

Article

Spatial Interactions Between the Water–Energy–Food Development Level and Ecosystem Services in the Yellow River Basin

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Abstract

Understanding the spatial spillover effects of ecosystem services (ESs) on the water–energy–food (WEF) development level is critical for regional sustainability, yet empirical evidence remains limited. Using prefecture-level units in the Yellow River Basin (YRB), this study investigated the relationship between four ESs, i.e., water yield, carbon storage, food production, and soil conservation, with the WEF development level from 2000 to 2020. A spatial Durbin model and geographically and temporally weighted regression were employed to quantify global spatial spillover effects and local heterogeneity. Results showed that both the WEF development level and ESs improved over the study period. At the basin scale, carbon storage exhibited the strongest positive effects on WEF development, with direct, spillover, and total effects of 0.29, 0.89, and 1.18, respectively. At the regional scale, water yield was positively associated with the WEF development level in northern Shaanxi and Shanxi Provinces but negatively associated in western Inner Mongolia Autonomous Region. Carbon storage maintained weak but consistently positive associations across most regions. Food production showed strong positive associations in eastern Shandong Province but moderate negative associations in southern Shanxi and western Henan Provinces. Soil conservation showed strong positive associations in western Inner Mongolia and parts of Qinghai, whereas strong negative associations occurred in eastern Shandong and Henan provinces. These findings underscore the critical role of carbon storage in supporting coordinated WEF development and emphasize the need to enhance carbon storage and adopt region-specific ecosystem management strategies for sustainable development in the YRB.

Keywords: spatial spillover; spatial Durbin model; geographically and temporally weighted regression; regional sustainability; river basin management



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1. Introduction

Global climate change and rapid economic growth have further intensified the supply–demand pressure on critical resources such as water, energy, and food. These resources constitute the foundation of human well-being and socioeconomic sustainability [1–3]. It is projected that by 2050, global demand for water, energy, and food will increase by 55%, 80%, and 60%, respectively [4]. Because these resources are closely interconnected through multiple biophysical and socioeconomic processes, they are increasingly conceptualized as the water–energy–food (WEF) nexus [5].

The traditional WEF nexus framework emphasizes that water, food, and energy are fundamental natural resources for achieving regional sustainable development. However, focusing solely on the interactions among these three sectors cannot fully explain how natural ecosystem support source availability and socioeconomic development [6]. Therefore, incorporating ecosystem services (ESs) into WEF nexus analysis and decision making is essential. Ecosystems are an integral component of natural resources, supporting the production and supply of water, energy, and food through their service functions [7,8]. However, growing human demand for these three resources has placed increasing pressure on ecosystem functioning, reducing the capacity of multiple ecosystems to sustain ES provision and increasing ecosystem vulnerability [9–11]. Similarly, declines in ES supply may undermine the stable provision of these three resources, thereby further affecting WEF nexus sustainability [12]. For instance, water scarcity in the Black Sea catchment has intensified trade-offs among water, energy, food, and ecosystem demands [10], while mismatches between ecosystem service supply and demand have constrained sustainable resource management in the Yellow River Basin [13]. These findings highlight that ESs are both a prerequisite for and a constraint on sustainable WEF development, highlighting the importance of understanding their interactions.

As research on the WEF nexus and ESs has received growing attention in recent years, increasing efforts have been devoted to understanding their interaction mechanisms [14,15]. Existing studies generally suggest that ESs play an important role in shaping the WEF nexus, although the effects vary among individual ESs. For example, Ding et al. [16] employed Spearman's rank correlation analysis and found a significant negative correlation between the WEF nexus and ESs. Wang et al. [17] used the coupling coordination degree and geographic detector models to analyze the interaction between the WEF nexus and ESs supply–demand, identifying the supply–demand ratio of carbon storage as the dominant factor. Ding et al. [12] found that the coupling coordination between WEF nexus and water yield improved steadily, whereas that with grain production declined significantly. Although these studies have improved our understanding of ES–WEF relationships, they have primarily focused on correlation analysis or coupling coordination models using methods such as linear regression and coupling coordination degree models. However, ESs are generated through ecological processes that transcend administrative boundaries. Through the movement of water, energy, materials, and ecological functions, changes in ESs in one region may affect resource availability and environmental conditions in neighboring regions [18]. Such cross-regional influences are referred to as spatial spillover effects, whereby the impacts of ecological changes extend beyond the locations they originate. For example, upstream water regulation can influence downstream water availability, while carbon storage and soil conservation can generate ecological benefits that extend across regions. Consequently, ESs may exert not only local effects on the WEF nexus but also indirect effects on neighboring areas. Meanwhile, differences in resource endowment, ecological conditions, and socioeconomic development may lead to substantial spatial heterogeneity in these relationships. Therefore, traditional methods struggle to accurately capture the spatial spillover effects and local heterogeneity of ES–WEF interactions. To address these limitations, this study employed spatial econometric approaches that explicitly account for cross-regional dependence and local heterogeneity, enabling a more rigorous characterization of the spatial interactions between ESs and the WEF nexus.

The Yellow River Basin (YRB) is a critical ecological security barrier and economic development zone in China, yet it has long faced challenges including ecological fragility, water resource scarcity, and limited environmental carrying capacity [19]. To restore the ecological pattern and ensure regional livelihood development, existing studies have developed various evaluation indicator systems to quantitatively assess the WEF development

level and explore optimization pathways for ESs supply–demand matching from a WEF perspective [13,20,21]. While previous studies have explored ES–WEF relationships in the YRB, they have primarily focused on direct correlations or coupling coordination at provincial or watershed scales. The direct and indirect spatial effects of individual ESs, particularly their local versus spillover contributions, have not been systematically quantified, nor have the prefecture-level spatial heterogeneity patterns been identified across the basin. Moreover, few studies have integrated global spatial dependence and local spatiotemporal heterogeneity within a unified analytical framework. To address these gaps, this study aims to (1) quantify the WEF development level and four key ESs; (2) estimate the direct, spillover, and total effects of ESs on WEF development using the spatial Durbin model; and (3) identify the local spatiotemporal heterogeneity of these effects using the geographically and temporally weighted regression model. By integrating global spatial econometric analysis with local spatially varying regression, this study provides a new insight into the mechanisms through which ESs influence WEF development and offers a scientific basis for ecological protection and coordinated resource management in the YRB.

2. Materials and Methods

2.1. Study Area

The YRB, situated between 32–42° N and 96–119° E, is the basin of the Yellow River, the second longest river in China [22]. Originating from the Bayan Har Mountains in Qinghai Province, the river flows through nine provinces and autonomous regions (Qinghai, Sichuan, Gansu, Ningxia, Inner Mongolia, Shaanxi, Shanxi, Henan, and Shandong) and has a total length of approximately 5464 km. The basin covers an area of 795,000 km² and exhibits considerable topographic elevation differences, following a general pattern of higher elevation in the west and lower elevation in the east. The region experiences a temperate continental climate, with mean annual temperatures ranging from −13 °C to 16 °C and a mean annual precipitation of approximately 500 mm [23]. Under the combined influence of topography and climate, significant spatial heterogeneity is observed in vegetation and land use across the basin. Forests and shrubs dominate the eastern region, whereas grasslands and deserts are predominant in the western and northern regions (Figure 1).

In this study, prefecture-level administrative units were selected as spatial evaluation units. Compared with natural watershed units that cross administrative boundaries, prefecture-level units offer more comprehensive socioeconomic and statistical data and are better aligned with the implementation of ecological management and policy, making them more suitable for empirical analysis. Based on the basin boundaries delineated by the Yellow River Conservancy Commission, the prefecture-level units were systematically integrated to ensure spatial integrity and hydrological connectivity. This process identified 68 evaluation units along the mainstream of the YRB, including prefecture-level cities, autonomous prefectures, and leagues. The specific units corresponding to the upper, middle, and lower reaches of the YRB are detailed in Table S1.

