

Article

Evaluation of Cultivated Land System Health and Its Driving Factors in the Dabie Mountains Using a TOPSIS–GRA Model

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Abstract

Cultivated land health is fundamental to regional food security and sustainable agricultural development, particularly in hilly and mountainous areas where land fragmentation and natural constraints are pronounced. Taking Macheng City in the Dabie Mountains as the study area, this study constructed a 23-indicator cultivated land health evaluation system based on the Driving Force–Pressure–State–Impact–Response (DPSIR) framework using multi-source spatial and socioeconomic data for 2014 and 2024. Indicator weights were determined by the Criteria Importance Through Intercriteria Correlation (CRITIC) method, and cultivated land health was evaluated using a TOPSIS–GRA coupling model. Hot spot analysis and the geographical detector were used to identify spatiotemporal patterns and driving factors. The combined proportion of healthy and very healthy cultivated land increased from 54.08% to 58.92%, although the five DPSIR subsystems showed divergent trends. High-value clusters were concentrated in western plains and river valleys, while persistent cold spots occurred in eastern mountainous areas. Agricultural mechanization was the dominant driver in 2024 ($q = 0.4946$). The driving mechanism shifted from labor and material inputs toward the joint influence of mechanization and natural background conditions. These findings provide empirical evidence that improvement in an aggregate cultivated land health index does not necessarily indicate balanced improvement across the underlying subsystems, offering a case-based reference for mountain–hill agricultural regions undergoing similar transitions.

Keywords: DPSIR framework; spatiotemporal evolution; geographical detector; spatial heterogeneity; agricultural mechanization



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1. Introduction

Cultivated land is a fundamental resource for ensuring food security and sustainable agricultural development [1,2]. With the rapid advancement of industrialization and urbanization, cultivated land use in China faces multiple pressures, including non-grain production and ecological degradation [3,4]. In response to these challenges, China's cultivated land protection has gradually shifted from an emphasis on both quantity and quality toward coordinated protection of quantity, quality, ecology, and function [5,6]. Against this background, cultivated land health extends beyond the conventional concept of cultivated land quality. Cultivated land quality mainly reflects the current biophysical and site conditions of cultivated land and its capacity to support agricultural production,

whereas cultivated land health places greater emphasis on the overall functioning and sustainability of the cultivated land system [7,8]. Therefore, cultivated land quality constitutes an important basis for cultivated land health but does not fully represent it.

A healthy cultivated land system should not only maintain favorable soil and site conditions but also continuously provide productive, ecological, and socioeconomic functions and respond to external disturbances and pressures over time [9,10]. Socioeconomic factors such as land transfer can also affect cultivated land use efficiency [11]. Existing studies on cultivated land health have developed various evaluation frameworks, including Pressure–State–Response (PSR), Driving Force–Pressure–State–Impact–Response (DPSIR), and multidimensional functional assessment frameworks [12,13]. Among these frameworks, DPSIR organizes natural and socioeconomic indicators along a driving force–pressure–state–impact–response causal chain, making it well suited to characterizing the interactions between human activities and land systems [14,15]. In terms of evaluation methods, multi-criteria decision-making and objective weighting approaches can effectively account for differences among indicators and their relative importance and have been widely applied to the comprehensive evaluation of complex systems [16,17], with increasing applications in cultivated land quality and health assessment [18]. Spatially, cultivated land health is jointly influenced by topography, soil properties, climate, and human land use, resulting in pronounced spatial heterogeneity [18,19]. Spatial statistical methods have therefore been widely used to identify the clustering patterns and evolutionary characteristics of cultivated land health [20,21]. The geographical detector can identify spatial stratified heterogeneity and quantitatively assess the explanatory power of individual factors and their interactions [22].

Previous studies have investigated cultivated land health in different regional contexts in China [10]. From a broader international perspective, mountain agriculture is undergoing profound social–ecological transformation. Mountain farming systems commonly face constraints associated with topography and accessibility, while agricultural modernization, rural population decline, and changing land-use intensity may lead to the concentration of agricultural activities in more accessible areas and the marginalization or abandonment of less favorable land [23,24]. Similar challenges are also evident in China, where the ageing and decline of the rural labor force and cultivated land fragmentation increasingly affect the sustainability and technical efficiency of agricultural production [25,26]. However, relatively limited attention has been paid to how these socioeconomic transitions interact with natural constraints to reshape cultivated land system health over time in mountain–hill transition regions.

Macheng City provides a suitable case for examining this issue because it contains pronounced internal contrasts in both natural conditions and agricultural production. Elevation ranges from 22 to 1336 m, with relatively flat plains and river valleys in the western part of the study area and more strongly dissected hilly and mountainous terrain in the eastern part. Agricultural production also varies along this terrain gradient: relatively intensive double-cropping systems are common in plains and river valleys, whereas some higher-elevation mountainous areas are dominated by single cropping. These contrasts correspond to substantial differences in cultivated land fragmentation, accessibility, and suitability for mechanized farming, allowing the interactions between agricultural modernization and natural constraints to be examined within the same regional system. The period from 2014 to 2024 also coincided with rapid changes in rural labor structure, agricultural mechanization, and cultivated land protection in China. Accordingly, this study constructed a DPSIR-based cultivated land health evaluation system comprising 23 indicators using multi-source spatial data for 2014 and 2024. Hot spot analysis and the geographical detector were further employed to characterize temporal changes, spatial

clustering patterns, and shifts in the underlying driving mechanisms. By examining both overall cultivated land health and its internal subsystem changes, this study provides an empirical case for understanding the evolution of cultivated land systems in mountain–hill regions undergoing agricultural modernization.

2. Materials and Methods

2.1. Study Area

Macheng City is located in northeastern Hubei Province, on the southern foothills of the central Dabie Mountains and the northern side of the middle reaches of the Yangtze River (Figure 1), and is one of the core areas of the Dabie Mountains Revolutionary Base Area in Hubei Province. The coexistence of low-elevation plains and river valleys with higher-elevation hilly and mountainous areas creates pronounced internal gradients in terrain conditions, cropping intensity, farmland fragmentation, and mechanization suitability, making Macheng a suitable case for examining the transformation of cultivated land systems in mountain–hill transition regions. It borders Anhui Province to the east, Luotian and Tuanfeng Counties to the south, Hong'an County to the west, and Henan Province to the north. The city extends from 114°40′–115°28′ E and 30°52′–31°36′ N. Elevation ranges from 22 to 1336 m above sea level. The region has a subtropical humid monsoon climate with continental characteristics, featuring distinct seasons, abundant sunshine, concurrent rainfall and heat, a long frost-free period, and a mean annual temperature of 16.8 °C. Macheng City comprises 24 township-level administrative units. In 2024, its total annual grain production reached 365,700 t and had remained above approximately 350,000 t for 13 consecutive years. The main grain crops include rice, wheat, maize, soybeans, and tuber crops, while non-grain crops such as oilseed rape and vegetables are also commonly cultivated. Rice-based cropping systems predominate in paddy fields. Double cropping is common in plains and river valleys, with typical cropping patterns including rice–wheat, rice–rapeseed, and wheat/rapeseed–maize rotations, whereas single cropping occurs in some higher-elevation mountainous areas [27]. The total cultivated land area is 90,120.23 ha, including 51,965.21 ha of paddy fields (57.66%), 2241.65 ha of irrigated land (2.49%), and 35,913.37 ha of dryland (39.85%).

2.2. Data Sources

Using 2014 and 2024 as the two study years, a cultivated land health evaluation database for Macheng City was constructed by integrating multiple data sources. The data included the following four categories: (1) Land-use data: Cultivated land boundaries for the two study years were derived from the corresponding official land survey datasets of Macheng City. Dryland, paddy fields, and irrigated land were consistently extracted as the evaluation units for both periods according to the same land-use classification criteria. (2) Soil property data: The soil variables included pH, soil organic matter, available phosphorus, available potassium, and cation exchange capacity (CEC). Because field sampling data were unavailable for 2014, the soil data for that year were obtained from the National Earth System Science Data Center. For 2024, a total of 1982 soil sampling points were collected, of which 1458 located within cultivated land were used for the present analysis. These samples were randomly divided into training and validation datasets at a ratio of 80% and 20%, respectively. Several geostatistical interpolation methods were compared, and the method with the best validation performance was selected to generate the soil raster data. Prediction performance was evaluated using the coefficient of determination (R^2) and root mean square error (RMSE). (3) Remote sensing and topographic data: Digital elevation model (DEM) data with an original spatial resolution of 30 m were obtained from the Resource and Environment Science and Data Center. Normalized Difference

Vegetation Index (NDVI) data with an original resolution of 30 m were obtained from the National Ecosystem Science Data Center, and Net Primary Productivity (NPP) data with an original resolution of 500 m were obtained from the United States Geological Survey (USGS). (4) Socioeconomic data: Population density, total power of agricultural machinery, and other socioeconomic variables were obtained from the Macheng Statistical Yearbook for the corresponding years [27,28]. In addition, spatial indicators such as heavy metal pollution risk, irrigation capacity, and drainage capacity were derived from basic vector datasets. To ensure spatial consistency, the raster data were resampled to 5 m through multiple experiments, guaranteeing that all cultivated land patches could be extracted.

