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Original Research

Pattern and Formation Mechanism of Cultivated Land Ecological Security Based on Interactions: A Case Study on the Middle and Lower Reaches of the Yellow River, China

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Abstract

Cultivated land ecological security is vital for preventing human–land relationship deterioration, enhancing ecosystem service value, and promoting sustainable development. This study constructed a DPSIR-based evaluation index system and applied an improved TOPSIS method to assess county-level cultivated land ecological security subsystems in the middle and lower reaches of the Yellow River in 2020. Interactions among subsystems were further analyzed using Pearson correlation and geographically weighted regression to capture both overall and local spatial heterogeneity. The main findings are as follows: (1) The overall level of cultivated land ecological security in the study area remains in a marginally secure and transitional state, and the spatial distribution shows a west-high–east-low pattern. The ranking of subsystem levels is: State > Driving Force > Response > Impact > Pressure. (2) Subsystems are closely and intricately interlinked, such that changes in any single subsystem may trigger chain reactions in others; however, the strength of these correlations varies significantly across subsystem pairs. (3) Subsystem combinations can be classified into global and local correlations. Globally positive correlations include D → P, P ↔ S, P ↔ R, I ↔ S, and I ↔ R. Globally negative correlations include D → I, D → S, D → R, and S ↔ R. Locally autocorrelated combinations include P → D, I → D, S → D, and R → D.

Keywords: DPSIR, improved TOPSIS method, GWR model, cultivated land ecological security, middle and lower reaches of the Yellow River

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Introduction

China is currently undergoing a profound phase of social transformation. With a shrinking cultivated land area, declining quality, and deteriorating ecological conditions, cultivated land ecological security has become a core focus in land resource security research [1]. In 2017, China issued the Opinions on Strengthening Cultivated Land Protection and Improving the Balance of Occupation and Supplement, which explicitly established a policy framework for protecting cultivated land through the integrated management of quantity, quality, and ecology [2]. Cultivated land ecological security directly impacts the inherent attributes of cultivated land in terms of both quantity and quality [3], while also providing a crucial foundation for alleviating human-land conflicts and advancing the sustainable utilization of cultivated land [4].

Cultivated land ecological security refers to a condition in which, within a specific spatiotemporal scope, the cultivated land ecosystem – despite ecological threats and disturbances – maintains its functional structure while satisfying the requirements of socio-economic sustainability [5]. Research on cultivated land ecological security has primarily focused on assessment [6], spatial differentiation and spatiotemporal dynamics [7], and forecasting changes with early-warning mechanisms [8, 9]. Quantitative approaches primarily employ big data analytics, GIS, and other related techniques to construct ecological security frameworks through optimized land-use allocation [10-14]. Evaluation methods include traditional comprehensive assessment [8], fuzzy comprehensive assessment [6], artificial neural networks [2], and the TOPSIS model [15, 16]. In addition, the natural-economic-social integrated evaluation system [4], the Pressure-State-Response (PSR) model [17], and the Driving Force-Pressure-State-Impact-Response (DPSIR) model have been widely applied to develop indicator systems.

However, most existing studies employing the DPSIR model to evaluate cultivated land ecological security are largely confined to isolated subsystem analyses and general assessments of overall system status. Notably, when applied to cultivated land ecological security, the DPSIR framework accounts only for potential causal relationships among subsystems, while neglecting internal uncertainty, cumulative causality, and spatial heterogeneity [16]. These limitations obscure internal differences and structural contradictions, underestimate system complexity and uncertainty, hinder the identification of key subsystem roles, and weaken both the policy relevance of governance and the effectiveness of optimization. Therefore, adopting a systems-thinking approach to evaluate and analyze the interaction mechanisms among subsystems of cultivated land ecological security has become an urgent research priority.

The middle and lower reaches of the Yellow River represent one of China's most important grain-producing regions. Safeguarding cultivated land ecological security in this area is fundamental to national food and ecological security, while also playing a pivotal role in maintaining social stability and promoting sustainable economic development. In response, this study proposes a DPSIR-based theoretical framework and constructs an evaluation indicator system for cultivated land ecological security. By integrating subsystem interrelationships and their impacts on the overall system, this study employs an improved TOPSIS method to evaluate the status and spatial characteristics of cultivated land ecological security and its subsystems across counties in the middle and lower reaches of the Yellow River in 2020. Based on the identified correlation types and strengths across different subsystem combinations, this study applies the geographically weighted regression (GWR) model to examine spatial heterogeneity in both overall and local relationships among subsystems, thereby revealing their underlying interaction mechanisms. The findings provide theoretical and methodological support for optimizing regional governance strategies, carrying significant theoretical implications and practical value for enhancing cultivated land ecological security in the region.

Materials and Methods

Materials

Theoretical Framework and Basic Interpretation

The PSR framework was introduced in 1979 by Canadian statisticians David J. Rapport and Tony Friend, originally for the development of indicator systems related to economic accounting and environmental issues [18]. In 1993, the Organisation for Economic Co-operation and Development (OECD) extended its application to environmental studies [19]. In 1995, the European Environment Agency (EEA) expanded the PSR framework into the DPSIR model [20]. The DPSIR model integrates the strengths of both DSR (Driving Force-State-Response) and PSR (Pressure-State-Response), thereby facilitating the incorporation of resources, development, environment, and human health [21] while capturing the system's causal relationships [22].

This study investigates the causal mechanisms within the cultivated land ecological security system by applying the DPSIR theoretical framework. Drawing on system boundary and general system theories, this study reinterprets the DPSIR framework to fully characterize cultivated land ecological security as an open, complex system. Departing from the traditional linear causal structure, we extend the model into a semi-circular dynamic feedback framework operating within an open system. This framework underscores that cultivated land ecological security emerges from continuous interactions between external socioeconomic inputs and internal ecological regulation. In accordance with system boundary theory, the cultivated land ecosystem is defined as an "internal system" with explicit structure and functions, whereas the socioeconomic and environmental context constitutes its "external environment". The exchange of material, energy, and information across boundaries drives the input–output processes underlying cultivated land ecological security. Within this framework, Driving Force, Pressure, and Impact are designated as external input elements. Specifically, (1) Driving Force and Pressure characterize disturbances stemming from anthropogenic activities within the external socioeconomic environment. (2) In contrast to the conventional DPSIR framework, where Impact is treated as a terminal outcome, this study reconceptualizes Impact as a feedback-related outcome derived from open systems and feedback theory. Essentially, Impact serves as an external "information signal" reflecting the socioeconomic and environmental consequences triggered by changes in cultivated land ecological security. (3) State and Response are categorized as the system's internal output elements. State denotes the structural and functional conditions of the cultivated land ecological security system, while Response is conceptualized as endogenous regulatory and adaptive behavior. This element signifies the system's capacity to maintain functional stability and achieve structural optimization under external disturbances. Based on this conceptualization, an integrated research framework was developed (Fig. 1).

"Driving Force" in cultivated land ecological security was defined as the set of factors causing system changes, divided into natural and anthropogenic drivers. Natural drivers were considered relatively stable, with short-term variations exerting minimal impact on cultivated land ecological security. In contrast, anthropogenic drivers were identified as exerting substantial temporal and spatial impacts, thus serving as the dominant factors in cultivated land ecological security analysis. Population growth increases food demand and residential land use, while economic development and urbanization lead to rising demand for industrial land, expansion of impervious surfaces, and increased pollution pressure [23], which directly or indirectly affect cultivated land ecological security. Accordingly, socio-economic drivers were emphasized, measured using population growth rate, GDP per capita, and urbanization rate.

"Pressure" on cultivated land ecosystems was imposed by human activities in production and daily life and was categorized as direct or indirect [22]. Direct pressure was attributed to the inefficient use of agricultural chemicals (fertilizers, pesticides, and plastic film), which led to excessive nutrient release and land degradation [24, 25], and was represented by indicators such as cultivated land plastic film load, fertilizer load per unit of cultivated land, pesticide load per unit of cultivated land, and soil erosion volume. Indirect

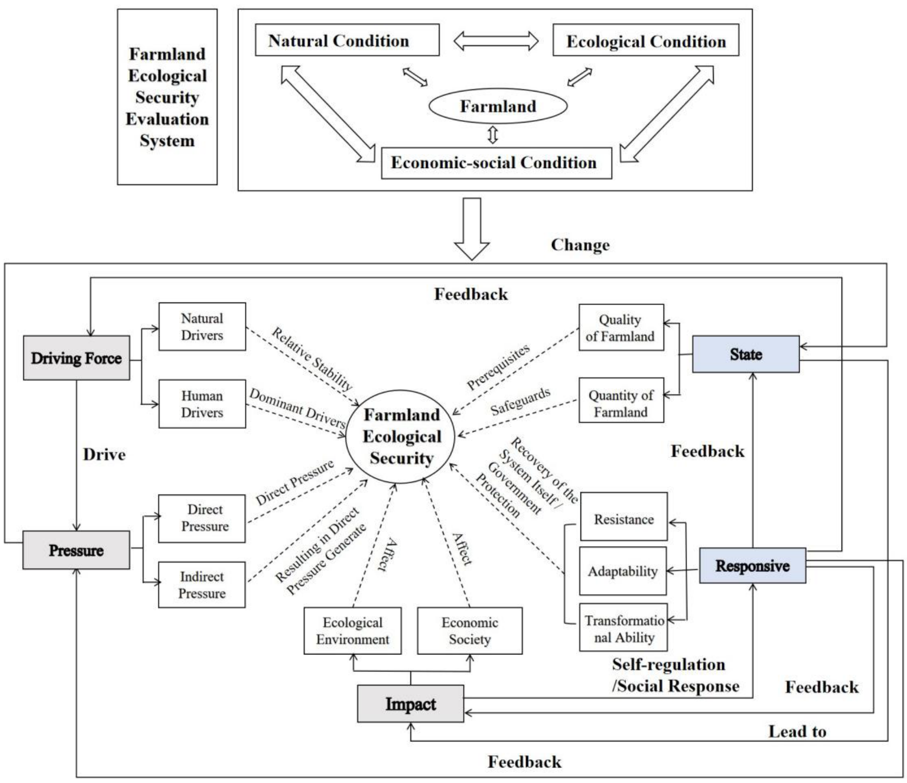

Fig. 1. Theoretical framework for cultivated land ecological security assessment based on the dpsir model (specific indicators included in each subsystem are listed in Table 1).

