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Research article

Parameter assignment for InVEST habitat quality module based on principal component analysis and grey coefficient analysis

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Abstract: The Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) model is a concise approach to evaluate the status of habitat quality for supporting ecosystem management and decision making. Assigning parameters accurately in the InVEST model is the premise for effectively simulating habitat quality. The purpose of this study is to propose an available method for assigning the important parameters in the Habitat Quality module of InVEST. Herein, the methods of principal component analysis (PCA) and grey relational analysis (GRA) were utilized to assign the weights of threat factors and the sensitivity of each habitat type to each threat factor, respectively. Through a case study of the habitat quality of Fuzhou City, we find that using PCA and GRA methods to assign parameters is feasible. Generally, the habitat quality of Fuzhou City in 2015 and 2018 was above the fair suitable level, and the proportion of fair suitable and good suitable habitats was about 83%. The areas with higher habitat quality were mainly concentrated in forest, wetland and grassland ecosystems. The spots with lower habitat quality were scattered all over the main urban areas of districts and counties, and their periphery. GDP per capita and population density were the main factors that affect the habitat quality of Fuzhou City. Narrowing the economic imbalance gap is an important way to reduce population shift and relieve the pressure of the urban environment in economically developed areas. This study is expected to provide an effective method for assigning parameters in the InVEST Habitat Quality Module and support regional ecosystem conservation.

Keywords: habitat quality; principal component analysis; grey coefficient analysis; InVEST model;

driving factors

1. Introduction

Habitat quality refers to the capability of an ecosystem to provide the necessary resources and conditions for all its wildlife or specific populations. It is considered to be a sustainable variable that ranges from low to medium to high, depending on the resources available to survive and reproduce and the persistence of each population [1]. However, accompanied with vigorous economic development and population growth, China's ecosystem and environment experienced severe degradation or unsustainable development over the past few decades [2,3]. From 1995 to 2015, the ecosystem service intensity level in China experienced a continuously decreasing trend, especially in the large metropolitan areas [4]. That was because urbanization and industrialization derived Land Use and Land Cover Changes (LULC) that impact ecosystem services by changing the structures, processes and functions of ecosystems [5]. Thus, exploring the changes of habitat quality and their mechanisms are necessary to provide guidance for ecosystem management and implementation of related policies.

Actually, there are various approaches to assess habitat quality. The early methods obtained related parameters in the study area through field investigation and constructed an evaluation index system by using certain mathematical methods to comprehensively evaluate the target habitat quality [6]. In recent years, some researchers have evaluated habitat quality through various model simulations, such as the Habitat Suitability Index (HIS) model [7], the biodiversity evaluation CA-Markov model [8], the Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) Habitat Quality model [9], etc. These models have a complete evaluation system to assess habitat quality, which can reduce randomness in terms of the selection of evaluation indices and could provide a more scientific theoretical foundation in the assessment of habitat quality. In particular, the InVEST Habitat Quality model can estimate habitat quality based on land use/cover data and habitat threat data. It provides a concise approach to evaluating the status of habitat quality when there are limited available data and an unsampled area [10]. What's more, the InVEST Habitat Quality model attracts significant attention due to its small data demand and visual results. When evaluating the habitat quality by the InVEST model, it needs to determine some parameters which are important for evaluating the ecosystem service because the practicality of the weight will affect the reliability of the results [11]. However, a limitation of the InVEST Habitat Quality model is that parameters rely on empirical values, and many studies only cited other literature to assign the parameters [12–15]. Subsequently, the flood of empirical data makes model users confused about how to assign the parameters to evaluate the habitat quality of the target area. On one hand, the weight of the same threat factor is assigned differently. For example, the weight of the cropland threat factor is cited from 0.1 to 0.85 in the existing studies but without citing description [8,13,14,16]. On the other hand, the sensitivity of the same habitat type to a threat source is assigned inconsistently. For example, the sensitivity of woodland to cropland is cited from 0.2 to 0.85, also without citing description [17–19]. So, the model users don't know how to cite the empirical values for assigning the weights of threat factors and the sensitivity of the habitat type in the target region. Recently, some studies have attempted to overcome the assignment problem by taking objective methods. For example, Zhu et al [20] modified the assessment of habitat quality in land ecosystems by utilizing the normalized difference vegetation index (NDVI). Wu et al [21] applied Kendall's rank correlation method to assign the parameter of sensitivity and performed well in assessing the habitat quality of the Guangdong-Hong Kong-Macao Greater Bay Area. In the InVEST Habitat Quality module, there are R weights and $R \times J$ sensitivities to be assigned (R represents the number of threat factors; J represents the number of land use types). Thus, it is necessary to find an objective and regional method for assigning the important parameters. In fact, factor analysis based on Principal Component Analysis (PCA) and correlation coefficients based on Grey Relational Analysis (GRA) can meet the aforementioned requirements. The PCA method has been widely applied in the studies of the physical field [22–24], environmental management [25] and habitat quality [26–28]. Since the load matrix can derive the importance of the variables, some researchers studied the weights of the variables through the PCA method. For example, Wang et al [26] and Xie et al [27] applied the importance of the variables in the load matrix to assign the weights of all indicators when evaluating river (aquatic) habitat quality, and they derived credible results. Inspired by these studies, we define the weights of threat factors according to the importance of the variables derived from the PCA method. The GRA method mainly discusses the grey system's relational analysis. It shows the correlation between reference sequences and comparison sequences through quantitative analysis. Some researchers use correlation degrees to describe the relations, influences or contributions between reference sequences and comparison sequences. For example, Wang et al [29] and Zhou et al [30] have successfully applied the correlations through the GRA method to describe the contributions and influences when studying a weapon system selection problem and nutritional values among potato cultivars, respectively. In this study, we use the GRA method to assign the correlations between the reference sequences of habitat type and the comparison sequences of associated threat factors. The reference sequence of land use type j and the comparison sequence of threat factor r are denoted by y_j (j = 1,2,..., J) and x_r (r = 1,2,..., R), respectively. The correlation degree between y_j and x_r can be regarded as the sensitivity of land use type j to threat factor r. Since PCA and GRA methods are based on historical data in the target area, the calculation results for the target region are regional, objective and credible.

The objects of this study are as follows: (1) providing a general method (PCA and GRA) to assign the target region's parameters of weight of each threat factor and the sensitivity of habitat type to each threat factor in the Habitat Quality module of InVEST model; (2) taking Fuzhou City as a case study to present the effectiveness of assigning the important parameters in the InVEST model based on PCA and GRA methods.

