Analysis of Spatial Distribution Pattern and Change Characteristics of Cultivated Land Based on GIS and Spatial Autocorrelation Models: A Case Study of Longquanyi District, Chengdu City (Postprint)

Authors: Ren Ping, Wu Tao, Zhou Jieming

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Abstract

Farmland resources are fundamental resources for human survival and development, and scientifically determining the spatial distribution patterns and change characteristics of farmland is of great significance for promoting farmland protection and spatial optimization layout. This study utilizes land use data from 2005, 2009, and 2013 in Longquanyi District, Chengdu City, Sichuan Province to extract farmland data, and employs research methods such as kernel density estimation, farmland concentration index, and spatial autocorrelation to investigate the spatial distribution patterns and change characteristics of farmland. The research results indicate: 1) From 2005 to 2013, the spatial distribution density of farmland in Longquanyi District exhibited an agglomeration trend, with farmland overall showing a spatial distribution pattern of being dense in the northwest and north, and sparse in the central and southern regions. Specifically, high-density areas of farmland distribution demonstrated a trend of expansion from the northwest to the southwest, while low-density areas experienced sporadic diffusion centered around urban areas. 2) In terms of farmland area distribution, the overall pattern exhibited a spatial distribution characteristic of being higher in the north and lower in the south. Farmland distribution was relatively concentrated, with a further strengthening trend observed over the time series, though regional differences in farmland spatial changes were quite significant. 3) The spatial distribution of farmland exhibited significant global spatial positive correlation, yet local spatial heterogeneity was enhanced. Spatial units with higher proportions of farmland area were concentrated in the northern and northwestern regions, showing a trend of westward contraction, while spatial units with lower proportions of farmland area were distributed in built-up areas and fringe zones centered around urban areas, experiencing both expansion and contraction phases. From 2005 to 2013, local heterogeneity "hot spots" and "cold spots" emerged due to the impacts of urban construction occupying farmland and rural land consolidation. These research findings provide theoretical methods and references for understanding regional farmland spatial change trends and formulating farmland protection and optimization layout policies to a certain extent.

Full Text

Analysis of Spatial Distribution Pattern and Evolutionary Characteristics of Cultivated Lands Based on GIS and Spatial Autocorrelation Models—A Case Study of Longquanyi District, Chengdu, China

REN Ping, WU Tao, ZHOU Jieming

(Key Lab of Land Resources Evaluation and Monitoring in Southwest, Ministry of Education / Collaborative Innovation Center for Land Resources Development and Protection, Sichuan Normal University, Chengdu 610066, China)

Abstract

Cultivated land represents one of the most fundamental resources for human survival and development. Scientifically determining the spatial distribution patterns and evolutionary characteristics of cultivated land is crucial for promoting cultivated land protection and spatial optimization. This study extracted cultivated land data from land use datasets of Longquanyi District, Chengdu, Sichuan Province for the years 2005, 2009, and 2013, and analyzed the spatial distribution patterns and change characteristics using kernel density estimation, cultivated land concentration index, and spatial autocorrelation methods. The results indicate that: (1) From 2005 to 2013, the spatial distribution density of cultivated land in Longquanyi District exhibited an agglomeration trend, with overall dense distribution in the northwest and north and sparse distribution in the central and southern regions. High-density areas showed expansion from northwest to southwest, while low-density areas sporadically diffused outward from urban centers. (2) In terms of cultivated land area distribution, the spatial pattern was characterized by high values in the north and low values in the south, with relatively concentrated distribution that further strengthened over the time series, though regional differences in spatial changes were significant. (3) Cultivated land distribution demonstrated significant global spatial positive correlation, though local spatial heterogeneity increased. Spatial units with high cultivated land proportions were concentrated in the northern and northwestern regions, showing a westward contraction trend, while units with low proportions were distributed in built-up areas and fringe zones centered on towns, experiencing expansion and contraction phases. During 2005–2013, local heterogeneity "hot spots" and "cold spots" emerged due to urban construction

occupying cultivated land and rural land consolidation. These findings provide theoretical methods and references for understanding regional cultivated land change trends and formulating protection and optimization policies.

