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City-level assessment of green economy development and its driving factors: empirical evidence from 14 prefecture-level cities in Guangxi, China based on DPSR-GTWR integrated model

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Developing the green economy is a fundamental requirement for China's new development stage, aimed at applying new concepts, building new patterns, and achieving high-quality growth. Guangxi, as a vital engine of China's green economy, strongly supports this process. This study establishes a green economy evaluation system for Guangxi using the DPSR model, applies the entropy weight-TOPSIS and obstacle degree models to assess its development from 2012 to 2022, and identifies key obstacles. It further analyzes the spatial-temporal heterogeneity of nine major factors through OLS and GTWR models. Findings reveal that Guangxi's green economy is progressing with a "dual-core" pattern centered on Nanning and Liuzhou, faces significant pressures mainly from the pressure and state dimensions, and experiences varying impacts from key factors across regions and over time. These insights offer theoretical foundations and policy recommendations to improve Guangxi's green economic development.

KEYWORDS

regional green economy, DPSR evaluation system, influence effects, GTWR model, heterogeneity analysis

1 Introduction

In July 2024, the Central Committee of the Communist Party of China and the State Council issued the "Opinions on Accelerating the Comprehensive Green Transformation of Economic and Social Development," underscoring that green transformation is essential for achieving high-quality development and a core strategy to address ecological and environmental challenges. The report of the 20th National Congress further stressed that fostering green economic growth and harmony between the economy and ecosystems are vital for the long-term stability and sustainability of China's development.

In Guangxi, General Secretary Xi Jinping has emphasized the importance of green economic development during three inspection tours since the 18th National Congress, urging Guangxi to pioneer a new path toward green growth. Nevertheless, Guangxi faces significant challenges, including entrenched high-pollution, high-energy-consumption

industrial structures, inefficient resource use, severe environmental issues, and uneven green economic development across regions and time periods. There is thus an urgent need to construct a robust evaluation index system to measure Guangxi's green economy development and to deeply analyze spatial-temporal variations and influencing factors, providing theoretical and practical foundations for policy formulation and strategic planning.

Globally, green economy research has gained prominence in response to escalating environmental concerns. The term “green economy,” first introduced by [Pearce et al. \(2013\)](#) in *Blueprint for a Green Economy*, addressed the underestimation of environmental and social costs. The United Nations Environment Programme ([UNEP, 2011](#)) defines a green economy as one that improves human well-being and social equity while reducing environmental risks, integrating economic, social, and environmental dimensions.

Recent studies have advanced frameworks for evaluating green economic development. [Schmalensee \(2012\)](#) proposed a model combining traditional economic metrics and environmental indicators. [Chen et al. \(2019\)](#) built a green growth evaluation system using the DPSIR model and entropy weight-TOPSIS methods. Other scholars, such as [Zhang \(2021\)](#) and [Shang and Xu \(2022\)](#), designed comprehensive evaluation systems focusing on economic, social, and environmental aspects. Internationally, [Hickel and Kallis \(2020\)](#) suggested a degrowth framework that prioritizes ecological sustainability beyond GDP. [Stjepanovic et al. \(2022\)](#) constructed a Green GDP database for 160 countries over a 50-year period, which corrects the deficiencies of traditional GDP by subtracting the costs of environmental degradation and natural resource depletion to provide a more realistic measure of the green economy.

Methodologically, [Gómez-Calvet et al. \(2014\)](#) were early to combine the directional distance function with the slack-based measure (SBM) model to evaluate energy efficiency in the EU, offering a methodological reference for green economic efficiency research. [Hou et al. \(2021\)](#) reconstructed a green productivity index, while [Hu et al. \(2024\)](#) evaluated green tourism development using super-efficiency SBM models. Research into spatial patterns has also evolved: [Lin et al. \(2017\)](#) explored spatial spillovers using the spatial Durbin model, while [Gu and Ge \(2018\)](#) examined provincial green economy evolution with spatial panel models. International analyses by [Robaina-Alves et al. \(2025\)](#) and [Barbier and Burgess \(2020\)](#) highlighted regional disparities and policy impacts using spatial econometrics.

However, existing studies often focus on national or regional levels, with limited research at the provincial scale, particularly regarding unified evaluation systems and spatial-temporal influencing factors. This gap warrants attention, as research on multi-level governance indicates that sub-national levels play a critical role in translating sustainable development policies into concrete actions ([Sandmann et al., 2024](#)). Furthermore, most studies address green economic efficiency rather than development levels, creating gaps in the literature.

This study focuses on Guangxi, constructing a green economic development evaluation system based on the DPSIR model across the four dimensions of driving forces, pressures, states, and responses. Crucially, unlike prior work, we apply the Geographically and Temporally Weighted Regression (GTWR) model to comprehensively

account for spatial and temporal dynamics in analyzing influencing factors.

The remainder of this paper is structured as follows: Section 2 presents the research methodology and data sources, including the construction of the evaluation system and analytical techniques. Section 3 discusses the results, including the assessment of Guangxi's green economy development level, identification of obstacle factors, and analysis of influencing factors. Section 4 concludes with policy recommendations.

2 Research methodology and data sources

2.1 Construction of the evaluation index system

Green economic development is an evolving process that requires an evaluation system attentive not only to current drivers and states but also to future development trends ([Chen et al., 2019](#)). The DPSIR model—an enhancement of the PSR framework initially proposed by the OECD ([Adriaanse, 1993](#)) and UNEP ([Tong, 2000](#))—provides a causal-relationship-based structure for systematically assessing interactions between human activities and natural ecosystems across four dimensions: Driving forces, Pressures, States, and Responses ([Troian et al., 2021](#)).

Economic development, inherently dynamic, involves the continuous use of ecosystems to meet social needs. High-intensity socio-economic activities often exert negative pressures on ecosystems; however, technological advancements and rising environmental awareness can mitigate these effects, shifting development toward greener pathways without clear-cut boundaries between positive and negative impacts ([Halkos, 2023](#)).

In this study, indicators such as registered year-end population and urbanization rate are assigned to the Driving layer, representing socio-economic drivers. Indicators reflecting environmental pressures, including wastewater discharge and industrial sulfur dioxide emissions, are categorized under the Pressure layer. Measures of environmental conditions, such as air quality compliance rate and groundwater resource volume, represent the State layer. Lastly, management responses, including the harmless treatment rate of domestic waste and green coverage rate in built-up areas, are placed in the Response layer.

This integration of socio-economic and environmental factors is consistent with the best international practices. [Hickel \(2020\)](#) emphasizes that effective green economy evaluation must incorporate both economic growth and ecological constraints, while [Stern and Stiglitz \(2021\)](#) advocate frameworks that jointly consider human well-being and environmental sustainability. Our DPSIR-based approach aligns with these perspectives, offering a holistic view that accounts for both socio-economic drivers and environmental impacts.

