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Spatio-Temporal Evolution Characteristics and Driving Mechanisms of Rural Settlement Morphology from a Long-Term Perspective: A Case Study of Fuzhou (1990–2025)

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Abstract

Under the macro background of the rural revitalization strategy and urban-rural integrated development, rural settlements are undergoing a profound transformation from physical morphology to functional connotation. However, existing studies mainly focus on the expansion of single land elements, lacking long-term quantitative monitoring of the coupling relationship between rural development and policy texts. Taking Fuzhou City as a case study, this research selects long-term Global Human Settlement Layer (GHSL) and Night-Time Light (NTL) data from 1990 to 2025, combined with policy text quantification methods. Based on rural development units, the Coupling Coordination Degree Model (CCDM), Macro-Micro Matching Index (MMI), and gravity center migration analysis are employed to systematically reveal the spatiotemporal evolution characteristics and driving mechanisms of rural settlement morphology under policy institutional changes. The research results indicate that: (1) Fuzhou's rural settlements exhibit relatively stable gravity centers of construction land, while the gravity center of economic vitality has significantly shifted toward the southeastern coastal area under policy guidance; (2) The coupling coordination degree of rural human–land relationships has generally increased, but with significant spatial heterogeneity, forming a pattern of high-quality coordination in coastal areas and low-efficiency lag in mountainous regions; (3) The shift in policy orientation from scale expansion to functional enhancement has driven economic factors to concentrate in key policy areas ahead of physical spatial expansion. The analytical framework combining remote sensing monitoring and policy quantification constructed in this study reveals the precedence of factor flow and the lag of physical space driven by policies, providing a scientific basis for the differentiated governance of rural areas in coastal mountainous cities.

Keywords: rural settlements; spatio-temporal evolution; coupling coordination; rural Fuzhou

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1. Introduction

Under the macro background of the rural revitalization strategy and urban-rural integrated development, traditional settlements, as the core carriers of agrarian civilization [1], have made their spatio-temporal evolution patterns a research hotspot in rural geography [2,3]. However, rural settlements currently face widespread challenges, such

as imbalances in human–land relationships, and uneven urban-rural development. These issues urgently require long-term, multi-dimensional spatio-temporal evolution research to provide scientific support for their sustainable development [4].

The theoretical system of rural restructuring and rural settlement transformation provides a fundamental analytical framework for this study. Classical rural restructuring theory points out that in the process of rapid urbanization, rural areas will undergo systematic changes in economic restructuring, social restructuring, and spatial restructuring [2,5]. Among them, the morphological evolution of rural settlements, as the most intuitive and explicit spatial representation of rural restructuring, directly reflects the restructuring of rural functions and changes in the flow pattern of urban-rural production factors [6,7]. The theory of rural settlement transformation further clarifies that rural settlement evolution is a process of transformation from single agricultural production to multi-functionality, accompanied by changes in spatial form and functional vitality [8]. Existing international studies have confirmed that rural settlement transformation in European, North American, and Southeast Asian countries shows phased characteristics under different institutional and geographical backgrounds [9,10], which provides a global comparative perspective for this study.

In terms of research themes of rural settlements, the morphological evolution and driving mechanisms of rural settlements constitute one of the core themes, with abundant accumulations achieved in relevant studies. Regarding spatio-temporal patterns, research has shifted from static description to long-term dynamic analysis, which has revealed differentiated evolutionary laws such as the phased expansion of rural-urban fringes and the fragmented reconstruction of mountain-edge settlements against diverse backgrounds [9], verified the fractal self-organization and scale dependence of large-scale settlement systems [10], and identified that policies on large-scale infrastructure can drive the transformation of scattered smallholder settlements towards agglomeration [11]. Studies on driving mechanisms have been expanded to multi-level analysis: the bottleneck effect of natural basic constraints and the mismatch between land use and suitability [12,13], the impact of micro-level individual quality of life and place attachment on settlement vitality [14], the institutional and economic effects of macro-level land reform and land fragmentation [15], as well as the construction of sustainable evaluation frameworks, have all been verified [16]. In addition, the integration of GIS (Geographic Information System) with various quantitative analysis tools has provided crucial technical support for this research field [17,18].

From the perspective of research technologies and methods, long-term remote sensing technologies, represented by the Global Human Settlement Layer (GHSL) and Night-Time Light (NTL) data, have become the mainstream and well-validated tools for global rural settlement evolution research.

For the GHSL, as the world's first global standardized long-term built-up land monitoring dataset developed specifically for human settlement research, it has been widely applied in cross-regional comparative studies on rural settlement expansion and spatial reconstruction in existing research [19,20]. Unlike traditional land use data with inconsistent identification standards, GHSL adopts a globally unified built-up land extraction algorithm, which eliminates radiation saturation defects and ensures cross-temporal and cross-regional comparability [21]. This unique advantage perfectly matches the 35-year, long-term longitudinal analysis needs of this study, and has been widely verified in rural settlement studies in complex geographical environments similar to the study area [22].

For NTL data, numerous similar studies have confirmed that it is a reliable and robust proxy indicator for rural socio-economic vitality and human activity intensity in rural geography research [23,24]. It can effectively capture the implicit functional changes in

rural areas that cannot be reflected by physical land use data, such as non-agricultural industry development, rural tourism vitality, and population agglomeration [25], which makes up for the limitation that traditional built-up land data can only characterize static physical morphology. Existing studies have widely verified that the combination of GHSL and NTL can break through the bottleneck of traditional rural settlement research that only focuses on the expansion of a single land element [26,27], which forms the core data logic and methodological foundation of this study.

The Coupling Coordination Model has also been maturely applied in urban-rural system studies [28] to evaluate the coordination of human–land relationships [29,30]. Additionally, text quantification methods are increasingly becoming important tools for analyzing the effects of policy interventions on spatial evolution, such as using bibliometric analysis to examine research development characteristics and emerging research themes [31], analyze the evolutionary trends of rural environmental governance research [32], and propose future directions for rural tourism research [33].

Despite these advancements, existing studies still exhibit several common limitations. First, there is a geographical bias in coverage. Most existing studies focus on plains [34] or urban fringe areas [6,35], with insufficient attention given to complex geographical environments such as coastal mountainous regions, making it difficult to reveal the evolution patterns of rural settlements under the constraints of unique natural conditions. Second, the research dimensions are relatively singular. Most existing studies focus on the impact of single driving factors such as land policies [36,37], industrial transformation [38], or topographical differences [39]. Few studies systematically conduct quantitative analyses of the relationships among spatial morphology, economic vitality, and policy interventions [7,40], making it challenging to uncover the asynchronous evolution characteristics of multiple factors in complex environments. Third, there are limitations in the research scale. Existing studies tend to emphasize short-term evolution [41], lacking long-term quantitative monitoring of the dynamic interaction between rural development and policy texts, which makes it difficult to capture the long-term patterns of their synchronous evolution.

As a typical mountain-sea city, Fuzhou has seen insufficient attention paid to the long-term settlement evolution and the transformation of its driving mechanisms. This study investigates the driving mechanisms behind the spatio-temporal evolution of rural settlement morphology, rural vitality dynamics, and their coupling/mismatch under long-term policy interventions. This study conducts an in-depth analysis of this issue to fill the gap in regional research and provide scientific support for rural revitalization and territorial spatial planning.

Accordingly, this study puts forward the following hypotheses: (1) During 1990–2025, there is a significant asynchrony between morphological expansion and vitality growth of rural settlements in Fuzhou, with considerable differences in their overall expansion directions and expansion magnitudes; (2) In terms of local spatial agglomeration, the diffusion range of morphological hotspots is significantly larger than that of vitality hotspots. Vitality hotspots remain long-term stable in the central urban area and key nodes, whereas morphological hotspots vary considerably; (3) The coupling coordination degree between rural morphology and vitality has generally evolved from low-level coordination to high-quality synergy, while spatially maintaining a gradient pattern of "high in the center and low in the periphery"; (4) Policy intervention exhibits a transmission mechanism of "vitality first, morphology later" and differentiated time lags in driving rural development. This study aims to provide scientific support for rural revitalization planning and spatial governance in coastal mountainous cities in developing countries during a period of rapid economic growth.

2. Materials and Methods

This study focuses on the rural settlement system within the Fuzhou region, aiming to construct a comprehensive analytical framework based on multi-source remote sensing data and text quantification techniques to reveal the spatio-temporal evolution characteristics and driving mechanisms of rural settlements against the background of policy and institutional changes. First, long-term GHSL and NTL data are utilized to quantitatively measure the spatiotemporal trajectories of rural settlement land expansion and economic vitality growth in Fuzhou from 1990 to 2025. The Coupling Coordination Degree Model (CCDM) and Macro-Micro Matching Index (MMI) are then applied to evaluate the coordination and compatibility of human–land relationships. Second, text quantification methods are used to analyze the evolution patterns and focal points of policy texts, constructing an index system for policy intensity. Finally, correlation analysis is conducted to clarify the driving effects of policy and institutional changes on the spatial reconstruction of rural settlements, revealing the response mechanisms of rural evolution during different policy stages.

2.1. Study Area

Fuzhou, as a typical representative of a mountainous city on the southeastern coast of China, has a unique terrain characterized by a west-high-east-low, stepwise descending structure. The Jiufeng and Daiyun mountain ranges, together with the three major river basins of the Minjiang, Aojiang, and Longjiang Rivers, form four major landforms: mountains, hills, plains, and coasts, creating a three-dimensional and complete natural geographical foundation [42]. At the same time, Fuzhou's rural settlements carry diverse cultural legacies, including Min-yue culture, overseas Chinese culture, and clan culture [43]. Their evolution not only deeply responds to national macro-policies, such as land system reforms and the rural revitalization strategy, but also closely adapts to the intertwined natural landscape, making Fuzhou an ideal case study for analyzing the evolution of rural settlements in complex coastal geographical environments [44]. This study takes Fuzhou City, Fujian Province, as the core research area. The location of Fuzhou is shown in Figure 1.

2.2. Data Sources

This study relies on the GHSL and NTL data as the core remote sensing data sources. The two datasets are matched in time series, complementary in monitoring dimensions, and have been widely verified in global and regional rural settlement evolution studies, providing a reliable data foundation for this study.

The technical details of the two core types of remote sensing data used in this study are as follows.

Night-Time Light Data (NTL): The saturation level of the data was quantified by counting the proportion of saturated pixels in the study area. The GHSL-assisted correction method was applied to restore the real light intensity of saturated pixels using the unsaturated built-up land density from GHSL, thereby eliminating saturation distortion. The corrected data show a strong linear correlation with the rural GDP statistics of all counties in Fuzhou ($R^2 > 0.85$), which ensures data accuracy.

