributions and performed county-level aggregation accordingly; (3) soil attributes were derived from Harmonized World Soil Database and aggregated using weighted averaging; (4) population, GDP, and agricultural public expenditure data were directly sourced from county-level statistics and standardized where necessary; and (5) per capita disposable income was obtained from county statistical yearbooks to ensure data representativeness. To ensure consistency, all spatial data were converted to a common spatial reference frame, specifically the WGS84 coordinate system and Albers equal area conic projection.

Identification of social-ecological driving factors and their path

Definition and selection of core elements of SESF

The SESF is an effective tool for identifying the factors that influence ES and their relationships<sup>28,29</sup>. To improve the efficiency of public management of ES in the study area, we placed ES and their relationships at the core of SESF (Fig. 3). This framework consists of the resource system, resource unit, governance system, and stakeholders, along with their interactions<sup>30</sup>. The resource and governance systems provide the biophysical and social-



economic conditions for the co-production of ES. The resource unit acts as an input factor, and stakeholders are the social participants involved in the production of ES. Resource systems encompass all elements that maintain ecosystem structure and function, while governance systems include the organizations and rules governing ES. Resource units consist of both static and dynamic features of land use or ecosystems, and stakeholders include all individuals and groups directly or indirectly benefiting from ES.

Selection and quantification of ESs

Selecting appropriate metrics is crucial for accurately estimating ESs<sup>31</sup>. The ESs in Shanxi Province were evaluated based on their regional importance, the need to cover a variety of ESs, and the availability of relevant data. The specific criteria for selection included: (1) consistency with the ecosystem classification of the Millennium Ecosystem Assessment to ensure comparability with other studies<sup>2</sup>; (2) indicators closely related to the natural, ecological, social, and economic conditions of the study area; and (3) availability of data for calculating ES indicators at the county scale in China. Based on these criteria, we selected three key ES indicators: crop production (CP), water retention (WR), and soil conservation (SC) (Table 2). In this study, we employed three commonly used and well-validated models and parameters to quantify CP, WR, and SC. The following section provides a detailed explanation of the models and the rationale for parameter selection:

- (1) Quantification of CP. To quantify CP services, we selected “crop yield per square kilometer” (ton/km<sup>2</sup>) as the evaluation indicator. Specifically, we calculated the total crop yield in each county and normalized it by the respective area. This method is straightforward and widely applied in agricultural research and ecosystem service assessments, effectively capturing the spatial variation of CP.
- (2) Quantification of WR. The quantification of WR services was based on the water balance equation, which evaluates a region’s WR capacity by assessing the input–output dynamics of water resources. Given the significant spatial and temporal variations in precipitation and WR capacity across Shanxi Province, this approach effectively considers these differences, integrating the influences of precipitation, runoff, and evapotranspiration. This is particularly valuable in mountainous areas, as it provides insights into water accumulation and loss after precipitation events.
- (3) Quantification of SC. The quantification of SC services was conducted using the Universal Soil Loss Equation (USLE). The USLE model is widely applied in soil erosion studies and well-suited for assessing SC capacity across diverse terrain conditions in Shanxi Province.
- (4) The selection of the models and parameters was based on the following considerations: (1) the effectiveness of all selected models and parameters have been extensively applied and validated in accurately evaluating CP, WR, and SC in multiple studies; (2) the chosen models and parameters can effectively reflect the distinct geographic and climatic features in study area; (3) the selected parameters are primarily derived from publicly available observational data and existing literature, which have been extensively validated under various climatic and environmental conditions.

Selection of driving variables corresponding to core elements

The selection of indicators in this study was guided by the specific context of the SESF in ES trade-offs/synergies, based on the following criteria: (1) Reference to previous studies. Selected variables must adequately represent the core elements within the SESF framework that influence ESs<sup>38</sup>. (2) For socio-economic variables, priority was given to those that can be adjusted through policy interventions in the study area<sup>39</sup>. (3) The variables must be available at the county scale to capture the governance system and stakeholder influences. (4) Variables that are static over time or not subject to human alteration (e.g., elevation and slope) were excluded, as they do not exhibit temporal variation in ES dynamics. Similarly, land use and population variables were excluded because land use is a primary modeling variable for CP, WR, and SC, and population serves as a fundamental metric for socio-economic indicators. Their strong correlations with ESs and other socio-economic variables would violate path analysis assumptions by introducing collinearity issues.

Based on these criteria, we selected six driving variables for this study: annual mean temperature (Tem) and total annual precipitation (Pre, resource system variables), Net Primary Productivity (NPP, resource unit variable), per capita GDP (GDP) and agricultural, forestry, and water fiscal expenditure (Exp, governance system variables), and urban and rural per capita disposable income (Inc, stakeholder variable). Table 1 provides the data sources for each driving variable.

ES Indicator	Code	Model or Proxy	Unit	Assessment Process
Crop production	CP	Crop yield per square kilometer	ton/km <sup>2</sup>	CP was calculated by dividing the crop yield of each county by its territory to illustrate per-unit provision service
Water retention	WR	Water balance equation	m <sup>3</sup> /km <sup>2</sup>	$TQ = \sum_{i=1}^j (P_i - R_i - ET_i)$ TQ is WR, $P_i$ is the annual average rainfall (mm), $R_i$ is the annual average surface runoff (mm), and $ET_i$ is the annual evapotranspiration (mm)
Soil conservation	SC	USLE (Universal Soil Loss Equation)	t/(hm <sup>2</sup> ·a)	$\Delta A = R \times K \times L \times S(1 - C \times P)$ $\Delta A$ = soil conservation (t/ (hm <sup>2</sup> ·a)), $R$ = rainfall erosivity index (MJ·mm/ (hm <sup>2</sup> ·h·a)), $K$ = soil erodibility factor (t·hm <sup>2</sup> ·h/ (MJ·mm·hm <sup>2</sup> )), $L$ $S$ = slope length and steepness factor (unitless), $C$ = cover and management factor (unitless), $P$ = conservation practice factor (unitless). The parameters $R$ were from Wischmeier and Smith <sup>32</sup> , $K$ from Williams <sup>33</sup> , $L$ $S$ from McCool et al. <sup>34</sup> and Liu et al. <sup>35</sup> , $C$ from Cai et al. <sup>36</sup> , and $P$ from Kumar et al. <sup>37</sup>

Table 2. ES indicators and their quantitative methods, units, and ES variable requirements.

### *Hypothesis of the relationships between the driving variables and ESs*

Resource systems, resource units, governance systems, and stakeholders are the four key elements of an ecosystem, each influencing CP, WR, and SC through corresponding indicators. Based on the inherent relationship between the SES framework and ESs, this study proposes the following three hypotheses and their theoretical foundations, which constitute the core logic of the conceptual model.

