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RECEIVED 16 September 2024

ACCEPTED 10 March 2025

PUBLISHED 24 March 2025

CITATION

Xu Z, Ke F and Yu J (2025) Spatio-temporal evolution and influencing factors of rural production-living-ecological function: A case study of mountainous counties in Zhejiang Province, China.

Front. Environ. Sci. 13:1495778.

doi: 10.3389/fenvs.2025.1495778

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Spatio-temporal evolution and influencing factors of rural production-living-ecological function: A case study of mountainous counties in Zhejiang Province, China

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Production-living-ecological function (PLEF) represent the core dimensions of rural systems. However, systematic studies on PLEF in mountainous counties along China's southeastern coast remain insufficient. Additionally, the dominant factors influencing rural functional evolution require deeper investigation, as these insights are crucial for regional sustainable development. This study focuses on mountainous rural areas in Zhejiang Province, a leading region in China's rural revitalization. A PLEF evaluation index system was established. Using comprehensive evaluation methods, exploratory spatial data analysis (ESDA), and geographical detector (GeoDetector) models, we measured the PLEF development index of mountainous counties in Zhejiang Province from 2005 to 2020. Spatio-temporal evolution and spatial autocorrelation analyses were conducted, followed by identification of influencing factors. The results show that: (1) The average PLEF development index increased from 0.88 in 2005 to 1.56 in 2020, with growth contributions ranked as: living function (LF) > ecological function (EF) > production function (PF); (2) The developmental stages of PF, LF and EF transitioned from a "low-low-medium" pattern to a "medium-medium-high" configuration; (3) PLEF exhibited spatial agglomeration characteristics; however, the spatial agglomeration weakened and spatial dependency decreased during the study period; (4) Dominant factors shifted across subsystems: PF transitioned from agricultural production functions to non-agricultural production functions; LF shifted from life support functions to social welfare functions; EF remained primarily driven by ecological provisioning functions. These findings offer theoretical foundations for coordinating rural PLEF development and enhancing sustainability.

KEYWORDS

mountainous county, evaluation system, spatial pattern, influencing factor, production-living-ecological function

1 Introduction

Achieving human development and wellbeing while preserving ecological environments constitutes one of the most pressing global challenges and represents a core objective of the United Nations Sustainable Development Goals (SDGs) (Wood et al., 2018; Xu et al., 2020). The spatial patterns of PLEF based on rural functions are linked to 16 SDGs (Song et al., 2024), with SDG2 (Zero Hunger) and SDG15 (Life on Land) directly addressing agricultural production and ecological conservation. While improvements in global agricultural productivity have advanced poverty alleviation, malnutrition reduction, and human rights protection, they have concurrently caused ecological degradation and uneven rural development (Fanzo et al., 2021; Tudi et al., 2021). Rural areas not only serve as hubs for agricultural production but also require multifunctional roles encompassing economic, ecological, and cultural dimensions (Holmes, 2006; Wilson, 2008). To enhance rural economic resilience and ecological value, agricultural objectives must integrate sustainability principles, emphasizing coordinated functional development to address practical challenges (Hunter et al., 2017).

China is undergoing a critical phase of urbanization. On one hand, urban expansion has accelerated rural transformation and restructuring, partially constraining production spaces, fragmenting living spaces, and disrupting ecological balances (Cheng, 2021; Duan et al., 2021). On the other hand, the influx of technological, informational, and digital resources into rural areas has intensified challenges in resource utilization and allocation (Ma, 2023). Against this backdrop, the coordination of PLEF has emerged as a central priority for China's ecological civilization and sustainable development strategies (Yang et al., 2020). Since 2012, China has advocated for "intensive and efficient production spaces, livable and moderate living spaces, and pristine ecological spaces," marking a policy shift from production-centric approaches to PLEF coordination (Zhu and Qin, 2012). This transition has spurred extensive research on territorial spatial planning (Liao et al., 2022; Tian et al., 2020). In rural development, initiatives such as the New Rural Construction, New Urbanization, Beautiful Countryside, and Rural Revitalization strategies aim to enhance multifunctionality and drive rural transformation (Li et al., 2018; Long et al., 2011; Long et al., 2019). Nevertheless, persistent imbalances and inadequacies in rural PLEF development remain critical challenges requiring urgent resolution (Tu and Long, 2017). Consequently, understanding the evolutionary processes, interactions, and driving factors of rural PLEF is essential for evaluating the coordination and adaptability of China's rural development under rapid urbanization.

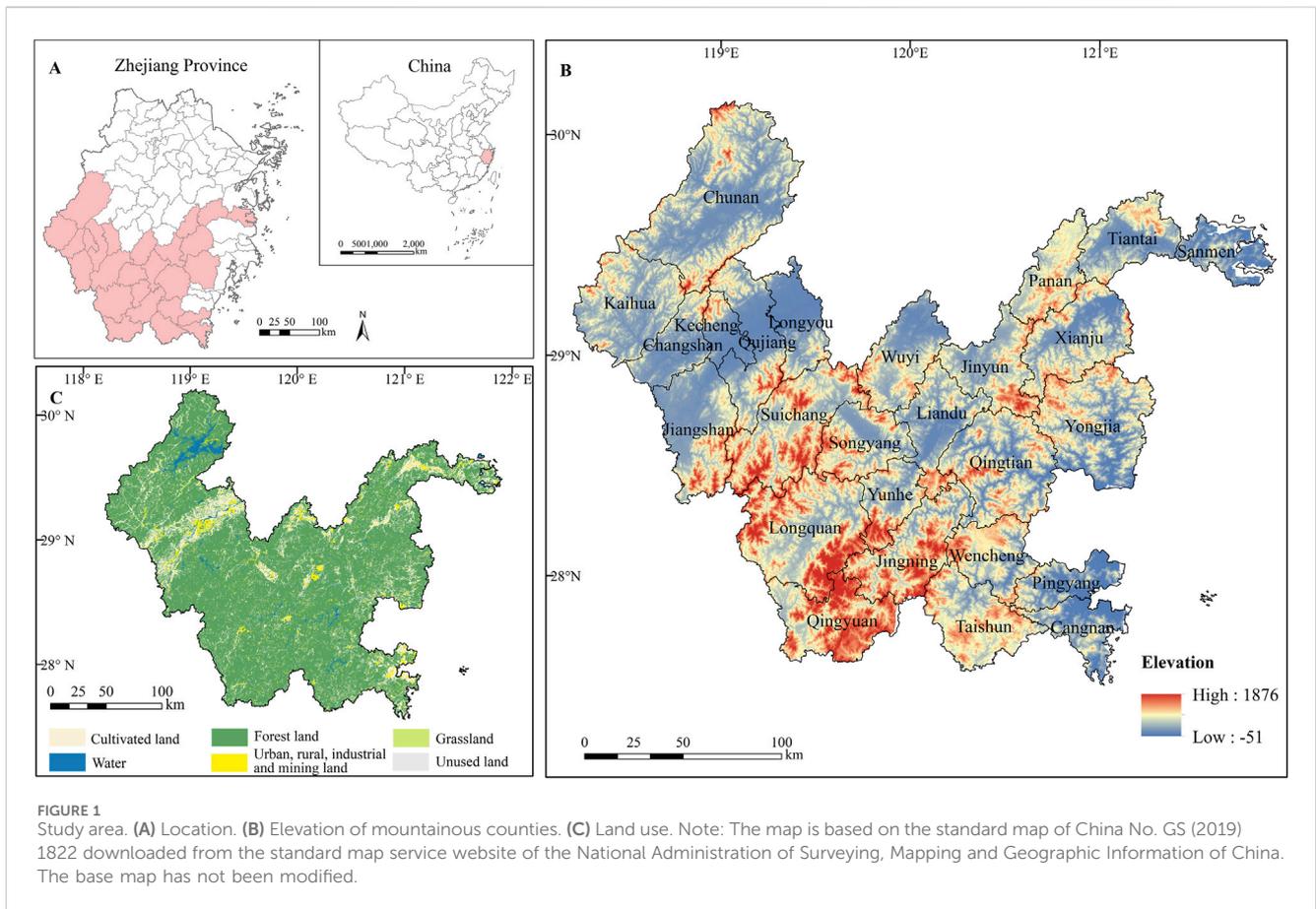
PF, LF, and EF are recognized as the core dimensions of rural systems (Zhou et al., 2024). PLEF research primarily encompasses functional evaluation, spatiotemporal evolution, and dynamic mechanisms (Holmes, 2006; Long et al., 2019; Qu et al., 2017; Liu et al., 2023; Zhao and Zhao, 2023; Zhou et al., 2024). The evaluation of PLEF serves as the foundation for rural functional studies, with existing methodologies predominantly relying on land use classification and index system construction (Li H. et al., 2024; Yu et al., 2024). While land use-based approaches enable fine-scale PLEF identification, they often inadequately address functional complexity and spatial heterogeneity (Ji et al., 2020; Wang

J. et al., 2023; Xia et al., 2023). Alternatively, index system methods comprehensively assess PLEF across production, living, and ecological dimensions, utilizing techniques such as entropy weighting and coupling coordination models. Though these methods demonstrate strong specificity and integration, significant variability persists in indicator selection (Yang DR. et al., 2024). Current evaluation frameworks predominantly employ statistical indicators, with limited integration of spatial data, land use data, and multi-source datasets.