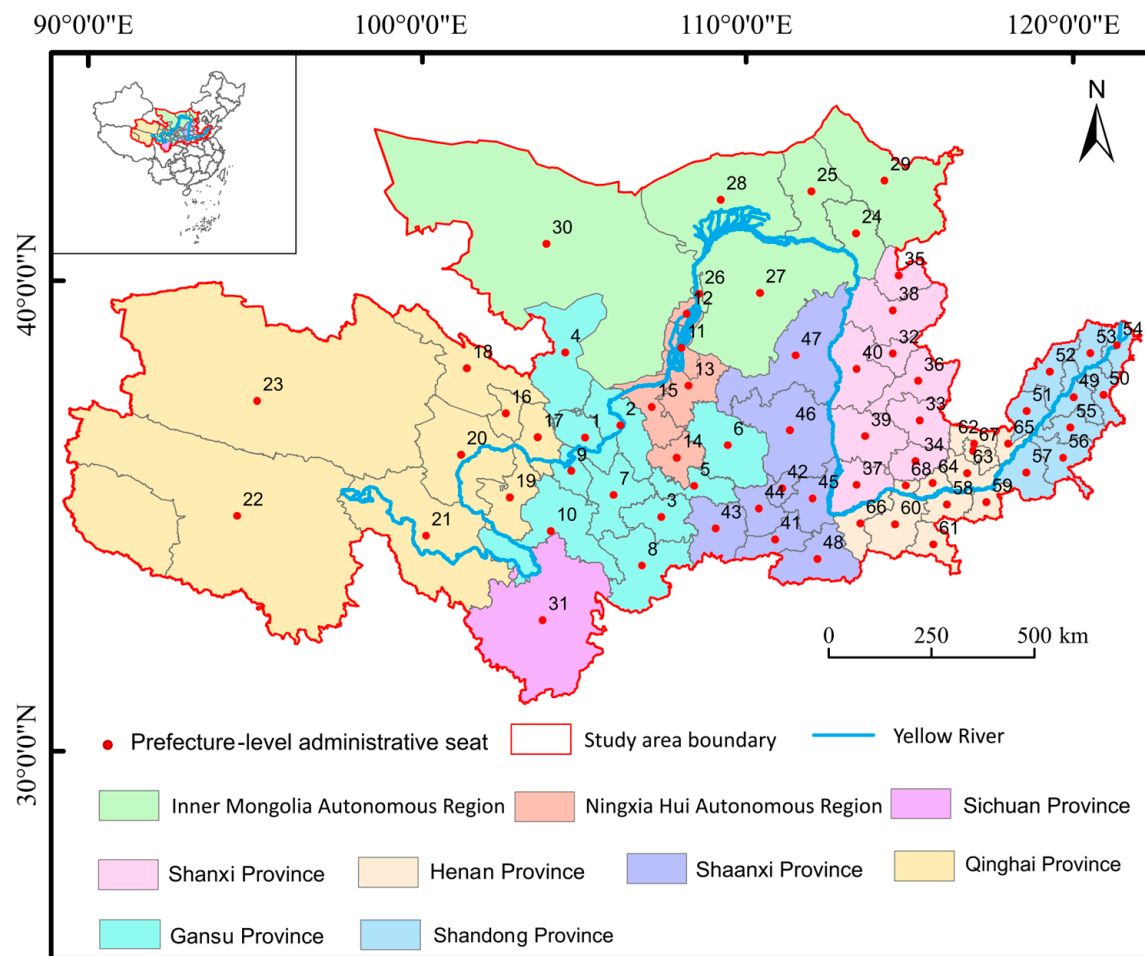


Figure 1. Administrative divisions and prefecture-level units of the study area in the Yellow River Basin. The numbered units correspond to the prefecture-level administrative divisions listed in Table S1, along with their names and reach classifications (upper, middle, and lower).

2.2. Data Sources

The datasets used to quantify ESs, including land use, meteorology and soil data, are listed in Table 1. Data for evaluating the WEF development level were collected from water resources bulletins, municipal statistical yearbooks, environmental statistics yearbooks, and rural yearbooks. Detailed information on the indicator selection for the WEF development level evaluation system is presented in the subsequent Methods section. ES variables were derived from raster datasets at a spatial resolution of $1 \text{ km} \times 1 \text{ km}$, whereas socioeconomic and statistical data were collected at the prefecture-level city level. Raster-based ES variables were subsequently aggregated to prefecture-level units using area-weighted zonal statistics to ensure spatial consistency across datasets. Missing values in the statistical datasets were processed before analysis. Linear interpolation was applied for short-term missing time-series data, while isolated missing values were supplemented using mean substitution based on adjacent years or similar administrative units.

Table 1. Data sources and spatial scales.

Data Type	Spatial Scale	Sources
Basin boundary	—	Yellow River Data Center (https://www.huanghe.ac.cn/)
Land use	30 m	Resource and Environment Science and Data Center (http://www.resdc.cn/)
Annual average precipitation	1000 m	Resource and Environment Science and Data Center (http://www.resdc.cn/)
Potential annual evapotranspiration	1000 m	National Earth System Science Data Center (https://www.geodata.cn/)
Normalized Difference Vegetation Index	1000 m	Resource and Environment Science and Data Center (http://www.resdc.cn/)
Soil physical and chemical properties data	1000 m	National Cryosphere Desert Data Center (http://www.ncdc.ac.cn/)
Digital elevation model	30 m	Yellow River Data Center (http://huanghe.ncdc.ac.cn)
Annual average temperature	1000 m	National Earth System Science Data Center (https://www.geodata.cn/)
Population density	1000 m	WorldPop datasets (https://www.worldpop.org/)
Carbon emission	Prefecture-level	Carbon Emission Accounts and Datasets (http://www.ceads.net/)
Food production and consumption; water consumption	Prefecture-level	National Statistical Yearbook (https://www.stats.gov.cn/); Statistical yearbooks and Water Resources Bulletin for nine provinces
Nighttime light data	1000 m	National Tibetan Plateau/Third Pole Environment Data Center (http://data.tpdac.cn/)

3. Methods

3.1. Analytical Framework

A five-step analytical framework was constructed to assess the spatial effects of ESs on the WEF development level in the YRB (Figure 2). Step 1 quantified the WEF development level using an integrated development model based on the water, energy, and food subsystems. Step 2 quantified four key ESs, namely water yield, carbon storage, food production, and soil conservation, followed by standardization to obtain a comprehensive ES index. Step 3 employed the spatial Durbin model (SDM) to estimate the global spatial effects of ESs on the WEF development level, with the total effects decomposed into direct, indirect, and spatial spillover effects. Step 4 used the geographically and temporally weighted regression (GTWR) model to capture local spatiotemporal heterogeneity, revealing the spatial distribution and temporal evolution of the influence coefficients of each ES. Step 5 synthesized policy and management implications based on the empirical findings from both the global and local perspectives.

