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Influencing mechanism of climate and human activities on ecosystem health in the middle reaches of the Yellow River of China

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ABSTRACT

Global and regional environmental changes caused by climate and human activities have profoundly affected terrestrial ecosystem health. Nevertheless, few studies have been deeply dissected the influencing mechanism of climate and human activities on ecosystem health. In this study, the Middle Reaches of the Yellow River (MRYR) was choosed as the study area, and the improved VORS model was adopted to dynamically assess the ecosystem health level in the MRYR. Then, the influence mechanism of climate and human activities on ecosystem health was deeply analyzed. Our results showed: (1) The ecosystem health level in the rapidly urbanized areas, the ecologically fragile areas in the midwest regions and the mountainous - plain transition zone has a dynamic local spatial structure and spatiotemporal interaction process. (2) Topography, land urbanization, economic urbanization, population urbanization, agricultural activities, environmental pollution, and regional policy have a significant effect on the ecosystem health. (3) In the mid-eastern urban agglomerations, the impervious surface increase and the decrease of ecological land use lead to the increased negative effects of potential evapotranspiration on the ecosystem health of urban agglomerations. Topography has a long-term inhibitory effect on urban expansion, which weakens the negative impact of urbanization on mountain ecosystem health. The negative impact of economic urbanization on the mid-eastern shows a "core-edge" structure with Xi'an metropolitan area, Luohe River Basin, Fenhe River Basin, Taiyuan metropolitan area and Zhengzhou metropolitan area as the core. (4) In terms of the interaction between influencing factors, the interaction between climate and human activities on ecosystem health shows significant differences between the east, middle and west.

1. Introduction

Global climate change and increasing human activities had significantly negative impacts on terrestrial ecosystem health (Pimm et al., 2014;Haddad et al., 2015; Li et al., 2022), and the damage of ecosystem health had become a major environmental problem faced by mankind (Fu, 2010; chase et al.,2020; Jin et al., 2020a, 2020ba, 2020b). Under the dual influence of climate and human activities, the ecologically fragile areas in western China have produced a series of eco-problems, including soil erosion (Zhou et al.,2018), water and soil environmental pollution (Hu et al., 2018; Lu et al., 2020; Peter, 2020), over exploitation of water resources (Huang et al., 2012; Zhang et al., 2020a, 2020b), land desertification vegetation degradation (Xu and Xu, 2017; Wu and Ding, 2019; Tian et al., 2021; Li et al., 2023), which seriously jeopardized the healthy development of regional ecosystem. Therefore, under the background of vigorously promoting eco-environmental protection and high-quality development strategy, how to accurately quantify the level of regional ecosystem health and clarify the driving mechanism of regional ecosystem health has become a scientific problem to be solved.

The exploration of ecosystem health assessment methods began in the late 1980s. With the development of ecosystem health theory, the comprehensive index assessment method has been emerging and developed and improved in practical application (Wang et al., 2007; Shen et al., 2020). According to the proposed time order, the comprehensive index evaluation method mainly includes: vigor-organization-

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resilience (VOR) model, subsystem model, pressure-state-response (PSR) model, vigor-organization-resilience-ecosystem services (VORS) model. The PSR model too much emphasis on people and the environment interaction and causality, leads to overlap and the application difficulties; In addition, it ignores changes in ecosystem landscape pattern and assessment of ecosystem service supply capacity (Su et al., 2019; Shen et al., 2020). The subsystem model place emphasis on the evaluation of concrete aspects of each subsystem, but ignores the overall landscape pattern change and ecosystem service supply (Shen et al., 2021). VORS model further considers the ecosystem service value based on the VOR model. To some extent, VORS model can all-sided reflexion the internal and complexity characteristics of regional ecosystem as well as the interaction between natural ecosystem and human socioeconomic system under the ideological framework of human-earth system coupling and sustainable development. Therefore, the overall health level of regional composite ecosystem can be comprehensively and systematically represented (Sun, et al., 2016; He et al., 2019). However, there are still problems in the following aspects: Firstly, in terms of setting the weight of resistance and resilience in the calculation formula of ecosystem resilience, previous studies have judged the overall economic development level and human activity intensity of the study area based on personal experience, and then assigned the weight of resistance and resilience respectively (Peng et al., 2017a, 2017b; Pan et al., 2020). However, in large-scale studies, the economic development level and human activity intensity of different units within the study area have spatial heterogeneity, so the weights of resilience and resistance of different research units need to be assigned separately. Secondly, a small number of scholars have been begun to keep a watchful eye on spatial proximity effect for the past few years (He et al., 2019; Pan et al., 2020), but there are still two limitations. On the one hand, most studies only represent the service value of each ecosystem in the research unit through the service value coefficient of each ecosystem, without considering the difference of the total value of ecosystem services in each research unit. On the other hand, when calculating the spatial proximity effect coefficient, the existing research only considers the influence of the adjacent pixel on the four sides around the center pixel, But the center pixel is not only affected by the four pixel adjacent to the edge, but also by the four pixel adjacent to the point. Therefore, the influence of 8 adjacent pixel should be considered when calculating the spatial proximity effect coefficient. Based on this, this study attempts to modify the ecosystem resilience formula and ecosystem services formula based on the VORS model.

For the past few years, the focus of ecosystem health research has increasingly shifted from quantitative evaluation to analysis of driving forces and mechanisms. Different scholars selected different typical regions to analyze the linear impacts of natural environmental factors (topographic geology, climate and hydrology) and human socio-economic factors (population, urbanization, environmental pollution, land use and regional policy) on ecosystem health (Shi et al., 2020) and spatial heterogeneity impacts (Li and Shen, 2021; Li et al., 2021), interaction effects (He et al., 2019; Shen et al., 2020; Li et al., 2021) and spatial spillover effects (Li et al., 2021). However, there are still four limitations: First, in terms of driving factors, the influence of agricultural activities, urban expansion form and regional policy factors is seldom considered. Second, when quantifying factors of population urbanization at the scale of township and grid, existing studies mostly select population density of research units to represent (Xiao et al., 2020; Shi et al., 2020), but it cannot reflect the change of urban population density caused by population migration, that is, population urbanization. Third, when quantifying the factors of economic urbanization at the grid scale of township and grid, the existing studies mostly use GDP (Gross domestic product) density to represent it (Peng et al., 2017a, 2017b; Xiao et al., 2020; Shi et al., 2020). Economic urbanization, however, is mainly refers to agricultural production factors to non-agricultural production, the production process of structure adjustment, mainly reflects on the change of industrial structure, namely, the proportion of secondary and tertiary industry accounted for industry increase gradually, gradually increased proportion of non-agricultural industries, optimize industrial structure (Cao et al., 2018). Therefore, the proportion of secondary and tertiary industries should be adopted to represent economic urbanization. Fourthly, studies on the spatio-temporal effects and interaction mechanisms of climate factors and human activities on ecosystem health in arid areas or ecologically fragile areas are relatively weak, and lack of long-term systematic studies. With the support of multiple data and methods, this study attempts to select and measure the influencing factors from the aspects of climate, urbanization, agricultural activities, environmental pollution and regional policies, and systematically analyze the effect mechanism of climate and human activities on ecosystem health.

As the main area for water and soil conservation and pollution prevention and control in the Yellow River Basin, the MRYR is an important ecological function area (Huang et al., 2012; Tian et al., 2022), as well as a typical climate-sensitive area and densely populated area. However, the MRYR are a region where various environmental problems are very concentrated and prominent in China. Ecosystem degradation has badly imperiled the ecosystem health of the MRYR and even the entire basin (Shen et al., 2020). Hence, it is of enormous meaning to scientifically assess the ecosystem health, and systematically analyze the influence mechanism of climate and human activity on regional ecosystem health, which is of enormous meaning for promoting ecosystem health.

2. A conceptual framework for the impact of climate and human activities factors on ecosystem health

The problem of ecosystem health in ecological vulnerable human-land system is a typical manifestation of the contradiction between human and land. Therefore, under the guidance of the theoretical framework of human-land relationship, we construct the conceptual framework of the driving mechanism of climate and human activities factors on regional ecosystem health from the comprehensive visual angle of the spatial differentiation and interaction of natural geographical environment and human activities. As shown in Fig. 1, there is a complex, mutual feedback, near and long-range coupling dynamic balance relationship between topography, climate, human activities and ecosystem health. In the process of temporal and spatial evolution of ecosystem health, the main driving forces and action mechanisms in different evolution stages and regions are not exactly the same. However, the above driving forces are not completely separated, but participate in the whole process of evolution, but play different roles in different stages and regions. Therefore, analyzing the spatio-temporal impact and interacting effects of driving factors such as climate and human activities on ecosystem health is a prerequisite and important step to reveal the driving mechanism of ecosystem health.

From the general mechanism of influencing factors: (1) Climatic factors. Climate change poses a universal and increasingly global menace to biodiversity and ecosystems. Climate affects single species and the way they interact with other organisms and their habitats, thereby altering the structure and functionality of ecosystems and the commodity and services that natural systems furnish to human society (Weiskopf et al., 2020). (2) Topographic factors. Topography is an important substrate for the exchange of matter and energy between land and environment in terrestrial ecosystems. It can profoundly affect the formation and development of regional ecosystems and their vertical distribution patterns by influencing the spatial differentiation and recombination of temperature, precipitation, light, heat, runoff and soil properties. In addition, it can affect the feed and consumption of ecosystem services and the spatial differentiation of regional ecosystem health to some extent by limiting or promoting the intensity of human activities. (3) Urbanization factors. Population, resources and industries continue to gather in urban areas, and urbanization has become one of the most significant features of social development (Fang et al., 2018; Li et al., 2021). Urbanization affects landscape heterogeneity, landscape

