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Spatiotemporal Variations in Gross Ecosystem Product and Its Relationship with Economic Growth in Ecologically Vulnerable Watershed Areas: A Case Study of Yongding River Basin

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Abstract: Ecosystem service value is crucial for balancing economic growth and ecological preservation in ecologically vulnerable watershed areas. Although Gross Ecosystem Product (GEP) has received significant attention, most existing studies have focused on how to measure it. Few studies have explored spatiotemporal variations in GEP and how land-use changes affect these variations regarding ecological restoration at the river basin level. Additionally, while many studies have examined the relationship between ecosystem service value and economic growth, there is little research on how components of GEP influence economic growth. Analyzing the spatiotemporal structure of GEP and its components could offer new insights into optimizing ecological restoration strategies and promoting sustainable development in vulnerable watershed regions. In this study, we used ArcGIS, InVEST, SPSS, and Python to analyze spatiotemporal variations in GEP in the Yongding River Basin within the Beijing–Tianjin–Hebei Economic Region from 1995 to 2020. Moran's Index and variance decomposition were applied to analyze the spatiotemporal structure. The grey prediction model forecasted GEP trends from 2025 to 2035. The random forest model was used to assess land-use changes' impacts on GEP. Paired T-tests were used to compare GEP and GDP, and a dynamic panel model was used to examine how ecosystem service value factors influenced economic growth. The results show the following: (1) Regarding values, GEP accounting and variance decomposition results indicated that ecosystem cultural service value (ECV) and ecosystem regulating service value (ERV) each contributed about half of the total GEP. Ecosystem provisioning service value (EPV) showed an upward trend with fluctuations. Regarding the spatial distribution, Moran's I analysis showed significant positive spatial correlations for EPV and ERV. The grey prediction model results indicated significant growth in GEP from 2025 to 2035 under current ecological restoration policies, especially for ERV and ECV. (2) In terms of the influence of land-use changes, random forest analysis showed that the forest land area was consistently the most influential factor across GEP, EPV, and ERV. Unused land area was identified as the most significant factor for ECV. (3) Before 2010, GEP was larger than GDP, with significant differences between 1995 and 2000. From 2010 onwards, GDP surpassed GEP, but the differences were not statistically significant. Dynamic panel regression further showed that the water conservation value significantly boosted GDP, whereas the water purification value significantly reduced it. This study highlights the importance of integrating GEP into ecological restoration and economic development to ensure the sustainability of ecologically vulnerable watershed areas.

Keywords: ecosystem service value (ESV); Gross Ecosystem Product (GEP); river basin; sustainability

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1. Introduction

Ecosystem product value realization, a concept introduced by the Chinese government, concerns turning ecosystem products into economic gains. This process plays a crucial role in achieving carbon peaking and carbon neutrality goals. Ecosystem product value

realization can be achieved through industrial development, market transactions, financial backing, government regulation, and social engagement [1–3]. Ecosystem product value realization addresses not only ecological value but also economic and social considerations [3,4]. By converting ecological benefits into economic gains, it helps balance economic growth, environmental protection, and social well-being.

Ecosystem product value realization is based on Gross Ecosystem Product (GEP), a concept that is similar to ecosystem service value (ESV). Coordinating product value realization and economic development is crucial for local policymakers, human well-being, and sustainable development [4–7]. GEP includes ecosystem provisioning service value (EPV), ecosystem regulating service value (ERV), and ecosystem cultural service value (ECV) [1–3]. By assessing different ecosystem services in ecologically vulnerable watershed areas, stakeholders can make more informed decisions. Quantifying the GEPs of ecologically vulnerable river basins and understanding their synergistic effects on ecological restoration are crucial. However, few studies have focused on dynamic changes in GEP related to the ecological restoration of degraded river basin ecosystems. This study addresses this gap by providing a comprehensive analysis of how GEP evolves in response to ecological restoration efforts, offering new insights for sustainable watershed area management.

Land-use management impacts various ecosystem service values [8]. Changes in land use can impact water regulation by affecting the natural flow and filtration of water bodies [7,9,10]. Carbon sequestration can also be influenced by altering vegetation cover, crucial for capturing and storing carbon dioxide [9–11]. Additionally, land-use practices affect biodiversity by preserving natural habitats. Programs like Grain-for-Green shift ecosystem service trade-offs and highlight the importance of land management strategies, showing how land-use changes shape ecosystem service dynamics [7,9–15]. However, few studies have examined how different land-use changes influence the spatiotemporal structures of GEPs in ecologically vulnerable river basin areas. This study addresses this gap by providing a detailed analysis of the impact of land-use changes on GEP in vulnerable watershed areas.

To balance ecological restoration and economic development, scholars have previously studied spatiotemporal variations in ESV and its relationship with economic growth [4,16,17]. As for carbon management, components of ESV highlight a growing emphasis on sustainability by focusing on activities like afforestation, forest conservation, wetland restoration, and sustainable agricultural practices to enhance carbon sequestration and reduce emissions [18–21]. Scholars have explored certain plants that support ESV through biomass conversion via photosynthesis, providing a cost-effective way to reduce fossil fuel emissions and meet climate goals. In drylands, precipitation's crucial role in vegetation productivity underscores the need for an adequate water supply to optimize biomass production and enhance these ecological services. This approach involves implementing efficient water management practices, such as rainwater harvesting and sustainable irrigation techniques [22–25]. Other scholars found that water conservation is essential for mitigating environmental degradation. By implementing ecological strategies, such as efficient irrigation systems, rainwater harvesting, and the restoration of natural water bodies, it is possible to preserve water resources, reduce soil erosion, and maintain healthy ecosystems [26–28]. In addition, cultural services offer a comprehensive perspective on ESV by prioritizing recreational opportunities, aesthetic enjoyment, spiritual enrichment, and educational experiences [29]. However, the link between specific GEP values and economic development in vulnerable watershed areas remains underexplored. This research specifically addresses this relationship, providing a deeper understanding of how specific ecosystem service values can influence economic development in vulnerable watershed areas.

The Yongding River Basin, renowned for its diverse terrain, economic importance, and remarkable ecological restoration outcomes, was chosen as a location for studying the link between GEP and economic development within a basin. This study aims to (1) examine

changes in the EPV, ERV, and ECV of GEP; (2) analyze the impacts of land-use changes on these values; and (3) identify key GEP factors affecting economic growth. The logical framework of this study is shown in Figure 1.

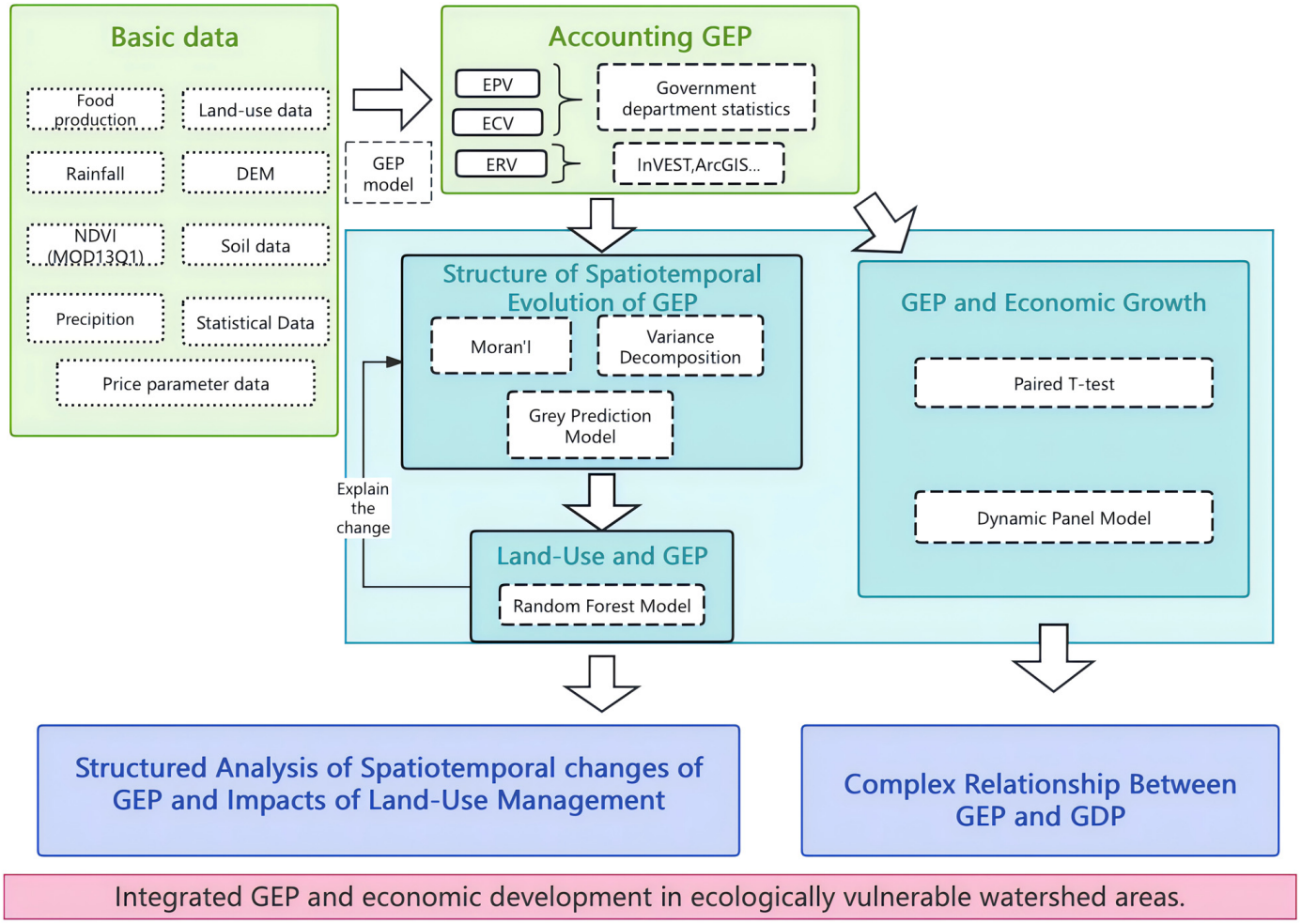


Figure 1. Logical framework of this study.

