Quantitative Assessment of Ecosystem Service Supply-Demand Risks and Their Impact Thresholds in the Fen River Basin Postprint

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Abstract

The Fen River Basin, an ecological barrier zone in the middle reaches of the Yellow River with developed industry and agriculture, provides a valuable reference for studying ecosystem service supply-demand risks to support ecological protection and high-quality development in the region. Existing research exhibits deficiencies in quantitative assessment of supply-demand risks and analysis of driving mechanisms. This study designs a supply-demand risk calculation formula, utilizing the InVEST model, eXtreme Gradient Boosting (XGBoost), and SHapley Additive exPlanations (SHAP) to elucidate spatiotemporal differentiation characteristics of supply-demand matching for carbon sequestration, soil conservation, and water yield services, and to reveal threshold characteristics of factors influencing supply-demand risks. The results show that: (1) From 2000 to 2020, supply and demand levels of carbon sequestration and soil conservation services continued to increase. The temporal trend of water yield service supply was relatively complex but increased substantially in 2020, while water yield demand showed an overall increasing trend. Carbon sequestration and water yield demands exhibited a spatial pattern of higher values in the Fen River Valley and lower values in surrounding mountainous areas, whereas spatial trends of carbon sequestration supply, soil conservation supply, and demand showed the opposite pattern. (2) Over the 20-year period, supply-demand ratios of both carbon sequestration and soil conservation displayed decreasing trends. From 2000 to 2015, the water yield service supply-demand ratio decreased in most areas, but this trend reversed in 2020. Carbon sequestration services were entirely within supply-demand risk zones, while high, medium, and low risk zones for soil conservation supply-demand were interwoven. The Linfen region faced the greatest carbon sequestration and soil conservation supply-demand risks, with medium and high risk zones accounting for 21.73% and 18.14% of the basin area, respectively. The Fen River Basin was primarily in the supply-demand safe zone for water yield services, with only the Taiyuan and Yuncheng regions having relatively higher proportions of high-risk areas at merely 6.74%. (3) Population density and GDP exacerbated carbon sequestration supply-demand risk in a nearly linear manner, with a critical threshold of 10 ℃ for the promoting effect of mean annual temperature on supply-demand risk, beyond which the risk intensified. Soil conservation supply-demand risk increased with the proportion of cropland or grassland, rising more rapidly when slope $< 11°$ or precipitation < 600 mm, and changing slowly beyond these thresholds. Water yield supply-demand risk decreased with increasing precipitation and grassland proportion, while increasing with GDP and population density. The influence of mean annual temperature exhibited three stages—mild promotion, no effect, and strong promotion—with 7 ℃ and 12 ℃ as critical thresholds. Therefore, ecological restoration, economic development, and precipitation changes over the past 20 years have jointly driven spatiotemporal pattern evolution of ecosystem service supply and demand and supply-demand risks. The supply-demand risk index constructed in this study has application value for ecosystem service supply-demand risk management.

Full Text

Quantitative Assessment of Ecosystem Service Supply-Demand Risks and Their Impact Thresholds in the Fenhe River Basin

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Abstract

The Fenhe River Basin serves as an ecological barrier in the middle reaches of the Yellow River and features developed industry and agriculture. Studying ecosystem service supply-demand risks provides valuable insights for supporting ecological protection and high-quality development in this region. Previous research has inadequately addressed quantitative risk assessment and driving mechanism analysis. This study designs supply-demand risk calculation formulas and employs the InVEST model, Extreme Gradient Boosting (XGBoost), and Shapley Additive Explanations (SHAP) to elucidate spatiotemporal differentiation characteristics of carbon sequestration, soil conservation, and water yield supply-demand matching from 2000 to 2020, as well as threshold features of factors influencing supply-demand risks. The results show that: (1) From 2000 to 2020, the supply and demand levels of carbon sequestration and soil conservation services continuously increased. The temporal trend of water yield supply was relatively complex but increased substantially in 2020, while water yield demand generally showed an increasing trend. Carbon sequestration and water yield demand displayed higher values in the Fenhe valley and lower values in surrounding mountainous areas, whereas carbon sequestration supply, soil conservation supply and demand exhibited inverse spatial patterns. (2) Carbon sequestration services were all in supply-demand risk zones, while soil conservation exhibited a mixed pattern of high, medium, and low-risk areas. Among them, Linfen region faced the greatest supply-demand risks of carbon sequestration and soil conservation, with medium-high risk zones accounting for 21.73% and 18.14% of basin area respectively. The Fenhe River Basin was mainly in supply-demand safety zones for water yield, with only Taiyuan and Yuncheng regions having relatively high proportions of high-risk zones, accounting for just 6.74%. (3) Population density and GDP nearly linearly intensified carbon sequestration risks. Annual mean temperature exhibited a critical threshold of 10°C, beyond which risks were escalated. Soil conservation risks increased with cropland or grassland coverage, while slope gradient (11°) and precipitation (600 mm) served as inflection points: risks rose rapidly below these thresholds but stabilized above them. Water yield risks decreased with precipitation and grassland coverage but increased with GDP and population density. With thresholds of 7°C and 12 people/km^2, annual mean temperature' s impact showed three stages: mild promotion, no effect, and strong promotion. Thus, ecological restoration, economic development, and precipitation changes have collectively driven the spatiotemporal evolution of ecosystem services supply, demand, and associated risks. The supply-demand risk index developed in this study offers practical value for managing ecosystem service supply-demand dynamics.

