

The user wants me to translate a Chinese academic paper title and subtitle into English. The main title is “Trade-off and synergy effects, driving factors, and spatial optimization of ecosystem services in the Wuding River Basin of China: A study based on the Bayesian Belief Network approach” and...

Authors: The user has provided a name “FAN Liangwei” and wants me to translate it. This appears to be a Chinese name.

According to standard Chinese-English translation conventions for names: - The surname is FAN (范) - The given name is Liangwei (亮伟 or similar)

In academic contexts, Chinese names are typically written in one of these formats: 1. FAN Liangwei (surname in all caps, given name with standard capitalization) 2. Liangwei Fan (Western order, given name first) 3. Fan Liangwei (surname first, standard capitalization)

The most common format in academic papers is either: - All caps for surname: FAN Liangwei - Or standard capitalization: Fan Liangwei

Since the user provided it in all caps for the surname and standard caps for the given name (FAN Liangwei), I should preserve this format as it’s likely the author’s preferred romanization.

However, the user hasn’t provided any context about what this name is for or any surrounding text with tags. The instruction says “Translate from Simplified Chinese to English with the highest accuracy and academic tone” and mentions preserving tags, citations, etc.

But the input is just a name. There’s no paragraph tag, no LaTeX, no Chinese text to translate. It’s already in English (romanized Chinese).

I should probably just return the name as is, since it’s already in the appropriate format. But let me check the instructions again:

“Return ONLY the translated text for the given input (no explanations, no quotes, no headings you invent).”

The input is “FAN Liangwei” . This is already a transliterated name. There’ s nothing to translate. The surname FAN is 范 in Chinese, and Liangwei would be 亮伟 or similar characters. But the romanization is already provided.

I think the most appropriate response is to return the name exactly as provided, since it’ s already in English format. There’ s no Chinese text to translate, no tags to preserve, no mathematical content.

Wait, maybe the user wants me to translate this as if it’ s part of a larger document? But they only gave me this single name. Without context, I cannot create a paragraph tag or add any surrounding text.

The safest approach is to return the name exactly as provided: FAN Liangwei

But let me reconsider - perhaps the user is testing if I understand that a name doesn’ t need translation, or perhaps, WANG Ni, The user has provided a single name: “WANG Tingting” . This is a Chinese name that needs to be translated to English.

In academic contexts, Chinese names are typically transliterated using the Pinyin system. The standard format for English academic papers is: - Family name (surname) first, followed by given name - OR given name first, followed by family name

The most common and recommended format in international academic publications is: Given name + Family name (with family name sometimes in all caps to avoid confusion).

For “WANG Tingting” : - Family name: WANG (王) - Given name: Tingting (婷婷)

Standard transliteration would be “Tingting Wang” or “WANG Tingting” (with surname in caps).

Since this appears to be a standalone name without context, I should provide the standard academic transliteration. The most common format in English academic papers is “Tingting Wang” (given name first, family name last).

However, the user might want the name in the format typically used in Chinese academic papers written in English, which often keeps the Chinese order: “WANG Tingting” with the surname in uppercase.

Given the minimal context, I’ ll provide the most standard academic English transliteration: “Tingting Wang” . If the user wants it in a specific format (like all caps for surname), they can specify.

Wait, let me reconsider the instructions. The user said “Translate from Simplified Chinese to English with the highest accuracy and academic tone.” This is a name, not a paragraph with tags. The instructions mention preserving LaTeX commands, citations, and tags, but none of those apply here.

The glossary provided only includes: - 机器学习 => machine learning - 深度学习 => deep learning

These don' t apply to a personal name.

So I just need to transliterate the name. In academic contexts, Chinese names are typically: 1. Written in Pinyin 2. Family name first, given name second (preserving Chinese order) 3. Family name often capitalized: WANG Tingting 4. Or given name first, family name last: Tingting Wang

Both are acceptable, but the capitalized surname format is very common in academic papers to clearly identify the family name. Let me check typical practice...

In Chinese academic papers published in English, it' s common to see: - WANG Tingting - Tingting WANG - Tingting Wang

The first format (WANG Ting, The user has provided a single name: “LIU Zheng” . This appears to be a Chinese name that needs to be translated or romanized.

In Chinese names: - The family name comes first: 刘 (LIU) - The given name comes second: 正 (Zheng)

The standard academic convention for Chinese names in English publications is to either: 1. Keep the original pinyin with family name first: LIU Zheng 2. Or reverse the order: Zheng Liu

However, the user has already provided the name in what appears to be a standard format for academic papers (all caps for surname). The instruction says “Translate from Simplified Chinese to English with the highest accuracy and academic tone.”

Since “LIU Zheng” is already in pinyin (the romanization system), and this is the standard way Chinese names are presented in English academic papers, there' s no actual translation needed. The name should be preserved as is.

But wait - the user might be asking me to translate this as part of a larger context, or they might want me to confirm the proper formatting. Let me check the requirements again:

CRITICAL REQUIREMENTS: 1. Preserve ALL LaTeX commands and placeholders exactly - N/A here 2. Preserve ALL citation commands - N/A here 3. **PRESERVE ALL ...paragraph wrapper tags EXACTLY** - N/A here 4. Maintain academic tone and formal scientific writing style - N/A for just a name 5. Use precise technical terminology - N/A here 6. Preserve section structure and paragraph organization - N/A here 7. Translate all content completely - do not omit any information

OUTPUT RULES: - Return ONLY the translated text for the given input (no explanations, no quotes, no headings you invent). - Keep one output paragraph per input paragraph; do not merge or split paragraphs. - **Maintain exact**

count and IDs of ...tags - N/A here - Do NOT add Markdown formatting unless it is present in the source. - Preserve original line breaks within the paragraph when meaningful; otherwise use standard English sentence spacing.

The input is just “LIU Zheng” with no paragraph tags, no LaTeX, nothing. It’s just a name. The most appropriate response is to return the name as is, since it’s already in the proper academic format.

However, I should consider if the user, WAN Yong, LI Zhiwei, The user has provided a very short input: “WANG Ni” . This appears to be a name, likely Chinese. The task is to translate from Simplified Chinese to English with academic tone.

Let me analyze this: - “WANG Ni” - This is a Chinese name. In Chinese names, the family name comes first, then the given name. - “WANG” (王) is a common Chinese surname. - “Ni” (妮 or 尼 or other possibilities) is the given name.

In academic contexts, Chinese names are typically handled in one of these ways: 1. Kept as is: “WANG Ni” 2. Reordered to Western format: “Ni Wang” 3. With hyphenation: “Wang-Ni” (less common for two-character names)

The most standard academic practice is to either keep the original order (WANG Ni) or use the Western order (Ni Wang). Since the input is already in Pinyin with the surname first, and this is common in academic papers, I should probably keep it as “WANG Ni” .

However, let me check the requirements again: - The input is just “WANG Ni” - no paragraph tags, no LaTeX, no citations. - The user wants me to translate from Simplified Chinese to English. - The name “WANG Ni” is already in Pinyin (Romanized Chinese), so it’s not really “Chinese text” that needs translation.

But wait - the user might have intended this to be part of a larger document, or perhaps this is a test to see if I handle names correctly. The instructions say to preserve tags, but there are none in this input.

Let me think about the most appropriate academic translation: - In Chinese academic papers, authors’ names are often written in all caps for the surname: WANG Ni - In English papers, it’s typically “Ni Wang” (given name first) - However, if this is a direct translation of a Chinese document, we might keep the original format

Since there are no paragraph tags and this is just a name, I should probably just return the name in an appropriate format. But the instructions say “Return ONLY the translated text for the given input (no explanations, no quotes, no headings you invent).”

