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Spatiotemporal Dynamics and Driving Forces of Ecological Environment Quality in Coastal Cities: A Remote Sensing and Land Use Perspective in Changle District, Fuzhou

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Abstract: In the face of persistent global environmental challenges, evaluating ecological environment quality and understanding its driving forces are crucial for maintaining the ecological balance and achieving sustainable development. Based on a case study of Changle District in Fuzhou, China, this research employed the Remote Sensing Ecological Index (RSEI) method to comprehensively assess ecological environment quality and analyze the impact of various driving factors from 2000 to 2020. Based on the GeoSOS-FLUS model, this study simulated and predicted land use classifications if maintaining the RSEI factors. The results reveal an overall improvement in the southern and southwestern regions, while the northwest and eastern areas face localized degradation. The RSEI index increased from 0.6333 in 2000 to 0.6625 in 2022, indicating significant ecological shifts over the years. The key driving factors identified include vegetation coverage, leaf area index, and aerosol levels. Industrial emissions and transportation activities notably affect air quality, while land use changes, particularly the expansion of construction land, play a critical role in altering ecological conditions. If maintaining the current RESI factors without any improvement, Changle District will experience continued urbanization and development, leading to an increase in built-up areas to 32.93% by 2030 at the expense of grasslands. This study offers valuable insights for policymakers and environmental managers to formulate targeted strategies aimed at reducing industrial and traffic emissions, optimizing land use planning, and enhancing ecological sustainability. The methodology and findings provide a robust framework for similar assessments in other rapidly urbanizing regions, contributing to the broader discourse on sustainable land use and ecological conservation. By advancing the understanding of ecological environment quality and its driving forces, this research supports the development of informed environmental protection and sustainable development strategies for coastal regions in developing countries globally.

Keywords: risk-screening environmental indicators; land use classification; driving force analysis; Geodetector; Changle District

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1. Introduction

Rapid urbanization is raising global attention, especially in developing countries. As global environmental challenges persist, the assessment of ecological environment quality and the analysis of its driving forces have become pivotal areas of research for safeguarding the ecological balance and achieving sustainable development [1]. The United Nations estimates that by 2050, nearly 68% of the world's population will reside in urban areas, significantly up from 55% in 2018 [2]. Industrialization and urbanization contribute to socioeconomic progress but also have substantial effects on global environmental changes [3,4].

These processes notably influence ecological aspects such as hydrology, climate, soil quality, and biodiversity [5–9]. The rapid rate of urbanization and economic expansion has profoundly contributed to land use changes [10,11], posing significant challenges to achieving Sustainable Development Goals (SDGs), including SDG 11 (Sustainable Cities and Communities), SDG 13 (Climate Action), and SDG 15 (Life on Land). Therefore, it is essential to conduct a comprehensive evaluation and analysis of ecological environment quality, with a specific focus on the changes in land use patterns driven by urbanization, to uncover challenges and provide a scientific basis for decision-making in environmental protection.

The Remote Sensing Ecological Index (RSEI) is crucial for quantifying the impacts of urbanization and economic growth on ecological systems, serving as a tool for monitoring ecosystem health and promoting sustainable management practices. Ecological environment quality refers to the evaluation of the overall well-being of natural systems and the services they provide. Researchers have developed many indexes to assess the ecological environment quality, including the Environment Quality Index [12–14]. Researchers have found that these indexes mainly rely on subjective assessments or limited field measurements. The RSEI is a refined tool designed to provide a more detailed and comprehensive understanding of ecological environment quality using remote sensing data integrating multiple indicators, including greenness, moisture, dryness, and heat [15]. The RSEI utilizes consistent and repeatable data collection methods, which enhances the reliability and comparability of ecological assessments across different regions and time periods [16]. However, current studies have mainly utilized the RSEI framework only to assess the ecological environment quality. For instance, Nazanin and Raoof (2023) assessed and analyzed the ecological environment quality of Karaj County from 2010 to 2020, and they found that the RSEI has decreased from 0.59 to 0.25 [15]. Jayanta et al. (2024) utilized the RSEI to develop land use management strategies in urban areas of English Bazar, and they found higher RSEIs were primarily located around the wetland, and the areas with lower RSEIs were located in the industrial areas [16]. Therefore, it is necessary to further explore the application of the RSEI framework for land use prediction and management to protect environmental quality.

In recent years, research on land use monitoring, stimulation, and prediction for improving ecological environment quality has received increasing attention. Scholars have used various methods for prediction, such as cellular automata, Markov chains, and machine learning algorithms. However, these methods often lack spatial explicitness and cannot capture spatial dependencies and interactions, making it difficult to understand the underlying processes driving land use changes [17]. GeoSOS-FLUS is a comprehensive spatial process simulation and optimization system that inherits the principles of the Geographic Simulation and Optimization System (GeoSOS) and extends them based on the FLUS model [18–20]. It serves as an analytical platform integrating spatial process simulation, optimization, and prediction. Furthermore, many researchers using GeoSOS-FLUS typically create simulations using a few predefined significant factors, without integrating influencing factors comprehensively, leading to limitations such as oversimplification, inadequate factor interaction consideration, and a limited adaptability to different ecological contexts [21]. The Geodector model offers several advantages in this context, including handling high-dimensional data efficiently, capturing complex nonlinear relationships, identifying and ranking the importance of different variables, being robust to overfitting due to its ensemble nature, and being flexible and scalable to various data types and scales [19]. These characteristics make the Geodector model particularly suitable for analyzing the factors that influence ecological environment quality. This integration of the Geodector model and GeoSOS-FLUS could potentially enhance the predictive capabilities of the RSEI for ecological quality and land use changes, providing more comprehensive tools for environmental management and planning. Despite its advantages, integrating the Geodector model and GeoSOS-FLUS within the RSEI framework still requires further application and validation.

Research on ecological environment quality has primarily focused on various types of cities, including flat, mountainous, and metropolitan cities. In metropolitan areas like New York and Los Angeles, studies have addressed issues such as biodiversity loss and the impacts of urbanization on climate change. For instance, Zhang et al. (2024) studied the Production–Living–Ecological Spaces impacted by rapid urban expansion in mountainous cities [22]. Coastal cities have unique characteristics due to their proximity to the ocean. They face challenges such as coastal erosion, sea level rises, and vulnerability to natural disasters like hurricanes and tsunamis [23]. These cities often have diverse ecosystems, including estuaries and mangroves, requiring specific conservation efforts [24]. Coastal cities are also economic hubs for trade and tourism, leading to intensive land use and potential environmental conflicts. Effective management in coastal cities necessitates balancing development with environmental protection and disaster preparedness [25,26]. However, relatively few studies have been conducted to assess and simulate the ecological environment quality in coastal cities.

Changle District, as a key economic development area and coastal ecologically fragile area in in Fuzhou, Fujian Province, holds substantial importance for regional sustainability. However, the economic activities and urbanization processes in Changle District have introduced environmental issues, including industrial pollution, traffic emissions, and land use conflicts [27]. Consequently, a comprehensive evaluation and analysis of the ecological environment quality in Changle District is imperative to uncover challenges and provide a scientific basis for decision-making in environmental protection. In light of this, this study focuses on the central urban area as the research area, aiming to explore the following three questions: (1) What are the spatial and temporal characteristics of the ecological environment quality from 2000 to 2020? (2) What are the main factors that affect the ecological environment quality? (3) What will be the land use conditions in the 2030s if maintaining ecological environment quality factors? By evaluating ecological environment quality and analyzing its driving factors based on the RSEI model, this study provides valuable insights for urban planners and policymakers to develop targeted environmental management strategies. The use of remote sensing data and advanced machine learning models can be implemented globally in coastal cities, particularly in developing countries. Additionally, understanding the mechanisms behind ecological degradation can support international efforts to achieve SDGs, specifically those related to sustainable cities and communities (SDG 11) and climate action (SDG 13) [28].

