



# Ecological performance assessment of ecologically fragile areas: a perspective of spatiotemporal analysis

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## Abstract

Sustainable development in ecologically fragile areas (EFAs) has faced significant challenges in recent years, but the traditional analytical approaches fail to provide an ideal assessment for ecological performance due to spatiotemporal variability in EFAs. This paper evaluates the ecological performance of EFAs based on a modified ecological footprint model, and ecological footprint intensity (EFI) is considered an essential indicator to measure ecological performance, especially for EFAs. Empirically, taking the II-shaped Curve Area in the Yellow River basin of China as the study area, the spatiotemporal heterogeneity of EFI of 17 cities in the area is analyzed. Then, the extended STIRPAT and geographically and temporally weighted regression (GTWR) models are employed to explore the spatiotemporal heterogeneity of the factors driving EFI. The results show that from 2006 to 2019, the overall level of EFI in the area has decreased; EFI of the area offers a significant spatial agglomeration effect; results of the GTWR model suggest that factors driving EFI have spatiotemporal heterogeneity; the impact of population size, openness, marketization, technology, industrial structure rationalization, and information communication level on EFI was two-sided, while that of affluence, government scale, environmental regulation, and industrial structure advancement show inhibitory impact with the intensity of inhibition varying across periods and cities.

**Keywords** Ecologically fragile areas · Ecological performance · Spatiotemporal heterogeneity · GTWR · Driving factors

## Introduction

Ecologically fragile areas (EFAs), also known as ecotone, account for more than half of the total land surface areas (Nguyen and Liou 2019) and usually locate in transitional

areas between different landscapes (Chen et al. 2022). These areas perform as essential places of human settlement and cultural intermingling in human history. According to statistics (Huang et al. 2009), Asia has the largest fraction of EFAs (74.6%), followed by Africa (19.6%). Simultaneously, inevitable overlap exists between EFAs and poverty-stricken areas (Hu et al. 2021). Hence, equally significant attention attached to the regional development in EFAs is necessary for the sustainability of the whole region.

The ecosystems in EFAs have substantial spatiotemporal volatility, weak anti-interference ability, significant edge effects, and poor spontaneous recovery ability (Qiu et al. 2022; Yan et al. 2017) but play critical roles in environmental diversity and ecological barriers. However, anthropogenic interference in local areas has caused severe damage to the local ecosystem (e.g., soil erosion, land desertification, and natural disasters) during the past decades. Due to historical reasons, most EFAs are relatively less developed compared to those coastal cities at both economic and institutional levels (Li et al. 2022a, b). Meanwhile, the crossing areas of different landscapes, where EFAs locate, are often rich in mineral resources due

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to Paleo-activities and crustal movement (Nguyen and Liou 2019). Thus, despite that EFAs are ecologically vulnerable, large-scale industrial activities that will cause severe environmental damage are often located in these areas. The natural conditions and anthropogenic interventions in EFAs have led to unsustainable development in these areas. Consequently, to defuse the dilemma of coordinating eco-environment and socioeconomic development in EFAs, it is essential to investigate sustainable performance considering the characteristics of EFAs and coordinate the relationships between local economic growth and ecological quality from a sustainable perspective.

The connotation of sustainable development is to acquire the most remarkable development with a minor ecological cost (Ruggerio 2021), which provides the basic idea for coordinating the nexus between eco-environment and economic development. It serves as a reference for the coordination of their relationship (Dong et al. 2021). To balance this relationship, a considerable amount of literature on maximizing economic benefits while minimizing ecological costs has been conducted (Liu et al. 2020; Wang et al. 2015). These studies mainly focus on the measurement and force identification of environmental efficiency (Guo & Luo 2021; Kaneko & Managi 2004; Liu et al. 2021; Long et al. 2018; Song et al. 2013) and eco-efficiency (de Araújo et al. 2021; Han et al. 2021; Liu et al. 2020; Long et al. 2017; Passetti & Tenucci 2016; Tang et al. 2022; Van Caneghem et al. 2010) with the scope of countries, regions, industrial sectors, and even companies. Ecological performance proposed by Schaltegger and Sturm (1990) is prevalently used to measure the impact of economic development on the eco-environment.

### Approaches to evaluating ecological performance

Since the concept of ecological performance has been put forward, the evaluation methods of this indicator have gradually developed. Ratio approach (Callens & Tyteca 1999; Jin et al. 2020; Yang & Yang 2019), index system approach (Passetti & Tenucci 2016), material flow analysis (Besné et al. 2018; Wang et al. 2016), frontier approach (Long et al. 2018; Rebolledo-Leiva et al. 2017; Xing et al. 2018), input-output analysis (Zurano-Cervelló et al. 2018), life cycle assessment (Valente et al. 2019), and emergy analysis (Li et al. 2011) are several common approaches to evaluate ecological performance.

Among all the methods mentioned above, the ratio approach, index system approach, and frontier approach are the three most frequently used methods of ecological performance measurement (Chen et al. 2021a, b). The ratio approach defines eco-efficiency as the ratio of the economic value added to eco-environmental impacts added (Yang & Yang 2019). Maxime et al. (2006) argued that eco-efficiency is essentially an “eco-intensity” and can be given by the

total eco-environmental impact divided by the amount of the economic value added. The difficulty of the ratio approach is to accurately measure the economic value added and the environmental impacts added. The index system approach incorporates various efficiency indicators to measure eco-efficiency. It can comprehensively reflect the degree of sustainable development, but it is limited to overcoming the influence of subjective factors in empowering environmental and economic indicators. The frontier method contains multiple inputs and outputs of various dimensions, and no weight is determined to obtain comprehensive indicators. The estimation results, which are relative values and cannot be confirmed using specific test standards, are impressionable to the choice of inputs and outputs (Yang & Zhang 2018). Meanwhile, the frontier approach (e.g., data envelopment analysis) widely adopted by most existing studies cannot reflect the objective conditions of the eco-environment from the long-term time series, and they merely focus on the link between economic growth and pollutant discharge, ignoring the impact of human activities (Yang & Yang 2019). In contrast, the ratio approach reports the actual condition between economic growth and eco-environmental pressure through an absolute value, ensuring that efficiency is authentic and comparable across periods.

### Determinants of ecological performance

In the research regarding driving factors of ecological performance, econometric models are widely adopted. Whether a spatial matrix is introduced into the regression formula, the regression models can be divided into non-spatial and spatial regression models. For the non-spatial econometric model, it is confirmed that economic development, openness, environmental protection, and population density are the key factors influencing environmental efficiency via a panel tobit model (Song et al. 2013); it is also found that economic growth, industrial structure, openness, technological progress, and environmental regulation significantly affect the ecological efficiency of Guangdong Province via a panel regression model (Zhou et al. 2018). For the spatial econometric model, it is demonstrated that regional GDP per capita, science and technology expenditure, retail sales of social consumer goods, and population size are the factors influencing the ecological efficiency of Chengdu-Chongqing urban agglomeration via a spatial panel model (He & Hu 2022); it is also found that the factors influencing China's urban ecological efficiency include economic development, industrial structure, import and export trade, information level, local government expenditure, and retail sales of social consumer goods via a spatial autocorrelation panel regression model (Liu et al. 2020). However, the results of these studies are not consistent; for instance, Zhou et al.

(2018) found that the level of technology is conducive to the improvement of ecological efficiency, while He and Hu (2022) presented the opposite result; He and Hu (2022) found that the retail sales of social consumer goods promote the improvement of ecological efficiency, while Liu et al. (2020) showed the opposite result. The reason for this inconsistency is that the geographic spatiotemporal data is highly non-stationary, and the changes in time and geospatial location will lead to changes in the relationship and structure between variables (Chen et al. 2021a, b). The ubiquitous temporal and spatial effect involving spatiotemporal dependence and heterogeneity was neglected by multitudinous econometric technology. Therefore, the traditional econometric regression models cannot meet the analysis requirements of complex spatiotemporal data.

### Perspective of the research layer

Most of the existing literature surrounding ecological performance has studied at the national level (Dong et al. 2021; Song et al. 2013) and urban level (Guo & Luo 2021; Liu et al. 2020; Ren et al. 2020; Zhou et al. 2018), which undoubtedly provide potent tools for the design of ecological protection and management policies at the national and urban levels.

In terms of EFAs, these studies either place the EFAs within a country or evaluate the ecological performance of the EFAs in the same pattern as other regions and expect to provide decision-making support for the sustainable development of EFAs through a “facet-to-point” approach. However, due to the unique characteristics of EFAs, such as substantial spatiotemporal volatility and extraordinary physical and geographical conditions, their sustainable development conditions differ from other areas, and the common treatment approach is unsuitable for providing policy support for the development of EFAs. As far as we know, the current research lacks a comprehensive assessment of ecological performance based on the complex environmental conditions of EFAs, which is unfavorable to comprehensively grasp the sustainable level and alleviate the increasingly acute contradiction between eco-environment and economic development in EFAs. Therefore, targeted research on ecological performance in EFAs is necessary.

Based on the aforementioned analysis, scholars have conducted extensive and in-depth research on ecological performance, which has deepened the understanding of sustainable development and provided a basis for policy formulation. However, the reality shows that the EFAs are widely distributed. Their geographical location and lagging economic development stage lead to the spatial and temporal differentiation of their sustainable development status. The multitudinous econometric technology used in the existing research does not conform to the characteristics of the

changeability of the objective conditions in EFAs and the resulting spatiotemporal fluctuations of the drivers. Thus, different from other regions, spatiotemporal differentiation has to be taken into account in the assessment of ecological performance in EFAs. The geographically and temporally weighted regression (GTWR) model proposed by Huang et al. (2010) adds both temporal and spatial effects to the ordinary panel regression model, thus providing the possibility to evaluate the heterogeneity of temporal and spatial dimension parameters. Therefore, it is more appropriate to apply GTWR to the assessment of ecological performance drivers in EFAs.

Contributions of this paper are (1) the shortcomings that previous studies attempted to support policy formulation for EFAs through a “facet-to-point” approach were pointed out. Accordingly, this study specifically evaluates the ecological performance of EFAs. The ecological performance of EFAs is evaluated by adopting the ratio approach, and objective conditions of local eco-environment and anthropogenic activities are considered using a modified ecological footprint model. Specifically, the equivalent factors applicable to local conditions are employed, and the ecological footprint account is enriched. (2) The factors driving EFI are discussed from the perspective of the operation of industrial and residential systems. Meanwhile, the GTWR model compatible with EFAs is creatively employed to analyze the evolution trend of each driver from temporal and spatial dimensions, which aims to overcome the defect that most previous studies did not focus on the spatiotemporal integration of ecological performance. (3) The research area selected in this paper is of practical significance to the sustainable development of EFAs. The II-shaped Curve Area in the Yellow River Basin of China, a representative area of EFAs and a significant ecological barrier to Central and Western China, has not received enough attention regarding the dynamic relationship between the eco-environment and economic development in existing research.

