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# Scale effect and spatially explicit drivers of interactions between ecosystem services—A case study from the Loess Plateau

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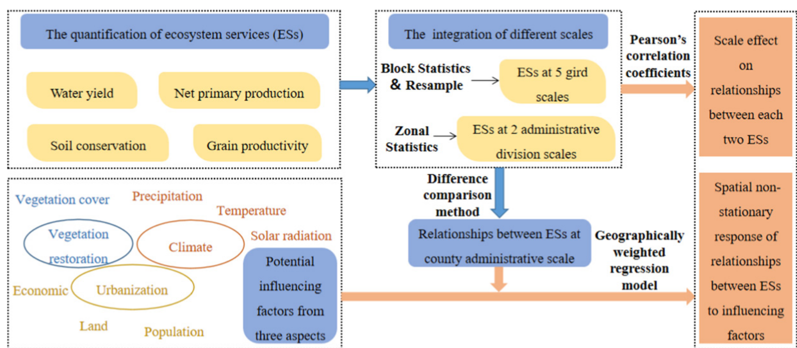
## HIGHLIGHTS

- The scale effect of relationships between ESs was analyzed and the driving force of spatialization identified.
- Most relationships between ESs were synergistic and robust at all seven scales considered.
- These relationships are enhanced as the scale increases.
- The response of the trade-offs/synergies to climate, vegetation and urbanization varied spatially in property and intensity.

## GRAPHICAL ABSTRACT

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## ABSTRACT

Identifying the scale effect of relationships between ecosystem services (ESs), and determining which factors affect such relationships and the spatial distribution patterns of these effects can assist in the sustainable management of ESs. Taking the Loess Plateau (LP) as a study area, we compared and analyzed the change in the trade-offs and synergies between four ESs (i.e. water yield, net primary production, soil conservation, and grain production) at seven different scales. In addition, the spatial correlations between these trade-offs/synergies and factors related to climate, vegetation restoration and urbanization at the county administrative scale were analyzed using a geographically weighted regression (GWR) model. The results showed that most relationships between ESs were synergistic and robust across all seven scales, and most correlations between ESs are enhanced as the scale increases, as a result of the "peak cutting and valley filling" process of scale synthesis. In addition, almost all the relationships between ESs had the strongest synergies or the weakest trade-offs at the municipality administrative scale. The occurrence of trade-offs/synergies between ESs was closely related to climatic factors, vegetation restoration factors and urbanization factors, and, in addition, properties and intensity of the correlations varied spatially. Among these factors, vegetation cover (VEG), annual average temperature (TEM), and construction land percentage (CLP) were more highly correlated with the trade-offs/synergies. This study contributes to extending our understanding of the way in which interactions between ESs depend on spatial scale, and could inform decision-makers about how to control various influencing factors to improve the local ecology under local conditions.



## 1. Introduction

Ecosystem services (ESs) refer to the environmental conditions and utilities provided by ecosystems that can sustain human life (Costanza

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et al., 1997; MA, 2005). Deterioration in ecosystem services has been recognized from the global scale (MA, 2005; Costanza et al., 2014) to regional and local scales (Mendoza-González et al., 2012; Helfenstein and Kienast, 2014; Su et al., 2014). Action is urgently needed to support sustainable use of ecological resources. However, inappropriate ecological management strategies may cause harm to the ecology of systems. For example, decision-makers tend to ignore trade-offs and synergies between ESs and blindly pursue the maximization of the supply of one ecosystem service (ES), often resulting in a significant reduction in the supply capacity of another (Bennett et al., 2009; Feng et al., 2017). In addition, understanding the trade-offs and synergies at a single scale is often insufficient, as cross-scale interactions between ecological processes tend to produce outcomes that cannot be predicted on a single scale (Wu, 2004), which will not provide effective information for decision-makers of different scales. Therefore, it is necessary to explore trade-offs and synergies from a multi-scales perspective, to identify the factors related to them, and to determine how they are related. In this way, decision-makers can scientifically manage the local ecology by encouraging producing certain services or controlling certain influencing factors according to local conditions, thus maintaining the stability of the ecosystem and delivering ecosystem services sustainably.

The synergy, which denotes a situation in which two services increase or decrease at the same time; and trade-off, in which one ES increases as another ES decreases (Bennett et al., 2009; Raudsepp-Hearne et al., 2010). Numerous researchers have reported trade-offs and synergies with respect to the relationships between ESs (Howe et al., 2014; Jiang et al., 2016; Wu et al., 2017; Liu et al., 2018), but most literature relates to a specific single scale, which may distort or miss interactions between ESs (Raudsepp-Hearne and Peterson, 2016). One study in the Baota District of the Loess Plateau has found that there are trade-offs between water yield, habitat quality and evapotranspiration at the pixel scale, but these disappeared when expanded to the town scale (Hou et al., 2017). Another study showed that the correlation between ecological diversity and grassland productivity varied with changes in the observation scale (Yue et al., 2005). Therefore, scientists should be aware that trade-offs and synergies may change across spatial scales, so considering scale effect on interactions between ESs is beneficial to ecosystem management.

Decision-makers have long sought to maximize the delivery of ESs through effective management policies (Xiao et al., 2016; Tammi et al., 2017). Based on this, in addition to considering the relationship between ESs, further work is need to identify the main drivers that lead to changes in such relationships, which is essential when making decisions about interventions that could enhance positive effects and minimize negative effects (Gong et al., 2017; Zhang et al., 2020). However, research concerning the drivers of such relationships is very limited. Feng et al. (2017) made an attempt to address this issue, and identified global relationships between environmental factors and ESs. Qiu and Turner (2013) found several explanatory variables for the global relationships between ESs at the local (cell) and landscape scales. However, these studies were based on global regression without considering the variation of regression parameters with geographic location, so the result is an average for the whole study area. Since potentially correlated factors, such as precipitation, temperature, etc., are not uniformly distributed in space (Turner et al., 2013), the correlations between ES relationships and these factors are also spatially heterogeneous (Zhang et al., 2020). In this case, global regressions (e.g. ordinary least squares regression (OLS)), which can only reflect the "average" or "global" of parameters, mask the local characteristics of any relationships between variables, thus masking the actual phenomena (Fotheringham and Brunsdon, 1999). Local regression, especially the geographically weighted regression (GWR) model, has gradually replaced global regression for analyzing spatial relationships in ecological processes (Fotheringham and Brunsdon, 1999; Jetz et al., 2005), since an increasing number of studies have proved the ability of the GWR model to address the aforementioned problem (Han et al., 2019; Zhang et al., 2020).

Due to the fragile ecological environment and high-intensity human activities on the Loess Plateau (LP) of China, this area has become an ideal area for conducting research on ESs, and research results have been abundant (Su and Fu, 2013; Jiang et al., 2018; Liu et al., 2018). Unfortunately, to our knowledge, only a small number of studies have considered the spatial-scale effect on trade-offs and synergies between ESs, and there are few studies that consider the administrative division scale. In addition, the fact that the response of ES relationships to the influencing factors may be spatially heterogeneous is often neglected in quantitative studies of driving factors (Turner et al., 2013). These research deficiencies prevent us gaining a comprehensive understanding of the way in which complex interactions between ESs depend on spatial scale. In addition, if we neglect spatial heterogeneity that can induce errors in statistical analysis of the impacts of related factors on such relationships, meaning that decisions regarding ecosystem service management may be flawed because they are based on incorrect results. We thus chose to focus on these issues in relation to the LP. We compared and analyzed the scale effect on relationships between four key ESs (water yield, net primary production, soil conservation, and grain production) using two kinds of scale: a grid scale based on 1, 5, 10, 15 and 20 km grid squares, and an administrative division scale, including the county level and municipality level. Based on the county level scale, which is the basic scale of ecological management decision-making in China, we calculated spatial correlations between ESs relationships and multiple factors related to climate, vegetation restoration, and urbanization, using a GWR model. We aimed to determine: (1) how the relationships between ESs on the LP behave at different scales; and (2) the spatial non-stationary correlations between such relationships and the influencing factors considered.

## 2. Study area

The LP (33°43′7″–41°16′7″N, 100°54′7″–114°33′7″E) is located around the upper and middle reaches of the Yellow River in central China (Fig. 1a). It is the most concentrated and largest distribution of loess material in the world, covering an area of about 640,000 $km^2$, with an elevation range of 60–5200 m (Fig. 1b). The LP contains 44 municipalities (Fig. 1c) and 286 counties (Fig. 1d), comprising 6.67% of the territory of China and supporting 8.5% of the country's population. The main land use classes on the LP are agricultural land, grass land and forested land (Fig. 1e). It experiences a continental monsoon climate. Annual precipitation is commonly <500 mm, increasing from 200 mm in the northwest to about 700 mm in the southeast (Fu et al., 2017). Annual average temperature is about 3.6 to 14.3°C (Jia et al., 2019, 2020).