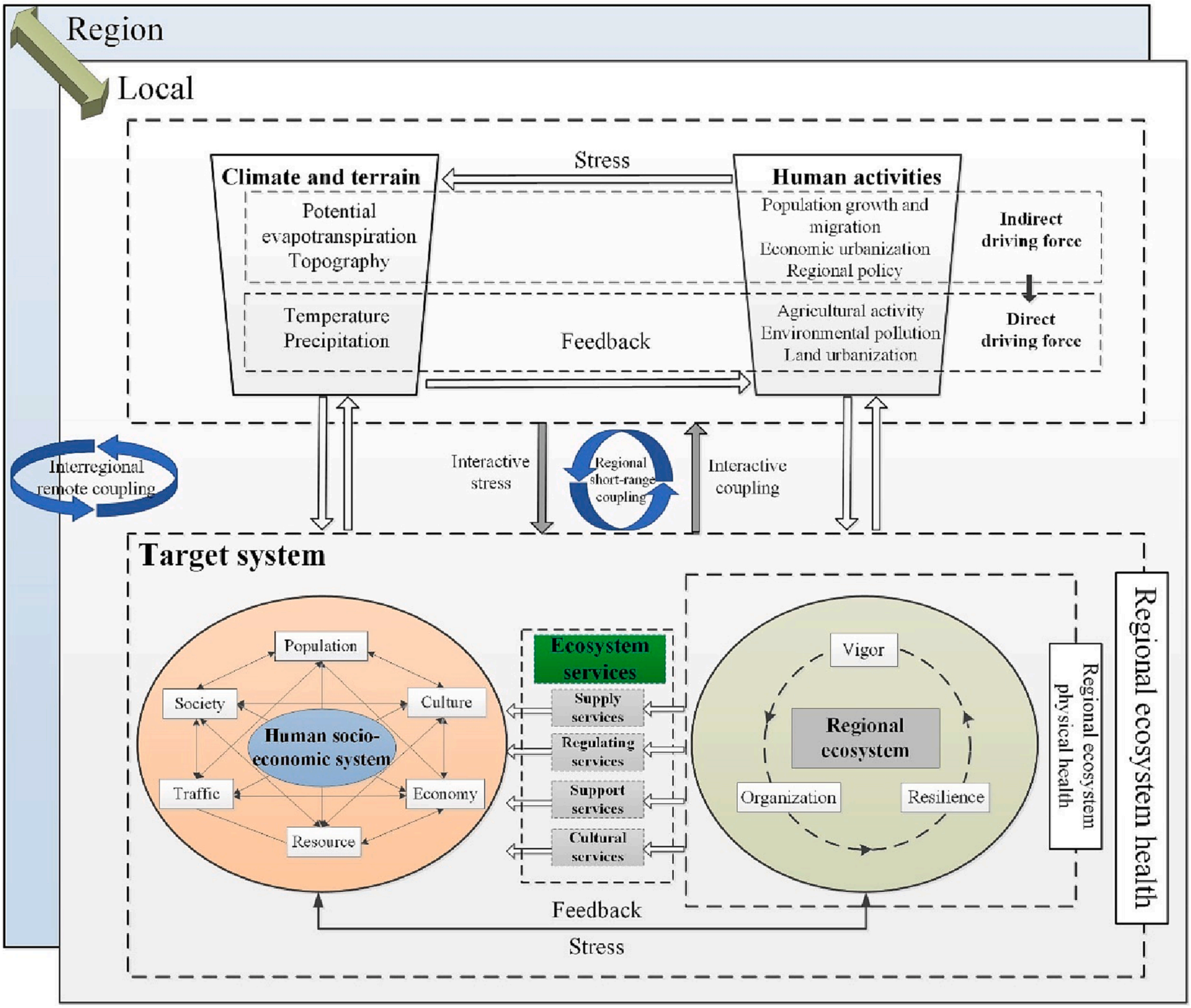

Fig. 1. Conceptual framework for the impact of climate and human activities factors on ecosystem health.

connectivity and ecosystem services through changes or impacts on land use/land cover, population distribution, regional climate and environmental quality, thus affecting the overall health of ecosystems and human well-being. Urbanization is a multidimensional concept, and its connotation mainly includes three aspects: demographic urbanization, economic urbanization, and land urbanization. (5) Agricultural activity. Agricultural activity also play an vital character in land use/cover change. In the past five decades, the impact of human activities on the ecosystem has been more extensive than any other period in history, among which agricultural activities have directly or indirectly affected many fields of the eco-environment (Puech et al., 2015; Angelella et al, 2016; Li et al., 2019). (6) Environmental pollution factors. Environmental pollution harms regional ecosystems directly and indirectly from lots of aspects, and has a latent inactive effect on human well-being (Häder et al., 2020; Ji and Ma, 2021). (7) Regional policy factors. Studies have found that, Regional ecological policies can increase vegetation coverage and carbon storage (Chen et al., 2015), reduce soil erosion (Zhang et al., 2016), runoff change (Li et al., 2014), reduce annual sediment transport in rivers (Wang et al., 2016), promoting non-agricultural employment (Li et al., 2020), and improving ecosystem health (He et al., 2019).

3. Materials and methods

3.1. Study area and data sources

In this study, the Middle Reaches of the Yellow River (MRYR) were used as the study area. The study area includes 244 counties, and its scope passes through 40 prefecture-level cities and 6 provinces (Fig. 2). The area of research region is about 36.3×10^4 km^2, accounting for 48.1% of the total area of the Yellow River Basin. The MRYR is not only the most typical climate sensitive area and important ecological function area in the Yellow River Basin, but also the main area where environmental problems such as ecological degradation occur. Therefore, the MRYR is the most typical case area for ecosystem health research. To explore the influencing mechanism of climate and human activities on ecosystem health in the MRYR is of great significance for promoting regional ecological protection, environmental governance and high-quality economic development.

The data sources of in this study are shown in Table 1. The normalized vegetation index (NDVI) is based on the Landsat MSS, Landsat TM/ETM and Landsat 8 series remote sensing images, and uses the Google Earth Engine (GEE) platform to synthesize monthly and annual NDVI data using Maximum Value Composite (MVC), including 7

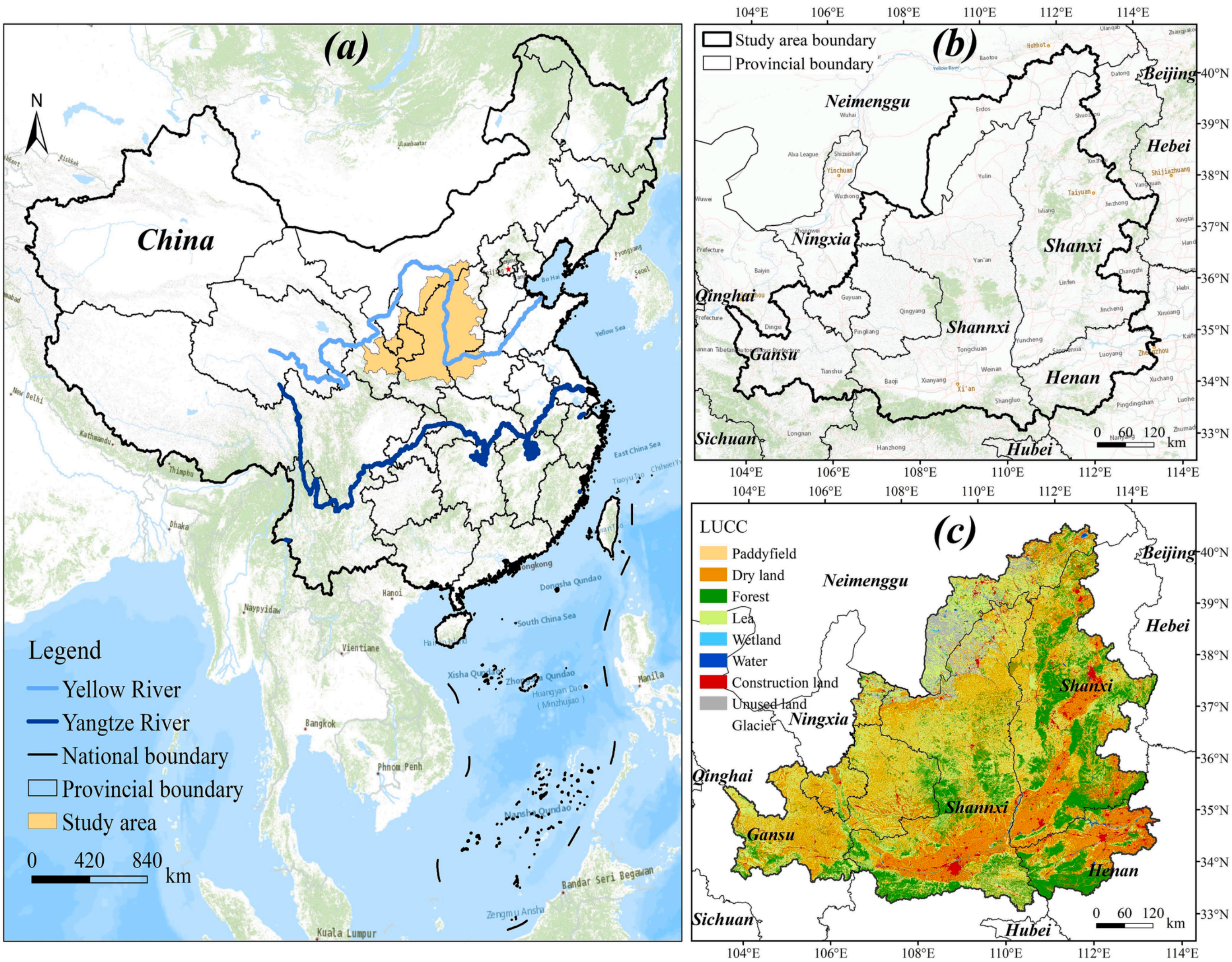

Fig. 2. (a) The Middle Reaches of the Yellow River (MRYR) in China, (b) Overview and zoning of the MRYR, and (c) Land use map of the MRYR in 2018. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 1
Data sources in the study.

Variable name	Data type/ Resolution	Sources
Land use data	Raster data/30 m	https://www.resdc.cn
Normalized difference vegetation index	Raster data/ 250 m	https://www.resdc.cn
Annual precipitation	Raster data/1 km	https://www.geodata.cn
Annual average temperature	Raster data/1 km	https://www.geodata.cn
Potential evapotranspiration	Raster data/1 km	https://www.geodata.cn
Meteorological station data	–	https://data.cma.cn
Net primary productivity	Raster data/5 km	https://www.geodata.cn
Elevation	Raster data/ 500 m	https://www.resdc.cn
Soil data	Raster data/30 m	https://westdc.westgis.ac.cn
Annual mean PM2.5	Raster data/1 km	https://sites.wustl.edu/acag/datasets/surface-pm2-5/
DMSP-OLS night light data	Raster data/1 km	https://www.ngdc.noaa.gov/

periods (1990, 1995, 2000, 2005, 2010, 2015, 2018) of normalized vegetation index raster data. The socioeconomic statistical data adopted in this paper were obtained from urban statistical yearbook, provincial statistical yearbook, and statistical bulletin of national socioeconomic development of counties. The data on the economic value of grain crops per unit comes from the agricultural product price survey yearbook of China.

3.2. Framework of ecosystem health assessment

The study object of regional ecosystem health is the “nature-economy-society” complex ecosystem integrating natural ecosystem, economic system and social system (Wang et al., 2007; Shen and Li, 2022). From the perspective of systems science, regional complex ecosystems have basic characteristics such as integrity, openness, stability, dynamics and hierarchy. Ecosystem health can be defined as that the regional composite ecosystem has the ability to remain its spatial structure and ecosystem process, self-regulation and self-renewal, and self-recovery in front of external stress, and can ensure the sustainable supply of ecosystem service function (Costanza, 2012; Peng et al., 2017a, 2017b; Shen and Li, 2022). A healthy regional complex ecosystem should firstly have certain productivity and metabolic capacity (Xiao et al, 2019), and secondly, it must maintain its own structure and function integrity, self-organization, self-regulation and sustainable development capacity (Xiao et al, 2019; He et al, 2019), and the capacity to provide stable and sustainable ecosystem services for humans (Kang et al, 2018). This study adopts the assessment framework of VORS to organize various subsystems and evaluation indicators based on the concept, intension and research content of ecosystem health (Fig. 3). The VORS framework reflects the sustainability of ecosystem services provided by ecosystems to humans, and strengthens the connection between natural ecosystems and human social system (Liu and Hao, 2017; Peng et al., 2017a, 2017b; Shen and Li, 2022).

3.3. Ecosystem health assessment

3.3.1. Optimal analysis scale selection based on semi-variogram

In this research, grid units were used as basic research units. Due to the spatial variability of landscape pattern index at different analysis scales, it is necessary to determine the optimal analysis scale before calculating landscape indicators. In this research, the Nugget-Sill ratio (CO/(C + CO)) calculated by the semi-variance function was used to determine the optimal analysis scale. On the basis of previous experience (Ramzan et al., 2017; Yang et al., 2021), when the Nugget-Sill ratio reaches a stable state, it indicates that the spatial variation of landscape index tends to be stable, and the scale at this time can be judged as the characteristic scale of the research region.

