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Spatiotemporal evolution characteristics and influencing factors of eco-efficiency of cultivated land use in southern mountainous regions of China

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Against the backdrop of multiple pressures on cultivated land protection and the advancement of ecological civilization construction, enhancing the ecological efficiency of cultivated land utilization (ECLU) is crucial for sustainable agricultural development in the hilly and mountainous regions of southern China. This study takes 76 counties/districts in Fujian Province, a typical hilly and mountainous province, as research units. Based on panel data from 2013 to 2022, it employs the Super-SBM model considering undesirable outputs to measure ECLU. Combined with Exploratory Spatial Data Analysis (ESDA), Random Forest (RF), and Geographically and Temporally Weighted Regression (GTWR) models, the study reveals the spatiotemporal evolution characteristics and influencing factors of ECLU. The results indicate that: (1) The overall ECLU in Fujian Province is relatively low (0.54–0.73), showing a fluctuating upward trend. Spatially, it exhibits a significant "higher in the northwest, lower in the southeast" differentiation pattern, with efficiency generally higher in inland areas than in coastal areas. (2) ECLU demonstrates significant positive spatial autocorrelation. High–High (HH) clusters are mainly distributed in the northwestern inland region, while Low–Low (LL) clusters are concentrated in the southeastern coast. (3) The Random Forest model identified agricultural planting structure, cultivated land management scale per laborer, and proportion of agricultural output value as key influencing factors. The GTWR model further revealed significant spatiotemporal heterogeneity in the effects of these factors, with fertilizer input level being the primary negative driver. This research provides a scientific basis for optimizing cultivated land resource allocation and enhancing ecological efficiency in southern China's mountainous regions. Key recommendations include controlling fertilizer input, optimizing planting structure, developing moderate-scale operations, and strengthening regionally differentiated policy guidance.

KEYWORDS

eco-efficiency of cultivated land utilization, Fujian Province, influencing factors, mountainous regions of southern China, spatiotemporal evolution

1 Introduction

Cultivated land serves as the fundamental resource underpinning human survival and development. It not only bears the responsibility for ensuring food security but also plays a crucial role in maintaining the balance of global ecosystems (Li L. et al., 2025). However, under the combined pressures of population growth, urban expansion, industrialization, and climate change, global cultivated land resources are facing multiple threats. These include declining quantity, degrading quality, and weakening ecological functions (FAO, 2022). Consequently, the United Nations Sustainable Development Goal (SDGs)—particularly Goal 2 (Zero Hunger) and 13 (Climate Action)—urgently call on all nations to explore and implement land-use models that integrate efficient agricultural production with ecological and environmental protection.

Against this global backdrop, China, as the world's most populous economy, sustains one-fifth of the global population with less than 9% of the world's arable land (Sun et al., 2023). Therefore, the protection and sustainable use of cultivated land are pivotal for ensuring national food security and advancing ecological civilization. However, as China's new urbanization and industrialization deepen, the substantial conversion of cultivated land to construction uses, alongside prominent issues of industrial pollution and high-intensity agricultural inputs, has imposed multiple pressures on cultivated land protection. These pressures include guaranteeing food production, maintaining ecosystem health, and accommodating development needs (Ju et al., 2016; Wang et al., 2018; Jiang et al., 2021). In response, China introduced the "Trinity" protection system in 2017, which integrates the quantity, quality, and ecology of cultivated land. The 2025 No. 1 Central Document further emphasizes "Strengthening Cultivated Land Protection and Quality Improvement," focusing on establishing a long-term mechanism. This strategic approach aims to balance immediate and long-term objectives by promoting the integrated utilization and conservation of cultivated land to maintain and enhance soil fertility. It seeks to meet current demands while preserving development potential for future generations. Achieving this goal critically depends on striking a balance between the productive and ecological functions of cultivated land (Wang M. et al., 2024). The Eco-efficiency of Cultivated Land Utilization (ECLU) serves as a crucial indicator for assessing the coordination between cultivated land use and the ecological environment (Ke et al., 2023).

ECLU represents an extension of ecological efficiency within the realm of land use. Its fundamental essence involves optimizing the structure of input factors and resource allocation methods to maximize economic and ecological benefits concurrently, while minimizing resource consumption and adverse environmental impacts. Currently, scholars primarily assess ecological efficiency by developing indicator systems that analyze inputs and outputs, employing models such as the Super-Slack Based Measure (Super-SBM) model, which has established a relatively mature research paradigm (Li M. et al., 2023b; Yang et al., 2023; Xu et al., 2025). In recent years, academic inquiry into ecological efficiency has intensified. Research has focused on spatiotemporal evolution characteristics, influencing factors, driving mechanisms, and coordination relationships, yielding significant findings. Regarding research methodologies, Exploratory Spatial Data Analysis (ESDA) (Wu et al., 2022), kernel density estimation (Peng et al., 2025), Dagum Gini coefficient (Liu et al., 2025), Markov chains (Li X. et al., 2023), are frequently employed to investigate spatiotemporal evolution characteristics comprehensively. Models such as Geographically and Temporally Weighted Regression (GTWR) (Bai et al., 2024), Geographically Weighted Regression (GWR) (Yin et al., 2022), the Tobit model (Li et al., 2024), and the geographical detector (Wang et al., 2025) are frequently used in studies examining influencing factors. Research scales vary across provincial, prefectural, and county levels. Provincial-level studies typically analyze panel data across provinces, autonomous regions, and municipalities at a macro scale (Han and Zhang, 2020). In contrast, prefectural-level research primarily focuses on significant grain-producing areas, such as the middle and lower reaches of the Yangtze River (Ke et al., 2023), the Yellow River Basin (Liu et al., 2025), and the Northeast Black Soil Region (Feng et al., 2023). County-level studies examine internal disparities within specific provinces, including Hubei (Wu et al., 2022) and Jiangsu (Li et al., 2021), some scholars investigate issues at the more granular farm household level (Qu et al., 2021). Research perspectives are increasingly diverse. For instance, the "Dual Carbon" perspective, encompassing Peaking Carbon Emissions and Achieving Carbon Neutrality, is a prevailing viewpoint in contemporary discourse (Tian and Shi, 2024; Li Y. et al., 2025). Furthermore, studies employ multiple analytical frameworks, including systems coupling and coordinated development (Liu, 2025), spatial network analysis (He et al., 2024), agricultural socialization services (Huang et al., 2024), land use green transition (Zhou et al., 2022), and farmer behavior-livelihood perspectives (Liu et al., 2020; Li W. et al., 2025), among others. The analysis of influencing factors typically encompasses the natural environment, socio-economic conditions, agricultural production circumstances, and other related aspects. The direction and magnitude of the impacts from resource endowment, economic development levels, natural conditions, and production factors on the eco-efficiency of cultivated land utilization vary across provinces and years (Yang et al., 2021; Ma et al., 2022). Specific findings indicate that the urbanization rate, farmer income levels, and precipitation are the predominant drivers of overall agricultural eco-efficiency (Hou et al., 2019; Wang J. et al., 2024; Chen et al., 2025). The coupling coordination between Cultivated Land Use Eco-Efficiency and New-type Urbanization in Henan Province is predominantly driven by socio-economic factors, particularly residents' income and economic activity intensity; while the influence of natural factors is gradually weakening, it remains significant in mountainous areas (Liu, 2025). In the karst region of Southwest China, the value per unit of cultivated land exerts the most significant positive effect on the green utilization efficiency of cultivated land (Zhang J. et al., 2024). Moreover, the multiple cropping index, industrial structure, irrigation index, mechanized farming level, and per capita cultivated land area have been identified as critical determinants influencing the eco-efficiency of cultivated land utilization in the Beijing-Tianjin-Hebei region, with these factors exhibiting notable spatiotemporal heterogeneity (Jiao et al., 2024).