The study period spans from 1990 to 2025, but the available time span for night-time light data is from 1992 to 2023. Therefore, the 1992 data is used as a substitute for 1990, and the 2023 data is used as a substitute for 2025. Considering the slow evolution of rural settlements, a 2–3 year data discrepancy will not alter the overall long-term (35 years) evolutionary trend. To address the incompatibility between the Defense Meteorological Satellite Program (DMSP)/Operational Linescan System (OLS) and Suomi National Polar-orbiting Partnership (NPP)/Visible Infrared Imaging Radiometer Suite (VIIRS) datasets, this study adopts a cross-sensor calibration method based on pseudo-invariant feature

areas [45], constructing a continuous long-term NTL dataset with a resampled spatial resolution of 500 × 500 m. This dataset is used to characterize the intensity of human activities and economic vitality.

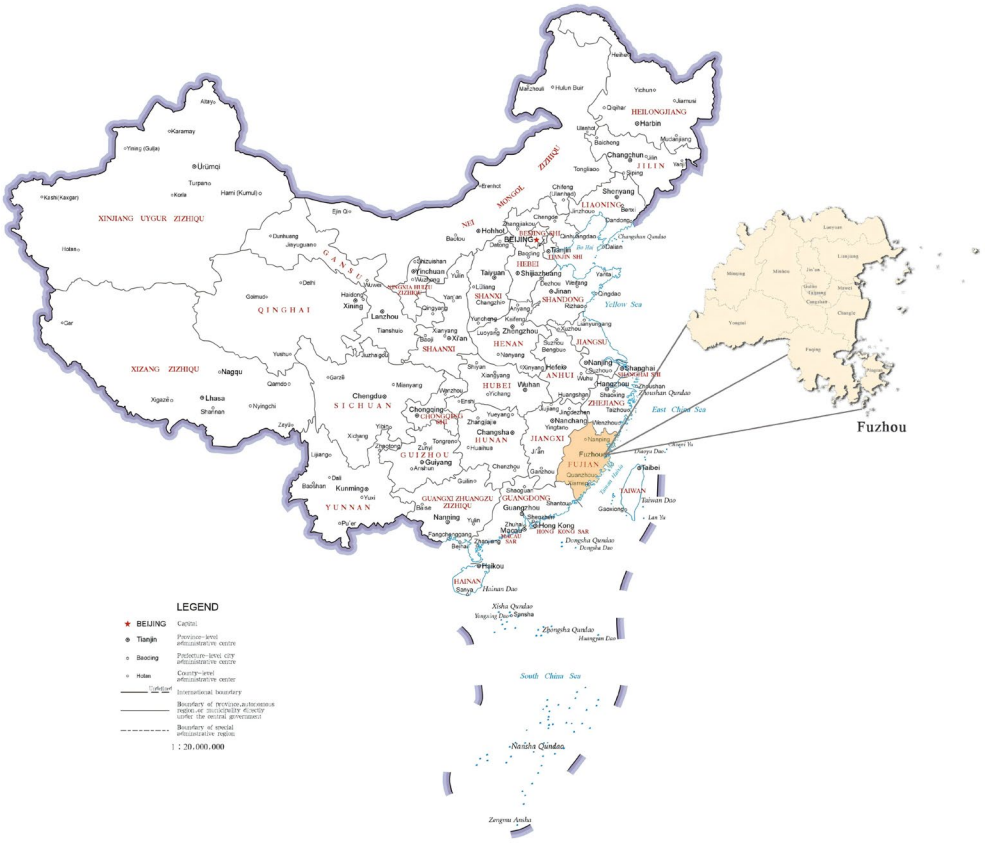

Figure 1. Location Map of Fuzhou. The map of China was provided by the Ministry of Natural Resources of China (approval number: GS(2019)1673).

Built-up Land Data: This dataset adopts a globally consistent built-up land identification algorithm and has no radiation saturation defects. It provides full coverage of rural areas in Fuzhou with no missing values, and its accuracy in identifying built-up land has been widely validated in existing studies on rural settlements. Preprocessing steps include unified coordinate projection, annual time-series interpolation, and extraction of rural built-up land.

The GHS-BUILT-S raster data from the GHSL [22] for the years 1990–2025 is used to extract the development intensity of built-up land for each year. This dataset effectively reflects the development level of the Earth's physical space.

The rationale for selecting the above data in this study is that NTL data can reflect the implicit functional vitality of rural settlements and form a complete two-dimensional monitoring system with GHSL data, which characterizes physical spatial morphology. This combination overcomes the limitation of traditional research that only focuses on the expansion of a single land-use element, enabling a comprehensive portrayal of the overall transformation process of rural settlement morphology. Meanwhile, compared with rigid physical construction land, NTL data is more sensitive to policy intervention and capital input, and can effectively capture early changes in rural development prior to the expansion of construction land, providing data support for identifying the asynchronous evolution pattern of rural elements in this study. In addition, its continuous time series is

highly consistent with the 35-year study period, ensuring the comparability of this research with similar international studies.

Policy Text Data: A total of 408 rural development policy entries from 1990 to 2025 were collected from the official websites of the State Council of China, the National Development and Reform Commission, and the Fuzhou Municipal Gov.

All these documents are of direct guiding and binding significance to rural development, while routine administrative notices and non-substantive meeting minutes have been excluded. According to core themes and intervention objectives, the policies are divided into 4 categories: (1) Rural construction and land consolidation policies: focusing on regulating the physical spatial expansion of rural settlements, covering new rural construction, homestead system reform and land consolidation; (2) Industrial development and rural revitalization policies: the core driver of rural economic vitality growth, including modern agriculture, rural tourism and three-industry integration supporting documents; (3) Ecological protection and urban-rural integration policies: shaping the overall spatial pattern of rural settlements, involving ecological red line management, infrastructure equalization and regional coordinated development; (4) Rural human settlement and public service policies: affecting the sustained agglomeration of rural population and vitality, including public service improvement and living environment renovation.

The temporal distribution of these policies is highly consistent with the three stages of rural development in Fuzhou, fully reflecting the 35-year institutional changes in the study area.

Using a combination of web crawling, manual screening, and keyword retrieval, the policies were sorted and organized by issuing date, issuing institution, and document level. Policy enrolment and the Fuzhou Yearbook effectiveness scores (P) were determined based on the issuing authority and level, while content scores (N) were derived based on the type of document. The total score (Z) was calculated as $Z = P \times N$, enabling the measurable representation of institutional factors. The scores of all policies issued in a given year were summed to generate the Annual Policy Power Index (APPI), which reflects the intensity of government intervention in rural development.

Auxiliary Data: Includes administrative boundary data, 2025 Fuzhou administrative village point data, DEM digital elevation model, etc. The sources, parameters, and analysis methods' descriptions of this study are shown in Table 1.

Table 1. Description of research data sources, parameters and analysis methods.

Category	Name	Parameters/Time Span	Source	Preprocessing and Implementation Details	Corresponding Core Variables/Formulas
Basic Data Sources	Global Human Settlement Layer (GHSL)	1990–2025, 5-year intervals, 100 m native resolution	Programme of the European Union, JRC	Clipping, Resampling to 500 m, Linear Interpolation	Core variable S (normalized built-up land density), applied in Formulas (1)–(5)
	Night-time Light Data (NTL)	1992–2023, annual, 500 m native resolution	NASA	Inter-calibration, Continuity Correction, Saturation Correction	Core variable L (normalized night-time light intensity), applied in Formulas (1)–(5)
	Agriculture-related Policy Documents	1990–2025, annual	Fuzhou Municipal Government Official Website, Fuzhou Yearbook	Text Segmentation, Keyword Extraction, Quantitative Scoring	Core variable Annual Policy Power Index (APPI), applied in Formula (7)
	Administrative Divisions/DEM	30 m resolution, 2020	Resource and Environment Science and Data Center, CAS	Mask Extraction, Relief Degree of Land Surface Calculation	Auxiliary data for rural unit screening

Table 1. *Cont.*

Category	Name	Parameters/Time Span	Source	Preprocessing and Implementation Details	Corresponding Core Variables/Formulas
Analysis Methods	Grid Generation (Basic Unit)	2 × 2 km standard fishnet grid	Self-constructed based on the study area boundary	Unified coordinate projection, spatial matching with multi-source data, and rural unit screening	Basic analysis unit for all formulas
	Coupling Coordination Degree Model (CCDM)	0–1 index range, equal weight	Classic coupling coordination framework	Min-Max standardization, coupling and coordination degree calculation, threshold classification	Formulas (1)–(4)
	Macro-Micro Match Index (MMI)	Standard deviation classification	Supply and demand balance theory	Indicator normalization, hollowing/agglomeration risk diagnosis	Formula (5)
	Hot Spot Analysis (Getis-Ord Gi*)	Queen contiguity weight matrix, 90%/95%/99% confidence levels	Classic spatial statistical method	Weight matrix construction, Gi* statistic calculation, and significant cluster identification	Formula (6)
	Standard Deviational Ellipse (SDE)	1 standard deviation confidence level	Classic spatial distribution method	Ellipse parameter calculation, centroid migration trajectory analysis	Auxiliary spatial analysis, no core formula
	Time-Lagged Cross-Correlation (TLCC)	Lag period k = 0–5 years	Time series correlation framework	Z-Score standardization, optimal lag period identification	Formula (7)

2.3. Methods

As shown in Figure 2, this study establishes a six-stage analytical framework that integrates multi-source remote sensing monitoring and policy text quantification methods, which can be widely applied to research on rural settlement evolution in diverse geographical contexts. The research process and core methods of each stage are as follows: (1) Multi-source data collection and preprocessing. A long-term, multi-dimensional basic dataset is constructed. Four types of data are collected and preprocessed: GHSL data, NTL data, rural development policy texts, and auxiliary geographic data. (2) Construction of basic analysis units. Rural spatial signals are accurately extracted. With 2 × 2 km standard grids as the basic analysis units, valid rural development units are screened using the administrative village point control method to avoid interference from core urban areas. (3) Characterization of spatio-temporal evolution patterns. The global and local evolution characteristics of rural settlements are revealed. The gravity center migration trajectory is analyzed using SDE, and the spatial agglomeration patterns of built-up land and economic vitality are identified through Getis-Ord Gi* analysis. (4) Diagnosis of rural human–land relationships. The coordinated development level and development risks of rural settlements are evaluated. The coordination level of the human–land system is measured using CCDM, and the hollowing and over-agglomeration risks of each rural unit are diagnosed using MMI. (5) Identification of driving mechanisms. The driving effects of policy interventions on rural settlement evolution are quantified. An annual policy intensity index is constructed using a quantitative scoring method, and the time-lag effects of policies on different rural elements are identified using TLCC. (6) Proposal of differentiated governance pathways. Targeted policy recommendations are put forward based on the research findings.