3.3.2. Ecosystem health assessment based on the improved VORS method

Considering the limitations of VORS model, this study introduced the spatial weight coefficient and the modified spatial proximity effect coefficient to improve the VORS model. The formula of the improved VORS model is expressed as follows:

$$EHI = \sqrt{PHI \times ES} \quad (1)$$

$$PHI = \sqrt[3]{EV \times EO \times ER} \quad (2)$$

In the above formula, EHI represent the ecosystem health level, PHI represent the ecosystem ontology health level. EV is ecosystem vigor, EO is ecosystem organization, ER is ecosystem resilience, and ES represent ecosystem service value.

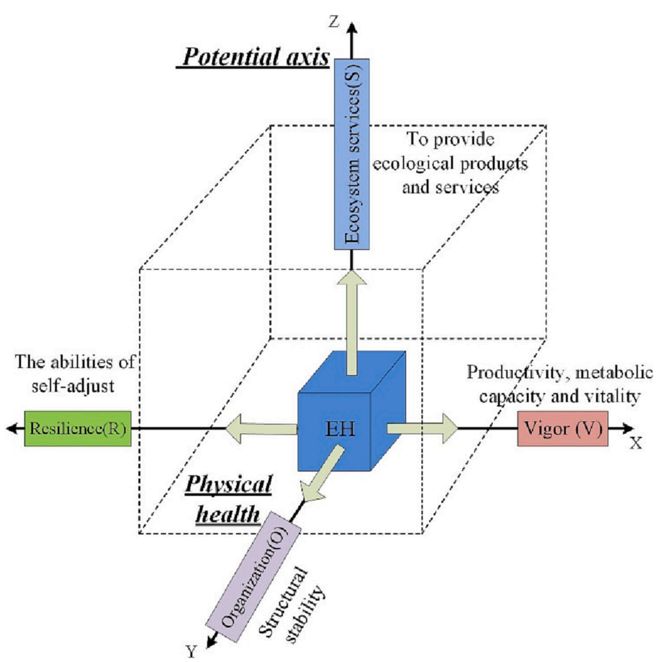

Fig. 3. Framework of ecosystem health assessment.

(1) Ecosystem vigor (EV). EV refers to the metabolic or primary prolificacy of regional ecosystem (He et al., 2019; Shen and Li, 2022). The NDVI is compactly relevanted to vegetation growth and net primary prolificacy, and has been broadly shown to be an valid index for evaluating ecosystem vigor level (Xiao et al., 2020; Li and Shen, 2021; Shen and Li, 2022). Hence, this study chose NDVI to represent the ecosystem vigor level.

(2) Ecosystem organization (EO). EO refers to the diversity of composite ecosystem elements composition and processes, i.e., the completeness and complicacy of regional ecosystem structure and functionality (Wang et al., 2007; Li and Shen, 2021). Ecosystem organization can be characterized by landscape heterogeneity (LH), holistic landscape connectivity (LC), and connectivity of important ecosystems (CIE) (Xiao et al., 2020; Shen and Li, 2022). Among them, landscape heterogeneity is currently characterized by Shannon's diversity index (SHDI) and area-weighted patch fractal dimension (AWMPFD). The landscape division index (DIVISION) and landscape contagion index (CONTAG) are usually used to characterize the holistic landscape connectivity (He et al., 2019; Xiao et al., 2019; Pan et al., 2020). The patch fragmentation index (PFN) and patch connectivity index (CON) of woodlands, grasslands and watersheds are utilized to represent the important ecosystems connectivity (Pan et al., 2020; Shen and Li, 2022). The calculation formula of PFN refers to Ding and Liang (2004). With reference to existing studies (He et al., 2019; Xiao et al., 2019; Pan et al., 2020), the weights of LH, LC and CIE are assigned as 0.35, 0.35 and 0.3.

$$\begin{aligned} EO &= 0.35LH + 0.35LC + 0.3CIE \\ &= (0.1 \times \mathrm{AWMPFD} + 0.25 \times \mathrm{SHDI}) + (0.2 \times \mathrm{DIVISION} + 0.15 \\ &\quad \times CONTAG) + (0.07 \times PFN_f + 0.03 \times CON_f + 0.07 \times PFN_w + 0.03 \\ &\quad \times CON_w + 0.07 \times PFN_g + 0.03 \times CON_g) \end{aligned} \quad (3)$$

In the formula, PFN_f、PFN_g and PFN_w are the patch fragmentation indices of forest, grassland and water, respectively. CON_f、CON_g and CON_w are the patch connectivity indices. In order to eliminate the possible differences in dimensions and magnitudes between indicators, we use the extreme value standardization method to standardize the data.

(3) Ecosystem resilience (ER). ER delegates to the capacity of a regional ecosystem to overcome internal and external pressures (resistance) during the stress process and the ability to restore its own structure and functionality (resilience) after the stress disappears (Wang et al., 2007; He et al., 2019; Pan et al., 2020). Referring to the mature practice of pre-existing study (Xiao et al., 2019), we use the resistance and resilience coefficient to measure the resistance value and resilience value (Table 2). Existing studies have judged the overall economic development level and human activity intensity of the study area based on personal experience, and then assigned the weights of resistance and resilience accordingly (He et al., 2019; Pan et al., 2020; Shen and Li, 2022). However, the level of economic development and the intension of human activity in different units within the study area are spatially heterogeneous, so it is necessary to spatially assign the weights of resilience and resistance to different study units. In view of this, this paper draws on the idea of piecewise function and introduces spatial weight coefficients to spatially correct the ecosystem elasticity formula. The subsection interval of the weight coefficient is based on the ratio between the per capita GDP of the research unit and the per capita GDP of the research region. The revised formula is:

Table 2
Resistance and resilience coefficients.

Landscape type	paddy field	dry land	woodland	grassland	wetlands	Water	construction land	unused	glacier
Resistance	0.6	0.5	1	0.7	0.6	0.8	0.3	0.2	0.1
Resilience	0.3	0.4	0.6	0.8	0.7	0.7	0.2	0.1	0.1

$$\mathrm{ER}_i = w_i \times \sum_{m=1}^{9} (P_m \times Resil_m) + (1 - w_i) \times \sum_{m=1}^{9} (P_m \times Resist_m) \tag{4}$$

$$w_t^i = \begin{cases} 0.7, 1.5 < \frac{\mathrm{PerGDP}_i}{\overline{\mathrm{PerGDP}}} \\ 0.6, 1.1 < \frac{\mathrm{PerGDP}_i}{\overline{\mathrm{PerGDP}}} \leq 1.5 \\ 0.5, 0.9 < \frac{\mathrm{PerGDP}_i}{\overline{\mathrm{PerGDP}}} \leq 1.1 \\ 0.4, 0.5 < \frac{\mathrm{PerGDP}_i}{\overline{\mathrm{PerGDP}}} \leq 0.9 \\ 0.3, 0 < \frac{\mathrm{PerGDP}_i}{\overline{\mathrm{PerGDP}}} \leq 0.5 \end{cases} \tag{5}$$

$$\mathrm{PerGDP}_i = \frac{GDP_i}{POP_i} \tag{6}$$

In above formula, ER_i is the ecosystem resilience.P_m is the ratio of the area of each landscape type to the total area of the study unit. w_i is the ecosystem resilience weight, $1 - w_i$ is the ecosystem resistance weight. $Resist_m$ is the resistance coefficient, $Resil_m$ is the resilience coefficient (Table 2). GDP_i, PerGDP_i and $\mathrm{Per}\bar{G}DP$ were the total GDP, the per capita GDP and the average of per capita GDP, respectively. POP_i is the total amount of population.

(4) Ecosystem services (ES). ES delegates to the life-sustaining products and services acquired immediately or mediately through the structure, process and functionality of the ecosystem. It is compactly connected with human health and well-being (Costanza et al., 2017; Xie et al., 2017; He et al., 2019; Shen and Li, 2022). From the perspective of ecosystem service flow, ecosystem services can be delivered to spatially adjacent regions (Bagstad et al., 2013; Peng et al., 2017a, 2017b; Shen and Li, 2022). Therefore, we should consider the spatial proximity interaction effect when calculating ecosystem services, and further revise the assessment results of ecosystem services. Calculation steps of ecosystem service value based on spatial proximity interaction effect: 1) Compute the amount of ecosystem service value of the standard equivalent factor of each research unit, the calculating formula is expressed with Eq. (7) (R 4.0.5 software was used for calculation). 2) According to the three temporal and spatial dynamic factors of net primary productivity of vegetation (NPP), precipitation and soil retention, correct the basic equivalent table of ecosystem service value (Table S1), and then use the equivalent factor method to compute the total value of ecosystem services in each year and each research unit, the formula is expressed with Eq. (8). 3) Compute the spatial proximity total effect coefficient of each study unit, the formula is expressed with Eq. (9). 4) Calculation of the ecosystem service value based on the spatial proximity effect, the formula is expressed with Eq. (9).

$$D_i = 1/7 \times \left[\frac{1}{A_i} \sum_{k=1}^{l} (S_{ki} \times V_{ki}) \right] \tag{7}$$

$$F_{nij} = \begin{cases} N_{ij} \times F_{n1} \\ R_{ij} \times F_{n2} \\ S_{ij} \times F_{n3} \end{cases} \tag{8}$$

$$ESV_{ij}(\mathrm{SNE}) = ESV_{ij} \times C\mathrm{SNE}_{ij}$$

$$= \sum_{a=1}^{10} \left(D_{ij} \times F_{ij}^{a} \times LA_{ij}^{a} \right) \times \left[\frac{\sum_{k=1}^{m} \left(1 + \frac{\sum_{c=1}^{8} S_k^c}{100} \right)}{m} \right]$$

$$= \sum_{a=1}^{10} \left(D_{ij} \times F_{ij}^{a} \times LA_{ij}^{a} \right) \times \left[\frac{\sum_{k=1}^{m} \left(1 + \frac{(S_k^1 + S_k^2 + S_k^3 + S_k^4 + S_k^5 + S_k^6 + S_k^7 + S_k^8)}{100} \right)}{m} \right] \tag{9}$$

Where D_i is the ecosystem service value of the standard equivalent factor of the ith research unit. S_{ki} is the yield (kg) of the ith research unit and the kth food crop (three food crops, rice, wheat and corn are selected); V_{ki} is the unit food crop of the ith research unit and the kth food crop economic value (yuan/kg); A_i are the total sown area (ha) of food crops. $n1$ represents the service functions of food production, raw material production, gas regulation, climate regulation, environmental purification, maintenance of nutrient cycle, biodiversity and aesthetic landscape, $n2$ represents the service function of water resources supply and hydrological regulation, and $n3$ represents the service function of soil conservation. N_{ij} is the spatiotemporal dynamic correction factor of NPP; R_{ij} is the temporal and spatial dynamic correction factor of precipitation; S_{ij} is the temporal and spatial dynamic correction factor of soil conservation. Revised universal soil loss equation (RUSLE) was adopted to compute the soil retention (Sun et al., 2014).ESV_{ij} is the total value of ecosystem services;LA_{ij}^{a} is the area of land type a. $ESV_{ij}(\mathrm{SNE})$ is the ecosystem service value based on the spatial proximity effect; $C\mathrm{SNE}_{ij}$ is the total effect coefficient of spatial proximity; S_k^c is the spatial proximity effect coefficient of ecosystem services corresponding to the c-th pixel around the central pixel k (Table 3); m is the number of pixels included in research unit i. It should be noted that, referring to the previous study results (Peng et al., 2017a, 2017b; He et al., 2019), we combined desert and bare land into unused land for unified calculation in the process of calculating the total effect coefficient of spatial proximity.