### Methodology and materials

In this paper, eco-intensity is employed to characterize ecological performance where the gross domestic product (GDP) serves as a denominator, and ecological footprint is used as a numerator, namely, ecological footprint intensity (EFI). Ecological footprint considers the environmental impact caused by resource utilization and human activities and converts them into biologically productive land areas. It not only reflects the sustainability of a region to some extent, but also warns against ecological risks with an absolute value. Meanwhile, the calculation of ecological footprint in this study takes the natural conditions and human activities of EFAs into consideration, which is more appropriate for

the analysis requirements of ecological performance in EFAs. Meanwhile, the GTWR model is employed to analyze driving factors, while the panel regression model is used as a benchmark reference. Overall, the aims of this study are first, assessing the ecological performance in EFAs based on the constructed ecological footprint model and second, investigating the spatial and temporal variation of factors driving ecological performance in EFAs.

## Measurement of EFI

EFI is used to characterize the ecological performance. The smaller the EFI is, the higher the utilization efficiency of the eco-environment is. EFI can be expressed as

$$EFI = \frac{EF}{GDP} \quad (1)$$

where  $EF$  represents ecological footprint and  $GDP$  represents economic output. The calculation formula of EF is as follows:

$$EF = \sum_{j=1}^7 \sum_{i=1}^n (r_j \times \frac{C_i}{P_i}) \quad (2)$$

where  $r_j$  is the equivalence factor;  $j=1, 2, 3, \dots, 7$  represent seven ecological footprint land-use types, respectively: arable land, forest land, grassland, water area, water resource land, fossil energy land, and construction land;  $i$  represents the type of consumption items;  $C_i$  is the annual consumption of  $i$ ; and  $P_i$  is the global average output of  $i$  produced by bio-productive land.

The indicators of the EF account are determined according to the conceptual model of EF and the actual situation of the study area. The modified equivalence factors of seven types of bio-productive land applicable to local conditions are determined by referring to the existing literature (Li et al. 2022a, b; Sun & Wang 2022; Huang et al. 2018). Due to the space limitation, detailed information on the EF account is shown in Appendix 1.

## Method of driving factors analysis

### Extended STIRPAT model of EFI

EFI is affected by various factors in the regional socioeconomic system. Theoretically, the IPAT equation was first proposed to reflect the relationship between various socioeconomic factors and eco-environmental indicators (Ehrlich et al., 1972). Since there is only the same transformation proportion between the driving factors and eco-environmental indicators in the IPAT model, the influence of driving factors on eco-environmental indicators cannot be objectively reflected. Based on the IPAT model,

the stochastic impacts by regression on population, affluence, and technology (STIRPAT) model was established (Dietz & Rosa., 1994), which is expressed as

$$I = aP^b A^c T^d e \quad (3)$$

where  $I$ ,  $P$ ,  $A$ , and  $T$  represent impact, population, affluence, and technology, respectively;  $a$  is the model coefficient;  $e$  is the model error term;  $b$ ,  $c$ , and  $d$  are the condition indices of population, affluence, and technology, respectively. For ease of parameter estimation, the logarithmic model is

$$\ln I = \ln a + b(\ln P) + c(\ln A) + d(\ln T) + \ln e \quad (4)$$

The regular operation of industrial and residential systems requires a large number of various material resources. This process will produce masses of pollutants while bringing economic output, resulting in the EFI. Based on the STIRPAT model and previous research, population size, affluence, and technology have been selected as the variables of  $P$ ,  $A$ , and  $T$ , respectively. Additionally, industrial structure advancement and rationalization, openness, information communication level, government scale, environmental regulation, and marketization were added to the STIRPAT model. The influencing paths of drivers (M1–M10) are shown in Fig. 1.

**Population size (POP)** On the one hand, population agglomeration may cause a “crowding effect,” which not only increases the consumption of regional material resources but also reduces the efficiency of regional economic operation; on the other hand, population agglomeration may bring a “scale effect” (ren et al. 2020), which exerts great importance in optimizing the regional input-output structure and improving regional economic operation efficiency.

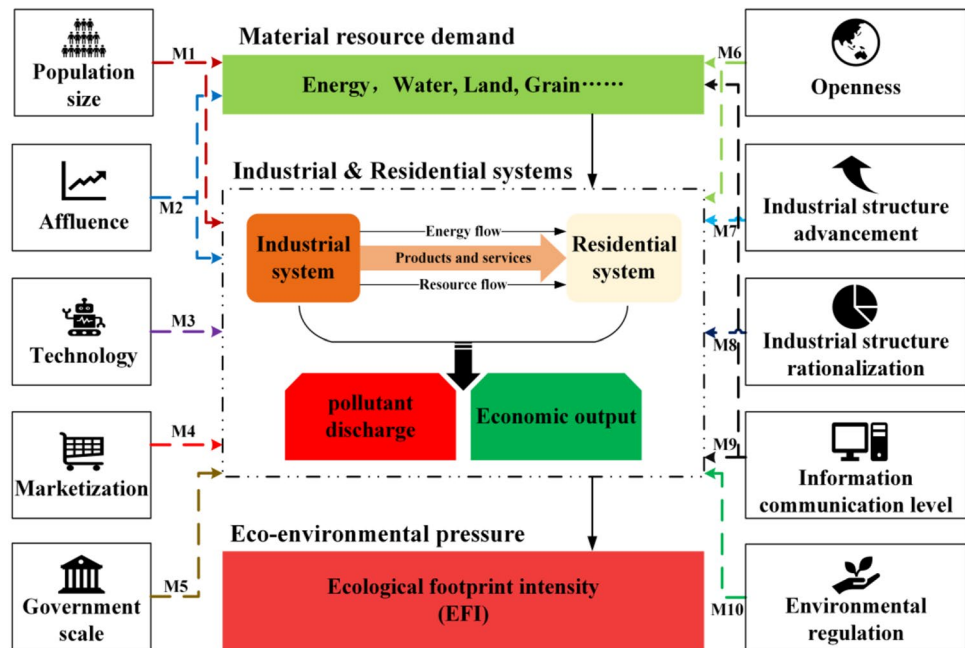
M1: POP affects the EFI by influencing the demand for material resources and the regional economic operation efficiency.

**Affluence (GDPPC)** For affluence, it represents the level of regional economic development. On the one hand, production and consumption would be driven by a higher level of economic development, thereby creating more demand for material resources. On the other hand, economic development promotes the living standards of city residents, and high requirements for a better life can strengthen the construction of eco-environment.

M2: GDPPC affects the EFI by stimulating the vitality of the material resources demand and promoting the construction of eco-environment.

**Technology (TECL)** Technological progress would alter the operational pattern of industrial and residential systems,

**Fig. 1** The extended STIRRPAT model of EFI



that is, the production mode of industries and the residents' lifestyles (Zhou et al. 2018). The total factor productivity of industrial and residential systems can be promoted, and thereby, resource utilization efficiency can be enhanced.

M3: TECL affects EFI by enhancing resource utilization efficiency through promoting operational efficiency of industrial and residential systems.

**Marketization (MAR)** Marketization not only represents the market transaction level but also potentially indicates the consumption status of society. Previous studies have shown that the social consumption level has different effects on the eco-environment (He & Hu 2022; Liu et al. 2020). Therefore, marketization may affect the EFI in the Curve Area.

M4: MAR affects EFI by influencing market transactions and thus the vitality of material resource consumption.

**Government scale (GOVS)** Governments often give guidance on how to stimulate economic growth and protect the eco-environment. The scale of the government plays a crucial role in the protection of eco-environment and enhancement of economic development. Therefore, the scale of government may have an impact on the EFI.

M5: GOVS affects EFI by promulgating economic and environmental policies and legal regulatory institutions.

**Openness (OPEN)** Openness shows the frequency of economic activities between regions and other countries. First, while expanding the demand for material resources,

regional foreign trade helps areas enjoy the fruits of world technological progress and thereby improve local economic efficiency; second, under the assumptions of "pollution paradise" and "pollution halo," openness may have distinct effects on the eco-environment (Liu et al. 2020).

M6: OPEN affects EFI by expanding the demand for material resources and altering the state of regional industrial and residential systems.

**Industrial structure advancement (ISA)** Industrial structure advancement is a dynamic change process of the industrial structure center, mainly manifested in the continuous transfer from the primary sector to the secondary and tertiary sectors (Zhao et al. 2020). The input-output efficiency of the three sectors is different. Generally, the input-output efficiency of the expected output in the tertiary sector is the highest while that of the unexpected output in the secondary sector is the highest.

M7: ISA affects EFI by influencing the input-output efficiency in industries.

**Industrial structure rationalization (ISR)** Industrial structure rationalization refers to the effective allocation of elements among sectors, which reflects the coupling degree of the input and output structure of elements (Shen et al. 2021). When the industrial structure is unreasonable, the allocation of factors is blocked, and the economic system will be distorted. Hence, the low efficiency of economic operation will lead to the reduction of output.

M8: ISR affects EFI by influencing economic productivity via the efficiency of resource allocation among sectors.

**Information communication level (INL)** The improvement of information communication level is conducive to reducing information asymmetry, thereby increasing the market transaction volume and stimulating regional economic output. Besides, the progress in information communication level potentially increases the demand for material resources (Usman et al. 2021; Van Heddeghem et al. 2014).

M9: INL affects EFI by stimulating economic development and furthering the demand for material resources.

**Environmental regulation (ERI)** Previous studies have studied the relationship between environmental regulation and the environmental impact, mainly including theoretical disputes such as “follow cost,” “pollution shelter hypothesis,” and “Porter Hypothesis” (Yin & Wu 2021; Zheng 2018), which emphasize the importance of environmental regulation to altering the operational mode of enterprises (e.g., mode of production and waste treatment). These studies show that environmental regulation may improve or exacerbate the eco-environment.

M10: ERI may improve or exacerbate the eco-environment by altering the operational mode of enterprises, thus affecting EFI.

