

Research Article

Exploration of the Spatio-Temporal Evolution and Influencing Factors of Fragmentation of Cultivated Land in China

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Abstract

From the perspective of food security, cultivated land fragmentation is a major constraint to agricultural modernization. Based on 1-km resolution land use data from 1995 to 2020 in China, this study builds a comprehensive evaluation system and applies a Geographically Weighted Random Forest (GW-RF) model with SHAP interpretation to explore spatial-temporal patterns and the nonlinear, multi-factor drivers of fragmentation. Key findings include: (1) Fragmentation first intensified then eased, with clear regional differences—engineering efforts reduced fragmentation in the southwest by up to 18.7%, while urbanization and lagging land transfer increased it in the Huang-Huai-Hai region; the Qinghai-Tibet Plateau showed a unique “expansion–fluctuation” pattern under ecological policies. (2) Slope and population density are dominant nonlinear drivers, with threshold effects observed for precipitation, temperature, and elevation. For example, fragmentation rises sharply with slopes of 0–3° or population densities over 125 persons/km². (3) Spatial heterogeneity reveals that natural drivers vary by region and can be reshaped by policy—e.g., rainfall effects reversed in the southwest due to terracing, elevation constraints offset by farmland projects in Huang-Huai-Hai, and ecological policies reduced the impact of population density by 35% on the Plateau. The model highlights key thresholds (e.g., 800 mm rainfall, 3° slope) that support the need for region-specific governance.

Keywords

Cultivated Land Fragmentation, Nonlinearity, GW-RF Model, Machine Learning

1. Introduction

Food security constitutes a fundamental pillar of national strategic security, while the sustainable utilization of cultivated land resources serves as the essential foundation for realizing agricultural production potential [1]. As the most populous country in the world, China supports nearly 20% of the global population with less than 9% of the world's arable land. However, this achievement is increasingly challenged by the severe issue of cultivated land fragmentation [2]. With the deepening of agricultural transformation, fragmentation has become an increasingly prominent constraint, emerging as

a critical bottleneck to the modernization and scale development of agriculture in China [3]. According to data released by the Ministry of Agriculture and Rural Affairs in 2021, China's total cultivated land area is approaching the 1.8 billion mu red line, with pronounced spatial fragmentation—average farmland per household is less than 10 mu, divided into 5.8 plots, with an average plot size of only 1.6 mu [“Interpretation of the Central Economic Work Conference | Rural Revitalization Must Be Promoted in Synchrony with New-Type Urbanization,” Chinese Social Sciences Net,

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2022.]. The fragmented land-use pattern not only constrains agricultural mechanization and large-scale operations but also exacerbates land marginalization and hidden abandonment. Empirical investigations show that a 1% increase in land fragmentation leads to a 0.05% reduction in rice yield and a 0.03% decline in production efficiency [“Research | How to Solve the Problem of Farmland Fragmentation and Promote Rural Industry Development,” Sohu.com, 2023].

The formation of this structural contradiction is rooted in China’s unique trajectory of institutional change [4]. From the land rights restructuring during the collectivization period (1949–1978), through the “equalized and solidified” land distribution under the household responsibility system (1978–2000), to the stagnation of land transfer in the market-oriented reform phase (2001–2012), and the tension surrounding land tenure confirmation since 2013, the path-dependent nature of institutional evolution has gradually shaped a spatial-temporal pattern characterized by “intensive consolidation in the east and fragmented markets in the central and western regions.” [5]. Particularly in the current phase of synchronized advancement of new-type urbanization and agricultural modernization, the institutional tension between land resource allocation efficiency and food security capacity has become increasingly salient. Against this backdrop, systematically uncovering the spatio-temporal evolution and driving mechanisms of cultivated land fragmentation is not only a critical entry point for addressing the dilemmas of agricultural transformation, but also a scientific foundation for safeguarding the 1.8 billion mu arable land red line. It holds dual practical significance for promoting the sustainable use of land resources and ensuring national food security [6].

Cultivated land fragmentation is characterized by a dual structure of decentralized land tenure and spatial morphological disintegration [7]. Its formation is constrained not only by natural conditions such as topography but is also closely linked to the evolution of China’s distinctive rural land institutions (Cui Baoyu & Gao Ge, 2024; Feng Lei et al., 2013). Existing studies predominantly focus on the micro scale [8], employing quantitative measures such as landscape pattern indices [9] and plot fragmentation indices to reveal spatial heterogeneity, while also using household survey data to examine the impact of fragmentation on production efficiency [10]. In terms of formation mechanisms, scholars have highlighted institutional drivers including the egalitarian principles during the early implementation of the household responsibility system (Liu Shouying, 2022), the inertia of land readjustment (Wang Xiansheng et al., 2024; Zhang Hongyu, 2002), and inheritance-based land division (Wang Junli, 2024; Cheng Zongzhang, 2002). Notably, with the advancement of new-type urbanization and land transfer policies, cultivated land fragmentation has exhibited new spatio-temporal dynamics: in eastern coastal regions, land consolidation has reduced fragmentation levels, while in labor-exporting regions of central and western China, a coexistence of “passive intensification” and “latent fragmentation” has emerged [11].

This regional differentiation underscores the need to re-evaluate the explanatory power of traditional theories in capturing the dynamics of cultivated land fragmentation during the current period of socio-economic transition.

In summary, existing research on cultivated land fragmentation presents three main limitations. First, temporal analyses are often confined to cross-sectional data, lacking continuous observation of dynamic evolution processes. Second, spatial analyses tend to focus on individual regions, limiting the ability to uncover finer-scale spatio-temporal interactions at the county level. Third, few studies have integrated machine learning techniques with geographically weighted models to address the inherent linearity constraints of conventional approaches.

In response, this study examines the period from 1995 to 2020 (selecting six representative time points) and integrates machine learning algorithms with spatial econometric methods to achieve the following breakthroughs. First, in contrast to traditional province-level analyses, this paper takes the lead in revealing a gradient differentiation pattern—driven by land transfer in eastern regions, engineering interventions in central and western regions, and ecological constraints on the Qinghai-Tibet Plateau—at the scale of nine major agricultural zones and county-level units. Second, it transcends the limitations of traditional linear models by employing a Geographically Weighted Random Forest (GW-RF) model coupled with SHAP interpretation. This allows, for the first time, the statistical identification of threshold effects for key factors such as slope and population density, enabling dynamic simulation of fragmentation processes and capturing complex nonlinear interactions. Third, the study systematically uncovers significant spatial heterogeneity in the drivers of cultivated land fragmentation. Unlike conventional models that assume global homogeneity, the proposed model precisely captures spatial variations in the direction and magnitude of natural and socio-economic influences, demonstrating that the same factor may exert opposing effects under different geographical conditions. These insights aim to provide a robust empirical basis for the development of refined cultivated land protection policies, the promotion of efficient and large-scale land use, and the advancement of agricultural and rural modernization.

2. Literature Review

Scholarly understanding of cultivated land fragmentation has evolved through three conceptual phases. Early research primarily characterized fragmentation through a dual structural lens: spatial disaggregation of physical plots and tenure dispersion of land rights [12]. Manjunatha established critical quantification frameworks by developing indices like LAND FRAG [13], while Deininger demonstrated China’s exceptional case where tenure fragmentation exceeded physical fragmentation by 37% due to institutional path dependencies. Subsequent mechanistic investigations bi-

furcated into natural-determinist and institutionalist schools [14]. The former emphasized topographic constraints, with Liu et al. quantifying an 18% probability increase in plot division per degree of slope incline [15]. Conversely, institutionalists highlighted unique Chinese policy drivers—Xu et al. attributed initial fragmentation to egalitarian land allocation during decollectivization [16], while Zhao and Feng identified land adjustment inertia as a perpetuating factor [17]. The synthesis era emerged when Liu et al. documented regional divergence: land consolidation programs reduced eastern fragmentation through engineering interventions [15], whereas central and western labor-export regions exhibited paradoxical "passive intensification" alongside latent fragmentation, exemplifying [18] "institutions reshaping landscapes" thesis.

Methodologically, fragmentation analysis has progressed from descriptive metrics to computational modeling. Manjunatha et al. pioneered landscape pattern indices like MPS and PD through Fragstats software, later expanded by Falco et al. into the multidimensional Frag6D index system. Recent breakthroughs integrate machine learning [19]; Tan et al. utilized Random Forests to identify non-linear thresholds in fragmentation drivers, revealing how slope angles beyond 15° trigger morphological disintegration [20]. Despite advances, persistent limitations plague current scholarship. Temporal analyses remain constrained by cross-sectional data, failing to capture dynamic fragmentation trajectories across urbanization phases [21]. Spatially, provincial-scale studies obscure county-level heterogeneity in land transfer markets and agro-ecological contexts [22]. Most critically, conventional linear models cannot resolve complex spatial non-stationarities—where identical factors like population density exert opposite effects in different regions—due to their inability to detect geographic threshold effects and interactive feedback loops [23]. These gaps necessitate novel methodological integrations to advance fragmentation research beyond its current theoretical impasse.

3. Methodology and Data

3.1. Methodology

3.1.1. GW-RF Model

The Random Forest (RF) model is a non-parametric ensemble learning method that constructs multiple decision trees to capture complex nonlinear relationships, offering an effective solution to challenges faced by government statistical systems in the digital economy era. Unlike traditional parametric models, RF does not require prior assumptions about variable correlations and is capable of efficiently handling high-dimensional data. However, conventional RF models generally treat spatial data as homogeneously distributed, assigning equal weights to all observations and thereby overlooking spatial heterogeneity. This limitation hinders

their ability to detect localized differences across geographical contexts [24]. The Geographically Weighted Regression (GWR) model, by contrast, is a local regression technique that incorporates a spatial weight matrix (SWM) to assign localized regression coefficients to each spatial unit (e.g., counties), thereby effectively capturing spatial heterogeneity. GWR reveals how the influence of explanatory variables on the dependent variable varies across geographic space. Nonetheless, it typically relies on linear assumptions and is thus unable to model nonlinear relationships among variables effectively [25]. To overcome the respective limitations of RF and GWR, this study employs the Geographically Weighted Random Forest (GW-RF) model. GW-RF integrates the nonlinear modeling capabilities of RF with the spatial weighting mechanism of GWR, enabling simultaneous accommodation of spatial heterogeneity and nonlinear interactions among variables. Specifically, GW-RF trains local random forest models using spatially weighted data, thereby providing a more accurate representation of spatial characteristics and nonlinear effects across different regions.