2. Materials and Methods

2.1. Study Area

The Yongding River Basin, located between 112° E–117°45′ E and 39° N–41°20′ N, spans the regions of Beijing, Tianjin, Hebei, Shanxi, and Inner Mongolia, covering an area of approximately 47,000 km^2. Originating in Ningwu County in Shanxi and Xinghe County in Inner Mongolia, it is the longest river flowing through Beijing and considered the cradle of Chinese civilization. Flowing through the Beijing–Tianjin–Hebei Economic Region, the river has faced challenges related to China's economic development, including frequent floods, water shortages, ecological damage, and pollution. Thanks to gradual management efforts, the river basin's ecological quality has steadily improved. The study area is shown in Figure 2.

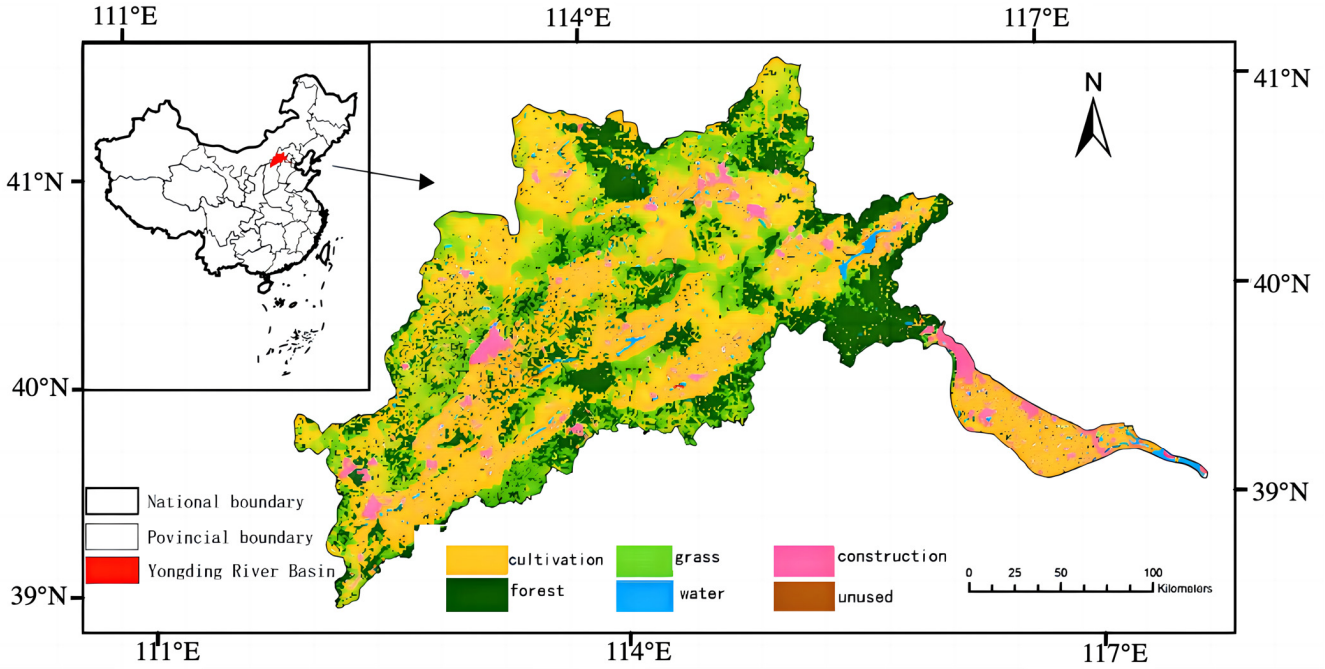


Figure 2. Study area: the Yongding River Basin.

2.2. Data Acquisition and Source Integration

The datasets used for the environmental assessment were selected to provide a comprehensive view of ecosystem services. Data on food production, soil conservation, water retention, carbon storage, and socioeconomic factors were gathered from various sources, including statistical yearbooks, meteorological centers, soil databases, and national departments (Table 1).

Table 1. Data source.

Dataset Name	Data Source
Food production (grain, meat, milk, etc.)	Statistical Yearbook for Regional Economy in China, Development Yearbook in Gansu Province, and Rural Statistical Yearbook in Gansu Province
Land-use data	China Ecosystem Assessment and Ecological Security Database http://www.ecosystem.csdb.cn/ (accessed on May–July 2023)
Monthly and annual rainfall	National Meteorological Information Center (http://data.cma.cn/) (accessed on May–July 2023)
DEM	United States Geological Survey (http://glovis.usgs.gov/) (accessed on May–July 2023)
Soil data (sand, silt, clay, organic carbon content, etc.)	Scientific Data Center for Cold and Arid Regions (http://westdc.westgis.ac.cn/) (accessed on May–July 2023)
NDVI (MOD13Q1)	Level 1 and Atmosphere Archive and Distribution System (https://ladsweb.nascom.nasa.gov/search/) (accessed on May–July 2023)
Meteorological data such as temperature, rainfall, actual water pressure, and so on	National Meteorological Information Center (http://data.cma.cn/) (accessed on May–July 2023)
DEM	United States Geological Survey (http://glovis.usgs.gov/) (accessed on May–July 2023)
Soil depth, soil type, and root data	National Earth System Science Data Sharing Infrastructure (http://www.geodata.cn/) (accessed on May–July 2023)
Soil data (sand, silt, clay, etc.)	Scientific Data Center for Cold and Arid Regions (http://westdc.westgis.ac.cn/) (accessed on May–July 2023)
Soil depth and soil type	National Earth System Science Data Sharing Infrastructure (http://www.geodata.cn/) (accessed on May–July 2023)
Volume weight of soil, organic carbon, soil thickness, and gravel percentage	Scientific Data Center for Cold and Arid Regions (http://westdc.westgis.ac.cn/) (accessed on May–July 2023)
Statistical data	Data on agriculture, forestry, fisheries, water use, and tourism were sourced from reports by Chinese government agencies.
Price parameter data	Prices were gathered from pricing departments, market research, and literature.

2.3. Methodology

2.3.1. Accounting Model

The GEP provided a comprehensive evaluation of ecosystem services [1–3], including specific indicators for river basins. Functional quantities represented the outputs of ecosystem products or services. The GEP was the sum of the EPV, ERV, and ECV. Based on the previous literature [1–3,30–33], the EPV encompassed the values from agriculture, forestry, livestock, and fisheries. The ERV included the carbon sequestration value, soil conservation value, water conservation value, water purification value, air purification value, and climate regulation value for the Yongding River Basin. The ECV represented the value of leisure tourism. Formula (1) demonstrates the relationship between GEP, EPV, ERV, and ECV.

$$GEP = EPV + ERV + ECV \quad (1)$$

Based on approaches in previous studies [34–45], the water conservation value, soil conservation value, carbon sequestration value, water purification value, air purification value, and climate regulation value were calculated using ArcGIS and InVEST.

To calculate the water conservation value ($V_{Water\text{-}conservation}$), Formulas (2)–(6) were used [43]. The calculation involved the annual water quantity (Y_{xj}), the annual actual evapotranspiration (ET_{xj}), and the natural climate's non-physical parameters (ω_x). It also included the Budyko dryness index (R_{xj}), the Zhang coefficient (Z), the grid x annual mean plant available water content (AWC_X), the evapotranspiration coefficient of vegetation (K_{xj}), and the average annual reference crop evapotranspiration level (ET_0).

$$Y_{x,j} = (1 - \frac{ET_{x,j}}{P_x}) \times P_x \quad (2)$$

$$\frac{AET_{x,j}}{P_x} = \frac{1 + \omega_x + R_{xj}}{1 + \omega_x R_{x,j} + \frac{1}{R_{x,j}}} \quad (3)$$

$$\omega_x = Z \times \frac{AWC_x}{P_x} \quad (4)$$

$$R_{x,j} = \frac{ET_{O_x} K_{x,j}}{P_x} \quad (5)$$

$$V_{Water\text{-}conservation} = Y_{xj} \times P_0 \quad (6)$$

To calculate the soil conservation value ($V_{Soil\text{-}conservation}$), Formulas (7)–(14) were used [37,42,43,45,46]. The soil retention value was determined by several factors ($SEDRET_{xD}$): potential soil erosion ($RKLS_x$), actual soil erosion ($USLE_x$), the amount of sediment retention ($SEDR_x$), the retention rate (SE_x), and the actual amount of soil erosion ($USLE_y$). It also involved sediment retention (SE_z), the rain erosion force factor (R_X), the soil erodibility factor (K_X), the slope length factor (LS_X), the soil conservation measure factor (P_X), and the vegetation management factor (C_X). The forestry annual income was adjusted according to the 2018 industrial producer purchase price index (the base year was 1995; the value was 1.66), resulting in a value of RMB 707 (P_f). The nutrients measured in the soil included α_N (N nutrient content, 0.09%), α_p (P nutrient content, 0.04%), and α_k (K nutrient content, 0.98%). Nutrients measured in fertilizers included β_N (nitrogen content in diammonium phosphate, 14.0%), β_p (phosphorus content in diammonium phosphate, 15.0%), and β_k (potassium content in potassium chloride, 50.0%). The discount rate r was 8.00%. The market average cost of sediment removal was RMB 7.89/m^2 (P_{soil}). The average price of urea was RMB 3100/t (P_N). The average price of calcium phosphate was RMB 4200/t (P_p).