Based on the analysis of determinants of EFI, the extended STIRPAT model of EFI is constructed as follows:

$$\ln EFI_{it} = \beta_0 + \beta_1 \ln POP_{it} + \beta_2 \ln GDPPC_{it} + \beta_3 \ln OPEN_{it} + \beta_4 \ln MARL_{it} + \beta_5 \ln GOVS_{it} + \beta_6 \ln ISR_{it} + \beta_7 \ln TECL_{it} + \beta_8 \ln INL_{it} + \beta_9 \ln ERI_{it} + \beta_{10} \ln ISA_{it} + \varepsilon_{it} \tag{5}$$

Appendix 2 shows the details of the variables used in the formula. The actual GDP was deflated to the 2006 constant price.

**Global econometric model**

Global and local regression models are two common forms of multivariate regression analysis (Wang et al. 2014). The global regression model reflects the relationship between independent and dependent variables under the assumption of stationary space and time. In contrast, the relationship in the local regression model is assumed to change in the spatiotemporal dimension. A local regression model can be adopted to solve the heterogeneity dilemma.

The ordinary panel regression model is the most commonly used global regression model. The formula of the model is as follows:

$$\ln EFI_{it} = \alpha_0 + \sum \beta_{kit} \ln x_{kit} + \mu_i + \sigma_t + \varepsilon_{it} \tag{6}$$

where the subscript *i* represents the city, *t* represents the year, and *k* represents the number of explanatory variables;  $\beta$  denotes the regression parameter;  $\mu_i$  is the urban fixed effect;  $\sigma_t$  is the year fixed effect; and  $\varepsilon_{it}$  is the stochastic error term.

**Exploratory spatial data analysis (ESDA)**

The core of ESDA is to measure the correlation of geographical elements in different spatial locations and reflect the spatial distribution of geographical segments (Huang et al. 2021). Global Moran’s *I* index is applied to judge the spatial correlation of EFI. The calculation formula is shown below:

$$I = \frac{n \sum_{i=1}^n \sum_{j=1}^n w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^n \sum_{j=1}^n w_{ij} \sum_{i=1}^n (x_i - \bar{x})^2} \tag{7}$$

where *n* represents 17 cities in the Curve Area,  $x_i$  and  $x_j$  represent the EFI of cities *i* and *j*, respectively,  $\bar{x}$  is the mean value of EFI, and  $w_{ij}$  denotes the unit in the spatial weight matrix *W*, and the specific form of *W* is shown as follows:

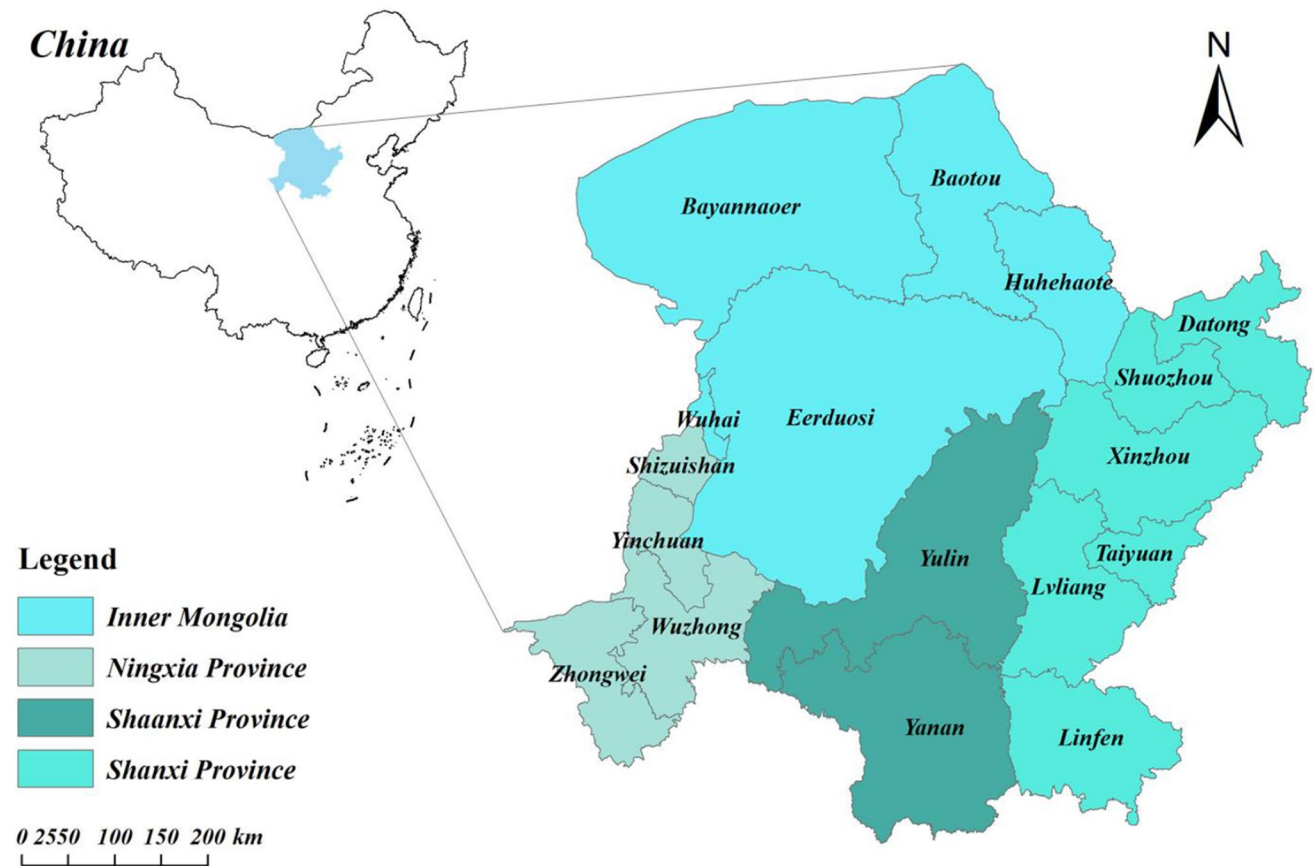
$$\begin{bmatrix} w_{11} & w_{12} & \dots & w_{1n} \\ w_{21} & w_{22} & \dots & w_{2n} \\ \dots & \dots & \dots & \dots \\ w_{n1} & w_{n2} & \dots & w_{n3} \end{bmatrix} \tag{8}$$

$$w_{ij} = \begin{cases} \frac{1}{d_{ij}}, & i \neq j \\ 0, & i = j \end{cases} \tag{9}$$

where  $d_{ij}$  is the Euclidean distance between cities *i* and *j*. The value of Global Moran’s *I* is between −1 and 1, with closer proximity to −1 indicating a more pronounced spatial dispersion trend. In comparison, closer proximity to 1 means a more pronounced spatial aggregation trend. A Moran index equal to 0 indicates that there is no spatial correlation between the units.

**Local econometric model**

Different from the traditional temporally weighted regression (TWR) and geographically weighted regression (GWR) models, only considering the spatial or temporal dimension, the geographically and temporally weighted regression (GTWR) model can reflect the spatiotemporal evolution relationship of variables, and the regression results are closer to reality (Huang



**Fig. 2** Geographic location of the study area

et al. 2010). Given the temporal and spatial variability of EFAs, GTWR, rather than traditional econometric technology, is more suitable for analyzing driving forces of ecological performance in EFAs. The formula is detailed below:

$$y_i = \beta_0(u_i, v_i, t_i) + \sum_{k=1}^K \beta_k(u_i, v_i, t_i)x_{ik} + \varepsilon_i \quad (10)$$

$$\beta(u_i, v_i, t_i) = (X^T W(u_i, v_i, t_i) X)^{-1} X^T W(u_i, v_i, t_i) Y \quad (11)$$

$$W(u_i, v_i, t_i) = \text{diag}(w_{i1}, w_{i2}, \dots, w_{ij}) \quad (12)$$

where  $y_i$  represents the dependent variable,  $(u_i, v_i, t_i)$  represents the Mercator projected coordinates of the city  $i$  in year  $t$ ,  $\beta_0$  represents the regression intercept term,  $\beta_k$  represents the regression parameter estimation value,  $\varepsilon_i$  represents the stochastic error term, and  $W$  is the spatiotemporal weight matrix<sup>1</sup>.

<sup>1</sup> The specific calculation process of the spatiotemporal weight matrix is shown in Appendix 3.

## Data

### Study area

The study area of this paper is the II-shaped Curve Area across the middle and upper reaches of the Yellow River Basin in China, including 17 prefecture cities in four provinces (Fig. 2). The Curve Area, which has been identified as a distinct area suffering from a “resource curse” in numerous studies, has triple characteristics of fragile ecology, abundant resources, and economic poverty. Besides, in response to vegetation degradation and soil erosion in this area, the Chinese government has implemented a variety of ecological restoration projects (e.g., the projects of returning farmland to forests and grasslands). The natural conditions in this area have changed dramatically, resulting in changes in ecological performance on a spatial and temporal scale. Therefore, targeted research regarding the spatiotemporal evolution characteristics of the area’s ecological performance is required.