The specific logical framework of this study is shown in Figure 2:

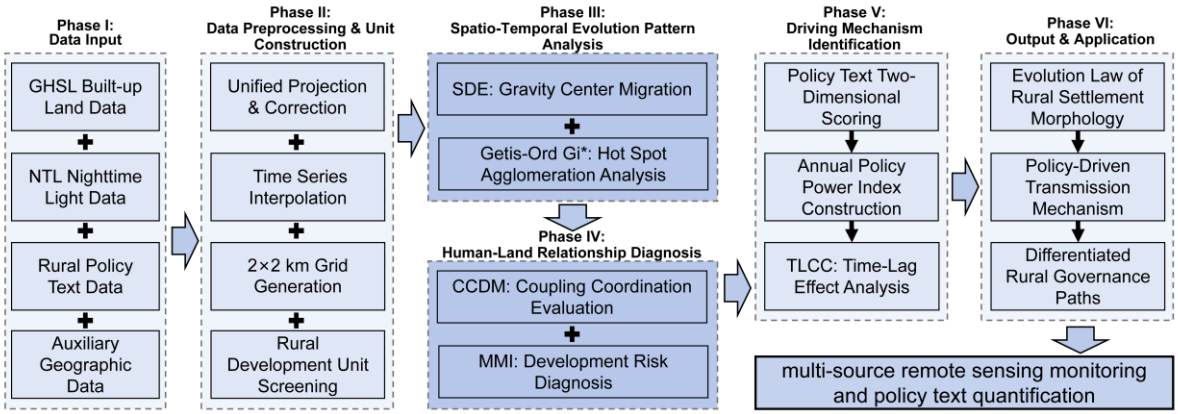

Figure 2. Logical framework diagram.

2.3.1. Data Processing and Spatial Unit Definition

To achieve spatial matching of multi-source heterogeneous data and accurately extract rural spaces, this study established the following data processing workflow:

Grid Generation (Fishnet Construction)

Considering the balance between the study area's scale and data accuracy, this study created a standard 2 × 2 km fishnet as the basic spatial analysis unit. This scale can filter out overly microscopic noise while effectively identifying settlement centers at the township level. All raster data were resampled and uniformly projected onto this grid system to ensure spatial reference consistency.

Extraction of Rural Spatial Units

Given that night-time light and built-up land data mix urban and rural information, it is necessary to exclude urban areas to focus on rural development. To avoid the interference of urban core areas and uninhabited areas, and to fully retain the rural areas in the urban-rural fringe with drastic transformation, the core exclusion principle of this method is clearly defined as: Only grids covering contiguous core urban areas without any administrative villages and uninhabited mountainous areas are excluded by this method. All grid units containing at least one administrative village point, including the rural units in the urban-rural fringe, are fully retained and defined as valid Rural Development Units. This study adopts the Administrative Village Point Control Method to extract rural layers, with the following steps: First, the geographic coordinate point data of administrative villages across Fuzhou City were obtained. Second, the administrative village points were spatially joined with the 2 × 2 km fishnet. Finally, grid units containing at least one administrative village point were identified and defined as Rural Development Units. Grids without administrative village points (mainly contiguous core urban areas or uninhabited mountain areas) were excluded. Rural areas in the urban-rural fringe with complete administrative village points are all retained and included in the rural development units. Ultimately, 1395 rural grid units were identified, serving as the foundational samples for subsequent coupling coordination degree calculations and spatial analysis. This step effectively avoids the masking of rural weak signals by urban bright lights and high-density built-up areas, ensuring the specificity of the research results. This exclusion principle ensures that we will not omit the rural areas in the urban-rural fringe with drastic transformation, and ensures the comprehensiveness and representativeness of the research samples.

Given the temporal discontinuity of GHSL (5-year intervals) and NTL (missing data for certain years), this study used the linear interpolation method to complete data for non-observed years, aligning with the annual resolution of policy data. Based on the assumption that rural elements evolve continuously over time, a continuous annual time series dataset for 1990–2025 was constructed.

2.3.2. Construction of Coupling Coordination Degree Model (CCDM)

In this study, Coordination of rural development specifically refers to the level of coupling interaction and collaborative development between the two subsystems of the rural settlement system: the physical built-up space and the socio-economic vitality. It is the core index to measure whether the rural human–land relationship is coordinated. To evaluate the coordination of rural development, this study constructed the CCDM following the steps below.

Data Standardization: Since L (normalized night-time light intensity, representing the physical spatial morphology of rural settlements, sourced from NTL) and S (normalized rural built-up land density, representing the physical spatial morphology of rural settlements, sourced from GHSL) have different dimensions, the Min-Max Normalization method was first used to map the data to the [0, 1] range [40]. The formula is as follows:

$$X_{ij}\prime = \frac{X_{ij} - \min(X_j)}{\max(X_j) - \min(X_j)} \quad (1)$$

Coupling Degree (C) reflects the intensity of interactions between system elements (physical space S and economic vitality L, defined in Formula (1) [46], and its calculation formula is as follows:

$$C = 2 \times \sqrt{\frac{L \times S}{(L + S)^2}} \quad (2)$$

where L represents the normalized night-time light intensity, and S represents the normalized built-up land density. A higher C value indicates stronger resonance between the two.

The coupling degree alone cannot reflect the overall development level of the system (e.g., low-level resonance) [47]. Therefore, a coordination index (T) is introduced to calculate the Coupling Coordination Degree (D), with the core variables L and S consistent with the previous definition. The formula is as follows:

$$T = \alpha L + \beta S \quad (3)$$

$$D = \sqrt{C \times T} \quad (4)$$

This study considers population economic activity and land development to be equally important, thus setting the weights as $\alpha = \beta = 0.5$. The value of D ranges from [0, 1], with higher values indicating better coordination levels.

2.3.3. Macro-Micro Match Index (MMI)

To accurately diagnose the risks of hollowing out or overloading in rural development, this study introduces the MMI. This index is based on the theory of supply-demand balance [48], and its core input indicators are consistent with the CCDM model: L_i (normalized night-time light intensity of the i-th grid unit, from NTL dataset) and S_i (normalized built-up land density of the i-th grid unit, from GHSL dataset). The calculation formula is as follows:

$$MMI = \frac{L_i - S_i}{\sqrt{L_i^2 + S_i^2}} \quad (5)$$

where L_i and S_i represent the normalized values of light and land use for the ith grid unit, respectively.

MMI < 0 (Negative): Indicates S > L, meaning land development is ahead of economic activity, suggesting a risk of hollowing out (Hollowing Risk).

MMI > 0 (Positive): Indicates L > S, meaning the intensity of economic activity exceeds land carrying capacity, suggesting a risk of overcrowding (Overcrowding Risk).

MMI ≈ 0: Indicates that the two are well-matched, representing a state of balanced development (Balanced Development).

To facilitate spatial identification, this study uses the Standard Deviation Method to classify the MMI results, identifying five types: severe hollowing out, potential hollowing out, balanced development, mild clustering, and high clustering.

2.3.4. Spatial Analysis Methods

The Standard Deviational Ellipse (SDE) is used to analyze the spatial distribution, orientation and migration trajectory of the centroids for GHSL and NTL [49]. The long axis of the ellipse represents the dominant direction of the distribution, while the movement of the centroid reflects the overall trend of spatial evolution [50].

The Hot Spot Analysis (Getis-Ord Gi*) statistic is used to identify high-value clusters (hot spots) and low-value clusters (cold spots) of GHSL and NTL [51]. The formula is as follows:

$$G_i^* = \frac{\sum_{j=1}^{n} w_{ij}x_j - \overline{X}\sum_{j=1}^{n} w_{ij}}{S\sqrt{\frac{n\sum_{j=1}^{n} w_{ij}^2 - \left(\sum_{j=1}^{n} w_{ij}\right)^2}{n-1}}} \quad (6)$$

where x_j is the normalized value of the GHSL/NTL indicator for the j-th grid unit, w_{ij} is the Queen contiguity spatial weight matrix, $\overline{X}$ is the mean value of the indicator, S is the standard deviation of the indicator, and n is the total number of grid units.

This method can effectively filter random noise and locate spatial clustering areas with statistical significance.

2.3.5. Time-Lagged Cross-Correlation (TLCC)

Considering the objective time lag between policy implementation and factor response, this study introduces Time-Lagged Cross-Correlation (TLCC) analysis to measure the dynamic relationship between policy interventions and rural evolution [52].

To scientifically measure the driving effect of policy factors on rural development and evolution, this study establishes a two-dimensional policy effectiveness evaluation system based on the "level of issuing institutions" and the "attributes of document types." The administrative binding force of policy documents is positively correlated with the administrative level of the issuing institution; the higher the level, the stronger its top-down driving force, which is defined as policy effectiveness (P). At the same time, different types of policy documents have varying timeliness and guiding significance; strategic and planning documents usually have a more profound impact than routine notifications, which are defined as policy content (N). The specific quantitative scoring criteria are detailed in Table 2.

The policy scoring method in this study refers to the mature quantitative paradigm of policy texts widely used in existing rural geography research [40], and the full scoring work was completed by the authors of this paper. All participating authors have a professional background in rural geography and urban-rural planning, with more than 3 years of research experience in rural development in Fuzhou, and have a systematic grasp of the local policy system, which ensures the professional accuracy of the scoring. The specific standardized scoring process is as follows: (1) Unified rule calibration: All scorers conducted centralized interpretation of the scoring criteria in Table 2, and completed pre-scoring of 20 randomly selected samples. The pre-scoring results were confirmed to meet the excellent consistency standard; (2) Double-blind independent scoring: Two core authors completed independent double-blind scoring of all 408 policy documents one by one, with

no access to each other's results during the process; (3) Discrepancy review: For samples with a score difference of ≥3 points, all authors conducted a joint review against the original text and criteria, and determined the final score through consensus; (4) Final verification: The corresponding author completed the full review of the scoring results to ensure data accuracy. The final scores were used to construct the APPI for this study.

Table 2. Quantitative Scoring Standards for Rural Development Policy Effectiveness.

