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Understanding trade-offs and synergies among soil functions to support decision-making for sustainable cultivated land use

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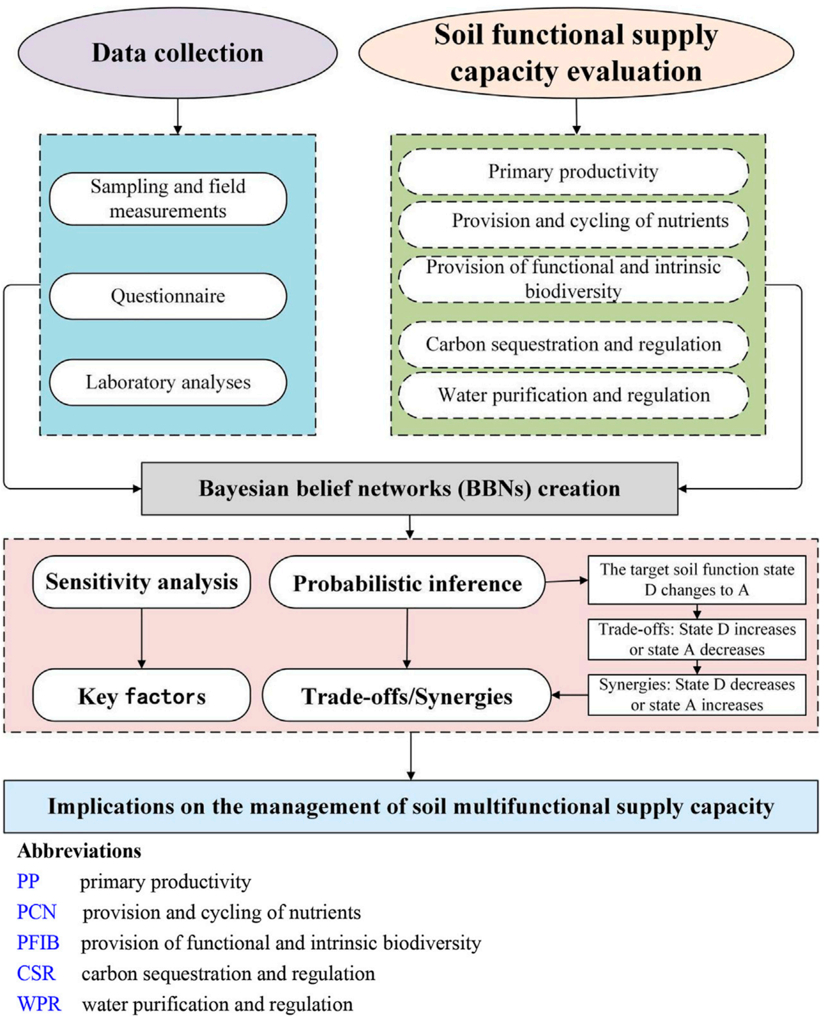
Soil provides a diverse and complex range of ecosystem services. Understanding the trade-offs and synergies among soil functions is foundational for effective soil ecosystem management and human well-being. In contrast, the long-term pursuit of solely productive functions in cultivated land use has resulted in soil degradation and weakened other ecological functions. This study collected soil, topographic landform, climate, and management data from 151 fields in four counties and three climatic zones in China. The Integrated Valuation of Ecosystem Services and Trade-offs (InVEST) model was used to evaluate nutrient retention, water production, and carbon storage, and the market value method was used to evaluate the value of the soil production function. A semi-quantitative model of Bayesian belief networks (BBNs) was used to simulate soil processes, thus revealing factors potentially influencing the supply capacity of five soil functions. Sensitivity analysis was used to identify the key variables influencing soil functional supply, and the probabilistic inference was used to identify interactions among soil's multiple functions. The main findings were as follows: 1) In four counties, the spatial heterogeneity in the supply of the five soil functions was relatively high. 2) The primary variables influencing the supply of soil's multiple functions were climatic conditions, management level, carbon storage, soil nutrients, soil biology, soil structure, and topography. 3) Trade-offs existed among primary productivity (PP), water purification and regulation (WPR), and carbon sequestration and regulation (CSR). Moreover, the provision of functional and intrinsic biodiversity (PFIB), WPR, and CSR were synergistic; specifically, the CSR and WPR services synergized with the nutrient provision and cycling (PCN). This research may aid in understanding the supply of, and interactions among soil's multiple functions, thus aiding in using BBNs to analyze soil ecosystem services. In addition, this study may provide a reference

Abbreviations: PP, primary productivity; PCN, provision and cycling of nutrients; PFIB, provision of functional and intrinsic biodiversity; CSR, carbon sequestration and regulation; WPR, water purification and regulation.

for management decision-making to maximize the overall benefits of soil functions in cultivated land use.

KEYWORDS

agro-ecosystem, bayesian belief networks, soil ecosystem services, soil parameters, soil multi-functionality



GRAPHICAL ABSTRACT

Highlights

1) To model the soil function supply process, a Bayesian belief network was built.
2) Soil supply services have trade-offs with regulating services.
3) The study is beneficial for exploring soil service mechanisms and prudent soil management.
4) Understanding soil biodiversity is extremely important for sustainable agricultural use.

Introduction

To meet the United Nations Sustainable Development Goals (SDGs) and national development strategies, soil use and management can play essential roles (Zhang G. L. et al., 2022). As an important source of ecosystem service diversity, Soil provides beneficial services that support most agro-pastoral production systems (Baveye et al., 2016). Soil function indicates a soil-based ecosystem service that consists of a series of soil processes that support the provision of ecosystem services and contribute to the production of goods and services that are beneficial to human social requirements and the environment (Barrios, 2007; Ghaley et al., 2014). Soil is critical to sustainable development, including fresh water and energy supplies, climate change, biodiversity loss, and food security (Lal et al., 2021). An overemphasis on increasing food production capacity leads to soil overuse, which is detrimental to Soil's other ecological services (Zhao et al., 2021; Zhao and Wu, 2021). Stakeholders with input regarding how land is managed may have different expectations or needs regarding how well the land performs each soil function (Greiner et al., 2018; Bampa et al., 2019; Schulte et al., 2019), thereby resulting in trade-offs among food production and other ecosystem services. Farmers, for example, may maximize soil productivity (Eliasson et al., 2010; Jafarzadeh et al., 2021) but may unintentionally affect the soil's purification or regulation functions. Consequently, emphasizing the multifaceted role of Soil in sustainable environmental policy and management is an essential component of sustainable soil management (Adhikari and Hartemink, 2016).

The functions closely associated with agricultural and forestry production, such as primary productivity (PP), provision and cycling of nutrients (PCN), provision of functional and intrinsic biodiversity (PFIB), water purification and regulation (WPR), and carbon sequestration and regulation (CSR), are driven by the concept of functional land management (O'Sullivan et al., 2015). The EU LANDMARK project's Soil Navigator decision support model is a representative soil function assessment method used in five European countries: Austria, Germany, Denmark, France, and Ireland (Debeljak et al., 2019). As a semi-natural and semi-artificial system, the cultivated soil system is subject to various selection preferences and utilization methods. Interactions among different soil function types occur under specific spatial and temporal conditions, thus resulting in a complex interactive relationship that consists primarily of trade-offs or synergies with mutual gains and losses (Zwetsloot et al., 2021). Because of these trade-offs and synergies, not every soil function can achieve maximum utility simultaneously (Vrebos et al., 2021). Zwetsloot et al. (2021) assessed five soil functions at 94 sites in 13 European countries across five climatic zones for two land use types: cultivated land and grassland. They have confirmed that synergies and trade-offs among soil functions vary by climatic zone and land-use type. Knowledge of the trade-offs and synergies in multiple soil functionalities is critical for providing farmers and policymakers with management options for the sustainable use of cultivated land resources (O'Sullivan et al., 2022).

Soil properties are helpful for assessing the potential of landscapes to provide terrestrial ecosystem services, but they are affected by anthropogenic activities and environmental factors, including landscape attributes (Syrbe and Walz, 2012; Takoutsing et al., 2018). Because of the complexities of soil function supply processes and the difficulty in precise measurement, current research on soil multi-functionality simulates supply and demand for a single soil function or the effects of various factors on specific soil functions (Valujeva et al., 2016). However, studies on soil function's trade-offs and synergistic effects are uncommon, particularly when more than two soil function models are used. The soil functional models used in recent studies have exhibited data input overlap. For example, four of the five function models have used soil organic matter or soil organic carbon as data inputs (Zwetsloot et al., 2021). Correlations observed among soil functions in the field may also be caused by overlapping indicator data during the evaluation process. Previous studies have widely used predictive analysis (forward reasoning) of Bayesian belief networks (BBNs) (Delen et al., 2020; Vrebos et al., 2021; Peng et al., 2022), whereas dependency and diagnostic analysis (reverse reasoning) have been underutilized. BBNs can link soil and environmental factors to multiple soil functions, visually simulate soil processes, and input various inferential hypotheses, depending on the purpose of the study. The outcomes of process-based models have improved our understanding of the complex potential roles of these soil processes concerning Soil, topographic, and climatic factors (Vrebos et al., 2021).