2.3. Construction of the Evaluation Indicator System

The DPSIR framework was used to operationalize cultivated land system health through five interconnected dimensions: driving force, pressure, state, impact, and response [10,14]. These dimensions represent different roles in the functioning of the cultivated land system rather than simply different categories of available data. The driving force dimension represents the socioeconomic support for the continued use and maintenance of cultivated land; the pressure dimension represents anthropogenic stresses imposed on the system; the state dimension describes the current biophysical and site conditions of cultivated land and is therefore the component most closely related to conventional cultivated land quality; the impact dimension reflects the realized productive and ecological performance of the system; and the response dimension represents the management and adaptive capacity to maintain or improve system functions.

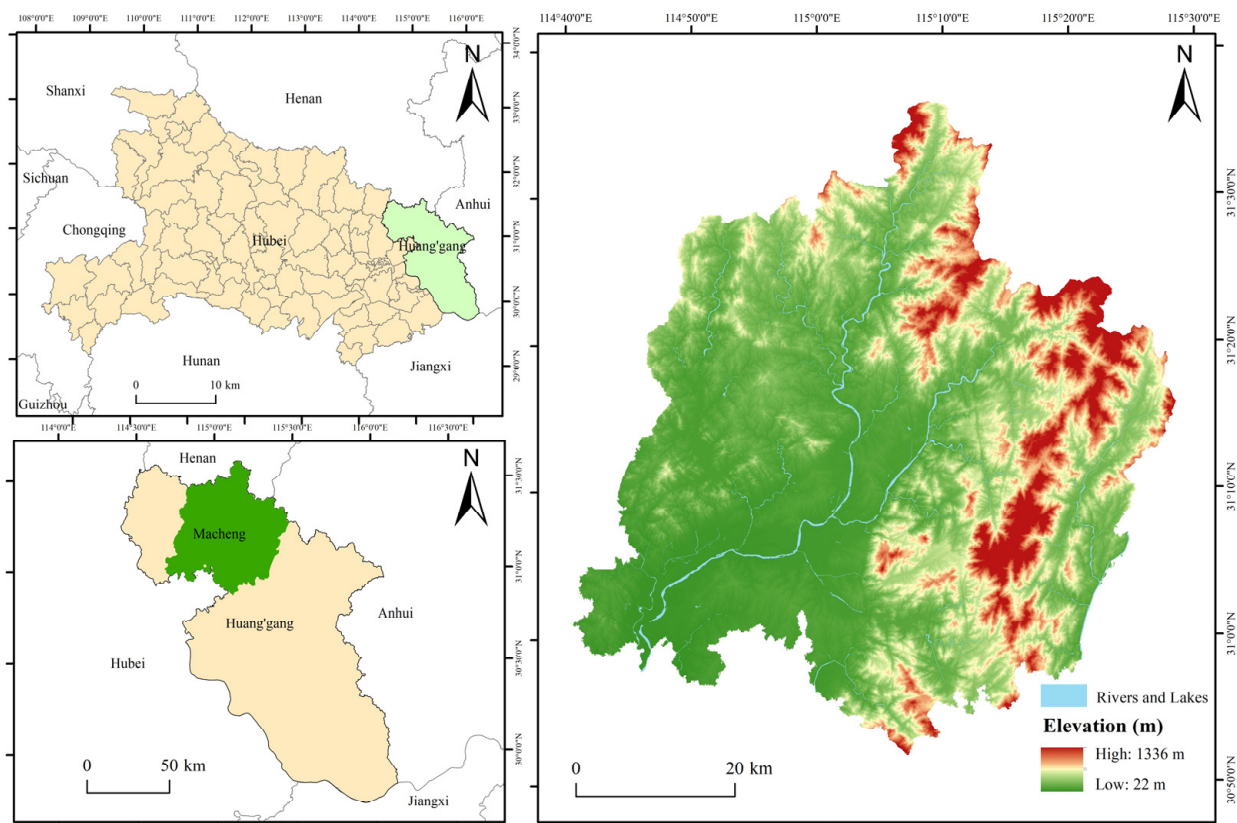


Figure 1. Geographical location of the study area.

Based on this conceptual structure and previous studies of cultivated land health, 23 indicators were selected to characterize the external forcing, current condition, functional performance, and response capacity of the cultivated land system (Table 1). Indicators in the driving force and pressure dimensions are therefore not interpreted as direct manifestations of health in isolation, but as socioeconomic support and external stresses that influence system health. In contrast, the state, impact, and response dimensions more directly characterize land condition, realized functions, and management capacity, respectively. The weights of the indicators were objectively determined using the CRITIC method after data standardization. This method determines indicator weights by considering both the variability of each indicator and its correlation with other indicators; indicators with greater variability and less information overlap are assigned relatively higher weights. The calculated weights are presented in Table 1.

Table 1. Evaluation indicator system for cultivated land health in Macheng City.

Dimension	Factor	Indicator	Operational Meaning for System Health	Direction	Weight
Driving force (D)	Socioeconomic conditions	Population density	Proxy for local socioeconomic and labor support related to cultivated land use and management	Positive	0.0446
		Per capita agricultural income	Economic capacity to support cultivated land management and protection	Positive	0.0473
		Proportion of agricultural workers	Labor support for the continued operation and maintenance of cultivated land	Positive	0.0632
Pressure (P)	Agricultural inputs	Fertilizer application intensity	Chemical-input pressure that may affect soil and ecological conditions	Negative	0.0628
		Pesticide application intensity	Chemical pressure associated with potential ecological risks to cultivated land	Negative	0.0523
	Potential mining-related pollution exposure	Soil heavy metal pollution	Potential exposure to heavy metal pollution associated with nearby industrial/mining activities, represented by the Euclidean distance from cultivated land to the nearest industrial/mining land	Positive	0.0459
	Land-use intensity	Cultivated land-use intensity	Intensity and continuity of cultivated land use, reflecting the degree to which cultivated land remains actively used for agricultural production	Positive	0.0847
	Soil properties	Soil pH	Soil acidity/alkalinity affecting nutrient availability	Negative	0.0371
		Soil organic matter	Core indicator of soil fertility	Positive	0.0362
Available phosphorus		Soil phosphorus-supply capacity	Positive	0.0283	
Available potassium		Soil potassium-supply capacity	Positive	0.0288	
Cation exchange capacity (CEC)		Soil nutrient-retention capacity	Positive	0.0381	
State (S)	Topography	Slope	Topographic condition constraining cultivation, mechanization, and soil conservation	Negative	0.0314
	Hydrological conditions	Irrigation capacity	Water-supply condition supporting stable agricultural production	Positive	0.0317
		Drainage capacity	Capacity to reduce waterlogging stress and maintain stable production	Positive	0.0421
	Ecological condition	Vegetation cover (NDVI)	Vegetation vigor and cover reflecting ecological condition	Positive	0.0250
		Net primary productivity (NPP)	Ecosystem productivity reflecting the functional condition of cultivated land	Positive	0.0261
	Impact (I)	Production impact	Grain yield	Realized productive function of the cultivated land system	Positive
Ecological impact		Soil erosion modulus	Ecological impact reflecting soil loss and degradation risk	Negative	0.0265

Table 1. Cont.

Dimension	Factor	Indicator	Operational Meaning for System Health	Direction	Weight
Response (R)	Input response	Total power of agricultural machinery	Technological response capacity for maintaining agricultural production	Positive	0.0541
		Rural electricity consumption	Infrastructure support capacity for agricultural production and management	Positive	0.0479
		Number of agricultural technicians	Technical support capacity for maintaining and improving system functions	Positive	0.0550
	Engineering response	Field regularity	Land-management response reflecting suitability for efficient agricultural operation	Negative	0.0331

Note: Soil pH is the absolute value of pH minus 7.

2.4. Research Methods

2.4.1. CRITIC Objective Weighting Method

The CRITIC method objectively determines indicator weights based on the variability of individual indicators and the conflicts among them [16]. A greater degree of variability and stronger conflict with other indicators indicate a larger amount of information and, consequently, a higher weight. Compared with the entropy weighting method, CRITIC is more suitable for comprehensive evaluation problems involving correlations among indicators. In addition, the inter-indicator correlation incorporated in the CRITIC method helps reduce the influence of redundant information among highly correlated indicators on the weighting results. In this study, the CRITIC method was used to determine the weights of the indicators in the cultivated land health evaluation system. To ensure comparability between the two study periods, the 2014 and 2024 data were pooled after standardization to calculate a single set of CRITIC weights, which was consistently applied to both years. The calculation procedure is described as follows:

The standard deviation was used to characterize the variability of each indicator. A larger standard deviation indicates greater variation in the indicator values and, consequently, a larger amount of information. The standard deviation S_j was calculated using Equation (1):

$$S_j = \sqrt{\frac{1}{n-1} \sum_{i=1}^n (X'_{ij} - \bar{X}_j)^2} \quad (1)$$

where n is the number of evaluation units, and $\bar{X}_j$ is the mean of the standardized values of the j -th indicator.

The conflict among indicators was measured using the correlation coefficients between indicators. The conflict coefficient R_j was calculated using Equation (2):

$$R_j = \sum_{k=1}^m (1 - r_{jk}) \quad (2)$$

where m is the total number of indicators, and r_{jk} is the correlation coefficient between the j -th and k -th indicators. A larger R_j indicates weaker correlations between the j -th indicator and the other indicators, lower information redundancy, and greater conflict.