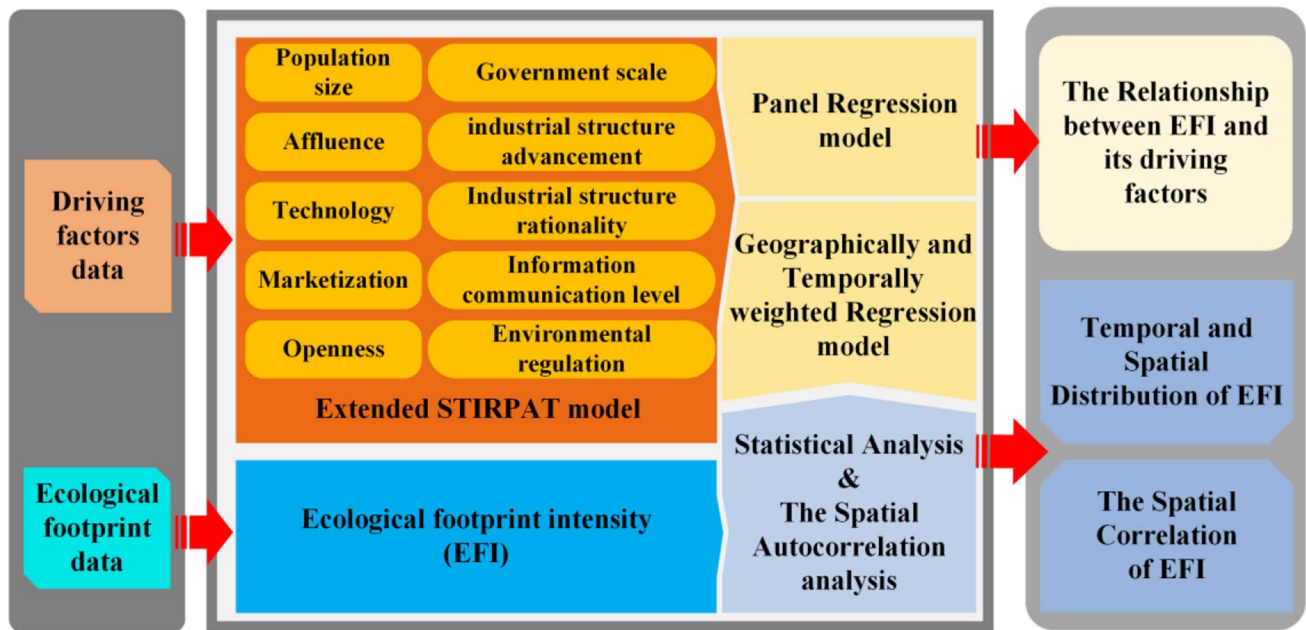


Fig. 3 The flowchart of the methodology

### Data source and descriptive statistics

The data used in this paper are from China's National Bureau of Statistics, CEIC database, China Urban Statistical Yearbook, China Regional Economic Statistical Yearbook, China Urban Construction Statistical Yearbook, Ningxia statistical yearbook, Shaanxi statistical yearbook, Shanxi statistical yearbook, Inner Mongolia statistical yearbook, statistical yearbooks of 17 prefecture cities, and Statistical Bulletins of national economic and social development of 17 cities over the years. For some missing data, the interpolation method is used in this paper. The descriptive statistics of relevant data are shown in Appendix 4.

Based on the above models and data, the regression analysis is performed (Fig. 3).

## Results

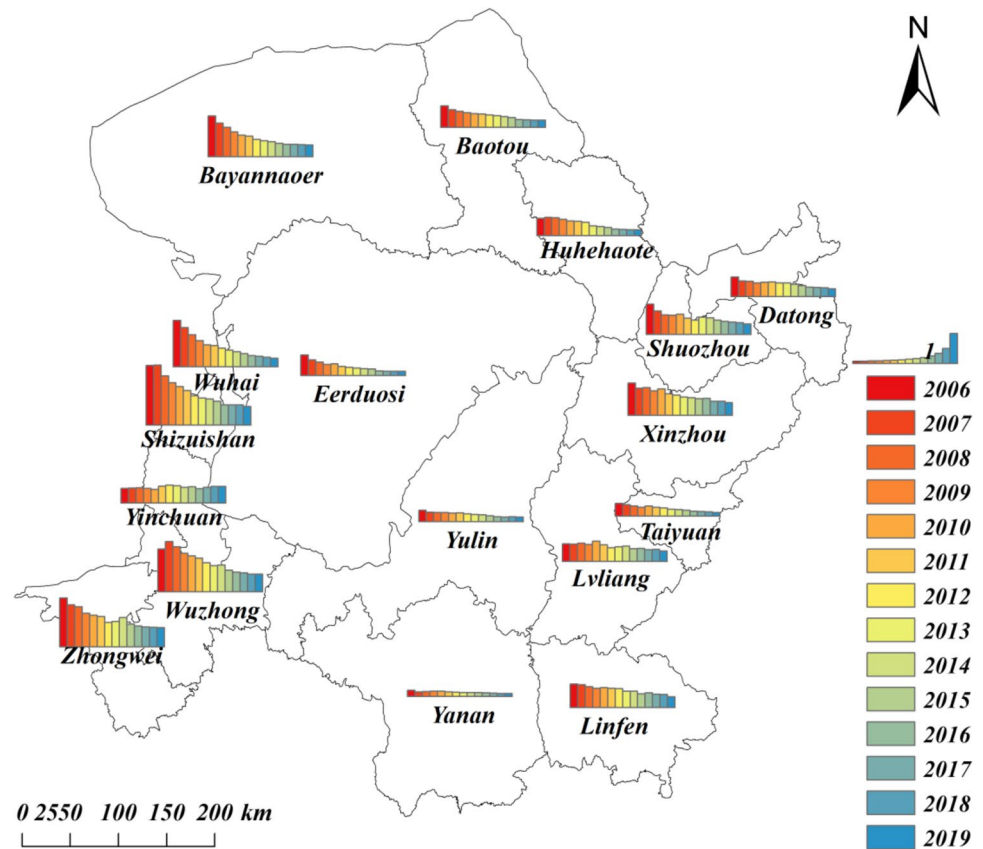
### Spatiotemporal characteristics of EFI

The spatiotemporal evolution pattern of the EFI of 17 cities in the Curve Area from 2006 to 2019 is reflected in Fig. 4. Temporally, the EFI of Yinchuan shows a fluctuating and stable state during the study period while that of the other 16 cities shows a gradually decreasing trend in general. This indicates that the Curve Area is progressively approaching the development vision of ecological balance, environmental protection, and economic growth. This conclusion is different from that drawn from the national

scale study: the environmental efficiency of developing countries is gradually decreasing (Salman et al. 2022). Spatially, significant differences exist in the EFI of different cities. Firstly, from the overall trend, the EFI of cities in the west of the Curve Area is significantly higher than that in the east; the EFI of the northern cities is higher than that of the southern cities; the EFI of cities in the central area is lower than that of the surrounding area. Secondly, from the perspective of provincial administrative regions, the overall level of EFI of four cities in Ningxia is significantly higher than that of cities in the other three provinces during the study period; the EFI of two cities in Shaanxi (Yulin and Yanan) is basically at the lowest level during the study period; the EFI of cities in Inner Mongolia and Shanxi is relatively at a moderate level. Notably, the EFI of provincial capital cities is significantly lower than that of other cities in the same province, such as Yinchuan in Ningxia, Huhehaote in Inner Mongolia, and Taiyuan in Shanxi. This is related to the agglomeration strategy of "strong provincial capitals" implemented in this area since the beginning of this century. As a result, a large number of talents and high-tech industries have gathered in provincial capitals, which enables the provincial capital cities to reduce environmental pollution while improving economic efficiency. In addition, the huge difference in the quality of ecological development between the provincial capital cities and the surrounding cities also indicates that the Curve Area is facing the problems of the weak driving force of the core cities, low degree of synergy, and low level of equalization of public services to a certain extent.



**Fig. 4** Temporal and spatial pattern of EFI in the Curve Area



Meanwhile, we also investigate the EFI of biological resource, energy resource, water resource, and pollution discharge—four components of the ecological footprint account. The evolution trends vary among these four indicators, but the spatial distribution trends are roughly the same. For lack of space, detailed information is shown in Appendix 5.

Further, it can be inferred from Fig. 4 that the spatial distribution of EFI shows a pattern of high-high clustering and low-low clustering. To verify this spatial correlation feature, Global Moran's  $I$  index of EFI is calculated with GeoDa 1.20 (Table 1). Global Moran's  $I$  indices of EFI in years except 2006 and 2010 are significantly positive, suggesting that the EFI of cities in the Curve Area has a significant spatial positive correlation. That is, it shows the characteristics of high-high and low-low clustering. Meanwhile, Global Moran's  $I$  indices show an increasing trend in general, rising from 0.144 in 2006 to 0.413 in 2019, indicating that the positive spatial correlation of EFI intensified successively.

### Driving factors of EFI

Before performing the regression, a multicollinearity test should be conducted for all independent variables to avoid estimation deviation. As shown in Table 2, the VIF values of all variables are less than 10, indicating the lack of severe

multicollinearity and the preparation of global and local regression models.

### Results of global regression

Table 3 shows the estimation results of panel regression models. To screen out the model more compatible with

**Table 1** Global Moran's  $I$  index of EFI

Year	Moran's $I$	$Z$	$P$ value
2006	0.144	1.282	0.117
2007	0.236	1.848	0.044
2008	0.236	1.760	0.046
2009	0.212	1.622	0.057
2010	0.142	1.243	0.108
2011	0.287	1.881	0.041
2012	0.320	2.054	0.030
2013	0.315	1.990	0.035
2014	0.305	1.936	0.042
2015	0.341	2.114	0.032
2016	0.212	1.583	0.058
2017	0.329	2.001	0.038
2018	0.299	2.061	0.029
2019	0.413	2.637	0.008

**Table 2** Results of multicollinearity test

Variables	lnGDPPC	lnINL	lnISA	lnMARL	lnPOP	lnGOVS	lnISR	lnTECL	lnERI	lnOPEN
VIF	5.28	5.06	4.38	4.16	3.84	3.41	2.45	2.18	2.12	1.87

**Table 3** Estimation results of the panel regression model

Variables	Pooled regression model (1)	Random effects model (2)	Individual fixed effects model (3)	Two-way fixed effects model (1) (4)	Two-way fixed effects model (2) (5)
lnPOP	0.019 (0.19)	0.016 (0.10)	-0.456** (-2.33)	1.213*** (6.24)	1.205*** (6.34)
lnGDPPC	-0.383*** (-3.11)	-0.705*** (-3.90)	-0.851*** (-9.03)	-0.550*** (-4.10)	-0.548*** (-4.13)
lnOPEN	0.084 (1.72)	0.026 (0.94)	0.006 (0.3)	0.037** (2.43)	0.035** (2.4)
lnMARL	-0.142 (-0.85)	-0.078 (-0.45)	-0.287** (-2.24)	0.873*** (6.62)	0.863*** (6.65)
lnGOVS	-0.159 (-0.84)	0.057 (0.55)	0.233** (2.54)	-0.343*** (-4.59)	-0.341*** (-4.58)
lnISR	-0.161** (-2.27)	-0.057 (-1.19)	-0.028 (-1.13)	-0.002 (-0.13)	
lnTECL	0.034 (0.40)	-0.333 (-0.47)	-0.039 (-1.05)	0.017 (0.61)	
lnINL	-0.171** (-2.16)	-0.038 (-0.46)	0.025 (0.54)	0.138*** (3.59)	0.142*** (3.74)
lnERI	-0.501*** (-6.70)	-0.194*** (-2.94)	-0.178*** (-4.96)	-0.139*** (-4.78)	-0.139*** (-4.78)
lnISA	-0.349* (-1.91)	-0.501*** (-3.14)	-0.470*** (-6.53)	-0.231*** (-3.63)	-0.230*** (-3.81)
Constant	0.411 (0.49)	-0.125 (-0.12)	2.294** (2.36)	-10.424*** (-8.47)	-10.360*** (-8.50)
R <sup>2</sup>	0.791	0.804	0.815	0.907	0.907
LM test	Inspection value: 294.84 P value: 0.0000			Hausman test	Inspection value: 35.93 P value: 0.0002

Note:

\*\*\*significance at 0.01

\*\*significance at 0.05

\*significance at 0.1

the sample data, relevant statistical tests are carried out. Firstly, the Lagrange multiplier (LM) test suggests that the random effects model is more suitable than the pooled regression model; secondly, the Hausman test shows that the individual fixed effects model is more ideal than the random effects model. While the time dummy variables are added to the model, it is found that the *P* values of the time dummy variables in all years are equal to 0.000, less than 0.05, indicating that the null hypothesis of no time effects is repelled. Therefore, the two-way fixed effects model should be adopted. Column 4 in Table 3 shows the estimation results of the two-way fixed effects model. According to the estimation results, POP, GDPPC, OPEN,

MARL, GOVS, INL, ERI, and ISA have a significant impact on EFI. In contrast, the effect of ISR and TECL on EFI is not statistically significant.

