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Research article

The dynamic relationships between landscape structure and ecosystem services: An empirical analysis from the Wuhan metropolitan area, China

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ABSTRACT

Environmental managers have been striving to optimize landscape structure to achieve a sustained supply of ecosystem services (ESs). However, we still lack a full understanding of the relationships between landscape structure and ESs due to the absence of thorough investigations on the variability of these relationships in space and time. To fill this critical gap, we assessed landscape structure alongside four important ESs (agricultural production (AP), carbon sequestration (CS), soil conservation (SC), and water retention (WR)) in the Wuhan metropolitan area (WMA), and then analyzed the spatiotemporal impacts of landscape structure on ESs from 2000 to 2020 using Geographically and Temporally Weighted Regression. The results show only AP maintained a stable growth trend over the past two decades, while the other ESs fluctuated considerably with a noticeable decline in SC and WR. The importance of landscape structure in influencing ESs varies by time and place, depending on the local landscape composition and configuration. In general, landscape composition has a stronger and less temporally stable impact on ESs compared to configuration. Furthermore, increases in landscape diversity, as measured through Shannon's diversity index, and the percentage of woodlands were found to contribute to the simultaneous benefits of multiple ESs, but in most cases the effects of landscape structure on different ESs were different or even opposite, suggesting that trade-offs are critical in landscape management. The findings highlight the complex response of ESs to dramatically changing landscapes in the WMA and can guide decision-makers in precise spatial arrangement and temporal adjustments to improve current landscape management.

1. Introduction

Ecosystem services (ESs) refer to the multiple benefits people obtain from ecosystems and are seen as the basis for human survival and development (Costanza et al., 1997; Daily, 1997; Gong et al., 2021; MEA, 2005; Torres et al., 2021). Humans have long been accelerating resource exploitation and land development to meet the needs of a growing population (Davisa et al., 2016; Kremen and Merenlender, 2018; Verhagen et al., 2016). These actions have driven dramatic landscape changes and caused numerous adverse ecological consequences, such as habitat fragmentation, soil erosion, and water pollution, among others (Abera et al., 2021; Estoque and Murayama, 2016; IPBES, 2019). Fortunately, a global movement to prevent the degradation of ecosystems is emerging and has inspired a great deal of exploratory research. As a discipline concerned with heterogeneous landscape change and how it affects ecosystem function, landscape ecology works to reconcile the dynamic relationship between humans and nature (Forman, 1995; Karimi et al., 2021). It asserts any landscape can be managed to optimize specific ecological functions as well as the supply and delivery of ESs (Forman, 1995; Lee et al., 2015). As a result, managers often attempt to shape optimal spatial patterns of landscape structure to maintain a sustainable supply of ESs (Haines-Young and Chopping, 1996; Wu, 2021). In this context, studying how landscape structure drives ESs is increasingly seen as a first step toward better landscape management for multiple services (Eigenbrod, 2016; Tran et al., 2021).

Landscape structure is the arrangement of land use and land cover (LULC) across a landscape and is characterized by both the composition

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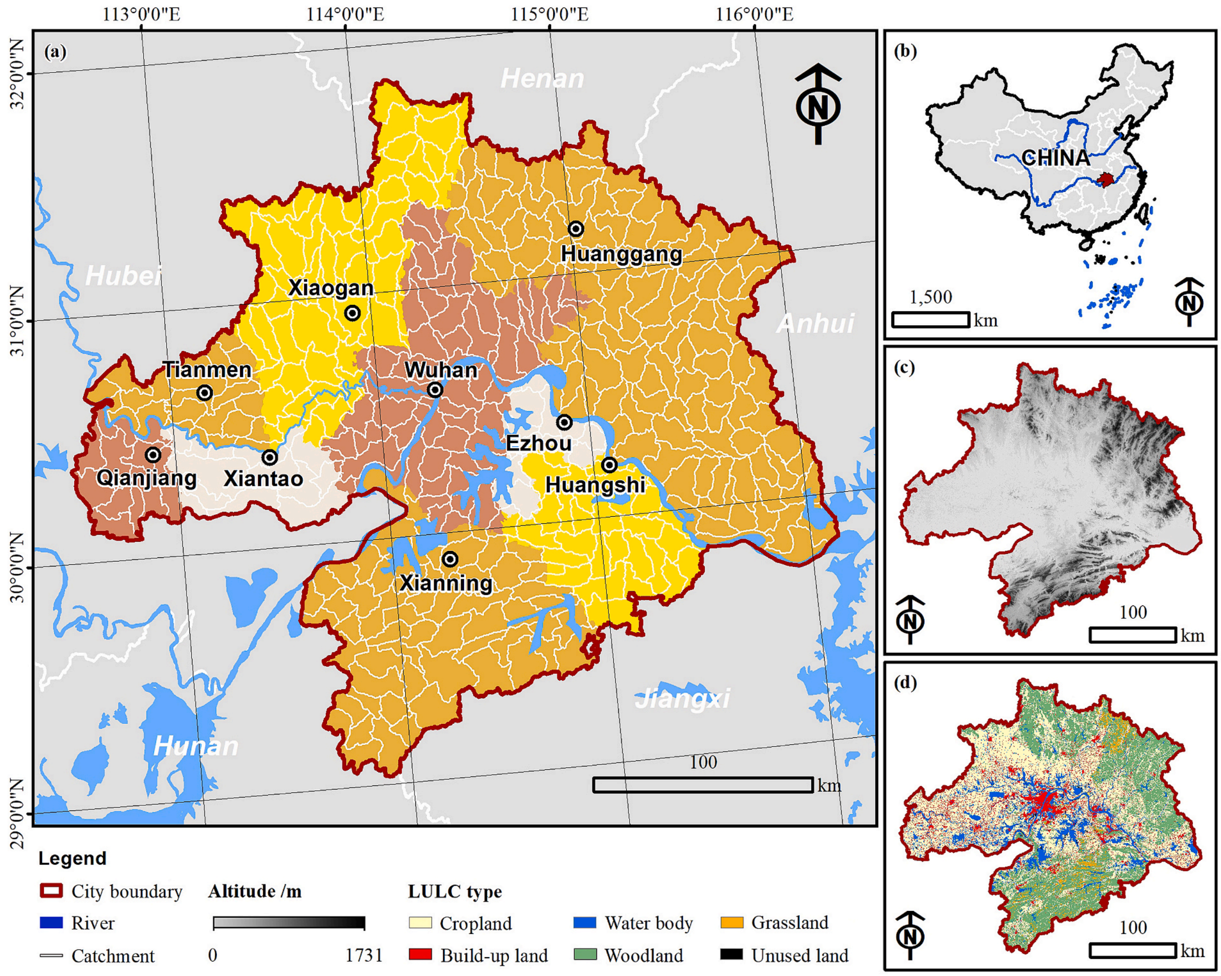

Fig. 1. The administrative districts and catchments of the WMA (a), location of the WMA in China (b), variation in elevation (c), and land use/land cover types in 2020 (d).

(i.e., amount) and configuration (i.e., spatial arrangement) of LULC types (Eigenbrod, 2016; Karimi et al., 2021; Šímová and Gdulová, 2012). Heterogeneous landscapes accommodate the dynamic flows of energy and material and thus control many ecological processes (Chen et al., 2021; Haines-Young and Chopping, 1996; Turner et al., 2001). These processes are often disrupted by landscape structure changes, causing a decline in biodiversity and ecological functions, which in turn leads to a loss of ESs (Hu et al., 2021; Kindu et al., 2016). For example, the decline of mangroves on a global scale caused a loss of about 86 Mt of carbon stock between 2000 and 2012 (Hamilton and Friess, 2018). Thus, landscape structure change is one of the most significant, widespread, and long-lasting drivers of ESs (Estoque and Murayama, 2016; Pan et al., 2021; Sonter et al., 2017; Xu et al., 2020). The first effect that is usually observed is the impact of changes in landscape composition, i.e., increased competition among ESs in the region (Lamy et al., 2016; Yohannes et al., 2021). A common example is deforestation to support growth in agricultural areas, which increases local food production but weakens other services such as timber supply, climate regulation, and water retention. ESs have been also found to be affected by landscape configuration (Kremen and Merenlender, 2018; Xu et al., 2020), and it is generally accepted that higher fragmentation or low connectivity can result in a vulnerable ecosystem and jeopardize the formation of ESs (Guiomar et al., 2015; Zeng et al., 2017). Conversely, proper landscape management can help maintain ESs. For instance, Lee et al. (2015) found that the configuration of paddy rice fields is critical for regulation services including flood mitigation and microclimate regulation. In summary, the importance of landscape structure for different ESs has been disclosed by numerous studies and has become a key reference for landscape management (Duarte et al., 2018; Verhagen et al., 2016).