#### **H1** Resource systems, resource units, governance systems, and stakeholders directly influence CP, WR, and SC.

The direct effects of resource systems on ESs: Tem and Pre are fundamental environmental factors in natural ecosystems that directly impact ecological processes and resource availability. Studies have shown that Tem and Pre significantly affect plant growth, soil moisture retention, and water supply capacity. For example, excessive temperature may accelerate soil moisture evaporation, while variations in precipitation directly impact WR and SC (e.g., insufficient precipitation increases soil erosion risk).

The direct effects of resource units on ESs: NPP is a key indicator of plant growth in ecosystems, directly reflecting ecosystem productivity. High NPP typically indicates strong material production capacity, contributing to CP and WR. Additionally, high NPP implies greater vegetation coverage, which helps reduce soil erosion and maintain soil structure.

The direct effects of governance systems on ESs: GDP reflects the level of economic development in a region, which influences agricultural technology adoption and resource management capacity. Higher GDP facilitates better agricultural technology implementation (e.g., irrigation techniques) and optimized land resource management, enhancing CP efficiency and water resource management. Fiscal expenditures on agriculture, forestry, and water resources directly impact investments in agriculture, water resources and soil, supporting more effective soil protection measures and sustainable water management practices.

The direct effects of stakeholders on ESs: Inc reflects the economic status of urban and rural residents, influencing consumer and agricultural practices. Higher income levels encourage farmers to adopt more efficient agricultural technologies, reduce environmental degradation, and thereby improve CP efficiency, optimize water resource utilization, and strengthen SC.

#### **H2** Resource units mediate the relationship between resource systems and ESs, while stakeholders mediate the relationship between governance systems and ESs.

The relationship between resource systems and ESs is not direct but mediated through resource units. Ecological theory suggests that resource system variables such as Tem and Pre influence NPP, which in turn determines the supply capacity of ESs<sup>40,41</sup>. Resource units serve as direct carriers of ES provision, mediating the impact of resource systems through ecological processes. Previous studies have shown that changes in Tem and Pre affect vegetation growth and photosynthesis, subsequently influencing the spatial patterns and dynamics of NPP<sup>42</sup>. In many ecosystems, climate changes impact ESs indirectly via NPP rather than through direct mechanisms.

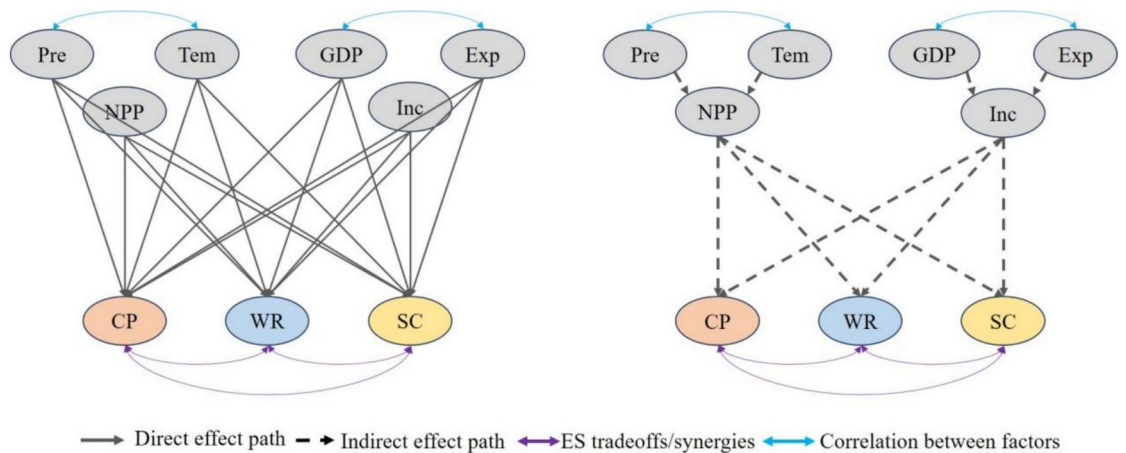
Similarly, governance system impacts need to be mediated through stakeholder decision-making processes before affecting ES supply. Environmental economics and ecological governance theories suggest that governance system effects are typically realized through socio-economic actors (i.e., stakeholders) who depend on and interact with ecosystems<sup>43</sup>. Prior research indicates that increasing GDP generally leads to higher rural and urban household incomes, which in turn influence ecological behaviors. For example, higher-income groups are more likely to adopt sustainable agricultural practices, reduce chemical fertilizer and pesticide use, and improve water resource conservation, thereby enhancing WR and SC<sup>44</sup>.

#### **H3** The dominant factors influencing ESs at a single time point are natural and ecological variables, while long-term ES changes are primarily driven by governance systems and stakeholder factors.

At a single time point, natural and ecological variables (e.g., precipitation, temperature) serve as the dominant factors influencing ES provision<sup>45</sup>. In the short term, fluctuations in these climate variables significantly affect CP and WR, reflecting the immediate response of ecosystems to environmental changes. However, over the long term, governance systems and stakeholder factors become the primary drivers of ES changes. Policies, fiscal expenditures, and socio-economic development influence ESs by shaping rural incomes, agricultural technology adoption, and resource conservation strategies. These governance-driven interventions gradually reshape CP, WR, and SC, highlighting the increasing role of human decision-making in ecosystem management over extended timescales<sup>46</sup>.

### *Conceptual model construction of the relationships between driving variables and ESs*

Based on the theoretical foundation of the aforementioned hypotheses, we identified the possible direct and indirect interaction pathways among core elements and how they collectively drive the ES relationships. To visually present the internal logic of these theoretical assumptions, we constructed a social-ecological system conceptual model for exploring the driving mechanism path of the driving variable to ES relationships (Fig. 4). In this model, we mapped core elements to specific indicators and demonstrated their interrelationships and interaction pathways. The diagram includes three types of relationships: Trade-offs/synergies among CP, WR, and SC; direct impacts of resource systems, resource units, governance systems, and stakeholder indicators on ESs; the mediating role of resource units between resource systems and ESs and the mediating role of stakeholders between governance systems and ESs.



**Fig. 4.** The priori theoretical model of path analysis for driving mechanisms of ES relationships.

## Method for testing hypothesis

### Path analysis model

Path analysis model is a component of SEM that focuses on the direct pathways between variables and serves as a method for studying causal relationships<sup>47</sup>. By quantifying these relationships through path coefficients, the analysis is based on the conceptual model constructed in the previous section<sup>48</sup>. In this study, path analysis is used to examine the effects of driving variables on ESs within the SESF. A recursive model ensures that causal relationships are unidirectional. Path coefficients indicate the magnitude and direction of these effects, where positive values signify enhancement and negative values indicate inhibition<sup>49</sup>. Correlation coefficients assess synergies (positive values) and trade-offs (negative values) between ESs. The analysis was conducted using SPSSAU software.

### Mediating effect model

In cases where the path analysis model does not yield significant indirect effects of driving variables on ESs<sup>50</sup>, it is necessary to further examine the potential mediation mechanisms. Since ESs are influenced by multiple interacting factors, certain effects may not be directly observable in a traditional path analysis framework. Mediation effect analysis allows for a more detailed investigation by assessing whether variables such as NPP and disposable income act as intermediaries in transmitting these effects<sup>51</sup>. Furthermore, the Bootstrap method enhances the statistical power in detecting indirect effects, making it a robust approach for this study. Thus, we employs multiple regression analysis and the Bootstrap method to test the mediation effect.

