



Applying a projection pursuit model for evaluation of ecological quality in Jiangxi Province, China

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ABSTRACT

Monitoring and evaluating ecological quality and changes are crucial for policy formulation to guide ecosystem management and socioeconomic sustainable development. However, evaluation of ecological quality is still very challenging due to difficulties in determination of its associated indicators and weights. This paper proposes supporting, providing and regulating ecosystems services-based indicators to describe ecological quality, and applies a Projection Pursuit Model to eliminate redundant indicators and objectively determine weights for an ecological quality index (EQI) on a regional scale. Taking Jiangxi Province, China, as a demonstration area, the data for indicator measures were retrieved from satellite remote sensing and ecosystem modelling with a spatial resolution of 1 km for the three years 2005, 2010 and 2015. The results suggest that Normalized Difference Vegetation Index (NDVI) and water use efficiency (WUE) should be weighed higher and leaf area index (LAI) and Bowen ratio should be weighed lowest in the calculation of an EQI for Jiangxi Province. For 2015, the regional EQI was calculated to be 55.32 on a scale from 0 as the worst to 100 as the best, with higher values ascribed to the hills and mountains and the lower values existing near urban areas. The EQI increased from 52.26 in 2005 to 55.32 in 2015 with an increased area of good-and-above grade from 25.47% to 36.8% for the whole province. The changes in EQI could be attributed to a warmer and wetter climate trend playing a positive dominant effect, while urbanization and afforestation have negative and positive effects, respectively. This study demonstrates that it is feasible to evaluate ecological quality based on a comprehensive set of indicators and PPM-based weight determination, which could be further applied in regular ecological quality monitoring and evaluation on the regional, or even the national scale.

1. Introduction

Globally, most ecosystems' quality is decreasing because of the considerable pressures arising from a growing population and economic development (Fang, 2009; Yin et al., 2017; Zhao et al., 2016). This is recognized as a serious threat to sustainable development (Bai et al., 2009; Pimentel et al., 1976; Yin et al., 2017). Therefore, to monitor and evaluate ecological quality and change are crucial for policy formulation regarding ecosystem management and socioeconomic sustainable development.

It is of great importance to identify spatial distribution and changes in ecological quality. However, evaluation is still very challenging due to

difficulties in determination of associated indicators and weights of those indicators, even though various evaluation methodologies have been developed and applied in the past. For example, the ecological footprint (Chen et al., 2021; Sarkodie, 2021; Vačkář, 2012) and the pressure-state-response methods (Das et al., 2020; Hazbavi et al., 2020) both aim to evaluate eco-environmental sustainability, but these methods are mostly focused on human stressors. Remote sensing-based evaluations generally use several indicators linked to physical aspects of ecosystems; for example, land use changes and the normalized difference vegetation index (NDVI) (Alatorre et al., 2016; Ghosh and Maiti, 2021), vegetation coverage (Feng et al., 2021), and net primary productivity of vegetation (McClelland et al., 2021). Remote sensing-based,

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ecological quality indices have been widely applied to evaluate ecological quality (Hu and Xu, 2018; Nourani et al., 2021; Song and Xue, 2016); however, there are few studies that consider ecosystem services functions as indicators in ecological quality evaluation. In an effort to monitor and evaluate ecological quality on a national scale, Wang et al. (2019) suggested a framework to evaluate ecological quality through a comprehensive indicator system including eco-environmental factors, ecosystem service functions and biodiversity. However, its performance has not been demonstrated in practice until now.

Ecosystem service functions are the benefits that ecosystems generate through ecological function for society (Daily, 1997; Holdren and Ehrlich, 1974; MA, 2005), widely applied in ecosystem assessments in terms of the condition and trend of ecosystems in both monetary values and biophysical quantity (MA, 2005; Ouyang et al., 2020; Trabucchi et al., 2012; Zheng et al., 2019b). For example, Paetzold et al. (2010) proposed to assess ecological quality by observing the ratio of sustained provision to expected provision from ecosystem services. Ecosystem services were summarized as four types: supporting, providing, regulating, and cultural functions (MA, 2005). Therefore, the first three service-based ecosystem functions form an easily understandable and practical set of indicators to describe ecological quality, while excluding cultural functions due to unavailability of data of pixel scale.

Biodiversity, as an important fundament in ecosystem function and the provision of ecosystem services (Brockerhoff et al., 2017), is considered in assessing ecological quality at the habitat scale (Niu et al., 2021) and at the county scale (State Council Information Office, 2021). However, due to the unavailability of spatial distribution data for species biodiversity, vegetation condition data, such as a vegetation index from remote sensing, has mostly been applied to quantify biodiversity on the regional or national scale (Fan et al., 2019; Sahraoui et al., 2021). This suggests that remote sensing-based vegetation indices can only be a potential indicator to quantify biodiversity on the regional or national scale.

Many methods have been applied in ecosystem assessments or evaluations and can be characterized as mostly incorporating subjective weighting determination (Liu et al., 2019; Wang and Yang, 2020; Wen et al., 2021). Methods used include principal component analysis (Zitko, 1994), analytic hierarchy process (Saaty, 1987), fuzzy comprehensive evaluation (Zheng et al., 2019a), etc. Projection pursuit modeling (PPM), used in the research reported here, projects high-dimensional data into a low-dimensional space and finds the optimum projection vector of data in one-dimension that can highlight the original high-dimensional data features to the greatest extent (Friedman and Tukey, 1974; Liu et al., 2017) and has been widely applied in many fields (Hu, 2018; Liu et al., 2019; Wang and Yang, 2020). PPM is relatively sensitive to change in each data indicator, and evaluative outcomes are determined by comparing the magnitude of the projection values, which is considered to overcome the shortcomings of traditional assessment methods, where the evaluation weight is too subjective and the contribution and its negative or positive direction of indices to the total objective is unclear (Fang et al., 2010; Liu et al., 2019). Meanwhile, PPM has the advantageous qualities of robustness, anti-interference, strong operability, and high accuracy (Deng et al., 2013; Jiang et al., 2011; Li, 1997). By avoiding the interference associated with subjective factors, a projection pursuit model will provide objective and reasonable results (Liu et al., 2019), which would make this method of great value for application in ecological quality evaluation.

Jiangxi, a province in southeastern China, has initiated many ecological programs since the 1980 s to restore degraded ecosystems (Huang et al., 2010; Le, 2020). Comparing the 8th National Forest Inventory in 2009 to 2013, to the 9th Inventory in 2014 to 2018 shows that Jiangxi has increased its forest area by 1.92%, its volume stock by 24.06%, and its plantation area by 8.89% (NFGA, 2019). However, the tension between economic development and ecological-environmental protection is still prominent, which results in enormous pressure for

ecological-environmental protection (Xu, 2017; Yu, 2016). Therefore, the current trend in Jiangxi's ecological environment from degradation to restoration, as well as current pressure for socio-economic development, is also a microcosm of the ecological-environmental changes across China in the last 20 years (Lu et al., 2019).

This study first explores a regional comprehensive multi-indicator-based ecological quality index based on the conceptual framework of regional ecological quality monitoring indicators suggested by Wang et al. (2019). Then the projection pursuit model (PPM) is applied to select indicators and determine their weights objectively based on the relationships among indicators. Through analyzing the spatial variation characteristics of ecological quality and possible causes, we evaluate the applicability and performance of the method for ecological quality evaluation on a regional scale. However, the final aim of this study is to provide a method to evaluate ecological quality on the regional and even national scale.

2. Materials and methods

2.1. Study area

Jiangxi Province is located in southeast China (Fig. 1) with a geographic range from 24°29'14"N to 30°4'41"N 30°04'41"N and from 113°34'36" E to 118°28'58" E, with an average elevation of 254.6 m above sea level. Its topography is characterized by hills and mountains in the eastern, western, and southern parts of the province; hills and valley plains dominate the middle of the province, and Poyang Lake Plain is in the north. Jiangxi Province has a subtropical, warm and humid monsoon climate, with an annual mean temperature of around 20 °C and an annual total precipitation of around 1400 mm to 1800 mm (Ding et al., 2013). Most vegetation is subtropical evergreen broad-leaved forest, and the forest coverage proportion is over 63%, according to forest survey data. Land use and cover change maps, from remote sensing-based data, exist for 2005 and 2015 (Fig. 1, European Space Agency (ESA) Land Cover CCI v2.0.7(ESA, 2017)). As a province, located in the middle and lower reaches of the Yangtze River economic belt, it is important for Jiangxi Province ecosystems to provide stability in ecosystem services, including grain-production, conserving and regulating water, etc. (Yang et al., 2018; Yang et al., 2015; Yu et al., 2010).