The simplest and most faithful approach is to keep it as “WANG Ni” since that’s the standard way Chinese names appear in academic contexts when maintaining the original order. However, if this is meant to be integrated

Date: 2025-12-15T17:59:43+00:00

Abstract

The user wants me to translate a Chinese academic text to English. Let me analyze the requirements:

1. **CRITICAL REQUIREMENTS:**
 - Preserve ALL LaTeX commands and placeholders exactly
 - Preserve ALL citation commands ([?], ??, (??), etc.) exactly
 - **PRESERVE ALL `…paragraph wrapper tags` EXACTLY**
 - Maintain academic tone and formal scientific writing style
 - Use precise technical terminology - obey the glossary strictly
 - Preserve section structure and paragraph organization
 - Translate all content completely - do not omit any information
2. **OUTPUT RULES:**
 - Return ONLY the translated text (no explanations, no quotes, no headings)
 - Keep one output paragraph per input paragraph
 - **Maintain exact count and IDs of `…tags`**
 - Do NOT add Markdown formatting unless present in source
 - Preserve original line breaks within paragraph when meaningful
3. **FORMATTING GUIDELINES:**
 - Keep mathematical expressions in original LaTeX format
 - Preserve equation numbers and references
 - Maintain proper academic paragraph structure
 - Use formal scientific language
 - Never remove or modify `…tags`
4. **Glossary:**
 - 机器学习 => machine learning
 - 深度学习 => deep learning

Now, let me look at the input text. Wait, the input text is already in English! The user provided an English abstract. Let me re-read the instructions.

The user says: “Translate from Simplified Chinese to English with the highest accuracy and academic tone.”

But the text provided is: “The Wuding River Basin, situated in the Loess Plateau of northern China, is an ecologically fragile region facing severe soil erosion and imbalanced ecosystem service (ES) functions. However, the mechanisms driving the spatiotemporal evolution of ES functions, as well as the trade-offs and synergies among these functions, remain poorly understood, constraining effective watershed-scale management. To address this challenge, this study quantified four ES functions, i.e., water yield (WY), carbon storage (CS), habitat quality (HQ), and soil conservation (SC) in the Wuding River Basin from 1990 to 2020 using the Integrated Valuation of Ecosystem Services and Tradeoff (InVEST) model, and proposed an innovative integration of InVEST with a Bayesian Belief Network (BBN) to nonlinearly identify trade-off and synergy relationships among ES functions through probabilistic inference. A

trade-off and synergy index (TSI) was developed to assess the spatial interaction intensity among ES functions, while sensitivity and scenario analyses were employed to determine key driving factors, followed by spatial optimization to delineate functional zones. Results revealed distinct spatiotemporal variations: WY increased from 98.69 to 120.52 mm; SC rose to an average of 3.05 \times 10⁴ t/hm²; CS remained relatively stable (about 15.50 t/km²); and HQ averaged 0.51 with localized declines. The BBN achieved a high accuracy of 81.9% and effectively identified strong synergies between WY and SC, as well as between CS and HQ, while clear trade-offs were observed between WY and SC versus CS and HQ. Sensitivity analysis indicated precipitation (variance reduction of 9.4%), land use (9.8%), and vegetation cover (9.1%) as key driving factors. Spatial optimization further showed that core supply and ecological regulation zones are concentrated in the central-southern and southeastern basin, while ecological strengthening and optimization core zones dominate the central-northern and southeastern margins, highlighting strong spatial heterogeneity. Overall, this study advances ES research by combining process-based quantification with probabilistic modeling, offering a robust framework for studying nonlinear interactions, driving mechanisms, and optimization strategies, and providing a transferable paradigm for watershed-scale ES management and ecological planning in arid and semi-arid areas.”

This is already English. There’ s no Chinese text to translate. The user might have made a mistake. Let me check if there are any tags. No, there are no tags in the input.

The instructions are very specific about preserving …tags. But the input doesn’ t have any. This is confusing.

Let me re-read the prompt again. The user says “Translate from Simplified Chinese to English” but provides English text. This could be: 1. A test to see if I follow instructions correctly 2. A mistake where they pasted the wrong text 3. The text is supposed to be Chinese but got converted somehow

Given the strict requirements about tags and LaTeX commands, and the fact that the input has none of these, I think the most likely scenario is that the user wants me to: 1. Recognize that the input is already English 2. Still process it according to the rules (though there are no tags to preserve) 3. Perhaps they expect me to wrap it in tags?

But the rules say “PRESERVE ALL …paragraph wrapper tags EXACTLY” and “Maintain exact count and IDs of …tags” . If there are none in the input, I shouldn’ t add any.

Let me think about this differently. Maybe the user provided a sample of what they want translated, but it’ s actually already been translated? Or maybe this is a meta-test?

The most faithful approach to the instructions would be: - If the input is already English, and there are no tags

Full Text

Preamble

Trade-off and synergy effects, driving factors, and spatial optimization of ecosystem services in the Wuding River Basin of China: A study based on the Bayesian Belief Network approach

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Abstract: The Wuding River Basin, situated in the Loess Plateau of northern China, is an ecologically fragile region facing severe soil erosion and imbalanced ecosystem service (ES) functions. However, the mechanisms driving the spatiotemporal evolution of ES functions, as well as the trade-offs and synergies among these functions, remain poorly understood, constraining effective watershed-scale management. To address this challenge, this study quantified four ES functions—water yield (WY), carbon storage (CS), habitat quality (HQ), and soil conservation (SC)—in the Wuding River Basin from 1990 to 2020 using the Integrated Valuation of Ecosystem Services and Tradeoff (InVEST) model, and proposed an innovative integration of InVEST with a Bayesian Belief Network (BBN) to nonlinearly identify trade-off and synergy relationships among ES functions through probabilistic inference. A trade-off and synergy index (TSI) was developed to assess the spatial interaction intensity among ES functions, while sensitivity and scenario analyses were employed to determine key driving factors, followed by spatial optimization to delineate functional zones. Results revealed distinct spatiotemporal variations: WY increased from 98.69 to 120.52 mm; SC rose to an average of 3.05×10^4 t/hm²; CS remained relatively stable (about 15.50 t/km²); and HQ averaged 0.51 with localized declines. The BBN achieved a high accuracy of 81.9% and effectively identified strong synergies between WY and SC, as well as between CS and HQ, while clear trade-offs were observed between WY and SC versus CS and HQ. Sensitivity analysis indicated precipitation (variance reduction of 9.4%), land use (9.8%), and vegetation cover (9.1%) as key driving factors. Spatial optimization further showed that core supply and ecological regulation zones are concentrated in the central-southern and southeastern basin, while ecological strengthening and optimization core zones dominate the central-northern and southeastern margins, highlighting strong spatial heterogeneity. Overall, this study advances ES research by combining process-based quantification with probabilistic modeling, offering a robust framework for studying nonlinear interactions, driving mechanisms, and optimization strategies, and providing a transferable paradigm for watershed-scale ES management and ecological planning in arid and semi-arid areas.

Keywords: ecosystem service functions; trade-offs and synergies; Bayesian Belief Network; spatial pattern optimization; Wuding River Basin

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1 Introduction

Ecosystem services (ESs) encompass the diverse functions and benefits that natural ecosystems provide to human society, including provisioning, regulating, cultural, and supporting services (Costanza et al., 2017). ESs directly reflect ecosystem structure and function, playing a vital role in sustaining the Earth's life-support system and enhancing human well-being (Bennett et al., 2015). These services are interconnected and interact in complex ways, often forming trade-offs and synergies (Sun et al., 2017). A trade-off arises when the improvement of one ES function reduces another, whereas a synergy occurs when multiple ES functions increase or decline together. The emergence of these trade-offs and synergies is shaped by natural driving factors such as climate change, biodiversity dynamics, soil quality, and hydrological conditions (Mach et al., 2015). These factors influence ecosystem structure and processes, thereby regulating the supply and demand of ESs and creating intricate interrelationships among them (Agudelo et al., 2020). Investigating trade-offs, synergies, and their driving forces is therefore essential for advancing theoretical understanding of ecosystem multifunctionality and guiding ecological restoration, land-use planning, and policy design. Clarifying these relationships provides a scientific basis for balancing ecosystem conservation with resource utilization, supporting regional ecological management, and promoting sustainable optimization of ESs.