3.4. Selection and measurement of influencing factors

According to the analysis of the general mechanism of influencing factors on ecosystem health (Fig. 1), we assume that the driving factors of ecosystem health in ecologically fragile areas mainly include climate factors, terrain, economy urbanization, population urbanization, land urbanization (including urban land scale, urban expansion scale, urban expansion intensity and urban expansion form), agricultural activities, environmental pollution, regional policies, a total of 19 factors. The selected influencing factor indexes (Table 4) and calculation methods are as follows:

(1) Topographic factors. According to the existing research experience (Feng et al., 2007; Zhang et al., 2019), we selected the topographic relief index to represent the topographic factors to analyze the influence of topographic factors on ecosystem health. (2) Climate factors. The

Table 3
Spatial proximity effect coefficients of ecosystem services for each land use type.

Land use type of adjacent pixel	Land use type of center pixel								
	Woodland	Grassland	Water	Paddy field	Dry land	unused	Construction land	Wetlands	glacier
Woodland	+5	+5	+5	+5	+4	+4	+4	+5	+3
Grassland	+4	+5	+4	+2	+2	+3	+3	+4	+2
Grassland	+5	+4	+5	+4	+2	+4	+4	+4	+1
Paddy field	−1	−1	−5	+4	+2	−1	+1	−2	−1
Dry land	−1	−1	−4	+1	+2	−1	+1	−3	−1
unused	−1	−2	+5	−3	−3	+1	−1	−3	−1
Construction land	−2	−3	−5	+2	+2	−2	+1	−4	−3
Wetlands	+4	+3	+5	+3	+2	+3	+3	+5	+2
glacier	−4	−1	−2	−5	−5	−1	−1	−2	+1

MRYR is located in the interior of China and have arid and semi-arid climates. It is also one of the typical climate-sensitive areas in China. On the basis of existing research experience, we selected five variables to represent climate factors, including SPI, SPEI, PET, TEM, and PRE (Liu et al., 2021; Peng et al., 2017a, 2017b). (3) Population urbanization. The population density of urban construction land was selected to reflect the change of population density of urban construction land caused by population migration, that is, population urbanization. Specifically, ArcGIS software is used to overlay land use raster data and population density raster data, and then use reclassification tools, regional statistics tools and raster calculators to calculate the average population density of urban construction land raster cells. The processing process of population density kilometer grid data refers to the research methods of Lai et al. (2021) and Jiang et al. (2021). (4) Economic urbanization. The proportion of secondary and tertiary industries is selected to represent the Eco-Urban. The specific calculation process is based on the research results of Liao et al. (2015) and Zhang (2019) (Liao et al., 2015; Zhang et al., 2019), and the land use impact model is adopted to spatialize the output value statistics of the primary, secondary and tertiary industries respectively, and finally obtain the spatial raster data of the ratio of the secondary and tertiary industries with a resolution of 1 km (Fig. S1). (5) Land urbanization. the scale of construction land, expansion intensity of construction land, expansion rate of construction land, and urban expansion form are selected to characterize land urbanization. (6) Agricultural activity. This paper selected the patch connectivity index and patch cohesiveness index of cultivated landscapes to reflect the fragmentation process of agricultural landscapes (Wang et al., 2014; Lu et al., 2019). (7) Environmental pollution. Considering the availability of data on environmental pollution factors at long time series and microscale as well as the representativeness of environmental pollution factors, this paper selects PM2.5 concentration index to characterize the environmental pollution level at grid scale. (8) Regional policy. Since the late 1980s, the MRYR and its surrounding regional areas have successively carried out ecological and environmental restoration projects led by government departments, such as the sloping land remediation project, the fallow forest restoration project and the natural forest protection project (Lin and Yao, 2014; Delang and Yuan, 2015; Huang et al., 2021). Therefore, in this paper, the deforestation index (DFI) and soil erosion index (SEI) are selected to quantify regional ecological environmental policies. The deforestation index (DFI) uses the land use transfer matrix model, GIS reclassification tool and regional statistical tool to calculate the percentage of cropland and unused land converted to forest and grassland in each study year compared to 1980, respectively. The soil erosion index was used the generalized soil loss equation (RUSLE) to compute (Sun et al.,2014).

3.5. Multiple linear regression model

In this study, the multiple linear regression model (MLR) was adopted to analyze the influencing factors of ecosystem health. Among

Table 4
Index system of influence factors of ecosystem health.

Influence factors	The first classification	The secondary classification	Factors	Indicators
Topography	Topography	Topography	Topography	Relief degree of land surface (RDLS)
Climate	Climate	Potential evapotranspiration	Potential evapotranspiration	Potential evapotranspiration (PET)
		Dry and wet conditions	The degree of drought	Standardized precipitation evapotranspiration Index (SPEI)
				Standardized precipitation Index (SPI)
			Precipitation	Annual precipitation (PRE)
		Temperature	Temperature	Annual mean temperature (TEM)
Human activities	Urbanization	Economic urbanization	Economic urbanization	Proportion of secondary and tertiary industries (Eco-Urban)
		Land urbanization	Scale of construction land	Proportion of construction land (PUA)
			Scale of urban expansion	Expansion area of construction land (OEA)
			Rate of urban expansion	Expansion rate of construction land (AER)
			Urban expansion form	Largest patch index (LPI)
				Landscape shape index (LSI)
				Patch cohesion index (COHESION)
		Population urbanization	Population urbanization	The population density of urban construction land (Pop-Urban)
	Agricultural activity	Agricultural land connectivity	Agricultural land connectivity	Agricultural landscape fragmentation index (FN)
				Agricultural landscape connectivity index (CONNECT)
	Environmental pollution	Atmospheric pollution	Atmospheric pollution	PM2.5 concentration (PM2.5)
	Regional policy	Regional ecological and environmental policies	Returning farmland to forest and shelterbelt projects	Returning farmland to forest index (DFI)
			Soil and Water conservation policy	Soil and water loss index (SEI)

them, the ecosystem health level is the explained variable, and the climate and human activity factors are the explanatory variables. The MLR model formula:

$$Y_i = \beta_0 + \sum_{j=1}^{n} \beta_j x_{ij} + \varepsilon_i \tag{10}$$

Where Y_i represents the ecosystem health level of the ith sample, x_{ij} represents the observed value. ε is the error term, β_0 is the regression constant.

3.6. Geographically weighted regression model

Considering the limitations of the traditional linear regression model in the spatial characteristics of independent variables (Yang et al., 2012), we further use the geographically weighted regression model (GWR) to analyze the spatial heterogeneity impact of climate and human activities on regional ecosystem health. The model formula as follows:

$$Y_i = \beta_0(S_i, T_i) + \sum_{j=1}^{n} \beta_j(S_i, T_i) x_{ij} + \varepsilon_i \tag{11}$$

$$\beta_j(S_i, T_i) = (X^T W(S_i, T_i) \mathrm{X})^{-1} X^T W(S_i, T_i) y_i \tag{12}$$

Where Y_i is the ecosystem health level, $(\mathrm{S}_i, \mathrm{T}_i)$ is the central geographic location coordinate, $\beta_j(S_i, T_i)$ is regression parameter, x_{ij} is the observed values of influencing factors. X^T is the transport matrices, $W(S_i, T_i)$ is the spatial weightiness matrices.

3.7. Optimal parameters-based geographical detector model

The optimal parameter-based geographical detector (OPGD) model is an improved model based on the GD model (Wang and Xu, 2017; Song et al., 2020). The model formula as follows:

(1) Detection of factors. The factor detector was adopted to analyse the influencing factors of the spatial variation of ecosystem health. The specific calculation formulas:

$$q = 1 - \left[\frac{\sum_{h=1}^{L} \sum_{i=1}^{N_h} (Y_{hi} - \bar{Y}_h)^2}{\sum_{i=1}^{N} (Y_i - \bar{Y})^2} \right] = 1 - \frac{\sum_{h=1}^{L} N_h {\sigma_h}^2}{N\sigma^2} = 1 - \frac{SSW}{SST} \tag{13}$$

$$SSW = \sum_{h=1}^{L} \sum_{i=1}^{N_h} (Y_{hi} - \bar{Y}_h)^2 = \sum_{h=1}^{L} N_h {\sigma_h}^2 \tag{14}$$

$$SST = \sum_{i=1}^{N} (Y_i - \bar{Y})^2 = N\sigma^2 \tag{15}$$

Where q value is the explanatory power of influence factor. h is the amount of layers, N_h is the amount of samples, N is the amount of samples. σ_h is the variance of the ecosystem health, σ is the variance of the ecosystem health of the study region. Y_i is the ecosystem health level.

(2) Detection of factor interactive effect. Interaction detectors were adopted to recognize interactions between influencing factors, that is, to assess the impact of joint effects on ecosystem service values. The criteria for various interaction types are shown in Fig. 4.

4. Results

4.1. Optimal analysis scale of ecosystem health

The year selected for semi-variogram analysis was the middle year of the study period, namely 2005, and the analysis scale selected included 4 km to 11 km. By analyzing the variation trend of Nugget-Sill ratio of landscape pattern index at different scales (Fig. 5), we found that the Nugget-Sill ratio reaches a stable status at 8 km to10km, which indicates that the spatial variation of landscape pattern index at this analysis scale tends to be stable, and the scale can be determined as the optimal analysis scale (characteristic scale) of the study area. In addition, large scale will cause more spatial information loss. Therefore, the optimal analysis scale selected in this research is 8 km × 8 km, with a total of 6,600 grid units.

4.2. Spatial pattern evolution of ecosystem health

According to the data distribution of ecosystem health index (EHI), the study region was divided into five types zone: low level zone ($0 < \mathrm{EHI} \leq 0.25$), Lower level zone ($0.25 < \mathrm{EHI} \leq 0.4$), Middle level zone ($0.4 < \mathrm{EHI} \leq 0.5$), Higher level zone ($0.5 < \mathrm{EHI} \leq 0.6$), High level zone (EHI greater than 0.6).

The ecosystem health level in the MRYR from 1990 to 2018 showed the hierarchical structure characteristics of alternating distribution of low value zone and high value zone (Fig. 6). In detail, the high-level zones is primarily distributed in the mountainous and hilly areas in the south of the study area, including Liupan Mountain in the southwest, Qinling Mountain, Gushan Mountain in the southeast and the west side of Funiu. In addition, restricted by complex terrain conditions and ecological protection policies, their human activities and socio-economic development level are low. The higher and medium level zone are primarily distributed in the Northern Shaanxi plateau, Fenhe River Basin, Luliang Mountain Area and the south of Taihang Mountain in the middle region. Among them, the northern Shaanxi Plateau region maintained a high level of health during the research period, and from 2010, the area of the higher and medium level had obvious expansion. The low level zones and lower level areas are mainly distributed in the south of Kubuqi Desert, the east and south of Mu Us sandy land,

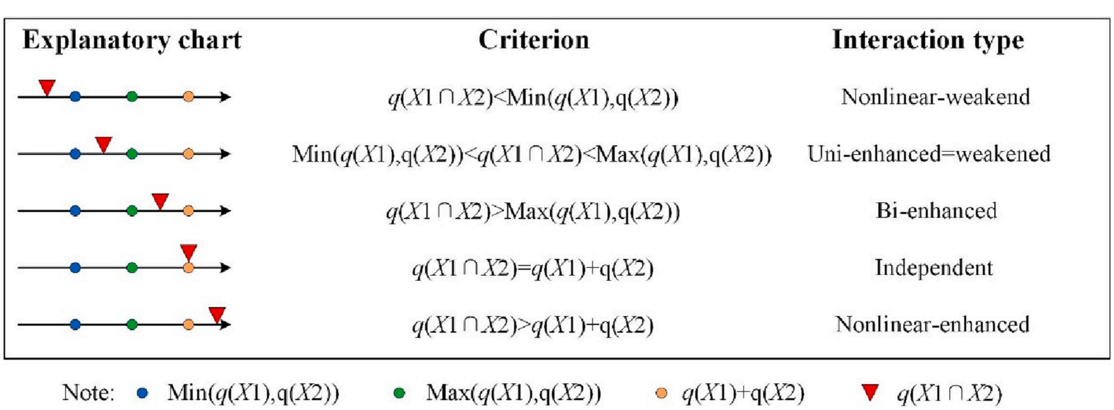

Fig. 4. Interaction type diagram.