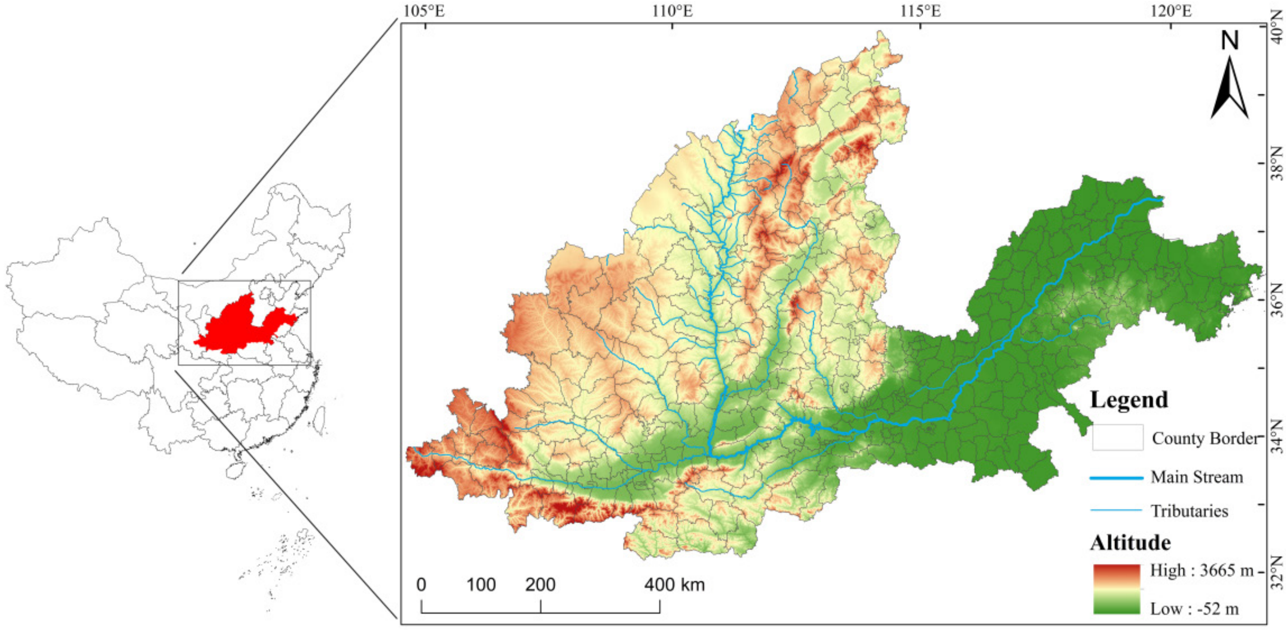

Fig. 2. Overview of the study area

pressure was attributed to increased population density and the expansion of construction land, which reduced cultivated land area and indirectly threatened cultivated land ecological security. These were represented by population density and construction land area.

"Impact" was defined as the set of consequences resulting from changes in cultivated land ecological security on regional resources, the environment, and socio-economic development [26]. Such impacts were reflected in two aspects: (1) ecological effects, measured by environmental quality; and (2) socio-economic effects, measured by rural household per capita net income and the total power of agricultural machinery.

The "State" of cultivated land ecological security was defined as encompassing both land quality and quantity [21]. Cultivated land quantity was measured by per capita cultivated land area and reclamation rate, while quality was measured by grain yield per unit area, net primary productivity (NPP), and mean patch size.

In previous studies, "Response" was narrowly defined as government-led protection measures and financial investment in cultivated land ecological security [27]. However, this one-dimensional interpretation was found to overlook the particularities of cultivated land ecosystems. As complex open systems with self-organizing properties, cultivated land ecosystems were observed to exhibit significant self-regulation and self-restoration through interactions among internal components and with external systems [28]. The more complex the system structure, the stronger its ability to resist external disturbances and maintain functional stability. Therefore, government intervention alone was deemed insufficient to capture the full range of response mechanisms. Building on previous research, the definition of "Response" was broadened to include resistance, adaptability, and transformation, thereby reflecting the comprehensive feedback of cultivated land ecosystems to external pressures. Specifically, resistance was represented by cultivated land stability, vegetation condition index [29], and soil and water conservation service value, indicating the capacity to maintain function under stress. Adaptability was measured by irrigation infrastructure maintenance and agricultural production diversification, reflecting the ability to adjust structures and functions to cope with environmental changes. Transformation was captured by the net transfer intensity of unstable cultivated land and road connectivity, revealing the system's capacity for renewal through spatial restructuring and element flow. This multidimensional approach moved beyond the traditional reliance on government investment, instead highlighting endogenous mechanisms that more fully revealed the dynamic response characteristics of cultivated land ecological security across resistance, adaptability, and transformation.

Study Area

Following the delineation of the Yellow River Basin proposed in previous studies [30], this study selects 225 counties in the middle and lower reaches of the Yellow River – across Gansu, Shaanxi, Shanxi, Henan, and Shandong – as the basic research units (Fig. 2). The study area covers 551,811.59 km². In 2020, it supported a population of 23.55 million, a GDP of CNY 2.48 trillion, a cultivated land area of 150,700 km², and a grain output of 11.51 million tons. This region, a traditional agricultural heartland of China, is characterized by large-scale crop production and plays a critical role in ensuring national food security [31]. Historically,

Table 1. Evaluation indicator system of the cultivated land ecological security system.

Subsystem Characteristics	Subsystems		Factor layer	Interpretation of indicators	Weight
Input terminal	Driving Force	Anthropogenic Drivers	population growth rate	population growth as a driver of cultivated land ecological security	0.0623
			per capita GDP	economic development as a driver of ecological security of arable land	0.0633
			urbanization rate	urban development as a driver of cultivated land ecological security	0.0612
	Pressure	Direct Pressures	per unit cultivated land plastic film load	pressure of agricultural activities on the ecological security of arable land	0.0054
			per unit cultivated land fertilizer load		0.0273
			per unit cultivated land pesticide load		0.0393
			water and soil loss area	soil erosion is an important indicator of cultivated land degradation	0.0291
		Indirect Pressures	population density	pressure of population density on the ecological security of arable land	0.0113
			urban land area	pressure on the ecological security of arable land from the continued expansion of built-up land area	0.0503
	Impact	Environment	ecological environment quality	impact on the ecological quality of arable land	0.0683
		Socio-economic	per capita net income of rural resident households	impact on farmers' income	0.0469
			total power of mechanical cultivation	impact on agricultural mechanization	0.0350
Output terminal	State	The Quality of cultivated land	area grain yield	per capita status of arable land resources	0.0512
			land fertility elements	cultivated land utilization status	0.0669
		The Quantity of Cultivated Land	per unit area grain yield	land productivity and level of agricultural production	0.0038
			average patch size of arable land	size of arable land plots in the region	0.0529
			net primary productivity	energy supplied by crops on arable land for human consumption in one year	0.0698
	Response	Resistance	Cultivated land stability	expressed as an annual invariant of the area of cultivated land	0.0589
			vegetation condition index	response of vegetation status	0.0572
			value of soil and water conservation services	response of the ecological conservation function of arable land	0.0474
		Adaptability	irrigation infrastructure maintenance	drought resilience of cultivated land systems	0.0151
			diversity of agricultural output sources	diversity of ways in which cultivated land systems respond to disturbance	0.0236
		Transformability	net outflow intensity of unstable cultivated land area	potential flexibility for structural reorganization and land-use adjustment	0.0123
			road connectivity	initiative of arable systems to communicate with exogenous systems	0.0411

unsustainable practices such as deforestation, land reclamation, and steep-slope cultivation have intensified soil erosion and degraded cultivated land quality. Currently, the drive for high-quality agricultural development is constrained by the persistent tension between intensive resource use and ecological fragility, underscoring the urgent need to safeguard cultivated land ecological security.

Data Sources and Preprocessing

The research relies on two categories of data: (1) Geospatial data, including land use, vegetation net primary productivity (NPP), soil erosion, and vegetation condition index (VCI). Land use data were obtained from the CLCD dataset published by Huang Xin of Wuhan University; NPP data from the National Tibetan Plateau Data Center; soil erosion and soil conservation data from the China Soil Conservation Capacity Dataset; and the 2020 VCI raster dataset, derived from MOD13A3 using the maximum value composite method. Because soil conservation and soil erosion data were available only up to 2019, the 2019 values were used to represent 2020 conditions. (2) Socio-economic data, primarily drawn from the 2020 county-level Statistical Yearbooks and Statistical Bulletins on National Economic and Social Development.

This study incorporates multi-source spatial data with varying original resolutions. Prior to analysis, all datasets were standardized to a consistent spatial scale. Specifically, raster data were spatially registered using a unified geographic coordinate system in ArcGIS 10.8. Using the Zonal Statistics method, the mean value of each raster within county-level administrative boundaries was extracted and converted into vector-based attribute data. Accordingly, all indicators were analyzed at the county scale as the minimum analytical unit, ensuring spatial comparability across variables. It should be noted that integrating multi-source spatial data inherently introduces uncertainties associated with spatial scale transformation, particularly the modifiable areal unit problem (MAUP). Aggregating high-resolution raster data to the county scale may smooth local micro-scale spatial heterogeneity and could potentially influence the local significance of GWR regression coefficients. However, this study focuses on meso-scale spatial differentiation and interaction mechanisms among cultivated land ecological security subsystems rather than fine-scale field-level processes. Given the objectives of this study, the county scale represents both the optimal scale for available statistical data and the fundamental unit for regional cultivated land management and policy implementation. Therefore, standardizing the analysis at the county scale is both methodologically justified and necessary. Moreover, robustness tests on kernel function types and bandwidth parameters indicate that GWR regression results remain relatively stable in both direction and spatial pattern under different parameter settings. This suggests that uncertainties introduced during scale integration did not substantially affect the main conclusions.