Following the principles of scientific rigor, hierarchical structure, dynamism, and practical operability, and drawing on the work of [Tang and Zhang \(2020\)](#) and [Chen et al. \(2019\)](#), we construct a comprehensive evaluation system for Guangxi's green economic development, selecting 17 indicators across the four DPSIR dimensions (see [Table 1](#)).

TABLE 1 Guangxi green economy development level evaluation system.

Target layer	Criterion layer	Indicator layer	Indicator unit	Indicator direction	Indicator weight	Indicator code
Green Economic Growth Indicator System of 14 Cities in Guangxi	Driving Force (D) 0.1797	GDP	100 million yuan	+	0.0780	D1
		Year-end registered population	10,000 persons	–	0.0433	D2
		Urbanization rate	%	+	0.0282	D3
		Share of secondary industry	%	–	0.0302	D4
	Pressure (P) 0.5025	Total water consumption	100 million m^3	–	0.0492	P1
		Annual wastewater discharge	10,000 tons	–	0.1380	P2
		Industrial SO ₂ emissions	tons	–	0.1948	P3
		Liquefied petroleum gas supply	tons	–	0.1204	P4
	State (S) 0.2756	Green coverage area	hectares	+	0.1674	S1
		Groundwater resource volume	100 million m^3	+	0.0469	S2
		Wastewater treatment rate	%	+	0.0071	S3
		Good air quality rate	%	+	0.0152	S4
		Air quality composite index	Index	+	0.0390	S5
	Response (R) 0.0422	Harmless treatment Rate of household waste	%	+	0.0058	R1
		Centralized treatment rate of sewage plants	%	+	0.0220	R2
		Green coverage rate in built-up areas	%	+	0.0101	R3
		Water supply coverage rate	%	+	0.0043	R4

2.2 Research methods

2.2.1 Entropy weight-TOPSIS model

Following the approaches of Zhao C. et al. (2024), Zhao W. et al. (2024), and Zournatzidou et al. (2024) for panel data analysis, this study applies the entropy weight-TOPSIS method to calculate the weights and comprehensive scores for Guangxi's green economic development evaluation system. Widely adopted in global green economy assessments (Almulhim, 2024), the entropy weight method objectively determines indicator weights based on information variability, while the TOPSIS method evaluates alternatives by calculating their distance from ideal and anti-ideal solutions. As these methodologies are standard, detailed formulas are omitted here for brevity.

2.2.2 Obstacle degree model

To further diagnose obstacles to green economic transition, the obstacle degree model is employed to calculate the obstacle degrees

of various indicators and subsystems, helping to identify key barriers and guide adjustments in economic strategies and policies (Zhi and Liu, 2022). This model, similar to applications in sustainable supply chain management research (Mardani et al., 2017), calculates obstacle degrees using the following steps (Yao et al., 2015):

$$D_j = 1 - Y_{\theta ij}; h_j = D_j^* F_j / (D_j^* F_j) * 100\% \quad (1)$$

$$H_j = \sum h_{\theta j} \quad (2)$$

Where D , F , H , and h represent indicator deviation, factor contribution, and obstacle degree, respectively. D measures the gap between actual and target values, F indicates the weight of each indicator, and H and h quantify the subsystem and individual indicator obstacles, respectively. Here, $Y_{\theta ij}$ is the standardized value, with θ ranges from $[1, 11]$, spanning 2012–2022 (11 years),

i representing 14 cities in Guangxi, and j covering 17 evaluation indicators.

2.2.3 Geographically and temporally weighted regression model

To capture spatial–temporal heterogeneity in influencing factors, this study employs the Geographically and Temporally Weighted Regression (GTWR) model, an extension of the GWR model that integrates both spatial and temporal dimensions. GTWR enables more accurate mapping of regional variations in green economy drivers, utilizing tools like ArcGIS for spatial visualization. This approach aligns with global practices, such as Ren et al. (2023), who applied spatial regression methods to examine environmental regulation and green innovation in Chinese cities.

Before GTWR estimation, Ordinary Least Squares (OLS) regression is conducted to ensure model robustness, following Zhao et al. (2023). All control variables are introduced, and backward elimination is performed to exclude non-significant factors (Li et al., 2021). The GTWR model is expressed as:

$$y_i = \beta(u_i, v_i, t_i) + \sum_k^n \beta(u_i, v_i, t_i) x_{ik} + \varepsilon_i \quad (3)$$

Where: y_i represents the dependent variable of the i -th sample; x_{ik} is the observed value of the k -th independent variable at the i -th sample point; n is the number of sample points; (u_i, v_i, t_i) is the spatial–temporal coordinate position of the i -th sample point; $\sum_k^n \beta(u_i, v_i, t_i) x_{ik}$ is the regression coefficient of the k -th independent variable at the i -th sample point; $\beta(u_i, v_i, t_i)$ is the spatial–temporal intercept of the i -th sample point; and ε_i is the residual.

The GTWR model offers key advantages over traditional methods: it captures spatial and temporal heterogeneity (Fotheringham et al., 2015), provides localized parameter estimates revealing regional differences (Li et al., 2021), and identifies spatial clusters of influencing factors critical for targeted green economy policymaking (Matthews and Yang, 2012).

2.3 Data sources

All indicator data used in this study are sourced from the Guangxi Statistical Yearbook (2013–2023), prefecture-level National Economic and Social Development Statistical Bulletins and Environmental Status Bulletins, and supplemental data provided by the Guangxi Zhuang Autonomous Region Department of Ecology and Environment.

3 Analysis and results

3.1 Evaluation and analysis of Guangxi's green economic development level

3.1.1 Evaluation and analysis of Guangxi's green economic development level based on the DPSIR model

Based on the entropy weight calculation, the system and indicator weights are summarized in Table 1. The weights for the

driving force, pressure, state, and response systems are 0.1797, 0.5025, 0.2756, and 0.0422, respectively. The pressure system holds the highest weight, underscoring its dominant role in evaluating Guangxi's green economic development level. This indicates that the environmental and resource pressures induced by economic activities are the central concern in assessing green development performance in Guangxi. Conversely, the response system has the lowest weight, suggesting minimal variation across the 14 cities in Guangxi regarding policy and management responses, and implying a regional deficiency in effective green development strategies and policy adaptation.

The relatively high weights of the driving force and state systems highlight the significant influence of socio-economic dynamics and current environmental conditions on green economic development outcomes. This finding aligns with the broader literature: Geels (2011) emphasized that green transitions require not only technological innovation but also shifts in policies, practices, and market structures, while Barbier (2012) noted that rapidly developing regions often struggle to match ecological pressures with adequate policy responses.