Significant progress has been achieved in both domestic and international research on cultivated land use eco-efficiency (ECLU), providing important theoretical and methodological support for sustainable agricultural development and cultivated land protection. Nevertheless, several limitations remain. First, systematic investigations of ECLU in mountainous and hilly regions are still relatively scarce. These areas are typically characterized by complex terrain, ecological vulnerability, and severe constraints on cultivated land resources, which distinguish them markedly from plains and

major grain-producing regions. Second, existing studies often rely on overly simplified analytical frameworks. Cultivated land systems operate as complex socio-ecological systems, in which efficiency outcomes and their driving factors are intertwined through nonlinear interactions. As a result, conventional global regression models and static spatial approaches are frequently insufficient to capture the pronounced spatiotemporal heterogeneity of these relationships.

In response to these research gaps, this study takes Fujian Province—a representative region of China's southern mountainous areas—as the empirical case. Based on panel data from 76 counties and districts spanning 2013–2022, the Super-SBM model incorporating undesirable outputs was employed to measure ECLU. Subsequently, Exploratory Spatial Data Analysis (ESDA), Random Forest (RF), and Geographically and Temporally Weighted Regression (GTWR) models were integrated to systematically reveal the spatiotemporal evolution patterns, spatial dependence characteristics, and spatiotemporal heterogeneity of influencing factors. Accordingly, this study aims to quantify the spatiotemporal evolution of ECLU in Fujian Province, identify key driving factors and their spatial heterogeneity, and formulate differentiated policy recommendations tailored to cluster-specific characteristics, thereby providing targeted insights for cultivated land management in mountainous and hilly regions.

2 Materials and methods

2.1 Study area

Fujian Province is located on the southeastern coast of China and exhibits pronounced topographic heterogeneity, with elevations decreasing from the mountainous northwest to the coastal southeast. Its physical geography is commonly described as "80% mountains, 10% water, and 10% farmland," with mountain systems such as the Wuyi and Daiyun ranges dominating the interior and cultivated land concentrated in river valleys, basins, and coastal plains. This terrain strongly constrains agricultural production and land use. Cultivated land is fragmented and largely sloping, limiting mechanization and economies of scale and encouraging relatively intensive inputs of fertilizers, pesticides, and energy, thereby influencing agricultural carbon emissions and non-point source pollution. Steep slopes, high precipitation, and dense river networks further promote runoff-driven nutrient and pollutant transport from farmland to downstream water bodies, weakening the ecological regulation capacity of cultivated land. Under combined natural constraints and rapid socio-economic development, Fujian faces ongoing challenges of cultivated land loss, soil degradation, and declining ecological functions. The distinctive "mountain–water–farmland" structure intensifies trade-offs among food production, carbon emission reduction, and environmental protection, making Fujian a representative case for analyzing the spatial differentiation and driving mechanisms of ECLU in hilly and mountainous regions of southern China (Figure 1).

2.2 Data sources

The data for all indicators in this paper are sourced from the Fujian Agricultural and Rural Statistical Yearbooks (2013–2022). Due to continuous optimization of official statistical indicators, methods, and statistical caliber, interpolation was used to handle some missing values and outliers to ensure data continuity. The administrative base

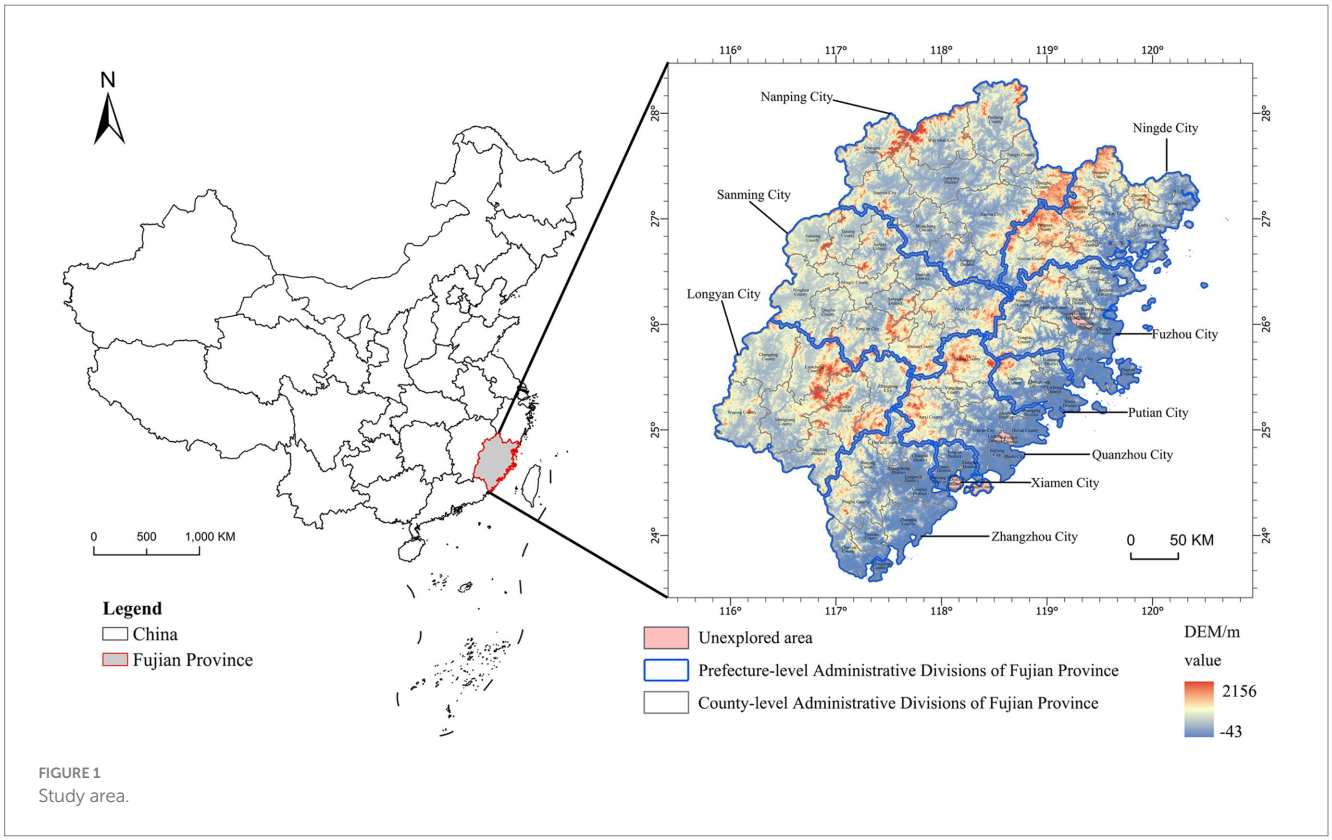

FIGURE 1
Study area.

map of Fujian's counties/districts comes from the National Geospatial Information Public Service Platform,[1] Map Review No.: GS (2024)0650, with no modifications to the base map. Due to missing data on cultivated land use in some areas, this study selected only 76 counties/districts for analysis.

2.3 Research methodology

2.3.1 Super-slack based measure

The Super-Slack Based Measure (Super-SBM) model, proposed by Tone (2001), is a non-radial and non-oriented extension of traditional Data Envelopment Analysis (DEA). Unlike radial DEA models, the Super-SBM explicitly incorporates input and output slacks into the efficiency evaluation, thereby avoiding the bias caused by proportional scaling assumptions. Moreover, the super-efficiency framework allows efficiency scores to exceed unity, enabling effective discrimination among decision-making units (DMUs) that are otherwise evaluated as fully efficient. The Super-SBM model operates by minimizing input excesses and undesirable outputs while maximizing desirable outputs under a set of production possibility constraints. This structure is particularly suitable for evaluating systems characterized by multiple inputs, multiple outputs, and environmental externalities. In the context of cultivated land use, the inclusion of undesirable outputs such as carbon emissions allows the model to better reflect the trade-offs between agricultural production and ecological impacts. The specific model is as follows:

$$\rho^* = \min \frac{1 - \frac{1}{m}\sum_{i}^{u} \frac{\overline{X}}{X_{it}}}{1 + \frac{1}{S_1 + S_2}\left(\sum_{k=1}^{S_1} \frac{\overline{Y^q}}{Y_{kt}^q} + \sum_{r=1}^{S_2} \frac{\overline{Y^f}}{Y_{rt}^f}\right)}$$

$$\overline{X} \geq \sum_{j=1;\neq 0}^{n} \lambda_{ij} X_j$$

$$\overline{Y^q} \leq \sum_{j=1;\neq 0}^{n} \lambda_{kj} Y_j^q$$

$$\overline{Y^f} \geq \sum_{j=1;\neq 0}^{n} \lambda_{rj} Y_j^f$$

$$\overline{X} \geq X_t; \overline{Y^q} \leq Y_t^q; \overline{Y^f} \geq Y_t^f; \lambda_j \geq 0$$