The LP is characterized by severe water shortages and soil erosion (Wang et al., 2006; Feng et al., 2016). According to the research of Cai (2001), the average erosion modulus of the LP is in the range 5000–10,000 $t \cdot km^{-2} \cdot yr^{-1}$, with the highest value being up to 20,000–30,000 $t \cdot km^{-2} \cdot yr^{-1}$; the area is the main source of sediment reaching the Yellow River. The problems are compounded by the relatively arid climatic conditions and significantly increased population pressure.

## 3. Data and methods

### 3.1. Data sources and descriptions

We used two types of data — spatial data and statistical data. Spatial data included: (1) land use/cover data for the years 2000 and 2015 at a spatial resolution of 30 m × 30 m, supplied by the Resources and Environmental Science and Data Center, Chinese Academy of Sciences (http://www.resdc.cn/); (2) soil data at a spatial resolution of about 1000 m × 1000 m, including soil depth, soil organic carbon, soil type, and soil particle composition, extracted from the China soil map based on the harmonized world soil database (HWSD) (v1.1), supplied by

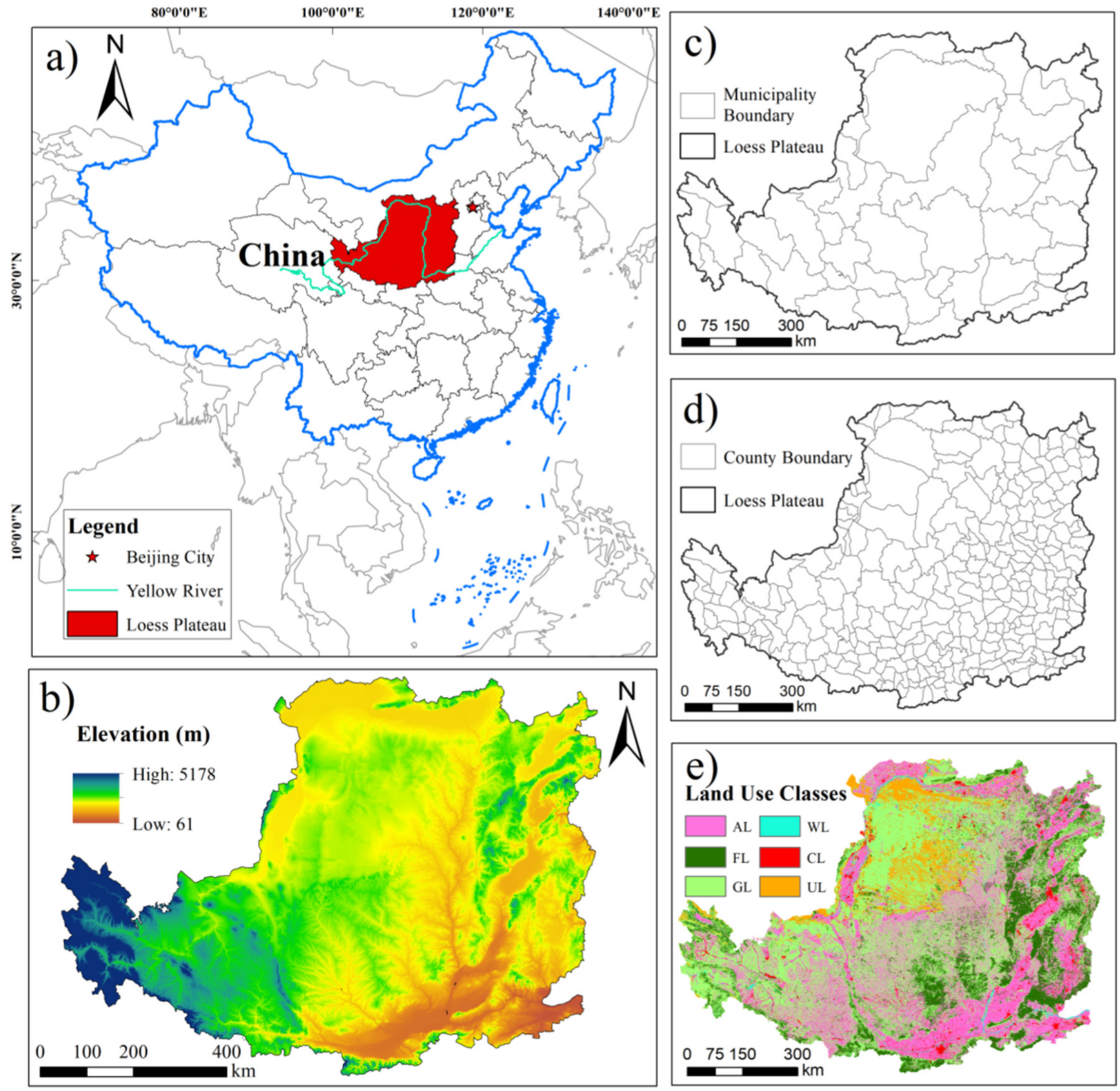


**Fig. 1.** Overview of the study area: a) geographical location, b) digital elevation model, c) municipality boundaries, d) county boundaries, and e) land use classes in 2015 on the Loess Plateau (AL: agricultural land; FL: forested land; GL: grassland; WL: water bodies; CL: construction land; UL: unused land).

the National Tibetan Plateau Data Center (http://westdc.westgis.ac.cn); (3) digital elevation model (DEM) data at a spatial resolution of 90 m × 90 m, supplied by Geospatial Data Cloud (http://www.gscloud.cn/); (4) normalized difference vegetation index (NDVI) data for the years 2000 and 2015 at a spatial resolution of 1 km × 1 km, supplied by the Resources and Environmental Science and Data Center, Chinese Academy of Sciences (http://www.resdc.cn/); and (5) meteorological data for the years 2000 and 2015, including monthly rainfall, monthly mean temperature, and monthly total solar radiation, supplied by the China Meteorological Data Sharing Service System (http://data.cma.cn). The data were interpolated using the ordinary Kriging method, which is effective for the LP (Su et al., 2020), in order to cover the whole area to allow further spatial analysis in ArcGIS 10.2. The statistical data included grain yield, GDP, and population at the county administrative scale and was obtained from the 'Data Set of Rural Social and Economic Development and New Rural Construction in the Loess Plateau from 1990 to 2015', supplied by National Earth System Science Data Center, National Science & Technology Infrastructure of China (http://www.geodata.cn). When calculating the ESs, the data sets used were converted to a 1 km grid resolution, and were projected onto the same coordinate system.

### 3.2. Methods

The study was conducted based on the following four steps: (1) the quantification of ESs; (2) the integration of different scales; (3) determining the relationships between ESs at different scales; and (4) geographically weighted regression between identified relationships and the multiple influencing factors. The following sections give details of each of these steps.

#### 3.2.1. The quantification of ESs

Due to the differences in the main ESs of different ecosystems, choosing appropriate indicators to quantify the ESs in the study area is a huge challenge. Choosing too many indicators may confuse the public and decision-makers, while choosing too few may mean that the research results do not actually reflect the real situation (Su et al., 2012). Therefore, we need to choose ESs that best reflect the ecological problems faced by the study area (Wallace, 2007). There are many severe ecological problems on the LP, such as spatially and temporally uneven precipitation, a serious shortage of water resources, erosion of the loess soil, and vegetation degradation. In order to consider these local problems, especially the serious water shortage, soil erosion and vegetation degradation (Su et al., 2012), we selected three ESs: water yield (WY), net primary production (NPP) and soil conservation (SC) to assess the ecological status of the LP. In addition, following the implementation of the Grain for Green Program (GFGP) on the LP since 1999, a large amount of cultivated land was converted to forest and grassland, which affected the grain security of the study area. Therefore, we also selected grain production (GP) as an indicator of the ecosystem service reflecting this issue. We believe that these four ESs are key in relation the ecosystem supporting humans in the study area, and these four ESs can quite comprehensively represent the urgent demands of the population of the LP for ESs (Su and Fu, 2013; Geng et al., 2020; Su et al., 2020). The detailed calculation of the four ESs is too lengthy to include here, so the following is a brief explanation of their derivation.