2. Methodology and materials

2.1. Habitat Quality module of InVEST Model

InVEST is a model system developed by the Natural Capital Project team of the United States, and it is used to evaluate ecosystem services and their economic values and support ecosystem management and decision-making [10]. The Habitat Quality module of the InVEST model (version 3.8.0) processing is based on Land use / land cover (LULC) data. Combining a LULC map with data on threats to habitats and habitat response, it can produce habitat quality maps as outputs [21]. The input data in the Habitat Quality module of the InVEST model require a LULC map of raster type, a threat factors map of raster type and some parameters, including stress level, the maximum impact distance of a threat factor on the habitat, the weight of a threat factor, the relative sensitivity of land use type to a threat factor and the habitat suitability. These parameters appear in the three important formulas (Eq. (1)–Eq. (3)) of the Habitat Quality module of the InVEST model. The stress level I_{rxy} of the threat factor r in the grid y to the habitat grid x can be calculated as in Eq. (1), i.e.,

$$I_{rxy} = \begin{cases} 1 - \left(\dfrac{d_{xy}}{d_{r\max}} \right) & if \quad linear \\ \exp\left(-\left(\dfrac{2.99}{d_{r\max}} \right) d_{xy} \right) & if \quad \text{exponential} \end{cases} \tag{1}$$

where d_{xy} is the linear distance between grid x and grid y, and d_{rmax} is the maximum impact distance of the threat factor on the habitat. D_{xj} denotes the total threat level of grid x in habitat type j, which can be formulated by the following:

$$D_{xj} = \sum_{r=1}^{R} \sum_{y=1}^{Y_r} \left(\frac{\omega_r}{\sum_{r=1}^{R} \omega_r} \right) r_y I_{rxy} \beta_x S_{jr} \tag{2}$$

where R is the number of threat factors. Y_r indicates the number of grid cells of the threat factor r in the land use map. W_r is the weight of threat factor r. r_y is the number of stress factors on grids. $\beta_x \in (0,1)$ indicates the level of legal accessibility of grid x, and we set $\beta_x = 1$, which implies complete accessibility. S_{jr} indicates the sensitivity of land use type j to threat factor r.

The habitat quality index of grid x in land use type j is denoted by Q_{xj}. It can be calculated by the following formula:

$$Q_{xj} = H_j \left(1 - \left(\frac{D_{xj}^z}{D_{xj}^z + l^2} \right) \right) \tag{3}$$

where H_j is the habitat suitability of land use type j. The constant l is the half-saturation constant (we set $l = 0.05$), and z is a default parameter (we set $z = 2.5$).

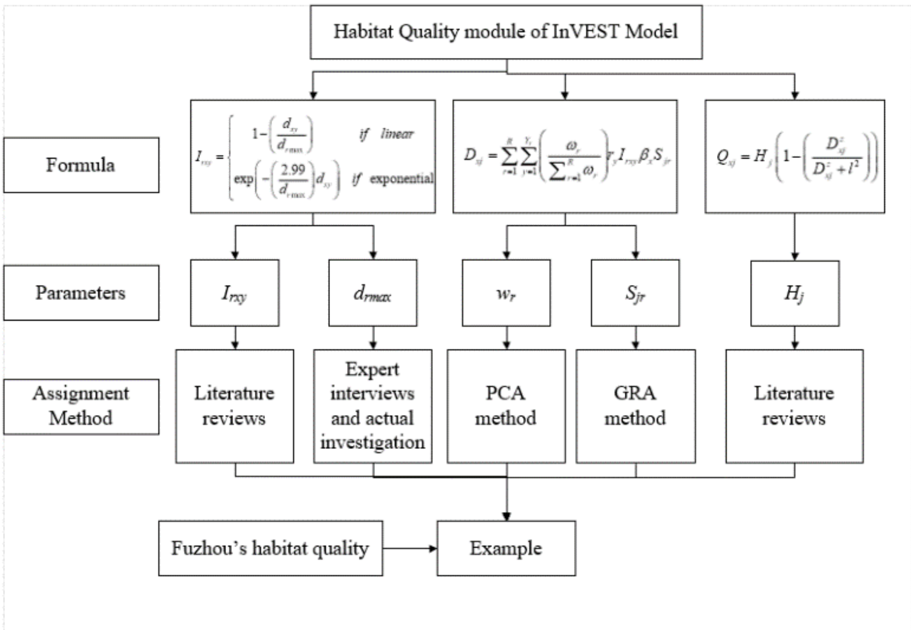

Figure 1. The organization flow chart of this study.

From the above three formulas (Eq. (1)–Eq. (3)), the parameters of I_{rxy}, d_{rmax}, w_r, S_{jr} and H_j need be assigned. There are R+R+R×J+J values that should be properly assigned (R represents the number of threat factors; J represents the number of land use types). Usually, the parameters of I_{rxy}, H_j and d_{rmax} can be assigned by expert interviews according to the actual situation or empirical values. Among the above assignment values, the parameter assignment proportion of w_r *and* S_{jr} is large, accounting for $\frac{R+R\times J}{R+R+R\times J+J}$ % (For example $R=7$, $J=6$ in our study, and then the parameter assignment proportion of w_r and S_{jr} accounts for about 80% of the total parameters). Hence, the assignments for w_r and S_{jr} are crucial when simulating habitat quality by the InVEST model. In this study, we utilized quantitative analysis methods of PCA and GRA to determine the parameters of w_r and S_{jr}. The parameters of I_{rxy} and H_j were assigned by literature reviews. The parameter of d_{rmax} was assigned by expert interviews according to the actual investigation. Meanwhile, the habitat quality of Fuzhou City was evaluated as a case study by using the parameters assigned by the above method. The organizational flow chart of this study is shown in Figure 1.

2.2. Application of PCA in weight data set

PCA aims to use fewer dimensions to describe the original data information on the premise of retaining the original information as much as possible [28]. From the load matrix, we can obtain the importance of the variables. Based on the importance of the variables, we can define the weights of threat factors.

Supposing there are R threat factors with m years' sample data, the original matrix is denoted as $X=\left(x_{ir}\right)_{m\times R}$, where x_{ir} denotes the value of the threat factor r in the i th year. To determine the weights w_r (r = 1, 2, …, R), there are four steps.

Step 1: Determine the number of principal components k and initial factor load matrix $F=\left(f_{rj}\right)_{R\times k}$ by SPSS software.

Step 2: Calculate a_{rj}, the importance of threat factor r to the principal component j, which is defined by the following formula.

$$a_{rj}=\frac{f_{rj}}{\sqrt{\lambda_j}},a=\left(a_{rj}\right)_{R\times k} \tag{4}$$

Step 3: Calculate v_j, the importance of principal component j to other principal components, which is defined by the following formula.

$$v_j=\frac{\lambda_j}{\sum_{j=1}^{R}\lambda_j}\left(j=1,2,\cdots,k\right) \tag{5}$$

Step 4: Calculate w_r, the weight of threat factor r, which is defined by the following formula.

$$\omega_r=\sum_{j=1}^{k}\left|a_{rj}\right|\times v_j,r=1,2,\cdots,R. \tag{6}$$

Through the SPSS software, the PCA method can assign R weight values simultaneously. For example, supposing there are 7 threat factors with 5 years' sample data, then X is a matrix with $X=\left(x_{ir}\right)_{5\times 7}$. The standardization Z, correlation matrix E, k principal components and load matrix F

can be obtained by the SPSS software. Through Eq. (4)–Eq. (6), we can compute the vector $w=\{w_1,w_2,...,w_7\}$, where w is the weight of the threat factors.

2.3. Application of GRA in sensitivity data set

GRA is used to evaluate the correlation degrees between reference sequences and comparison sequences. The reference sequence is the data sequence reflecting the behavior characteristics of the system, and the comparison sequence is the data sequence composed of factors that affect the behavior of the system. Here, the land use types and threat factors are regarded as reference sequences and comparison sequences, respectively. Suppose there are J land use types and R threat factors with m years' sample data. The reference sequence of land use type j and the comparison sequence of threat factor r are denoted by $y_j=\{y_j(i)\text{: } i=1, 2, \ldots, m\}$, $j=1, 2, ..., J$, and $x_r=\{x_r(i)\text{: } i=1, 2, ..., m\}$, $r=1, 2, ..., R$, respectively.