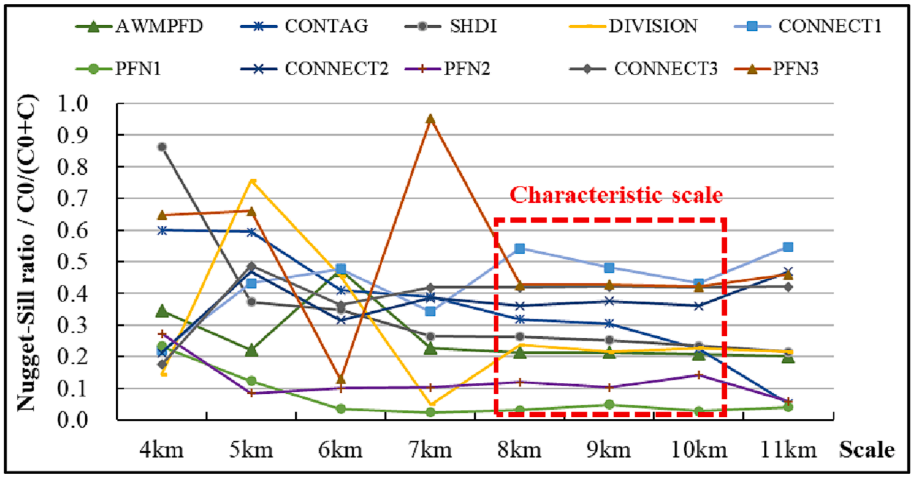

Fig. 5. The Nugget-Sill ratio change of landscape pattern indexs at different analytical scales.

Yinchuan City, Guanzhong Basin with dense population and cities, Luohe River Basin, Fenhe River Basin and the west of North China Plain.

From the perspective of spatial change characteristics, the overall spatial changes of ecosystem health were relatively drastic from 1990 to 2005, but tended to be flat from 2005 to 2018. Locally, the areas where temporal and spatial changes occurred are mainly distributed at the junction of the northwest low-value belt and the central high-value belt, Hohhot and Ulanqab, the surrounding areas of the provincial capital Taiyuan City, Dingxi City, Gansu Province, the surrounding areas of the central Shaanxi Plateau, and Baoji City, Xi'an metropolitan area, Zhengzhou-Luoyang-Jiaozuo urban belt.

4.3. Spatio-temporal impacts of climate and human activities on ecosystem health

4.3.1. Global impacts of climate and human activities on ecosystem health

First, we eliminated 4 variables with a variance inflation factor (VIF) greater than 7.5, including SPI, Tem, PUA, and LSI, the VIF of the remaining variables meets the basic requirements of regression analysis. Then, the multiple linear regression model was adopted to analyze the global impact of climate and human activities on the ecosystem health. The results are shown in Table 5.

As can be seen from Table 5, under the significance level of 5%, in addition to the AER and CONNECT, RDLS, PET, SPEI, PRE, Eco-urban, OEA, LPI, COHESION, Pop-Urban, FN, PM2.5, DFI and SEI had prominent impacts on ecosystem health. From the perspective of the action orientation of influencing factors, the estimated coefficient directions of RDLS, PET, PRE, Eco-urban, LSI, COHESION, Pop-urban, FN, CONNECT, PM2.5 and SEI were in line with theoretical expectations. The estimated coefficient directions of SPEI, OEA, AER, FN and DFI do not accord with the theoretical expectation. The underlying reason for the contrary expectation may be the spatial instability of influencing factors. As for the real reason that the estimated coefficient direction of the above factors does not conform to the theoretical expectation, the next step is to use GWR model to analyze the spatial difference of the intensity of the action direction of significance factors in different regions, so as to reveal the real reason that does not conform to the theoretical expectation.

4.3.2. Spatial heterogeneity of climate and human activities impacts on ecosystem health

In this paper, adaptive Bi-Square kernel function is adopted as the ownership function, AICc method is used to determine the bandwidth. Based on the analysis results of MLR model, we finally selected 13 significant variables including RDLS, PET, SPEI, PRE, Eco-Urban, OEA, LPI, COHESION, POP-Urban, CONNECT, PM2.5, DFI and SEI as independent variables of the geographically weighted regression model.

By comparing the analysis results of MLR and GWR model (Table 6), it can be seen that the AICc and residual sum of squares (RSS) of GWR model decreased significantly from 1990 to 2018 compared with MLR model. Secondly, Secondly, the goodness of fit (adjusted R^2) of GWR model from 1990 to 2018 was much greater than that of MLR model. Thirdly, the residual of MLR model has significant positive spatial autocorrelation, while the residual of GWR type does not, indicating that the geographically weighted class model considering spatial heterogeneity is superior to the global model in dealing with the spatial autocorrelation of residual. In conclusion, the fitting results of GWR model are superior than MLR model, and the interpretation effect is better.

The statistical analysis results of the local regression coefficients of the GWR Model from 1990 to 2018 show (Fig. S2) that the symbols of the maximum and minimum values of the local regression coefficients of all variables are different, indicating that there is a spatial unstable relationship between regional ecosystem health and influencing factors. In order to furniture probe the driving mechanism of influencing factors on ecosystem health, we use the spatial visualization function of ArcGIS software to depict the spatial differentiation map of the impact of influence factors on regional ecosystem health (Fig. 7). In detail:

(1) Terrain factor. From 1990 to 2018, topographic relief mainly had a positive impact on ecosystem health, and the negative impact areas were primarily distributed in southwest Shanxi, Eastern Shanxi, southern Gansu and Ordos, Inner Mongolia. The positive impact area is characterized by large (small) topographic relief and high (low) ecosystem health level, which is in line with the basic law of human activities.
(2) Climatic factors. In terms of the factors of potential evaporation, the overall improvement of the ecological environment in Northern Shaanxi plateau, central Gansu plateau and Weihe River Basin in the west region, coupled with the increase of potential evapotranspiration, makes the ecosystem health tend to be positively correlated with potential evapotranspiration. In the central and eastern urban agglomeration areas, the increase of impervious surface, the decrease of ecological land use and the expansion of agricultural land use may lead to the increase of potential evapotranspiration and the decrease of ecosystem service function. Therefore, the negative impact of potential evapotranspiration on urban agglomeration areas is enhanced. In terms of standardized precipitation evapotranspiration index and annual precipitation, the spatial effects of standardized precipitation evapotranspiration index and annual precipitation on ecosystem health are mainly negative. The stability of the negative influence region is primarily distributed in the west and

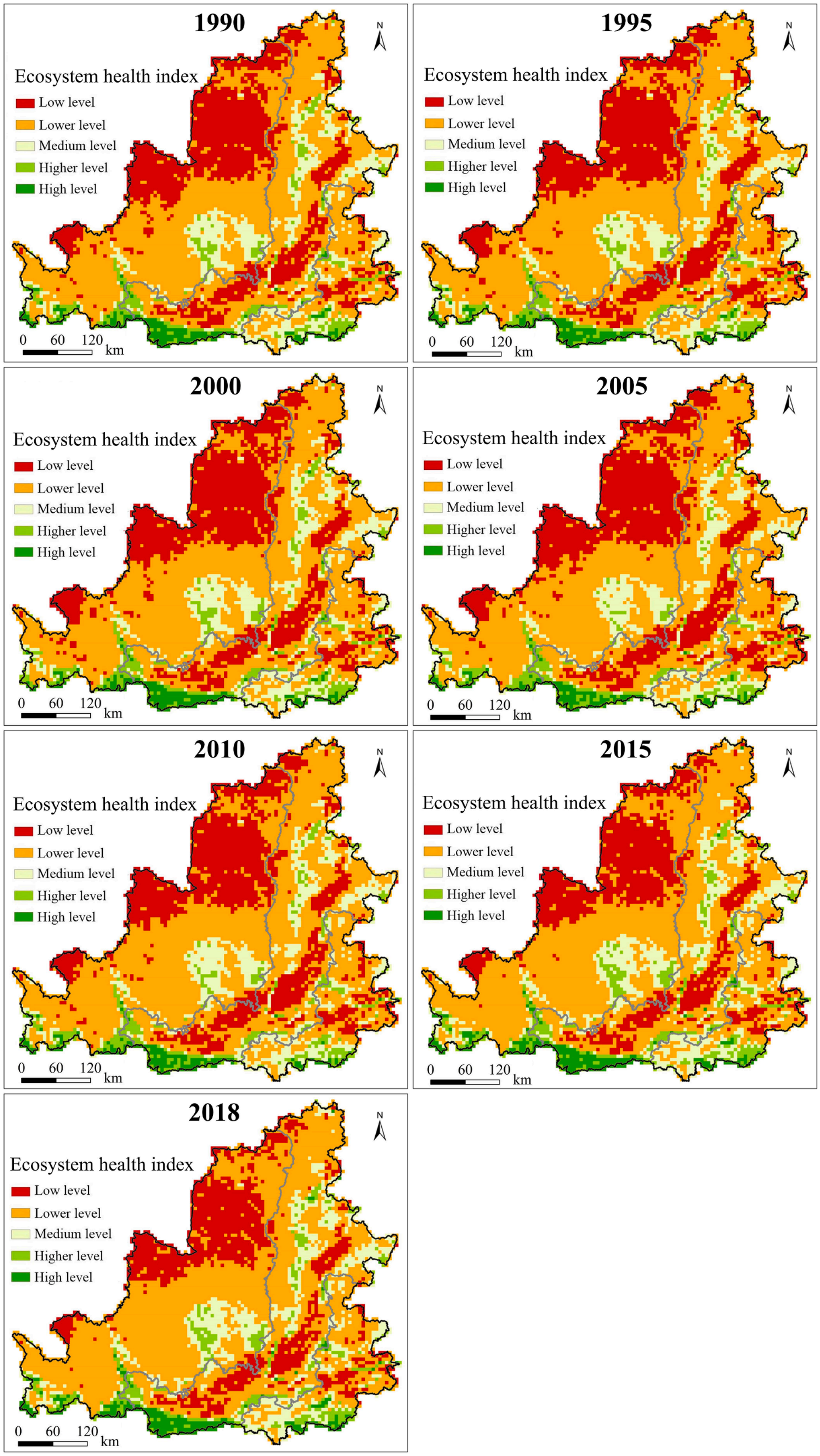

Fig. 6. Spatial pattern evolution of ecosystems health in the MRYR from 1990 to 2018.