Researchers have characterized landscape structure (often using landscape metrics) based on LULC derived from remote sensing and assessed the physical or economic value of ESs (Chen et al., 2021; Petroni et al., 2022; Redhead et al., 2020; Zhang et al., 2020). Regression models or spatial analysis are then used to detect the relationship between landscape structure and ESs (Lamy et al., 2016; Yohannes et al., 2021; Yuan et al., 2021). However, most prior studies assume that the relationship is spatiotemporally stationary (Chen et al., 2021; Tran et al., 2021). Few studies provide insight into how the effects of landscape structure on ESs vary in time and space. This is an important limitation for environmental management, resulting in the inability to know when and where a plan should be implemented (Wu, 2021). To fill this critical gap, local regression models can provide an alternative (Lyu et al., 2022; Nassauer, 1995; Wu et al., 2018). A recent study in New Zealand addressed the spatial stationarity limitation by using spatial local regression models to support local, spatially differentiated landscape management (Tran et al., 2021). When temporal nonstationarity must also be considered, geographically temporally weighted regression (GTWR) can offer a solution by establishing spatiotemporal weights (Guo et al., 2017; Huang et al., 2010; Ma et al., 2018). This work introduces GTWR to study the dynamic relationship between landscape structure and ecosystem services.

The Wuhan metropolitan area (WMA) is located in the geographical center of China and consists of nine major cities, where hundreds of mountains and numerous rivers and lakes form a particularly distinctive

Table 1
Details and sources for the datasets used in this study.

Data	Detail	Source
Administrative boundaries	Shapefile, polygon	Data Center for Resources and Environmental Sciences, Chinese Academy of Sciences (http://www.resdc.cn)
Digital elevation model (DEM)	Rater, 30 m	
LULC data	Rater, 30 m	
Catchment boundaries	Shapefile, polygon	HydroSHEDS dataset (https://hydrosheds.org)
Meteorological data	Shapefile, point	China Meteorological Data Service Centre (http://data.cma.cn)
Net primary productivity (NPP)	Rater, 500 m	US National Aeronautics and Space Administration (http://modis.gsfc.nasa.gov)
Normalized difference vegetation index (NDVI)	Rater, 1 km	Geospatial Data Cloud (http://www.gscloud.en/); US Geological Survey (USGS) (https://www.usgs.gov)
Socioeconomic data	Text, county level	Statistical Yearbook of Hubei province and cities in the WMA
Soil data	Rater, 1 km	Harmonized World Soil Database (HWSD) version 1.21, International Institute for Applied Systems Analysis (IIASA), https://iiasa.ac.at/

and complex ecosystem (Chen et al., 2021; Zeng et al., 2015). Rapid urban expansion in recent years has driven drastic changes in the spatial structure and landscape characteristics in the WMA, increasing the risk of ecological resource losses and degradation of ecosystem functioning (Wen et al., 2021). The primary aim of this study is to detect how landscape structure dynamically affects ESs across time and space based on the spatiotemporal heterogeneity of drivers. To that end, we first assess four typical ESs (i.e., agricultural production, carbon sequestration, soil conservation, and water retention) alongside the landscape composition and configuration characteristics of 336 hydrological catchments in the WMA. GTWR is then applied to analyze spatiotemporal relationships between landscape structure and ESs during the period 2000–2020. The results of the study can be utilized by managers and planners to improve current landscape management.

2. Materials and methods

2.1. Study site

The WMA is located in the eastern part of Hubei province where the Yangtze and Han rivers merge (Fig. 1). It is a regional economic hub centered on the mega-city of Wuhan and encompassing eight peripheral cities (Ezhou, Huanggang, Huangshi, Qianjiang, Tianmen, Xiaogan, Xiantao, and Xianning). The 58,000 km^2 of land comprises a variety of landforms, including plains, hills, and mountains. The WMA has long been known as the “land of fish and rice”. The rich cropland and wetlands not only provide a large number of agricultural products but also create a unique idyllic landscape, making the WMA a popular tourism destination. Meanwhile, benefiting from the favorable natural conditions and transportation network, the WMA has played a crucial role in China’s modernization. In the last two decades, this region has become one of the fastest growing and largest metropolitan areas in China. Driven by the “Rise of Central China” plan, the population has grown to 32 million, and the GDP is around 2.64 trillion. However, the growth process has not been entirely positive as environmental pollution and ecological degradation have also risen. The continuous expansion of built-up areas has encroached on the surrounding natural and high-quality arable lands, creating habitat fragmentation and a decline in biodiversity. Approximately 15,000 ha of lakes in Wuhan alone have been converted to alternative land uses, which has weakened the regulating function of ecosystems considerably and led to increased natural disasters (Zeng et al., 2015). In Huangshi and Ezhou, more than 10,000 ha of abandoned mining lands have caused serious waste and pollution, threatening the health and well-being of residents. Today, led by the Chinese government, the WMA is making great efforts to build a resource-saving and environment-friendly society. However, it is still a formidable challenge to effectively balance socio-economic development and environmental protection. This particular context provides a

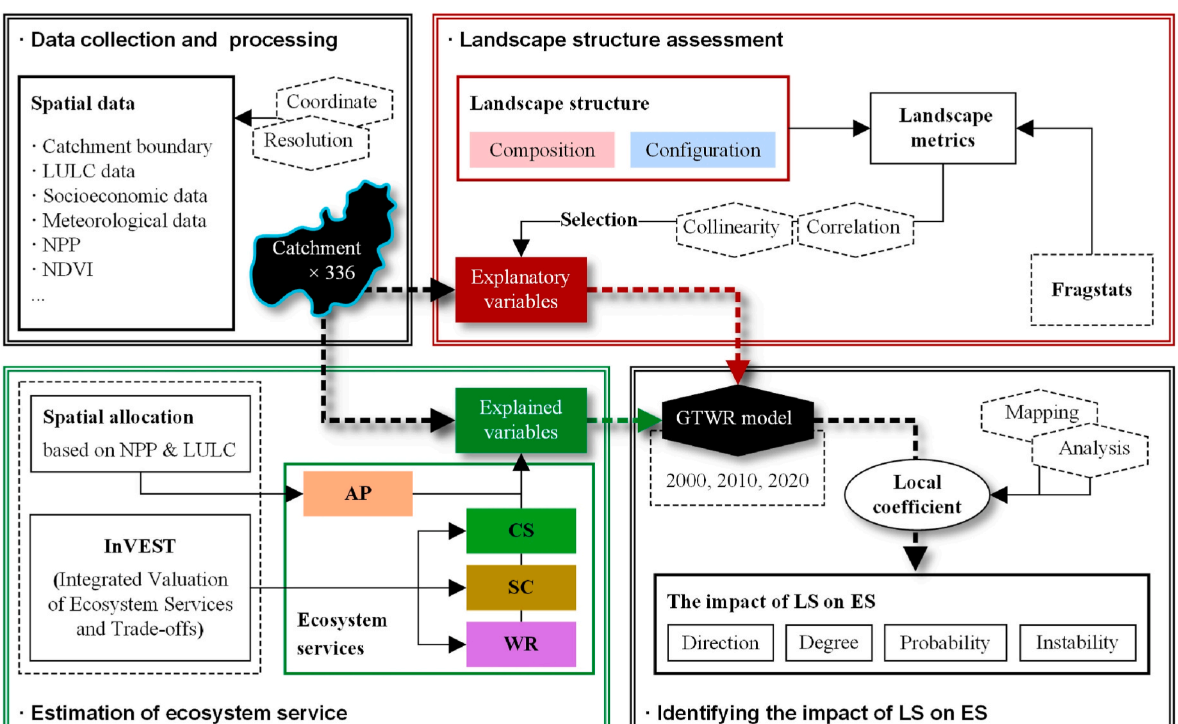

Fig. 2. A flowchart for analyzing the relationship between landscape structure and ESs. Notes: AP—Agricultural production, CS—Carbon sequestration, SC—Soil conservation, and WR—Water retention.

Table 2
Explanation and calculation method for the four ecosystem services.