With the other conditions unchanged, EFI will increase by 1.213%, 0.037%, 0.873%, and 0.138% for every 1% increase in POP, OPEN, MARL, and INL, respectively; every increase of 1% in GDPPC, GOVS, ERI, and ISA is adjoint with a decrease of 0.550%, 0.343%, 0.139%, and 0.231% in the EFI, respectively. The results of the two-way fixed effects model exhibit that POP enhances the EFI to the largest extent, followed by MARL, INL, and OPEN; meanwhile, GDPPC exerts the strongest negative effect on EFI, followed by GOVS, ISA, and ERI.

**Table 4** Assessment of the TWR, GWR, and GTWR models

Model	TWR	GWR	GTWR
$R^2$	0.8404	0.9799	0.9906
AICc	82.96	-278.33	-304.73
Residual sum of squares	15.0075	1.8918	0.8819
Sigma	0.2511	0.0892	0.0609

On this basis, the insignificant variables (ISR and TECL) are eliminated, and the two-way fixed effects model has performed again. The estimation results are presented in column 5 in Table 3. It can be found that after removing the variables ISR and TECL, the regression coefficients of other variables show inconspicuous change and are still significant, indicating that the previous regression results are robust. Here, the regression results of the global regression model have been analyzed. The result of the ideal two-way fixed effect model shows that factors affecting EFI have prominent individual and time effects. Still, these effects cannot be reflected in the global regression model. Therefore, the GTWR model that takes into account the spatiotemporal heterogeneity should be adopted. The conclusion from the global regression model reflects the influence of factors from a global perspective and can serve as a baseline reference for the local regression model.

### Results of local regression

Using ArcGIS 10.2, the GTWR model is performed to estimate the regression coefficients of various factors in different cities at different times. Table 4 shows the details of TWR, GWR, and GTWR. The goodness-of-fit coefficient ( $R^2$ ) of the GTWR model is 0.9906, higher than that of the TWR (0.8404) or GWR (0.9799) model, thus showing that the goodness of fit of the GTWR model exceeds that of the TWR and GWR models. Similarly, the residual sum of squares, sigma, and Akaike information criterion (AICc) values provided by the GTWR model are lower than those provided by the GWR or TWR model. In conclusion, the local regression details suggest that the optimum model is GTWR.

Results of the GTWR model show that all independent variables have specific regression coefficients in different cities and years, indicating the spatiotemporal volatility of EFI drivers. Appendix 6 shows the descriptive statistics of the regression parameters of the GTWR model. It can be seen that the parameters of some variables vary strikingly and have both positive and negative values, indicating that spatiotemporal heterogeneity exists in different driving

factors. Moreover, Fig. 5a–j elaborately illustrates the varying influence of each driver over time. Due to the time continuity of local coefficients, the varying spatial effect can be more intuitively reflected via average coefficients of years (Bai et al. 2022). Fig. 6a–j presents the spatial distributions of average coefficients of years.

POP exerts both stimulative and inhibitory effects on EFI, with values fluctuating between  $-0.652$  and  $1.796$ , distinct from the positive impact ( $1.213$ ) obtained in the two-way fixed effects model. Concerning the time variation presented in Fig. 5a, the effect shows a slow downward trend, and the lowest mean value was achieved in 2019. This indicates that the suppressive effect of POP on EFI has strengthened in recent years. For the spatial variation presented in Fig. 6a, POP was confirmed to play an inhibitory role in Eerduosi, Huhehaote, and cities in Shanxi province but a positive effect in the west of the Curve Area. These results indicate that the enhancement of the POP would exert opposite effects in the west and east of the Curve Area.

GDPPC has an inhibitory impact on EFI, with most values varying between  $-1.641$  and  $0$ , which is accordant with the inhibitory effect ( $-0.550$ ) obtained in the two-way fixed effects model. This result suggests that GDPPC inhibits EFI, but the intensity of the inhibitory changes across periods and cities. Concerning the time variation illustrated in Fig. 5b, the impact presents a downward trend, and the lowest mean value was achieved in 2019. This suggests that GDPPC exerts a suppressive effect on EFI with a tendency to be increasingly strengthened. For spatial variation, as depicted in Fig. 6b, the weaker impact of GDPPC occurred in Yulin ( $-0.052$ ), while the more significant effect was found in the other 16 cities.

OPEN exerts both stimulative and inhibitory effects on EFI, with values fluctuating between  $-0.168$  and  $0.124$ , distinct from the positive result ( $0.037$ ) obtained in the two-way fixed effects model. Concerning the time variation depicted in Fig. 5c, the impacts present a pattern of an “inverted-U” shape, with the mean value achieving its highest point ( $0.019$ ) in 2010. This implies that even though OPEN once promoted EFI, its promoting effect has gradually weakened and turned into an inhibitory impact recently. For the spatial variation as illustrated in Fig. 6c, the more substantial negative impact appeared in cities on the edge of the Curve Area (especially the eastern part), including Bayannaoer ( $-0.038$ ), Huhehaote ( $-0.087$ ), Shuozhou ( $-0.049$ ), Datong ( $-0.023$ ), Xinzhou ( $-0.044$ ), Taiyuan ( $-0.049$ ), and Linfen ( $-0.004$ ). In contrast, a positive impact appeared in the other cities. This suggests that the enhancement of OPEN would bring a better decrease in EFI in the eastern part of the Curve Area.

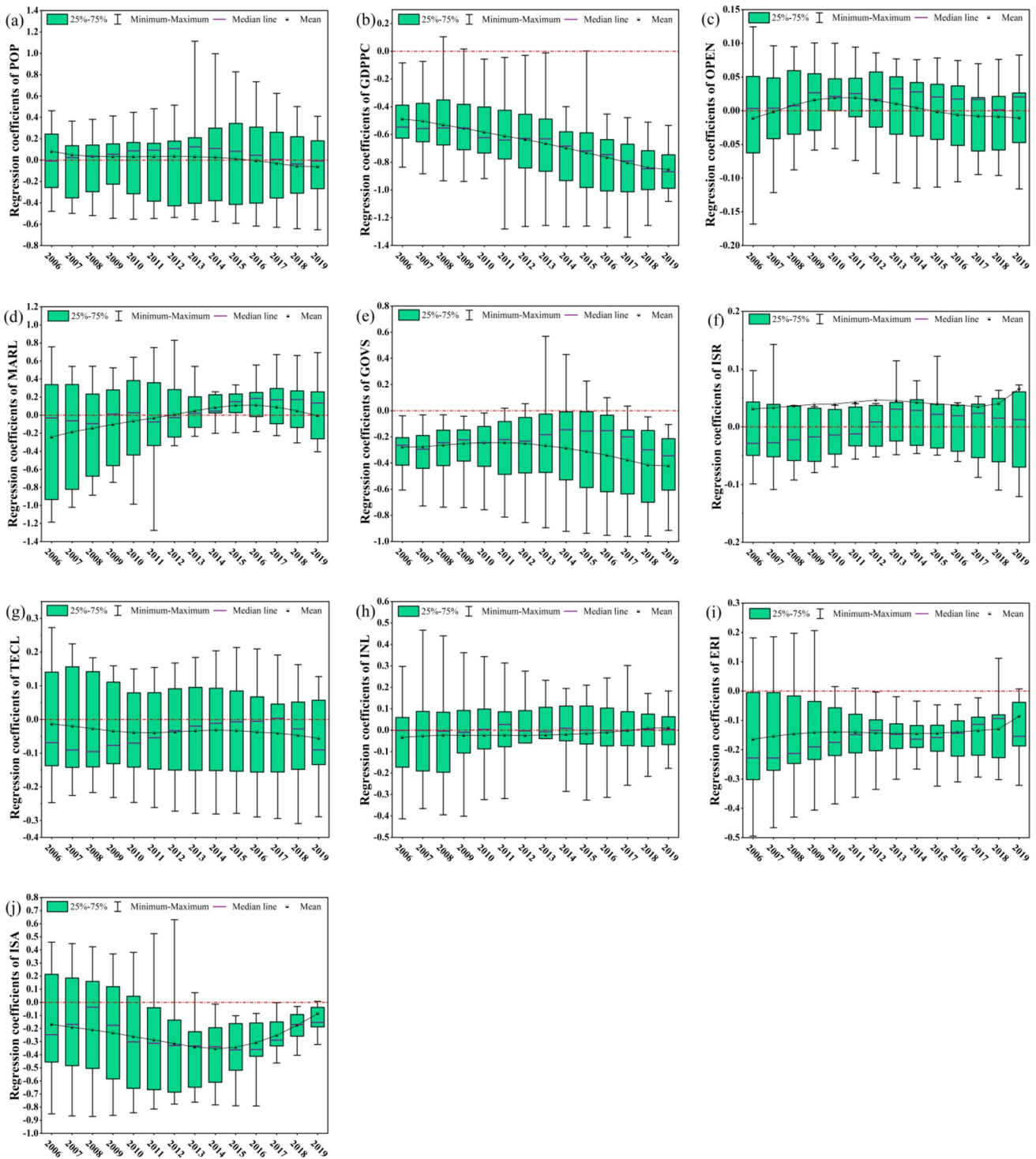


Fig. 5 a–j Boxplots of local coefficients for different factors, 2006–2019

MARL has both stimulative and inhibitory effects on EFI, with values waving between  $-1.498$  and  $0.903$ , distinct from the positive impact ( $0.873$ ) obtained in the two-way

fixed effects model. For the time change plotted in Fig. 5d, the effect presents a pattern similar to that of OPEN, with the mean value achieving its highest point ( $0.112$ ) in 2016.