## Results

### Spatial patterns of ES and driving factors

#### Spatial patterns of CP, WR and SC

In the years 2000, 2010, and 2020, the spatial distribution of CP exhibited a pattern of high values in the east and lower values in the central regions (Fig. 5). Between 2000 and 2010, a decline in CP was observed in the northern, southeastern, and southwestern counties, whereas counties in the east and west experienced significant increases. From 2010 to 2020, CP in the central, southeastern, and southwestern regions declined sharply, with increases primarily concentrated in the northern, eastern, and western areas.

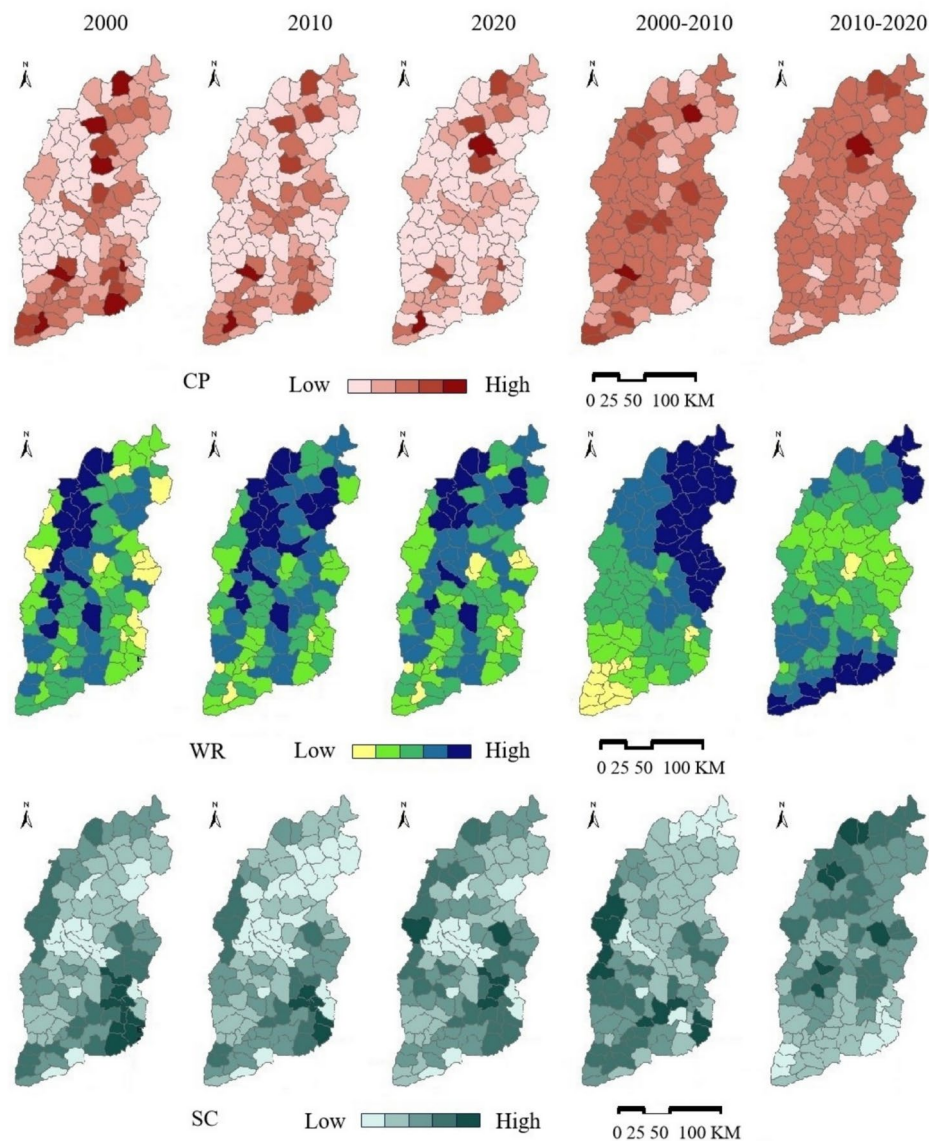
WC displayed higher values in the northern part of the study area compared to the south. During 2000–2010, WC variation followed a distinct northeast-southwest gradient of decline, with the most substantial growth in the eastern and northeastern counties, relatively stable outer counties, and a decline in the southwestern fringe. Between 2010 and 2020, WC showed significant recovery, with a marked reduction in decline areas and expansion of growth areas, particularly in the northern and southern counties.

SC was predominantly high in the southeastern part of the study area. From 2000 to 2010, the most significant increase in SC occurred in the western and southeastern counties, while the northern counties showed modest growth. Between 2010 and 2020, some counties in the southeast and southwest experienced a decrease, whereas counties in the north and certain areas in the south showed slight increases.

#### Spatial patterns of Tem, Pre and NPP

Figure 6 illustrates the spatial distribution and temporal changes of Tem, Pre, and NPP across the 107 counties in the ecological subsystem.

Tem increased slightly from 2000 to 2020, with higher values in the south and lower values in the north. From 2000 to 2010, the increase in Tem was more pronounced in the northeast and less so in the southwest, showing a significant difference compared to the 2010–2020 period. Pre displayed a spatial pattern of higher values in the southeast and lower values in the northwest, with an overall increasing trend over the past 20 years. During 2000–2010, Pre decreased in the southeastern counties, while other areas saw varying increases. From 2010 to 2020, Pre decreased most in the northern counties and increased the most in the central counties. NPP



**Fig. 5.** Spatial distributions of CP, WR and SC across the 107 counties of Shanxi Province.

increased substantially from 2000 to 2020, showing higher values in the east and lower values in the west. The most significant increases were in the western regions from 2000 to 2010, with decreases concentrated in the southeastern regions. From 2010 to 2020, there was considerable growth in the central districts and a decrease in the northern districts.