The province has seen very fast economic growth. Its gross domestic product (GDP) increased by 10.5%, 2.2% higher than the whole country GDP in 2015, along with fast urbanization, according to the Jiangxi Statistical Yearbook (JPBS, 2015). In 2015, urban and construction areas increased by nearly 13.7 and 2.6 times, respectively, compared to 2005 (Wu et al., 2015). The province has experienced a series of eco-environmental problems, such as land degradation, soil erosion, and the reduction of biodiversity (Liang et al., 2008); and has initiated a series of ecological programs to resolve problems since the 1980 s (Huang et al., 2010; Le, 2020). With a background of intense human activities along with global climatic changes, the evaluation of its ecological quality has very important implications for policy related to ecosystem protection and economic development, both with a sustainability emphasis.

2.2. Methods

2.2.1. Building of an integrated indicator system

A conceptual framework has been suggested for monitoring ecological quality using biodiversity, ecosystem function, and environmental condition indicators, but specific indicators were not defined (Wang et al., 2019). This study proposes 11 potential indicators representing three ecosystem functions (Table 1), though the match between indicators and functions need further improvement due to different understanding and interpretations of concepts, terminology and definition (La Notte et al., 2017).

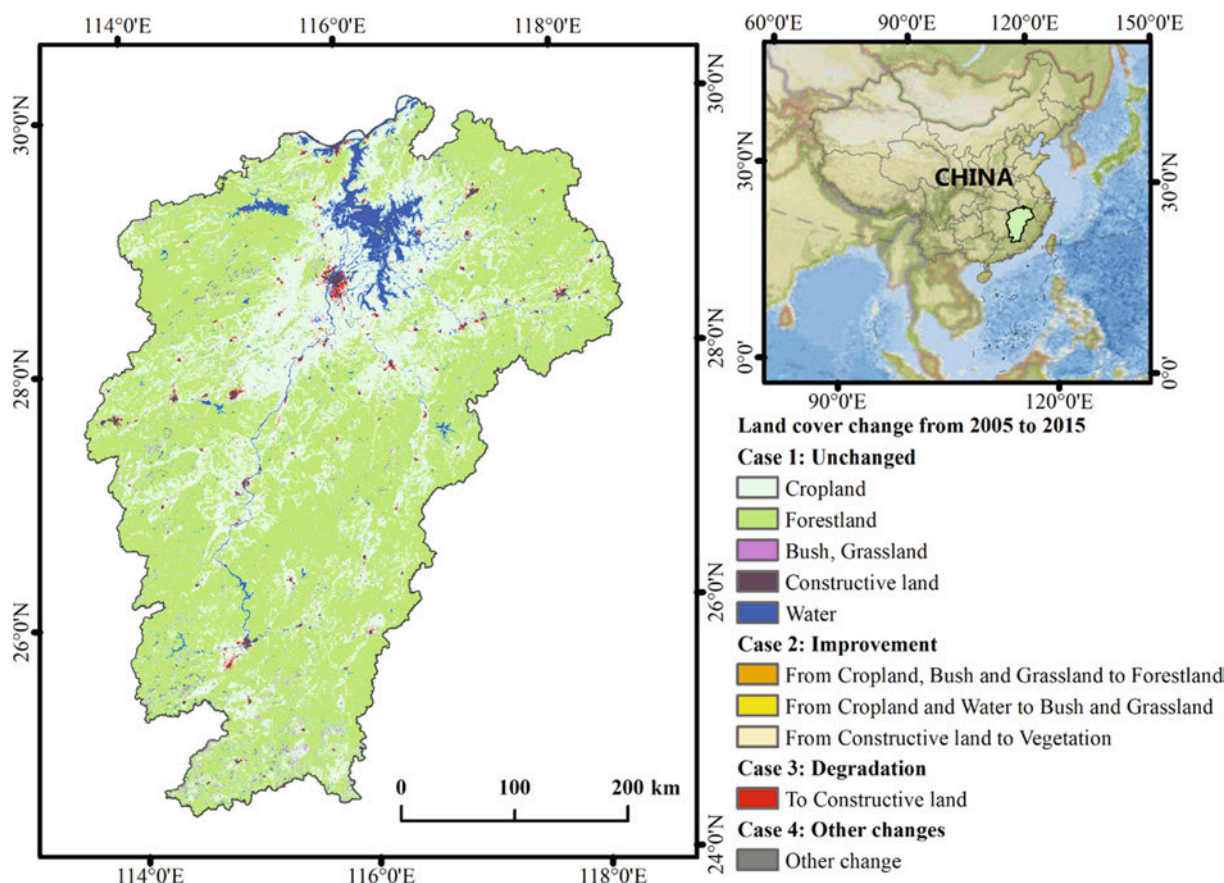


Fig. 1. The location of the study area, Jiangxi Province, China, and its land cover and land use changes from 2005 to 2015.

Table 1

The potential indicators, data processing and data sources used to evaluate the ecological quality of terrestrial ecosystems in Jiangxi Province, China.

Theme	Indicators	Data processing	Data sources
Maintaining Function	Normalized Difference Vegetation Index (NDVI) Fractional vegetation coverage (FVC)	Savitzky-Golay Filter (SG Filtering)	MOD09A1
Supporting function	Leaf-area Index (LAI) Gross Primary Productivity (GPP) Net Primary Productivity (NPP)	GLOPEM-CEVSA	(Wang, 2007)
Regulating Function	Net Ecosystem Productivity (NEP) Water Use Efficiency (WUE) Ecosystem Water Storage Index (WSI) Moisture Index (IM) Bowen Ratio(β) Land Surface Temperature (LST)	GLOPEM-CEVSA $WUE = GPP/ET$ $WSI = (P - ET)/GPP$ $IM = 100 \times (P/PET - 1)$ $\beta = (Rn - \lambda E + G)/\lambda E$ Savitzky-Golay Filter (SG Filtering)	(Wang, 2007) (Liu et al., 2014) (Cui, 2019) MOD11A2

Note: Rn , λE , G are the net radiative flux, latent heat flux (the product of latent heat exchange coefficient λ taken as 2.45 and actual evapotranspiration ET), and soil heat flux, respectively. P is precipitation, PET is potential evapotranspiration.

These 11 indicators represent multiple attributes and processes of an ecosystem from its vegetation structure to photosynthesis and land surface energy process: 1) Normalized Difference Vegetation Index (NDVI), as a measure of vegetation greenness (Wang et al., 2021), is often used to scale species richness (Geller et al., 2017; Gillespie, 2005; Wang and Gamon, 2019; Wang et al., 2016), in part due to the well-known link between productivity and biodiversity (Oehri et al., 2017; Tilman et al., 2001; Zhang et al., 2012). Based upon the above, this study uses NDVI as an indicator to maintain biodiversity; 2) Fractional vegetation coverage (FVC) is directly related to maintaining the fertility of soil by preventing erosion (Gu et al., 2018; Reicosky and Forcella, 1998; Tang et al., 2020); 3) Leaf area index (LAI) is often used to quantify plant photosynthesis production, evapotranspiration and the land surface energy exchange between ecosystem and atmosphere (Fang et al., 2019;

Qu and Zhuang, 2018); Plant photosynthesis production is generally quantified by 4) gross (GPP); or 5) net (NPP) primary production, which are necessary for the maintenance of all other ecosystem services (Garland et al., 2021); 6) Net ecosystem production (NEP) is defined as the net budget of carbon fixation by photosynthesis and losses by autotrophic and heterotrophic respiration (Landsberg and Gower, 1997). A NEP positive value implies an ecosystem acting as a sink of atmosphere CO_2 , by which ecosystems play a role in regulating global climate changes (Landsberg and Gower, 1997).

Local climate is influenced by ecosystem changes and may be quantified by latent heat flux or evapotranspiration (ET), land surface temperature and so on (Anderson-Teixeira et al., 2012; Peng et al., 2014; Yue et al., 2019; Zhai and Tao, 2021; Zhu et al., 2016). Considering the closer relationship among photosynthesis, evapotranspiration and

precipitation, the three indicators, 7) water use efficiency (WUE) (Kim et al., 2021), 8) water storage index (WSI) (Tian et al., 2018; Velicogna et al., 2015) and 9) moisture index (IM) (Zhao et al., 2019), are suggested as potential indicators in terms of hydrological regulation. 10) The Bowen ratio and 11) land surface temperature (LST) are important aspects of heat regulation (Anderson-Teixeira et al., 2012; Zhao et al., 2021). Land use and land cover were not directly considered, but were indirectly quantified by the above indicators; for example, the algorithm of LAI data product generally uses biome type as a primary input (Knyazikhin et al., 1998).

Therefore, these 11 potential indicators, shown in Table 1, cover most attributes of an ecosystem for evaluating ecological quality in a more holistic manner on the regional scale, though more indicators could be considered in local-scale studies as demonstrated by Hu et al. (2018).

2.2.2. Indicators selection

Selection of key features to include in assessments requires determination of the most relevant contributors (Deisy et al., 2007). If a feature is redundant with other features, this feature is not only ineffective in improving the accuracy of the results, but also brings more data collection and computation to a large-scale study (Hsu and Hsieh, 2010). In this study, the method of examination of correlation coefficients was applied to eliminate redundant indicators (Dong et al., 2020). Correlation coefficients, r , of 0.9 or higher could be considered to represent features that are strongly correlated, to determine whether there is redundant information among the indicators according to our calculation experiments. When two indicators have strong correlation, these two indicators are analyzed separately with other indicators for correlation, and the one with higher correlation with other indicators is removed. Finally, 8 indicators were selected from the initial 11 candidates, as shown in Table 1.