Methods

Indicator System and Weight Calculation

Building upon the theoretical framework and fundamental interpretations established in previous Section, and informed by previous studies on cultivated land ecological security, this study develops a comprehensive indicator system (Table 1) through the DPSIR framework. The system encompasses five interconnected subsystems: Driving Force, Pressure, Impact, State, and Response, with explicit consideration of their mutual interactions and feedback mechanisms. To ensure methodological rigor in weight determination, we employ the entropy weight method, which calculates weights based on the inherent dispersion characteristics of the dataset. This approach effectively minimizes subjective bias in weight assignment, thereby enhancing the scientific validity and accuracy of the evaluation system. The computational procedure is expressed as follows:

$$H_j = -\frac{1}{lnr}\sum_{i=1}^{r} P_j ln(P_j)$$

$$G_j = 1 - H_j$$

$$W_j = \frac{G_j}{\sum_{j=1}^{m} G_j} \tag{1}$$

Where H_j is the information entropy of indicator j, P_j is the standardized value of indicator j, r is the number of research units, G_j is the difference coefficient of indicator j, W_j is the weight of indicator j, and m is the number of indicators.

Improved TOPSIS Evaluation Model

This study utilizes an improved Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) to assess the levels of the cultivated land ecological security system and its subsystems [32]. TOPSIS is a commonly used decision-making technique in multi-objective decision analysis in systems engineering. In view of the holistic nature of the cultivated land ecological security system, the improved TOPSIS method adopted in this research establishes a decision matrix based on subsystems. It utilizes the coefficient of variation to adjust the proximity of cultivated land ecological security, enhancing the overall impact of subsystems and objectively depicting the essential characteristics of the cultivated land ecological security system and its subsystems. The specific implementation steps are as follows:

$$I_{iv} = \sum_{n=1}^{m} P_{ij} W_j \tag{2}$$

Where I_{iv} is the index of the cultivated land ecological security subsystem v of the research unit i, v = 1, 2, 3, 4, and 5, respectively, represent the five subsystems of driving force, pressure, state, impact, and response, and m denotes the number of indicators. P_{ij} represents the standardized value of indicator j for research unit i, and W_j represents the weight of indicator j.

$$V = I_{i*v} = \begin{matrix} I_{11} & \dots & I_{15} \\ \dots & \dots & \dots \\ I_{i1} & \dots & I_{i5} \end{matrix} \tag{3}$$

Where V refers to the cultivated land ecological security index of research unit i; i = 1, 2,..., i, represents the research unit; v represents the index of each subsystem of cultivated land ecological security.

$$Z^+ = (\max I_{ij}, j \in J; \min I_{ij}, j \in J^*; i = 1,2,\cdots,r) = (Z_1^+, Z_2^+, Z_3^+)$$

$$Z^- = (\min I_{ij}, j \in J; \max I_{ij}, j \in J^*; i = 1,2,\cdots,r) = (Z_1^-, Z_2^-, Z_3^-)$$

$$D_i^+ = \sqrt{\sum_{j=1}^{5} (I_{ij} - Z_j^+)^2} \quad (i = 1,2,\dots r)$$

$$D_i^- = \sqrt{\sum_{j=1}^{5} (I_{ij} - Z_j^-)^2} \quad (i = 1,2,\dots r)$$

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-} \tag{4}$$

Where Z^+ is the positive ideal solution, Z^- is the negative ideal solution, J is the positive indicator set, J^+ is the negative indicator set, D_i^+ and D_i^- are the distances between the cultivated land ecological security index of research unit i and the positive and negative ideal solutions; C_i is the proximity of the cultivated land ecological security index of research unit i to the ideal solution.

$$K = \frac{\sqrt{\sum_{j=1}^{5}(I_{ij} - \frac{1}{5}\sum_{J=1}^{5} I_{ij})^2/5}}{I^*}$$

$$C_i' = C_i(1 - k) \tag{5}$$

Where K is the coefficient of variation, C'_i is the subsidy rate after the coefficient of variation has been corrected, representing the level of cultivated land ecological security, and the larger the value, the higher the level in the research unit.

Geographically Weighted Regression Model

Geographically Weighted Regression (GWR) is a local linear regression technique designed to capture spatially varying relationships. This model elucidates the directionality (positive or negative) of subsystem interactions [33] and reveals local spatial heterogeneity among variables. To address the uneven spatial distribution of the research units, an adaptive Bi-square Kernel was employed in this study. The optimal bandwidth was determined via the corrected Akaike Information Criterion (AICc) minimization approach. Separate GWR models were constructed for each subsystem: for each regression, one subsystem was designated as the dependent variable, while the others served as explanatory variables. To assess model robustness, sensitivity analyses were performed by varying the kernel function type and bandwidth search range, while holding the explanatory variables constant. The direction and significance of the resulting regression coefficients were compared across different parameter settings. Results indicate that, across various kernel functions and bandwidth ranges, the signs of interaction coefficients remain consistent, and the spatial patterns of significant areas show no substantial deviations. These findings confirm that the GWR results are robust to bandwidth and kernel function specifications, thereby validating the reliability of the conclusions. The calculation formula for the GWR model is as follows:

$$y_i = \beta_0(u_i, v_i) + \sum_{i=1}^{k} \beta_i(u_i, v_i) x_{ik} + \varepsilon_i \tag{6}$$

Where (u_i, v_i) represents the geographic coordinates of observation *i*, which define the spatial location of the research unit rather than serving as fixed regression coefficients. β_i changes with the location, and each local β_i is used to estimate its adjacent spatial observation value. It embodies the GWR model's ability to account for spatial heterogeneity. This means that regression coefficients differ across geographic locations, providing a more nuanced understanding of variable interactions at a local scale.

Results

Spatial Characteristics of Cultivated Land Ecological Security Subsystems and Overall System Pattern

The improved TOPSIS model was applied to evaluate the levels of the subsystems within the cultivated land ecological security (Table 2). The results indicated that the ranking of the lower quartile (Q1), median (Q2), and upper quartile (Q3) across subsystems remained highly consistent, following the order: State > Driving Force > Response > Impact > Pressure. This stability

Table 2. Descriptive statistics of cultivated land ecological security subsystems and overall pattern in the middle and lower reaches of the Yellow River.

Subsystems	Minimum	Maximum	Lower Quartile	Median	Upper Quartile	Mean	Percentage of Counties Above the Mean
Driving Force	0.0106	0.1325	0.0456	0.0604	0.0704	0.0556	40.89%
Pressure	0.0000	0.0701	0.0067	0.0164	0.0234	0.0127	37.83%
Impact	0.0002	0.0911	0.0316	0.0366	0.0429	0.0370	52.25%
State	0.0000	0.1420	0.0588	0.0752	0.0942	0.0768	52.72%
Response	0.0020	0.1264	0.0434	0.0551	0.0665	0.0556	51.06%
Cultivated Land Ecological Security	0.0901	0.3193	0.1931	0.2122	0.2312	0.2108	52.01%

across distribution intervals indicates a certain degree of synchronization and co-movement among subsystems.

Specifically, the State and Driving Force subsystems exhibited the highest levels, indicating that the overall condition of cultivated land ecology was favorable and that the developmental drivers were relatively strong. However, the relatively high medians and wide interquartile ranges of these two subsystems reveal pronounced heterogeneity in State and Driving Force across counties. The Response and Impact subsystems were at moderate levels, suggesting that governance measures and the self-regulation capacity of the system were generally adequate, while the negative impacts on cultivated land ecology had not yet reached a critical level. In contrast, the Pressure subsystem exhibited the lowest level with limited inter-county variation, indicating that the external pressures faced by the cultivated land ecosystem in the study area were relatively low overall.

The county-level cultivated land ecological security index in the study area ranges from 0.0901 to 0.3193, exhibiting moderate overall dispersion. The mean (0.232) and median (0.231) are closely aligned, with 52.01% of counties exceeding the mean, indicating a relatively balanced and symmetric distribution. Based on classification using the natural breakpoint method (Fig. 3f)), both the mean and median fall within the third-level interval (0.2034-0.2599), suggesting that cultivated land ecological security in the middle and lower reaches of the Yellow River generally corresponds to a marginally secure state. This level indicates that the regional cultivated land ecological system maintains a degree of foundational stability but remains susceptible to potential degradation toward lower security levels. Examining the quartile distribution, the lower quartile lies near the boundary between the second and third levels, indicating that approximately 25% of counties are at relatively low security levels and should be prioritized for future management interventions. The upper quartile is situated in the upper portion of the third level, showing that some counties have achieved relatively robust ecological states, although they have not yet reached a high-security status. Overall, the spatial pattern of cultivated land ecological security in the study area exhibits intermediate concentration with divergence at both tails, reflecting a transitional state between moderate and polarized ecological security.

Further analysis examined the spatial characteristics of cultivated land ecological security and its subsystems (Fig. 3). The high-value areas of the Driving Force subsystem were mainly concentrated in urban districts, showing a clustered distribution (Fig. 3a)). These higher levels can be attributed to advanced economic development that attracts substantial labor inflows. Combined with urban expansion and land-use transformation, these factors intensify Driving Force, making cultivated land ecosystems more vulnerable to ecological security alterations.

The pressure subsystem levels were significantly higher in the eastern low-elevation plains than in the western high-altitude mountainous areas (Fig. 3b)). Two factors explain this pattern: (1) the plains are densely populated with frequent economic activities, leading to greater disturbances and ecological degradation; and (2) as agricultural production hubs, these plains experience excessive and improper use of fertilizers and pesticides, undermining ecosystem health. By contrast, in the western mountainous areas, fragmented cultivated land, low agricultural intensification, limited economic activity, and restricted land development result in weaker disturbances and consequently lower pressures on cultivated land ecosystems.