Specifically, the Geographically Weighted Random Forest (GW-RF) model constructs a localized forest regression model at each County Unit (CU) location based on its neighborhood data. This process centers around the Spatial Weight Matrix (SWM), integrating geographic distance information into the sample weighting mechanism. For each geographic unit, the weight between it and the sample is defined as. In this study, an adaptive kernel and bi-square weighting kernel function are employed to compute the spatial weights, with the calculation formula as follows:

$$w_{ij} = \begin{cases} \left[1 - \left(\frac{d_{ij}}{bandwidth} \right)^2 \right]^2, & d_{ij} \leq bandwidth \\ 0, & d_{ij} > bandwidth \end{cases} \quad (1)$$

Here, d_{ij} denotes the distance between County Unit i and j , while $bandwidth$ represents the bandwidth parameter. Based on this weighting function, a local training set can be formed for each geographic unit i by selecting its neighboring samples, upon which a localized random forest model is constructed [26]. Therefore, the prediction result of GW-RF at location i can be expressed as $f_{(u_i, v_i)}(x^*)$, where $f_{(u_i, v_i)}(x^*)$ represents the GW-RF prediction for I , and (u_i, v_i) denotes the coordinates of center point CU_i :

$$Y_i = f_{(u_i, v_i)}(x^*) + \varepsilon_i \quad (2)$$

3.1.2. SHAP Model

To enhance the interpretability of the model, this study adopts SHAP (Shapley Additive Explanations) to quantify the

contribution of each influencing factor to cropland fragmentation and to reveal its direction of effect [27]. SHAP values are derived from the Shapley value in cooperative game theory, aiming to assign each feature a contribution value to the model's prediction. For a model with a feature set and an input sample, the SHAP value of a feature is defined as:

$$\phi_i = \sum_{S \subseteq F/\{i\}} \frac{|S|!(|F|-|S|-1)!}{|F|!} [f_x(S \cup \{i\}) - f_x(S)] \quad (3)$$

where S is a subset of features that does not include feature i , $f_x(S)$ denotes the model output when only the features in subset S are used for prediction, and $|F|$ represents the total number of features.

3.1.3. Getis-Ord G_i^* Hotspot Analysis

Hotspot analysis (Getis-Ord G_i^*) is a spatial statistical technique used to detect clustering patterns in geographic data. When analyzing the spatial distribution of cultivated land fragmentation in China, this method helps identify areas with significant concentrations of high or low values, thereby distinguishing “hotspots” and “cold spots.” By calculating the G_i^* statistic and its corresponding Z -score for each county unit, one can determine whether a given region exhibits significant clustering of cultivated land fragmentation [28]. The calculation formulas are as follows (4) and (5):

$$G_i^* = \frac{\sum_j^n W_{ij} X_i}{\sum_j^n X_j} \quad (4)$$

$$Z = \frac{G_i^* - E(G_i^*)}{\sqrt{\text{Var}(G_i^*)}} \quad (5)$$

In equation (5), G_i^* denotes the clustering index of county unit i ; Z represents the standardized value, reflecting the deviation between the expected value and the variance. When the Z -value is greater than 0 and the P -value is less than 0.1, the location is identified as a hotspot; conversely,

when the Z -value is less than 0 and the P -value is less than 0.1, the location is identified as a cold spot.

3.2. Indicator Selection and Data Sources

The cropland fragmentation index, as an important tool for measuring the degree of cropland fragmentation, has been widely validated in previous studies. In the context of data governance and the modernization of government statistics, this study adopts a multi-indicator comprehensive evaluation approach, emphasizing the shared-economy-oriented statistical monitoring methods. Drawing on both domestic and international literature, the study constructs a composite index system by selecting nine representative indicators, including the PLAND, LPI, SHAPE_MN, FRAC_MN, PARA_MN, PLADJ, COHESION, DIVISION, AI. All indicators are calculated at the county-unit level using Fragstats 4.2 software.

To simplify the modeling and interpretation of the complex nonlinear relationships between cropland fragmentation and multiple factors, principal component analysis (PCA) was introduced to reduce the dimensionality of landscape indices. After extracting the principal components, they were weighted and integrated to form the comprehensive cropland fragmentation index LF [29]. The calculation formula is as follows, where $j=1,2,\dots,k$ represents the j extracted principal component, and its corresponding weight is the variance contribution rate of that component:

$$LF = \sum_{j=1}^m W_j \cdot Z_j \quad (6)$$

The data used in this study come from the following sources: 1 km resolution land use remote sensing monitoring data of China for the years 1995, 2000, 2005, 2010, 2015, and 2020; the nine major agricultural zoning datasets of China; China's SRTM 3 arc-second (90m) DEM data; annual precipitation and temperature data; population and GDP data sourced from the Resource and Environmental Science and Data Center of the Chinese Academy of Sciences (<http://www.resdc.cn/>).

Table 1. Typical indicators of Landscape Fragmentation.

Indicator level	Indicator meaning
PLAND	proportion of cropland area in the entire landscape (%)
LPI	degree of cropland concentration (%)
SHAPE_MN	shape complexity of cropland patches
FRAC_MN	morphological complexity of cropland patches
PARA_MN	irregularity of patches

Indicator level	Indicator meaning
PLADJ	adjacency of same-type cropland
COHESION	cropland connectivity (%)
DIVISION	degree of landscape fragmentation
AI	continuity of cropland distribution (%)

4. Results

4.1. Spatiotemporal Pattern Analysis of Farmland Fragmentation

4.1.1. Spatiotemporal Evolution Characteristics of Farmland Fragmentation in China

From 1995 to 2020, the cultivated land landscape in China exhibited a staged evolution characterized by “initial concentration followed by subsequent fragmentation” (Table 2). However, the direction and magnitude of changes across different dimensional indicators varied significantly, reflecting the complexity and regional heterogeneity of the fragmentation process. The composite fragmentation index *LF* increased from 0.0139 in 1995 to a peak of 0.0208 in 2005, before gradually declining to 0.0112 by 2020. Although the overall trend of fragmentation at the national scale has moderated, localized fragmentation pressures have continued to intensify. During this period, the trajectories of cultivated land concentration, morphological complexity, and spatial connectivity diverged, resulting in a governance dilemma characterized by “macro-level improvement and micro-level deterioration.”

In terms of cultivated land quantity and concentration, both

the percentage of landscape (PLAND) and the largest patch index (LPI) showed slight increases from 40.2% and 32.1% in 1995 to 40.6% and 32.6% in 2000, indicating initial progress in large-scale land use. However, both indicators declined steadily after 2000, reaching 37.4% and 28.7%, respectively, reflecting intensified patch fragmentation. Regarding morphological complexity, the mean shape index (SHAPE_MN) decreased from 1.92 to 1.80, suggesting that high-standard farmland construction contributed to more regular macro-level boundaries. In contrast, the mean perimeter-area ratio (PARA_MN) increased from 30.1 to 31.5, indicating a worsening of edge fragmentation, such as jagged boundaries and nested micro-patches. The mean fractal dimension (FRAC_MN) remained relatively stable between 1.04 and 1.05, implying low-level fluctuations in geometric boundary complexity. In terms of spatial connectivity, the percentage of like adjacencies (PLADJ) declined from 54.2 to 51.7, the aggregation index (AI) fell from 57.8 to 55.0, and the landscape cohesion index (COHESION) dropped from 86.0 to 84.4, all of which indicate increasing spatial dispersion of patches. Meanwhile, the landscape division index (DIVISION) rose from 0.808 to 0.839, further suggesting a heightened degree of patch isolation. This multifaceted pattern—characterized by “scale contraction, edge fragmentation, and spatial dispersion”—underscores the need for integrated governance approaches that coordinate both quantitative control and morphological optimization of cultivated land.

Table 2. The degree of Landscape Fragmentation in China from 1995 to 2020.