Ecosystem service	Unit	Model	Required data
Agricultural production	million yuan/ha	Spatial allocation based on LULC and NPP	LULC maps, NPP data, gross agricultural production data, and administrative boundaries
Carbon sequestration	t/ha	InVEST carbon storage and sequestration model	LULC maps, NDVI, and the carbon stock parameters.
Soil conservation	t/ha	InVEST sediment retention model	DEM, LULC maps, meteorological data, NDVI, soil data, and empirical parameters.
Water retention	m^3/ha	InVEST water yield model based on the Budyko curve and water balance principle	DEM, LULC maps, meteorological data, soil data, and empirical parameters.

valuable opportunity to explore the sustainable management of landscapes in urbanized areas, making the WMA well suited for this study.

2.2. Materials

The data used in this study are administrative and catchment boundaries, a digital elevation model (DEM), LULC data, meteorological data, net primary productivity (NPP) data, normalized difference vegetation index (NDVI), economic statistics, and soil data (Table 1). Administrative and catchment boundaries were used as the basic units of analysis and mapping; LULC data (cropland, woodland, grassland, water body, built-up land, and unused land) were used to compute landscape pattern. The remaining datasets are used to assess ESs. Data are for the years 2000, 2010, and 2020 except for the DEM, boundary, and soil, which are invariant. Meteorological monitoring station data were converted into continuously distributed spatial data using kriging interpolation. All spatial data were converted to the same coordinate system and spatial resolution (500m × 500m).

2.3. Methods

This study was conducted following the workflow in Fig. 2. First, 336 hydrological catchment units for mapping and analysis were created based on the HydroSHEDS dataset. Catchments are an appropriate unit because of their association with many ecological processes (Lehner and Grill, 2013; Xu et al., 2020; Zhang et al., 2022). Incomplete catchments located at the edge of the WMA (usually less than 1 km^2 in area) were incorporated into the nearest superior catchment to which they belong. We then assessed the landscape structure characteristics (see section 2.3.1) and ESs (see section 2.3.2) of each catchment in 2000, 2010, and 2020. Finally, local regression models were constructed with landscape structure and ESs as explanatory and explained variables, respectively, and used to analyze the effects of changes in landscape structure on four different ESs (see section 2.3.3).

2.3.1. Quantification of landscape structure

Landscape metrics are important tools for measuring landscape composition and configuration (Duflot et al., 2017; Lausch et al., 2015). In this study, the landscape composition in each catchment was characterized by Shannon's diversity index (SHDI), largest patch index (LPI), percentage of landscape (PLAND), and patch density (PD), while the landscape configuration was characterized by interspersion & juxtaposition index (IJI), edge density (ED), area-weighted mean patch shape index (AWMSI), and aggregation index (AI) (see Appendix A for a detailed description of the metrics). Note that PLAND, PD, AWMSI, and AI computed at the class level were only applied to the three most important LULC types with the largest areas in the WMA: cropland, woodland, and water bodies. Change in built-up land is closely related to the three aforementioned LULC types, while grasslands and unused lands occupy relatively less area in the study region. These metrics were selected to: (1) include a reasonable mix of metrics to comprehensively characterize the spatial structure of the landscape, such as landscape diversity, spatial heterogeneity, and fragmentation (Zhang et al., 2020); (2) include highly recommended and reliable metrics with reference to previous studies (Su et al., 2012); (3) prioritize easily understood and computable landscape metrics to improve understanding and replicability for decision-makers; and (4) use the smallest number of parsimonious and independent metrics possible to reduce information redundancy (Duarte et al., 2018; Machado et al., 2017). All landscape metrics were computed using FRAGSTAT v4.2 (McGarigal et al., 2012).

2.3.2. Estimation of ecosystem services

We selected four critical and representative ESs based on the situation in the WMA: agricultural production, carbon sequestration, soil conservation, and water retention. The Jianghan Plain, where the WMA is primarily located, has traditionally been called the "land of fish and rice", providing rich agricultural products for the central China region and beyond. Thus, protecting a stable supply of agricultural products is important for regional food security. Meanwhile, land degradation and natural disasters caused by soil erosion have threatened the sustainability of agriculture and the environment due to vegetation clearance and agricultural development. Therefore, the protection of soil conservation services should be considered a priority for ecological management (Li et al., 2021). In addition, water retention and carbon sequestration services play a key role and have an extensive impact on the water cycle and climate regulation, and therefore need to be considered in this study (Lamy et al., 2016; Primmer et al., 2021). Note that while cultural services related to leisure and recreation are an important component of residents' well-being, they are not considered here because of their subjective nature and the lack of sophisticated measurement methods. The summary of the models and data used in each service is given in Table 2. These services were quantified using spatial analysis tools in ArcGIS and Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST), developed by the Natural Capital Project (Abera et al., 2021; Nelson et al., 2009) (see Appendix B for calculation principles and procedures).

2.3.3. Identifying the relationships between landscape structure and ecosystem services

The GTWR model was selected to analyze the dynamic effects of landscape structure on each ecosystem service from 2000 to 2020. As a temporal extension of geographically weighted regression (GWR), GTWR embeds time information into regression parameters to assess the local relationships between explanatory and explained variables (Liang et al., 2019; Wu et al., 2018). The model can be defined as:

$$Y_i = \beta_0(u_i, v_i, t_i) + \sum_k \beta_k(u_k, v_k, t_k)X_{ik} + \varepsilon_i \quad i = 1, 2, 3, ..., n \tag{1}$$

where Y_i is the explained variable for the ith sample; X_{ik} is the kth explanatory variable for the ith sample; (u_i, v_i, t_i) is the space-time coordinate of the ith sample; β_0 (u_i, v_i, t_i) is the intercept value, and β_k (u_i, v_i, t_i) is a set of parameter values the ith sample; ε_i is the random error.

Similar to GWR, the local regression coefficient of GTWR is estimated based on locally weighted least squares and can be expressed as:

$$\widehat{\beta}(u_i, v_i, t_i) = \left[X^T W(u_i, v_i, t_i)X\right]^{-1} X^T W(u_i, v_i, t_i)Y \tag{2}$$

where the weighting matrix W (u_i, v_i, t_i) is an $m \times n$ diagonal matrix and

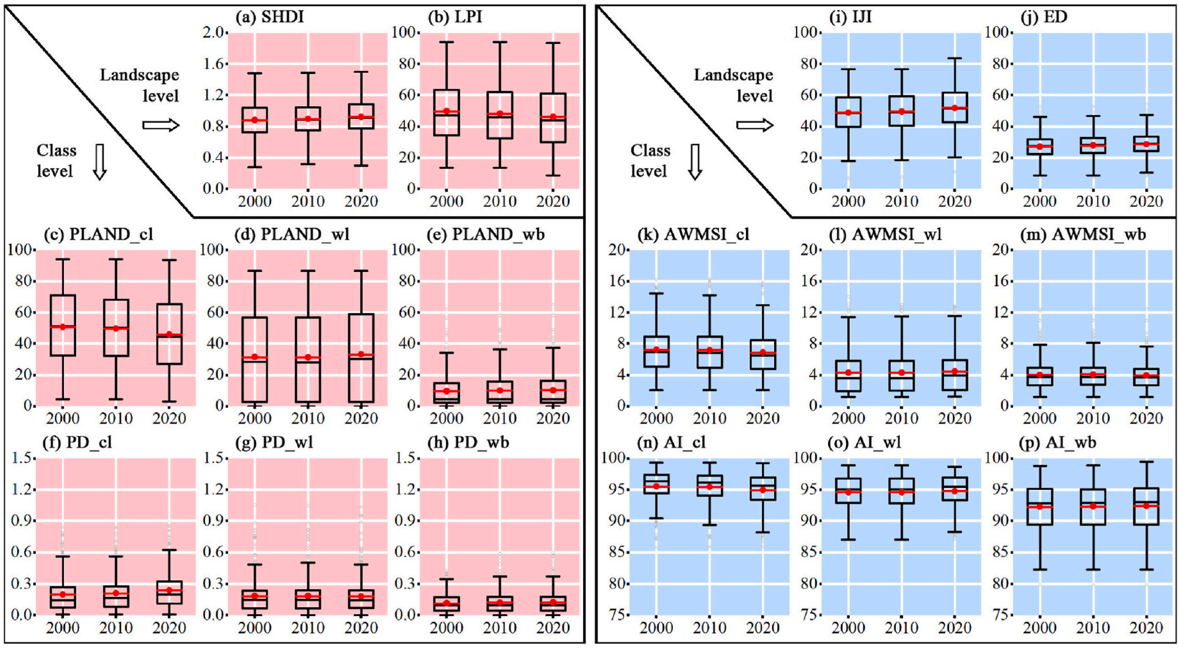

Fig. 3. Variation in landscape metrics in terms of composition (a–h) and configuration (i–p). Note: The name of each class-level metric is distinguished by the abbreviation of the corresponding LULC type (i.e., cropland (cl), woodlands (wl), and water bodies (wb)).