At the indicator level, industrial sulfur dioxide emissions carry the highest weight at 0.1948, emphasizing the critical role of air pollution control in Guangxi's green economic development. This reflects the province's industrial legacy, characterized by a dominance of heavy industry, high pollution, and energy-intensive sectors (Yang et al., 2023). The second highest weight is green coverage area at 0.1674, highlighting the importance of ecological infrastructure in providing environmental services such as water conservation, air purification, climate regulation, and biodiversity support—factors that foster new green industries like ecological agriculture and eco-tourism (Mo et al., 2024).

In contrast, indicators such as the harmless treatment rate of domestic waste (0.0058) and water supply coverage rate (0.0043) have low weights, suggesting limited variability among cities and less information contribution to distinguishing green development levels.

Similar patterns have been observed in other emerging economies. Sanye-Mengual et al. (2018) found air quality metrics to be among the highest-weighted indicators in assessments of urban green economy potential in Mediterranean cities, while Lu et al. (2016) emphasized the importance of industrial pollution control in the green development of China's eastern provinces.

3.1.2 Evolution analysis of Guangxi's green economic development level

Using the TOPSIS method, this study calculates the relative closeness degree (C_i) for Guangxi's green economic development and its four subsystems from 2012 to 2022 (Figure 1). Following Sun and Jing's (2012) classification standards, development stages are determined and summarized in Table 2.

3.1.2.1 Temporal evolution

Guangxi's overall green economic development remained within the development stage over the decade, exhibiting modest fluctuations. The C_i rose from 0.6156 in 2012 to 0.6273 in 2015, declined to 0.5970 by 2017, and recovered to 0.6015 by 2022.

Subsystem analysis reveals divergent trends. The driving force subsystem (Figure 2a) showed a steady rise, underpinned by sustained economic growth (7.9% average annual GDP) and increased investment in green technologies, aligning with international

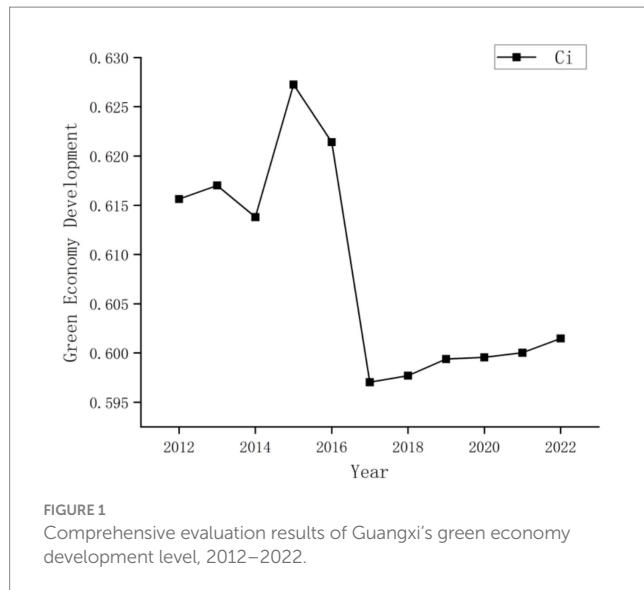


FIGURE 1
Comprehensive evaluation results of Guangxi's green economy development level, 2012–2022.

TABLE 2 Classification of the level of green economy development in Guangxi.

Green economy development level value	[0.0–0.5]	[0.5–0.7]	[0.7–1.0]
Classification	Starting Stage	Development Stage	Mature Stage
Cities	Chongzuo	Guilin, Qinzhou, Fangchenggang, Beihai, Hechi, Baise, Yulin, Guigang, Laibin, Wuzhou, Hezhou	Nanning, Liuzhou

observations of economic growth phases fostering green innovation (Borel-Saladin and Turok, 2013; Thi and Do, 2024).

Conversely, the pressure subsystem (Figure 2b) declined from 0.5559 to 0.4399, reflecting Guangxi's persistent industrial dependence a pattern consistent with Mathews (2012) and Cosbey (2011), who note that structural transitions away from high-pollution industries are inherently slow.

The state subsystem (Figure 2c) showed initial improvement followed by slight decline, with fluctuations linked to the gradual effectiveness of green policies and recent global economic volatility.

The response subsystem (Figure 2d) exhibited a stable and significant rise, maintaining a mature stage level throughout, demonstrating Guangxi's commitment to ecological protection and green governance.

3.1.2.2 Spatial evolution

Spatial disparities are evident across Guangxi's 14 cities (Table 2). A “dual-core” structure emerged, with Nanning and Liuzhou reaching maturity (levels > 0.70), while 79% of the cities remained at the development stage. Chongzuo lagged behind in the starting stage (0.4996).

These patterns mirror broader trends, where green economy development clusters around urban centers with stronger institutional capacity and innovation ecosystems (Demirel et al., 2019; Hansen and Coenen, 2015).

3.2 Diagnosis of obstacle factors for Guangxi's green economic development level

Building upon the methodology proposed by Shu et al. (2024) and other scholars—who advocate for diagnosing systemic obstacle factors prior to investigating influencing factors—this study employed Equations 1, 2 to calculate and rank the obstacle degrees of 17 evaluation indicators pertaining to Guangxi's green economic development between 2012 and 2022. Due to space constraints, the top seven indicators were selected for detailed statistical analysis, as presented in Table 3.

Table 3 illustrates that, throughout 2012–2022, the obstacles impeding Guangxi's green economic development remained relatively concentrated and stable. These obstacles were primarily located within the “pressure” and “state” layers, with key factors including green coverage area, industrial sulfur dioxide emissions, annual wastewater discharge, and liquefied petroleum gas supply—all exhibiting obstacle degrees exceeding 0.1. During this period, Guangxi experienced rapid industrialization and urbanization; however, the expansion of corresponding environmental infrastructure lagged behind, industrial pollution control technologies remained outdated, and regulatory oversight was insufficient.

As depicted in Figure 3, the trends in obstacle degrees across the eight selected indicators displayed complex fluctuations. Notably, the obstacle degree for industrial sulfur dioxide emissions (P3) remained persistently high and exhibited an upward trajectory, suggesting that sulfur dioxide pollution constituted a major and persistent barrier to Guangxi's green economic advancement. Conversely, the obstacle degree for the air quality excellence rate (S5) demonstrated a steady decline and, post-2015, fell outside the top seven indicators, indicating progress in air pollution control measures, such as tighter regulation of non-industrial emission sources including vehicular exhaust and dust. Meanwhile, the obstacle degree for green coverage area (S1) showed a fluctuating yet overall rising trend, reflecting early gains in afforestation efforts followed by a subsequent slowdown. The groundwater resource volume (S2) obstacle degree also increased, highlighting the mounting complexity of water resource management challenges. In contrast, the obstacle degrees for GDP (D1), annual wastewater discharge (P2), and liquefied petroleum gas supply (P4) declined, suggesting that improvements in these areas contributed positively to Guangxi's green economic recovery, underpinned by enhanced wastewater management, optimized energy supply systems, and sustained economic growth.