In the above equation, n is the number of counties/cities; each DMU's cultivated land use system has m types of inputs, S_1 types of desirable outputs, and S_2 types of undesirable outputs. X_{it} represents the i-th input variable for county t; Y_{kt}^q is the quantity of the k-th desirable output for county t; Y_{rt}^f is the quantity of the r-th undesirable output for city t. $\overline{X}$, $\overline{Y^q}$, $\overline{Y^f}$ represent input redundancy, desirable output shortfall proportion, and undesirable output redundancy, respectively. ρ^* is the ECLU value for a county. When the efficiency value ≥ 1, it indicates the region's ecological efficiency is effective; when the efficiency value <1, it indicates insufficient ecological efficiency requiring improvement.

2.3.2 Evaluation index system for eco-efficiency of cultivated land utilization

Based on the conceptual framework of Eco-efficiency of Cultivated Land Utilization (ECLU) and drawing upon established methodologies (Yang et al., 2021; Ke et al., 2023; Wang and Wang, 2024), we constructed an evaluation index system tailored to Fujian Province. This system integrates provincial cultivated land use characteristics and is detailed in Table 1.

Input indicators encompassed three categories: (1) Land input, represented by the sown area of crops; (2) Labor input, measured by the number of agricultural workers; and (3) Capital input, comprising key agricultural production materials: fertilizer, pesticide, agricultural plastic film, and agricultural diesel usage. Desirable outputs included: (1) Social output, quantified by total grain yield; (2) Economic output, measured as the gross output value of agriculture (narrow sense, i.e., planting industry); and (3) Positive environmental effects, assessed via

TABLE 1 Evaluation index system for eco-efficiency of cultivated land utilization.

Indicator type	Sub-indicator	Variable and description	Unit
Input indicators	Land input	Crop sown area	Hectares (ha)
	Labor input	Agricultural labor force	Person
	Capital input	Pesticide application	Tons (t)
		Pure fertilizer application	Tons (t)
		Agricultural diesel	Tons (t)
		Agricultural plastic film usage	Tons (t)
Desirable output indicators	Social output	Total grain yield	Tons (t)
	Economic output	Gross agricultural output value	yuan
	Positive environmental effect	Carbon sink (carbon absorption of rice, wheat, corn, legumes, etc.)	Tons (t)
Undesirable output indicators	Negative environmental effect	Carbon emissions (carbon emissions from pesticides, agricultural film, fertilizers, agricultural diesel, etc.)	Tons (t)
		Non-point source pollution (pollution from N/P/K losses in fertilizers, pesticide runoff, plastic film residue)	Tons (t)

1 https://www.tianditu.gov.cn/

the carbon sink capacity of major crops (rice, legumes, sweet potatoes, peanuts). Undesirable outputs accounted for negative environmental externalities: (1) Carbon emissions generated from the application of fertilizers, pesticides, agricultural film, and agricultural diesel; and (2) non-point source pollution, estimated from losses of fertilizer-derived nitrogen (N), phosphorus (P), and potassium (K), pesticide runoff, and residual plastic film. The calculation methods for carbon sink and carbon emissions referred to those used by Cao et al. (2022). The calculation of Non-point Source Pollution referred to the method used by Xu et al. (2021).

Cultivated land use carbon sinks refer to the net primary production formed by grain crops grown on cultivated land through the fixation of carbon dioxide via photosynthesis, that is, the amount of carbon sequestered, which is of great significance for mitigating climate change (Li M. et al., 2023a). The calculation formula for cultivated land use carbon sinks is as follows:

$$C_t = \sum_{i=1}^{n} c_i \times q_i \times \frac{(1-r_i)}{h_i}$$

Where C_t denotes the total carbon sink from cultivated land use in a given city of Fujian Province (t); i represents the crop type; n is the number of crop types; c_i represents the carbon absorption rate of crop i (%); q_i denotes the output of crop $i(t)$; r_i represents the moisture content of crop i; and h_i denotes the economic coefficient of crop i (%). The economic coefficient, moisture content, and carbon absorption rate (Li, 2002; Shen et al., 2025) are shown in Table 2.

Based on the current status of cultivated land use in Fujian Province and data availability, this study selects fertilizers, pesticides, diesel, and plastic films as the main sources of carbon emissions for calculation. The formula for calculating carbon emissions from cultivated land use is as follows:

$$E = \sum_{i=1}^{n} (T_i \times \delta_i)$$

Where E denotes the total carbon emissions from cultivated land use; i represents the type of carbon source; T_i denotes the consumption or usage amount of carbon source i; and δ_i represents the carbon emission coefficient of carbon source i. The emission coefficients of various carbon sources and their reference sources are shown in Table 3.

Non-point source pollution from cultivated land use is a complex environmental problem, mainly arising from the unreasonable use of chemical inputs such as fertilizers, pesticides, and plastic film during agricultural production, as well as the untimely or improper treatment of livestock and aquaculture waste and crop residues. Based on the current status of cultivated land use in Fujian Province and data availability, this study selects fertilizers, pesticides, diesel, and plastic films as the main sources of carbon emissions for calculation (Zhang S. et al., 2024). The formula for calculating carbon emissions from cultivated land use is as follows:

$$E = F_C + F_P + F_N + P_e + P_F$$

Where F_C, F_P, and F_N denote the total nitrogen (N) and phosphorus (P) contents contained in compound fertilizer, nitrogen fertilizer, and phosphate fertilizer, respectively; P_e represents pesticide residues, and P_F denotes residual agricultural plastic film. The pollution coefficients of nitrogen and phosphorus in compound fertilizer are 33 and 15%, respectively; the pollution coefficient of nitrogen in nitrogen fertilizer is 1; and the pollution coefficient of phosphorus in phosphate fertilizer is 43.66% (Mengba et al., 2022). It is assumed that the utilization rates of nitrogen fertilizer, phosphate fertilizer, and compound fertilizer are identical. According to the utilization rates of the three major grain crops released by the Ministry of Agriculture and Rural Affairs of China in 2020, the fertilizer utilization rate is 40.2% and the pesticide utilization rate is 40.6%. The residual rate of agricultural plastic film is 18.6% (Zhang et al., 2021) (Table 4).

TABLE 2 Economic coefficient, moisture content, and carbon absorption rate of crops.

Crop type	Carbon absorption rate	Moisture content	Economic coefficient
Rice	0.414	0.120	0.450
Soybean	0.450	0.130	0.340
Tubers	0.423	0.700	0.650
Peanut	0.450	0.100	0.430

2.3.3 Kernel density estimation (KDE)

Kernel Density Estimation (KDE) is a non-parametric method for estimating probability density functions in three-dimensional space. It uses the characteristics of the sample data itself to fit its spatial distribution density. Unlike traditional histograms, KDE uses smooth kernel functions to provide a continuous density estimate, effectively revealing the distribution characteristics and evolution trends of data. The specific formula is as follows:

$$f(x) = \frac{1}{nH} \sum_{i=1}^{n} K\left(\frac{X_i - x}{H}\right)$$

In the above equation, n is the total number of sample units; H is the bandwidth; X_i is the ECLU value of the study unit; $K()$ is the kernel function, and this paper uses the Gaussian kernel function for estimation.