*3.2.1.1. Water yield (WY).* In this study, the Integrated Valuation of Ecosystem Services and Trade-offs (InVEST) model based on the Budyko curve equation was used to assessed water yield. The main model is as follows:

$$Y_x = \left(1 - \frac{AET_x}{P_x}\right) \times P_x \tag{1}$$

where $Y_x$ is the annual water yield for pixel $x$ (mm), $AETx$ is the annual actual evapotranspiration for pixel $x$ (mm) and $P_x$ is the annual precipitation for pixel $x$ (mm). Details of the calculation for$AETx$can be found in the InVEST 3.5.0 User's Guide. Reference evapotranspiration was determined by a "modified Hargreaves" equation (Droogers and Allen, 2002). Vegetation rooting depth and the evapotranspiration coefficient were obtained from local literature (Yang et al., 2020). Plant available water content (PAWC) was calculated on the basis of soil texture and soil organic matter content (Zhou et al., 2005).

*3.2.1.2. Net primary production (NPP).* In this study, the Carnegie-Ames-Stanford Approach (CASA) model was used to calculated the NPP (Potter et al., 1993). Three basic equations are involved:

$$NPP(x, t) = \sum [APAR(x, t) \times \varepsilon(x, t)] \tag{2}$$

$$APAR(x, t) = SOL(x, t) \times FPAR(x, t) \times 0.5 \tag{3}$$

$$\varepsilon(x, t) = T_{\varepsilon 1}(x, t) \times T_{\varepsilon 2}(x, t) \times W_{\varepsilon}(x, t) \times \varepsilon^* \tag{4}$$

where $APAR(x,t)$ is the photosynthetically active radiation absorbed by pixel $x$ in month $t$ ($MJ \cdot m^{-2}$), and its value is calculated by the total solar radiation (SOL) ($MJ \cdot m^{-2}$) and the proportion of the incident photosynthetic active radiation absorbed by plants (FRAR); the constant 0.5 reflects the proportion of effective solar radiation that can be used by vegetation in comparison to total solar radiation; $\varepsilon(x,t)$ represents the actual light energy utilization rate of pixel $x$ in month $t$ ($g \cdot MJ^{-1}$); $T_{\varepsilon 1}(x,t)$, $T_{\varepsilon 2}(x,t)$ and $W_{\varepsilon}(x,t)$ are parameters describing the stress coefficients of the highest temperature and the lowest temperature and the water stress coefficient for pixel $x$ in month $t$, respectively; $\varepsilon*$ refers to the possible efficiency of different vegetation types under ideal conditions.

*3.2.1.3. Soil conservation (SC).* In this study, we used the Revised Universal Soil Loss Equation (RUSLE) to estimate the amount of potential and actual soil erosion on the LP (Renard, 1997). The amount of potential soil erosion minus the amount of actual soil erosion represents the amount of soil conservation in the ecosystem. It is calculated as follows:

$$Ac = Ap - A = R \times K \times LS \times (1 - C \times P) \tag{5}$$

where $Ac$ is the soil conservation ($t \cdot ha^{-1} \cdot yr^{-1}$); $Ap$ is the potential soil erosion ($t \cdot ha^{-1} \cdot yr^{-1}$); $A$ is the actual soil erosion ($t \cdot ha^{-1} \cdot yr^{-1}$); $R$ is the rainfall erosivity factor ($MJ \cdot mm \cdot ha^{-1} \cdot h^{-1} \cdot yr^{-1}$); $K$ is the soil erodibility factor ($t \cdot ha \cdot h \cdot ha^{-1} \cdot MJ^{-1} \cdot mm^{-1}$); $L$ is the slope length factor; $S$ is the slope steepness factor; $C$ is the vegetation cover and management factor; and $P$ is the conservation support practice factor. $L$, $S$, $C$, and $P$ are dimensionless factors. For the more detailed information on calculation of the key parameters, please refer to Supplementary material.

*3.2.1.4. Grain productivity (GP).* GP is an important supply service of ecosystems, especially agricultural ecosystems. Based on land use classification, GP is allocated to agricultural land. Since there is a significant linear relationship between grain yield and the NDVI (Kuri et al., 2014; Peng et al., 2017), by referencing the work of Wu et al. (2017), we spatialized the grain yield statistics based on the NDVI with positive values for agricultural land. On this basis, the GP supply capacity of the LP was evaluated. The specific formula is as follows:

$$GPx = \frac{NDVIx}{NDVIsum, i} \times GPsum, i \tag{6}$$

where $GPx$ is the grain yield of pixel $x$ ($t \cdot km^{-2} \cdot yr^{-1}$); $GPsum, i$ is the total grain yield of county $i$ ($t \cdot yr^{-1}$); $NDVIx$ is the NDVI of pixel$x$; $NDVIsum, i$ is the sum of the NDVI of the agricultural land in county $i$ on the LP.

*3.2.2. The integration of different scales*

Using our 1 km scale ecosystem service grid maps, we created two types of scale: one grid-based and the other using administrative divisions. For the grid, we used the Block Statistics and Resample tools in ArcGIS 10.2. The Block Statistics tool divides the input raster into non-overlapping blocks and calculates statistical data for each block, then assigns the relevant value to all cells in each block of the output. Resample was then used to change the raster dataset by altering the cell size. The sizes of the grid squares used here were 5 km, 10 km, 15 km and 20 km, plus the original 1 km scale, giving a total of five different grid scales. For the administrative division scales, we used the Zonal Statistics tool in ArcGIS 10.2, which calculates the statistical information for the raster values within the zones of another dataset. Here we adopted two administrative division scales: the county level and the municipality level. In order to reflect the average situation of "blocks" and "zones", the statistic used by the Block Statistics and Zonal Statistics tools was "mean". The results are shown in Fig. S1 (Supplementary material).

*3.2.3. The relationships between ESs*

We used the Pearson's correlation analysis, calculated using IBM SPSS Statistics 22, to examine the relationships between different ESs at seven scales in 2000 and 2015. When the correlation coefficient between two ESs was negative and significant, they were considered to have a trade-off relationship; when the correlation coefficient was positive and significant, the two services were considered to have a synergistic relationship.

*3.2.4. Geographically weighted regression (GWR) model*

The GWR model uses the relevant information for the neighboring area to estimate local regression parameters, and finally produces coefficients for the regression model in different regions that change with the different geographic locations; this is a geographic spatial variable coefficient regression (Fotheringham and Brunsdon, 1999). The GWR model extends OLS for characterizing spatial non-stationarity, so that the correlations between variables can change with changes in spatial position (Zhang et al., 2020). Since the GWR model requires input of spatially independent and dependent variables, we took the following steps when conducting our study.

First, we adopted the difference comparison method (Zhang et al., 2020) to spatialize the trade-offs and synergies between ESs. Specifically, we assessed the relationship between two ESs by comparing the differences in these ESs between 2000 and 2015 (Supplementary material, Fig. S1). If the product of the variation between the two ESs was greater than 0, then we considered that there was a synergistic relationship between the two services, otherwise, we considered that there was a trade-off between the two. Based on this, we constructed a binary data layer characterizing the relationships between ESs as the dependent variable, that is, a value of 1 represents synergy and a value 0 represents a trade-off.

Next, potential influencing factors were selected as independent variables in relation to three aspects: climate, vegetation restoration, and urbanization. Among these, the influence of climate was represented by the factors annual average precipitation (PRE), annual average temperature (TEM), and annual average solar radiation (SR); vegetation restoration was represented by vegetation cover (VEG). When selecting the influencing factors to represent urbanization, we referred to previous studies (Peng et al., 2017), and selected population density (POP), construction land percentage (CLP) and gross domestic product per unit area (GDPP), representing three aspects — population urbanization, land urbanization and economic urbanization. Since the relationships between ESs were calculated based on the changes in the ESs from 2000 to 2015, we also used the changes in each potential influencing factor from 2000 to 2015 as potential independent variables.

Finally, we used the GWR model to explore the spatial nonstationary correlations between dependent variables and independent variables. Specifically, we explored these correlations by taking county administrative scale as an example. The reason why we chose this scale for the research was that the spatial planning of ESs often depends on administrative divisions, and the county administrative scale is the basic scale of ecological management decision-making in China, which has significant implications for policy formulation and implementation. The GWR model was constructed with ArcGIS Pro software, using the Geographic Weighted Regression instrument with the binary option.

## 4. Results

### 4.1. Relationships between ESs

The Pearson's correlation coefficients of different ESs across different scales are presented in Fig. 2 for 2000 and 2015. As the scale changed, with the exception of the reversal in the trade-off/synergy relationship between GP and SC, all other pairs of ESs exhibited synergistic relationships.