Year	PLAND	LPI	SHAPE_MN	FRAC_MN	PARA_MN	PLADJ	COHESION	DIVISION	AI	LF
1995	40.2	32.1	1.91	1.05	30.1	54.2	86.0	0.808	57.8	0.0139
2000	40.6	32.6	1.92	1.05	30.2	54.2	86.3	0.805	57.5	0.0194
2005	39.9	31.7	1.89	1.05	30.5	53.6	85.8	0.813	56.9	0.0208
2010	39.5	31.2	1.87	1.04	30.7	53.2	85.5	0.818	56.5	0.0205
2015	38.9	30.4	1.84	1.04	31.0	52.5	85.1	0.824	55.8	0.0196
2020	37.4	28.7	1.80	1.04	31.5	51.7	84.4	0.839	55.0	0.0112
1995	40.2	32.1	1.91	1.05	30.1	54.2	86.0	0.808	57.8	0.0139

Notably, despite a later moderation in the overall fragmentation trend, spatially continuous cold and hot spot clusters of cultivated land fragmentation emerged across all six periods from 1995 to 2020 (Figure 1). Hot spots were predominantly distributed in the central-eastern Northern Arid and Semi-Arid Region, the southern Qinghai-Tibet Plateau Region, the Yunnan-Guizhou Plateau, South China, and the southern Yangtze River Middle-Lower Reaches, while cold spots were primarily concentrated in the central Northeast China Plain, the Huang-Huai-Hai Plain, the eastern Loess Plateau, the northern Yangtze River Middle-Lower Reaches, and the Sichuan Basin. Further analysis revealed significant spatio-temporal dynamics in the fragmentation process within these zones: Hot spots in western and northeastern Xinjiang (Northern Arid and Semi-Arid Region) fluctuated through phases of "expansion-contraction-insignificance", contrasting with an "initial intensification followed by mitigation" trend observed in western Inner Mongolia. The Songnen

Plain (Northeast China Plain) remained dominated by cold spots with peripheral hot spots, exhibiting marked cold spot expansion during 1995–2000 and 2015–2020. Qinghai (Qinghai-Tibet Plateau) experienced hot spots that "initially contracted before expanding later"; concurrently in Tibet, increased cultivated land converted some counties into hot spots alongside an expansion of insignificant areas. A noticeable reduction in cultivated land occurred in parts of the eastern Loess Plateau and Huang-Huai-Hai Plain around 2005. In the Sichuan Basin, cold spots shrank and partially transitioned to hot spots during 1995–2000, re-expanded by 2005, and subsequently stabilized with minor fluctuations. The Yangtze River Middle-Lower Reaches displayed relatively stable patterns, bisected by an insignificant zone with persistent hot spots in the south and cold spots in the north, showing minimal overall change. Throughout the study period, the Yunnan-Guizhou Plateau and South China consistently maintained concentrated hot spot distributions.

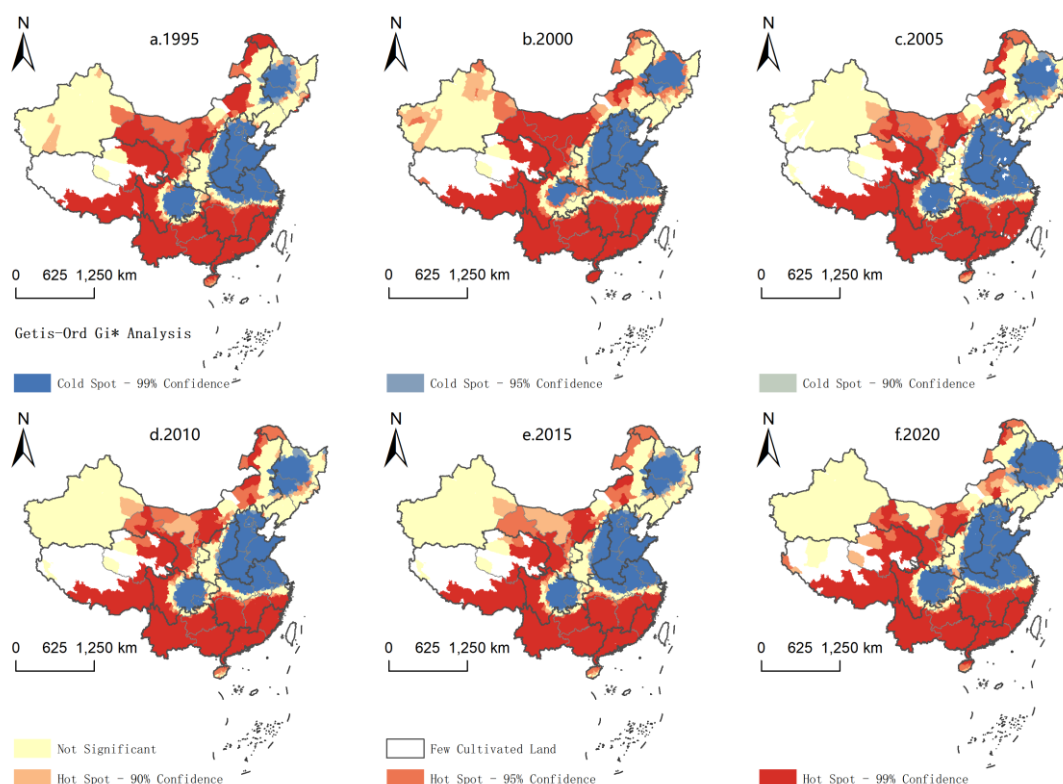


Figure 1. Spatiotemporal Evolution of Farmland Fragmentation in Major Agricultural Regions of China.

4.1.2. Spatiotemporal Evolution of Farmland Fragmentation in Major Agricultural Regions of China

Based on this foundation, this study investigated the cultivated land fragmentation patterns across China's nine major agricultural regions from 1995 to 2020, revealing significant regional differentiation and phased evolutionary characteristics.

The Percentage of Landscape (PLAND) exhibited an inverted V-shaped pattern in the Northeast China Plain, Huang-Huai-Hai Plain, Loess Plateau, Yunnan-Guizhou Plateau, and South China, rising from 1995 to a peak of 40.6% in 2000 before gradually declining to 37.4% by 2020. Conversely, PLAND in the Yangtze River Middle-Lower Reaches and Sichuan Basin showed a continuous decrease, while the Northern Arid and Semi-Arid Region experienced steady

growth from 32.1% to 35.8%. The trend of the Largest Patch Index (LPI) was highly coupled with PLAND; the Qinghai-Tibet Plateau displayed a distinct fluctuating pattern of "increase–decrease–recovery", declining from 32.6% to 28.7% before rebounding to 30.2%, whereas LPI in the Yangtze River Middle-Lower Reaches decreased continuously from 33.5% to 26.8%. Among morphological complexity metrics, the Mean Shape Index (SHAPE_MN) in the Northeast China Plain underwent two cycles of fluctuation, rising from 1.82% to 1.85% before falling to 1.79%; SHAPE_MN in the Huang-Huai-Hai Plain increased from 1.89% to 1.93% and then decreased to 1.78%. The Mean Perimeter-Area Ratio (PARA_MN) increased in the Northeast China Plain (from 30.1% to 31.5%) and the Yangtze River Middle-Lower Reaches (from 29.3% to 32.1%), indicating intensified edge fragmentation. Regarding spatial connectivity, the Percentage of Like Adjacencies (PLADJ) decreased in the Huang-Huai-Hai Plain (from 54.2%

to 49.4%) and the Yangtze River Middle-Lower Reaches (from 53.1% to 48.9%). Landscape Cohesion (COHESION) decreased from a peak of around 86.0% to 84.4% in most regions, while it increased in the Qinghai-Tibet Plateau (from 83.5% to 85.2%). The Landscape Division Index (DIVISION) increased in the Huang-Huai-Hai Plain (from 0.808 to 0.839) and the Yangtze River Middle-Lower Reaches (from 0.795 to 0.827). The Aggregation Index (AI) decreased in the Huang-Huai-Hai Plain (from 57.8% to 53.2%) and fluctuated in the Qinghai-Tibet Plateau (from 51.5% down to 49.8% before recovering to 50.6%). Overall, the period around 2000 marked a critical turning point, with declining concentration and intensifying fragmentation in most regions. The Northern Arid and Semi-Arid Region exhibited contrary growth in PLAND (+3.7%), while the Qinghai-Tibet Plateau demonstrated a unique fluctuating trajectory driven by ecological policy interventions.

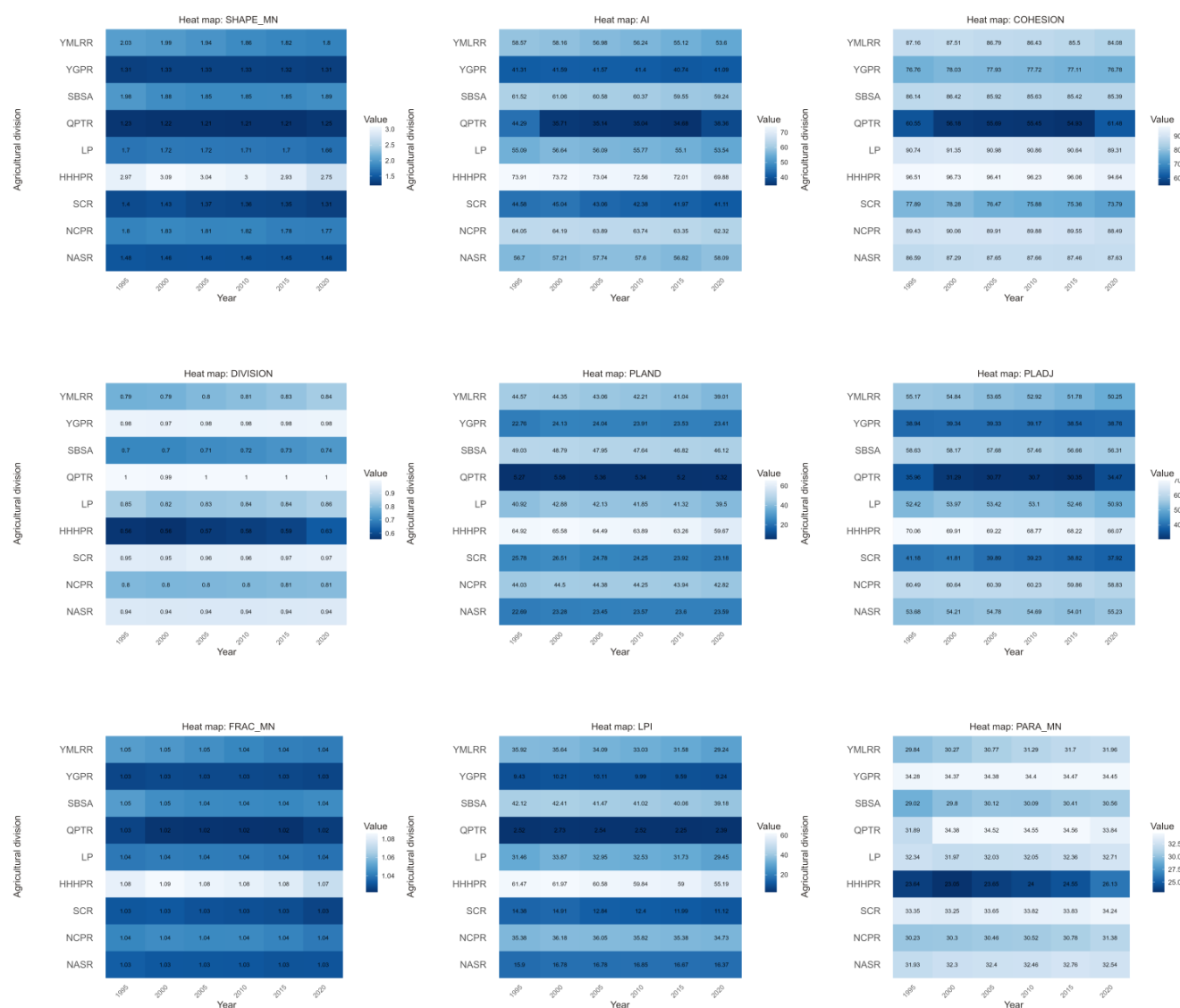


Figure 2. Landscape fragmentation in nine major agricultural areas of China from 1995 to 2020.

