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Pixel-scale historical-baseline-based ecological quality: Measuring impacts from climate change and human activities from 2000 to 2018 in China

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ABSTRACT

Widespread concern about ecological degradation has prompted development of concepts and exploration of methods to quantify ecological quality with the aim of measuring ecosystem changes to contribute to future policy-making. This paper proposes a conceptual framework for ecological quality measurement based on current ecosystem functions and biodiverse habitat, compared with pixel-scale historical baselines. The framework was applied to evaluate the changes and driving factors of ecological quality for Chinese terrestrial ecosystems through remote sensing-based and ecosystem process modeled data at 1 km spatial resolution from 2000 to 2018. The results demonstrated the ecological quality index (EQI) had a very different spatial pattern based upon vegetation distribution. An upward trend in EQI was found over most areas, and variability of 46.95% in EQI can be explained well by change in climate, with an additional 10.64% explained by changing human activities, quantified by population density. This study demonstrated a practical and objective approach for quantifying and assessing ecological quality, which has application potential in ecosystem assessments on scales from local to region and nation, yet would provide a new scientific concept and paradigm for macro ecosystems management and decision-making by governments.

1. Introduction

Terrestrial ecosystems support a significant portion of global biodiversity and provide important ecosystem services (MA, 2005). Growth in the world's population and economic activities have resulted in serious degradation of ecosystem quality (Krausmann et al., 2013), which will negatively affect human wellbeing and hinder global sustainable development (Dong et al., 2013; Foley et al., 2005; Rillig et al., 2021; UN, 2021). Therefore, measuring ecosystem quality is of great importance to prompt ecological protection, guide changes in regional economic development strategies, and achieve society sustainability.

Ecosystem quality has been defined as the ability of the environment to maintain desirable vital signs, to handle stress, and to recover equilibrium after perturbations (He et al., 2020; Wang et al., 2019; Wu et al., 2019). Paetzold et al. (2010) pointed out that such a definition relies on measures that implicitly or explicitly utilize naturalness as a key criterion, which is practically complex for human-dominated ecosystems. They proposed a framework for assessing ecological quality based on the ecosystem services profile expected by society and sustainably provided by ecosystems (Paetzold et al., 2010). This approach is based on human-centered evaluation through quantifying ecosystem services. He et al. (2020) recommended a new concept, termed ideal reference, involving comparison of areas of interest to conserved and undisturbed ecosystems, or probability distribution of ecosystem attributes, for quickly assessing ecosystem quality at regional and national scales (Kennedy and Eberhart, 1995). The concept of ideal reference can be thought of as a return to ecosystem-centered evaluation by considering changes in the ecosystem itself. The major challenge would be the

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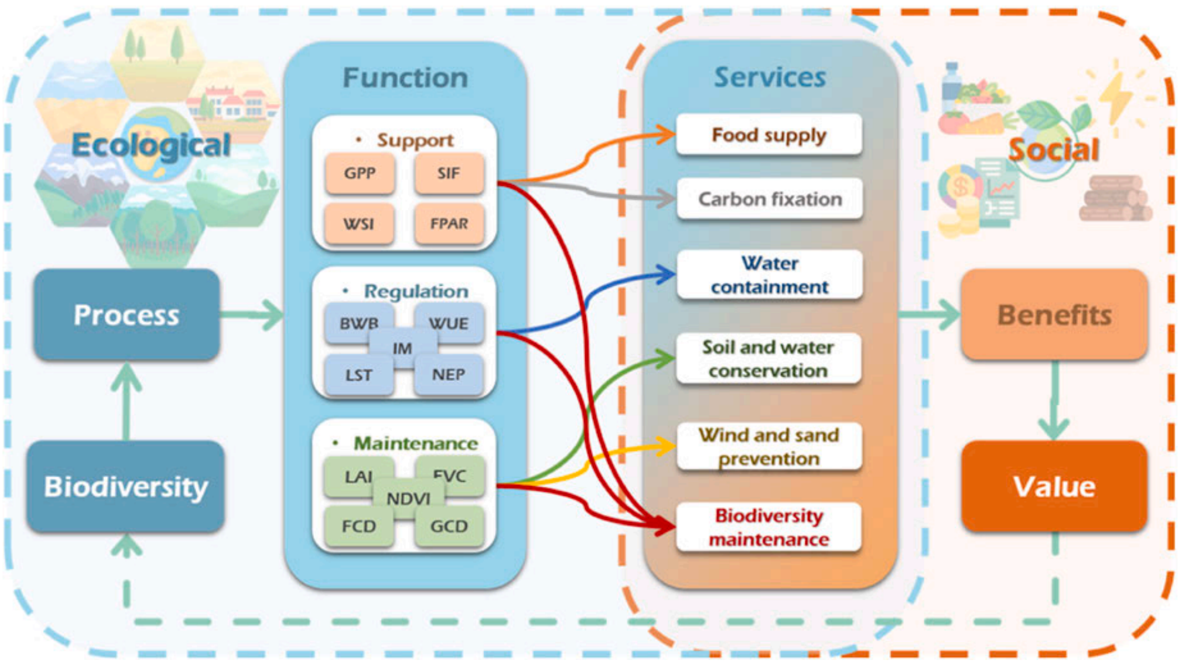

Fig. 1. The concept framework of ecological quality based on ecosystem functions that support ecosystem services and human well-being as social benefits.

scarcity of appropriate context-specific data on expectations for ecosystem services or the ideal ecosystem in the present anthropocene era (Chan et al., 2006; Crutzen, 2002; Paetzold et al., 2010). Therefore, a probability distribution-based baseline would provide a practical reference for evaluation, and could be utilized as a practical option to measure ecosystem quality at regional or national scales.

Biodiversity, an important element in ecosystem function and the provision of ecosystem services (Brockerhoff et al., 2017), has commonly been considered in assessing ecosystem quality at the habitat scale (Niu et al., 2021) or at the national scale (State Council Information Office, 2021). However, vegetation condition data, such as a vegetation index from remote sensing, has mostly been applied to quantify biodiversity on the regional or national scale due to the unavailability of spatial-temporal distribution data of species-scale biodiversity (Fan et al., 2019; Sahraoui et al., 2021). This means biodiversity could be quantified better in terms of habitat diversity by including remotely sensed vegetation measures.

Ecosystem function and services are commonly confused concepts, though defined very differently (Brockerhoff et al., 2017). Ecosystem function, as an ecosystem-centered concept, is defined as "the biological, geochemical, and physical processes that operate within an ecosystem, sustaining it and enabling it to supply ecosystem services" (Edwards et al., 2014). Meanwhile, ecosystem services, a more human-centered concept, is defined as the benefits that ecosystems generate, through ecological function, for human wellbeing (MA, 2005). Focusing on function allows scientists to understand changes in key ecological processes driving the integrity or maintenance of ecosystems, and allows managers or policy makers to move ecosystem management from human oriented to more ecosystem-centered (Daily and Matson, 2008; MA, 2005; Ouyang et al., 2020). For example, traditional ecosystem management has paid more attention to edible grass species for husbandry, while ignoring its other functions, such as to conserve soil and water, which is more important for sustainability of fragile ecosystems (Ouyang et al., 2020; Shao et al., 2017b). Therefore, we argue, an ecosystem function-based quality assessment is a useful tool for quantifying the status and trend of ecological quality changes.

Many mathematical methods have been applied to determine weighting for ecosystem quality indexes. Some methods used include an analytic hierarchy process (AHP) (Saaty, 2008), principal component analysis (PCA) (Jolliffe, 2002), and fuzzy comprehensive evaluation (Lu et al., 2021; Wang et al., 2021; Wei et al., 2021). Most of these examples involved weighting determination through some level of expert consultation, which would tend to be subjective and distort assessment results (Liu et al., 2019; Wang and Yang, 2020).

The projection pursuit model (PPM) is a data reduction algorithm, used to reduce data from a higher to a lower number of dimensions (Friedman and Tukey, 1974) and has been widely applied in evaluation research (Hu, 2018; Liu et al., 2019; Wang and Yang, 2020). The PPM is considered to have several advantages, including robustness, anti-interference, strong operability, and high accuracy (Deng et al., 2013; Fang et al., 2010; Jiang et al., 2011; Li, 1997; Liu et al., 2019). The PPM algorithm has been accelerated by use of Particle Swarm Optimization (PSO) and has demonstrated good performance in regional ecological-quality evaluations (Ouyang et al., In Review). Considering spatial heterogeneity in ecosystems and wide-availability of remote sensing data, a pixel-scale PPM-PSO method could provide a spatially-explicit assessment that is more objective and easily used for ecosystem management applications.

China has experienced rapid economic growth, with a decoupling trend for major pollutants control since 2015, while strong coupling remains with CO_2 emissions (Lu et al., 2019), attracting worldwide attention on changes in the environment and ecosystems. Recent satellite data reveal a greening pattern in China, which alone accounts for 25% of the global net increase in leaf area, though China has only 6.6% of global vegetated area. During the period 2000–2017, China initiated very ambitious programs to conserve and expand forests with the goal of mitigating ecosystem degradation, environment pollution and climate change (Chen et al., 2019). However, ecological quality involves multiple aspects of the environment and various ecosystem functions, so an evaluation of changes in ecological quality is very essential to understand the effects of these initiatives in China.