These findings align with patterns identified in global sustainability transition research. For instance, Markard et al. (2012) emphasized industrial infrastructure lock-in as a persistent barrier to sustainability transitions worldwide, while Loorbach and Rotmans (2006) noted that in developing economies, environmental governance often lags behind rapid industrialization, leading to temporary spikes in pollution before governance structures adapt.

3.3 Analysis of influencing factors of Guangxi's green economic development level

Building upon the preceding analysis, and to further investigate the spatiotemporal evolution of influencing factors on Guangxi's green economic development—as well as to uncover the spatial–temporal

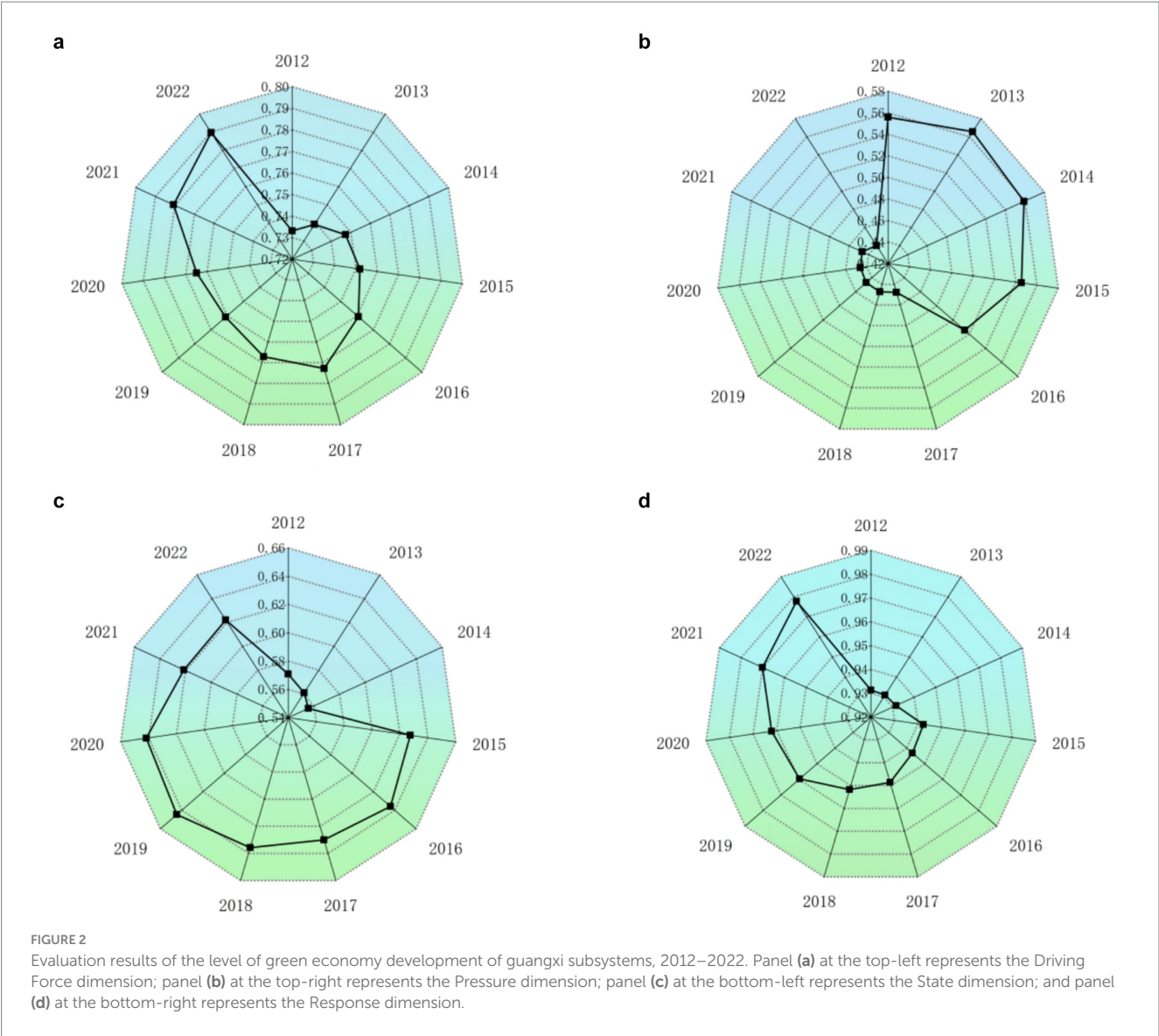
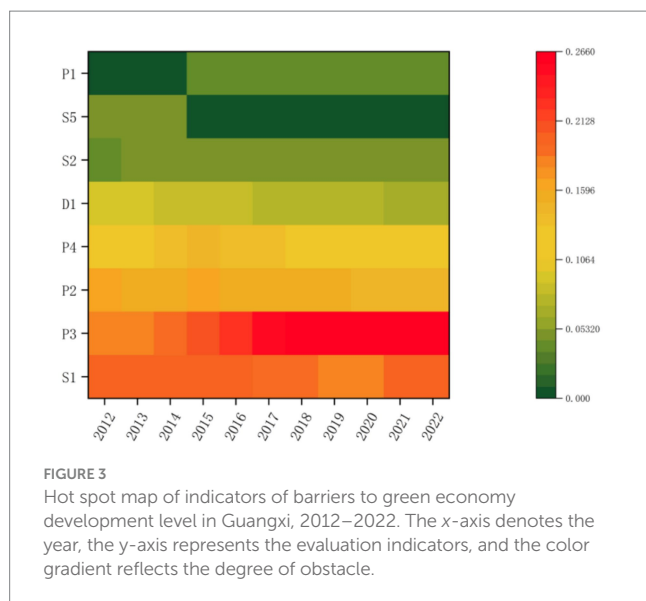


TABLE 3 Barrier analysis table of evaluation indicators, 2012–2022.