Keywords: ecosystem services supply and demand; spatiotemporal characteristics; machine learning; threshold; Fenhe River Basin

1. Introduction

Ecosystem services refer to the various benefits humans obtain from ecosystems, with the ultimate goal of maintaining human well-being [1]. Ecosystem service supply refers to ecosystems producing products and services for humans, while ecosystem service demand represents human consumption and use of ecological products and services. Supply and demand reflect the flow of ecosystem services from natural ecosystems to human well-being. Human activities cause global land use changes, mainly manifested as type conversion, structural simplification, reduced natural components, altered material cycling pathways, and habitat fragmentation, which profoundly affect ecosystem service supply capacity [2]. According to Millennium Ecosystem Assessment results, among the evaluated 24 ecosystem services, 15 (approximately 60%) showed degradation trends [3]. Meanwhile, rapid socioeconomic development has gradually increased demand for ecosystem services. Consequently, ecosystem service supply-demand contradictions have become increasingly prominent. Therefore, ecosystem service supply and demand have received widespread attention, and analyzing spatiotemporal characteristics of supply-demand matching and their driving mechanisms can provide theoretical foundations for territorial spatial planning and ecological restoration practices, supporting sustainable urban and regional development [4-6].

Spatial expression of ecosystem service supply and demand forms the basis for supply-demand relationship research. However, due to differences in research purposes, objects, and data, spatialization methods are diverse with respective advantages and disadvantages. Burkhard et al. [7] proposed the supply-demand relationship matrix approach, which first constructs a supply-demand relationship matrix through expert knowledge, then uses GIS for spatialization. Chen et al. [8] improved this method by modifying the comprehensive index of fully permuted polygons, adding uncertainty analysis of model results. The most widely used supply-demand spatialization method combines model assessment with statistical data, using models like InVEST for ecosystem service supply estimation and statistical yearbooks, water resources bulletins, and other statistical materials for demand calculation [9-11]. After spatialization, quadrant matching and bivariate local spatial autocorrelation can identify supply-demand matching relationships and spatial aggregation states, which belongs to qualitative identification of supply-demand matching [12-13]. The ratio or difference between supply and demand can quantitatively characterize supply-demand matching degree [14-15]. The problem with supply-demand ratio is that ratio operations change data distribution, limiting subsequent statistical analysis. Therefore, supply-demand difference is most widely applied, often standardized by the mean of supply and demand maximum values to obtain dimensionless supply-demand matching degree [16-17], which can exaggerate or diminish actual supply-demand differences when extreme values exist in maxima. Thus, supply-demand matching quantification methods need further improvement.

When supply-demand contradictions develop to a certain extent, they evolve into supply-demand risks. Wang et al. [18] proposed a regional ecosystem service supply-demand risk assessment framework that comprehensively identifies risk areas through supply-demand ratio, ratio trends, supply and demand trends, and trade-off/synergy relationships, breaking through static supply-demand matching research limitations. This has been applied to supply-demand risk identification and management for water yield, soil conservation, grain production, and other services [19-20]. However, risk levels based on this framework belong to qualitative categories, with certain subjectivity in level classification. Comprehensive quantitative assessment considering both supply-demand status and trends remains insufficient.