The correlation coefficient between y_j and x_r ($r=1, 2, ..., R$) is denoted by S_{jr}, which can be regarded as the sensitivity of land use type j to threat factor r. To determine the sensitivity S_{jr} ($j=1, 2, ..., J$, $r=1, 2, ..., R$), there are three steps.

Step 1: Calculate the standardization z_r of x_r for a certain land use type j.

For the certain land use type j, if x_r and y_j have a positive correlation, let

$$z_r=\left(1,\frac{x_r(2)}{x_r(1)},\ldots,\frac{x_r(m)}{x_r(1)}\right)^T \tag{7}$$

If x_r and y_j have a negative correlation, let

$$z_r=\left(1,\frac{x_r(1)}{x_r(2)},\ldots,\frac{x_r(1)}{x_r(m)}\right)^T \tag{8}$$

Step 2: Calculate the sensitivity of land use type j to threat factor r, denoted by S_{jr}.

The correlation coefficient z_r and y_j on the index i is calculated by the following equation.

$$\xi_{jr}(i)=\frac{\min_s\min_t\left|y_j(t)-z_s(t)\right|+\rho\max_s\max_t\left|y_j(t)-z_s(t)\right|}{\left|y_j(i)-z_r(i)\right|+\rho\max_s\max_t\left|y_j(t)-z_s(t)\right|},i=1,2,\cdots,m,r=1,2,\cdots,R \tag{9}$$

where $\rho\in(0,1)$ is the resolution coefficient (we set ρ=0.5). The sensitivity of land use type j to threat factor r can be calculated by the following formula.

$$S_{jr}=\frac{1}{m}\sum_{i=1}^{m}\xi_r(i),r=1,2,\cdots,R \tag{10}$$

Then, $S(j)=\{S_{jr}\text{: } r=1, 2, ..., R\}$ is the sensitivity of land use type j to all threat factors.

Step 3: Determine all the sensitivities of land types to threat factors when $j=1, 2, ..., J$.

$$S=\{S(1),S(2),\cdots,S(R)\}=\left(S_{jr}\right)_{J\times R} \tag{11}$$

Through MATLAB software, the GRA method can assign $R\times J$ sensitivity values simultaneously. Taking forest land as an example, we suppose reference sequence y_1 is the area of forest land with 5 years' sample data, i.e., $y_1=\{y_1(i)\text{: } i=1, 2, ..., 5\}$. Suppose there are 7 threat factors with 5 years' sample data, i.e, $x_r=\{x_r(i)\text{: } i=1, 2, ..., 5\}$ ($r=1, 2, ..., 7$). Through Eq. (7) – Eq. (10), we can obtain $S(1)=\{S_{1r}$:

r=1, 2, ..., 7}. It is the sensitivity vector, where S_{1r} is the sensitivity of forest land to threat factors.

2.4. Example study area of Fuzhou City

To present the effectiveness of assigning parameters in the Habitat Quality module of the InVEST model based on PCA and GRA methods, we take Fuzhou City as a case study. Fuzhou (25°15' – 26°39' N, 118°08' – 120°31' E) is the capital of Fujian province and the largest prefecture-level city in China. It is also one of the birthplaces of the ancient maritime Silk Road. It governs 5 districts and 8 counties (Figure 2), covering a total land area of 11862 km^2 and sea area of 10573 km^2 [31]. With a humid subtropical climate influenced by the East Asian Monsoon, Fuzhou has long, hot and humid summers and short, mild and dry winters. The annual mean temperature is 19.7 °C, and the annual precipitation ranges from 796 mm to 1913 mm [31]. Forest and arable land are the main types of land use in Fuzhou, accounting for more than 70% of the total land area. Subtropical monsoon rain forest and middle subtropical evergreen broad-leaved forest are the main vegetation zones. Until 2018, the area of forestry land in Fuzhou was 7500.00 km^2, with a forest coverage rate of 57.26% and a forest volume of 41.73 million cubic meters. The continental coastline is 920 km, accounting for 25% of the total coastline in Fujian Province. The interstitial beach covers an area of 641.96 km^2.

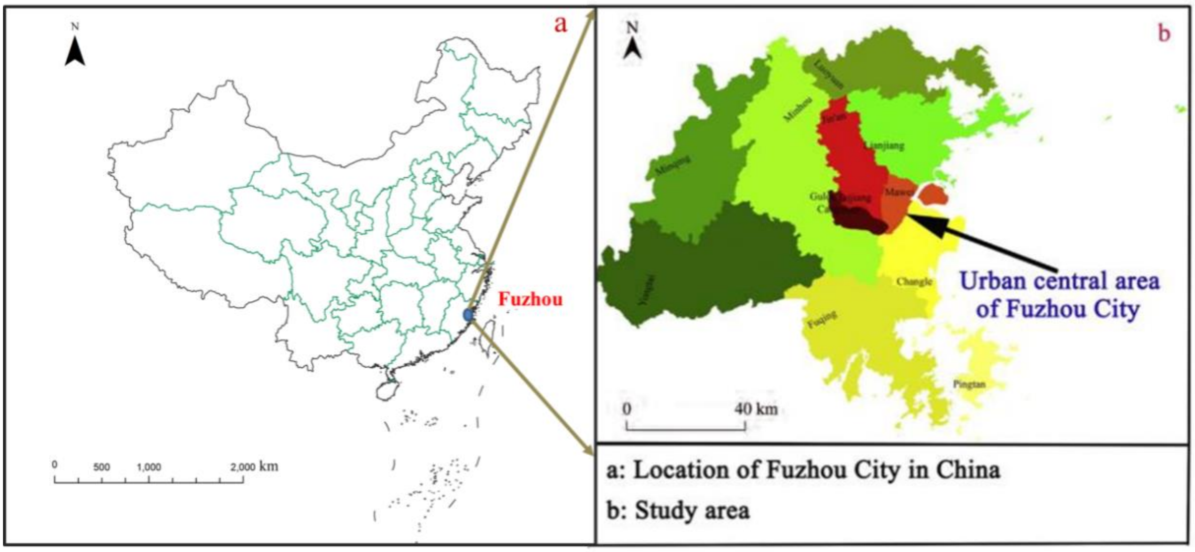

Figure 2. Location of Fuzhou City.

