Measurement of Urban Ecological Welfare Performance and Its Driving Factors in the Yellow River Basin: A Postprint

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Date: 2023-06-28T00:00:00+00:00

Abstract

The improvement of Ecological Welfare Performance (EWP) is an inevitable choice for ecological civilization construction and holds significant importance for regional sustainable development. From the perspective of ecological welfare, an indicator system was constructed, and based on panel data, the undesirable output superefficiency SBM model was employed to measure the EWP of 59 prefecture-level cities in the Yellow River Basin from 2006 to 2019. Spatial exploratory methods and Geographically and Temporally Weighted Regression (GTWR) model were utilized to analyze the spatial distribution characteristics and driving factors of EWP in the basin. The results indicate: (1) The EWP values of cities in the Yellow River Basin are generally low, with an average improvement potential of 19.7%. (2) Significant positive spatial autocorrelation exists in the EWP of cities in the Yellow River Basin; "hotspot" high-high type cities are mainly distributed in the upstream regions with low population density, while "coldspot" low-low type cities are mostly those with rapid economic development and relatively concentrated populations in the middle and lower reaches of the Yellow River. (3) Precipitation, education development level, and industrial structure level have significant promoting effects on the improvement of urban EWP, while population density, economic intensity, and financial development level have obvious inhibiting effects on the improvement of urban EWP. Among them, precipitation, education development level, and population density have relatively large marginal effects on urban EWP. The research findings compensate for the deficiency in analyzing the "spatio-temporal" non-stationarity of EWP influencing factors and can provide a reference basis for relevant departments to formulate urban EWP policies.

Full Text

Abstract

The improvement of ecological well-being performance (EWP) represents an inevitable choice for ecological civilization construction and holds significant implications for regional sustainable development. From an ecological welfare perspective, this study constructs an evaluation index system and employs an undesirable output super-efficiency SBM model to measure the EWP of 59 prefecture-level cities in the Yellow River Basin from 2006 to 2019 based on panel data. Spatial exploratory methods and a geographically and temporally weighted regression (GTWR) model are then utilized to analyze the spatial distribution characteristics and driving factors of urban EWP in the basin. The results demonstrate that: (1) The EWP values of cities in the Yellow River Basin are generally low, with an average improvement potential of 19.7%. (2) Significant positive spatial autocorrelation exists in urban EWP across the Yellow River Basin. "Hot spot" high-high type cities are predominantly distributed in upstream areas with low population density, while "cold spot" low-low type cities are mainly located in the middle and lower reaches of the Yellow River, characterized by rapid economic development and relatively concentrated populations. (3) Precipitation, educational development level, and industrial structure level exert significant positive effects on urban EWP, whereas population density, economic intensity, and financial development level demonstrate notable inhibitory effects on EWP improvement. Among all influencing factors, precipitation, educational development level, and population density exhibit the largest marginal effects on urban EWP. These findings address the deficiency of "time-space" non-stationarity analysis and can provide reference for relevant departments in formulating urban EWP improvement policies.

Keywords: ecological well-being performance; SBM model; remote sensing data; GTWR model; Yellow River Basin

1. Study Area Overview

The Yellow River originates from the Qinghai-Tibet Plateau and flows through nine provinces and autonomous regions: Qinghai, Sichuan, Gansu, Ningxia, Inner Mongolia, Shaanxi, Shanxi, Henan, and Shandong, covering a basin area of 75$\times$10^{4}$ km^2. This region constitutes a crucial ecological functional zone and economic corridor in China [?, ?]. However, due to climate change and human activities, the Yellow River Basin faces increasingly prominent environmental issues, including ecosystem degradation [?], declining water conservation capacity, severe soil erosion, and insufficient ecological flow [?]. As the carrier of economic development and ecological governance, cities serve as the core driving force for promoting green and coordinated development in the basin [?]. Therefore, this study selects prefecture-level cities as the research unit to explore pathways for coordinated advancement of urban ecological protection and high-quality development. Drawing upon existing literature [?, ?] and considering the basin boundaries published by the Yellow River Conservancy Commission, along with data availability, 59 prefecture-level and above cities (Fig. ??) are selected as the study objects.