4.1.3. Spatiotemporal Evolution of Farmland Fragmentation at the County Level

To gain deeper insights into the spatial heterogeneity and regional evolutionary characteristics of cultivated land fragmentation in China, Figure 3 systematically depicts its spatial distribution patterns and dynamic trends based on the change rates of the cultivated land fragmentation index at the county/district scale from 1995 to 2020. Nationally, 1,321 counties/districts exhibited decreased fragmentation levels, with Yunnan (-18.7%), Sichuan (-15.2%), Guangxi (-12.1%), Guangdong (-10.8%), and Hunan (-9.3%) showing the most significant reductions. However, this improvement displayed spatial imbalance: Sichuan (+8.4%), Henan (+7.9%), Hebei (+7.2%), Heilongjiang (+6.5%), and Anhui (+5.8%) simultaneously ranked among provinces with the most severe fragmentation intensification, forming a concentrated intensification cluster centered on the Huang-Huai-Hai Plain (annual increase: 4.1%). This contradictory pattern reflects asynchronous land-use transitions across regions—slope-to-terrace conversion projects reduced average slope gradients by 15 ° in southwestern hilly areas, directly driving fragmentation down, while urbanization (annual growth: 1.2%) in the Huang-Huai-Hai Plain triggered farmland fragmentation through non-agricultural conversion.

Temporally, the proportion of counties experiencing fragmentation intensification showed a "rise-fall-rise" fluctuation across three periods: intensification occurred in 21.3% (1995–2000), 18.7% (2000–2010), and 23.4% (2010–2020) of counties, with 68.2% of intensifying counties exceeding a 5% increase. This indicates phased reversals in fragmentation

control effectiveness, and the post-2010 intensification trend exhibited spatio-temporal coupling with slowing land transfer growth (annual decline: 2.1%).

The Qinghai-Tibet Plateau showed fragmentation expansion post-2010 (annual rise: 3.7%), with pronounced increases in northern Tibet and Qinghai, reflecting unique challenges in balancing cultivation with ecological constraints under a 15.6% increase in ecological protection redline coverage that compressed marginal farmland. Although southwestern and north-eastern Xinjiang maintained high fragmentation levels (>0.35), the region saw an overall 12.6% reduction by 2020, particularly in northwestern counties (-18.9%), demonstrating combined effects of border security policies and land consolidation initiatives (implemented since 2010, covering 870,000 ha). High-fragmentation zones (>0.4) in western and northeastern Inner Mongolia showed marginal improvement (-9.4%) during 2010–2020, potentially linked to the Grassland Subsidy Policy (annual subsidy growth: 12%) and scaled farming promotion (land transfer increase: 15.7%). Southwestern provinces (Yunnan, Guangxi, Guangdong, Hunan) achieved systemic improvement through slope-to-terrace conversion (>3 million ha cumulative implementation) and land consolidation, while the Huang-Huai-Hai Plain (Henan, Hebei, Anhui) and North-east China Plain (Heilongjiang) experienced intensification due to strained human-land relations (per capita farmland decreased to 0.08 ha). This provincial divergence—"southern alleviation versus northern intensification"—reflects both natural constraints (63% of southwestern farmland has slopes >15 °) and regional disparities in agricultural development strategies (e.g., lagging scaled operations in northern grain-producing regions).

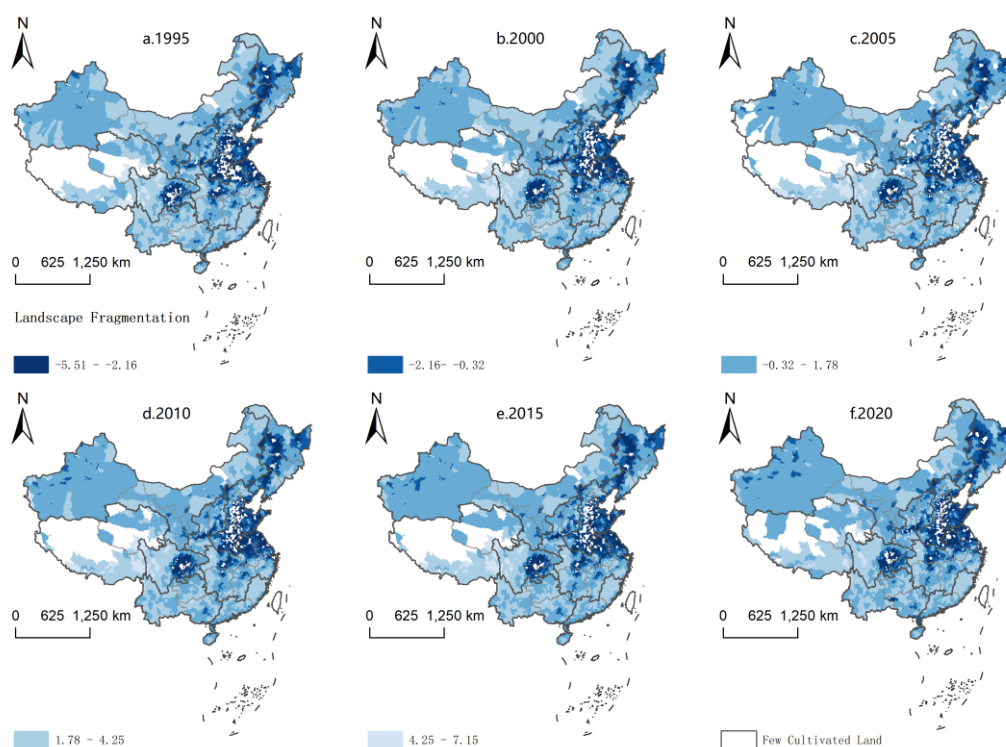


Figure 3. The rate of landscape fragmentation at county level in China from 1995 to 2020.

4.2. In-Depth Analysis of Influencing Factors of Farmland Fragmentation

4.2.1. Attribution Analysis of Farmland Fragmentation in China

(i). Selection of Influencing Factors

To comprehensively analyze the combined effects and interactions of factors influencing cultivated land fragmentation (LF), this study selects LF as the dependent variable and identifies six representative independent variables reflecting natural environmental and socioeconomic influences. First, annual precipitation is chosen as a critical natural factor affecting agricultural production. Precipitation directly influences soil moisture, crop growth cycles, and agricultural management practices, thereby impacting land parceling and utilization efficiency. Second, the annual average temperature serves as a vital climatic variable. Suitable temperature conditions facilitate healthy crop growth, whereas unfavorable temperatures can reduce yields or degrade quality, consequently affecting land use patterns and fragmentation levels. Third, mean elevation significantly affects natural conditions such as climate, soil, and vegetation, which in turn influence agricultural practices and land use efficiency. High-altitude areas typically experience lower temperatures and uneven precipitation distribution, leading to more scattered land distribution and higher fragmentation

degrees. Fourth, slope represents a key topographic factor influencing land use and agricultural production. Steep slopes restrict the application of mechanized farming, increase cultivation difficulty and costs, thereby affecting land use efficiency and fragmentation. Fifth, per capita regional GDP reflects the level of economic development, which strongly impacts land use and agricultural structure. Higher GDP generally implies stronger economic capacity and greater agricultural investment, potentially promoting large-scale land operations and land consolidation, thus reducing fragmentation. Sixth, population density directly affects land use and agricultural activities. Densely populated areas often face greater land pressure, leading to increased land parceling and higher fragmentation levels.

(ii). Spatial Autocorrelation Analysis

To assess the spatial clustering characteristics of cultivated land fragmentation (LF), Moran's I index was employed for spatial autocorrelation analysis. Moran's I is a widely used statistic for measuring the degree of spatial clustering in a dataset, with values ranging from -1 to 1. Positive values indicate spatial positive autocorrelation, negative values indicate spatial negative autocorrelation, and values near zero suggest spatial randomness. The analysis results reveal that throughout the study period from 1995 to 2020, LF values consistently exhibited significant positive spatial autocorrelation ($p < 0.01$).

Table 3. Spatial autocorrelation test results.

Year	Moran's I	P	Spatial autocorrelation diagnosis
1995	0.8756	0.0000	Significantly positive correlation
2000	0.8736	0.0000	Significantly positive correlation
2005	0.8689	0.0000	Significantly positive correlation
2010	0.8650	0.0000	Significantly positive correlation
2015	0.8597	0.0000	Significantly positive correlation
2020	0.8527	0.0000	Significantly positive correlation

(iii). Multicollinearity Diagnosis

By calculating and analyzing the Variance Inflation Factors (VIF) of the independent variables across different years (1995–2020), the results indicate that the VIF values for all variables in each year remain well below the commonly accepted threshold of 10. Specifically, the VIF values across years are relatively stable and consistently low, suggesting

the absence of serious multicollinearity among the explanatory variables. This confirms the appropriateness of variable selection and provides a robust foundation for subsequent model construction and analysis, effectively avoiding issues such as unstable coefficient estimates, inflated standard errors, and reduced model interpretability caused by multicollinearity.