2.3.4 Exploratory spatial data analysis (ESDA)

ESDA is a spatial data analysis method combining visualization and statistical techniques. It can identify spatial structures, trends, and anomalies, revealing the spatial distribution and interaction of geographical phenomena. This paper uses the Global Moran's I and Local Moran's I to explore the spatiotemporal characteristics of ECLU in Fujian (Liu et al., 2023).

2.3.5 Random Forest regression model

The Random Forest (RF) regression model is an ensemble machine learning method that constructs multiple decision trees using bootstrap sampling and random feature selection, and then aggregates their predictions to improve accuracy and robustness (Speiser et al., 2019). Compared with traditional linear regression

TABLE 3 Carbon emission coefficients related to cultivated land use.

Sources	Coefficient	Unit	Reference
Fertilizer	0.8956	Kg C kg^{-1}	Oak Ridge National Laboratory (ORNL)
Pesticides	4.9341	Kg C kg^{-1}	Oak Ridge National Laboratory (ORNL)
Diesel	0.5927	Kg C kg^{-1}	Intergovernmental Panel on Climate Change (IPCC)
Plastic films	5.1800	Kg C kg^{-1}	Institute of Agricultural Resources, Ecosystems and Environment, Nanjing Agricultural University (IREEA)

TABLE 4 Calculation method for non-point source pollution.

Pollution source		Calculation formula
Fertilizer	Compound fertilizer	Amount of compound fertilizer × nitrogen and phosphorus pollution coefficients × (1 − utilization rate)
	Nitrogen fertilizer	Amount applied × pollution coefficient × (1 − utilization rate)
	Phosphate fertilizer	Amount applied × pollution coefficient × (1 − utilization rate)
Pesticide		Amount applied × (1 − utilization rate)
Plastic film		Amount used × residual rate

models, RF does not require strict assumptions about data distribution or variable independence and can capture complex nonlinear relationships and interaction effects among explanatory variables. The operational procedure of the RF model includes repeated random sampling of the original dataset to generate training subsets, construction of decision trees based on randomly selected predictor variables at each node, and averaging the individual tree predictions. Variable importance is evaluated by measuring the increase in prediction error when the values of a given variable are permuted, thereby providing insights into each driving factor's relative contribution. In this study, the Random Forest regression model is applied to identify and rank the key driving factors influencing the spatial differentiation of ECLU in Fujian Province.

ECLU is the result of the combined effects of natural, social, and economic factors. Based on previous research (Yin et al., 2022; Fan et al., 2024; Zhang J. et al., 2024), considering the current situation of cultivated land use in Fujian and data availability, relevant indicators were selected from natural, social, and economic dimensions for study. In the natural dimension, agricultural planting structure (X1) and cultivated land management scale per laborer (X2) were selected. In the social dimension, to overcome the limitation of the single indicator "Total Agricultural Machinery Power" (X3) in hilly and mountainous areas, "Actual Mechanized Cultivation Area" (X4) was also selected to comprehensively characterize mechanization level; additionally, fertilizer application per unit area (pure) (X5) and expenditure on agriculture, forestry, and water affairs (X6) were selected. In the economic dimension, rural residents' per capita disposable income (X7) and urbanization rate (X9) were selected. The specific definitions and explanations of each indicator are detailed in Table 5.

2.3.6 Geographically and temporally weighted regression model

The Geographically and Temporally Weighted Regression (GTWR) model is a regression analysis method for spatial data. Its characteristic is the addition of weights in space and time to account for the impact of spatiotemporal changes on regression relationships. The specific formula is as follows:

$$\rho_i = \beta_0\left(\mu_i,v_i,t_i\right)+\sum_{i=1}^{p}\beta_k\left(\mu_i,v_i,t_i\right)x_{ik}+\varepsilon_i$$

In the above equation, ρ_i is the explained variable for the i-th sample point, i.e., the ECLU value; p is the number of explanatory variables; $\left(\mu_i,v_i,t_i\right)$ are the spatiotemporal coordinates of sample point i; $\beta_0\left(\mu_i,v_i,t_i\right)$ is the regression constant for the sample point at spatiotemporal coordinates $\left(\mu_i,v_i,t_i\right)$, x_{ik} is the k-th explanatory variable for sample point i; ε_i is the model residual; $\beta_k\left(\mu_i,v_i,t_i\right)$ is the regression coefficient for the k-th explanatory variable of the sample point at spatiotemporal coordinates $\left(\mu_i,v_i,t_i\right)$.

3 Results

3.1 Spatiotemporal evolution analysis of eco-efficiency of cultivated land utilization

3.1.1 Temporal analysis

Given the extensive volume of county-level data, it is impractical to present all ECLU measurement results directly. Thus, the average ECLU values across counties and districts within each city were used to illustrate temporal trends (Figure 2). The results show that the overall average ECLU in Fujian Province from 2013 to 2022 remained relatively low, fluctuating between 0.54 and 0.73, while exhibiting a general upward trend. A significant decline occurred during 2016–2017, which may be attributed to adjustments in statistical methodology, resulting in notable deviations from previous estimates. From a regional perspective, Nanping, Sanming, and Longyan—located in inland Fujian—consistently recorded the highest ECLU values throughout the study period, indicating comparatively rational and stable cultivated land utilization patterns. In contrast, coastal cities generally exhibited lower ECLU levels, suggesting persistent constraints on eco-efficient land use. Moreover, Quanzhou, Putian, and Xiamen showed marked interannual fluctuations, reflecting frequent adjustments in land use practices and highlighting the need for context-specific management strategies. Taken together, these findings indicate that although provincial ECLU has improved overall, coastal regions remain a critical bottleneck requiring targeted policy interventions.

Kernel Density Estimation plots for ECLU in Fujian Province from 2013 to 2022 were generated using MATLAB software to elucidate data distribution characteristics and evolutionary trends,

TABLE 5 Factors influencing eco-efficiency of cultivated land utilization in Fujian Province.

Dimension	Specific factor	Indicator description
Natural dimension	Agricultural planting structure (X1)	Grain crop sown area/total crop sown area
	Cultivated land management scale per laborer (X2)	Crop sown area/ agricultural labor force
Social dimension	Total agricultural machinery power (X3)	Actual mechanized cultivation area/crop sown area
	Mechanized cultivation area (X4)	Actual mechanized cultivation area
	Fertilizer input level (X5)	Fertilizer usage (pure)/ crop sown area
	Fiscal support level (X6)	Expenditure on agriculture, forestry, and water affairs
Economic dimension	Farmers' income level (X7)	Rural *per capita* disposable income
	Proportion of agricultural output value (X8)	Gross agricultural output value/gross regional product
	Urbanization rate (X9)	Urban population/total population

as depicted in Figure 3. First, in terms of distribution position, the overall distribution curve of ECLU in Fujian Province exhibited a rightward shift over time, signifying a continuous enhancement in the overall level of ECLU. In recent years, Fujian Province has implemented numerous policies and measures to protect and improve the quality of cultivated land, contributing to this ECLU advancement. Second, with respect to curve morphology, the inland region transitioned from a right-skewed tail to a left-skewed tail, indicating practical improvements in ECLU. In contrast, the coastal region displayed a pronounced right-skewed tail, suggesting that while certain areas achieved higher ECLU, low ECLU levels still predominated. Third, concerning peak changes, the number of peaks in the inland region followed an evolutionary trajectory of initially decreasing and then increasing, with peak width inversely correlated to the number of peaks. This pattern reflects slower ECLU improvements in some inland areas, necessitating targeted interventions. The number of peaks in the coastal region remained relatively stable; however, the height of the central peak fluctuated downward, while a secondary peak tended to evolve into the central peak, indicating an increase in high-efficiency areas along the coast.

3.1.2 Spatial analysis

To elucidate the spatial evolution characteristics of ECLU in Fujian Province during the study period, all values were categorized into five levels using the natural breaks method: Low Efficiency Zone (0, 0.3120], Relatively Low Efficiency Zone (0.3120, 0.4764], Medium Efficiency Zone (0.4764, 0.6647], Relatively High Efficiency Zone (0.6647, 0.8864], and High Efficiency Zone (0.8864, 1.4649]. The spatial distribution maps for 2013, 2016, 2019, and 2022 are shown in Figure 4.