Keywords: Spatial distribution of cultivated land; Kernel density; Concentrating index of cultivated land; Spatial autocorrelation; GIS

Introduction

Cultivated land resources constitute fundamental resources for human survival and development. Under the reality of large population and limited land in China, cultivated land plays a critical role in ensuring national and regional food security. Strengthening cultivated land protection represents a basic national policy. However, during China' s new urbanization and industrialization processes, cultivated land resources have inevitably been extensively occupied, making land use conversion a key focus for coordinating conflicts among population, resources, and environment. In recent years, due to urban construction occupation, agricultural restructuring, ecological conversion to forests and grasslands, and natural disasters, China' s cultivated land resources have shown a continuous decreasing trend with declining quality. Coupled with severe shortages of reserve cultivated land resources, these factors have intensified conflicts among economic and social development, population growth, and cultivated land protection. Influenced by regional differences in socio-economic development, spatial changes caused by cultivated land occupation have altered grain production patterns to some extent, further highlighting regional food security issues. These practical problems have increased pressure on cultivated land protection and food security, creating unfavorable conditions for sustainable socio-economic development amid increasingly prominent contradictions between cultivated land protection and urbanization/industrialization. Therefore, correctly revealing the spatial distribution patterns and dynamic evolution laws of cultivated land resources and understanding their main influencing factors are theoretically and practically valuable for promoting optimal spatial layout and rational utilization of cultivated land.

Current research on cultivated land spatial patterns primarily focuses on spatio-temporal changes, spatial distribution patterns and morphological changes, driving mechanisms, and change prediction. Study areas have expanded from national and macro-regional scales to provincial and municipal/county mesoscales. Traditional mathematical methods, spatial data analysis, and geostatistical methods have been widely applied, with some scholars investigating spatial distribution characteristics of cultivated land in specific historical periods based on data reconstruction. High-resolution, high-precision land use/cover change data constitute the main data type. These fruitful research findings provide important references for cultivated land spatial distribution studies, yet several deficiencies remain: traditional research mainly reveals current distribution patterns at macro and meso scales but lacks revelation of dynamic change regularities; moreover, conventional studies insufficiently address spatial correlation issues in cultivated land distribution. Based on these gaps, this paper takes Longquanyi District of Chengdu as the study area and administrative villages as geographic units, focusing on land use data from 2005, 2009, and 2013. Using kernel density calculation, cultivated land concentration index, and spatial autocorrelation methods at the micro level, this study analyzes dynamic change patterns and characteristics of cultivated land spatial distribution in Longquanyi District through comparative analysis of different periods, aiming to provide theoretical and practical references for cultivated land dynamic change monitoring, protection, and spatial optimization.

1.1 Study Area

Longquanyi District is located in the southeastern part of central Chengdu City, in the middle section of Longquan Mountain, serving as Chengdu' s eastern subcenter and eastern main urban area. It represents a typical metropolitan fringe development region. The geological structure is relatively complex, belonging to a tectonic plate between a faulted depression zone and a mountain fold uplift zone. The western part is dominated by plains, while the eastern part features interspersed mountains and hills. Plains, hills, and mountains account for 57.07%, 2.86%, and 39.07% of the total area, respectively, forming a transitional zone from the Chengdu Plain to the parallel ridge-valley mountains of eastern Sichuan. The district covers an area of 555.75 km², governing 4 subdistrict offices, 7 towns, and 1 township, comprising 128 administrative villages. As a suburban district of Chengdu, Longquanyi has experienced rapid socioeconomic development in recent years. In 2013, its GDP reached 83.706 billion yuan, a year-on-year increase of 19.0%, with a primary-secondary-tertiary industrial structure ratio of 3:81:16, indicating absolute dominance of the secondary industry. Per capita GDP reached 106,112 yuan, growing by 17.2%. The total registered population was 614,900 in 2013, including 319,000 non-agricultural residents, with an urbanization rate of 51.88%. In recent years, leveraging its location advantages as a national economic and technological development zone and eastern sub-center, Longquanyi has vigorously developed an automobile industry-dominated industrial economy, leading to rapid urban development and increasing demand for construction land. Meanwhile, following ecological construction strategic requirements, the district has vigorously promoted rural land consolidation and agricultural structural adjustment through "ecological migration," facilitating farmer relocation to towns. During this process, significant changes have occurred in the spatial patterns and scales of cultivated land distribution in Longquanyi, providing a realistic foundation for this research.