Investigating spatio-temporal changes in regional PLEF constitutes a fundamental research task. Established analytical methods include gravity center models (Li XM. et al., 2024), land use transition matrices (Huang JT. et al., 2024), spatial autocorrelation analysis (Aruhan and Liu, 2024), kernel density estimation (Wang X. et al., 2024), standard deviational ellipse (Ke et al., 2025), landscape indices (Gong et al., 2024). While extensive research has focused on urban and territorial spaces, recent studies have expanded to rural and ecologically fragile areas (Ke et al., 2025; Li et al., 2022). Findings reveal significant transformations in China's rural industrial structures, living services, and ecological environments, accompanied by increasingly pronounced spatial differentiation of PLEF (Liu et al., 2023; Wang J. et al., 2016; Zhou et al., 2020). Temporally, studies predominantly analyze PLEF characteristics during rapid rural transitions (2000–2010), while spatially, investigations span global, national, regional, urban agglomeration, watershed, municipal, and county scales (Li Y. et al., 2024; Ren et al., 2024; Fu et al., 2023). Geographically, research has addressed PLEF in plains, coastal zones, and arid northwestern regions (Wubuli et al., 2024; Yang L. et al., 2024), yet mountainous counties along China's southeastern coast remain understudied.

The analysis of factors influencing PLEF spatial heterogeneity contributes to functional optimization. Researchers have applied correlation analysis, principal component analysis, grey relational analysis, GeoDetector, and random forest methods to investigate the impacts of natural environments, economic development, socio-cultural factors, policy systems, and technological progress on PLEF (Zhang et al., 2023; Zhang et al., 2022; Huang Y. et al., 2024). Specifically, rural PF is primarily influenced by natural conditions, agricultural productivity, and output value; LF by infrastructure, public services, and income levels; and EF by land use structure, global change, and pollution control (Zhou et al., 2024). However, the interactions among these influencing factors remain insufficiently explored.

Mountainous counties experience intensified PLEF conflicts due to complex terrain and limited development space (Zhu et al., 2024), rendering their PLEF coordination critical for regional sustainable development. China's Rural Revitalization Strategy has prioritized mountainous areas, with Zhejiang Province implementing progressive policies. In 2015, Zhejiang replaced GDP-based evaluations for mountainous counties with ecological protection and income growth metrics, initiating programs such as the Mountain-Coastal Collaboration Project, the Poverty Alleviation Campaign for Underdeveloped Townships, and the Special Support Policy for Key Underdeveloped Counties. The province further classifies mountainous counties into two categories: 15 designated for leapfrog development and 11 for ecological conservation. Nevertheless, systematic investigations into PLEF patterns and mechanisms in Zhejiang's mountainous counties remain lacking.



In summary, current PLEF studies exhibit three limitations: insufficient integration of multi-source data in evaluation systems, inadequate mechanistic analysis of spatio-temporal heterogeneity in southeastern coastal China, and limited exploration of factor interactions. This study addresses these gaps by constructing a county-level PLEF evaluation framework for Zhejiang’s mountainous counties. Through spatial autocorrelation analysis and driving factor identification, the findings provide theoretical and empirical support for optimizing rural PLEF coordination and promoting regional sustainable development.

2 Materials and methods

2.1 Overview of the study area

Zhejiang Province is located in the southern Yangtze River Delta along China’s southeastern coast, spanning 27°02’N to 31°11’N latitude and 118°01’E to 123°10’E longitude (Figure 1). Bordered by the East China Sea to the east, it adjoins Shanghai and Jiangsu Province to the north, Anhui and Jiangxi Provinces to the west, and Fujian Province to the south, with a total area of 105,500 km². As of 2024, the province governs 11 prefecture-level cities and 90 county-level administrative units (including municipal districts and county-level cities), achieving an urbanization rate of 75.5%.

Ranked fourth in China by GDP, Zhejiang represents a highly developed provincial economy with robust county-level

development, hosting 17 counties listed among China’s Top 100 Counties. It maintains one of the nation’s lowest urban-rural income disparities, recording a ratio of 1.83 in 2024. The province encompasses 26 mountainous counties, including Chunan, Yongjia, Pingyang, Cangnan, Wencheng, Taishun, Wuyi, Panan, Kecheng, Qujiang, Changshan, Kaihua, Longyou, Jiangshan, Sanmen, Tiantai, Xianju, Liandu, Qingtian, Jinyun, Suichang, Songyang, Yunhe, Qingyuan, Jingning, and Longquan. Primarily situated in southwestern Zhejiang’s hilly and mountainous terrain, these counties exhibit comparatively lower socio-economic development levels than non-mountainous regions, serving as focal areas for Zhejiang’s high-quality development and the construction of a common prosperity demonstration zone. Mountainous counties occupy approximately 45% of the province’s land area and account for nearly 24% of its population.

2.2 Data sources

Land use data for Zhejiang Province (2005, 2010, 2015, 2020) with a spatial resolution of 30 m were obtained from the Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, demonstrating over 93% accuracy in primary land use classification (Ning et al., 2018). Surface PM_{2.5} concentration data were sourced from Washington University in St. Louis, featuring a spatial resolution of 0.01° × 0.01° (Shen et al., 2024). The NDVI dataset was acquired from the PKU GIMMS

TABLE 1 Data sources in this study.

Date aspect	Data content	Time	Date source	Data declaration
Land use	Cultivated land, forest land, grassland etc.	2005, 2010, 2015, 2020	https://www.resdc.cn/	Raster (30 × 30 m)
Terrain	NASA DEM	2020	https://earthdata.nasa.gov/esds/competitive-programs/measures/nasadem	Raster (30 × 30 m)
NDVI	Global NDVI data in half-month	2005, 2010, 2015, 2020	https://zenodo.org/records/8253971	Raster (1/12° × 1/12°)
PM _{2.5}	Satellite-derived PM _{2.5}	2005, 2010, 2015, 2020	https://sites.wustl.edu/acag/datasets/	Raster (0.01° × 0.01°)

NDVI database (spatial resolution: 1/12° × 1/12°; temporal resolution: biweekly; temporal coverage: 1982–2022) (Li et al., 2023). County-level socioeconomic statistics were compiled from provincial statistical yearbooks (Zhejiang Statistical Yearbook), national statistical compilations (China Civil Affairs Statistical Yearbook, China Statistical Yearbook for Regional Economy), municipal yearbooks, and county-level statistical bulletins on national economic and social development. Administrative boundary data were provided by the National Geomatics Center of China (Table 1).

2.3 Theoretical framework

Rural systems, as multidimensional complexes, can be categorized into production, living, and ecological spaces, forming the PLEF dominated by PF, LF, and EF (Lu et al., 2024). PF serves as the foundation of rural PLEF. Its scope extends beyond agricultural output to encompass diverse agricultural, industrial, and service activities contributing to local economies and community wellbeing (Achu et al., 2021), specifically comprising agricultural production functions and non-agricultural production functions. Agricultural production functions focus on agricultural product supply capacity, including fundamental capacities like cropland utilization and food security, as well as enhanced capacities through technological advancements such as agricultural efficiency improvements and mechanization. Non-agricultural

production functions reflect rural areas’ wealth-generation capabilities beyond agriculture, primarily through supporting service economies and secondary/tertiary industries like rural tourism and handicrafts. LF quantifies rural residents’ living standards through socio-cultural and economic dimensions. It encompasses basic service provision, housing, and infrastructure supporting daily life, along with social welfare systems and safety net implementation (Qin et al., 2024). EF is crucial for maintaining environmental security and sustaining human livelihoods. It involves ecosystem service provision—clean water, air, soil, and biodiversity conservation—enhancing rural climate change resilience and disaster mitigation. Integrating ecological considerations into agricultural practices facilitates production-ecology balance.

PLEF components exhibit mutually reinforcing yet constraining relationships through complex feedback loops. PF provides material foundations for LF while generating ecological negative externalities. LF influences agricultural production patterns and consumes ecological resources. EF underpins agricultural sustainability and community viability. Synergistically, coordinated PLEF development enhances holistic rural sustainability and promotes high-quality development. Thus, rural PLEF emphasizes coordinated symbiosis among functional spaces, advocating scientific development paradigms over environmentally detrimental models. Its objectives include efficient resource utilization, improved resident wellbeing, and ecological conservation through functional harmonization (Figure 2).