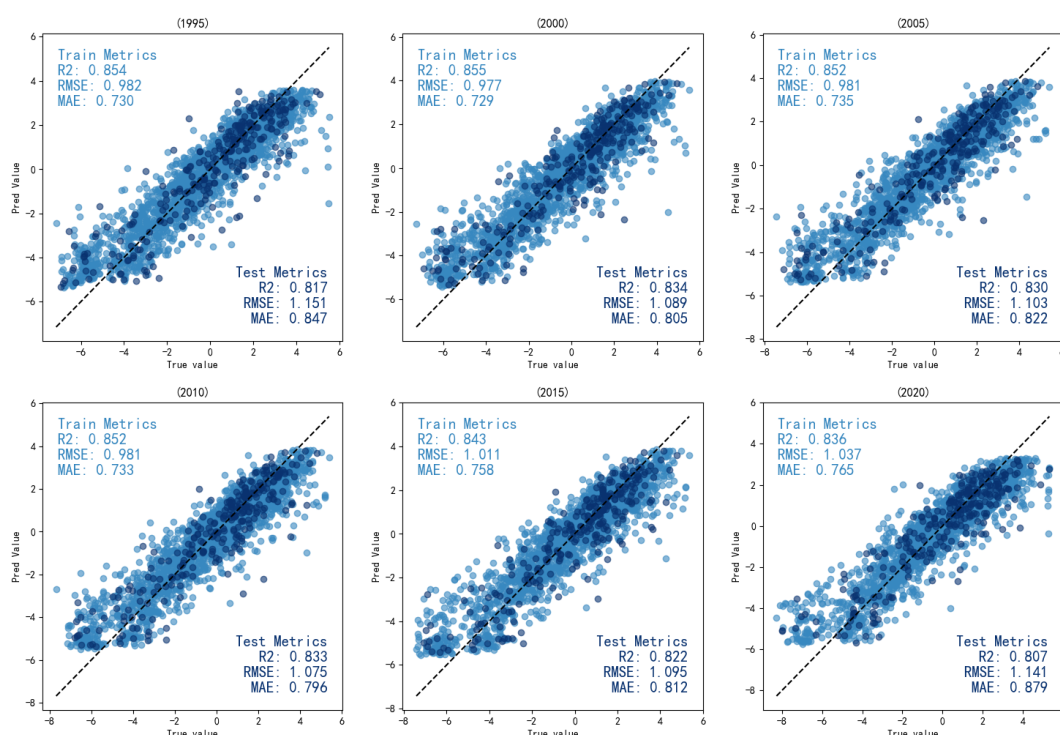
Table 4. Variable multicollinearity diagnostic results.

project	Precipitation	Temperature	Elevation	Slope	GDP	Population
VIF1995	2.7267	3.3090	3.3956	2.7152	2.0951	2.1705
VIF2000	3.1507	3.5970	3.2616	2.8004	1.7909	1.8573
VIF2005	2.8242	3.0799	3.2943	2.7278	2.0352	1.9849
VIF2010	2.3174	2.4466	3.2502	2.7448	2.0890	1.9632
VIF2015	2.7539	3.2584	3.3385	2.6461	3.2871	3.3652
VIF2020	2.6272	2.9979	3.4849	2.6846	2.9722	3.0861

(iv). Model Selection

The dataset was divided into training, validation, and test sets in an 8:1:1 ratio, and the GW-RF model was employed for training and prediction. Scatter plots were generated for each dataset to visually assess the model's fitting performance, illustrating the relationship between predicted and actual values in both the training and test sets. In the plots, training data points are represented by light blue circles, while test data points are shown as dark blue circles. Performance met-

rics, including R2, RMSE, and MAE, are also displayed to provide a comprehensive evaluation of the model's performance. As shown in Figure 4, for all six time points, the models achieved R2 values of approximately 0.8, and the differences in performance metrics between the training and test sets were minimal. This indicates that the models did not suffer from overfitting. These results further confirm the effectiveness of the GW-RF model as a robust approach for capturing spatial heterogeneity and nonlinear relationships in the analysis of cultivated land fragmentation in China.

**Figure 4.** The fitted scatter plot of the GW-RF model.

(v). Descriptive Analysis

As shown in Table 5, variable importance in the GW-RF

model is measured by the percentage increase in mean squared error (%IncMSE). The results for 2020 indicate that slope (180.65) and population density (178.34) contributed the most

to model prediction, suggesting that topographic complexity and the intensity of human activity are the primary driving factors. Elevation (172.50) and precipitation (115.78) followed in importance, highlighting the significant influence of natural geographical conditions on regional fragmentation patterns. In contrast, temperature (81.25) and GDP (60.36) showed lower importance scores, possibly due to interactions with other variables or region-specific effects. The descriptive statistics of these variables further reveal strong spatial heterogeneity.

Slope and population density exhibited large standard deviations (10.22 and 13.56, respectively), indicating highly uneven spatial distributions and the presence of local extremes. Precipitation and temperature had moderate standard deviations (33.94 and 25.30), reflecting regional climatic differences with relatively stable variability. GDP displayed the smallest standard deviation (13.08), which may suggest a more balanced level of regional economic development or the presence of spatial smoothing effects in the data.

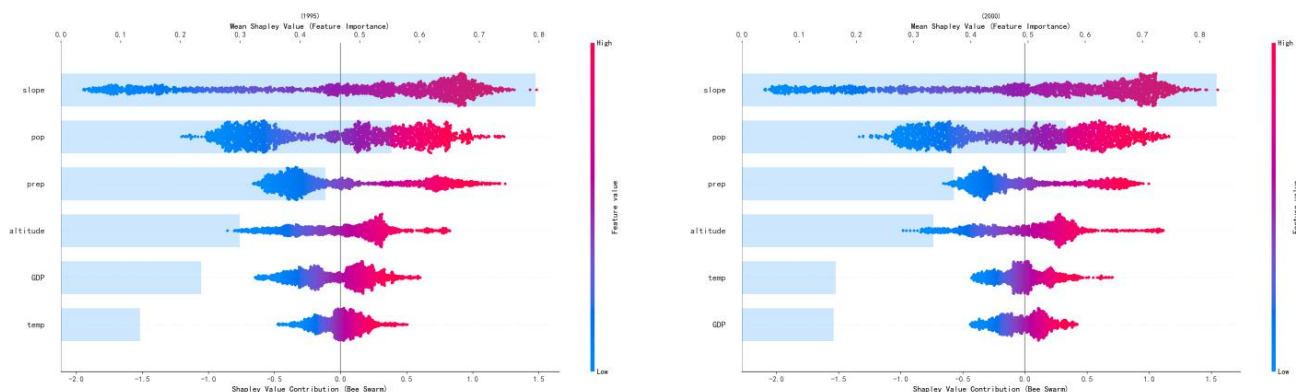
Table 5. Variable multicollinearity diagnostic results.

Variables/Indicators	%IncMSE	Minimum	Maximum	Mean	Standard
Precipitation	115.78	2.34	180.69	80.56	33.94
Temperature	81.25	6.78	35.89	56.95	25.30
Elevation	172.50	-14.32	56.78	14.35	11.68
Slope	180.65	-3.85	55.06	21.94	10.22
GDP	60.36	0.75	119.08	84.48	13.08
Population	178.34	0.06	98.06	54.32	13.56

4.2.2. Analysis of Nonlinear Effects of Influencing Factors

Figure 5 combines bee swarm plots and feature dependence plots to illustrate the SHAP values of the influencing factors of cultivated land fragmentation from 1995 to 2020. This visualization reveals both the positive and negative effects of each factor on fragmentation, as well as their relative importance rankings in the GW-RF model. The bar charts show that slope and population density consistently ranked as the top two contributors to cultivated land fragmentation

throughout the study period, with slope being the most important factor, followed by population density. From 1995 to 2015, precipitation had a greater influence on fragmentation than elevation; however, from 2015 to 2020, elevation surpassed precipitation in importance. In contrast, GDP and temperature had relatively minor effects on fragmentation. Specifically, before 2000, GDP exerted a greater influence than temperature. Between 2000 and 2015, temperature played a more significant role than GDP, while in the 2015–2020 period, GDP once again became more influential than temperature.