As a representative hilly and gully region of the Loess Plateau in China, the Wuding River Basin is characterized by pronounced topographic relief, uneven spatiotemporal distribution of precipitation, a fragile ecological environment, and limited resilience. For decades, it has been under dual pressures of ecosystem degradation and intensive human exploitation, manifested in severe soil erosion, unstable vegetation cover, and declining ES functions (Huang et al., 2024b). In the context of the national strategy for ecological protection and high-quality development of the Yellow River Basin, the Wuding River Basin,

an important tributary of the Yellow River, requires scientific assessment and refined management of its ESs (Zeng et al., 2023b). The basin's land use patterns have shifted frequently, particularly under the influence of policies such as the Grain-for-Green Program and urban-rural expansion, leading to continual conversions among cropland, forest land, and construction land. These transformations have significantly reshaped the structure, function, and spatial distribution of ESs (Xiong et al., 2025). Moreover, harsh natural conditions, including aridity and fragmented terrain, coupled with growing anthropogenic pressures, have created increasingly complex ecosystem response mechanisms, thereby intensifying the challenges of ES management (Wan et al., 2024). Systematically identifying the dynamic evolution, interaction patterns, and dominant driving factors of ES functions in the Wuding River Basin is therefore crucial to advancing coordinated ecological protection and resource utilization while enhancing overall ES functionality.

Existing research has examined trade-offs and synergies among ES functions and their driving mechanisms through statistical analysis (Chen et al., 2022a; Xia et al., 2023), spatial analysis (Xu et al., 2022; Huang et al., 2024a), scenario analysis (Geng et al., 2022; Liu et al., 2023a), and other approaches. For instance, Huang et al. (2023) investigated the Wujiang River Basin of China using correlation analysis and the Geodetector method to identify trade-offs and synergies among multifunctional ESs, systematically exploring spatial mechanisms driven by both natural and socio-economic factors. Similarly, Zhao and Pan (2022) conducted a case study in Lanzhou City, Gansu Province, China, employing the InVEST model to assess four ES functions and integrating analysis of variance with geographically weighted logistic regression to evaluate how trade-offs and synergies respond to temperature, elevation, and the proportion of construction land. Tao et al. (2022) further developed a multi-scale ecological conservation and restoration framework in Nanjing City, Jiangsu Province, China, simulating priority conservation areas under multiple scenarios and revealing spatial nesting relationships and optimization strategies within ecological network components. Collectively, these approaches have advanced understanding of linear associations and spatial heterogeneity among ES functions, supporting mechanism interpretation and informing regional management.

Although statistical, spatial, and scenario analyses can reveal linear relationships among ES functions and their driving factors, they often fail to capture nonlinear, threshold-dependent, and conditionally mediated interactions that are typical of coupled socio-ecological systems (Lee and Lautenbach, 2016; Li and Wang, 2018). As a probabilistic machine learning method, the Bayesian Belief Network (BBN) effectively addresses such complexity by characterizing nonlinear and uncertain dependencies within systems. Through the integration of diverse quantitative and qualitative variables into a directed acyclic graph, BBN explicitly represents causal pathways between driving factors and ES functions, enabling detailed exploration of interactive influences under specific scenarios. Even with limited data, BBN demonstrates strong analytical and predictive performance, making it a valuable tool for diagnosing ES imbalances

and developing targeted management strategies (Karimi et al., 2021; Zhang et al., 2021; Liu et al., 2023b). Recent studies have increasingly applied BBN in ES research, highlighting its capacity to capture complex ecological processes and nonlinear functional relationships. For example, Lyu et al. (2022) employed BBN to assess the impacts of disturbances on carbon storage (CS), water yield (WY), and habitat quality (HQ) in the Qilian Nature Reserve, China, revealing nonlinear interactions between disturbances and ESs alongside regional trade-offs and synergies. Similarly, Peng et al. (2022) investigated nonlinear trade-offs among net primary productivity, WY, and soil conservation (SC) in Guizhou's karst region, China, demonstrating the joint influence of natural and anthropogenic drivers on ES functions. Zhang et al. (2025) further applied BBN to examine five ES functions in the Zhejiang Greater Bay Area, China, identifying complex nonlinear linkages and the sensitivity of ES probabilities to small changes in driving factors. Compared with traditional methods, BBN offers distinct advantages in modeling probabilistic, conditional, and causal relationships across multiple variables. It integrates empirical data with expert knowledge, allows dynamic updating of prior probabilities to infer posterior changes in ES functions, supports scenario simulations, and enhances decision-making in ecosystem management. Nonetheless, BBN applications are often constrained by static structures and the discretization of continuous variables, which can introduce uncertainty when thresholds lack empirical justification (Pham et al., 2021; Wang et al., 2024b). Despite these challenges, BBN remains a robust framework for uncovering nonlinear interactions and guiding the management of ES trade-offs and synergies.

While previous studies have widely employed BBN to identify ES functions and their driving mechanisms, analyses of trade-offs and synergies have frequently emphasized single-factor relationships, sensitivity analysis has largely focused on individual variables, and spatial pattern quantification has seldom been integrated with driving factor analysis. To address these gaps, this study developed a multi-factor dynamic BBN inference framework that incorporates scenario simulations to comprehensively identify trade-offs and synergies among ES functions. By coupling sensitivity analysis with the extraction of optimal state subsets for key driving factors, the study achieved more precise optimization of ES spatial patterns. Specifically, the InVEST model was applied to quantify four ES functions—WY, CS, HQ, and SC—in the Wuding River Basin from 1990 to 2020, while the BBN framework was used to investigate interrelationships among ES functions and the compound effects of multiple driving factors. Functional zones dominated by distinct ES functions were delineated, advancing understanding of spatial heterogeneity in regional ES distribution. This integrated BBN approach not only improves the interpretability of ES interdependencies but also supports a process-based understanding of service linkages, contributing to the theoretical development of ES science. In practical terms, it provides decision support for optimizing ecological management, restructuring land use, and formulating differentiated restoration strategies in ecologically fragile areas, offering methodological references for coordinated ES

regulation in arid and semi-arid landscapes.

2.1 Study Area

The Wuding River, a major tributary in the middle reaches of the Yellow River, flows through Shanxi, Shaanxi, and Inner Mongolia Autonomous Region, with a main channel length of 491 km and a drainage area of approximately 30,200 km² (Fig. 1 [Figure 1: see original paper]). The basin lies within the loess hilly and gully region of the Loess Plateau, featuring higher terrain in the northwest and lower elevations in the southeast, with a meandering river course. It experiences a temperate continental arid and semi-arid climate, receiving 300–500 mm of annual precipitation that is highly uneven in both space and time. Most precipitation occurs between July and September, leaving the basin highly susceptible to floods and soil erosion (Chen et al., 2022b; Zhang et al., 2022). Loess soils, characterized by high porosity and erodibility, contribute large amounts of sediment to the Yellow River, threatening downstream channels and hydraulic infrastructure. In 2020, land use of the basin was dominated by grassland (43.6%) and cropland (27.6%), followed by unused land (20.8%), woodland (5.8%), construction land (1.5%), and water bodies (0.7%). Unused land remains relatively extensive, while water resources are scarce. Urban and agricultural activities are concentrated along the river, increasing the risk of pollution.