Table 5
Estimated results of the OLS model from 1990 to 2018.

Factors	Regression coefficients						
	1990	1995	2000	2005	2010	2015	2018
Constant	0.33	0.45	0.43	0.37	0.58	0.57	0.42
RDLS	0.40***	0.33***	0.29***	0.35***	0.32***	0.36***	0.43***
PET	−0.15***	−0.15***	−0.22***	−0.20***	−0.38 ***	−0.28***	−0.22***
SPEI	−0.09***	−0.41***	−0.03***	−0.09***	0.16***	0.07***	−0.03***
PRE	0.40***	0.19***	0.46***	0.46***	0.34***	0.22***	0.19***
Eco-Urban	−0.14***	−0.20***	−0.17***	−0.20***	−0.15***	−0.18***	−0.15***
OEA	0.02***	0.01**	0.02***	0.03***	0.02***	0.04***	0.03***
AER	0.00	0.01	0.00	0.01	0.01**	−0.01	0.05**
LPI	−0.05***	−0.03***	−0.04***	−0.04***	−0.03***	−0.04***	−0.04***
COHESION	0.06***	0.05	0.07***	0.05***	0.06***	0.03***	0.03***
POP	0.07***	0.08***	−0.04***	−0.01*	−0.04***	−0.04***	−0.07***
FN	−0.14***	−0.17***	−0.16***	−0.19***	−0.18***	−0.17***	−0.18***
CONNECT	−0.01**	0.01	0.01	0.00	−0.01	−0.03***	−0.02***
PM2.5	−0.07***	−0.18***	−0.01*	−0.09***	−0.16***	0.14***	0.23***
DFI	−0.07***	−0.12***	−0.08***	−0.11***	−0.09***	−0.06***	−0.06***
SEI	−0.17***	−0.10***	−0.13***	−0.13***	−0.06***	−0.15***	−0.20***
Adjust R^2	0.801	0.788	0.792	0.775	0.791	0.766	0.756

Note: *** means significant at 0.01 level, ** means significant at 0.05 level, * means significant at 0.1 level.

Table 6
Contrast of fitting results between MLR and GWR model.

Year	Model	Adjusted R^2	RSS	AICc	Bandwidth
1990	MLR	0.801	23.382	−18482.763	–
	GWR	0.935	6.841	−25386.668	317.50
1995	MLR	0.788	24.017	−18306.026	–
	GWR	0.934	6.655	−25579.472	317.52
2000	MLR	0.792	24.652	−18133.704	–
	GWR	0.937	6.774	−25520.589	317.52
2005	MLR	0.775	24.801	−18093.961	–
	GWR	0.936	6.542	−25692.300	317.50
2010	MLR	0.791	23.086	−18566.968	–
	GWR	0.932	6.660	−25559.875	317.52
2015	MLR	0.766	27.582	−17392.568	–
	GWR	0.929	7.476	−24792.536	317.52
2018	MLR	0.756	28.118	−17280.828	–
	GWR	0.926	7.477	−24777.275	317.52

north of the study area, while the positive influence region is primarily distributed in the Guanzhong Basin, the lower reaches of Fenhe river and Luohe River, Taiyuan metropolitan area, Linfen-Changzh-Jincheng urban belt and western Henan area. The northern Shaanxi Plateau and southern Inner Mongolia were negatively affected from 1990 to 2000, but gradually changed to positively affected from 2000 to 2018. The reason is that after the implementation of the ecological conservation policy, the eco-environment in northern Shaanxi Plateau and southern Inner Mongolia has been greatly improved, the health level of the ecosystem has been significantly improved, and the regional climate conditions have also been improved.

(3) Economy urbanization (Eco-Urban). According to the overall spatial distribution of local regression coefficients, there are obvious east–west differences in the direction and intensity of impacts of Eco-Urban on ecosystem health, namely, the central and eastern regions mainly show negative impacts, while the western regions mainly show positive impacts (Fig. 7). In detail, The negative impact of economic urbanization on the central and eastern regions shows a “core-edge” structure with Xi ’an metropolitan area, Luohe River Basin, Fenhe River Basin, Taiyuan metropolitan area and Zhengzhou-Luoyang urban area as the core. From the comparison of eastern and western regions, the eastern region is more affected by human activities factors, and the direction, degree and scope of the impact of Eco-Urban on the ecosystem health of eastern region are in line with normal expectations. However, the level of Eco-Urban and ecosystem health in western region are different, so the direction and degree of the impact of Eco-Urban on ecosystem health show spatial heterogeneity.

(4) Land urbanization (Land-Urban). The impact of urban expansion scale on ecosystem health in the central and eastern region shows a core edge structure in spatial distribution and phased evolution in time series (Fig. 7). According to the theory of urban growth stage and “diffusion agglomeration” theory, this spatial evolution law can be explained, that is, in the initial stage, urban development mainly expands in the urban core area; In the middle stage, urban development began to expand to the periphery of the core area, and new development centers began to appear in the periphery of the core area; Then, when the core area develops to a certain extent and is limited by space, it begins to change from disorderly expansion to the way of filling the gap between existing urban patches. At the same time, the new center outside the core area has become the main object of urban expansion. The direction and magnitude of the impact of urban expansion form (LPI and COHESION) on ecosystem health are spatially heterogeneous and stable in time scale. The spatial impact of LPI was mainly negative, while COHESION was mainly positive. In general, the spatial relation between Land-Urban and ecosystem health is deeply affected by topography, river and economic development level. Among them, the urban development scale and development pattern in the mountainous regions of midwest and the ecologically fragile regions were affected by topography and economic development level. The terrain of basin and plain area mainly expands outward in the form of edge expansion, and the urban landscape scale is large. In addition, restricted by topography, land planning and soil and water conservation policies, the scale and maximum patch index of urban landscape in Luohe River and Fenhe River Basin along the Yellow River are small, but the degree of urban landscape cohesion is high. The study of Peng and Wang (2019) et al also pointed out that topography has a long-term inhibitory effect on urban expansion (Peng and Wang, 2019).

(5) Population urbanization (Pop-Urban). The impact of Pop-Urban on ecosystem health from 1990 to 2018 have obvious evolution trend in time scale (Fig. 7). From 1990 to 2005, the negative influence areas were primarily distributed in the southeast of Mu us Sandy Land, northern Shaanxi Plateau, western Guanzhong Basin, Luohe and Fenhe river basins, midwest Shanxi plain and western Henan region. From 2005 to 2018, the negative impact area tends to shift to the middle and east. The negative impact

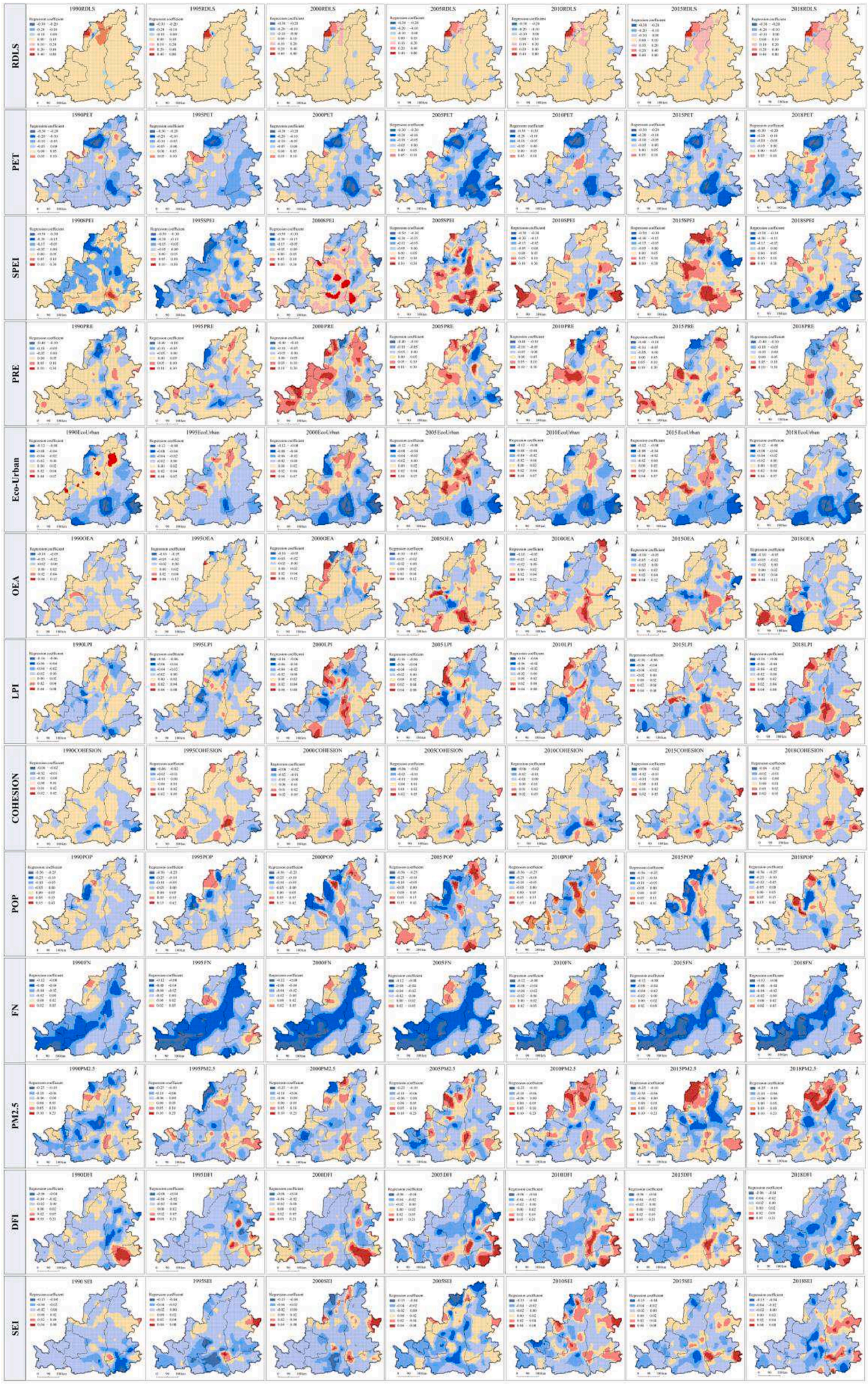

Fig. 7. Spatial differentiation map of the impact of influence factors on regional ecosystem health.

area of population urbanization is characterized by evolution from west to east, from mountainous areas to plain, and from remote areas to big cities.

(6) Agricultural activities (Fig. 7). The negative influence areas are primarily distributed in the mountainous areas of central and western, including the Longzhong Plateau, Liupanshan area, Northern Shaanxi Plateau, Luliang Mountain range and Taiyue Mountain area. The positive influence area is mainly distributed in the Mu Us sandy land and its surrounding areas in the west region, the central Henan plain and the south of Guanzhong Basin. On the whole, terrain and climate factors shape the east–west differentiation pattern of the spatial relationship between agricultural activities and ecosystem health. At the same time, the interaction of terrain, climate factors and human activities further drives the evolution of the local spatial relationship between agricultural activities and ecosystem health.