The spatial distribution of the Impact subsystem indicates that cultivated land ecological security in the western high-altitude mountainous areas and the Loess Plateau is subject to significantly greater impacts than in the eastern low-elevation plains (Fig. 3c)). This disparity reflects differences in natural conditions: fragile environments and frequent soil erosion in the west exacerbate instability, while the plains – benefiting

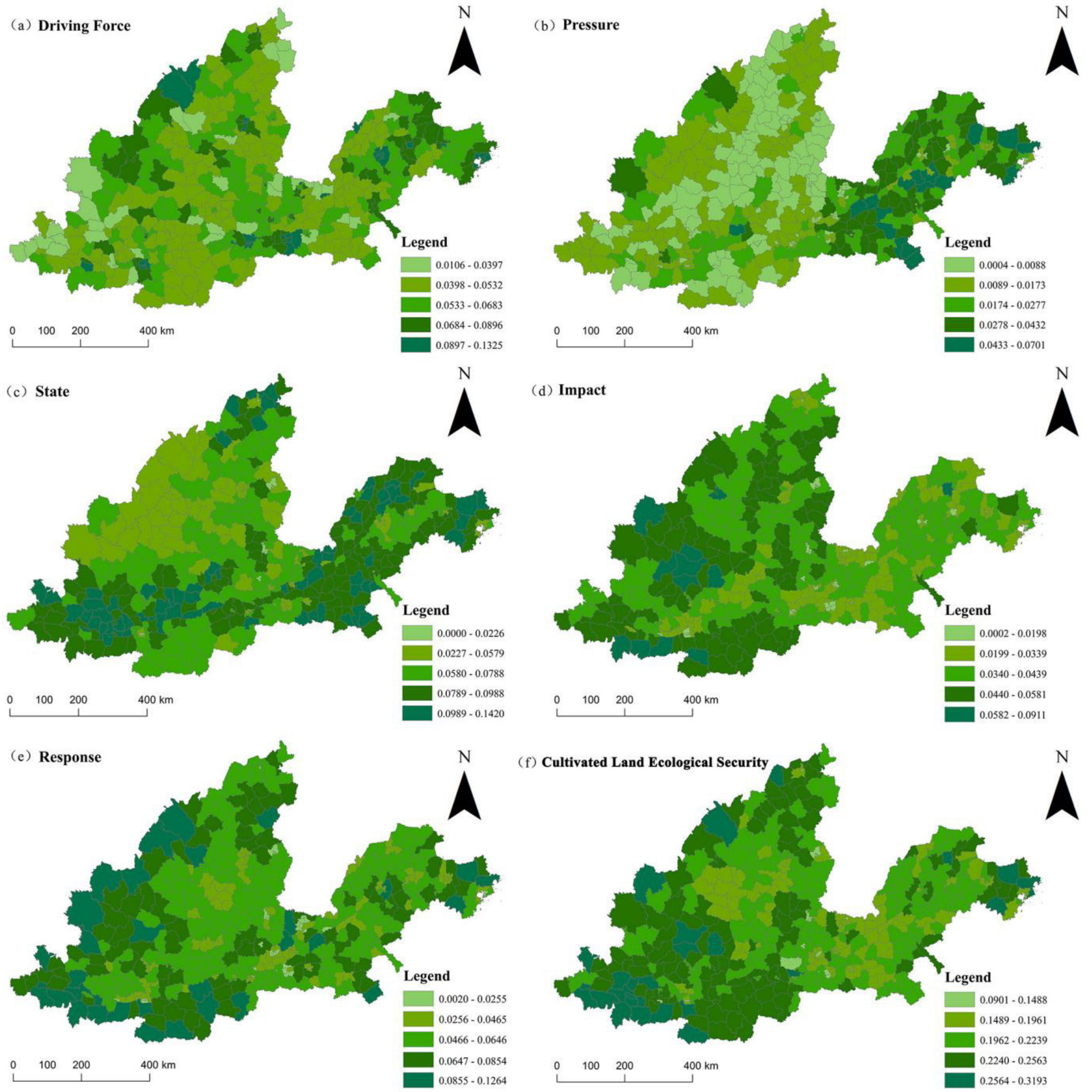

Fig. 3. Pattern and characteristics of cultivated land ecological security and its subsystems in the middle and lower reaches of the Yellow River.

from fertile soils, flat terrain, and higher agricultural investment – support more stable and productive ecosystems, thereby reducing exposure to negative impacts.

Higher State subsystem levels were concentrated in the eastern low-elevation plains and the Weihe River Basin in the southwest (Fig. 3d)). This can be explained by the contiguous and less fragmented nature of plains cultivated land, which favors large-scale management and concentrated protection. Additionally, fertile low-elevation soils provide comparative advantages in both land quality and productivity.

High-value areas of the Response subsystem are primarily located in the high-altitude mountainous areas and the Loess Plateau in the western and southern parts of the study area, with a smaller share in the economically developed urban districts and counties in the east (Fig. 3e)). This spatial differentiation reflects the combined effects of resilience, adaptability, and transformability. While low-elevation areas experience more frequent human disturbances, the strong ecological stability and favorable vegetation conditions in high-altitude regions enhance resilience. This resilience partly compensates for weaker adaptability and transformability, resulting in relatively high response levels.

Table 3. Pearson correlation analysis results of the internal subsystems of cultivated land ecological security.

Subsystems	Driving Force	Pressure	Impact	State	Response
Driving Force	-	- 0.146**	-0.489**	-0.542**	- 0.410**
Pressure	-	-	0.025	0.421**	0.375**
Impact	-	-	-	0.316**	0.732**
State	-	-	-	-	0.334**

Note: "**" in the table indicates significance at the 0.01 level (two-tailed).

Table 4. Spatial autocorrelation results of the internal subsystems of cultivated land ecological security.

	Driving Force	Pressure	Impact	State	Response
Moran's I	0.4770	0.5888	0.5640	0.5808	0.4854
Z	15.5288	19.1702	18.3634	18.8824	15.7968
P	0.00	0.00	0.00	0.00	0.00

Table 5. GWR model results of the internal subsystems of cultivated land ecological security.

	Driving Force	Pressure	Impact	State	Response
Bandwidth	145200.4666	193994.3126	189673.1866	153900.8115	191342.0677
Residual Squares	0.0628	0.0170	0.0145	0.0857	0.0354
Effective Number	64.0493	43.6322	43.8760	59.3500	44.2252
Sigma	0.0132	0.0067	0.0062	0.0154	0.0097
AIC	-2417.8223	-3008.0232	-3075.8335	-2295.1880	-2697.6060
R^2	0.6187	0.7477	0.7811	0.6870	0.8122
Adjusted R^2	0.5517	0.7194	0.7563	0.6368	0.7908

Overall, cultivated land ecological security displays pronounced spatial heterogeneity, with higher levels in the west and lower levels in the east (Fig. 3f)). The southwestern mountainous areas and parts of the Loess Plateau generally maintain higher ecological security, whereas the eastern plains remain low. This pattern reflects complex topography, low-intensity land use, sparse populations, and limited economic activity in the west, which reduce human disturbance and enhance security. By contrast, the eastern plains – with flat terrain, dense populations, intensive farming, and strong economic activity – face higher human disturbances, leading to lower ecological security.

Overall Correlation Analysis of Subsystems Based on Pearson Coefficients

Pearson correlation analysis was applied to assess the direction, strength, and statistical significance of relationships among the subsystems (Table 3). The results showed that, except for the Pressure–Impact correlation, which was not statistically significant ($p>0.05$), all other subsystem correlations were significant at the 0.001 level. This suggests that: (1) in the middle and lower reaches of the Yellow River, the subsystems of cultivated land ecological security are highly interconnected, such that changes in one subsystem can trigger cascading effects across the others; and (2) although correlations exist among all subsystems, the strength and direction of these linkages vary considerably, reflecting the complexity and heterogeneity of their interactions. Specifically, strongly correlated pairs include Impact-Response, which shows a significant positive relationship, forming a "problem-solution" linkage mechanism; and Driving Force-State, as well as Driving Force-Impact, both showing significant negative relationships, reflecting negative feedback effects. This indicates that Driving Force and Impact are the most active core subsystems, and their conflicting relationship constitutes the critical nodes of system dynamics. Therefore, while maintaining existing causal linkages, greater emphasis should be placed on regulating Driving Force, mitigating its negative relationships with State and Impact, and reinforcing the positive Impact-Response feedback loop to enhance coordination among subsystems. Moderately correlated