The amount of information C_j contained in the j -th indicator was jointly determined by its variability and conflict, as calculated using Equation (3):

$$C_j = S_j \times R_j \quad (3)$$

A larger C_j indicates that the indicator provides more information within the evaluation system and should therefore be assigned a higher weight.

The weight W_j of the j -th indicator was calculated using Equation (4):

$$W_j = \frac{C_j}{\sum_{k=1}^m C_k} \quad (4)$$

2.4.2. TOPSIS–GRA Coupling Model

TOPSIS evaluates the relative performance of alternatives based on their distances from the positive and negative ideal solutions and is well suited to comprehensive ranking problems involving multiple indicators [17]. In contrast, GRA focuses on the similarity of geometric patterns among data sequences [29], but pays relatively less attention to their absolute numerical proximity.

To overcome the limitations of using a single evaluation method, a TOPSIS–GRA coupling model incorporating CRITIC-derived weights was employed in this study. The model first determines indicator weights objectively and then integrates TOPSIS with GRA, thereby considering both the distances between evaluation units and the ideal solutions and the relational degrees between indicator sequences and ideal sequences. The calculation procedure is as follows:

- (1) Construction of the weighted normalized decision matrix. The weighted normalized decision matrix was constructed by multiplying the standardized indicator matrix by the corresponding indicator weights:

$$V = (v_{ij})_{m \times n} = (w_j \cdot x_{ij})_{m \times n} \quad (5)$$

where m is the total number of spatial evaluation units, and n is the total number of evaluation indicators.

- (2) Determination of the positive and negative ideal solutions

$$V^+ = (v_1^+, v_2^+, \dots, v_n^+) = (\max(v_{i1}), \max(v_{i2}), \dots, \max(v_{in})) \quad (6)$$

$$V^- = (v_1^-, v_2^-, \dots, v_n^-) = (\min(v_{i1}), \min(v_{i2}), \dots, \min(v_{in})) \quad (7)$$

- (3) Calculation of Euclidean distances and grey relational degrees

The Euclidean distances between the i -th evaluation unit and the positive and negative ideal solutions, denoted by D_i^+ and D_i^- , respectively, were calculated as follows:

$$D_i^+ = \sqrt{\sum_{j=1}^n (v_{ij} - v_j^+)^2} \quad (8)$$

$$D_i^- = \sqrt{\sum_{j=1}^n (v_{ij} - v_j^-)^2} \quad (9)$$

Grey relational analysis was subsequently used to calculate the grey relational degrees R_i^+ and R_i^- between the i -th evaluation unit and the positive and negative ideal solutions. Taking the positive ideal solution as an example, the grey relational coefficient ξ_{ij}^+ and the grey relational degree R_i^+ were calculated as follows:

$$\xi_{ij}^+ = \frac{\min_i \min_j |v_j^+ - v_{ij}| + \rho \max_i \max_j |v_j^+ - v_{ij}|}{|v_j^+ - v_{ij}| + \rho \max_i \max_j |v_j^+ - v_{ij}|} \quad (10)$$

$$R_i^+ = \frac{1}{n} \sum_{j=1}^n \xi_{ij}^+ \quad (11)$$

Following previous research [30], the distinguishing coefficient ρ was set to 0.5.

(4) Calculation of the integrated relative closeness

The values of D_i^+ , D_i^- , R_i^+ , and R_i^- were first normalized to eliminate dimensional effects, after which the dimensionless integrated closeness measures were constructed.

$$d_i^\pm = \frac{D_i^\pm}{\max(D_i^\pm)} \quad (12)$$

$$r_i^\pm = \frac{R_i^\pm}{\max(R_i^\pm)} \quad (13)$$

$$E_i^+ = \alpha d_i^- + \beta r_i^+ \quad (14)$$

$$E_i^- = \alpha d_i^+ + \beta r_i^- \quad (15)$$

where α and β are preference coefficients representing the relative importance assigned to distance-based closeness and sequence-based relational degree, respectively. In this study, the two components were considered equally important; therefore, $\alpha = \beta = 0.5$.

(5) Comprehensive cultivated land health evaluation index

$$C_i = \frac{E_i^+}{E_i^+ + E_i^-} \quad (16)$$

Based on previous studies of cultivated land health classification and the distribution of index values in the study area, the comprehensive index was divided into four health classes [12,31]: unhealthy [0, 0.35), sub-healthy [0.35, 0.50), healthy [0.50, 0.65), and very healthy [0.65, 1.00].

To examine the robustness of the evaluation results, two alternative settings were additionally tested. First, all 23 indicators were assigned equal weights ($w_j = 1/23$) while retaining the TOPSIS–GRA coupling model. Second, the original CRITIC weights were retained, but cultivated land health was evaluated using TOPSIS alone. The temporal trends and spatial patterns obtained under these alternative settings were compared with those of the baseline model.

2.4.3. Geographical Detector

The geographical detector is a statistical method for identifying spatial stratified heterogeneity and its driving factors [22]. Its underlying principle is that if an explanatory variable has a substantial influence on a dependent variable, their spatial distributions should exhibit a certain degree of similarity. The method does not rely on linear assumptions and can effectively handle categorical variables. It includes modules such as factor detection and interaction detection and has been widely applied to the analysis of spatial associations between natural and socioeconomic factors. Because the geographical detector does not rely on a linear regression framework, conventional multicollinearity correction procedures, such as variance inflation factor-based variable elimination, were not required in this study.

The 23 indicators in Table 1 were used to construct the cultivated land health evaluation index, whereas the 11 factors used in the geographical detector served as explanatory variables for analyzing its spatial differentiation. These factors were selected based on representativeness, spatial variability, data availability, and their relevance to natural and socioeconomic conditions.

Before geographical detector analysis, continuous explanatory variables were discretized using the quantile method. To ensure comparability between 2014 and 2024, the data from both years were pooled to determine a common set of breakpoints, and each continuous variable was divided into five strata based on the 0%, 20%, 40%, 60%, 80%, and 100% quantiles. Categorical variables, including soil type, soil texture, and irrigation capacity, retained their original categories without further discretization. Detailed discretization settings and significance results are provided in Tables A1 and A2.

$$q = 1 - \frac{1}{N\sigma^2} \sum_{h=1}^L N_h \sigma_h^2 \quad (17)$$

where q represents the explanatory power of a factor and ranges from 0 to 1, with a larger value indicating stronger explanatory power; L is the number of strata of the factor; N and σ^2 are the total number of units and the overall variance, respectively; and N_h and σ_h^2 are the number of units and variance within stratum h , respectively. The statistical significance of the q -value was assessed using an F -test. Interaction detection determines the type of interaction between two factors by comparing the q -values of individual factors with that of their combined effect, thereby revealing the joint effects of multiple factors on the spatial differentiation of cultivated land health.

2.4.4. Hot Spot Analysis

Hot spot analysis was conducted in ArcGIS 10.8 using the Getis–Ord G_i^* statistic to identify spatial clusters of cultivated land health in 2014 and 2024 and of changes in the comprehensive index between the two years [32]. The standardized G_i^* statistic was calculated as follows:

$$G_i^* = \frac{\sum_{j=1}^n w_{ij} x_j - \bar{X} \sum_{j=1}^n w_{ij}}{S \sqrt{\frac{n \sum_{j=1}^n w_{ij}^2 - \left(\sum_{j=1}^n w_{ij} \right)^2}{n-1}}} \quad (18)$$

$$\bar{X} = \frac{\sum_{j=1}^n x_j}{n} \quad (19)$$

$$S = \sqrt{\frac{\sum_{j=1}^n x_j^2}{n} - \bar{X}^2} \quad (20)$$

where x_j is the cultivated land health index of spatial unit j , w_{ij} is the spatial weight between units i and j , n is the total number of spatial units, $\bar{X}$ is the mean of x_j , and S is its standard deviation. The G_i^* statistic is expressed as a standardized z-score. A statistically significant positive G_i^* value indicates a cluster of high values (hot spot), whereas a statistically significant negative value indicates a cluster of low values (cold spot).

3. Results

3.1. Temporal Evolution of Cultivated Land Health

3.1.1. Temporal Evolution of Cultivated Land System Health

From 2014 to 2024, the health status of the cultivated land system in Macheng City underwent a marked shift in its health-class structure (Figure 2). During the study period, the total area of cultivated land decreased from 104,093.68 ha to 90,120.23 ha. Despite the overall decline in cultivated land area, the proportion of cultivated land classified as healthy increased from 52.84% in 2014 to 57.66% in 2024. Areas classified as healthy were mainly distributed in Chengmagang Town, Shunhe Town, and Tiemengang Township. In contrast, the proportions of unhealthy and sub-healthy cultivated land decreased by 1.24

and 3.61 percentage points, respectively. In particular, the area of unhealthy cultivated land declined from 2536.65 ha to 1082.49 ha. These changes indicate a shift in the aggregate health-class composition toward higher health levels (Table 2).