The average price of quick available potassium was RMB 3600/t (P_K). Formulas (7)–(13) were defined as follows:

$$SEDRET_{xD} = RKLS_x - USLE_x + SEDR_x \quad (7)$$

$$SEDR_x = SE_x \sum_{y=1}^{x-1} USLE_y \prod_{z=y+1}^{x-1} (1 - SE_z) \quad (8)$$

$$RKLS_X = R_X \times K_X \times LS_X \quad (9)$$

$$USLE_X = R_X \times K_X \times LS_X \times P_X \times C_X \quad (10)$$

$$V_{Soil\text{-}fixation} = S \times P_{soil} \times r = \frac{SEDRET_{xD}}{pb \times h} \times p_f \times r \quad (11)$$

$$V_{retaining\text{-}fertilized} = (SEDRET_{xD} \times \alpha_N \times \beta_N \times P_N + SEDRET_{xD} \times \alpha_p \times \beta_p \times P_p + SEDRET_{xD} \times \alpha_K \times \beta_K \times P_K) \times r \quad (12)$$

$$V_{Mud\text{-}reduction} = SEDRET_{xD} \div \theta \times a \times r \quad (13)$$

$$V_{Soil\text{-}conservation} = V_{Soil\text{-}fixation} + V_{retaining\text{-}fertilized} + V_{Mud\text{-}reduction} \quad (14)$$

To calculate carbon sequestration value ($V_{Carbon\text{-}sequestration}$), Formulas (15) and (16) were used [43]. $V_{Carbon\text{-}sequestration}$ included various components of carbon storage values, such as above-ground carbon storage (C_{above}), partially underground carbon storage (C_{below}), soil carbon storage (C_{soil}), and dead organic carbon storage (C_{dead}). The economic value of carbon sequestration was calculated using the 2022 average carbon price derived from the Beijing Carbon Exchange (P_C), which was RMB 40.0/t, and a discount rate of 8%(r). Formulas (15) and (16) were defined as follows:

$$C_{Carbon\text{-}sequestration} = C_{above} + C_{below} + C_{soil} + C_{dead} \quad (15)$$

$$V_{Carbon\text{-}sequestration} = C_{Carbon\text{-}sequestration} \times 44/12 \times P_C \times r \quad (16)$$

To calculate the water purification value, Formulas (17)–(20) were used [43,47–50]. The water purification value ($V_{Water\text{-}purification}$) was determined using various factors. The pollutant output of grid cells (X_{expi}) and the nitrogen and phosphorus output rate (NDR_i) were used to calculate the adjusted pollutant load value (modified.load (x, i)) based on the pollutant load value (load (x, i)). The hydrological sensitivity score (RPI_i), runoff coefficient (RP_i), and average runoff coefficient (RP_{av}) were also considered. Purified nitrogen content (ΔQ_N) and purified phosphorus content (ΔQ_P) were valued using the 2022 market purification values for nitrogen (α_N), priced at RMB 9.06/kg, and phosphorus (α_P), priced at RMB 3.17/kg. The calculations were adjusted using a discount rate (r) of 8.00%. Formulas (17)–(20) were defined as follows:

$$X_{expi} = \text{modified.load (x, i)} \cdot NDR_i \quad (17)$$

$$\text{modified. load (x, i)} = \text{load (x, i)} \cdot RPI_i \quad (18)$$

$$\text{modified. load (x, i)} = \text{load (x, i)} \cdot RPI_i \quad (19)$$

$$V_{Water\text{-}purifification} = (\Delta Q_N \times \alpha_N + \Delta Q_P \times \alpha_P) \times r \quad (20)$$

To calculate the air purification value, Formula (21) was used [36,48–50]. The air purification value ($V_{Air\text{-}purification}$) was composed of several components: the value of providing negative ions (V_f), dust retention (V_d), and absorbing pollutants (V_h). Factors contributing to these values included the area of the ecosystem (A), the average height of the vegetation (H), the concentration of negative ions (Q_f), and the ions' survival time (L).

Additionally, dust retention per unit area (Q_d) and the amounts of the pollutants absorbed by the ecosystem (Qi) were important. The costs associated with these processes were the production cost of negative ions (K_f), the treatment cost of dust retention (K_d), and the treatment cost of absorbing class i pollutants (K_i). Regarding the air purification capacity per unit area of different ecosystem types, the SO^2 absorption capacity of the cultivated land was 47.5 kg/hm^2, the HF absorption capacity was 0.50 kg/hm^2, and the dust absorption capacity was 36,100 kg/hm^2. For woodland, the SO_2 absorption capacity was 117 kg/hm^2, the HF absorption capacity was 8.50 kg/hm^2, the NO^x absorption capacity was 8.2 kg/hm^2, and the dust retention capacity was 10,110 kg/hm^2. Grassland had a SO_2 absorption capacity of 40.0 kg/hm^2, an HF absorption capacity of 0.33 kg/hm^2, a NO^x absorption capacity of 3.00 kg/hm^2, and a dust retention capacity of 30.0 kg/hm^2.

$$V_{\text{Air-purification}} = V_f + V_d + V_h = 5.256 \times 1015 \times A \times H \times K_f\,(Q_f - 600)/L + K_d \times Q_d \times A + \sum_{i=1}^{n} K_i \times Q_i \times A \quad (21)$$

To calculate the climate regulation value (E), Formula (22) was used [39]. E encompassed various factors, including the transpiration value of plants (Ev) and the evaporation value of the water surface (E_W). It accounted for the heat consumed by transpiration per unit area of the forest and grassland ecosystems (F_i), which measured as 2837.27 KJ·m^{-2}·d^{-1} (d) and 969.83 KJ·m^{-2}·d^{-1} (d), respectively. The area of each class i ecosystem (S_i) and the number of open days of air conditioning (d) were considered, with (d) being 3. The energy efficiency ratio of air conditioning (R) and the electricity price (P) were also considered, with (P) set to RMB 0.53/kW·h in 2008 and RMB 0.56/kW·h in 2018. The water body area (W) and the average annual total evaporation of the water surface (E_n) were included, with the energy consumed by evaporation per unit volume of water (β) being 2.43 × 10^6/kJ·m^3. Additionally, the power consumption required by a humidifier to convert 1 m^3 of water into steam (γ) was 125/kW·h. Formula (22) was defined as follows:

$$E = E_v + E_W = \frac{\sum_{i=1}^{2} F_i \times S_i \times d}{3600 \times R} \times P_e + \left(\frac{W_a \times E_p \times \beta}{3600 \times R} + W_a \times E_p \times \gamma\right) \times P_e \quad (22)$$

2.3.2. Variance Decomposition

To analyze the contributions of EPV, ERV, and ECV to GEP, we used the variance decomposition method, which relies on the statistical properties of variance and covariance. This is a traditional statistical method [51], and it enabled us to understand the roles that different ecosystem service values play in influencing GEP. Formulas (23) and (24) were defined as follows:

$$\text{Var (GEP)} = \text{Cov (EPV + ERV + ECV, GEP)} = \text{Cov (EPV, GEP)} + \text{Cov (ERV, GEP)} + \text{Cov (ECV, GEP)} \quad (23)$$

$$1 = \text{Cov (EPV, GEP)/Var (GEP)} + \text{Cov (ERV, GEP)/Var (GEP)} + \text{Cov (ECV, GEP)/Var (GEP)} \quad (24)$$

2.3.3. Moran's Index

Moran's Index is a spatial statistic that measures the degree of spatial autocorrelation within a dataset [52]. It quantifies the way in which a variable is spatially clustered across a geographic area. In this study, Moran's Index was utilized to examine the spatial patterns of GEP, EPV, ERV, and ECV.

2.3.4. Grey Prediction Model

The grey prediction model is a forecasting technique ideal for datasets with limited data or low reliability [53]. By employing differential equations, it extracts essential information, ensuring high accuracy with minimal input. This model is widely applied for economic forecasting and market demand prediction.

2.3.5. Random Forest Algorithm

The random forest algorithm is an ensemble method that consists of multiple decision trees, offering improved performance and reducing the risk of overfitting compared to a single decision tree [54]. It generates new training sets by randomly selecting samples with replacement and only uses a subset of features for each tree. Each decision tree is constructed by selecting the best splitting attribute until no further splits are possible. For the prediction, each tree provides a classification result, and the final prediction is determined by the majority vote among the trees. We employed this method to evaluate the impact of land-use changes on the GEP, EPV, ERV, and ECV.

2.3.6. Paired T-Test Model

The paired T-test is a statistical method used to compare the means of two related groups [55]. It is appropriate to use when two measurements are taken on the same subject. In this article, we used appropriate methods to compare the differences between the GEP and GDP.