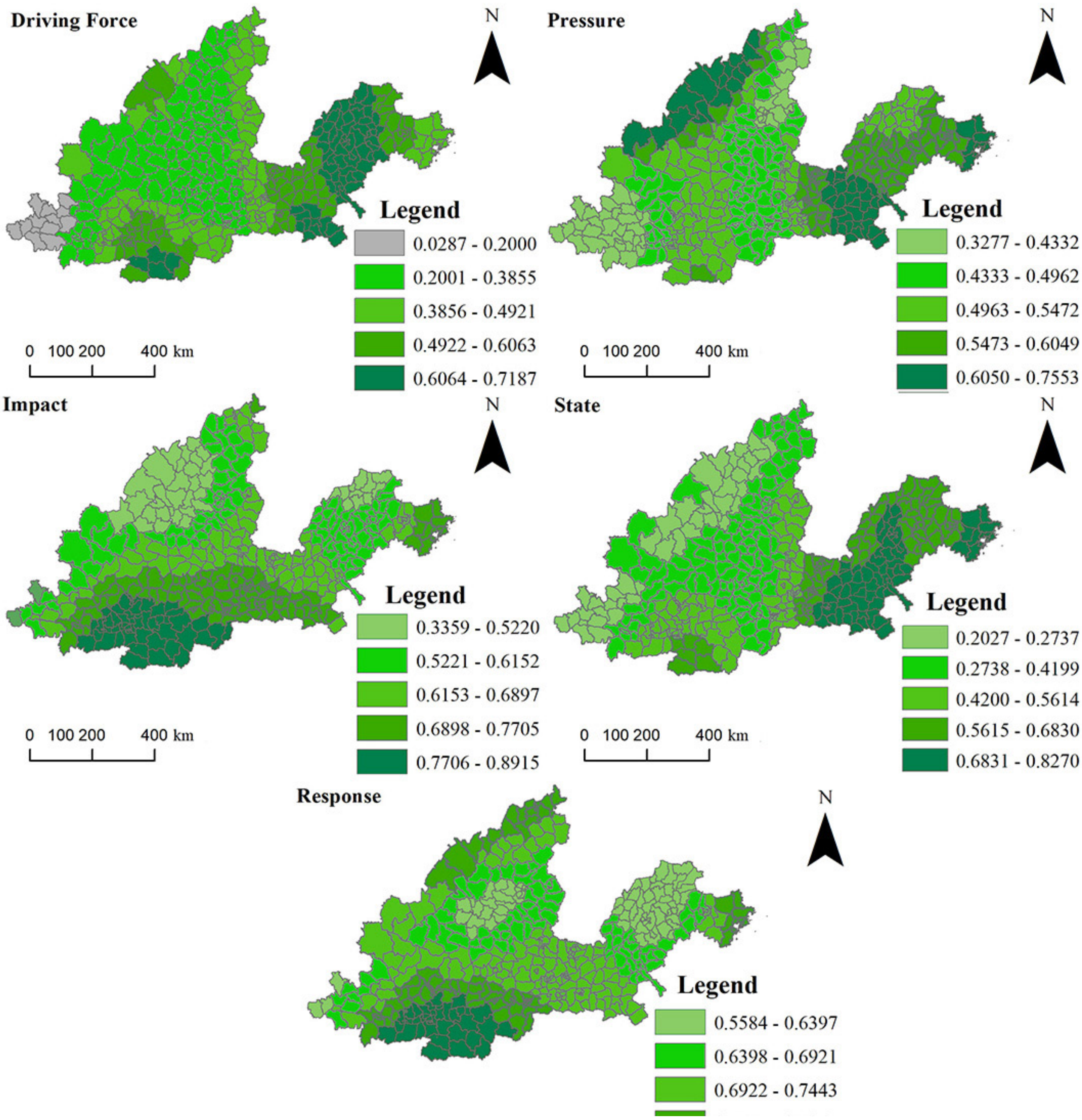

Fig. 4. Spatial distribution of local R^2 values in GWR models for cultivated land ecological security subsystems.

pairs include Pressure-State, Driving Force-Response, Pressure-Response, State-Response, and State-Impact. All examined relationships show positive correlations, except for Driving Force–Response, which exhibits a moderate negative correlation. The moderately active subsystems are State and Response, suggesting the need to improve the quantity and quality of cultivated land, increase protection and investment, and strengthen self-recovery capacity, thereby ensuring cultivated land ecological security based on stability and reinforced by active responses. Weakly correlated pairs include Driving Force-Pressure, which exhibits a weak negative correlation. This suggests that the direct impact of Driving Force on the Pressure subsystem is limited and may instead affect cultivated land ecological security indirectly through intermediate factors.

Spatial Heterogeneity Analysis of Interactions among Cultivated Land Ecological Security Subsystems

Pearson correlation coefficients reveal the overall relationships among cultivated land ecological security subsystems, but spatial variations must also be considered. To address this, the model GWR was employed to examine spatial heterogeneity and the strength of interactions among subsystems. The Pressure-Impact pair was excluded from the

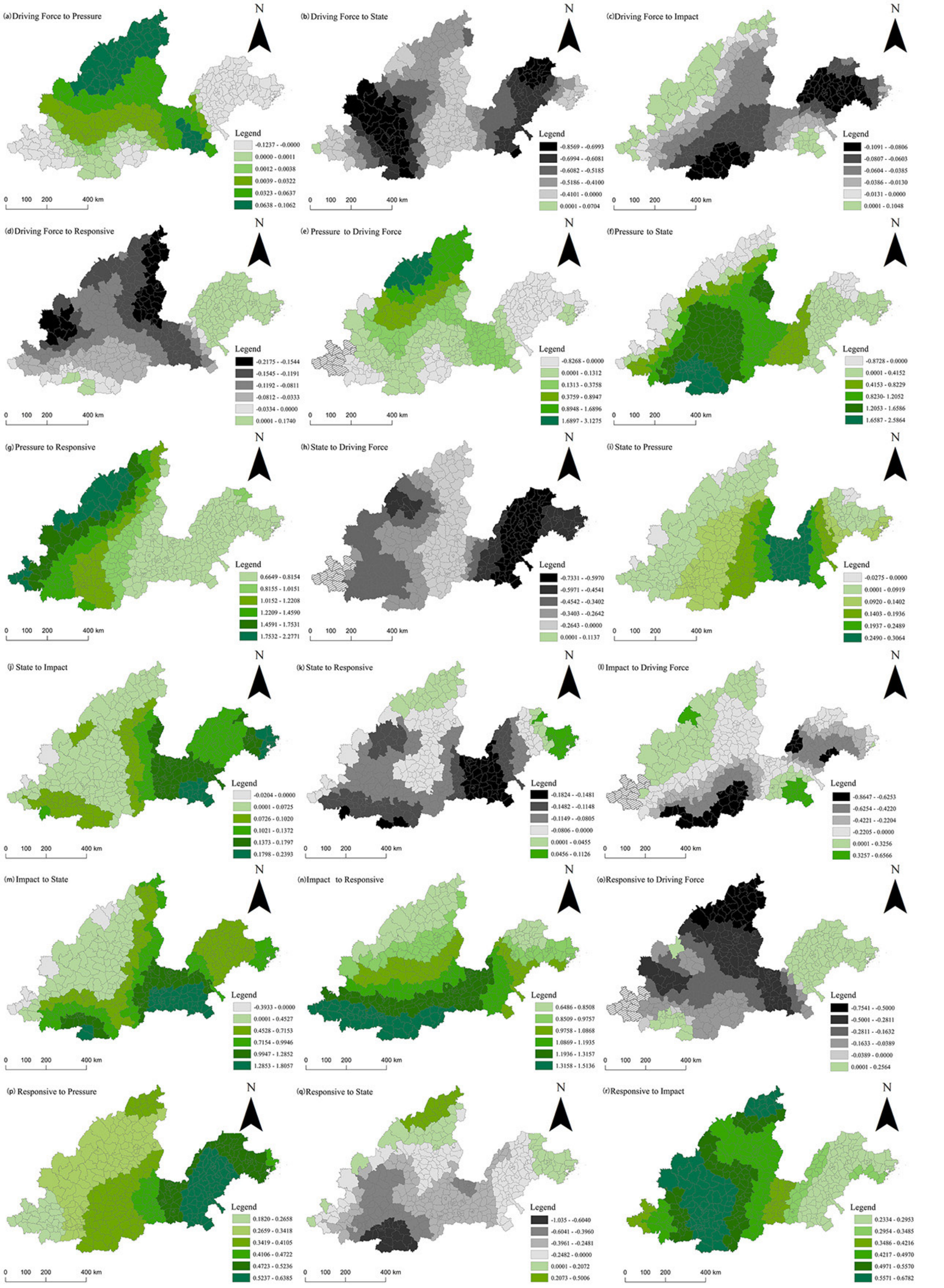

Fig. 5. Spatial distribution of relationships among cultivated land ecological security subsystems in the middle and lower reaches of the Yellow River.

Table 6. Types of globally correlated subsystem combinations.

Nature of correlation	Type of combination	Mean value of the regression coefficient	Mechanism of action
Positive Interactions	D→P	0.0062	A weak positive correlation suggests that Driving Force may slightly exacerbate Pressure on cultivated land ecological security, though the effect is limited.
	P↔S	0.8034/0.1415	A strong unidirectional promoting effect (P→S) indicates that increased pressure significantly degrades the state of cultivated land ecosystems. However, the reverse effect (S→ P) is relatively weak, implying limited feedback from ecological conditions to pressure mitigation.
	P↔R	0.9920/0.4097	Pressure strongly triggers governance Response, but the feedback effect (R→ P) is moderate, suggesting room for improving response mechanisms.
	I↔S	0.1053/0.7759	The influence of S→I is weak, while the effect of I→S is significant.
	I↔R	0.1097/0.4322	Impacts weakly trigger Response, but the reverse effect (R→I) is relatively strong.
Negative Interactions	D→I	-0.0482	A weak negative correlation suggests that Driving Force may slightly mitigate the negative Impact on cultivated land ecological security, though the overall effect is limited.
	D→S	-0.5055	A strong negative correlation indicates that Driving Force may significantly degrade the State of cultivated land ecological security.
	D→R	-0.0547	A weak inhibitory effect suggests that Driving Force may slightly hinder Response, though the effect is minimal.
	S↔R	-0.0875/-0.2376	A bidirectional negative correlation indicates mutual inhibition between the State and Response.

GWR analysis, as its correlation was not statistically significant.

Multicollinearity diagnostics confirmed the model's reliability: the conditional numeric fields (COND) of the output elements were within the expected range, with no missing or out-of-range values, indicating no multicollinearity among the independent variables. In addition, the global Moran's I index was calculated using the spatial autocorrelation tool in ArcGIS 10.8 to assess the spatial distribution of the subsystems. As shown in Table 4, all regression parameters yielded Moran's I values greater than 0 and Z-scores above 2.58, significant at the 0.01 level, indicating clear spatial clustering of the selected parameters.

Overall, the GWR model effectively captured the spatial heterogeneity of relationships among subsystems, offering a comprehensive depiction of interaction strengths and regional differences.

The results (Table 5) further show that the R^2 values for regional subsystems ranged from 0.62 to 0.81, indicating strong explanatory power for subsystem interactions. To further examine regional variations in the applicability of the GWR model under different geographic and socio-economic contexts, this study analyzed the spatial distribution of local R^2 values for each subsystem regression model (Fig. 4). Overall, counties in the eastern plains exhibited consistently higher local R^2 values in models where Driving Force, Pressure, and State were the dependent variables. This suggests that, in the eastern plains – where human activity intensity is high and input structures are relatively uniform – the explanatory variables effectively account for variations in socio-economic Driving Force, resource and environmental Pressure, and cultivated land ecological State. In contrast, southern mountainous areas and some traditional agricultural zones displayed pronounced clustering of high values in models with Impact and Response as dependent variables. This spatial pattern indicates that these southern regions, as ecologically sensitive areas, exhibit cultivated land ecological security dynamics primarily driven by the combined effects of environmental sensitivity and strong responsiveness. In such regions, minor fluctuations in other subsystems can be magnified, translating into noticeable ecological and economic Impact and triggering governmental governance actions as well as system self-regulatory Response.