Various methods have been developed to evaluate changes and trends in terrestrial ecosystems in China. Methods explored have included multiple-source data from multiple-sensor based remote sensing, on-ground observations, and ecosystem modelling, applied in condition and trend assessments based on concepts from the Millennium Ecosystem Assessment (MA) for terrestrial ecosystems (Liu et al., 2016). China's Ministry of Ecology and Environment has applied these methods

Table 1
The indicators to represent ecological quality of terrestrial ecosystems and the methods of data acquisition.

Ecological Functions	Indicators	Methods	Data Description
Maintenance Function	Normalized Distribution Vegetation Index (NDVI) Fraction of Vegetation Coverage (FVC) Leaf Area Index (LAI)	Processed by remote sensing data such as SG filtering	Based on MODIS-MOD09A1 Surface reflectivity products
Support Function	Gross Primary Productivity (GPP) Net Primary Productivity (NPP) Net Ecosystem Productivity (NEP)	GLOPEM-CEVSA Model	Temperature, precipitation (Wang, 2007)
Regulation Function	Bowen Ratio (β)	$\beta = \frac{Rn - \lambda E + G}{\lambda E}$	Rn: Net radiation flux λE: Latent heat flux (The latent heat exchange coefficient λ is taken as the product of 2.45 and the actual evapotranspiration ET) G: Surface heat flux (The annual fluctuation change is small and is ignored as 0 here) Cui (2019)
	Land Surface Temperature (LST)	Processed by remote sensing data such as SG filtering	Based MODIS- MOD11A2 Surface reflectivity products
	Moisture Index (IM)	$IM = 100 \times \left(\frac{P}{PET} - 1\right)$	P: precipitation;
	Water Storage Index (WSI)	$WSI = (P - ET)/GPP$	PET: Potential evapotranspiration (Liu et al., 2014)
	Water Use Efficiency (WUE)	$WUE = GPP/ET$	

and implemented remote sensing investigation and assessment of eco-environment changes from 2000 to 2010 in China (Wang and Ouyang, 2015).

In the past, the annual status of the eco-environment was calculated from biodiversity richness measures, vegetation proportion, water coverage, soil erosion or urbanization, and pollutant measures based on standards prescribed by the Ministry of the Environment (Ministry of Environment of People's Republic China, 2015). However, for human-centered aspects, biodiversity was assessed through habitat quality, weighted according to land use and land cover classification, and ignored the multiple functions of ecosystems. As a status assessment, those indexes always show lower quality for some ecosystems (i.e., desert), and always better in others (i.e., forest), but cannot be easily used to evaluate changes, which would be of more interest by the government, scientists and the public. An ecosystem function-based index, evaluating temporal changes, has not been proposed until now.

This paper proposes an Ecosystem Function quality Index (EcoFun Index) to evaluate ecosystem changes, with weights developed from a pixel-scale PPM-PSO method based on an historical baseline. The EcoFun Index was calculated for Chinese terrestrial ecosystems through data from remote sensing and ecosystem process modeled data of 1 km spatial resolution, spanning from 2000 to 2018. The primary objectives of this study are to (1) establish an ecosystem function-based quality index based on an historical baseline; and (2) evaluate changes in the quality of terrestrial ecosystems in China over the past 20 years and explore the driving influences for these changes. The overall purpose is to propose a new scientific and objective tool for measuring ecosystem quality, by which we can apply a new scientific concept and paradigm for macro ecosystems management and decision-making for governments (Bhardwaj et al., 2011; Saha et al., 2020; Shraderfrechette, 1994), at regional, national and global scales (FAO, 2015; GEF, 2019).

2. Concept and framework of EcoFun Index

Ecosystems are sometimes characterized based on their ecosystem multifunctionality; that is, the ability of ecosystems to simultaneously provide multiple functions and/or services (Garland et al., 2021). These functions overlay and are complex, very challenging for scientific classification. However, for a given terrestrial ecosystem, it is generally characterized as having the fundamental functions of maintaining biodiversity or habitat, conserving water and soil, supporting nutrient and energy cycling, and regulating climate (La Notte et al., 2017). Those functions could be classified as maintaining, supporting and regulating functions though classification cannot completely comprise all functions.

An ecosystem function-based ecological quality index (EcoFun Index) was sought to quantify this ecosystem multifunctionality, including the roles of supporting, maintaining and regulating functions (Fig. 1, Table 1). Ecosystems support material recycling and energy flow, the formation of life and soil, presenting the ability of supporting other ecosystem functions. The gross (GPP) and net (NPP) primary production can be considered as indicators to quantify the initial material and energy entering the ecosystem (Young and Collier, 2009), while NPP is the amount of GPP minus the vegetation autotrophic respiration, and is applied to quantify vegetation quality (Sun et al., 2020).

Ecosystems maintain the Earth's natural balance for primary production, decomposition of dead matter and nutrient recycling. The **maintaining** function mainly describes the status and changes of biodiversity, vegetation photosynthetic activity, soil and water conservation and material supply in terrestrial ecosystems. The Normalized Difference Vegetation Index (NDVI) has been widely used to quantify habitat quality (Saha et al., 2020), pasture quality (Lugassi et al., 2019), and ecosystem health (Chellamani et al., 2014); furthermore, the retrieved fractional vegetation cover (FVC) and leaf area index (LAI) from remote sensing has been used to estimate ecosystem function, such as water and soil conservation, and carbon sequestration (Novara et al., 2018; Wang, 2018). Therefore, NDVI, FVC and LAI retrieved from satellite remote sensing could be considered as the most relevant indicator candidates.

A critical function of ecosystems is to **regulate** climate effects, and influence soil, water and air quality (De Frenne et al., 2021; Smith et al., 2013). The urban heat island effect, a phenomenon of higher air temperature or land surface temperature in urban areas than that in surrounding rural areas (Voogt and Oke, 2003), would be the most easily understood example of an ecosystem's climate regulation function (Ren et al., 2021). Land surface temperature (LST) is a remote sensing-based measure to quantify the thermal radiation absorbed by the land surface and reflects the thermal regulation ability of vegetation in the environment where the ecosystem is located (Tayebi et al., 2019). Both atmospheric moisture index (IM) and soil water storage index (WSI) were suggested to quantify hydrological regulating capability of ecosystems. IM is defined as the ratio of precipitation to potential evapotranspiration, which can reflect large-scale climate suitability (Wang et al., 2017c). WSI is defined as the difference between precipitation and evapotranspiration, which reflects the water surplus and deficit of the ecosystem, including water storage capacity of the ecosystem (Tian et al., 2018). Hydrological and solar radiation energy is a coupled process, measured by evapotranspiration and radiation energy exchanges between the atmosphere and land surface (Zhang et al., 2021). The

Bowen ratio (β), defined as the ratio of surface sensible heat flux to latent heat flux (Monteith and Unsworth, 2013), is suggested to be an indicator of the hydrological and radiation energy coupled regulating function of ecosystems (Zhao et al., 2021). Water use efficiency (WUE), defined as the ratio of GPP to evapotranspiration (Huang et al., 2016), is an indicator coupling water and carbon cycles to quantify water use capacity of the ecosystem from the perspective of plant physiology (Kim et al., 2021). Moreover, net ecosystem production (NEP) is equivalent to carbon exchanges between the atmosphere and terrestrial ecosystems that is one of the crucial measures of the sink or source of atmospheric carbon dioxides (He et al., 2019). Terrestrial ecosystems take up and sequestrate carbon dioxide from the atmosphere, which has been assumed to mitigate climate warming (Fang et al., 2021; Mendes et al., 2020; Zhang et al., 2016).

Therefore, a total of 11 indicators (Table 1) were considered as candidates to evaluate ecological quality of terrestrial ecosystems. From an ideal reference perspective for ecosystem assessments, a probability distribution-based baseline was used in this study. Therefore, the indicators' data must be easily accessible, be spatially explicit and for a longer time series, which is essential to retrieve a pixel-scale baseline and understand changes of an ecosystem relative to its history. Therefore, the EcoFun index was defined as a measure of the changes in ecosystem function over a given historical period.

3. Data and method

3.1. Data description

3.1.1. Meteorological data

Meteorological raster data were interpolated with observations from 836 stations in China and 345 stations in surrounding countries (Wang et al., 2017b). The observations were shared by the China Meteorological Science Data Sharing Service Network, including meteorological variables of daily total precipitation (Prc, mm), daily minimum (Tmin, ^{o}C), maximum (Tmax, ^{o}C) and average (Tavg, ^{o}C) temperature, daily relative humidity (RHU, %), and sunshine hours (SH, h). The interpolated data, having a spatial resolution of 1 km and a time-step of 8 days, were produced by the software ANUSPLIN version 4.2, an interpolation of noisy multivariate data using thin plate smoothing splines (Hutchinson, 1995). The elevation is used as the independent covariate and the data were resampled to a 1-km digital elevation model (DEM) from a 90 m Shuttle Radar Topographic Mission (SRTM) database, v4.1 (Farr, 2007; Rabus et al., 2003).