2.3.7. Dynamic Panel Model

The dynamic panel model is a sophisticated analytical tool used to examine relationships over time while addressing issues such as endogeneity and unobserved individual effects [56]. The dynamic panel model can be expressed in the manner shown in Formula (25). GDP_{it} represents the GDP for unit i at time t, and it is the dependent variable. GDP_{it-1} is the lagged GDP. The values of carbon sequestration, soil conservation, water conservation, water purification, air purification, and climate regulation at time t are explanatory variables related to ERV. In the model, α represents the constant term, β represents the coefficients of the explanatory variables, u_i represents unobserved individual effects, and ϵ_{it} represents the error term. Formula (25) was defined as follows:

$$GDP_{i,t} = \alpha + \beta_1 GDP_{i,t-1} + \beta_2 \text{carbon sequestration value}_{i,t} + \beta_3 \text{soil conservation value}_{i,t} + \beta_4 \text{water conservation value}_{i,t} + \beta_5 \text{water purification value}_{i,t} + \beta_6 \text{air purification value}_{i,t} + \beta_7 \text{climate regulation value}_{i,t} + u_i + \epsilon_{i,t} \quad (25)$$

3. Results

3.1. Spatiotemporal Variations in the GEP

As shown in Figure 3, the GEP of the Yongding River Basin experienced significant growth from 1995 to 2020. In 1995, the GEP was RMB 0.61 trillion. In 2000, it increased to RMB 0.69 trillion. In 2005, this upward trend continued, with the GEP reaching RMB 0.75 trillion. In 2010, the GEP rose to RMB 0.96 trillion, and in 2015, it rose to RMB 1.18 trillion. In 2020, the GEP reached RMB 1.19 trillion.

The EPV within the Yongding River Basin showed an overall upward trend with notable fluctuations (Figure 4). Over 25 years, the EPV rose significantly from RMB 39.1 billion in 1995 to RMB 0.14 trillion in 2020, with the average rate of increase being 11.1% of total GEP. Upstream areas were crucial for maintaining the health of downstream ecosystems. In the upstream segment, Shanxi's EPV increased from RMB 0.04 billion in 1995 to RMB 0.04 trillion in 2020, with its share of total EPV rising from 1.10% to 27.8%. Hebei's EPV was RMB 1.47 billion in 1995, accounting for 37.6% of total EPV, and it rose to RMB 5.18 billion in 2020, accounting for 38.0% of total EPV.

The ERV within the Yongding River Basin was consistently important, showing steady growth and representing a significant portion of total GEP, which underscored its importance in supporting ecosystem stability and health (Figure 5). The ERV in the basin grew from RMB 0.36 trillion in 1995 to RMB 0.46 trillion in 2020, representing a 26.0% increase. In the upstream segment, the ERV in Shanxi increased from RMB 14.8 billion to RMB 18.8 billion between 1995 and 2010, accounting for around 40.0% of the total ERV. Similarly, the ERV in Hebei rose from RMB 14.6 billion to RMB 18.3 billion in the same period, also making up about 40.0% of the total ERV. Although the ERV of Beijing was smaller at about 8.00%, it showed a trend of growth. Tianjin had the smallest ERV. Additionally, among the

six types of regulating services, the air purification value and climate regulation value held the most significant shares. The average air purification value accounted for 53.9% of the total ERV, while the average climate regulation value comprised 42.7%.

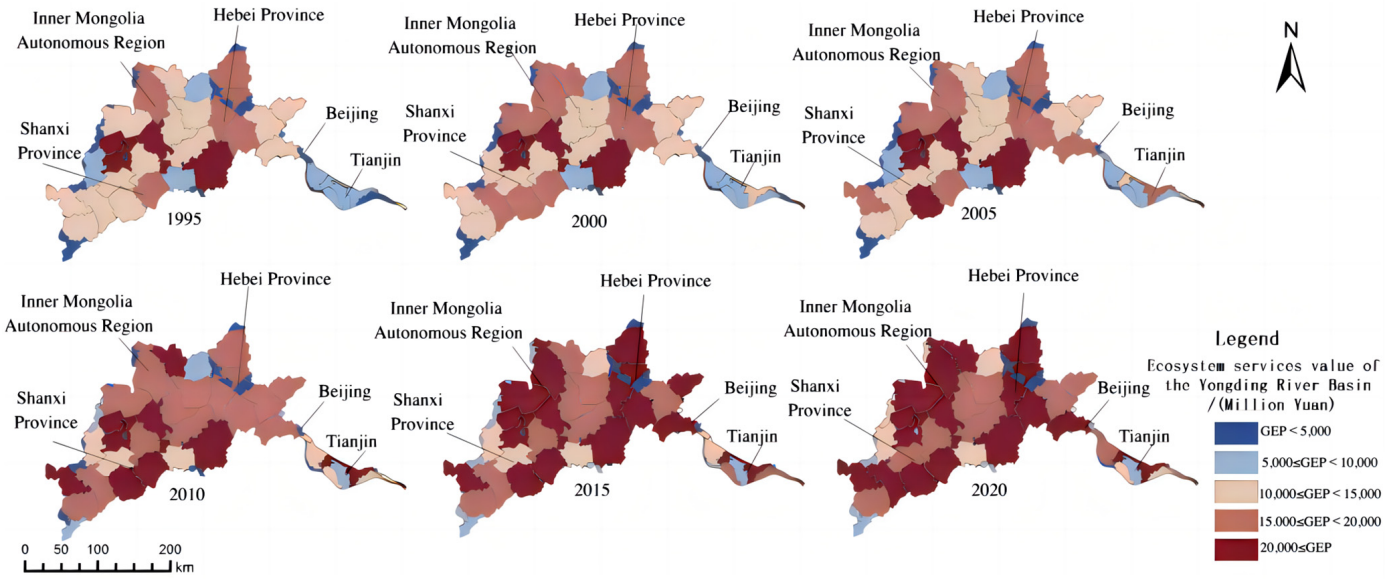


Figure 3. GEP of the Yongding River Basin.

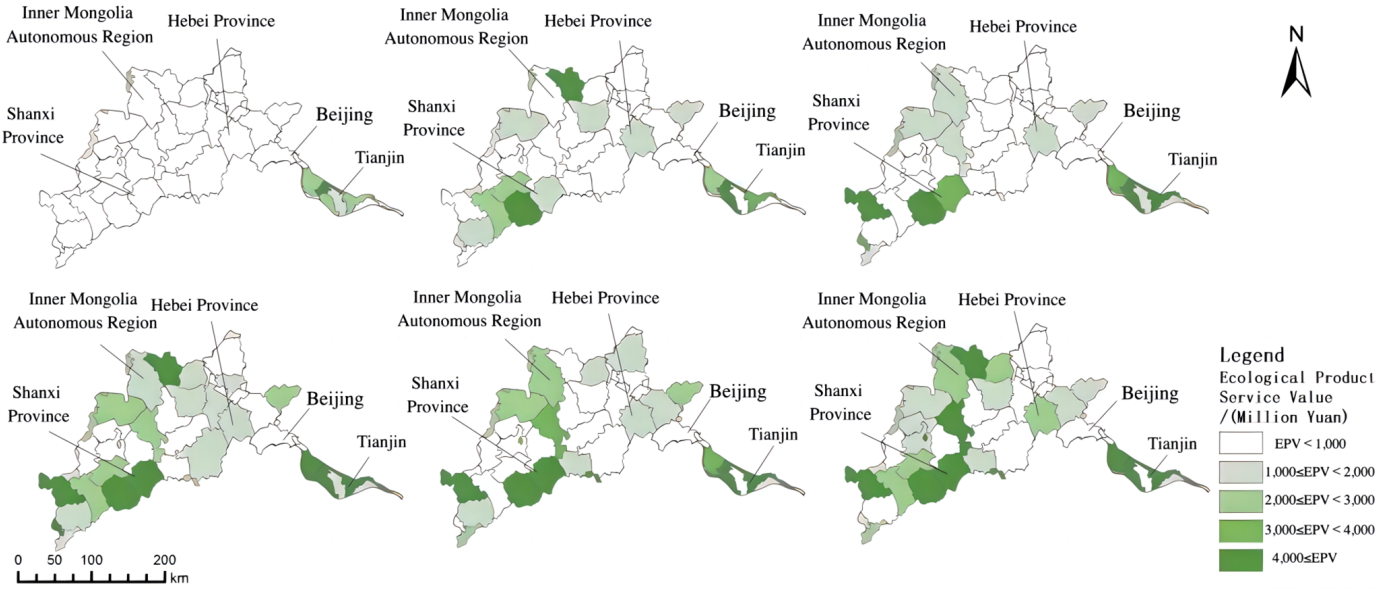


Figure 4. The EPV of the Yongding River Basin.

The ECV in the Yongding River Basin showed a consistent upward trend, underscoring the increasing value of cultural and recreational services derived from ecological resources over time (Figure 6). From 1995 to 2020, the ECV experienced significant growth. In 1995, ECV was RMB 0.21 trillion, but by 2020, it had increased to RMB 0.60 trillion. The average contribution of the ECV to the GEP was 42.5%. In the upstream section of the Yongding River Basin in Shanxi, ECV accounted for more than half of the total ECV. Hebei's ECV also increased during this period. Beijing's ECV had an average share of 14.8% from 1995 to 2020. Tianjin's share of the ECV share significantly increased over the entire period.