Consequently, BBNs have a high potential for use in investigating trade-offs and the synergistic effects of soil functions (Landuyt et al., 2016). Changes in network nodes can be easily detected with BBNs, thus revealing the differences in soil functional relationships (Gonzalez-Redin et al., 2016; Feng et al., 2021). Vrebos et al., 2021) used BBNs to model relationships among soil functions at the European scale, primarily by relying on indirect indicators. Such models have been dominated by soil physical and chemical processes, such as nitrogen mineralization, nitrification, and denitrification, while seldom considering soil biological components and activities (Li et al., 2022). The main goal of this research was to identify interaction patterns among functions, incorporating the concept of trade-offs and synergies into evaluating soil multiple functions in China to provide a reference for targeted cultivated land management policies. For this purpose, three specific sub-objectives were defined, based on 151 fields in China, from different climatic zones and soil types. They were: 1) to select network nodes based on soil processes and build a network model of the supply of five soil functions, 2) to identify critical drivers of the formation of soil multifunctional relationships through sensitivity analysis of BBNs, and 3) identify functional trade-offs and synergistic relationships in soils through probabilistic inference.

Materials and methods

Study site and characteristics

The study sites are located in China (Figure 1). We investigated a total of 151 fields with three types of cultivated land use in four specific county-level administrative regions: the China Northeast Black Soil Area, Huang Huaihai Fluvo Aquic Soil Area, Loess Hilly Brown Soil Area, and Jianghuai Hilly Aquorizem Area (dry land, paddy field, and irrigated land). Natural environments, geographical locations, crop types, and soil types vary across

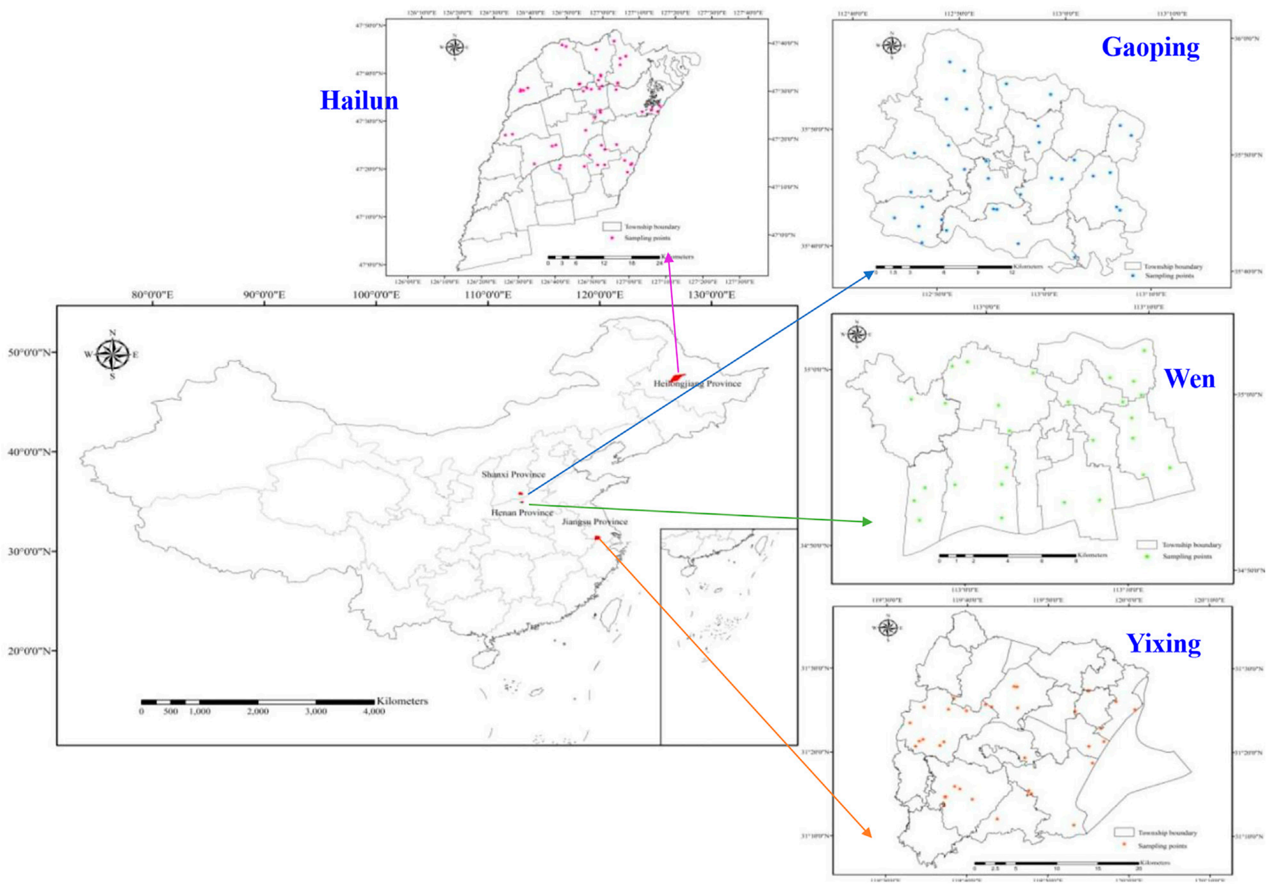


FIGURE 1
Location of the study area and distribution of sampling plots.

TABLE 1 Representative essential characteristics of sample location.

Samples site	Climate	Terrain	Soil types Soil Classification (WRB)	Main crops	Number of plots
Northeast Black Soil Area——Hailun County, Heilongjiang Province	North temperate continental monsoon climate zone	Hilly	Pheaozems	Soybean, rice	53
Huang Huaihai Fluvo Aquic Soil Area——Wen County, Henan Province	Warm temperate continental monsoon climate	Plains	Cambisols	Corn, wheat	28
Loess Hilly Brown Soil Area——Gaoping County, Shanxi Province	Warm temperate continental monsoon climate	Terrace	Luvisols	Corn, wheat	36
Jianghuai Hilly Aquorizem Area——Yixing County, Jiangsu Province	North subtropical monsoon climate	Low hills	Anthrosols	Rice	34

these four counties (Table 1). With an average annual precipitation of 550 mm and an average annual temperature of 1.5°C, Hailun County in Heilongjiang Province is at the heart of the Sonnen Plain's black Soil. It is a grain production center in northeast China. Yixing County, Jiangsu Province, with an average annual temperature of 15.7°C and precipitation of 1200 mm, this area is a commodity food base in the Yangtze River Delta. Wen County, Henan Province, is nationally renowned for its wheat yield of 7500 kg/ha; it has an average annual temperature of 14.4°C and 600 mm of precipitation. Gaoping County, Shanxi Province, with 600 mm of annual precipitation and 10.4°C annual temperature, is the birthplace of Chinese agricultural civilization in the Loess Hills area. Most cultivated land is terraced with rain-fed agriculture. The selection of study areas can reveal the related issues of soil protection and sustainable management and utilization in different climatic regions, different soil types, and different food crops or economic crop regions in China, and provide a scientific basis for promoting the healthy development of soil resources, which is typical and feasible.

Sampling and field measurements

The 151 soil samples from georeferenced locations (Figure 1) were collected from the upper 20 cm of Soil from September 2017 to October 2020. We used steel rolling pins to break up the bulk soil samples before mixing them to ensure uniformity and soil purity and the removal of litter and other debris on the soil surface before sampling. A sample of approximately 1 kg was extracted from each mixture with the quartering method. The samples were then sealed in sterile polyethylene bags and stored in a portable refrigerator away from heat and light. The depth of the tillage layer was measured with a drill rod at each soil sampling location. With a rubber hammer and a wooden block, the 15.24 cm diameter cutting ring was pressed down to a depth of 7.62 cm, and the soil surfaces inside were wrapped in plastic wrap to cover the Soil and the cutting ring fully. The cutting ring was filled with 300 ml of water measured with a graduated cylinder, and the water remained inside the ring after the plastic wrap was gently removed. The timer was then started and was not stopped until the soil surface inside flashed to record the time required for the water to penetrate the Soil. The ring-cutting method was used to determine the bulk density of the Soil. A total of 75 g of each Soil retained in the 2-mm sieve was used to determine water-stable aggregates, according to Kemper and Chepil (1965). A questionnaire was also used to poll farmers regarding their fertilizer, crop, irrigation, drainage, and pest control practices (Sandén et al., 2019). Drainage capacity, irrigation conditions, average annual temperature, annual precipitation, field slope, and terrain location were derived from the Natural Resources Bureau's Gradation on Agriculture Land Quality database and field surveys.

Laboratory analyses

Air-dried soil samples were passed through a 2-mm sieve. Soil particle sizes were determined with a full range laser particle size analyzer (Microtrac S3500), and the clay percentage (below 2 μm), silt content (silt percentage, 2–50 μm), and sand content (sand percentage, 50–2000 μm) were determined. To calculate soil water content, we used the original Soil's mass loss after drying a constant mass at 105°C. The pH was determined with a 1:2.5 soil-to-distilled-water suspension ratio. Soil organic matter was measured with potassium dichromate oxidation spectrophotometry. The ammonium acetate method was used to determine soil cation exchange capacity (Sumner and Miller, 1996). Soil total nitrogen, phosphorus, available nitrogen, available phosphorus, and available potassium were determined according to Chinese Soil Society guidelines (Lu et al., 2019). To determine dissolved organic carbon, we used the dichromate oxidation method (Jenkinson and Powlson, 1976). The carbon and nitrogen content of soil microbial biomass was determined with the chloroform fumigation–extraction method (Brookes et al., 1985). A CIRAS-2 (PPSystems, Amesbury, United States) portable CO_2 analyzer was used to measure soil respiration (soil CO_2 flux chamber). The carbon dioxide concentration was measured in g CO_2/m/h (Bojarszczuk et al., 2017).