1.2 Data Sources and Preprocessing

The primary data used in this study include land use status data at a scale of 1:1,000 for Longquanyi District from 2005, 2009, and 2013, as well as vector maps of administrative boundaries at the village level. The land use data were extracted from the Chengdu land use status database for 2005 and 2009 and the 2013 land use change database, all provided by the Sichuan Provincial Land Surveying and Planning Institute. Using ArcGIS 9.3, the Select tool under Analysis Tools was first employed to extract cultivated land feature layers for 2005, 2009, and 2013. Subsequently, the Identify tool was used to overlay these cultivated land features with the administrative village boundary vector maps, providing the data foundation for subsequent analysis.

2.1 Cultivated Land Concentration Index

The basic concept of the cultivated land concentration index originates from the geographic concentration index, which measures the degree of spatial concentration of cultivated land and is primarily used to analyze the spatial distribution status of cultivated land. A higher concentration index indicates more concentrated spatial distribution, while a lower value suggests more dispersed distribution. The calculation model for the cultivated land concentration index is as follows:

$$G = \sqrt{\frac{\sum_{i=1}^{n} \left(\frac{x_i}{T}\right)^2}{n}}$$

where G represents the cultivated land concentration index, x_i is the cultivated land area in spatial unit i, T is the total cultivated land area, and n is the number of spatial units.

2.2 Kernel Density Calculation

Kernel density estimation is a non-parametric density estimation statistical method and a valuable exploratory approach for identifying and analyzing hot spots and cold spots. In cultivated land spatial distribution research, kernel density calculation measures the overall agglomeration status of cultivated land across the study area based on input data. Generally, higher kernel density values indicate greater spatial distribution density of cultivated land. The kernel density is typically defined as follows: given independent and identically distributed samples $x_1, x_2, \dots, x_n$ drawn from a distribution with density function f, the Rosenblatt-Parzen kernel estimation model is commonly used to estimate f at point x:

$$f_n(x) = \frac{1}{nh} \sum_{i=1}^{n} k\left(\frac{x - x_i}{h}\right)$$

where f_n is the kernel density estimate for cultivated land parcel distribution, n is the number of cultivated land parcels, k is the kernel function, $x - x_i$

represents the distance from estimated parcel x to sample parcel x_i, and h is the bandwidth for kernel density estimation.

2.3.1 Global Spatial Autocorrelation

Global spatial autocorrelation describes the spatial characteristics of geographic feature attribute values across an entire region, typically analyzing the overall degree of spatial association and differentiation through statistics such as global Moran' s I, Geary' s C, and Getis-Ord G. This study selected the global Moran' s I index to measure the global spatial autocorrelation degree of cultivated land area proportion (cultivated land area as a proportion of administrative village area) across villages. The calculation model is as follows:

$$\text{Moran's I} = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} \sum_{i=1}^{n}(x_i - \bar{x})^2}$$

where n is the total number of administrative village spatial units, x_i and x_j are observed values of cultivated land area proportion in spatial units i and j, $\bar{x}$ is the mean cultivated land area proportion in the study area, and w_{ij} is the spatial weight matrix. The standardized Z-score is commonly used to test the significance level of global Moran' s I, calculated as:

$$Z_{\text{score}} = \frac{I - E(I)}{\sqrt{\text{VAR}(I)}}$$

where $E(I)$ and $\text{VAR}(I)$ represent the expected value and variance of Moran' s I, respectively. When $Z_{\text{score}} > 1.96$ or $Z_{\text{score}} < -1.96$ ($\alpha = 0.05$), it indicates significant spatial autocorrelation in cultivated land area proportion among spatial units. The global Moran' s I value ranges between $[-1, 1]$. At a given significance level, if Moran' s I > 0, it indicates positive spatial autocorrelation, meaning regions with high (or low) cultivated land proportions are significantly clustered; if Moran' s I < 0, the opposite is true.

2.3.2 Local Spatial Autocorrelation

While global spatial autocorrelation describes the overall spatial autocorrelation degree of cultivated land distribution across a region, it cannot effectively express differences in spatial autocorrelation levels among different spatial units within the study area. Local spatial autocorrelation examines the correlation between each spatial unit' s location and its neighboring units' attributes, effectively analyzing spatial differentiation degrees and significance levels between different units and their neighbors. This study selected the local Moran' s I index, corresponding to the global measure, to assess the internal spatial distribution of cultivated land across villages and measure spatial differences between a given unit and its neighbors. The calculation model is as follows:

$$\text{Moran's I}_i = \frac{(x_i - \bar{x})\sum_{j=1}^{n} w_{ij}(x_j - \bar{x})}{S^2}$$

where x_i and x_j are observed values of cultivated land area proportion in spatial units i and j, $\bar{x}$ is the mean cultivated land area proportion, w_{ij} is the spatial weight matrix, S^2 is the variance of cultivated land area proportion across spatial units, n is the number of administrative villages, and m is the number of neighboring units for spatial unit i. At a given significance level (typically $\alpha = 0.05$), if local Moran' s I > 0, it indicates small spatial differences in cultivated land distribution, suggesting spatial clustering; if local Moran' s I < 0, it indicates significant spatial differences.

3.1 Regional Distribution and Change Characteristics of Cultivated Land

The regional spatial distribution of cultivated land area in Longquanyi District shows that villages with larger cultivated land areas are primarily located in the northern towns of Xihe and Huangtu, followed by Luodai Town in the east, Wanxing Township, and Damian Sub-district Office in the west. In contrast, Baihe Town in the south and Longquan and Tong' an Sub-district Offices in the central region have less cultivated land, presenting an overall pattern of high values in the north and low values in the south. Temporal variations reveal significant regional differences in cultivated land changes. Specifically, from 2005 to 2013, cultivated land area in northern towns such as Xihe and Huangtu showed substantial increases due to rural land consolidation and agricultural structural adjustment. Luodai Town exhibited minimal change in the early period but rapid cultivated land increase in the later stage due to rural residential land consolidation and reclamation. Hong' an Town and Damian Sub-district Office experienced slight increases under the dual effects of rural land consolidation and urban development, while Shiling Sub-district Office, Longquan Sub-district Office, and Tong' an Sub-district Office saw minor decreases due to urban expansion. Wanxing Township, Chadian Town, Shanquan Town, and Baihe Town showed negligible cultivated land changes despite scattered rural residential consolidation, primarily due to agricultural structural adjustment. Overall, cultivated land increases were concentrated in the northern, northeastern regions, and western Damian Sub-district Office, while decreases occurred mainly in central-southern regions and northwestern Shiling Sub-district Office.

Assuming uniform distribution of cultivated land in Longquanyi District, the theoretical concentration index would be 8.84. However, calculations using ArcGIS 9.3 at the village level yielded actual concentration indices of 14.32, 14.72, and 14.89 for 2005, 2009, and 2013, respectively, indicating relatively concentrated spatial distribution of cultivated land that further strengthened over time.