#### *Spatial patterns of GDP, Inc and Exp*

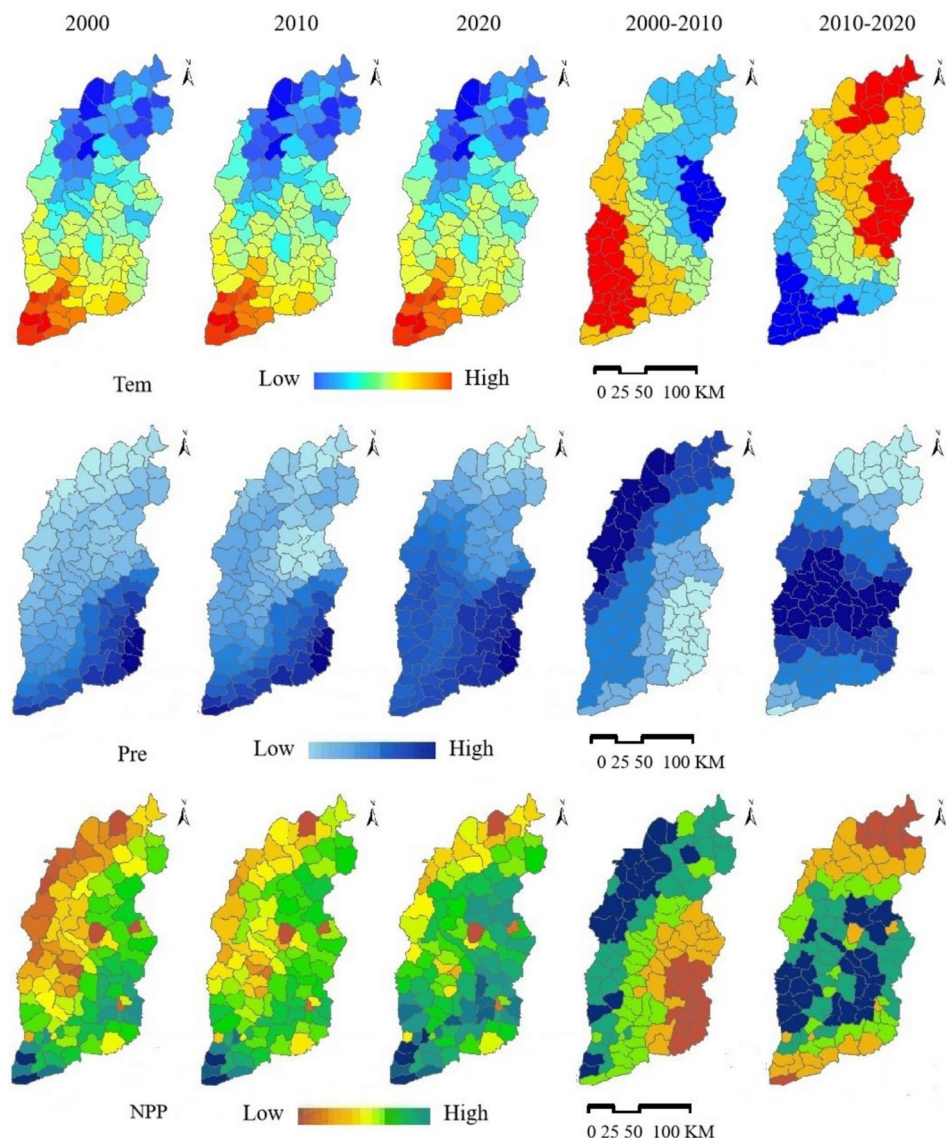
Figure 7 presents the spatial distribution and temporal changes of GDP, Exp, and Inc in the 107 counties of the social subsystem.

GDP rose from 3664 yuan in 2000 to 56,919 yuan in 2010, then decreased to 47,357 yuan in 2020. The significant increase in GDP during 2000–2010 was concentrated in urban areas of the Datong Basin, Xinzhou Basin, and Fenhe River Basin. In contrast, the significant increase in GDP between 2010 and 2020 was more dispersed. Exp increased from 20 million yuan in 2000 to 123 million yuan in 2010, continuing to rise to 290 million yuan in 2020, with an average annual growth rate of 13.5%. The lowest increase in Exp was in urban areas such as the Fenhe River Basin, Linfen Basin, Yuncheng Basin, and Jincheng Basin, while the highest increase occurred in forested and grassland areas like Luliang Mountain, Taihang Mountain, and Yueshan Mountain. Inc increased from 303 yuan in 2000 to 2,322 yuan in 2020. The spatial distribution difference of Inc narrowed significantly from 2000 to 2020, with high-growth areas becoming more scattered.

#### **Trade-offs and synergies among ESs temporally and spatially**

Path analysis quantified the relationships among the three ES indicators (Fig. 8). The results revealed that CP and WR exhibited a trade-off relationship consistently across 2000, 2010, 2020, 2000–2010, and 2010–2020, with





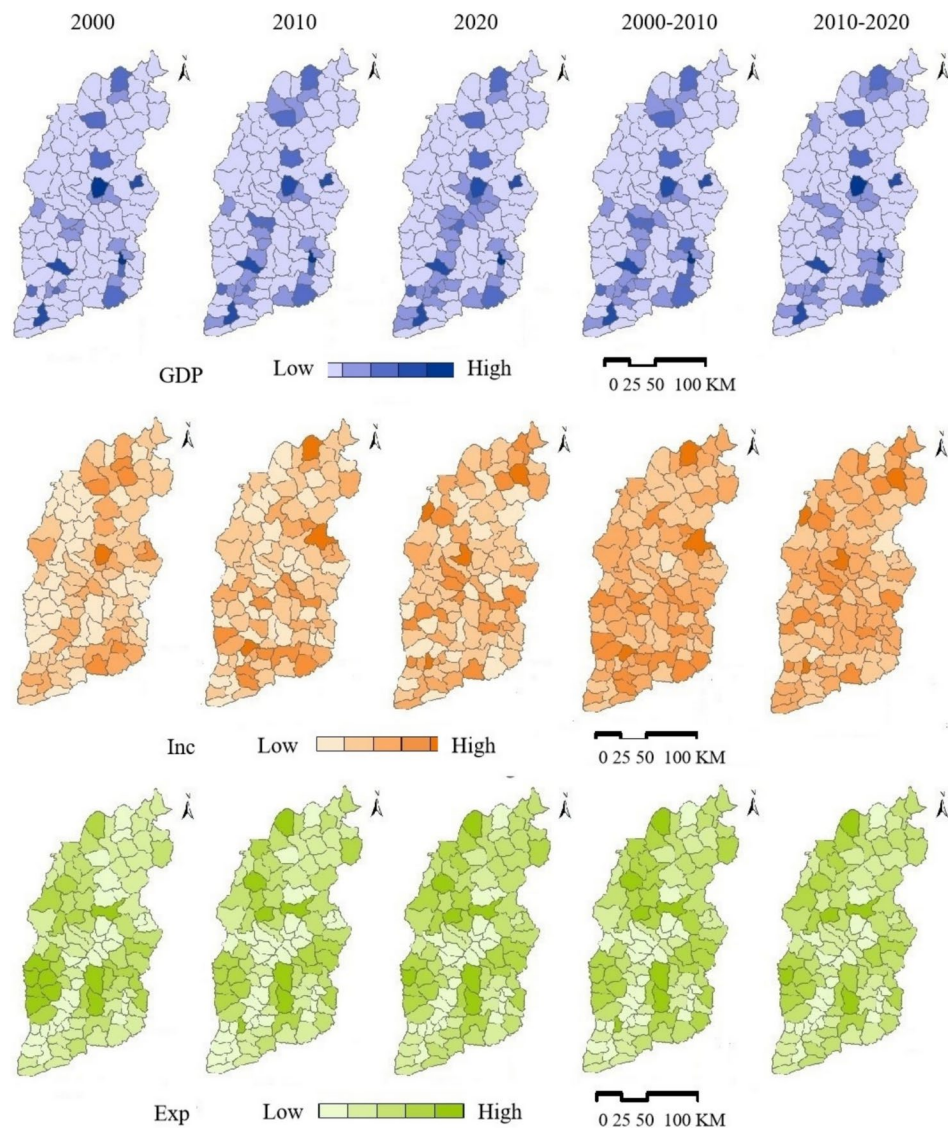
**Fig. 6.** Spatial distribution of Tem, Pre and NPP across the 107 counties of Shanxi Province.