Dimension	Classification	Criteria/Keywords	Score
I. Policy Effectiveness (P) (Based on the level of the issuing unit)	Core Decision-Making Level	City Committee, City Government (and above)	10
	Functional Department Level	City-level Departments/Bureaus	8
	District/County Execution Level	District/County Government	7
	Township Grassroots Level	Town/Township Government	5
	Other Agencies Level	Other Departments/Temporary Agencies	4
II. Policy Content (N) (Based on document type)	Strategic Planning Category	Decision, Outline, Plan Note: Involves top-level design and long-term goals	10
	Policy Guidance Category	Opinion, Regulation, Measures Note: Involves specific guiding principles and norms	8
	Implementation Scheme Category	Scheme, Implementation Plan Note: Involves specific action deployment	7
	Routine Notice Category	Notice, Announcement Note: Involves communication of daily administrative affairs	6
	Other Types	Plan, Points, Meeting Minutes, Reply Note: Involves supplementary or temporary documents	5

First, the policy index series X and the rural morphology series Y are standardized using the Z-Score method to eliminate dimensional differences. Then, the Pearson correlation coefficient r_k is calculated for different lag years k (k = 0, 1,. . ., 5):

$$r_k = \frac{\sum(x_i - \overline{x})(y_{i+k} - \overline{y})}{\sqrt{\sum(x_i - \overline{x})^2}\sqrt{\sum(y_{i+k} - \overline{y})^2}} \quad (7)$$

The value of k corresponding to the maximum r_k represents the best lag period (Best Lag) for the element's response to the policy.

3. Results

3.1. Geographical Background of Rural Settlements

Topography is the primary natural factor restricting the spatial distribution of rural areas in Fuzhou. As shown in Figures 3 and 4, the spatial distribution of administrative villages in Fuzhou exhibits a significant tendency toward lowland areas.

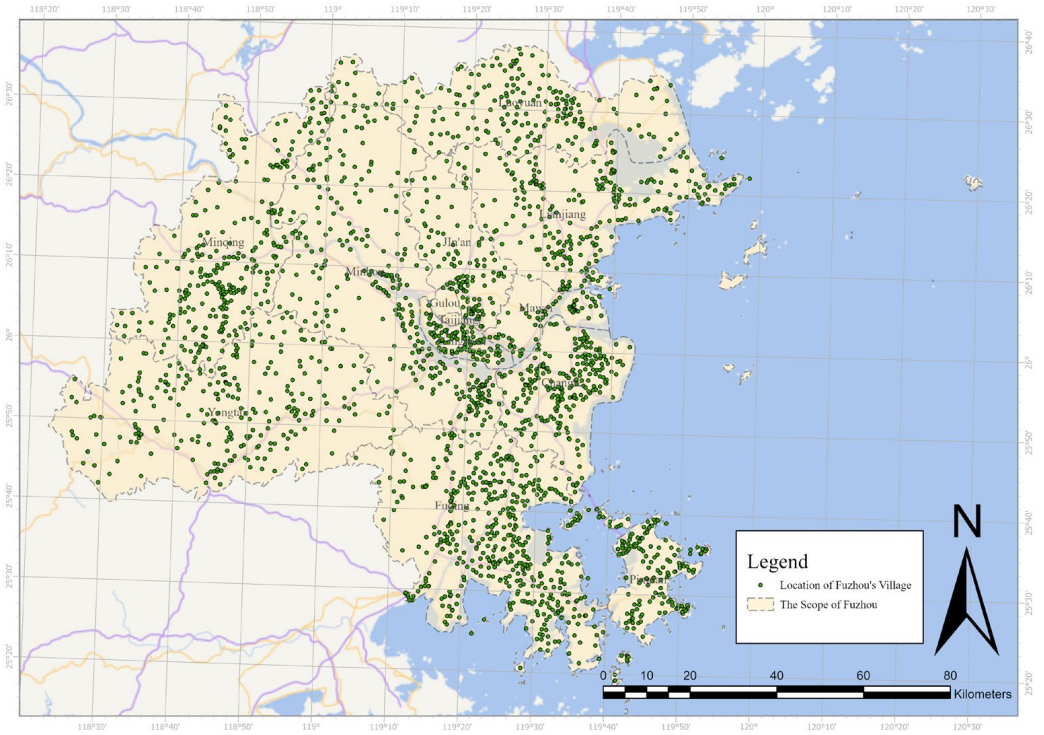

Figure 3. Spatial distribution map of administrative villages in Fuzhou.

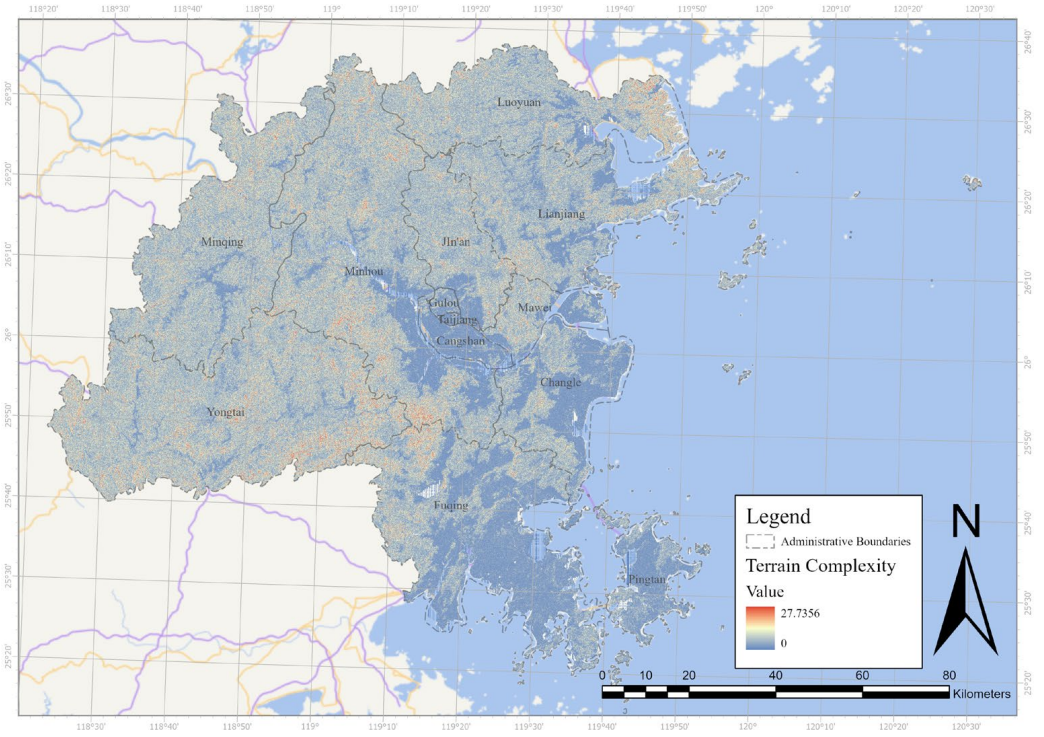

Figure 4. Topographic complexity map of Fuzhou.

Overlay analysis shows that the vast majority of rural settlements are concentrated in the downstream plain of the Minjiang River and coastal terraces. Statistical results indicate that over 70% of administrative villages are located in areas where the topographic complexity is below the average level of Fujian Province. This spatial pattern provides a physical foundation for subsequent land-use expansion and infrastructure development but also limits the development potential of rural areas in the western mountainous regions.

3.2. Spatio-Temporal Evolution of Human–Land Elements

Between 1990 and 2025, both GHSL and NTL in Fuzhou have shown a rapid expansion trend, but their spatial evolution patterns differ.

As shown in Figure 5, the expansion pattern of built-up land exhibits a typical concentric outward push model, with Fuzhou's main urban area as the core, spreading along the Minjiang River axis toward the coastal areas in the southeast.

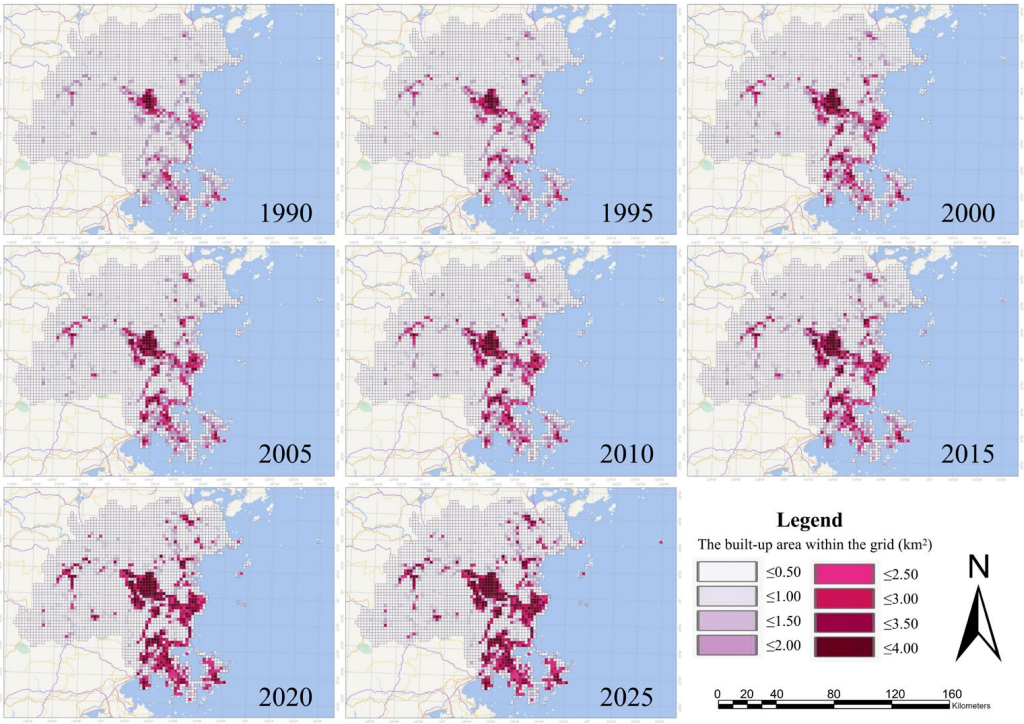

Figure 5. Built-up area map of Fuzhou (1990–2025) (Data Source: Programme of the European Union, JRC).

Directional Distribution and Center of Gravity Shift: Using Standard Deviation Ellipse (SDE) analysis, it was found that the main axis directions of the built-up area (Figure 6) and nighttime lighting (Figure 7) both maintain a northwest-southeast orientation, which aligns closely with Fuzhou's urban development strategy of advancing eastward and southward.