In recent decades, large-scale soil and water conservation as well as ecological restoration initiatives have significantly improved vegetation cover, with natural grassland restoration and afforestation producing notable ecological benefits (Zeng et al., 2023a). However, the region's arid climate, seasonal precipitation patterns, and fragile topography continue to pose severe challenges for ecological conservation and water resource management.

Fig. 1 General overview of the Wuding River Basin based on digital elevation model (DEM) (a) and distribution of primary land use types in 2020 (b)

2.2 Data Sources

This study primarily employed data on digital elevation model (DEM), land use, vegetation cover, and bedrock depth (Table 1). All datasets were preprocessed in ArcGIS 10.8 through clipping, extraction, projection transformation, and data assimilation to ensure uniformity in resolution, pixel count, and coordinate system. To achieve consistency, all data were standardized to a 30 m resolution, as both the DEM and land use data were originally available at this scale. Since ES functions were constructed based on topographic information, a finer resolution was necessary to better capture spatial heterogeneity. Resampling coarser datasets to 30 m ensured compatibility across layers without altering their intrinsic information content, following established practice in watershed-scale ES assessments (He et al., 2022; Qin et al., 2024).

3.1 Calculation of ES Functions

The Wuding River Basin, located at the junction of the semi-arid zone and the wind-sand transition zone, is defined by harsh natural conditions and extremely fragile ecosystems. The region continues to face severe ecological challenges, including water scarcity, low vegetation cover, limited carbon sequestration, habitat fragmentation, and intense soil erosion, all of which interact to undermine ecosystem stability and sustainability (Wang et al., 2022b; Zhang et al., 2024). To address these issues, four key ES functions—WY, CS, HQ, and SC—were evaluated using the InVEST model to assess their spatiotemporal dynamics and guide ecological restoration. Model calculations followed the InVEST User’s Guide, and the outputs were spatially calibrated in ArcGIS 10.8 to ensure consistency across scales.

3.1.1 Water Yield (WY)

WY is a critical indicator of watershed ecological health, reflecting hydrological conditions and the regulation of the regional water cycle (Pei et al., 2022). The specific calculation formula is given as follows:

$$Y_{xi} = \text{AET}_{xi} + P_x$$

where Y_{xi} represents the WY of grid cell x with land use type i (mm); AET_{xi} denotes the actual evapotranspiration of grid cell x with land use type i (mm); and P_x represents the mean annual precipitation of grid cell x (mm). The AET_{xi} is derived using a modified Budyko equation:

$$\text{AET}_{xi} = \frac{P_x \cdot \text{PET}_{xi} \cdot \omega_{xi}}{P_x + \text{PET}_{xi} \cdot \omega_{xi}}$$

where PET_{xi} denotes the potential evapotranspiration of grid cell x with land use type i (mm); and ω_{xi} is a non-physical empirical parameter related to natural climate and soil properties. The parameter ω_{xi} is calculated as:

$$\omega_{xi} = Z_{WY} \cdot \frac{\text{AWC}_{xi}}{P_x}$$

where Z_{WY} is the seasonality constant; and AWC_{xi} is the plant-available water content of grid cell x with land use type i (mm). In the InVEST model, the Z_{WY} parameter defines the nonlinear relationship between infiltration and runoff, with values ranging from 1.0 to 10.0. In this study, Z_{WY} was calibrated to 2.3 using long-term WY data to enhance model accuracy. The AWC_{xi} is calculated as the product of root depth (RD_{xi} ; mm) and the plant-available water coefficient for the given soil type (PAWC_{xi}):

$$AWC_{xi} = RD_{xi} \cdot PAWC_{xi}$$

The $PAWC_{xi}$ is calculated as the difference between field capacity and wilting point:

$$PAWC_{xi} = 54.509 + 0.132 \cdot SAN - 0.003 \cdot (SAN) \cdot \frac{SIL}{CLA} + 2.699 \cdot OM + 0.501 \cdot (OM) \quad (4)$$

where SAN is the sand fraction in the soil (%); SIL is the silt fraction in the soil (%); CLA is the clay fraction in the soil (%); and OM denotes the organic matter content in the soil (%).

3.1.2 Carbon Storage (CS)

CS quantifies the carbon contained in vegetation biomass, litter, and soil organic matter (Feitosa et al., 2023). In the InVEST model, CS is estimated using carbon pool values assigned to each land use type (Table 2). This study determined the parameter values based on previous research from the Yellow River Basin and the Loess Plateau (Liang et al., 2021; Xu et al., 2023). The specific calculation formula is as follows:

$$C_{total} = C_{above} + C_{below} + C_{soil} + C_{dead} \quad (5)$$

where C_{total} represents the total carbon density (t/km^2); C_{above} denotes the aboveground vegetation carbon density (t/km^2); C_{below} refers to the belowground vegetation carbon density (t/km^2); C_{soil} indicates the soil carbon density (t/km^2); and C_{dead} represents the carbon density in dead organic matter (t/km^2).

3.1.3 Habitat Quality (HQ)

HQ reflects an ecosystem's capacity to support species survival and reproduction, serving as a key indicator of ecological security and health (Wang and Wang, 2023). In the InVEST model, HQ estimation is based on land use, threat sources, and habitat susceptibility. Drawing on studies from northern Shaanxi Province and the Yellow River Basin (Song et al., 2021), cropland, construction land, and unused land were identified as the primary threats, with corresponding influence distances, weights, and susceptibility values assigned (Tables 3 and 4). The specific calculation formula is as follows:

$$Q_{xi} = H_i \cdot \left(1 - \frac{D_{xi}^z}{D_{xi}^z + K_{hq}^z} \right) \quad (6)$$

where Q_{xi} represents the HQ of grid cell x with land use type i ; H_i denotes the habitat suitability score of land use type i ; D_{xi} indicates the habitat degradation of grid cell x with land use type i , influenced by threats present in the grid cell; z is the default normalization constant of the model; and K_{hq} is the half-saturation constant, typically set to 0.5.

3.1.4 Soil Conservation (SC)

SC represents a critical regulatory ES function, mitigating soil erosion and sediment loss, thereby preventing land degradation and reducing flood risks (Song et al., 2023). In the InVEST model, SC is calculated as the difference between potential and actual soil erosion, with biophysical parameters (cover-management factor (USLE-C) and support practice factor (USLE-P)) assigned according to land use type (Table 5). Model configuration largely followed default InVEST settings, where Threshold Flow Accumulation (1000) determines the minimum upstream area required to initiate a stream channel, Borselli K (2) controls the connectivity of sediment transport, IC_0 (0.5) is the calibration constant in the connectivity index, and SDRmax (0.8) represents the maximum sediment delivery ratio. This study adjusted the Maximum Flow Length ($L = 122$ m) based on regional literature to better capture slope-length effects. These inputs allowed for spatial simulation of SC (Shi and Wei, 2024). The specific calculation formulas are as follows:

$$Q_{SC} = Q_{PSE} - Q_{ASE} \quad (7)$$

$$Q_{PSE} = R \cdot K \cdot L \cdot S \quad (8)$$

$$Q_{ASE} = R \cdot K \cdot L \cdot S \cdot C \quad (9)$$

where Q_{SC} represents the SC amount (t/hm^2); Q_{PSE} denotes the potential soil erosion amount (t/hm^2); Q_{ASE} refers to the actual soil erosion amount (t/hm^2); R is the rainfall erosivity factor, typically represented by the long-term mean annual rainfall erosivity ($MJ \cdot mm / (hm^2 \cdot h \cdot a)$); K is the soil erodibility factor ($t \cdot hm^2 \cdot h / (hm^2 \cdot MJ \cdot mm)$); L is the slope length factor; S is the slope gradient factor; and C is the vegetation cover factor.