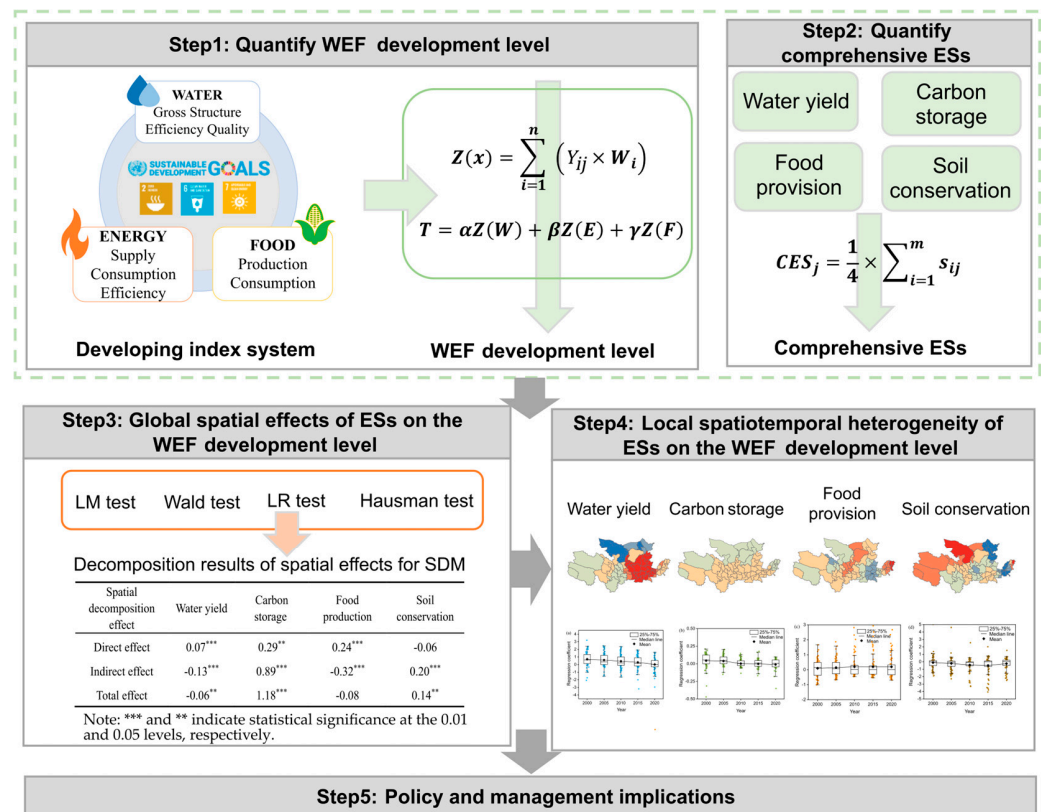


Figure 2. The analytical framework of this study.

3.2. Evaluation of WEF Development Level

An evaluation index system was constructed to comprehensively characterize the WEF development level [17,24,25] across four dimensions including resource endowment, utilization efficiency, environmental pressure, and structural characteristics (Table S2). The water sector, which characterizes regional water conditions, was measured by indicators such as total water resources, water use per capita, and wastewater discharge. The energy sector was measured by indicators including energy consumption per capita, SO₂ emissions, and CO₂ emissions. The food sector was measured by indicators such as grain production per capita, grain consumption per capita, and grain production capacity. The calculation of the WEF development level is detailed in Equations (1)–(8).

1. Matrix setting. An $n \times m$ matrix A was established based on m evaluation subjects and n evaluation metrics (Equation (1)):

$$A = (x_{ij})_{n \times m} \quad (1)$$

where x_{ij} is the initial value of the i -th indicator in year j ; n is the number of indicators; and m is the number of city-year observations.

2. Data standardization. To eliminate dimensional differences among indicators, the min–max normalization method was applied to all prefecture-level city-year observations in the full panel dataset (2000–2020), ensuring spatial and temporal comparability [26].

Positive indicator:

$$Y_{ij} = \frac{x_{ij} - \min(x_i)}{\max(x_i) - \min(x_i)} \quad (2)$$

Negative indicator:

$$Y_{ij} = \frac{\max(x_i) - x_{ij}}{\max(x_i) - \min(x_i)} \quad (3)$$

where Y_{ij} is the standardized value of the i -th indicator in the j -th year. $Max(x_i)$ and $min(x_i)$ are the uppermost and lowermost values of the i -th indicator, respectively.

3. Weighting calculation. Each indicator's weight was determined by the entropy weight method [17], formulated as follows. A small constant (0.0001) was added to all standardized values before entropy estimation to avoid the zero-value problem in logarithmic transformation. Entropy weights were calculated using the full panel dataset (68 cities $\times$ 5 years = 340 observations) to capture the variability of each indicator across the study period. The resulting weights were fixed over the entire period to ensure temporal comparability of the WEF development index as follows:

$$S_{ij} = \frac{X_{ij}}{\sum_{j=1}^m x_{ij}} \quad (4)$$

$$E_i = -\frac{1}{\ln(m) \sum_{j=1}^m s_{ij} \ln s_{ij}} \quad (5)$$

$$w_i = \frac{1 - E_i}{\sum_{i=1}^n (1 - E_i)} \quad (6)$$

where S_{ij} is the proportion of the i -th indicator in the j -th year; E_i is the entropy value of the i -th indicator; W_i is the weight of the i -th indicator; n is the number of indicators; and m is the number of city-year observations.

4. Derivation of development level. Using an integrated development model (Equation (7)), the development levels of the water, energy, and food sectors were quantitatively evaluated [24]. The WEF development level was then calculated as follows:

$$Z(x) = \sum_{i=1}^n (Y_{ij} \times W_i) \quad (7)$$

$$T = \alpha Z(W) + \beta Z(E) + \gamma Z(F) \quad (8)$$

where $Z(x)$ represents the composite development level of the water (W), energy (E), and food (F) subsystem; Y_{ij} is the normalized value of the i -th indicator in the j -th year; W_i represents the weight of the i -th indicator; and n is the total number of indicators; T is the WEF development level; α , β , and γ denote the weighting factors that quantify the relative significance of the water subsystem, energy subsystem, and food subsystem, respectively ($\alpha + \beta + \gamma = 1$). According to sustainable development theory, the three subsystems are equally important [17,27]; thus, $\alpha = \beta = \gamma = 1/3$. The value of T ranges from 0 to 1, with values closer to 1 indicating higher levels of development.

3.3. Assessment of ESs

This study selected four types of ESs, including water yield (WY), carbon storage (CS), soil conservation (SC), and food production (FP). The calculation methods for each ecosystem service supply are detailed in Table S3.

In this study, the comprehensive ecosystem service level (CES) was determined through overlay analysis of ESs. This index comprehensively reflects the overall supply capacity of multiple ESs and provides a quantitative basis for assessing regional ecosystem benefits [28]. The specific calculation formula is as follows:

$$CES = \frac{1}{4} \times \sum_{i=1}^4 ES_i \quad (9)$$

$$ES_i = \frac{ES_{i,obs} - ES_{i,min}}{ES_{i,max} - ES_{i,min}} \quad (10)$$

where CES represents the comprehensive ecosystem service value; ES_i is the normalized value of ecosystem service i ; $ES_{i,obs}$ is the observed value of ecosystem service i ; and $ES_{i,min}$ and $ES_{i,max}$ are the minimum and maximum values of ecosystem service i , respectively. To avoid introducing subjective bias, this study assumes that the four ES s are equally important [29,30].

3.4. Construction of Spatial Panel Data Model

Before constructing the spatial panel data model, an appropriate spatial weight matrix needs to be defined. This study adopted the Queen contiguity rule to assign the spatial weight matrix [31]. We considered three spatial panel data models: the spatial lag model (SLM), the spatial error model (SEM), and the spatial Durbin model (SDM). The SLM primarily captures the spatial spillover effects of the dependent variable, whereas the SEM reflects the spatial correlation present in the random error term. The SDM incorporates spatial lags of both the dependent and independent variables, representing a general extension of the previous two models [32,33]. The general specification of the SDM is as follows:

$$Y = \rho WY + X\beta + \theta WX + \epsilon \quad (11)$$

where Y and X denote the dependent variable matrix and independent variable matrix, respectively; W represents the spatial weight matrix; β is the regression coefficient of independent variables, measuring the direct impact of local independent variables on the dependent variable; ρ refers to the spatial autoregressive coefficient of the dependent variable; θ is the spatial lag coefficient of independent variables, which is used to measure the spillover effect of independent variables in adjacent regions on the local dependent variable; and ϵ denotes the random error term.