3.2 Spatial Distribution and Change Characteristics of Cultivated Land Density

In ArcGIS 9.3, cultivated land polygon data were first converted to point data using the Feature to Point tool. The Kernel Density tool was then applied to calculate kernel density values for these points. Using 2005 as the base year, the Natural Breaks method was employed to classify the kernel density estimates into five levels: 0–29 parcels・km ^{2}, 29–69 parcels・km ^{2}, 69–122 parcels・km ^{2}, 122–188 parcels・km ^{2}, and 188–341 parcels・km ^{2}. The same classification breakpoints (29, 69, 122, and 188 parcels・km ^{2}) were applied to 2009 and 2013 data to generate spatial distribution maps of cultivated land kernel density for different years.

The kernel density maps [Figure 2: see original paper] reveal that maximum density values increased from 341 parcels・km ^{2} in 2005 to 374 parcels・km ^{2} in 2009 and 389 parcels・km ^{2} in 2013, indicating a clear increasing trend in cultivated land parcel density in some areas. High-density areas were consistently concentrated in flat plain regions, including most of Huangtu and Xihe towns in the northwest and north, western Luodai Town, and parts of northeastern and southwestern Damian Town. Medium-value areas were mainly distributed in mountainous and hilly regions in the northeast and east, including eastern Luodai Town, most of Wanxing Township, and northern Chadian Town. Low-value areas encompassed the four sub-district offices of Longquan, Tong' an, Damian, and Shiling, plus Shanquan and Baihe towns and southern Chadian Town. This pattern remained consistent across the three years, showing dense distribution in the northwest and north and sparse distribution in the central and southern regions.

From 2005 to 2013, areas with density values above 188 parcels・km ^{2} showed central diffusion trends centered on Sancun Village in Huangtu Town and Longjing Village and Dongfeng Village in Xihe Town, tending toward concentrated contiguous distribution. Areas within the 122–188 parcels・km ^{2} range partially transformed to higher density levels, though their peripheral continuous distribution remained largely unchanged. Areas with 69–122 parcels・km ^{2} expanded in central and eastern regions, including villages such as Dingfosi and Ping' an in Longquan Sub-district Office, Yangguang and Hongxing in Tong' an Sub-district Office, and Dalong and Huanglong in Xihe Town in the central region, as well as Gongping, Dashi, Dawan, Liyu, and Zhimadian in Wanxing Township and Caoping and Xinqiao in Tong' an Sub-district Office in the eastern region. Low-density areas showed only sporadic expansion or contraction with minimal overall change. The spatial change trend indicates that high-density areas expanded from northwest to southwest, particularly in boundary regions of Shiling, Damian, and Longquan Sub-district Offices, while low-density areas sporadically expanded outward from urban centers.

These findings demonstrate that high-density cultivated land areas were relatively concentrated, mainly distributed in the northwestern and northern plains, including Huangtu Town, Xihe Town, eastern Luodai Town, eastern Damian Sub-district Office, and northern Longquan Sub-district Office. Eastern mountainous areas also contained high-density zones but at significantly lower levels than northwestern and northern plains, indicating that topographical conditions substantially influence cultivated land spatial distribution.

3.3.1 Global Spatial Autocorrelation

Using ArcGIS 9.3, the Spatial Join tool was employed to associate cultivated land parcel attributes with administrative villages for each year. The Field Calculator was then used to compute the cultivated land area proportion for each village. Finally, GeoDa software was used to calculate global Moran' s I indices for the cultivated land area proportions of 128 villages in Longquanyi District for 2005, 2009, and 2013, with significance tests performed. The results are presented in Table 1 .

The global Moran's I indices for all three years were substantially greater than 0, with standardized Z-scores of 9.907, 10.174, and 10.819 for 2005, 2009, and 2013, respectively—all significantly exceeding the critical value of 1.96 and passing the significance test at $\alpha = 0.05$. This indicates significant spatial autocorrelation in cultivated land area proportions across villages, demonstrating clear agglomeration patterns where villages with high cultivated land proportions cluster together, as do those with low proportions. The increasing trend in global Moran' s I values shows that spatial autocorrelation strengthened over time, with the clustering of high- or low-proportion villages becoming more pronounced.