2.1 Data Sources and Processing

Data sources include the Atmospheric Composition Analysis Group at Dalhousie University for PM2.5 concentrations, annual mean habitat quality data from the National Earth System Science Data Center (data ID: V4.GL.02), and remaining data from the *China City Statistical Yearbook*, water resources bulletins, and other sources for 2006–2019. Missing data were obtained through interpolation and extrapolation methods. Based on the study area map data, ArcGIS 10.8 software was employed to perform projection, clipping, and zonal statistics on the original remote sensing raster data, thereby constructing a multi-source database integrating statistical yearbooks and remote sensing imagery.

2.2.1 Selection of Measurement Indicators

Referencing existing literature [?, ?] and adhering to principles of scientific rigor, systematicity, and operability, this study constructs indicator system criterion layers. The input criterion layer comprises resource-based inputs and non-resource-based inputs. Resource-based inputs primarily include energy, water resources, and land resources, while non-resource-based inputs mainly consist of capital and labor. The output criterion layer is typically divided into desired outputs and undesired outputs. Desired outputs primarily encompass three dimensions: economy, education, and health, while undesired outputs include wastewater, waste gas, and waste residue. Based on the criterion layer definitions, specific indicators are determined, including 8 input indicators and 7 output indicators (Table ??).

2.2.2 Super-Efficiency SBM-DEA Model

To enable comparative evaluation of decision-making units (DMUs) on the production frontier, this study adopts an output-oriented super-efficiency SBM model based on non-radial and non-angle principles to measure urban EWP in the Yellow River Basin. Assuming a production system with n DMUs, each DMU consists of input, desired output, and undesired output vectors, using m units of input to produce r_1 units of desired output and r_2 units of undesired output. The model [?] is constructed as:

sk + q = min = 1, ≠ = 1, ≠ qj λj sj λj, y xij λj, y = 1, 2, , ≥ j λj ≥ 0 = 1, 2, , *

where * ** is the target efficiency value; x_{ik} and x_{ij} represent the i-th input of the k-th and j-th DMUs, respectively; y^{d}*{sk} and* y^*{d}*{sj} represent the s-th desired output of the k-th and j-th DMUs, respectively; y^{u}*{qk} and* y^*{u}*{qj} represent the q-th undesired output of the k-th and j-th DMUs, respectively; vectors s^-, $s^\{d\}$, and $s^\{u\}$ denote the slack variables for inputs, desired outputs, and undesired outputs, respectively; and λ is the weight vector.

2.3.1 Selection of Driving Factors

Urban EWP is influenced by multiple factors. Considering the regional characteristics of the Yellow River Basin, this study comprehensively examines the impacts of natural, social, and economic factors on urban EWP. Specific proxy variables and measurement methods are presented in Table **??**.

2.3.2 Global Spatial Autocorrelation

Thiessen polygons were constructed, and a global autocorrelation model was employed to explore the spatial clustering characteristics of EWP in the Yellow River Basin. This study adopts Moran's I index, calculated as:

M ran's I = (n/ W_{ij}) × (W_{ij}(x_i - x̄)(x_j - x̄)) / (x_i - x̄)^2

where x and x represent the EWP values of geographic units i and j; n is the number of city units; W_{ij} is the spatial weight matrix defined by adjacency criteria; and $\bar{x}$ is the mean EWP value. Moran's I ranges from -1 to 1, with values closer to 1 indicating stronger positive spatial correlation and values closer to -1 indicating stronger negative spatial correlation. Statistical significance is tested using Z-test and P-test.

2.3.3 Local Spatial Autocorrelation

Local spatial autocorrelation measures the degree of spatial autocorrelation for local units relative to the entire study area [**?**]. This study employs the Local Moran's I index, calculated as:

Local M ran's I = (x_i - x̄) / m × W_{ij}(x_j - x̄)

where x and x represent the EWP values of geographic units i and j; n is the number of city units; W_{ij} is the spatial weight matrix defined by adjacency criteria; m is the number of polygons adjacent to city unit i; and $\bar{x}$ is the mean EWP value.