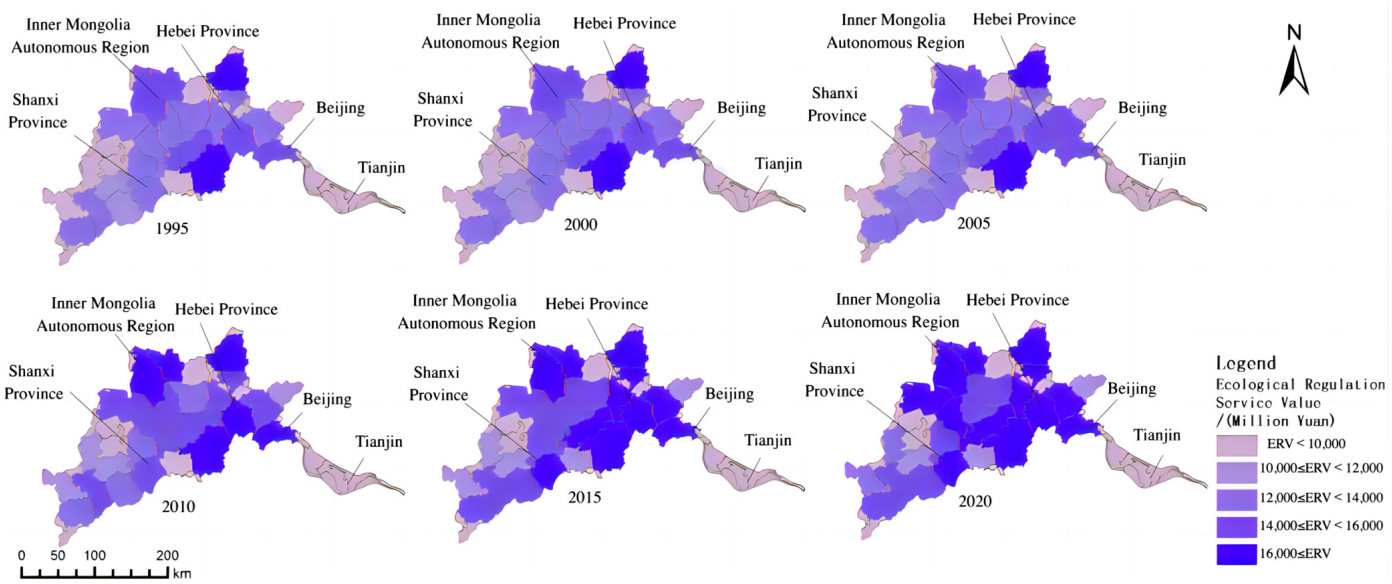


Figure 5. The ERV of the Yongding River Basin.

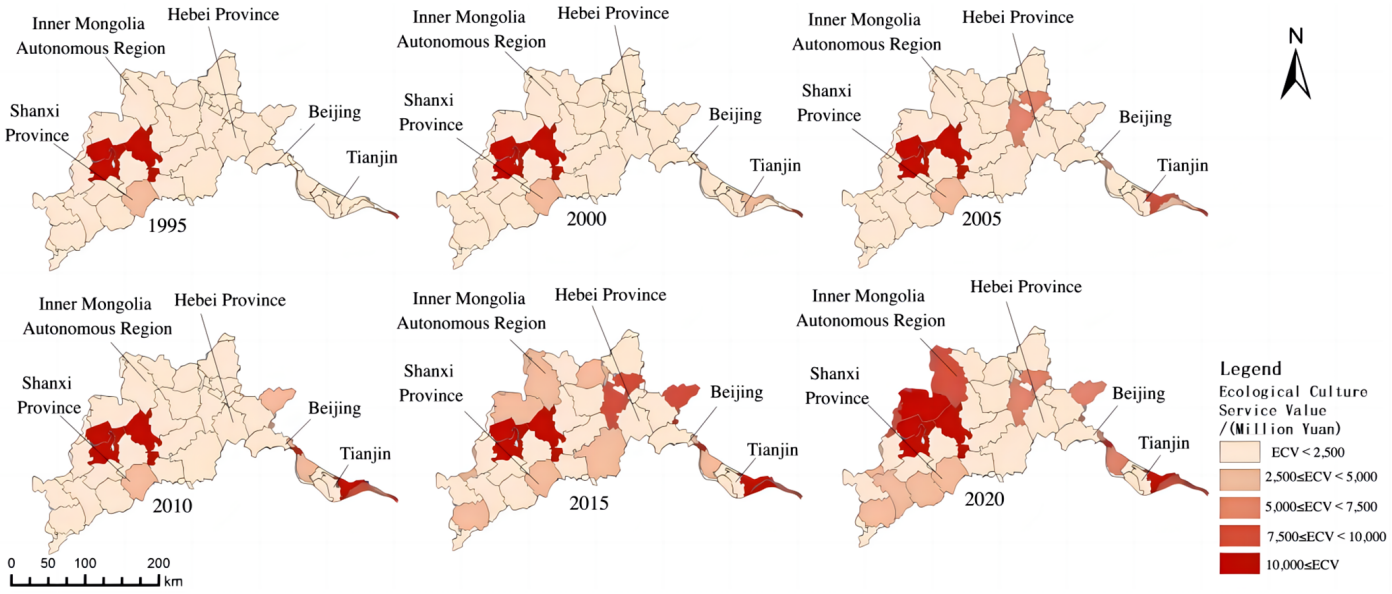


Figure 6. The ECV of the Yongding River Basin.

As shown in Figure 7, from 1995 to 2020, GEP components in the Yongding River Basin exhibited distinct spatiotemporal trends, with the ERV being generally high but fluctuating, the ECV showing significant growth, and the EPV steadily increasing. In 1995, the ERV was high, the ECV was moderate, and the EPV was low. In 2000, the ECV slightly decreased, while the ERV and EPV increased. In 2005, the ECV and EPV increased, but the ERV decreased. In 2010, the ECV and ERV remained stable, albeit with a slight increase in the EPV. In 2015, the ECV significantly increased, while the ERV and EPV stayed stable. In 2020, the ECV and ERV increased, the EPV remained stable, and the overall GEP was high. Each service exhibited unique trends, reflecting their roles and importance in the ecosystem over time. Overall, the EPV started low and consistently increased over time. The ERV maintained high values with slight fluctuations, remaining crucial for ecosystem services. The ECV had notable values at the start of the study period, experienced variations, and saw significant growth, especially in later years.

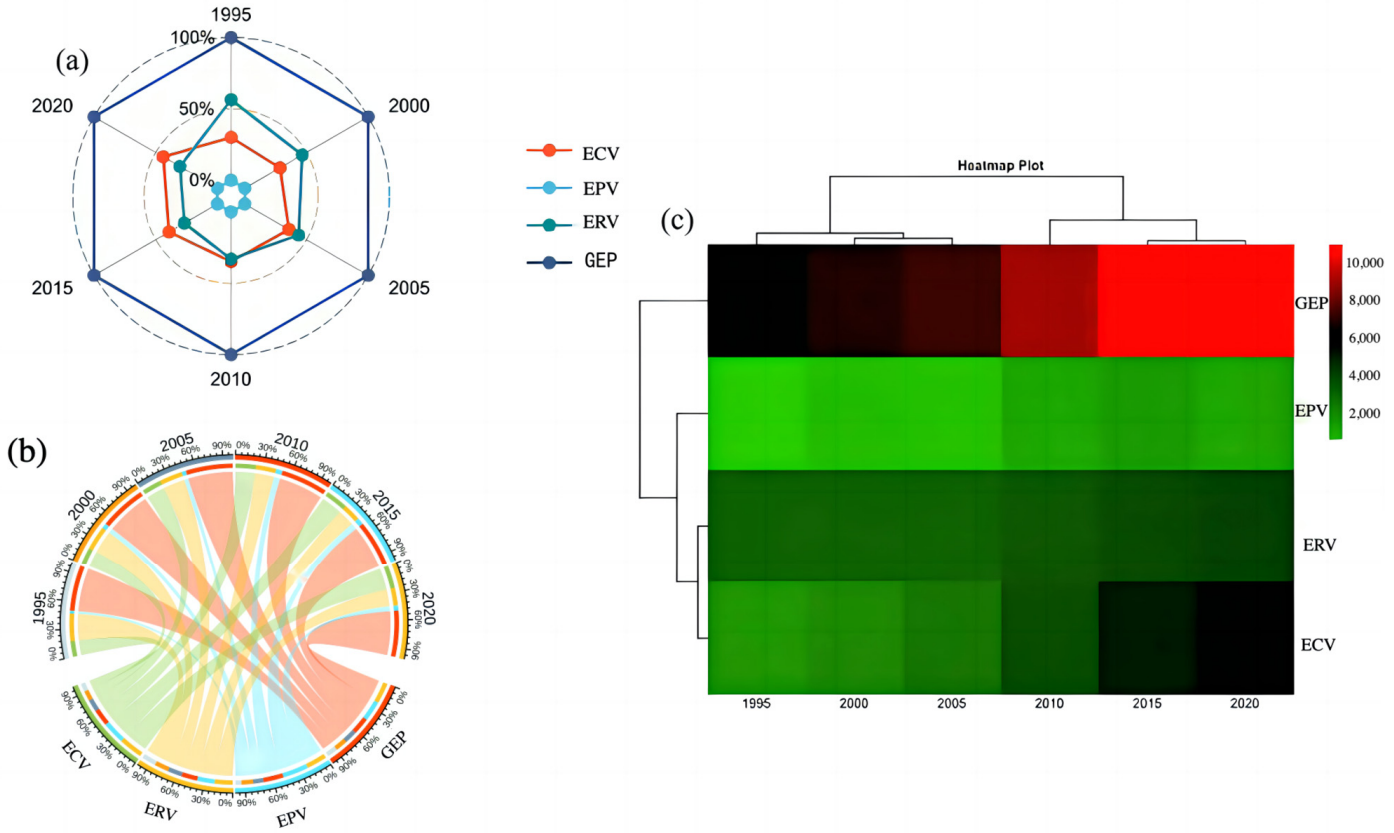


Figure 7. Changes of GEP, EPV, ERV, and ECV. (**a**) Radar chart. (**b**) Chord diagram. (**c**) Heatmap.