By using stations in surrounding countries, a larger area was interpolated and was then considered as part of the research area to remove the boundary effects, especially across the Qinghai-Tibetan Plateau where there are fewer stations. Interpolated sunshine hours data were applied to estimate daily total downward shortwave solar radiation (SWrad) through the solar radiation model developed by Bonan (1989), and the ratio of actual sunshine hours to daylight hours was applied to replace the cloud cover estimated from temperature and precipitation (Wang et al., 2017a, 2017b).

3.1.2. Remote sensing data

The latest Collection 6 products of MODIS were used in this study and the products included the NDVI of MOD09A1 (Vermote, 2015), the FPAR and LAI of MOD15A2 (Myneni et al., 2002) and the LST of MOD11A2 (Wan et al., 2015). The 8-day products have a significant number of missing data due to unfavorable atmospheric conditions, such as cloudiness and heavy aerosols. The S-G filtering method of TIMESAT 3.2 (Jönsson and Eklundh, 2004) was used to eliminate the noise and smoothen the images. The FVC was retrieved from NDVI by the method described in Liang and Wang (2020).

3.1.3. Modeled data

The GLOPEM-CEVSA model, simulating terrestrial carbon budgets by coupling remote sensing with ecosystem process simulation (Wang et al., 2011), was applied to estimate the NPP, GPP and NEP. Also, the ARTS model was used to simulate the evapotranspiration process and calculate the Bowen ratio, WUE and WSI. The ARTS model was developed by Yan et al. (2012), is based on remote sensing data, and considers vegetation transpiration and soil evaporation.

3.1.4. LUCC, population data

LUCC data (Fig. S1), having a 1-km spatial resolution, were from the resource and environment scientific data center of the Institute of Geographic Sciences and Natural Resources Research, CAS. The LUCC data in 2015 were produced from visual interpretation based on the Landsat data over the period from 2014 to 2016 (Liu et al., 2002, 2010).

The population data were provided by WorldPop (2018), dividing the population into pixels and matching the country total from the official UN population estimates. The data were processed by an unconstrained top-down modelling method into a resolution of 30 arc-seconds.

3.2. Methodology

3.2.1. Data preprocessing and indicator selection

The 1 km raster data for the 11 indexes (Table S1) were produced for the period from 2000 to 2018 for terrestrial ecosystems in China. To avoid the dimensional differences of each indicator, it was necessary to normalize in negative and positive directions. Min-max scaling was chosen as the normalization method, which can linearly rescale data values into a range of 0–1. For those indicators that grow with benefits, forward normalization was applied. Indicators that were smaller needed the negative normalization. Equations (1) and (2) present the min-max scaling method:

$$\text{Forwardnormalization}: \ F_i = \frac{I_i - I_{min}}{I_{max} - I_{min}} \tag{1}$$

$$\text{Negativenormalization}: \ F_i = \frac{I_{max} - I_i}{I_{max} - I_{min}} \tag{2}$$

Where F_i represents the normalized value of the pixel; I_i donates the pixel value; I_{max} donates the maximum value of the pixel over 19 years; I_{min} donates the minimum value of the pixel over 19 years.

Additionally, to ensure the complete presentation of information without redundancy, correlation analysis was applied to the 11 indicators. Correlations that reached 0.9 were regarded as reaching the threshold value to distinguish strong correlation and determine whether to remove an index. The result showed that IM and WSI (0.981), NDVI and FVC, LAI (1), GPP and NPP (0.977) are strongly correlated. Therefore, those indicators with weaker correlations (β, WSI, WUE, NDVI, GPP and LST) were selected to form the final ecological quality evaluation model.

3.2.2. Project Pursuit Clustering based on Particle Swarm Optimization algorithm

Particle Swarm Optimization (PSO) algorithm is a random search algorithm based on group cooperation, put forward by Kenny and Eberhart (1995). The algorithm iterates like a flock of birds foraging for food. Each particle in the model, like a bird in a flock, has an initial fitness value used to determine goodness. Also, there is a velocity determinant controlling the direction and speed of each particle. During the iteration process, all of the particles share the information and tend to move in the known best fitness direction to find two optimal solutions.

Project Pursuit Clustering (PPC) based on PSO optimizes the pursuing process and can figure out an infinite target value. Overall dispersion and local density are the main idea of the model (Friedman and Tukey, 1974), which maximizes the product of the standard deviation (S_z) of the sample projection and local density value (D_z) and was defined as the target function, $Q(a)$:

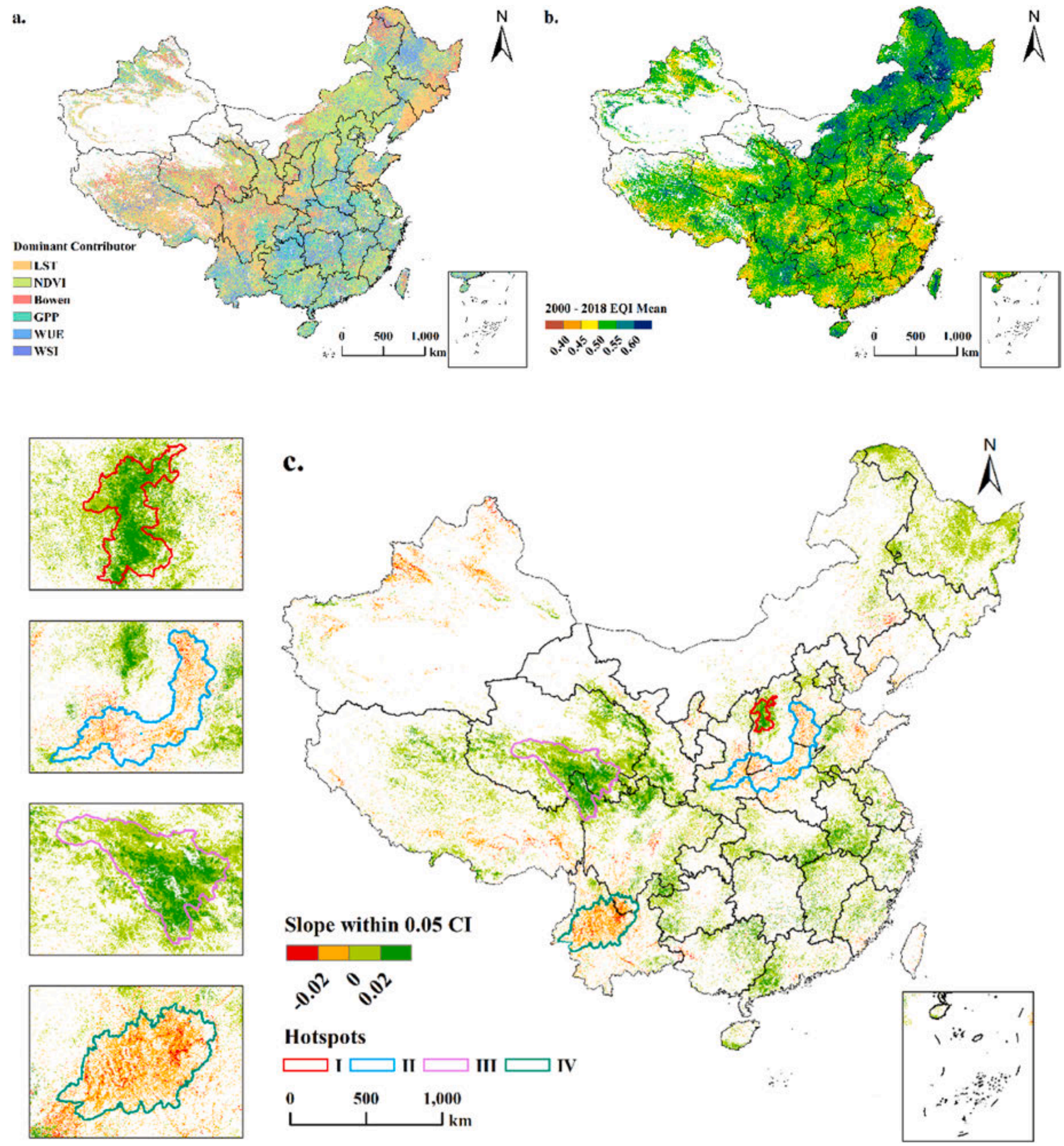

Fig. 2. The dominant indicators quantified by weights (a), the averaged EcoFun Index (b), and the inter-annual trend (c) of the EcoFun index for the terrestrial ecosystems of China during the period from 2000 to 2018.

$$Q(a) = \max(S_z \times D_z) \tag{5}$$

Where Q (a) is the target function. Iterations calculation was applied to solve equation (5) and search the optimized projection direction, a. The details on the algorithm can be seen in Ouyang et al. (2021).