In recent years, driving mechanisms of supply-demand relationships have attracted attention. Scholars have used stepwise regression, redundancy analysis, geographically weighted regression, structural equation models, random forest models, geographical detectors, and other methods to reveal influencing factors of supply-demand matching [21-24]. However, because supply-demand relationships themselves contain the comprehensiveness of human-natural system coupling, and natural and social factors intertwine, complicating driving patterns, systematic analysis of driving mechanisms remains in its infancy and requires strengthening. Machine learning attribution methods have been widely applied in supply-demand relationship driving mechanism research, among which the Extreme Gradient Boosting (XGBoost) algorithm has become an important machine learning method. This algorithm is an optimized ensemble learning method based on gradient boosting decision trees. Zhang et al. [25] found XGBoost outperformed gradient boosting decision trees and random forest models in Fujian ecosystem service research. However, the "black box" characteristics of most machine learning models still constrain in-depth mechanism analysis. Lundberg et al. [26] proposed the Shapley Additive Explanations (SHAP) method, which further constructs an interpretable "transparent box" model, demonstrating unique advantages in identifying threshold characteristics of driving variables and effectively enhancing machine learning model interpretability. Therefore, it is necessary to couple XGBoost and SHAP methods to systematically analyze driving mechanisms of supply-demand matching and even supply-demand risks.

The Fenhe River Basin is located in the middle reaches of the Yellow River, representing a densely populated, economically developed, and important ecological functional area in Shanxi Province, holding a very important position in Shanxi' s economic and social development. The basin faces multiple challenges in ecological security barrier construction, economic transformation development, and "dual carbon" goal achievement. Key ecosystem services such as carbon sequestration, soil conservation, and water yield form the foundational support for sustainable development of the basin' s human-environment system. Previous research has made progress in spatiotemporal evolution characteristics, trade-off/synergy relationships, supply-demand matching, and scenario prediction of ecosystem services in the Fenhe River Basin [27-30], but studies on supply-demand risks and their driving mechanisms remain insufficient. Based on this, this study designs supply-demand matching and risk quantification formulas, using InVEST model and machine learning methods to answer: (1) reveal spatiotemporal pattern evolution of ecosystem service supply-demand relationships; (2) identify key driving factors of supply-demand risks and their impact thresholds. This study will provide comprehensive quantification methods and key scientific basis for watershed ecosystem service supply-demand risk management, supporting watershed ecological protection, restoration, and sustainable development.

2. Data and Methods

2.1 Study Area Overview

The Fenhe River is the largest river in Shanxi Province and the second largest tributary of the Yellow River, with a mainstream length of 716 km, flowing from north to south through Xinzhou, Taiyuan, and other cities. The basin is located on the eastern side of the Loess Plateau, with higher terrain in the north and lower in the south, surrounded by mountains on all sides. The landform features alternating mountain hills and valley plains. Soils are mainly cinnamon soil, fluvo-aquic soil, and loessial soil. The basin has a temperate continental monsoon climate with concentrated precipitation in summer and severe soil erosion. The Fenhe River Basin has concentrated industry and agriculture, with prominent human-land contradictions, making it a typical region for ecosystem service supply-demand risk research.

2.2 Data Sources

Net primary productivity, land use, GDP, and population density data were obtained from the Chinese Academy of Sciences Resource and Environmental Science and Data Center (https://www.resdc.cn). Digital elevation model data were downloaded from the Geospatial Data Cloud Platform (https://www.gscloud.cn). Soil, normalized difference vegetation index, evapotranspiration, and precipitation data were downloaded from the National Earth System Science Data Center (https://www.geodata.cn). Water use data were obtained from the Shanxi Province Water Resources Bulletin. Energy consumption data were obtained from the Shanxi Province Statistical Yearbook.

2.3 Ecosystem Service Calculation Methods

2.3.1 Water Yield Service Water yield service supply was calculated through the InVEST model water yield module using the following formula:

$$WY_{xj} = P_x - AET_{xj}$$

where WY_{xj} is the annual water yield in grid cell x for land use type j (mm); AET_{xj} is the actual evapotranspiration in grid cell x for land use type j (mm); and P_x is the precipitation in grid cell x (mm). Related parameters were determined based on existing research [31].

Water yield service demand is the sum of industrial, agricultural, domestic, and ecological water use. Water use data were allocated to corresponding land use types to achieve spatialization of water yield service demand: industrial water use was allocated to industrial and mining land, agricultural water use to cropland, domestic water use to residential land, and ecological water use to forest, grassland, and water areas.