2. Methods

2.1. Study Area

Changle District, Fuzhou City, is located in the southeast coastal area of Fujian Province, China, in the west of the downtown area of Fuzhou, at 118°39′ east longitude and 25°57′ north latitude [29]. Changle District has a total area of about 440 square kilometers and is one of the important administrative regions of Fuzhou City. The terrain of the region is undulating, interlaced with mountains and hills, and the geographical environment is diverse, including mountains, plains, and waters. Changle District is an important economic growth pole and transportation hub in Fuzhou City, with good development potential and location advantages. With the advancement of urbanization in recent years, the region's economy has flourished, and industries, commerce, and residential areas have continued to expand (Figure 1). However, this rapid economic development has also brought a series of environmental problems and ecological pressure, and the ecological environment of Changle District has been affected by various factors [30]. Through an in-depth understanding of the ecological environment problems and main driving factors in Changle District, this study can provide important references for government departments and decision makers, help formulate targeted environmental protection and sustainable development strategies, and promote the improvement and sustainable development of Changle District's ecological environment.

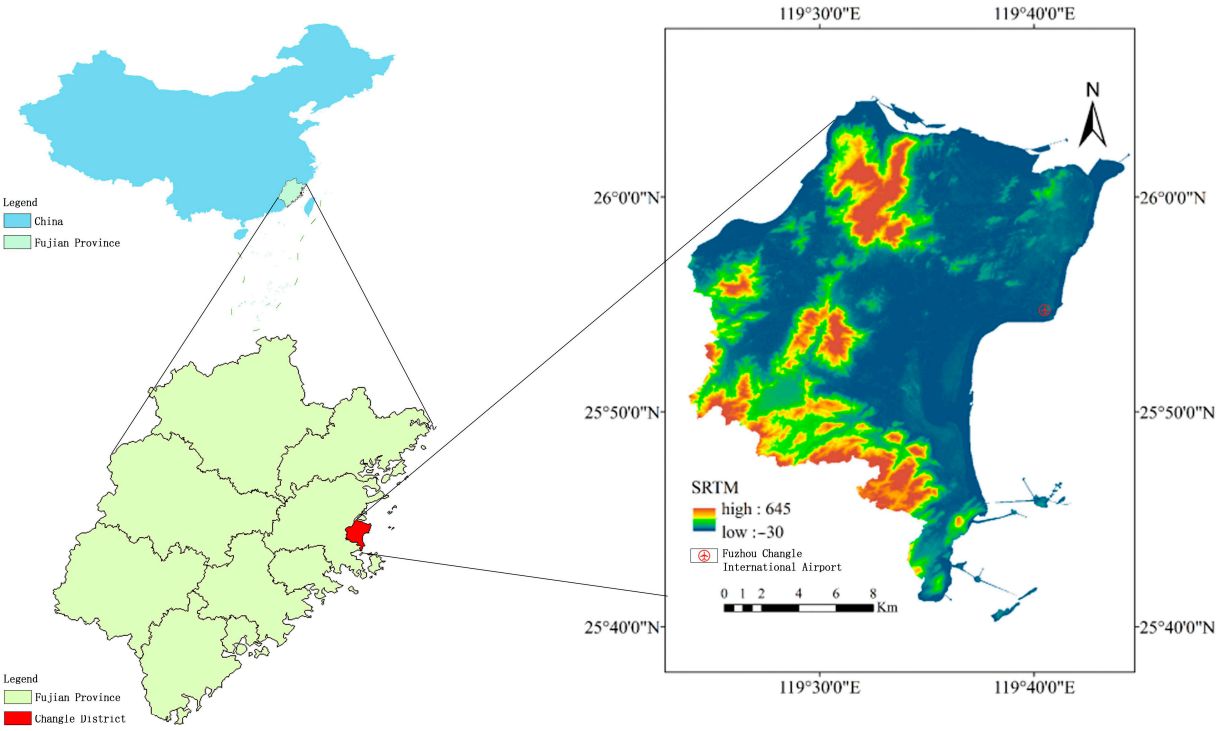

Figure 1. Research area.

2.2. Data Sources

The quality of the ecological environment is jointly affected by natural and human factors, but the intensity of each factor's impact on the ecological environment and the interaction between various factors are difficult to quantify [31]. Therefore, this study selects slope, annual average precipitation, annual average temperature, aerosols, vegetation coverage, leaf area index, and population density as the factors affecting the temporal and spatial changes in the RSEI in Changle District, Fuzhou City (Table 1). Among them, the slope data are calculated through the GEE cloud platform using SRTMGL1_003 data; the annual average precipitation data are obtained through the GEE cloud platform, using ERA5 data to calculate the annual average value, and the ERA5 data come from the official website of the ECMWF (https://www.ecmwf.int/ accessed on 9 August 2024); the annual average temperature is obtained by reversing the land surface temperature from Landsat8 data using the radiative transfer equation method on the GEE cloud platform; the vegetation coverage is calculated by using the Landsat8 data via GEE; the leaf area index is synthesized by the MODIS 15A2H leaf area index for 8 days through the GEE platform; the aerosol data are obtained by using the MCD19A2 AOD product data in MODIS, and the annual average value is obtained through GEE; and the population density index comes from the official website of the WorldPop project (https://www.worldpop.org/ accessed on 9 August 2024). Due to varying data sources, there are significant differences in spatial resolution. To facilitate calculations and ensure consistency across datasets, the data have been uniformly resampled to a resolution of 30 m × 30 m. This approach helps to retain the detailed information from high-precision layers while maintaining consistency.

Table 1. Overview of influencing factors.

Name	Year	Source	Resolution
Slope	2000, 2010, 2020	SRTMGL1_003	30 m
Precipitation	2000, 2010, 2020	ERA5	11,132 m
Temperature	2000, 2010, 2020	Landsat8	30 m
AOD	2000, 2010, 2020	MCD19A2	1000 m

Table 1. *Cont.*

Name	Year	Source	Resolution
FVC	2000, 2010, 2020	Landsat8	30 m
LAI	2000, 2010, 2020	MOD15A2H	500 m
GDP	2000, 2010, 2020	Socioeconomic statistics	1000 m
POP	2000, 2010, 2020	WorldPop	100 m

2.3. Technical Route

Through principal component analysis, this study first assessed the RSEI from 2000 to 2020, integrating four key indicators, including greenness, humidity, dryness, and heat. Then, this study employed Geodetector to analyze the spatial heterogeneity of the RSEI and identify the factors influencing ecological environment quality. Land use classification was performed using the Random Forest algorithm to classify land. Finally, we used the GeoSOS-FLUS model to simulate and predict land use changes, while maintaining the current ecological environment quality factors scenario and proposed suggestions about future land use and urban development (Figure 2).

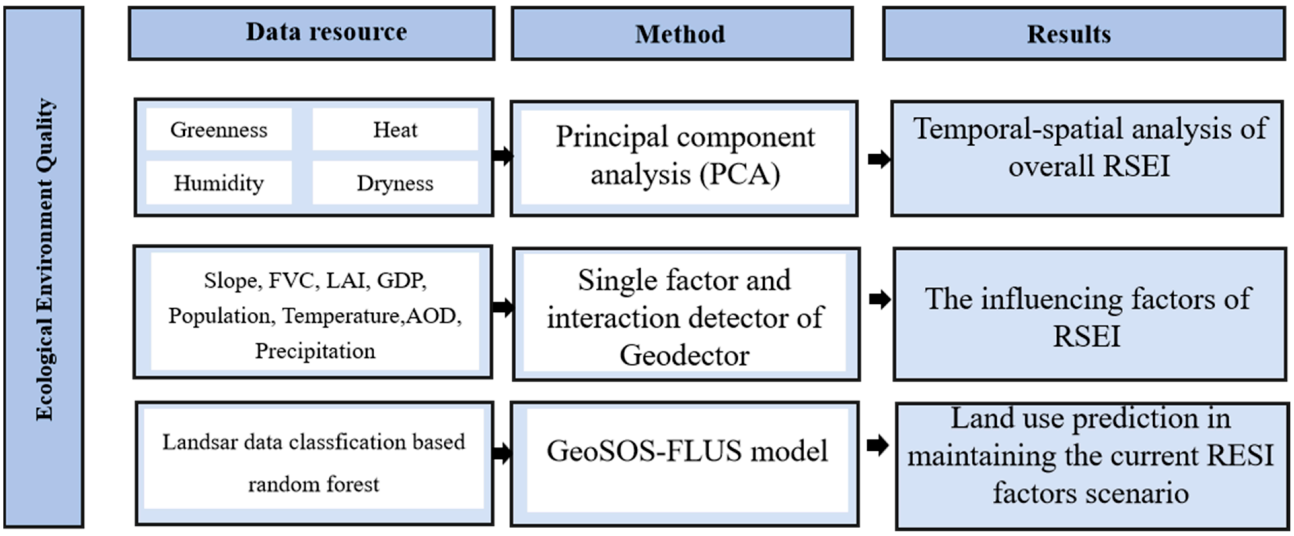

Figure 2. Research framework.

