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Exploring the regional differences of ecosystem health and its driving factors in China

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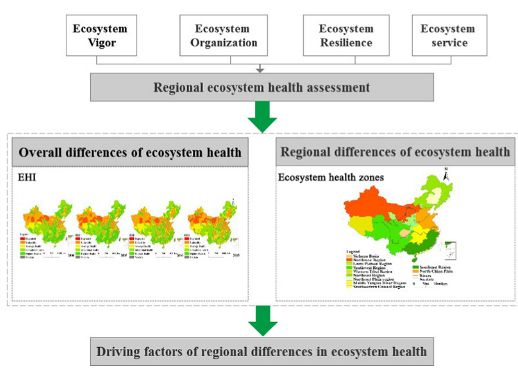
HIGHLIGHTS

- The ecosystem health level in China was assessed based on county administrative units.
- Eleven zones were presented to depict the regional differences of ecosystem health.
- Moisture index and land use intensity primarily drove the ecosystem health change.

GRAPHICAL ABSTRACT



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ABSTRACT

A better understanding of regional differences in ecosystem health and its driving factors is conducive to ecosystem management and restoration. Although various studies on ecosystem health have been carried out in different regions, few studies have been devoted to the insightful exploration of the spatial heterogeneity of ecosystem health and its driving forces at a national scale. In this study, we used an evaluation framework in terms of vigor, organization, resilience, and ecosystem service functions to assess the ecosystem health level in China from 2000 to 2015. Then, spatial agglomeration and regional differences in ecosystem health were examined using the spatial autocorrelation method and K-means clustering analysis, and the factors driving the regional differences of ecosystem health were explored based on the geographical detector model. Our results showed the following: (1) the ecosystem health level in China spatially increases from the northwest to the southeast, exhibiting significant global spatial autocorrelation and local spatial agglomeration; (2) eleven zones with three types were identified to indicate the regional differences of ecosystem health; (3) In terms of the driving factors, the moisture index and land use intensity contributed 24.5% and 20.7% to the variation in ecosystem health at the national scale. The ecosystem health changes were influenced by the interaction of meteorological and socio-economic factors in most regions with high ecosystem health types. Socio-economic factors act as a bridge that linked and reinforced the other factors in most regions with low and medium ecosystem health types. Ecologically protected factors were found to exert a remarkable impact in the southwestern region and the Loess Plateau

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region. Our findings can provide more effective and detailed decision-making support for ecosystem conservation and management in China.

1. Introduction

With rapid urbanization and industrialization, intensive human activities have significantly altered the structure and function of ecosystems (Li et al., 2016; Li et al., 2017; Qiu et al., 2015), which have caused severe ecosystem degradation and in turn threatened human survival and socioeconomic development (Cheng et al., 2018; Chi et al., 2018). Balancing socioeconomic development and ecosystem conservation has become a widespread issue, especially in China (Su et al., 2010; Zeng et al., 2016). After nearly 40 years of development, China is now in urgent need of a systematic evaluation of ecosystem health to support the formulation of ecosystem management policies.

Regional ecosystem health refers to the sustainability and self-maintenance ability of ecosystem mosaics, and their stability to provide ecosystem services at a certain spatial and temporal scale (Costanza, 2012; Peng et al., 2007). Ecosystem health assessments allow us to systematically understand the expected status of the ecosystem and the threshold of ecological degradation. To date, many studies on ecosystem health assessments have been conducted at various scales, such as provinces (Meng et al., 2018b), large cities (Su and Fath, 2012), urban agglomerations (Kang et al., 2018; Zeng et al., 2016), rivers (Cheng et al., 2018; Li et al., 2015), wetlands (Chi et al., 2018) and forests (Styers et al., 2010). Nevertheless, few studies have focused on nationwide scale and have diagnosed regional differences in ecosystem health within an entire country. China, as one of the largest countries in the world, features significant differences in natural conditions (e.g., climate, vegetation, and hydrology) and socioeconomic development levels (e.g., urbanization rate and population density) in different regions. These factors have formed regional differences of ecosystem health. Furthermore, the implementation of a range of policies of ecological protection by Chinese government, such as, Grain to Green and Three-North Protection Forest System, also has affected the status of ecosystem health to some extent. The evaluation of ecosystem health in China will help determine the different ecological health levels across the country and over time, and what drives those differences. Meanwhile, national scale research based on county administrative units can provide more spatially explicit support for the delineation of ecological conservation areas than previous research at the provincial administrative scale.

A systematic assessment of ecosystem health should address two issues: the diagnosis of ecosystem health levels and the exploration of its driving forces. First, ecosystem health diagnoses are generally performed based on the multi-criteria decision analysis technique. Three groups of analysis frameworks for regional ecosystem health evaluation have been proposed: subsystem evaluation, PSR (pressure-state-response) and VORS (vigor, organization, resilience and ecosystem service). Early efforts selected indicators in view of inclusive subsystems, e.g., resource-environment-society-economy compound subsystems (Meng et al., 2018a, 2018b). Then, the ecosystem health evaluation emphasized the causal relationship between the ecosystem quality and human activities, and established various indicator systems, such as PSR (pressure-state-response) (Sun et al., 2016; Yu et al., 2013) and DPSIR (Drivers-Pressures-State-Impact-Response) (Spiegel et al., 2001). These two groups can only measure the status and external disturbances of ecosystems, and they overlook evaluating the provision capability of ecosystem services. Nevertheless, the framework of vigor, organization, resilience ecosystem service function (VORS) can improve the above drawback. The VORS framework is an expansion of the vigor, organization, and resilience (VOR) framework (Costanza et al., 1992), which measures an ecosystem's health from aspects of both naturalistic ecosystem quality and ecological services for humans (Rapport et al., 1998). In the VORS framework, the vigor component reveals the activity, metabolism or primary productivity of regional ecosystems, the organization component measures the number and diversity of interactions between the various subecosystems, the resilience component indicates the capacity of an ecosystem to maintain its original structure and function while facing an external disturbance, and the ecosystem service function component diagnoses the ecological service provision under the impact of spatial adjacency relations of different ecosystems (Costanza et al., 1992; Peng et al., 2007; Rapport et al., 1998). Due to the comprehensive measurement of the natural states of ecosystem, we used the VORS framework to evaluate the ecosystem health of China.

Second, explorations of factors that affect ecosystem health are usually conducted based on statistical methods. In practice, correlation analysis (Cheng et al., 2018; Styers et al., 2010), principal component analysis (Bebianno et al., 2015), and regression analysis (Bae et al., 2010) have been applied to discuss the relationship between ecosystem health and its driving factors, especially the influence of human activity on ecosystem health at the regional scale (Cheng et al., 2018; Peng et al., 2017; Zhang et al., 2017). However, traditional statistical analyses or spatial analysis methods cannot quantify the interactions of the driving factors and their combining effects on ecosystem health that are induced by the complexity of geographic processes (Xie et al., 2017). Compared with the traditional statistical analysis method, the geographical detector is a promising method for exploring the spatial heterogeneities of geographical phenomena and variation among these driving factors (Wang et al., 2016). It can not only analyze the relative importance (or effect intensity) of driving factors, but also explore the interactions of these factors on ecosystem health that have been neglected in previous studies.

In this article, taking China as an example, we analyzed regional differences in ecosystem health and identified the factors that affected ecosystem health from 2000 to 2015. We aim to explore the following: (1) the spatial heterogeneity of ecosystem health in China, for instance, agglomeration and zones; (2) the changes of ecosystem health and what drives these changes at the national and regional levels. Our study will provide assistance for formulating ecological conservation policy in China.