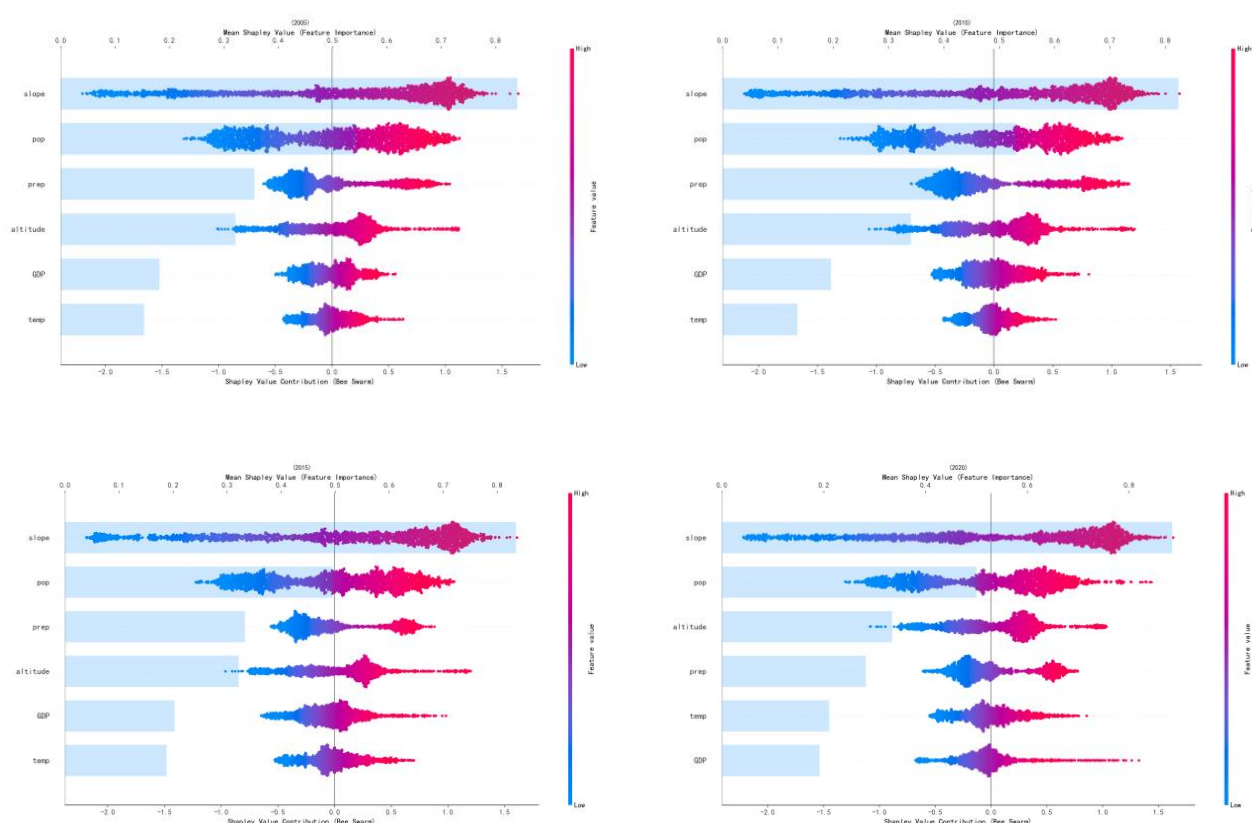


Figure 5. Global interpretation graph.

The bee swarm plots visualize the SHAP values of each variable across all county units (CUs), indicating both the direction and magnitude of their effects. In the plots, red dots represent higher feature values, while blue dots denote lower ones. A SHAP value above zero indicates a positive contribution to cultivated land fragmentation, whereas a value below zero indicates a negative contribution. Overall, slope, population density, precipitation, elevation, GDP, and temperature all show a positive correlation with land fragmentation. Regions with higher levels of fragmentation correspond to higher SHAP values, while areas with lower fragmentation levels show lower SHAP values—demonstrating that, from 1995 to 2020, regions with higher values of these factors tended to experience greater degrees of fragmentation. Specifically, for slope, the SHAP values of low-slope regions extend further left to below -2.0 , suggesting a strong mitigating effect of gentle terrain on fragmentation, promoting land contiguity. In contrast, high-slope regions show positive SHAP values, with cluster centers shifting rightward over time—from left of 1.0 to beyond—indicating that the impact of steep terrain on fragmentation intensified year by year. For population density, SHAP value clusters in sparsely populated areas gradually decreased over time, while those in densely populated regions remained consistently higher and extended rightward, reaching up to 1.5 by 2020. This trend confirms that the influence of sparsely populated areas on fragmentation has weakened over time, whereas the impact of densely populated areas has grown, especially by 2020, when higher population

density became a more significant contributor to fragmentation. Regarding precipitation, a clustering pattern is observed in low-precipitation areas, while SHAP values in high-precipitation areas initially extend rightward. After 2015, this extension diminishes and clustering emerges. This suggests that prior to 2015, the intensifying effect of high precipitation on fragmentation outweighed the mitigating effect of low precipitation. However, after 2015, the effects of both high and low precipitation levels on fragmentation tended to balance out. In terms of elevation, high-elevation areas show SHAP value clusters between 0 and 0.5 , extending up to around 1.0 . In contrast, low-elevation areas show fewer clusters, with values extending only to about -0.1 , indicating a more pronounced effect of high elevations on fragmentation. For GDP, SHAP values in high-GDP areas first exhibit a reduced rightward extension, then increase again, while those in low-GDP areas cluster between -0.5 and 0 . This suggests that from 1995 to 2005, the effects of GDP increases and decreases on fragmentation were roughly balanced. However, from 2005 to 2020, the effect of rising GDP in intensifying fragmentation clearly exceeded the mitigating effect of GDP declines. Lastly, for temperature, between 1995 and 2010, the rightward extension of SHAP values in high-temperature areas remained around 0.5 , while that of low-temperature areas remained flat. From 2015 to 2020, the extension in high-temperature zones increased significantly, indicating a growing intensifying effect of rising temperatures on cultivated land fragmentation.

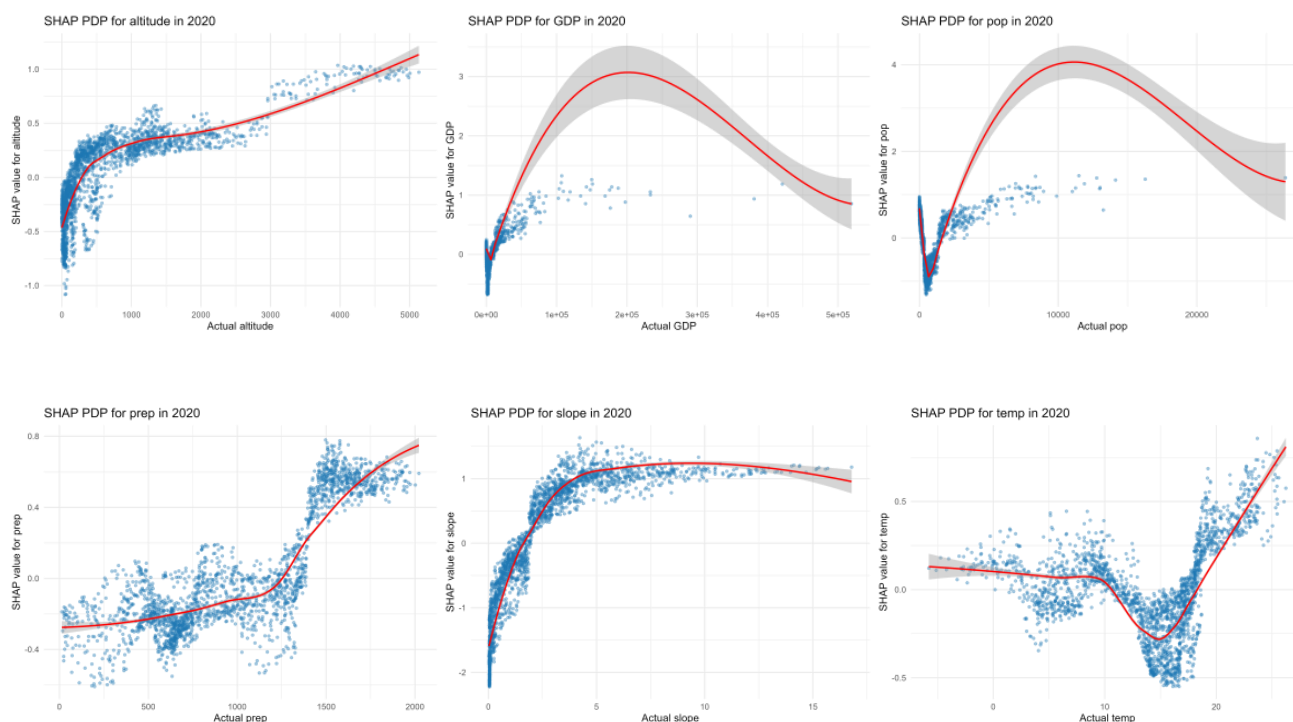


Figure 6. SHAP-PDP graph.

The marginal effects of the key influencing factors on cultivated land fragmentation (LF) reveal distinct nonlinear patterns, as captured by SHAP value analyses: Elevation exhibits a pronounced nonlinear positive relationship with LF. In low-elevation areas (approximately 0–200 m), SHAP values are largely negative, indicating a suppressive effect on fragmentation. As elevation increases to 200–1000 m, SHAP values rise sharply into positive territory, suggesting increasing fragmentation pressure. Beyond 1000 m, SHAP values continue to increase, implying that higher elevations significantly exacerbate land fragmentation due to harsher natural conditions and scattered land use patterns. Slope shows a steep increase in marginal contribution to fragmentation at lower degrees, followed by a stabilization. When slope is low (0–3°), SHAP values rapidly shift from negative to positive, indicating that even small increases in slope can significantly reduce land suitability and increase fragmentation. Between 3° and 5°, SHAP values plateau, and beyond 5°, they remain high but relatively stable, suggesting diminishing marginal effects in steeper regions—likely because such areas are already highly fragmented. Temperature demonstrates a U-shaped nonlinear relationship. In low-temperature zones (0–10 °C), the SHAP values fluctuate slightly around zero, indicating weak influence. Starting around 10 °C, the marginal impact becomes increasingly negative, peaking at approximately 18 °C—implying that moderate warming enhances land use efficiency and reduces fragmentation. However, beyond 20 °C, SHAP values rise sharply into positive territory, peaking near 25 °C. This suggests that in high-temperature (tropical/subtropical) zones, elevated temperatures may increase fragmentation due to natural hazards and limited agricultural viability. Precipitation shows a

sine-like nonlinear pattern: an initial decline, followed by an increase, and then another decline. In areas with low precipitation (<625 mm), SHAP values decrease as rainfall increases, reaching a minimum around 625 mm, suggesting improved land cohesion with better moisture availability. Between 625 mm and 1200 mm, SHAP values rise and turn positive, indicating that excess rainfall starts contributing to fragmentation—potentially due to erosion or reduced land usability. SHAP values peak around 2000 mm, then decline again at extremely high precipitation levels, reflecting complex hydrological impacts and diminishing marginal effects. GDP follows a "check-mark" shaped nonlinear path. In less developed areas (GDP < 12.5 million CNY), GDP and SHAP values are negatively correlated, indicating that economic development helps consolidate land and reduce fragmentation. Around 12.5 million CNY, the relationship reverses, and fragmentation increases with rising GDP—peaking around 43 million CNY—likely due to urban expansion and land-use transformation. However, as GDP exceeds 116.5 million CNY, SHAP values begin to decline slightly, suggesting that advanced economies may mitigate fragmentation through land-use planning and policy interventions. Population shows a combined "check-mark" and inverted U-shaped relationship. In counties with populations under 1.25 million, SHAP values decline with increasing population, suggesting that moderate population growth supports land consolidation. After 1.25 million, SHAP values begin to rise, turning positive around 2.5 million, and peaking at nearly 10 million—indicating intensifying fragmentation due to high population pressure. Beyond this point, SHAP values gradually decrease, implying that in extremely high-population regions, fragmentation effects may taper

off—potentially due to urban land consolidation or saturation effects. These findings underscore the complex, threshold-driven nature of fragmentation drivers and highlight the importance of region-specific policies for sustainable land management.