2.2.3. Undimensionalization of data

Assuming the indicator data are $[X_{ijk}|i = 1, 2, 3, \dots, n; j = 1, 2, 3, \dots, m; k = 1, 2, 3, \dots, p]$, n , m and p denote the total number of pixels, indicators and years respectively, X_{ijk} denotes the j -th indicator value for the i -th pixel in the k -th year. In order to reduce effects of dimensions, a undimensionalization process is carried out for the indicators on the pixel scale and expressed as:

$$F_{ij} = \begin{cases} \text{Positiveindicator} : \frac{X_{ij} - X_{jmin}}{X_{jmax} - X_{jmin}} \\ \text{Negativeindicator} : \frac{X_{jmax} - X_{ij}}{X_{jmax} - X_{jmin}} \end{cases} \quad (1)$$

in which X_{ijmax} and X_{ijmin} denote the maximum and the minimum value of the j -th indicator over all pixels in the research area in the three years of 2005, 2010 and 2015 for this study. On the other hand, the method provides baselines of indicators for ecological quality evaluation, by which it is possible to diagnose changes in ecosystems and determine differences among ecosystems and regions.

2.2.4. Weight-determination algorithm

A particle swarm optimization algorithm-based projection pursuit model (PSO-PPM) was applied to determine the indicators' weights. The model was developed using Matlab's scripts language based on code published on the website: <https://github.com/S-Driscoll/Projection-pursuit>. The PSO algorithm, first proposed by Kenney and Eberhart in 1995, is a computational iterative optimization method based on swarm-intelligent evolution (Kennedy, 1998; Kennedy and Eberhart, 1995; Shi and Eberhart, 2001). After finding two optimal solutions, the particle updates its velocity and position, according to the following equations (2) and (3), until the maximum number of cycles or termination conditions is reached; the global, optimal solution is the final result:

$$a \cdot \hat{v}_{ik}(t+1) = c_0 \cdot \hat{v}_{ik}(t) + c_1 \cdot \hat{r}_{1k}(t) \cdot \hat{A} \cdot (pb_{ik} - x_{ik}(t)) + c_2 \cdot \hat{r}_{2k}(t) \cdot \hat{A} \cdot (gb_k - x_{ik}(t)) \quad (2)$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \quad (3)$$

where n represents the number of particle swarms, and m represents the spatial dimension of each particle search. x_i and v_i , respectively, represent the current position and velocity vector of particle i . pb_i is the best position vector that particle i attains, and gb is the current global optimum—that is, the best position vector that all particles attain. c_0 , is the inertia factor, c_1 and c_2 are acceleration factors, and r_{1k} and r_{2k} are two random numbers varying in the range $[0, 1]$.

The PSO-PPM uses the PSO algorithm to optimize the projection pursuit model. The first step involves randomly selecting a number of initial projection directions a_j ($-1 \leq a_j \leq 1$) and the optimal projection direction can be estimated by maximizing the projection index function, $Q(a)$, that is, the product of the standard deviation S_z of the sample projection value and the local density value D_z :

$$Q(a) = \max(S_z \times D_z) \quad (4)$$

The standard deviation, S_z , is calculated for each particle swarm:

$$S_z = \sqrt{\left\{ \sum_{i=1}^m [Z(i) - E(z)]^2 \right\} / n} \quad (5)$$

where $Z(i)$ is the projection feature value of the indicator values of the i -th pixel in the projection direction, that is $Z(n) = \sum_{k=1}^m x_{ij} \cdot a_{ik} \cdot E(z)$ is the average value of the projection feature value of the n samples in the projection direction, that is, $E(z) = \sum_{i=1}^n Z(i) / n$. The local density values are calculated for particle swarms as sample class D_z :

$$D_z = \sum_{i=1}^n \sum_{j=1}^n (R - r_{ij}) \cdot u(R - r_{ij}) \quad (6)$$

where R is the local density window radius, the distance $r_{ij} = |Z(i) - Z(j)|$, $u(R - r_{ij})$ between the indicator projection points of samples i and j is the unit step. This step is assumed to be 1 when $R \geq r_{ij}$; otherwise, it is assumed to be 0.

Particle velocity and position are derived through an iteration algorithm of equations (2) to (6). For our experimental calculation, the maximum number of iterations was experimentally set as 2000, so it will output the final weights if a relative change in $Q(a)$, see equation (4), is $< 5\%$, or the maximum number of iterations was reached. Finally, the EQI in percentage is calculated based on the projection vector a as the weights and the indicator values by equation (7) at the pixel level over the three years:

$$G_j = \left(\sum_{i=1}^n \sum_{j=1}^m x_{ij} \cdot a_j \right) \times 100 \quad (7)$$

The algorithm with parallel computing is realized using script language in the Matlab environment. In this study, the computational program was used to calculate the EQI of the terrestrial ecosystems of Jiangxi Province using eight indicators: normalized-vegetation index (NDVI), leaf-area index (LAI), net primary productivity (NPP), net ecosystem productivity (NEP), water-use efficiency (WUE), ecosystem-water-storage index (WSI), Bowen ratio (β) and land surface temperature (LST) in 2005, 2010, and 2015.

2.2.5. EQI grade classification

EQI is a unidimensional score from 0 to 100 to quantify the ecological quality from very poor to excellent in the study area. To capture variation and visualize results for ecosystem status evaluation in China (PRC State Environmental Protection Administration, 2015) and the ecological quality assessment (Hang et al., 2020; Hu and Xu, 2018; Xiong et al., 2021), an equal interval distinction method was applied to

classify the EQI in five levels: above 80 is classified as excellent; between 60 and 80 is good; between 40 and 60 is medium; between 20 and 40 is poor; and <20 is very poor.

2.2.6. Method used to analyze driving factors

(1) Climate impact analysis

This study mainly analyzes the impact of temperature and precipitation changes on ecological quality. Linear regression was used to analyze the inter-annual variability and trends in temperature, precipitation, and vegetation index from 2005 to 2015. The climate impact is quantified through the regression coefficients and multiple correlation coefficient (R^2).

(2) Impact analysis of land use and cover change (LUCC)

The impact of LUCC on ecological quality was analyzed by examining the two aspects of afforestation and urbanization in Jiangxi Province for the same period. The linear regression was done between the afforestation area and the annual mean NDVI over the whole province to analyze the impact of afforestation on ecological quality from 2005 to 2015. The effect of urbanization was analyzed based upon the proportion of area of urban land in each region according to the LUCC data (ESA, 2017) and the impervious data (Gong et al., 2020), and compared with the changes in the ecological quality index to explore the impacts from urbanization.

(3) Gradient analysis

To further illustrate the indicators' contributions to EQI, the EQI and other indicators were averaged along a NDVI gradient and a latitude gradient, respectively. The NDVI gradient was sampled with all input data from the minimum of 0.05 to the maximum of 0.95 by a step of 0.05 as a theoretical analysis. The latitude gradient, for experimental analysis, was arbitrarily sampled along the middle zone with the width of 30 pixels from the northern to southern parts of the province.

2.3. Data and process

2.3.1. Meteorological data

The air temperature and precipitation data used in this study were retrieved from meteorological stations from the China Meteorological Science Data Sharing Service Network, including 92 stations in Jiangxi Province and 112 stations in surrounding provinces. The ANUSPLIN interpolation software package (Hutchinson, 1991, 1998; Tan et al., 2016) was used for spatial interpolation, and thereby obtained temperature and precipitation data with a spatial resolution of 1 km at 8-day intervals during 2005–2015. Previous studies have shown that temperature and precipitation interpolations obtained using ANUSPLIN can explain 90% and 77% of the spatial variability, respectively; i.e., this data can represent spatial variations very well (Wang et al., 2017b). Based on the 8-day interval interpolated meteorological data, the annual temperature and precipitation data were calculated for further analysis.

2.3.2. Remote sensing data

(1) NDVI data

NDVI data were retrieved using MOD13A1 Version 6 with a 500 m spatial resolution and a 16-day temporal step for 2005–2015. The product was obtained from NASA's Earth Observing System. The data were processed to the Albers equal-area conic projection using the MODIS Reprojection Tool (MRT) of NASA. Then, smoothing and noise reduction of the NDVI data were conducted using the S-G filtering method of TIMESAT3.2 (Jönsson and Eklundh, 2004), and then the

smoothed NDVI is used to calculate the annual total NDVI (ATN) for the indicator data.

(2) FPAR and LAI data

The FPAR and LAI were retrieved from the latest product of MODIS Collection 6 (MCD15A2) from 2005 through 2015 and used as model inputs. The product has a 1-km spatial resolution and an 8-day temporal resolution. However, some data are missing due to unfavorable atmospheric conditions, such as cloudiness and heavy aerosols. These data gaps were filled using the S-G filtering method of TIMESAT3.2 (Jönsson and Eklundh, 2004). The annual mean LAI was calculated and used as input data.