2.5. Data resources and preparation

When using PCA and GRA methods to accomplish the assignments, it requires at least 5 years of relevant data, including the target year. Like all statistical methods, the larger the sample size, the closer the assignment result is to the true value. However, the acquisition of sample data has a close relationship with its cost. Therefore, the sample size should be reasonably determined according to the difficulty of data acquisition. In this study, the LULC data of Fuzhou City in the years of 1995, 2000, 2005, 2015 and 2018 were used to assign the threat data values and sensitivity data values. The LULC map from Landsat Thematic Mapper (TM) acquired for 1995, 2000, 2005, 2015 and 2018 were used to examine land cover changes. The LULC data in 2015 and 2018 originated from the Fuzhou Ecological Environment Bureau. Other LULC data originated from the Data Center for Resource and

Environmental Science of the Chinese Academy of Sciences. The classification system of land cover developed by the Chinese Academy of Sciences [http://www.dsac.cn/ServiceCase/Detail/265970] and National current land use classification (GB/T21010–2017) were employed, and six land cover types in Fuzhou were identified as follows: cropland, forestry land, grassland, waters, built-up land and unused land. The overall accuracy of kappa coefficients in all classes was more than 0.80, indicating that the classification results were applicable [3]. When the InVEST Habitat Quality Module runs, it requires raster data, including an LULC map and threat factors map, defined in this study in a gridded map of 30 m square cells (900 m^2 per pixel), where an LULC class is assigned to each raster cell. Meanwhile, some parameters, including I_{rxy}, d_{rmax}, w_r, S_{jr} and H_j, are also approved.

The data required for calculating Q_{xj} and D_{xj} include land cover maps, threat data and sensitivity values of land cover types to each threat, as well as spatial data on the distribution and intensity of each threat. Most studies have taken transportation land, cropland, urban land, rural residential land and bare land as threat factors. For example, Yang et al (2021) took urban land, rural residential land, cropland, other land and unused land as threat factors when they studied the space-time and influencing factors of habitat quality in the Yellow River Basin [13]. Dai et al (2019) took cropland, urban land, rural residential land, industrial and mining land, transportation land and facility agricultural land as threat factors to study the impact of land use change on habitat quality [8]. Some studies also regarded population and GDP as threat factors. For example, Liu et al (2017) took population, GDP, construction land and roads as threat factors of ecological space to study urban development boundary delineation [32]. In fact, population and GDP are main causes of regional LULC change. Population growth can increase the demand for food, leading to an excessive reclamation of cropland, and even the degradation of land quality and the ecological environment. Meanwhile, the increase of population also can lead to the expansion of construction land area. The changes and adjustments of various land types are usually to meet the needs of social and economic development. Therefore, according to the relevant data of Fuzhou, combining the application cases of InVEST Habitat Quality and existing research achievements, we take typical indicators of socioeconomic development in this target region as threat factors, including transportation land (TL), cropland (CL), population density (PD), GDP per capita (PCG), urban land (UL), rural residential land (RRL) and bare land (BL). The data resources of area statistics on TL, CL, RRL and BL originated from the Data Center for Resource and Environmental Science of the Chinese Academy of Sciences and the Fuzhou Ecological Environment Bureau. The data resources of statistics on PD and GDP per capita come from the Fuzhou Statistical Yearbook. Using these statistical data for the years of 1995, 2000, 2005, 2015 and 2018, we compute w_r and S_{jr} in 2015 and 2018 as target years to evaluate the habitat quality for verifying the rationality of the assignment method.

3. Results

3.1. Changes in land use types and threat factors

Six land use types, including cropland, forestry land, grassland, waters, built-up land and unused land, were identified in Fuzhou City. Through analysis, it was found that the average proportion of forestry land was the highest, at around 60%. Next is cropland, which accounts for around 15%. The last was grassland, only taking up around 1% (Table 1). During 1995–2018, built-up land and waters showed a growing trend, increasing by 8.94% and 0.93%, respectively. For the built-up land area, it increased about 969.09 km^2 from 1995 to 2018, and its proportion in 2018 was four times that in 1995. Forestry land, cropland, grassland and unused land showed declining trends during 1995–2018, among which the area reduction in forestry land was large, with a reduced area of 2703.56 km^2 and average change rate of −8.42%.

Table 1. Proportion of different land use types during 1995–2018.

Land use type	Proportion (%)					Average change rate (1995-2018)
	1995	2000	2005	2015	2018	
Cropland	15.34	13.60	13.38	14.88	14.68	−0.66
Grassland	1.09	1.14	1.15	1.00	1.00	−0.09
Waters	9.07	9.15	10.06	10.13	10.00	0.93
Forestry land	67.86	66.04	64.06	59.57	59.43	−8.42
Built-up land	2.42	5.76	7.09	10.81	11.36	8.94
Unused land	4.23	4.31	4.26	3.62	3.54	−0.69

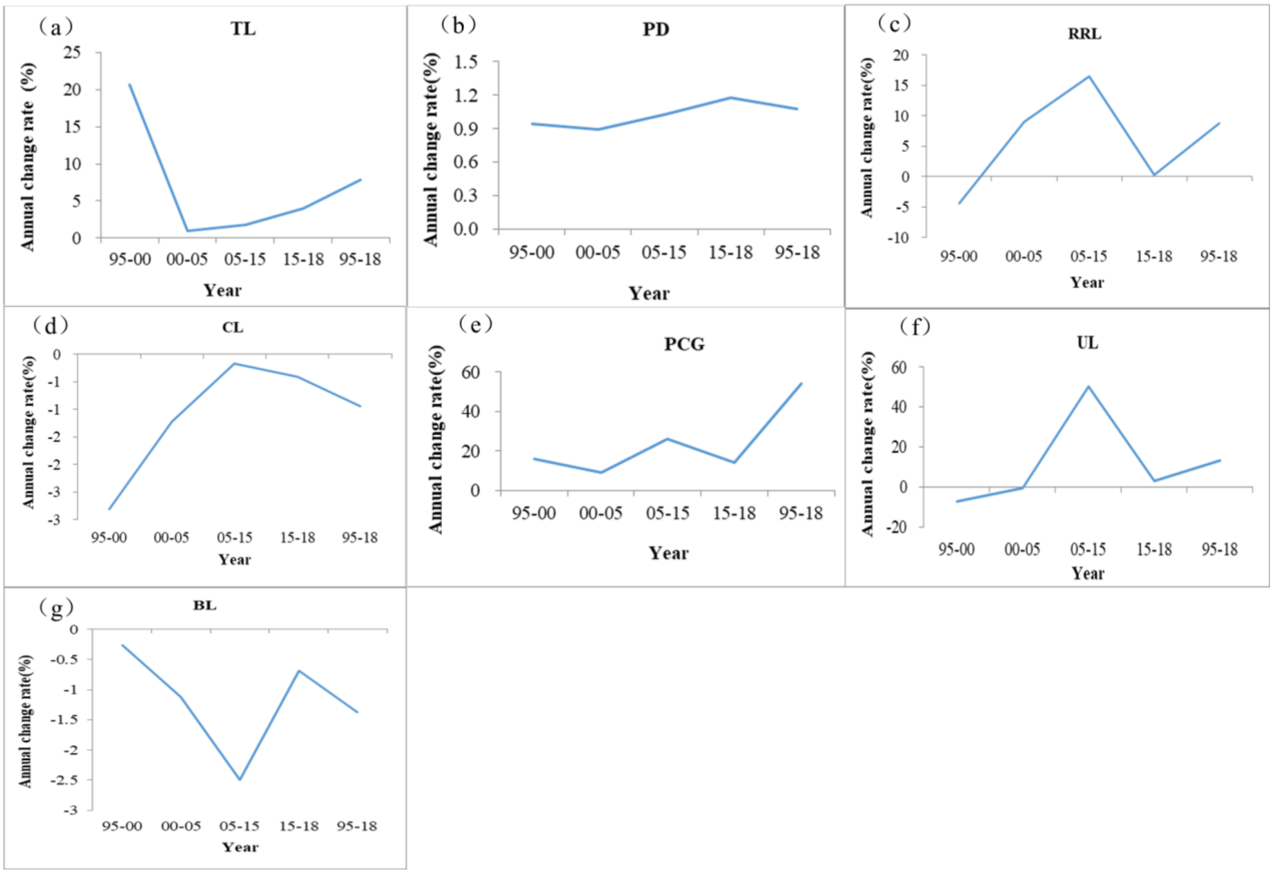

Figure 3. The annual change rates of threat sources during 1995–2018. **(a)** the annual change rate of transportation land (TL); **(b)** the annual change rate of population density (PD); **(c)** the annual change rate of rural residential land (RRL); **(d)** the annual change rate of cropland (CL); **(e)** the annual change rate of GDP per capita (PCG); **(f)** the annual change rate of urban land (UL); **(g)** the annual change rate of bare land (RL)**.**