2.4. Research Methods

2.4.1. Remote Sensing Ecological Index

In the ecological environment, the four indicators of greenness, humidity, dryness, and heat are closely related to human production and life. Through the calculation of these four indicators, the quality of the ecological environment can be intuitively judged [32]. According to these four indicators, Xu Hanqiu synthesized a new ecological environment index, the RSEI, to evaluate the quality of the ecological environment, which can quickly monitor and evaluate the environment of the experimental area [33]. By using principal component transformation to determine the index weight, the results obtained can rely on the nature of the data itself, effectively avoiding the influence of other factors, such as humans [34]. The Remote Sensing Ecological Index (*RSEI*) is normalized, and the obtained *RSEI* value range is [0,1]. The closer the *RSEI* value is to 1, the better the ecological quality of the year, and vice versa. The formula is as follows:

$$RSEI0 = 1 - \{PC1[f(NDVI, Wet, NDSI, LST)]\} \quad (1)$$

$$RSEI = (RSEI0 - RSEI0min)/(RSEI0max - RSEI0min) \quad (2)$$

In the formula, *NDVI* represents the greenness index, *Wet* represents the humidity index, *NDBSI* represents the dryness index, *LST* represents the heat index, and *PC1* is the result of the first principal component analysis after the normalization of the four indexes.

Based on the principle of dividing the ecological environment quality by the *RSEI* index [35], the RSEI index of each year is divided into five ecological grades, including very poor (0, 0.2], poor (0.2, 0.4], medium (0.4, 0.6], good (0.6, 0.8], and excellent (0.8, 1.0] (Table 2).

Table 2. Ecological environment status grading table.

Grade	Index	Describe
very poor	$0 \leq \text{RSEI} \leq 0.2$	The conditions are relatively harsh, and human activities are restricted to a certain extent.
poor	$0.2 \leq \text{RSEI} \leq 0.4$	Vegetation coverage is poor, and there are factors that obviously limit human activities.
medium	$0.4 \leq \text{RSEI} \leq 0.6$	Moderate vegetation coverage, more suitable for human life
good	$0.6 \leq \text{RSEI} \leq 0.8$	High vegetation coverage, rich biodiversity, suitable for human habitation
excellent	$0.8 \leq \text{RSEI} \leq 1.0$	High vegetation coverage, rich biodiversity, stable ecological environment

(1) Greenness Index

The greenness index is represented by the most widely used normalized difference vegetation index (*NDVI*) at present, and the vegetation coverage can reflect the growth status of regional vegetation [36]. The *NDVI* can be calculated and obtained through the inverse values of the near-infrared and red bands, and its value range is [−1,1], which can represent the coverage of vegetation [37]. The formula is:

$$NDVI = \frac{NIR - Red}{NIR + Red} \tag{3}$$

In the formula, *NIR* stands for the near-infrared band, and *Red* stands for the infrared band.

(2) Humidity index

The humidity index is mainly used to describe the important index of moisture information in the soil. In this paper, the method of extracting the third humidity component in the tasseled cap transformation is used to represent the humidity index [38]. The expression is as follows [39]:

$$Wet = 0.1511\rho_2 + 0.1973\rho_3 + 0.3283\rho_4 + 0.3407\rho_5 - 0.7117\rho_6 - 0.4559\rho_7 \tag{4}$$

In the formula, *Wet* represents the humidity component, and *ρ_2*, *ρ_3*, *ρ_4*, *ρ_5*, *ρ_6*, and *ρ_7* represent the reflectance of the 2, 3, 4, 5, 6, and 7 bands of the Landsat8_OLI data.

(3) Dryness index

The *NDBSI* index can comprehensively reflect the dryness caused by bare soil and construction land, so the *NDBSI* index is used as the dryness index [40]. Within it, the degree of dryness caused by the bare soil part uses the Soil Index (Soil Index, *SI*), and the construction land part uses the Index-based Built-up Index (*IBI*) index, which is calculated by calculating the average value of the *SI* and *IBI* dryness index [41]; the specific expression is as follows:

$$NDBSI = (IBI + SI)/2 \tag{5}$$

$$IBI = \frac{2\rho_6/(\rho_6 + \rho_5) - [\rho_5/(\rho_5 + \rho_4) + \rho_3/(\rho_3 + \rho_6)]}{2\rho_6/(\rho_6 + \rho_5) + [\rho_5/(\rho_5 + \rho_4) + \rho_3/(\rho_3 + \rho_6)]} \tag{6}$$

$$SI = \frac{(\rho_6 + \rho_4) - (\rho_5 + \rho_2)}{(\rho_6 + \rho_4) + (\rho_5 + \rho_2)} \quad (7)$$

In the formula, *ρ_2*, *ρ_3*, *ρ_4*, *ρ_5*, *ρ_6*, and *ρ_7* represent the reflectivity of the 2, 3, 4, 5, 6, and 7 bands of the Landsat8_OLI data.

(4) Heat indicator

In this paper, the surface temperature is used to represent the heat index, and the GEE cloud computing platform is used to invert the surface temperature of Changle District in 2000–2020 based on Landsat8 image data using the radiation transfer model method. The specific formula is shown in Table 3:

Table 3. Radiative transfer equation calculation formula.

	Formula	Explain
Law of infrared radiation	$E(\lambda, T) = \frac{2\pi hc^2}{\lambda^5} * \frac{1}{e^{ch/\lambda kT}-1}$	$E(\lambda, T)$ is the absolute black body radiation output $W/(m^2 * um)$; speed of light c = 2.99793 $\times 10^8$ $m*s^{-1}$; Planck constant $h = 6.626 * 10^{-34}$ Jcs; Boltzmann constant $K = 1.3806 * 10^{-23}$ J/K; T is the absolute temperature of the black body; λ is the wavelength.
Surface emissivity	$\varepsilon_{water} = 0.996$ $\varepsilon_{surface} = 0.9625 + 0.0614 p_v - 0.0461 p_{v2}$ $\varepsilon_{building} = 0.9589 + 0.086 p_v - 0.0671 p_{v2}$ $p_v = \frac{NDVI - NDVI_s}{NDVI_V - NDVI_S}$	According to previous studies, remote sensing images are divided into three types: water body, town, and natural surface [42–44]; water represents the pixel specific radiation rate of the water body, and *ε_surface* represents the pixel specific radiation rate of the natural surface; *ε_building* represents the specific radiation rate of urban pixels; *p_v* represents the degree of vegetation coverage; *NDVI* is the normalized difference vegetation index; *NDVI_S* represents the *NDVI* value of bare soil pixels or areas without vegetation coverage, *NDVI_V* represents the *NDVI* value of vegetation, and the empirical values *NDVI_V* = 0.70 and *NDVI_S* = 0.05 [37].
Black body radiance	$L_\lambda = [(\varepsilon * B(Ts) + (1-\varepsilon) L\downarrow)]\tau + L\uparrow$ $B(Ts) = (L_\lambda - L\uparrow - \tau(1-\varepsilon) L\downarrow)/(\tau\varepsilon)$	ε represents the specific emissivity of the surface; τ represents the transmittance in the thermal infrared band of the atmosphere; *Ts* represents the true temperature of the surface (in K); *B(Ts)* represents the thermal radiation brightness of the black body. The atmospheric transmittance τ in the thermal infrared band, the atmospheric upward thermal radiation brightness $L\uparrow$, the atmospheric downward thermal radiation brightness $L\downarrow$ and other radiation parameter information can be found on the official website of the NASA Atmospheric Correction (http://atmcorr.gsfc.nasa.gov/ (accessed on 9 August 2024)) on the remote sensing image imaging time of the study area and the longitude and latitude of the center point of the remote sensing image.
Real surface temperature	$Ts = K_2 / \ln\left(\frac{K_1}{B(Ts)} + 1\right)$	K_1, K_2 indicate the constant preset by the satellite before launch; for Landsat8 TIRS Band 10, K_1 = 774.89 $W/(m^2 * \mu m * sr)$, K_2 = 1321.08 *K*.