It is worth noting that the spatial evolution trajectories of the two exhibit significant asynchrony. As shown in Figure 6, between 1990 and 2025, the center of gravity of GHSL shifted by a very small amplitude, showing an overall slow drift toward the northwest. This indicates that despite the construction of the coastal new city, Fuzhou's traditional central urban areas (Gulou and Taijiang) and the western hinterland (Minhou) still dominate the stock of built-up land, demonstrating a strong spatial lock-in effect. In contrast, the center of gravity of NTL (Figure 7) shows significant volatility and a large-scale southeastward shift. The center of gravity of nighttime lighting is accelerating its shift toward coastal areas. This implies that while the physical spatial center of gravity remains in the old city, the center of economic activity and population vitality has already advanced eastward and southward, with the land-use efficiency in coastal areas rapidly improving.

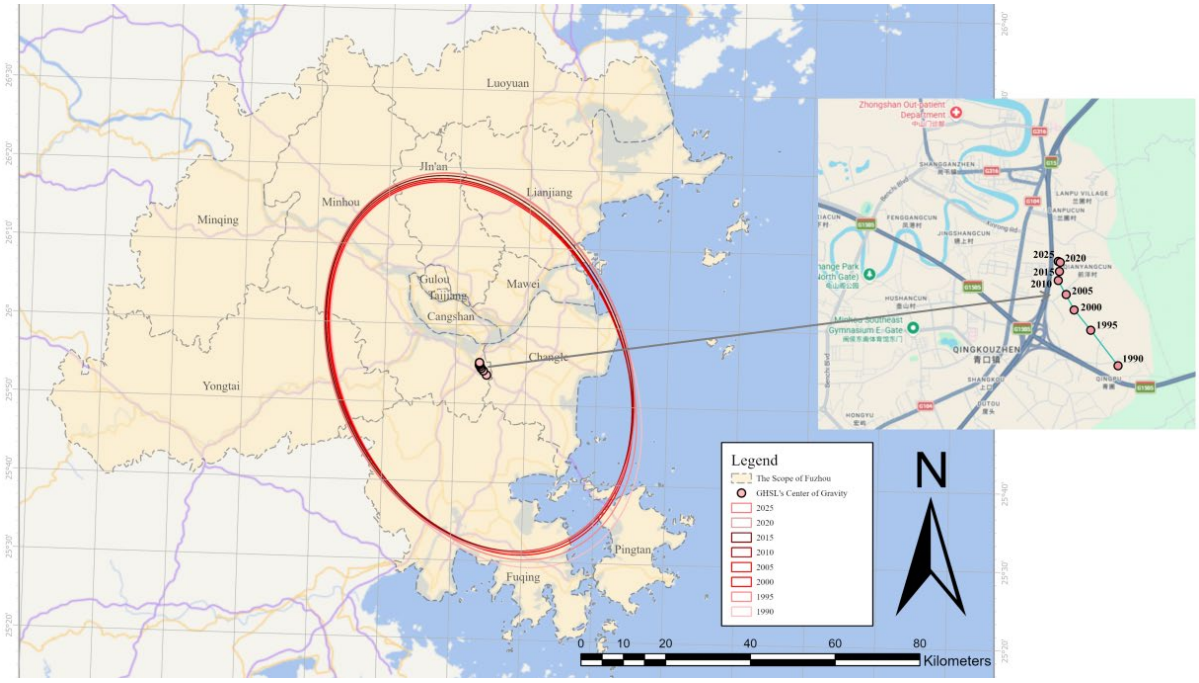

Figure 6. Directional distribution and center of gravity shift map of GHSL.

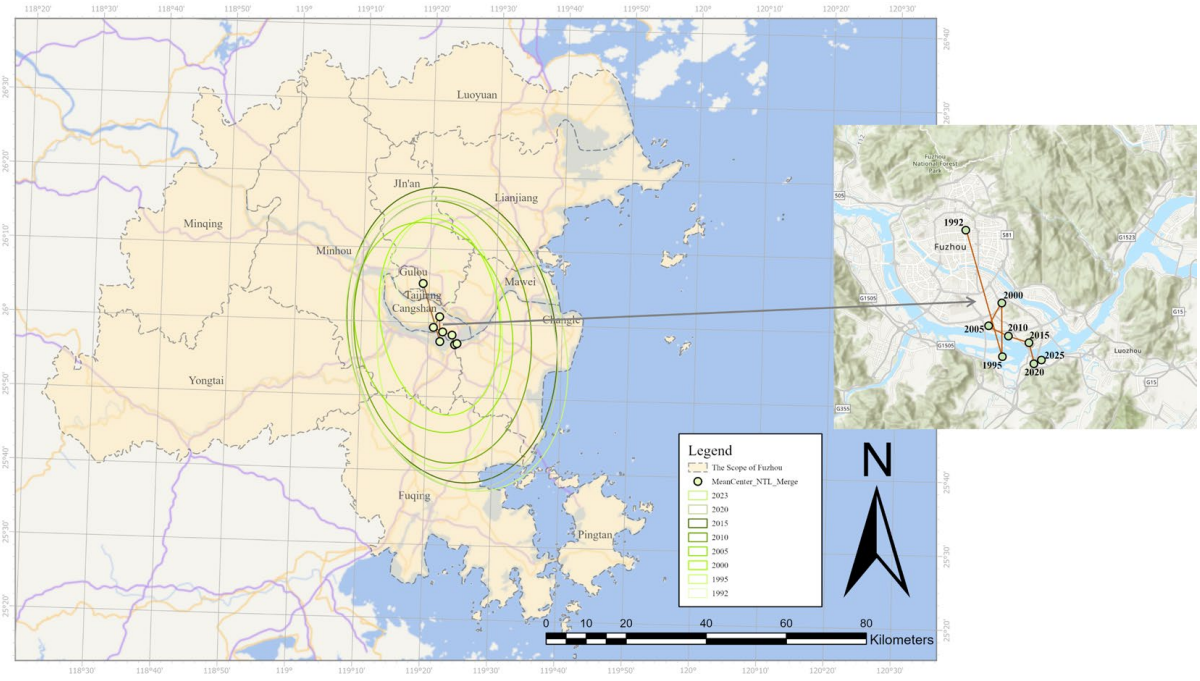

Figure 7. Directional distribution and center of gravity shift map of NTL.

3.3. Local Spatial Agglomeration Patterns

To identify growth hotspots, this study adopted Hot Spot Analysis (Getis-Ord Gi*). During 1995–2010, the hotspots of GHSL were mainly concentrated in core urban areas such as Gulou and Taijiang. After 2015, the hotspots shifted significantly to Changle (Coastal New City) and Minhou (University Town), forming a multi-center spatial structure, as shown in Figure 8.

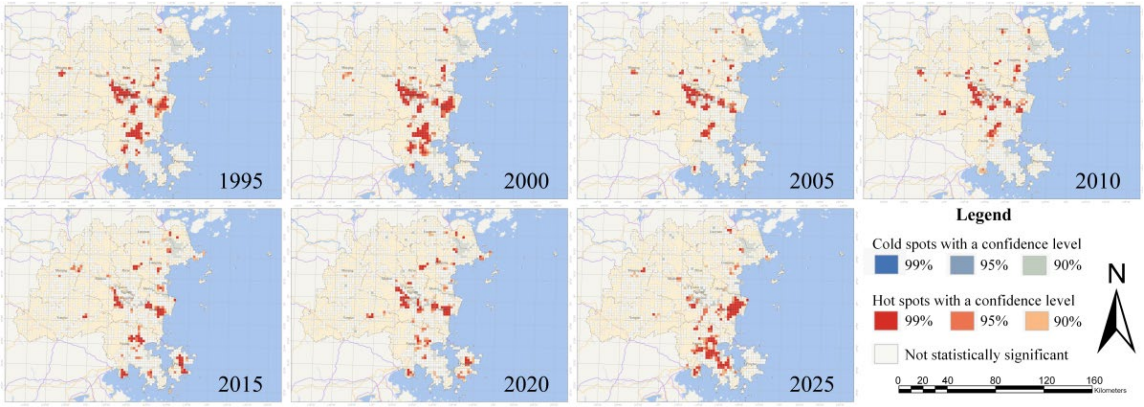

Figure 8. GHSL hot spot analysis map.

The distribution range of NTL hotspots (Figure 9) is relatively more concentrated. High-confidence (99% Confidence) hotspots are consistently located in the central urban area and key industrial nodes.

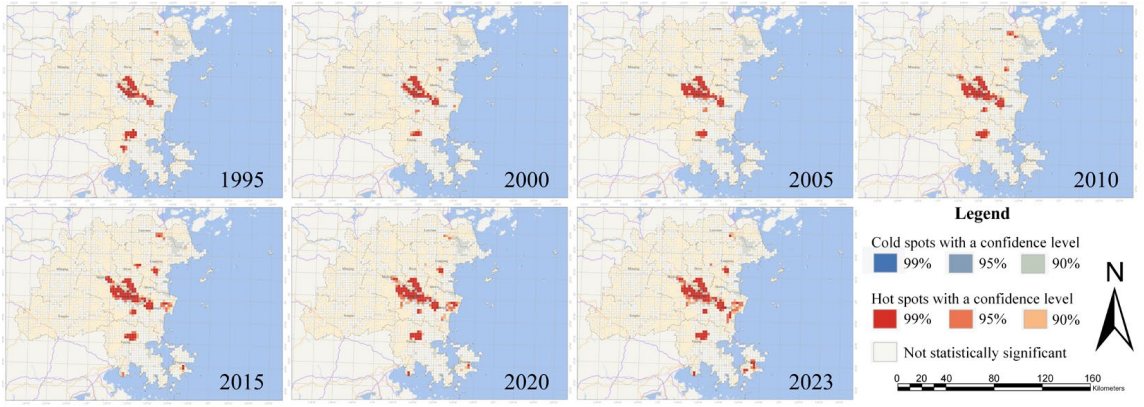

Figure 9. NTL hot spot analysis map.

The above situation indicates that the diffusion range of GHSL hotspots is broader than that of NTL hotspots, suggesting a certain degree of land-led urbanization in Fuzhou. This means that the intensity of land development in peripheral areas exceeds the intensity of population and economic activity aggregation.

The gravity center migration trajectory and spatial agglomeration patterns show a high degree of consistency, forming a logical chain of "local agglomeration driving global shift". The slight northwestward shift in the GHSL gravity center is directly driven by the continuous expansion of built-up land hot spots in Minhou University Town and the western hinterland. The significant southeastward migration of the NTL gravity center corresponds to the stable high-value agglomeration of vitality hot spots in Changle Coastal New City and southeast coastal industrial nodes. The mismatch of the two trajectories further verifies the asynchronous evolution of physical space and economic vitality of rural settlements.