For the threat factors, almost all the threat factors showed upward trends from 1995 to 2018, except for cropland. From the perspective of annual growth rate (Figure 3), it is found that the proportion of area change in urban land was large, increasing by 356.48 km^2 from 1995 to 2018, with an annual growth rate of 13.26%, even reaching 55.79% during 2005–2015. This was followed by the rural residential land, which increased by 307.07 km^2 with an annual growth rate of 8.77%. The area of bare land decreased by 187.82 km^2. While population density and GDP per capita showed increasing trends since 2005, the change rate of GDP per capita was large, with an annual increase rate of 54.16% from 1995 to 2018. This means that these threat sources will have an impact on the habitat quality of Fuzhou City.

3.2. Setting the maximum impact distance and weights based on PCA method

Some parameters, d_{rmax}, I_{rxy} and w_r, that are relative to the threat factors need to be assigned. We adopted from other studies [13–15,33] that the stress levels I_{rxy} of transportation land, cropland, population density and GDP per capita are assigned as linear, and the stress levels I_{rxy} of urban land, rural residential land and bare land are exponential (Table 2). For the maximum impact distance d_{rmax}, we adopted the assignment values of transportation land, cropland, urban land, rural residential land, population density and GDP per capita as 2, 1, 5, 3, 6 and 7, respectively, based on expert interviews [8,33]. Through the PCA method for assigning the weight of threat factor w_r, we obtained the weight of each threat factor for the target region of Fuzhou City in 2018 (Table 2). It is shown that the weights of GDP and population density are very close to other threat factors' values. This indicates that these two factors are worthy of consideration in habitat quality assessment, although they are rarely regarded as threat sources in the previous literature. In fact, population and GDP are the main causes of regional LULC change. Population growth can increase the demand for food, leading to excessive reclamation of cropland and even the degradation of land quality and the ecological environment. Meanwhile, the increase of population also leads to the expansion of construction land area. The changes and adjustments of various land types are usually to meet the needs of social and economic development. In addition, the successful quantitative calculation and one time assignment for the weights according to the historical data in Fuzhou suggested that the assignment of w_r by the PCA method through SPSS software is objective and convenient.

Table 2. The threats and their maximum impact distances and weights of threat factors in 2018.

	TL	**CL**	**PD**	**PCG**	**UL**	**RRL**	**BL**
w_r	0.319	0.286	0.354	0.345	0.332	0.340	0.350
d_{rmax}	2	1	6	7	5	3	1
I_{rxy}	Linear	Linear	Linear	Linear	Exponential	Exponential	Exponential

Note: TL, CL, PD, PCG, UL, RRL and BL indicate transportation land, cropland, population density, GDP per capita, urban land, rural residential land and bare land, respectively. w_r is the weight of the threat factor. d_{rmax} and I_{rxy} are the maximum impact distance and stress level, respectively. The same is below.

3.3. Setting sensitivities of habitat types to threats based on GRA method

In this subsection, the parameters of H_j and S_{jr} need to be assigned. For the parameter of H_j, we adopted from other studies that assigned the habitat suitability H_j of forestry land, waters, cropland, grassland, built-up land and unused land as 1, 0.9, 0.8, 1, 0.1, and 0.1 according to the literature reviews [8,19] and special geographical environment of Fuzhou. Through the GRA method, we obtained the sensitivity values of S_{jr} in 2018. From Table 3, it is shown that the sensitivity of land use type to threat factor was almost greater than 0.5, which showed that these threats have a great impact on land use change. Specifically, cropland is more sensitive to population density and rural residential land. Grassland is more sensitive to cropland and bare land. Waters are more sensitive to population density and bare land. Forestry land is more sensitive to cropland and bare land. Built-up land is more sensitive to GDP per capita and transportation land. Unused land is more sensitive to cropland and population density. Similarly, the quantitative calculation and one time assignment for the sensitivity according to the historical data in Fuzhou suggested that the assignment of S_{jr} by the GRA method through the MATLAB software is rational and convenient.

Table 3. Habitat suitability and sensitivities of habitat types to threats in 2018 through GRA method.

LULC	TL	CL	PD	PCG	UL	RRL	BL	H_j
Forestry land	0.564	0.884	0.734	0.540	0.576	0.647	0.938	1
Waters	0.566	0.792	0.813	0.533	0.538	0.665	0.804	0.9
Cropland	0.582	1.000	0.820	0.555	0.565	0.660	0.488	0.8
Grassland	0.577	0.869	0.806	0.552	0.555	0.655	0.919	1
Build-up land	0.896	0.531	0.630	0.876	0.733	0.757	0.537	0.1
Unused land	0.578	0.845	0.757	0.556	0.570	0.655	1.000	0.1

Note: Parameter of H_j is adopted from other studies [8,19], and S_{jr} in 2018 is assigned by GRA.

3.4. The habitat quality through InVEST model based on PCA and GRA methods

According to the actual situation and another study [30], the habitat quality in Fuzhou City can be graded as three levels: good suitable (0.8–1), fair suitable (0.4–0.8) and poor suitable (0–0.4). From the result obtained by the Habitat Quality module of the InVEST model based on PCA and GRA methods, the habitat quality of Fuzhou City was generally fair suitable, with a grade value of 0.74, but it also presented a great regional imbalance (Figure 4 and Table 4). Generally, the area proportion of good and fair habitat quality took up 84%, and the poor habitat quality accounted for 16%. This is mainly because the study area has a vast natural habitat of forest, wetland and a large area of cultivated land. Meanwhile, Fuzhou City is an excellent tourist city and national tourism center in China, owing the title of "National Forest City." A famous historical and cultural city, like Fuzhou City, pays more attention to the protection and construction of the ecological environment.

Geographically, the poor habitat quality in Fuzhou City is concentrated in the urban central area, including Gulou District, Taijiang District and Cangshan District, only accounting for 1.40% of the area of Fuzhou. These regions belong to the economically developed areas that gathered large population (2000 people/km^2) and produce high GDP (accounting for 35% of total GDP). Generally, these areas are dominated by the built-up land type with a relatively small natural ecosystem. The intense human activities in these areas induced relatively poor habitat quality. Yongtai County, Mingqing County, Luoyuan County and Pingtan County showed good habitat quality (more than 0.80), accounting for 33.39% of the area of Fuzhou, due to a large distribution of forest and wetland ecosystems (approximately 50%) and low population density (not more than 300 people/km^2). The habitat quality in other regions of Fuzhou City was fair suitable, and the habit quality values in Changle District and Fuqing City were relatively small, at about 0.6 (Table 6). Lianjiang County, Changle District and Fuqing City actually are the important service bases that provide ecosystem function services to ensure the economic development in developed areas. Since certain ecological damage and environmental pollution may occur during production activities, ecological and environmental protection is crucial, and economic growth at the cost of resource destruction should be avoided.