a relatively stable trade-off intensity and a slight increase in the correlation coefficient from  $-0.336$  in 2000 to  $-0.328$  in 2020. CP and SC showed a synergistic relationship in 2000, 2010, and 2020, with coefficients of 0.206, 0.282, and 0.332, respectively. During 2000–2010 and 2010–2020, a trade-off relationship was observed between CP and SC, with coefficients of  $-0.308$  and  $-0.354$ , respectively. WR and SC exhibited a trade-off relationship in 2000, 2010, and 2020, with coefficients of  $-0.283$ ,  $-0.357$ , and  $-0.294$ , respectively, but showed synergy during 2000–2010 and 2010–2020, with coefficients of 0.515 and 0.294. The trade-off between CP and WR remained consistent over time, while the relationships between CP and SC and WR and SC shifted from trade-offs to synergies between the change periods of 2000–2010 and 2010–2020.

### Confirming Hypothesis 1: Resource systems, resource units, governance systems, and stakeholders directly influence CP, WR, and SC

Hypothesis 1 is confirmed. According to the path diagram (Fig. 4), we examined the relationships between six driving variables and three ES indicators. The model fitting indicators passed the significance test for 2000, 2010 and 2020 (Table 3), although not all pairwise relationships were significant. We extracted relationships with significance levels greater than 0.05 (Fig. 8).

In 2000, CP was dominated by Pre, NPP, GDP, and Inc, with Pre having a negative impact and GDP exerting the largest effect. WR was negatively affected by Tem and GDP, with GDP having a greater influence than Tem. SC was positively influenced by Pre and negatively by NPP, with Pre having a much larger impact than NPP. In 2010, significant effects on CP were observed from Pre, NPP, and GDP, with GDP having the most considerable impact. WR was mainly affected by Tem, NPP, and GDP, with Tem being the most significant factor. For SC, Pre



**Fig. 7.** Spatial distribution of GDP, Exp and Inc across the 107 counties of Shanxi Province.

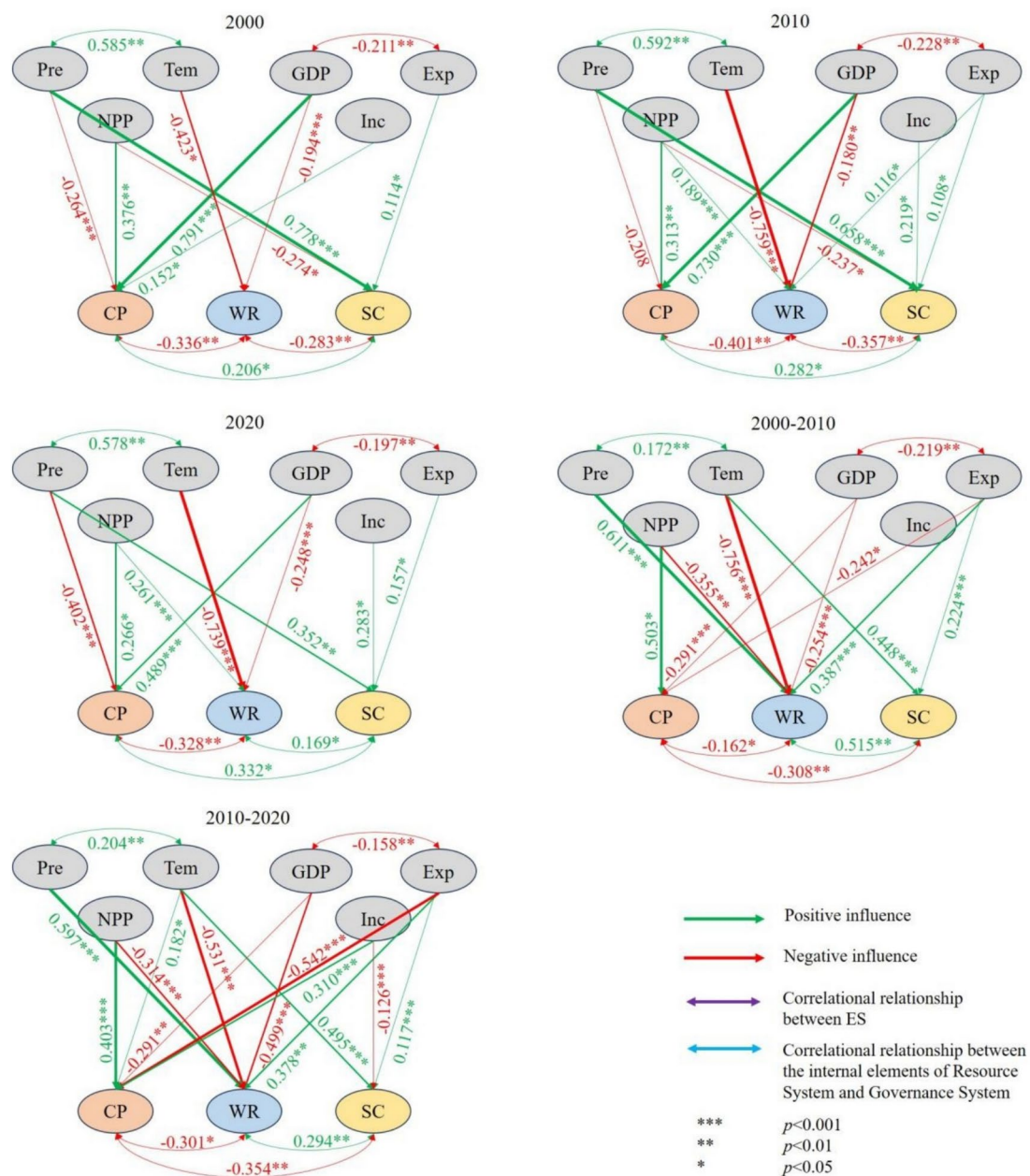
and NPP had significant effects, with Pre having the greater impact. In 2020, the influencing factors for CP and WR remained consistent with 2010, while Pre became the significant factor for SC.

Comparing across years, GDP was the most significant driver of CP, though its impact decreased from 0.791 in 2000 to 0.489 in 2020. For WR, Tem was the most influential factor, with its coefficient increasing from -0.423 in 2000 to -0.739 in 2020. The primary influence on SC was Pre, with its effect diminishing from 0.778 in 2000 to 0.352 in 2020.