This study adopted the Lagrange Multiplier (LM) test, Wald test, Likelihood Ratio (LR) test and Hausman test to select the spatial econometric model. Using the Queen contiguity matrix, all LM and robust LM tests were significant at the 1% level, indicating significant spatial correlation in the dataset. Accordingly, the SDM was initially selected. The Wald and LR tests were significant at the 5% level, which verifies that the SDM cannot be degraded into the spatial lag model or the spatial error model. The Hausman test statistic was 159.73 and significant at the 1% level, which finally determines the adoption of the fixed-effects SDM (Table 2).

Table 2. Results of spatial econometric model.

Test Category		Eigenvalue
LM test	LM-error	12.81 ***
	Robust LM-error	19.44 ***
	LM-lag	16.36 ***
	Robust LM-lag	14.99 ***
Wald test	Wald-lag	22.11 **
	Wald-error	22.11 **
LR test	LR-lag	20.69 **
	LR-error	20.81 **
Hausman test		159.73 ***

Note: *** and ** indicate statistical significance at the 0.01 and 0.05 levels, respectively.

3.5. Decomposition of Spatial Effects

Because the regression coefficients in the SDM do not directly reflect the marginal effects of independent variables on the dependent variable, this study used the partial differentiation matrix approach proposed by LeSage and Pace [32] to decompose the spatial

effects of multiple ESs on WEF development level into direct, indirect, and total effects [34]. The direct effect is the average of the diagonal elements of the spatial impact matrix (Equation (12)). The indirect effect is the average row sum of the off-diagonal elements (Equation (13)). The total effect is the sum of the direct and indirect effects (Equation (14)):

$$DE = \left\{ \left(I - \rho W \right)^{-1} \times (\beta_n I + \theta_n W) \right\}^{\bar{d}} \quad (12)$$

$$IE = \left\{ \left(I - \rho W \right)^{-1} \times (\beta_n I + \theta_n W) \right\}^{\overline{rsum}} \quad (13)$$

$$TE = DE + IE \quad (14)$$

where DE , IE , and TE denote the direct, indirect, and total effects, respectively; β and θ are estimated parameters; I is the identity matrix; W is the spatial weight matrix; and $\bar{d}$ and $\overline{rsum}$ represent the row means of the diagonal and off-diagonal elements of the matrix, respectively.

3.6. Geographically and Temporally Weighted Regression

The geographically and temporally weighted regression (GTWR) model, extended from the classical geographically weighted regression (GWR) model by Huang et al. [35], incorporates the temporal dimension to form a local spatial econometric model with spatiotemporal dependence. This model effectively handles spatiotemporal non-stationarity in variable relationships and reveals their spatiotemporal evolution characteristics [36]. By integrating both temporal and spatial dimensions, the GTWR model effectively addresses the potential bias arising from the absence of the temporal dimension in the GWR model [37]. Given the spatiotemporal heterogeneity in the effects of multiple ESs on WEF development level observed in this study, it is necessary to adopt the GTWR model to reveal the relationship between them from both temporal and spatial dimensions. The calculation procedure of the GTWR model is as follows:

$$y_i = \beta_0(u_i, v_i, t_i) + \sum_{k=1}^p \beta_k(u_i, v_i, t_i) X_{ik} + \varepsilon_i \quad (15)$$

where (u_i, v_i, t_i) represents the spatiotemporal location of the i -th prefecture-level city in year t ; $\beta_k(u_i, v_i, t_i)$ is the regression coefficient of the k -th independent variable for the i -th spatiotemporal unit; and X_{ik} and ε_i are the independent variables and the error term of the model, respectively.

An adaptive Gaussian kernel function was used in the estimation, and the optimal bandwidth was selected based on the corrected Akaike Information Criterion (AICc), following the default settings of the GTWR plugin in ArcGIS 10.8. The search range for bandwidth was 0.1–2.0, and the optimal spatiotemporal bandwidth selected by the model was 1.58, with a corresponding temporal scaling parameter of 0.85. The spatiotemporal distance metric combined spatial (Euclidean) and temporal distances using a scale factor to balance the two dimensions, with temporal scaling optimized during bandwidth selection. All variables were standardized prior to estimation. Spatial coordinates were projected using the Albers Equal Area Conic projection to ensure consistency in distance measurement across the study area. Local multicollinearity was diagnosed using variance inflation factors, and no severe multicollinearity was detected.

This study classifies the regression coefficients into six categories: strongly positive (>1), moderately positive (0.5–1), weakly positive (0–0.5), weakly negative (−0.5–0), moderately negative (−1–−0.5), and strongly negative (<-1). It should be noted that this

classification is descriptive and used only to facilitate visualization of spatial heterogeneity rather than statistical inference.

4. Results

4.1. Spatial-Temporal Evolution of WEF Development Level

At the basin scale, the development levels of the water, energy, and food subsystems, as well as the WEF development level, increased by 10.2%, 10.0%, 13.8%, and 11.2%, respectively (Figure 3). Spatially, the highest average development level of the water subsystem was observed in the UYRB (0.37), the energy subsystem performed best in the MYRB (0.64), and the DYRB ranked first in both the food subsystem (0.49) and the overall WEF development level (0.48), followed by the MYRB (0.46) and the UYRB (0.44) (Figure 3). These results indicate that the DYRB holds a comparative advantage in coordinated development. At the prefectural level, marked spatial heterogeneity was observed. In the UYRB, Yushu Prefecture (Qinghai Province) and Guoluo Prefecture (Qinghai) recorded the highest values (above 0.50), while Haixi Prefecture (Qinghai), Alxa League (Inner Mongolia Autonomous Region), and Yinchuan City (Ningxia Hui Autonomous Region) recorded the lowest (below 0.42). In the MYRB, Yuncheng City (Shanxi Province) achieved the highest value (0.53), whereas Yulin City (Shaanxi Province) and Yan'an City (Shaanxi) recorded lower values (below 0.44). In the DYRB, Dezhou City (Shandong Province), Liaocheng City (Shandong), Heze City (Shandong), and Jining City (Shandong) exhibited the highest values (above 0.55), while Zhengzhou City (Henan Province) and Luoyang City (Henan) showed relatively lower values (around 0.45–0.50).

4.2. Spatial-Temporal Evolution of ESs

During the study period, the CES of the YRB increased from 0.32 to 0.42, indicating an overall improvement in ecosystem provision (Figure 4). Among the four ESs, water yield and soil conservation capacity exhibited a rise-decline-rise trend, reaching a maximum in 2020 (96.51 mm and 538.23 t/ha). Carbon storage showed a slight downward trend, reaching a minimum in 2020 (61.33 t/ha). Food production showed a continuously increasing trend, reaching a maximum in 2020 (4.02 t/ha) (Figure 4). Spatially, the DYRB had the highest water yield and food production, at 129.20 mm and 3.18 t/ha, respectively. The MYRB had the highest carbon storage and soil conservation, at 71.68 t/ha and 677.99 t/ha, respectively (Figure 4). Overall, the comprehensive ESs in the UYRB were significantly lower than those in the MYRB and DYRB (Figure 4). At the prefectural level, pronounced heterogeneities were observed. In the UYRB, Gannan Tibetan Autonomous Prefecture (Gansu Province), Aba Tibetan and Qiang Autonomous Prefecture (Sichuan Province), and Longnan City (Gansu) recorded the highest CES values (above 0.70), while Haixi Mongolian and Tibetan Autonomous Prefecture (Qinghai Province), Alxa League (Inner Mongolia Autonomous Region), and Wuhai City (Inner Mongolia) recorded the lowest (below 0.15). In the MYRB, Shangluo City (Shaanxi Province) achieved the highest value (above 0.70), followed by Baoji City (Shaanxi) and Xi'an City (Shaanxi) (above 0.55); Yulin City (Shaanxi) and Yan'an City (Shaanxi) showed lower values (below 0.35) but exhibited increasing trends. In the DYRB, Luoyang City (Henan Province) and Sanmenxia City (Henan) recorded the highest values (above 0.55), whereas most cities in Shandong Province, including Dezhou City (Shandong), Liaocheng City (Shandong), Binzhou City (Shandong), and Dongying City (Shandong), exhibited low values (below 0.40).