Measurement of multiple soil functions

The multi-functionality of Soil can be viewed as a "trade-offs" black box: although the internal trade-offs among multiple soil functions cannot be directly identified, the external functional products provided by the output of multiple soil functions can easily be depicted (Kearney et al., 2019), and the existence of a variety of functional products often indicates multiple types of soil functions (Jiang et al., 2020).

The Integrated Valuation of Ecosystem Services and Trade-offs (InVEST) model was used to evaluate nutrient retention, water production, and carbon storage in each grid with grid sizes set to 100 m. Then, each sample field was assigned with the point extraction method (Feng et al., 2021). FRAGSTATS software calculated the Shannon Diversity Index as a biodiversity measure (Jiang et al., 2020). The sample field's central grain crop unit's production potential value was used to represent the soil's production function, and the market value method was used to evaluate the value of the soil production function with Eq. 1:

$$V = \sum_{i=1}^{m} W_i Y_i \tag{1}$$

Where V represents the unit production function value of the Soil (CNY, Chinese Yuan), W_i denotes the average production potential of the ith crop (kg/ha), and Y_i denotes the market price of the ith crop (CNY/kg).

Because the units and magnitudes of different soil function service values differ, the data needed to be standardized to make the soil function service values in Eq. 2 fall between 0 and 1:

$$SF_{stdi} = (SF_{obsi} - SF_{\min i}) / (SF_{\max i} - SF_{\min i}) \tag{2}$$

Where SF_{stdi} is the soil function service value after standardization, SF_{obsi} is the value to be assessed, SF_{mini} is the minimum value of each soil function service, and SF_{maxi} is the maximum value of each soil function service.

Bayesian belief networks (BBNs)

BBNs are probabilistic network models based on Bayesian causal probabilistic inference that reflect the partial state of the corresponding real world and show how these states are related by probabilities (Scrieciu et al., 2021). In BBNs, the variables involved in the research questions are represented by nodes. Each network node corresponds to a variable, which can be discrete, continuous, or logical (true/false). Users can customize the variables' discrete states and methods (Zhou et al., 2014; Wu et al., 2022). A BBN is a probabilistic graphical network, with each node containing a directed acyclic graph and a conditional probability table. Because BBNs are semi-quantitative, they can learn and infer under limited, incomplete, and uncertain information and can effectively address scientific problems involving uncertainties and human reasoning (Feng et al., 2021). Soil functions are groups of soil processes that emerge from interactions among Soil's physical, chemical, and biological components (Vogel et al., 2019). Towards cultivated land, agricultural management practices strongly influence the physical, chemical, and biological components of soil ecosystems (Sanaullah et al., 2020). Due to a large number of soil function indicator variables, multivariate analysis is recommended as an effective method and widely used in soil quality or soil function studies (Rezaei et al., 2006; Zuber et al., 2017; Rottler et al., 2019). On the basis of our existing data resources, we selected 37 variables, which also pave the way for the subsequent sensitivity analysis. In this study, the Netica software was used to build BBNs according to soil process principles and multifunctional soil supply, thus demonstrating the interactions among five soil function supply processes. In addition to the five soil functions, 37 variables were chosen to create the BBNs, and the network nodes were discrete, as shown in Table 4 (because of the large number of variables, some nodes were combined). Carbon storage was determined, for example, by bulk density, organic matter, tillage layer depth, and soil texture). Given the model's accuracy and complexity, each node was assigned one of four states: D (ex poor), C (poor), B (medium), or A (good). The structures of the BBNs (the node settings, the determination of connection and direction) are generated from expert knowledge, previous literature, and the causality among the variables (Vrebos et al., 2021). Probabilistic inference and sensitivity analysis were performed after the BBNs were completed.

Sensitivity analysis

The sensitivity analysis performed by Netica determined the independence and dependence of each node in the network. Variance reduction is the most effective sensitivity indicator because it reflects the influence of a

TABLE 2 Summary of the descriptive soil parameters (n = 151).

Soil parameter	Mean	SEM	Median	Min	Max	SD	Skewness	Kurtosis	CV	
Tillage layer depth	cm	33.54	0.81	35.00	15.00	60.00	10.01	0.25	-0.57	0.30
Aggregate stability	%	74.88	1.14	77.18	27.92	98.70	14.06	-0.77	0.32	0.19
Bulk density	g/cm3	1.26	0.01	1.27	0.69	1.70	0.18	-0.26	0.32	0.14
Soil water content	%	0.30	0.01	0.29	0.16	0.53	0.07	0.86a	1.49b	0.22
pH	—	7.50	0.08	7.20	5.43	9.82	1.02	0.05	-1.37b	0.14
Total N	g/kg	1.81	0.08	1.67	0.39	9.88	0.98	3.81a	29.17b	0.54
Total P	g/kg	0.62	0.02	0.57	0.09	1.54	0.25	0.61a	0.62	0.41
Available P	mg/kg	18.99	1.52	13.15	0.80	107.60	18.73	2.31a	6.90b	0.99
Available K	mg/kg	112.96	5.88	98.50	14.97	489.42	72.23	2.07a	6.56b	0.64
Available N	mg/kg	126.23	4.88	118.51	27.08	315.91	60.01	0.45a	-0.53	0.48
Dissolved organic carbon	g/kg	0.42	0.01	0.40	0.25	1.15	0.11	2.29a	11.90b	0.27
Organic matter	g/kg	28.42	1.19	25.93	3.65	75.34	14.60	0.62	-0.18	0.51
Cation exchange capacity	cmol/kg	18.76	0.44	19.97	4.80	26.70	5.44	-0.77	-0.20	0.29
Microbial biomass C to N ratio	—	10.22	0.21	9.50	6.53	16.80	2.54	0.72	-0.36	0.25
Soil respiration	g/m/h	0.76	0.05	0.63	0.18	7.76	0.64	9.04a	97.62b	0.84

a, the standardized skewness value is not within the range expected for data from a normal distribution; b, The standardized kurtosis value is not within the range expected for data from a normal distribution.

TABLE 3 Descriptive statistics of the soil properties in different regions.

Soil property	Unit	Region	Mean	SD	CV	Soil property	Unit	Region	Mean	SD	CV
Tillage layer depth	cm	HL	41.89	6.17	0.15	Available K	mg/kg	HL	136.61	83.04	0.61
		WC	33.07	9.68	0.29			WC	141.85	71.08	0.50
		GP	28.61	8.64	0.30			GP	85.34	37.21	0.44
		YX	26.15	6.13	0.23			YX	81.55	57.32	0.70
Aggregate stability	%	HL	83.47	8.49	0.10	Available N	mg/kg	HL	184.78	39.45	0.21
		WC	60.28	14.14	0.23			WC	79.01	28.03	0.35
		GP	67.86	10.43	0.15			GP	72.81	29.68	0.41
		YX	80.95	10.02	0.12			YX	130.43	40.80	0.31
Bulk density	g/cm3	HL	1.19	0.13	0.11	Dissolved organic carbon	g/kg	HL	0.45	0.11	0.25
		WC	1.42	0.14	0.10			WC	0.36	0.08	0.22
		GP	1.31	0.14	0.10			GP	0.38	0.07	0.17
		YX	1.17	0.20	0.17			YX	0.45	0.13	0.30
Soil water content	%	HL	0.31	0.06	0.19	Organic matter	g/kg	HL	40.94	10.32	0.25
		WC	0.26	0.06	0.21			WC	14.03	4.29	0.31
		GP	0.29	0.05	0.19			GP	23.63	13.77	0.58
		YX	0.32	0.08	0.26			YX	25.84	10.64	0.41
pH	—	HL	6.88	0.84	0.12	Cation exchange capacity	cmol/kg	HL	21.72	2.60	0.12
		WC	8.43	0.32	0.04			WC	11.37	4.07	0.36
		GP	8.52	0.13	0.02			GP	22.85	2.40	0.10
		YX	6.63	0.53	0.08			YX	15.92	3.99	0.25
Total N	g/kg	HL	2.45	0.49	0.20	Microbial biomass C to N ratio	—	HL	10.72	2.61	0.24
		WC	1.09	0.32	0.29			WC	10.07	2.61	0.26
		GP	1.48	1.46	0.99			GP	9.93	2.48	0.25
		YX	1.76	0.59	0.33			YX	9.85	2.26	0.23
Total P	g/kg	HL	0.68	0.26	0.38	Soil respiration	g/m/h	HL	0.81	0.32	0.40
		WC	0.67	0.21	0.31			WC	1.05	1.33	1.27
		GP	0.53	0.22	0.41			GP	0.52	0.09	0.18
		YX	0.57	0.27	0.48			YX	0.69	0.17	0.25
Available P	mg/kg	HL	28.41	17.91	0.63						
		WC	11.93	7.60	0.64						
		GP	6.58	5.36	0.82						
		YX	23.28	24.67	1.06						

HL, *Hailun County (53 samples)*; WC, *Wen County (28 samples)*; GP, *Gaoping County (36 samples)*; YX, *Yixing County (34 samples).*

specific variable on the target variable: the more significant the variance reduction, the greater the influence of the input factor.