3.4. Spatio-Temporal Differentiation of CCDM

The evolution of the rural human–land relationship is essentially a process of mutual adaptation between socio-economic vitality and spatial physical form. The calculated coupling coordination degree D quantitatively characterizes the quality of this relationship. To further analyze the development differences among various rural units, this study establishes an evaluation ladder ranging from "disordered decline" to "high-quality co-

ordination" based on the D value. This standard aims to identify whether rural areas are experiencing uncoordinated states, such as hollowing out or overcrowding. The specific classification criteria are shown in Table 3.

Table 3. Classification of CCDM in Fuzhou's rural areas.

Numerical Range	Class Name	Physical Meaning
$0.0 < D \leq 0.4$	Disordered Decline Class	Lagging rural construction, lack of economic vitality
$0.4 < D \leq 0.6$	Barely Coordinated Class	Low-level balance between construction and vitality
$0.6 < D \leq 0.8$	Intermediate Coordination Class	Positive interaction between construction and vitality
$0.8 < D \leq 1.0$	High-quality Coordination Class	High-level integrated development of industry and city

The classification threshold of CCDM in this study adopts the universal classification standard widely used in the field of coupling coordination research in rural geography [51], which has been verified by empirical studies and has high academic recognition. The specific classification connotation is adjusted according to the characteristics of rural development to ensure the applicability of the standard.

Figure 10 shows the spatio-temporal evolution of CCDM in the Fuzhou region from 1990 to 2025. Overall, CCDM demonstrates a temporal trend of progressing from low-level disorder to high-quality coordination, along with a spatial characteristic of stepwise decline from the center to the periphery.

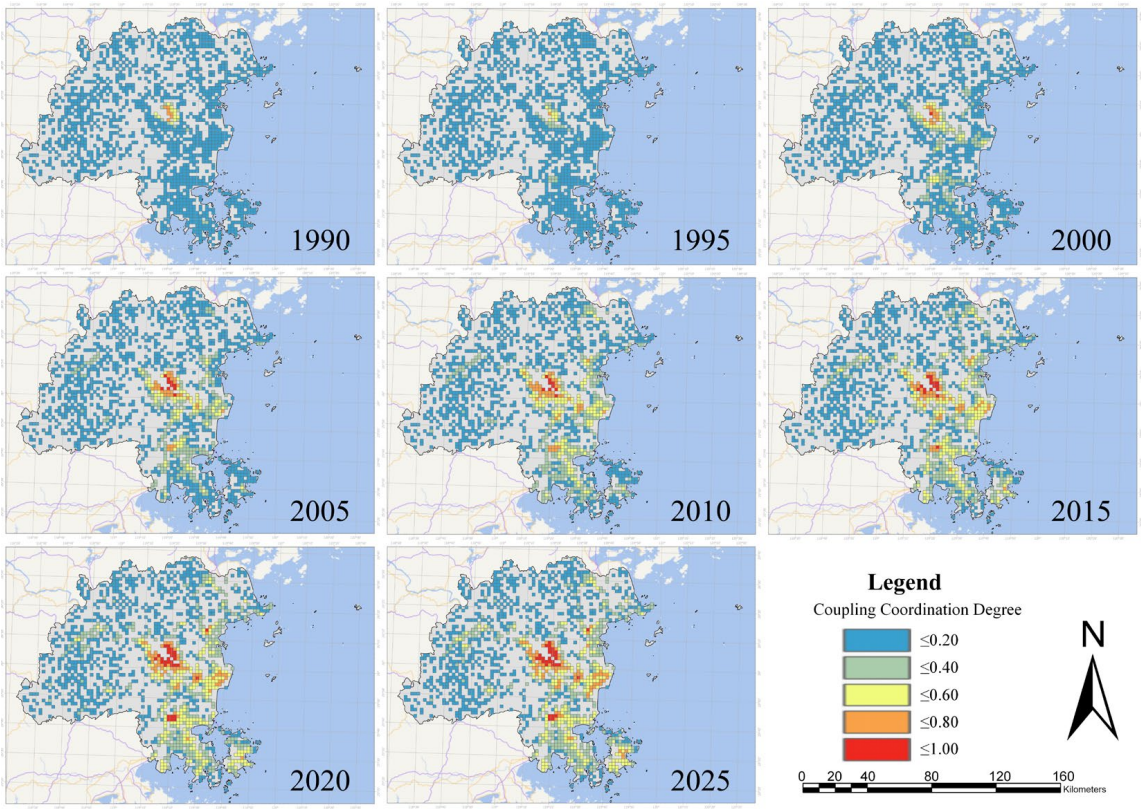

Figure 10. CCDM Map of GHSL-NTL in Fuzhou's Rural Areas from 1990 to 2025.

From 1990 to 2005, the entire region was primarily in low-value zones (blue), with rural development in a state of low-level equilibrium. From 2010 to 2025, high-value zones (red/orange) expanded rapidly. Notably, after Fuzhou New Area was approved in 2015, the coupling coordination degree in coastal areas significantly improved, forming a distinct

high-level coastal development belt. However, western mountainous counties (such as Yongtai and Minqing) have remained in low-coordination zones for an extended period, highlighting persistent regional development imbalances.

3.5. Spatio-Temporal Evolution Characteristics of Rural Settlement "Hollowing" Based on the MMI Model

To further reveal the degree of alignment between the physical space of rural settlements and socio-economic vitality in Fuzhou, this study introduces the MMI model to spatially visualize the rural human–land relationship from 1990 to 2025 (Figure 11). The MMI value reflects the relative rate difference between built-up land expansion and nighttime light growth. To avoid the subjectivity of artificial threshold setting and ensure the continuity of classification, we adopted the standard deviation (σ) classification method widely used in spatial statistical analysis to grade MMI results [53]. σ (approximately equal to 1.4) is the standard deviation of full-sample MMI values of 1395 rural development units from 1990 to 2025. The classification standard is shown in Table 4, which divides the rural human–land matching state into five types with fully continuous numerical ranges, to identify the hollowing risk, agglomeration risk and balanced development state of rural settlements.

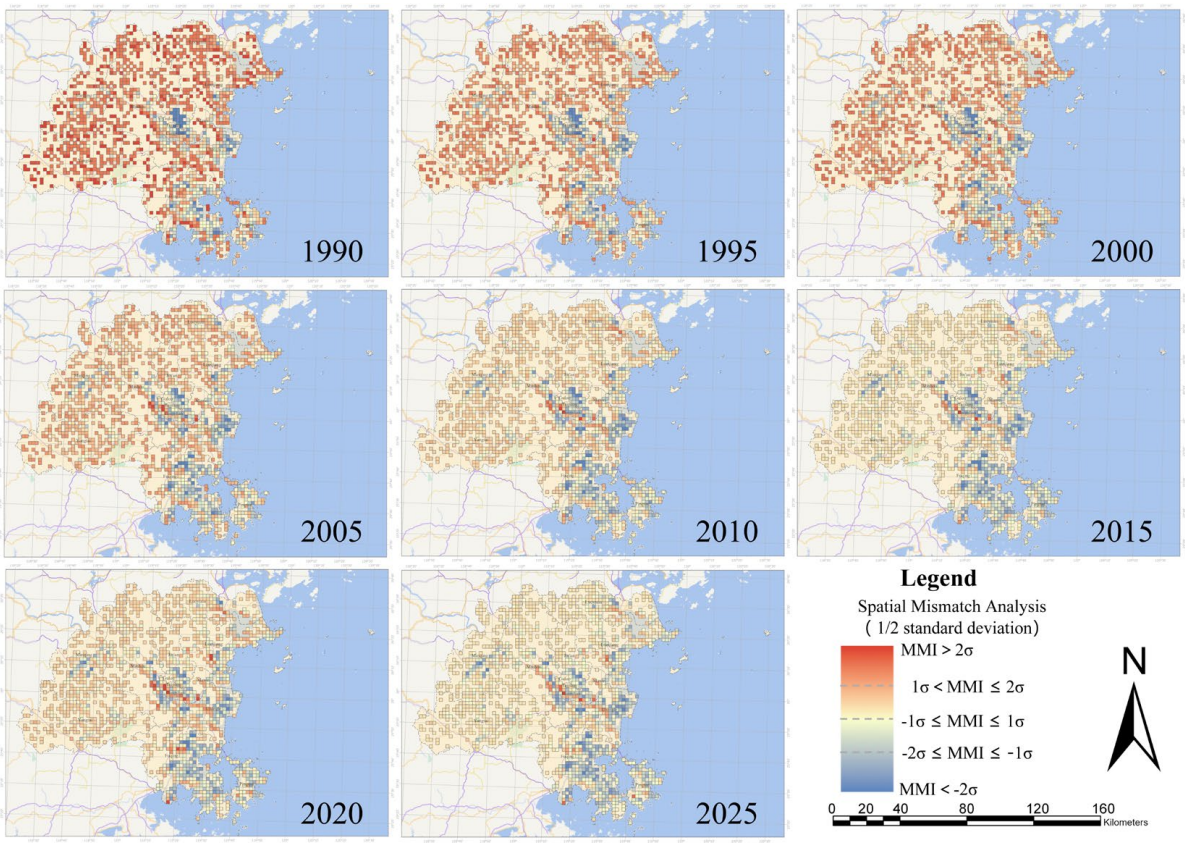

Figure 11. Spatio-temporal evolution map of rural MMI in Fuzhou City from 1990 to 2025.

From a temporal perspective, rural settlements in Fuzhou have undergone a significant process of de-agglomeration. The period from 1990 to 2000 was characterized by high agglomeration, with large areas of red and dark orange patches (High Agglomeration) visible on the map, mainly distributed in surrounding counties such as Minhou and Lianjiang. During this time, the scale of rural construction land was relatively small, and population outflow had not yet occurred on a large scale. The intensity of social activities per unit of construction land was high, reflecting a compact traditional settlement pattern.

Table 4. MMI value range and classification standard based on standard deviation.

Numerical Range	Class Name	Physical Meaning
MMI > 2σ	High Agglomeration	Economic vitality far exceeds the carrying capacity of construction land, with significant overcrowding and overloading risk
1σ < MMI ≤ 2σ	Mild Agglomeration	Economic vitality is slightly higher than land carrying capacity, showing a good agglomeration momentum with no obvious overload risk
−1σ ≤ MMI ≤ 1σ	Balanced Development	Construction land expansion and economic vitality growth are basically synchronous, with a balanced and stable human–land relationship
−2σ ≤ MMI < −1σ	Potential Hollowing	Land development is ahead of economic vitality, with preliminary idle construction land and potential hollowing risk
MMI < −2σ	Severe Hollowing	Large-scale construction land expansion lacks corresponding economic vitality support, with serious land idleness and significant hollowing risk

From 2005 to 2015, the region entered a transitional phase, during which red patches rapidly receded and turned into light yellow. This change reflects the acceleration of urbanization, as large numbers of rural populations migrated to cities. Although construction land was retained in rural areas, the intensity of activities declined relatively, and the human–land relationship began to loosen.