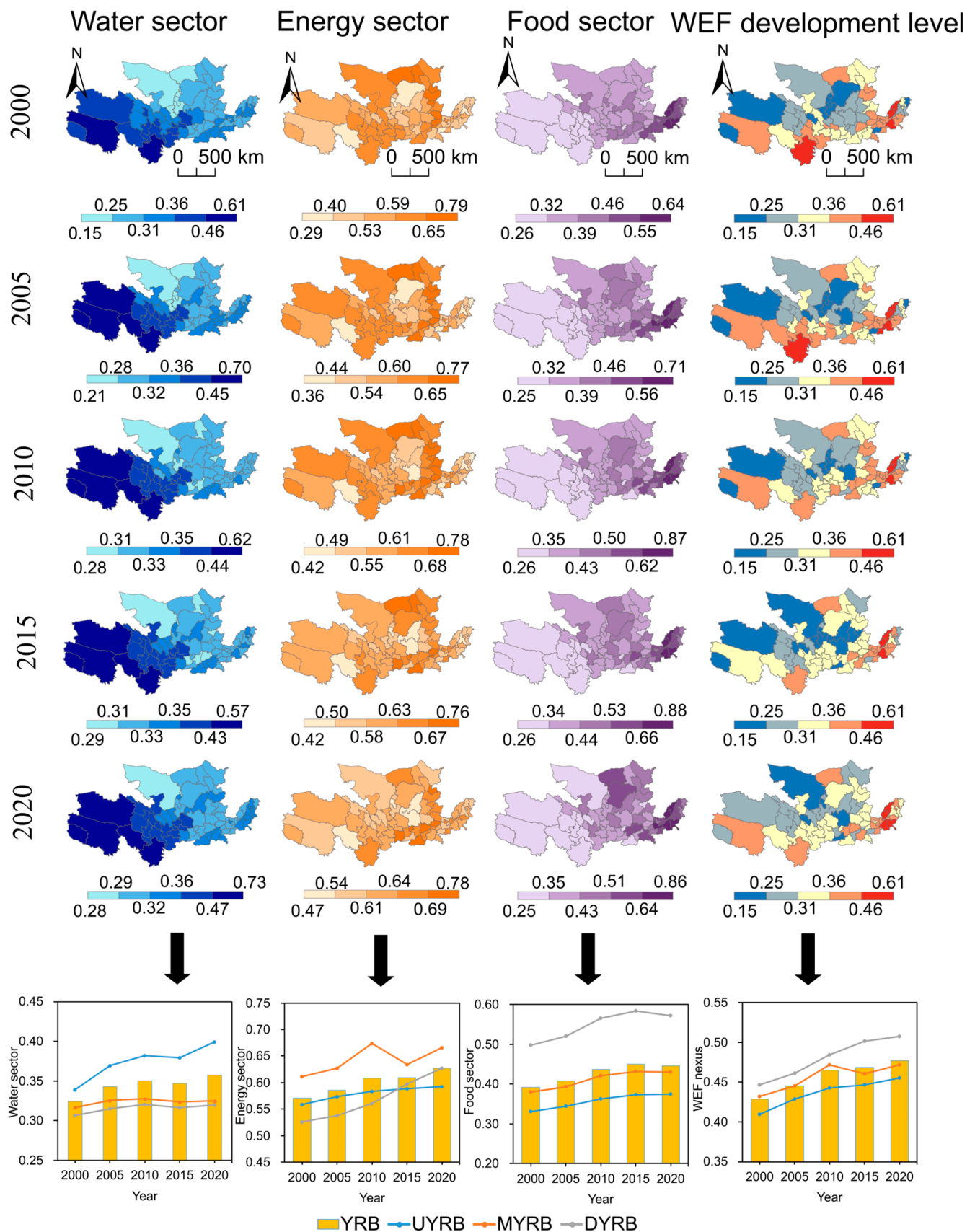


Figure 3. Development levels of three sectors and WEF development level in the Yellow River Basin from 2000 to 2020. Color scales are year-specific, and the minimum and maximum values of each color bar correspond to the observed minimum and maximum values for that sector in that year.

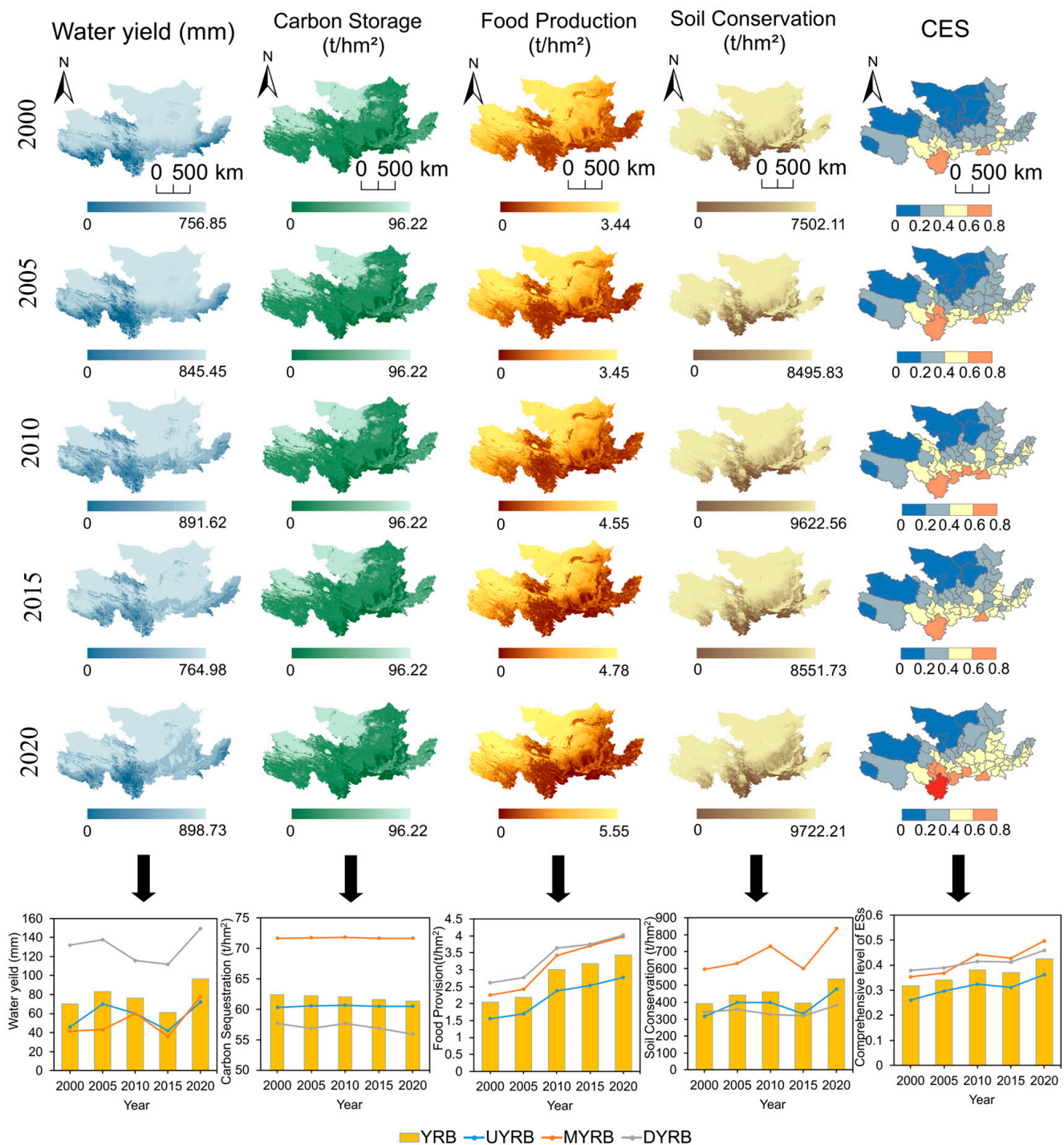


Figure 4. Spatial–temporal pattern of ESs in the Yellow River Basin from 2000 to 2020. Color scales are year-specific, and the minimum and maximum values of each color bar correspond to the observed minimum and maximum values for that sector in that year.