Year	Obstacle Factor 1	Obstacle Factor 2	Obstacle Factor 3	Obstacle Factor 4	Obstacle Factor 5	Obstacle Factor 6	Obstacle Factor 7
2012	S1/0.2016	P3/0.1840	P2/0.1613	P4/0.1318	D1/0.0922	S5/0.0476	S2/0.0423
2013	S1/0.1996	P3/0.1851	P2/0.1594	P4/0.1321	D1/0.0894	S2/0.0464	S5/0.0456
2014	S1/0.1955	P3/0.1902	P2/0.1581	P4/0.1366	D1/0.0856	S2/0.0489	S5/0.0455
2015	P3/0.2095	S1/0.1988	P2/0.1613	P4/0.1422	D1/0.0864	S2/0.0470	P1/0.0379
2016	P3/0.2222	S1/0.1968	P2/0.1589	P4/0.1418	D1/0.0833	S2/0.0450	P1/0.0386
2017	P3/0.2542	S1/0.1878	P2/0.1527	P4/0.1352	D1/0.0765	S2/0.0471	P1/0.0382
2018	P3/0.2586	S1/0.1872	P2/0.1542	P4/0.1284	D1/0.0771	S2/0.0473	P1/0.0378
2019	P3/0.2640	S1/0.1794	P2/0.1548	P4/0.1287	D1/0.0754	S2/0.0478	P1/0.0384
2020	P3/0.2659	S1/0.1790	P2/0.1496	P4/0.1285	D1/0.0737	S2/0.0483	P1/0.0417
2021	P3/0.2581	S1/0.2001	P2/0.1455	P4/0.1283	D1/0.0695	S2/0.0510	P1/0.0403
2022	P3/0.2613	S1/0.1981	P2/0.1439	P4/0.1301	D1/0.0672	S2/0.0515	P1/0.0412



heterogeneity of these drivers—this study employed OLS and GTWR models, following the methodological frameworks proposed by Zhao Junwei, Li Jiaxin, and others.

3.3.1 Selection of significant factors based on the OLS model

Initially, a backward stepwise regression was conducted using the OLS model in Stata 17, wherein the significance levels of both the explanatory variables and the dependent variable were evaluated. Through this process, nine key indicators were identified as significant determinants of Guangxi's green economic development: registered year-end population, urbanization rate, proportion of secondary industry, industrial sulfur dioxide emissions, green coverage area, groundwater resource volume, air quality excellence rate, harmless treatment rate of domestic waste, and centralized treatment rate of sewage treatment plants. The model exhibited a high goodness-of-fit, with an R^2 value of 0.9763, and all nine variables demonstrated p -values below 0.1.

To guard against pseudo-regression, a collinearity diagnostic was performed based on the principle of variable independence. Utilizing Stata 17, the variance inflation factor (VIF) analysis revealed an average VIF of 1.53 and a maximum VIF of 1.99, all well below the critical threshold of 5, thus confirming the absence of multicollinearity and the robustness of the selected variables.

This approach to variable selection adheres to established international best practices in econometric modeling of green economy drivers. For example, York et al. (2003) applied comparable stepwise regression methodologies to identify transition factors in developing economies, while Larsen (2018) emphasized the importance of VIF analysis to ensure the integrity of sustainability indicator models within regional development research.

3.3.2 Regression results of the GTWR model

Using ArcGIS 10.8 and the GTWR calculation plugin developed by Huang et al. (2010), further regression analysis was conducted on the previously screened factors, based on the GTWR model shown in Equation 3, with the results presented in Table 4. The findings reveal that the adjusted R^2 of the GTWR model is 0.998202, notably higher than that of the OLS model (0.9749), and the AICc value is -990.513 ,

TABLE 4 GTWR model parameters.

Model parameters	Value
Bandwidth	0.140444
ResidualSquares	0.001382
Sigma	0.002996
AICc	-990.513
R^2	0.998308
R^2 Adjusted	0.998202

collectively indicating that the GTWR model provides a superior goodness of fit.

As shown in Table 5, the GTWR regression results display both positive and negative coefficients, with considerable variation in magnitude across regions. This variation further corroborates that the parameter estimates derived from the OLS model merely capture the average characteristics across Guangxi, thereby obscuring the localized dynamics within each of Guangxi's 14 prefecture-level cities. These results underscore that the relationship between Guangxi's green economic development level and its influencing factors is not uniformly linear, but rather characterized by pronounced spatial heterogeneity (Zhao et al., 2023).

The existence of spatial heterogeneity in green economy drivers has similarly been recognized in broader regional studies. For instance, Balland et al. (2019) demonstrated that the effectiveness of green innovation policies varies markedly across regions with different industrial structures and institutional capacities. Likewise, McCauley and Heffron (2018) showed that identical policy instruments can yield divergent green economy outcomes depending on variations in governance structures and resource endowments.

3.3.3 Spatial heterogeneity analysis of influencing factors on Guangxi's green economic development level

To further explore the variation characteristics and impact intensity of influencing factors in space, based on the regression coefficient results of 9 influencing factors at the beginning (2012) and end (2022) of the period obtained using the GTWR model, the natural breaks method was adopted, and ArcGIS 10.8 was used to visualize the results for more intuitive spatial variation analysis of each influencing factor, as shown in Figures 4, 5. Due to space limitations, this paper selected 5 influencing factors with significant changes from the four criterion layers for the following analysis.

Registered year-end population exhibited notable spatial and temporal dynamics throughout the study period. At the outset in 2012, elevated coefficients predominantly characterized cities such as Hechi, Baise, and Chongzuo, with a discernible gradient showing higher values in western Guangxi relative to eastern regions. By 2022, a general decline in these coefficients was observed, accompanied by an eastward shift of high-value areas; conversely, cities such as Yulin and Hezhou in the east transitioned to lower-value regions. In the "Qinzhou-Beihai-Fangchenggang" corridor, the positive influence of registered population on Guangxi's green economy intensified, attributable to increased urbanization and demographic influx from western regions. These cities, serving as key gateways to ASEAN, attracted substantial labor and talent, fostering rapid economic growth while promoting green development. The apparent decline in Yulin

TABLE 5 GTWR model regression results.