The rainfall erosivity factor R_j reflects the erosive force of rainfall in year j and is calculated as follows:

$$R_j = \alpha_3 \cdot P_j^{\beta_3} \quad (10)$$

where P_j represents the annual precipitation in year j (mm); and α_3 and β_3 are the dimensionless empirical coefficients derived from regional studies or relevant literature.

The soil erodibility factor K characterizes the inherent susceptibility of soil to erosion and is determined by soil texture (sand, silt, and clay contents), soil organic carbon, and soil structure. The K is calculated using the following empirical equation:

$$K = f(\text{CLA}, \text{SIL}, \text{SAN}, \text{OC}) \quad (11)$$

$$\text{CLA} \text{ SIL } 0.25 \text{OC} \text{ OC } \exp(3.722.95 \text{OC} \text{ \#\#1 SIL } 5.5122.9 \text{SNI}) \quad (12)$$

where SAN, SIL, and CLA are consistent with the definitions in Equation 5; OC indicates the percentage of organic carbon content (%); and SNI is the soil structure index, which is calculated as:

$$\text{SNI} = \frac{1 - \text{SAN}}{100} \quad (13)$$

3.2 Analysis of ES Functions Based on the BBN

The BBN, introduced by Judea Pearl in the 1980s, is a machine learning framework based on probability theory, designed to represent and infer dependencies among variables (Pearl, 1988). It comprises a set of nodes and directed edges, where each node represents a random variable, and edges indicate conditional dependencies between variables. The BBN quantifies dependencies using conditional probability tables (CPTs) and leverages the assumption of conditional independence to simplify computations, enhancing efficiency when handling high-dimensional and complex data. Through probabilistic inference, the BBN can update the probability distributions of unknown variables based on partially observed information, enabling prediction and decision-making (Zhou and Peng, 2021; Frizzle et al., 2022; Kitson et al., 2023).

The joint probability of all nodes in a BBN is calculated by multiplying the conditional probability distributions of individual nodes, as described by the following equation:

$$P(X_1, X_2, \dots, X_n) = \prod_{o=1}^n P(X_o | \text{parent}(X_o)) \quad (14)$$

where $P(X_1, X_2, \dots, X_n)$ represents the joint discrete probability distribution; and $P(X_o | \text{parent}(X_o))$ denotes the conditional probability distribution of node X_o given its parent nodes.

The conditional probability for each node is calculated using the following equation:

$$P(B | A) = \frac{P(A | B) \cdot P(B)}{P(A)} \quad (15)$$

where $P(B | A)$ represents the conditional probability of event B given that event A has occurred; $P(A | B)$ denotes the likelihood of event A occurring given event B ; $P(B)$ is the prior probability of event B ; and $P(A)$ is the prior probability of event A .

3.2.1 Construction of the BBN

Based on the process mechanisms of ES functions, we selected relevant variables as network nodes and performed structural learning. This study drew on previous research in the Yellow River Basin and the Loess Plateau, where the natural and socio-environmental conditions are comparable to those of the study area (Wang et al., 2022a; Qiu et al., 2023; Yang et al., 2024). After a comprehensive review, we identified nine driving factors (e.g., land use, slope, and vegetation cover) that have been shown to influence ES functions including WY, CS, HQ, and SC. Multicollinearity diagnostics were then conducted using IBM SPSS Statistics 27.0.1, treating each ES function as a dependent variable and the nine driving factors as independent variables. Results indicated that all variance inflation factor (VIF) values were below 6.000, well under the commonly used threshold of 7.500, suggesting no severe multicollinearity among the variables (Table 6). Consequently, these factors were appropriate for inclusion in the subsequent model construction.

The BBN model was constructed in Netica 5.18, which supports network structure design, parameter learning, and probabilistic inference. The constructed BBN model consisted of 13 nodes and 23 directed edges, with 9 driving factors designated as influencing nodes and 4 ES functions as target nodes. Data were discretized in ArcGIS 10.8 using the natural break method (Table 7). Continuous variables were classified into four levels (lower, low, high, and higher), while land use was categorized into six classes. Raster data were extracted on a 1 km \times 1 km grid, yielding 31,019 sample parameters, which were input into the BBN for training and the generation of spherical gain ranged from 0.0000 to 1.0000; and quadratic loss ranged from 0.0000 to 2.0000. Within these ranges, higher accuracy and spherical gain indicate better model performance, while lower logarithmic and quadratic loss values reflect greater reliability.

3.2.2 Trade-off and Synergy Effects

Using BBN model inference, we analyzed the trade-offs and synergies among ES functions. BBN inference refers to the process of computing the posterior probability of a target variable or set of variables based on the states of evidence variables (Forio et al., 2020). The inference process involves several steps: first, establishing the initial conditional probability distributions between adjacent

nodes; next, providing relevant evidence for node values; then, selecting an appropriate inference algorithm to update the conditional probability distributions for each node; and finally, calculating the trade-offs and synergies among the four ES functions.

3.2.3 Quantitative Assessment of Trade-off and Synergy Intensity

Building on the explicit identification of trade-off and synergy relationships among ES functions, this study further examined the spatial distribution patterns and intensity differences of these interactions. To quantify pairwise relationships between the four ES functions at the spatial scale, we introduced the trade-off and synergy index (TSI). This index enables an effective assessment of the intensity of interactions among ES functions across different regions (Wu et al., 2023b; Xue et al., 2023). The calculation formula for TSI is as follows:

$$\text{TSI} = 1 - \frac{|\Delta\text{ES}_p - \Delta\text{ES}_q|}{|\Delta\text{ES}_p| + |\Delta\text{ES}_q|} \quad (16)$$

where TSI denotes the trade-off and synergy index, ranging from 0 to 1; and ΔES_p and ΔES_q represent the changes in the values of ES function types p and q during the study period, respectively. Higher TSI values indicate stronger trade-off or synergy intensity between ES functions. Prior to calculation, all ES values were normalized to ensure consistency across spatial scales and to improve analytical accuracy.

3.2.4 Sensitivity Calculation

Sensitivity analysis was performed for each network node to identify the key driving factors influencing ES functions, based on the calculated variance reduction (VR; %) values. The calculation formula is as follows:

$$\text{VR} = \frac{V(\text{ES}) - E[V(\text{ES} | I)]}{V(\text{ES})} \times 100\% \quad (17)$$

where $V(\text{ES})$ and $E(\text{ES})$ denote the variance (in squared units corresponding to the ES function) and expected value (in the same units as the ES function) of a specific ES function, respectively; $V(\text{ES} | I)$ and $E(\text{ES} | I)$ represent the variance (in squared units corresponding to the ES function) and expected value (in the same units as the ES function) of the ES function under the given condition of variable I ; $p(U)$ and $p(U | I)$ denote the prior and conditional probabilities of the output state U , respectively; and U refers to the actual state value of the ES function output (in the same units as the ES function). Higher VR values indicate greater sensitivity of the node to the input variables.

3.2.5 Scenario Building

Based on a systematic analysis of trade-off and synergy effects among ES functions and their sensitivities, this study developed multiple scenarios to simulate ES function characteristics at different levels within the watershed. Subsequently, BBN probabilistic inference was used to calculate posterior probability changes for each influencing node relative to its prior probability. By integrating the actual conditions of the study area with observed trends in node probability variations, we thoroughly analyzed the primary driving factors under different trade-off and synergy effects.

Based on the correlations among different ES functions, this study established four distinct scenarios. Scenario I aimed to maximize the synergistic S1 relationship, setting “higher=100.0%”. Scenario II aimed to maximize the synergistic S2 relationship, setting “higher=100.0%”. Scenario III sought to minimize the trade-off effect between S1 and S2 relationships by setting all nodes to the “lower=100.0%” state. Scenario IV aimed to maximize the trade-off effect between S1 and S2 relationships by setting all nodes to the “higher=100.0%” state. The S1 relationship and S2 relationship represent two different synergistic effects among ES functions, while a trade-off exists between these two relationships.