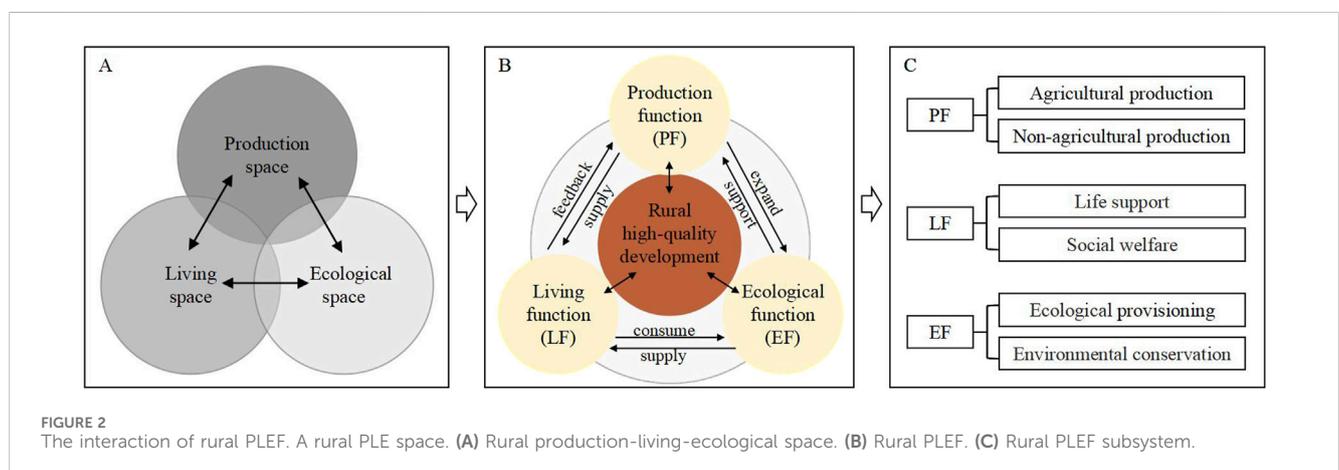


FIGURE 2 The interaction of rural PLEF. A rural PLE space. (A) Rural production-living-ecological space. (B) Rural PLEF. (C) Rural PLEF subsystem.

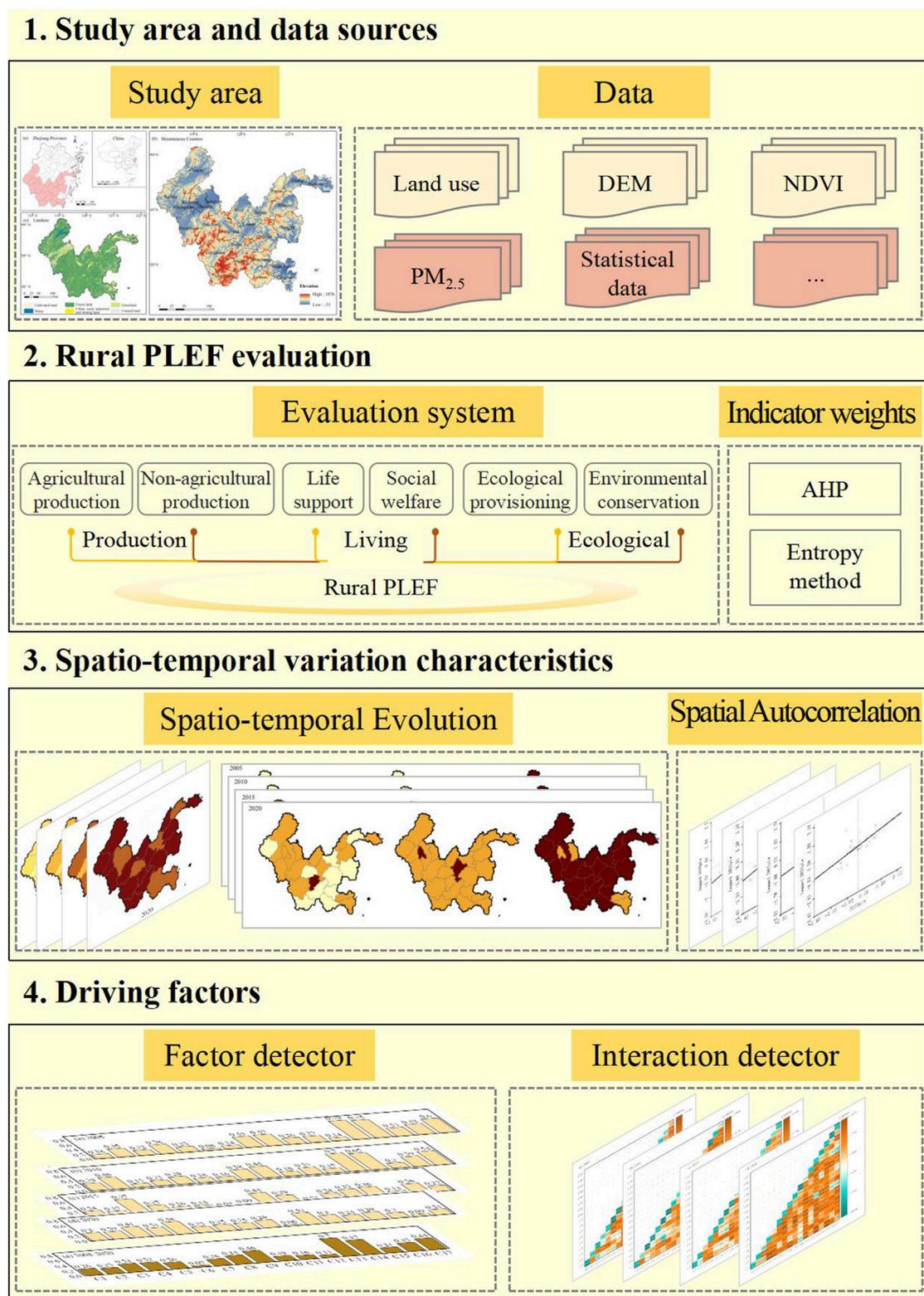


FIGURE 3 Framework of research concepts.

The conceptual framework of this study is illustrated in Figure 3. First, the research area was delineated, and multi-source data were collected and preprocessed. Subsequently, a rural PLEF evaluation

index system was constructed, with weights determined using a comprehensive evaluation method. This was followed by an analysis of spatial evolution characteristics and spatial autocorrelation

TABLE 2 County-level rural PLEF development index evaluation system.

Functions	Primary indicators	Secondary indicators	Direction
PF	Agricultural production	Rural <i>per capita</i> arable land area (C ₁)	Positive
		Rural <i>per capita</i> grain yield (C ₂)	Positive
		Agricultural labor productivity (C ₃)	Positive
		Agricultural mechanization level (C ₄)	Positive
	Non-agricultural production	Per capita output value of agriculture-related services (C ₅)	Positive
		Proportion of rural non-agricultural employment (C ₆)	Positive
LF	Life support	Per capita housing area of rural residents (C ₇)	Positive
		Per capita disposable income of rural residents (C ₈)	Positive
		Per capita electricity consumption of rural residents (C ₉)	Positive
		Engel coefficient of rural residents (C ₁₀)	Negative
	Social welfare	Proportion of rural residents receiving minimum living allowance (C ₁₁)	Negative
		Number of hospital beds per 10,000 rural residents (C ₁₂)	Positive
EF	Ecological provisioning	Forest coverage rate (C ₁₃)	Positive
		Mean NDVI (C ₁₄)	Positive
	Environmental conservation	Fertilizer application intensity (C ₁₅)	Negative
		Pesticide application intensity (C ₁₆)	Negative
		Annual average PM _{2.5} concentration (C ₁₇)	Negative

patterns of rural PLEF from 2005 to 2020. Finally, the influencing factors of each functional dimension and their interactive effects were systematically investigated.

2.4 Methods

2.4.1 Evaluation index system

Building upon the theoretical framework and referencing established methodologies (Wang S. et al., 2023; Yang et al., 2020), this study developed a county-level rural PLEF evaluation index system through comprehensive consideration of indicator stability and county-level data availability. After consulting nine domain experts from the Institute of Geographic Sciences and Natural Resources Research (Chinese Academy of Sciences), The Chinese University of Hong Kong, Zhejiang University, Zhejiang University of Finance and Economics, and Zhejiang Academy of Agricultural Sciences, the final system comprised 17 indicators across three dimensions: PF, LF, and EF (Table 2). For PF, agricultural production functions were assessed through four indicators: rural *per capita* arable land area (reflecting land resource endowment), rural *per capita* grain yield (food security), agricultural labor productivity (production efficiency), and agricultural mechanization level. Non-agricultural production functions were evaluated using *per capita* output value of agriculture-related services and the proportion of rural non-agricultural employment. LF evaluation incorporated two sub-dimensions: life support functions and social welfare functions. Life support metrics included rural *per capita* housing area (housing security), *per capita* disposable income of rural residents (income security), *per capita* electricity consumption of rural residents (living

service provision), and the Engel coefficient (consumption structure). Social welfare metrics featured the proportion of rural residents receiving minimum living allowance and number of hospital beds per 10,000 rural residents. EF assessment addressed ecological provisioning and environmental conservation. Ecological provisioning functions utilized forest coverage rate and mean NDVI, while environmental conservation functions employed fertilizer application intensity, pesticide application intensity, and annual average PM_{2.5} concentration.