As shown in Table 2, the ECV had the highest contribution to the total variation in the GEP, namely 86.6%. The ERV contributed moderately to this variation, while the EPV had the least impact on the overall variation.

Table 2. Variance decomposition of GEP.

Item	Cov	Variance Decomposition Value	Percentage
EPV	1361.463	0.033	3.34%
ERV	4117.779	0.101	10.09%
ECV	35,319.814	0.866	86.57%
		Var = 40,799.055	

To understand the spatial distribution of and changes in the GEP in the Yongding River Basin, in 1995, the global Moran's Index showed significant positive spatial autocorrelation, indicating a clustering trend in the spatial distribution of the GEP. However, from 2000 to 2015, the global Moran's Index gradually increased but was not statistically significant. Since the global Moran's Index was not significant for six consecutive years, the local Moran's Index was not considered.

For the EPV, the global Moran's Index exhibited fluctuating changes from 1995 to 2020. Since the global Moran's Index was significant for five years, the local Moran's Index was considered. Hebei and Tianjin were dominant in high-value clusters, while Beijing consistently showed low-value clustering (Figure 8).

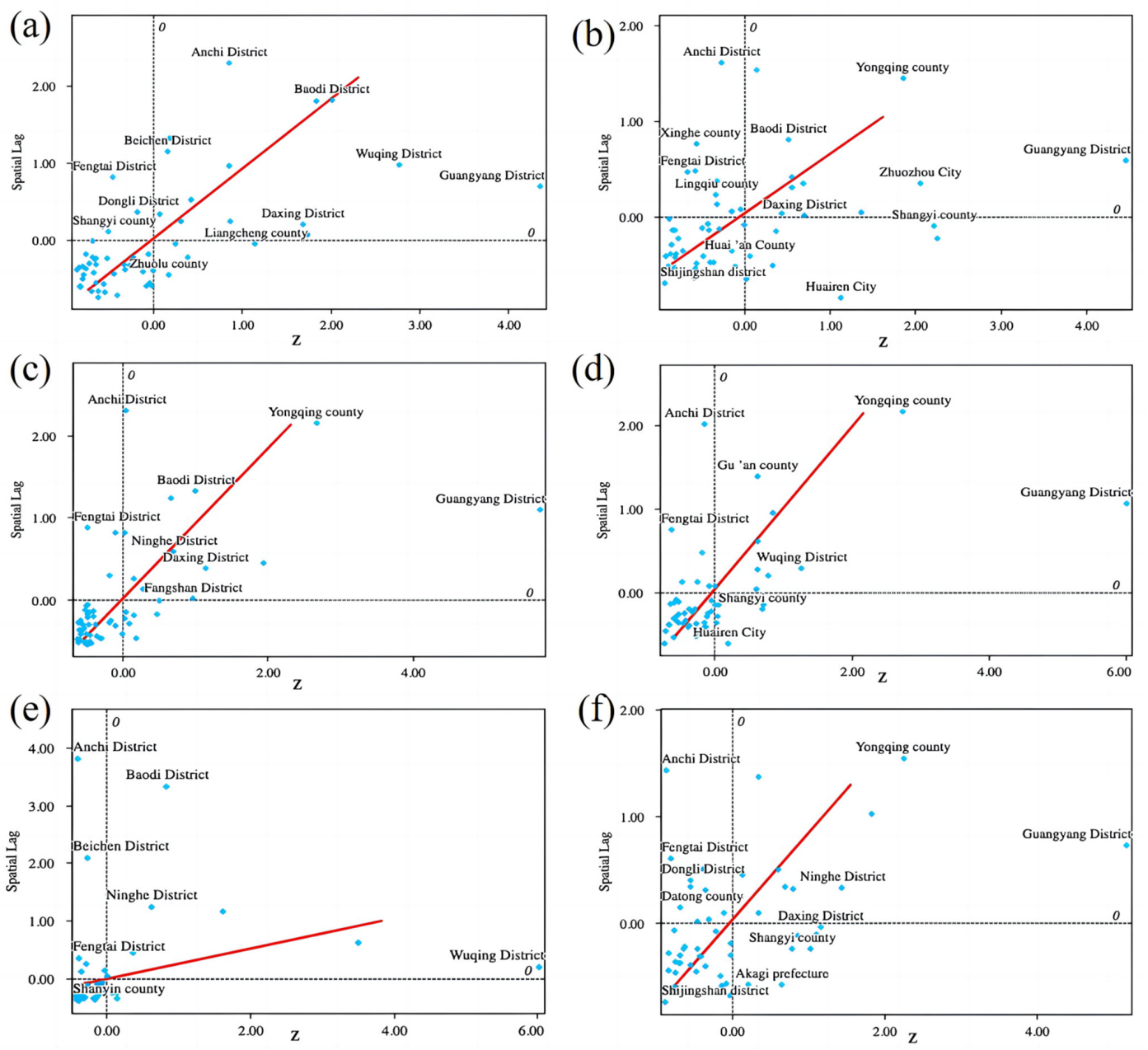


Figure 8. EPV local Moran's Index from 1995 to 2020 (**a**–**f**): (**a**) 1995: Moran's I = 0.416; (**b**) 2000: Moran's I = 0.177; (**c**)2005: Moran's I = 0.367; (**d**) 2010: Moran's I = 0.321; (**e**) 2015: Moran's I = 0.170; (**f**) 2020: Moran's I = 0.230. The red line represents the regression line for Moran's I, which is commonly used to analyse spatial autocorrelation.

For the ERV, the global Moran's Index analysis of ERV variables from 1995 to 2020 showed significant positive spatial correlations. Since the global Moran's Index was significant for six consecutive years, the local Moran's Index was considered. The high ERV was consistently clustered in the upstream and downstream segments (Figure 9). Spatial analysis revealed strong positive autocorrelation, with significant clustering of high and low values in specific segments of the river basin.

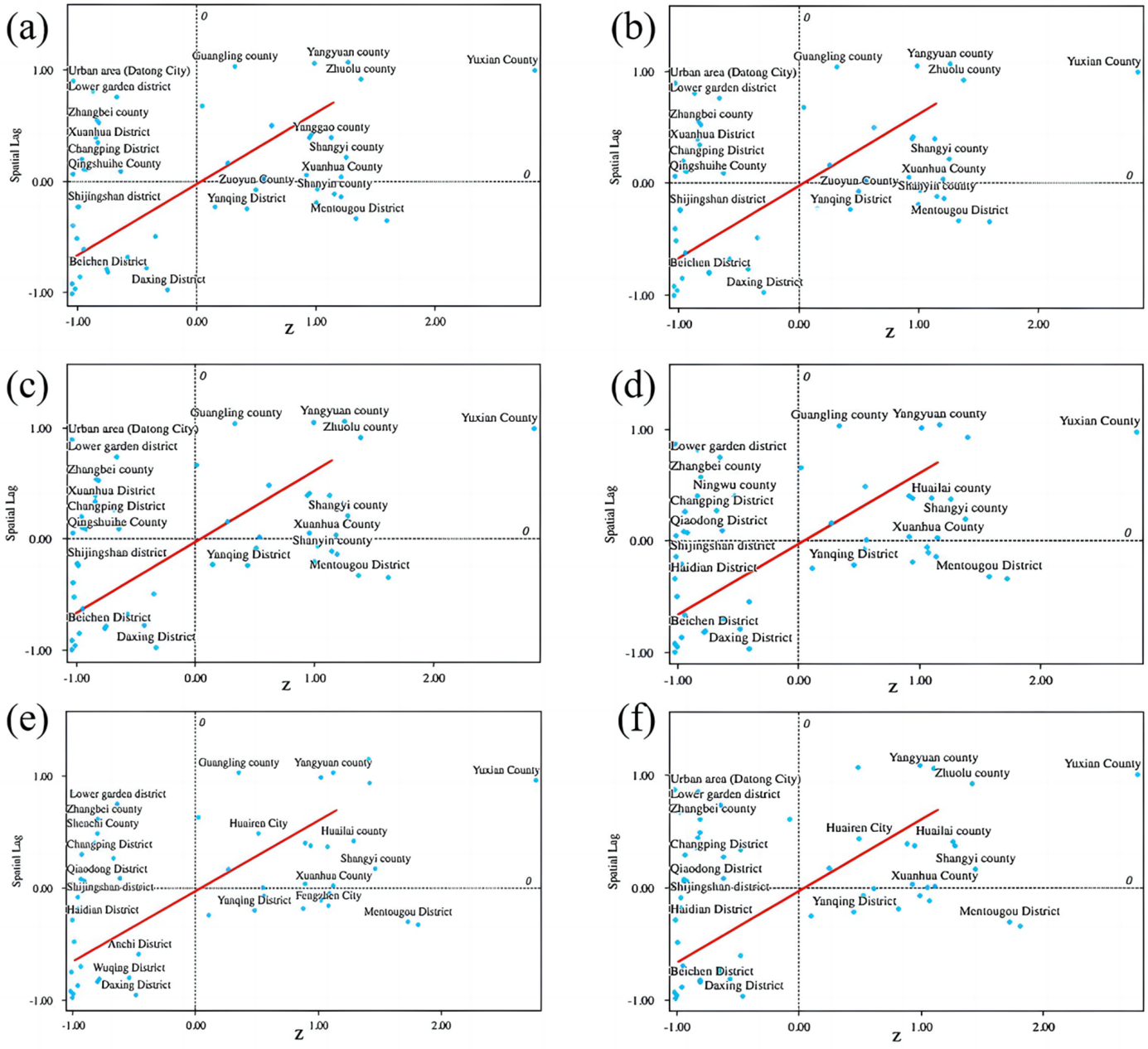


Figure 9. ERV local Moran's I from 1995 to 2020. (**a**–**f**): (**a**) 1995: Moran's I = 0.225; (**b**) 2000: Moran's I = 0.227; (**c**) 2005: Moran's I = 0.227; (**d**) 2010: Moran's I = 0.223; (**e**) 2015: Moran's I = 0.222; (**f**) 2020: Moran's I = 0.230. The red line represents the regression line for Moran's I, which is commonly used to analyse spatial autocorrelation.