Figure 4 shows that ECLU in Fujian Province displays considerable spatial heterogeneity, increasing progressively from the southeastern coast to the northwestern inland. Low Efficiency Zones are primarily concentrated in the eastern and southern coastal regions. These areas, which include significant ports, are characterized by well-developed foreign trade, economies dominated by secondary and tertiary industries, high urbanization rates, and market-oriented agriculture emphasizing high-value crops such as fruits and tea. As a result, grain output remains relatively low, and the quest for high returns from cultivated land often necessitates substantial applications of chemical fertilizers, pesticides, and other agrochemicals, thereby contributing to diminished ECLU. In contrast, High Efficiency Zones and Relatively High Efficiency Zones are predominantly situated in inland regions. This distribution can be attributed to two main factors: first, socio-economic conditions in inland areas are less advanced than those in coastal regions, rendering agriculture essential for local development and necessitating higher standards for the utilization of cultivated land. Secondly, in recent years, Fujian Province has increased fiscal transfers to major grain-producing areas and consistently enhanced funding for production-related construction projects. Nanping City, Longyan City, and Sanming City, as the primary grain-producing regions in Fujian, have benefited from these resource advantages, prompting their local governments to prioritize grain production as a strategic focus. Over time, the number of Low Efficiency Zones and Relatively Low Efficiency Zones has declined, while the number of High Efficiency Zones and Relatively High Efficiency Zones has fluctuated upward. However, particular areas, such as Shun-chang County and Yanping District, have developed into "efficiency depressions." These regions, often urban districts within their respective prefecture-level cities, exhibit higher urbanization rates and relatively developed economies but possess limited cultivated land. This limitation hinders the establishment of large-scale, sustainable agricultural models, ultimately slowing agrarian development.

3.2 Spatial autocorrelation analysis

To further quantify spatial dependence, Global Moran's I and Local Indicators of Spatial Association (LISA) were computed using GeoDa. As shown in Table 6, Global Moran's I values for ECLU remained positive throughout 2013–2022, with *Z*-scores exceeding 1.96 and *p*-values below 0.05 in most years, indicating statistically significant positive spatial autocorrelation. This suggests that counties and districts with high (low) ECLU tend to be spatially proximate to other high- (low-) efficiency units, forming distinct spatial clusters. The temporal fluctuations in Moran's I align with the observed dynamics of ECLU evolution, shifts in sustainable agricultural models, and the slowing pace of agrarian development discussed earlier.

The LISA cluster maps (Figure 5) provide further insights into local spatial patterns of ECLU in Fujian Province. High–High (HH) clusters and High–Low (HL) outliers are predominantly located in western Fujian, whereas Low–Low (LL) clusters and Low–High (LH) outliers are concentrated along the eastern coastal belt. From 2013 to 2016, HH clusters expanded northward and toward central areas, while LL clusters extended southward, indicating a widening

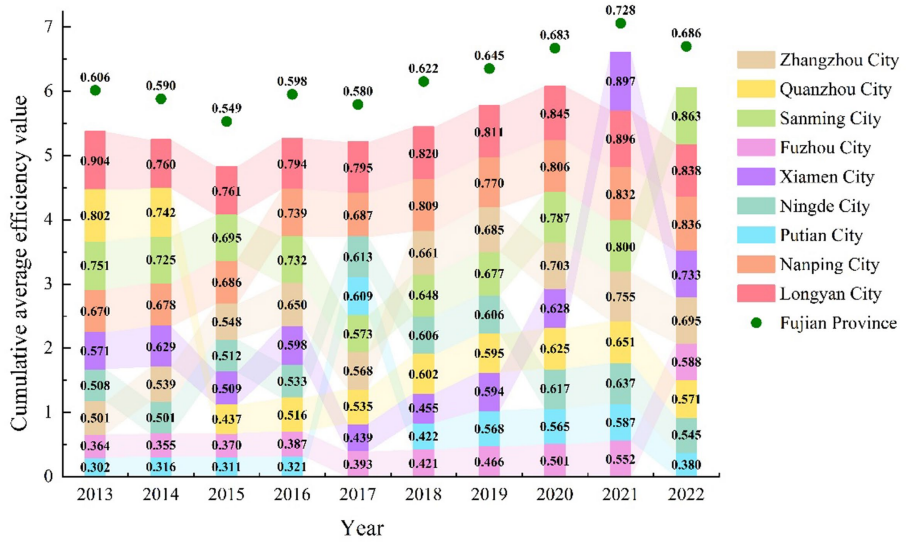

FIGURE 2
Trends in eco-efficiency of cultivated land utilization from 2013 to 2022.

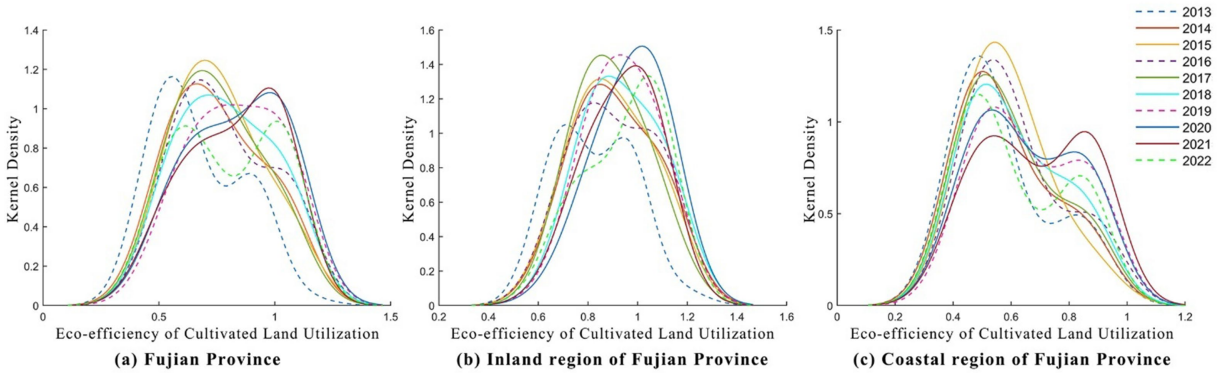

FIGURE 3
Kernel density estimation of eco-efficiency of cultivated land utilization.

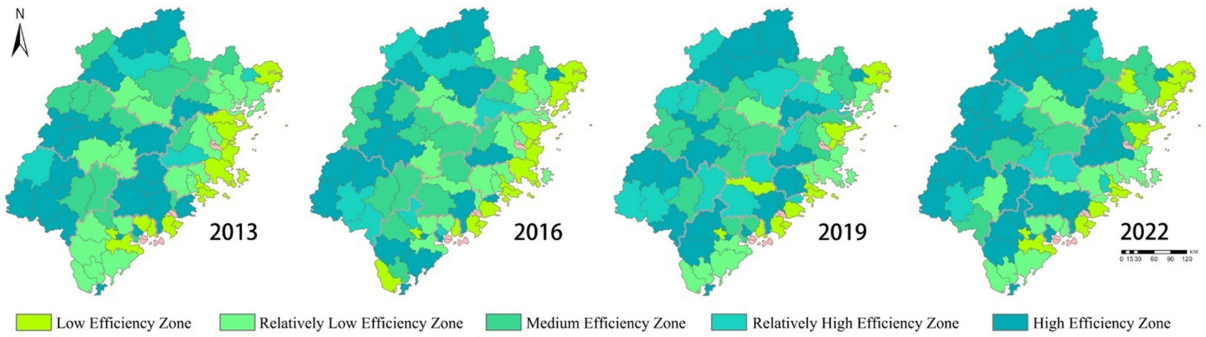

FIGURE 4
Distribution of eco-efficiency of cultivated land utilization.

TABLE 6 Global Moran's I eco-efficiency of cultivated land utilization from 2013 to 2022.