As a result of the evidence input from node *F*, the expected value of node Q's expected variance decreased, thus reducing variance [0, V(*Q*)] was the variance reduction range. The stronger the interrelationship among node *Q* and node *F* when independent, the more significant the variance reduction. The variance reduction was determined as follows.

$$V_r = V(Q) - V(Q|F) \tag{3}$$

$$V(Q) = \sum_q P(q) \cdot \left[X_q - E(Q)\right]^2 \tag{4}$$

$$V(Q|f) = \sum_q P(q|f) \cdot \left[X_q - E(Q|f)\right]^2 \tag{5}$$

$$E(Q) = \sum_q P(q) \cdot X_q \tag{6}$$

where *Q* is the target variable, *F* is the change variable, *q* is the state of the target variable, *f* is the change variable's state, *Xq* is the real numerical value corresponding to state *q*, ∑ is the sum of all *q* of node *Q*, *E*(*Q*) is the expected value of *Q* before any new evidence was input, *E(Q|f)* is the expected value of *Q* after the new evidence *f* of node *F* was input, and *V(Q)* is the variance of the actual value of *Q* before any new evidence was input.

TABLE 4 Description of some network nodes.

Variable	Type	States and ranges	Unit
Soil texture	Discrete	D (gravelly Soil), C (sandy Soil), B (clay), A (loam)	—
Tillage layer depth	Continuous	D, C, B, A; [0, 10], (10, 15], (15, 20], >20	cm
Soil configuration	Discrete	D (sticky/sand/sand, all sand, all gravel), C (sand/sticky/sand, loam/sand/sand), B (loam/sticky/loam), A (all loam, loam/clay/loam)	—
Aggregate stability	Continuous	D, C, B, A; [0, 20], (20, 40], (40 50], (50,100]	%
Soil infiltration	Discrete	D, C, B, A; [0, 1]/>40, (1, 3]/[30, 40], (3, 5]/[20, 30], (5, 20]	min
Bulk density	Continuous	D, C, B, A; >1.55, (1.45, 1.55], (0, 1]/(1.25, 1.45], (1, 1.25]	g/cm3
Soil water content	Continuous	D, C, B, A; [0, 30], (30, 50], (50, 70], (70, 100]	%
pH	Continuous	D, C, B, A; [0, 4.5]/≥9.0, [4.5, 5.0), [5.0, 6.0)/[7.9, 9.0), [6.0, 7.9)	—
Total N	Continuous	D, C, B, A; [0, 0.9], (0.9, 1.5], (1.5, 2], >2	g/kg
Total P	Continuous	D, C, B, A; [0, 0.5], (0.5, 0.8], (0.8, 1], >1	g/kg
Available P	Continuous	D, C, B, A; [0, 5], (5, 10], (10, 15], >15	mg/kg
Available K	Continuous	D, C, B, A; [0, 50], (50, 100], (100, 150], >150	mg/kg
Available N	Continuous	D, C, B, A; [0, 200], (200, 300], (300, 400], >400	mg/kg
Organic matter	Continuous	D, C, B, A; [0, 10], (10, 20], (20, 40], >40	g/kg
Cation exchange capacity	Continuous	D, C, B, A; [0, 10], (10, 15], (15, 20], >20	cmol/kg
Dissolved organic carbon	Continuous	D, C, B, A; [0, 0.3], (0.3, 0.4], (0.4, 0.5], >0.5	g/kg
Microbial biomass C to N ratio	Continuous	D, C, B, A; [0, 5]/>10, (5, 6], (6, 7], (7, 10]	—
Soil respiration	Continuous	D, C, B, A; [0, 400], (400, 700], (700, 1000], >1000	g/m/h
Field slope	Continuous	D, C, B, A; >15, (6, 15], (2, 6], [0, 2]	°
Terrain location	Discrete	D (mountains), C (plateaus), B (hills), A (plains)	—
Average annual temperature	Continuous	D, C, B, A; [0, 5], (5, 10], (10, 15], >15	℃
Annual precipitation	Continuous	D, C, B, A; [300, 400], (400, 500], (500, 600], >600	mm

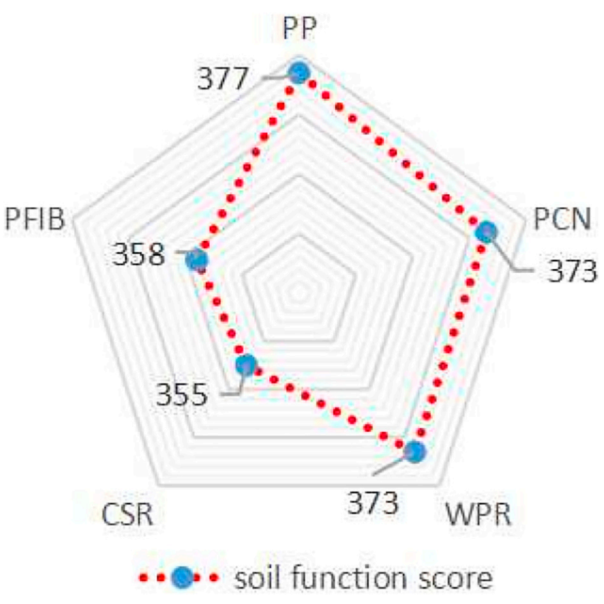


FIGURE 2
Pentagon diagram of Soil multifunction.

Results

The capacity to supply multiple soil functions

A regular pentagon area model indicated soil versatility and the degree of interaction among various functions. The soil function scores of the 151 sample plots in this study (converted to function grades, from A grade = 4 to D grade = 1) did not form a regular pentagon (Figure 2), thus indicating that a trade-off indeed existed among the five functions. When the functional strengths did not differ significantly, the soil's multi-functionalization and ecosystem stability were most extraordinary (Jiang et al., 2020; Li et al., 2021).

We detected that no single field supplied all five soil functions at a high level (such that all five soil functional grades were A simultaneously) and that no single field supplied all five soil functions at a low level (such that all five soil function grades were D simultaneously). According to Figure 3, PP and PCN were frequently supplied at a high grade, owing to the intensive utilization of most arable land plots; WPR, CSR, and PFIB were typically supplied at medium capacity with slight variation in

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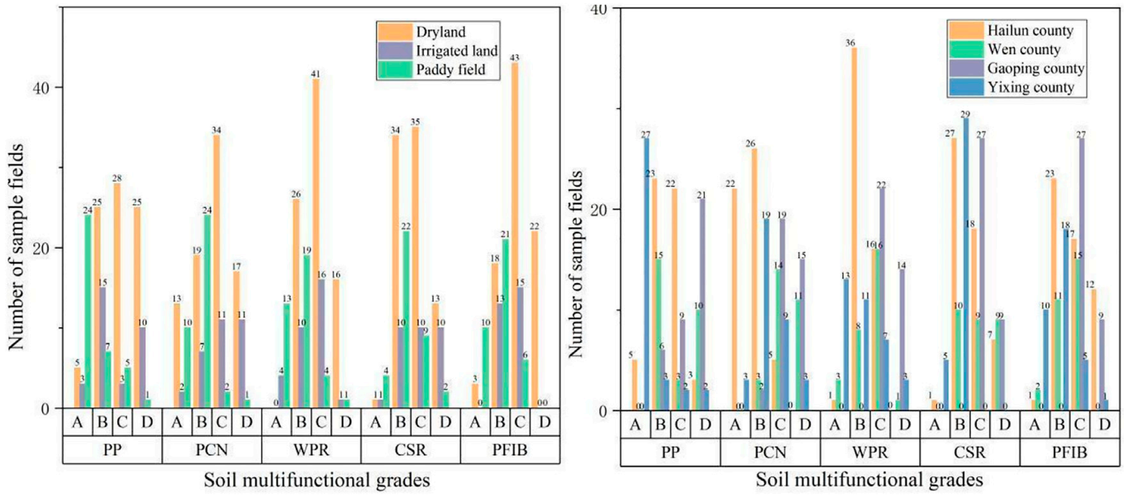

FIGURE 3
Soil multifunctional supply capacity in different land types and counties.

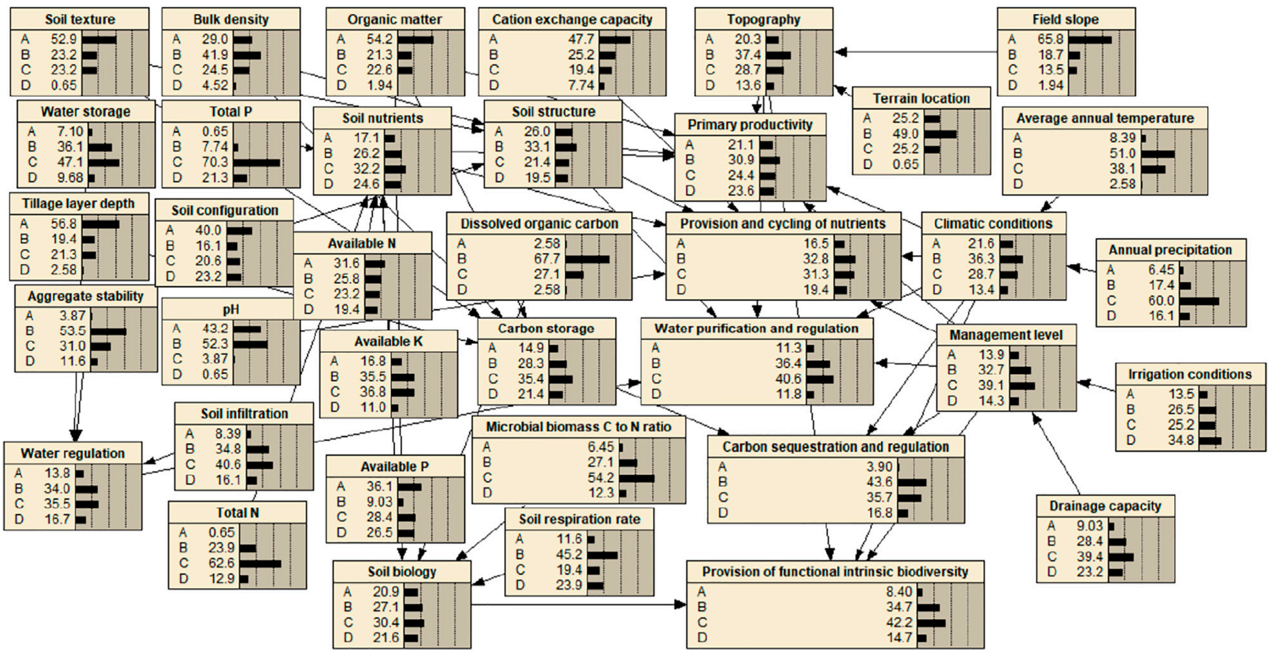

FIGURE 4
The compiled BBN

quantity, primarily in Yixing and Hailun paddy fields. The most notable feature was Gaoping's poor performance in terms of WPR, CSR, and PFIB, which was also associated with a lack of water in farmland (dependent on natural rainfall) and complex terrain. Altitude has also affected soil biodiversity by influencing temperature and precipitation (Kouser et al., 2021). Yixing County had the highest PP and PFIB of the four areas, owing to the county's favorable climatic conditions, the farming system of three crops per year, and paddy fields being the most common type of cultivated land.