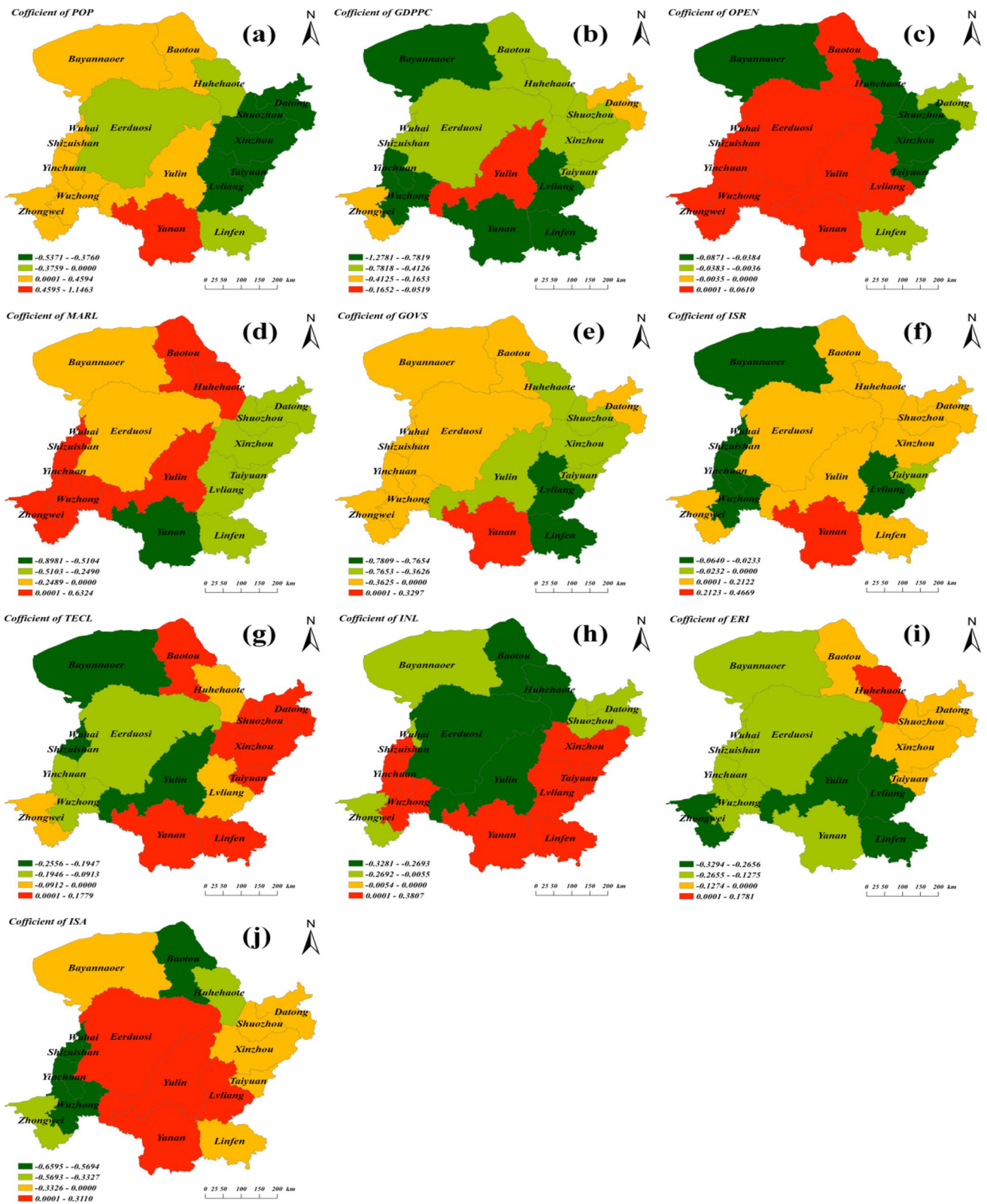


Fig. 6 a–j The spatial distribution of annual mean value for different factors

This indicates that although MARL has promoted the EFI in recent years, the promoting effect has gradually weakened. Concerning the spatial variation mapped in Fig. 6d, cities with stronger negative effects are primarily located in the east of the region. In contrast, cities in the west perform a slightly negative or positive impact.

GOVS has an inhibitory impact on EFI, with most values waving between  $-0.961$  and  $0$ , which is accordant with the negative effect ( $-0.343$ ) reported by the two-way fixed effects model. This result implies that GOVS inhibits EFI, despite the intensity of the inhabitation changes across different years and cities. As per the time variation illustrated in Fig. 5e, the inhibitory impact presents a tendency of first stability followed by a fall, with the mean value reaching its lowest point ( $-0.422$ ) in 2019, indicating that the negative effect of GOVS has strengthened recently. Regarding the spatial variation shown in Fig. 6e, the favorable outcome ( $0.329$ ) occurred in Yanan, while the inhibitory effect was recorded in the other 16 cities. Besides, the inhibitory effect of the cities in the east of the region is more potent than that of the western cities.

ISR exerts both stimulative and inhibitory effects on EFI, with values fluctuating between  $-0.121$  and  $0.678$ , distinct from the insignificant negative outcome ( $-0.002$ ) obtained in the two-way fixed effects model. Concerning the time variation presented in Fig. 5f, the overall state shows a trend of initial plateaus and then rising, with the mean values waving reposefully between  $0.031$  and  $0.046$  during 2006–2018 and achieving the highest point ( $0.066$ ) in 2019, indicating that the effect of ISR has strengthened during the past few years. For the spatial variation, as presented in Fig. 6f, the greater promoting effect ( $0.467$ ) occurred in Yanan. In comparison, the greater inhibitory effect was recorded in Bayannaer ( $-0.064$ ), Wuhai ( $-0.059$ ), Shizuishan ( $-0.060$ ), Yinchuan ( $-0.046$ ), Wuzhong ( $-0.031$ ), and Lvliang ( $-0.024$ ).

TECL exerts both stimulative and inhibitory effects on EFI, with values fluctuating between  $-0.309$  and  $0.273$ , distinct from the insignificant positive impact ( $0.017$ ) reported by the two-way fixed effects model. For time variation (Fig. 5g), the mean values of the coefficients exhibit a slow downward trend, indicating that the inhibitory effect has strengthened recently. This trend may be related to China's green innovation in recent years to curb the emission of sulfur dioxide and other pollutants (Luo et al. 2023). Regarding the spatial distribution mapped in Fig. 6g, promoting effect exists in cities in the east of the region, while the inhibitory effect occurs in the west. This implies that the promotion of TECL would exert opposite effects in the western and eastern cities of the area.

INL exerts both positive and negative effects on EFI, with values waving between  $-0.413$  and  $0.468$ . The result differs

from the positive impact ( $0.138$ ) obtained in the two-way fixed effects model. For the temporal variation depicted in Fig. 5h, the mean values show a gradually rising trend, with the highest point ( $0.011$ ) in 2019. This result indicates that the inhibitory effect has weakened and turned into a promoting effect. Regarding spatial distribution (Fig. 6h), a positive impact occurred in cities in Ningxia and Shanxi province except for Zhongwei, Datong, and Shuozhou. In contrast, a negative impact was found in the other nine cities. This suggests that the improvement of INL is probably not conducive to the reduction of EFI in Ningxia and Shanxi.

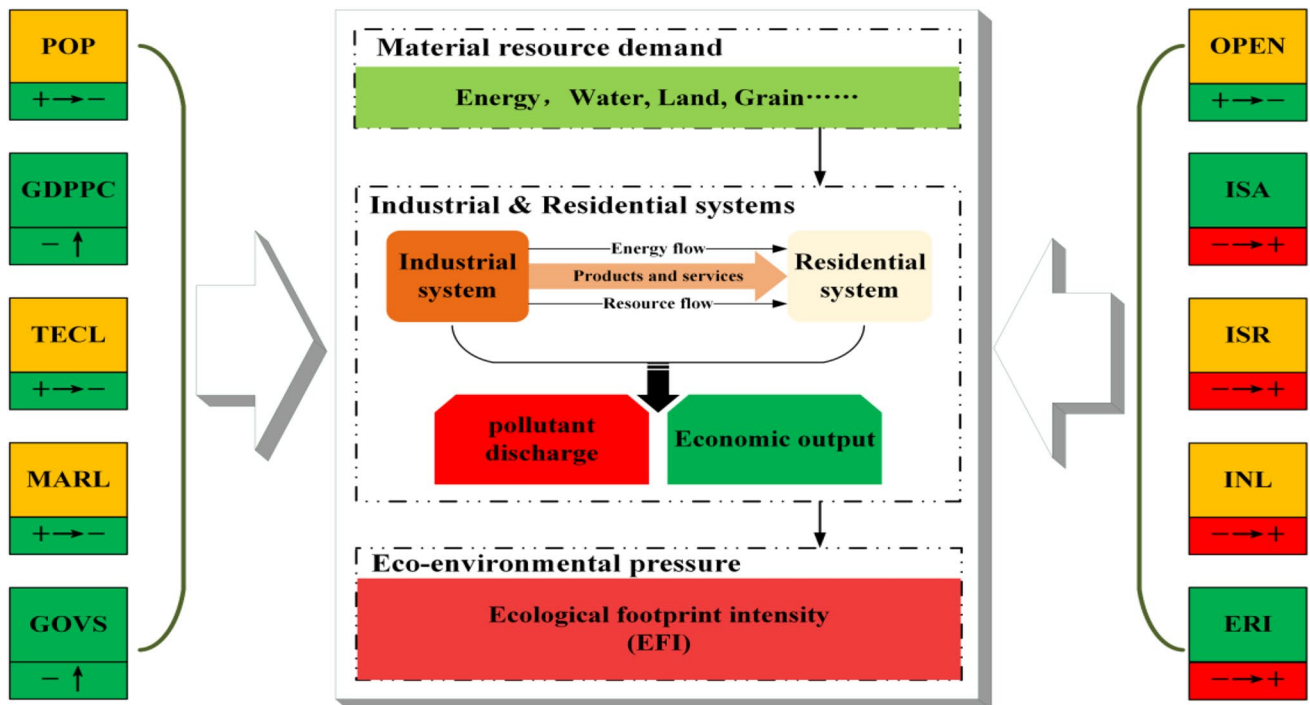
ERI exerts a negative impact on EFI, with most values fluctuating between  $-0.495$  and  $0$ . This result is accordant with the effect ( $-0.139$ ) observed in the two-way fixed effects model, suggesting that ERI facilitates the EFI, despite the strength of the facilitation changes across periods and cities. As per the time variation illustrated in Fig. 5i, the negative effects present a tendency of first stability followed by a rise, with values varying between  $-0.164$  and  $-0.086$ . This result suggests that the negative effects have weakened recently. For the spatial distribution (Fig. 6i), promoting effect appeared in Huhehaote ( $0.159$ ), while a negative impact occurred in the rest of the cities.