$W(u_i, v_i, t_i) = diag(W_{i1}, W_{i2} \ldots W_{ij} \ldots W_{in})$; $W_{ij}(1 \le j \le n)$ is the spatiotemporal distance decay function, which is determined by the spatiotemporal distance and bandwidth (Guo et al., 2017; Ma et al., 2018).

In the GTWR model, each observation has a unique spatiotemporal weight matrix, and the degree to which the regression coefficient of an observation is influenced by other observations decays with increasing spatiotemporal distance. In this study, the Euclidean distance and Gaussian distance–decay-based functions are used to calculate the spatiotemporal weights (Dong et al., 2019; Huang et al., 2010). The mathematical expression is:

$$w_{ij} = exp\left[-\left(d_{ij}^{ST}\right)^2 \Big/ h^2\right] \tag{3}$$

$$d_{ij}^{ST} = \sqrt{\lambda\left[\left(u_i - u_j\right)^2 + \left(v_i - t_j\right)^2\right] + \mu\left(t_i - t_j\right)^2} \tag{4}$$

where d^{ST} is the spatiotemporal distance; λ and μ are the spatial factor and distance factor, respectively; h is the bandwidth. The optimal bandwidth is chosen based on the minimum cross-validation (CV) value.

GTWR performance was evaluated based on a comparison of two traditional models (i.e., OLS and GWR), and ANOVA tests were performed to obtain statistical parameters (Guo et al., 2017; Liang et al., 2019; Ma et al., 2018).

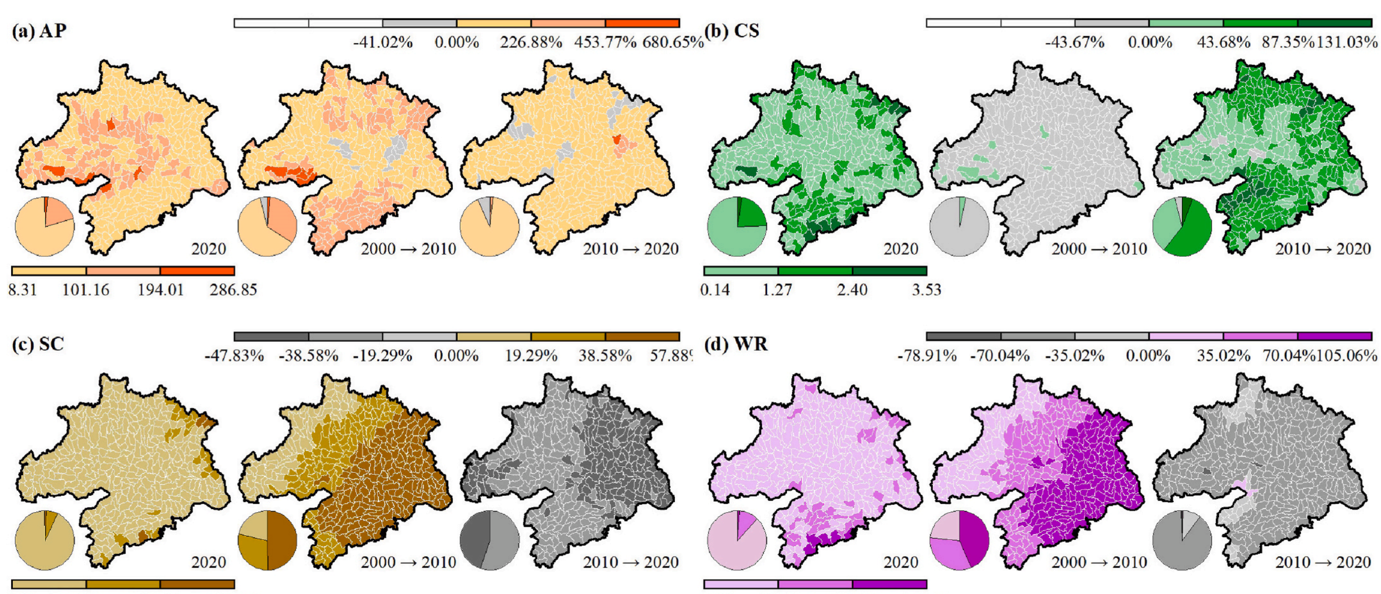

Fig. 4. The distribution and changes of AP (agricultural production), CS (carbon sequestration), SC (soil conservation), and WR (water retention) in the WMA. Notes: The units for AP, CS, SC, and WR are million-yuan, million t, million t, and million m^3, respectively.

Table 3
ANOVA comparison between GTWR and OLS/GWR model.

Variable	Model	R^2	RSS	AICc
AP	OLS	0.412	591.642	2345.496
	GTWR-OLS	0.507	−510.230	−1356.843
	GWR	0.451	553.077	2346.700
	GTWR-GWR	0.468	−471.665	−1358.047
CS	OLS	0.602	401.021	1953.496
	GTWR-OLS	0.300	−302.263	−820.016
	GWR	0.722	280.298	1791.240
	GTWR-GWR	0.180	−181.541	−657.760
SC	OLS	0.566	437.082	2038.294
	GTWR-OLS	0.293	−294.629	−617.074
	GWR	0.816	185.120	1384.670
	GTWR-GWR	0.042	−42.667	36.550
WR	OLS	0.574	429.413	2022.450
	GTWR-OLS	0.403	−405.498	−2401.526
	GWR	0.619	383.666	1952.710
	GTWR-GWR	0.357	−359.751	−2331.786

3. Results

3.1. Changes in landscape structure and ecosystem services from 2000 to 2020

LULC changes in the WMA over the past 20 years have been dominated by a considerable decrease in cropland and an increase in built-up land and woodland. The 16 metrics assessing landscape composition and configuration show changing landscape patterns in the WMA, with an increase in landscape heterogeneity, diversity, and patch shape complexity over the 20-year study period (Fig. 3). Specifically, SHDI, IJI, and ED increased, while LPI decreased, indicating the expansion of non-dominant patches, the increased interspersion of landscape types, and the fragmentation trend of patches in the WMA. At the class level, there were considerable differences between LULC types. Temporal trends were similar for woodlands and water bodies but different from croplands. For instance, the percentage and shape complexity of woodlands and water bodies has been continuously increasing, while cropland has been decreasing. Although cropland and woodland have higher metrics values, they exhibit greater variation between catchments. In contrast, the water bodies exhibit smaller areas and more regular shapes in most of the catchments (Fig. 3c–h and 3k–p).

In 2020, the total agricultural production (AP), carbon sequestration (CS), soil conservation (SC), and water retention (WR) in the WMA were 228.86 billion CNY, 335.44 billion tons, 4034.43 billion tons, and 11358.41 billion m^3, respectively. During 2000–2020, AP maintained a stable growth trend as the demand and agricultural productivity continued to improve, while the other ESs fluctuated considerably with a noticeable decline in SC and WR. The catchment-level AP, CS, SC, and WR ranged from 8.31 to 286.85, 0.14–3.53, 0.11–13.95, and 2.43–160.18, respectively (Fig. 4). The four ESs show different spatial patterns, despite all having many catchments with low values. The higher AP catchments are mainly concentrated in the midwestern regions, which is related to the distribution of cropland. The higher catchments of other services are mainly distributed in the north and south, showing a greater spatial association with woodlands. AP is also the only service dominated by continuous growth catchment though out the study area, whereas CS decreased extensively from 2000 to 2010 and then increase rapidly (Fig. 4a and b). For SC and WR, they showed a broad increase in the first decade with larger growth in the East, and an overall decline in the second decade (Fig. 4c and d).