3.2.3. Comprehensive evaluation score gradation

To better interpret the regional distribution, the EQI scores were graded into 5 groups by each 0.2 interval from 0 to 1, which were bad, poor, moderate, good, and excellent. The annual ecological quality evaluation results for China from 2000 to 2018 were produced. Furthermore, a map of climatic regions was used to investigate spatial-temporal changes in EQI and responses to climate change and human activities in different climatic regions. The map classified the country into four climatic regions, i.e., temperate continental region (TCR), temperate monsoonal region (TMR), Qing-Tibetan Plateau alpine region (QTPAR) and subtropical–tropical monsoonal region (STMR).

3.2.4. Factor analysis

Climate change and human activities were assumed to be the two dominant drivers of the temporal trend in ecological quality. Multiple linear regressions were done for EcoFun Index with the climate factors by equation (6) and human activities factor by equation (7), respectively:

$$y = b_0 + b_1x_1 + b_2x_2 + b_3x_3 \tag{6}$$

$$y = b_0 + b_1x_1 + b_2x_2 + b_3x_3 + b_4x_4 \tag{7}$$

where, x_i ($i = 1, 2, 3$) was the factor climate change, here represented by the annual average air temperature (TAVG), annual total precipitation (PRCP) and annual total solar shortwave radiation (SWRad). The x_4 refers to human activity, quantified through annual population data.

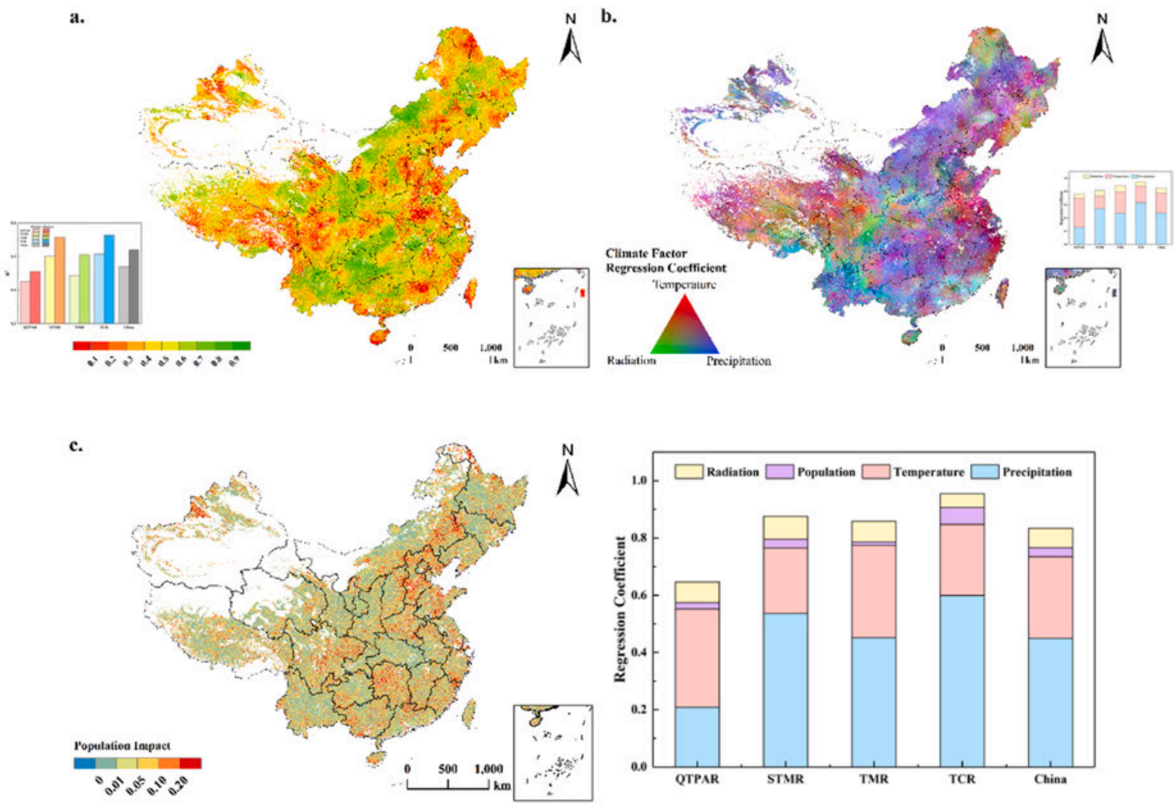

Fig. 3. The impacts of climate change and human activity on the inter-annual variability in the EcoFun index for the terrestrial ecosystems in China in the period from 2000 to 2018. (a) the multiple correlation coefficient (R^2), (b) the composition of the regression coefficient of temperature, radiation and precipitation as red, green and blue color band respectively. (c) the impact of human activity quantified by the difference between the R^2 of the two regressions with the only climate factors (Eq. (10)) and the climate and population factors (Eq. (11)). The subset figures were the regional means of the corresponding data for the four regions and whole country (QTPAR: Qinghai-Tibet plateau alpine region, STMR: subtropical-tropical monsoon region, TMR: temperate monsoon region, and TCR: temperate continental region).

The b_i was the regression coefficients and explained as contribution of each independent variable. The multiple correlation coefficients (R^2) for the regression equation (6) and the difference between the two R^2 for equations (6) and (7) were applied to quantify the impacts from climate change and from human activities, respectively.

Considering the EcoFun Index as the result of weighted indicators, the temporal trend of each indicator was analyzed by linear regression to explore and attribute the trend of EcoFun Index to specific indicators. It is important to discover changes in the whole ecosystem, but we wanted to also discover specific aspects of the ecosystems that are changing.

4. Result

4.1. Weights and spatial patterns

The weights were calculated explicitly for each indicator on the pixel scale with well quantified spatial heterogeneity and the major contributor with the maximum weight among the seven indicators at each pixel (Fig. 2a, Fig. S2 a-g). Over the whole country, GPP has the highest contribution with the highest weight (0.30 $\pm$ 0.30), followed by WUE (0.27 $\pm$ 0.34), WSI (0.22 $\pm$ 0.39), NDVI (0.19 $\pm$ 0.37) and the Bowen ratio (0.14 $\pm$ 0.40), while LST shows the lowest contribution with a negative weight value (-0.06 ± 0.40).

The major contributor varies among the four climate regions (Figure S2 h). Both GPP and WUE show higher contributions in most regions except in TCR. The weights of GPP and WUE are almost the same, 0.29 and 0.28 for the GPP and WUE in QTPAR, 0.33 for both indicators in STMR, and 0.22 and 0.25 in TMR. In TCR, as an inland dryland area, the WSI highlights its effect with its highest weight (0.37) to quantify available water content in the atmosphere due to the amount of precipitation and evapotranspiration. The weight of NDVI varies from 0.13 (STMR) to 0.25 (TCR) and is neither very high nor very low, indicating that NDVI quantifies the change of vegetation status (coverage, greenness) and its role very well, although not very prominent, but it cannot be ignored. The weights of the Bowen ratio are lower in the monsoon climate region with values of 0.04 (STMR) and 0.05 (TMR), while they are higher in the alpine plateau (0.21) and inland continental climate regions (0.25). LST is the only indicator with a lower absolute value less than 0.15, comparing to the other indicators. And the weight for LST is positive in STMR and negative in the other three regions. Maintaining and supporting functions are of almost the same importance in TMR and TCR, while there are significant differences between the two functions in QTPAR and STMR. In STMR, the maintenance function has an extremely low projection value (0.0256), which may illustrate that the maintenance function had less impact on ecological quality than the function of regulating hydrothermal and energy transmission in this area.

The dominant contributor in each pixel may refer to the most sensitive factor to the pixel (Fig. 2a and Table S2). NDVI is the most extensive major contributor over the study area (34.02%), which is mainly distributed in the northeast of the TCR (54.11%). LST, as the second outstanding contributor (22.94%), appears in the north and the east of the TMR (28.37%) and the southwest of the QTPAR (35.29%). WUE (8.09%) and WSI (8.02%) are the two most subordinate factors, distributed in the center of STMR and northeast of China. In terms of ecological function, the regulation function accounts for the greatest proportion (49.29%), due to the larger weight of the regulatory function, which may indicate that the regulatory function of the terrestrial ecosystem in China has changed distinctly.

4.2. Spatial pattern of EQI

The historic baseline-based EcoFun Index showed very different spatial patterns (Fig. 2b). The regional mean Index was 0.52 over the whole country but there was small variance among the climate regions and among the LUCC. Specifically, the indices of TCR and TMR were higher with the values of 0.54 and 0.53, with lower values in QTPAR (0.51) and STMR (0.50). The ANOVA (Table S3) found differences were insignificant among the climate regions ($p = 0.28$) or among the LUCC ($p = 0.45$). Generally, the warmer and wetter climate has better vegetation conditions than that in a dry or cold region, which responds more to the climate or vegetation background. In contrast, the EcoFun Index, based on the pixel-scale baseline only, quantifies relative changes comparing to its historical maximum and minimum and is not a measure of the climate or vegetation condition that is quantified by any indicators, such as LST, NDVI or GPP.