3.3.2 Local Spatial Autocorrelation

While global spatial autocorrelation analysis revealed overall clustering of cultivated land distribution with a strengthening trend, regional distribution patterns showed substantial internal differences. Therefore, local spatial autocorrelation was employed to analyze heterogeneity in spatial autocorrelation levels among the 128 villages.

Using GeoDa software, local Moran' s I indices were calculated for village-level cultivated land proportions in 2005, 2009, and 2013. Scatter plots were generated with local Moran' s I values on the x-axis and corresponding spatial lag vectors on the y-axis [Figure 3: see original paper]. In these plots, positive x-values indicate villages with high cultivated land proportions, while negative values indicate low proportions. Positive y-values signify that neighboring units have high proportions, and negative values indicate low proportions. The scatter plots were divided into four quadrants: Quadrant I represents positive correlation "high-high" clusters, Quadrant II represents negative correlation "low-high" outliers, Quadrant III represents positive correlation "low-low" clusters, and Quadrant IV represents negative correlation "high-low" outliers.

The local Moran' s I scatter plots for 2005–2013 exhibit several key characteristics. First, "high-high" and "low-low" type villages dominated, numbering

105, 107, and 101 in 2005, 2009, and 2013, respectively. These villages showed spatial clustering characteristics, with "low-low" clustering being particularly evident. In contrast, villages falling in Quadrants II and IV ("low-high" and "high-low" types) were relatively few, numbering 23, 21, and 27 across the three years. Second, comparing time periods, the number of "high-high" and "low-low" villages increased from 2005 to 2009, indicating expanded spatial clustering and reduced spatial differentiation. The 2009 plot shows slightly more "low-low" villages with denser point distribution, while "high-high" villages in Quadrant I decreased and became more dispersed. This stage can be summarized as featuring both contraction and diffusion of clustering ranges. From 2009 to 2013, the number of "low-high" and "high-low" villages increased, indicating enhanced local spatial heterogeneity, particularly in Quadrant II. This heterogeneity enhancement suggests that the spatial extent of "high-high" and "low-low" clusters contracted, with high- or low-proportion areas tending toward more localized clustering. This stage is characterized by clustering range contraction. Third, overall spatial clustering trends are evident, with data points from 2005, 2009, and 2013 increasingly distributed along trend lines and fewer points deviating far from them.

To more intuitively express differences in spatial autocorrelation levels and their change trends, LISA cluster maps were generated at $\alpha = 0.05$ significance level using ArcGIS 9.3, matching each spatial unit' s type to its geographic location [Figure 4: see original paper]. The LISA maps reveal four distinct patterns:

1. **"High-High" Cluster Areas**: These villages have high cultivated land proportions surrounded by similarly high-proportion neighbors, representing local homogeneous distribution. From 2005 to 2013, these areas were concentrated in the northern and northwestern regions of Xihe Town, Huangtu Town, and Hong' an Town, showing a westward contraction trend. This indicates declining cultivated land proportions in eastern Luodai Town and most of Wanxing Township, reflecting substantial impacts of ecological construction on cultivated land changes. In northwestern Luodai Town and southeastern Xihe Town, "high-high" clusters increased due to land consolidation. Notably, Lujiao Community in Xihe Town transitioned from "high-high" to "low-high" type by 2013 due to urban construction, enhancing internal heterogeneity within this large region.

2. **"Low-Low" Cluster Areas**: These villages have low cultivated land proportions with low-proportion neighbors, showing local clustering of low values. These areas were concentrated in built-up urban areas and fringe zones centered on Longquan Sub-district Office. Changes differed across stages: the area expanded from 2005 to 2009 due to urban construction and agricultural restructuring in Baihe Town, then contracted by 2013 due to rural land consolidation and residential demolition reclamation, consistent with the previously described diffusion and contraction phases.