4.2.3. Analysis of Spatial Heterogeneity of Influencing Factors

This study further investigates the spatial heterogeneity in the effects of precipitation, temperature, elevation, slope, GDP, and population on cultivated land fragmentation. Spatial distribution maps of local regression coefficients reveal significant regional disparities in how each factor influences fragmentation. Among natural factors, precipitation shows a strong positive influence in the central Northeast Plain and southern Qinghai–Tibet Plateau, suggesting that increased rainfall may exacerbate land fragmentation in these areas. Temperature, by contrast, generally exhibits a negative effect, especially in western Sichuan, the Qinghai–Tibet Plateau, Inner Mongolia, and parts of Hunan, where large negative coefficients are observed. However, in the northern Yangtze River Delta and southern Huang-Huai-Hai region, temperature has a positive influence, reflecting differing regional climate adaptations. Regarding topographical factors, elevation predominantly has a positive impact on fragmentation,

indicating that higher altitudes are generally unfavorable to land consolidation. Yet, in northern Northeast China, the northern Huang-Huai-Hai Plain, and eastern middle-lower reaches of the Yangtze River, elevation effects are negative, suggesting that high-standard farmland construction or policy interventions may mitigate the negative impacts of elevation in these regions. Slope tends to have a negative effect overall, with particularly large negative coefficients in western parts of the Northeast Plain, possibly due to the constraints slope places on agricultural mechanization, which leads to increased fragmentation. Conversely, some areas in the central-northern Huang-Huai-Hai Plain show positive coefficients, underscoring regional variability in slope impacts. Among socioeconomic factors, GDP generally has a positive effect on fragmentation, indicating that economic development may promote land subdivision and fragmented land use. Population, however, shows a more pronounced and widespread influence—especially across major plain regions—highlighting population pressure as a key driver of land fragmentation. In contrast, in the western Yunnan-Guizhou Plateau, both GDP and population exhibit negative effects, likely due to successful land consolidation policies or terrain constraints that limit development intensity in these mountainous areas.

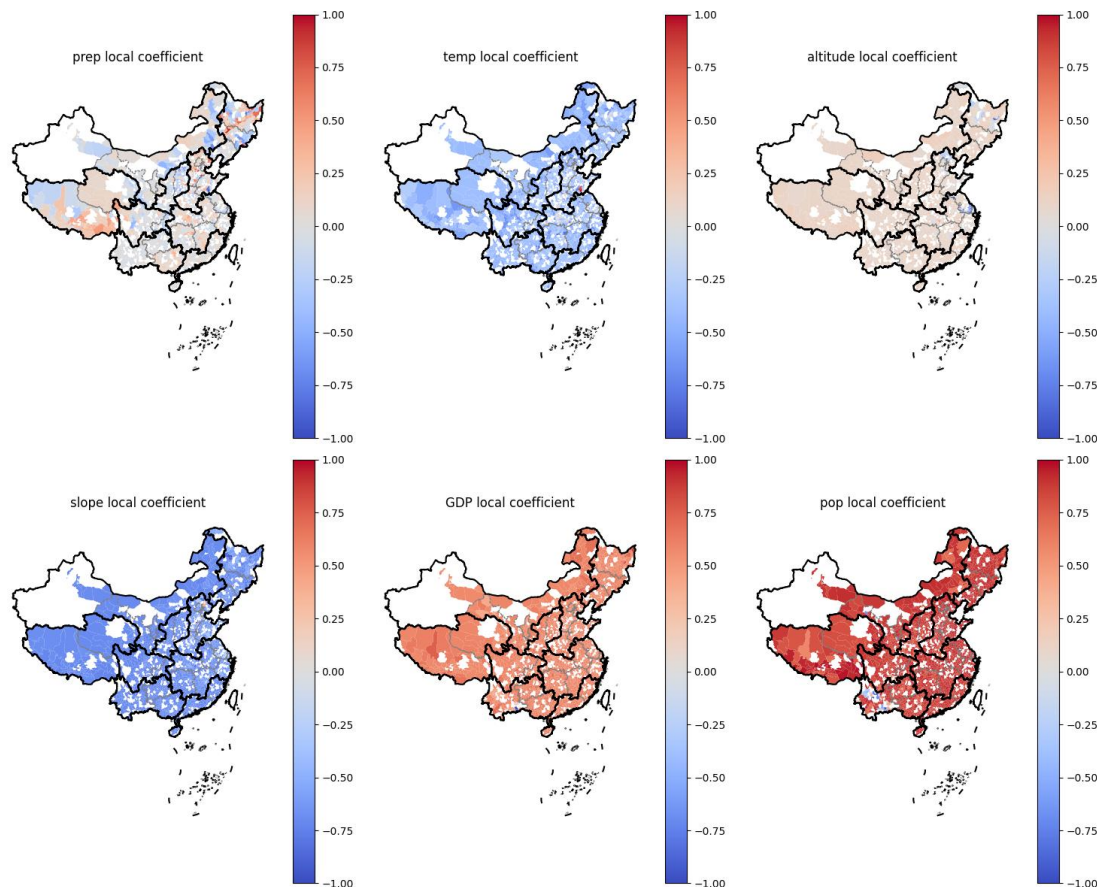


Figure 7. Local coefficient diagram of GW-RF model.

5. Discussion

Building on the above findings, this study concludes that there remains considerable room for improvement in the governance of cultivated land fragmentation in China. Effective management requires not only a macro-level perspective for coordinated advancement but also region-specific, targeted interventions tailored to local conditions. First, promote regionally adaptive land consolidation projects to address spatial differentiation challenges. In the southwestern hilly regions, where topographical constraints are pronounced, it is necessary to upgrade the “slope-to-terrace plus” integrated model. This involves aligning with funding mechanisms under the National High-Standard Farmland Construction Plan, and expanding the scope of interventions from individual plots to include coordinated development of irrigation infrastructure, road networks, and ecological slope protection. This would enable a “slope reduction–land connectivity–yield stabilization” integrated framework. In the Huang-Huai-Hai Plain, a “mandatory contiguous land transfer” system should be implemented. Utilizing provincial-level land exchange platforms, a minimum block transfer threshold (≥ 50 mu) should be enforced. Eligible entities may receive agricultural machinery purchase subsidies (as per the Shandong Provincial Land Management Measures), and an early warning system for cultivated land fragmentation should be established to monitor urbanization encroachment risks in real time. Second, establish compensation mechanisms for cultivated land protection in ecologically fragile zones to reconcile conservation and utilization goals. In ecologically sensitive areas such as the Qinghai–Tibet Plateau and the northern grassland belt, a Negative List for Cultivated Land Use within the Ecological Red Line should be formulated to delineate prohibited and restricted cultivation zones. Simultaneously, a combined “grain-for-green compensation plus land quality enhancement” policy should be implemented. Drawing on pilot practices in Nagqu, Tibet, farmers withdrawing from cultivation should receive tiered ecological compensation based on land fertility (2,000–5,000 CNY per mu per year). This should be accompanied by soil improvement measures, including topsoil replacement and organic fertilizer subsidies, to ensure both ecological security and food production capacity are enhanced. Third, develop intelligent tools for cultivated land fragmentation governance to enhance nonlinear threshold-based regulation. A Cultivated Land Fragmentation Risk Early Warning Platform should be developed, integrating geographically weighted regression and machine learning algorithms. This system would incorporate threshold parameters (e.g., slope $>3^\circ$, population density >125 people/km²) to trigger automatic alerts and dynamically generate zoned management plans. In precipitation-sensitive areas such as the Northeast Plain, a “precipitation–fragmentation” response model should be established and incorporated into farmland water management planning. In the southwestern regions, an “intervention effectiveness evaluation module” should be promoted to

quantify the extent to which slope-to-terrace projects reverse precipitation-driven fragmentation effects, enabling precision in policy targeting.

6. Conclusions

This study reveals that cultivated land fragmentation in China from 1995 to 2020 followed a trajectory of “intensification followed by mitigation,” with pronounced spatial heterogeneity driven by interactions between natural conditions and socioeconomic policies. The Geographically Weighted Random Forest model identified slope and population density as the most critical nonlinear drivers, while targeted interventions—such as slope-to-terrace projects in the southwest and land consolidation in arid regions—effectively reduced fragmentation, demonstrating the pivotal role of policy in balancing ecological conservation and agricultural productivity. Regional governance strategies must address context-specific thresholds in natural and socioeconomic factors to sustainably manage land fragmentation.