ArcGIS was employed to visualize the GWR regression results (Fig. 5). Counties with insignificant coefficients, shown with hatching, are primarily located in the mountainous areas of the upper Weihe River, while significant correlations are observed in other regions. In the middle and lower reaches of the Yellow River, cultivated land ecological security subsystems exhibit globally correlated patterns, comprising unidirectional correlations (Driving Force → Pressure, Driving Force

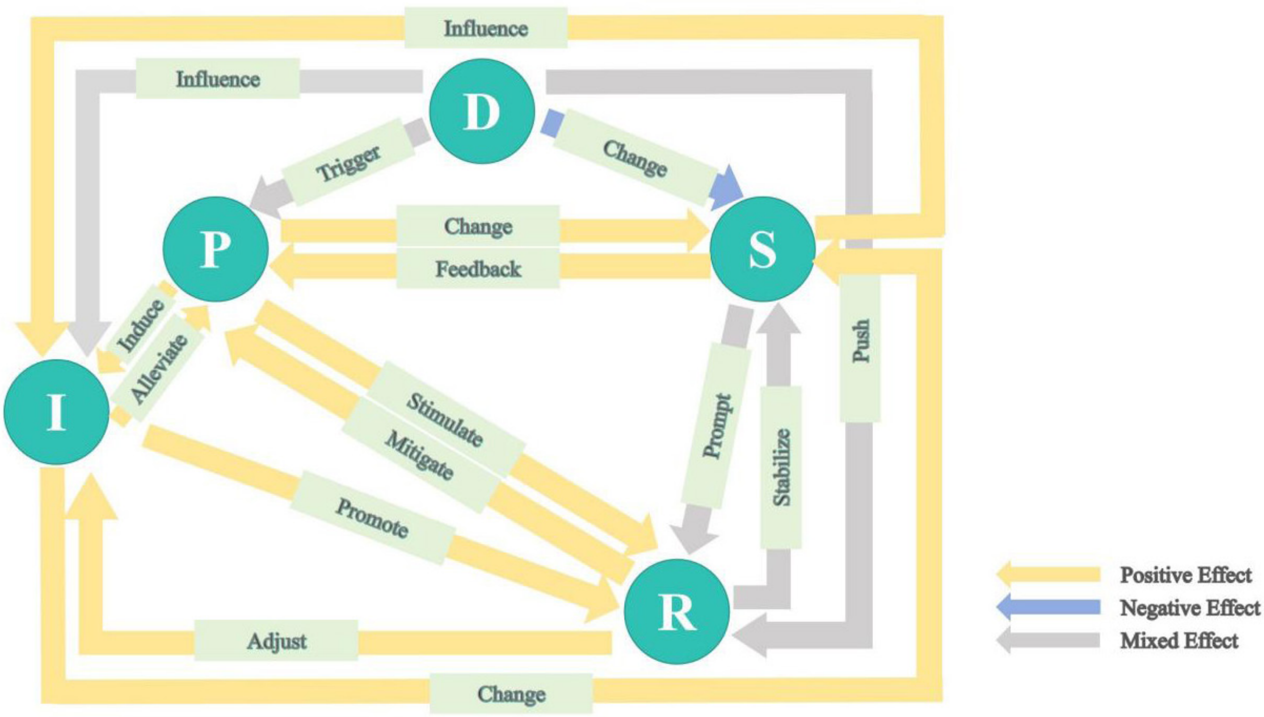

Fig. 6. Mechanism of interactions among cultivated land ecological security subsystems.

→ Impact, Driving Force → State, Driving Force → Response) and bidirectional correlations (Pressure ↔ State, Pressure ↔ Response, Impact ↔ State, Impact ↔ Response, State ↔ Response). The characteristics, mean regression coefficients, and mechanisms of each combination type are summarized in Table 6 and Fig. 4.

For unidirectional effects: (1) Driving Force → Pressure coefficients (–0.1237 to 0.1062) are predominantly positive, with negative values concentrated in the northeastern plains and parts of the southern mountainous counties, showing a gradual north–south decrease. (2) Driving Force → Impact coefficients (–0.1091 to 0.1048) are mostly negative, while positive values appear in the western mountains and southeastern plains, displaying a latitudinal pattern in the lower Yellow River plain and a longitudinal pattern in the middle reaches. (3) Driving Force → State coefficients (–0.8569 to 0.0704) are generally negative, with two low-value areas and a stepwise latitudinal increase outward. (4) Driving Force → Response coefficients (–0.2175 to 0.1740) are mainly negative, but positive values occur in a few southern mountainous counties and the northeastern plains, also reflecting latitudinal trends in the lower Yellow River plain and longitudinal trends in the middle reaches.

For bidirectional interactions: (1) Pressure ↔ State coefficients are mostly positive. Pressure's effect on State (–0.8728 to 2.5864) peaks in the central southern mountains and decreases outward, while State's effect on Pressure (–0.0275 to 0.3064) gradually declines from the center toward the east and west. (2) Pressure ↔ Response coefficients are positive across the region, with Pressure → Response (0.6649–2.2771) showing an east-west decreasing trend, and Response → Pressure (0.1820-0.6385) exhibiting a mirror pattern, decreasing from west to east. (3) Impact ↔ State coefficients are also generally positive. State → Impact (–0.0204 to 0.2393) decreases from the southeast outward, whereas Impact → State (–0.3933 to 1.8057) shows two high-value zones in the southern mountains and southeastern plains, decreasing stepwise outward. (4) Impact ↔ Response coefficients remain positive, with Impact → Response (0.6486-1.5136) decreasing from south to north, and Response → Impact (0.2334-0.6782) decreasing from west to east. Finally, State ↔ Response coefficients (–0.1824 to 0.1126; –1.0350 to 0.5006) are dominated by negative values, forming a gradual south-north increasing trend across the region.

At the local scale, interactions among cultivated land ecological security subsystems in the middle and lower reaches of the Yellow River are primarily unidirectional, including Pressure → Driving Force, Impact → Driving Force, State → Driving Force, and Response → Driving Force (Fig. 4). The specific influences and their spatial effects are as follows: (1) Pressure → Driving Force coefficients (–0.8268 to 0.3127) are mainly positive, with negative values concentrated in the northeastern plains and a few southern mountainous counties, exhibiting a gradual north–south decline. (2) Impact → Driving Force coefficients (–0.8647 to 0.6566) are largely negative, with positive values occurring mainly in the western mountains and southeastern plains. (3) State → Driving Force coefficients (–0.7331 to 0.1137) are generally negative, except for two southwestern counties where positive values occur, showing a decreasing trend from the central area toward both east and west. (4) Response → Driving Force coefficients (–0.7541 to 0.2564) are predominantly negative, while positive values are concentrated in a few southern mountainous counties and the northeastern plains.

Discussion

Contributions of This Study

The DPSIR model provides an effective framework for analyzing interactions between the environment and socio-economic development and has been widely applied in studies of human-environment systems, with numerous scholars proposing refinements to the model. Kandziora et al. incorporated ecosystem services into the model [34]; Du et al. assessed ecological security in the eastern Liao River region of Liaoning Province using the DPSIRM framework [35]; Zhang et al. integrated the DPSIR framework with the PLS-SEM model [36]; Yang et al. combined the DPSIR framework with the DEA model [37]. Considering the characteristics of cultivated land ecological security, this study modifies the general DPSIR causal chain by dividing the framework into input and output components, thereby facilitating the analysis of internal interactions among subsystems. Moreover, while Response is traditionally defined as government protection measures and financial investments, few studies incorporate the resilience of the system itself. By integrating ecosystem resilience, this study extends the theoretical framework of cultivated land ecological security and provides an empirical contribution based on the middle and lower reaches of the Yellow River, offering a theoretical foundation for future research.

The conventional understanding of the DPSIR causal chain posits that Driving Force fundamentally generates Pressure, which subsequently induces changes in both Driving Force and State, thereby triggering cascading effects across the system. Response then feeds back to the other four components, initiating a new causal cycle [38, 39]. Building on this theoretical foundation, this study empirically analyzes cultivated land ecological security in the middle and lower reaches of the Yellow River. By examining both the interaction strength and spatial heterogeneity of subsystems, it identifies the dominant interaction modes and their variations at different spatial scales. The formation mechanism of subsystem interactions consists of three main stages (Fig. 6). First, the Driving Force-Pressure-State mechanism represents the core pathway shaping cultivated land ecological security in the study area. Driving Force acts as the primary determinant of ecological security pressures, exerting a direct influence on both Pressure and State, while the intensity of Pressure further regulates changes in State. Changes in State trigger internal adjustments within the cultivated land ecological security system and influence its overall stability, which in turn feeds back to Pressure, forming a dynamic feedback loop. However, the positive feedback from State to Pressure is relatively weak, indicating a strong path dependence in agricultural production within the middle and lower reaches of the Yellow River. Although local improvements in State have been observed, they have not effectively translated into a shift toward sustainable agricultural practices or a reduction in socioeconomic Pressure. Instead, enhancements in State are often perceived as an ecological buffer that supports further intensification of production; specifically, improvements in State incentivize increased fertilizer and pesticide application as well as intensified economic Pressure. The observed relatively weak feedback can be attributed to strict regulatory constraints, such as ecological redlines and policies mandated to reduce fertilizer and pesticide use, which limit the marginal increase of Pressure. Nevertheless, the underlying unsustainable logic – exploiting ecological surplus to pursue greater economic output – persists, reflecting that the region is currently undergoing a challenging phase in the transition toward green agricultural intensification. Second, the Driving Force-Impact-State mechanism highlights the bidirectional coupling between ecological conditions and socio-economic outcomes. Driving Force and Impact jointly exert direct influences on the State of cultivated land ecological security. The State – reflected in land-use patterns, agrochemical application intensity, and agricultural production modes – subsequently constrains and reshapes ecological and socio-economic Impacts. This reciprocal relationship underscores that ecological degradation and economic outcomes are not unidirectional consequences of development pressures, but rather co-evolve through continuous feedback between environmental conditions and human activities. Third, the Driving Force-Pressure-Impact-State-Response mechanism captures the activation of governance and self-regulatory processes within the cultivated land ecological security system. Under the combined effects of Driving Force, Pressure, and Impact, changes in State directly activate system Responses, encompassing both government-led interventions and intrinsic self-regulation mechanisms. Through these responses, negative effects associated with excessive Pressure, State degradation, and adverse Impacts can be mitigated, forming dynamic feedback processes that help stabilize the system and promote sustainable development. However, the effectiveness and timeliness of these responses vary spatially, reflecting differences in environmental sensitivity, governance capacity, and socio-economic context. Overall, cultivated land ecological security in the middle and lower reaches of the Yellow River is not determined by any single subsystem or a limited set of subsystems. Instead, the five subsystems operate as an integrated whole, forming an interconnected network that collectively governs the level and spatiotemporal patterns of cultivated land ecological security.