Year	G-Moran's I	*Z*-scores	*p*-values
2013	0.1435	3.8555	0.001
2014	0.1822	4.6095	0.001
2015	0.2397	5.8464	0.001
2016	0.1941	5.1381	0.001
2017	0.0534	1.8860	0.044
2018	0.1518	3.9965	0.001
2019	0.0813	2.5840	0.010
2020	0.1169	3.4572	0.001
2021	0.0869	2.5488	0.010
2022	0.1483	3.9794	0.001

inland–coastal efficiency gap and strengthening spatial spillovers. During 2016–2019, both HH and LL clusters declined in number and became more spatially dispersed, suggesting weakened agglomeration effects among high-efficiency counties and uneven progress in formerly low-performing areas. From 2019 to 2022, HH clusters re-expanded northward, accompanied by a notable increase in HL and LH outliers and further fragmentation of LL clusters along the coast. This evolving pattern reflects persistent east–west disparities and increasingly complex spatial interdependencies across Fujian's agricultural landscape.

3.3 Analysis of influencing factors of ECLU in Fujian Province

3.3.1 Random Forest model results

Using ECLU as the dependent variable and the selected indicators as explanatory variables, a Random Forest regression model was estimated in MATLAB. The model achieved a high goodness-of-fit ($R^2 = 0.9384$). Feature importance rankings (Figure 6) indicate that agricultural planting structure (X1), cultivated land management scale per laborer (X2), and the proportion of agricultural output value (X8) are the most influential factors. By contrast, fiscal support level (X6) contributed least and was therefore excluded from subsequent analysis. Given that total agricultural machinery power (X3) and mechanized cultivation area (X4) both reflect mechanization levels, X3 was retained due to its higher importance score.

3.3.2 GTWR model results

While the Random Forest model captures overall factor importance, it does not reveal spatiotemporal heterogeneity. Therefore, a Geographically and Temporally Weighted Regression (GTWR) model was employed. Multicollinearity diagnostics indicated that all variables satisfied independence requirements (VIF < 3; Table 7). Model comparison results (Table 8) show that the GTWR model outperformed both OLS and GWR models, with an adjusted R^2 of 0.7377 and the lowest AICc value.

The statistical results of the regression model (Figure 7) indicate that over 75% of the coefficients for all influencing factors are statistically significant, demonstrating robust explanatory power. The sign of each coefficient denotes promotion (positive) or inhibition (negative), while its absolute value quantifies the strength of the impact.

Figure 7 illustrates the temporal variation in GTWR coefficients. Fertilizer input level (X5) exerted the most substantial adverse effect on ECLU, with coefficients following an inverted U-shaped trajectory and increasing regional heterogeneity over time, reflecting diminishing marginal returns and escalating environmental costs. Cultivated land management scale per laborer (X2) and agricultural planting structure (X1) showed positive effects overall. The influence of X2 strengthened steadily and became uniformly positive after 2017, consistent with the expansion of land transfer markets and moderate-scale operations. By contrast, the effect of X1 initially increased and then weakened, accompanied by increasing spatial differentiation. Urbanization rate (X9) and total agricultural machinery power (X3) exhibited relatively weaker effects. X9 generally promoted ECLU, evolving from a compensatory role to a strengthening role, whereas X3 showed predominantly negative coefficients with increasing heterogeneity. Rural residents' disposable income (X7) generally promoted ECLU, although its effect weakened over time and became more heterogeneous after 2020. The proportion of agricultural output value (X8) consistently exerted a strengthening positive influence, suggesting that non-agricultural economic development may indirectly support eco-efficient cultivated land use.

Figure 8 shows the spatial distribution of the average regression coefficients of the GTWR influencing factors for ECLU in Fujian Province from 2013 to 2022, after removing coefficients with a confidence level below 95%.

The regression coefficient for Agricultural Planting Structure (X1) exhibited a north–south differentiation. A significant negative impact was identified in Zhangzhou City and the adjacent counties/districts of Longyan City in the south. In contrast, the positive effects were primarily concentrated in the coastal areas of Ningde City, Putian City, and Quanzhou City, and in the western region of Longyan City. The spatial heterogeneity of the regression coefficient for Cultivated Land Management Scale per Laborer (X2) was not significant, indicating a mixed high-low distribution across the region. At the same time, land consolidation in certain areas enhanced contiguity, but the pervasive issue of fragmented land ownership continued to severely limit scale operations and unified management severely. The regression coefficient for Total Agricultural Machinery Power (X3) demonstrated notable spatial heterogeneity. Nanping City in the north benefited from policies aimed at promoting agricultural mechanization upgrades, resulting in a significant positive effect on ECLU. Conversely, the adverse effect exhibited a trend of increasing inhibition from the central region toward the east and west. The regression coefficient for Fertilizer Input Level (X5) displayed a ring-shaped pattern with a northern concentration. A positive effect was observed in the surrounding junction area of Xiamen-Zhangzhou-Quanzhou-Longyan, suggesting that the benefits from fertilizer input temporarily outweighed the associated environmental costs. Conversely, significant adverse impacts on ECLU were observed in the northern region and certain parts of the aforementioned junction area due to excessive fertilizer application, underscoring substantial environmental pressures on cultivated land. The regression coefficient for Rural Resident Disposable Income per Capita (X7) revealed a pattern characterized by "promotion in the north and south, inhibition in the center." Increased income facilitated enhancements in ECLU in the

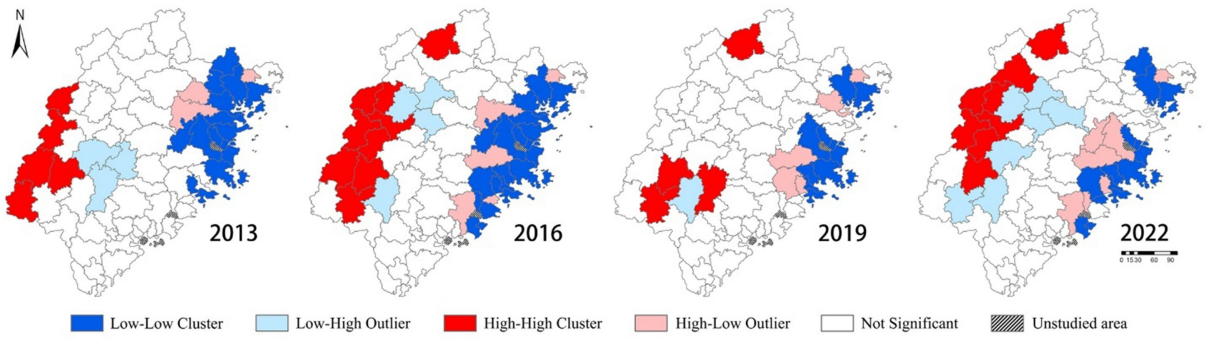

FIGURE 5
Agglomeration of eco-efficiency of cultivated land utilization in Fujian Province.

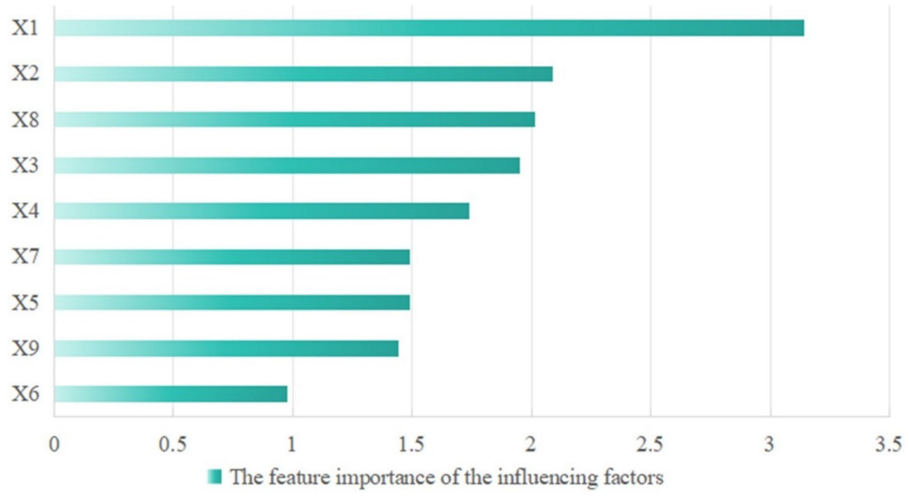

FIGURE 6
Importance of characteristics of influencing factors.