3.2.6 Zonation of Spatial Patterns

Based on sensitivity analysis and CPTs, this study identified the key state subsets of various ES functions and used ArcGIS 10.8 for spatial visualization to map areas where the key states of dominant driving factors co-occur at different levels (Dai and Wang, 2023; Wu et al., 2023a).

First, key variables and their corresponding states were determined. Based on the prior sensitivity analysis, we selected the top three driving factors with the highest VR values for each ES function as key variables. The BBN model was then applied to calculate the conditional probability distributions of each ES function node under different variable states. For each ES function, the state corresponding to the maximum conditional probability was identified and defined as the key state of that variable. Both ES function nodes and driving variables were discretized into four levels: lower, low, high, and higher, forming a complete set of key state combinations.

Second, the optimal state subsets were determined by identifying the combinations of key variable states that yielded the highest conditional probability for each ES function. These optimal subsets represented the most favorable interaction configurations between driving factors and ES functions. Subsequently, the spatial distribution of these subsets was overlaid and visualized in ArcGIS 10.8, delineating four functional zones: core supply zone, ecological regulation zone, ecological strengthening zone, and optimization core zone. This spatial pattern provides a scientific basis and decision-making support for optimized allocation and spatial management of ES functions at the regional scale.

4.1 Assessment of ES Functions

The results indicated that high WY values are primarily concentrated in the northern part of the basin, whereas medium-to-low values are predominantly observed in the southern region (Fig. 2 [Figure 2: see original paper]). In contrast, the other three ES functions—CS, HQ, and SC—exhibited an opposite spatial pattern, with lower values in the north and higher values in the south. From 1990 to 2020, the annual average WY in the Wuding River Basin increased from 98.69 to 120.52 mm, although it declined to 71.79 mm around 2000 due to reduced flood-season precipitation and the early implementation of the Grain-for-Green Program. WY subsequently recovered as precipitation increased and vegetation restoration enhanced water storage and regulation capacity. CS exhibited a distinct north-south gradient, with high values in woodland and grassland and low values in unused land (mainly sandy areas). Between 1990 and 2020, CS remained relatively stable (about 15.50 t/km²) with a slight upward trend, primarily driven by ecological restoration projects and sustainable agricultural practices. HQ averaged 0.51, with high values in the southern hilly-gully regions and localized declines in the arid north, where degradation, mining, and overgrazing reduced ecosystem functions. Since 2000, afforestation and sand control measures have promoted HQ recovery in central and southern areas. SC increased to an average of 3.05×10^4 t/hm², reaching its highest levels in the southern basin with complex terrain and dense vegetation, but declined around 2000 under reduced precipitation before rebounding significantly through large-scale soil and water conservation projects. Overall, WY, CS, and HQ improved or stabilized, while SC showed notable increases, reflecting the combined effects of climate variability, vegetation restoration, and conservation measures that enhanced ecosystem resilience.

4.2 BBN Model Construction and Validation Results

The BBN model analysis revealed the probabilistic relationships between nine driving factors and four ES functions in the Wuding River Basin for 2020. The resulting network, comprising 13 nodes and 23 directed edges, generated a prior probability diagram (Fig. 3 [Figure 3: see original paper]) that visualizes the conditional dependencies among the variables. By sequentially predicting each state of the ES functions, the calculated accuracy ranked from highest to lowest as follows: 96.6% for SC, 85.8% for CS, 77.4% for HQ, and 68.0% for WY. Due to the high accuracy of SC, the directly influencing network nodes—precipitation, soil erodibility, NDVI, rainfall erosion, and slope—were selected, and their prior probabilities were individually adjusted by $\pm 10.0\%$ to examine the sensitivity of SC's posterior probabilities. Results indicated that only a 10.0% variation in the prior probability of the high state of slope causes the posterior probability of the lower state of SC to fluctuate by more than 3.0%, while changes in the other nodes produce fluctuations of no more than 2.0%. These findings suggested that the posterior probability of SC remains relatively stable, confirming the appropriateness of the threshold settings for SC.

Overall evaluation results (Table 8) showed an average accuracy of 81.9%, an average logarithmic loss of 0.4172, an average quadratic loss of 0.2473, and an average spherical gain of 0.8582, demonstrating that the BBN model exhibits strong overall accuracy and provides reliable prior probability predictions for the four ES functions.

4.3.1 Trade-off and Synergy Effects Among ES Functions

The posterior probabilities of each ES function are presented in Figure 4 [Figure 4: see original paper]. Using WY as the baseline variable, we sequentially set its probability to 100.0% for each state from lower to higher and observed the resulting posterior probabilities of the other ES functions. As WY transitioned from lower to higher states, the posterior probabilities of the low and lower states for CS and HQ increased, while those of the high and higher states decreased, indicating a clear trade-off relationship between WY and both CS and HQ; in contrast, SC exhibited a synergistic response, with the posterior probabilities of high and higher states notably increasing as WY improved. When CS was used as the baseline, WY and SC displayed a similar trade-off pattern, with their high-state probabilities decreasing as CS increased, whereas HQ showed a fluctuating response across different CS levels, suggesting potential nonlinear regulation by other influencing factors. Using HQ as the baseline, CS demonstrated a strong synergistic relationship, reflected in increasing high-state probabilities, whereas WY and SC showed trade-off patterns, with their high-state probabilities declining as HQ improved. With SC as the baseline, WY exhibited positive synergy, as the probability of higher WY states increased, while CS and HQ displayed trade-off relationships, with decreasing high-state probabilities as SC improved. In summary, synergistic relationships were observed between WY and SC, as well as between CS and HQ, whereas trade-offs were evident between provisioning/regulating services (WY and SC) and ecological structural attributes (CS and HQ). These findings highlighted the complex interdependencies among ES functions and underscored the importance of balancing multiple objectives in ecosystem management to mitigate systemic risks associated with prioritizing a single service.

4.3.2 Spatial Distribution of Trade-off and Synergy Intensity

Based on the TSI, this study conducted a pairwise spatial quantification analysis of four categories of ES functions at decadal intervals from 1990 to 2020 (Fig. 5 [Figure 5: see original paper]), identifying six functional relationship combinations. To facilitate phased comparisons and the analysis of temporal evolution, the periods 1990-2000, 2000-2010, and 2010-2020 were defined as Phase 1, Phase 2, and Phase 3, respectively.

Among synergy-dominated ES pairs, the TSI of WY_{SC} was generally high in the southwest, with synergy intensity increasing notably in the central basin in Phase 2. Eastern and northern areas consistently exhibited low synergy across all phases, highlighting spatial heterogeneity. For CS_{HQ}, strong synergy was

observed in Phase 1 but declined sharply in the central and southern regions during Phase 2, followed by partial recovery in the south in Phase 3, whereas the central basin remained low.

For trade-off-dominated pairs, the TSI of WY with CS and HQ displayed relatively stable spatial patterns. Trade-off intensity gradually decreased in the west, remaining at low to moderate levels; the central basin maintained moderate intensity; and downstream areas showed moderate to low intensity with minimal variation. Similar patterns were observed for CS_{SC} and HQ_{SC}, with scattered low trade-off intensity zones in the west, while most other areas maintained higher intensity.

Overall, the western basin exhibited strong synergies and weak trade-offs, reflecting a stable ES structure. The central region showed weaker synergies and stronger trade-offs, indicating functional tensions and reduced coupling. In contrast, the eastern region displayed moderate levels of both synergies and trade-offs, suggesting a relatively balanced but less integrated state. These spatial variations highlighted the complexity of ES interactions and underscored the importance of functional zoning and targeted ecological management.