City	Year	Year-end registered population	Urbanization rate	Share of secondary industry	Industrial sulfur dioxide emissions	Green coverage area	Groundwater resource volume	Good Air quality rate	Harmless treatment rate of household waste	Centralized treatment rate of sewage plants
Nanning	2012	0.047	−0.013	0.040	0.224	0.207	0.021	0.009	0.066	0.014
Qinzhou	2012	0.024	−0.002	0.000	0.306	0.188	0.058	0.009	0.061	0.021
Beihai	2012	0.026	−0.004	0.016	0.302	0.193	0.070	0.009	0.056	0.025
Fangchenggang	2012	0.017	−0.003	−0.005	0.315	0.191	0.069	0.011	0.061	0.024
Guigang	2012	0.035	0.033	0.024	0.221	0.193	0.024	0.001	0.036	0.020
Liuzhou	2012	0.072	0.035	0.060	0.218	0.165	0.019	−0.009	0.023	0.038
Guilin	2012	0.052	0.035	−0.007	0.272	0.220	0.048	0.012	−0.001	−0.011
Wuzhou	2012	0.046	0.018	0.024	0.315	0.304	0.048	0.019	0.006	0.016
Hezhou	2012	0.043	−0.010	0.019	0.299	0.400	0.042	0.018	−0.004	0.006
Baise	2012	0.429	−0.011	0.099	0.158	−0.010	0.090	0.005	−0.026	0.043
Hechi	2012	0.109	0.062	0.044	0.197	0.092	−0.016	0.006	0.052	0.048
Chongzuo	2012	0.095	0.030	0.054	0.261	0.148	0.011	0.017	0.045	0.021
Laibin	2012	0.043	0.031	0.059	0.214	0.172	0.006	−0.018	0.031	0.038
Yulin	2012	0.037	0.000	0.018	0.241	0.208	0.036	0.015	0.047	0.017
...										
Nanning	2022	0.078	0.016	0.045	0.349	0.137	0.015	0.064	0.186	0.075
Qinzhou	2022	0.101	0.001	0.082	0.488	0.151	0.000	0.058	0.189	0.057
Beihai	2022	0.078	−0.005	0.081	0.213	0.203	0.004	0.034	0.209	0.040
Fangchenggang	2022	0.125	−0.003	0.108	1.030	0.150	−0.040	0.069	0.180	0.049
Guigang	2022	0.062	0.035	0.065	0.187	0.166	0.064	0.031	0.200	0.043
Liuzhou	2022	0.070	0.086	0.039	0.211	0.124	0.070	0.016	0.204	0.019
Guilin	2022	0.096	0.009	0.044	0.221	0.322	0.037	0.018	0.217	0.018
Wuzhou	2022	0.063	0.060	0.045	0.277	0.264	0.069	0.021	0.200	0.031
Hezhou	2022	0.057	0.051	0.045	0.345	0.308	0.065	0.022	0.202	0.029
Baise	2022	0.068	0.083	0.060	0.688	0.124	0.030	0.032	0.186	0.041
Hechi	2022	0.081	0.075	0.053	0.479	0.117	0.070	0.017	0.193	0.035
Chongzuo	2022	0.076	0.029	0.036	0.867	0.147	−0.065	0.057	0.192	0.065
Laibin	2022	0.071	0.069	0.062	0.335	0.133	0.071	0.022	0.194	0.037
Yulin	2022	0.052	0.009	0.052	0.486	0.198	0.054	0.026	0.216	0.032



FIGURE 4

Spatial distribution of regression coefficients for factors affecting green economic development in Guangxi, 2012.

and Hezhou may reflect their comparatively weaker economic bases, rendering them more susceptible to demographic and developmental shifts. Such spatial population redistribution aligns with international research patterns—[Fan et al. \(2019\)](#) documented similar migration-driven effects on green economies in developing coastal zones, while [Chen and Partridge \(2013\)](#) highlighted initial environmental diseconomies followed by efficiency gains in urbanizing regions due to scale effects.

Regarding industrial sulfur dioxide emissions, the spatial regression coefficients demonstrated an east–west increasing trend in 2012, which reversed by 2022, manifesting a decreasing east–west pattern despite an overall increase in emission levels. This shift likely reflects intra-regional industrial transfers; Guangxi's ongoing industrial restructuring, characterized by the persistence of traditional, pollutant-intensive industries and transitional technological upgrades, contributed to short-term emission increases. This pattern resonates with [Rodrik's \(2014\)](#) analysis of industrial pollution during early stages of regional economic restructuring, where pollution often intensifies as industries relocate before subsequent decline, and with [Coenen et al. \(2015\)](#), who identified “pollution haven” effects during industrial transition phases.

The spatial distribution of green coverage area coefficients remained largely consistent over the decade, characterized by low values in the west and high in the east in 2012, with Baise and Hechi exceptions. By 2022, negative coefficients vanished, and these western regions transitioned to positive values. This shift may be attributed to topographical constraints mountainous terrain and limited water resources alongside relatively underdeveloped economies that hinder green infrastructure investments. Literature by [Zhang et al. \(2021\)](#) underscores the influence of terrain on green space efficacy, while [Gao and Bryan \(2017\)](#) note that challenging geography diminishes returns on green infrastructure investments.

Air quality excellence rates displayed a “north low, south high” pattern in 2012, with Baise, Hechi, Liuzhou, and Laibin exhibiting negative coefficients. By 2022, these regions experienced a transition to positive coefficients, reflecting substantial improvements. This change likely results from strengthened environmental regulations and a shift towards ecological industries such as ecological tourism and agriculture. This transformation aligns with [Zhang and Crooks \(2012\)](#), who describe an environmental Kuznets curve in industrial regions, and [Barbier \(2016\)](#), who emphasizes air quality as an indicator of broader green economy advancements.