4.3. The Global Spatial Effects of ESs on the WEF Development Level

The SDM results revealed significant differences in the direct, spillover, and total effects of individual ESs on WEF development (Table 3). Direct effect results showed that carbon storage, water yield, and food production have significant positive effects on WEF development level, with carbon storage exhibiting the largest direct effect coefficient (0.29). Specifically, a one-unit increase in normalized carbon storage was associated with a 0.29-unit increase in the WEF development index. Regarding indirect effects, carbon storage and soil conservation exhibited significant positive spatial spillover effects, with

coefficients of 0.89 and 0.20, respectively, thereby being positively associated with the WEF development level of adjacent regions (Table 3). Conversely, water yield and food production show negative indirect effects (−0.13 and −0.32), which are negatively associated with development level in neighboring regions. Total effect results indicated that carbon storage and soil conservation were positively associated with the overall WEF development level in the YRB, with total effect coefficients of 1.18 and 0.14 (Table 3). In contrast, water yield exhibited weak inhibitory effects, with a coefficient of −0.06 (Table 3). Overall, carbon storage was the most strongly associated factor with WEF development level in the basin, with a notable contribution from spatial spillover effects. To test robustness, we replaced the Queen contiguity matrix with an inverse-distance spatial weight matrix and re-estimated the SDM (Table S7). The significance, sign, and relative magnitude of the main results remained largely consistent with Table 3, confirming the robustness of our model. However, it should be noted that the total effect of water yield shifted from −0.06 ($p < 0.05$) under Queen contiguity to 0.07 ($p < 0.05$) under inverse-distance weighting. While the sign reversed, the magnitude remained very small in both specifications, indicating that water yield's overall influence on WEF development is weak regardless of the spatial weight matrix choice. This sign reversal does not affect our core conclusion that carbon storage is the dominant associated factor.

Table 3. Decomposition results of spatial effects for SDM.

Spatial Decomposition Effect	Water Yield	Carbon Storage	Food Production	Soil Conservation
Direct effect	0.07 ***	0.29 **	0.24 ***	−0.06
Indirect effect	−0.13 ***	0.89 ***	−0.32 ***	0.20 ***
Total effect	−0.06 **	1.18 ***	−0.08	0.14 **

Note: *** and ** indicate statistical significance at the 0.01 and 0.05 levels, respectively.

4.4. The Local Spatiotemporal Heterogeneity of ESs on the WEF Development Level

4.4.1. Model Comparison

To identify the optimal model, we compared the fitting performance of ordinary least squares (OLS), GWR, and GTWR (Table 4), using the corrected Akaike information criterion (AICc), residual sum of squares (RSS), and the coefficient of determination (R^2) as evaluation metrics. Although GWR and GTWR yielded the same R^2 value, GTWR produced lower AICc and RSS values, indicating higher fitting accuracy and smaller error after incorporating the temporal dimension (Table 4). Therefore, GTWR was selected for subsequent spatiotemporal heterogeneity analysis. To further assess the adequacy of the GTWR model specification, we performed Moran's I tests on the model residuals for each year from 2000 to 2020. The results (Table S8) indicate that residual spatial autocorrelation was not significant at the 5% level for all five tested years, although the 2020 result was marginal ($p = 0.055$), confirming that the GTWR model effectively captured the spatial structure in the data.

Table 4. Comparison indicators of model fitting results.

Model	AICc	R^2	RSS
OLS	−974.28	0.56	1.10
GWR	−1503.95	0.86	0.24
GTWR	−1639.82	0.86	0.16

4.4.2. Spatially Heterogeneous Responses

The interactions between the WEF development level and four ESs in the YRB exhibited significant spatiotemporal heterogeneity (Figure 5). The associations between the WEF development level and water yield services showed clear regional differentiation. Northern Shaanxi and Shanxi provinces exhibited consistently strong positive associations, western Inner Mongolia Autonomous Region showed persistently strong negative associations, while Gansu and Qinghai provinces were mostly characterized by weak positive or weak negative associations (Figure 5). For carbon storage, no strong associations were observed across the basin. Most regions, including Shanxi, Shaanxi, and Henan provinces, showed persistent weak positive associations, whereas parts of Shandong Province and Inner Mongolia Autonomous Region exhibited weak negative associations (Figure 5). Regional differences were particularly pronounced for food production services. Eastern Shandong Province experienced strong positive associations, while southern Shanxi and western Henan provinces showed moderate negative associations, with the remaining areas exhibiting weak associations (Figure 5). For soil conservation services, strong positive associations were found in western Inner Mongolia Autonomous Region and parts of Qinghai Province, whereas strong negative associations occurred in eastern Shandong and Henan provinces (Figure 5). Overall, significant heterogeneity was confined to localized areas within the YRB, whereas most areas exhibited weak responses across ESs.