(3) LUCC data

Land cover data were retrieved using European Space Agency (ESA) Land Cover CCI v2.0.7 (ESA, 2017). The data in 2005 and 2015 were used to analyze land use changes, which was re-categorized to the seven types: cultivated land, woodland, thickets and grasslands, urban, bare land, water bodies, and permanent ice and snow from its original 37 types.

The impervious layer data were retrieved from the high-resolution global artificial impermeable area (GAIA) dataset (Gong et al., 2020), and the data in 2005 and 2015 were used to determine the impact of urbanization in the study. Jiangxi Statistical Yearbook afforestation data were used to compare and analyze the impact of artificial urban expansion and ecological protection on ecological quality.

2.3.3. Modeled data

The GPP, NPP and NEP data were estimated using GLOPEM-CEVSA, a coupled model between a remote-sensing-based global production efficiency model and a vegetation, atmospheric, and soil carbon-exchange model (Wang et al., 2011). In the GLOPEM-CEVSA, NPP is calculated as the difference between gross primary productivity (GPP) and the estimated plant autotrophic respiration for the maintenance of life and growth, according to biomass, temperature, and autotrophic respiration coefficients. GPP is estimated from the photosynthetically active radiation absorbed by vegetation, the potential light-use efficiency, and the environmental stresses linked to light-use efficiency. The model simulates soil heterotrophic respiration (R_h) then NEP is simulated as the difference between NPP and R_h . The all three data were obtained from the same model, which would decrease the estimation uncertainties due to the methods difference on the great extent. Detailed descriptions of the model can be found in Wang et al. (2009) and Wang et al. (2011).

The ARTS model was applied to calculate the evapotranspiration (ET) which is used to estimate the Bowen ratio, ecosystem-water-storage index, and the WUE. The model is a dual-source model of evapotranspiration based on remote sensing; that is, it considers vegetation transpiration and soil evaporation (Yan et al., 2012). ET under the condition of sufficient soil water is estimated first. Then, the actual evapotranspiration is estimated by considering soil moisture (Yan et al., 2012; Yan et al., 2014). Referring to Cui et al. (2019), the annual ET with a 1-km spatial resolution was modeled using meteorological data interpolated from observations from meteorological stations across China, as well as FPAR and LAI data obtained by satellite remote-sensing in this study.

3. Results

3.1. Weighting evaluation indicators

The weights were estimated using the PSO-PP model for indicators on the pixel scale (Table 2). The NDVI had the highest contribution to the ecological quality index with a weight of 0.2385, followed by WUE (0.1592); the NPP, LST and WSI would be grouped as third level with a

Table 2

Indicators and their weights averaged for the whole study region, Jiangxi Province, China.

Theme	Indicator	Weights
Maintaining function	Normalized Difference Vegetation Index, NDVI	0.2385
	Leaf-area Index, LAI	0.0447
Supporting function	Net Primary Productivity, NPP	0.1399
Regulating function	Net Ecosystem Productivity, NEP	0.1057
	Water Use Efficiency, WUE	0.1592
	Ecosystem Water Storage Index, WSI	0.1354
	Bowen Ratio, β	0.0437
	Land Surface Temperature, LST	0.1324

weight of about 0.13, and NEP in the fourth level. Meanwhile, the LAI and β showed minimum weights with values around 0.04.

3.2. Spatial and temporal pattern of EQI

The EQI was calculated using the PSO-PP model for Jiangxi Province in 2005, 2010, and 2015, and is shown in Fig. 2. The province, taking 2015 as an example, had a medium grade of ecological quality, with an average EQI of 55.32. More specifically, 92.71% of the whole provincial land area had an EQI equal to and above the medium grade, while 8.29% of the area had an average EQI below the medium grade in 2015.

Spatially, the ecological quality index calculations resulted in lower values in the main stream area along the Ganjiang River, while higher values were found on the hills and mountains around the Ganjiang River, as shown in Fig. 2. According to the regional averages (Fig. 3a), (except Nanchang with its ecological quality in the poor grade with the lowest quality index of 40), all regions were in the good grade with the highest quality index of 70 in Jingdezhen. Of course, in each region, there were good and poor grades with varying area percentages (Fig. 3b). Jingdezhen, Shangrao and Fuzhou have more than half of the regions with good and above grade; most of Xinyu region (77.38%) was at medium level, followed by Ganzhou, Pingxiang, Yingtan and Yichun where more than half of these areas were at medium levels. Nanchang has no more than 5% of the region with EQI above good grade. The results implied that the regions with a higher degree of urbanization were characterized by lower EQI grade.

Temporally, the EQI of the whole province increased from 52.26 in 2005 to 53.19 in 2010, and to 55.32 in 2015 (Fig. 2, Fig. 3a), and the

proportion of good and above grade area specifically increased from 25.47% in 2005 to 29.43% in 2010, and to 36.8% in 2015 (Fig. 3b). The area of good grade and above increased in the hilly areas, such as Jingdezhen and Shangrao, while the change was not significant in the plain areas, such as Nanchang, Yichun and Ganzhou. The EQI was found to increase over most areas from 2005 to 2015, though increases were most prevalent in the hilly area in the northeast, the center and southern province (that is most of Shangrao, Jingdezhen, and the small parts of northern Ganzhou and Linchuan). Meanwhile, there was an area of decreasing condition mainly around Nanchang and southern Ganzhou.

3.3. Driving factors of EQI change

3.3.1. Temporal changes in indicators and impacts from climate change

The temporal changes in EQI is a comprehensive expression of all indicators' changes because the EQI is calculated through the undimensionalized indicators and their respective weights. All included indicators showed very different spatial patterns when compared between 2005 and 2015 (Fig. 4 b to i). On the provincial scale, all indicators increased, from vegetation greenness and coverage (FVC), to photosynthesis capability, hydrological and heat regulation. For example, NDVI increased 7.3% and 10.4% in 2015 (to 0.65) from that in 2010 (0.61) and 2005 (0.59). GPP (NPP) increased 20.9% (18.5%) and 35.5% (36.6%) under the same comparison. Land surface temperature was 22.9 °C, 24.0 °C and 23.6 °C in 2005, 2010 and 2015 respectively according to the regional mean for the whole province, that is, the temperature increased by 1.1 °C in 2010 and then decreased 0.4 °C in 2015. Meanwhile, the hydrological indicators, the IM and WSI, in 2015 respectively increased 14.5% and 6.8% over that in 2010, 81.3% and 32.3% than that in 2005. As a heat indicator, the Bowen ratio increased to 0.27 in 2015 from 0.24 in both 2005 and 2010. Considering both quantity and the weight, NDVI contributed the most to the increase of EQI with 24.3%, followed by NPP (22.6%), WSI (21.6%), and WUE (21.2%); meanwhile, land surface temperatures and Bowen ratio made negative contributions to the increase of EQI, and their contributions were -6.8% and -5.6%, respectively. It indicates that EQI mainly reflects the condition of vegetation greenness and productivity, while the improvement of moisture condition in the area will be beneficial to EQI, while the climate warming and the increasing Bowen ratio will decrease EQI.

Vegetative condition was improved according to the NDVI data in

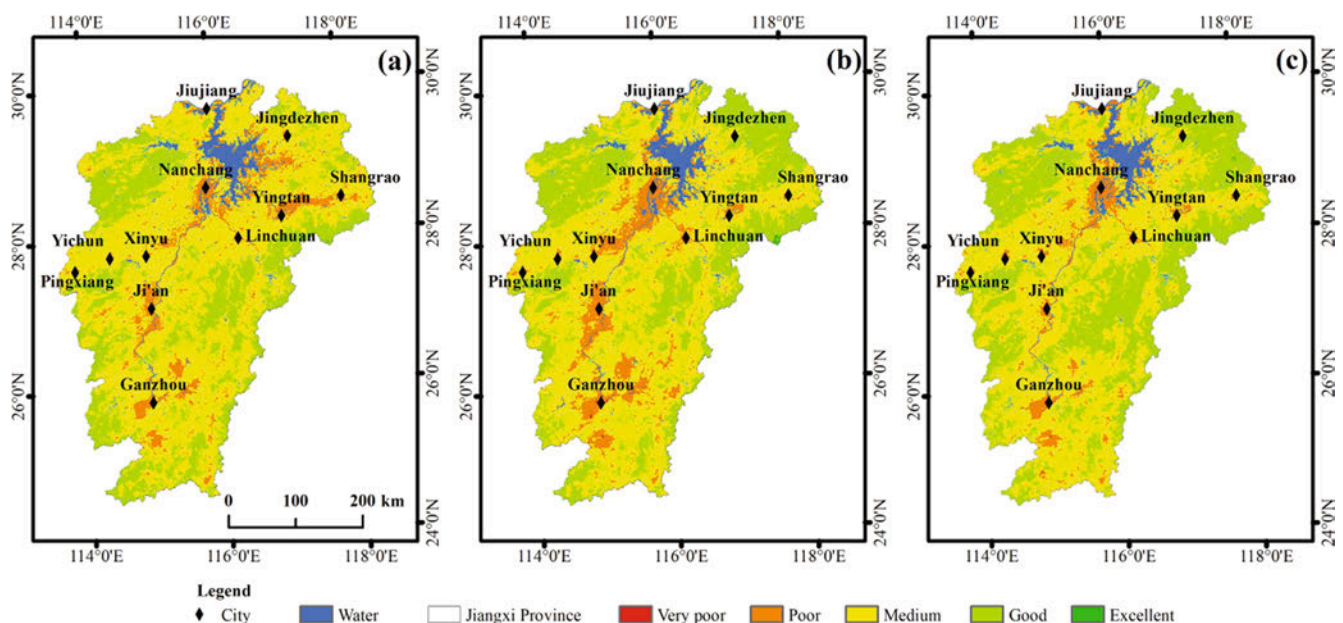


Fig. 2. Spatial distribution for an ecological-quality index in Jiangxi in 2005 (a), 2010 (b), and 2015 (c).