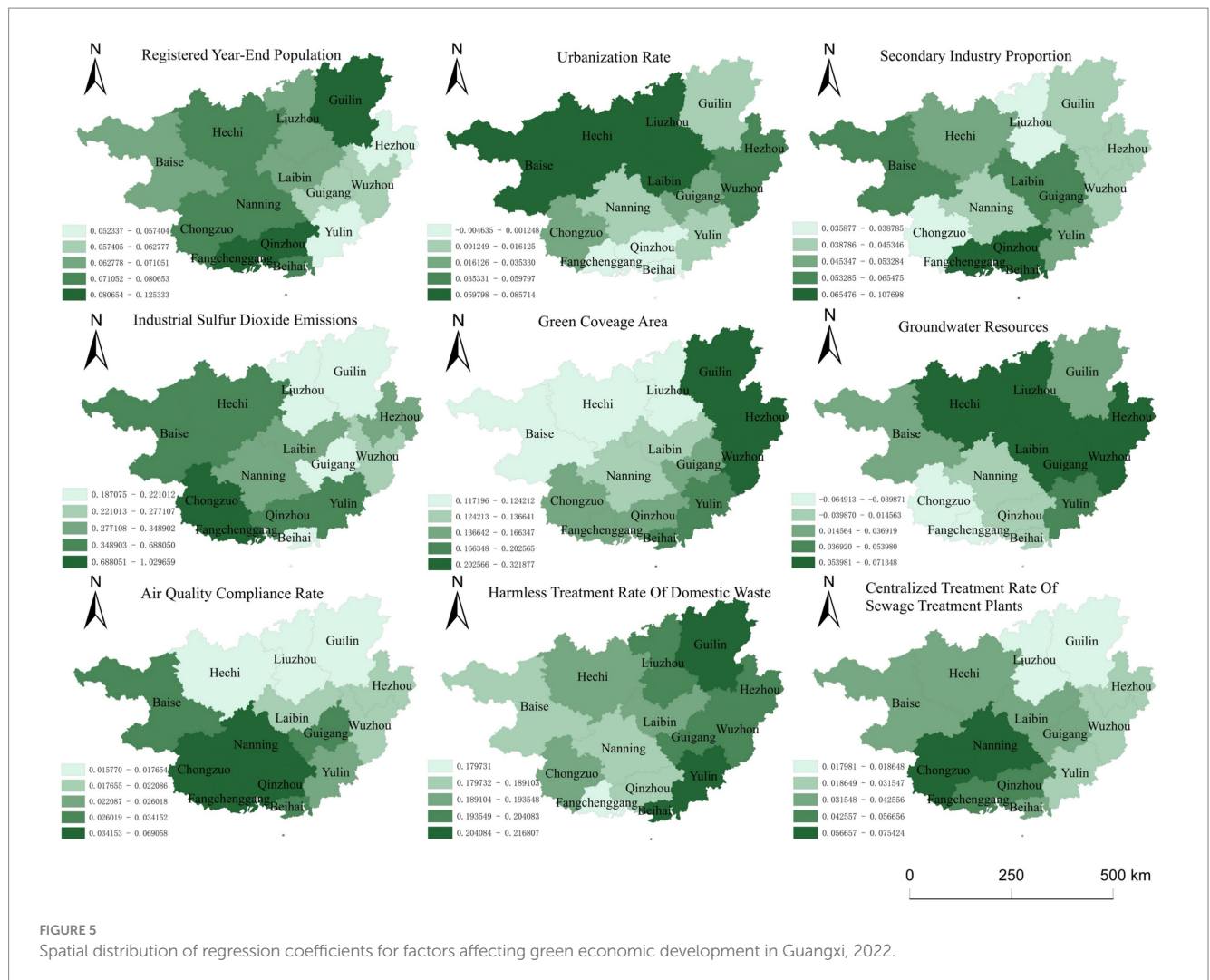


FIGURE 5

Spatial distribution of regression coefficients for factors affecting green economic development in Guangxi, 2022.

Centralized Treatment Rate of Sewage Treatment Plants. The centralized sewage treatment rate coefficients were negative in eastern Guangxi cities and Nanning in 2012, indicating limited impact at that stage. By 2022, the negative coefficients disappeared, with Nanning notably increasing its treatment capacity, suggesting enhanced infrastructure investments. Such spatial patterns in wastewater infrastructure effects are consistent with [Spirandelli \(2015\)](#), who observed higher returns in major urban centers with stronger governance, and with the [World Bank \(2019\)](#), which emphasizes the importance of institutional capacity in realizing environmental and economic benefits from wastewater treatment investments.

In sum, these spatial and temporal shifts in population, industrial emissions, green coverage, air quality, and wastewater infrastructure underscore complex interactions between regional development, environmental policies, and geographic factors, reflecting broader patterns identified in international green economy research.

3.3.4 Temporal evolution analysis of Guangxi's green economic development level influencing factors

Analysis of the GTWR-derived regression coefficients for nine factors from 2012 to 2022 reveals distinct temporal dynamics across multiple layers ([Figure 6](#)).

In the driving force layer, the registered year-end population's positive influence on green economic development declined modestly over time, with coefficients predominantly between 0.0 and 0.15, indicating a consistent yet diminishing impact. Urbanization rate exhibited an overall increasing trend in its positive effect, signifying its role as a driver. Conversely, the secondary industry's impact fluctuated downward; although initially promoting green development, its influence waned post-2021, suggesting that reductions in secondary industry proportion facilitated progress—aligning with international findings where urbanization and industrial restructuring underpin green transitions ([Loorbach et al., 2017](#); [Shahbaz et al., 2016](#)).

Within the pressure layer, industrial sulfur dioxide emissions displayed a persistent upward trend in their positive coefficients, implying escalating environmental pressure despite green advancements. This pattern parallels transition models where high-emission industries coexist with emerging green structures ([Geels, 2014](#); [Kivimaa and Kern, 2016](#)).

In the state layer, green coverage area maintained a stable, positive influence, supporting its role in promoting green economy growth. Groundwater resource volume exhibited a fluctuating yet positive effect, with nonlinear relationships such as “U” and inverted “U” curves observed between 2012–2016 and 2017–2022,