(5) Principal component analysis

Principal component analysis (PCA) is often used in multi-band remote sensing image transformation and enhancement. Its mathematical meaning is mainly to select a small number of important variables from multiple variables through a linear transformation. In the field of remote sensing, it is mainly used to compress and interpret data [45,46]. Using principal component transformation to determine the weight of the index can effectively avoid the deviation caused by other factors, such as human beings, and make the result more accurate [35]. Before calculating the principal components, it is necessary to

normalize the four indicators of greenness, humidity, dryness, and heat so that their values are between 0 and 1, and then perform PCA calculations to calculate the four indicators. The first principal component, the formula, is as follows:

$$NI_i = (I_i - I_{min})/(I_{max} - I_{min}) \quad (8)$$

In the formula, *NI_i* is an index value after normalization, *I_i* is the value of the index in pixel *i*, *I_max* is the maximum value of the index, and *I_min* is the minimum value of the index.

2.4.2. Geodetector

Geodetector is a statistical method for measuring the heterogeneity of spatial stratification [47]. It is based on the theory of geospatial differentiation and is used to detect the determinants of the dependent variable, the relative importance among the factors, etc. This method is based on the following assumptions [48,49]: If an independent variable X has an important influence on the dependent variable Y, the spatial distribution of variables Y and X will have strong spatial similarity. The q value serves as a tool for evaluating the quality and robustness of the Geodetector model. Consistently high q values across different scenarios or datasets suggest that the model is reliable in explaining the observed spatial patterns. The formula is shown below.

$$q = 1 - \frac{\sum_{h=1}^{L} N_h {\sigma_h}^2}{N\sigma^2} \quad (9)$$

In the formula, q is a measure of the explanatory power of driving factors on the *RSEI*, and the value ranges from 0 to 1. The larger the value of q, the greater the impact of this factor on the *RSEI*. L represents the stratification of the *RSEI* or factors, and N_h represents the h-th layer; σh^2 represents the variance of the h-th layer, N represents the number of units studied, and σ^2 represents the variance studied.

This paper selects 8 influencing factors to explore their impact on the ecological environment quality of Changle District—X1 (vegetation coverage), X2 (average annual precipitation), X3 (aerosols), X4 (average annual temperature), X5 (per capita fiscal revenue), X6 (population density), X7 (slope), and X8 (leaf area index)—to study the change in ecological environment quality in Changle District from 2000 to 2020, in order to eliminate the differences in the dimensions and value ranges of different factors.

2.4.3. Land Use Classification

The Random Forest algorithm, introduced by Breiman and Adele in 2001, is a machine learning technique that constitutes a "forest" of numerous decision trees. Each tree individually classifies the input samples by assessing their attributes, and the final classification result is determined through a voting process. The implementation process of the Random Forest algorithm involves several key steps: (1) Randomly sampling N instances from the training dataset with replacements, where 2/3 of the data are used for constructing decision trees (in-bag data) and the remaining 1/3 for testing the trees (out-of-bag data). (2) Constructing decision trees using a subset of M randomly selected features at each node for splitting, repeating the process to achieve a user-defined number of trees. (3) Evaluating the classification performance of each tree by computing error estimates, and averaging these estimates to assess the out-of-bag error of the Random Forest algorithm. The final classification is determined by a majority vote based on the predictions of individual trees. Moreover, the Random Forest algorithm requires the specification of two key parameters: the maximum number of features randomly selected during each tree construction and the number of decision trees in the forest. The former parameter influences the robustness of the generated trees, with larger values enhancing the robustness but potentially increasing inter-tree correlation. The latter parameter affects the convergence of the classification model, with larger values promoting convergence but also leading to longer runtimes

and the potential for overfitting. This study first utilized the Kappa coefficient agreement between the model's classifications and the actual land use categories, confirming high reliability (Table 4). Additionally, the overall accuracy was utilized to assess the model's precision in classification tasks.

Table 4. Land use classification type.

	Type Land	Scope
I	Grassland	Including grasslands, meadows, savannas, and artificial grasslands
II	Cultivated land	Including land for growing crops and shrub cash crops
III	water	Including rivers, lakes, ponds, and reservoirs
IV	Forest land	Including forests, woodlands, greening, cultivated land, and other green vegetation-covered areas
V	Construction land	Including urban construction land, cement, asphalt pavement, and transportation construction land

2.4.4. GeoSOS-FLUS Model Simulation Prediction

GeoSOS-FLUS is a comprehensive spatial process simulation and optimization system that inherits the principles of the Geographic Simulation and Optimization System (GeoSOS) and extends them based on the FLUS model [50–52]. It serves as an analytical platform integrating spatial process simulation, optimization, and prediction. Widely applied in the analysis of land use changes and future forecasts, GeoSOS-FLUS is a crucial tool for geographical spatial optimization and decision-making [18,53]. In the probability calculation module of the GeoSOS-FLUS software, which is based on neural networks, input factors such as the natural environment and the socioeconomic drivers of land use change are considered. The module utilizes neural network algorithms to integrate and calculate the probability of each land use type at each pixel within the study area based on the input data. The FLUS model improves upon traditional Cellular Automaton (CA) models by employing a multi-layer feedforward neural network algorithm. Using land use data for a specific period and drivers of land use change (e.g., elevation, slope, and socioeconomic data such as railways and roads), the model assesses the suitability probability for future land use changes. Subsequently, employing an adaptive inertia competition mechanism based on roulette wheel selection, the model produces predictions for land use changes.

This article utilizes the 2020 land use status data of Changle District as the initial dataset. ArcGIS, after normalizing the driving force factor data, inputs it into a BP-ANN model. By employing a uniform sampling method, 20% of the raster pixels are extracted as training samples to obtain the probability of land use suitability for the region. On this basis, water bodies extracted from land use data are designated as restricted development areas, as water areas are typically unsuitable for construction and cultivation. This setting aids in simulating future land use scenarios more realistically. Subsequently, cellular automaton parameters are obtained for each land class, used in simulating the 2020 land use data. The simulated results are then validated against the 2020 land use data of Changle District. Model effectiveness is assessed using the FOM index and Kappa index, with the Kappa coefficient primarily measuring the model's classification accuracy and the FOM index focusing on the balance between false positive and false negative rates of the classification results.

3. Results

3.1. Descriptive Analysis of RSEI Components Based on Principal Component Analysis

In this study, we employed principal component analysis (PCA) to comprehensively assess the ecological environment quality in the Changle District of Fuzhou, China (Table 5). The analysis focused on four key indicators: greenness, humidity, dryness, and heat. The period under consideration spanned from 2000 to 2022. The results revealed that Principal Component 1 (PC1) played a pivotal role, contributing significantly to the Regional Standard Ecological Index (RSEI), with contribution rates of 69%, 62.87%, 61.5%,

62.95%, 62.08%, and 62.94% for the respective years. PC1 accounted for over 60% of the total variation in the dataset, indicating its capacity to capture the predominant characteristics of the four indicators. The dominance of PC1 in explaining the variance suggests that it effectively avoids biases introduced by subjective weighting during RSEI calculation. Notably, within PC1, the contribution rates of the four indicators—NDVI (normalized difference vegetation index), Wet, NDBSI (Normalized Difference Built-up and Shadow Index), and LST (land surface temperature)—exhibited distinct patterns. NDVI and Wet displayed positive contributions, aligning with the understanding that a higher greenness and humidity positively impact the ecological environment. Conversely, NDBSI and LST demonstrated negative contributions, consistent with the adverse effects associated with dryness and heat on the ecological environment. While PC2 to PC4 exhibited intermittent positive and negative contributions from the four indicators, their collective influence posed challenges in explaining ecological phenomena effectively. Therefore, the study advocates for the utilization of PC1 as a robust component for constructing the RSEI, given its ability to encapsulate the majority of key environmental characteristics and mitigate potential biases arising from subjective weighting.