In terms of spatial characteristics, the findings indicate that although the intensity and combination types of subsystem interactions vary, their spatial distribution patterns exhibit distinct regularities. Specifically, the Driving Force → Pressure, Pressure → Driving Force, and Impact → Response pathways follow latitudinal (east-west) orientations, whereas Driving Force → State, State → Driving Force, State → Pressure, Pressure → State, Pressure → Response, Response → Pressure, and Response → Impact show longitudinal (north-south) orientations. This pattern suggests that natural conditions exert a fundamental control over cultivated land ecological security, while geographical variability shapes its spatial structure. Crucially, the observed north-south and west-east differentiation does not represent a mere geometric or statistical pattern but rather reflects the spatial manifestation of long-term coupling between the region's unique natural background and human activities. Latitudinally differentiated interactions are closely linked to the marked north-south climate gradient and corresponding differentiation in agricultural production systems. The middle and lower reaches of the Yellow River span from the warm temperate zone in the south to the mid-temperate zone in the north. This thermal gradient directly affects cropping systems, the intensity of cultivated land use and agricultural input structures, thereby shaping differentiated interaction relationships among subsystems across latitudinal belts. By contrast, longitudinally differentiated interactions more strongly reflect the pronounced west-east topography-hydrology-ecology gradient. In the western Loess Plateau, fragmented terrain, a high proportion of sloping cultivated land, and severe soil erosion impose strong constraints on subsystem interactions. Moving eastward to the North China Plain, flatter terrain and the heavy reliance on groundwater for irrigation increase the sensitivity of subsystem interactions to human activity. Over-extraction of groundwater and the resulting secondary soil salinization further amplify these effects. Additionally, the lower reaches of the Yellow River feature a "suspended river" pattern and extensive flood control infrastructure, which impose stringent constraints on land use and the spatial layout of cultivated land, further modulating the direction and strength of human-induced subsystem interactions. Overall, the combined influence of natural gradients and engineering constraints produces pronounced north-south and west-east differentiation in the spatial interactions among cultivated land ecological security subsystems, rather than merely representing a simple statistical spatial pattern.

Comparison with Previous Studies

It is important to note that this study employs indicators such as population, GDP, and urbanization rate to quantify Driving Force, aiming to characterize the fundamental pressures that regional socio-economic systems exert on cultivated land ecosystems. In this context, these indicators primarily capture negative pressures associated with resource consumption, land occupation, and environmental stress, which explains the empirically observed significant negative effect of Driving Force → State. Nevertheless, in the middle and lower reaches of the Yellow River, policy factors can exert a substantive influence on cultivated land ecological security evolution during specific periods. Theoretically, if strong ecological protection or agricultural support policies were incorporated as "positive Driving Force" within the Driving Force subsystem, they could statistically attenuate or even offset the negative pressures arising from economic development. This could alter the strength of the Driving Force → State pathway and, under certain circumstances, even produce a positive relationship. However, such pathway changes primarily reflect the mitigating or corrective effect of policy on existing economic pressures, rather than a replacement of the underlying population-economic-land use driving mechanisms. Due to the limited availability of high-resolution, temporally continuous, and consistently quantified policy funding data, constructing a refined model that simultaneously incorporates both positive and negative Driving Force remains challenging. Future studies with access to more detailed policy input and implementation intensity data could extend the DPSIR framework to quantitatively capture the dynamic interplay between policy-driven and economic-driven forces, thereby providing a more comprehensive understanding of the mechanisms driving the evolution of cultivated land ecological security.

China's unique resource endowment and demographic characteristics make food security a fundamental pillar of national security. Cultivated land, as the material basis for food production, possesses a productive function that distinguishes it from general natural ecosystems and shoulders the critical mandate of ensuring the survival and development of a large population. Therefore, emphasizing ecological protection without considering production realities does not reflect the objective context of cultivated land use in China. This study contends that true cultivated land ecological security must be grounded in food supply capacity; any cultivated land that has lost its productive function, regardless of favorable ecological indicators, cannot be considered truly secure in a substantive sense. To capture this dual function, the study incorporates both net primary productivity (NPP) and grain yield into the State evaluation system. NPP represents the intrinsic ecological function and carbon sequestration capacity of the cultivated land ecosystem, while grain yield reflects actual food production under current management. The integration of these two indicators enables the framework to effectively capture and quantify the inherent tension between ecological sustainability and production intensification, rather than obscuring this objective trade-off. It should be emphasized that the cultivated land ecological security defined in this study is not equivalent to high yield. To avoid biasing the assessment toward purely production-oriented outcomes, the framework introduces a balancing mechanism through Pressure. Although high yield can enhance the State score, the associated excessive application of agrochemicals and potential soil erosion exert a negative penalty on the overall ecological security index. Therefore, the “security” represented by this indicator system reflects long-term system resilience and sustainability rather than short-term yield maximization. This design successfully balances the inherent trade-offs between ecological and productive functions in cultivated land, ensuring that the evaluation authentically reflects ecological security while remaining clearly distinguishable from single-dimensional food security metrics.

The weight distribution within the Response subsystem reveals the functional logic of cultivated land ecological security maintenance. Results obtained using the entropy weight method reflect both the relative importance of different response indicators and their contribution to the system's information content. First, resistance indicators dominate. Cultivated land stability, vegetation condition index, and the value of soil and water conservation services carry the highest weights in the Response subsystem, indicating that the spatial heterogeneity of cultivated land ecological security under natural background conditions is most pronounced in the middle and lower reaches of the Yellow River. As the first line of defense against external disturbances, this ecologically based “endogenous resistance” is a key determinant of response capacity at the current stage. Second, the structural support provided by infrastructure is significant. In particular, the weight of road connectivity significantly exceeds that of some traditional adaptive indicators, highlighting the critical role of spatial connectivity in the response of cultivated land ecological security. As Shi et al. noted, infrastructure plays a critical role in complex human-land systems [40]. Within cultivated land systems, higher road connectivity not only improves the efficiency of material and information flow but also strengthens the system’s potential for transformation through spatial restructuring. Compared with traditional ecological security assessments that primarily emphasize government-led investment or protection measures, the Response subsystem in this study underscores the role of endogenous adaptive capacity and structural transformation mechanisms. Specifically, cultivated land ecological security largely depends on the system’s self-restorative ability. These findings highlight the necessity of shifting from single-dimensional governance toward integrated management strategies, where ecological regulation and spatial structure optimization are integrated with policy interventions.

Notably, the GWR results show that, in the mountainous areas of the upper Weihe River, local regressions with Driving Force as the dependent variable yield statistically insignificant coefficients across several counties. These findings suggest that the remaining subsystems do not adequately explain the spatial variation in Driving Force. These results do not indicate model inadequacy; rather, they reflect the region’s distinctive natural-socioeconomic coupling mechanisms. First, topographical constraints obstruct feedback mechanisms. The southwestern mountainous areas of the upper Weihe River are characterized by highly fragmented and complex terrain. In many socio-ecological systems, changes in Pressure, State, Impact, and Response are translated into socioeconomic Driving Force – such as population growth and economic expansion – through industrial development and market mechanisms. However, in this region, complex topographic conditions disrupt this feedback pathway, preventing ecological changes from being effectively transmitted to the socioeconomic system. As a result, local regression coefficients do not reach statistical significance. Second, Driving Force in this region depends strongly on exogenous inputs. Most counties in the study area are designated as national key ecological function zones or were formerly classified as part of contiguous poverty-stricken regions. Their development trajectories differ markedly from the endogenous growth models observed in plain areas, which rely on local resource endowments and market dynamics. Instead, regional Driving Forces are largely shaped by central government fiscal transfers, ecological compensation schemes, and policy-driven poverty alleviation programs, resulting in a pronounced exogenous input-oriented pattern. Under this development mode, Driving Forces are primarily influenced by macro-level policy orientation and administrative resource allocation rather than by local Pressure, State, Impact, or Response variables. Consequently, the explanatory power of other subsystems for Driving Force is statistically insignificant.