To ensure indicator comparability, panel data underwent standardized processing. The min-max normalization method (Li et al., 2012) was employed, with distinct formulas applied to positive and negative indicators (Equation 1):

$$\begin{aligned}
 Y_{\lambda ij} &= (x_{\lambda ij} - x_{\min}) / (x_{\max} - x_{\min}), \text{ Positive indicators} \\
 Y_{\lambda ij} &= (x_{\max} - x_{\lambda ij}) / (x_{\max} - x_{\min}), \text{ Negative indicators}
 \end{aligned}
 \tag{1}$$

Where $x_{\lambda ij}$ denotes the original value of the j th indicator for county i in year λ , and $Y_{\lambda ij}$ represents the normalized value.

2.4.2 Indicator weights

Weight assignment methods are categorized into subjective and objective approaches. Subjective methods, including Delphi, Analytic Hierarchy Process (AHP), and Analytic Network Process, rely on expert judgment. AHP, the most widely applied technique, establishes hierarchical goal-criteria-subcriteria structures to align weights with theoretical expectations, though results remain expert-dependent (Watson and Hudson, 2015). Objective methods such as factor analysis, principal component analysis, and entropy weighting derive weights mathematically. The

entropy method, rooted in thermodynamic principles, eliminates subjective bias but risks data-driven distortions (Hussain et al., 2020). This study combines AHP and entropy weighting to calculate composite weights for the county-level rural PLEF development index, mitigating individual method limitations (Zhou et al., 2024). The procedure involves:

Step 1: AHP method. First, relative importance scores were assigned by nine experts to determine indicator priorities. Second, judgment matrices were constructed to calculate eigenvalues. Finally, consistency checks were performed to validate and finalize factor weights (Suganthi, 2018).

Step 2: Entropy Method. First, normalized processing of indicators was conducted (Equation 2). Second, the information entropy of each indicator was computed (Equation 3). Finally, indicator weights were determined (Equations 4, 5).

$$P_{\lambda ij} = Y_{\lambda ij} / \sum_{\lambda=1}^t \sum_{i=1}^m Y_{\lambda ij} \tag{2}$$

$$E_j = -\frac{1}{\ln(t \times m)} \sum_{\lambda=1}^t \sum_{i=1}^m P_{\lambda ij} \ln(P_{\lambda ij}) \tag{3}$$

$$W_{j(p,l,e)} = (1 - E_j) / \sum_{j=1}^n (1 - E_j) \tag{4}$$

$$Z_{\lambda i(p,l,e)} = \sum_{j=1}^n P_{\lambda ij} W_j \tag{5}$$

Where $P_{\lambda ij}$ represents the normalized value of the indicator, E_j denotes information entropy, W_j is the weight of each indicator, and $Z_{\lambda i(p,l,e)}$ corresponds to the annual county-level evaluation scores for rural PF, LF, EF. t denotes the number of time cross-sections (4 years), n is the number of indicators, and m represents the number of counties.

Step 3: Composite Weight. The final composite weights were derived by averaging the weights obtained from AHP and entropy methods. The development indices for rural PF, LF, and EF were categorized into three tiers: low level (0–0.3), medium level (0.3–0.6), and high level (0.6–1) (Cheng et al., 2019).

2.4.3 ESDA

ESDA, a widely applied spatial econometric method, is primarily employed to characterize spatial distribution patterns and structural features of data while revealing spatial autocorrelation characteristics (Ma and Pei, 2010). This study utilizes global and local spatial autocorrelation analyses under the ESDA framework to investigate the spatial interdependencies and associations of rural PLEF development index. The formulas are as follows (Equation 6):

$$I_i = \frac{X_i - \bar{X}}{\sum_{i=1}^n (X_i - \bar{X})^2} \sum_{j=1}^n W_{ij} (X_j - \bar{X})$$

$$I = \frac{n \sum_{i=1}^n \sum_{j=1}^n W_{ij} (X_i - \bar{X})(X_j - \bar{X})}{\sum_{i=1}^n (X_i - \bar{X})^2 \sum_{j=1}^n W_{ij}}$$

$$W_{ij} = 1 / d_{ij}^2 \tag{6}$$

Where I_i represents the local spatial autocorrelation index, I is the global spatial autocorrelation index, X_i and X_j are the spatial sequences of counties i and j , W_{ij} is the spatial weight matrix based on geographic distance, d_{ij} is the Euclidean distance between the geographic centroids of counties i and j , and n is the number of county-level units. This study employed K-nearest neighbors methodology to construct spatial weight matrices based on Euclidean distance measurements between geographic centroids.

2.4.4 GeoDetector

GeoDetector is a spatial statistical method primarily employed to identify spatial heterogeneity of variables and analyze influencing factors and their interactions on geographic element differentiation (Wang Y. et al., 2016). It comprises four sub-detectors: factor detector, risk detector, interaction detector, and ecological detector. This study applied factor detection to assess the explanatory power of influencing factors on spatial heterogeneity of rural PLEF development indices, while interaction detection examined factor interdependencies (Hou et al., 2022). The computational formula is expressed as Equation 7:

$$q = 1 - \frac{1}{N\sigma^2} \sum_{i=1}^n N_i \sigma_i^2 \tag{7}$$

where q quantifies the explanatory power of influencing factors on rural PLEF development levels, with values ranging [0, 1]. Higher q values indicate stronger explanatory capacity for spatial heterogeneity of PLEF, and *vice versa*. The implementation involved two phases:

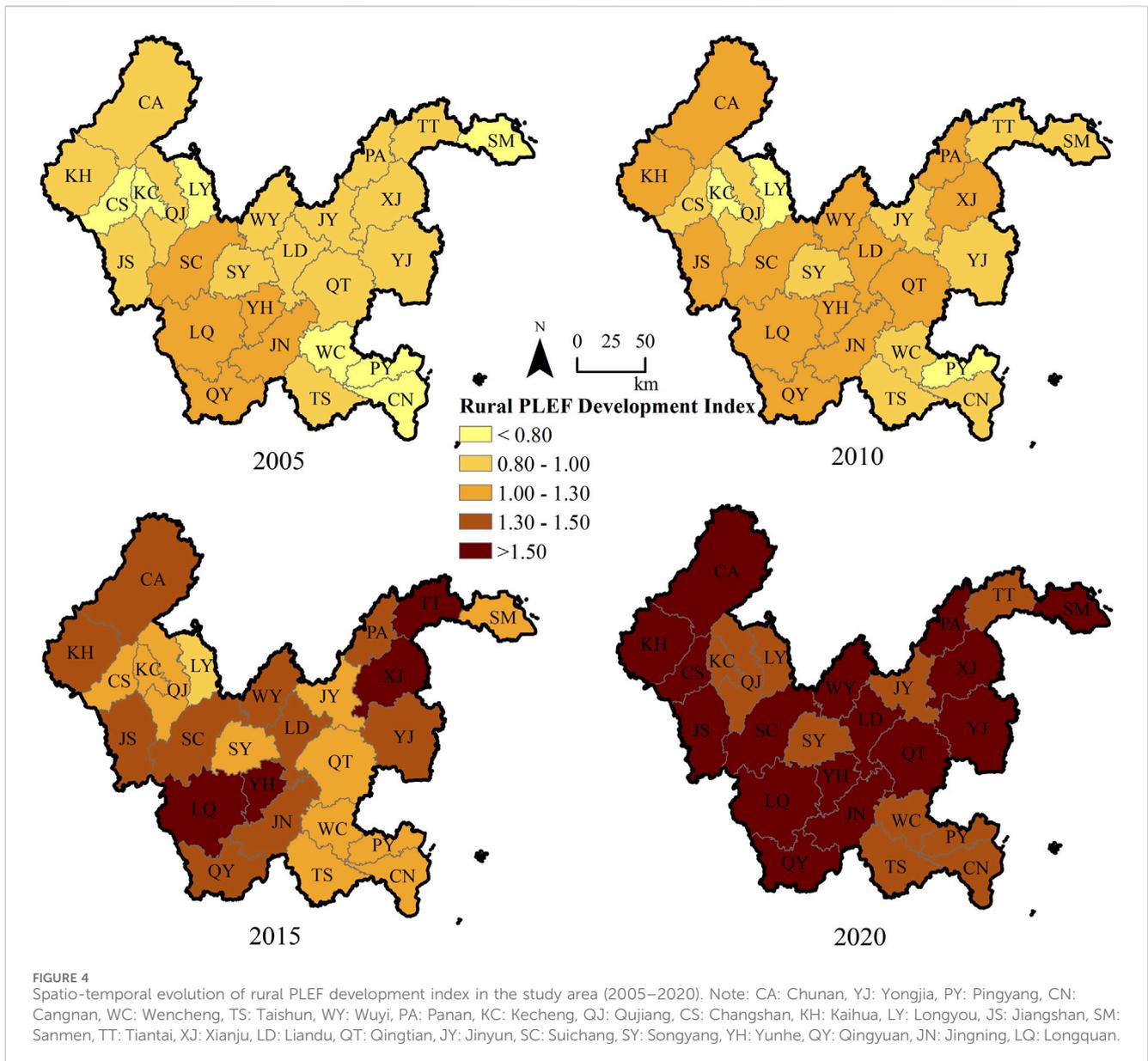
Step1: Data discretization. Continuous independent variables were discretized using the natural breaks method. A file geodatabase was created in ArcGIS software, followed by importing feature classes. Data classification was performed through attribute-based symbology representation before exporting processed datasets.