2. Materials and methods

2.1. Study area

China (3°51′–53°33′N, 73°33′–135°05′E) is located in eastern Asia, and covers 9.6 million km^2 (Fig. 1). The terrain in China is high in the east and low in the west, showing three ladder-like distributions in space. The country has multiple climate zones, including the subtropical monsoon, the temperate monsoon, the tropical monsoon, the temperate continental climate, and the alpine climate. The proportions of grass land, forest, arable land, unused land, built-up land and water are 31.5%, 23.6%, 18.8%, 20.1%, 2.3% and 2.8% respectively, in 2015. China has been undergoing rapid economic development and industrialization since 1978. The gross domestic product (GDP) increased from 10.03 in 2000 to 68.91 trillion Chinese Yuan in 2015, the population increased by 8.52% from 1.27 to 1.38 billion, and the urbanization rate increased from 36.22% to 56.1% (data derived from the China Statistical Yearbooks in 2001 and 2016). Meanwhile, the dramatic development imposed great threats on the ecological environment, which even affected the socioeconomic sustainability (Li et al., 2017). To reconcile the conflicts between economic development and ecological protection,

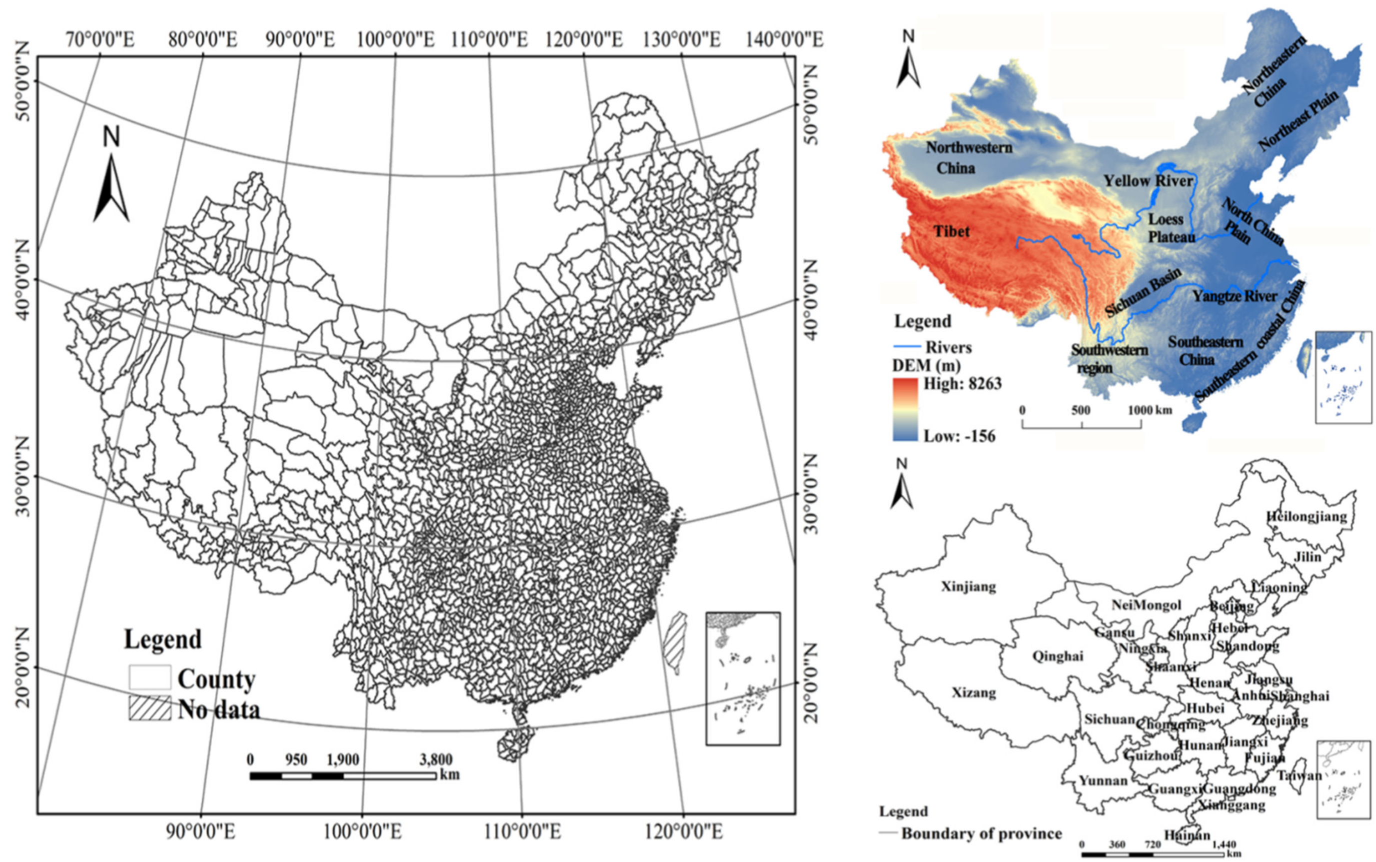


Fig. 1. Location of the study area.

a series of ecological conservation projects and policies have been implemented by the Chinese government at national, regional, and local levels since the 1990s (Huang et al., 2018). However, ecological deterioration has not been effectively mitigated, and the conflicts between ecological conservation and large-scale development are still prominent. Therefore, it is urgent to formulate targeted ecological protection policies, and the diagnosis of ecosystem health is important for distinguishing ecological protection policy making and ecological civilization construction in China.

2.2. Data source and processing

In our study, the study area covers the mainland China (excluding Taiwan, HongKong, Macao regions), including 2859 counties (counties, autonomous counties, county-level cities and municipal districts). The data can be classified into two categories: spatial data and statistical data. The spatial data were supported by the Data Center for Resources and Environmental Sciences, Chinese Academy of Sciences (http://www.resdc.cn/), involving land use and cover data (spatial resolution of 1 km), meteorological data with 500 × 500 m resolution (i.e., annual mean precipitation, annual mean temperature, moisture index, aridity index), administrative boundary of Chinese counties, normalized difference vegetation index (NDVI) and digital elevation model (DEM) (spatial resolution of 1 km).

The statistical data, including population density, per area GDP, urbanization rate and the number of ecological conservation projects, were mostly collected from Chinese County Statistical Yearbook (2001–2016), China Statistical Yearbook (2001–2016), Statistical yearbooks of different provinces (2001–2016), the statistical bulletin of Ministry of Ecology and Environment of the People' Republic of China. The data were preprocessed using ArcGIS 10.2 and Fragstats 4.2 software. The landscape indices of ecosystems were calculated using Fragstats 4.2 software. The ecosystem resilience and ecosystem services were calculated using R platform.

2.3. Methods

We proposed a framework to assess the ecosystem health of China. The framework includes three components: evaluating the ecosystem health levels; analyzing the regional differences in ecosystem health; and exploring the driving factors of ecosystem health change (Fig. 2). Each component is described in detail below.

2.3.1. Regional ecosystem health assessment

The assessment indicators of ecosystem health include vigor, organization, resilience and ecosystem services function (Costanza et al., 1992; Rapport, 1989; Rapport et al., 1998). The ecosystem health index (EHI) is expressed as follows (Kang et al., 2018):

$$EHI = \sqrt{PHI \times ES} \tag{1}$$

$$PHI = \sqrt[3]{EV \times EO \times ER} \tag{2}$$

where *EHI* and *PHI* denote the regional ecosystem health index and ecosystem physical health; and *EV*, *EO*, *ER* and *ES* are the indicators of ecosystem vigor, ecosystem organization, ecosystem resilience and ecosystem services. *EHI*, *PHI*, *EV*, *EO*, *ER* and *ES* were normalized to the range of 0 to 1. The ecosystem health levels were categorized into five grades using an equal-interval approach (Cheng et al., 2018): Degraded (0–0.2), Unhealthy (0.2–0.4), Average Health (0.4–0.6), Suboptimal Health (0.6–0.8), and Highest Health (0.8–1.0).