2.3.2 Soil Conservation Service Soil conservation service supply was calculated through the InVEST model soil conservation module:

$$SEC_x = SLP_x - SLA_x + SEC_{upstream}$$

where SEC_x is the soil conservation service supply in grid cell x ($t \cdot hm^{-2}$); SLP_x is the potential soil loss in grid cell x ($t \cdot hm^{-2}$); SLA_x is the actual soil loss in grid cell x ($t \cdot hm^{-2}$); and $SEC_{upstream}$ is the sediment interception from upstream outflow ($t \cdot hm^{-2}$).

$$SLP_x = R_x \times K_x \times LS_x$$

$$SLA_x = R_x \times K_x \times LS_x \times C_x \times P_x$$

where R_x is the rainfall erosivity factor ($MJ \cdot mm \cdot (hm^2 \cdot h)^{-1} \cdot (hm^2 \cdot MJ \cdot mm)^{-1}$); K_x is the soil erodibility factor ($t \cdot h \cdot (MJ \cdot mm)^{-1}$); LS_x is the slope length and steepness factor; C_x is the vegetation cover and management factor; and P_x is the soil and water conservation practice factor. Model factors were determined based on related research [32-33].

Since people do not desire soil loss, actual soil loss (SLA_x) was used as soil conservation service demand (SD):

$$SD = SLA_x$$

2.3.3 Carbon Sequestration Service Carbon sequestration service supply was estimated using methods and parameters recommended in the "Specification for the Calculation of Gross Ecosystem Product" [34]:

$$NEP = NPP \times \alpha$$

where NPP is net primary productivity ($t \cdot hm^{-2} \cdot a^{-1}$); NEP is net ecosystem productivity (carbon sequestration service supply) ($t \cdot hm^{-2} \cdot a^{-1}$); and α is the conversion coefficient between NEP and NPP.

Carbon sequestration service demand was represented by carbon emissions, calculated using carbon emission coefficients for coal, oil, natural gas, and other energy consumption. Population density raster data were used to spatialize carbon sequestration service demand:

$$CARD_x = CAR_{per} \times Pop_x$$

$$CAR_{per} = CAR_{sum} \div P$$

where $CARD_x$ is the carbon sequestration service demand in grid x ($t \cdot hm^{-2} \cdot a^{-1}$); CAR_{per} is per capita carbon emissions ($t \cdot person^{-1} \cdot a^{-1}$); Pop_x is the population in grid x (persons); CAR_{sum} is the total carbon emissions in each region ($t \cdot a^{-1}$); and P is the population of each region (persons).

2.4 Ecosystem Service Supply-Demand Ratio and Risk Index Calculation

Previous studies often used the quotient of supply-demand difference and the mean of supply-demand maxima to represent the supply-demand ratio [35], which can easily result in very small ratio values when extreme values exist in supply or demand, thereby masking actual supply-demand differences. This study standardized the supply-demand difference using the overall standard deviation of supply and demand to obtain a new supply-demand ratio formula:

$$ESD = \frac{S - D}{\sqrt{\sigma_S^2 + \sigma_D^2}}$$

where ESD is the supply-demand ratio; S and D represent ecosystem service supply and demand quantities; and σ_S^2 and σ_D^2 are the standard deviations of supply and demand, respectively.

Building on the qualitative risk level identification concept from reference [18], we designed a quantitative supply-demand risk method. Positive and negative ESD values indicate supply-demand surplus and deficit, respectively. Higher surplus/lower deficit means lower risk, while lower surplus/higher deficit means higher risk. Therefore, we added a negative sign before ESD to quantify risk. Meanwhile, we used the correlation coefficient (r) between annual supply-demand ratio and year to represent temporal trends. An increasing ratio trend means decreasing risk, while a decreasing ratio trend means increasing risk. The risk index was constructed as follows:

$$ESDI = -ESD \times (2 + r) \quad \text{when } ESD > 0$$

$$ESDI = -ESD \times (2 - r) \quad \text{when } ESD < 0$$

where $ESDI$ is the supply-demand risk index. Larger negative absolute values indicate higher risk, while larger positive values indicate lower risk; ESD is the supply-demand ratio; and r is the correlation coefficient. When $ESD > 0$, an increasing trend over years ($r > 0$) increases the negative absolute value, while a decreasing trend ($r < 0$) reduces the negative absolute value. When $ESD < 0$, an increasing trend ($r > 0$) reduces the risk index value, while a decreasing trend ($r < 0$) increases the risk index value. Adding/subtracting 2 when combining with r avoids issues when r approaches 0. Finally, we identified regions with $ESDI$ values close to 0 as supply-demand safety zones, and classified the top 20% of $ESDI$ values as high-risk zones, middle 20% as medium-risk zones, and lower 20% as low-risk zones.