4.3. Temporal trend in EcoFun Index

The inter-annual trend was quantified by the slope of the linear regression for the pixel-scale EcoFun Index for terrestrial ecosystems in China from 2000 to 2018 (Fig. 2c). The slope reveals that most regions (18.97%) of China have experienced a significant upward trend ($p < 0.05$) in the EcoFun Index and the overall increasing rate was 0.00425 yr^{-1} ($R^2 = 0.24$, $p = 0.04$) for the whole country from 2000 to 2018. The regions with larger improving trends are generally found in northeast China, Loess Plateau, Qing-Zang Plateau, and south China, where the trend of the EcoFun Index generally has an increasing rate of larger than 0.015 yr^{-1}. Meanwhile, the EcoFun Index significantly decreased for less than 4.63% of the study regions, mainly in Southwest, North China and Northwest China, where the rate of the EQI trend was less than −0.015 yr^{-1}.

The trend evident in the EcoFun Index greatly varied across climate zones and also across land covers (Fig. S3a). Overall, the EcoFun Index of the four climate zones increased at a rate of from 0.00057 ($R^2 = 0.00$, $p > 0.05$) to 0.00770 per year ($p < 0.01$). Specifically, the EcoFun Index experienced a significant increasing trend over the Qing-Tibetan Plateau alpine region (QTPAR) and temperate monsoon region (TMR), while insignificantly increasing in the subtropical-tropical monsoon region (STMR), and temperate continental region (TCR).

All land cover/use types had up-ward trends and the largest rate happened in wetlands, followed by forest and desert by the EcoFun Index for 2000 to 2018 (Fig. S3b). The EcoFun Index of forest and wetland increased by 0.00520 yr^{-1} ($R^2 = 0.15$, $p = 0.10$) and 0.00662 yr^{-1} ($R^2 = 0.33$, $p = 0.01$), respectively, while it slowly and insignificantly increased by 0.00189 yr^{-1} ($R^2 = 0.02$, $p > 0.05$) in urban land and by 0.00357 yr^{-1} ($R^2 = 0.10$, $p > 0.05$) in cultivated land. The results clearly suggest that the ecosystem function-based quality improved on the whole in the terrestrial ecosystems in China over the period of this study.

4.4. Analysis of driving factors

4.4.1. Impacts from climatic changes

Impacts were analyzed through multiple linear regression for the pixel-scale EcoFun Index, with climate variables of annual average air temperature (TAVG), annual total precipitation (PRCP) and annual total solar shortwave radiation (SWRad). Results are shown in Fig. 3. The observed trends in the EcoFun Index can be explained well by changes in PRCP, TAVG, and SWRad. These three variables together were found to explain over 46.95% of the variance, with a confidence level over 90%, for the improvement trend of EcoFun Index for all terrestrial ecosystems in China. Over the TCR and STMR, climate change exerted more impacts and can explain 63.01% and 54.01% of the changes in the EcoFun Index with a confidence level of over 92% and 90%, while 44.35% and 42.61% of the variability in the EcoFun Index can be attributed to these three factors in TMR and QTPR, respectively.

Standardized regression coefficients were applied to determine the relative contribution of the three climate factors on interannual variability in the EcoFun Index. Results are shown by the composite regression coefficient of temperature, radiation and precipitation as red, green and blue color bands respectively (Fig. 3b). For all terrestrial ecosystems in China, the contribution of precipitation accounts for 55.6% of the climate change contribution quantified by the sum of the regression coefficients, while temperature and solar shortwave radiation account for 35.3% and 9.0%, respectively.

Among the four regions, precipitation made a major contribution except for in QTPR, where temperature played the major role (Fig. 3b). Precipitation contributed as a major factor, varying from 52.9% (TMR), to 66.9% (TCR) and 66.1% (STMR), while the contribution of temperature was 36.5%, 26.7% and 22.9% for the corresponding three regions, respectively. For QTPR, however, temperature made a major contribution (58.0%) while precipitation's contribution was only 33.7%. However, the SWRad made a minor contribution over all four regions with the values of 6.4% (TCR), to 8.3% (QTPAR), 10.6% (TMR) and 11.0% (STMR). These results illustrated that water availability most strongly limits the ecological quality of the terrestrial ecosystems characterized by monsoon and inland continental climate regions, whereas temperature limits ecological quality of the high-cold climate region.

4.4.2. Human activities

As a proxy for human activities, the annual population density, with 1 km spatial resolution, was applied to quantify impacts from human activities, in addition to the climate factors in multiple linear regression equation (11). Results are shown in Fig. 3. On the national scale, climate change and human activities could explain 52% ($R^2 = 0.52$, $p = 0.11$) of the variation as prescribed in equation (11), and an increase of 10.64% for R^2 for equation (10), which would mean the impact of human activity is 10.64%. On the spatial pattern, the population only had a high influence in a few areas, such as the southeast of China with dense cities, and the areas near the capital, the northern area of Northeast China, and northern Xinjiang. In contrast, the influence from human activity was smaller in the sparsely populated areas, such as the northwest region and Qinghai-Tibet region. According to the regional mean, the R^2 differences between the two equations is the larger over the temperate monsoon climate region (TMR) than that over the other three climatic regions, indicating that this region is more affected by population factors. The TMR includes many industrial cities and the absolute majority of the population, which inevitably leads to changes in the ecological environment, which in turn affects ecological quality.

However, precipitation and temperature were still the two factors that had the largest influence on the inter-annual variation of the EcoFun Index, even when population was considered as an independent variable (Table S4). The regression coefficient of radiation was only 0.048 in TCR and about 0.075 in the other areas. The regression coefficient of population was almost the smallest among the four factors, which only exceeds the regression coefficient for radiation in the TCR region, indicating that the influence of population on EQI in all regions was relatively small, especially in TMR, where the regression coefficient of population was only about 0.01.

5. Discussion

5.1. Framework for ecological quality evaluation

This study has developed a conceptual framework for ecological quality evaluation for terrestrial ecosystems, with some strengths evident in its indicators, use of baselines and calculation of algorithms to determine weights.