Ecosystem vigor can be expressed as ecosystem metabolism or net primary productivity (Rapport et al., 1998). NDVI was selected to represent ecosystem vigor in this study because it is closely related to net

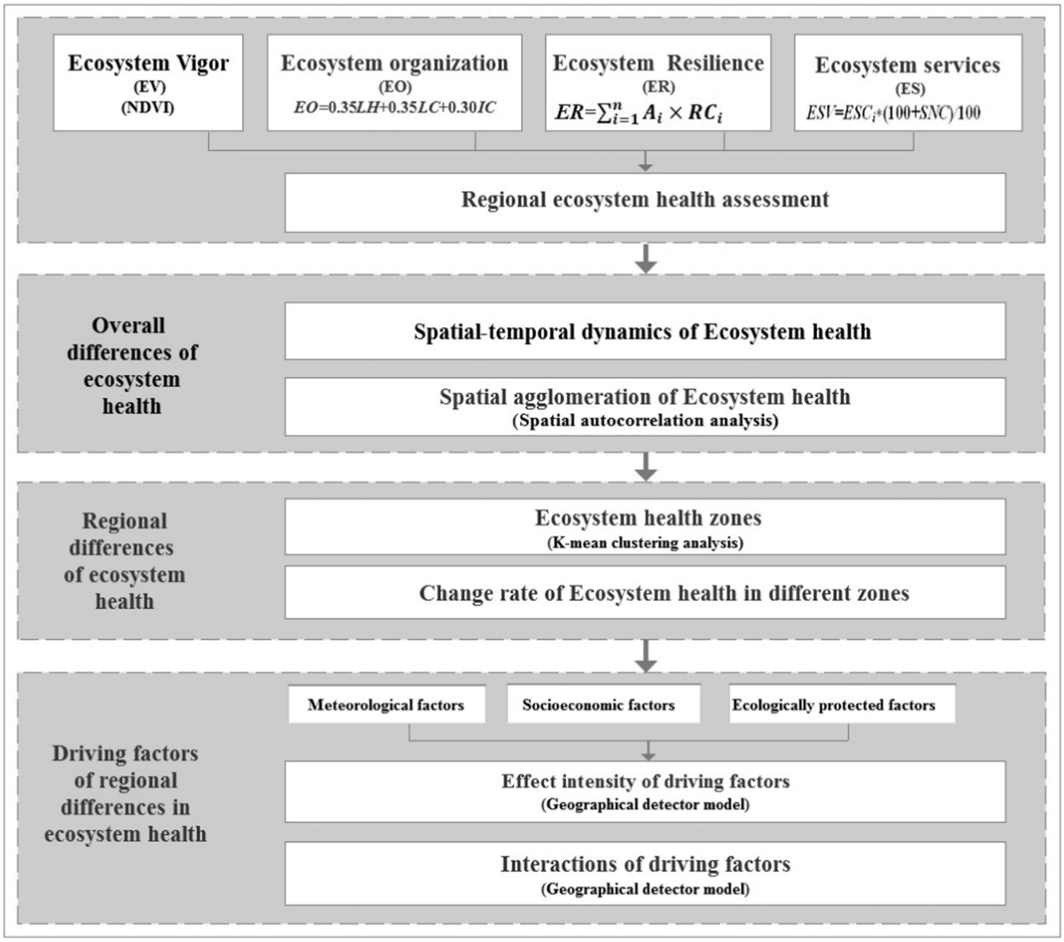


Fig. 2. The analysis framework of this study.

primary productivity (Wang et al., 2017b) and has been widely proven to be effective in assessing the ecosystem vigor (Costanza, 2012; Liao et al., 2018; Peng et al., 2017). NDVI can be computed as NDVI = (NIR-RED) / (NIR + RED), NIR and RED respectively denotes the near-infrared waveband and visible red band.

Ecosystem organization refers to the stability of ecosystems structure (Costanza, 2012), which is mostly measured by the landscape pattern index in terms of landscape heterogeneity and connectivity (Howell et al., 2018). Landscape heterogeneity was calculated using Shannon's diversity index and the area-weighted mean patch fractal dimension. Landscape connectivity represents the connectivity of the overall landscape and important ecosystems, such as forest, water and grass land that are highly related to soil conservation, windbreaks and sand fixation, climate regulation, nutrient circulation and ecological balance (Cheng et al., 2018; Lavorel et al., 2017; Styers et al., 2010). The landscape fragmentation index and landscape contagion index were selected to indicate the overall landscape connectivity, and the fragmentation index and patch cohesion index of forest land, water, and grass land were used to measure the connectivity of important ecosystems. We utilized a weighted aggregation method to calculate the ecosystem organization indicator and fixed the weights of landscape heterogeneity, landscape connectivity and the patch connectivity index of the important ecological functions as 0.35, 0.35 and 0.30, respectively (Frondoni et al., 2011; Kang et al., 2018; Peng et al., 2015). The ecosystem organization indicator equation is as follows:

$$\begin{aligned} EO = 0.35LH + 0.35LC + 0.30IC = (0.25SHDI + 0.10AWMPFD) \\ +(0.25FN_1 + 0.10CONT) + (0.07FN_2 + 0.03COHESION_1 \\ +0.07FN_3 + 0.03COHESION_2 + 0.07FN_4 + 0.03COHESION_3) \end{aligned} \tag{3}$$

where EO is ecosystem organization; LH denotes landscape heterogeneity; LC stands for landscape connectivity; IC indicates the patch connectivity index of the important ecosystem (forest, water and grass land); $SHDI$ represents Shannon's diversity index; $AWMPFD$ refers to the area-weighted mean patch fractal dimension index; FN_1 indicates the landscape fragmentation index; $CONTAG$ is the landscape contagion index; and FN_2, FN_3, FN_4, $COHESION_1$, $COHESION_2$, and $COHESION_3$ denote the fragmentation index and patch cohesion index of forest, water and grass land, respectively.

Ecosystem resilience reflects the ability of an ecosystem to maintain structure and pattern in the presence of external disturbance (Costanza, 2012). A healthy ecosystem possesses adequate resilience to survive various small-scale perturbations (Rapport et al., 1998). Since land use has a significant effect on ecosystem resilience (Colding, 2007), the summation of area-weighted ecosystem resilience coefficients for all land use types were employed to measure ecosystem resilience. Specifically, the ecosystem resilience coefficients (ERC) were acquired based on expert knowledge and related references (Kang et al., 2018; Peng et al., 2017) (Table 1). Ecosystem resilience was calculated as follows:

$$ER = \sum_{i=1}^{n} A_i \times ERC_i \tag{4}$$

where ER stands for ecosystem resilience; A_i represents the area ratio of land use type i; ERC_i denotes the ecosystem resilience coefficient of land use type i; and n is the number of land use types.

Ecosystem service function refers to the capacity of ecosystem to provide goods and services for human society. We calculated the ecosystem services coefficient (ESC) for each land use type according to

Table 1
The ecosystem resilience coefficient (ERC) and ecosystem services coefficients (ESC) of land use types in China.