For the ECV, the global Moran's Index from 1995 to 2020 showed generally low and statistically insignificant spatial autocorrelation.

Under current ecological restoration policies, we used the grey prediction model to predict the GEP, EPV, ERV, and ECV from 2025 to 2035 (Figure 10). The results indicated that the GEP will reach approximately RMB 14.6 billion in 2025, before further growing to RMB 16.9 billion in 2030 and RMB 19.6 billion in 2035. The ERV is projected to reach RMB 4.93 billion in 2025, RMB 5.27 billion in 2030, and RMB 5.63 billion in 2035. The ECV is anticipated to reach RMB 7.46 billion in 2025, RMB 8.75 billion in 2030, and RMB 10.2 billion in 2035.

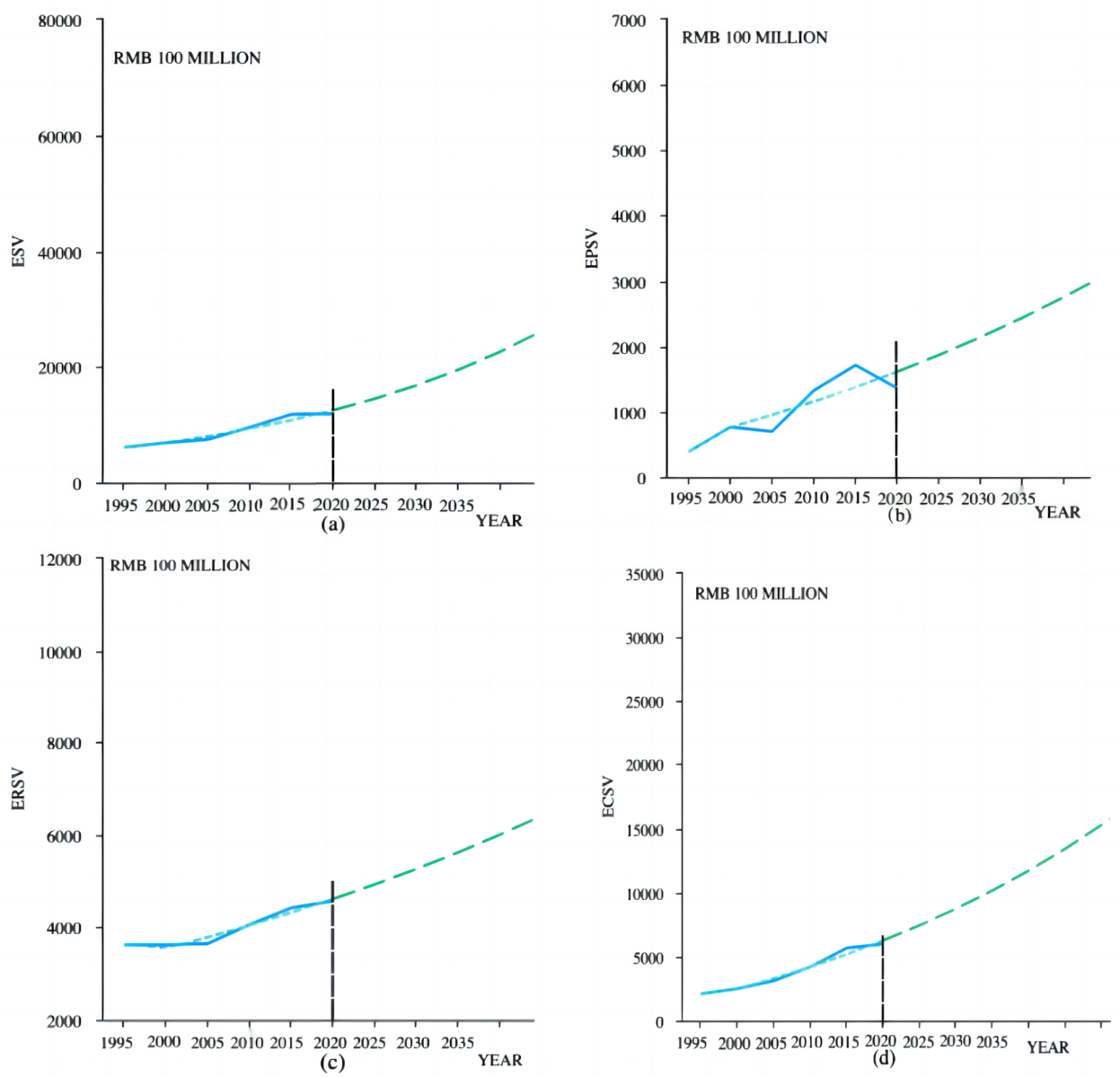


Figure 10. Grey prediction model to forecast GEP, EPV, ERV, and ECV from 2020 to 2035 (**a**–**d**): (**a**) GEP; (**b**) EPV; (**c**) ERV; (**d**) ECV.The blue line represents actual observed data, showing historical changes. The green line represents the projected future trend, showing the expected change in the variable.

3.2. Impacts of Land-Use Changes on GEP

As shown in Figure 11, for the GEP, the forest land area had the highest weight at 0.30, followed by the grassland area at 0.24 and the cultivated land area at 0.23, collectively making up 76.5% of the total feature importance. Regarding the EPV, the forest land area again ranked highest with a weight of 0.43, followed by grassland area at 0.26 and construction land area at 0.10, together representing 79% of the total importance. For the ERV, the forest land area was the most influential type with a weight of 0.50, followed by the grassland area at 0.31 and the cultivated land area at 0.14, making up 94.6% of the total feature importance. Regarding the ECV, the unused land area had the highest weight at 0.51, followed by the cultivated land area at 0.27 and the construction land area at 0.11, accounting for 88.4% of the total.

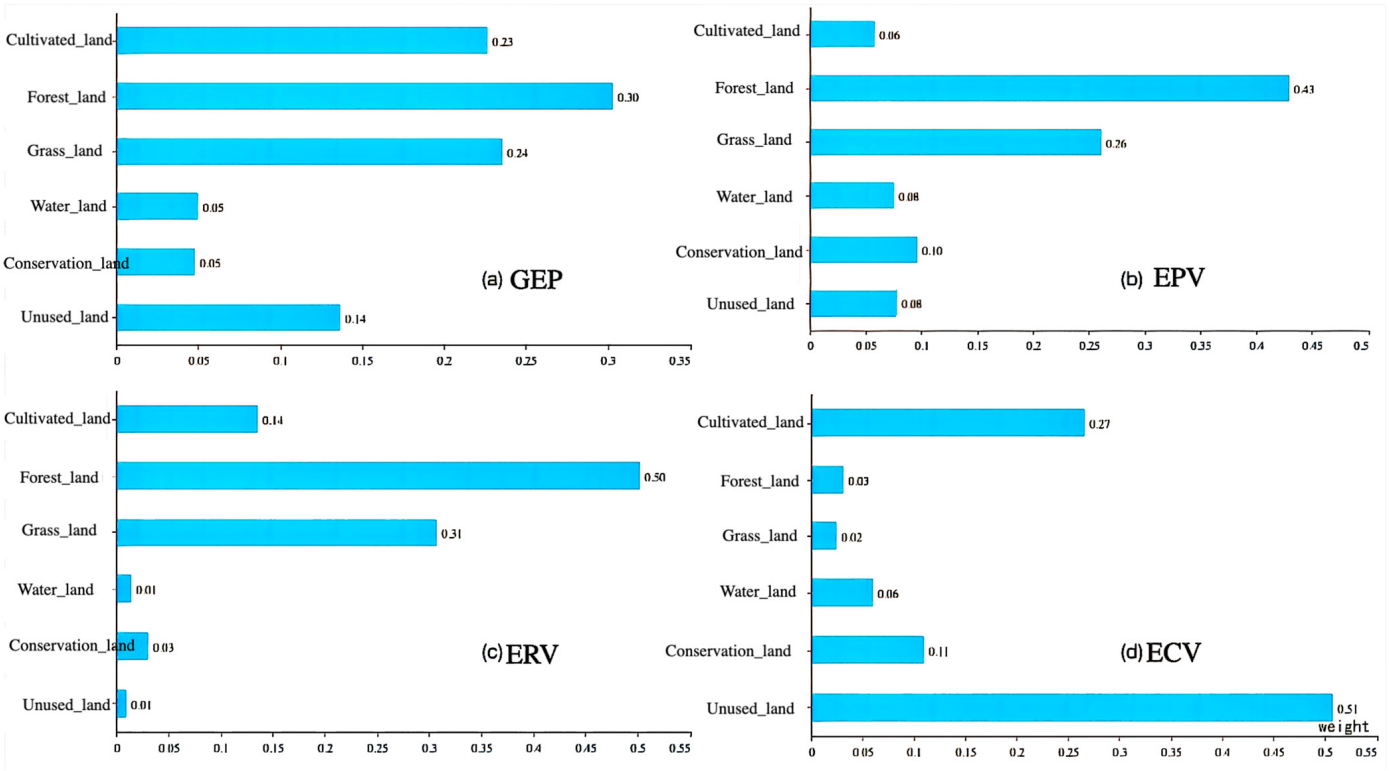


Figure 11. Influences of land-use changes on different components of GEP.