3. **"High-Low" Outlier Areas**: These villages have high cultivated land proportions but are surrounded by low-proportion neighbors, showing

strong negative spatial correlation and heterogeneity. This pattern was not prominent overall, with only Zhaobi Village in Chadian Town added in 2009. Leveraging its location near Longquan Lake scenic area, this village developed agritourism and ecological agriculture, maintaining a high cultivated land proportion that became a spatial heterogeneity "cold spot."

4. **"Low-High" Outlier Areas**: These villages have low cultivated land proportions surrounded by high-proportion neighbors, representing local heterogeneity "hot spots." Few villages exhibited this pattern, with no change between 2005 and 2009 (Hong' an Railway Station Community and Wen' anchang Community in Hong' an Town). In 2013, Lujiao Community in Xihe Town transitioned from "high-high" to "low-high" type due to urban construction reducing its cultivated land proportion, becoming a new "hot spot."

4 Conclusions and Discussion

Based on GIS spatial analysis methods, this study analyzed cultivated land spatial distribution patterns in Longquanyi District using kernel density estimation, cultivated land concentration index, and spatial autocorrelation, comparing patterns across 2005, 2009, and 2013 to identify change trends and characteristics. The main conclusions are:

1) Kernel density analysis shows that cultivated land spatial distribution density in Longquanyi District exhibited agglomeration trends that strengthened from 2005 to 2013. High-density areas were concentrated in the northwestern and northern plains, presenting an overall pattern of dense distribution in the northwest and north and sparse distribution in the center and south. High-density areas expanded from northwest to southwest, while low-density areas sporadically extended from urban centers. Eastern mountainous areas showed increased density but remained significantly lower than northwestern and northern plains, demonstrating substantial topographical influences.

2) Regional distribution of cultivated land area showed a north-high, south-low pattern with relatively concentrated distribution that strengthened over time. However, significant regional differences existed across periods, with increases concentrated in northern, northeastern areas, and western Damian Sub-district Office, while decreases occurred in central-southern regions and northwestern Shiling Sub-district Office.

3) At the global scale, cultivated land distribution showed significant positive spatial correlation, with high- or low-proportion villages exhibiting clear clustering that strengthened over time. However, local spatial heterogeneity also increased. High-proportion clusters were located in northern and northwestern regions with a westward contraction trend, while low-proportion clusters were distributed in built-up areas and urban fringes, experiencing expansion and contraction phases. During 2005–2013, local

heterogeneity "hot spots" and "cold spots" emerged due to urban construction and rural land consolidation, located in Lujiao Community of Xihe Town and Zhaobi Village of Chadian Town, respectively.

As fundamental resources for human survival and development, cultivated land protection must be based on scientific research of spatial distribution and evolution patterns. This study, from a micro perspective using GIS and spatial autocorrelation models, analyzed cultivated land spatial distribution patterns and evolution characteristics in Longquanyi District, highlighting dynamic change trends and spatial correlations. The findings provide references for cultivated land protection and rational layout, supplementing traditional research deficiencies in dynamic change regularities and spatial correlation analysis. The study also reveals influencing factors on cultivated land distribution evolution: lower density in eastern mountainous areas compared to northwestern plains demonstrates topographical impacts; reduced cultivated land in urban fringe areas aligns with actual urban expansion and rural tourism development; and changes in spatial position, morphology, and scale of cultivated land distribution correspond with the spatial implementation of "ecological migration" and agricultural structural adjustment policies. However, cultivated land evolution is influenced by multiple factors including natural conditions, socio-economic development, and policy systems, with varying mechanisms across different periods. Achieving refined, quantitative, and dynamic representation requires further exploration and research.

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Note: Figure translations are in progress. See original paper for figures.