### Refuting Hypothesis 2: The mediating role of resource units and stakeholders in the relationship between resource systems, governance systems, and ESs

Path analysis results indicate that Tem, Pre, GDP, and Exp all have significant direct effects on ESs. However, whether NPP mediates the relationship between Tem, Pre, and ESs, and whether Inc mediates the relationship between GDP, Exp, and ESs, requires further verification. Therefore, this study primarily tests the following two mediation pathways: (1) The mediation effect of climate variables: Does temperature and Pre influence ESs indirectly through NPP? (2) The mediation effect of economic variables: Does GDP influence ESs indirectly through Inc?

To verify the role of NPP in the relationship between climate variables and ESs, we first analyzed the impact of Tem and Pre on NPP. Table 4 presents the regression analysis results, showing that both Tem and Pre have significant positive effects on NPP. Among them, Pre has a more pronounced effect ( $\beta = 0.30, p < 0.01$ ), indicating that water availability plays a crucial role in promoting vegetation growth. We further examined whether NPP mediates the relationship between climate variables (Tem, Pre) and ESs (CP, WR, and SC) (Table 4). The results



**Fig. 8.** Path model diagram of three ESs and six social-ecological variables.

Common index	$\chi^2$	df	p	Chi-square degree of freedom ratio $\chi^2/df$	GFI	RMSEA	RMR	CFI	NFI	NNFI
Model fit index (2000)										
Judgment criteria	–	–	>0.05	<3	>0.9	<0.10	<0.05	>0.9	>0.9	>0.9
Value	3.682	3	0.298	1.227	0.988	0.046	0.002	1.000	0.998	0.995
Model fit index (2010)										
Judgment criteria	–	–	>0.05	<3	>0.9	<0.10	<0.05	>0.9	>0.9	>0.9
Value	4.428	2	0.109	2.214	0.992	0.107	0.013	0.996	0.994	0.937
Model fit index (2020)										
Judgment criteria	–	–	>0.05	<3	>0.9	<0.10	<0.05	>0.9	>0.9	>0.9
Value	2.852	3	0.415	0.951	0.994	0.000	0.005	1.000	0.993	1.005

**Table 3.** Fitting test of the path analysis model of six social-ecological variables and three ESs in 2000, 2010 and 2020.



Variable	NPP	Standardized Regression Coefficient ( $\beta$ )	Significance
Tem	NPP	0.15	*
Pre	NPP	0.30	**
Variable	Inc	Standardized Regression Coefficient ( $\beta$ )	Significance
GDP	Inc	0.80	***
Exp	Inc	0.25	n.s

**Table 4.** The Effect of Climate Variables on NPP and the Effect of Climate Variables on Inc.

	Ecosystem Service	Direct Effect	Indirect Effect	Total Effect	Mediation Effect Type
Climate Variable					
Tem	CP	0.12 *	0.10 *	0.22 **	Partial Mediation
	WR	0.14 *	0.09 *	0.23 **	Partial Mediation
	SC	0.11 *	0.08 *	0.19 *	Partial Mediation
Pre	CP	0.18 **	0.15 **	0.33 ***	Partial Mediation
	WR	0.22 **	0.12 **	0.34 ***	Partial Mediation
	SC	0.17 **	0.09 *	0.26 **	Partial Mediation
Economic Variable					
GDP	CP	0.10 *	0.24 **	0.34 ***	Partial Mediation
	WR	0.12 *	0.20 **	0.32 ***	Partial Mediation
	SC	0.09 *	0.16 *	0.25 **	Partial Mediation
Exp	CP	0.20 *	n.s	0.20 *	No Mediation Effect
	WR	0.25 **	n.s	0.25 **	No Mediation Effect
	SC	0.18 *	n.s	0.18 *	No Mediation Effect

**Table 5.** Mediation Effect Analysis of NPP and Inc. \* indicates that the significance level is 0.05; \*\* indicates that the significance level is 0.01; \*\*\* indicates that the significance level is 0.001.

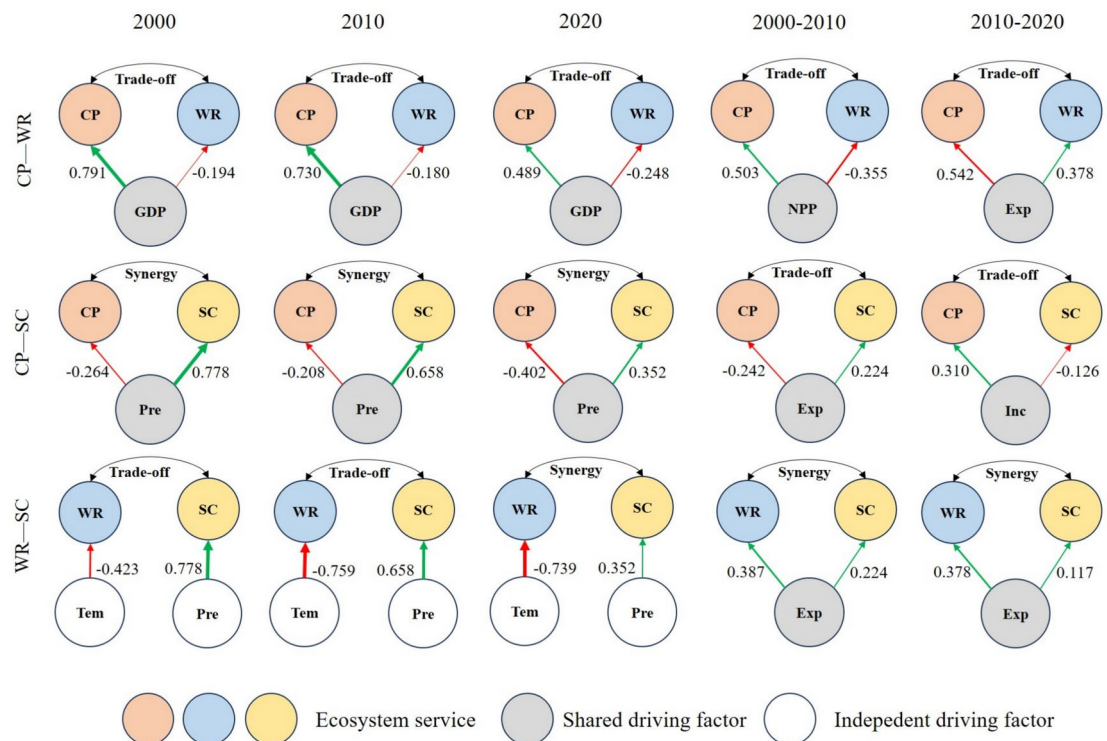
Common index	$\chi^2$	df	p	Chi-square degree of freedom ratio $\chi^2/df$	GFI	RMSEA	RMR	CFI	NFI	NNFI
Model fit index (2000–2010)										
Judgment criteria	–	–	> 0.05	< 3	> 0.9	< 0.10	< 0.05	> 0.9	> 0.9	> 0.9
Value	0.006	-1	0.310	-0.006	1.000	0.000	0.049	1.000	1.000	1.012
Model fit index (2010–2020)										
Judgment criteria	–	–	> 0.05	< 3	> 0.9	< 0.10	< 0.05	> 0.9	> 0.9	> 0.9
Value	0.003	0	0.115	1.392	1.000	0.000	0.023	1.000	1.000	1.010