3.3. Relationship Between GEP and GDP

As shown in Table 3, in 1995 and 2000, GEP was significantly larger than GDP, and the differences between GEP and GDP were statistically significant. GEP remained slightly larger than GDP in 2005, but the difference was not statistically significant. From 2010 onwards, GDP surpassed GEP, with mean differences becoming negative. The differences in the later years were not statistically significant.

Table 3. Paired T-test for GEP and GDP from 1995 To 2020.

Year	Item	Mean (RMB 100 Million)	Standard Deviation	Mean Difference (RMB 100 Million)	t	*p*
1995	GEP	107.59	156.39	88.19	4.089	0.000 ***
	GDP	19.4	36.7			
2000	GEP	121.29	160.21	84.69	3.64	0.001 ***
	GDP	36.6	77.38			
2005	GEP	131.33	170.06	50.8	1.583	0.119
	GDP	80.53	215.15			
2010	GEP	168.51	196.29	−35.21	−0.444	0.659
	GDP	203.72	661.97			
2015	GEP	207.53	236.3	−165.85	−1.11	0.272
	GDP	373.39	1225.7			
2020	GEP	209.44	255.03	−140	−1.575	0.121
	GDP	349.44	799.18			

*** $p < 0.001$.

As shown in Table 4, we explored how ERV components affected GDP. Dynamic panel regression analysis was used to reveal the effects of ERV components on GDP. The Hansen test showed a *p*-value of 0.298, indicating that the instrumental variables were valid. The AR(2) test for autocorrelation yielded a *p*-value of 0.252, confirming that there were no autocorrelation issues and demonstrating the model's robustness. The regression analysis indicated that the water conservation value had a coefficient of 0.227 (z = 2.047),

having a statistically significant positive impact on GDP at the 0.05 level ($p < 0.05$). In contrast, the water purification value had a coefficient of −0.124 (z = −2.698), having a statistically significant negative impact on GDP at the 0.01 level ($p < 0.01$). Both the carbon sequestration value and soil conservation value exhibited slight negative impacts on GDP, but these impacts were not statistically significant. Meanwhile, the air purification value and climate regulation value had almost no impact on GDP in the Yongding River Basin.

Table 4. Dynamic panel regression analysis of the impacts of ERV components on GDP.

Item	Coefficient of Regression
L1.GDP	0.017 (1.349)
carbon sequestration value	−0.003 (−1.248)
soil conservation value	−0.005 (−0.721)
water conservation value	0.227 * (2.047)
water purification value	−0.124 ** (−2.698)
air purification value	−0.000 (−0.139)
climate regulation value	−0.000 (−0.436)
N	342
Hasen	$\chi^2(34) = 37.837$, $p = 0.298$
AR(1)	z = −1.428, $p = 0.153$
AR(2)	z = 1.144, $p = 0.252$

* $p < 0.05$, ** $p < 0.01$. Values in parentheses are z-values.

4. Discussion

4.1. Importance of the ECV and ERV Within the River Basin

The ECV and ERV were vital in the Yongding River Basin, playing essential roles in maintaining ecological health, supporting economic growth, and enhancing community well-being. As cities like Beijing and Tianjin expanded, the demand for recreational spaces grew. This trend highlights the significance of ECV in urban planning and public health. The reasons for these trends were as follows: On the one hand, ecological cultural services enhanced economic sustainability and supported local jobs without causing pollution [4,57]. On the other hand, ecological cultural services boosted education and conservation awareness [6,7,58], preserving biodiversity and maintaining local cultural identities and heritage [59,60]. In the future, the promotion and utilization of watershed culture should be incorporated into ecological restoration policies.

The ERV also constituted a significant part of the GEP, with high-ERV areas forming clusters that served as strategic zones for ecological restoration. This clustering likely stemmed from natural conditions or conservation efforts [23]. High-ERV concentrations in upstream segments suggested that regulating services in these regions could greatly enhance ecological productivity [61]. Prioritizing upstream management and ecological restoration could deliver substantial benefits for the entire basin. Among the key ERV components, air purification, climate regulation, and water conservation played crucial roles, as vegetation's air purification services were vital for maintaining air quality and public health [61]. Climate regulation was essential for global climate stability [41], while water conservation enhanced the capacity of the Yongding River Basin to retain and filter water [6,58]. Therefore, ecological restoration should be further advanced to enhance air purification, climate regulation, and water conservation in the upstream segments of watersheds.

4.2. Integrating Forest and Grassland Areas into Plans in the River Basin

Different types of land use significantly impacted various ecosystem services, highlighting the need for strategic land management to effectively enhance these services [61–64]. Effective land-use management strategies were essential for balancing ecological sustainability with economic development. Forest, grassland, cultivated land, and water areas each played important roles in boosting GEP. Forests and grasslands sequestered carbon and reduced pollutants, improving air quality and climate. Cultivated lands increased GEP

by using sustainable practices that enhanced soil health and reduced erosion. However, intensive farming could harm habitats and biodiversity, making it important to balance farming with ecological benefits. Water areas were crucial for purifying water, supporting aquatic life, and providing recreation [23,60]. Effectively managing water resources was essential for preserving these benefits and ensuring the sustainability of the river basin.

4.3. Complex Relationship Between GEP and Economic Development

In both 1995 and 2000, GEP was significantly larger than GDP. This discrepancy might have been related to the characteristics of ecologically vulnerable river basins, where rich ecological services were present but not adequately reflected in industrial development. The contemporary economic structures were cautiously focused on traditional industries, which often did not account for these ecological services. The market mechanisms for translating GEP into GDP, such as through sustainable practices or eco-friendly technologies, were not as prevalent or efficient. Consequently, ecological contributions were recognized but not fully reflected in GDP calculations, leading to a higher GEP [41,61,62]. From 2010 onwards, GDP consistently surpassed GEP. This trend may be attributed to the use of ecological restoration policies and advancements in technology. These factors jointly increased the efficiency of converting ecological resources into economic value.

After exploring how ERV components impacted GDP, we found that the water conservation value had a statistically significant positive effect on GDP, underscoring the critical role of water management in supporting economic productivity within ecologically vulnerable river basins. Conversely, the water purification value negatively impacted GDP because ecological restoration efforts required significant investment, which might initially outweigh economic gains [65,66]. The slight negative effects of carbon sequestration and soil conservation on GDP, though not statistically significant, might have been due to the costs of investments and the challenges associated with ecologically fragile areas. While these efforts were crucial for long-term sustainability, they may not have yielded immediate economic returns due to the need for substantial resource allocation and alterations in water areas, highlighting a potential area for policy improvement [4,11,40]. The air purification value and climate regulation value had minimal impacts on GDP, as these benefits may not have been immediately apparent in the short term. However, in the long term, it is necessary to enhance the values of air purification and climate regulation.

5. Conclusions

This study conducted a comprehensive analysis of the Yongding River Basin's GEP from 1995 to 2020, examining the spatial and temporal dynamics of the ESV. Additionally, we used the random forest algorithm to analyze the impacts of different land-use changes on these ecosystem services. Furthermore, we employed the paired T-test model and dynamic panel regression analysis to explore the relationship between GEP and economic development, with a particular focus on the impact of ERV components on GDP. The following is a summary of this study's key findings:

(1) From 1995 to 2020, the Yongding River Basin experienced significant growth in GEP, highlighting effective ecological restoration efforts. The rise in ERV and ECV underscored their vital roles in supporting ecosystem stability and contributing to economic prosperity. The ERVs and ECVs of upstream regions showed notable contributions to the GEP of the Yongding River Basin.

(2) The analysis demonstrated that forest, grassland, and cultivated land significantly influenced GEP. Forest lands had the highest importance for EPV and ERV, while grassland and cultivated land also contributed significantly. Unused land had the highest weight for ECV. Therefore, implementing effective land management practices that prioritize these key land types could further amplify ecological benefits.

(3) In 1995 and 2000, GEP was significantly larger than GDP, with substantial mean differences and high statistical significance. In 2005, although GEP was still slightly larger, the difference lost statistical significance. From 2010 onwards, GDP consistently

surpassed GEP, with negative mean differences; however, these differences were not statistically significant. Additionally, the water conservation value positively impacted GDP, but the water purification value had a negative economic effect, illustrating the intricate relationship between the enhancement of ecological value and economic development.

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Data Availability Statement: The datasets used and analyzed during the current study are available from the corresponding author on reasonable request.

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