Table 5. RSEI indicator principal component analysis.

		NDVI	Wet	NDBSI	LST	Eigenvalues	Eigenvalue Contribution Ratio (%)
2000	PC1	0.5617	0.3245	−0.6835	−0.3347	0.0255	69.00
	PC2	0.7568	−0.4477	0.4633	−0.1098	0.0076	20.65
	PC3	−0.3030	−0.1351	0.1434	−0.9324	0.0036	9.68
	PC4	−0.1407	−0.8222	−0.5456	0.0809	0.0002	0.66
2005	PC1	0.6857	0.1659	−0.5590	−0.4357	0.0224	62.87
	PC2	−0.6258	0.1336	−0.1388	−0.7558	0.0077	21.64
	PC3	−0.3543	0.3728	−0.7047	0.4887	0.0054	15.01
	PC4	−0.1128	−0.9031	−0.4142	0.0099	0.0002	0.48
2010	PC1	0.4464	0.2589	−0.4711	−0.7154	0.0224	61.50
	PC2	0.8058	−0.3690	0.4476	−0.1191	0.0076	20.96
	PC3	−0.3603	−0.1448	0.2972	−0.8723	0.0062	16.92
	PC4	0.1471	0.8808	0.4467	−0.0548	0.0002	0.62
2015	PC1	0.6974	0.1428	−0.5435	−0.4448	0.0210	62.95
	PC2	−0.6687	0.1355	−0.2648	−0.6814	0.0082	24.42
	PC3	−0.2494	0.2811	−0.7219	0.5811	0.0041	12.37
	PC4	−0.0651	−0.9393	−0.3369	0.0079	0.0001	0.26
2020	PC1	0.5451	0.2559	−0.6780	−0.4215	0.0253	62.08
	PC2	−0.8158	0.2417	−0.2939	−0.4355	0.0088	21.60
	PC3	−0.1542	0.2961	−0.5064	0.7951	0.0065	15.87
	PC4	−0.1164	−0.8879	−0.4443	0.0251	0.0002	0.44
2022	PC1	0.6758	0.2219	−0.6334	−0.3091	0.0203	62.94
	PC2	0.7323	−0.3091	0.5546	0.2461	0.0069	21.47
	PC3	−0.0292	−0.1709	0.3515	−0.9200	0.0049	15.06
	PC4	0.0785	0.9089	0.4094	−0.0149	0.0002	0.53

3.2. Temporal–Spatial Analysis of Overall RSEI

From the spatial distribution of the RSEI, regions with lower and relatively poorer ecological conditions are mainly concentrated in the northwestern and eastern parts of the Changle District, while areas with higher RSEI grades and better ecological quality are prominently found in the northern, southern, and southwestern regions. Analyzing Figure 3, it is evident that the proportion of areas with a "good" RSEI grade is the highest, with the smallest proportion belonging to the "poor" grade category. Examining the trends over the period 2000 to 2022, there is a notable shift towards improved ecological environment quality in Changle. Specifically, there is a decline in the proportion of areas with

"moderate" and "good" RSEI grades, decreasing by 9% and 15%, respectively. Concurrently, the proportions of areas with "poor", "fair", and "excellent" RSEI grades have witnessed an increase of 15%, 8%, and 3%, respectively. In summary, the overall trend in the Changle District indicates a positive development in ecological environment quality.

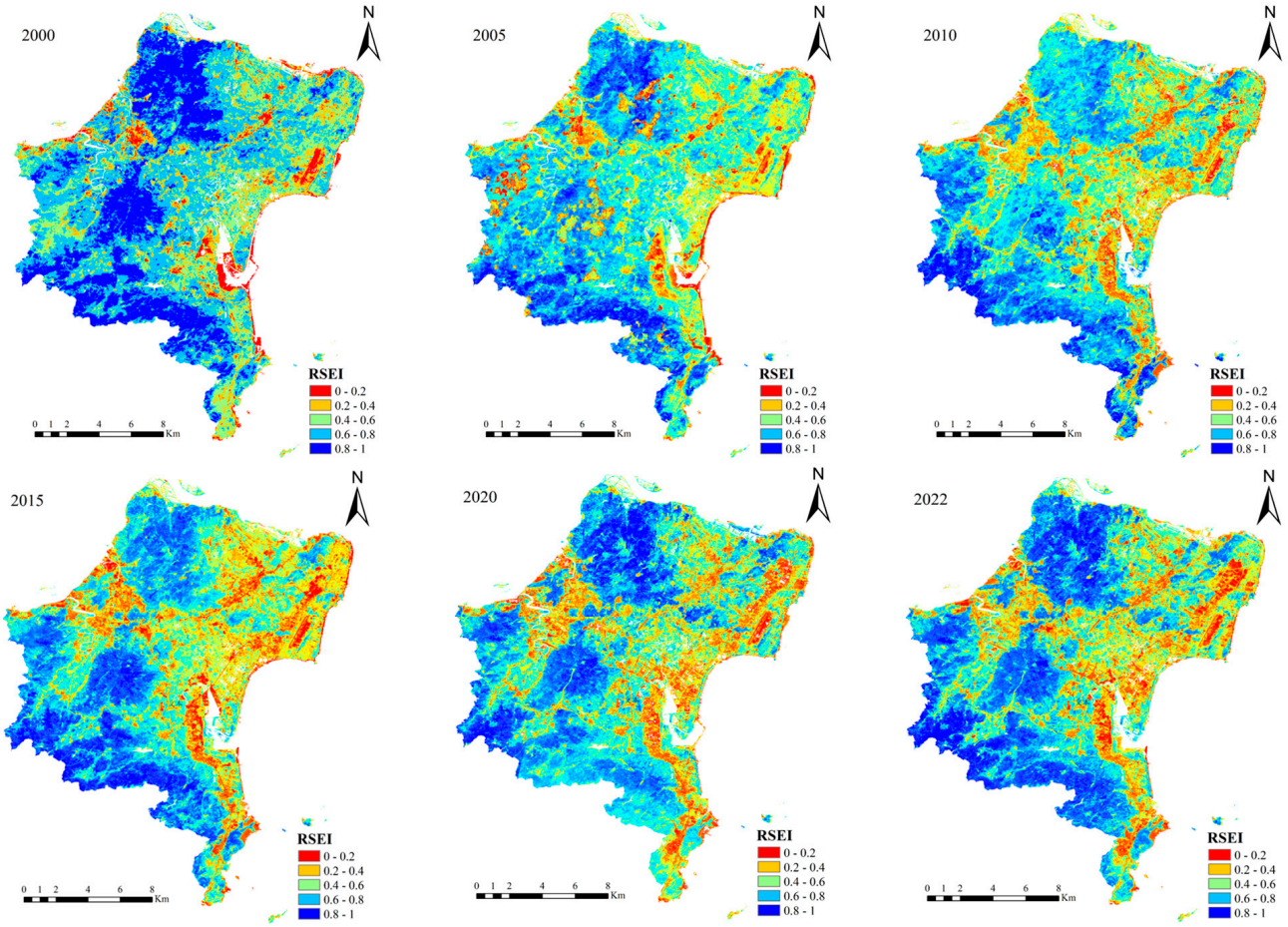

Figure 3. Spatial distribution of RSEI in Changle District from 2000 to 2020.