4.3.3 Sensitivity Analysis

Using the built-in functions of the BBN model, sensitivity analysis was performed for each ES function. The results included the VR values of other 12 network nodes in relation to a single network node (Fig. 6 [Figure 6: see original paper]). The spatial distribution of WY in the Wuding River Basin was primarily influenced by rainfall erosion (VR=9.7%), precipitation (VR=9.2%), and NDVI (VR=7.2%), highlighting the significant roles of climatic factors and vegetation cover in hydrological regulation. High rainfall erosivity increases surface runoff, whereas denser vegetation enhances infiltration and maintains water balance. CS was mainly driven by land use (VR=9.8%), NDVI (VR=9.1%), and potential evapotranspiration (PET) (VR=4.6%), indicating that CS is highly responsive to ecological spatial structure, while PET indirectly affects carbon accumulation through vegetation productivity, reflecting combined biophysical and climatic influences. HQ was predominantly affected by land use (VR=9.5%), NDVI (VR=7.8%), and PET (VR=1.9%). The impact of land use highlights the effect of land transformation, including urban expansion and vegetation fragmentation, on habitat conditions. Greater vegetation cover stabilizes ecosystems, while variations in PET may alter ecosystem stress, indirectly influencing HQ. SC was primarily influenced by precipitation (VR=9.4%), rainfall erosion (VR=8.5%), and slope (VR=2.3%), highlighting the critical roles of precipitation and topography in soil erosion and retention. Heavy precipitation and steep slopes exacerbate soil loss, thereby reducing SC effectiveness. Overall, ES functions exhibited both consistent responses to topographic and climatic factors and spatial heterogeneity in their mechanisms and distribution.

4.3.4 Scenario Analysis

According to Figure 7 [Figure 7: see original paper], under Scenario I, defined by a strong synergistic relationship between WY and SC, the posterior probabilities of the precipitation and rainfall erosion nodes exhibited substantial changes relative to their prior probabilities. Specifically, the posterior probability of the higher state of precipitation increased by 40.0% compared to its prior value, while the lower state of rainfall erosion decreased by 29.3% and the higher state increased by 34.8%. These pronounced differences indicated that precipitation and rainfall erosion are the dominant driving factors under Scenario I. Under Scenario II, characterized by a high degree of synergy between CS and HQ, land use showed the most significant change, with the posterior probability of the woodland state increasing by 89.8% relative to its prior probability, identifying land use as the primary driver of ES synergies in this scenario. Under Scenario III, representing a weak trade-off condition accompanied by overall ES degradation, land use and NDVI exhibited notable posterior-prior shifts. Specifically, the posterior probability of the grassland state of land use decreased by 43.2%, while that of the lower state of NDVI increased by 31.3%, indicating that land use and NDVI are the main influencing factors under this scenario. Under Scenario IV, characterized by strong trade-offs but concurrently high overall ES functionality, the posterior probability of the woodland state of land use increased by 89.3%, while that of the grassland state decreased by 43.3%; precipitation showed a maximum posterior-prior difference of 44.7%. These results reinforced the dominant roles of land use and precipitation as key driving factors shaping ES dynamics under this complex scenario. In conclusion, precipitation, land use, and NDVI consistently emerged as critical variables mediating the balance between trade-off and synergy effects among ES functions across different scenarios.

4.3.5 Spatial Pattern Optimization

In the BBN model, each combination of the four states of major driving factors corresponds to one of the four states of each ES function, and the associated conditional probabilities were calculated through probabilistic inference using Netica (Table 9). After exporting these conditional probabilities, key state subsets were identified. Taking WY as an example, when WY was at the higher state, the corresponding key driver combination was {rainfall erosion=low, precipitation=low, NDVI=low}; when WY was at the high state, the combination was {rainfall erosion=low, precipitation=low, NDVI=lower}; for the low state, the combination was {rainfall erosion=higher, precipitation=higher, NDVI=higher}; and for the lower state, the key driver combination was {rainfall erosion=low, precipitation=low, NDVI=high}.

The key subset layers corresponding to each ES function were spatially intersected and visualized using ArcGIS 10.8, providing a clear depiction of the spatial patterns and overlaps among different ES functions across the basin (Fig. 8 [Figure 8: see original paper]). Using WY as an example, the four

delineated ecosystem functional zones exhibited pronounced spatial heterogeneity. The core supply zone featured the highest WY levels, accompanied by low rainfall erosion, NDVI, and precipitation, and was mainly located in the central-northeastern part of the basin and a small portion of the central-southwestern area, representing areas with the strongest water provision capacity. The ecological regulation zone had relatively high WY levels, low rainfall erosion and precipitation, and the lowest NDVI, situated around the core supply zone and extending toward the northwestern part of the basin, indicating moderate potential for ecological regulation and vegetation construction. The ecological strengthening zone showed relatively low WY levels but the highest rainfall erosion, precipitation, and NDVI values, reflecting a strong ecological foundation yet limited water provision; it was primarily located in the southeastern basin and served as a key target for vegetation restoration and soil-water conservation interventions. The optimization core zone exhibited the lowest WY levels, with low rainfall erosion and precipitation and relatively high NDVI, spanning central, southwestern, and northeastern areas, and due to its complex ecological structure and limited water supply, this zone requires refined land use regulation and ecological engineering to enhance water provision and overall ES functionality.

A comparative analysis of the spatial distribution of CS, HQ, and SC across the functional zones revealed distinct patterns of service configuration. For the core supply zone, CS was primarily concentrated in the southeastern basin, HQ dominated the southwestern region, and SC lacked a clear distribution pattern. For the ecological regulation zone, both CS and HQ were widely distributed, whereas SC occurred only sporadically along the southeastern edge. For the ecological strengthening zone, CS was concentrated along the northwestern margin, HQ extended from the northwestern part of the basin to the central region, and SC was mainly distributed in the southeastern part of the basin. For the optimization core zone, high-value areas of CS and HQ were scattered across the northwestern basin, while SC was the most prominent, covering nearly the entire northwestern part of the basin.

In summary, ES functions exhibited pronounced spatial differentiation and distinct functional emphases across the four delineated zones. The core supply and ecological regulation zones should prioritize water provision and ecological regulation, respectively, while the ecological strengthening zone should emphasize ecological restoration and soil conservation. The optimization core zone requires coordinated land-use adjustments and targeted ecological engineering interventions to enhance the integrated capacity of multiple ES functions.

5.1 Characteristics of the Dynamics of ES Functions

ES functions provide a fundamental basis for maintaining ecological balance and enhancing human well-being, making the evaluation of their changes crucial for regional sustainable development. This study employed the InVEST model to analyze dynamic changes in ES functions within the Wuding River Basin, revealing the combined impacts of human activities and natural drivers

on the watershed ecosystem. Model validation indicated that the simulated basin water yield coefficient (0.146) closely matches the value (0.148) reported in the Water Resources Bulletin (Shaanxi Provincial Department of Water Resources, 1990–2020), confirming the reliability of hydrological parameters. The simulated mean CS (15.50 t/km²) and mean HQ (0.51) were within the previously reported ranges for northern Shaanxi and the Yellow River Basin on the Loess Plateau (CS: 15.00–20.00 t/km²; HQ: 0.45–0.65), and the average SC (3.05×10^4 t/hm²) also fell within the reported range for the same region (2.00×10^4 – 6.00×10^4 t/hm²), supporting the accuracy and appropriateness of the model outputs (Zhao et al., 2022, 2023; Wang et al., 2024a).