ISA harms EFI, with most values waving between  $-0.871$  and  $0$ , which is principally accordant with the result ( $-0.231$ ) found in the two-way fixed effects model. From the temporal trend in Fig. 5j, the mean values exhibit a U-shaped trend with the lowest point ( $-0.354$ ) in 2014, indicating that ISA weakens EFI, despite the intensity changes in different years and cities. For the spatial distribution in Fig. 6j, a promising effect was found in cities of the central region, including Eerduosi ( $0.133$ ), Yulin ( $0.065$ ), Lvliang ( $0.003$ ), and Yanan ( $0.311$ ). At the same time, a negative impact appeared in the other cities of the region.

## Discussion

The overall level of EFI in the Curve Area continued to decrease during the study period, which is similar to those of earlier studies (Han et al. 2021; Song et al. 2013). This result indicates that the reduction of EFI in the region has made great progress. Besides, the EFI exhibits significant spatiotemporal differences, probably due to the strategic difference in provincial development and orientation of economic interaction. The result also implies that the spatiotemporal heterogeneity of EFI should be considered when designing sustainable strategies.

As shown in Fig. 7, the impact of POP, OPEN, MARL, TECL, ISR, and INL on EFI was verified to be two-sided. POP, OPEN, MARL, and TECL have the potential to transform the favorable effect into an inhibitory effect,



**Fig. 7** Current status and future evolution trend of each driving factor

while ISR and INL show the opposite. POP restrains EFI in the east of the region but promotes it in the west of the region, and this is probably attributed to the fact that cities in the eastern region are closer to the developed coastal areas in China and thus easier to enjoy the “scale effect” brought by population agglomeration. In contrast, cities in the western region are relatively closed and difficult to introduce high-tech talents, thus accompanied by the “crowding effect.” Unlike the western region of the study area, the eastern region is close to the coastline, and OPEN stimulates the economy of the eastern region and thus restrains EFI. The inverted U-shaped influence of MARL on EFI shows that the promotion of marketization reduces the EFI to a certain extent. However, the marketization level of the Curve Area at the current stage is still significantly lower than that of the national average level (An & Zhang 2021), indicating that there is still some room to restrain EFI through marketization promotion. TECL hinders EFI in the east of the region but promotes it in the west of the region, which is related to the fact confirmed by (Ke et al. 2021) that innovation improvement increases ecological footprint in Western China but reduces it in Central China. ISR seems not conducive to the reduction of EFI in the Curve Area; this is principally attributed to the fact that the rationalization of industrial structure is accompanied by

the transfer of labor among different sectors, and the gap between technology required by industries and the existing skills of labors leads to the low efficiency of economic operation, which is unfavorable to the improvement of eco-efficiency. INL significantly reduces EFI in relatively developed cities such as Baotou, Huhehaote, Eerduosi, and Yulin, while the opposite effect is in poorer cities. This may be because the infrastructure support capacity in developed cities is completed, and the improvement of information and communication level will further improve the eco-efficiency.

Although GDPPC, GOVS, ERI, and ISA significantly inhibit EFI (Fig. 7), the intensity of the inhibition varies across periods and cities. GDPPC suppresses EFI, which is consistent with the previous research (Liu et al. 2020; Wang & Chen 2020). The decreasing negative effect of GDPPC foregrounds the noticeable improvement in the transformation of regional economic development from “quantity” to “quality.” GOVS inhibits EFI, which is similar to the result of Guangdong (Zhou et al. 2018). However, the result is contrary to that at the national level (Liu et al. 2020). This finding suggests that GOVS is conducive to improving the eco-efficiency in EFAs.

The inherent fragile nature of EFAs’ environment indicates that GOVS has a higher marginal effect on regulating the eco-environment. ERI represses EFI, which

aligns with the findings of Ren et al. (2020) and Yu et al. (2019). This suggests that environmental regulation is an effective policy tool for the governments to improve environmental performance in the Curve Area. ISA restrains EFI, which is consistent with current relevant studies (Han et al. 2021; Wang & Chen 2020) but different from that in Chengdu-Chongqing urban agglomeration (He & Hu 2022). Although the Curve Area is a gathering area for heavy industry, the accelerated development of the tertiary industry reduces the EFI and is thus beneficial to the eco-environment.

According to the summarization of the current status and future evolution trend of each driving factor (Fig. 7), the decision-making basis for the design of sustainable development path in EFAs (the Curve Area) can be concluded. Firstly, economic development and government support are of primary importance to the sustainable development of EFAs. In the future, improving the level of economic development and further expanding government functions will be the focal points to promote the construction of ecological civilization in EFAs. Secondly, POP, TECL, MARL, and OPEN have made some achievements in accelerating the green and high-quality development of EFAs. Controlling population density, increasing investment in scientific and technological innovation, optimizing the market environment, and rationally introducing foreign capital are the aspects that need further efforts in the following years. Thirdly, although ISA and ERI are conducive to the development of EFAs at the current stage, they may not be beneficial to the sustainable development of EFAs in the future. Therefore, it is nonnegligible to accurately position the current industrial situation, promote the optimization of industrial structure, and control the level of environmental regulation to coordinate the relationship between urban development and resources and environment. Fourthly, ISR and INL are the two most unfavorable drivers, and their evolutionary trend is worsening. Consequently, on the one hand, strengthening human resource management, such as providing support for labor distribution among industry sectors and reinforcing the skills training of the labor force floating among sectors, is extremely essential. On the other hand, propelling the construction of information infrastructure in backward areas and narrowing the information gap between EFAs and other developed areas would help curb this negative tendency.

## Conclusions

Currently, the eco-environment is deteriorating increasingly against the background of global change, and the sustainable development of EFAs is facing great challenges. To evaluate

the ecological performance and its forces in EFAs, a multi-factor GTWR model of EFI is applied in the selected Curve Area. This paper aims to support and theoretically extend regional integration and differentiated governance strategies for the sustainable development of the Curve Area, providing a valuable reference for other EFAs. The main conclusions are as follows:

(1) During the study period, the overall level of EFI in the Curve Area decreases, and regional ecological performance shows a continuously improving trend. (2) The EFI in the Curve Area shows a significant spatial agglomeration effect of “high-high and low-low clustering.” Urban coordinated development is expected to alleviate ecological pressure in EFAs. (3) Driving factors of EFI in the Curve Area exhibit evident spatiotemporal heterogeneity. Population size, openness, marketization, technology, industrial structure rationalization, and information communication level imparted a two-sided impact on EFI, while affluence, government scale, environmental regulation, and industrial structure advancement significantly inhibit EFI, with the intensity of inhibition varying across periods and cities. The formulation of policies supporting the sustainable development of EFAs needs to grasp the temporal and spatial characteristics of various factors accurately.

From the empirical case in this study, it can be concluded that ecological performance and its determinants in EFAs have strong spatiotemporal volatility. However, such ecological performance and its determinants are specific to the context. That is, ecological performance and its determinants are distinct in EFAs with different geographical locations and development stages. Therefore, to formulate sustainable development policies for various EFAs, it is necessary to fully consider their geographical conditions and development stages to understand the future evolution trend. This study combines GIS and econometric methods, providing a reference for assessing the current sustainable development level and tracking the future development status of EFAs.

Herein, the conclusions of the study are summarized. They are not only conducive to understanding the forces and spatiotemporal dynamics of ecological performance in EFAs, but also provide a decision-making basis for dealing with the eco-environmental issues in EFAs and realizing sustainable development in the future. However, some limitations still exist. Although this paper selects indicators as comprehensively as possible when calculating the EFI, relevant indicators would still be omitted for the restriction of data acquisition, and it might exert a specific influence on the calculation results. In addition, a series of human and natural factors, including time and space, are considered in the analysis of driving forces. Still, due to the difficulty in quantifying other factors, such as policies (e.g., ecological compensation), climate, and environment, they have to be abandoned. Finally, the panel regression model mentioned



in most previous studies is adopted to obtain influencing factors, and other methods (e.g., the GeoDetector) to determine the influencing factors could also be adopted. However, due to the limitation of the length of the paper, we could not elaborate on all these works clearly in the current paper. In future work, we will further excavate the essence of sustainable development in EFAs; take complete account of

the differences in policies, climate, environment, and other factors in different regions based on further improving the assessment system of EFI; and use methods such as the GeoDetector to identify factors driving EFI in EFAs for ease of providing support for scientifically formulating and implementing focused and localized development strategies for EFAs.

## Appendix 1 Details of the EF account

**Table 5** Information about the EF account

Account	Sub-account	Products	Land type (modified equivalence factor)
Biological resource	Arable products	Wheat, rice, corn, soybean, cotton, potato, rapeseed, peanut, vegetable, poultry egg, pork, and poultry meat	Arable land (4.02)
	Forest products	Fruits	Forest land (0.63)
	Grass products	Dairy, beef, and mutton	Grassland (0.09)
	Aquatic products	Freshwater aquaculture	Water area (0.05)
Energy consumption	Fossil fuel	Coal, natural gas, and petroleum	Fossil energy land (0.18)
	Electricity	Electricity	Construction land (4.02)
Water resource	Water	Domestic water, production water, public water, and other water	water resource land (5.19)
Pollution discharge	Wastewater	Industrial wastewater and municipal sewage	Water area (0.05)
	Waste gas	Industrial sulfur dioxide and industrial smoke dust	Forest land (0.63)
	Solid waste	Industrial solid waste and household waste	Arable land (4.02)

It should be noted that the EF of biomass is the ecological footprint of local biomass production, while the EF of fossil energy is its consumption footprint (Luo et al. 2018). Therefore, biomass production is used to calculate the EF of biological resources, while energy consumption is used to calculate the EF of energy. Besides, pollution discharge and energy consumption are treated separately due to the particularity of the EF accounting methods. For pollution discharge, industrial solid waste and domestic waste are converted into arable land according to 109,100 t/hm<sup>2</sup>; industrial wastewater and urban wastewater are converted into water area according to 365 t/hm<sup>2</sup>; industrial sulfur dioxide and industrial smoke dust are converted into forest land at the rate of 0.08865 t/hm<sup>2</sup> and 10.11 t/hm<sup>2</sup>, respectively (Li et al. 2022). The calculation formula of EF of pollutants is as follows:

$$EF_{\text{pollutant}} = \sum_{i=1}^3 r_i \times \frac{Q_i}{AC_i} \quad (13)$$

where  $r_i$  is the equivalence factor,  $Q_i$  refers to the emission of pollutants,  $AC_i$  is the ability of different lands to absorb pollutants, and  $i$  represents different pollutants. The EF of energy consumption is calculated according to the method proposed by Sun and Wang (2022), which is expressed as follows:

$$EF_{\text{energy}} = \sum_{j=1}^4 r_j \times \frac{R_j \times 293080}{V_j} \quad (14)$$

where  $r_j$  is the equivalence factor,  $R_j$  is the total energy consumption (10,000 t of standard coal),  $V_j$  represents the global average energy footprint, and  $j = 1, 2, 3, 4$  represent coal, natural gas, petroleum, and electricity, respectively.