Table 4. The comparison of weights obtained by literature and PCA.

Threat source	PCA	Literature
TL	0.319*,0.370**	0.1[8],0.4[6],0.5[33,34], 0.6[17,34],0.75[21],1[21,35]
CL	0.286*,0.362**	0.1[8],0.3[6] ,0.5[35],0.6[13,34],0.68[21],0.85[14]
PD	0.354*,0.359**	0.3[17,34],0.4[16],0.8[33]
PCG	0.345*,0.368**	0.9[33]
UL	0.332*,0.377**	0.3[8,16], 0.7[35],0.8[17,34],1[6,13]
RRL	0.340*,0.378**	0.2[8],0.4[17,34],0.5[21],0.6[6],0.7[35],0.8[13]
BL	0.350*,0.368**	0.2[21],0.3[35],0.4[13]

Note: Values with * and ** symbols are assigned by PCA method for 2018 and 2015, respectively.

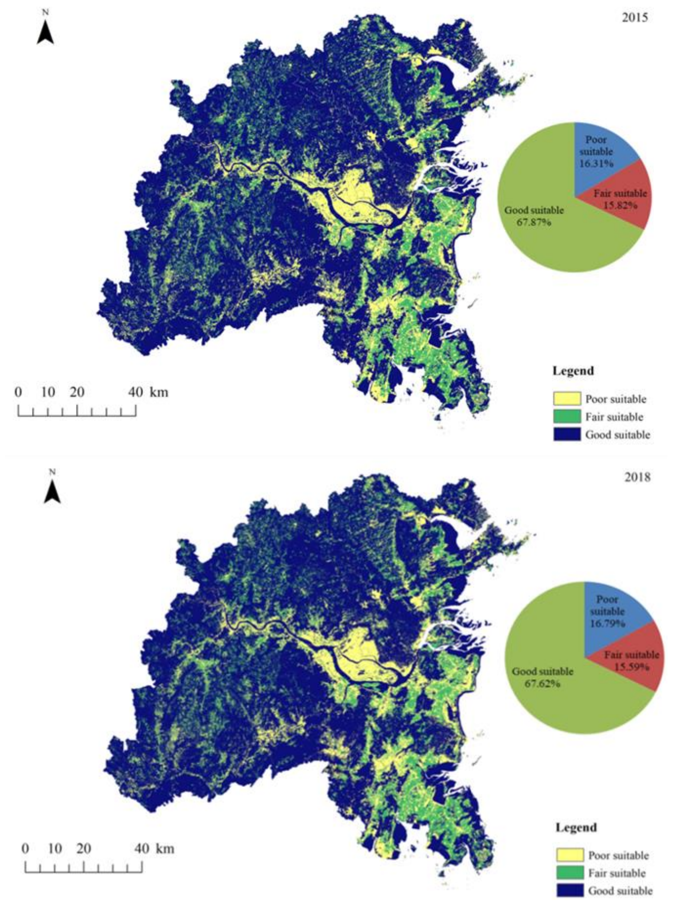

Figure 4. Fuzhou City habitat quality and its proportion in different grades.

There was no obvious change in habitat quality of Fuzhou City from 2015 to 2018, with 81.35% basically unchanged, 8.82% got better, and 9.33% got worse. The area of poor habit quality increased by 58.32 km^2 mainly originating from the fair suitable level and good suitable level. The area of fair suitable habitat quality decreased 26.66 km^2, mainly transforming into good suitable level. The area of good habitat quality decreased by 25.71 km^2 mainly shifting into poor and fair suitable levels. The regional habit quality changes were, significantly, mainly concentrated in Changle District, Minhou County, Yongtai County and Minqing County, accounting for 82% of the changes (Figure 5).

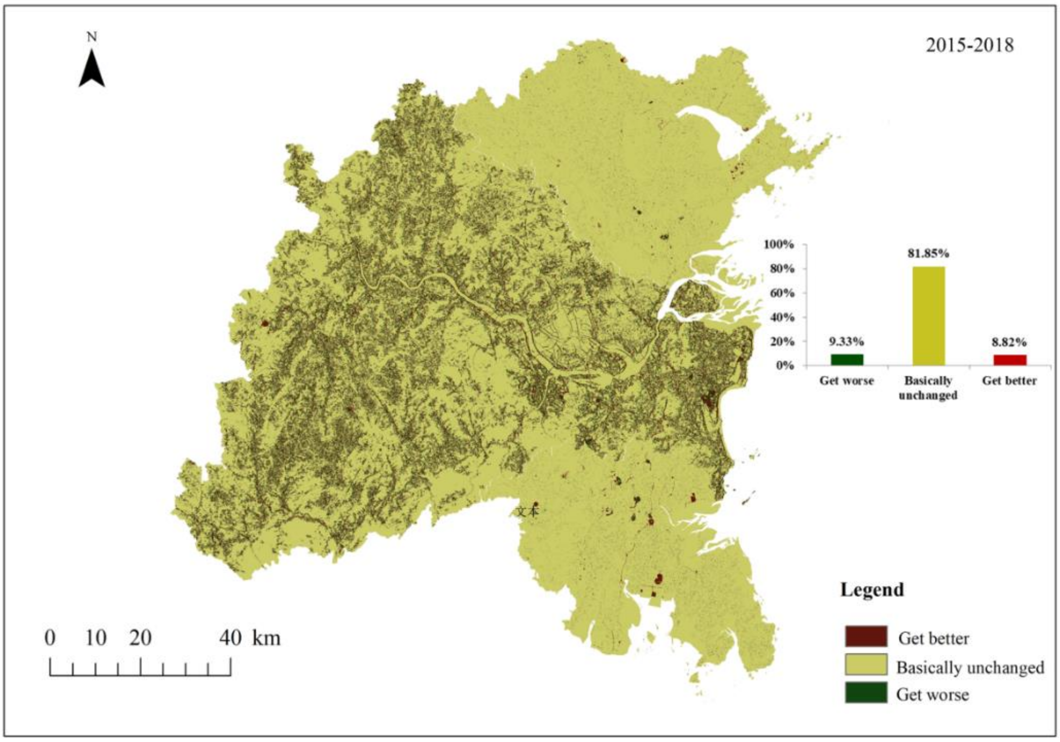

Figure 5. The changes of Fuzhou City habitat quality from 2015 to 2018.

4. Discussion

4.1. The weights and sensitivity values assigned by PCA and GRA

From 2005 to 2018, the main changes of LULC in Fuzhou City were the decrease of forest land and the increase of built-up land. Built-up land is the most concentrated embodiment of human activities in all land use types. Urban land expansion, urbanization, rapid economic development, industrialization and population growth have posed a threat to other natural ecosystems, destroying the surface vegetation and degrading the habitat quality. GDP and population have a close relationship with built-up land. The large population and high GDP output must rely on sufficient land, which usually comes from urban expansion. From the above results, it can be seen that the selected threat factors have an impact on the habitat quality of Fuzhou. Almost all the sensitivity values of habitat types to threat factors are more than 0.5, which revealed that these threat sources are reasonable.