2.3.4 GTWR Model

The GTWR model is a spatial analysis technique that incorporates spatial and temporal dimensions, enabling examination of spatial autocorrelation among independent variables [**?**] while addressing temporal characteristics. This provides a foundation for analyzing the "time-space" non-stationarity of urban EWP impact factors [**?**], facilitating exploration of spatiotemporal variation characteristics and patterns [**?**]. The model is expressed as:

Y_i = β_0(u_i, v_i, t_i) + $\beta k(u\_i,\ v\_i,\ t\_i) X$\{ik\} + _i where Y is the observed value; u and v represent the latitude and longitude of the i-th observation point; t is the temporal sequence; (u , v , t) are the spatiotemporal coordinates of the i-th observation point; $\beta_0(u , v , t)$ is the regression constant; β (u , v , t) is the regression coefficient for the k-th independent variable; X_{ik} is the value of the k-th independent variable at point i; and is the residual.

The core of GTWR estimation lies in the spatiotemporal weight matrix and bandwidth determination [?]. The estimation formula for coefficient β (u , v , t) is:

β(u_i, v_i, t_i) = [X W(u_i, v_i, t_i)X]$^{-1}$X W(u_i, v_i, t_i)Y

where $\beta(u , v , t)$ is the estimated value of β (u , v , t); $W(u , v , t)$ is the spatiotemporal weight matrix; X is the matrix of independent variables; X is the transposed matrix; and Y is the matrix of observed values. To avoid "long-tail effects" caused by data dispersion, this study adopts an adaptive bi-square kernel function:

W_{ST,ij} = [1 - (d_{ST,ij}/b_i)^2]^2

where W_{ST,ij} is the spatiotemporal weight matrix; b is the bandwidth, determined using the Akaike Information Criterion (AICc) method with an adaptive kernel type; and d_{ST,ij} is the spatiotemporal distance between observation points i and j, calculated as:

d_{ST,ij} = √[δ((u_i - u_j)^2 + (v_i - v_j)^2) + (t_i - t_j)^2]

where u , v , and t represent the latitude, longitude, and temporal sequence of observation point i; u , v , and t represent those of point j; δ is the ratio of spatial bandwidth parameter to spatiotemporal bandwidth parameter; and is the ratio of temporal bandwidth parameter to spatiotemporal bandwidth parameter.

3.1 Urban EWP Measurement Results

The super-efficiency SBM model was employed to calculate urban EWP in the Yellow River Basin. Due to space limitations, only the top 5 cities in terms of mean EWP and growth rate are presented (Table **??**). The analysis reveals that the overall EWP level is relatively low, with a mean value of 0.803, indicating poor coordination between economic development and ecological environment in the Yellow River Basin, and a 19.7% improvement potential. In terms of mean values, the top 5 cities are Dingxi, Longnan, Tianshui, Qingyang, and Yulin, while the bottom 5 are Tongchuan, Yangquan, Datong, Lanzhou, and Xining. Geographically, cities with higher and lower mean EWP values are predominantly located in the upper and middle reaches of the Yellow River Basin. Regarding average annual growth rate, the fastest-growing cities are Baoji (12.81%), Jinan, Taiyuan, Xi'an, and Wuhai, while the slowest-growing are Longnan, Shizuishan, Yuncheng, Guyuan, and Tongchuan, with Tongchuan experiencing a negative growth rate of -9.02%.

3.2 Urban EWP Spatial Correlation Analysis

The overall low EWP level and significant regional disparities necessitate deeper analysis of spatial correlation characteristics. Based on the EWP panel data, global autocorrelation analysis was conducted using ArcGIS 10.8 software (Table **??**). Except for 2006, all years passed the significance test at the 0.05 level, indicating significant positive spatial autocorrelation in the Yellow River Basin's urban EWP, with prominent spatial effects. This suggests that a city's EWP is influenced by neighboring cities. To identify typical clustering patterns, local spatial autocorrelation analysis was performed for 2006 and 2019 (Fig. **??**). All results passed the 0.05 significance test, revealing significant local clustering characteristics. The number of cities exhibiting positive spatial correlation decreased from 23 in 2006 to 19 in 2019. Specifically, low-low type cities decreased from 13 to 8, while high-high type cities decreased from 10 to 7, indicating a weakening of local spatial clustering features in the Yellow River Basin.