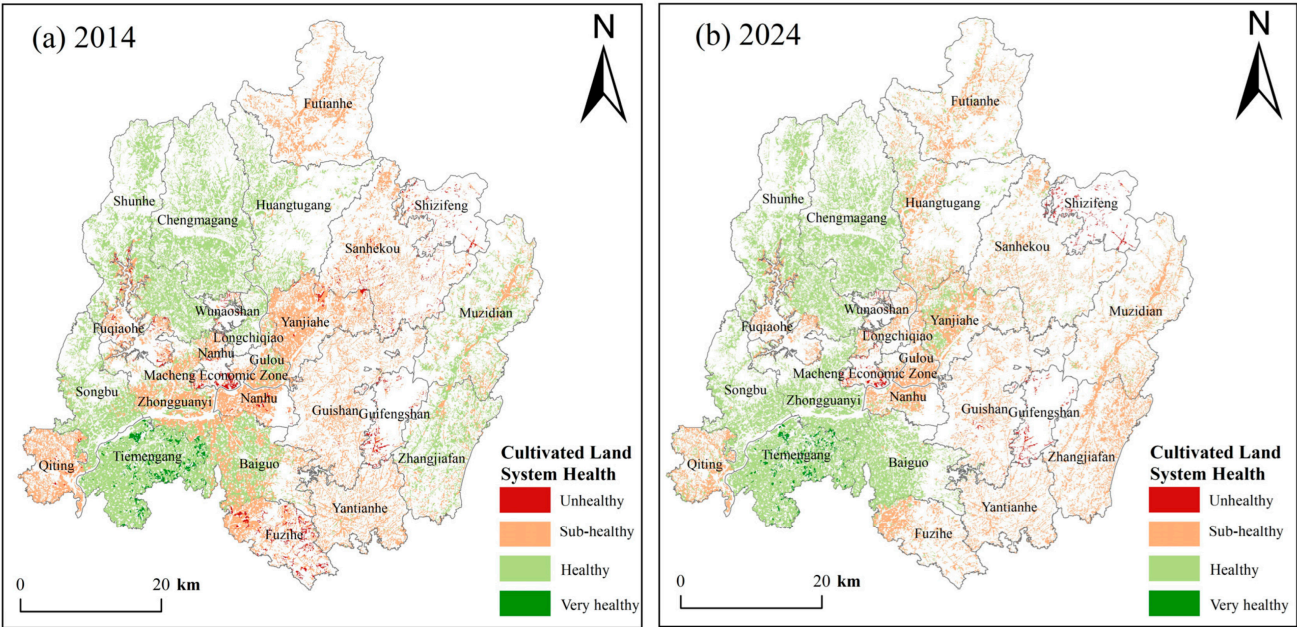


Figure 2. Spatial distribution of cultivated land system health classes in 2014 and 2024.

Table 2. Areas and proportions of cultivated land by health class in Macheng City in 2014 and 2024.

Health Class	2014		2024	
	Area (ha)	Proportion (%)	Area (ha)	Proportion (%)
Unhealthy	2536.65	2.44%	1082.49	1.20%
Sub-healthy	45,257.86	43.48%	35,934.38	39.87%
Healthy	55,006.32	52.84%	51,967.74	57.66%
Very healthy	1292.85	1.24%	1135.62	1.26%
Total	104,093.68	100%	90,120.23	100%

This change can be partly attributed to improvements in natural conditions and ecological restoration. Macheng City is located in the low- and middle-mountain hilly region of the Dabie Mountains, where some sloping cultivated land affected by soil erosion initially exhibited relatively poor health conditions. With the implementation of ecological protection and restoration projects in recent years, marginal cultivated land previously classified as unhealthy has been effectively rehabilitated. Socioeconomic investment has also played an important role in improving cultivated land health. From 2014 to 2024, Macheng City continuously promoted high-standard farmland construction, particularly in plains and river valleys such as Shunhe Town and Tiemengang Township. Improvements in farmland water-conservancy infrastructure and the application of cultivated land quality protection technologies contributed to the transition of substantial areas of cultivated land from the sub-healthy to the healthy class. Consequently, the combined effects of ecological restoration and agricultural technological inputs increased the proportion of cultivated land in the higher health classes in Macheng City.

3.1.2. Temporal Evolution of Cultivated Land Subsystem Health

From 2014 to 2024, the five DPSIR subsystems of cultivated land in Macheng City exhibited markedly different trends in health status (Figure 3). The impact subsystem

showed the most pronounced improvement, with its mean score increasing from 0.4977 to 0.7082. The most substantial change occurred in the area classified as very healthy, which increased from 17,231.72 ha to 63,036.36 ha. The state subsystem remained relatively stable, with its mean score increasing slightly from 0.5134 to 0.5170 and the combined proportion of healthy and very healthy cultivated land rising from 60.37% to 63.25%. In contrast, the health status of the driving force subsystem declined markedly, with its mean score decreasing from 0.4353 to 0.3714. The combined area of healthy and very healthy cultivated land decreased from 44,573.03 ha to 14,455.84 ha, corresponding to a decline in proportion from 42.82% to 16.04%. For the pressure subsystem, the mean score decreased from 0.5118 to 0.4925, while the combined area of healthy and very healthy cultivated land declined from 54,029.68 ha to 30,046.49 ha, with its proportion decreasing from 51.90% to 33.34%. The response subsystem showed a slight decrease in its mean score, from 0.5654 to 0.5592, while the combined area of healthy and very healthy cultivated land decreased from 60,817.70 ha to 46,265.51 ha, and its proportion declined from 58.43% to 51.34%.

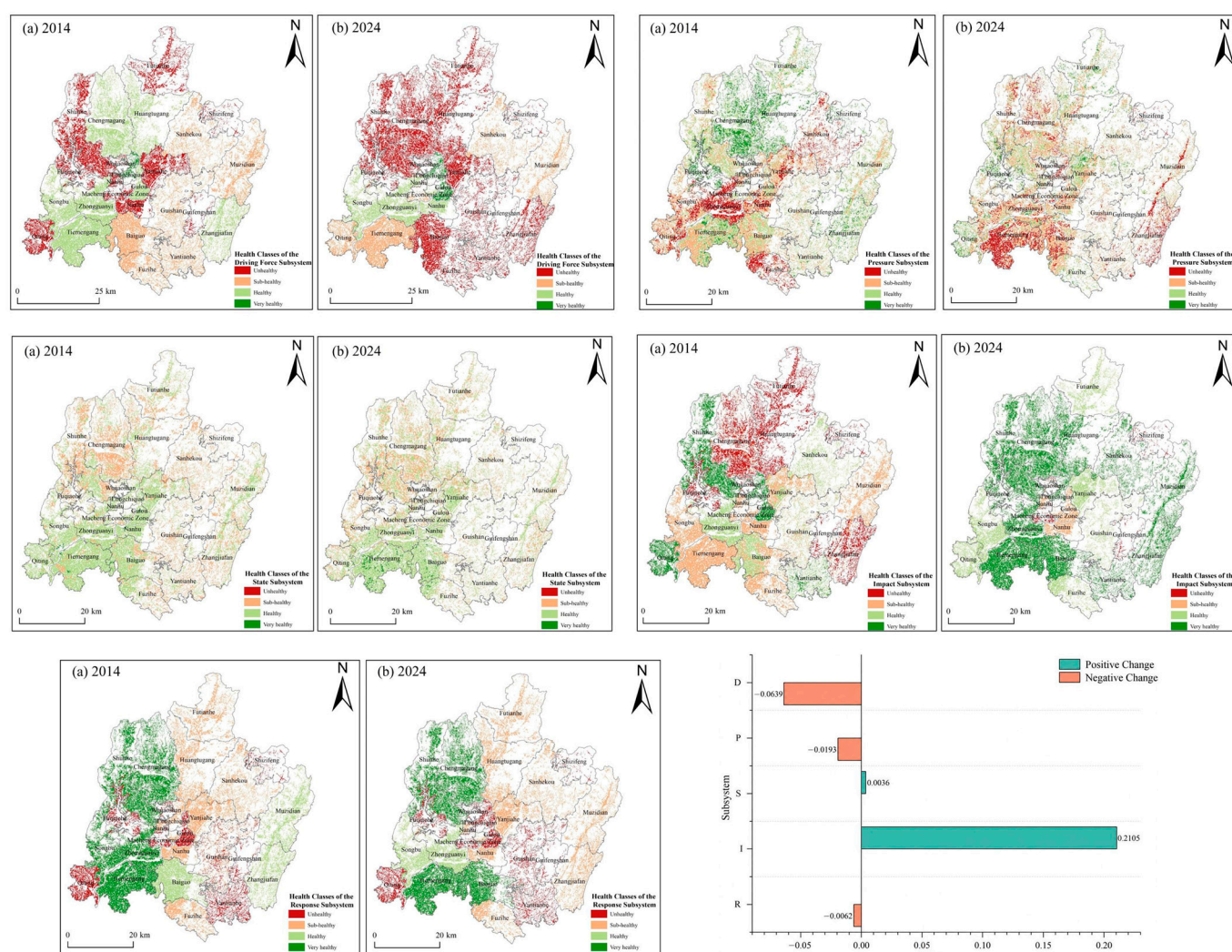


Figure 3. Changes in the health levels of the DPSIR subsystems between 2014 and 2024. For each subsystem, (a) represents 2014 and (b) represents 2024. The bar chart shows the changes in the mean health scores (Δ Mean) of the five subsystems.