**Table 6.** Fitting test of the path analysis model of six social-ecological variables and three ESs in 2000–2010 and 2010–2020.

indicate that NPP serves as a partial mediator in the effect of climate variables on ESs. The indirect effect of Pre is stronger than that of temperature, suggesting that Pre enhances ES functions by promoting vegetation growth. To further explore the mediating role of Inc in the impact of economic variables on ESs, we first analyzed the impact of GDP and Exp on Inc (Table 5). The results show that, GDP has a significant positive effect on Inc ( $\beta=0.80, p<0.001$ ). The effect of Exp on Inc is not significant ( $p>0.05$ ). Subsequently, we examined whether Inc mediates the relationship between economic variables and ESs (Table 5). The results indicate that, GDP influences ESs partially through Inc. The indirect effect of Exp is not significant.

**Confirming Hypothesis 3: The dominant factors influencing ESs at a single time point are natural and ecological variables, while long-term ecosystem service changes are primarily driven by governance systems and stakeholder factors**  
Hypothesis 3 is confirmed. The model fitting indicators passed the significance test for 2000–2010, and 2010–2020 (Table 6). From 2000 to 2010, CP was significantly influenced by NPP, GDP, and Exp, with NPP having the greatest effect (Fig. 8). WR was affected by Tem, Pre, NPP, GDP, and Exp, with Tem being the most influential. SC was primarily affected by Tem and Exp, with Tem having a slightly greater impact. From 2010 to 2020, CP was influenced by Tem, NPP, GDP, Exp, and Inc, with Exp and NPP being the most significant. WR was affected by Pre, Tem, NPP, GDP, and Exp, with GDP and Tem being the most influential. SC was influenced by Tem, Exp, and Inc, with Tem having the greatest effect. The results indicate that, in 2000, 2010, and 2020, ecosystem factors





**Fig. 9.** Driving mechanistic path in which drivers affect ES can affect the relationships between paired ES. (Red lines indicate negative effects (-), green lines indicate positive effects (+), and the thickness of the lines represents the magnitude of these effects.)

were the primary drivers of WR and SC, whereas social system factors dominated during the change periods of 2000–2010 and 2010–2020.

## Discussion

### The driving mechanism path of ES relationships in space: resource systems and governance systems as dominant determinants

This study has validated Hypothesis 1, which states that resource systems, resource units, governance systems, and stakeholders directly influence CP, WR, and SC. These findings emphasize the crucial role of natural and socio-economic factors in shaping the dynamics of ESs in Shanxi Province.

Based on the path analysis results in Fig. 8, we identified the most influential shared driving factors for paired ecosystem services and visualized them in Fig. 9. CP and WR exhibit a trade-off relationship, with GDP serving as their shared driving factor. From a spatial perspective (Fig. 5), the trade-off between CP and WR is mainly driven by land-use competition<sup>52</sup>, which align with previous findings of spatial competition between CP and WR<sup>53</sup>. From a driving factor perspective, increased GDP correlates with increased CP and decreased WR. Economic growth-driven agricultural expansion reduces forest cover, thereby diminishing water retention capacity<sup>54</sup>. This trend is particularly evident in the semi-arid northern regions of Shanxi Province, where limited precipitation and large-scale land development exacerbate the trade-offs between provisioning and regulating services.

CP and SC demonstrate synergy in 2000, 2010, and 2020, which contradicts the expected trade-off between provision services and regulation services<sup>55</sup>. Pre emerged as the primary shared driver influencing both CP and SC. In the study area, the highest precipitation areas are mainly in the mountainous and hilly regions of the southeastern semi-humid zone, where terrain restricts large-scale grain cultivation<sup>56</sup>. To enhance CP, local residents have cultivated dry-land terraces in these mountainous areas, relying heavily on chemical fertilizers and pesticides<sup>57</sup>. Thus, while increased precipitation has a negative impact on CP due to limited cultivation areas, it positively affects SC by promoting vegetation growth, soil retention, and grain yield improvement. Therefore, CP and SC exhibit a synergistic relationship.

WR and SC exhibit a trade-off relationship in 2000, 2010, and 2020, differing from previous studies that suggest synergies between regulatory services<sup>58</sup>. This discrepancy may be attributed to regional climatic and topographic variations. Prior studies focused on areas with stable precipitation and vegetation cover, reinforcing synergies, whereas our study area exhibits significant climatic heterogeneity. In northern and northwestern Shanxi, semi-arid regions with high altitudes and low temperatures experience lower precipitation but retain relatively high WR due to reduced runoff and evapotranspiration<sup>59</sup>. In contrast, sub-humid regions in the south and southeast receive more precipitation, but higher temperatures increase evapotranspiration, reducing WR. SC also varies, with semi-arid areas dominated by grasslands and shrublands, while sub-humid regions

feature denser woodlands, leading to stronger SC<sup>60</sup>. This spatial heterogeneity drives distinct WR-SC responses: in humid regions, higher vegetation cover enhances both, fostering synergy, whereas in semi-arid regions, it improves SC but increases water consumption, reducing WR and resulting in the observed trade-off.

### The driving mechanism path of ES relationships in time: Short-Term vs. Long-Term drivers of ES

This study has validated Hypothesis 3, which states that short-term ES variations are primarily driven by natural and ecological variables, whereas long-term changes are mainly influenced by governance systems and stakeholders. During the periods of 2000–2010 and 2010–2020, CP and SC exhibited a trade-off relationship, whereas WR and SC showed a synergistic relationship (Fig. 9). WR and SC changes were predominantly controlled by Tem, Pre in the year of 2000, 2010 and 2020, aligning with global studies that indicate short-term fluctuations in ESs are mainly influenced by natural factors. However, during the periods of 2000–2010 and 2010–2020, governance factors—particularly Exp, as well as changes in Inc—gained increasing influence, reflecting the long-term impacts of China's national ecological policies such as the “Grain for Green” program<sup>61,62</sup>.

Our study area, located in the Loess Plateau region, is characterized by mountainous and valley terrain, where soil erosion presents a long-term ecological management challenge. During the study period, various ecological engineering projects have been executed in this area<sup>63</sup>, including restoring vegetation on abandoned farmland, converting some sloping lands in mountainous areas to forests and grasslands, and conducting long-term tree and grass planting in semi-arid areas showing desertification trends. Similar trends have been observed in other regions implementing large-scale ecological restoration projects<sup>64</sup>. For instance, in Europe and North America, short-term ecosystem service variations are primarily governed by natural factors, while long-term policy-driven interventions, such as forest management and wetland restoration, have had profound effects on ecosystem structure and function<sup>65</sup>. Furthermore, studies in China's semi-arid regions indicate that while WR services initially respond to climate fluctuations, they become increasingly dependent on policy interventions over time<sup>66</sup>. These findings further support the crucial role of governance systems and stakeholders in shaping long-term ES relationships.