3.3.1 Traditional Regression Model Estimation Results

To investigate the global impacts of various factors on urban EWP in the Yellow River Basin, an ordinary least squares (OLS) model was first applied to estimate factor significance levels and other characteristics [**?**]. As shown in Table **??**, the variance inflation factor (VIF) values for all factors are below 10, indicating reasonable factor selection without multicollinearity issues. At the 0.1 significance level or below, six factors significantly influence urban EWP, ranked by importance as: educational development level (X_3), financial development level (X_5), precipitation (X_1), population density (X_2), industrial structure level (X_6), and economic intensity (X_4). Among these, financial development level (X_5), population density (X_2), industrial structure level (X_6), and economic intensity (X_4) show negative coefficients, while precipitation (X_1) and educational development level (X_3) show positive coefficients. The Koenker (BP) statistic is highly significant, indicating model instability and potential spatial heterogeneity in influencing factors (Table **??**). In other words, the OLS model, which only considers global regression coefficient characteristics, cannot effectively address EWP variations caused by spatial location and temporal effects. Therefore, introducing a spatial econometric model is necessary to better explore local coefficient features. Considering model validity, precipitation (X_1), financial development level (X_5), and industrial structure level (X_6) were selected for GTWR analysis.

3.3.2 GTWR Model Estimation Results

Based on the above analysis, the GTWR model was applied using projected coordinates to determine spatial locations and a fixed Gaussian function as the spatial weight function, with the AICc method determining optimal bandwidth. According to existing research [?], smaller AICc values indicate better model fit. If the difference between the adjusted R^2 of GTWR and OLS exceeds 0.1, the GTWR results are more ideal and applicable [?]. As shown in Table ??, the GTWR regression generates location-specific coefficients for each city unit. Descriptive statistics of factor coefficient estimates (Table ??) reveal substantial variation in regression coefficients, indicating that factor impacts on urban EWP are not stationary but rather influenced by spatial location and temporal changes. The mean and median values show consistent directions, suggesting that the nature of factor impacts is similar across most spatial ranges.

3.3.3 Analysis of Urban EWP Influencing Factors

To visually depict the local effects of driving factors on urban EWP, the natural breaks method was applied for visualization (Figs. ?? and ??), combined with regression coefficient analysis to examine spatiotemporal heterogeneity.

Natural factors' impact on urban EWP. Precipitation significantly promotes EWP improvement with a positive regression coefficient of 0.0001. Increased precipitation enhances urban EWP. Spatially, precipitation's impact exhibits a "west-high, east-low" pattern, with the greatest effects in cities of Gansu, Ningxia, and Qinghai provinces. The positive coefficient areas were concentrated in the upper and middle reaches in 2006, while negative areas appeared mainly in the lower reaches. By 2019, the positive area expanded further but remained dominated by the upper and middle reaches. Cities in these regions are located in arid and semi-arid zones where precipitation is a key factor for vegetation growth, thus precipitation's positive effect is more pronounced in these areas.

Social factors' impact on urban EWP. Social factors include population density and educational development level. Population density primarily exerts negative effects. In 2006, its inhibitory effect gradually decreased from west to east, with the most significant negative impacts concentrated in cities of Gansu, Ningxia, and Shaanxi. By 2019, the impact direction diverged: positive in upstream and downstream regions but negative in the middle reaches. Educational development level shows predominantly positive correlation with urban EWP. In 2006, the most significantly affected areas were concentrated in southern Gansu and the Guanzhong region of Shaanxi, while in 2019, the focus shifted to the middle and lower reaches, including Zhengzhou, Kaifeng, and Nanyang. This may be attributed to more complete education systems and institutions in these downstream cities, yielding higher returns on education expenditure.

Economic factors' impact on urban EWP. Economic factors comprise economic intensity, financial development level, and industrial structure level. Overall, economic intensity and financial development level constrain urban EWP, while industrial structure level promotes it. In 2006, cities with significant economic intensity constraints included Longnan, Dingxi, Tianshui, Lanzhou, and Baiyin, while financial development constraints were notable in Xining, Wuwei, Ulanqab, and Bayannur. By 2019, economic intensity constraints weakened, whereas financial development constraints intensified. Conversely, industrial structure level positively promotes urban EWP. In 2006, high-impact areas were prominent in Xining, Wuwei, Sanmenxia, and Nanyang, while in 2019, high-value areas shifted to Nanyang, Pingdingshan, Luoyang, and Zhengzhou.