2.5 Data Analysis

We selected slope, soil organic matter content, annual mean temperature, annual precipitation, population density, GDP, normalized difference vegetation index, and proportions of various land use types as influencing factors. The XGBoost algorithm and SHAP method were used to identify the importance, direction, and threshold characteristics of factors influencing supply-demand risks. Analysis was completed using the xgboost and shapviz packages in R.

3. Results

3.1 Spatiotemporal Differentiation of Ecosystem Service Supply and Demand

As shown in [Figure 2: see original paper], average carbon sequestration supply in the Fenhe River Basin from 2000-2020 showed an increasing trend, with prefecture-level cities showing highest values in Xinzhou and Lvliang, medium in Taiyuan and Jinzhong, and lowest in Linfen and Yuncheng. Soil conservation supply also showed an increasing trend from 2000-2020, developing by the end of the study period (2020) into a pattern with Linfen highest, Jinzhong, Xinzhou, and Yuncheng in the middle, and Taiyuan and Lvliang lowest. Linfen and Jinzhong showed the greatest variation in soil conservation data. The changing trends of water yield supply among cities were inconsistent from 2000-2020, with declining supply in some cities requiring attention. However, most cities showed significantly increased water yield supply in 2020. The high precipitation in 2020 broke existing water yield supply trends across cities.

Average carbon sequestration demand from 2000-2020 showed an increasing trend ([Figure 2: see original paper]), with average values showing Taiyuan > Yuncheng > Jinzhong > Linfen > Lvliang > Xinzhou. However, after sorting by median values, Taiyuan dropped to the second-to-last position because extremely high carbon sequestration demand in Taiyuan' s urban area caused the average to far exceed the median and even the upper quartile ([Figure 2: see original paper]). Soil conservation demand across cities showed a fluctuating increasing trend, with Linfen, Xinzhou, and Jinzhong having relatively high average and median values, while Taiyuan, Lvliang, and Yuncheng were relatively low. Water yield demand across cities from 2000-2020 generally showed an increasing trend, with the highest increase rate in Taiyuan, little change in Linfen (its average even decreased slightly), but increases in median and quartile values. Average water yield demand showed Taiyuan and Yuncheng highest, Jinzhong and Linfen second, and Lvliang and Xinzhou lowest.

From a spatial distribution perspective, high-value areas of carbon sequestration supply were mainly distributed in mountainous areas at the basin edge, while low-value areas were located in the Taiyuan Basin and Linfen Basin of the Fenhe valley ([Figure 3: see original paper]). Ecological restoration activities since 2000 caused high-value carbon sequestration supply areas to expand from the basin edge toward the Fenhe valley. Carbon sequestration demand showed opposite spatial distribution, with high-value demand areas gradually expanding from the Fenhe valley to surrounding mountains over time. Soil conservation supply showed higher values in northwestern and central-southern mountains and lower values in the Taiyuan Basin and Linfen Basin, with high-value areas gradually expanding spatially in 2020 ([Figure 4: see original paper]). Changes in the spatial pattern of soil conservation demand from 2000-2020 were not obvious, but high-value areas increased in 2020 due to higher precipitation causing increased soil erosion. The spatial distribution trends of water yield supply were inconsistent across cities, showing a decreasing trend in the south and increasing trend in the north ([Figure 5: see original paper]). In 2020, water yield supply increased across most of the basin, with high-value areas expanding from the Fenhe valley to the basin edge. The spatial distribution of water yield demand in 2000 and 2020 was similar, with high-value areas mainly distributed in the industrially and densely populated Fenhe valley, and low-value areas in mountainous regions at the basin edge.

3.2 Spatiotemporal Differentiation of Ecosystem Service Supply-Demand Ratio

As shown in [Figure 6: see original paper], all cities had negative carbon sequestration supply-demand ratios showing a clear decreasing trend, with average values showing Xinzhou > Lvliang > Jinzhong > Yuncheng > Linfen > Taiyuan, completely opposite to the trend of carbon sequestration demand. The average soil conservation supply-demand ratio was negative and showed a decreasing trend. Comparing temporal trends of supply and demand revealed that the ratio was mainly determined by the demand side, i.e., soil erosion amount. Average soil conservation supply-demand ratios across cities showed Xinzhou > Lvliang > Jinzhong > Taiyuan > Yuncheng > Linfen.