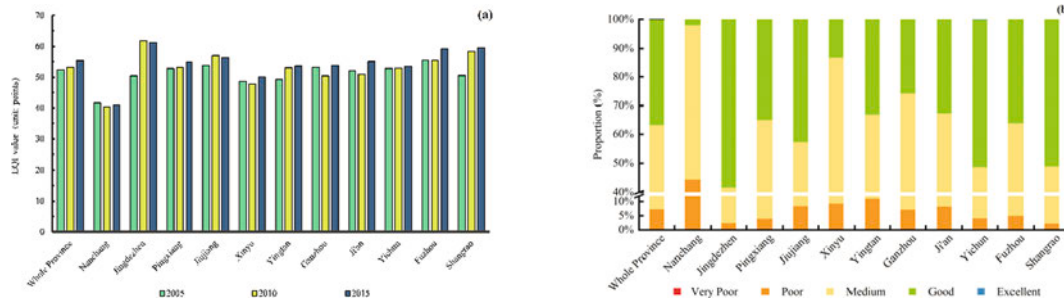


Fig. 3. The zonal mean EQIs (a) for the three years (2005, 2010, and 2015) for each administrative region within the area as a proportion (b) of its EQIs grade in 2015 for the study area Jiangxi Province.

Jiangxi Province during the period from 2005 to 2015 (Fig. 5 and Table 3). The NDVI had a significant upward trend with a slope of 0.49% ($R^2 = 0.82$, $p < 0.001$) from linear regression for the whole province, and with a slope of from 0.30% ($R^2 = 0.55$, $p = 0.01$) in Nanchang to 0.58% ($R^2 = 0.79$, $p < 0.001$) in Pingxiang. Meanwhile, climate influences led to a significant warming and an insignificant wetting trend in this period (Fig. 5 and Table 3). Specifically, the annual mean air temperature shows a significant warming trend by a rate of $0.118\text{ }^{\circ}\text{C a}^{-1}$ ($R^2 = 0.60$, $p < 0.01$) over the whole province. Rates varied from the regional mean of $0.0775\text{ }^{\circ}\text{C a}^{-1}$ ($R^2 = 0.34$, $p = 0.06$) in Jiujiang, to $0.1274\text{ }^{\circ}\text{C a}^{-1}$ ($R^2 = 0.54$, $p = 0.01$) in Ji'an. The annual total precipitation insignificantly increased ($R^2 = 0.11$, $p = 0.31$) in the same period.

The interannual variability in NDVI can be explained by corresponding changes in annual mean temperature (AMT) and annual total precipitation (ATP) in the same period from 2005 to 2015 (Fig. 5, Table 3). The NDVI was significantly correlated with AMT ($R^2 = 0.539$, $p = 0.010$), and was insignificantly correlated with ATP ($R^2 = 0.146$, $p = 0.247$) (Shown in Fig. 6, Table 4). However, both climate variables can explain 64.2% of the variation in the NDVI data for the whole province, and 49.6% to 72.4% for most regions during the study period from 2005 to 2015. For example, both AMT and ATP can explain 72.4% of the variation ($R^2 = 0.724$, $p = 0.006$) in NDVI in Fuzhou. However, both variables cannot explain much variability in NDVI for some regions, such as Nanchang ($R^2 = 0.387$, $p = 0.141$), Jingdezhen ($R^2 = 0.386$, $p = 0.142$), Xinyu ($R^2 = 0.449$, $p = 0.092$) and Pingxiang ($R^2 = 0.440$, $p = 0.099$). Those results imply that climate change, especially climate warming, can be attributed to an improved vegetative condition and, further, an improvement in this ecological quality index in most study regions. Meanwhile, in some regions, climate changes were not dominant drivers of ecological quality changes in the study area of Jiangxi Province, China.

3.3.2. Land use and land cover change

No more than 10% of the total area changed in its type of land use and land cover according to the remote sensing-based data from 2005 and 2015 (Fig. 1). Specifically, for the land area, about 0.13% changed from grassland or cropland to forestland. That is likely a result of ecological-protection programs, such as returning arable land to forest and afforestation in 2015, compared to 2005. Moreover, the cumulative afforestation area increased, though the area per year increased to a peak in 2008, according to the Jiangxi Statistical Yearbook, which was consistent with the changes of the NDVI that almost continually increased during the study period (Fig. 7). The afforestation area is significantly correlated with the annual mean NDVI over the whole province ($R^2 = 0.77$, $p < 0.001$) for the period. The analysis indirectly indicates that more ecological protection programs would have improved the ecological quality in the study region.

Urbanization quickly increased in the study region, which would result in decreasing ecological quality for specific areas to a great extent. The urban area of the whole province increased by 78.17% and mainly occurred around Nanchang, Ganzhou, Jiujiang and Yichun, respectively

increasing by 94.94%, 61.97%, 86.69% and 103.53% by 2015 from 2005, according to ESA land use data. The amount of impervious surface area increased 121.37%, 113.79% and 185.04% in Nanchang, Ganzhou and Jiujiang, respectively, according to GAIA data for the same period (Fig. 8). The expansion of impervious surface area suppressed the growth of NDVI, with an average increase of 0.01 in urban areas during the period from 2005 to 2015. The EQI decreased by 0.82 for the urban area of the whole province. The EQI decreased by 3.71, 4.00, and 1.80 for the urban areas of Nanchang, Ganzhou and Jiujiang, respectively.

4. Discussion

4.1. Comprehensive Multi-dimensional indicator

Based on the conceptual framework suggested by Wang et al. (2019), this study proposed a regional comprehensive Multi-dimensional indicator-based Ecological Quality index, applying a Projection Pursuit Model (MEQ-PPM). The index, first of all, represented the changes in status, comparing to the best and worst reference conditions in the study periods over the study area for the multiple indicators. This was realized through the method of maximum-minimum dimensioning of the data to satisfy the requirements of the projection pursuit model (PPM). A historical period, even a specific year, is often set as reference condition (Cabello et al., 2012; Hughes and Convey, 2010; MA, 2005; Pollock et al., 2012; Wen et al., 2021), which could distort evaluation results due to impacts from climate variability (Pollock et al., 2012). In this study, the reference condition was based on the best and worst for the given temporal and spatial range covering the whole study period and whole region, which is more rational and objective.

Weights quantify the relative contribution of indicators to the ecological quality index. In this study, NDVI made the greatest contribution. As an index of vegetation greenness and photosynthetic capacity retrieved through remote sensing (Cabello et al., 2012), NDVI is widely applied in ecological evaluations, such as for regional ecosystem function (White et al., 2020; Zelený et al., 2021). The potential application of NDVI has been discussed in biodiversity monitoring, available through satellite remote sensing; however, studies have been more focused on the diversity of landscapes or ecosystems, or habitat function. Biodiversity monitoring on the species scale has faced great challenges until the present (Geller et al., 2017). However, this study demonstrated that NDVI is a very useful and informative indicator in ecological quality evaluation for any terrestrial ecosystem in the study province.

LAI had a low influential weight on the EQI in this study, which was different with NDVI though they were retrieved from a remote sensing data source together. It was found that LAI showed a slow increase from 0.0 to 0.15 if NDVI was < 0.7 and a fast increase from 0.15 to 0.60 if NDVI was larger than 0.7 (Fig. 9a); that is, LAI was not sensitive to changes in vegetation greenness, but was to the changes of EQI, which would result in the lower weight of LAI.