## Appendix 2 Description of driving factors

**Table 6** Description of driving factors

Variable name	Notation	Variable measure
Population size	POP	Population density
Affluence	GDPPC	Per capita regional GDP
Technology	TECL	The proportion of employees in the science and technology industry in total employees
Marketization	MARL	The proportion of retail sales of social consumer goods in regional GDP
Government scale	GOVS	The proportion of government public financial expenditure in regional GDP
Openness	OPEN	The proportion of total import and export trade in regional GDP
Industrial structure advancement	ISA	The ratio of the total output value of the tertiary industry to the total output value of the secondary industry
Industrial structure rationality	ISR	$ISR = \sqrt{\sum_{i=1}^3 (\frac{l_i}{L} - \frac{p_i}{P})^2}$ (Shen et al. 2021)
Information communication level	INL	The proportion of Internet-access households in the total population
Environmental regulation	ERI	$ERI = \frac{1}{(\sum_{j=1}^3 \frac{e_j/y}{E_j/Y})^{1/3}}$ (Zhang & Qin 2018)

Note: in the formula of ISR,  $i = 1,2,3$  represent the primary, secondary, and tertiary industries,  $l_i/L$  refers to the labor force share of the  $i$ th industry,  $p_i/P$  refers to the output value share of the  $i$ th industry; in the formula of ERI,  $j = 1,2,3$  represent industrial wastewater, industrial sulfur dioxide, and industrial wastewater,  $e_j/y$  refers to the emission of pollutant  $j$  per unit industrial output value of the region, and  $E_j/Y$  refers to the emission of pollutant  $j$  per unit industrial output value in China

## Appendix 3 Calculation of the spatiotemporal weight matrix

Generally, the Gaussian kernel function is used to define the spatial weight matrix, and the formula is as follows:

$$w_{ij} = \exp(-(\frac{d_{ij}}{h})^2) \tag{15}$$

where  $d_{ij}$  represents the spatial distance between regions  $i$  and  $j$  and  $h$  represents the bandwidth, which refers to the non-negative attenuation parameter of the functional relationship between weight and distance and is calculated by the cross-validation (CV) method according to the criterion of minimizing the sum of squared errors. The formula of the CV method is as follows:

$$CV = \frac{1}{n} \sum_{i=1}^n [y_i - \hat{y}_{\neq i}(h)]^2 \tag{16}$$

where  $y_i$  is the predicted value and  $\hat{y}_{\neq i}(h)$  represents the function of bandwidth  $h$ , and the bandwidth  $h$  takes the corresponding value of the minimum CV value.

For the measurement of spatiotemporal distance ( $d^{ST}$ ), spatial parameter  $\tau$  and temporal parameter  $\mu$  need to be introduced to balance dimensional differences in time and space. The formula of  $d^{ST}$  is as follows:

$$d_{ij}^{ST} = \sqrt{\tau [(u_i - u_j)^2 + (v_i - v_j)^2] + \mu (t_i - t_j)^2} \tag{17}$$

Combining Eqs. (13) to (15),  $w_{ij}$  in the spatiotemporal weight matrix can be obtained:

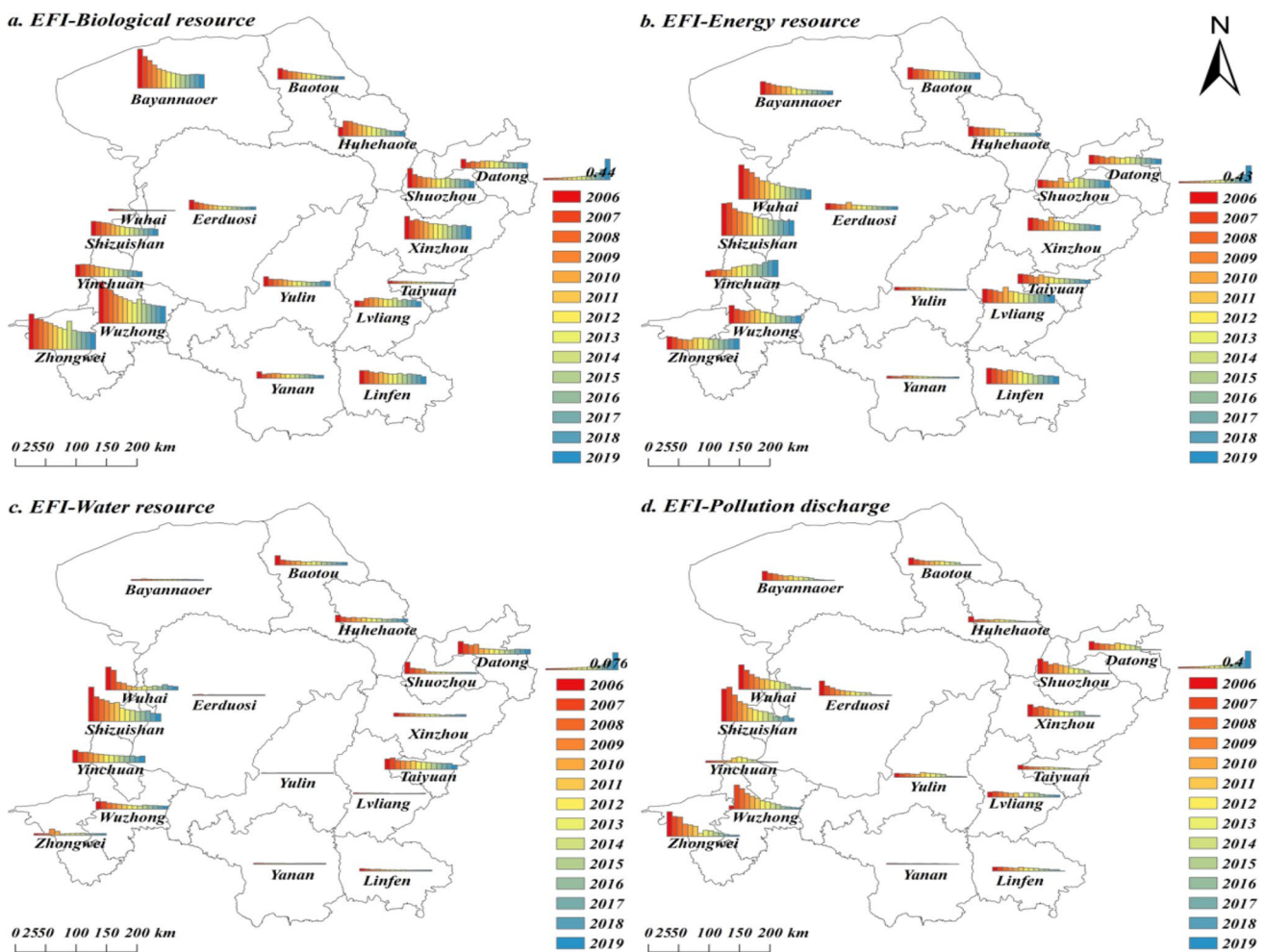
$$w_{ij} = \exp(-(\frac{d_{ij}^{ST}}{h})^2) = \exp\left[-\left(\frac{\tau [(u_i - u_j)^2 + (v_i - v_j)^2]}{h^2} + \frac{\mu (t_i - t_j)^2}{h^2}\right)\right] \tag{18}$$

### Appendix 4 Descriptive statistics of relevant

**Table 7** Descriptive statistics of relevant data

Variable	Unit	Mean	Std. dev.	Min	Max
EFI	hm <sup>2</sup> /10,000 yuan	0.570	0.350	0.0900	2.020
POP	persons/km <sup>2</sup>	162.3	139.9	18.66	751.3
GDPPC	10,000 yuan	3.800	2.280	0.640	11.98
TECL	%	1.650	1.170	0.200	6.190
MARL	%	32.02	15.53	9.380	66.92
GOVS	%	21.06	7.980	9.490	44.42
OPEN	%	6.440	8.060	0.0500	48.07
ISA	—	0.890	0.450	0.190	2.490
ISR	—	24.98	16.22	0.910	80.32
INL	households/person	13.81	9.150	1.490	56.78
ERI	—	0.290	0.410	0.0300	3.230

### Appendix 5 Temporal and spatial pattern of EFI of four subcategories



**Fig. 8** a–d Temporal and spatial pattern of EFI of four subcategories

## Appendix 6 Descriptive statistics of regression parameters of the GTWR model

**Table 8** Descriptive statistics of regression parameters of the GTWR model

Variable	Mean	Std. dev.	Min	Max
Intercept	0.658	2.986	−10.815	6.164
lnPOP	0.016	0.433	−0.74	1.355
lnGDPPC	−0.682	0.332	−2.044	−0.002
lnOPEN	0.017	0.058	−0.286	0.143
lnMARL	−0.07	0.427	−1.441	0.789
lnGOVS	−0.298	0.326	−1.249	0.523
lnISR	0.041	0.145	−0.121	0.678
lnTECL	−0.035	0.147	−0.309	0.273
lnINL	−0.031	0.211	−0.492	0.624
lnERI	−0.167	0.17	−0.514	0.349
lnISA	−0.247	0.332	−0.835	0.463

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Guangwen Hu: validation and writing—review and editing

Liang Xie: software and supervision

Xianzhong Mu: project administration, funding acquisition, conceptualization, supervision, validation, and resources

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**Data availability** Data will be made available on request.

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**Ethics approval and consent to participate** Not applicable.

**Consent for publication** Not applicable.

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