3.2. Relationship between landscape structure and ecosystem services

3.2.1. Identifying the relationships using the GTWR model

Multicollinearity among landscape variables and their correlation with ESs were first tested to screen for appropriate explanatory variables to construct each service prediction model. Ten landscape structure variables were used to predict AP, CS, and WR. Nine were used to predict SC. All selected landscape variables are statistically and significantly correlated with ESs, and there was no severe multicollinearity detected between them (see Appendix C for details). GTWR outperformed OLS and GWR according to most metrics (Table 3). R^2 increases when using GTWR and is 0.412 and 0.451 higher than OLS and GWR in the estimation of AP. The RSS of the GTWR model is also reduced by at least 294.629 and 42.667 compared to the RSS of the OLS and GWR models, respectively. This suggests a significant improvement in the prediction ability of GTWR. In addition, GTWR has the lowest AICc for all ESs except SC, which suggests that it is more appropriate to model the relationship between landscape structure and ESs with the GTWR

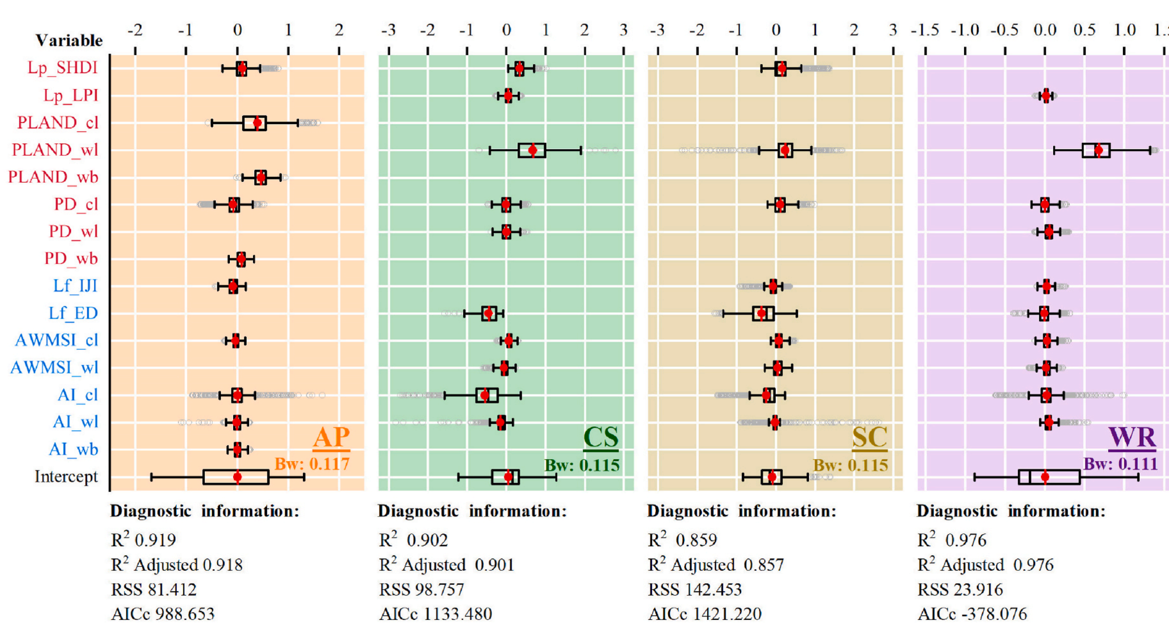

Fig. 5. Boxplots for regression coefficients of AP, CS, SC, and WR. Notes: Bw is the bandwidth of the GTWR model, RSS is the residual sum of squares, and AICc is the Akaike's information criterion adjusted for small sample sizes. The landscape composition and configuration variables are marked in red and blue, respectively. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

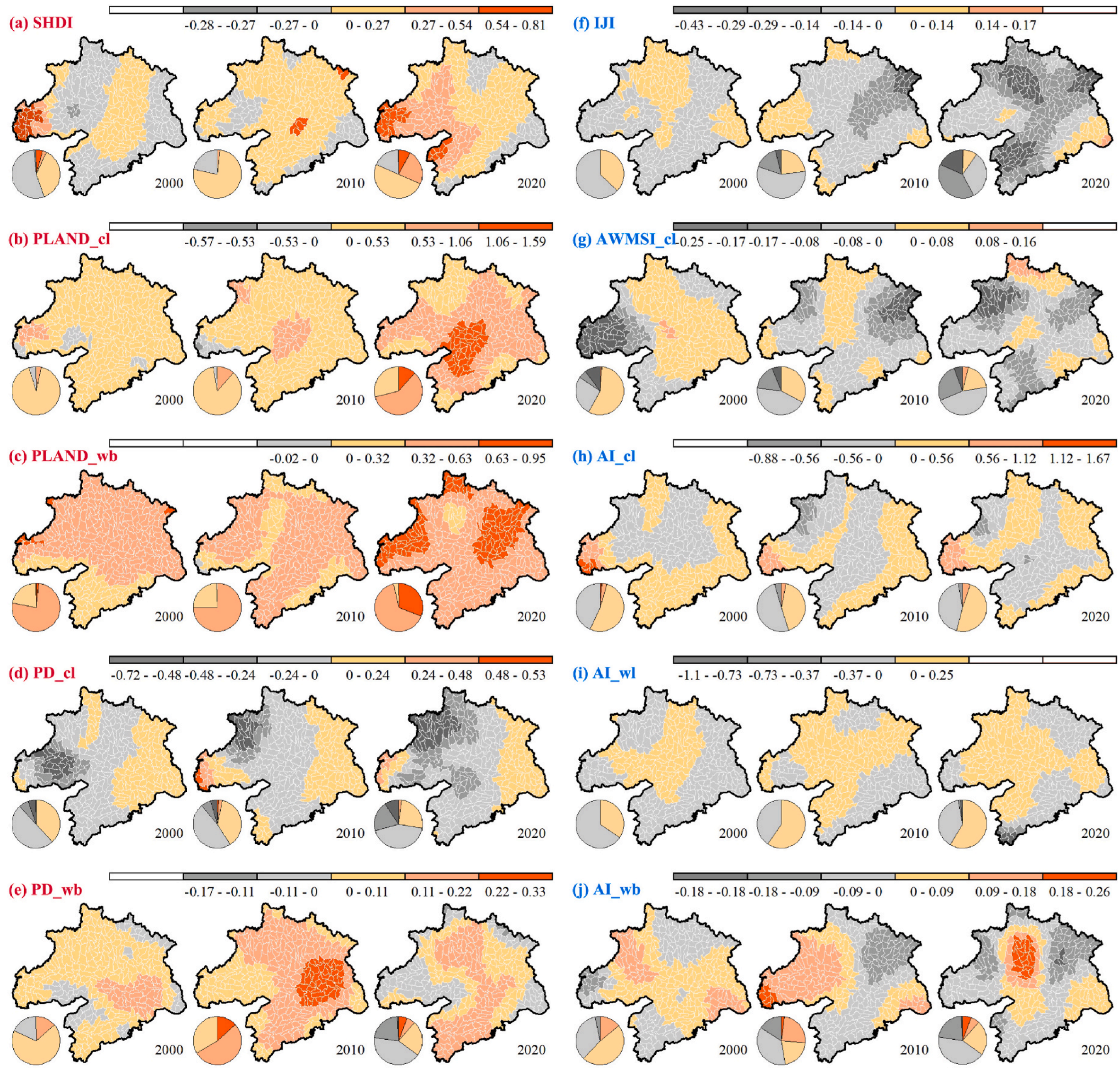

Fig. 6. Spatial patterns of regression coefficients in estimating AP (Agricultural production) in 2000, 2010, and 2020. Note: The landscape composition and configuration variables are marked in red and blue, respectively. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

model.

The results of the GTWR showed good performance in predicting ESs. The R^2 for the AP, CS, SC, and WR prediction models suggest that the selected landscape structure variables explain 91.9% of the variance for AP, 90.2% for CS, 85.7% for SC, and 97.6% for WR. Landscape composition contributes more to ESs, as their regression coefficients have overall larger absolute values compared to configuration metrics. The coefficient signs indicate that the landscape variables have both positive and negative effects on ESs. It can also be found that the effects of landscape structure on different ESs were different or even opposite. For instance, approximately 90% of the catchments where AI_cl showed positive correlation with AP were found to have negative impacts on CS. Additionally, the strongest positive metrics are PLAND_wb for AP and PLAND_wl for CS, SC, and WR while the strongest negative metrics are PD_cl for AP, AI_cl for CS, and Lf_ED for SC and WR (Fig. 5).

3.2.2. Spatiotemporal pattern of the relationships

By assigning regression coefficients to catchment distribution maps for each year, the spatiotemporal patterns of the relationships between landscape metrics and AP, CS, SC, and WR are mapped in Figs. 6–9, respectively. For agricultural production, the metrics PLAND_cl and PLAND_wb indicate these structural components may impact agricultural production to a greater degree in the WMA because the mean absolute values of their coefficients are higher than the other variables (Fig. 6b and h). It also can be seen that PLAND_cl, PD_cl, and PD_wb are mainly positive in their direction of influence during 2000–2020, while IJI, AWMSI_cl, and PD_cl have more extensive negative effects. The effects of all observed landscape variables are complex both in the temporal and spatial dimensions. On the one hand, the coefficients of different levels are dispersed across the landscape. On the other hand, the heterogeneity of relationships is also increasing over time, with more and more dispersed small clusters emerging, such as for SHDI, AWMSI_cl, PLAND_wb, and AI_wb (Fig. 6a, f, g, and j).