	Paddy field	Dryland	Water	Built-up land	Forest	High coverage grass land	Moderate coverage grass land	Low coverage grass land	Wetland	Unused land	Glacier and snow
ERC	0.40	0.30	0.80	0.20	0.90	0.80	0.70	0.60	0.90	0.10	0.10
ESC	0.52	0.41	0.85	0.33	1	0.85	0.82	0.73	0.93	0.013	0.017

the ratio of the ecosystem service value of a certain land use type to the average ecosystem service value for all land use types. Ecosystem service value for each land use type can be calculated using the method of (Xie et al., 2017). According to the actual situation of ecosystem services in the study area, the ecosystem services coefficients were calculated with a threshold of [0, 1] regarding forest land as a standard (Dobbs et al., 2011; Peng et al., 2015), as shown in Table 1. Additionally, the measurement of ecosystem services also needs to consider the spatial neighboring of land use types (Marulli and Mallarach, 2005; Peng et al., 2015). The coefficients of the spatial neighboring effects (SNE) on ecosystem services of land use types were determined based on the actual situation of the study area and the existing references (Kang et al., 2018; Peng et al., 2017). The ecosystem service calculation formula is as follows:

$$ES = \sum_{j=1}^{n} ESC_j \times \left(1 + \frac{SNE_j}{100}\right)/n \quad (5)$$

where ES is the ecosystem service index; ESC_j is the ecosystem services coefficient of land use type connected with pixel j; SNE_j denotes the sum of the spatial neighboring effect coefficients of the four adjoining pixels on the ecosystem services of pixel j; and n is the number of pixels.

2.3.2. Spatial autocorrelation analysis

We applied spatial autocorrelation analysis to investigate the spatial dependence and agglomeration pattern of ecosystem health in China. Spatial autocorrelation, which includes global and local spatial autocorrelation, can indicate the degree of interdependence and agglomeration between attributes in a specific area and attributes in other areas. Moran's I index was used to analyze the global spatial agglomeration of the entire study area, as shown in Eq. (6) (Moran, 1950). The local indicator of spatial association (Anselin, 1995) (LISA) is largely exerted to reflect the spatial correlation between a space attribute value and its adjacent space attribute value (Eq. (7)).

$$Moran's\ I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(x_i - \bar{x})(x_j - \bar{x})}{S^2 \sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}} \quad (6)$$

$$Local\ Moran's\ I = \frac{n(x_i - \bar{x})\sum_{j=1}^{m} w_{ij}(x_j - \bar{x})}{\sum_{i=1}^{n}(x_i - \bar{x})^2} \quad (7)$$

where n is the total number of counties in China; m is the number of counties geographically adjacent to county j; $i \neq j$, $S = 1/n\sum_{i=1}^{n}(x_i - \bar{x})^2$; x_i, x_j stand for the ecosystem health value of counties i and j; w_{ij} indicates the spatial weight matrix of units i and j; and $\bar{x}$ is the average ecosystem health value. The values of I range from −1 to 1, and higher absolute values of I reflect stronger spatial autocorrelations. There is a positive spatial correlation when $I > 0$, a negative spatial correlation when $I < 0$, and no spatial autocorrelation when $I = 0$. Local autocorrelation consists of four types: high-high (HH), low-low (LL), high-low (HL), and low-high (LH), which represent the aggregation of units with high ecosystem health levels, the aggregation of units with low ecosystem health levels, and a unit with a high (or low) ecosystem health value surrounded by units with low (or high) ecosystem health values, respectively.

2.3.3. Cluster analysis

The K-means clustering method was applied to analyze the regional differences in ecosystem health based on five composite indices (ecosystem vigor, organization, resilience, ES and EHI). The method consists of the following steps (Xu et al., 2018): (1) dividing all samples into k initial clusters; (2) calculating the mean value of each cluster as the barycenter; (3) calculating the Euclidean distance between each sample and barycenters of all the clusters and reassigning each sample to its nearest cluster; (4) repeating the previous step until all samples can no longer be calculated. We characterized the ecosystem health types using variance analysis and identified the contributing factors of each ecosystem health type in each region.

2.3.4. Geographical detector model

The geographical detector model was used to explore the factors that drive regional differences in ecosystem health at the national and zonal levels in China. This model explores the explanatory variables that substantially affect the dependent variable based on spatial variation analysis (Wang et al., 2016), which includes four modules: factor detector, risk factor detector, interaction detector, and ecological detector.

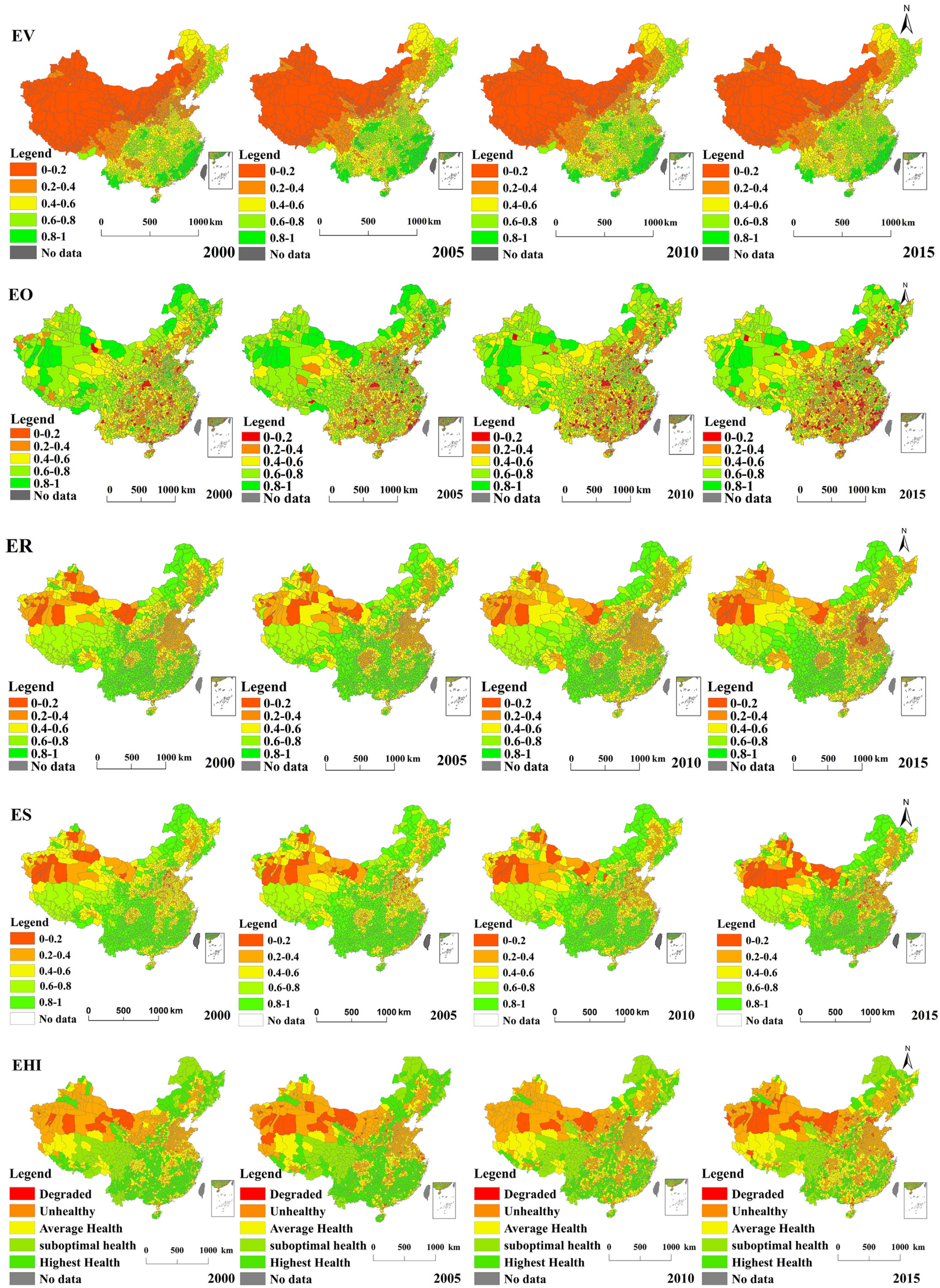
The factor detector was performed to measure the effect intensity of the driving factors on ecosystem health in this study. The expression is as follows:

$$q = 1 - \frac{\sum_{h=1}^{L} N_h \sigma_h^2}{N\sigma^2} \quad (8)$$

where L is the layer of independent variable X; N_h and σ_h represents the sample size and variance of the ecosystem health in layer h; and q is the explanatory power of the independent variable to the dependent variable, ranging from 0 to 1, which is capable of identifying the dominant factors of ecosystem health.

The interaction detector investigates the interactive effects of any two factors on ecosystem health. The interactive effect between two variables can be recognized by comparing the q values of a single variable and double variables. The types of interactions between two variables can refer to (Zhan et al., 2018). According to the input requirements of the geographical detector, the continuous variables need to be discretized (Wang et al., 2016). Moreover, Spearman correlation analysis was used to detect the effect direction of the driving factors on EHI in China.

Ten factors in terms of meteorology, socio-economics and ecological protection were selected based on previous studies (Bebianno et al., 2015; Cheng et al., 2018; Chi et al., 2018; Styers et al., 2010). Specifically, the meteorological condition was indicated using the annual mean precipitation (AMP), the annual mean temperature (AMT), the moisture index (MI), and the aridity index (AI). The socioeconomic development was represented by population density (PD), per area GDP (GDP), urbanization rate (UR), the proportion of built-up land area (BLA) and the land use intensity (LUI). The number of ecological conservation projects (ECP) was utilized to reflect the ecological conservation status. The detailed descriptions of the driving forces are shown in Appendix Table S1.


EV
Legend
0-0.2
0.2-0.4
0.4-0.6
0.6-0.8
0.8-1
No data
0 500 1000 km
2000
2005
2010
2015
N
EO
Legend
0-0.2
0.2-0.4
0.4-0.6
0.6-0.8
0.8-1
No data
0 500 1000 km
2000
2005
2010
2015
ER
Legend
0-0.2
0.2-0.4
0.4-0.6
0.6-0.8
0.8-1
No data
0 500 1000 km
2000
2005
2010
2015
ES
Legend
0-0.2
0.2-0.4
0.4-0.6
0.6-0.8
0.8-1
No data
0 500 1000 km
2000
2005
2010
2015
EHI
Legend
Degraded
Unhealthy
Average Health
suboptimal health
Highest Health
No data
0 500 1000 km
2000
2005
2010
2015

3. Results

3.1. Evaluation of ecosystem health

3.1.1. Spatial patterns of ecosystem health

Fig. 3 presents the spatial pattern of each ecosystem health indicator. Spatially, the ecosystem vigor in China showed a decreasing trend from the southeast to the northwest. The notable change in vigor was distributed in southwestern China, with an increasing trend from 2000 to 2005 and a slight decrease from 2005 to 2015.

The ecosystem organization gradually increased from southeast to northwest in China (Fig. 3). Slight changes in ecosystem organization were mainly concentrated in the northwestern regions, while great changes occurred in southern China. Southeastern China experienced a gradual decrease in ecosystem organization during the period from 2000 to 2015, especially in the southeastern coastal areas from 2010 to 2015.

A similar spatial distribution pattern can be observed between ecosystem resilience and ES (Fig. 3). The indices had high values in the areas with high vegetation coverage (e.g., in southwestern and southeastern China) but low values for built-up land, arable land and unused land (e.g., in the North China Plain, the Sichuan Basin and in northwestern China). In terms of temporal change, the ecosystem resilience and ES exhibited a great downward trend in the southeastern coastal region, Sichuan Basin, North China Plain and Northeast Plain region from 2005 to 2015.

As shown in Fig. 3, the level of ecosystem health in China increases from northwest to southeast. The high levels (suboptimal health and highest Health) were largely distributed in the southwestern and southeastern regions, parts of Inner Mongolia and the northeastern regions. The areas with low levels (degraded and unhealthy) were mostly located in the northwestern region, the North China Plain, the southeastern coastal region, the middle Yangtze River region and the Sichuan Basin region.

From the perspective of the entire country (Fig. 4), the counties with the unhealthy ecosystem level accounted for the largest proportion. Overall, the order of the number of counties with different levels of ecosystem health in China was as follows: unhealthy > suboptimal health > highest health > average health > degraded. The order of the area proportion was as follows: unhealthy > highest health > degraded > average health > suboptimal health from 2000 to 2015.

The number of counties above the average health level (suboptimal health and highest health) in 2000, 2005, 2010, and 2015 was 1166, 1249, 1146, and 1014, accounting for 42.18%, 45.96%, 41.09% and 36.09% of the total area in China, respectively. The county number and area proportion showed an upward trend from 2000 to 2005 and then decrease from 2005 to 2015. In contrast, the total number of counties below the average health level (degraded and unhealthy) in 2000, 2005, 2010 and 2015 was 858, 775, 884 and 923, accounting for 40.50%, 39.84%, 44.14%, and 47.34% of the total area, respectively. The county number and area proportion declined from 2000 to 2005 and increased from 2005 to 2015.

3.1.2. Spatial autocorrelation of ecosystem health

The global Moran's I index values were 0.6535, 0.6317, 0.5818, and 0.5412 in China from 2000 to 2015, respectively, which was significant at the 1% level. The results imply that the EHI has a significantly positive spatial autocorrelation in China. The counties with similar EHI had remarkable spatial agglomeration effects, and the agglomeration degree showed a gradual decrease from 2000 to 2015.

The local spatial autocorrelation demonstrates the high-high and low-low types of spatial agglomeration of ecosystem health from 2000 to 2015 (Fig. 5a). The high-high type was mostly distributed in southwestern, southeastern, and northeastern China, and the aggregation degree gradually decreased (especially in the southeastern and northeastern region) from 2005 to 2015. The low-low type was concentrated in the northwestern region, the North China Plain and the Northeast Plain region, and the aggregation degree increased (especially in the Northeast Plain) from 2005 to 2010.

3.2. Regional heterogeneity of ecosystem health

3.2.1. Ecosystem health zones in China

In this section, eleven zones with three types of ecosystem health were characterized using variance analysis (details in Appendix Table S2 and Fig. S1). The three regions exhibited high ecosystem health levels, including the southeastern region (SER), the northeastern region (NER) and the southwestern region (SWR). All three regions had high ecosystem vigor, organization, resilience, and ES, except the southeastern region, which has low organization, and the southwestern region, which has medium vigor (Appendix Table S2). Four regions presented medium ecosystem health status, including the western Tibet region (WTR), the middle Yangtze River region (MYRR), the southeastern coastal region (SCR) and the Loess Plateau region (LPR). These regions featured medium or high ecosystem vigor, organization, resilience and ES. However, the western Tibet region and the Loess Plateau region showed low vigor, and the southeastern coastal region had low organization (Appendix Table S2). The Sichuan Basin region (SBR), the Northeast Plain region (NPR), the northwestern region (NWR), and the North China Plain region (NCPR) were categorized as areas with low ecosystem health, which were all caused by low ecosystem resilience, ES.