Specifically, WY was significantly positively correlated with NPP, SC, and GP, as well as NPP with SC, and GP across all of the seven scales in 2000 and 2015. Among these pairs of ESs, WY and NPP, WY and SC, WY and GP, as well as NPP and SC exhibited a trend of increasing synergies as the scale of observation increased, whether grid or administrative division, in 2000 and 2015. The relationship between NPP and GP exhibited different directions of change with changes in scale: the synergistic effect as the grid scale increased exhibited a "U"-shaped trend, first decreasing and then increasing, with the weakest relationship at the 10 km grid scale. At the administrative scale, the synergistic relationship between NPP and GP was stronger at the municipality level than at the county scale in both 2000 and 2015. Although most pairs of ESs showed consistent relationships across scales, different relationships were found between SC and GP at the seven scales. For example, the interaction between SC and GP showed a synergistic relationship at the 1 km grid scale, but mainly exhibited a trade-off relationship at other grid scales and administrative division scales during the study period. In addition, we found that the intensity of the trade-off was gradually weakened as the scale of observation increased, and there were even signs of it developing into a synergistic relationship in the administrative division scales. It is worth noting that almost all ESs had the strongest synergy or the weakest trade-off effect at the municipality level scale in both 2000 and 2015.

### 4.2. Factors influencing the relationships between ESs

#### 4.2.1. Model diagnosis

Before performing geographically weighted regression, we tested the multicollinearity of the selected seven factors (i.e. PRE, TEM, SR, VEG, POP, CLP, and GDPP). We used a variance inflation factor (VIF) for diagnosis, which is the most commonly used measure of

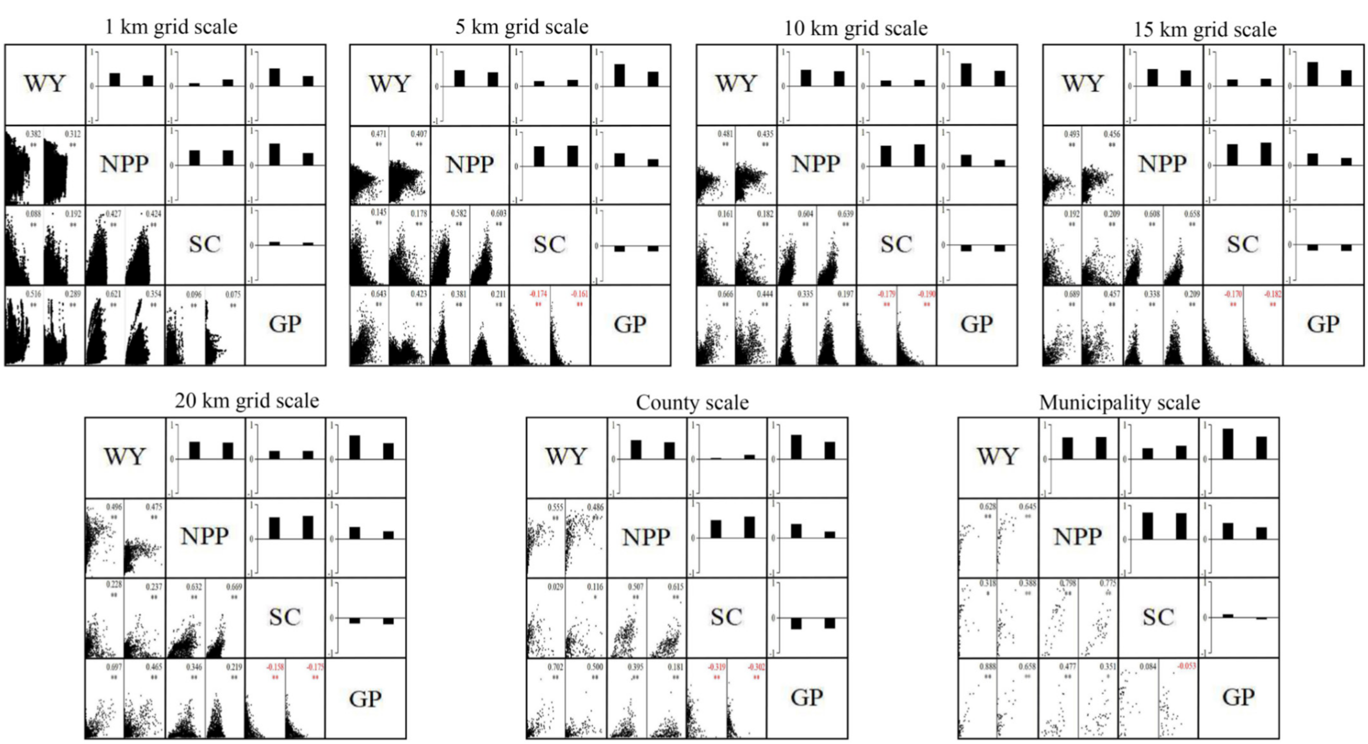


**Fig. 2.** Correlation coefficients between pairs of ESs and data points across the seven scales for 2000 and 2015. Positive correlations are in black, and negative correlations are in red. Bar charts in the upper right half of the figure show Pearson correlation coefficients corresponding to the coefficient values in the lower left half. The columns and bars on the left side of each smallest box are for 2000 and those on the right side of each smallest box are for 2015. The significance level is indicated by asterisks below each correlation coefficient (Pearson correlation, * indicates $p < 0.05$; ** indicates $p < 0.01$).

**Table 1**
Results of variance inflation factor.

| Variable | PRE | TEM | SR | VEG | POP | CLP | GDPP |
|---|---|---|---|---|---|---|---|
| VIF | 1.255 | 1.133 | 1.186 | 1.183 | 4.542 | 2.191 | 3.478 |

VIF: variance inflation factor; PRE: annual average precipitation changes from 2000 to 2015; TEM: annual average temperature changes from 2000 to 2015; SR: annual average solar radiation changes from 2000 to 2015; VEG: vegetation cover changes from 2000 to 2015; POP: population density changes from 2000 to 2015; CLP: construction land percentage changes from 2000 to 2015; GDPP: gross domestic product per unit area changes from 2000 to 2015.

multicollinearity. The VIF value of the regression variable should not be greater than 7.5 (VIF ≤ 7.5) to ensure that there is no multicollinearity and there are no redundant independent variables in the regression model (Sheng et al., 2017). Our results are shown in Table 1. The VIF value of all seven factors was less than 7.5, indicating that there was no multicollinearity among them.

The GWR model was used to explore the spatial correlations between the trade-offs/synergies between ESs and the seven factors. We first analyzed the standard residual of the geographically weighted regression, and the result is shown in Fig. S2 (Supplementary material).

**Table 2**
Parameters of the model diagnostic comparing GWR and OLS.

| Relationships between each pair of ESs | AIC | | Adjusted $R^2$ | | Moran's I | |
|---|---|---|---|---|---|---|
| | $AIC_O$ | $AIC_G$ | $R^2_O$ | $R^2_G$ | $Moran_O$ | $Moran_G$ |
| WY-NPP | 281.342 | 241.198 | 0.355 | 0.651 | 0.313 | 0.177 |
| WY-SC | 323.237 | 173.500 | 0.270 | 0.816 | 0.593 | 0.282 |
| WY-GP | 342.194 | 333.749 | 0.452 | 0.586 | 0.140 | 0.060 |
| NPP-SC | 213.054 | 178.469 | 0.366 | 0.635 | 0.199 | 0.079 |
| NPP-GP | 316.114 | 313.017 | 0.263 | 0.482 | 0.039 | 0.022 |
| SC-GP | 309.121 | 303.611 | 0.512 | 0.614 | 0.154 | 0.120 |

WY: water yield; NPP: net primary production; SC: soil conservation; GP: grain production; WY-NPP: relationships between WY and NPP; WY-SC: relationships between WY and SC; WY-GP: relationships between WY and GP; NPP-SC: relationships between NPP and SC; NPP-GP: relationships between NPP and GP; SC-GP: relationships between SC and GP; $AIC_O$: AIC value for OLS; $AIC_G$: AIC value for GWR; $R^2_O$: $R^2$ value for OLS; $R^2_G$: $R^2$ value for GWR; $Moran_O$: Moran's I value for OLS; $Moran_G$: Moran's I value for GWR.