WUE is one of the indicators with a higher weight in this study. It was defined as the capability and responses of maximal carbon capture by

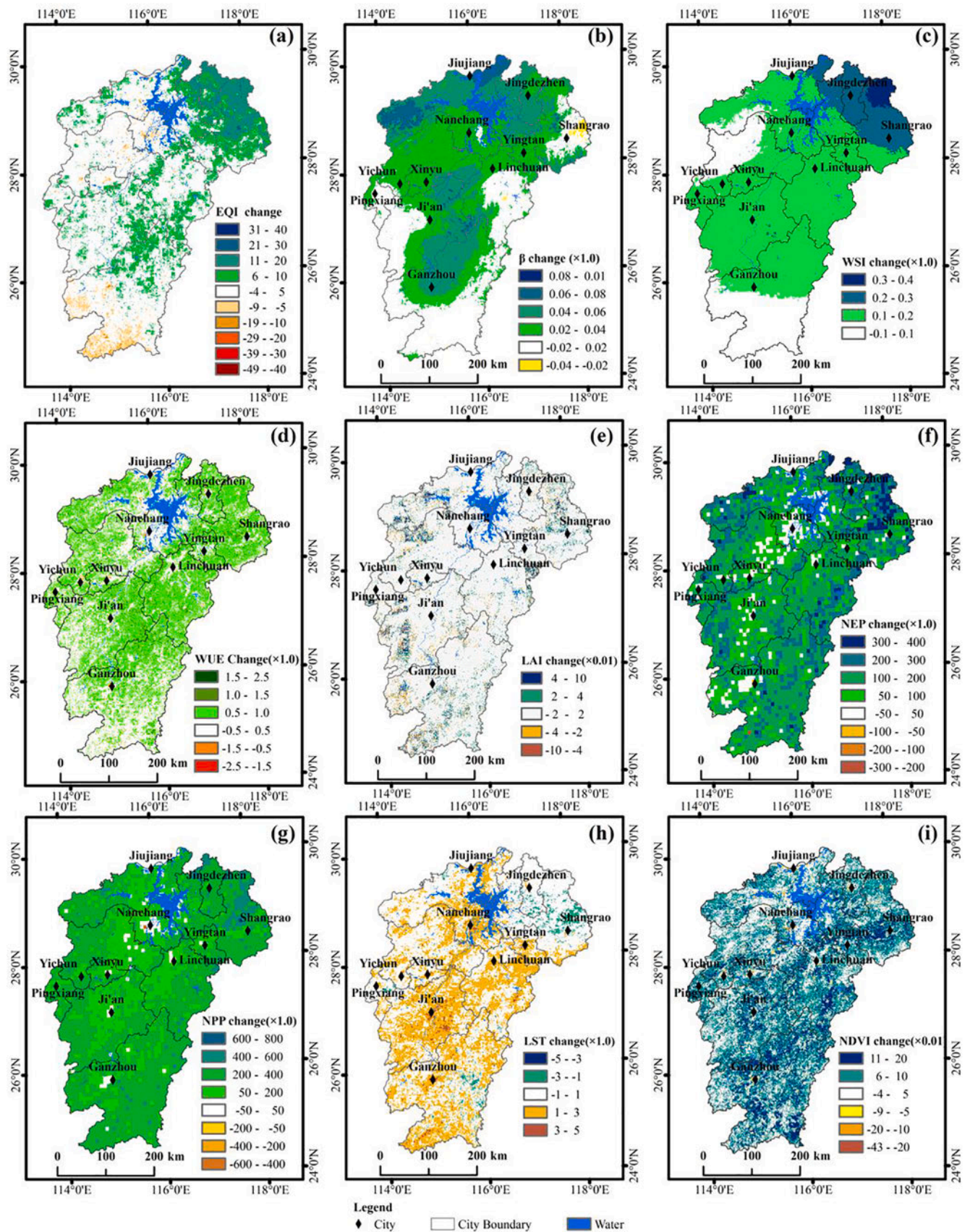


Fig. 4. The changes of the EQI and the all indicators in 2015 comparing with the corresponding values in 2005.

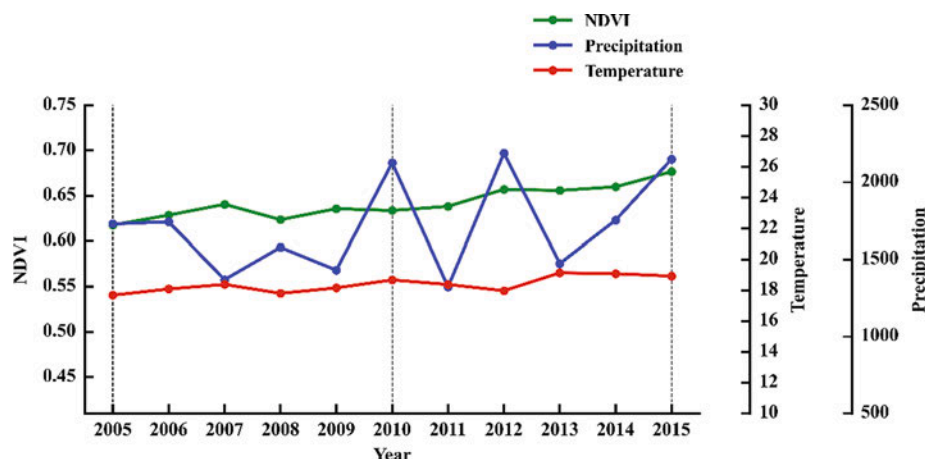


Fig. 5. Changes in annual average temperature, annual precipitation, and annual NDVI in Jiangxi Province from 2005 to 2015.

Table 3

Analysis of variation in trends of NDVI, precipitation, and temperature in all administrative regions from 2005 to 2015

Region	NDVI			Precipitation			Temperature		
	slope	R ²	p	slope	R ²	p	slope	R ²	p
Whole	0.0049	0.82	0.00	32.4766	0.11	0.31	0.1184	0.60	0.01
Nanchang	0.0030	0.55	0.01	39.4881	0.13	0.29	0.0831	0.42	0.03
Jiujiang	0.0044	0.87	0.00	39.3808	0.19	0.18	0.0775	0.34	0.06
Ganzhou	0.0054	0.73	0.00	2.7960	0.00	0.91	0.1573	0.70	0.00
Shangrao	0.0047	0.76	0.00	62.1146	0.25	0.12	0.0980	0.55	0.01
Jingdezhen	0.0040	0.67	0.00	71.9108	0.36	0.05	0.0794	0.42	0.03
Ji'an	0.0053	0.83	0.00	26.0183	0.08	0.40	0.1274	0.54	0.01
Fuzhou	0.0053	0.81	0.00	45.0561	0.11	0.32	0.1245	0.68	0.00
Yingtian	0.0041	0.71	0.00	48.0805	0.13	0.28	0.1102	0.63	0.00
Yichun	0.0042	0.87	0.00	35.7232	0.11	0.31	0.1012	0.51	0.01
Xinyu	0.0041	0.59	0.01	35.5289	0.11	0.33	0.0996	0.52	0.01
Pingxiang	0.0058	0.79	0.00	29.6738	0.11	0.32	0.1059	0.45	0.02

plant photosynthesis and transpiration under water conditions of dry or wet (Drake et al., 2017; Kim et al., 2021); therefore, the EQI considered the impacts of ecosystem functions on carbon uptake by photosynthesis under water stress.

The Bowen ratio (β) made the smallest contribution with its weight of 0.0437, which quantifies the allocation amount of net surface radiation as latent heat and sensible heat (Ping et al., 2018; Yue et al., 2019; Zhao et al., 2021). The Bowen ratio generally changes from the lower annual value of 0.17 in a tropical rainforest, to 0.35 in subtropical forest, 0.74 in temperate forest, and 0.8–9.9 in residential and urban areas (Cleugh and Grimmond, 2012). These well illustrate Bowen ratio can effectively differentiate the climatic effect of land use and land cover, and even that of ecosystem degradation and was proposed as an indicator for the regulating function of ecosystems (Zhao et al., 2021). Therefore, though having a lower weight, Bowen ratio is necessary to be considered in the EQI to represent the regulating function of the ecosystem.

Based on the above, by considering comprehensive, multiple indicators to quantify eco-environmental conditions and ecosystem service functions, the EQI is a more rational and objective index.

4.2. Biodiversity and ecological quality

Biodiversity is very important, but its measurement is very complex and faces great challenges for various scales, such as plant species, population, landscape and ecosystems, especially on the regional scale (Magurran and McGill, 2011). As a proxy, habitat quality is often evaluated by applying NDVI data from satellite remote sensing to quantify biodiversity (Geller et al., 2017). Therefore, this study considered biodiversity indirectly using NDVI as an indicator, relative to habitat quality. Biodiversity changes such as encroachment by non-

edible plants do reduce the ecological benefits available to humans on the one hand (Hughes and Convey, 2010), but on the other hand, there may be the possibility of enhanced ecological functions such as soil and water conservation and increased carbon sequestration due to increased vegetation cover (Guo et al., 2019; Shi et al., 2018). In other words, biodiversity changes may be harmful to humans, but they may also be beneficial to the enhancement of ecosystem functions themselves. Ecological quality index (EQI) has limitations in its ability to determine what changes are reflected in the index. As a management tool on the regional scale, however, it would provide a broad view of ecosystem status and changes from multiple aspects of ecosystem function.