From 2020 to 2025, the region transitioned into a balanced phase, with most areas appearing light yellow (Balanced Development). Thanks to the implementation of the rural revitalization strategy, improvements in infrastructure and the introduction of new industries have synchronized the growth rates of rural construction scale and activity intensity. This marks the beginning of a new dynamic equilibrium in the human–land relationship.

Although the overall trend is toward balance, blue patches (Severe Hollowing/Potential Hollowing) still exist in certain areas and exhibit specific spatial orientations. These hollowing regions are scattered mainly along coastal protrusions and the edges of some mountainous areas. While construction land in these regions exists or has even expanded, it lacks corresponding economic vitality support. This may be due to large-scale land reclamation, industrial park leveling, and other land development activities in some coastal areas where industries have not yet been fully introduced, or due to the phenomenon of population outmigration in remote mountainous areas, leaving houses vacant.

By 2025, only a few red high-agglomeration points remain in core towns, indicating that the rural development model has shifted from an extensive, generally high-density pattern to an intensive development model centered around key towns.

3.6. Time-Lag Characteristics of Rural Elements Driven by Policy

Based on the dataset constructed in the previous sections, this study extracted two core indicators, GHSL and NTL, for rural settlements in Fuzhou from 1990 to 2025. Through statistical analysis of the policy effectiveness index and coupling coordination degree at various time points, the overall evolution characteristics of the scale expansion rate and endogenous development quality of Fuzhou's rural areas during the rapid urbanization process can be intuitively reflected. To maintain the fluency of the discussion in the article, specific statistical values and changes for each year are provided in Supplementary Table S1.

From the perspective of evolution trends (Figure 12), the intensity of rural policy interventions in Fuzhou shows a significant fluctuating upward trend, which is highly consistent with the evolution of rural morphology.

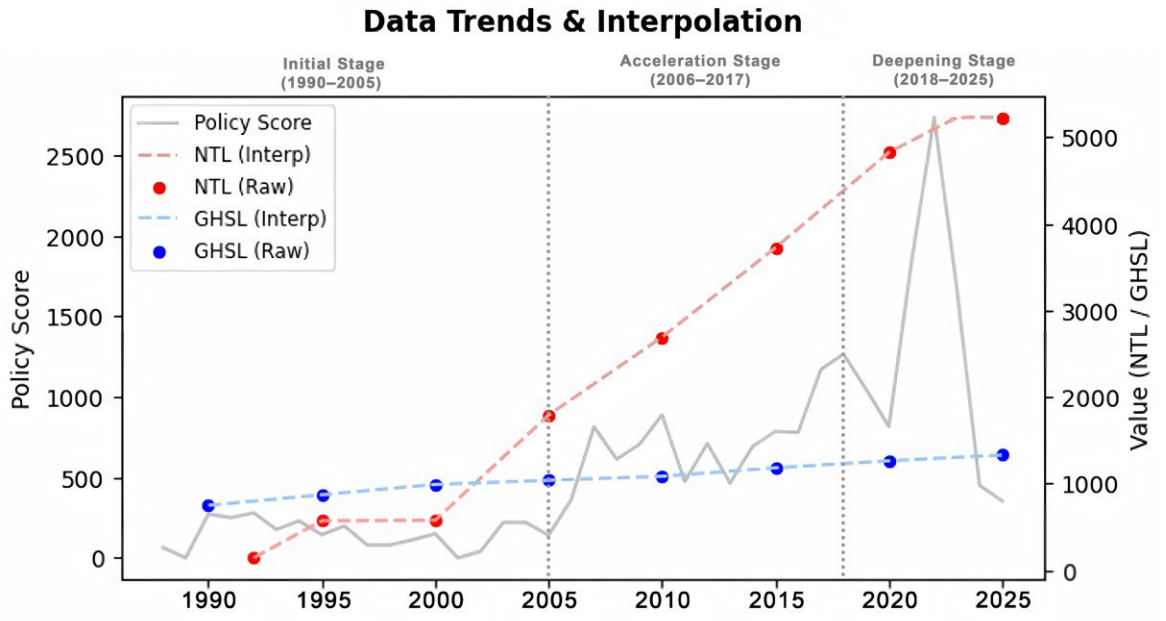

Figure 12. Evolution trend of rural policy effectiveness in Fuzhou from 1990 to 2025.

1990–2005 (Initial Stage): Policy scores were relatively low and fluctuated slightly, corresponding to the slow growth of rural construction land and light intensity. During this period, rural development was mainly driven by natural endogenous forces.

2006–2017 (Acceleration Stage): With the advancement of the "New Rural Construction" strategy, a policy peak occurred in 2007, driving an exponential increase in the subsequent nighttime light index.

2018–2025 (Deepening Stage): Driven by the "Rural Revitalization" strategy and the "14th Five-Year Plan," the policy effectiveness index reached its historical peak in 2021–2022, pushing the rural construction land area to exceed 1300 km^2. This marked the beginning of a high-intensity interaction phase in the flow of urban and rural factors.

The TLCC analysis results reveal the asynchrony characteristics of different rural elements in response to policies. As shown in Figure 13, the lag period of NTL response is three years (R = 0.870). NTL represents the socioeconomic vitality of rural areas and shows a very high correlation with policies (0.870). The three-year lag indicates that it typically takes about three years for policy funding and industrial project implementation to translate into significant economic output and electricity consumption.

As shown in Figure 14, the lag period of GHSL response is four years (R = 0.799). GHSL represents the physical spatial morphology of rural areas, and its optimal lag period is one year later than that of NTL. This indicates that there is a longer physical cycle from policy implementation to land planning approval, infrastructure construction, and final completion and utilization.

The above results validate the chain transmission mechanism of policy guidance, vitality stimulation, and spatial reconstruction. Policy benefits first activate rural socioeconomic vitality (NTL increase) in the third year through industrial support and public service improvements. Subsequently, in the fourth year, as economic activities solidify and infrastructure improves, this ultimately translates into significant expansion of the physical surface space (GHSL increase). This one-year time lag reflects the process of rural transformation from implicit functional changes to explicit morphological reshaping, providing an important time window reference for the government in rural planning. Specifically, the 3–4 years following policy implementation represent a critical period for controlling the disorderly expansion of rural space.

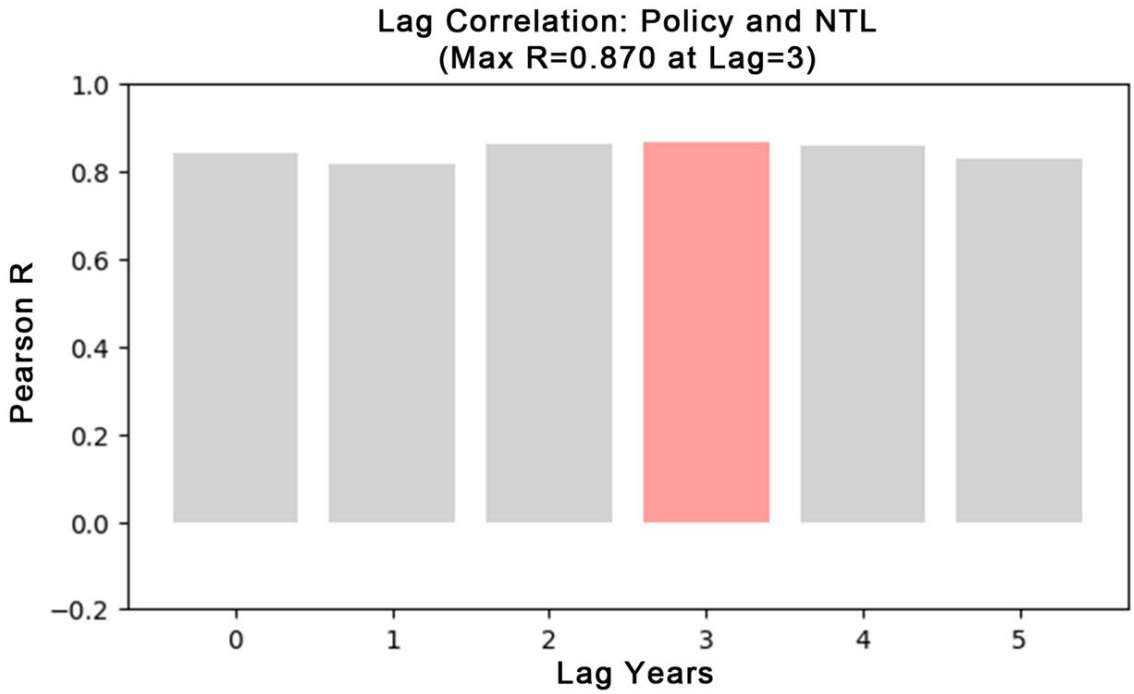

Figure 13. Cross-correlation analysis of rural policy effectiveness and NTL Lag in Fuzhou from 1990 to 2025.

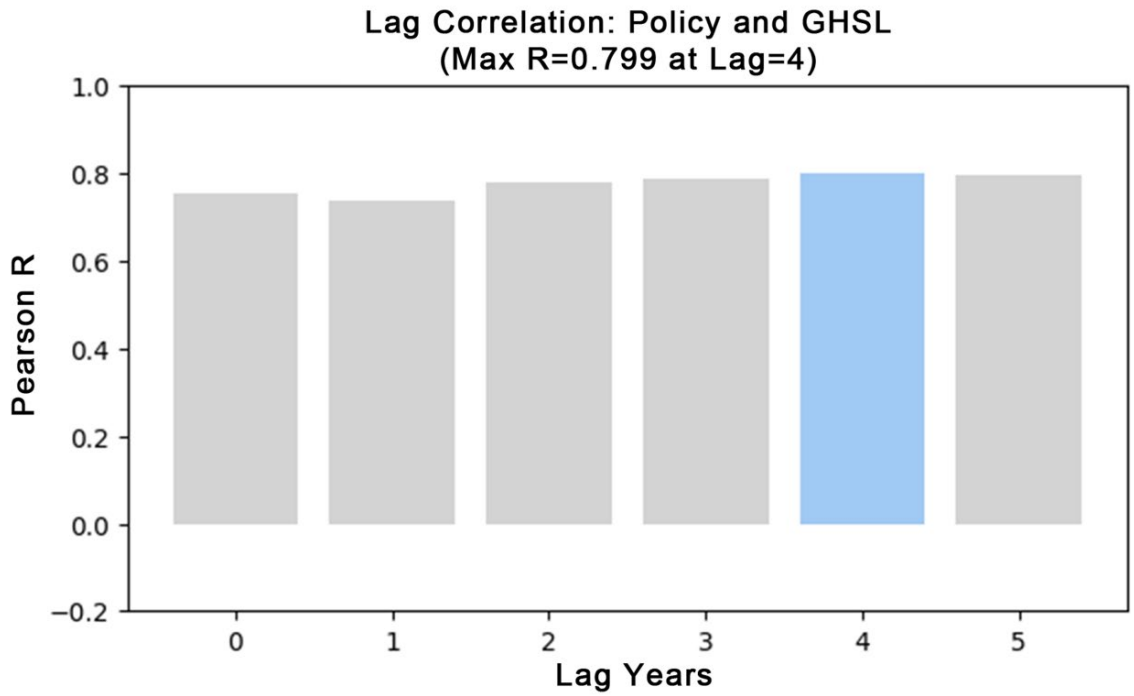

Figure 14. Cross-correlation analysis of rural policy effectiveness and GHSL Lag in Fuzhou City from 1990 to 2025.