Six landscape variables (PD_cl, PD_wl, ED, AWMSI_cl, AWMSI_wl, AI_cl, and AI_wl) showed mainly negative effects with carbon sequestration, evidenced by the dominant gray colors in Fig. 7. Regarding the direction of effects, PLAND_wl showed the strongest positive effects while AI_cl showed the strongest negative effects. The mean of their coefficients reached 0.68 and −0.543, respectively, which are much higher than the other variables. Note that despite the continuous change

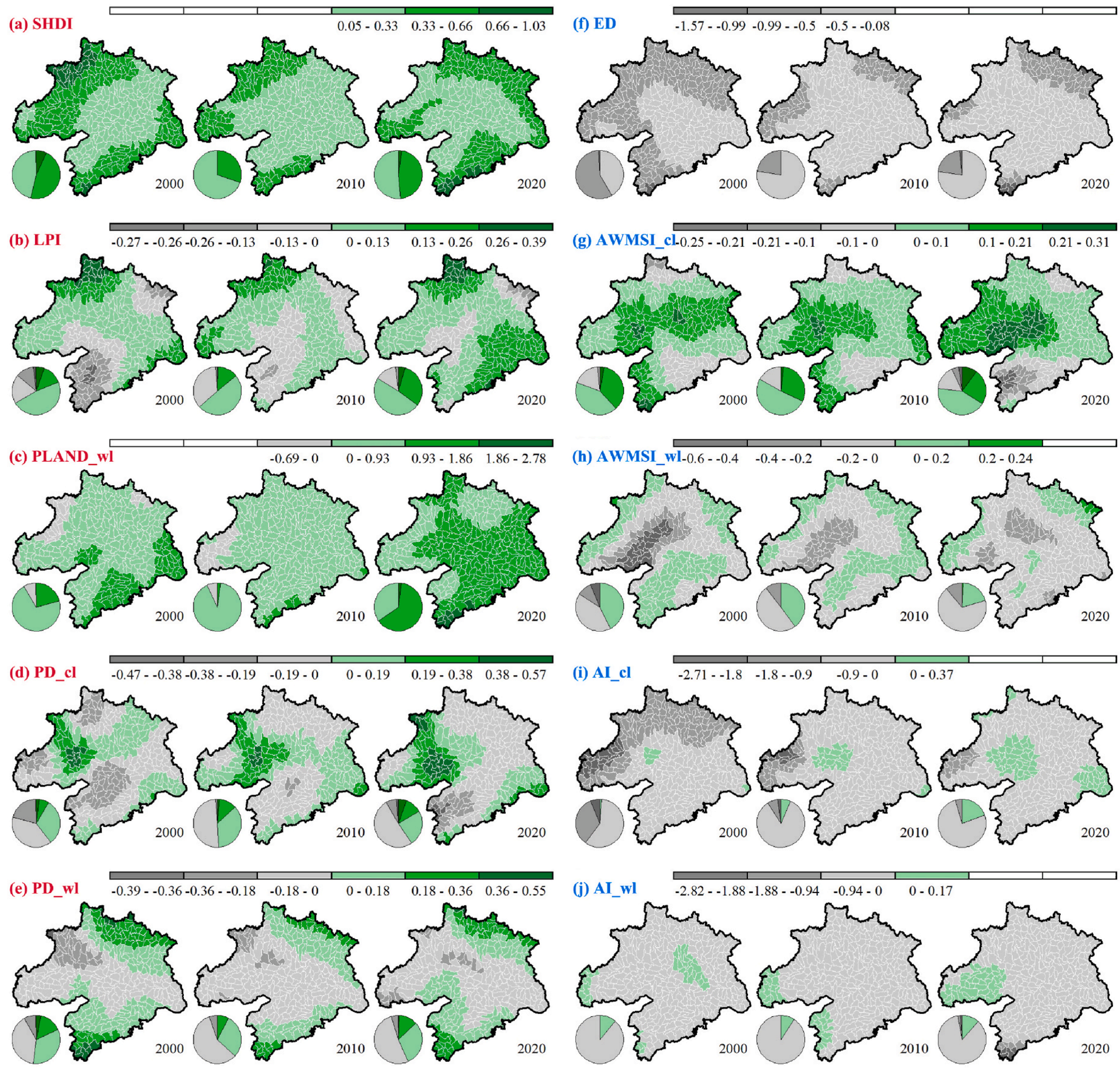

Fig. 7. Spatial patterns of regression coefficients in estimating CS (carbon sequestration) in 2000, 2010, and 2020. Note: The landscape composition and configuration variables are marked in red and blue, respectively. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

in the intensity of influence, all landscape variables except PLAND_wl maintain a relatively stable direction of influence. For example, few catchments switched from a positive to a negative coefficient for SHDI over the past two decades, and there was only a slight reduction in the number of highly positive areas (Fig. 7a).

As demonstrated in Fig. 8, catchments with positive coefficients for soil conservation are widely distributed in the WMA from 2000 to 2020, while catchments with negative relationships are mainly found for the configuration variables such as IJI, ED, and AI_cl. Spatially, the catchments with strong negative impacts are primarily located in the northwestern part of the WMA, which is a mountainous area with a concentration of woodlands. Furthermore, the relationships between many of the metrics and SC present a simpler pattern compared to agricultural production and carbon sequestration. In other words, catchments with the same directional relationships show clustering or continuous distribution characteristics, and this trend tends to further strengthen over time.

Results for water retention show a clear difference in the relationship with the landscape variables compared to other services (Fig. 9). In particular, the maps show the emergence of many turning points, that is, the temporal trends from the first decade were reversed in the second decade. For instance, many of the new purple areas in IJI in 2010 are replaced by gray areas in 2020 (Fig. 9d). A similar pattern can be observed for LPI, IJI, ED, PD_cl, PD_wl, AWMSI_cl, and AWMSI_wl. Another notable characteristic is the unbalanced ratio of the number of catchments with positive coefficients to that of catchments with negative coefficients (approximately 7:3). In addition, all landscape variables have a greater positive than negative impact on WR.

4. Discussion

4.1. The multiple roles of landscape structure in influencing ecosystem services

As our results confirm, the driving mechanism of ESs in the WMA is highly complex when combining temporal nonstationarity with spatial characteristics. To better understand this dynamic impact, we quantified the attributes of the four dimensions: the direction of the impact, the degree of the positive/negative impact, the probability of positive/negative impact, and the instability of the impact (Table 4, see Appendix