3.2.2. Ecosystem health change rate

From the perspective of temporal change (Fig. 5b), compared to the period of 2005–2010 and 2010–2015, 2000–2005 was the most marked period of ecosystem health change. From the perspective of spatial change (Fig. 5b), the EHI increased by >1% in the southwestern region (e.g., Guizhou, Yunnan and Sichuan provinces etc.) and the Loess Plateau region (especially during the period from 2000 to 2005), and decreased by over 5% in the North China Plain, the Northeast Plain, the southeastern coastal region, and the northwestern region (e.g., Xinjiang Province). In the middle Yangtze River region, the Sichuan Basin, and the southeastern region, the decrease in the EHI ranged from 1% to 5%. In the western Tibet region and most parts of the northwestern region, the EHI had a slight change, between −1% and 1%.

3.3. Driving factors of regional differences in ecosystem health

3.3.1. Factor detection analysis

Table 2 presents that annual mean precipitation and annual mean temperature had a significant positive impact on the EHI in the eleven regions, implying their fundamental cause of ecosystem health changes, whereas, aridity pose a relatively weak and negative effect in most regions. We can observe that moisture dominates the regional differences of ecosystem health in China, occupying 24.5% of the variation in ecosystem health. Nevertheless, the annual mean temperature was the key factor impacting ecosystem health in the northeastern region and the western Tibet region, which explained 34.4% and 28.2% of the health variation, respectively. In the northwest region, the explanatory power of moisture was 35.0%, which indicates that moisture largely contributes to ecosystem health.

The ecological conservation project variable was positively and weakly correlated with the ecosystem health in most regions (Table 2). However, in the Loess Plateau region, it was found to play a key role in ecosystem health, explaining 24.3% of the health variation.

Fig. 3. The spatial distribution pattern of ecosystem vigor, organization, resilience, ecosystem service and EHI in China from 2000 to 2015 (EV: ecosystem vigor; EO: ecosystem organization; ER:ecosystem resilience; ES: ecosystem service; EHI: ecosystem health index).

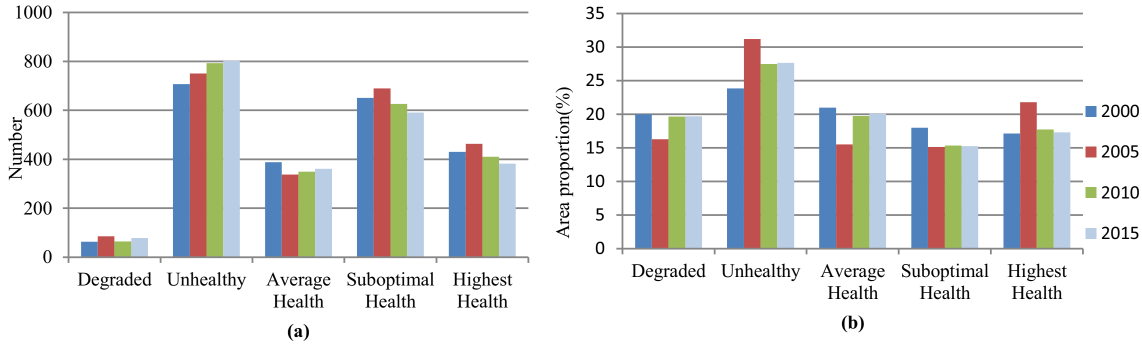


Fig. 4. The number (a) and area proportion (b) of counties with different ecosystem health levels during the period of 2000–2015.

The socioeconomic factors (i.e., the land use intensity, the proportion of built-up land area and the urbanization rate) exerted significant and negative influences on the ecosystem health in most of the regions, whereas, population density and per area GDP exert a relatively weak effect (Table 2). Land use intensity served as the second most influential factor of regional differences in ecosystem health in China with a q statistic of 20.7%. In the southeast, Northeast Plain, and southeastern coastal region, land use intensity was a leading driving determinant of ecosystem health change, with q statistics as high as 30%. In the middle Yangtze River region and the North China Plain region, the proportion of built-up land had the greatest influence on ecosystem health, explaining 28.1% and 27.4% of the variance in ecosystem health respectively. The urbanization rate was the dominant factor, with q statistics of 28.8% and 29.3% in the southwestern region and the Sichuan Basin region, respectively.

3.3.2. Interaction detection analysis

The results of interactive detector showed that the interactions among the driving factors had significant bi-enhanced or nonlinear enhanced effects on the ecosystem health, indicating that the synergetic effects exceeded the individual effects or the cumulative effects of the two factors. We listed the top four dominant interactions with significance levels of explanatory power at 1% (Table 3).

From a national scale, the interaction of the moisture index and land use intensity had the greatest explanatory power for the regional differences in ecosystem health in China, with a q statistic of 48.1%. From the regional scale, synergies between the meteorological factors and the socioeconomic factors enhanced the determinant power of ecosystem health variation in most regions with high ecosystem health types. For example, land use intensity and annual mean precipitation (56.4%) were dominant in the southeastern region, annual mean temperature and land use intensity (58.4%) were dominant in the northeastern region. In most regions with low and medium ecosystem health types, the combined impacts of any two socioeconomic factors were found to be the primary causes of the change in ecosystem health. For example, the proportion of built-up land area and land use intensity explained 54.1% of the health variation in the middle Yangtze River region, urbanization rate and land use intensity explained 54.9% in the Sichuan Basin region. Furthermore, some factors were found to have a relatively small impact on the ecosystem health change but presented remarkable synergy with the interaction of the socioeconomic factors (e.g. urbanization rate and land use intensity). This indicates that socioeconomic factors act as a bridge connecting and enhancing other driving factors in these regions.

In individual regions, the combined impacts of any two factors among the meteorological factors were strongly related to the ecosystem health change (Table 3). For instance, the annual mean temperature and aridity index resulted in 53.7% of the variation in ecosystem health in the western Tibet region, and moisture index and aridity index resulted in 57.1% of the variation in the northwestern region. In the southwestern region and the Loess Plateau, the interactions between the number of ecological conservation projects and other factors were significant contributors to the regional differences in ecosystem health. Such as ecological conservation projects and moisture index contributed 56.5% to the variation of ecosystem health in the southwestern region, and ecological conservation projects and annual mean precipitation contributed 45.6% to the variation in the Loess Plateau region.

4. Discussion

4.1. Comparison with previous studies

Our results show that the driving forces of ecosystem health present significant regional differences in China. The moisture index was identified as the primary factor influencing the regional heterogeneity of ecosystem health at the national scale, and its interaction with land use intensity enhanced the power of this factor to determine regional differences. Namely, regions with higher moisture indexes and lower land use intensity were likely to be categorized as a high ecosystem health type. Similar studies have suggested that climatic factors were the dominant determinants of regional ecological sensitivity (Meng et al., 2016; Ouyang et al., 2000; Zhang and Xu, 2017). However, the effect of land use intensity and its interaction with moisture on ecosystem health variation has been neglected. It may be because of the difference of research period. From 2000 to 2015, China was in a period of rapid urbanization (Qiu et al., 2015). Consequently, the influence of land use intensity on the ecosystem health change was great due to dramatic changes of land use (Metzger et al., 2006; Mitchell et al., 2015).