Generally speaking, in areas where the standard residual are not between −2.5 and 2.5, the credibility of the coefficient estimates in these areas needs to be questioned, and there may be problems in these areas (Martínez-Harms et al., 2016; Tenerelli et al., 2016; Sheng et al., 2017; Zhang et al., 2020). We found that counties with a standard residual value between −2.5 and 2.5 account for almost the whole of the study area, which indicates that the relationships between each of the seven factors and the six pairs of relationships are robust, and the results calculated by the GWR model are convincing across almost the whole of the study area.

In addition, we also compared the performance of the GWR and OLS in terms of predictive ability and ability to solve spatial autocorrelation problems, as shown in Table 2. AIC and adjusted $R^2$ have been widely used to describe the predictive ability of models (Su et al., 2014). Higher adjusted $R^2$ values represent better explained variances, and a lower AIC value represents a situation that is closer to reality. Moran's I is calculated to quantify the spatial autocorrelation of model residuals for GWR and OLS. If it is found that significant spatial autocorrelation exists in the model residuals, the assumptions for using OLS are violated and its validity is questionable. As seen in Table 2, the AIC for the GWR was lower than for OLS, and the adjusted $R^2$ for GWR was higher than that for OLS. These results indicate that GWR has a stronger explanatory ability. Moran's I for the OLS model residuals was significantly higher than for the GWR, which also indicated that GWR was better at solving spatial autocorrelation problems. Therefore, in our study, the GWR model was found to be stable and reliable, and was superior to global regression in explaining the correlation between the studied relationships and influencing factors.

#### 4.2.2. Estimates generated by the GWR model

The results of the GWR model indicated that the regression coefficients in different regions had different values. The local coefficients for PRE, TEM, SR, VEG, POP, CLP, and GDPP varied between counties on the LP, which fully reflected the obvious spatial heterogeneity in the trade-off and synergy between ESs within the LP. The spatially non-stationary response of the trade-offs/synergies to influencing factors from the GWR model was plotted by the regression coefficients of each factor (Figs. 3–9). A positive regression coefficient indicates that an increase in the influencing factors will increase the possibility of

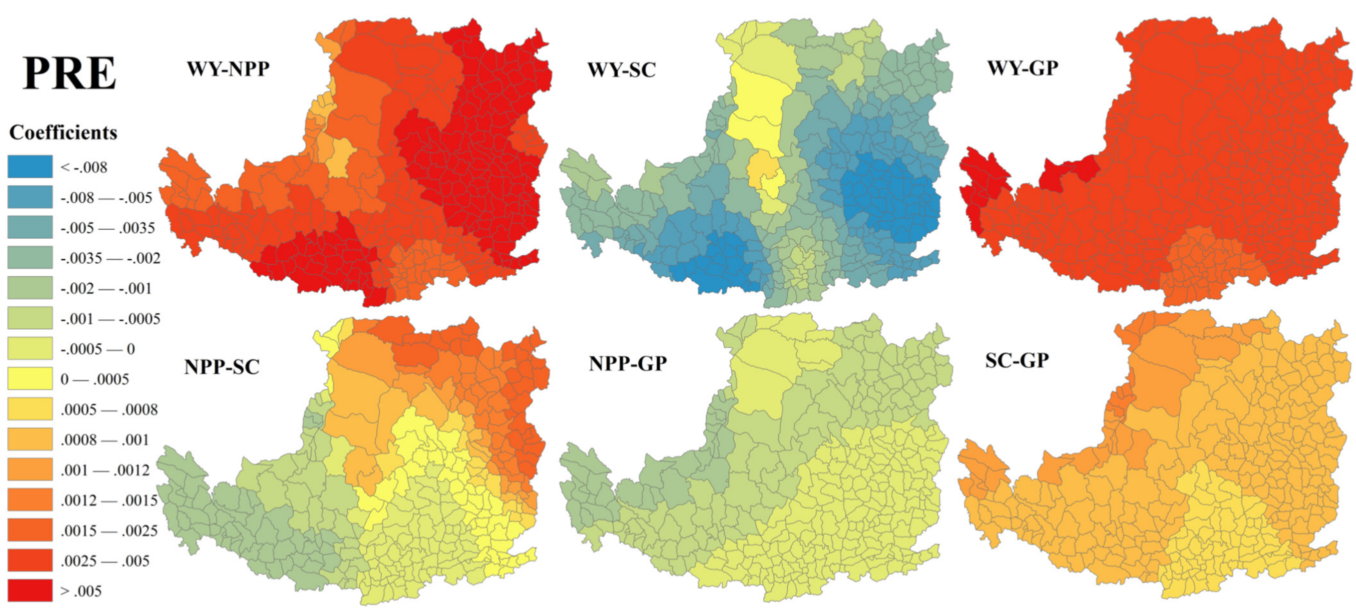


**Fig. 3.** Spatial variability of regression coefficients in the geographically weighted regression between PRE and ES relationships (PRE: annual average precipitation changes from 2000 to 2015; WY: water yield; NPP: net primary production; SC: soil conservation; GP: grain production; WY-NPP: relationships between WY and NPP; WY-SC: relationships between WY and SC; WY-GP: relationships between WY and GP; NPP-SC: relationships between NPP and SC; NPP-GP: relationships between NPP and GP; SC-GP: relationships between SC and GP).

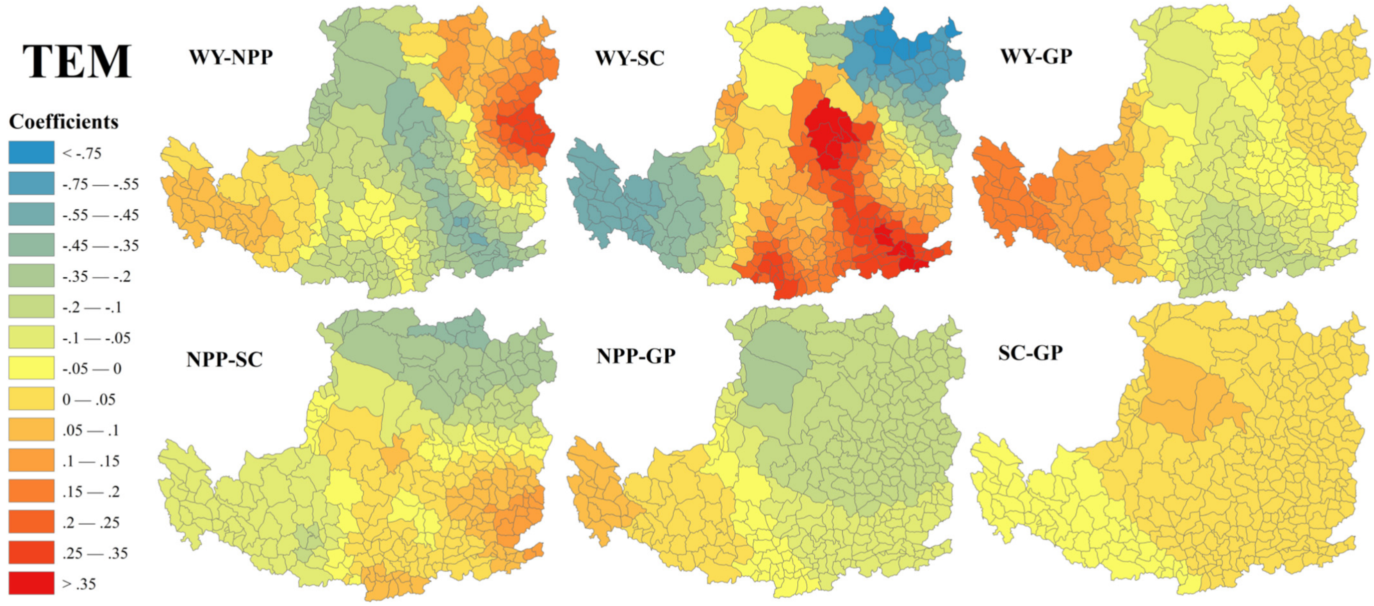


**Fig. 4.** Spatial variability of regression coefficients in the geographically weighted regression between TEM and ES relationships (TEM: annual average temperature changes from 2000 to 2015).

synergistic relationships between ESs, while a negative regression coefficient indicates that an increase in the influencing factors will decrease the possibility of synergetic relationships. As seen in Figs. 3–9, of the seven influencing factors we selected, VEG, TRM and CLP were more correlated than the other four influencing factors with the relationships between ESs.