The impact subsystem was the only subsystem in which the areas classified as healthy and very healthy expanded substantially, with a net increase of 47,282.14 ha. Meanwhile, the combined area of unhealthy and sub-healthy cultivated land decreased from 66,373.86 ha to

5118.26 ha. Tiemengang Township and Chengmagang Town exhibited the largest changes in the impact subsystem, with their scores increasing from 0.4124 to 0.9943 and from 0.3432 to 0.8136, respectively. In the driving force subsystem, the combined area of healthy and very healthy cultivated land decreased by 30,117.19 ha, with particularly large declines in subsystem scores observed in Guishan Town, Zhangjiafan Town, and Baiguo Town. For the pressure subsystem, the combined area of healthy and very healthy cultivated land decreased by 23,983.19 ha. Shizifeng Forest Farm showed the greatest decline, with its score falling from 0.7043 to 0.2644. Within the state subsystem, the area classified as unhealthy decreased from 8.59 ha to only 0.05 ha, although the combined area of healthy and very healthy cultivated land declined slightly. Overall, changes in this subsystem were limited. In the response subsystem, the combined area of healthy and very healthy cultivated land decreased by 14,552.19 ha. Muzidian Town exhibited the largest change, with its score declining from 0.5898 to 0.4338.

Overall, the five cultivated land health subsystems exhibited pronounced divergence between 2014 and 2024. The impact subsystem was the only subsystem to show a substantial expansion of higher health classes, indicating marked improvements in the positive outputs of the cultivated land system and the effectiveness of external interventions. The relative stability of the state subsystem suggests that the underlying structure and functions of the cultivated land system remained generally stable. By contrast, the driving force, pressure, and response subsystems deteriorated to varying degrees, highlighting increasingly prominent challenges associated with weakening socioeconomic drivers, persistent pressures from human activities, and insufficient capacity for protective responses.

3.2. Spatial Evolution of Cultivated Land Health

3.2.1. Spatial Clustering Characteristics of Cultivated Land Health

From 2014 to 2024, cultivated land health in Macheng City exhibited pronounced spatial inequality and clustering characteristics (Figure 4). In 2014, high-value clusters of cultivated land health were mainly distributed in western Macheng City, including Shunhe Town, Chengmagang Town, and Songbu Town, whereas low-value clusters were concentrated in the southeastern areas of Sanhekou Town, Guishan Town, Guifengshan Scenic Area, and Yanjiahe Town. By 2024, the spatial clustering pattern had changed, with hot spots expanding, becoming more statistically significant, and shifting toward the southwestern plains. Songbu Town and Tiemengang Township became hot spots significant at the 99% confidence level, indicating continued improvement in cultivated land health in these areas. In contrast, the cold-spot pattern in the southeastern mountainous areas remained relatively stable, with Guishan Town and Guifengshan Scenic Area continuing to exhibit cold spots significant at the 95% confidence level or higher. This persistence suggests that the low-value clustering of cultivated land health in these areas is strongly constrained by topographic conditions and the underlying ecological background.

The spatial clustering of changes from 2014 to 2024 revealed a clear pattern of greater improvement in the southwest and weaker improvement in the southeast. Hot spots of change were concentrated in Songbu Town, Tiemengang Township, and Qiting Town in the southwest, indicating that these areas were the core zones of cultivated land health improvement over the past decade. This pattern may be associated with their role as major grain-producing areas and the benefits derived from high-standard farmland construction and intensive agricultural management. In contrast, cold spots of change remained concentrated in the southeastern mountainous areas, indicating that these areas not only had relatively low baseline health levels but also experienced comparatively limited improvement over the decade. Overall, the spatial pattern of cultivated land health in Macheng City was jointly shaped by natural geographical conditions and the intensity of human

activities, resulting in continued improvement in the southwest and persistent low-value clustering in the southeast.

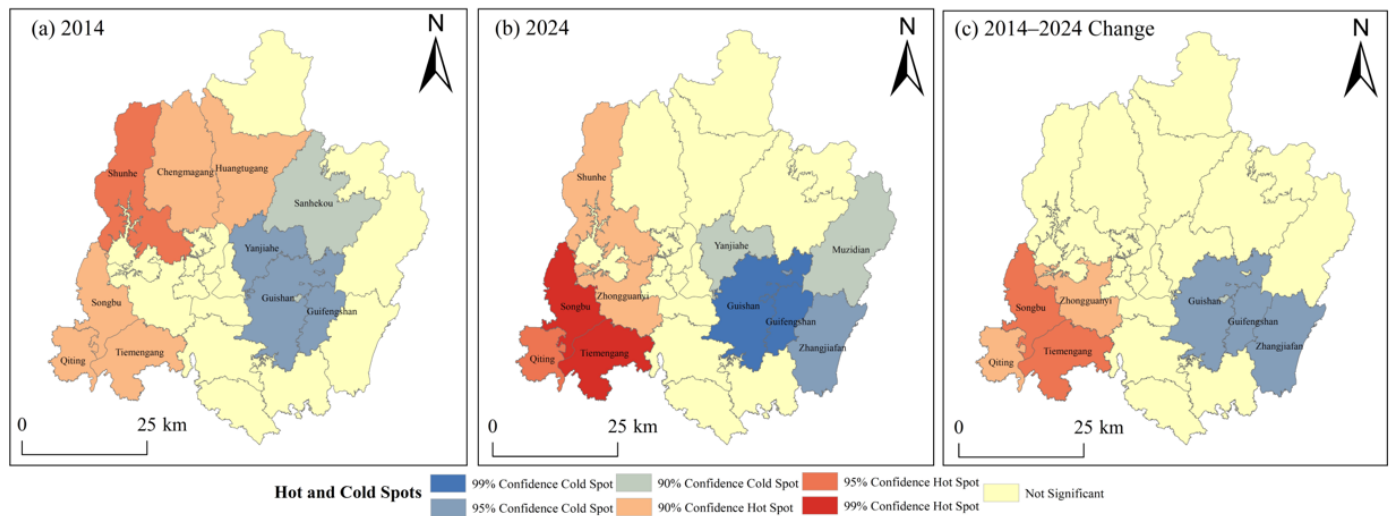


Figure 4. Spatial distribution of hot and cold spots of cultivated land system health in 2014 and 2024 and of changes between the two years.

3.2.2. Spatial Distribution Pattern of Cultivated Land Health

The comprehensive cultivated land health indices of the townships in Macheng City were classified using the equal-interval method and spatially visualized (Figure 5). The results revealed pronounced spatial differentiation, with cultivated land health generally exhibiting a west-high-east-low distribution pattern. In 2014, high-value areas of cultivated land health (index > 0.5470) were mainly concentrated in Shunhe Town, Chengmagang Town, and Tiemengang Township in the northwestern and southwestern parts of the city. These areas are characterized by relatively flat terrain and favorable agricultural production conditions and constituted the core high-value areas of cultivated land health in Macheng City. Medium-to-high-value areas (0.4638–0.5470) were the most widely distributed, forming contiguous zones across Baiguo Town, Songbu Town, Zhongguanyi Town, and several townships in the northern and eastern parts of the city. By comparison, low-value areas (0.3806–0.4638) were mainly distributed in the southeastern mountainous areas and around the central urban area, including Sanhekou Town, Guishan Town, Zhangjiafan Town, Shizifeng Forest Farm, and Longchiquiao Subdistrict. Very-low-value areas (0.2974–0.3806) were sparsely distributed and were mainly confined to localized ecological areas such as Wunaoshan National Forest Park.

By 2024, the spatial differentiation and contiguous evolution of cultivated land health had become more pronounced. High-value cultivated land health areas expanded markedly in the western part of the city. Songbu Town, Zhongguanyi Town, and Baiguo Town shifted from the medium-to-high-value class to the high-value class and became spatially connected with Shunhe Town, Chengmagang Town, and Tiemengang Township, forming a stable high-value cluster across western Macheng City. This expansion reflects the effectiveness of agricultural infrastructure investment in this region. Meanwhile, the spatial pattern in the eastern and south-central parts of the city underwent localized reorganization, resulting in pronounced differentiation among townships. Sanhekou Town improved markedly from the low-value class to the medium-to-high-value class. In contrast, ecological areas such as Shizifeng Forest Farm, Guishan Town, and Guifengshan Scenic Area shifted from the low-value class to the very-low-value class, resulting in a spatial expansion of very-low-value areas. The expansion of low-value areas in the eastern mountains was mainly

associated with pronounced topographic relief, cultivated land fragmentation in the middle- and high-mountain areas of the Dabie Mountains, and increasingly stringent ecological protection constraints in recent years. Overall, over the decade, the spatial distribution of cultivated land health in Macheng City evolved from a relatively balanced pattern toward one characterized by contiguous expansion of high-value areas in the west and localized low-value clustering in the east. This pattern visually reflects the combined constraints imposed by natural topographic conditions and human land-use practices.