The changing process of water yield supply-demand ratio means across cities from 2000-2020 was inconsistent. Taiyuan and Yuncheng had negative ratios in all years, while Xinzhou had positive ratios in all years. Lvliang, Jinzhong, and Linfen had low positive values in 2000, but negative or extremely low positive values in 2020. However, they became relatively high positive values in 2020, showing that the high precipitation in 2020 reduced water yield deficits and even achieved surpluses.

From a spatial perspective, low-value areas of carbon sequestration supply-demand ratio were mainly located in the Fenhe valley, with the Taiyuan Basin being the lowest, while high-value areas were in mountainous areas at the basin edge ([Figure 7: see original paper]). Low-value areas expanded from 2000-2020, while high-value areas shrank accordingly. The spatial distribution of soil conservation supply-demand ratio was similar in 2000 and 2020, but low-value areas increased significantly in 2020. High-value surplus areas of soil conservation service were scattered sporadically in the Fenhe valley, while severe deficit low-value areas were mainly distributed in mountainous areas at the northern and southern edges of the basin. From 2000-2020, water yield supply-demand ratio in the Fenhe valley was low (deficit state) and gradually expanding, but this expansion trend was reversed in 2020. The high precipitation in 2020 caused a sudden change in the spatial pattern of the supply-demand ratio, reversing the expanding trend of deficit areas.

3.3 Risk Zoning of Ecosystem Service Supply and Demand

Using supply-demand ratio trends from 2000-2020 to calculate the supply-demand risk index, zoning results are shown in [Figure 8: see original paper]. For carbon sequestration services, the entire Fenhe River Basin was within risk zones in 2020, with the Taiyuan Basin and Linfen Basin in high-risk zones, surrounding hilly mountains in medium-risk zones, and northern and southern mountainous areas in low-risk zones. Comparing across cities, Linfen City faced the greatest supply-demand risk, with medium-high risk zones accounting for 21.73% of basin area and 83.86% of city area, respectively. Jinzhong City ranked second, with medium-high risk zones accounting for 17.19% of basin area and 73.78% of city area. Xinzhou City had the lowest risk, with low-risk zones accounting for 8.63% of basin area and 98.64% of city area. In summary, the Fenhe River Basin had no supply-demand safety zones for carbon sequestration services. Developed industry and agriculture led to large carbon emissions that natural ecosystem carbon sequestration could not offset.

Soil conservation supply-demand high, medium, and low-risk zones were interspersed without large-scale aggregation ([Figure 8: see original paper]). Safety zones accounted for only 8.62% of basin area, mainly scattered in the Fenhe valley. Although vegetation cover in the Fenhe valley was not as good as surrounding mountains, the low slope resulted in small soil erosion. Linfen City had the largest medium-high soil conservation supply-demand risk area, accounting for 18.14% of basin area and 70.01% of city area. Jinzhong City ranked second, with medium-high risk zones accounting for 15.15% of basin area and 65.01% of city area. In summary, most areas of the Fenhe River Basin faced soil conservation supply-demand risks, especially in loess hilly mountainous areas with steep slopes, where risks may intensify under future climate change.

Water yield supply-demand safety zones dominated, accounting for 78.09% of basin area ([Figure 8: see original paper]). Only Taiyuan and Yuncheng regions had relatively high proportions of high-risk zones at just 6.74%. Xinzhou, Lvliang, Jinzhong, and Linfen had dominant safety zones, with proportions exceeding 90% of city area. The high precipitation in 2020 ensured supply-demand safety for water yield services in most areas, but water demand in population and industry concentration zones remained difficult to meet.

3.4 Driving Characteristics of Supply-Demand Risk Index

3.4.1 Driving Characteristics of Carbon Sequestration Supply-Demand Risk Index Using SHAP values (feature contributions to model predictions) to identify the importance of driving factors, population density and GDP had the greatest impact on carbon sequestration supply-demand risk index, together accounting for 84.7% of total explanatory power, indicating the demand side is the main aspect of the contradiction. From the direction of driving forces, population density and GDP nearly linearly intensified carbon sequestration risk. When annual mean temperature was below 10°C, the risk index increased only slightly with temperature; when exceeding 10°C (northern Taiyuan Basin and most southern basin areas), the risk index increased rapidly. The risk index showed a slowly increasing trend with cropland proportion. When NDVI was below 0.6, the risk index changed little; when exceeding 0.6, the risk index increased rapidly.

3.4.2 Driving Characteristics of Soil Conservation Supply-Demand Risk Index The top five driving factors for soil conservation supply-demand risk index were cropland proportion, grassland proportion, slope, annual precipitation, and forestland proportion ([Figure 11: see original paper]). The dependency plots show response characteristics of SHAP values to each driving factor. Since the sum of SHAP values and baseline values (average predictions) equals actual model predictions, dependency plots also reflect driving factor impacts on model predictions (risk index). [Figure 12: see original paper] only shows dependency plots for the top five factors.