(7) Environmental pollution (Fig. 7). The negative influence areas of PM2.5 concentration from 1990 to 2000 were mainly distributed in southern Inner Mongolia, Mu us Sandy Land, Northern Shaanxi Plateau, Central Longlong Plateau, Guanzhong Basin, Taiyuan metropolitan area and western Henan mountainous area. From 2005 to 2015, southern Inner Mongolia, Mu us Sandy Land, Northern Shaanxi Plateau and urban agglomeration core area gradually changed into positive influence areas. In urban agglomeration area, with the shortage of urban land, the increase of urban land cost and the restriction of environmental protection policy, the high energy consumption and high pollution industries in the core area of urban agglomeration begin to move to the surrounding areas. Therefore, the negative influence of the core area of the urban circle is gradually weakened, but the negative influence of the periphery area of the urban circle is increased. On the whole, the evolution of the spatial relationship between environmental pollution and ecosystem health in the central and eastern urban agglomerations accords with the economic development law of "agglomeration-diffusion" theory.

(8) Regional policy (Fig. 7). From 1990 to 2018, the impact of regional policy factors on ecosystem health showed significant East-West differences in space and obvious phased evolution Characteristics in time series. Among them, due to the implementation of the ecological conservation policy, the midwest regions showed obvious three-stage evolution characteristics along with the implementation of policies, including three stages from 1990 to 1995, 1995–2010 and 2010–2018. Different from the midwest regions, the eastern region has superior natural and geographical environment, higher vegetation coverage, and less soil erosion. The continuous expansion of the positive impact area of Taiyuan city circle, Zhengzhou - Luoyang city belt and Fenhe River Basin may be mainly related to urbanization, industrial activities and agricultural activities.

4.3.3. The interactive effects of climate and human activities on ecosystem health

The previous analysis results show that the effects of natural and human activities on ecosystem health show significant differences between the east and west, and the interaction between multiple factors may have complex interactive effects on ecosystem health. Based on this, in order to further explore and verify the complex interaction between factors on ecosystem health, we adopt OPGD model to analyze the interaction between natural and human activities on ecosystem health in the East, middle and west regions.

The common points of the eastern, central and western regions are as follows (Fig. 8): (1) RDLS factors play an momentously role in the multi-factor interaction. (2) Climate factors (PET, PRE, SPEI) have strong interactive effects on ecosystem health. (3) Land urbanization (OEA, LPI, COHESION), population urbanization (POP) and agricultural activities (FN), environmental pollution (PM2.5), regional policies (DFI, SEI) had a strong interaction. (4) There is a strong interaction among economic urbanization, land urbanization and population urbanization. (5) There is a strong interaction between agricultural activities and regional policies. (6) The interaction between climate factors and human activity factors shows a complex trend, and the complexity is greater in the west than in the middle, and greater in the middle than in the east.

The differences between the east and west regions are as follows (Fig. 9): (1) The interaction between human activity factors in the western region is generally less than that in the central and eastern regions. (2) The interaction of economic urbanization factors, population urbanization, land urbanization showed phased characteristics in time series, that is, the interaction was not significant in 1990–2000; After 2000 (2000–2018), it began to increase significantly. The interaction between Eco-Urban, Pop-Urban and Land-Urban in the mid-east regions shows phased characteristics in time series, that is, the interaction is not very significant from 1990 to 2000; After 2000 (2005–2018), it began to increase significantly. (3) The interaction among agricultural activities, environmental pollution and regional policy factors in the western and central regions is larger than that in the eastern region. (4) The interaction between climatic factors and human activities and their time evolution show east–west differentiation. The interaction between climate factors, agricultural activities, environmental pollution, and regional policy factors is the main part of the interaction between factors in the western region, while the central and eastern regions are more balanced (Fig. 9). (5) The interaction between climate factors and Eco-Urban factors in the eastern region is not clear, while it is more obvious in the midwest regions. (6) With the intensification of climate change and the expansion of the intensity of human activities, the interaction between human activities and climate factors in the midwest regions has gradually increased, reflecting that the interaction and feedback process between human activities and climate factors in the midwest regions be more complicated.

5. Discussion

5.1. Influencing mechanism of climate and human activities on ecosystem health

Based on the research results, we systematically sorted out the influencing mechanism of climate and human activities factors on ecosystem health, and drew a detailed influence mechanism diagram (Fig. 10). The detailed influence mechanism is as follows:

(1) The influence mechanism of climate factors. At spatial scales, climate elements such as precipitation, air temperature, and potential evapotranspiration can be combined with physical geographic elements such as topography, geology, soil, and hydrology to influence individual species and how they interact with other organisms and their habitats, and further Alter the structure, functions and processes of regional ecosystems, as well as the commodity and services that natural systems provide to society (Weiskopf et al, 2020). Hydrological factors are driven by climate factors, so hydrological factors can be used as intermediary variables to play an intermediary role in the impact of climate factors on ecosystem health. On the time scale, climate change affects water cycle processes and links such as water vapor transport, precipitation, runoff and soil water content through climate factors such as temperature, precipitation and potential evapotranspiration (Zawadzki and Kędzior, 2014; Sadeghi et al., 2017), and then affects crop growth, soil carbon emission, ecosystem structure and function and ecosystem services through regional water cycle, so as to drive the spatial pattern evolution of ecosystem health in ecologically fragile areas.

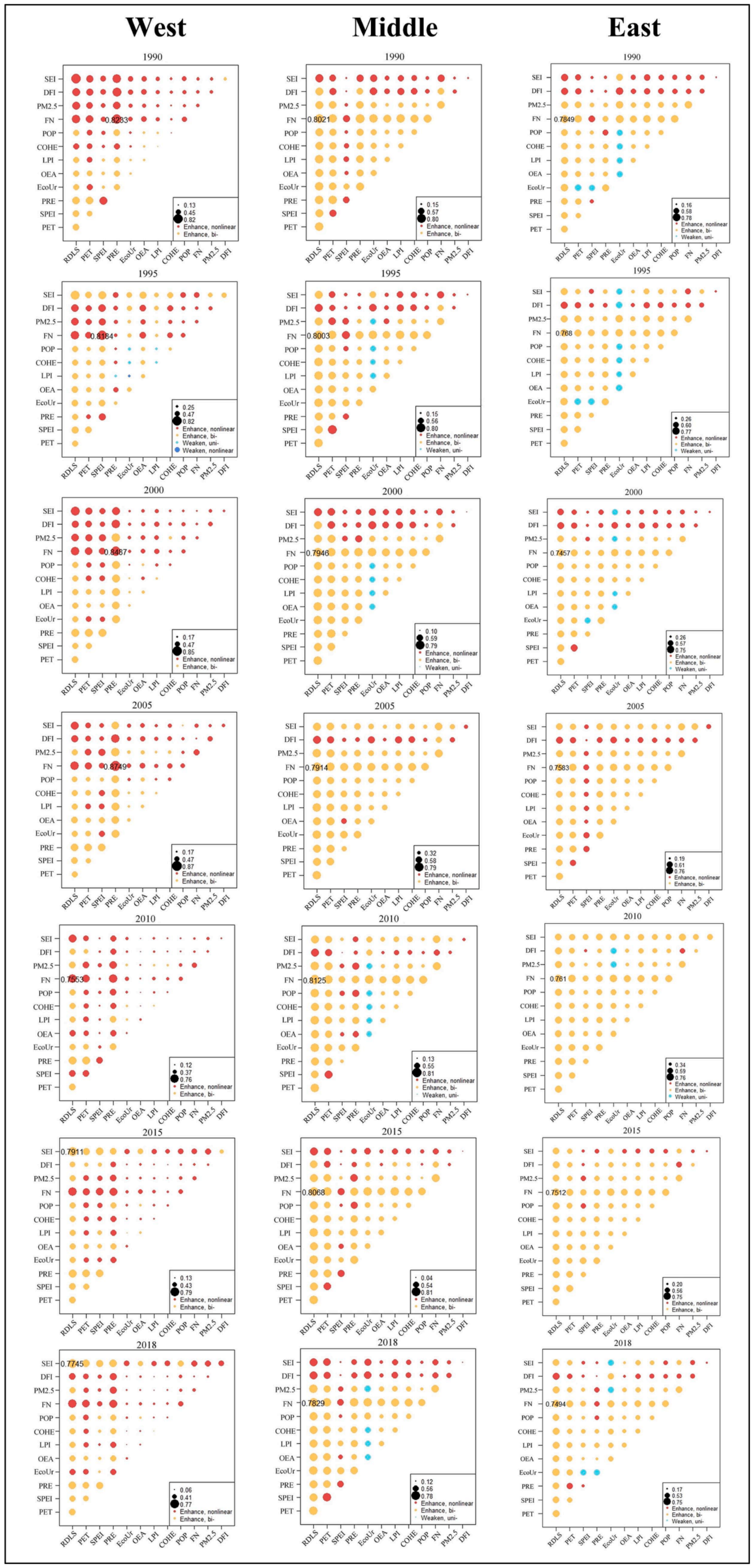

Fig. 8. Interaction diagram of influencing factors on ecosystem health in the eastern, central and western regions from 1990 to 2018.

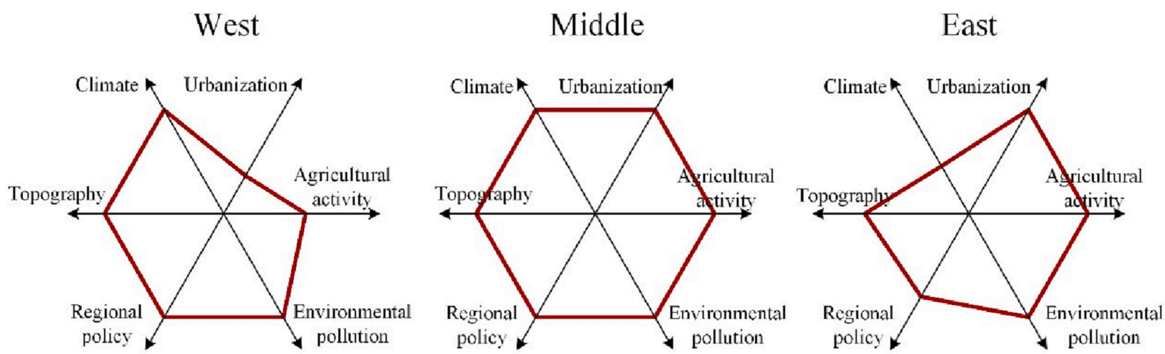

Fig. 9. Comparison of the interaction forces of influencing factors on ecosystem health.