4.3. Human activities and ecological quality

There is a particularly complex relationship between economic development, natural conditions and ecological processes (Alberti, 2005). Ecological quality is influenced by many factors including climate change and human activities. While it is relatively easy to quantify impacts from climatic change, there is difficulty in quantifying that from human activities (Jia et al., 2015; Jiang et al., 2009; Sun et al., 2016). Climate change affects biodiversity and ecosystem functions, such as photosynthesis, autotrophic respiration, and soil decomposition in terrestrial ecosystems (Cao and Li, 2000), therefore influencing ecological quality (Liu and Fu, 2001; Zhao et al., 2020; Zhou et al., 2014). Ecological protection and restoration programs, such as forestation and afforestation, were found to make an effective contribution to improved ecological quality. For example, vegetation restoration can prevent soil erosion effectively and improve ecological condition (Liu et al., 2016; Wang et al., 2017).

In contrast, rapid urbanization and fast GDP growth has led to

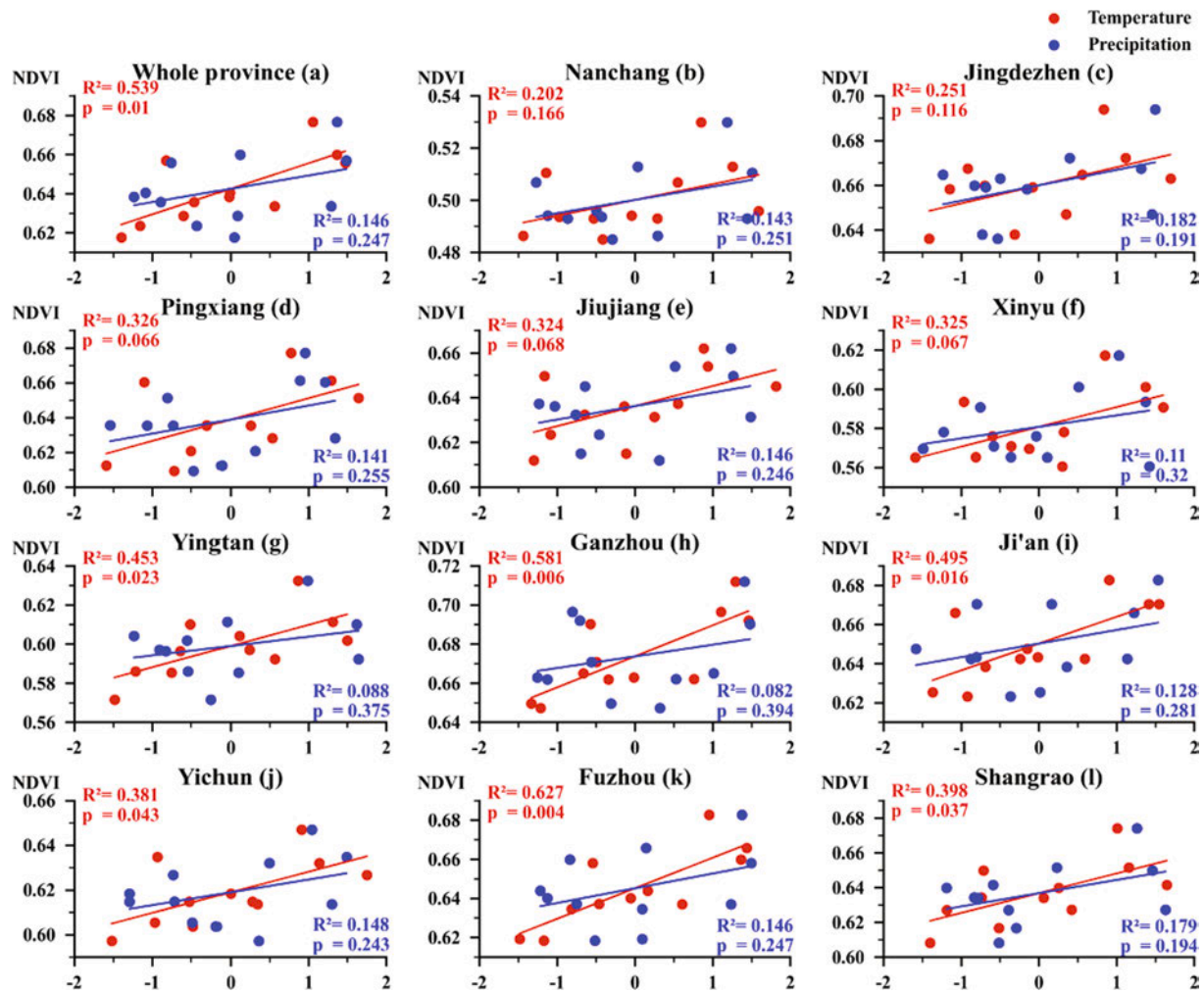


Fig. 6. Correlation analysis of mean annual temperature, annual precipitation (after standardization), and mean annual NDVI in Jiangxi Province and its municipalities from 2005 to 2015.

Table 4

The results of linear regression for NDVI with annual mean temperature (AMT), annual total precipitation (ATP) and the both variables for the whole province and its each administrative region in the period from 2005 to 2015

Region	NDVI = $b_0 + b_1$ AMT			-	NDVI = $b_0 + b_2$ ATP			-	NDVI = $b_0 + b_1$ AMT + b_2 ATP				
	b_1	R ²	p		b_2	R ²	p		b_0	b_1	b_2	R ²	p
Whole	0.013	0.539	0.010		0.007	0.146	0.247		0.64	0.013	0.006	0.642	0.016
Nanchang	0.006	0.202	0.166		0.005	0.143	0.251		0.5	0.007	0.006	0.387	0.141
Jiujiang	0.009	0.324	0.068		0.006	0.146	0.246		0.64	0.007	0.006	0.496	0.065
Ganzhou	0.016	0.581	0.006		0.006	0.082	0.394		0.67	0.012	0.007	0.687	0.01
Shangrao	0.011	0.398	0.037		0.008	0.179	0.194		0.64	0.009	0.007	0.498	0.064
Jingdezhen	0.008	0.251	0.116		0.007	0.182	0.191		0.66	0.010	0.006	0.386	0.142
Ji'an	0.014	0.495	0.016		0.007	0.128	0.281		0.65	0.010	0.004	0.604	0.024
Fuzhou	0.016	0.627	0.004		0.008	0.146	0.247		0.65	0.016	0.007	0.724	0.006
Yingtian	0.011	0.453	0.023		0.005	0.088	0.375		0.6	0.013	0.006	0.501	0.062
Yichun	0.009	0.381	0.043		0.006	0.148	0.243		0.62	0.010	0.006	0.563	0.036
Xinyu	0.010	0.325	0.067		0.006	0.110	0.320		0.58	0.015	0.006	0.449	0.092
Pingxiang	0.012	0.326	0.066		0.008	0.141	0.255		0.64	0.010	0.006	0.44	0.099

dramatic changes in land surface (Wang, 2013). Urbanization, including the massive expansion of road traffic and building areas, has greatly reduced the green area of the land surface, leading to changes in ecological functions in the area, reflected by an increase in the Bowen ratio, and thus a decrease in ecological quality (Ke and Mei, 2010; Peng et al., 2014). As Fig. 10 shows, EQI was significantly and negatively correlated with the GDP of Jiangxi Province and positively correlated with NDVI, which indicates that urban expansion and economic

development seriously influenced ecological quality. Sustainable urban development would be a good option for striving to achieve harmony with nature.

4.4. Uncertainties and future improvements

The evaluation of ecological quality is greatly dependent on what indicators are used and the change trajectory represented in time series

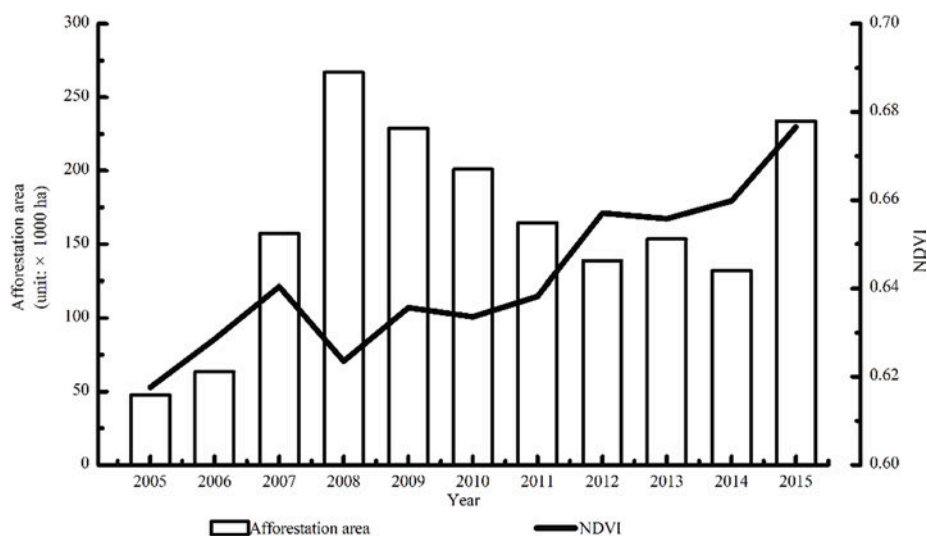


Fig. 7. NDVI and annual afforestation area in Jiangxi Province from 2005 to 2015.