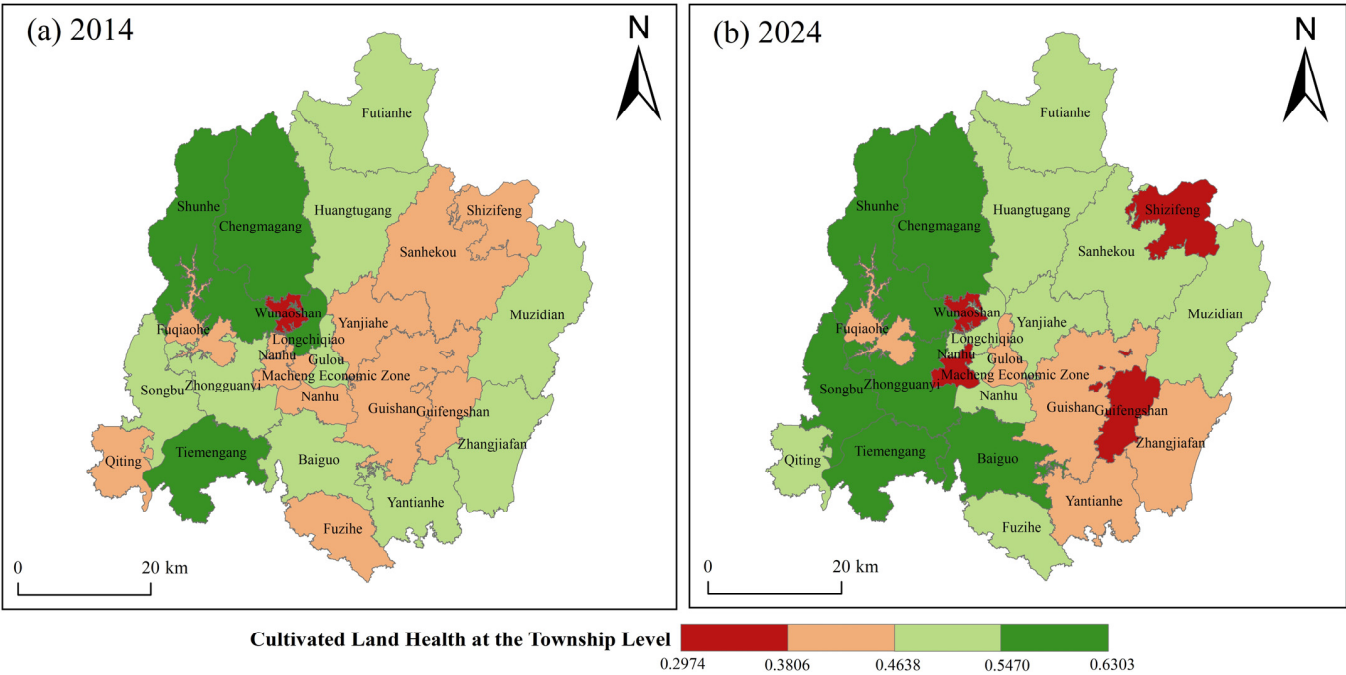


Figure 5. Spatial distribution of cultivated land health at the township level in 2014 and 2024.

Additional robustness analyses showed that the main conclusions were stable under the two alternative evaluation settings (Table A3). Both equal weighting and TOPSIS alone produced temporal changes broadly consistent with those of the baseline CRITIC–TOPSIS–GRA model. The main spatial pattern was also maintained, with relatively highly cultivated land health in the western plains and lower values in the eastern mountainous areas. These results indicate that the principal findings were not strongly dependent on the specific weighting scheme or the TOPSIS–GRA coupling procedure.

3.3. Driving Factors of Cultivated Land Health

Factor detection using the geographical detector was conducted to identify the drivers of the spatial differentiation of cultivated land health in Macheng City in 2014 and 2024. The results showed marked temporal changes in the explanatory power (q-value) of the factors X1–X11 (Table 3; Figure 6).

Table 3. Factor detection results for cultivated land health in Macheng City.

Factor	Code	q-Value in 2014	q-Value in 2024
Precipitation	X1	0.1580	0.2282
Soil type	X2	0.0105	0.0233
Soil texture	X3	0.0233	0.0851
NDVI	X4	0.0074	0.0067
Distance to major roads	X5	0.0733	0.0055
Irrigation capacity	X6	0.0456	0.0547

Table 3. Cont.

Factor	Code	q-Value in 2014	q-Value in 2024
Fertilizer application	X7	0.1522	0.0684
Level of agricultural mechanization	X8	0.2973	0.4946
Rural labor force	X9	0.3195	0.2558
Elevation	X10	0.0895	0.1896
Slope	X11	0.0611	0.1104

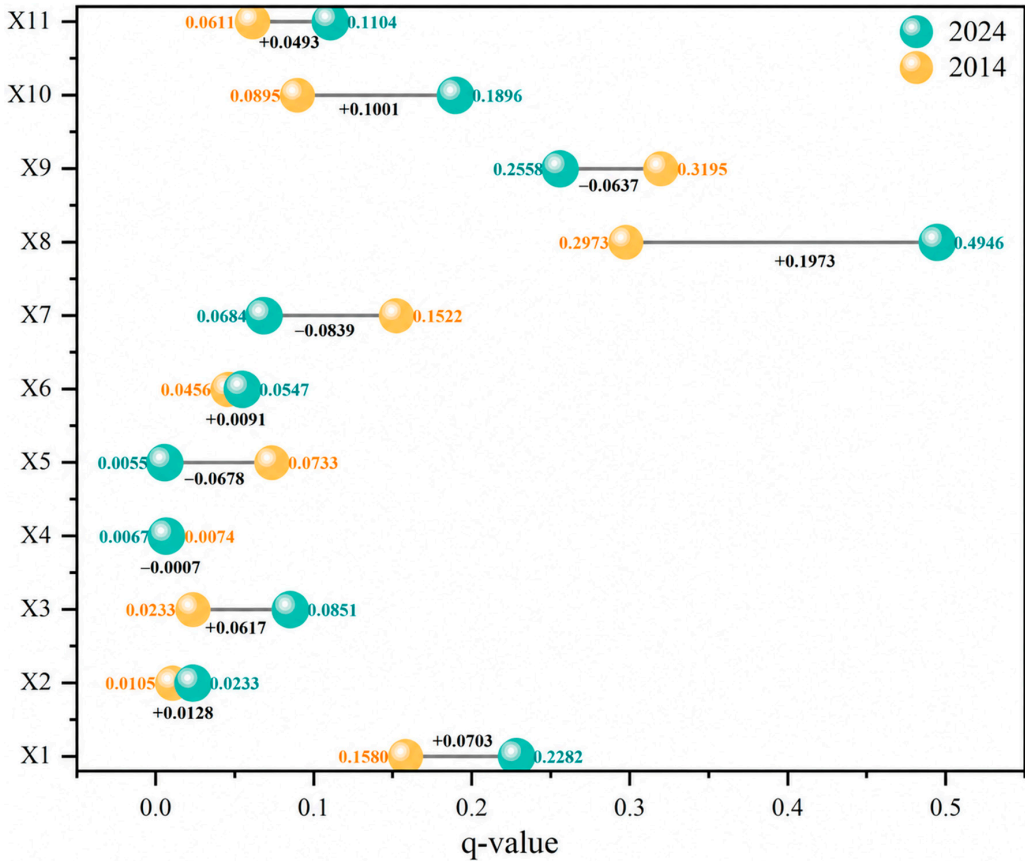


Figure 6. q-values of factors influencing cultivated land health in 2014 and 2024. Note: X1, precipitation; X2, soil type; X3, soil texture; X4, NDVI; X5, distance to major roads; X6, irrigation capacity; X7, fertilizer application; X8, level of agricultural mechanization; X9, rural labor force; X10, elevation; X11, slope.

In 2014, the major factors explaining the spatial differentiation of cultivated land health were the rural labor force (X9, $q = 0.3195$), level of agricultural mechanization (X8, $q = 0.2973$), precipitation (X1, $q = 0.1580$), and fertilizer application (X7, $q = 0.1522$), in descending order of explanatory power. During this period, socioeconomic conditions and agricultural inputs played dominant roles in the spatial differentiation of cultivated land health, indicating that traditional agricultural production activities, including labor input, mechanized operations, and fertilizer application, had relatively strong explanatory power for cultivated land use conditions and production levels. By 2024, the relative importance of the driving factors had changed markedly. The q-value of the level of agricultural mechanization (X8) increased to 0.4946, making it the dominant factor with the highest explanatory power. In contrast, the q-values of the rural labor force (X9) and fertilizer application (X7) decreased to 0.2558 and 0.0684, respectively. Meanwhile, the influence of natural background conditions became more pronounced. The q-values of precipitation (X1), elevation (X10), and slope (X11) increased from 0.1580, 0.0895, and 0.0611 in 2014

to 0.2282, 0.1896, and 0.1104 in 2024, respectively. This shift may be mainly attributed to the outflow of rural labor during urbanization, which has promoted a gradual transition toward mechanized agricultural production and increased the importance of mechanization. Meanwhile, the implementation of agri-environmental policies aimed at reducing fertilizer use while improving fertilizer-use efficiency may have weakened the direct contribution of chemical inputs to differences in cultivated land health. As human interventions have become increasingly large-scale and standardized, the constraints imposed by topographic conditions on mechanized farming and the fundamental role of climatic conditions, such as precipitation, in supporting agricultural production have become increasingly apparent. Overall, over the past decade, the mechanism underlying the spatial differentiation of cultivated land health in Macheng City has shifted from one dominated by labor and chemical inputs to one jointly shaped by agricultural mechanization and natural background conditions.