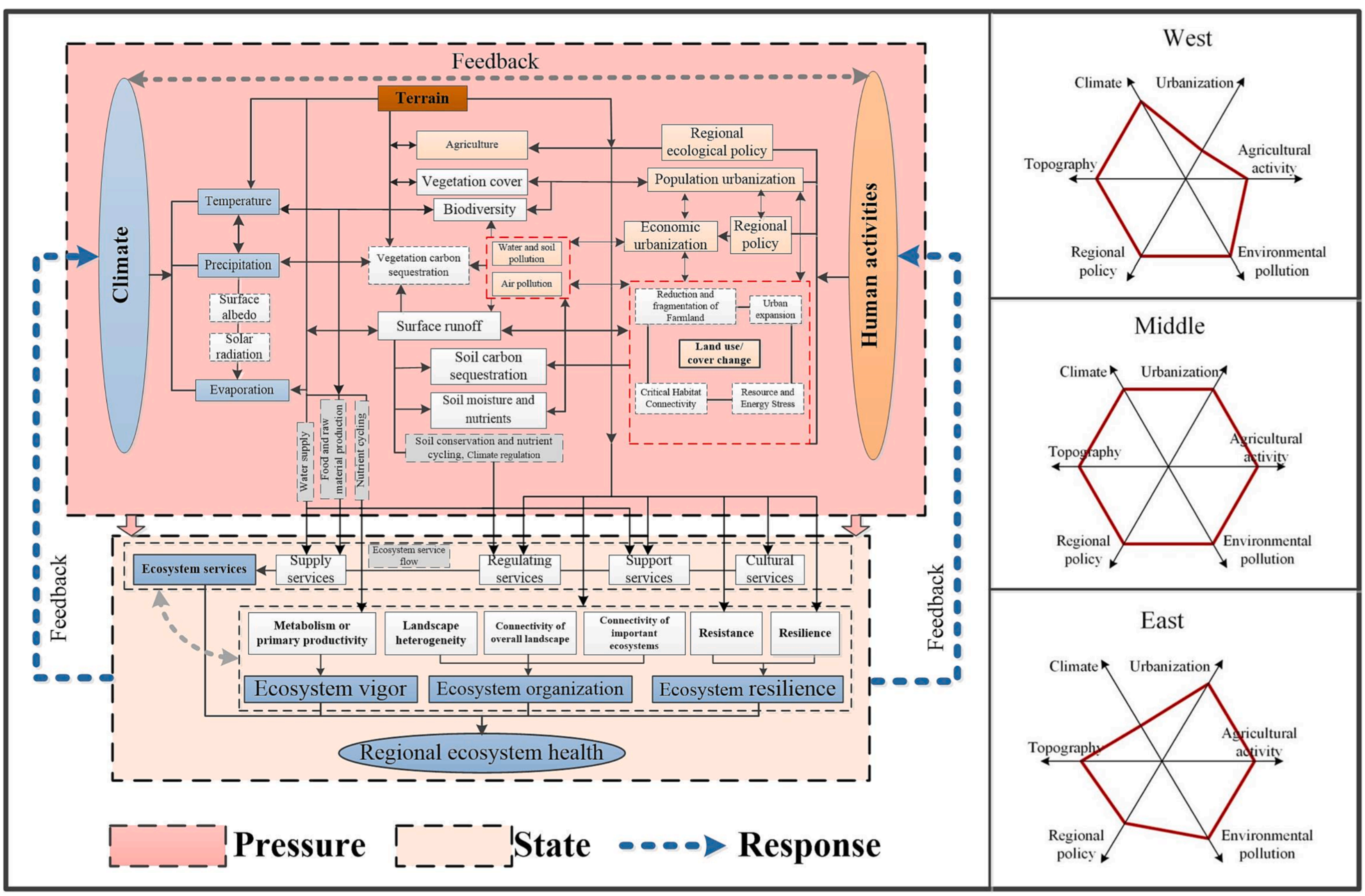

Fig. 10. Influencing mechanism of climate and human activities on ecosystem health in the MRYR.

(2) The influence mechanism of human activities factors. The MRYR is an important population and urban agglomeration area in northern China. In the process of industrialization and urbanization, a large amount of people migrate from rural regions to cities, from mountainous areas to plains, and from county cities to prefecture level cities and provincial capital cities, accelerating the frequent development of Pop-Urban in the mid-east regions. Pop-Urban will augment the furnish stress on the food, resources and energy, and promote the procedure of Land-Urban and Eco-Urban. The process of Land-Urban and Eco-Urban will further lead to drastic changes in land use / cover around cities and towns and environmental pollution. The increase of impervious surface area in the procedure of urbanization will bring about flood disaster and soil erosion risk, and then reduce the regulation and service function of ecosystem. In this process, topography and hydrology will limit the scale and form of urban expansion and industrial development, resulting in the spatial heterogeneity of land urbanization, economic urbanization and its environmental effects. The reduction of agricultural land area will directly affect the total productivity of cultivated land, soil organic carbon content and storage and ecosystem supply services. The decline of cultivated land connectivity will affect ecosystem service functions such as biodiversity. The reduction of forest land, grassland, wetland and water ecological land and the decline of connectivity have a direct impact on ecosystem vitality, ecosystem organization, ecosystem elasticity, ecosystem supply and regulation services. Environmental pollution will affect the regional atmospheric cycle and water cycle, and have a negative impact on the regulation and support services of agricultural ecosystem and urban ecosystem through regional

atmospheric cycle and water cycle. Regional ecological policies contribute to increased vegetation restoration and soil and water conservation in the mid-west of the MRYR, further affecting important ecosystem connectivity, biodiversity, food productivity, ecosystem vitality and resilience, as well as soil conservation, carbon sequestration and water production services. In terms of time evolution, affected by the development stage of urbanization, the staged evolution of land urbanization and economic urbanization drives the staged changes in agricultural activities, environmental pollution and regional policies, which in turn jointly affect the evolution of the spatial pattern of ecosystem health. Affected by the stage of economic development, industries with high energy consumption and high pollution are transferred from central cities to emerging cities and economically underdeveloped cities around urban agglomerations, and the environmental pollution caused by industrial development is also transferred from central cities to emerging cities and economic The evolution of the spatial relationship between environmental pollution and ecosystem health presents a law of economic development similar to the "agglomeration-diffusion" theory. Affected by the regional, staged and lagging effects of regional ecological policies, the impact of regional policies on ecosystem health has the characteristics of spatial heterogeneity, stages and lagging.

(3) The joint mechanism of climate and human activity factors. The increase of urban impervious water surface, decrease of ecological land and environmental pollution caused by urbanization, industrialization and agricultural activities can directly affect the hydrothermal and dynamic characteristics of urban underlying surface in rapid urbanization areas, and lead to regional climate and environmental changes through surface energy balance and regional water cycle. Climate and environmental change and human activities further affect ecosystem health through nonlinear interactions and complex positive and negative feedback mechanisms. This process is the combined effect of climate, urbanization, agricultural activities and environmental pollution on ecosystem health. Changes in regional water cycle and environment have increased the risk of drought and extreme meteorological disasters faced by agricultural production activities in ecologically fragile areas, and directly affected the total productivity of cultivated land, soil organic carbon content and storage, and ecosystem services. Although farmland production potential, soil organic carbon storage and ecosystem supply services have declined under the influence of farmland conversion policies and climate change. However, on the other hand, regional ecological policies have improved the regional water cycle and climate dry and wet conditions by restoring vegetation and increasing soil and water conservation, making a virtuous cycle between regional policies, agriculture and climate, which is conducive to the promption of the level of regional ecosystem health.

5.2. Shortcomings

(1) Improved VORS model. Based on the VORS model, this study introduced the spatial weight coefficient and the modified spatial proximity effect coefficient to modify the ecosystem resilience and ecosystem service value respectively, so as to realize the improvement of VORS model and make the ecosystem health assessment results more scientific. This is the first contribution of this study. However, the complexity and comprehensiveness of regional composite ecosystem determine the complexity of research methods and means to evaluate the health status of regional composite ecosystem. The evaluation indicators, evaluation models and health standards of ecosystem health are still in the stage of rapid development, and there are still many areas to be explored. In the future, we can explore new evaluation indicators and evaluation models by combining multidisciplinary models, RS and GIS technologies, providing new ideas and methods for existing research, and providing more accurate and comprehensive research results for future regional ecosystem health research.

(2) Influencing factors of ecosystem health. According to the general mechanism analysis of impact factors on ecosystem health (Fig. 1), we systematically selected influencing factors (19 specific factors) including climate, topography, economic urbanization, population urbanization, land urbanization, agricultural activities, environmental pollution and regional policies to analyze the driving factors of ecosystem health. Compared with existing studies, our study extends the index system of factors influencing ecosystem health as far as possible. However, the disadvantage is that the Middle Yellow River region is located in the inland of China, and water resources factors may also have an important impact on ecosystem health. However, due to the lack of long-term raster data of water resources (such as water resources volume), this study cannot temporarily discuss the impact of water resources factors on ecosystem health. And the combined effects of water resources and other factors on ecosystem health. Therefore, the factor of water resource quantity should be supplemented in the future research.

5.3. Future research direction

Up to now, the studies on the driving mechanism and multi-scenario simulation of ecosystem health are still weak. In detail: (1) Improving the driving mechanism of ecosystem health. Although this study systematically analyzed the influencing mechanism of climate and human activities on ecosystem health, the mechanism of the impacts has not been fully revealed. Therefore, the spatial–temporal impact process and interaction mechanism of climate and human activities on regional ecosystem health are still the focus and difficulty of future research. (2) Multi-scenario simulation of ecosystem health. Because it is difficult to obtain the auxiliary data of future scenarios required for the spatial simulation of ecosystem health, how to accurately simulate the spatial distribution of regional ecosystem health under the combined influence of future climate and human activities is still a challenge. In future research, multivariate data and a variety of model methods should be used to carry out long-term, high-precision, and multi-scenarios of ecosystem health spatial simulation research. (3) It is an momentous scientific and practical question to put forward a multi-scale ecological management zoning method and targeted ecological regulation strategy based on ecosystem health.

6. Conclusions

The impact and pressure of resources and environment in ecologically fragile areas caused by climate and human activities have become the main factors that constraint the sustainable development of the region. Therefore, it is of important meaning to systematically reveal the influence mechanisms of climate and human activities on ecosystem health. In this study, we adopted the improved VORS model to evaluate the spatiotemporal dynamics of ecosystem health in the MRYR. Then, the spatiotemporal impacts of climate and human activities on ecosystem health are systematically analyzed, and the influencing mechanism of climate and human activities on ecosystem health in the MRYR was discussed. The following dominating ultimateness of this study have been drawn:

Firstly, the ecosystem health level in the MRYR presents a spatially hierarchical structure with alternating low-value and high-value zones. Rapid urbanization areas, ecologically fragile regions in the mid-west regions, and transitional areas between mountain and plain have dynamic local spatial structures and temporal-spatial interaction processes, while other areas have strong path dependence and locking characteristics.

Secondly, topography, Pop-Urban, Eco-Urban, Land-Urban, agricultural activities, environmental pollution, regional policies and other factors all have a prominent impact on the ecosystem health in the MRYR.

Third, the negative impacts areas of SPEI and PRE are stably distributed in the west-north. The negative impact of PET on ecosystem health in urban agglomeration areas is enhanced. The negatively affected areas of Pop-Urban show the evolution characteristics from west to east, from mountainous areas to plains, and from remote areas to large cities. The spatial evolution relationship between Eco-Urban, Land-Urban and ecosystem health shows the phase characteristics of changing synchronously with urbanization. The evolution process of the spatial relationship between environmental pollution and ecosystem health in economically developed urban agglomerations and emerging urban belts conforms to the economic development law of the "agglomeration-diffusion" theory. The spatial relationship between regional policy and ecosystem health in central and western regions shows the characteristics of three-stage evolution lagging behind the policy node.

Fourth, topographic factors play an important role in the multi-factor interaction. There is a strong interaction between climatic factors in the east, middle and west regions. There are strong interactions among Eco-Urban, Land-Urban and Pop-Urban. Land-Urban, Pop-Urban and agricultural activities, environmental pollution, regional policies had a strong interaction in the east, middle and west regions. The interaction of Eco-Urban factor with Pop-Urban and Land-Urban in central and eastern regions shows stage characteristics in time series. The interaction among agricultural activities, environmental pollution and regional policy factors in the mid-west regions was larger than that in the eastern regions. The interaction and feedback process of human activities and climate factors in the middle and western regions tended to be complicated.

Fifth, the combination of MLR, GWR and OPGD model can more accurately describe the action mode, direction, path and intensity of influencing factors, and help to reveal the driving mechanism of ecosystem health.

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.

Data availability

The authors do not have permission to share data.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolind.2023.110191.

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