## 5. Discussion

### 5.1. Scale effect of trade-offs and synergies

Previous studies have also confirmed that the relationships between ESs on the LP may change with spatial scales, especially after the implementation of the GFGP (Hou et al., 2017). However, existing studies tend to cover particular areas of the LP, such as sub-watersheds (Su et al., 2020), towns (Hou et al., 2017) and counties (He et al., 2020). It is not appropriate simply to extrapolate existing knowledge of the local-scale to larger scales, as the functioning of the whole landscape is very unlikely to be equivalent to the sum of the small-scale functioning (Brandt, 2003; Mitchell et al., 2014). Therefore, we used the entire LP region to simulate the scale effect characteristics of ESs rather than simply considering a small watershed or a particular administrative region, allowing us to provide more accurate information on ecosystem service management for decision-makers at different scales across the LP.

We found that most relationships between ESs were robust at all scales in 2000 and 2015. For example, for all grid scales and the administrative division scales, of the six pairs of relationships between the four

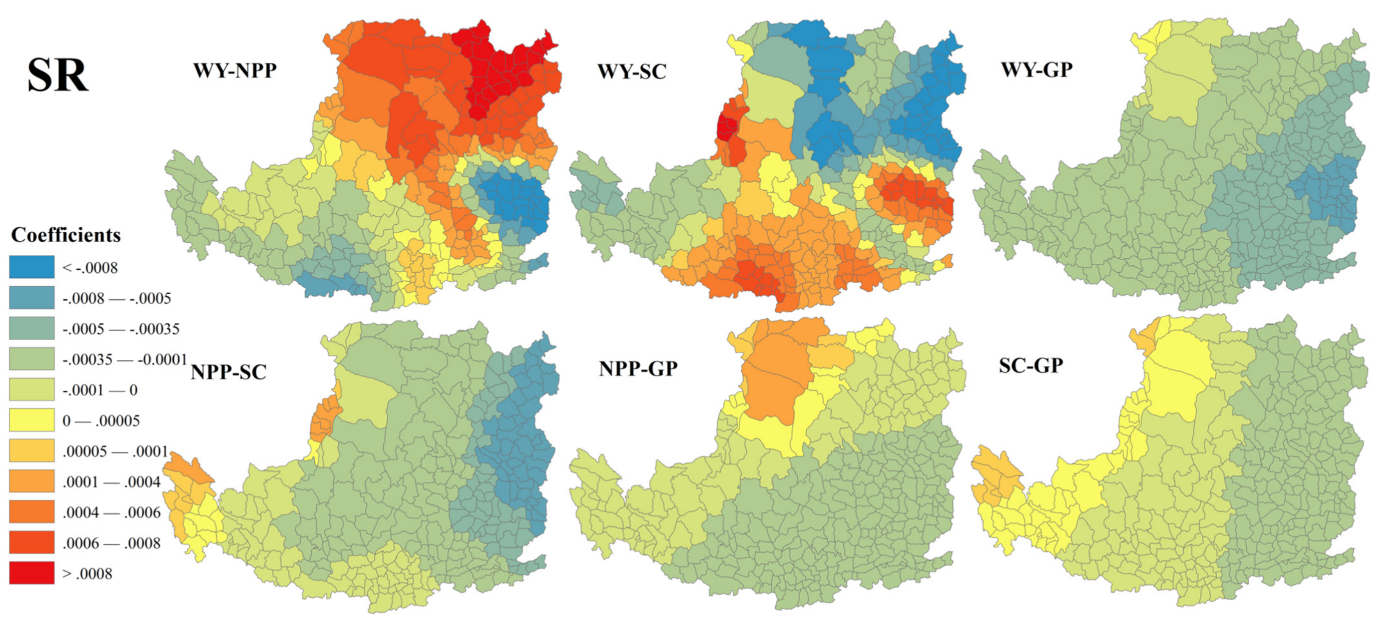


**Fig. 5.** Spatial variability of regression coefficients in the geographically weighted regression between SR and ES relationships (SR: annual average solar radiation changes from 2000 to 2015).

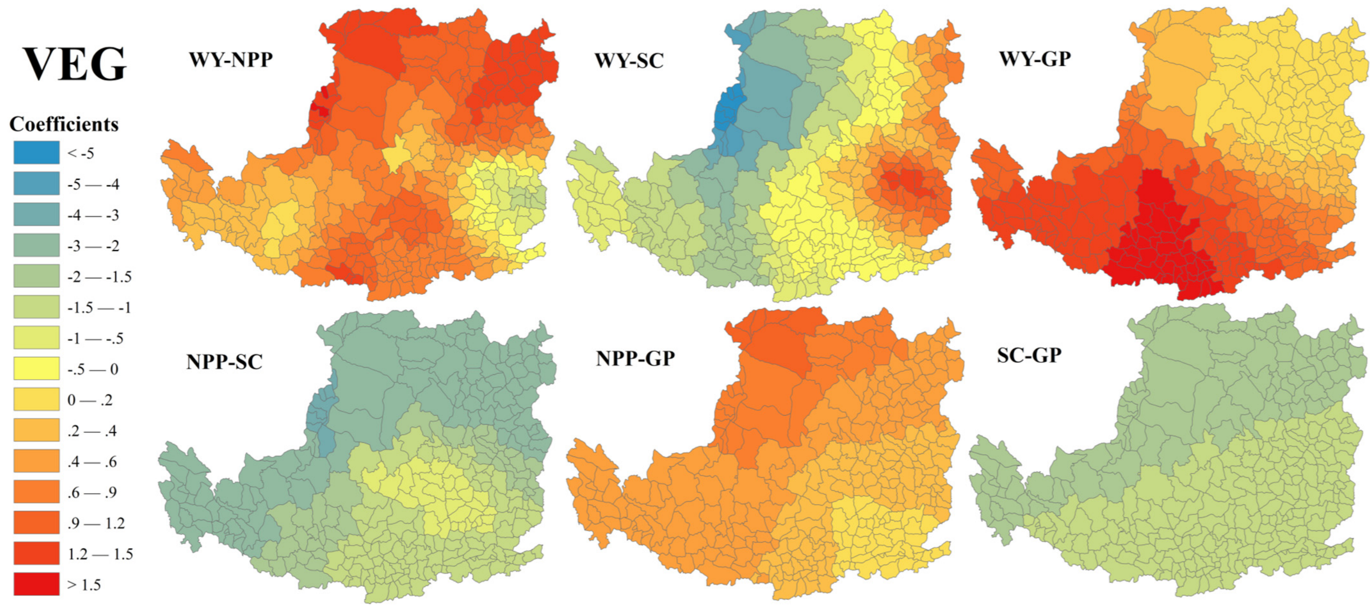


**Fig. 6.** Spatial variability of regression coefficients in the geographically weighted regression between VEG and ES relationships (VEG: vegetation cover changes from 2000 to 2015).

ESs, five pairs remained unchanged (Fig. 2). These findings are consistent with the research of Xu et al. (2017), which attributed this phenomenon to land use consistency, that is, a certain type of land use can be beneficial to two or more ESs simultaneously. Although most of the relationships between multiple ESs on the LP are synergistic and significant at all scales, there are still some differences between our results and other studies examining the LP. For example, the research of Su and Fu (2013) found a trade-off between WY and SC, which is the opposite of our results. One possible reason is the influence of scale. Su and Fu (2013) quantified the trade-off relationship between WY and SC based on 96 sub-watersheds of the LP, rather than the scale we counted. In terms of other pairs of synergistic relationships between ESs, our results coincide with Jiang et al. (2016) and Liu et al. (2018). In addition, we found that the correlations between ES synergies on the LP are enhanced as the scale increases, for example with the synergies between WY and the other three ESs. This may be because the process of scale synthesis from small to large scale is similar to the process of peak cutting and valley filling, in which high values are “cut” and low values are “filled”, leading to a gradual tendency towards a compromise one as the scale increases (Xu et al., 2017). Thus, the range of changes between ESs will be more synchronized, and synergy will be more significant. Another interesting phenomenon we found was that as the scale of observation changed, the synergy and trade-off relationships between certain ESs became inconsistent. For example, SC and GP show a synergistic relationship at the 1 km grid scale, but this disappeared at other scales and generally there was a trade-off relationship. This means that decision-makers working at different scales need to adopt a multi-scale approach when managing ecosystems, based on the interrelationships between ESs. This is also similar to the results of Pan et al. (2020), who studied the arid area of northwestern China, and found that the relationship between SC and GP changed from a synergy to a trade-off as the scale increased.