We also demonstrated that the meteorological factors and the socioeconomic factors had synergies and could enhance each other's effect on ecosystem health change in areas with high ecosystem health levels. Some studies also found that the changes of wetland, grassland and forest ecosystem were influenced by complex climatic and anthropogenic factors (Chi et al., 2018; Li et al., 2019; Liang et al., 2018; Wan et al., 2018). However, the findings were not in line with the studies of (Qiu et al., 2015; Zhang and Xu, 2017), which revealed that the influence of climate change on ecosystems was insignificant. A possible reason for this may be that since the basic unit of the study was province, the meteorological factors had less of an impact on the ecosystem with spatial changes in a small region. In addition, the interactions among driving factors were not fully taken into account. In most regions with low and medium ecosystem health types, for example, the southeastern coastal region and the North China Plain region, the ecosystem health changes mainly arose from socioeconomic factors. Continuous expansion of urban land occupied a large number of former wetlands and vegetated lands, directly resulting in the low ecosystem organization due to the increase of landscape diversity, fragmentation (Chuai et al., 2016; Meng et al., 2018a, 2018b; Tao et al., 2018; Wang et al., 2014).

In the western Tibet and northwestern region, ecosystems were less affected by human interventions due to slow socioeconomic development (Fang et al., 2013). Additionally, the effectiveness of ecological

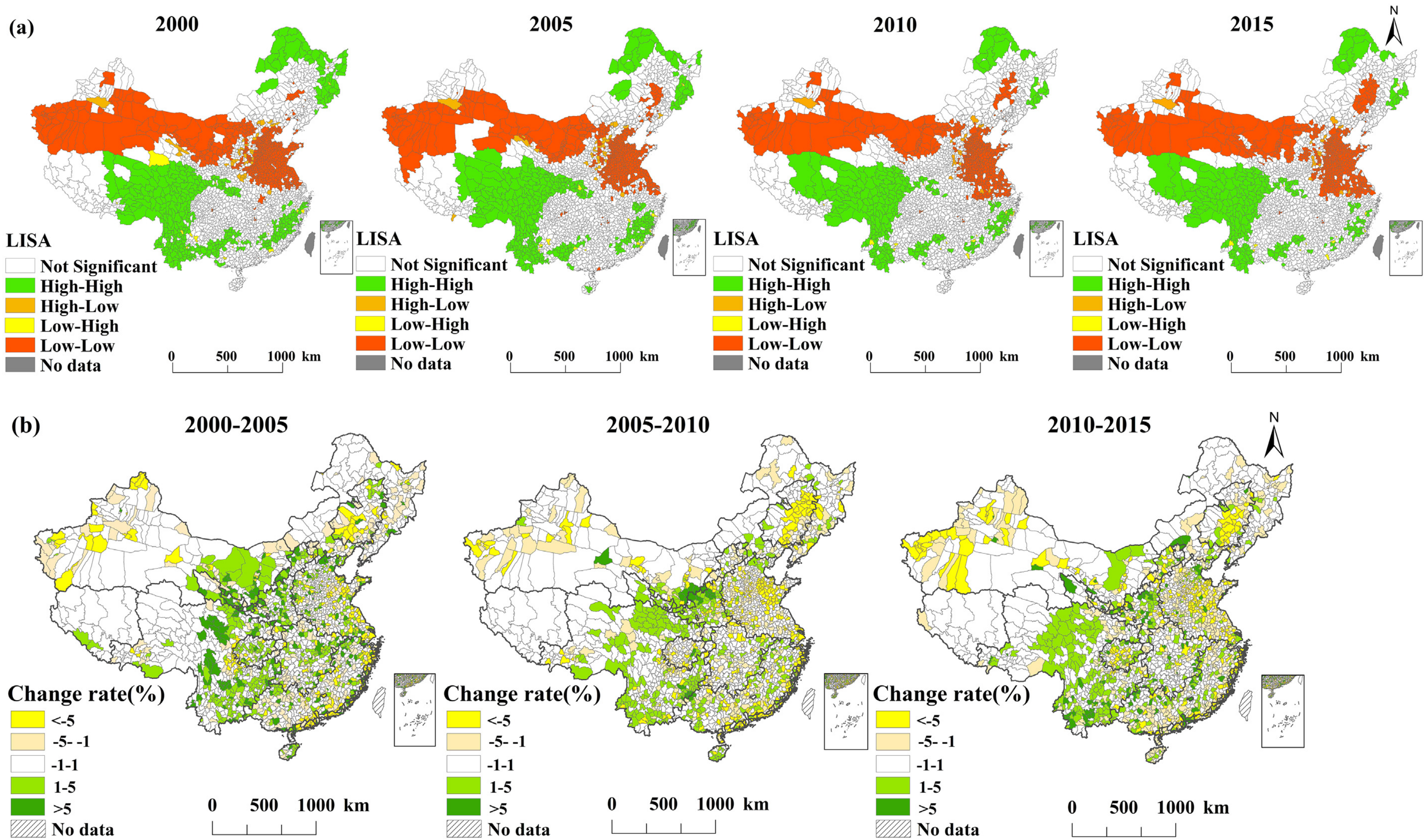


Fig. 5. The spatial agglomeration (a) and change rates (b) of ecosystem health index in China from 2000 to 2015.

Table 2
The explanatory power of driving factors of ecosystem health in different regions.

	PD	GDP	UR	BLA	LUI	MI	AMT	AMP	AI	ECP
Nation	0.078**	0.083**	0.104**	0.144*	0.207*	0.245*	0.124**	0.105*	0.053**	0.113*
SER	0.002	0.033**	0.053**	0.251*	0.373*	0.103*	0.031**	0.161*	0.061**	0.041
NER	0.003	0.028**	0.025*	0.018	0.221*	0.115*	0.344*	0.205*	0.101*	0.072*
SWR	0.007	0.012	0.288*	0.013	0.131*	0.267*	0.102*	0.117*	0.113*	0.258*
WTR	0.003	0.004	0.003	0.004	0.008**	0.218*	0.282*	0.155*	0.234*	0.073**
MYRR	0.053**	0.075**	0.188*	0.281*	0.231*	0.073**	0.083*	0.013**	0.013	0.045
SCR	0.071**	0.094*	0.107*	0.122*	0.330*	0.072**	0.084*	0.087**	0.033**	0.035
LPR	0.037**	0.048*	0.037*	0.016*	0.008	0.199*	0.203*	0.222*	0.122*	0.243*
SBR	0.032**	0.041*	0.293*	0.218*	0.235*	0.102*	0.032**	0.068**	0.019	0.062**
NPR	0.021	0.032*	0.212*	0.232*	0.311*	0.051	0.122*	0.077**	0.002	0.057
NWR	0.002	0.001	0.035**	0.003	0.003	0.350*	0.203*	0.171*	0.222**	0.153*
NCPR	0.097**	0.108*	0.122*	0.274*	0.215*	0.045**	0.043**	0.072**	0.024**	0.055
Effect direction	−	−	−	−	−	+	+	+	−	+

Notes: significance levels: *$p < 0.01$, ** < 0.05. "+" and "−" stand for the positive and negative correlation between driving factor and EHI respectively by Spearman correlation analysis.

protection was not significant (Zhang et al., 2016a; Zhu et al., 2016). The fragile extremely ecosystems are more susceptible to remarkable changes in meteorological elements (e.g., temperature, precipitation, etc.) due to the climate warming and frequent extreme weather events (Li et al., 2019; Wang et al., 2017a). In the southwestern region and the Loess Plateau region, ecologically protected factors were closely correlated with ecosystem health changes. Such results were consistent with that of (Hou et al., 2017; Liao et al., 2018; Pang et al., 2018; Zhang et al., 2016b), which demonstrated that ecological conservation projects are effective for vegetation restoration and ecosystem health improvement.