Abbreviations

PLAND	Percentage of Landscape
LPI	Largest Patch Index
SHAPE_MN	Mean Shape Index
FRAC_MN	Mean Patch Fractal Dimension
PARA_MN	Mean Perimeter-Area Ratio
PLADJ	Percentage of Like Adjacencies
COHESION	Patch Cohesion Index
DIVISION	Landscape Division Index
AI	Aggregation Index
YMLRR	Yangtze Middle and Lower Reaches Region
YGPR	Yunan-Guizhou Plateau Region
SBSA	Sichuan Basin and Surrounding Area
QPTR	Qinghai-Tibet Plateau Region
LP	Loess Plateau
HHHPR	Huang-Huai-Hai Plain Region
SCR	South China Region
NCPR	Northern Arid and Semi arid Region
LF	Landscape Fragmentation

Author Contributions

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Conflicts of Interest

The author declares no conflicts of interest.

References

- [1] Briones Alonso, E.; Cockx, L.; Swinnen, J. Culture and Food Security. *Global Food Security* 2018, 17, 113–127, <https://doi.org/10.1016/j.gfs.2018.02.002>
- [2] Xu, W.; Jin, X.; Liu, J.; Zhou, Y. Impact of Cultivated Land Fragmentation on Spatial Heterogeneity of Agricultural Agglomeration in China. *J. Geogr. Sci.* 2020, 30, 1571–1589, <https://doi.org/10.1007/s11442-020-1800-1>
- [3] Deng, F.; Jia, S.; Ye, M.; Li, Z. Coordinated Development of High-Quality Agricultural Transformation and Technological Innovation: A Case Study of Main Grain-Producing Areas, China. *Environ Sci Pollut Res* 2022, 29, 35150–35164, <https://doi.org/10.1007/s11356-021-18020-1>
- [4] Li, Y.; Wu, W.; Liu, Y. Land Consolidation for Rural Sustainability in China: Practical Reflections and Policy Implications. *Land Use Policy* 2018, 74, 137–141, <https://doi.org/10.1016/j.landusepol.2017.07.003>
- [5] Zheng, B.; Gu, Y.; Zhu, H. Land Tenure Arrangements and Rural-to-Urban Migration: Evidence from Implementation of China's Rural Land Contracting Law. *Journal of Chinese Governance* 2020, 5, 322–344, <https://doi.org/10.1080/23812346.2019.1638687>
- [6] Qu, L.; Liu, K.; Zhi, J.; Liu, W.; Fu, X.; Fan, T.; Wang, Z.; Zhou, Y. Spatiotemporal Dynamics and Driving Factors of Cultivated Land Fragmentation across China from 1990 to 2020. *Landsc Ecol* 2025.
- [7] Plexida, S. G.; Sfougari, A. I.; Ispikoudis, I. P.; Papanastasis, V. P. Selecting Landscape Metrics as Indicators of Spatial Heterogeneity—A Comparison among Greek Landscapes. *International Journal of Applied Earth Observation and Geoinformation* 2014, 26, 26–35, <https://doi.org/10.1016/j.jag.2013.05.001>
- [8] Long, J.; Nelson, T.; Wulder, M. Regionalization of Landscape Pattern Indices Using Multivariate Cluster Analysis. *Environmental Management* 2010, 46, 134–142, <https://doi.org/10.1007/s00267-010-9510-6>
- [9] Tan, S.; Heerink, N.; Kuyvenhoven, A.; Qu, F. Impact of Land Fragmentation on Rice Producers' Technical Efficiency in South-East China. *NJAS: Wageningen Journal of Life Sciences* 2010, 57, 117–123, <https://doi.org/10.1016/j.njas.2010.02.001>
- [10] Zeng, J.; Luo, T.; Gu, T.; Chen, W. How Does Cultivated Land Fragmentation Affect Soil Erosion: Evidence from the Yangtze River Basin in China. *Journal of Environmental Management* 2024, 360, 121020, <https://doi.org/10.1016/j.jenvman.2024.121020>
- [11] Zhou, Y.; Xu, K.; Feng, Z.; Wu, K. Quantification and Driving Mechanism of Cultivated Land Fragmentation under Scale Differences. *Ecological Informatics* 2023, 78, 102336, <https://doi.org/10.1016/j.ecoinf.2023.102336>
- [12] Niroula, G. S.; Thapa, G. B. Impacts and Causes of Land Fragmentation, and Lessons Learned from Land Consolidation in South Asia. *Land Use Policy* 2005, 22, 358–372, <https://doi.org/10.1016/j.landusepol.2004.10.001>
- [13] Manjunatha, A. V.; Anik, A. R.; Speelman, S.; Nuppenau, E. A. Impact of Land Fragmentation, Farm Size, Land Ownership and Crop Diversity on Profit and Efficiency of Irrigated Farms in India. *Land Use Policy* 2013, 31, 397–405, <https://doi.org/10.1016/j.landusepol.2012.08.005>
- [14] Deininger, K.; Savastano, S.; Carletto, C. Land Fragmentation, Cropland Abandonment, and Land Market Operation in Albania. *World Development* 2012, 40, 2108–2122, <https://doi.org/10.1016/j.worlddev.2012.05.010>
- [15] Liu, J.; Jin, X.; Xu, W.; Zhou, Y. Evolution of Cultivated Land Fragmentation and Its Driving Mechanism in Rural Development: A Case Study of Jiangsu Province. *Journal of Rural Studies* 2022, 91, 58–72, <https://doi.org/10.1016/j.jrurstud.2022.02.011>
- [16] Xu, W.; Jin, X.; Liu, J.; Zhou, Y. Analysis of Influencing Factors of Cultivated Land Fragmentation Based on Hierarchical Linear Model: A Case Study of Jiangsu Province, China. *Land Use Policy* 2021, 101, 105119, <https://doi.org/10.1016/j.landusepol.2020.105119>
- [17] Zhao, Y.; Feng, Q. Identifying Spatial and Temporal Dynamics and Driving Factors of Cultivated Land Fragmentation in Shaanxi Province. *Agricultural Systems* 2024, 217, 103948, <https://doi.org/10.1016/j.agsy.2024.103948>
- [18] Ye, S.; Ren, S.; Song, C.; Du, Z.; Wang, K.; Du, B.; Cheng, F.; Zhu, D. Spatial Pattern of Cultivated Land Fragmentation in Mainland China: Characteristics, Dominant Factors, and Countermeasures. *Land Use Policy* 2024, 139, 107070, <https://doi.org/10.1016/j.landusepol.2024.107070>
- [19] Di Falco, S.; Penov, I.; Aleksiev, A.; Van Rensburg, T. M. Agrobiodiversity, Farm Profits and Land Fragmentation: Evidence from Bulgaria. *Land Use Policy* 2010, 27, 763–771, <https://doi.org/10.1016/j.landusepol.2009.10.007>
- [20] Tan, S.; Heerink, N.; Qu, F. Land Fragmentation and Its Driving Forces in China. *Land Use Policy* 2006, 23, 272–285, <https://doi.org/10.1016/j.landusepol.2004.12.001>
- [21] Hao, W.; Hu, X.; Wang, J.; Zhang, Z.; Shi, Z.; Zhou, H. The Impact of Farmland Fragmentation in China on Agricultural Productivity. *Journal of Cleaner Production* 2023, 425, 138962, <https://doi.org/10.1016/j.jclepro.2023.138962>
- [22] Ciaian, P.; Guri, F.; Rajcaniova, M.; Drabik, D.; Paloma, S. G. Y. Land Fragmentation and Production Diversification: A Case Study from Rural Albania. *Land Use Policy* 2018, 76, 589–599, <https://doi.org/10.1016/j.landusepol.2018.02.039>

- [23] Qiu, L.; Zhu, J.; Pan, Y.; Wu, S.; Dang, Y.; Xu, B.; Yang, H. The Positive Impacts of Landscape Fragmentation on the Diversification of Agricultural Production in Zhejiang Province, China. *Journal of Cleaner Production* 2020, 251, 119722, <https://doi.org/10.1016/j.jclepro.2019.119722>
- [24] Quiñones, S.; Goyal, A.; Ahmed, Z. U. Geographically Weighted Machine Learning Model for Untangling Spatial Heterogeneity of Type 2 Diabetes Mellitus (T2D) Prevalence in the USA. *Sci Rep* 2021, 11, <https://doi.org/10.1038/s41598-021-85381-5>
- [25] Leong, Y.-Y.; Yue, J. C. A Modification to Geographically Weighted Regression. *Int J Health Geogr* 2017, 16, <https://doi.org/10.1186/s12942-017-0085-9>
- [26] Yu, Z.; Li, Z.; Yang, H.; Wang, Y.; Cui, Y.; Lei, G.; Ye, S. Contrasting Responses of Spatiotemporal Patterns of Cropland to Climate Change in Northeast China. *Food Sec.* 2023, 15, 1197–1214, <https://doi.org/10.1007/s12571-023-01379-z>
- [27] Antwarg, L.; Miller, R. M.; Shapira, B.; Rokach, L. Explaining Anomalies Detected by Autoencoders Using Shapley Additive Explanations. *Expert Systems with Applications* 2021, 186, 115736, <https://doi.org/10.1016/j.eswa.2021.115736>
- [28] Chen, E.; Ye, Z.; Wu, H. Nonlinear Effects of Built Environment on Intermodal Transit Trips Considering Spatial Heterogeneity. *Transportation Research Part D: Transport and Environment* 2021, 90, 102677, <https://doi.org/10.1016/j.trd.2020.102677>
- [29] Liu, J.; Jin, X.; Xu, W.; Sun, R.; Han, B.; Yang, X.; Gu, Z.; Xu, C.; Sui, X.; Zhou, Y. Influential Factors and Classification of Cultivated Land Fragmentation, and Implications for Future Land Consolidation: A Case Study of Jiangsu Province in Eastern China. *Land Use Policy* 2019, 88, 104185, <https://doi.org/10.1016/j.landusepol.2019.104185>