Through an analysis of the changes in RSEI results, the average values of RSEI in Changle District from 2000 to 2022 were as follows: 0.6333, 0.5896, 0.5781, 0.5222, and 0.5763 (Figure 4). The highest RSEI value in Changle District occurred in 2020 at 0.6625, while the lowest was recorded in 2015 at 0.5222. The annual average RSEI is 0.5937, indicating that the ecological environment quality in the Li River Basin is at a moderately high level. Overall, there is an upward trend in the ecological environment quality of the Li River Basin. The decrease in forest area may lead to ecosystem degradation and a reduction in biodiversity. Simultaneously, the expansion of farmland could result in ecosystem fragmentation and an increased risk of soil erosion. The proper planning of land use in Changle District is essential to promote the healthy development of ecosystems and mitigate the negative impact of human activities on the environment. It is crucial to strengthen monitoring and management to ensure the sustainability of land use, preventing excessive development and resource wastage. This proactive approach will contribute to maintaining a balance between human activities and environmental conservation.

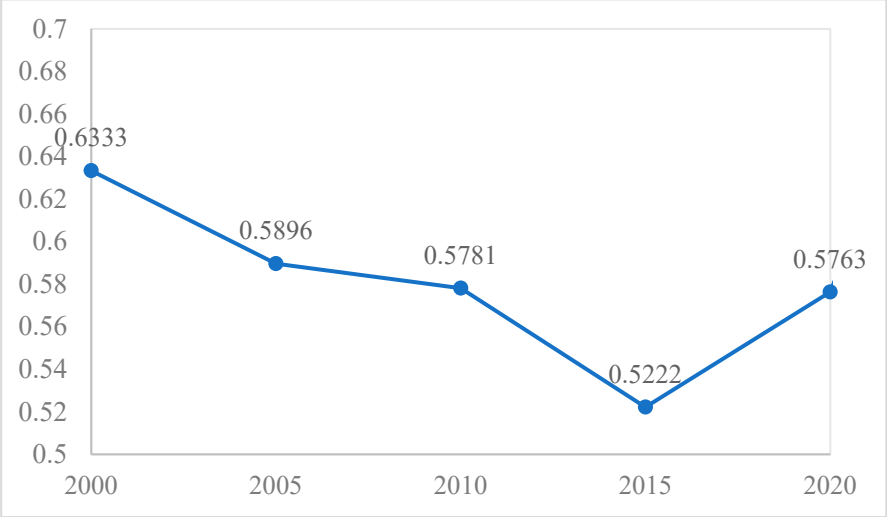

Figure 4. RSEI time series of Changle District from 2000 to 2022.

3.3. The Influencing Factors of RSEI Based on Geodetector

From 2000 to 2020, vegetation coverage (X1), leaf area index (X8), and aerosols (X3) are the leading factors that influence the RSEI (Figure 5). The q value of vegetation coverage (X1), leaf area index (X8) and aerosols (X3) is the highest among all the factors from 2000 to 2020. This result indicated that the impact of natural factors on the ecological environment of Changle District is greater than that of human factors. The average annual precipitation (X2), per capita fiscal revenue (X5), and slope (X7) are the factors that have the lowest influence on the RSEI in 2000 and 2010, but average annual temperature (X4) and population density (X6) are the factors that have the lowest influence on the RSEI in 2020.

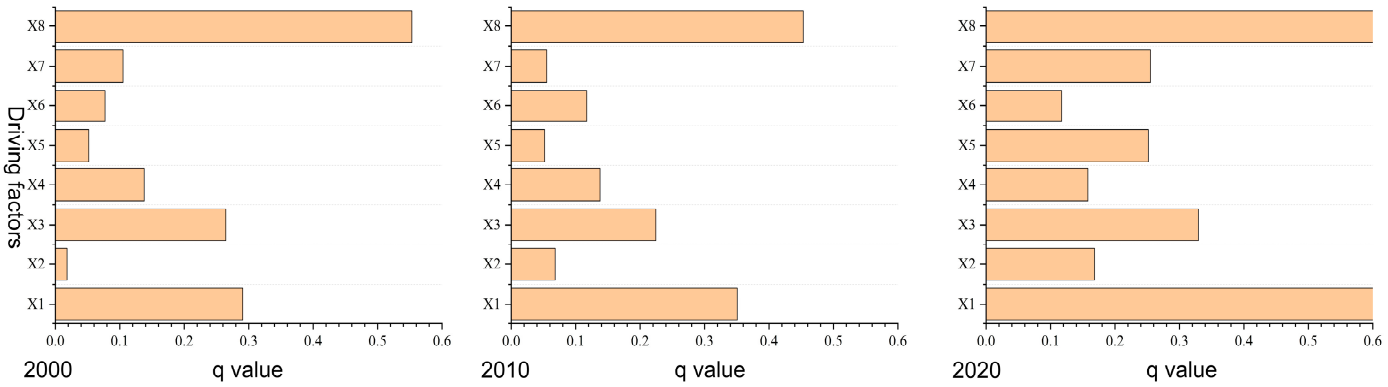

Figure 5. The results of single factor detection from 2000 to 2020. Note: X1 (vegetation coverage), X2 (average annual precipitation), X3 (aerosols), X4 (average annual temperature), X5 (per capita fiscal revenue), X6 (population density), X7 (slope), X8 (leaf area index).

Using the interaction detector to detect factor interaction, as shown in Figure 6, the interaction among the three factors X1, X3, and X8 is the strongest, and it is much stronger than their single factor detection. However, the explanatory power after the interaction is also greater than that of the separate single factor tests. The results show that the explanatory power of Changle District's factor interaction test is greater than that of the original single factor test, and the ecological environment quality of Changle District is affected by the interaction of multiple factors.

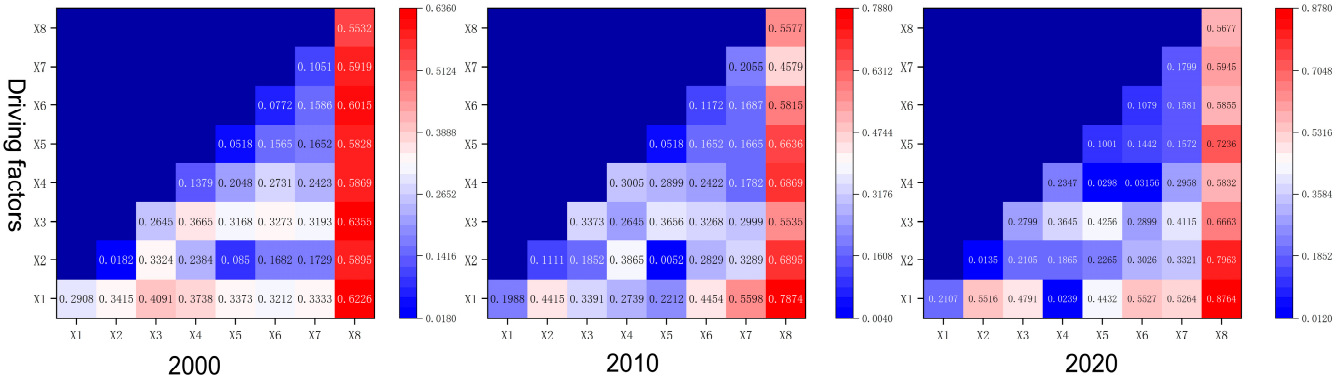

Figure 6. Interaction detection results from 2000 to 2020.

3.4. Land Use Prediction in Maintaining the Current RESI Factors Scenario Based on the GeoSOS-FLUS Model

The area of construction land gradually increases from 2000 to 2020 (Figure 7). The Kappa values for land use classification in Changle District are all above 90%, and the overall accuracy is consistently above 0.9, indicating a high reliability for subsequent analysis. Changle District is predominantly covered by forest land, accounting for over 50% of the entire watershed, while the smallest proportion is occupied by grassland, representing only about 1% of the watershed area. From the year 2000 to 2022, the areas of forest land, water bodies, and construction land have all increased. Notably, there is a significant expansion of construction land, primarily in the southeast, northeast, and a small part of the eastern regions of Changle District. Meanwhile, there is a noticeable decrease in the area of cultivated land. Additionally, the increase in construction land is mainly attributed to the conversion of cultivated land.