TABLE 7 Multicollinearity test.

Variable	X1	X2	X3	X5	X7	X8	X9
VIF	1.550	1.396	1.200	1.389	1.520	2.050	2.177
T	0.645	0.716	0.834	0.720	0.658	0.488	0.459

TABLE 8 Model comparison.

Model	R^2	R^2 adjusted	AICc	Residual squares
OLS	0.2706	0.2697	70.9960	47.8373
GWR	0.6624	0.6592	−369.0340	22.1729
GTWR	0.7402	0.7377	−430.8890	17.0656

northern and southern regions; however, in some central areas, income growth adversely affected ECLU. The regression coefficient for the Proportion of Agricultural Output Value (X8) revealed significant spatial variations. Xiamen City and its surrounding regions, benefiting from economic radiation effects, exhibited agricultural trends characterized by high efficiency, intensification, and ecological development, which positively influenced ECLU. Areas with sporadic negative impacts may be associated with the emphasis on increasing agricultural output value, leading to increased inputs. The regression coefficient for Urbanization Rate (X9) demonstrated distinct regional disparities. In the central-eastern regions, such as those surrounding Fuzhou and Xiamen, urbanization, despite experiencing labor outflow, generally exerted a positive effect on ECLU. This effect is likely attributable to technology and management spillovers from adjacent developed cities. Conversely, in the western, southern, and northern regions, which are more distant from core urban centers, urbanization primarily manifested as the occupation of cultivated land and labor loss, thereby inhibiting ECLU.

4 Discussion

4.1 Discussion of results

In terms of the spatial characteristics of ECLU, this study found that the ECLU in the economically developed coastal areas of Fujian

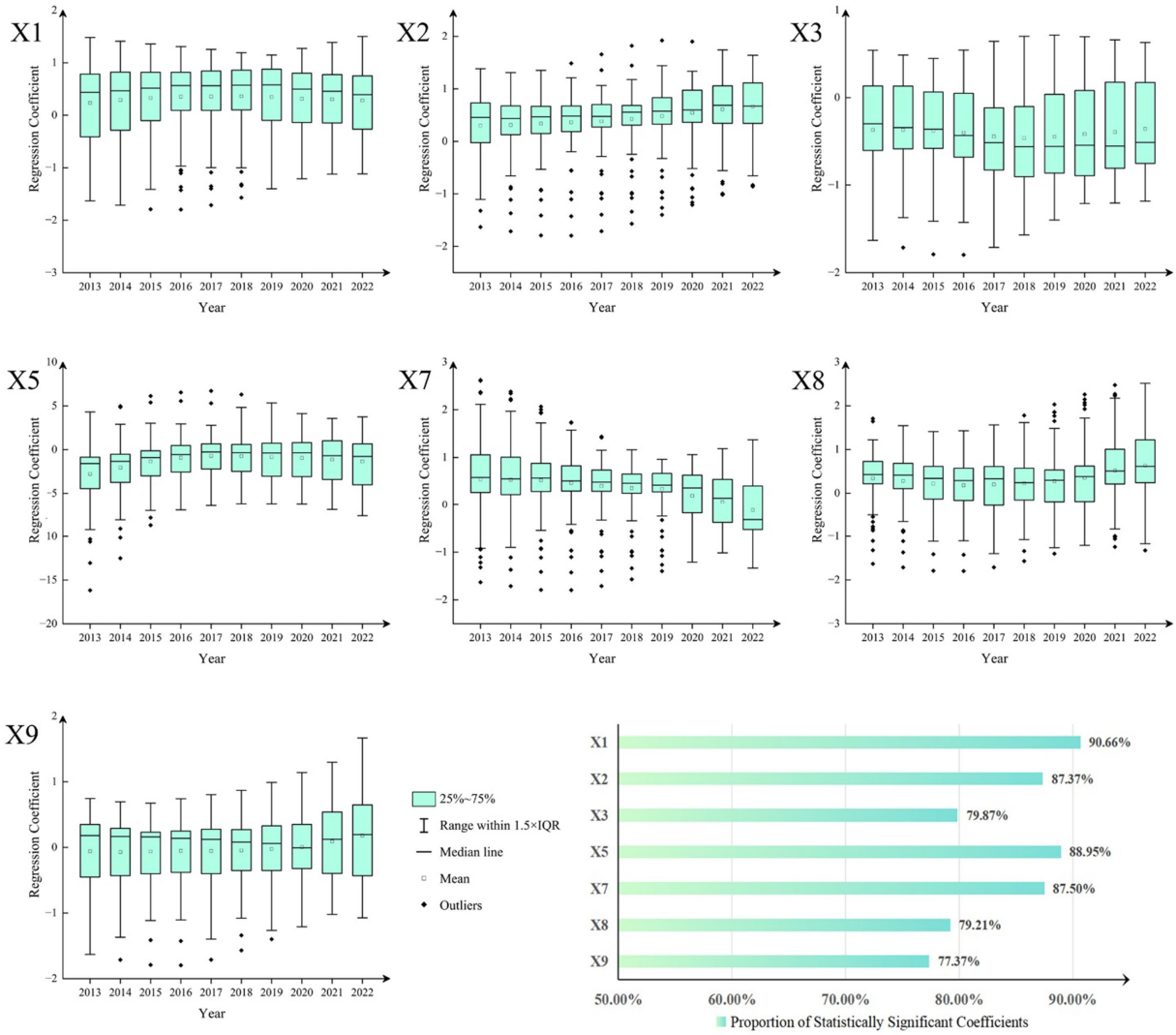

FIGURE 7
Changes in regression coefficients of GTWR influencing factors.

Province is lower than that in the relatively backward inland areas. The possible reason for this is that ECLU cannot be separated from both ecological and economic attributes (Wang et al., 2023), and the non-grain utilization rate in Fujian Province is relatively high (Chen et al., 2021), especially in the coastal areas. The grain output is lower than that in inland areas, while the carbon emissions and non-point source pollution are higher than those in inland areas, thus forming the current pattern of ECLU.

The analysis of influencing factors indicates that the effect of Urbanization Rate (X9) on ECLU in Fujian Province shifted from "compensating for shortcomings" to "forging strengths." This transition may be attributed to the increase in urbanization rates in Fujian's underdeveloped areas following the completion of the poverty alleviation campaign. Rising urbanization signifies population migration to urban centers, which inevitably alters the industrial structure Wang. During this process, urbanization may enhance agricultural production technology and improve management efficiency, thereby promoting intensification and scale (Zhao et al., 2022). Conversely, it may also lead to labor reduction and land idling in rural areas (Hou et al., 2021; Sheng et al., 2022). However, in the context of Fujian, technological advancement and optimized resource allocation during urbanization likely became the prevailing factors driving ECLU improvement. In contrast, over 86.54% of cities in the karst region of southern China exhibited an inhibitory effect (Zhang J. et al., 2024). This disparity may arise from the economic underdevelopment of the karst region, where urbanization remains in a preliminary stage focused on quantitative expansion. The significant outflow of population, combined with inadequate investment in capital and technology, hampers the effective replacement of the lost labor force and the ability to overcome challenging natural conditions (Tan et al., 2025). Furthermore, the positive impact of Agricultural Output Value Proportion (X8) on ECLU indirectly suggests that non-agricultural industrial development might feed back into and support cultivated land resource utilization. Non-agricultural industries could support cultivated land use through capital injection, technology empowerment, talent and management experience