Cropland proportion above and below approximately 20% had positive and negative contributions to the risk index baseline, respectively. Overall, risk index increased with cropland proportion. Grassland showed similar effects, with several small watersheds (scattered points above the red trend line) having grassland proportion exceeding 60% and high risk index values. These small watersheds are mainly located near the northern watershed divide with steep slopes, thus increasing risk. Forestland showed opposite effects to cropland and grassland. When slope was below 11°, risk increased with slope; when exceeding 11°, risk changed little, with the smooth curve above the SHAP=0 line indicating positive contributions of slope to risk. When annual precipitation was below 600 mm, risk increased with precipitation; when exceeding 600 mm, risk changed slowly. The smooth curve for annual mean temperature showed a decreasing then nearly flat trend because higher temperatures corresponded to plains and terraces in the central basin with small slopes, contributing little to risk changes.

3.4.3 Driving Characteristics of Water Yield Supply-Demand Risk Index Annual precipitation, GDP, grassland proportion, annual mean temperature, forestland, and cropland proportion were the main driving factors for water yield supply-demand risk index ([Figure 13: see original paper]). Precipitation impact (accounting for 30.9% of total explanatory power) far exceeded other factors, indicating the supply side is the main contradiction aspect. Higher precipitation, grassland, and construction land proportions suppressed risk, while lower values increased risk; GDP, annual mean temperature, forestland proportion, and population density showed opposite effects ([Figure 14: see original paper]).

When annual precipitation was below and above 560 mm, it had negative and positive contributions to the risk index baseline, respectively. Overall, risk index decreased with precipitation, with the steepest decline near 560 mm. Water yield risk increased with GDP and population density. When both were below 50,000 yuan/km^2 and 200 people/km^2, data points concentrated near SHAP=0; exceeding these thresholds (mainly corresponding to Taiyuan urban area) resulted in positive and rapidly increasing SHAP values, indicating intensified risk. Risk decreased with grassland proportion. With 7°C and 12 people/km^2 as thresholds, annual mean temperature’ s impact on risk showed three stages: increasing, unchanged, and rapidly increasing. This occurred because temperature had two spatial trends: increasing from east-west mountains toward the Fenhe valley, and increasing from north to south, with flat terrain leading to concentrated industry and agriculture, increasing water demand, while temperature increase enhanced evapotranspiration and reduced water yield, together intensifying risk. Forestland has strong evapotranspiration, thus intensifying risk. Although cropland evapotranspiration is weaker than forestland, when cropland proportion exceeded 40%, it still intensified risk because these areas had concentrated agriculture and population with greater water demand, masking cropland’ s positive effect on water yield supply. Construction land showed opposite effects to cropland, especially when its proportion exceeded 20%, because although urban water use was high, it remained lower than agricultural water use, and the high 2020 precipitation resulted in high water yield supply from construction land, ultimately reducing risk.

4. Discussion

4.1 Trends in Supply/Demand Patterns and Supply-Demand Risk Index

This study found that ecological restoration activities since 2000 promoted continuous improvement of carbon sequestration and soil conservation service supply in the Fenhe River Basin, consistent with results from Wang et al. [28] and Zhang et al. [29] in the Loess Plateau. The temporal trend of water yield supply was complex, with changes in surface vegetation evapotranspiration area causing fluctuations, and precipitation being an important external factor for water yield supply. Increased precipitation in 2020 caused substantial growth in water yield supply. The carbon-water relationship in arid regions is a research focus. Early studies on the Loess Plateau found vegetation restoration increased evapotranspiration, thereby reducing soil moisture and runoff, but recent research found regional precipitation increases exceeded evapotranspiration increases. Long-term observation data revealed increasing water yield trends in most Loess Plateau areas (82.3%), demonstrating the importance of vegetation-climate feedback [36]. This study verified this conclusion in the Fenhe River Basin, with similar findings by Zhao et al. [31], Wu et al. [32], and Xu et al. [33].

Water yield demand levels increased with socioeconomic development. The high precipitation in 2020 increased soil conservation service demand. Although water yield supply showed declining trends in some areas in 2020 and potential future precipitation fluctuations exist, proactive watershed-wide water resource management measures still require further research and formulation.