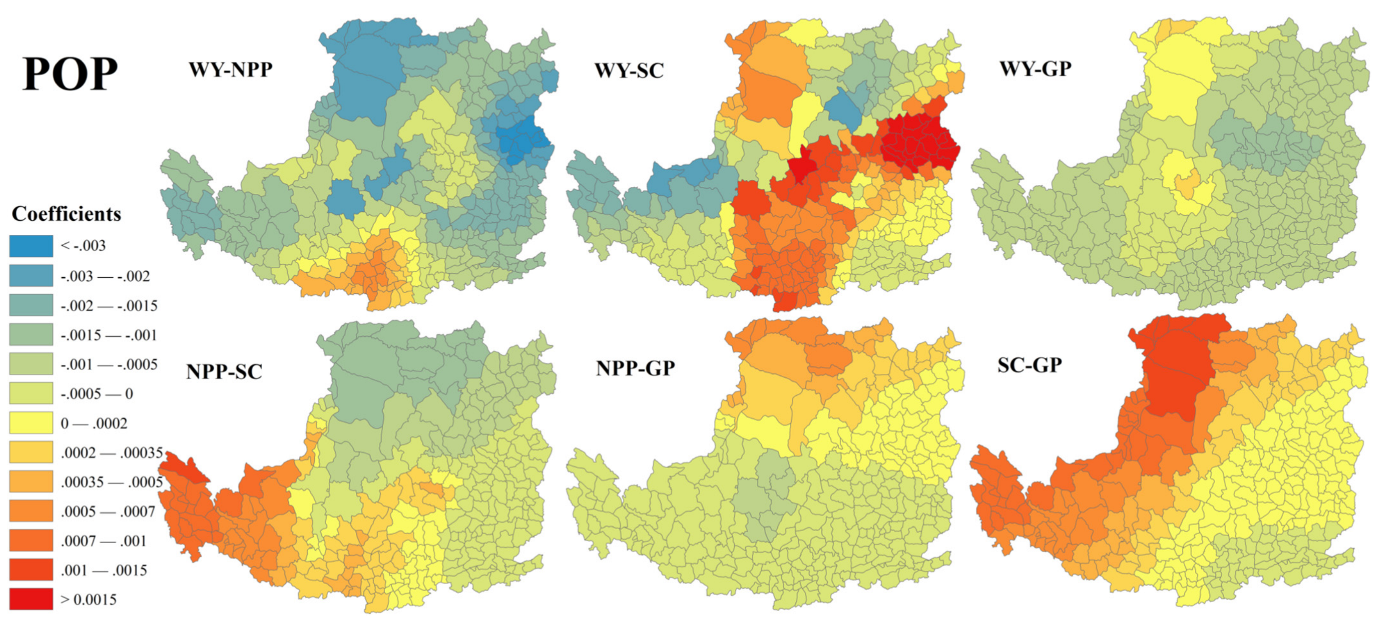


**Fig. 7.** Spatial variability of regression coefficients in the geographically weighted regression between POP and ES relationships (POP: population density changes from 2000 to 2015).

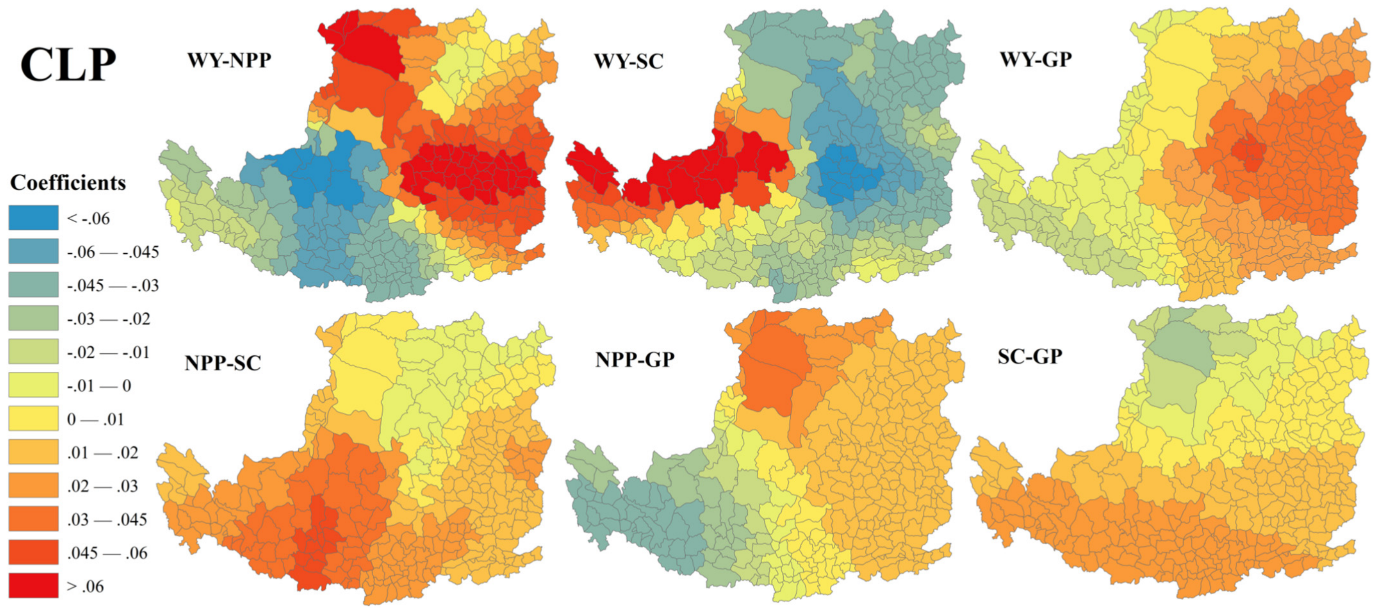


**Fig. 8.** Spatial variability of regression coefficients in the geographically weighted regression between CLP and ES relationships (CLP: construction land percentage changes from 2000 to 2015).

It is also worth noting that almost all the relationships between ESs are good for decision-makers at the municipality scale, that is, either the ESs had the strongest synergy or the weakest trade-off. However, this is not always true at other scales. For example, the trade-off effect between SC and GP was greatest at the county scale, and the synergy between NPP and GP was weakest at the 10 km grid scale. This finding indicates that the municipality scale on the LP is the most appropriate and easiest at which to manage ESs. At the same time, it also demonstrates the value of examining different scales to analyze the relationships between ESs, illustrating that multilevel analysis is a means of combining the advantages of both fine scale and coarse scale modeling without losing detail, as in Cui et al.'s (2019) work.

### *5.2. Implications of spatial non-stationary responses*

Our research revealed that the relationships between ESs were closely correlated with climate factors (PRE, TEM, and SR), vegetation restoration factors (VEG), and urbanization factors (POP, CLP, and GDPP), and the properties and intensity of the correlations also showed obvious spatial heterogeneity, highlighting that decision-makers designing interventions that could enhance synergistic effects may cause the opposite effect in other regions. Among all the influencing factors, VEG, TEM, and CLP were more correlated with the relationships between ESs than the other factors, which is similar to the result of Zhang et al. (2020), although their research did not consider the impact of vegetation.