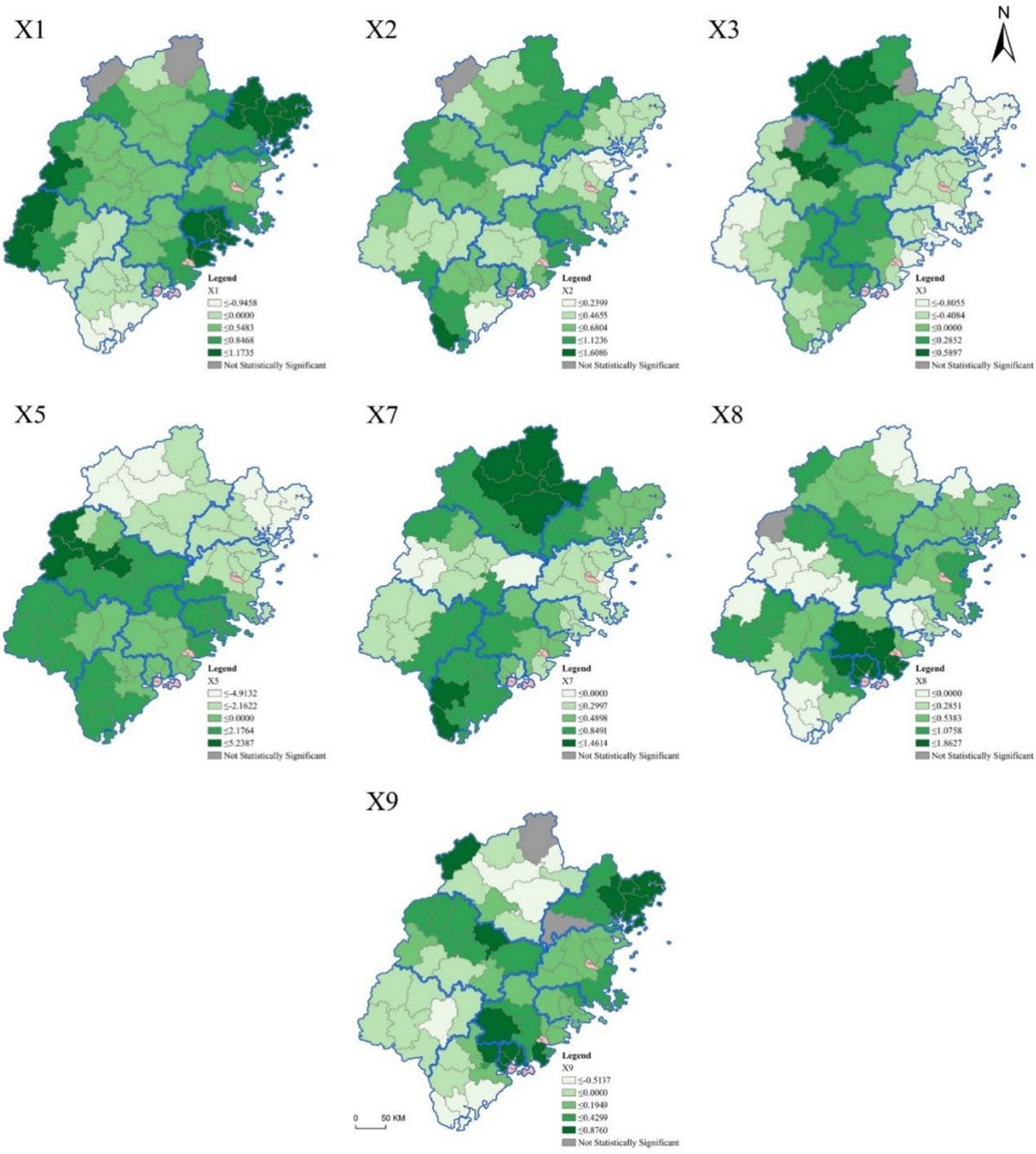

FIGURE 8
Spatial distribution of GTWR influencing factor coefficients.

transfer, and driving institutional innovation and market forces (Li W. et al., 2025).

4.2 Policy recommendations

Based on the empirical findings, the following regionally differentiated policy recommendations are proposed to enhance ECLU in Fujian Province.

Firstly, spatial analysis indicates that southeastern coastal regions (e.g., Xiamen, Zhangzhou, and Quanzhou) primarily constitute Low–Low (LL) efficiency clusters, mainly due to intensive fertilizer and pesticide applications associated with high-value cash crop systems. GTWR results show that the urbanization rate (X9) and agricultural output share (X8) exert significant positive effects in core cities such as Xiamen and Fuzhou, likely reflecting technology spillovers. To harness this potential, a "urban–rural synergy" mechanism should be strengthened: local governments can leverage the capital and technological advantages of metropolitan centers to establish smart agriculture demonstration zones and scale up precision fertilization and intelligent irrigation, thereby reducing non-point source pollution. Additionally, given the substantial negative impact of agricultural planting structure (X1) on ECLU in Zhangzhou

and surrounding counties, strict quota-based management of agrochemical inputs should be implemented to curb overuse in cash crop production.

Secondly, the northwestern inland (e.g., Nanping, Sanming, Longyan) forms High–High (HH) clusters and serves as Fujian's primary grain basket. GTWR analysis reveals that total agricultural machinery power (X3) significantly enhances ECLU in Nanping—a contrast to other areas. Policies should prioritize R&D and dissemination of small-scale, slope-adapted machinery suited to hilly landscapes, amplifying the benefits of expanded management scale per laborer (X2). Moreover, given the region's ecological importance, limited fiscal capacity, and the weak influence of fiscal support (X6), a "horizontal ecological compensation" mechanism is warranted, whereby economically advanced but low-efficiency coastal municipalities compensate inland grain-producing counties to sustain their ecosystem services.

Finally, as fertilizer input level (X5) emerges as the dominant negative driver with pronounced spatial heterogeneity, uniform reduction mandates should give way to a "regional input threshold" system. In northern areas with severe negative impacts (e.g., Nanping, Sanming), stringent reduction targets are needed; conversely, in the Xiamen–Zhangzhou–Quanzhou junction—where inputs still yield positive marginal returns—scientifically calibrated application rates may be permitted. Concurrently, to enhance the positive role of management scale (X2), a province-wide "trusteeship-based" land transfer model should be promoted to consolidate fragmented plots into moderate-scale units, enabling unified, eco-efficient cultivation.

4.3 Research limitations

The data used in this study primarily came from statistical yearbooks, whose statistical calibers were not entirely stable and may deviate from actual conditions. The research time span (2013–2022) was relatively short, potentially failing to capture long-term trends fully. Furthermore, cultivated land resources in southern mountainous regions are highly fragmented, yet indicators of fragmentation were not included in the influencing factors. Future research could extend the time range, specifically improve the indicator system, and adopt more microscopic perspectives (e.g., farm household level) to enhance analytical precision. Additionally, cross-regional comparative studies could further validate the applicability of the Fujian ECLU model, providing insights for other mountainous regions.

5 Conclusion

Based on an in-depth investigation into the spatiotemporal heterogeneity and driving factors of ECLU in Fujian Province from 2013 to 2022, this study reveals that the provincial average ECLU ranged between 0.54 and 0.73, exhibiting a fluctuating yet upward trend. Spatially, ECLU demonstrated significant regional disparities, with high-efficiency zones concentrated in western and northern regions while lower-efficiency zones predominated in the economically developed coastal areas; however, these spatial differences diminished over time, indicating a trend toward distributional equilibrium. Significant spatial clustering effects were observed, characterized by High–High (HH) clusters in western/northern regions and Low–Low (LL) clusters in eastern areas. Analytical modeling identified fiscal support level as the least influential factor through Random Forest regression, while the GTWR model further revealed fertilizer input as the primary negative driver. All influencing factors exhibited spatiotemporal heterogeneity in both direction and intensity across regions and periods. Although mechanization level, fiscal support intensity, and urbanization rate demonstrated relatively weaker impacts, they still possess certain optimization potential.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

TT: Funding acquisition, Methodology, Project administration, Writing – original draft, Writing – review & editing. JY: Data curation, Investigation, Software, Validation, Visualization, Writing – original draft. NZ: Conceptualization, Methodology, Software, Validation, Writing – original draft. JT: Conceptualization, Formal analysis, Funding acquisition, Project administration, Supervision, Writing – review & editing.

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Conflict of interest

The author(s) declared that this work 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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