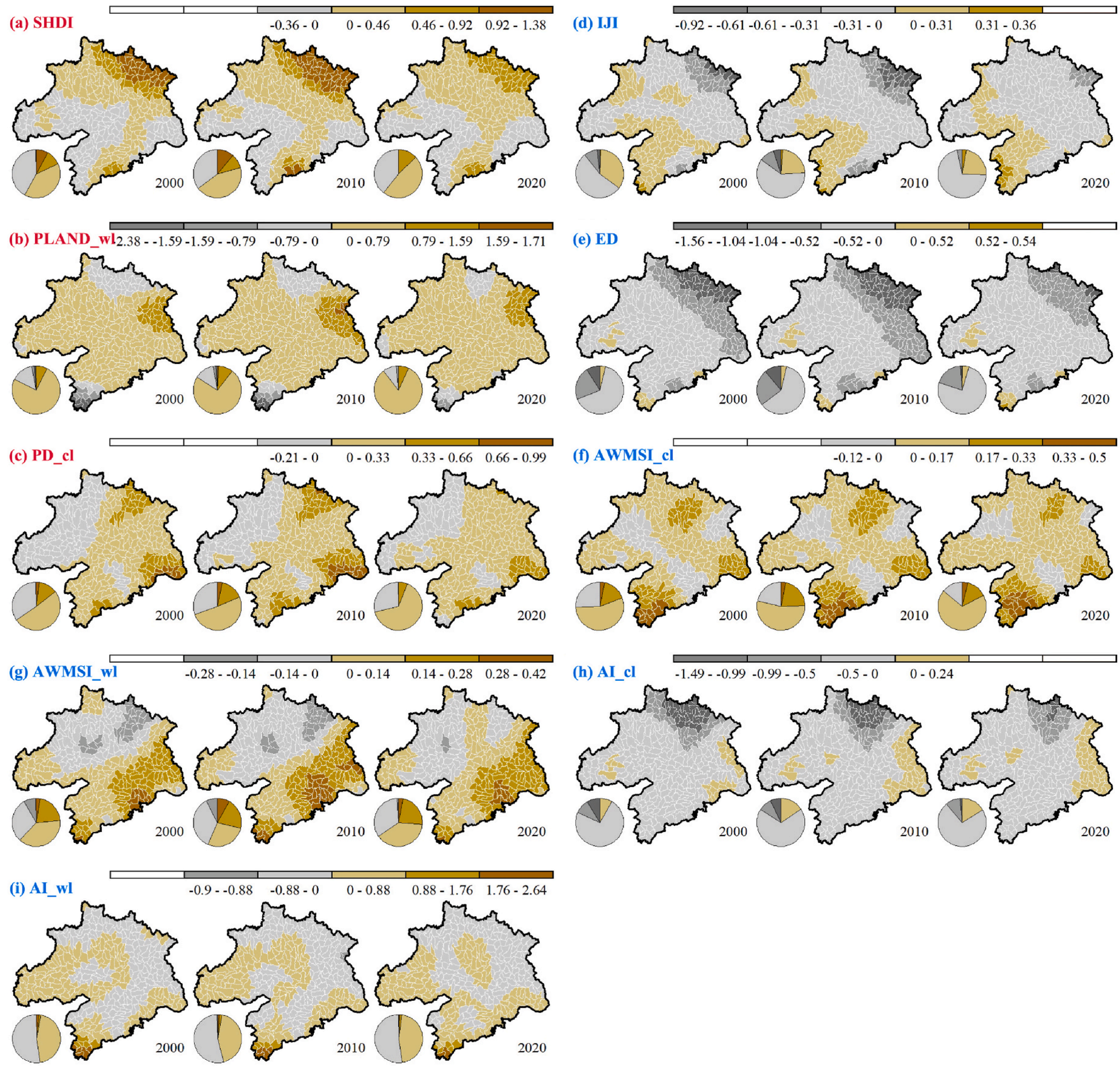

Fig. 8. Spatial patterns of regression coefficients in estimating SC (soil conservation) in 2000, 2010, and 2020. Note: The landscape composition and configuration variables are marked in red and blue, respectively. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

D for calculations of specific indexes). The key findings are summarized below.

First, most of the landscape variables in the WMA are both positively and negatively correlated with a particular service. Prior studies based on global regression techniques typically only report a simple relationship for two variables (e.g., a landscape variable and an ecosystem service variable) (Karimi et al., 2021; Yuan et al., 2021; Yushanjiang et al., 2018). This study provides a more detailed explanation of the relationship by capturing local variation through GTWR, which leads the findings to be quite different from previous studies. It can also be found that the effects of the metric SHDI on CS and PLAND_wl on WR are entirely positive, and the effects of ED on CS are entirely negative during the study period. Similarly, previous studies have identified that improving landscape diversity within a specific period of time can help increase biodiversity and further enhance CS (Jentsch et al., 2012; Whittinghill et al., 2014). However, these findings are specific to this study, and the same findings may not necessarily occur in other studies of larger scope and longer duration.

Second, landscape composition was generally more influential on the ESs than configuration, which is consistent with prior findings (Lamy et al., 2016; Yohannes et al., 2021). For AP, SC, and WR, the strength of the relationship between composition variables and ESs is 1.4–3.2 times higher than for the configuration variables. PLAND_cl and PLAND_wb contribute more to AP than the other variables, which is closely related to the agricultural structure of the WMA that has been dominated by food crops and fishery products. Meanwhile, PLAND_wl was found to be the most critical factor affecting CS, SC, and WR, which highlights the important ecological value of woodland resources. These findings certainly underscore the important fact that reducing the threat of urban development to natural and semi-natural habitats is essential to a sustainable future (Haines-Young and Chopping, 1996; Redhead et al., 2020; Yohannes et al., 2021).

Third, a landscape can promote one service while inhibiting others, which means that there are frequent trade-offs to be faced in the management of landscape change. For example, our findings confirm that AWMSI_cl primarily has the effect of weakening AP while increasing the other ESs. Therefore, managers need to be clear whether the goal is to pursue higher food supply capacity to meet social needs or maintain the multifunctionality of the agricultural landscape at the expense of capacity. The former leads to greater regularization of the shape of

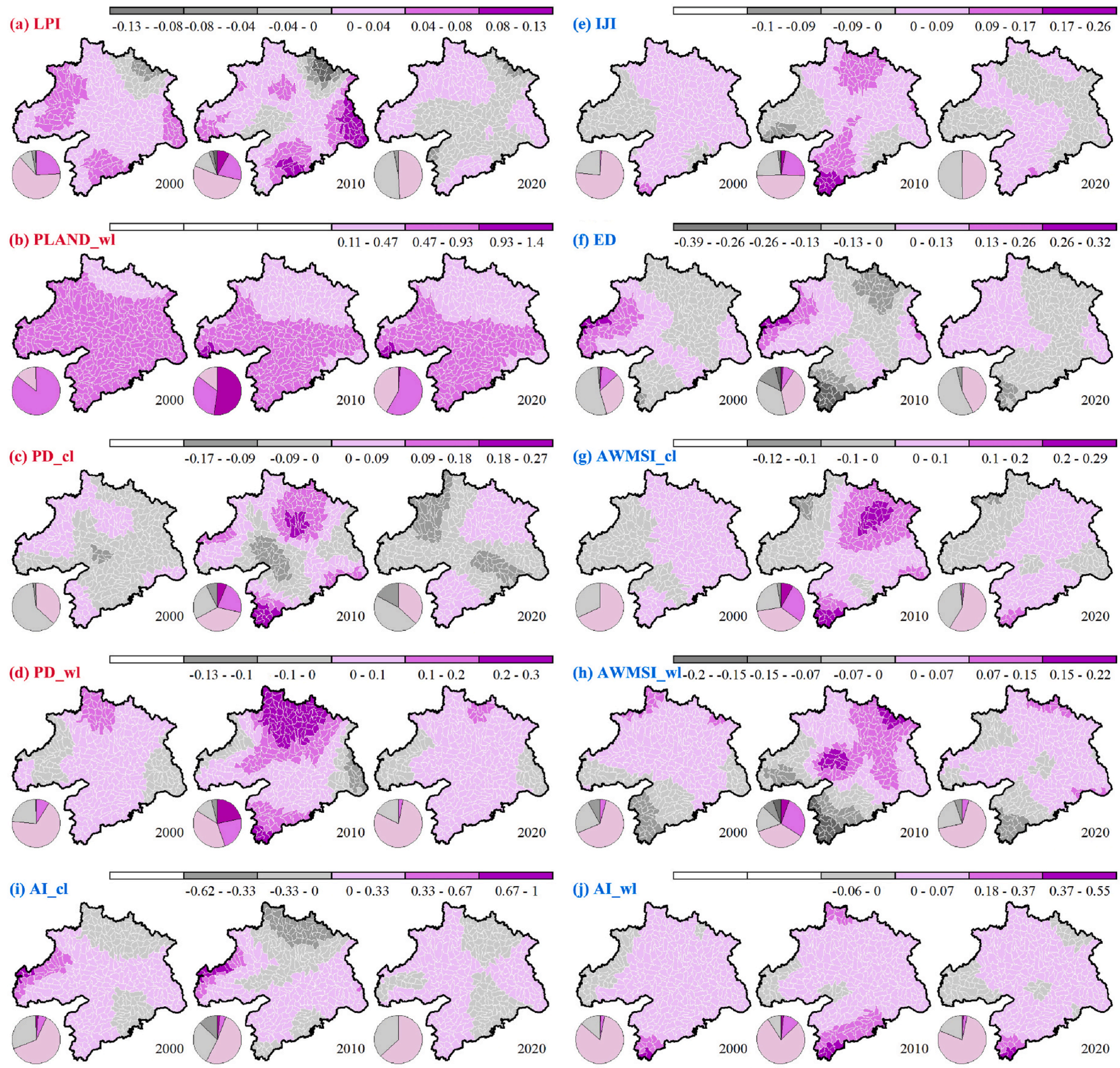

Fig. 9. Spatial patterns of regression coefficients in estimating WR (water retention) in 2000, 2010, and 2020. Note: The landscape composition and configuration variables are marked in red and blue, respectively. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

farmland to facilitate mechanization and large-scale production (Tran et al., 2021). The latter tends to maintain the previously complex boundaries of arable land for numerous ecological benefits, such as reducing water and nutrient loss and providing habitat for marginally dependent animals (Lamy et al., 2016). Moreover, previous studies have identified some landscape structure features that facilitate the simultaneous benefits of multiple ESs (Duarte et al., 2018; Guiomar et al., 2015; Zeng et al., 2017). This study also confirmed some of them, such as SHDI and PLAND_wl, which have a higher probability of being consistent in the direction of the impact on different ESs (Table 4).