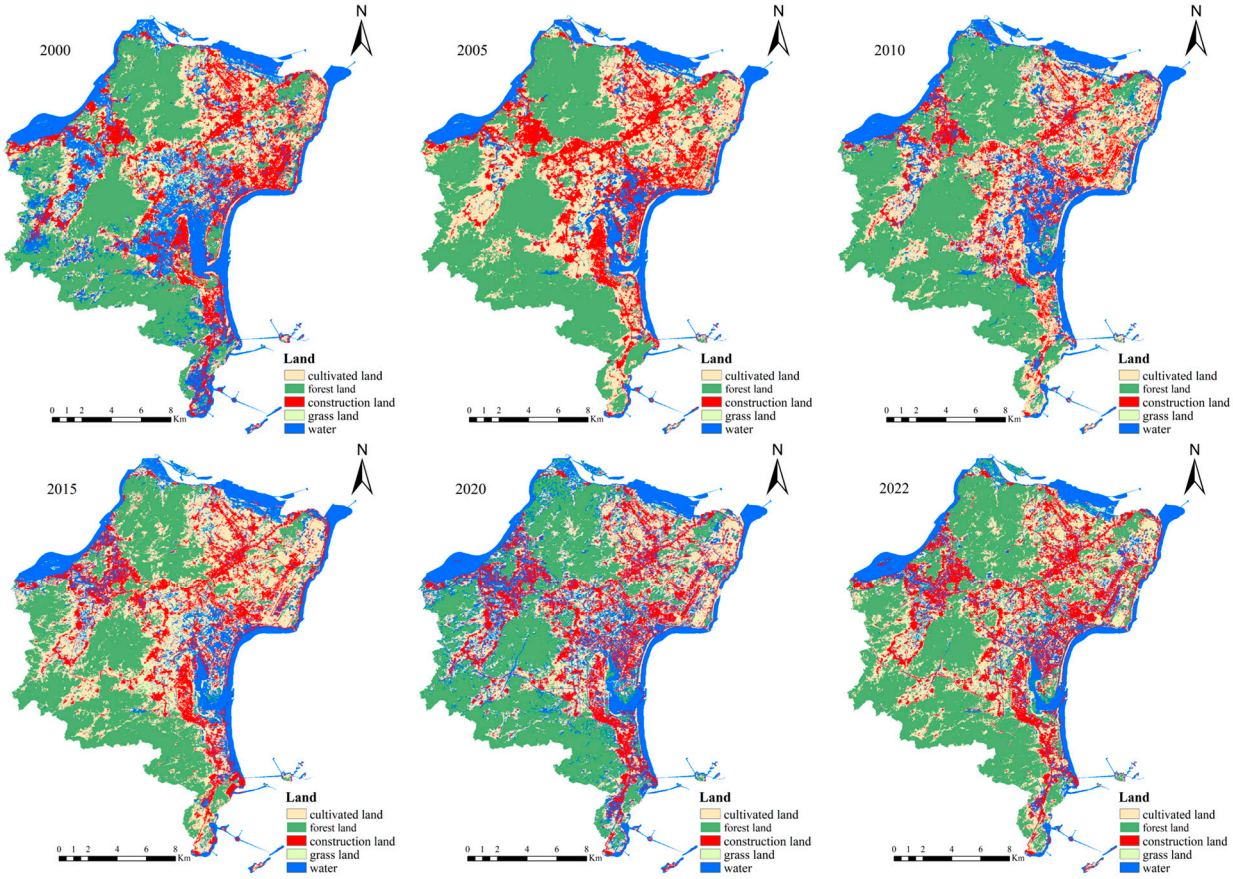

Figure 7. Land use classification of Changle District from 2000 to 2020.

If maintaining the current RESI factors without any improvement, Changle District will experience continued urbanization and development, leading to an increase in built-up areas to 32.93% by 2030, at the expense of grasslands (Figure 8). The validated Kappa coefficient is 0.76, and the FOM index is 0.005, both falling within a good range, indicating the reliability of the GeoSOS-FLUS model. According to the GeoSOS-FLUS model, Changle District is projected to remain predominantly covered by forest and built-up areas, accounting for 51.85% and 32.93%. Grassland occupies the smallest proportion, constituting only 0.06% of Changle District's total area. Influenced by urbanization and construction expansion, grassland areas have decreased, which is associated with factors such as urban expansion and agricultural land enlargement. In comparison to 2020, by 2030, all land classes in Changle District, except for arable land and built-up areas, show varying degrees of decline. Forest area exhibits the most significant decrease, followed by woodland and grassland. Arable land and built-up areas experience varying degrees of increase, possibly due to urbanization and agricultural development. Given the reduction in forest and grassland areas, it is essential to formulate sustainable land use planning for Changle District to protect natural ecosystems and biodiversity. In response to the increase in built-up areas in Changle District, effective urban planning and land use policies need to be devised to ensure the sustainability of urban development.

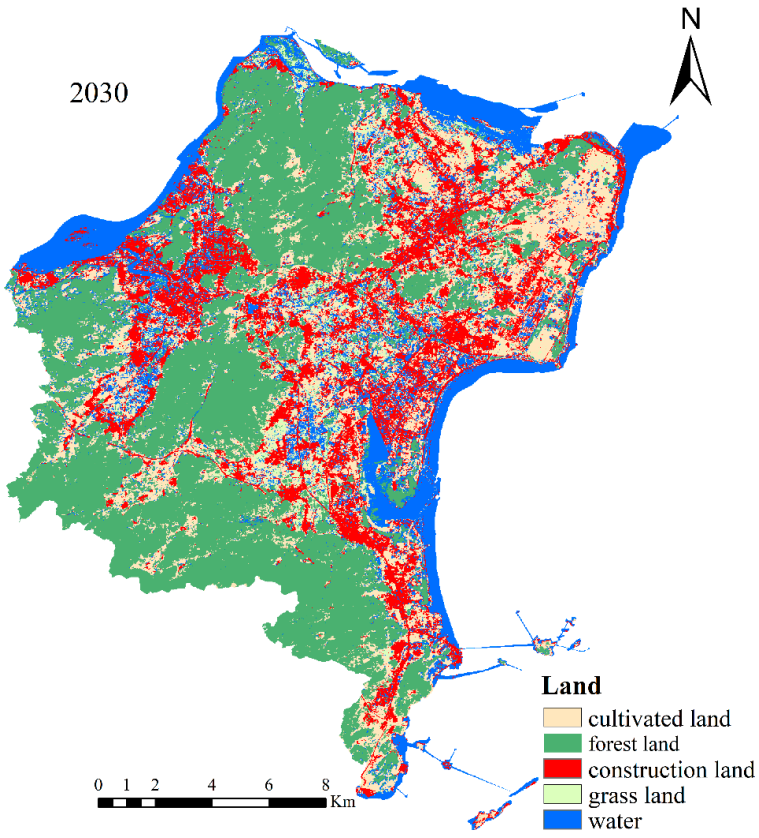

Figure 8. Land use prediction in maintaining the current RESI factors scenario.

4. Discussion

4.1. The Assessment of Ecological Environment Quality Based on RSEI and Its Driving Factors

The RSEI could serve as a great tool for assess the ecological environment quality. The results indicate that the overall ecological environment in the Changle District of Fuzhou is relatively good, but there are still some localized issues. This may be attributed to the efforts in environmental protection and policy measures implemented in the Changle District. The north, south, and southwest regions of the Changle District have areas with excellent and good RSEI grades, indicating a higher ecological level due to the presence of forests and grasslands. However, some areas are still affected by factors such as vegetation coverage

and leaf area index, especially facing pressure on air and water quality [54,55]. Therefore, further measures are needed to strengthen environmental management for the protection and improvement of the ecological environment quality in the Changle District.