Step2: Geographical detection. The GeoDetector software was utilized to import discretized independent variables and dependent variable data. Software execution generated geographical detection results, including q statistics and interaction matrices.

3 Results

3.1 Spatio-temporal evolution characteristics of rural PLEF

Overall, the average rural PLEF development index of mountainous counties in Zhejiang Province increased from 0.88 in 2005 to 1.56 in 2020, with a total growth of 0.67. The contributions to this growth ranked as follows: LF (46.05%) > EF (32.58%) > PF (21.36%). The average growth of PLEF development index in ecological conservation counties (0.63) was significantly smaller than that in leapfrog development counties (0.72). The spatial distribution of rural PLEF development index evolved



toward equilibrium. In 2005, high-value areas were concentrated in five ecological conservation counties; by 2010, high-value zones expanded significantly; in 2015, a “multi-core” spatial pattern emerged; by 2020, the distribution became more balanced, with 16 counties exceeding a PLEF index of 1.5, including nine ecological conservation counties (Figure 4).

The average PF development index increased from 0.19 in 2005 to 0.34 in 2020, transitioning from low to medium levels. Structurally, the score ratio of agricultural production functions to non-agricultural production functions shifted from 57.80:42.20 in 2005 to 48.95:51.05 in 2020, indicating a significant rise in non-agricultural contributions. Spatially, all counties were at low PF levels in 2005; by 2010, five counties reached medium levels; by 2020, 15 counties achieved medium or high PF levels (10 of which were leapfrog development counties), though spatial imbalances remained pronounced.

The average LF development index rose from 0.14 in 2005 to 0.46 in 2020, advancing from low to medium levels. Structurally, the ratio of life support function to social welfare function shifted from 60.26:39.74 in 2005 to 75.14:24.86 in 2020, driven by sustained growth in rural disposable income. Spatially, all counties remained at low LF levels from 2005 to 2010; by 2015, 25 counties reached medium levels; by 2020, two leapfrog development counties attained high LF levels.

The average EF development index improved from 0.54 in 2005 to 0.77 in 2020, progressing from medium to high levels. Structurally, the ratio of ecological provisioning function to environmental conservation function shifted from 44.27:55.73 in 2005 to 37.23:62.77 in 2020, reflecting strengthened environmental protection measures. Spatially, 12 counties had high EF levels in 2005, increasing to 22 counties by 2020, demonstrating continuous ecological improvements (Figure 5).

3.2 Spatial autocorrelation analysis of rural PLEF

Based on the rural PLEF development index scores in 2005, 2010, 2015, and 2020, the global Moran's I values were calculated using the spatial autocorrelation analysis tool in GeoDa software, with results shown in Table 3. All global Moran's I values were positive, with Z-scores significantly exceeding the upper limit of the uniform distribution interval and P-values below 0.05, passing the 5% significance test. These findings indicate significant positive spatial correlation in the rural PLEF development index of Zhejiang's mountainous counties, demonstrating spatial clustering. The global Moran's I values declined and stabilized over time, suggesting reduced spatial dependency among mountainous counties and an emerging spatial distribution pattern characterized by "small clusters with broad dispersion".

The local spatial autocorrelation analysis was conducted by plotting the rural PLEF development index scores on the horizontal axis against spatial lag values on the vertical axis, generating a scatter plot (Figure 6). Statistically significant points were categorized into four cluster types (Table 4). High-High (HH) clusters, located in the first quadrant, are characterized by both focal and neighboring counties exhibiting high PLEF development index, indicating localized positive spatial correlation. From 2005 to 2020, the number of counties in HH

TABLE 3 Global spatial autocorrelation of rural PLEF development index (2005–2020).

	2005	2010	2015	2020
Moran's I	0.293	0.271	0.155	0.191
Z-score	2.850	2.551	1.699	2.072
P-value	0.007	0.015	0.044	0.003

clusters within Zhejiang's mountainous counties gradually decreased, reflecting weakened spatial agglomeration. Low-High (LH) clusters, situated in the second quadrant, feature focal counties with low PLEF indices surrounded by neighboring counties with high indices, demonstrating spatial negative correlation and functioning as "depression zones" adjacent to high-value areas. SY county consistently remained an LH cluster throughout the study period. Low-Low (LL) clusters, occupying the third quadrant, exhibit low PLEF index in both focal and neighboring counties, representing localized spatial autocorrelation. Between 2005 and 2020, the spatial distribution of LL clusters shifted from western to southeastern regions. High-Low (HL) clusters, located in the fourth quadrant, are defined by focal counties with high PLEF indices adjacent to neighboring counties with low indices, indicating spatial negative correlation. The number of counties in HL clusters decreased over time, reaching zero by 2020.

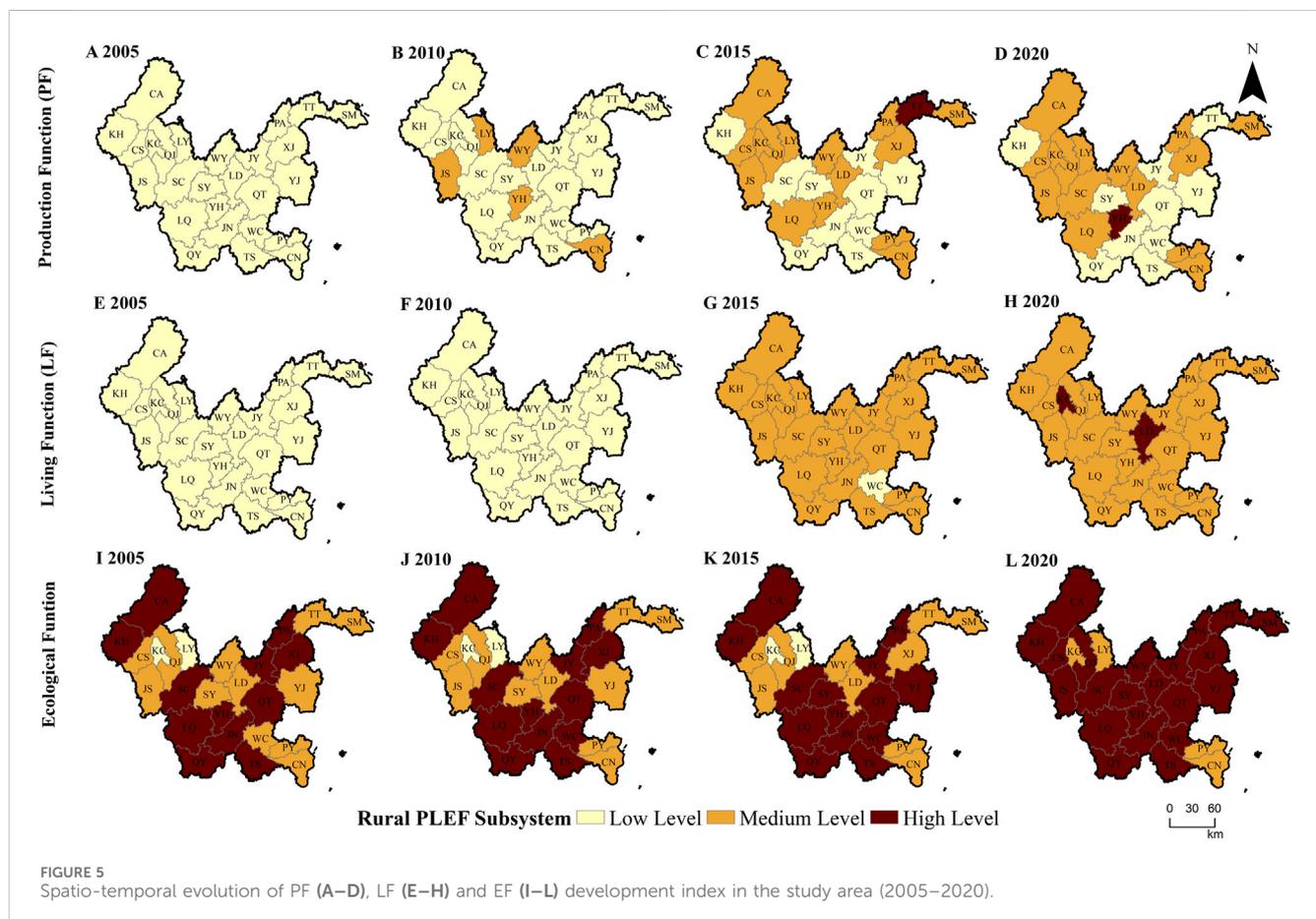


FIGURE 5 Spatio-temporal evolution of PF (A–D), LF (E–H) and EF (I–L) development index in the study area (2005–2020).