Furthermore, due to the high precipitation in Yixing County, warm and humid weather during the rainy season accelerates litter

TABLE 5 Results of BBN accuracy evaluation.

Node	Error rate (%)	Logarithmic loss	Quadratic loss	Spherical payoff
PP	39.13	0.8025	0.4873	0.8491
PCN	32.75	0.6728	0.4228	0.6856
WPR	34.67	0.7882	0.5549	0.6613
CSR	30.83	0.7353	0.5006	0.7315
PFIB	37.25	0.7296	0.5712	0.6892

decomposition, increasing microbial nutrient fixation (Lv et al., 2014; Dou et al., 2022). On the other hand, its soil type was black soil (also referred to Pheaozems), with a relatively high organic carbon content (the mean was 40.94 g/kg); Hailun County had a higher supply capacity for PCN and CSR than the other three counties. Furthermore, the field investigation discovered that most of the sampled fields in Hailun County had adopted measures such as returning straws to the fields and applying organic fertilizers. These measures can increase organisms' living space, improve the soil's physical structure, and increase soil fertility (Zhang S. et al., 2022). PP and PFIB supply frequency were higher in paddy fields, and the WPR was higher than in dry land. Because the unique paddy field management system regulates the redox-driven processes that occur in the Soil, affecting the transformation, turnover, and nutrient cycling of soil organic matter (Liu et al., 2021).

Furthermore, rice is almost uniformly planted in paddy fields, and the rice roots can release oxygen into the Soil, creating a unique aerobic microbial habitat in an anoxic rhizosphere environment (Kögel-Knabner et al., 2010). The use of intensive soil management activities that disrupt the structure of the Soil with heavy machinery, causing compaction, i.e., by increasing bulk density, reducing pore space, and breaking up soil aggregates (Rodríguez-Martín et al., 2019), and this is the case of Wen County has the highest mean bulk density at 1.42 g/cm^3. The CSR supply capacity is relatively low.

Construction and testing of BBNs

The BBNs structure of the supply of five soil functions comprised 37 nodes and 49 one-way arrows in the networks

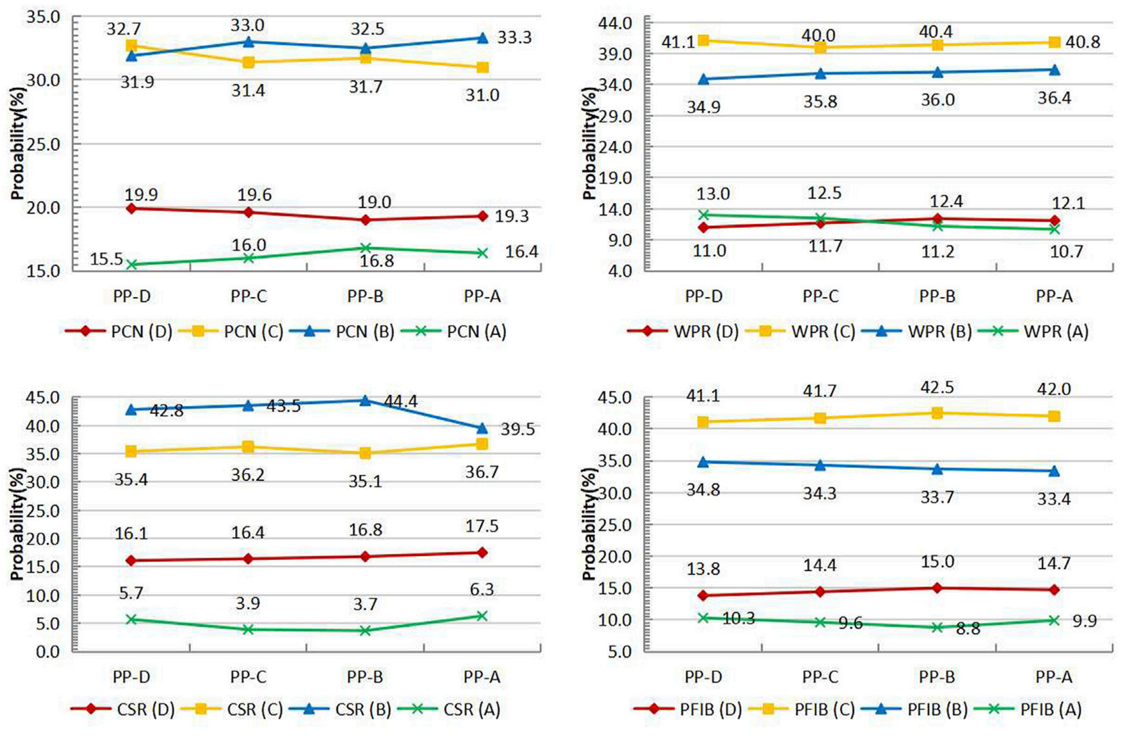

FIGURE 5
Changes in the PCN, WPR, CSR, and PFIB nodes.

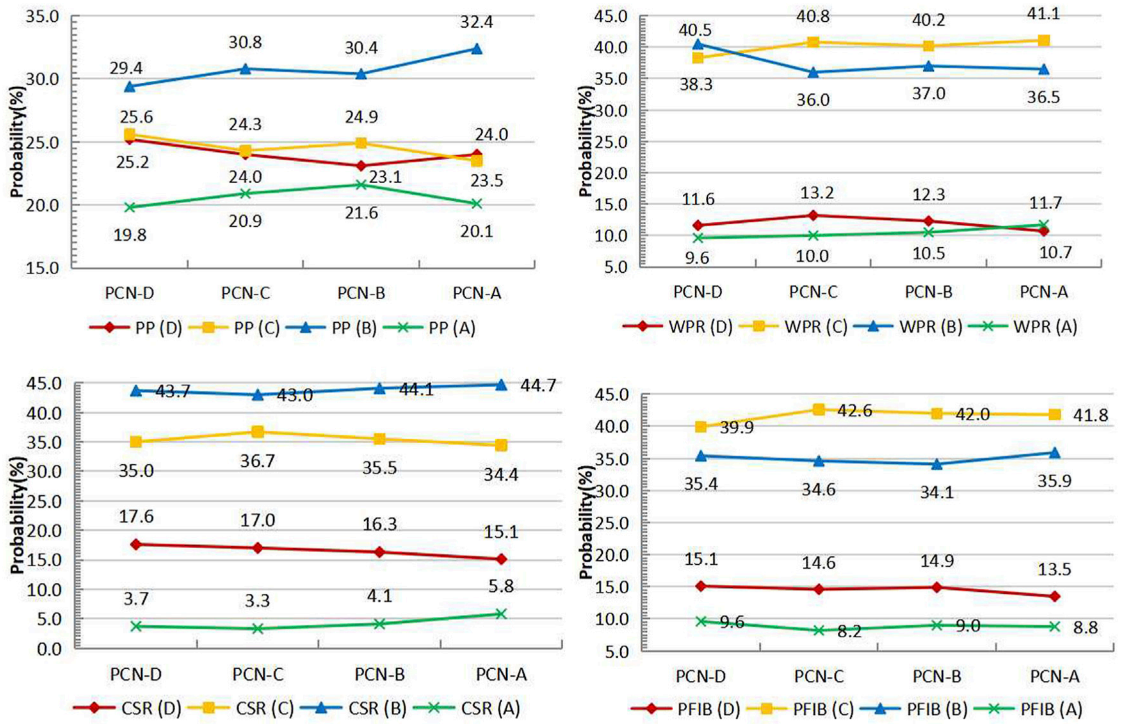

FIGURE 6
Changes in the PP, WPR, CSR, and PFIB nodes.

(Figure 4). All nodes were assigned one of four grades: A (excellent), B (medium), C (poor), or D (ex poor). The node name is at the top of the node hierarchy, followed by the node status, belief bar, and corresponding probability. More than half the farmlands had PP above medium, and 50.7% had PCN below medium, thus indicating that more than half had poor PCN. Only 11.3% of farmlands had a high level of WPR, and only 3.9% and 8.4% of farmlands had good CSR and PFIB regulation, respectively. Notably, only one farmland is located in the mountains and is not suitable for farming, and approximately one-quarter of farmlands have inadequate drainage capacity. Furthermore, 34.8% of farmlands had deplorable irrigation conditions, indicating that most farmland infrastructure was in poor condition and consequently indirectly affected soil multifunctional performance.