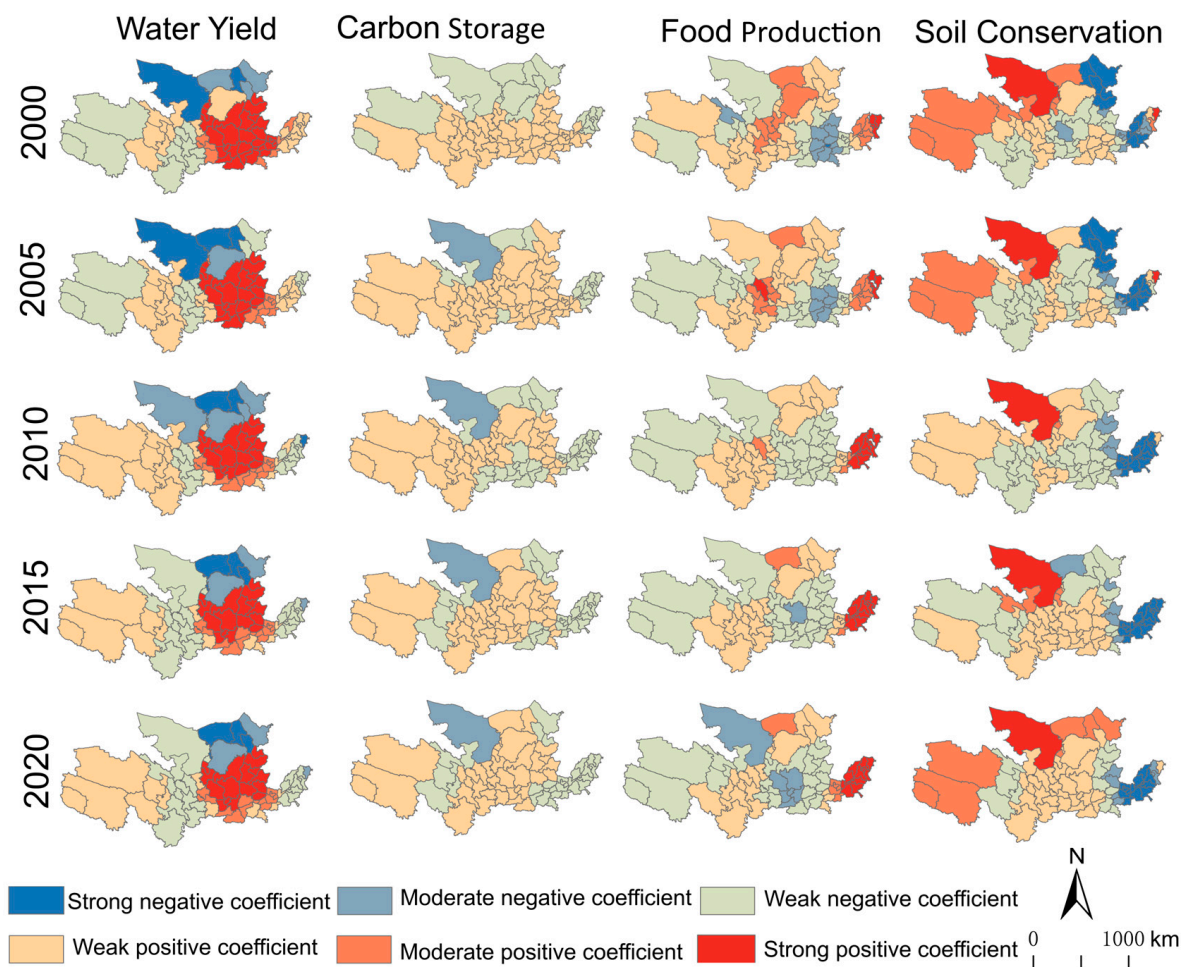


Figure 5. Spatial distribution of regression coefficients for relationships between the WEF development level and ESs in 2000–2020. Coefficient classes are defined as strong positive (>1.0), moderate positive ($0.5–1.0$), weak positive ($0–0.5$), weak negative ($–0.5–0$), moderate negative ($–1.0––0.5$), and strong negative ($<–1.0$).

4.4.3. Temporally Heterogeneous Responses

From 2000 to 2020, the mean regression coefficients between the WEF development level and the four ESs in the YRB exhibited distinct temporal trends (Figure 6). The coefficient for water yield decreased from 0.71 to 0.02, indicating a markedly weakened positive association (Figure 6a). For carbon storage, the coefficient fluctuated downward from 0.045 to -0.01 , shifting from positive to negative (Figure 6b). Food production showed an increase from 0.10 to 0.20, reflecting a steady but weak positive association (Figure 6c). The coefficient for soil conservation first dropped to -0.50 in 2015 before rising to -0.25 in 2020, indicating a negative association that intensified then lessened, remaining inhibitory overall (Figure 6d). Overall, the four associations remained weak throughout the study period, with clear differentiation only in their direction and temporal trends.

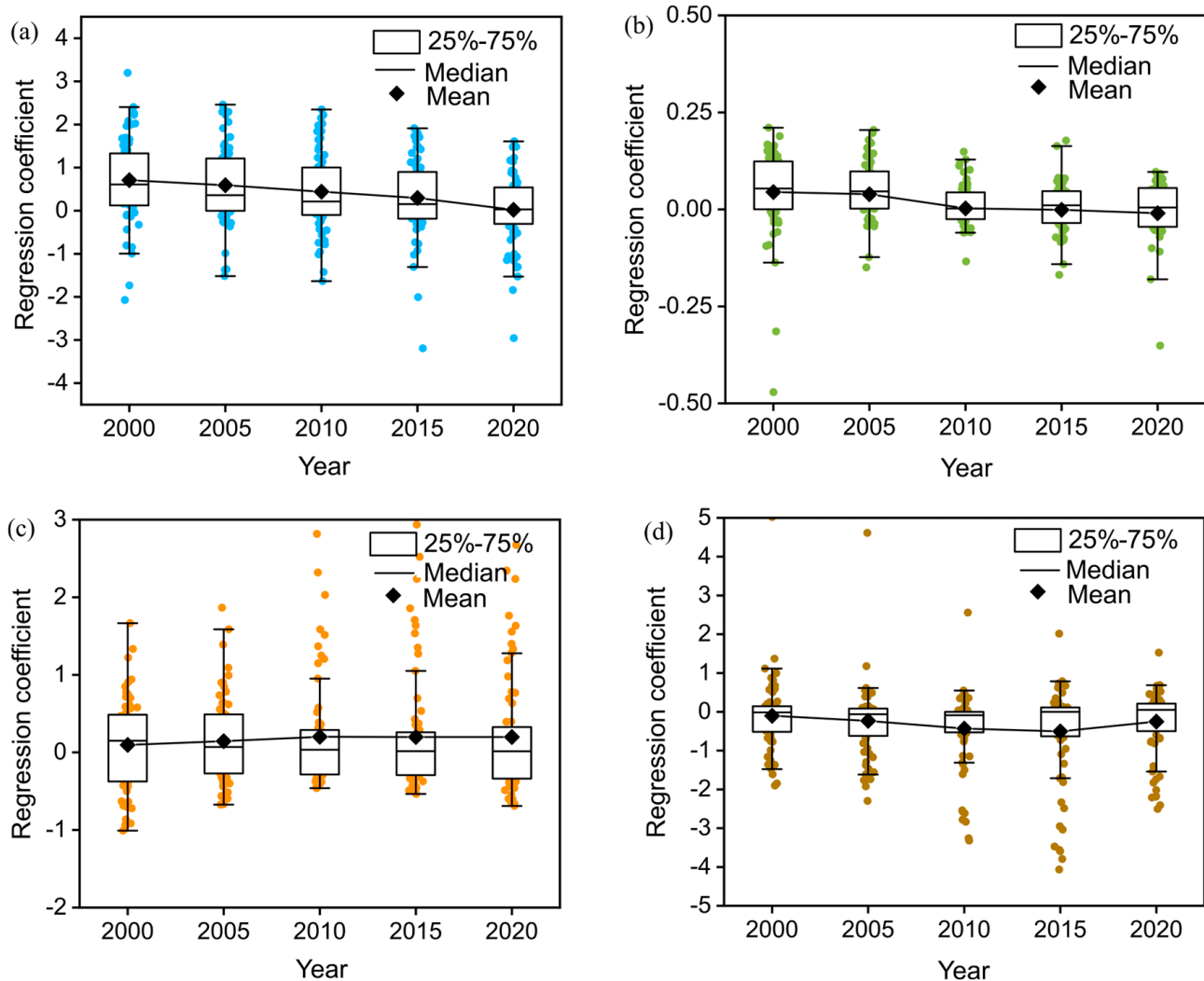


Figure 6. Box plot of the distribution of regression coefficients for relationships between the WEF development level and the four ESs: (a) water yield, (b) carbon storage, (c) food production, and (d) soil conservation.

5. Discussion

5.1. The Dominant Role of Carbon Storage in Global Spatial Effects

Among the four ESs, water yield, carbon storage, and food production exhibited significant direct positive associations with the WEF development level. Notably, carbon storage showed the largest direct coefficient, indicating that climate-regulating ecosystem functions provide stronger support for coordinated WEF development than other ESs. This finding

can be attributed to both ecological characteristics of the YRB and the multifunctional benefits associated with carbon storage. Extensive forests and grasslands, which are major carbon-storing land cover types, accounted for 73.38% of the basin area in 2020 [38]. This extensive carbon sink base not only enhances regional carbon storage but also improves ecosystem resilience, vegetation productivity, hydrological regulation capacity, and soil stability. Together, carbon storage is statistically associated with water security, agricultural sustainability, and ecological protection, thereby providing multiple co-benefits for the coordinated development of water, energy, and food systems.

More importantly, carbon storage exhibited the largest total effect and a significant positive spillover effect. This suggests that the benefits of ecosystem restoration are extended beyond individual administrative units and generate positive impacts on neighboring regions through ecological connectivity. Large-scale ecological restoration projects in the YRB, such as the Grain for Green Program and vegetation rehabilitation initiatives, have increased vegetation coverage and carbon storage across extensive areas [39]. Previous studies have mainly emphasized the ecological consequences of vegetation restoration or the interregional transfer of ecosystem service benefits [40]. Building upon these findings, this study further demonstrates that these cross-regional ecological processes translate into measurable spatial spillover effects on the development level. This finding extends current understanding of ES-WEF interactions by revealing that carbon-related ecosystem functions can be associated with basin-scale benefits beyond local ecological improvement.