### Re-examining Hypothesis 2: Why was it not validated?

Hypothesis 2 proposed that NPP and Inc mediate the relationships between resource systems, governance systems, and ESs. However, the results indicate that not all mediating effects along these pathways were significant.

NPP partially mediates the impact of climate variables on ESs, highlighting the critical role of vegetation productivity in translating climate fluctuations into ES changes. For example, higher precipitation levels and suitable temperatures promote vegetation growth, increasing NPP, which subsequently enhances soil conservation and water retention capacity<sup>67</sup>. GDP partially influences ESs through Inc, reflecting the indirect effects of economic growth on ESs. As the economy grows, rising Inc increase the potential for ecological investments, such as improved farmland management and water resource conservation, leading to enhanced ESs<sup>68</sup>.

However, Inc did not significantly mediate the relationship between Exp and ESs. In view of the social and economic development of counties in Shanxi Province, possible explanations for this include policy lag effects, policy implementation efficiency, and competing local economic priorities<sup>69</sup>. First of all, investments in agriculture and water conservation may require extended periods before their ecological benefits become apparent. For instance, the impacts of afforestation and wetland restoration often take decades to manifest in ESs<sup>70</sup>. Second, fiscal expenditures do not always translate directly into ES improvements due to potential resource misallocation or inefficiencies in execution. Some ecological protection funds may be allocated to infrastructure development rather than directly contributing to ecosystem restoration<sup>71</sup>. Third, county-level economic strategies may prioritize short-term economic growth over long-term ES enhancement. For example, certain regions may allocate fiscal expenditures toward industrial development and urban expansion rather than ecological protection<sup>72</sup>.

### Implications for policy making

This study demonstrated that while the synergistic relationship between WR and SC was enhanced in Shanxi Province from 2000 to 2020, the trade-off relationship between CP and WR and SC was weakened, with social factors being the dominant shared driving factor. However, at the three time points examined, the trade-off between WR and SC first increased and then decreased and showed synergy, whereas the trade-off between CP and WR initially increased and then decreased, with natural factors emerging as the dominant shared driving factor. This indicates that natural factors are rigid constraints on ES relationships in the study area, determining the spatial differences in ES and their interrelationships. Conversely, the utility of social factors exhibits a time lag, typically requiring ecosystem processes to manifest their effects on ES and their relationships.

To optimize ecosystem management, it is imperative to integrate the driving mechanism pathways of ES relationships with ecological restoration projects that combine natural conditions and social factors. Spatial management of ES trade-offs should be conducted across different regions within the study area. Policy decisions should consider regional ES relationships and local benefits<sup>73</sup>. For instance, in the southeastern sub-humid region with high vegetation coverage, green vegetation protection and appropriate agricultural technologies should be implemented to prevent trade-offs between CP and SC. Specifically, policies should promote ecological compensation mechanisms, such as subsidies for eco-friendly farming practices that enhance soil conservation while maintaining crop productivity. Additionally, a rotational farming system integrating cover crops and contour farming should be adopted to minimize soil erosion and optimize water retention.

In the semi-arid mountainous region of the northwest, vegetation restoration should focus on converting cultivated land back to forests and grasslands and restoring abandoned dry-lands due to rural migration. This

approach would promote local coordination between WR and SC and mitigate the trade-off between CP, WR, and SC<sup>74</sup>. To facilitate this, policies should implement afforestation programs with native drought-resistant tree species and support ecological migration initiatives that provide financial incentives and job opportunities for rural populations to engage in forest restoration projects. Additionally, water-efficient irrigation systems should be developed to balance water conservation efforts with agricultural needs.

These processes require not only increased financial investment from provincial to county-level governments in agriculture, forestry, and water conservancy but also leveraging other positive social factors. Establishing a multi-stakeholder governance framework that includes local governments, community organizations, and research institutions can ensure adaptive management strategies based on continuous ecological monitoring. Moreover, integrating ecological indicators into land-use planning and development policies will help maintain long-term ecosystem stability and service sustainability.

### Limitations and future research directions

This study has several limitations that suggest important directions for future research. First, the selection of social driving factors was constrained by data availability. While we aimed to reflect the influence of governance and management on ES changes, we relied on proxies such as GDP and financial expenditures due to the lack of detailed policy impact data<sup>75</sup>. Future research should integrate more direct indicators of ecological policy implementation, such as conservation investment, land-use regulations, and environmental enforcement data, to better quantify the role of governance in ES dynamics.

Second, in exploring the driving mechanism pathways, we excluded land use/cover and population variables to avoid strong collinearity. However, land use/cover changes serve as a critical intermediary through which biophysical and management factors influence ES relationships<sup>76,77</sup>. Future studies should incorporate land-use transitions and population dynamics as mediating variables in the analysis to capture the indirect effects of governance and ecological restoration on ES trade-offs and synergies.

Third, this study focused on county-level spatial units, which facilitated the analysis of social drivers but limited the ability to capture regional heterogeneity and scale effects<sup>78</sup>. Shanxi Province has diverse topography and ecological conditions, leading to spatial differences in ES relationships. Future research should adopt a multi-scale approach, analyzing ES drivers at finer spatial resolutions (e.g., watershed or landscape scale) and comparing regional patterns across different ecological zones (e.g., northwest, central, and southeastern Shanxi).

### Conclusions

Understanding the driving mechanisms behind ES trade-offs is essential for sustainable ES management. This study integrates Bennett's path model and the SESF to analyze the relationships among CP, WR, and SC and their key drivers (Tem, Pre, NPP, GDP, Exp, and Inc). Findings indicate that the dominant drivers of ESs vary over time, with GDP, Tem, and Pre playing major roles. CP and WR exhibited a trade-off, CP and SC a synergy, and WR and SC a trade-off, influenced by shifting socio-economic and climatic factors.

Effective ES management requires region-specific policy interventions. In agricultural areas, balancing economic growth and water conservation through efficient irrigation and ecological compensation is crucial. In ecologically fragile zones, afforestation, land-use regulations, and sustainable farming incentives can mitigate trade-offs. Multi-stakeholder governance should be strengthened to support adaptive ES management. Future research should incorporate land use change as a mediating variable, apply multi-scale analyses to capture spatial variations, and explore long-term policy effects on ES dynamics. This study underscores the importance of identifying the driving path of ES relationships to guide policy decisions and enhance ES sustainability.

### Data availability

The data generated and analyzed in this study is included in this article.

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## Author contributions

Y. Zhang and B. Liu contributed equally to this work. Specifically, Y. Zhang and B. Liu designed the study, collected the database and performed the research. Y. Zhang analyzed data, and wrote the paper. B. Liu was responsible for data processing and model calculation. The remaining authors contributed to discuss the results and revise the manuscript. All authors have read and approved this manuscript.

## Declarations

## Competing interests

The authors declare no competing interests.

## Additional information

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