After the construction of the BBNs, the networks' accuracy was tested with Netica's Network Test by Case function, 100 cases were obtained through random sampling with points, which were used to conduct accuracy tests. Five soil function supplies were selected as the nodes to be tested. Netica software was used to compare the generated predictions with the true values in the test case file, and the results are displayed in Table 5. The measures calculated by the Netica include the error rate, logarithmic loss, quadratic loss, and spherical payoff. According to the judgment rule mentioned by Feng et al. (2021) and Sun et al. (2022), the relatively high accuracy of the BBN created in this paper as a whole demonstrates that the BBN is considerably accurate in the simulation of the soil functions supply process and shows strong reliability to conduct the probabilistic inference of each soil function node.

Probabilistic inference for every soil function

According to the Bayesian theorem, using conditional probability tables, BBNs can infer unobserved nodes' posterior probabilities (i.e., conditioned on all current findings). Soil function trade-offs and synergies were determined by entering the findings for one node and recording the updating posterior probabilities of other nodes. First, the PP node states were set to the four known states, namely D = 100%, C = 100%, B = 100%, and A = 100%. The state of each network node was then updated. The posterior probabilities of the four-node states PCN, WPR, CSR, and PFIB were observed and recorded as they changed. Figure 5 depicts how the corresponding posterior probability distributions of the PCN and PFIB nodes changed irregularly and insignificantly as the PP node's state improved from D to A, making it difficult to identify the relationships among the PP, PCN, and PFIB services. On the other hand, the probabilities of the WPR nodes' A states decreased, while the probabilities of the

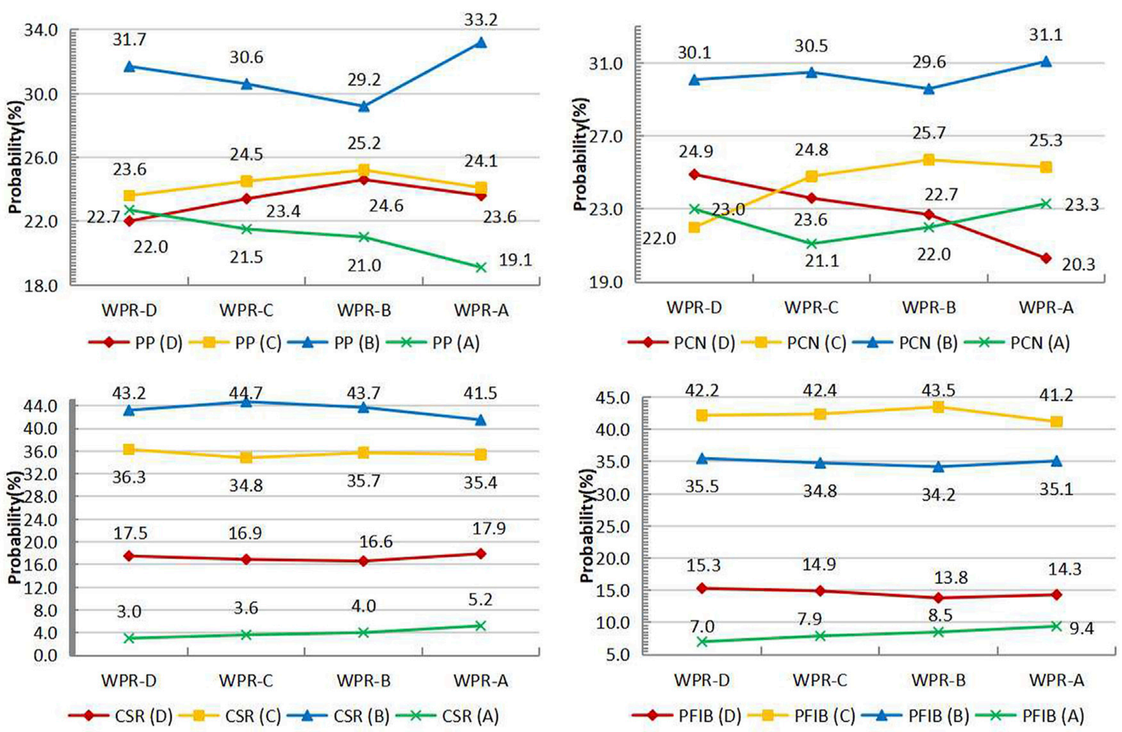

FIGURE 7
Changes in the PP, PCN, CSR, and PFIB nodes.

CSR nodes' D states increased. As a result, trade-offs were made between the PP service and the WPR and CSR services.

Second, the PCN node states were set to four known states, namely D = 100%, C = 100%, B = 100%, and A = 100%. Figure 6 shows that as the PCN node gradually improved from the D state to the A state, the probabilities of the CSR node remaining in the D state decreased. In the case of the WPR node, the likelihood of the A state increased. Consequently, the CSR and WPR services synergized with the PCN service.

Third, the WPR node states were set to four known states, namely D = 100%, C = 100%, B = 100%, and A = 100%. Figure 7 shows that the changes in the CSR, PCN and PFIB nodes were similar as the WPR node progressed from the D state to the A state. The probabilities of the A state of the CSR and PFIB showed an increasing trend, whereas the probabilities of the D state in the PCN showed a decreasing trend, and the probabilities of the A state of the PP showed a decreasing trend. Thus, synergies existed among the WPR, CSR, PCN, and PFIB services. A trade-off relationship was observed between the WPR and PP services.

Fourth, the CSR node states were set to four known states, namely D = 100%, C = 100%, B = 100%, and A = 100%. A line chart is presented in Figure 8. As the CSR node gradually improved from the D state to the A state, the PP node changed in the opposite direction. The probabilities of the A state of the PCN and PFIB nodes showed an increasing trend, whereas the probabilities of the D state showed a decreasing trend in the WPR node. Therefore, trade-offs occurred between CSR and PP services, the CSR service synergized with the PCN, WPR, and PFIB services.

Finally, the PFIB node states were set to four known values: D = 100%, C = 100%, B = 100%, and A = 100%. Figure 9 depicts the change in the CSR node as the state of the PFIB node gradually improved from the D state to the A state. The probabilities of the CSR node's D state decreased while the probabilities of the A state increased. Furthermore, the A state of the WPR grew gradually. As a result, trade-offs were observed between the PFIB and PCN services. According to the above analysis, the PFIB service collaborated with the CSR and WPR services.

Identification of critical factors

Network sensitivity analysis was performed in Netica with PP, PCN, WPR, CSR, and PFIB as target nodes, and the degree of influence of each node in the network on the target node was identified through variance reduction, thereby identifying the key variables affecting the supply of each soil function. Only the top

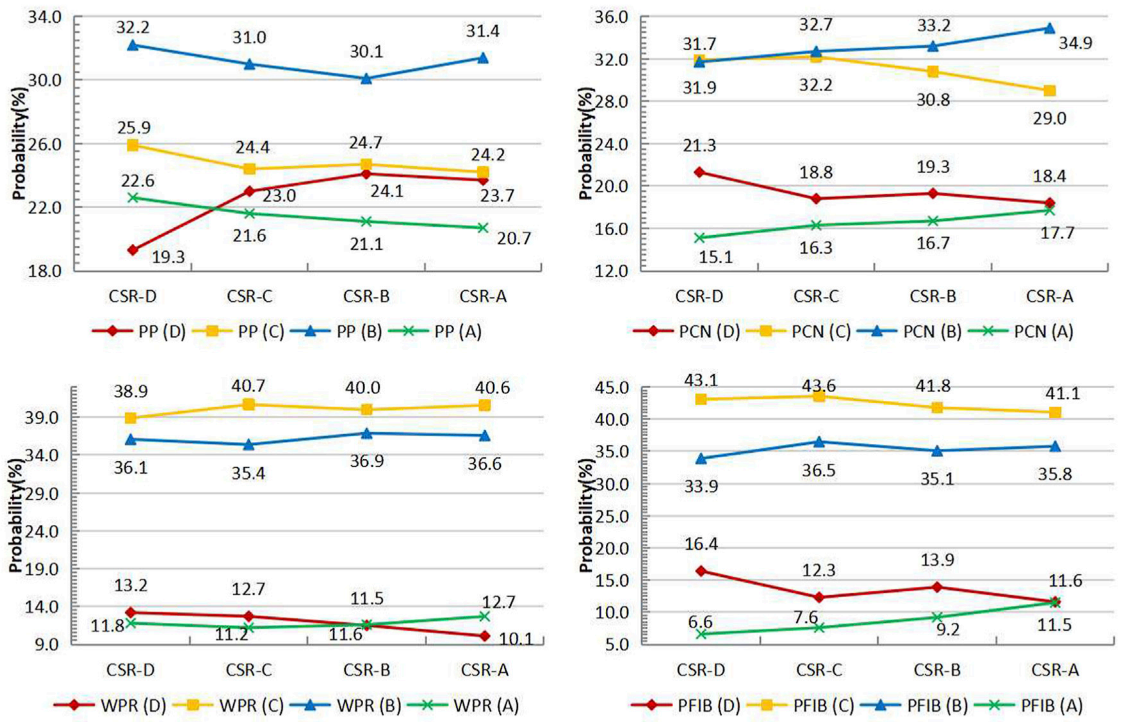

FIGURE 8
Changes in the PP, PCN, WPR, and PFIB nodes.