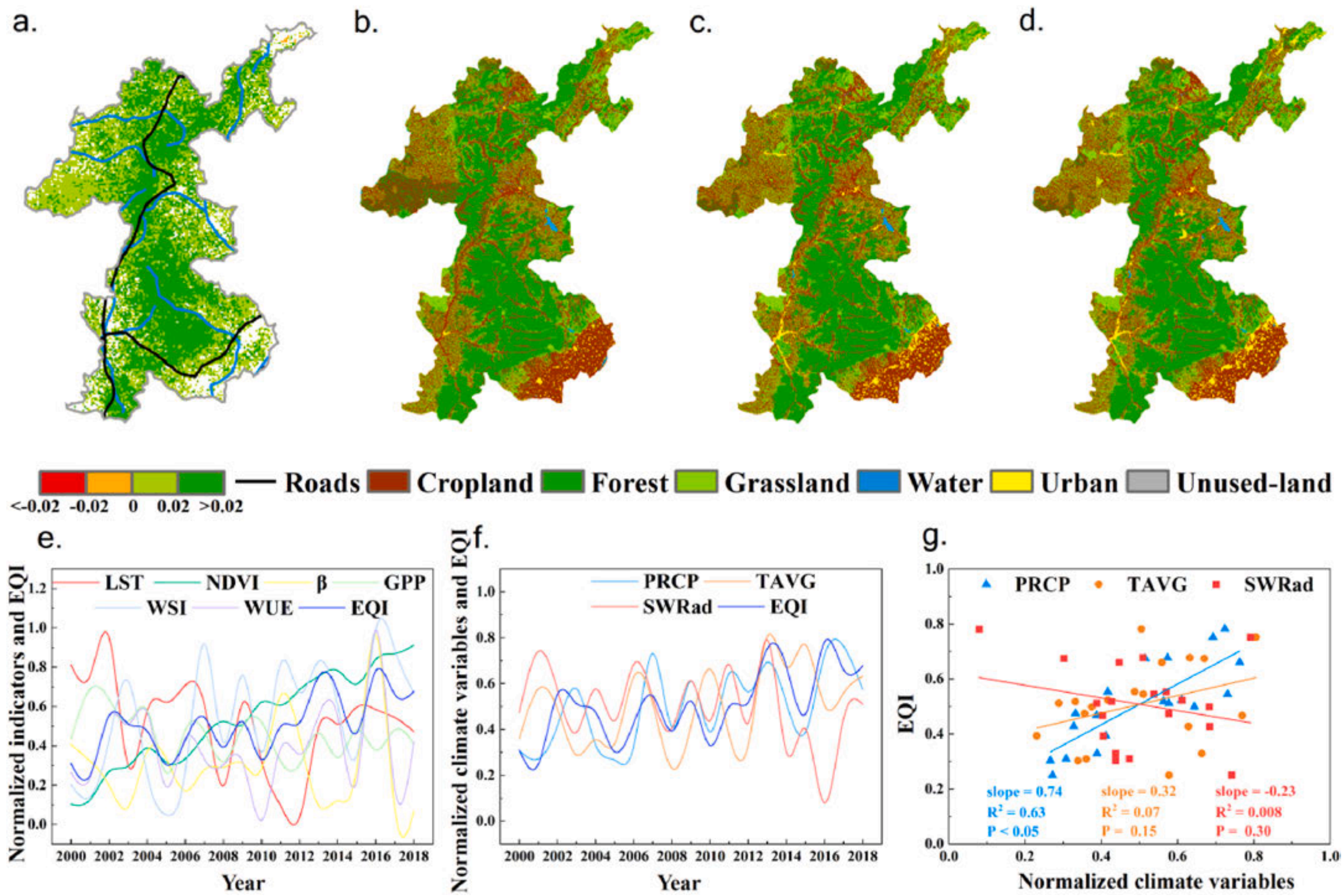

Fig. 4. Zone I: the inter-annual trend of EQI from 2000 to 2018 (a); the land use and cover in 2000 (b), 2010 (c) and 2018 (d); the inter-annual changes of the indicators (e), climate change (f), and the relationship (g) between EQI and climate variables in Lvliang, Shanxi Province.

5.1.1. *Indicators*

The index integrates the fundamental ecosystem functions for maintaining biodiversity or habitat, conserve water and soil, support nutrient and energy cycling, and regulate climate (La Notte et al., 2017). From the three functions (supporting, maintaining and regulating functions) the 11 indicators as shown in Table 1 have been tested and six have emerged, which were normalized differentials of vegetation index (NDVI), gross primary productivity (GPP), land surface temperature (LST), Bowen ratio (β), water use efficiency (WUE) and water storage index (WSI).

A theoretical relationship was analyzed between the indicators and the final ecological quality index. Random values were generated according to cumulative probabilities from 0 to 1 in steps of 0.01 for indicators with their probability distribution, with a normal distribution after the statistic test, and their respective means and standard deviations. The EQI values then were calculated with the random values and the weights given by the PPM-PSO algorithm used in this study.

As the results demonstrate in Fig. S4, due to differences in means and standard deviations, the GPP and WUE had left-skewed distributions, Bowen and LST were right-skewed, and WSI were far right-skewed. However, the NDVI showed a normal distribution and the final EQI was consistent with the NDVI, and they both showed almost the same distribution along cumulative probability, though the NDVI had a lower weight (Table S6). This illustrates that vegetation plays a very important role through the NDVI in the EQI, which is consistent with habitat evaluations that use NDVI (Wiegand et al., 2008), such as the InVEST model (Berta Aneseyee et al., 2020). Indicators of ecological quality were based on the concept of ecosystem functions, and was defined as the "capacity or capability of the ecosystem to do something that is potentially useful to people" (Turkelboom et al., 2013), and were used to quantify ecosystem multifunctionality. However, the EQI in this study considered more aspects of ecosystems by considering more reasonable indicators and produced a more objective indication of ecological quality.

5.1.2. *Baseline*

The maximum and minimum values in a given period were referred to as the upper and lower baselines for each indicator history and was applied to quantify ecological quality in this study. The baseline was defined as the status of a conserved undisturbed ecosystem and described as an ideal reference (He et al., 2020). But the major challenge is the scarcity of appropriate context-specific data on the expectations for ecosystem services or the ideal ecosystem in the present anthropocene era (Chan et al., 2006; Crutzen, 2002; Paetzold et al., 2010). The probability distribution analysis, that uses the indicators' values at given accumulative probability, such as the indicator values at 95% and 5% probability as the upper and lower baseline, provides a practical approach for assessing ecosystem quality at regional and national scales (Kennedy and Eberhart, 1995).

As a simplification, the maximum and minimum values were used as the baseline values of the index, using the method of probability distribution analysis with corresponding cumulative probability values of 100% and 0%, essentially. Because there would be lots of area outside of the range of the 95% and 5% probability, we could not identify their differences in ecological quality if the method was applied at a regional or national scale. A possible problem of the baseline values used in this study is that the value of EQI is compressed in general if the extreme exceptions are used as the baselines. Meanwhile due to the baselines

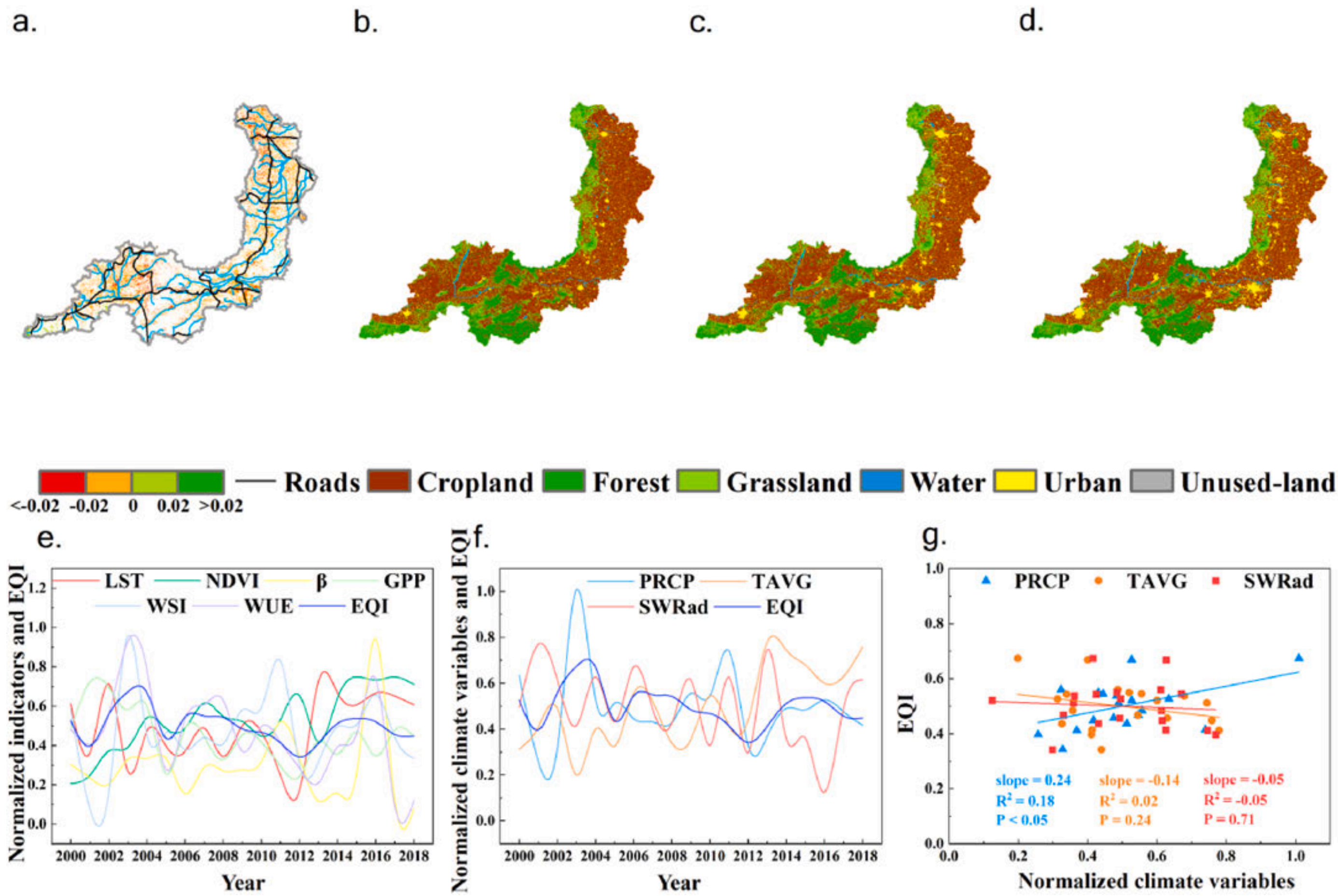

Fig. 5. Zone II: the inter-annual trend of EQI from 2000 to 2018 (a); the land use and cover in 2000 (b), 2010 (c) and 2018 (d); the inter-annual changes of the indicators (e), climate change (f), and the relationship (g) between EQI and climate variables in Shijiazhuang-Zhengzhou-Xi'an area.

being developed on the pixel scale, there is no comparability of spatial patterns but they could be compared on a temporal scale. The method of using an historical baseline provides a practical reference for evaluation and could be utilized as a practical option to measure ecosystem quality at regional or national scales.