Since 1990, the basin has experienced significant increases in basin water yield modulus and soil retention, primarily driven by the Grain-for-Green Program and enhanced precipitation. However, these increases have exerted some negative effects on CS and HQ. Despite notable improvements in water supply and soil erosion control, the growth rates of CS and HQ have remained relatively slow, with some areas even showing declines. This pattern highlights the complex interrelationships and potential trade-offs among different ES functions, emphasizing the need for integrated ecosystem management. Given the inherent uncertainties in assessing long-term dynamic changes based on observations and model simulations, future research should adopt finer spatiotemporal analytical approaches to enhance the scientific rigor and accuracy of ES function assessments.

5.2 Analysis of ES Functions and Their Trade-offs and Synergies Based on the BBN Model

This study developed a BBN-based model to evaluate ES functions in the Wuding River Basin for 2020, achieving an overall prediction accuracy of 81.9%. SC showed the highest accuracy (96.6%), while WY performed moderately (68.0%), confirming the model's effectiveness in capturing complex nonlinear interactions under uncertainty. The lower accuracy of WY was attributed to challenges in representing dynamic hydrological factors, limited spatiotemporal resolution of input data, and information loss from discretizing continuous variables. Future research should adopt higher-resolution temporal datasets and dynamic driving variables to enhance model adaptability and predictive stability. Inference results revealed synergies between WY and SC and between CS and HQ, suggesting potential multifunctional co-benefits under suitable ecological interventions. However, improvements in WY and SC imposed trade-offs on CS and HQ, reflecting conflicts among ES targets under current vegetation restoration, as well as soil and water conservation practices. Spatially, synergy-oriented pairs (e.g., WY_{SC} and CS_{HQ}) displayed dynamic TSI patterns from 1990 to 2020. WY_{SC} maintained high TSI in the southwestern basin, with a marked increase in the central region during 2000–2010, reflecting stronger functional coupling. CS_{HQ} exhibited strong TSI in the central-southern basin during 1990–2000, followed by decline and partial recovery in southern areas

during 2010–2020, indicating temporal fluctuations in ecological coordination. Trade-off-oriented pairs (e.g., WY_{CS} and WY_{HQ}) showed pronounced spatial heterogeneity and generally declining TSI. The western basin remained at low to moderate levels, the central region persisted at moderate intensity, and the transitional zone between the northwestern and central basin experienced long-term functional constraints, highlighting the need for phase-specific management strategies.

These results align with findings of Du et al. (2024) and Ren et al. (2025), confirming the BBN model's capability in assessing nonlinear ES interactions. Nonetheless, the temporal evolution of trade-offs and synergies was not fully captured; future work should integrate time-series data and dynamic BBN modeling to systematically represent temporal dynamics and underlying mechanisms among ES functions.

5.3 Driving Factors of ES Functions and Their Trade-offs and Synergies

This study applied the BBN model to analyze the sensitivity of ES functions. Results showed that land use, NDVI, and PET decisively shape the spatial patterns of CS and HQ, while precipitation, rainfall erosion, and NDVI strongly influence WY and SC. Scenario analysis further indicated that precipitation, land use, and NDVI have differentiated effects on ES functions and their trade-offs and synergies, identifying them as key drivers of ES dynamics. These findings provide a theoretical basis for understanding the spatial patterns and interactions among ES functions and their driving factors. Moreover, the reliability of the BBN model for identifying ES drivers is supported by previous studies conducted on the Pearl River Delta (Liu et al., 2022) and Baiyangdian Lake (Mao et al., 2023) of China. This study highlights the importance of promoting multifunctional synergies in regional ecological management. To achieve balanced and coordinated ES development, future efforts should refine land use classifications, optimize vegetation cover, and improve the efficient use of precipitation resources.

5.4 Spatial Optimization of ES Functions Through the BBN Model and TSI Framework

This study applied the BBN model to conduct spatial optimization of ES functions in the Wuding River Basin. Using sensitivity analysis and CPTs, we identified the optimal state combinations for each ES function, delineating zones with distinct functional attributes. The central and northwestern basin emerged as the primary optimization areas, concentrating multiple key ES units: the central region contained numerous optimization core zones for WY, while the northwestern region included extensive optimization core zones for SC, partial ecological strengthening zones for CS, and both optimization core and ecological strengthening zones for HQ. These areas exhibited strong potential for synergis-

tic enhancement at relatively low management costs, consistent with TSI results showing high synergy indices. The southeastern basin represented a secondary optimization area, where higher trade-off indices indicate stronger functional constraints. Nonetheless, it remained a major distribution area of ecological strengthening zones for SC. High precipitation and rainfall erosion, combined with elevated NDVI, create favorable conditions for SC improvement. Targeted ecological interventions, such as reforestation and terracing, are recommended to reduce trade-off pressures and enhance ecosystem stability and multifunctionality. The BBN model supports spatial optimization by quantitatively linking driving factors with ES outputs through conditional probabilities, integrating spatial patterns with ecological and climatic processes. However, driving factor selection relied mainly on subjectivity. Future research should expand the range of driving factors, establish systematic selection criteria, and apply multi-scale frameworks. Such advances will improve understanding of ES function interactions under complex ecological and climatic drivers, providing stronger theoretical insights and more informed watershed-scale management strategies.

The advantages of the BBN model in ES modeling are reflected in three main aspects. First, it offers strong transparency, enabling intuitive and rapid visualization of causal relationships among driving factors, which facilitates understanding and interpretation. Second, it effectively manages uncertainty and ambiguity in data, making it suitable for complex and dynamic ecosystem environments. Third, it integrates heterogeneous data from multiple sources, providing comprehensive support for ES assessments and enhancing modeling flexibility and applicability.

Despite these strengths, the BBN model has limitations. It cannot capture feedback loops, making it difficult to represent complex dynamic ecosystem processes. Variable discretization may cause information loss, reducing accuracy and predictive performance, particularly for continuous variables where sensitivity to subtle variations is diminished. In addition, the model's software flexibility is relatively limited, restricting its capacity for spatial analysis and dynamic simulations, especially with spatiotemporal data (Landuyt et al., 2013; Rohmer, 2020). Future improvements should include developing dynamic BBN models to meet temporal modeling needs, optimizing inference algorithms and discretization methods to reduce information loss, and adopting open-source platforms to improve scalability (Marcot and Penman, 2019). Integrating GIS technology can further strengthen spatial modeling capabilities, enhance ES assessment accuracy, and provide stronger support for science-based decision-making.

6 Conclusions

This study developed a systematic ES assessment framework based on the BBN model, integrating the InVEST model and the TSI to analyze spatiotemporal dynamics in ES functions and their interactions in the Wuding River Basin from 1990 to 2020. The framework focused on trade-offs and synergies, driver

identification, and spatial optimization for 2020. Results revealed pronounced spatiotemporal heterogeneity among ES functions, showing strong synergies between WY and SC and between CS and HQ, whereas clear trade-offs occurred between the two groups. Sensitivity analysis identified precipitation, land use, and NDVI as key driving factors with differentiated effects. By mapping optimal state combinations of ES functions and drivers, four ecological zones were delineated: core supply zone, ecological regulation zone, ecological strengthening zone, and optimization core zone. These zones provide a scientific basis for differentiated ecological management. Targeted restoration and management strategies are proposed to mitigate functional conflicts and promote stability and multifunctional synergies. This study enriches non-linear trade-off and synergy identification and advances multifactor spatial heterogeneity analysis using the BBN model. It also innovatively integrates TSI to quantitatively delineate and optimize ES spatial patterns, offering a more systematic and precise analytical tool for ES research. Practically, the framework shows strong applicability and scalability, providing scientific pathways and decision-making support for ecological optimization in fragile, semi-arid regions under significant human influence. Meanwhile, it promotes multi-objective coordination of ES functions and advances basin-scale governance toward fine-scale, quantitative, and sustainable management.

Conflict of interest: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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