15 most influential variables were counted because of the large number of variables. The findings (Figure 10) revealed that the key variables influencing PP included climatic conditions, topography, management level, soil nutrients, and carbon storage; the key variables influencing PCN included soil nutrients, soil structure, management level, climatic conditions, total N, and average annual temperature; the key variables influencing WPR included soil structure, soil infiltration, water storage, aggregate stability, and topography; CSR was influenced by factors including carbon storage, climatic conditions, management level, average annual temperature, and drainage capacity; and PFIB was influenced by factors including soil biology, topography, climatic conditions, average annual temperature, management level, and terrain location. Furthermore, the partial variance reductions among PP, PCN, WPR, CSR, and PFIB were more significant than zero, thus indicating that the five soil functions were correlated because they shared impact factors. However, owing to a large number of related variables in this study and their different effects on the soil functions, it was difficult to determine which factor was most sensitive to soil function supply. For example, soil texture, configuration, and bulk density influenced soil structure. Temperature and precipitation affect soil pedogenesis, affecting the soil's versatility (Geng et al., 2017). Because the level of land-use management affects soil properties directly or indirectly, we discovered that climatic conditions and management levels are almost simultaneously key variables of soil versatility. Combined with the statistical analysis of soil parameters in Table 2 and Table 3, the pH and bulk density exhibited low variation (CV = 0.14), indicating that the soil pH and bulk density values exhibited low dispersion.

On the other hand, soil respiration and available P were highly variable (CV = 0.84 and 0.99, respectively). The measured bulk density values ranged from 0.69 to 1.70 g/cm^3, with a mean value of 1.26 g/cm^3. An increase in bulk density is typically associated with a decrease in organic matter and soil moisture content (Nielsen et al., 2014). Thus, the observed difference in soil organic matter and water content could be explained by the higher mean bulk density levels in Wen County compared to other Counties. Soil's pH directly impacts the formation, transformation, and availability of soil nutrients (Zhang et al., 2019). As a result, their soil nutrient content is relatively high because Helen and Yixing's average pH values are close to 7 (pH = 6.88 and 6.63, respectively). Because of Soil waterlogging caused by rice cultivation, farmland soil becomes more acidic. Yixing County has the lowest pH mean at 6.63. The pool of biologically available P appears to regulate C and N accumulation in many terrestrial ecosystems (Lloyd et al., 2001). Because farmers in China prefer to apply high-P fertilizers such as diammonium phosphate or compound fertilizers to crops, high concentrations of P and N, P, and K imbalances frequently occur in intensively managed soils, affecting PCN supply capacity. The intensity of respiration can reflect soil organism activity and the

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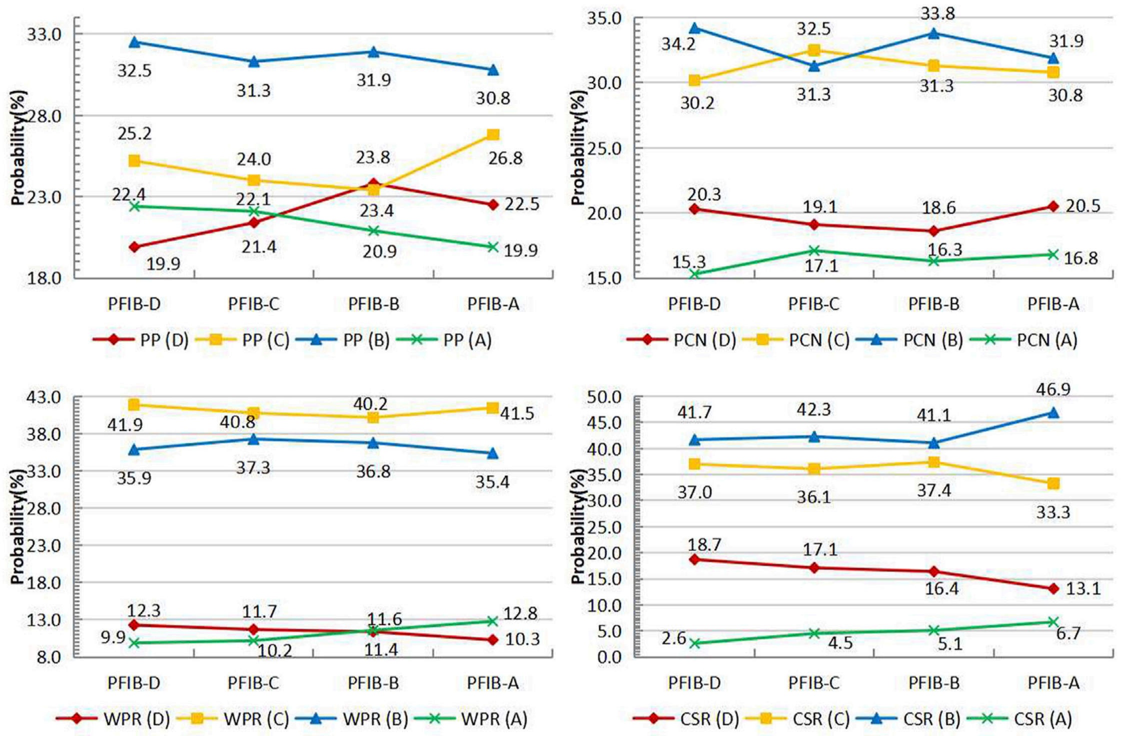

FIGURE 9
Changes in the PP, PCN, WPR, and CSR nodes.

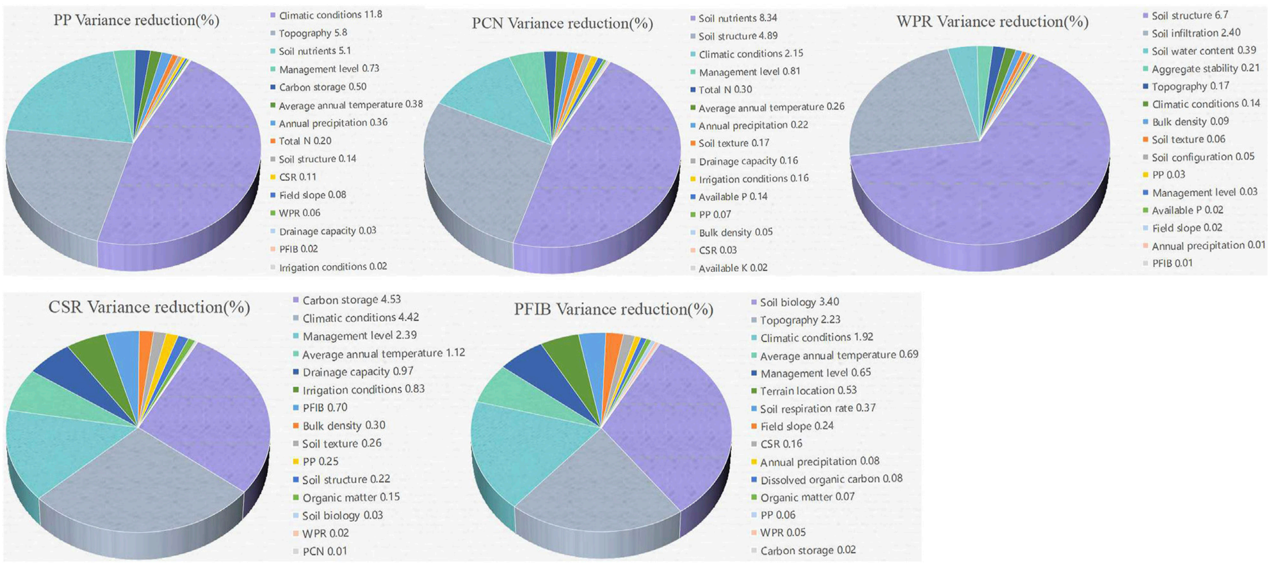

FIGURE 10
Results of BBN sensitivity analysis.

intensity of material metabolism (Wang, A., et al., 2023). Given that Helen planting soybeans has a relatively high average value of organic matter and dissolved organic carbon (mean = 40.94 g/kg and 0.45 g/kg, respectively), the cardamom agroforestry system may have the highest soil biodiversity, which may indicate that the microorganisms in the agroforestry system have a relatively better capacity to fix carbon. At the same time, soil respiration varied greatly depending on the plot location's temperature and moisture (climate conditions) (Gelybó et al., 2022).

Discussion

Trade-offs and synergies among soil multi-functionality

The ability of soils to perform multiple functions simultaneously is called multi-functionality (Creamer et al., 2022). Human demand preferences for soil functions and changes in natural conditions result in soil multifunction trade-offs, mainly when humans prioritize one or more soil functional services (Löbmann et al., 2022). Decision-makers, for example, may attempt to improve intensive cultivated land use while also increasing cultivation income at the expense of decreasing SOC (Fiantis et al., 2022; Gong et al., 2022). Zwetsloot et al. (2021) demonstrated that trade-offs between multiple soil functions are more pronounced in cropland than in grassland. Furthermore, O'Sullivan et al. (2015) highlighted the trade-off between primary productivity and carbon storage in Irish grassland. This trade-off relationship was also discovered in the soil function of cultivated land because the topography is regarded as the primary factor influencing the spatial distribution of both SOC and soil texture (Takoutsing et al., 2018).