4.2 Imbalance in Ecosystem Service Supply-Demand Changes and Threshold Effects of Driving Factors

Supply and demand, as two aspects of ecosystem service supply-demand contradictions, have unbalanced spatiotemporal changes, often causing supply-demand matching to be dominated by one side, forming primary and secondary aspects of the contradiction. From spatiotemporal patterns, the demand side was the primary aspect for carbon sequestration and soil conservation contradictions, while for water yield, the primary aspect was not obvious in 2000-2020, but the supply side became primary in 2020 ([FIGURE:9-14]). From driving factors, carbon sequestration risk index was mainly affected by population density and GDP ([Figure 9: see original paper]), demonstrating demand-side dominance. Soil conservation risk index was mainly affected by land use, slope, and precipitation ([Figure 11: see original paper]), which had greater impacts on soil conservation demand, also reflecting demand-side dominance. Water yield risk index was mainly affected by precipitation ([Figure 13: see original paper]), demonstrating supply-side dominance. Similar patterns were found in Li et al.' s [37] study on the Loess Plateau. Identifying primary and secondary aspects of supply-demand contradictions in ecosystem service management will facilitate targeted measures to promote supply-demand matching.

This study found threshold effects of annual mean temperature, construction land proportion, and NDVI on carbon sequestration supply-demand risk index. When annual mean temperature >10°C and construction land proportion >20%, risks increased rapidly, while NDVI <0.6 had minimal risk increase, but risks increased rapidly when exceeding 0.6. Xun et al. [38] found NDVI in the 0.6-0.7 threshold interval had the highest ecosystem service synergy supply level in Shaanxi, corroborating our results. When slope <11° or precipitation <600 mm, soil conservation risk increased rapidly, but changed slowly beyond these thresholds. Previous studies also found slope and precipitation' s dominant roles in soil erosion in Loess Plateau areas [36-37,27]. When population density exceeded 200 people/km^2, water yield risk intensified. Annual mean temperature' s impact on water yield risk showed three stages: mild promotion, no impact, and strong promotion. Notably, cropland and construction land proportions had opposite effects on risk despite both having low evapotranspiration and generally benefiting water yield supply [39]. This result reflects differences between agricultural and urban water demands, as well as water yield supply capacities under high precipitation, with construction land ultimately showing risk suppression after comprehensive supply-demand balancing. However, water yield supply-demand risks still require attention under future precipitation changes. It is worth noting that driving factors have similarities and differences across ecosystem services. Similarities provide leverage for joint regulation, while differences reveal potential trade-offs requiring comprehensive consideration of factor directions and interrelationships.

The supply-demand risk index developed in this study encompasses both final status and multi-year trends, offering practical value for ecosystem service supply-demand risk management. Future research should incorporate ecosystem service flows and trade-off/synergy relationships into risk index calculations for more comprehensive risk characterization.

5. Conclusion

From 2000-2020, carbon sequestration and soil conservation service supply capacities in the Fenhe River Basin strengthened while demand levels increased. Water yield supply showed complex temporal trends but increased substantially in 2020, while water yield demand generally showed growth. Carbon sequestration and water yield demand spatial patterns were high in the Fenhe valley and low in surrounding mountains, while carbon sequestration supply, soil conservation supply and demand showed opposite spatial trends.

From 2000-2020, carbon sequestration and soil conservation supply-demand ratios both showed decreasing trends. In most areas, water yield supply-demand ratios decreased in 2020, but this trend reversed in 2020. Water yield services in the Fenhe valley showed deficit states that gradually expanded, but this expansion was reversed in 2020. Carbon sequestration services were all in supply-demand risk zones. Soil conservation exhibited mixed high, medium, and low-risk zones. Linfen region faced the greatest carbon sequestration and soil conservation supply-demand risks. The Fenhe River Basin was mainly in water yield supply-demand safety zones, with high-risk zones primarily in Taiyuan and Yuncheng regions.

Carbon sequestration supply-demand risk was demand-side dominated, with population density and GDP nearly linearly intensifying risk. Annual mean temperature $>10°C$ accelerated risk escalation. Soil conservation risk was demand-side dominated, increasing with cropland or grassland proportion, with slope $<11°$ and precipitation <600 mm as inflection points where risk increased rapidly. Water yield supply-demand risk was supply-side dominated, decreasing with precipitation and grassland proportion, but increasing with GDP and population density. With thresholds of 7°C and 12 people/km^2, annual mean temperature's impact showed three stages: mild promotion, no impact, and strong promotion.

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Note: Figure translations are in progress. See original paper for figures.