However, the decomposition results revealed more complex spatial interactions for other ESs. Soil conservation showed a negative but non-significant direct effect and a significant positive spillover effect, suggesting that its benefits may be mainly transmitted across regions rather than immediately reflected locally. This may be because soil conservation in upstream erosion-prone areas can reduce sediment transport and improve downstream ecological conditions through hydrological connectivity [41]. Food production exhibited a significant positive direct effect but a significant negative indirect effect, resulting in a non-significant total effect. This indicates that agricultural improvement may benefit local WEF development while generating pressures on neighboring regions [42,43]. Increasing food production likely requires additional water, energy, and land inputs, which may intensify resource competition within the basin. However, this explanation should be regarded as a potential mechanism because interregional resource flows were not directly quantified in this study. Similarly, water yield showed a significant positive direct effect but a significant negative indirect effect. Increased water availability can alleviate local resource constraints, whereas its negative spillover effect may reflect competition for limited water resources among connected regions. Given the complex upstream–downstream hydrological relationships in the YRB, further hydrological analyses are needed to confirm this spatial transmission mechanism.

Overall, priority should be given to enhancing carbon storage through ecological restoration measures such as forest management, grassland improvement, and vegetation rehabilitation. At the same time, region-specific strategies should be adopted to improve soil conservation and optimize agricultural resource allocation, thereby promoting more balanced and sustainable development of the WEF development level across the YRB.

5.2. Local Spatiotemporal Heterogeneity of ESs on the WEF Development Level

Global spatial associations revealed average influences but failed to capture regional differences. Our GTWR results showed significant spatial heterogeneity in the associations of the four ESs. Water yield showed clear regional differentiation. Northern Shaanxi Province and Shanxi Province exhibited persistently strong positive associations, where high marginal benefits alleviated water scarcity on the Loess Plateau. Gansu and Qinghai

provinces showed weak positive or negative associations, reflecting abundant upstream water endowments and flattening marginal benefits. Western Inner Mongolia Autonomous Region exhibited strong negative associations, possibly due to unique ecological responses in arid desert regions, and it needs further investigation. Although the basin-wide mean coefficient of water yield declined from 0.71 to 0.02 during 2000–2020, strong positive associations persisted in northern Shaanxi and Shanxi. This suggested that the declining average does not reflect a uniform weakening across the basin, but rather increasing spatial differentiation, with positive associations concentrated in water-scarce regions and weaker or negative associations occurring elsewhere. Carbon storage showed no strong associations basin-wide. Most regions exhibit weak positive associations, whereas parts of Shandong Province and Inner Mongolia Autonomous Region showed weak negative associations, likely due to soil carbon loss caused by intensive agriculture, which undermines the service's positive contribution to the WEF development level. In eastern Shandong Province, food production showed a strong positive association with the WEF development level, benefiting from favorable irrigation conditions and advanced agricultural technologies that create efficient synergies [44]. In contrast, southern Shanxi and western Henan provinces exhibited moderate negative associations. In these hilly rain-fed areas, the mismatch between water and land resources implied that expanding food production may come at the cost of ecological water use. Soil conservation showed strong positive associations in western Inner Mongolia Autonomous Region and parts of Qinghai Province, where rugged terrain and high erosion risk give soil conservation high marginal ecological value in preventing desertification. Conversely, eastern Shandong and Henan provinces showed moderate to strong negative associations. These patterns may reflect soil degradation associated with intensive agricultural practices.

5.3. Policy and Management Implications

Based on the identified spatially heterogeneous relationships between ESs and the WEF development level in the YRB, several targeted policy and management implications are proposed to support the sustainable development of the basin's WEF development level.

- (1) Given the spatial variability of water yield services, water-deficient areas such as northern Shaanxi Province and Shanxi Province should prioritize optimized water allocation and efficient irrigation to relieve supply–demand pressure. In contrast, upstream water conservation areas should focus on maintaining ecological water quantity and quality to sustain stable hydrological and ecosystem functions.
- (2) Carbon storage is the most strongly associated factor for WEF development level sustainability. Ecological restoration measures, sustainable forest management, grassland improvement, and the Grain-for-Green program could be considered to consolidate the carbon sink, stabilize ecosystem functions, and improve the efficiency of regional resource cycling and allocation.
- (3) Hilly rain-fed areas such as southern Shanxi Province and western Henan Province are severely constrained by water–land resource mismatches. Advanced agricultural technologies and water-saving irrigation practices should be promoted to balance grain productivity improvement and ecological protection, to ensure coordinated development of agricultural production and WEF development level.
- (4) In upstream desertification-prone regions and middle–lower reaches under high soil erosion risk, intensified vegetation restoration and soil conservation engineering are necessary. Stricter regulation of excessive reclamation and irrational irrigation can effectively reduce human-induced soil degradation and enhance basin-scale ecological resilience.

- (5) Considering the widespread spatial heterogeneity of ESs associations, uniform basin-wide management should be replaced by region-specific tailored strategies. Optimizing spatial resource allocation and improving ecological compensation mechanisms would further enhance the WEF development level.

5.4. Limitations and Future Research

Several limitations should be acknowledged. First, entropy weights are confined by data variability, and the ES index adopts equal weights for the four services. Although both are common practices in WEF and ES assessments, alternative schemes could be explored in future research. Second, the prefecture-level analysis and spatial weight matrix may not fully capture fine-scale ecological processes and cross-regional ecosystem service flows. Future research could incorporate finer spatial units and hydrological connectivity-based approaches. Third, the GTWR model identifies spatiotemporal associations rather than causal mechanisms. Due to potential omitted variable bias, our results should be interpreted as spatial correlations, not independent causal effects. Future studies could integrate causal inference methods and the context of climate and land-use scenarios to better understand WEF–ESs interactions.

6. Conclusions

This study systematically investigated the spatial associations of four ESs—water yield, carbon storage, food production, and soil conservation—on the WEF development level in the YRB from 2000 to 2020. The main results are as follows: (1) Significant improvement in both the WEF development level and ESs occurred during the study period, though persistent spatial disparities highlight the uneven distribution of resource endowments and ecological conditions across the basin. (2) At the basin scale, carbon storage exhibits the largest direct effect (0.29) and a substantial positive spillover effect (0.89), making it the most important factor associated with WEF development level in the YRB. In contrast, water yield and food production show negative indirect associations, indicating cross-regional resource competition. (3) The associations of ESs on the WEF development level were highly location-dependent, revealing both positive synergies (e.g., water yield in northern Shaanxi and Shanxi provinces) and negative trade-offs (e.g., water yield in western Inner Mongolia Autonomous Region and food production in southern Shanxi and western Henan provinces). These spatially varying relationships suggest that uniform management approaches may be ineffective, and that enhancing carbon storage, along with differentiated water management and targeted soil conservation, may be a promising strategy for strengthening the WEF development level in the YRB.

Supplementary Materials: The following supporting information can be downloaded at <https://www.mdpi.com/article/10.3390/su18157653/s1>, Table S1: Administrative divisions of the study area: Cities and provinces in the upper, middle, and lower reaches of the Yellow River Basin; Table S2: The indicator system of WEF development level; Table S3: Methods for evaluating supply of ESs; Table S4: Parameterization of InVEST water yield module; Table S5: Carbon pool values by land-use type ($t \cdot hm^{-2}$); Table S6: RUSLE factor derivation for soil conservation; Table S7: SDM decomposition results using inverse-distance spatial weight matrix; Table S8: Moran's I test results for GTWR residuals (2000–2020). Refs. [45–49] were cited in Supplementary Materials.

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