A comparative analysis reveals distinct divergences between global and local statistical patterns. Both Driving Force–Response and State–Response pairs exhibit significant positive correlations in Pearson analysis, indicating global-level associations. However, GWR results reveal predominantly negative local regression coefficients for Driving Force → Response and State ↔ Response across most counties, with negative mean values. This contrast between global positive associations and local negative effects highlights pronounced spatial non-stationarity, consistent with Tobler’s First Law of Geography. The underlying mechanisms can be interpreted as follows: (1) regarding the Driving Force → Response relationship, the positive Pearson correlation indicates that, at the global scale, regions with stronger human Driving Force tend to exhibit stronger overall response capacity. In contrast, GWR identifies negative local relationships, indicating that in many counties with low to moderate development levels, an increase in Driving Force is frequently accompanied by habitat fragmentation and disruption of key ecological processes. These high-intensity external pressures often exceed ecosystem resilience thresholds, directly impairing self-regulation and recovery functions. As a result, at local scales, increasing Driving Force does not yet produce a parallel enhancement of response capacity; instead, response capacity is suppressed or sacrificed, resulting in a statistically significant negative association. (2) Regarding the State ↔ Response relationship, the global positive Pearson correlation suggests that regions with more favorable ecological states generally exhibit stronger responses, including both ecosystem self-regulation and policy intervention. At the local scale, however, two contrasting mechanisms become evident. First, the negative effect of State → Response indicates that high-intensity response measures are often triggered only after cultivated land ecological security has already deteriorated, reflecting a lagged and reactive governance pattern. Second, the negative feedback from Response → State suggests that neither ecosystem self-recovery nor intensive government intervention produces immediate improvements in cultivated land ecological security over the short term. Moreover, while Pearson analysis shows significant correlations between Driving Force and the other subsystems, GWR results indicate extremely low model fit in some mountainous counties of the upper Weihe River when Driving Force is treated as the dependent variable. This further confirms that subsystem interactions are spatially heterogeneous and jointly shaped by regional topography, policy interventions, and other contextual factors. Overall, while Pearson correlation captures general covariation patterns, it masks pronounced spatial differentiation in interaction directions. The local negative effects revealed by GWR complement rather than contradict the global positive correlations, providing a finer-scale understanding of the heterogeneous response mechanisms governing the cultivated land ecological security system.

Policy Implications

Given that the GWR model reveals pronounced spatial non-stationarity in the driving mechanisms of cultivated land ecological security, conventional one-size-fits-all management approaches are inadequate for addressing the complex regional characteristics of the middle and lower reaches of the Yellow River. Based on the GWR results, this study proposes the following region-specific management strategies: (1) Northeastern plains: In this region, the effects of Driving Force → State and Driving Force → Pressure are significantly negative. First, targeted measures should address the direct pressures of urbanization on ecological security, including strict enforcement of the balance between cultivated land occupation and compensation and the redlines for permanent basic cultivated land, effectively preventing the encroachment of construction land on high-quality cultivated land and safeguarding the ecological security baseline. Second, capitalizing on the favorable trend whereby Driving Force suppresses Pressure, the region's strong economic foundation should be used to increase investment in agricultural technological innovation, accelerating the transition toward low-input, high-efficiency modern agricultural practices, thereby maximizing the pressure-mitigation effect. (2) Western mountainous areas and the Loess Plateau: In this region, Response → Driving Force is mostly negative or insignificant, whereas Response → Impact is positive. The combination of these effects can easily trap the region in a cycle of poverty and ecosystem degradation. First, horizontal and vertical compensation mechanisms guided by ecological service values should be established, substantially increasing compensation standards for key ecological function areas such as the western mountains and the Loess Plateau. This approach internalizes the externalities of ecological protection and addresses the issue of "poverty among protectors". Second, environmentally friendly wealth-generating industries should be promoted to support livelihood transformation. Given the region's high environmental sensitivity and unique ecological baseline, initiatives such as agroforestry, eco-tourism, and specialty dryland agriculture should be encouraged. (3) Southern mountainous areas and traditional agricultural zones: In this region, the mutual inhibitory effects between State and Response are the strongest, while Impact ↔ State exhibits strong positive feedback. Policy governance should shift from reactive to proactive management. First, a dynamic monitoring network for cultivated land ecological security should be established to enable early intervention before severe deterioration occurs, thereby breaking the lagged response cycle in which worsening State triggers stronger Response. Second, integrated protection and restoration of mountains, rivers, forests, cultivated lands, lakes, grasslands, and deserts should be implemented, alongside high-standard cultivated land construction. Improving agricultural infrastructure, such as irrigation systems, can enhance the self-restoration capacity and resilience of the cultivated land ecological system, fundamentally reducing its sensitivity to external disturbances.

Limitations and Future Research

Despite the contributions of this study, several limitations should be acknowledged. First, to enhance the integration of the theoretical framework with the case study, and considering timeliness and specificity, this study focuses on the year 2020, analyzing the core characteristics and key challenges of cultivated land ecological security in the middle and lower reaches of the Yellow River at that time. Nonetheless, interactions among cultivated land ecological security subsystems exhibit strong spatiotemporal dependence and are dynamically evolving. Although no explicit time-series simulation was conducted, the negative Driving Force → State effects and the mixed Response

→ State feedback identified through GWR enable the proposal of two hypothetical future scenarios. (i) Inertia scenario: In the absence of strong interventions, the established Driving Force-dominated mechanism may amplify the negative impacts of Driving Force on ecosystems in the high-pressure eastern plains experiencing ongoing urbanization. Under this scenario, cultivated land ecological security levels in these areas could potentially degrade from sensitive to at-risk. (ii) Policy intervention scenario: Considering that, post-2020, China has implemented stricter policies such as the balance between cultivated land occupation and compensation and restrictions on non-grain production, continued policy strengthening could partially offset the traditionally negative Driving Force associated with population growth and economic expansion. Consequently, government-led Responses would exert relatively greater influence within the cultivated land ecological security system, potentially shifting the system state from passive pressure to proactive regulation. This suggests that targeted government interventions may counteract ecological degradation driven solely by economic factors. However, it must be noted that these scenarios are primarily based on theoretical extrapolation and qualitative assessment of policy evolution and require further empirical quantification.

Future research will therefore aim to develop long-term dynamic panel models to track nonlinear transformations in driving mechanisms before and after policy turning points, enabling proactive and adaptive policy guidance for sustainable cultivated land management.

Second, although the GWR model effectively addresses spatial non-stationarity through local weighting, it fundamentally operates under the assumption of local linearity. It is important to recognize that the evolution of cultivated land ecological systems often exhibits pronounced nonlinearities and threshold effects. For example, fertilizer and pesticide applications do not always exert a linearly cumulative Pressure; once pollution loads exceed the land's environmental carrying capacity, cultivated land ecological security may deteriorate precipitously, exhibiting exponential decay rather than linear progression. Consequently, the model employed in this study may oversimplify system dynamics under extreme pressures and underestimate ecological security risks in regions where critical thresholds have already been surpassed. To address these limitations, future research should not only focus on spatiotemporal evolution and predictive simulations but also consider integrating panel threshold regression models or machine learning-based approaches. These methods can more accurately characterize the nonlinear relationships among cultivated land ecological security subsystems across varying intensity ranges, thereby providing early warning signals of system collapse or abrupt changes. Third, because this study focused on counties in the middle and lower reaches of the Yellow River, the findings may primarily reflect regional characteristics. Subsequent research should explore subsystem interactions at multiple spatial scales and across alternative units, such as townships or grid cells. Such efforts will refine the theoretical framework of cultivated land ecological security and the DPSIR model, thereby strengthening the theoretical basis for policy-making and management strategies.

Conclusions

Based on the DPSIR framework and cultivated land ecological security theory, this study developed an evaluation index system and applied an improved TOPSIS method to assess subsystem status at the county level in the middle and lower reaches of the Yellow River in 2020. Building on correlation analysis, GWR model was employed to examine both global and local interactions among subsystems, thereby revealing the internal mechanisms of the cultivated land ecological security system. The main findings are as follows:

(1) Despite ongoing ecological construction efforts, the overall level of cultivated land ecological security in the middle and lower reaches of the Yellow River remains in a marginally secure and transitional state. This state is characterized by foundational stability yet a distinct susceptibility to potential degradation. Spatially, cultivated land ecological security exhibits a distinct "high-West to low-East" gradient, with higher levels observed in the southwestern mountains and the Loess Plateau, and lower levels concentrated in the eastern plains. The subsystem performance levels follow the order of State > Driving Force > Response > Impact > Pressure, reflecting a degree of synchronicity and resonance within the system. Specifically, the State and Driving Force subsystems are relatively robust, while the Response and Impact subsystems are at moderate levels; in contrast, the Pressure subsystem is generally weak.

(2) The subsystems of cultivated land ecological security in the region exhibit pervasive correlations. Except for the Pressure–Impact pair (not significant, $p>0.05$), all other subsystem correlations are significant at the 0.001 level, demonstrating close and complex linkages whereby changes in one subsystem may trigger cascading effects in others. The strength of correlations varies: strong correlations are observed between Impact-Response (positive, forming a "problem-solution" linkage) and Driving Force-State and Driving Force-Impact (negative, indicating inverse feedback). Moderate positive correlations include Pressure-State, Driving Force-Response, Pressure-Response, State-Response, and State-Impact. A weak negative correlation exists between Driving Force-Pressure, suggesting a limited direct effect likely mediated by other factors.

(3) The relationships among cultivated land ecological security subsystems are complex and exhibit distinct spatial patterns. The spatial applicability of the

GWR model reveals clear regional differentiation: the eastern plains exhibit strong explanatory power for the Driving Force, Pressure, and State subsystems, while the southern mountainous areas demonstrate a high model fit for the Impact and Response subsystems. Notably, counties with insignificant coefficients are primarily located in the mountainous areas of the upper Weihe River, while significant correlations are observed in other regions. These subsystem interactions can be classified into global and local patterns. Globally, positive correlations include Driving Force → Pressure, Pressure ↔ State, Pressure ↔ Response, Impact ↔ State, and Impact ↔ Response, whereas negative correlations characterize Driving Force → Impact, Driving Force → State, Driving Force → Response, and State ↔ Response. Locally, autocorrelated pairs include Pressure → Driving Force, Impact → Driving Force, State → Driving Force, and Response → Driving Force.

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AI Usage Disclosure Statement

Artificial intelligence (AI) tools (ChatGPT, OpenAI) were used solely to assist with language editing and improvement of manuscript readability. The authors reviewed and revised all AI-assisted content and take full responsibility for the final version of the manuscript. AI was not used for study design, data collection, data analysis, interpretation of results, or generation of scientific conclusions.

Conflict of Interest

The authors declare no conflict of interest.

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