Interaction detection was further used to examine how pairwise interactions among the driving factors influenced the spatial differentiation of cultivated land health in Macheng City (Figure 7). The results showed that, in both 2014 and 2024, the q-value of every pairwise interaction exceeded the q-values of the corresponding individual factors. All interactions were characterized by either bivariate enhancement or nonlinear enhancement, with no independent or weakening effects observed. These results indicate that the spatial differentiation of cultivated land health in Macheng City cannot be attributed to any single factor acting independently, but instead results from the complex interactions between natural background conditions and socioeconomic inputs.

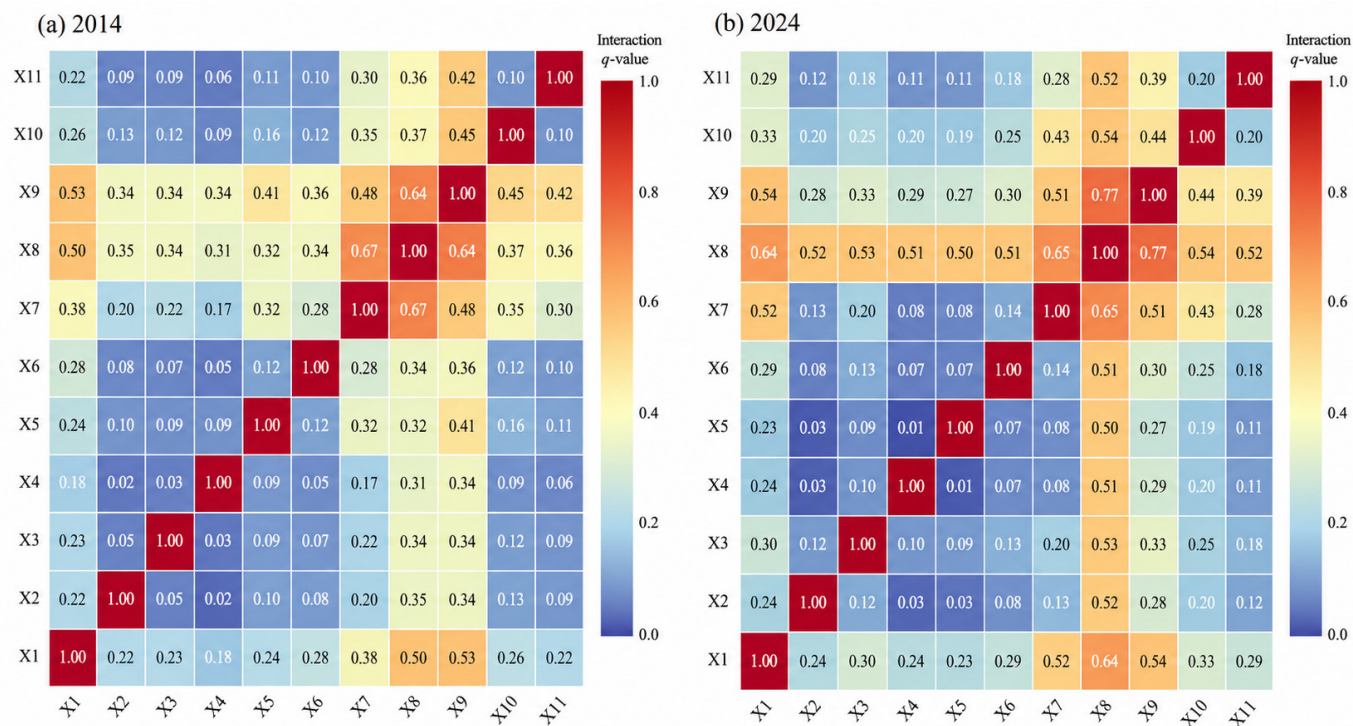


Figure 7. Heat maps of interactions among factors influencing cultivated land health in 2014 and 2024.

The dominant interaction patterns also changed markedly over time. In 2014, the strongest interactions mainly occurred between agricultural production inputs and labor-related factors. For example, the interaction between the level of agricultural mechanization (X8) and fertilizer application (X7) had a q-value of 0.67, while that between the rural labor force (X9) and the level of agricultural mechanization (X8) had a q-value of 0.64. This indicates that, at the beginning of the study period, the combined effects of intensive labor

input, mechanization, and fertilizer application played a dominant role in shaping the spatial pattern of cultivated land health. By 2024, the overall strength of factor interactions had increased substantially, with the level of agricultural mechanization (X8) emerging as the central factor in the interaction network. The interaction between X8 and X9 increased to a q-value of 0.77, making it the interaction with the highest explanatory power across the study area. At the same time, the enhanced interactions between X8 and natural background factors became particularly prominent. Its interactions with precipitation (X1), elevation (X10), and slope (X11) reached q-values of 0.64, 0.54, and 0.52, respectively. This shift suggests that, with the development of modern agriculture, agricultural mechanization has increasingly acted as a key factor that modifies and amplifies the effects of other drivers. However, in actual agricultural production, the extent and intensity of mechanized farming remain strongly conditioned by topographic relief and the suitability of climatic conditions such as precipitation. Therefore, the current spatial distribution of cultivated land health in Macheng City is primarily shaped by the joint effects of modern agricultural technology adoption and natural topographic constraints.

4. Discussion

Based on the DPSIR framework and the TOPSIS–GRA coupling model, this study comprehensively assessed the health of the cultivated land system in Macheng City over the past decade. From 2014 to 2024, the health-class composition of cultivated land in Macheng City shifted toward higher health levels, with an increase in the combined proportion of healthy and very healthy cultivated land. This finding suggests that external investments, such as improvements in farmland infrastructure, may contribute to enhancing the functioning of the cultivated land system [33,34]. This finding is broadly consistent with previous studies conducted in the middle and lower reaches of the Yangtze River and at the county scale, which have shown that cultivated land health is jointly influenced by natural background conditions, land-use conditions, and socioeconomic inputs [20,21]. However, compared with plain areas, Macheng City is located in the hilly and mountainous region of the Dabie Mountains, where topographic relief and cultivated land fragmentation are more pronounced. Consequently, improvements in cultivated land health were spatially uneven, with faster improvement in the western plains and river valleys and relatively limited improvement in the eastern mountainous areas. This spatial contrast provides empirical evidence that the effects of agricultural improvement measures can vary substantially within a mountain–hill transition region because of differences in natural conditions and agricultural production suitability.

The contribution of this study lies primarily in the empirical evidence revealed by the integrated assessment rather than in methodological innovation. TOPSIS and GRA are established multi-criteria evaluation approaches that characterize evaluation units from distance-based and relational perspectives, respectively [17,29]. Their integration in this study provides a consistent analytical framework for examining the multidimensional characteristics of cultivated land health, which cannot be adequately represented by a single soil property or production indicator [7,8]. More importantly, the results revealed a pronounced divergence among the five DPSIR subsystems. Although the overall cultivated land health improved from 2014 to 2024, this improvement was not accompanied by synchronous changes across all dimensions of the system. The impact subsystem improved substantially and the state subsystem remained relatively stable, whereas the driving force, pressure, and response subsystems declined to varying degrees. This divergence indicates that an increase in the overall health index does not necessarily imply balanced improvement across the cultivated land system. In particular, improvements in outcome-related indicators, such as grain production and ecological effects, coexisted with weakening so-

cioeconomic support, persistent pressures from human activities, and insufficient response capacity. Therefore, the aggregate improvement observed in Macheng City may partly mask structural imbalances within the cultivated land system.

This subsystem divergence also helps explain the spatially uneven evolution of cultivated land health. In the short term, land consolidation, infrastructure construction, and agricultural technology inputs can improve production conditions and system outputs; however, persistent challenges such as rural labor loss, the declining capacity of agricultural operators, and the marginalization of cultivated land use in mountainous areas may continue to constrain long-term system stability. The geographical detector results further revealed a shift in the mechanisms underlying the spatial differentiation of cultivated land health. In 2014, the rural labor force, level of agricultural mechanization, and fertilizer application were the major influencing factors, indicating that cultivated land health was strongly associated with labor and agricultural inputs. By 2024, agricultural mechanization had become the dominant driving factor, while natural background factors such as elevation, slope, and precipitation showed greater explanatory power. This result suggests that the effects of agricultural mechanization in hilly and mountainous areas are strongly conditioned by terrain and field characteristics [35,36], which is also consistent with studies of cultivated land marginalization in mountainous China that have identified slope, accessibility, and labor availability as important constraints [37]. In the western plains, relatively flat terrain and contiguous fields facilitate the substitution of labor by machinery, thereby supporting improvements in cultivated land health. In contrast, the eastern mountainous areas are constrained by steep slopes, fragmented fields, and limited accessibility, making the adoption of mechanized farming more difficult and resulting in slower improvements in cultivated land health.