5.1.3. *Method to determine weights*

The PPM-PSO algorithm was compared with the AHP, PCA and Entropy methods through use of the regional mean data for the whole country. The results are given in Table S6. The dominant indicator weights were different among the algorithms. The weights were not significantly different ($p > 0.8$) or correlative ($p > 0.14$) among the methods. First of all, the GPP was weighted as the maximum value (0.308) by the PPM-PSO, while it was the Bowen (0.246) and WSI (0.245) by the entropy weight method, and the NDVI (0.407) by the AHP. The third component of PCA was more correlative with the weights from the PPM-PSO, but the PCA-algorithm showed that NDVI had a higher weight (0.833). The AHP-based weights mainly depend on the discriminant matrix that should be determined through *a priori* order on the importance index; therefore, if NDVI is assumed as the most important index, the resultant score will be affected significantly by NDVI. As a linear dimensionality reduction method, whilst retaining as much as possible of the variation in the original data, the PCA seems to be more objective due to the data-based algorithm (Jolliffe, 2002). But the results showed that it needs at least 4 primary components to interpret 90% of variation in the input data, which is inefficient and redundant. The entropy weights method cannot truly display ecological quality while ignoring the relationship between data because the higher weights were assigned to the Bowen and WSI but NDVI received a lower weight, though it was considered as an objective approach that output a larger weight for an indicator with a higher discrete degree, though it cannot correctly reflect the distinction of water quality indices (Bao et al., 2020).

The third component (PC3) of the PCA was more correlative with the weights from the PPM-PSO, but the PCA-based method showed that NDVI had a much higher weight (0.833) according to the PC3. The PPM-PSO does not require *a priori* judgment on importance on an index and only depends on input data for each index.

In the PPM-PSO algorithm, uncertainty may stem mainly from the determination of several parameters in the algorithm. First, the R, the density window width in equation (7), may not be the optimal solution. Although the validation process indicated that the final solution was infinitely close to the optimal one, we have no idea how the little distance between compromise and optimal solutions could impact the veracity and validity of the assessment model. Thus, determining based on the R value could be a further research direction to improve the integrity of the evaluation model. Another limitation may be derived from the number of iterations required. As the number of iterations increases, the result will be more accurate; however, at the same time, it will take more time. Therefore, in order to reduce the uncertainty of the model, a trade-off should be made between the number of iterations and the time cost. Some of the uncertainties may also come from the quality of input data.

5.2. *Ecological quality in China*

The historic baseline-based EcoFun Index illustrated a unique spatial pattern (Fig. 2**a**) for ecological quality. The Ministry of Environment of People's Republic of China regularly issues the annual eco-environment

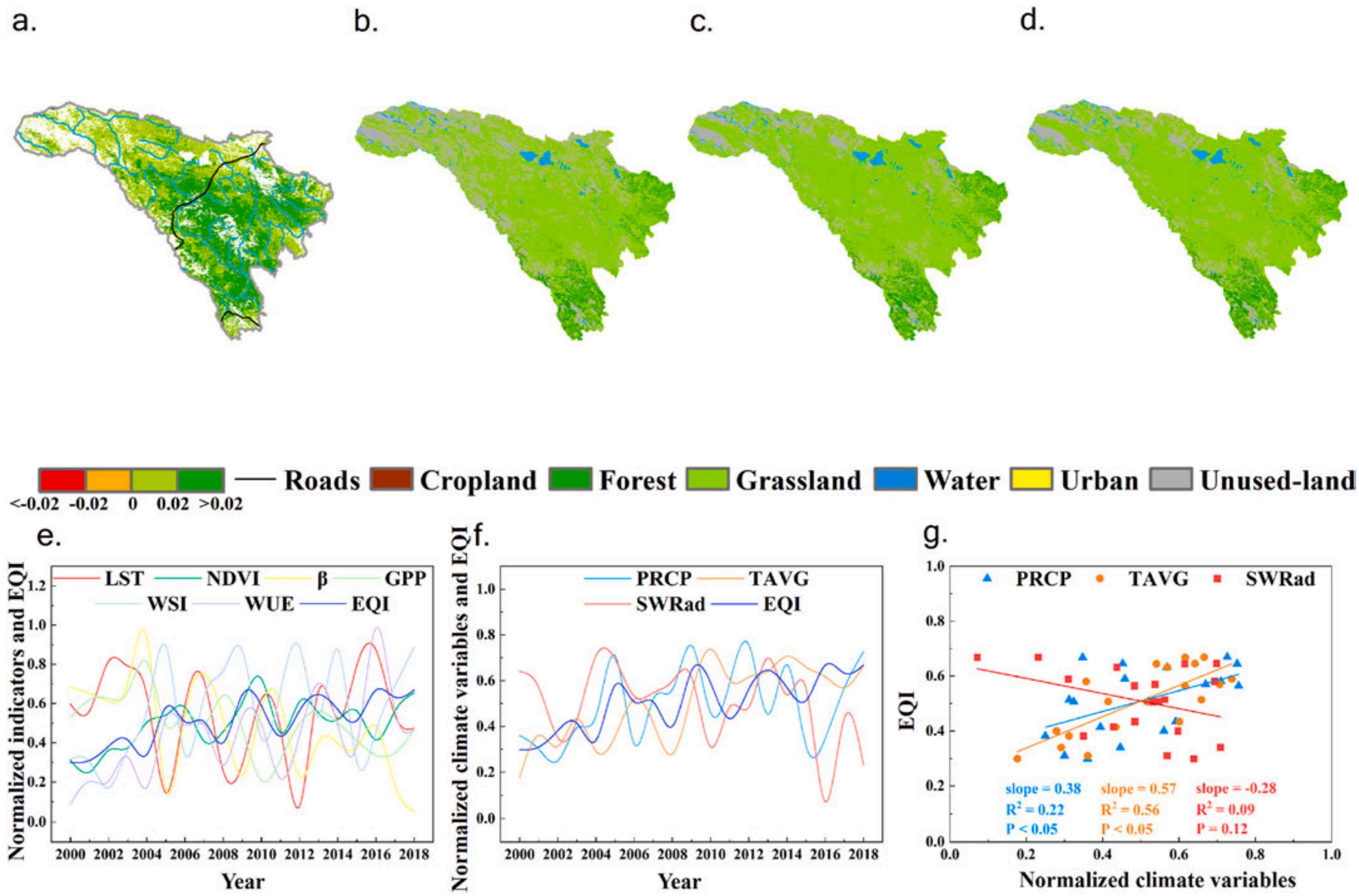

Fig. 6. Zone III: the inter-annual trend of EQI from 2000 to 2018 (a); the land use and cover in 2000 (b), 2010 (c) and 2018 (d); the inter-annual changes of the indicators (e), climate change (f), and the relationship (g) between EQI and climate variables in Yellow River Source area, Qinghai Province.

status with the ecological index calculated from biodiversity richness, vegetation fraction, water coverage, soil erosion or urbanization, and pollutants based on the *Technical Criterion for Ecosystem Status Evaluation* (Ministry of Environment of People's Republic China, 2015). However, biodiversity richness was substituted by habitat quality which was quantified by land use and land cover (LULC) and its weights. Its ecological index was calculated from vegetation coverage proportion and LULC, in essence, respectively for ecological function regions. Though the criterion considered biodiversity and ecological function regions, due to unavailability of data and pursuing operability on the national scale, ecosystem functions were only quantified through vegetation coverage proportion and land use and land cover, which ignored the multiple functions of ecosystems. It was an evaluation of the ecosystem status, not on the ecological quality. As a status assessment, those indexes always show lower quality for some ecosystems (i.e., desert), but always better for others (i.e., forest), and they cannot evaluate changes, which are of more concern to government, scientists and the public.

The ecosystem function-based index proposed in this study evaluated ecological quality by the temporal changes of indicators comparing to their maximum and minimum baseline values. The EcoFun Index is independent for climate regions or land cover/use classifications and only related to the ecosystem referenced and evaluated conditions. For example, based on the ecosystem's condition, the desert has a very low quality for its lower proportion of vegetation coverage, comparing to a forest having a relatively higher proportion of vegetation coverage, which cannot distinguish changes for desert ecosystems and cannot evaluate its quality. To date, most methods have directly assessed ecological status, then indirectly assessed ecological quality by comparing with the status for a specific preceding year (Hu and Xu, 2018; Liu et al., 2016; Ministry of Environment of People's Republic China, 2015; Wang and Ouyang, 2015), which would lower the value of assessment results due to the uncertainties of land use and land cover classifications. The method developed for use in this project can avoid that disorder by using baseline-based changes over a longer period.

5.3. Driving factors on temporal trends of EQI

The EQI demonstrates an overall positive trend for the whole country, while 18.97% of the research area had a significant upward trend ($p < 0.05$) from 2000 to 2018 (Fig. 2). The trends can be explained by changes in annual total precipitation (PRCP), annual averaged air temperature (TAVG), and annual total solar shortwave radiation (SWRad). These three variables together explained 46.95% of the variation in trends, with a confidence level over 90%, in the inter-annual EQI for all of the terrestrial ecosystems in China (Fig. 3). Human activity, quantified by population density, increases the explanation of impacts about 10.64%, but its negative effect showed a great spatial heterogeneity.