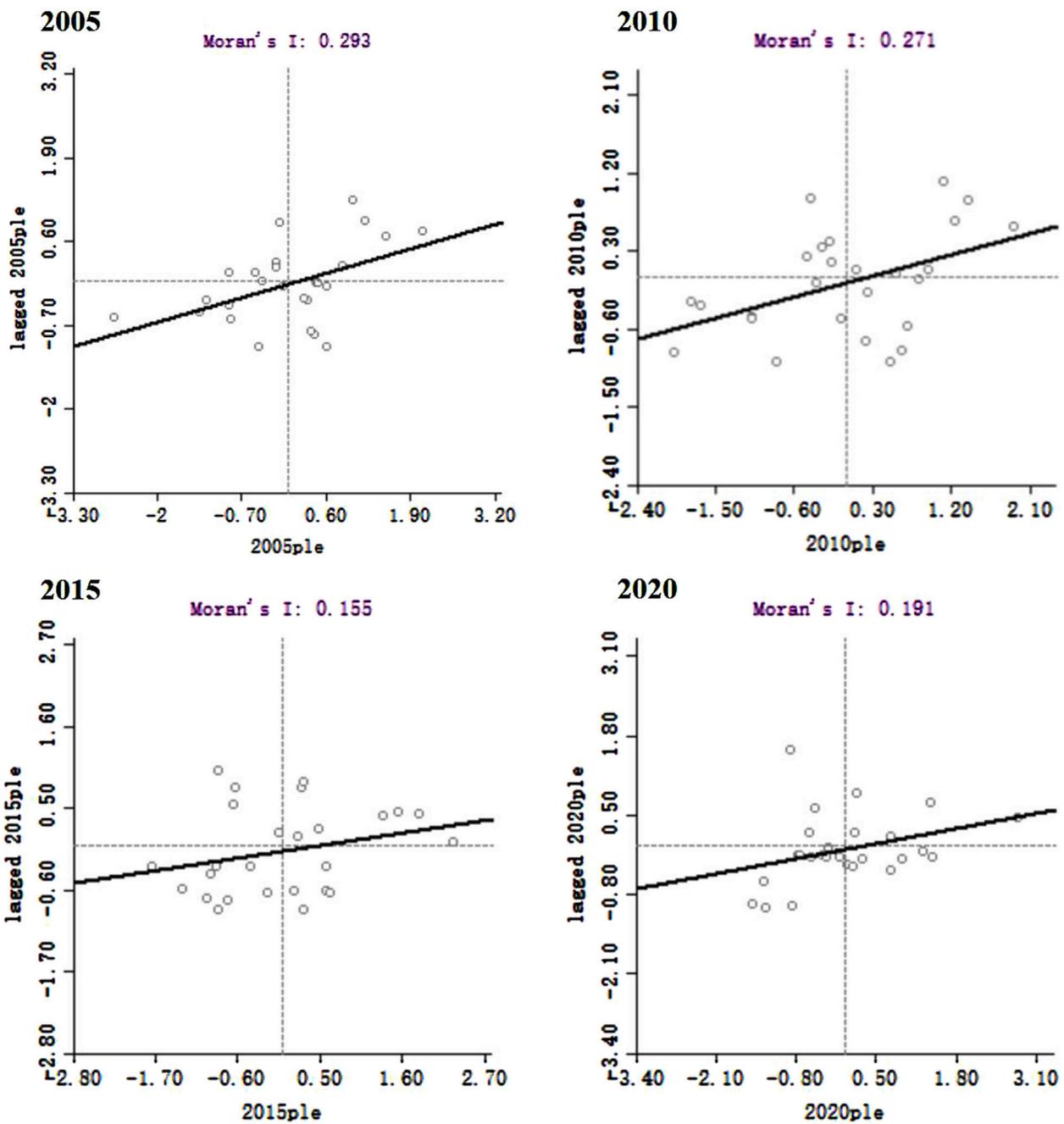


FIGURE 6 Local Moran's I scatter plot of Rural PLEF development index in the study area (2005–2020).

3.3 Identification of influencing factors for rural PLEF

Overall, agricultural labor productivity (C_3) and agricultural mechanization level (C_4) were the dominant influencing factors for PF, *per capita* electricity consumption of rural residents (C_9) and *per capita* disposable income of rural residents (C_8) for LF, and forest coverage rate (C_{13}) and mean NDVI (C_{14}) for EF. Temporal analysis revealed shifts in dominant drivers across years. For PF in 2005, the primary influencing factor was agricultural mechanization level

(C_4), which shifted to *per capita* output value of agriculture-related services (C_5) by 2020, indicating a transition from agricultural production focus to non-agricultural production emphasis. For LF, the main factor evolved from *per capita* electricity consumption of rural residents (C_9) to proportion of rural residents receiving minimum living allowance (C_{11}), reflecting a shift from basic life support to social welfare prioritization. For EF, the dominant factor transitioned from forest coverage rate (C_{13}) to mean NDVI (C_{14}), though ecological provisioning remained the core functional driver (Figure 7).

TABLE 4 Local spatial autocorrelation of rural PLEF development index (2005–2020).

Cluster type	2005	2010	2015	2020
HH	LQ, YH, QY, JN	LQ, QY	QY	QY
LH	SY	SY	SY, SM	SY
LL	KC, QJ	KC, QJ	CN	TS, PY, CN
HL	CA, KH	CA, KH	CA	-

The interaction detection results revealed nonlinear enhancement and bifactor enhancement effects, indicating that all interactive factors significantly amplified their explanatory power on the spatial heterogeneity of rural PLEF compared to individual factors (Figure 8). This demonstrates that the spatial differentiation of PLEF arises from the synergistic effects of multiple factors. In 2005, interactions involving *per capita* disposable income of rural residents (C_8), forest coverage rate (C_{13}), and mean NDVI (C_{14}) exhibited q-values exceeding 0.7, with the strongest interaction observed between agricultural labor productivity (C_2) and forest coverage rate (C_{13}) ($q = 0.973$). By 2010, interactions linked to forest coverage rate (C_{13}) and mean NDVI (C_{14}) dominated ($q > 0.7$),

peaking in the interaction between forest coverage rate (C_{13}) and fertilizer application intensity (C_{15}) ($q = 0.979$). In 2015, agricultural labor productivity (C_3) emerged as a key interactive factor ($q > 0.7$), while the interaction between the Proportion of rural residents receiving minimum living allowance (C_{11}) and forest coverage rate (C_{13}) showed the highest explanatory power ($q = 0.970$). By 2020, the Proportion of rural residents receiving minimum living allowance (C_{11}) became the primary factor influencing spatial heterogeneity, with the strongest interaction observed between rural *per capita* arable land area (C_1) and fertilizer application intensity (C_{15}) ($q = 0.931$).

4 Discussion

4.1 Discussion on the PLEF evaluation system

This study developed a PLEF evaluation system using multi-source data, establishing a research framework for measuring and analyzing the evolutionary patterns of rural PLEF at the county level. However, due to the inherent complexity of rural functions and limitations in data availability at the county scale, the indicator