4. Discussion

Measurement of urban EWP in the Yellow River Basin. Existing studies [?, ?] have inadequately considered ecological dimensions when constructing index systems. Building upon previous research [?, ?], this study establishes a multi-objective evaluation index system reflecting urban EWP, such as annual mean habitat quality. By incorporating remote sensing PM2.5 data as an air pollution indicator in undesired outputs, the study expands the undesired output indicators and explores remote sensing data as a data source for urban EWP research. The findings reveal significant PM2.5 impacts on EWP levels. Additionally, per capita green space area, representing ecosystem service level, was included in output indicators. Although further integration between ecosystem services and urban ecological well-being is needed, this inclusion represents a beneficial attempt, offering new research perspectives for scientifically measuring urban EWP.

Influencing factors of urban EWP. Current research primarily considers economic and social factors while largely neglecting natural factors such as temperature and precipitation [?, ?, ?]. This study finds that precipitation significantly and positively affects urban EWP in the Yellow River Basin, particularly in cities of Gansu, Ningxia, and Qinghai. Further analysis reveals distinct differences in how various factors affect different cities, though economic intensity and population density consistently show significant inhibitory effects on EWP, aligning with existing research [?, ?].

Spatial differentiation of urban EWP. Existing research has examined EWP at national [?, ?], provincial [?, ?, ?], and city scales [?, ?], revealing scale-dependent variations. This study focuses on the Yellow River Basin, characterized by significant differences in natural endowments, ecological conditions, and economic development levels. Spatial exploratory analysis identifies spatial heterogeneity in EWP, differing from studies [?, ?] that assume random distribution without considering spatial correlation. This provides a necessary prerequisite for establishing appropriate econometric models of urban EWP influencing factors, offering more comprehensive reflection of spatiotemporal variations than factor decomposition models [?, ?] or multiple regression models [?, ?] that only consider temporal changes.

Research limitations. The study has room for improvement in two aspects. First, due to data availability, the analysis is conducted at the prefecture-level city scale, not extending to the county scale, which limits effective identification of EWP impact mechanisms at finer scales—this will be a priority for future research. Second, regarding the index system, although this study adopts widely used indicators [?, ?] and includes "per capita green space area," more scientific integration of ecosystem services into urban EWP measurement remains a challenge for future research. Additionally, the EWP value declined by 28.8% during the study period, indicating that economic growth and ecological environment in the Yellow River Basin require better coordinated development.

5. Conclusions

This study constructs an urban EWP input-output index system, employs an undesirable output super-efficiency SBM model to measure EWP in the Yellow River Basin, and utilizes spatial autocorrelation methods and GTWR model to investigate the impacts of natural, social, and economic factors on urban EWP. The main conclusions are as follows:

(1) The overall EWP level of cities in the Yellow River Basin is relatively low, with a mean value of 0.803 during 2006–2019, indicating a 19.7% improvement potential. Geographically, cities with higher and lower mean EWP values are mainly located in the upper and middle reaches of the Yellow River Basin, while lower EWP values are observed in downstream cities.

(2) Urban EWP in the Yellow River Basin exhibits significant positive global and local spatial autocorrelation. High-high type cities are predominantly distributed in upstream areas with low population density, while low-low type cities are mainly concentrated in the middle and lower reaches with rapid economic development and dense populations. Meanwhile, local spatial clustering shows a convergent trend, implying that while urbanization improves overall EWP, spatial disparities are gradually narrowing.

(3) Precipitation, population density, educational development level, economic intensity, financial development level, and industrial structure level all significantly influence urban EWP with notable spatial variations. Specifically, precipitation, educational development level, and industrial structure level significantly promote urban EWP improvement, whereas population density, economic intensity, and financial development level exert significant inhibitory effects. Among all influencing factors, precipitation, educational development level, and population density demonstrate the largest marginal effects on urban EWP.

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Note: Figure translations are in progress. See original paper for figures.