4.2. Implications for ecological conservation in China

Identifying the regional differences in ecosystem health and its driving factors is important not only for the purpose of scientific research but also for informing policy and practice (Costanza, 2012; Kang et al., 2018; Tang et al., 2018). Our study can provide important suggestions for formulating differentiated ecological conservation and restoration measures.

Our results identified the regional differences of ecosystem health and their key driving factors, therefore, the ecological conservation measures that are adopted in a particular area should be in accordance with the region's ecosystem health level and its influencing factors. Priority should be given to areas with low ecosystem health levels. For instance, in the northwestern region, reducing the influence of meteorological factors on ecosystem and improving the effectiveness of ecological protection are the beneficial way to protect ecosystem. Plants with strong resistance to cold and drought could be selected to improve vegetation coverage. Precautionary measures, such as meteorological disaster monitoring, should also be carried out to reduce the disturbance of extreme weather to the ecosystem. In addition, we can improve the effectiveness of ecological protection by monitoring and evaluating the ecological benefits of ecological projects (Huang et al., 2017; Wei et al., 2018).

For the regions where the medium ecosystem health level is largely attributed to low ecosystem organization and socioeconomic factors (e.g., land use intensity, urbanization rate) are the principal contributors to the ecosystem health change, it is necessary to maintain sustainable development to balance economic growth and environmental protection. For instance, in the middle Yangtze River Region and the southeastern coastal region, we can increase ecosystem organization by appropriately controlling the speed of urban expansion, optimizing land use structure, and avoiding unreasonable reclamation and construction. Meanwhile, more ecological conservation and restoration projects should be implemented because there are few ecological conservation projects. Furthermore, in the Loess Plateau and the southwestern region, ecological protection projects, such as the Grain to Green program, can significantly improve vegetation cover, mitigate water and soil erosion, and restore ecological environment (Jiang et al., 2016; Pang et al., 2018; Wu et al., 2019; Zhang et al., 2016a). These can provide guidance for other areas to carry out ecological environmental protection and management.

Table 3
The dominant interactions between two variables in different regions.

	Dominant interaction 1	Dominant interaction 2	Dominant interaction 3	Dominant interaction 4
Nation	MI ∩ LUI 0.481△	MI ∩ BLA 0.398△	MI ∩ AMT 0.361□	LUI ∩ BLA 0.337△
SER	LUI ∩ BLA 0.672△	LUI ∩ AMP 0.564△	LUI ∩ MI 0.486△	BLA ∩ AMP 0.432△
NER	AMT ∩ LUI 0.584△	AMT ∩ AMP 0.569△	AMT ∩ MI 0.479△	LUI ∩ AMP 0.395□
SWR	ECP ∩ MI 0.565△	ECP ∩ UR 0.445△	MI ∩ UR 0.415□	MI ∩ AMP 0.418△
WTR	AMT ∩ AI 0.537△	AMT ∩ MI 0.521△	AI ∩ MI 0.461△	AMT ∩ AMP 0.426□
MYRR	BLA ∩ LUI 0.541△	BLA ∩ UR 0.458□	LUI ∩ AI 0.404□	BLA ∩ AMT 0.375△
SCR	BLA ∩ LUI 0.473△	LUI ∩ UR 0.457△	LUI ∩ GDP 0.454△	BLA ∩ MI 0.349△
LPR	ECP ∩ AMP 0.456△	ECP ∩ AMT 0.452△	ECP ∩ MI 0.433△	AMP ∩ AMT 0.375△
SBR	UR ∩ LUI 0.549△	UR ∩ BLA 0.532△	LUI ∩ AMP 0.448□	LUI ∩ MI 0.358△
NPR	BLA ∩ LUI 0.563△	LUI ∩ AMP 0.516□	BLA ∩ UR 0.464△	LUI ∩ AMT 0.423□
NWR	MI∩AI 0.571□	MI∩AMT 0.564△	MI∩AMP 0.552△	AMT ∩ ECP 0.456△
NCPR	BLA ∩ LUI 0.518△	BLA ∩ UR 0.427△	BLA ∩ GDP 0.394△	LUI ∩ MI 0.326□

Notes: △: nonlinear enhanced ($q(X1 \cap X2) > q(X1) + q(X2)$), □: bi-enhanced ($q(X1 \cap X2) > Max(q(X1), q(X2))$).

4.3. Limitations and future work

The weights of organization, resilience and ecosystem services are important for ecosystem health assessments because they directly affect the assessment results. Although the weights of the indicators were fixed according to the actual situation in China, they still have uncertainty. Our research suggests that the geographical detector has unique advantages in quantifying the interactions of the driving factors and their combined effects on ecosystem health. However, we also found that the discretization methods for classifying continuous variables into several categories might affect the results because these methods do not currently have definite standards.

Despite some limitations, we still believe that this study is meaningful. Although the weight determination was not perfect, the data processing quantification is far from arbitrary. The geographical detectors are statistical and are not a causality tool. It can not only analyze the relative importance of the driving factors but also explore the interactions of these factors on ecosystem health. The results can help researchers understand the spatial patterns of ecosystem health change with the impact of factors and provide scientific support for ecological conservation and restoration policy formulation in China. We only assessed the ecosystem health level in China based on the classical framework of vigor, organization, resilience and ecosystem service functions. The improvement of the framework still needs to be researched in depth because of the lack of interaction between the natural ecosystem and the socioeconomic system (Peng et al., 2017; Su et al., 2010).

5. Conclusions

In this article, we diagnosed the ecosystem health levels and explored the key factors that drive spatial differences in ecosystem health at the national and zonal levels from 2000 to 2015. This research contributes to the existing literatures on ecosystem health studies from several aspects, including identifying regional differences in ecosystem health at the national scale based on county administrative units, comprehensively considering both meteorological, socioeconomic and ecological protection factors as driving factors, and utilizing a promising method, i.e., the geographical detector model, to explore the effect intensity and interaction effects of the driving factors at the national and regional level. Our findings provide scientific support for ecological protection and management policy making in China.

The main findings of this study are as follows: the ecosystem health level in China increased from northwest to southeast and showed a trend of first rising and then declining from 2000 to 2015. We found that counties with similar EHI had notable spatial agglomeration effects, and the degree of spatial agglomeration gradually decreased from 2000 to 2015. We displayed regional differences of ecosystem health in China by dividing the country into eleven zones (e.g., SER, NER, SWR, MYRR, etc.) of three types (i.e., high, medium and low). Our findings also found that the synergies among the driving factors exerted nonlinear enhanced or bi-enhanced effects on the ecosystem health change. The moisture index and land use intensity account for 24.5% and 20.7% to the ecosystem health change in China. Driving forces influencing ecosystem health had strong spatial heterogeneity. Specifically, the meteorological factors (e.g., annual average precipitation and annual average temperature) were the basic and common driving factors affecting the variation of ecosystem health in each region. The interaction between the meteorological factors and the socioeconomic factors are found to primarily account for ecosystem heath changes in most regions with high ecosystem health types. However, the socioeconomic factors (land use intensity and urbanization rate) act as a bridge that linked and reinforced the other factors in most of the areas with low and medium ecosystem health types. Ecologically protected factors were found to exert a remarkable impact only in the southwestern region and the Loess Plateau region. The meteorological factors were strongly related to the ecosystem health change in the western Tibet region and the northwestern region. The identification of regional differences in ecosystem health and its driving factors in China can provide practical guidance for ecosystem management and restoration in different regions.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2019.03.465.

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