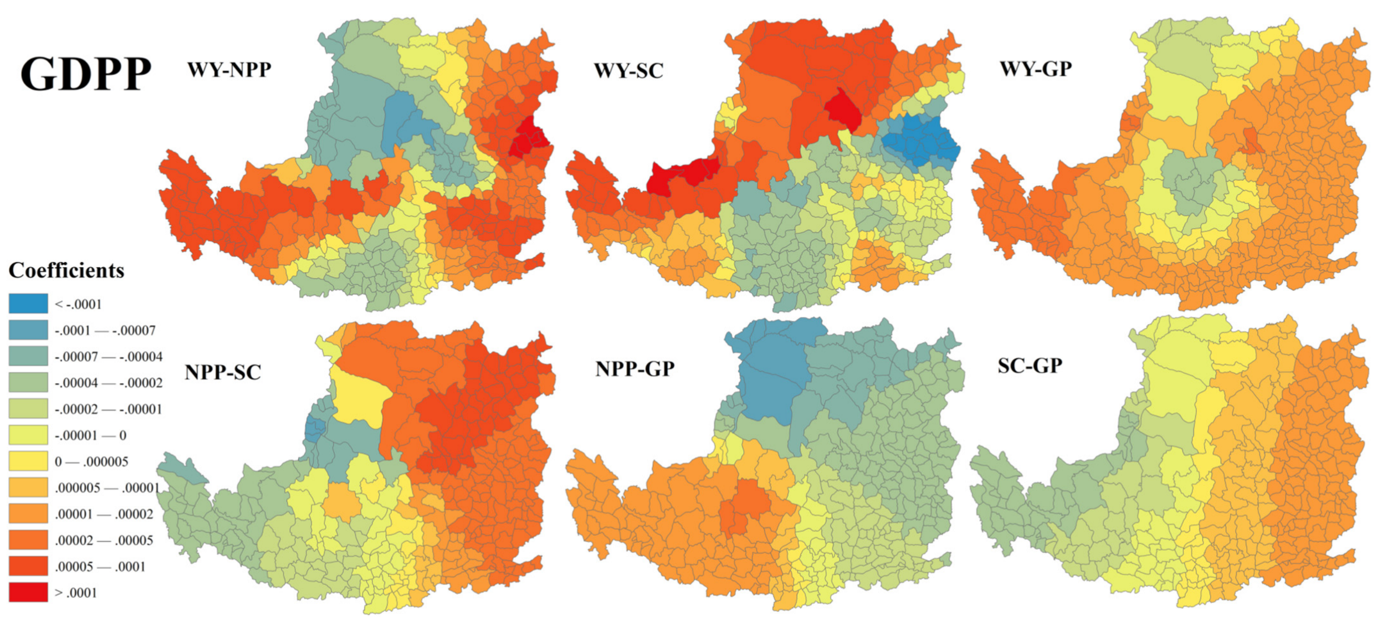


**Fig. 9.** Spatial variability of regression coefficients in the geographically weighted regression between GDPP and ES relationships (GDPP: gross domestic product per unit area changes from 2000 to 2015).

In our work, we selected the change in vegetation cover as a proxy for vegetation restoration activities on the LP, and found that vegetation cover had the greatest correlation with the relationships between ESs (Fig. 6). The relationships between WY and NPP, WY and GP, as well as NPP and GP were mainly positively correlated with vegetation restoration, but the intensity of the correlations was different spatially (Fig. 6). Generally speaking, vegetation restoration will increase NPP and decrease WY and GP (Liu et al., 2018; Chen et al., 2015), but we found that NPP has synergistic relationships with WY and GP (Fig. 2), and these relationships are enhanced as vegetation cover increases (Fig. 6). The possible reason for this phenomenon is that there are complex interactions between the ESs, and the common driving forces (such as GFGP) between them (Bennett et al., 2009). We also found that an increase in vegetation cover may reduce the possibility of there being a synergistic relationship between SC and the other three ESs, which may be due to enhanced soil retention as vegetation cover increases, resulting in a reduction in potential soil loss and a consequent decrease in actual soil retention (Liu et al., 2018).

Generally, different combinations of precipitation, temperature, and solar radiation have different effects on ESs in different regions and systems (Porter and Semenov, 2005). Our results show that the response of the relationship between ESs to each single climate factor had obvious regional differences in direction and degree (Figs. 3–5). However, the response of each ecosystem service to climatic factors is not a simple, isolated, linear one, but a combined response to a comprehensive group of conditions including multiple climatic factors, regional land use types and vegetation types (Zhang et al., 2020). Therefore, it is difficult to explain the mechanism underlying the relationship between two services in relation to a single climatic factor. However, through our results, decision-makers can begin to understand the spatial distribution of each response, and then control the relevant factors in order to increase the possibility of synergy between ESs. For example, among all the climatic factors, we found that temperature has the greatest correlation with the relationships between ESs, and exhibited a negative correlation in most parts of the study area (Fig. 4), suggesting that decision-makers should attempt to reduce temperature to improve the relationship between ESs. A previous study found that increasing clustered vegetation can effectively regulate the surface temperature (Estoque et al., 2016). In addition, urban design and structure (such as the size, shape and orientation of buildings) can also affect surface temperature by influencing wind flow (Rajagopalan et al., 2014). Therefore, dense low-rise buildings could be replaced by low-density and high open-sky view buildings (Yuan and Chen, 2011). Of course, in the regions where the relationships between ESs have a positive response to rainfall (Fig. 3) or a negative response to solar radiation (Fig. 5), planners could aim to increase forest canopy density to create shade in order to reduce water evaporation and solar radiation.

At present, the impact of urbanization on ESs is not clear on the LP. Our work has revealed that the effects of urbanization factors on the relationships between different ESs are spatially heterogeneous (Figs. 7–9), including the direction and intensity of the effect. This is consistent with Zhang et al.'s (2020) findings in Fujian Province of China. To some extent, this shows that the impact of urbanization on ecosystems is not consistent in different places. We found that CLP has a stronger correlation with the relationship between ESs than POP and GDPP among the urbanization factors. This may be related to the threshold of the response of ESs to POP and GDPP. Peng et al.'s (2017) research also supports this view. They found that there is no threshold for the impact of construction land expansion on ESs, but there are thresholds for population aggregation and economic growth with respect to driving ESs, and the impacts lag behind the impact of construction land change. Our results showed that the various urbanization factors will increase the likelihood of synergy between ESs in some regions. The possible reason is that, with the expansion of cities, construction land increasingly occupies ecological land, including cultivated land, woodland, grassland and water bodies (Peng et al., 2016), leading to the gap between the area of land types supporting various services to shrink, increasing the likelihood of synergy between ESs. However, this does not mean that urbanization is beneficial to the ecological environment. On the contrary, various studies have shown that the process of urbanization has increased pressure on natural ecosystems, having a negative impact on various ESs (Li et al., 2016; Peng et al., 2016; Peng et al., 2017). Therefore, by understanding the regional differences in the response of ESs to urbanization, decision-makers can consider controlling certain factors (such as population increase or construction land expansion) in areas with negative correlations in order to reduce trade-offs and increase synergies, thus alleviating the pressure of urbanization on the ecosystem to some extent.

### 5.3. Limitations

There are some limitations to our study. First, we analyzed the trade-offs/synergies between ESs based on correlation analysis, which assumes a linear relationship between ESs to some extent. Previous studies have found that there is a threshold for changes in the relationship between ESs (Jiang et al., 2018). Therefore, multiple regression or constraint line methods should be used to address the possible nonlinear relationship in subsequent research. Second, when performing GWR, we used the difference comparison method to spatialize the relationships between ESs, and the results obtained by this method are binary. Although local regression calculation can be supported to subsequently determine the spatial correlation between such relationships and the influencing factors, it cannot be determined the strength as continuous numerical results, further work is needed to determine spatial patterns with respect to the strength of interactions between ESs. Finally, we only determined the spatial non-stationary response relationships between trade-offs/synergies and influencing factors at the administrative division scale. Although this is convenient for the formulation and implementation of ecological management, the response relationships at different scales are likely to be different (Su et al., 2020). Therefore, we lack analysis of such response relationships at other scales. This was mainly due to the lack of statistical data at the grid cell scale. However, the scale effect of the response relationships could be studied if there was more research aimed at transforming the statistical data from the administrative division scale to the grid cell scale.

## 6. Conclusions

Most relationships between ESs were synergistic and robust across all scales, and there was a trend that most of the correlations between ESs were enhanced as the scale increased. We attribute this trend to the effects of "peak cutting" and "valley filling" in the process of scale synthesis, which led to a gradual tendency towards a compromise one as the scale increased, making the synergy appear more significant. It is worth mentioning that almost all the relationships between ESs had the strongest synergies or the weakest trade-offs at the municipality scale, demonstrating that it is most appropriate and easiest to manage ESs at the municipality scale on the LP. The relationships between ESs were robustly correlated to climatic factors, vegetation restoration factors, and urbanization factors, and the properties and intensity of the correlations varied spatially. Among these influencing factors, VEG, TEM, and CLP were most highly correlated with the relationships between ESs.

The study contributes to extending our understanding of the way in which interactions between ESs depend on spatial scale, and the results also demonstrate that decision-makers must be aware of scale effect on the relationships between ESs when managing them. Such awareness may help minimize the uncertainty associated with decision-making which affects trade-offs and synergies. At the same time, by determining the spatial non-stationary correlations between ES relationships and influencing factors, decision-makers can control the latter according to local conditions in order to manage the local ecology. This will enhance the output capacity of multiple local services and improve the sustainability of development.

## CRediT authorship contribution statement

**Menghao Yang:** Conceptualization, Methodology, Investigation, Formal analysis, Data curation, Validation, Writing – original draft. **Xiaodong Gao:** Conceptualization, Methodology, Investigation, Formal analysis, Validation, Writing – review & editing. **Xining Zhao:** Resources, Funding acquisition, Supervision, Project administration, Validation, Writing – review & editing. **Pute Wu:** Resources, Funding acquisition, Supervision, Project administration, Validation, Writing – review & editing.

## Declaration of competing interest

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

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## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2021.147389.

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