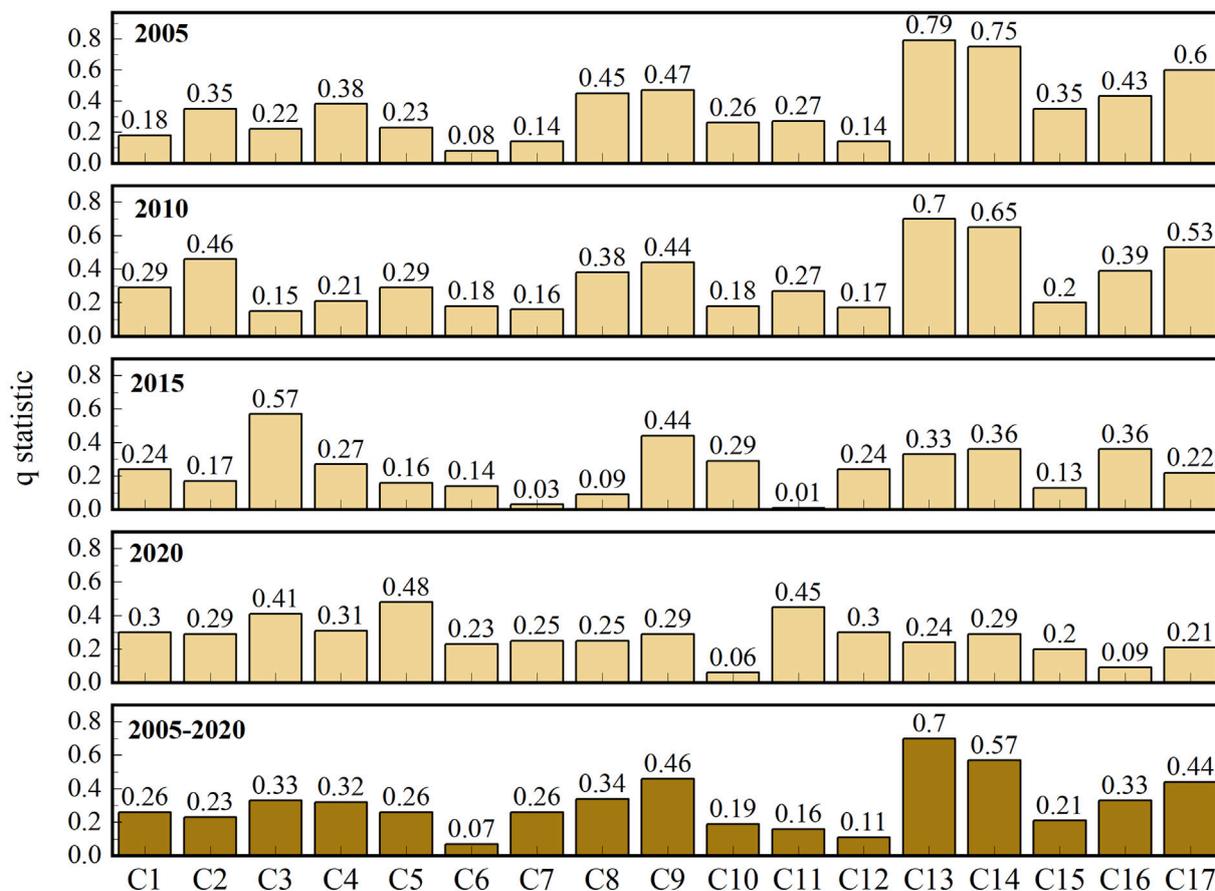
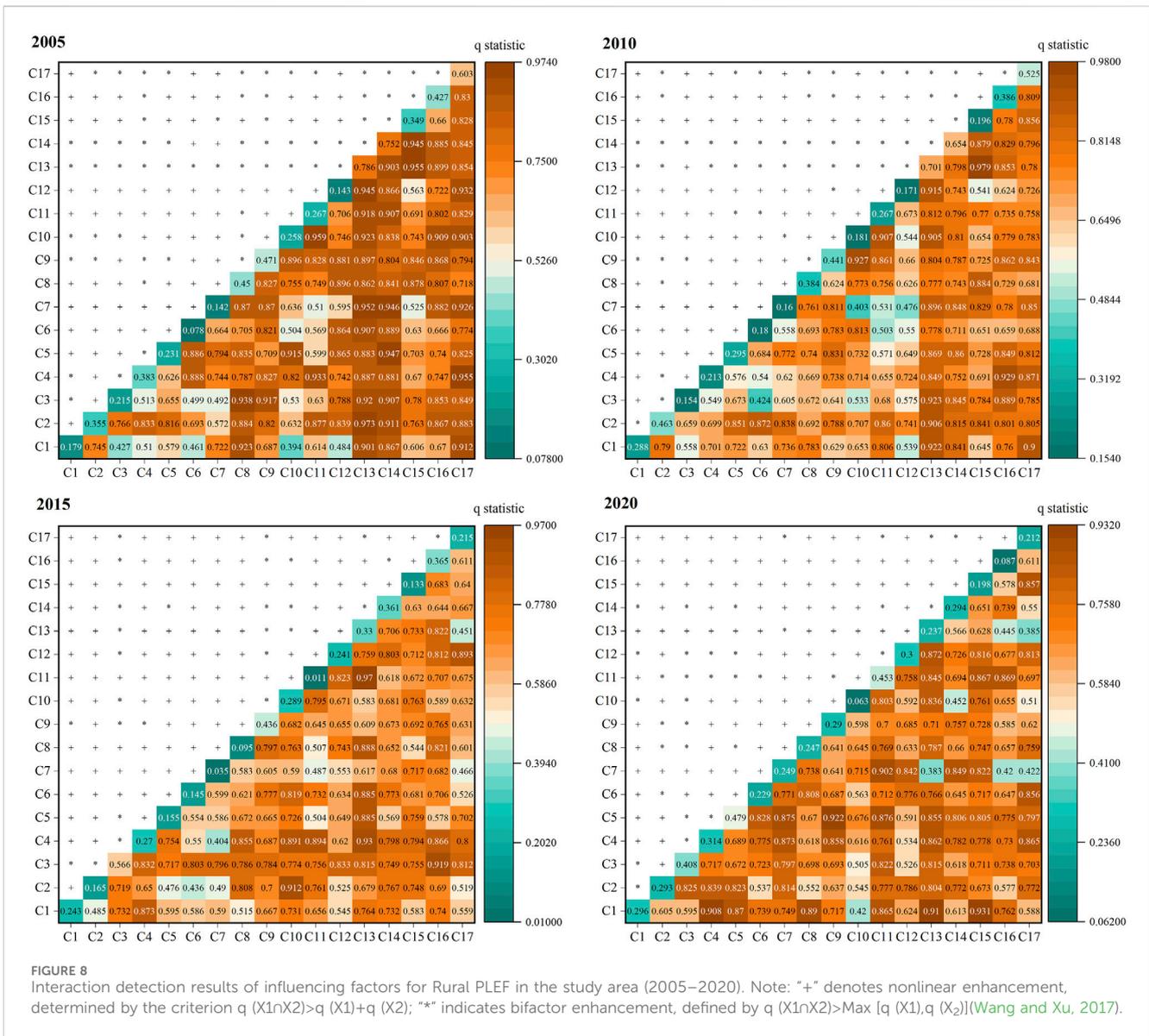


FIGURE 7 Geodetector results of influencing factors for rural PLEF development index in the study area (2005–2020).



design does not comprehensively cover all aspects of PLEF. While spatial data such as land use, PM_{2.5} concentration, and NDVI were incorporated, the majority of indicators remain statistics-based. Although statistical reporting standards are consistent across counties, absolute data accuracy cannot be fully guaranteed. Future research should integrate expanded data sources, including field surveys, POI data, and UAV monitoring, to enhance the evaluation system's precision and holistically capture the functional evolution of mountainous PLEF.

4.2 Differential responses of PLEF evolution in mountainous counties

Mountainous areas, covering over 60% of China's land area, represent a quintessential geographical feature. Existing studies indicate an overall upward trend in PF and LF, while EF exhibit

significant variability, particularly fluctuating in industrialized regions (Wang YF. et al., 2024). Economically developed coastal areas generally demonstrate improvements in EF (Zhang HZ. et al., 2024), aligning with the findings of this study conducted in the southeastern coastal region of China.

Regarding the influence of topographic factors on mountainous rural PLEF, prior research suggests that EF dominate at high elevations, whereas PF and LF are more prevalent in low-gradient areas (Zhang J. et al., 2024). Other studies highlight the adverse effects of topographic complexity on LF (Zhang W. et al., 2024). This study analyzed correlations between topographic factors (elevation and slope) and PLEF subsystem development levels in 2020, revealing no significant correlation between PF and topography, a significant negative correlation between mean elevation and LF, and significant positive correlations between mean elevation/slope and EF (Figure 9).



4.3 Driving mechanisms of rural PLEF

Regarding driving factors, all 17 factors exhibited either nonlinear enhancement or bifactor enhancement effects on rural PLEF, indicating mutually reinforcing interactions among factors. The driving mechanisms of rural PLEF are illustrated in Figure 10. During the 2005–2010 period, rural PLEF underwent infrastructure development and initial integration. Centered on the “Thousand Villages Demonstration, Ten Thousand Villages Renovation” project (referred to as the “Ten-Thousand Villages Project”), this phase prioritized rural infrastructure construction and environmental remediation. PF was dominated by traditional agriculture, with preliminary planning of grain production functional zones laying the foundation for subsequent modern agricultural development. LF focused on improving basic rural residential conditions, including gradual upgrades to electricity and water supply systems, while EF initially emphasized increasing forest coverage. From 2010 to 2015, rural PLEF transitioned toward ecological transformation and systemic enhancement. Guided by the “Beautiful Countryside Construction” initiative, this stage emphasized integrated development of ecological habitats, economies, environments, and cultures. PF shifted to modern agricultural parks, significantly boosting agricultural labor productivity. LF prioritized equal access to urban-rural public services, further improving rural living conditions. EF strengthened systematic governance and resource recycling, fostering green development trends. The 2015–2020 period marked high-quality development and multi-sectoral synergy. Driven by the Rural Revitalization Strategy, this phase promoted coordinated development of rural PLEF. Agricultural production advanced through digital transformation, while secondary and tertiary industries flourished. LF emphasized narrowing urban-rural disparities, with

increased focus on livelihood security for low-income rural populations. EF prioritized holistic governance and resilience enhancement through sustained ecological restoration efforts.