4. Discussion

4.1. The Physical Lag and Functional Advancement of Rural Settlements

This study, by comparing the spatiotemporal trajectories of GHSL and NTL, reveals significant asynchrony in rural settlements in Fuzhou, which deviates from the traditional theory of synchronized urbanization [9,52].

Consistent with the findings of Li et al. [7] in the Yangtze River Delta, we also observed that the growth of rural economic vitality often precedes physical spatial expansion in rapidly urbanizing regions; however, our study further identifies that topographic constraints in coastal mountainous cities will significantly amplify this asynchrony, which has been rarely discussed in previous plain-focused studies.

First, the physical lag of spatial expansion. The expansion of rural construction land is rigidly constrained by both terrain limitations and the red line for farmland protection. Once established, it is difficult to reverse in the short term, resulting in large amounts of idle construction land in some mountainous rural areas even after population outflows, exhibiting a hollowing physical characteristic.

Second, nighttime light responds more sensitively to policies and capital. The study found that during the early stages of Fuzhou's eastward and southward development strategy, the growth in light intensity in coastal new towns and riverside areas was significantly faster than the expansion of construction land. This indicates that under strong policy drivers, capital and economic activities often precede large-scale physical construction, entering rural areas through mechanisms such as enclave economies and infrastructure-first approaches. This functional advancement is a typical feature of rural transformation in rapidly urbanizing coastal regions.

4.2. The Spatiotemporal Transmission Mechanism of Rural Areas Under Policy Drivers

This study, through TLCC analysis, found that rural settlements in Fuzhou exhibit a significant lag effect in response to policies, displaying an asynchronous evolution pattern where NTL (lagging by 3 years) precedes GHSL (lagging by 4 years).

In terms of policy types, industrial development and rural revitalization policies are the core drivers leading the early response of NTL, while rural construction and land consolidation policies have a more direct and sustained impact on the expansion of GHSL, which further explains the 1-year lag between the two elements.

Policies do not take immediate effect from the time of their issuance to produce substantial spatial impacts. The high correlation of R = 0.870 confirms that government-led external interventions are the core engine of rural evolution [40], but this driving force requires an incubation period of about three years. During this period, policy benefits are primarily injected into rural areas in non-spatial forms, such as financial subsidies and industrial support, which first stimulate latent socioeconomic vitality represented by NTL (e.g., rural tourism night markets, nighttime operations in agricultural product processing, etc.).

The one-year time lag gap between NTL and GHSL validates the geographical hypothesis that functional transformation precedes spatial reconstruction. While existing studies, such as Wang et al. [40], have confirmed the overall driving effect of policies on rural settlement evolution; few have quantified the differentiated lag responses of physical morphology and functional vitality to policies, which is the core innovation of this study. In the third year of policy implementation, the functional dynamics within rural areas first undergo replacement and activation. With the continued accumulation of economic activities, the demand for physical space reaches a threshold in the fourth year, thereby driving or supporting substantial expansion of construction land (e.g., building new factories, expanding homestays, and road paving).

Combined with policy text analysis, the differences in policy focus at different stages also explain why the correlation coefficient of NTL (0.870) is higher than that of GHSL (0.799). Since the implementation of the "Rural Revitalization Strategy" in 2018, Fuzhou's rural-related policies have gradually shifted from early-stage new village construction and land consolidation to industrial development and improvement of living quality. The higher

sensitivity of nighttime light to policies reflects that recent policies have been more effective in promoting rural population return and industrial prosperity, rather than merely leading to real estate development or the expansion of hollow villages. This indicates that rural development in Fuzhou has begun to move away from the inefficient "sprawling" model and has entered a stage of high-quality development centered on cultivating endogenous driving forces. Most existing studies on rural human–land coupling coordination focus on plain regions [37], while our study supplements empirical evidence from complex coastal mountainous environments, providing a reference for differentiated rural governance in similar geographically complex areas.

4.3. Limitations

Although this study constructed a multidimensional coupling framework, there are still limitations:

4.3.1. Data Resolution Limitations

Despite the correction of DMSP/OLS and NPP/VIIRS data, the 500 m resolution still exhibits a mixed pixel effect when identifying small natural villages, potentially underestimating the vitality of scattered mountainous settlements.

4.3.2. Policy Quantification

While text metrics quantify policy attention, the time-lag effect of policies from issuance to implementation is complex. Future research needs to combine field investigations to further verify the micro-mechanisms of policy execution.

In addition, the analysis of social and cultural dimensions is lacking. NTL primarily reflects economic vitality and cannot fully capture social relationship networks. Future research could incorporate POI data, mobile signaling data, and social survey data to provide a more comprehensive depiction of rural settlements.

5. Conclusions

This study uses Fuzhou as an empirical case to quantitatively analyze the coupling evolution patterns of remote sensing monitoring of rural settlements and policy quantification from 1990 to 2025. The main conclusions are as follows:

First, rural settlements exhibit significant asynchronous evolution characteristics. The study found that, influenced by terrain barriers and the stock-locking effect, the migration of the center of gravity of rural construction land in Fuzhou shows a clear path dependency, remaining largely concentrated in the northwestern mountainous areas and the surroundings of old urban areas. In contrast, the center of NTL responds sensitively to external interventions, showing a significant leap toward the southeastern coastal areas. This spatio-temporal mismatch between physical space and functional vitality reveals a general pattern in the rural transformation of rapidly urbanizing regions, where the flow of elements tends to precede physical construction, which lags behind.

Second, policy and institutional changes are the core external forces driving rural spatial reconstruction and the shift in its center of gravity. Textual metrics indicate that the evolution of rural policies in Fuzhou has undergone a logical transition from quantitative expansion to qualitative functional improvement. The focus of policies has gradually shifted from early township enterprises and land development to ecological protection and urban-rural integration. This institutional transformation has directly led to a shift in rural development models: early policies drove extensive land sprawl across the region, while later policies, through precise planning guidance and resource allocation, have concentrated economic vitality in key policy areas such as coastal new towns, thereby reshaping the macro structure of rural areas.

Third, the human–land relationship in rural areas has formed a spatial pattern of high-quality coordination in coastal areas and low-efficiency lagging in mountainous areas. Based on the measurements of CCDM and MMI, the coupling coordination degree within Fuzhou's rural system shows an overall upward trend, but regional imbalances have intensified. The southeastern coastal plain, through policy stacking and industrial introduction, has achieved a high-level coupling of construction land and economic vitality. In contrast, the western and northern mountainous areas, constrained by ecological redlines and population loss, face dual pressures of idle construction land and declining vitality. This indicates that under complex geographical conditions, a single rural revitalization model is unlikely to be effective, and differentiated governance strategies based on human–land coupling characteristics must be implemented.

With regard to specific policy recommendations for Fuzhou, this study highlights the issue of uncoordinated development between coastal and mountainous areas [1], requiring Fuzhou's rural governance to abandon the "one-size-fits-all" approach and implement tailored strategies based on the characteristics of human–land coupling.

Coastal Agglomeration Area: For regions like Changle and Fuqing, caution should be exercised regarding the ecological risks posed by excessive hardening of construction land. Policy focus should shift from incremental expansion to tapping into existing resources, leveraging the vitality advantage of nighttime lights to develop rural tourism and modern service industries, thereby enhancing the economic output per unit of land.

Suburban Integration Area: For rural grids located around urban areas, efforts should focus on strengthening infrastructure connectivity with central urban areas to avoid becoming lagging zones or low-end industrial dumping grounds on the urban periphery.

Mountain Ecological Conservation Area: For hollowed-out areas such as Yongtai and Minqing, large-scale construction should not be forcibly implemented. The objective laws of population outflow should be respected, and a smart shrinkage strategy should be adopted. Through land consolidation and the reclamation of inefficient construction land, efforts should focus on developing ecological agriculture and health and wellness industries, maintaining a low-density balance between human activity and the land.

In summary, this study not only theoretically validates the effectiveness of integrating multi-source remote sensing and text metrics in rural geography research but also provides scientific evidence and decision-making support for optimizing land spatial planning, guiding rural classification, and regulating human–land relationships in Fuzhou and similar coastal mountainous cities. The coupling analysis framework constructed in this study, combining remote sensing monitoring and policy quantification, offers a quantifiable method for analyzing the interaction mechanisms between rural development and policies. This analytical framework possesses broad applicability and transferability, making it suitable for other regions worldwide undergoing rapid urbanization and institutional transformation. Future research could further extend this framework to a global scale, comparing the differences in the evolution of rural settlements under varying political systems and land tenure contexts, thereby contributing theoretical support to the development of a more inclusive global rural development system.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/land15050708/s1, Table S1: Statistics on the Evolution of Key Elements of Rural Settlements in Fuzhou (1990–2025).

Author Contributions: Conceptualization, B.J. and Y.W.; Data curation, B.J., X.F. and X.Z.; Formal analysis, B.J. and Y.Z.; Investigation, B.J., Q.W. and Y.Z.; Methodology, B.J., Y.W. and Y.Z.; Project administration, Y.W. and Y.Z.; Resources, B.J., Y.W. and Q.W.; Software, B.J., X.F. and X.Z.; Supervision, Y.Z. and Q.W.; Validation, B.J. and Y.Z.; Visualization, B.J. and Y.W.; Writing—original draft, B.J. and

Q.W.; Writing—review and editing, B.J., Y.W., Q.W., X.F. and X.Z. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest: The authors declare no conflicts of interest.

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