Finally, it can be found that the coefficients of PLAND_cl, PLAND_wl, and AI_cl exhibited higher temporal instability over time (i.e., higher Inst value) (Table 4). Although the Inst index cannot specifically indicate the absolute level of risk due to the lack of a threshold, it can help decision-makers make a relatively safe choice for spatial restructuring among relevant comparable strategies. From this perspective, optimizing the management of regional ESs by adjusting the landscape configuration, such as the shape and spatial spacing of the landscape, is a safer option in the WMA. These findings contribute a new temporal dimension for comparing different ESs drivers, which is an improvement over previous studies (Chen et al., 2021; Estoque and Murayama, 2016; Hou et al., 2020).

4.2. Policy implications for landscape management

Recent research has clarified the benefits of models that take into account the heterogeneity of drivers for ESs management (Tran et al., 2021). This study demonstrates how GTWR can produce local estimation parameters at different times and thus produces a multidimensional analysis and understanding of the impact of landscape structure on ESs, rather than a simple correlation estimate. First, it is possible to know at any place and time whether a particular landscape structure positively or negatively affects the provisioning of a particular service. Second, it permits the further comparison of different landscape structural features to control a certain service (i.e., the intensity of promotion or inhibition) and identify key drivers. Third, the probability of the positive or negative effect occurring can be estimated within an arbitrary range of regions, such as county or municipal administrative areas, using known data from the analysis catchments within the region. And finally, it is possible to assess the instability of the impact based on its change over

Table 4
Spatiotemporal variation characteristics of the impact of landscape structure on ecosystem services in the study area.

Metrics		Potential impact on															
		AP				CS				SC				WR			
		Direc	DoD	PoD	Inst	Direc	DoD	PoD	Inst	Direc	DoD	PoD	Inst	Direc	DoD	PoD	Inst
1	SHDI				0.124				0.087				0.068	n/a	n/a	n/a	n/a
2	LPI	n/a	n/a	n/a	n/a				0.059	n/a	n/a	n/a	n/a				0.023
3	PLAND_cl				0.314	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
4	PLAND_wl	n/a	n/a	n/a	n/a				0.363				0.101				0.213
5	PLAND_wb				0.120	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
6	PD_cl				0.111				0.074				0.044				0.059
7	PD_wl	n/a	n/a	n/a	n/a				0.047	n/a	n/a	n/a	n/a				0.049
8	PD_wb				0.074	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
9	IJI				0.101	n/a	n/a	n/a	n/a				0.046				0.032
10	ED	n/a	n/a	n/a	n/a				0.145				0.070				0.040
11	AWMSI_cl				0.060				0.045				0.022				0.044
12	AWMSI_wl	n/a	n/a	n/a	n/a				0.062				0.030				0.036
13	AI_cl				0.111				0.273				0.073				0.101
14	AI_wl				0.070				0.107				0.039				0.040
15	AI_wb				0.063	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a

Notes: Direc, DoD, PoD, and Inst represent the direction of the impact, the degree of positive/negative impact, the probability of positive/negative impact, and the instability of the impact, respectively. The blue represents the positive impact and the red represents the negative impact. n/a denotes that the metric is not used as an explanatory variable.

time, thus measuring the degree to which the observed information supports the decision-making. Along these pathways, we can further improve many aspects of current landscape management to obtain positive changes in ecosystem service provision.

Considering the possible negative consequences, future landscape management should first aim to maximize comprehensive benefits, i.e., fully consider the interactions between different landscapes, especially the conservation of landscape multifunction (Verhagen et al., 2016). For example, clear legislation should be introduced to control the intensity of agricultural land development and soil pollution to avoid the degradation of landscape diversity and environmental quality (Raudsepp-Hearnea et al., 2010). On this basis, a location-based landscape planning and management system should be also established (Tran et al., 2021; Wu, 2021; Zhu et al., 2020). Spatial prioritization can be set for all projected landscape pattern measures, based on the correlation between landscape structure and ESs identified in this study. For instance, farmland consolidation involving landscape shape adjustment should be prioritized for implementation in areas where AWMSI_cl has the strongest positive impact on ESs. Meanwhile, there is a need for more stringent protection of natural and semi-natural habitats, such as forests, wetlands, and agricultural landscapes, as they are the basis for the generation of numerous ecological functions (Duflot et al., 2017). As a specific measure advocated by the Chinese government, ecological “red zones” should be scientifically delineated and implemented in the WMA as soon as possible (Zhu et al., 2020). Additionally, improving adaptability to changes in landscape patterns and habitat quality is also critical. Real-time monitoring of changes in landscape patterns and analysis of long-term landscape histories can contribute to adaptive governance (Bürgi et al., 2015; Duan et al., 2019; Estoque and Murayama, 2013). For example, we can set thresholds and monitor the damage to ESs caused by future urban expansion in real-time, and take timely measures to ameliorate the impact so that the adverse consequences are always kept within reasonable limits. Finally, it is worth noting that it is difficult to accurately predict and control the consequences of landscape measures due to the non-linear response of ecosystems. Therefore, any interventions, especially those that are irreversible, need to be approached with caution to prevent ecological risks. Form this sense, nature-based solutions should receive more support for application to ecosystem governance (Virah-Sawmy et al., 2016).

4.3. Limitations

A limitation of this work is the varied data accessibility. Agricultural production data were unavailable in some counties and had to be substituted with data from higher administrative regions, which constrains more accurate spatial mapping of AP. Similarly, although the covered the last two decades, which includes the fastest period of environmental, modeling of longer time series is not possible due to a lack of data, which limits this work in detecting longer-term mechanisms by which landscape structure affects ESs. Therefore, it will be necessary moving forward to track new data and keep this work up to date. Another possible limitation is related to the resolution resampling of multi-source data and the spatial interpolation of meteorological data. These processes can add uncertainty that leads to deviations between the results and the actual situation (Yohannes et al., 2021). Furthermore, the mapping and analysis unit used in this study is the catchment, which does not completely overlap with administrative areas. Future research could consider the creation of other units that take into account ecological process modeling and management needs, such as units formed by intersecting small catchments with county-level administrative areas.

5. Conclusions

The pressure from landscape change in urbanized areas continually threatens the sustainability and stability of ecosystem service provision. In this study, the GTWR model was applied for the first time using 16 landscape structure metrics and four ESs (i.e., agricultural production, carbon sequestration, soil conversation, and water retention) to quantify the spatiotemporal changes in the relationship between landscape structure and ESs from 2000 to 2020.

Our results show that GTWR substantially improves the explanatory power of ESs compared to traditional OLS or GWR models while effectively capturing the spatiotemporal dynamic processes of the effects of landscape structure. In the past two decades, the WMA has experienced

LULC changes characterized by a significant decrease in cropland and a rapid increase in built-up land and forest land. As a result, the heterogeneity of the overall regional landscape continues to increase, while the composition of the landscape becomes more homogeneous and the morphology becomes more complex. Only agricultural production continued to grow among the four ESs, while the remaining ESs experienced significant fluctuations over time. Landscape structure has complex mechanisms of influence on ESs in the WMA. On the one hand, a landscape variable may be both positively and negatively correlated with a particular ES, implying a temporally variable relationship. On the other hand, a landscape variable may have opposite effects on different services at the same moment and region, which reflects the need for trade-offs in landscape management. Compared to landscape configuration, landscape composition has an overall higher degree of influence on ESs but also a higher degree of temporal instability and therefore should receive priority attention. All relationships have changed to varying degrees over the past two decades, with the most significant changes related to WR showing multiple clear turning points. These findings emphasize the importance of implementing a regional, dynamic and systematic strategy for ESs management in the WMA. The results of the study provide valuable references for policymakers to design effective landscape management systems to mitigate the degradation of ESs. More importantly, the successful application of the GTWR model in this study encourages space-time thinking in the analysis of ecosystem service driving mechanisms, which can be regarded as a good start for future research.

Credit author statement

Penglai Ran and Shougeng Hu contributed to the study conception and design. Material preparation, data collection, and analysis were performed by Penglai Ran, Xinyu Song, and Shengfu Yang. The first draft of the manuscript was written by Penglai Ran and Shijin Qu and edited by Amy E. Frazier. All authors read and approved the final manuscript.

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

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2022.116575.

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