This study primarily investigated the evolution and influencing factors of rural PLEF in mountainous counties but did not conduct comparative analyses with non-mountainous counties, which could further elucidate the distinctive characteristics of mountainous PLEF. Future research should strengthen interregional comparisons of PLEF and optimization strategies for rural PLEF. Additionally, while this study focused on the explanatory power of individual indicators within the evaluation system, it did not quantify the contributory weights of factors or explore potential driving effects from other variables. Future studies could systematically investigate multidimensional drivers of rural PLEF development and subsystem performance, including but not limited to policy formulation, population migration, land-use changes, economic development, and technological innovation.

4.4 Relationship between PLEF and rural policy

Since 2003, Zhejiang Province has implemented the “Ten-Thousand Villages Project” for over two decades, alongside a series of policies targeting rural construction and urban-rural integration in mountainous counties. These initiatives have significantly improved rural ecological environments and livability (Lin and Hou, 2023; Wang et al., 2019), effectively narrowed regional disparities, and promoted the gradual enhancement of rural PLEF development levels (Zhou et al., 2017). In 2023, Zhejiang’s experience with the “Ten-Thousand Villages Project” was nationally promoted. The 2024 Central No. One Document of China emphasized “learning and applying the

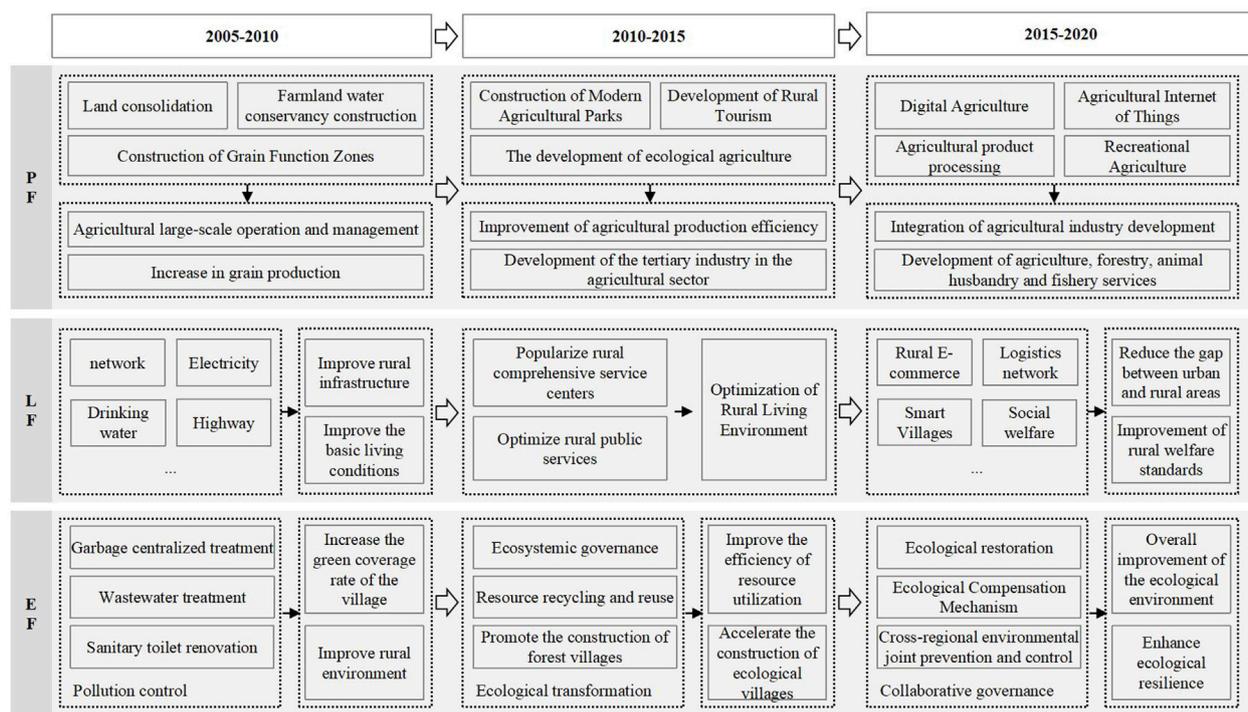


FIGURE 10 Driving mechanism of the rural PLEF.

development philosophy, methodologies, and implementation mechanisms embedded in the ‘Ten-Thousand Villages Project.’ The evolution of rural PLEF in Zhejiang’s mountainous counties has been synergistically driven by rural development policies, as follows:

First, the ‘Beautiful Countryside’ and common prosperity policies have enhanced rural LF. This study found that LF contributed most significantly to PLEF improvement in Zhejiang, attributable to the ‘Ten-Thousand Villages Project’s’ continuous upgrades to rural infrastructure and public services, alongside common prosperity policies that expanded farmers’ income channels and safeguarded basic welfare. Second, ecological prioritization and green development policies have strengthened rural EF. Guided by the ‘lucid waters and lush mountains are invaluable assets’ philosophy, Zhejiang has advanced ecological restoration, pollution control, and resource recycling. Mountainous counties have adopted the ‘Ecological County’ strategy to accelerate green agricultural development (Zhao et al., 2019). Third, industrial cultivation and targeted assistance policies have boosted PF. Focusing on whole-industry-chain development and technological empowerment, mountainous counties have upgraded PF toward high-value-added and specialized sectors. A classified development strategy categorizes mountainous counties into two types: leapfrog development counties focusing on eco-industries and technological innovation, and ecological conservation counties prioritizing distinctive advantageous industries. The ‘One County, One Policy’ framework promotes high-quality development, while strategies like ‘Mountainous Zhejiang’ and ‘Mountain-Sea Collaboration’ have spatially balanced PLEF development across regions.

However, challenges remain in Zhejiang’s mountainous PLEF development. First, PF require further enhancement. As rural industrial revitalization is the cornerstone of rural revitalization, this study identifies PF as the weakest link in mountainous PLEF. Urgent measures—including technological innovation, institutional reforms, and targeted assistance—are needed to improve agricultural productivity and accelerate modernization (Hu et al., 2023; Zhao and Li, 2022). Second, ecological conservation counties lag behind leapfrog development counties in PLEF performance. Prioritizing the development of ecological conservation counties is critical for Zhejiang’s goal of building a common prosperity demonstration zone.

5 Conclusion

Based on the theoretical framework, this study constructed a PLEF evaluation system comprising 17 indicators across three dimensions. Taking Zhejiang’s mountainous counties as the study area, the rural PLEF and subsystem development index were calculated for 2005, 2010, 2015, and 2020. Through analyzing the spatio-temporal evolution of PLEF, PF, LF, and EF, this study clarified the spatial heterogeneity of rural PLEF and identified key driving factors across different periods. The main conclusions are as follows:

- (1) From 2005 to 2020, the rural PLEF development index in Zhejiang’s mountainous counties increased significantly, with

LF contributing the most to PLEF growth (46.05%), followed by EF and PF. The growth rate of PLEF index in ecological conservation counties was notably lower than that in leapfrog development counties. The spatial evolution of rural PLEF exhibited distinct heterogeneity, transitioning from a “single-core” to a “multi-core” spatial pattern and ultimately achieving balanced development.

- (2) Disparities existed in the development levels of PLEF subsystems. During the study period, the PF development index transitioned from low-level to medium-level stages, with the proportion of non-agricultural PF rising from 42.20% to 51.05%. The LF development index advanced from low-level to medium-level stages, with a significant overall leap occurring between 2010 and 2015. The EF development index progressed from medium-level to high-level stages.
- (3) The rural PLEF development index exhibited positive spatial correlation with clustering characteristics. However, spatial dependency gradually weakened over time, evolving into a “small clusters with broad dispersion” distribution pattern.
- (4) The primary influencing factors for rural PF were agricultural labor productivity and agricultural mechanization levels, with the dominant function shifting from agricultural production to non-agricultural production during the study period. For rural LF, the key factors were rural *per capita* electricity consumption and disposable income, with the dominant function transitioning from life support to social welfare. For rural EF, forest coverage rate and NDVI were the main drivers, with ecological provisioning remaining the dominant function throughout the study period.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

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Ethics statement

No human studies are presented in the manuscript. No potentially identifiable images or data are presented in this study.

Author contributions

ZX: Conceptualization, Data curation, Formal Analysis, Investigation, Methodology, Software, Validation, Visualization, Writing–original draft. FK: Funding acquisition, Supervision, Validation, Writing–review and editing. JY: Validation, Writing–review and editing.

Funding

The author(s) declare that financial support was received for the research and/or publication of this article. This research was funded by the Soft Science Research Program Project of Zhejiang Province, grant number 2020C35002.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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