While most of the regions show a significant upward trend of EQI, some places still show a downward trend. Therefore, the four hotspots, as shown in Fig. 2c - Lvliang (Zone I), Shijiazhuang-Zhengzhou-Xian area (Zone II), Yellow River Source area (Zone III), and Yunnan area (Zone IV) - where EQI slopes are similar within 0.05 confidence, were given more attention in analyzing driving factors for the trends of EQI from 2000 to 2018. The significant upward-trending EQI are represented by the Lvliang area (I) and Yellow River Source area (III), while the significant downward-trending EQI were for the Shijiazhuang-

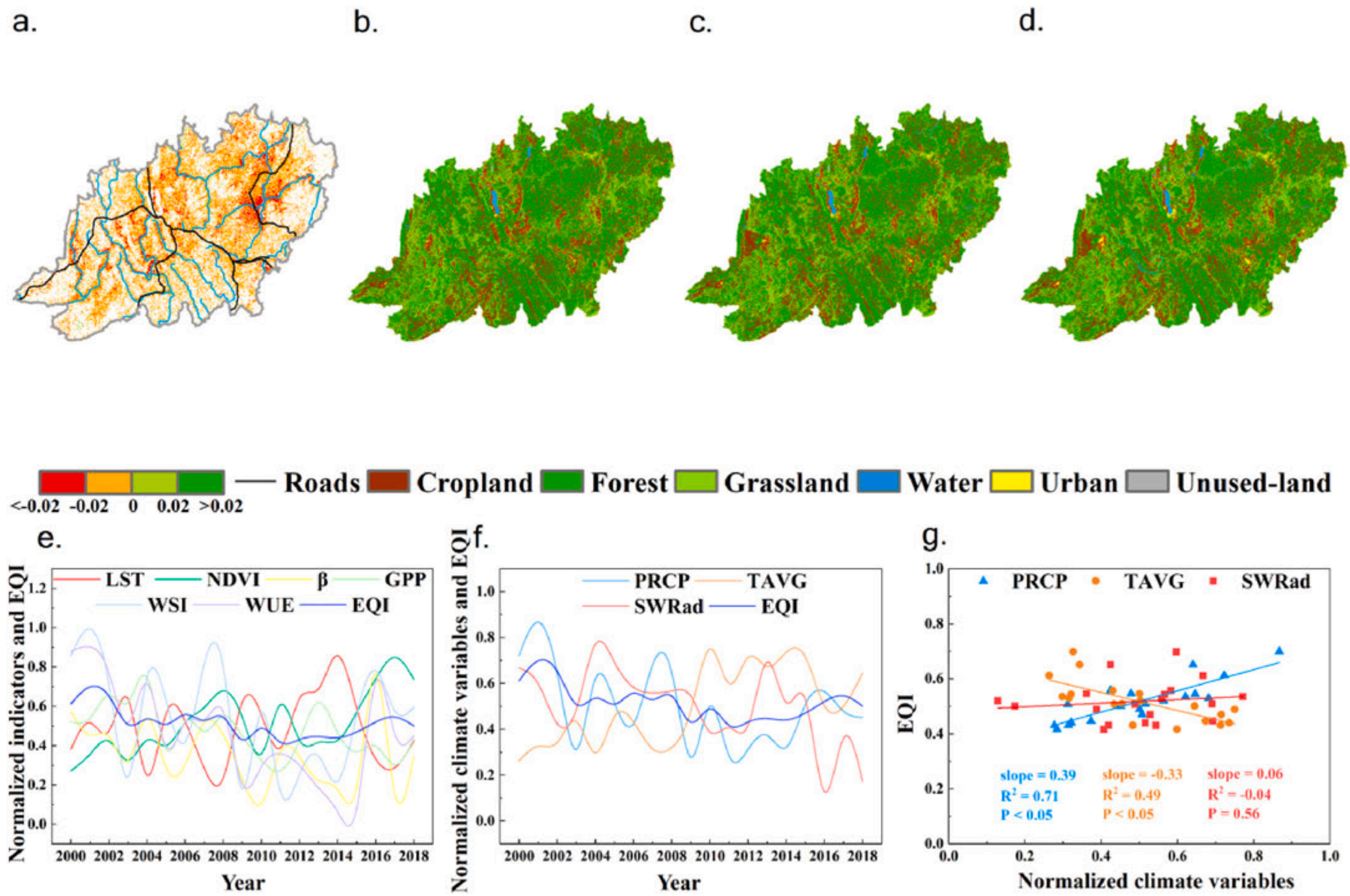

Fig. 7. Zone IV: the inter-annual trend of EQI from 2000 to 2018 (a); the land use and cover in 2000 (b), 2010 (c) and 2018 (d); the inter-annual changes of the indicators (e), climate change (f), and the relationship (g) between EQI and climate variables in Yunnan Province.

Zhengzhou-Xian area (Zone II) and Yunnan area (IV).

The increasing EQI in Zone I is believed to be mainly due to implementation of measures to convert farmland to forest and warmer and wetter climate conditions (Fig. 4). Yet the significant increasing EQI in Zone III was likely because of a warm and humid climate and the resultant large amount of conversion from desert to grassland (Fig. 6). Of the two regions with significant decreasing EQI, the reasons for the downward trend for Zone II (Fig. 5) and Zone IV (Fig. 7) are attributed to rapid urbanization and drought, respectively. By comparison, the degree of EQI decline in zone II and zone IV was lower, while the degree of EQI growth in zone I and zone III were higher. Slight decreases in High EQI level zones, like zone IV, can be captured sensitively in the future to analyze the interannual variance. The results reported here illustrate that the EQI can capture and objectively quantify actual changes in ecosystems, and the index therefore can be considered as a valuable tool to use in assessing ecosystem quality and changes in that quality.

5.4. Improvements and its potential applications in future

This study proposed a new ecological quality index to quantify the dynamic changes of ecosystem function through multiple indicators compared to their own baselines on the pixel scale. It provides an objective evaluation method based on concepts centered on ecosystems themselves through indicators reflecting fundamental functions, such as: vegetation greening through NDVI, the photosynthesis capability through GPP, etc., which further support various and different ecosystem services and human well-being (Chapin et al., 2000; Fu et al., 2017; La Notte et al., 2017). However, when measuring and evaluating biodiversity we should pay more attention in the future to habitat quality, which has been mostly measured by a surrogate vegetation index on the regional scale (MEE, 2020). Biodiversity has been considered to link ecosystem services to ecosystem functions (Brockerhoff et al., 2017; Isbell et al., 2017; Yu et al., 2017). The infrared camera-based monitoring of biodiversity provides a better approach to evaluate ecological quality by considering animal richness on a regional scale (Wang et al., 2019), but its application to the national scale still faces great challenges. Therefore, satellite remote sensing has been considered to be essential and practical in the monitoring and evaluating of biodiversity (Aneseyee et al., 2020; García-Palacios et al., 2018; Skidmore et al., 2021).

This study provided a methods framework to apply in not only evaluating ecological quality but also in assessing ecological restoration effect, ecological security and risk, and ecological vulnerability assessment, potentially. The ecological quality of terrestrial ecosystems can be evaluated regularly for any region as done in China (MEE, 2020). Ecological restoration effects have been assessed generally by comparing multiple ecosystem attributes with their baselines assumed as status or trends (Shao et al., 2017a; Zhen et al., 2018). It is expected to provide a relatively impartial basis for judgment for ecological legislation because of its relative objectivity (Paetzold et al., 2010). This study provided a practical and objective approach for quantifying and assessing ecological quality on the national scale though some improvements should be considered for the future.

6. Conclusion

This paper proposed a conceptual framework for ecological quality evaluation for terrestrial ecosystems based on historical baselines and changes in ecosystem functions along with a PSO-PPC algorithm to determine weights. The historic baseline-based EcoFun Index showed a very different spatial pattern dependent on its pixel-scale baseline and removal of the effects of climate or land use classification when it was applied to assess ecological quality in China from 2000 to 2018. An overall increasing trend in EQI was found over most areas and 46.95% of variation in EQI can be explained by climate change and an additional 10.64% was explained by human activities, quantified by change in population density. This study provided a practical and objective approach, though its indicators related to biodiversity need further improvement in the future, to quantify and assess ecological quality. The results reported here have potential for applications in assessments to understand the effects of ecological restoration on the national scale though some improvements should be considered for quantifying ecological quality trends in the future. This study proposed a new scientific and objective tool for ecosystem evaluation and a new scientific concept and paradigm for macro ecosystems management and decision-making for governments.

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CRediT authorship contribution statement

Junbang Wang: Conceptualization, Methodology, Writing – review & editing. **Yuefan Ding:** Data curation, Writing – original draft. **Shaoqiang Wang:** Conceptualization, Writing – review & editing. **Alan E. Watson:** Writing – review & editing. **Honglin He:** Conceptualization, Writing – review & editing. **Hui Ye:** Data curation, Software, Validation. **Xihuang Ouyang:** Software, Validation. **Yingnian Li:** Writing – review & editing.

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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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2022.114944.

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