Determining the weights and sensitivity values is one of the important links in the Habitat Quality module of the InVEST model. There were several studies had used some approaches to assign the parameters of the InVEST model. In the study of Wu et al [21], sensitivity values are calculated by Kendall's correlation coefficient, which performed well in assessing the habitat quality. In this paper, we attempted to assign both weight and sensitivity values by quantitative analysis through PCA and GRA methods, which have been widely applied in studies of the physical field [22–24], a weapon system selection problem [29], nutritional values among potato cultivars [30], environmental management [25] and habitat quality [26–28]. As shown in Table 4 and Table 5, the obtained values of sensitivity and almost all weights were within the ranges in the existing studies. Meanwhile, the total and regional distribution characteristics of habitat quality obtained by PCA and GRA methods are consistent with the distribution law of ecological environment index (EI) provided by local government [36]. This showed that the habitat quality simulated by the InVEST model through assigning weights and sensitivity parameters by PCA and GRA methods is rational, feasible and effective.

In order to further verify the rationality of the assignment by the PAC and GRA methods, we adopt three assignment methods to evaluate the habitat quality of Fuzhou in 2015. From comparison (Table 6), we found that there are great differences in habitat quality among different methods. The habitat quality results fluctuated greatly when assigning the parameters from other studies (Literature review assignment (1) and (2)), and even some habitat quality values changed across levels. Thus, the flood of parameters in the literature without reasonable quotation may generate invalid habitat quality results in the target area. Therefore, using target data to assign parameters of weights and sensitivities based on PCA and GRA methods can solve the confusion on how to assign critical parameters and draw rational local results.

Table 5. The comparison of the sensitivities obtained by GRA and literature.

Land use type	TL	CL	PD	PCG	UL	RRL	BL
Crop land	0.2[8,12,14,33],0.25 [14],0.4 [15,18],0.5[17] 0.6 [15,17,18],0.7 [13], **0.582***,**0.573****	0 [13,17],0.3[8,12,15], 0.4 [14],1 [18], **1***,**1****	0.6[33],0.8[17], **0.820***,**0.737****	0.7[33],**0.555*** **0.556****	0.3[8],0.4[18],0.5[15,17, 32],0.6[18],0.7[14],0.8[1 3],**0.565***,**0.638****	0.3[8],0.4[17],0.5[12, 33],0.6[13],0.7[14,15]，**0.660***,**0.708****	0.3[14],0.4[1 3,19],0.6[12], **0.488***,**0.836****
Forest land	0.2[8],0.3[18], 0.4[18,33],0.5[12,15,17],0.6[8,1 4,15,17 ,19],0.65[15],0.7[8,12,1 3,15,17],0.8[17,19],0.9[17] **0.564***,**0.603****	0.2[8],0.3[17],0.4[17],0. 5[17],0.6[8,13,15,18 ,19],0.7[13],0.8[13,19],0.8 5[14],**0.884***, **0.891****	0.6[17],0.7[17,32] **0.734***,**0.782****	0.8[33],**0.540*** ,**0.588****	0.2[18],0.3[8],0.4[18], 0.5[17,19], 0.6[8,15,17,19,24],0.7[1 5,19],0.8[8,13-15,19], **0.576***,**0.624****	0.2[8],0.4[17],0.5[8,1 7,19],0.6[15,19,32],0. 65[15],0.7[13,12,19]0 .8[8,14,15,19],0.85[1 5],**0.647***,**0.709****	0.2[13],0.5[12, 18],0.65[14] 0.8[35] **0.938***,**0.844****
Grassland	0.3[14,15,33],0.4[14,15,18], 0.35[15],0.5[18],0.6[8,13], 0.7[17,19],0.8[12],0.9[19] **0.577***,**0.618****	0.4[19],0.5 [8,12- 15 ,17],0.55[15],0.6[19] ,0.7[12],0.8[18,19], **0.869***,**0.854****	0.5[17],0.7[33] ,**0.806***,**0.836****	0.8[24], **0.552***,**0.601****	0.3[17],0.4[18], 0.6[8,15,19,33], 0.65[14,15]0.7[13], 0.8[19] ,**0.555*** **0.596****	0.2[17],0.5[13,15],0.5 5[15],0.6[8,12,15,33], 0.65[14],0.8[19], **0.655***,**0.718****	0.4[18],0.5[14] 0.6[12,13], **0.919*** **0.939****
Waters	0.2[8],0.4[14],0.5[14],0.6[8,15,2 4],0.65[18]0.7[13],0.75[18] 0.8[19],0.9[19] ,**0.566*** **0.598****	0.1[18],0.2[8],0.3[15], 0.4[13],0.5[8,12,15,18] 0.6[8],0.8[12,19],0.7[12 ,14],0.9[19] ,**0.792*** **0.795****	0.5[17],0.9[33], **0.813***,**0.855****	0.9[10], **0.533***,**0.576****	0.2[8],0.7[13],0.75[15],0 .8[8,12,15, 17-19], 0.85[14],0.9[19,33] **0.538***,**0.570****	0.2[8],0.5[15],0.6[12, 13],0.65[15] 0.7[8,12,17],0.8[19],0 .85[14],0.9[19,33], **0.665***,**0.724****	0.4[13],0.5[14] 0.6[12],0.7[12] 0.8[18],**0.804*** **0.852****
Built-up	0[8,13,33], 1[18] **0.896***,**0.903****	0[8,13] **0.531***,**0.568****	0[33],0.4[17],0.6[16],**0.630*** **0.653****	0[33], **0.876***, **0.902****	0[8,13,33],0.6[18], 1[17],**0.733*** **0.671****	0[8,13,32],0.6[18], **0.757***,**0.722****	0[13],1[17] **0.537*** **0.586****
Unused land	0[8,33],0.2[17],0.4[18],0.6[13], **0.578***,**0.618****	0[8],0.1[17],0.4[13], 0.5[18], **0.845*** **0.853****	0[33],0.3[17], **0.757***,**0.813****	0[33],**0.556*** **0.603****	0[8],0.1[17],0.3[18],0.4[18],0.6[13] **0.570***,**0.613****	0[8],0.1[17],0.5[13] **0.655***,**0.717****	0[13],0.4[18] **1***,**1****

Note: Bold numbers with * symbol and ** symbol are assigned by GRA method for 2018 and 2015, respectively.

Table 6. Habitat Quality of Fuzhou in 2015 and 2018.