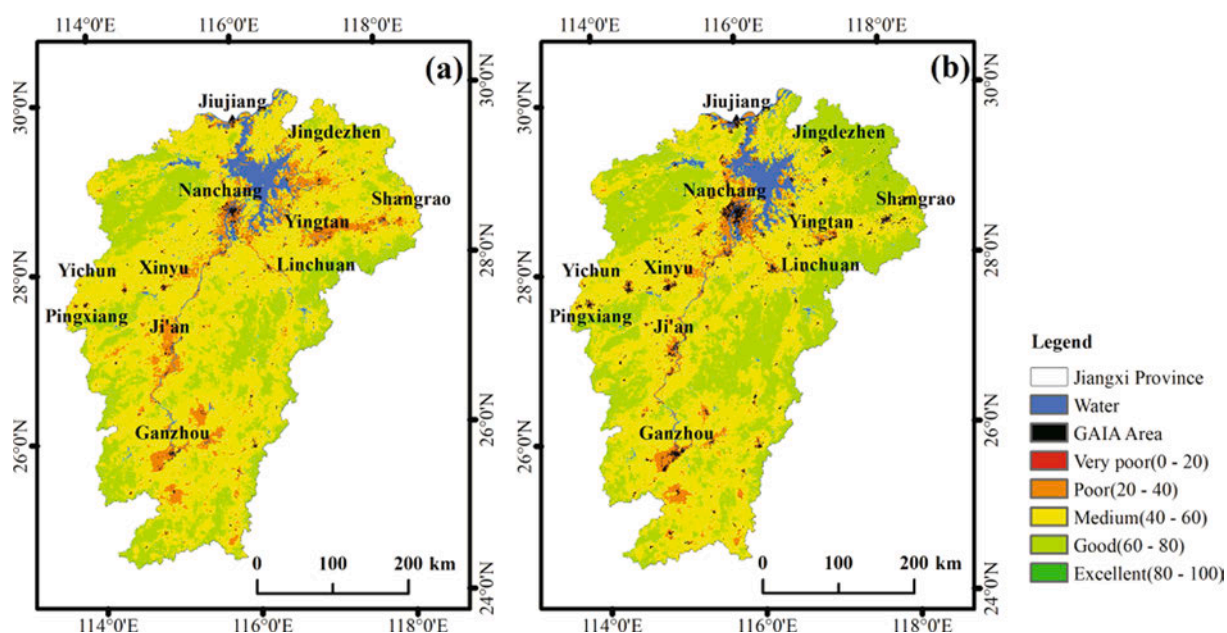


Fig. 8. Visualization results of evaluation grade in Jiangxi Province in 2005 (a) and 2015 (b), and the superposition map of impermeable water surface.

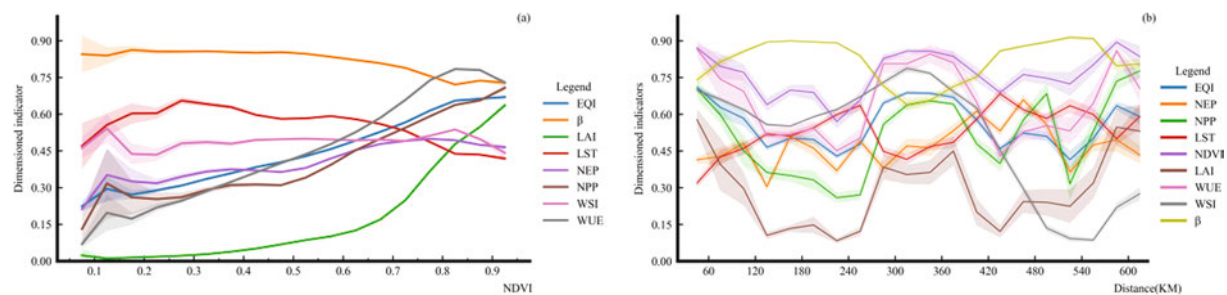


Fig. 9. The changes (a) of EQI and indicators along the NDVI gradient from 0.05 to 0.95 by steps of 0.05 for the whole region, and the north-to-south profiles (b) of EQI and all indicators on an arbitrarily selected 30 pixels wide zone in the middle of the study area, as an example to illustrate EQI quantifying ecological quality from poor to excellent.

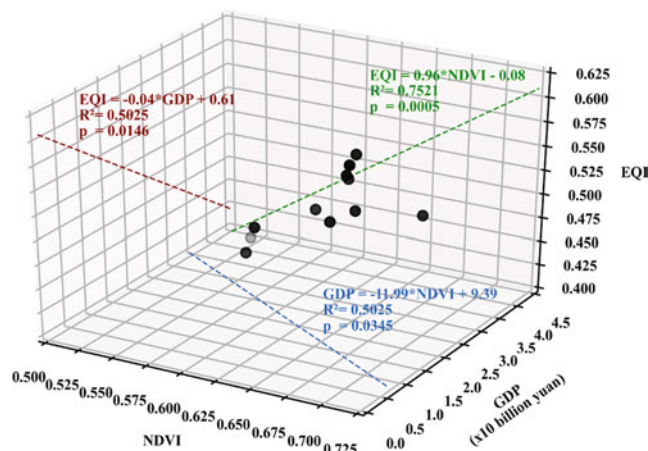


Fig. 10. Relationship between GDP, NDVI and EQI by municipal districts in the 2015 Ecological Quality Assessment.

data for the indicators. Therefore, a complete indicator system and long-term data are two very important aspects of evaluating changes in ecological quality objectively. In this study, 11 indicators were selected as candidates by considering data availability (Table 1), and eight of them entered the final evaluation after eliminating redundant indicators (Table 2). However, there are lots of ecosystem functions or services, such as use efficiency of carbon, radiance or light, and the landscape index, which could be considered as indicators and may be included in experiments in the future.

A methodology was proposed to evaluate ecological quality based on the best and worst reference condition estimated from the maximum and minimum values of each indicator over the whole study area but restricted due to availability of data. The period was too short to capture the inter-annual variation and the possible best and worst reference condition with data from the three years used. Therefore, reference conditions were estimated due to the shortage of the limited data temporal span. Though this study had derived the influences of human activities and climate change on EQI, some studies have shown that population and GDP growth will reach a certain inflection point and the trend of ecological deterioration will slow down if urbanization and economic development would move beyond a certain level, which will lead ecological quality to improve (Ding et al., 2020; Selden and Song, 1995). As the aim of this paper is to clarify the feasibility and validity of the methodology, the use of three data points over nearly 15 years would be limited for exploring the change trajectory of EQI in response to climate change and human activities.

It is a great challenge to quantify the impacts of human activities on ecological quality. With increased interest in cities' green spaces, data with a fine spatial resolution will be important to evaluate ecological condition by quantifying the structure and function of city environments, which would aide city planning and management. On the other hand, planting of economic crops is very popular in the study area, with crops such as tangerines, oranges, and tea highly desirable. Their impact on ecological quality should be considered when there are available data. However, the EQI improved in areas where land changed from cropland or grassland to forestland in the study, which is understandable from the perspective of a forest's service functions. During fast economic development, ecological quality should be regularly monitored and evaluated in order to keep such development sustainable and environmentally friendly.

5. Conclusion

The ecological quality index (EQI) was developed based on ecosystem service functions using the PSO-PP algorithm with Jiangxi Province, China, as a case study. Ecological quality was generally found

to be at the upper-middle level on the scale developed for this analysis and demonstrated an upward trend, according to the indicators of ecosystem maintenance, supporting and regulating functions in 2005, 2010, and 2015. An analysis of the spatiotemporal pattern and its driving factors found that an increasingly warm and wet climate trend contributed to improvements in the EQI; meanwhile, human activities exerted negative and positive effects on ecological quality through urbanization and afforestation, respectively. This study proposed a methodology to evaluate ecological quality, utilizing available datasets for terrestrial ecosystems on a regional scale, demonstrating its effectiveness, rationality, and feasibility by avoiding the use of a pre-defined baseline and attribute weights.

CRediT authorship contribution statement

Xihuang Ouyang: Methodology, Software, Formal analysis, Data curation, Supervision, Writing – original draft, Writing – review & editing. **Junbang Wang:** Conceptualization, Software, Investigation, Resources, Data curation, Supervision, Visualization, Writing – original draft, Project administration. **Xing Chen:** Data curation, Investigation, Visualization. **Xuanlan Zhao:** Writing – original draft, Investigation. **Hui Ye:** Writing – original draft. **Alan E. Watson:** Writing – original draft, Writing – review & editing. **Shaoqiang Wang:** Writing – review & editing, Project administration.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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