By analyzing the driving forces influencing land use, we reveal the fundamental reasons for differences in ecological environment quality, including economic development, urbanization processes, and agricultural activities. The pressures from economic development and urbanization in Changle District mirror those observed globally. In rapidly urbanizing areas in Asia, Africa, and Latin America, the expansion of urban spaces has often resulted in significant environmental degradation, driven by similar factors such as deforestation, pollution, and land use changes [56]. Understanding these driving forces assists government and decision-makers in making wiser decisions in land planning and ecological environment management. Furthermore, a comparison with similar studies in regions such as the Yangtze River Delta in China and the Mumbai Metropolitan Region in India reveals consistent findings in the relationship between economic activities and environmental degradation [57,58].

Vegetation coverage is the most significant factor affecting the ecological environment quality. This finding aligns with studies conducted in other regions of the world. For instance, research in the Amazon Basin has shown that deforestation and changes in vegetation cover are primary drivers of environmental degradation [59]. Similarly, studies in European countries have demonstrated that vegetation cover is crucial for maintaining ecological balance, especially in the face of urban expansion [60]. This is closely related to the environmental pressures generated during economic development and the urbanization process. To improve ecological environment quality, effective measures should be taken to reduce urban expansion, promote afforestation, improve lifestyle, optimize land use, and enhance environmental monitoring and management. Based on the analysis, the urban planner and governor should strengthen environmental regulations and regulatory measures, enhance emission control for industrial and transportation sectors, and restrict pollutant releases to promote ecological environment protection and sustainable development. Secondly, they should encourage the adoption of clean production technologies and sustainable transportation modes to reduce negative impacts on air quality. Additionally, there should be reinforced land use planning and management to ensure the sustainability of land development and to protect and restore ecosystems [61].

4.2. Land Use Simulation Prediction in Maintaining the Current RESI Factors Scenario

The land use simulation prediction highlights the importance of considering RESI factors. The simulation predicts high increases in urban areas at the expense of grasslands if maintaining the current RESI factors without any improvement. A similar concern is echoed in urban development studies worldwide, and similar trends have been observed in Lagos, Nigeria, where rapid urbanization has resulted in substantial environmental pressures, particularly in terms of land use changes and deforestation [62]. In São Paulo, Brazil, the expansion of urban areas has led to significant environmental challenges, such as loss of green spaces and increased pollution [63]. Compared to previous studies, our land use prediction model also considers RSEI factors in certain areas that face challenges such as vegetation cover, leaf area index, and air and water quality, emphasizing the necessity for enhanced management measures. To forecast the future trajectory of Changle District's ecological status, a land use simulation for the year 2030 was conducted. The simulation predicts potential increases in urban areas, posing risks to the ecological balance [64,65]. The continuous expansion of built-up areas may exert pressure on vegetation cover, leading to an overall decline in ecological quality. To counteract this trend, it becomes crucial to limit urban expansion, implement green infrastructure, and promote afforestation measures to maintain a harmonious balance between the urban development and ecological conservation. The simulation also reflects the influence of economic development on land use patterns. This is consistent with findings from studies in regions such as the American Midwest and the Rhine–Ruhr region in Germany, where industrial and transportation activities

have led to significant environmental pressures [66,67]. As economic activities intensify, particularly in the industrial and transportation sectors, pollutants and environmental pressures correspondingly increase [68]. This underscores the importance of strengthening environmental regulations and emission control, and promoting clean production technologies to mitigate negative impacts on the environment. Encouraging sustainable agriculture and reforestation and optimizing land use practices are vital for maintaining ecological balance and supporting biodiversity.

Based on the land use simulation for 2030, several policy recommendations are proposed to guide Changle District towards sustainable development and the improvement of ecological quality. Stringent environmental regulations and an effective enforcement mechanism are crucial for controlling emissions in the industrial and transportation sectors. This includes restricting pollutant emissions to ensure the continuous improvement of environmental quality. Encouraging the adoption of clean production technologies, sustainable transportation modes, and eco-friendly urban planning practices is essential to minimize adverse impacts on air quality and overall environmental health. Enhancing land use planning and management is emphasized, with a priority on ecological conservation and restoration. This involves protecting and restoring ecosystems, controlling urban sprawl, and ensuring the sustainability of land development [69]. Overall, the ecological environment quality assessment and driving force analysis for the Fuzhou Binhai Changle District, based on the Regional Socioeconomic Information System (RSEI), provide a crucial scientific foundation for the area's sustainable development. The simulation of land use patterns in 2030 allows us to anticipate challenges that may arise in the future and formulate corresponding policies and measures. However, further research is needed to refine methods and data, considering multiple factors comprehensively, to better address the ecological environment issues faced by Changle District and achieve the goal of sustainable development. While adopting the RSEI as an indicator for evaluating ecological environment quality, it is essential to consider its limitations. Future research could explore more comprehensive indicators, integrating multi-source remote sensing data and ground monitoring data to enhance the overall evaluation of the ecological environment. Furthermore, the establishment of more dynamic models that better capture the changing processes of ecosystems could be considered.

4.3. Litmations and Further Directions

This study has some limitations. The choice and availability of data may affect the research results, and the study is constrained by the time and spatial scope of the data. Further research can consider incorporating more data sources and methods for more accurate and comprehensive results [40]. Additionally, this study focuses only on the evaluation and driving force analysis of the ecological environment quality in the Changle District. Further exploration may be needed for specific environmental issues and ecosystem studies, such as monitoring and analyzing specific pollutants for targeted environmental issue resolution. Furthermore, the ecological environment quality in the Changle District is influenced by multiple factors, including government policies, economic development, social factors, etc. In future studies, these factors could be considered, to comprehensively understand the mechanism of ecological environment quality formation. Furthermore, due to the limitations of the GeoSOS-FLUS model, this research only predicted the land use based on the data in 2020. Future studies could develop new models that consider the data over several periods. Also, it is important to acknowledge that the relatively coarse spatial resolution may not capture localized variations in precipitation, particularly in areas with complex topography. Future studies could improve on that with higher-resolution data or local observation studies. Finally, this study only included Geodector to analyze the influencing factors of the RESI. Researchers could compare the effectiveness of multi-models in the analyses of RESI.

5. Conclusions

Based on the case study of the Binhai Changle District of Fuzhou, this study conducted an analysis of the Regional Ecological Security Index (RSEI) to evaluate ecological environment quality and utilized Geodector to analyze its driving forces. Based on the GeoSOS-FLUS model, this study simulated and predicted land use classifications if maintaining the RSEI factors. This study provides a scientific framework for the assessment of ecological environment quality and its driving forces, with broader implications for coastal regions in developing countries globally. The findings and recommendations herein could inform policy decisions aimed at promoting sustainable development and environmental conservation in diverse ecological contexts. The main conclusions of the study are as follows:

Through the analysis of the temporal and spatial changes in the RSEI, we observed significant variations in the ecological environment quality of Binhai Changle District in recent years. While the overall ecological environment in the Changle District of Fuzhou is relatively good, there are still some regional issues. The north, south, and southwest regions exhibit better environmental conditions, while the northwest and eastern parts face challenges. The overall ecological environment quality is on a declining trend, although the rate of decline has slowed. Factors such as vegetation coverage, leaf area index, and aerosols are the primary drivers influencing the ecological environment in Changle District. Industrial emissions significantly impact air and water quality, transportation has a substantial effect on air quality, and land use changes play a crucial role in the disruption of vegetation cover.

Through simulating and predicting land use classifications, we made reasonable speculations about the future land use patterns in Changle District. The model results indicate that as urbanization progresses, certain ecologically sensitive areas may be threatened, emphasizing the need for enhanced protection and management. For sustainable development, we underscore the importance of the rational planning and management of ecological lands such as farmland, water bodies, and green spaces. In future planning, careful consideration of the study results is necessary to formulate more scientific and feasible plans for ecological environment protection and land use. In the process of urbanization, strict environmental management policies should be implemented, emphasizing the rational layout of land use, particularly for the protection of ecologically vulnerable areas. Additionally, the monitoring and assessing of critical ecological functional areas should be strengthened to enhance the sustainability of land use, enabling Changle District to achieve coordinated development in its economic, social, and ecological aspects.

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Data Availability Statement: The data presented in this study are available on request from the corresponding author.

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

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