As a result, some farmlands with high terrain in Gaoping County perform very poorly regarding CSR and PFIB functions. Furthermore, increasing slope changes soil properties, resulting in changes in land cover and vegetation type (Pham et al., 2018) and crop yield (Ladoni et al., 2016). Witing et al. (2022) identified spatial heterogeneity and climate as critical drivers of synergies and trade-offs between agricultural production, regulation, and maintenance services to achieve landscape-level versatility. We also discovered that climatic conditions, topography, and land management all impact the trade-offs of soil multi-functionality, emphasizing the importance of tailoring sustainable cultivated land management measures to local conditions. A synergistic relationship between Soil regulating services (such as CSR and PFIB) is frequently observed in agro-ecosystems (Li et al., 2022).

In contrast, a trade-off exists between provisioning services (such as PP) and regulating services (such as WPR and CSR), that is, a trade-off between agricultural productivity improvement and the sustainability of ecological services (Zhong et al., 2020), which is consistent with our results. The critical role of soil carbon components in both functions explains the synergistic relationship between soil biodiversity and carbon storage (Van Leeuwen et al., 2019; Zwetsloot et al., 2021). An increase in PP is accompanied by a loss of performance for other soil functions, and Vrebos et al. (2021) also observed lower performance of other soil functions in areas with the highest PP. Because soil functions have synergies and trade-offs, maximizing the supply of all five soil functions simultaneously is difficult. None of the 151 fields in this study could provide all five soil functions simultaneously at a high level. Soil function supply varies primarily due to environmental and management factors and maximization of individual soil functions clearly shows different effects on other soil functions, as well as changes over time in response to policy interventions and environmental changes (Dade et al., 2019). It should be noted that the BBNs include multiple indicators for each soil function and may not provide accurate predictive information about the soil multi-functionality relationship. In the future, we propose using fewer indicators for soil multifunctional sensitivity analysis and re-validating the relationship between soil multi-functionality in a larger study area.

Multifunctional regulation of cultivated land soil for farmers

Farmers and farm owners are the primary subjects of cultivated land soil function regulation at the field scale, and their land management practices directly impact soil function provision (Tesfaye et al., 2022). They may seek to raise the carbon content of their soils to levels deemed sufficient to support soil structure, nutrient cycling, and primary production at the field scale (Eliasson et al., 2010). Farmers' most commonly used soil inputs are mineral fertilizers, organic materials, pesticides, and water (Singh et al., 2020). These practices were highly successful in increasing output and being economically appealing, but at the expense of environmental quality, increasing pollution, decreasing biodiversity, and other resources such as water and fossil fuels (Keesstra et al., 2016; O'Sullivan et al., 2015). Soil compaction and loss of soil structure have resulted in a high soil bulk density in Wen County as a result of the use of heavy machinery during the annual cultivation period. Daddow, 1983) showed that bulk density values greater than 1.63 g/cm^3 inhibit root growth in coarse loamy soils. The majority of fields in Gaoping County do not have access to irrigation. Farmers directly respond to reduced water constraints by applying higher mineral and organic fertilizer doses. The multi-functionality of soil is significantly impacted at the field level by organic soil management (fallow, no-till, cover crops, organic fertilizers, organic additions, and agrochemicals) (Gabriel et al., 2012). It is worth noting that the various effects of soil management measures should be considered under various climatic conditions. For example, no-tillage combined with straw mulching in arid areas reduces mechanical interference while increasing soil water and crop yield by about 7.3%. Long-term no-tillage in sticky soils can cause soil stiffness and poor drainage (Pittelkow et al., 2015). As a result, some fields in Hailun and Yixing County are ineligible for no-tillage. Nutrient cycling can be aided by crop residue management and fertilization timing (inputs) (Wang et al., 2018). Livestock manure application to dryland cropping systems can improve soil biological activity and physical properties affecting water infiltration and retention (Rayne and Aula, 2020). However, it can also contribute to increased soil P if applied at levels higher than crop needs (Calderón et al., 2018). Based on this, we suggest that Hailun County adopts the method of mixing livestock manure with straw, and Gaoping County adopts the method of returning straw to the field to improve soil conditions. Adding perennial forages to dry land cropping systems has increased soil C and improved structural-related properties (Duchene et al., 2019; Wachter et al., 2019). Short-term manure nitrogen can improve soil microbial community structure and diversity in a double-cropping paddy field (Tang et al., 2020). Cover crops have been proposed as a cost-effective method of maintaining Soil and water quality without reducing harvested agricultural products on irrigated lands (Gabriel and Quemada, 2011; Gabriel et al., 2021). In the short term, alternative soil management practices that promote soil-based ecosystem services rather than food production benefit society rather than farmers. As a result, innovative governance strategies are needed to help farmers perceive the ecological function of farmland and understand the benefits more intuitively (Struik and Kuyper, 2017).

It is worth noting that our study was carried out at the field scale, and the main body of soil multifunctional regulation was small farmers. It aimed to provide a reference for optimizing field management measures, changing soil dynamic properties, and maximizing soil functions. At the county or provincial scale at larger scale, it is still necessary to consider the characteristic attributes of cultivated land, such as field uniformity and road accessibility, in order to implement the policy requirements of a larger spatial scale and administrative level.

Understanding and managing soil biodiversity

Soil biodiversity is essential for controlling pest outbreaks, nutrient cycling, carbon sequestration, soil formation, pollution decontamination and bioremediation, food production, and water purification (Underwood et al., 2011). Most agricultural systems' biodiversity resides in Soil (Brussaard et al., 2007). Many measures or facts that violate traditional biodiversity protection, such as the use of chemical fertilizers and pesticides, and soil disturbance caused by cultivation, must be included in the human management of cultivated land (Wang, 2022). Tillage practices are inadequate for soil worms but good for soil accessibility to roots, weed control, and increased crop yields (Ahmed and Al-Mutairi, 2022). In particular, intensification of land use, crop rotation and crop species, fertilizers and pH, the type and frequency of periodic tillage, pesticide application, and pollution (eco-toxicological studies) are the main driving forces influencing biodiversity in agricultural soils (Aksoy et al., 2017). We indicate that PFIB is closely related to climatic regions and agricultural management. It has been established that increasing agricultural intensity reduces overall soil biodiversity (Tsiafouli et al., 2015).

On the other hand, loss of soil biodiversity can negatively impact ecosystem functions and services, such as decreased productivity or unbalanced nutrient cycling (Bach et al., 2020). No-tillage and conservation tillage management practices in agro-ecosystems can increase soil biodiversity (microbes and animals) and ecosystem services (Luo et al., 2020). Most of the fields studied are primarily intensive production, and using chemical fertilizers and pesticides encourages nutrient storage while endangering soil biological habitat and decreasing soil nutrient cycling capacity. Many agricultural management practices, such as intensive tillage, fertilization, and pesticide use, have been shown to reduce soil biodiversity (Bender et al., 2016), and the loss of specific species can potentially result in the loss of specific soil functions (Philippot et al., 2013). There is a trade-off between PP, PCN, and PFIB under this condition. Vazquez et al. (2021) demonstrated how PP and PCN significantly reduce soil biodiversity. However, based on data from 151 fields, we cannot clarify the relationship between PP, PCN, and PFIB for cultivated land in China. First, land managers' needs for each of these soil functions vary greatly; in pursuit of agricultural soil productivity, many chemical inputs and unreasonable management lead to the decline of soil biodiversity.

Additionally, second, organic farming management techniques like reduced soil tillage and the use of cover crops offer food and more stable soil moisture conditions for microbial communities (Campos-Herrera et al., 2019); that is, favorable interactions among multi-trophic organisms in agro-ecosystems can promote soil nutrient cycling and increase crop yield (Lupatini et al., 2019). Sustainable agricultural production aims to create a positive feedback loop in agricultural management and production. The continuous cropping obstacle in Wen County and Gaoping County dryland is a typical negative feedback effect, whereas soybean and corn intercropping in Hailun County is a positive feedback effect. As a result, improving the versatility of soil ecosystems through increased biodiversity necessitates a long-term development perspective (Zhang et al., 2020). Furthermore, there is still much to learn about how PFIB interacts with other soil functions, and the mechanism is not yet fully understood in this study.

Conclusion

The main objective of this research was to attempt, for the first time to identify the fundamental relationship between soil multi-functionality in Chinese farmed land using probabilistic inference of BBNs. In most studies, soil physical and chemical processes have dominated such models, whereas soil biological components and processes have rarely been considered. Our study has shown that cultivated soil's multifunctions are complex and interconnected, and there will be a trade-off between soil supply and regulation services. Farmers' soil management practices significantly influence this trade-off effect on cultivated land in stable climatic and topographic conditions. As a result, various soil health management methods such as fallow, no-till, planting cover crops, using organic fertilizers, organic amendments, and agrochemicals should be tailored to the problem under different types of cultivated land use.

This research incorporated the concept of trade-offs and synergies into evaluating multiple soil functions. PP and PCN were frequently supplied at high grade because most cultivated land was intensively used. Using chemical fertilizers and pesticides promotes nutrient storage while endangering soil biological habitat and decreasing soil nutrient cycling capacity. Bayesian belief networks include multiple indicators for each soil function and do not provide accurate information about the relationship between soil multi-functionality. We also showed that climatic conditions and land management significantly influenced the trade-offs of soil multi-functionality. Finally, soil function supply varied primarily due to the environment and management, showing different effects on soil functions and changes over time.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding author.

Author contributions

RZ, ZF, and KW contributed to the conception of the study; RZ, JG, and JR contributed significantly to analysis and manuscript preparation; RZ performed the data analyses and wrote the manuscript; RZ, JG, JR, ZF, and KW helped perform the analysis with constructive discussions.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fenvs.2022.1063907/full#supplementary-material

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