Based on the observed evolutionary characteristics and driving mechanisms, differentiated cultivated land health management strategies should be developed for Macheng City, while the identified contrasts between plains and mountainous areas may also provide a case-based reference for other mountain–hill agricultural regions facing similar constraints. In the high-value areas of western and southwestern Macheng City, management should focus on maintaining existing health conditions, preserving agricultural infrastructure, and controlling ecological pressures. Cultivated land protection in these areas should further shift from an emphasis on quantity alone toward coordinated protection of quantity, quality, ecology, and function [38,39]. For the cold-spot areas in the eastern mountains, priority should be given to field consolidation and mechanization-oriented land improvement to reduce the constraints imposed by steep slopes and cultivated land fragmentation on mechanized farming [35,40]. Recent evidence further indicates that machinery-oriented land consolidation can mitigate arable land fragmentation and improve agricultural machinery accessibility in hilly and mountainous areas [41]. On this basis, the long-term benefits of land use could be further enhanced through ecological intensification compatible with regional ecological functions [42].

Despite revealing the spatiotemporal evolution of cultivated land health in Macheng City, this study has several limitations. Because of the limited availability of long-term continuous statistical data, the evaluation system did not fully incorporate micro-level factors related to farmer behavior, such as cultivation preferences and land transfer decisions. Future studies should incorporate more detailed data on land transfer, cultivation choices, and household labor structure, as these farm management decisions can influence cultivated land use efficiency and the continuity of agricultural production [11,25]. In addition, because the analysis was based on a comparison of only two time points, it was difficult to capture short-term disturbances during the decade, such as extreme climatic events or temporary shifts in policy orientation. Future research could integrate

high-temporal-resolution remote sensing observations with participatory household survey data to develop a multiscale analytical framework, thereby providing more robust scientific support for the sustainable management of cultivated land system health in hilly and mountainous regions. Furthermore, although the present framework captures land condition, functional performance, external pressures, and management responses, direct dynamic manifestations of system health, such as interannual yield stability, recovery from climatic disturbances, soil biological activity, and biodiversity, could not be fully incorporated because consistent long-term data were unavailable. Future studies should further integrate such dynamic indicators to strengthen the characterization of resilience and long-term system health.

5. Conclusions

A cultivated land health evaluation system for Macheng City was constructed based on the DPSIR framework. By integrating CRITIC weighting, the TOPSIS–GRA coupling model, hot spot analysis, and the geographical detector, this study systematically analyzed the spatiotemporal evolution and driving mechanisms of cultivated land health in Macheng City from 2014 to 2024. The main conclusions are as follows:

- (1) From 2014 to 2024, the health-class composition of cultivated land in Macheng City shifted toward higher health levels. The combined proportion of cultivated land classified as healthy and very healthy increased from 54.08% to 58.92%. Among the DPSIR subsystems, the impact subsystem showed the greatest improvement, the state subsystem remained relatively stable, whereas the driving force, pressure, and response subsystems declined. These contrasting trends indicate that improvements in overall cultivated land system health were accompanied by insufficient internal support and structural imbalance among subsystems.
- (2) Cultivated land system health in Macheng City exhibited pronounced spatial differentiation, characterized by an overall west-high–east-low pattern. In 2014, high-value areas were mainly concentrated in the western and southwestern parts of the city, including Shunhe Town, Chengmagang Town, and Tiemengang Township. By 2024, cultivated land health had further improved in Songbu Town, Zhongguanyi Town, Baiguo Town, and surrounding areas, resulting in the contiguous expansion of high-value areas in western Macheng City. In contrast, improvements in the eastern and southeastern mountainous areas remained relatively limited because of constraints associated with elevation, slope, and cultivated land fragmentation.
- (3) The dominant drivers of the spatial differentiation of cultivated land health gradually shifted from traditional agricultural inputs toward the joint influence of agricultural mechanization and natural background conditions. In 2014, the rural labor force, level of agricultural mechanization, precipitation, and fertilizer application were the major influencing factors. By 2024, the q -value of agricultural mechanization had increased to 0.4946, making it the dominant driving factor, while natural factors such as elevation, slope, and precipitation showed greater explanatory power. Interaction detection showed that all factor pairs exhibited either bivariate enhancement or non-linear enhancement, indicating that the spatial differentiation of cultivated land health resulted from the combined effects of natural conditions, agricultural technology, and socioeconomic factors.
- (4) Based on these findings, region-specific and category-specific cultivated land health management strategies should be implemented in Macheng City and comparable hilly and mountainous areas of the Dabie Mountains. In the high-value areas of western and southwestern Macheng City, management should focus on maintaining existing health conditions and cultivated land quality, while continuing to strengthen

high-standard farmland construction, agricultural infrastructure maintenance, and ecological pressure control. In the low-value areas of the eastern mountains, priority should be given to ecological restoration and adaptive land use, with particular emphasis on the rehabilitation of sloping cultivated land, field consolidation, the adoption of small-scale agricultural machinery suited to mountainous terrain, and the development of specialty agriculture. Overall, cultivated land protection in hilly and mountainous regions should move beyond an emphasis on quantity protection and engineering interventions toward coordinated improvement in quantity, quality, ecology, and function, thereby enhancing the stability and sustainability of cultivated land systems.

- (5) More broadly, cultivated land health should be understood as a system-level concept that extends beyond conventional cultivated land quality. While cultivated land quality primarily reflects biophysical and site conditions, cultivated land health also incorporates functional performance, external pressures, socioeconomic support, and management response. The pronounced divergence among the DPSIR subsystems further demonstrates that improvement in the aggregate health index does not necessarily indicate balanced improvement across the cultivated land system. From a broader international perspective, the findings from Macheng City are consistent with ongoing transformations in mountain agriculture, where agricultural modernization, rural labor decline, changing land-use intensity, and natural constraints jointly reshape agricultural production. In particular, the contrast between the western plains and the eastern mountainous areas indicates that the benefits of mechanization and agricultural investment are strongly conditioned by terrain, field fragmentation, and accessibility.

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Abbreviations

The following abbreviations are used in this manuscript:

DPSIR	Driving Force–Pressure–State–Impact–Response
CRITIC	Criteria Importance Through Intercriteria Correlation
TOPSIS	Technique for Order Preference by Similarity to Ideal Solution
GRA	Grey Relational Analysis
PSR	Pressure–State–Response
CEC	Cation Exchange Capacity
DEM	Digital Elevation Model
NDVI	Normalized Difference Vegetation Index
NPP	Net Primary Productivity
USGS	United States Geological Survey

Appendix A

Table A1. Discretization settings for explanatory variables used in the geographical detector.

Code	Explanatory Variable	Variable Type	Discretization Method	Number of Strata
X1	Precipitation	Continuous	Quantile classification	5
X2	Soil type	Categorical	Original categories retained	Original classes
X3	Soil texture	Categorical	Original categories retained	Original classes
X4	NDVI	Continuous	Quantile classification	5
X5	Distance to major roads	Continuous	Quantile classification	5
X6	Irrigation capacity	Categorical	Original categories retained	Original classes
X7	Fertilizer application	Continuous	Quantile classification	5
X8	Level of agricultural mechanization	Continuous	Quantile classification	5
X9	Rural labor force	Continuous	Quantile classification	5
X10	Elevation	Continuous	Quantile classification	5
X11	Slope	Continuous	Quantile classification	5

Note: For all continuous variables, the 2014 and 2024 data were pooled to determine common classification breakpoints at the 0%, 20%, 40%, 60%, 80%, and 100% quantiles, thereby ensuring consistent stratification between the two study years.

Table A2. Factor detection results and statistical significance for cultivated land health in 2014 and 2024.

Factor	Code	q-Value (2014)	p-Value (2014)	q-Value (2024)	p-Value (2024)
Precipitation	X1	0.1580	5.134×10^{-10}	0.2282	5.897×10^{-10}
Soil type	X2	0.0105	6.181×10^{-10}	0.0233	9.205×10^{-10}
Soil texture	X3	0.0233	5.944×10^{-10}	0.0851	6.892×10^{-10}
NDVI	X4	0.0074	9.261×10^{-10}	0.0067	3.469×10^{-10}
Distance to major roads	X5	0.0733	6.632×10^{-10}	0.0055	9.917×10^{-10}
Irrigation capacity	X6	0.0456	5.350×10^{-10}	0.0547	7.200×10^{-10}
Fertilizer application	X7	0.1522	1.190×10^{-10}	0.0684	5.477×10^{-10}
Level of agricultural mechanization	X8	0.2973	3.374×10^{-10}	0.4946	5.110×10^{-10}
Rural labor force	X9	0.3195	1.723×10^{-10}	0.2558	6.378×10^{-10}
Elevation	X10	0.0895	2.610×10^{-10}	0.1896	1.320×10^{-10}
Slope	X11	0.0611	4.549×10^{-10}	0.1104	8.890×10^{-10}

Note: All factors were statistically significant ($p < 0.001$) in both study years.

Table A3. Robustness analysis under alternative evaluation settings.

Evaluation Setting	Indicator Weighting	Evaluation Model	Temporal Trend	Main Spatial Pattern
Baseline	CRITIC	TOPSIS–GRA	Reference	Reference
Equal weighting	Equal weighting	TOPSIS–GRA	Consistent	Consistent
TOPSIS alone	CRITIC	TOPSIS	Consistent	Consistent

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