Region	2015			2018
	Literature review assignment (1)	Literature review assignment (2)	PCA+GRA	PCA+GRA
Fuzhou City	0.56 (fair)	0.69 (fair)	0.743 (fair)	0.739 (fair)
Lianjiang County	0.55 (fair)	0.69(fair)	0.745 (fair)	0.742 (fair)
Changle District	0.46 (fair)	0.55(fair)	0.604 (fair)	0.596 (fair)
Minhou County	0.56 (fair)	0.70(fair)	0.753 (fair)	0.749 (fair)
Yongtai County	0.62 (fair)	0.77(fair)	0.818 (good)	0.817(good)
Minqing County	0.64 (fair)	0.78 (fair)	0.824 (good)	0.822(good)
Luoyuan County	0.62 (fair)	0.76(fair)	0.802 (good)	0.800(good)
Cangsan District	0.23 (poor)	0.26(poor)	0.288 (poor)	0.273 (poor)
Fuqing City	0.49 (fair)	0.59(fair)	0.647 (fair)	0.642 (fair)
Mawei District	0.52 (fair)	0.65(fair)	0.706 (fair)	0.696 (fair)
Pingtan County	0.57 (fair)	0.74(fair)	0.832 (good)	0.832(good)
Jinan District	0.55 (fair)	0.69(fair)	0.744 (fair)	0.739 (fair)
Gulou District	0.16 (poor)	0.18(poor)	0.188 (poor)	0.197 (poor)
Taijang District	0.18 (poor)	0.20(poor)	0.219 (poor)	0.219 (poor)

Note: Literature review assignment (1): The weights and sensitivity values take the minimum values in the references listed in Table 4 and Table 5. Literature review assignment (2): The weights and sensitivity values take the maximum values in the references listed in Table 4 and Table 5. PCA+GRA assignment: weights and sensitivity values are assigned by the PCA and GRA method, respectively, shown in Table 2 and Table 3.

4.2. Driving factors affecting habitat quality in Fuzhou

From 2015 to 2018, the distribution of habitat quality in Fuzhou City is basically consistent with the distribution of landscape types, with significant spatial heterogeneity. The areas of the ecological source dominated by forestry land, grassland, and wetland landscapes have high habitat quality, with values of 0.928, 0.918 and 0.820, respectively. Meanwhile, the habitat quality in the areas where construction land and cultivated land are concentrated is low, with values of 0.236 and 0.538. The decreased habitat quality values in Cangshan District, Mawei District and Changle District have negative correlation with their GDP per capita and urban land area. Usually, forestry land with high vegetation has high habitat quality, but built-up land with intense human activity has low habitat quality [37]. The developed economy, large population density, strong urban expansion and urban construction can destroy the surface vegetation and degrade the habitat quality [2-4, 33]. That was the main reason why the increased habitat quality value is in Cangshan District, which has increased forest area (increased by 59.22%).

In order to further analyze the driving factors affecting the habitat quality in Fuzhou City, we apply linear correlation analysis, which is also applied in other studies [12,38,39], to obtain the correlation coefficients between threat factors and habitat quality (Table 7). From the correlation results, it is shown that the correlation values between Fuzhou's habitat quality and threat sources are sorted in descending order: PD (0.847) > PCG (0.802) > CL (0.483) > BL (0.299) > TL (0.290) > RRL (0.256) > UL (0.114). This indicated that the population density, GDP per capita and urban land were the main factors that drive the changes of habitat quality in Fuzhou City.

Table 7. The correlation coefficients between threat factors and habitat quality.

Correlation coefficient	TL	CL	PD	PCG	UL	RRL	BL	Habitat quality
TL	1.000	0.796	-0.508	-0.481	0.718	0.919	0.653	0.290
CL	0.796	1.000	-0.500	-0.460	0.539	0.831	0.609	0.483
PD	-0.508	-0.500	1.000	0.893	-0.202	-0.562	-0.393	0.847
PCG	-0.481	-0.460	0.893	1.000	-0.184	-0.442	-0.362	0.802
UL	0.718	0.539	-0.202	-0.814	1.000	0.803	0.568	0.114
RRL	0.919	0.830	-0.562	-0.442	0.803	1.000	0.757	0.256
Habitat quality	0.290	0.483	0.847	0.802	0.114	0.256	0.299	1.000

Additionally, in recent years, with rapid economic development, more and more people have moved into Fuzhou City. Subsequently, its population density is far higher than the average level of Fujian province and China (Figure 6). Usually, the economically developed regions attract and gather a large number of people. The intense human activity will inevitably affect the city's habitat quality. Therefore, solving the unbalanced development of the economy and strengthening environmental protection are the important ways to alleviate the environment pressure of cities with developed economic regions such as Fuzhou.

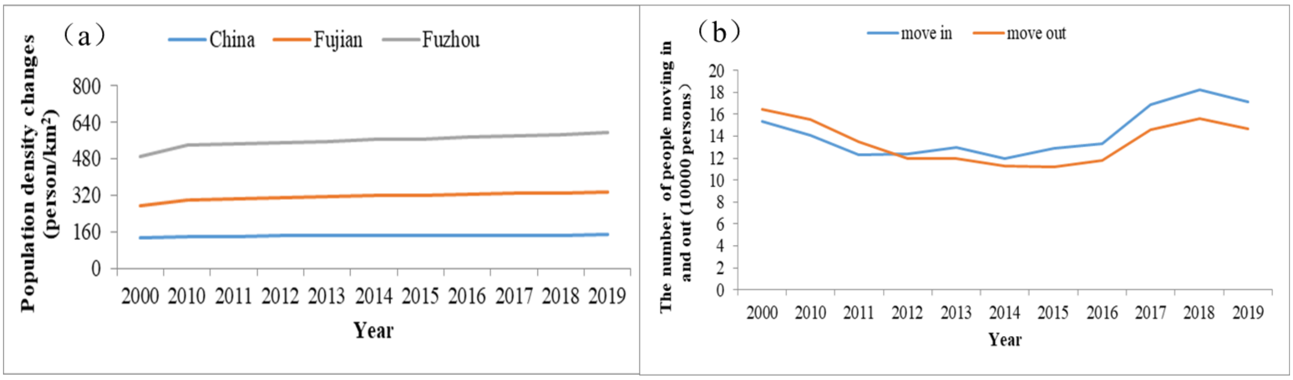

Figure 6. Population density changes and population migration figures during 2000–2019.

5. Conclusions

In the process of predicting and evaluating the habitat quality, rational parameter assignment is important for building the land ecosystem service evaluation. In this study, through PCA and GRA analysis, we approved a method of how to assign the parameters in the Habitat Quality module of the InVEST model. We clarified that determining parameters of weights of threat factors (w_r) and the sensitivity values of habitat types to threat factors (S_{jr}) are important for the habitat quality simulation by the InVEST model. Then, we estimated the spatiotemporal pattern and variation in habitat quality in Fuzhou City based on the optimized InVEST Habitat Quality model. We analyzed the differentiation of habitat quality across different ecosystem classifications. Finally, we explored the driving factors that affect the habitat quality in Fuzhou City through Pearson's correlation coefficients.

Through a case study of the habitat quality of Fuzhou City, we found that using PCA and GRA methods to assign parameters of weights and sensitivities is feasible, objective, convenient and effective. The distribution of habitat quality in Fuzhou City is basically consistent with the distribution of landscape types. The area of the ecological source dominated by forestry land, grassland and wetland landscapes has high habitat quality, while the habitat quality in the area where construction land and cultivated land are concentrated is low. Through Pearson correlation coefficient analysis, the main factors affecting the habitat quality in Fuzhou are population density and GDP per capita. The high population density in Fuzhou City caused by the increase in the influx of non-local population put great pressure on the local habitat quality. Narrowing the economic imbalance, formulating reasonable urban land use plans and accounting for environmental protection will be some important ways to alleviate the environmental pressure of cities with developed economic regions.

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Conflict of interest

The authors declare there is no conflict of interest.

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