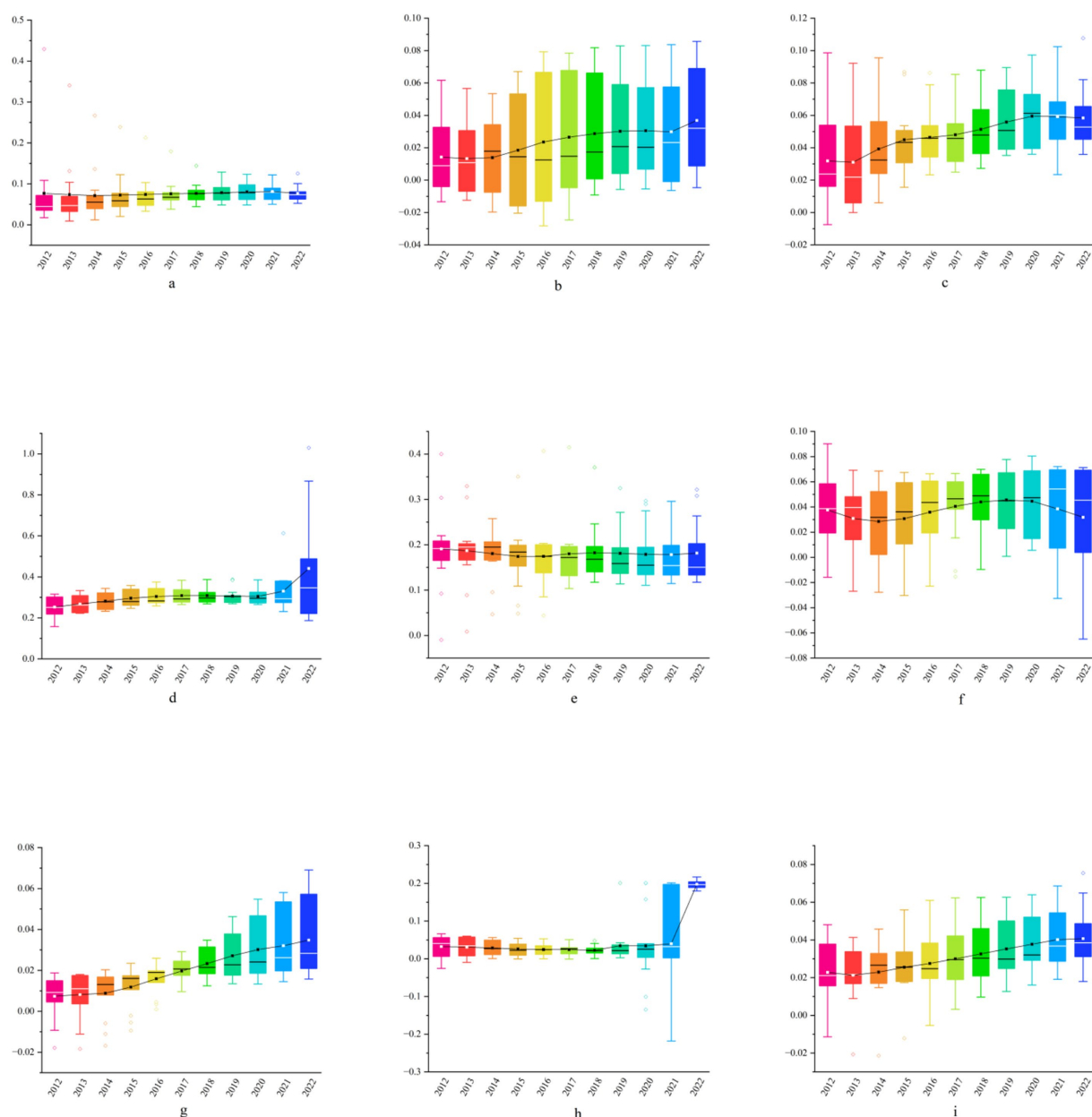


FIGURE 6

Phase line diagram of regression coefficients of GTWR model for impact factors, 2012–2022. In all nine diagrams, the x-axis represents the year and the y-axis denotes the fitted coefficients. Panel (a) corresponds to year-end registered population, (b) to urbanization rate, (c) to share of secondary industry, (d) to industrial carbon dioxide emissions, (e) to green coverage area, (f) to groundwater resource volume, (g) to good air quality rate, (h) to harmless treatment rate of household waste, and (i) to centralized treatment rate of sewage plants.

respectively—consistent with the complex thresholds identified by [Varis and Kummu \(2019\)](#). The air quality excellence rate showed a steady upward trend, corroborating research by [Derksen et al. \(2017\)](#) on the ecosystem service value of urban green infrastructure.

In the response layer, the harmless domestic waste treatment rate remained stable until a marked increase in 2021–2022, intensifying its positive impact. The centralized sewage treatment rate demonstrated a consistent upward trajectory, emphasizing the importance of waste management infrastructure in green economic development. This aligns with global observations that circular economy practices and advanced waste treatment systems serve as catalysts for sustainable growth ([Ghisellini et al., 2016](#); [Velenturf and Jopson, 2019](#)).

Overall, these temporal coefficient patterns underscore the evolving influence of socio-economic, environmental, and infrastructural factors on Guangxi's green economy, reflecting both local dynamics and international transition pathways.

4 Conclusions and recommendations

This study reveals pronounced spatial disparities in Guangxi's green economic development, characterized by a “dual-core” structure led by Nanning and Liuzhou. Most cities remain at the development stage, while Chongzuo persists in the starting stage, underscoring the

need for strategic interventions. Future policy should leverage the leadership of Nanning and Liuzhou by implementing targeted preferential support and encouraging knowledge transfer to surrounding areas through coordinated industrial relocation and infrastructure development, fostering regional green spillovers.

The analysis identifies industrial sulfur dioxide emissions, limited green coverage, and wastewater discharge as primary obstacles, reflecting Guangxi's continued reliance on heavy industry and the slow advancement of environmental infrastructure. In line with Schot and Geels' (2008) framework of strategic niche management, efforts should focus on gradually phasing out high-pollution sectors while simultaneously nurturing emerging green industries through regulatory support and innovation incentives.

Employing the GTWR model allowed a nuanced understanding of spatial-temporal heterogeneity among nine influencing factors, highlighting that the impact of drivers varies significantly across both geography and time. This supports the geography of sustainability transitions approach (Coenen et al., 2012), emphasizing the need for regionally tailored strategies rather than uniform policy prescriptions. Specifically, policies should prioritize optimizing population flows, promoting green urbanization, accelerating clean industrial upgrades, and enhancing environmental governance infrastructure, particularly in western Guangxi.

These findings collectively reinforce that achieving comprehensive green economic development in Guangxi requires multi-scalar, context-sensitive policy interventions that address both systemic barriers and localized development needs.

4.1 Theoretical implications

This study offers three key theoretical contributions. First, it proposes an integrated DPSR-GTWR analytical framework. By combining a causally oriented DPSR evaluation system with the Geographically and Temporally Weighted Regression (GTWR) model, the study develops a unified approach that quantifies the roles of *drivers*, *pressures*, *states*, and *responses* in urban green-economy development while capturing the spatiotemporal heterogeneity of the driving factors. This approach overcomes the limitations of space-invariant or single-time-slice models and provides an explicit geo-temporal perspective for theories of sustainable urban economic transition.

Second, it organically links obstacle diagnosis with mechanism analysis. Before implementing the GTWR regression, the research incorporates the entropy-weight TOPSIS and obstacle-degree models to identify heterogeneous constraints imposed by different influencing factors on urban green economic development. This connection strengthens the theoretical link between *transition bottlenecks* and *policy levers*, thereby enriching the conceptual foundation of ecological modernization and studies on urban green economy transformation.

Third, it expands the meso-regional research perspective within the context of emerging economies. Based on prefecture-level empirical evidence from Guangxi, the findings reveal how institutional capacity, industrial structure, and environmental infrastructure co-evolve to shape urban green economic outcomes. This underscores that green transition theory, when applied to

developing regions, should systematically account for intra-provincial heterogeneity and the sequencing of policy responses. The proposed framework thus provides a transferable analytical template for green-transition studies in other late-developing regions, particularly where historical development constraints and localized characteristics prevail.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

HY: Visualization, Formal analysis, Data curation, Writing – original draft. ZZ: Writing – review & editing, Validation, Methodology. LP: Supervision, Writing – review & editing. FZ: Funding acquisition, Writing – review & editing. LZ: Writing – review & editing, Supervision.

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Conflict of interest

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References

- Adriaanse, A. (1993). Environmental policy performance indicators. The Netherlands: Sustainable Development Programme.
- Almulhim, T. (2024). Assessment of Green Development Level Performance in G20 Countries: A Dynamic Evaluation Framework. *Heliyon* 10:e37622. doi: 10.1016/j.heliyon.2024.e37622
- Balland, P. A., Boschma, R., and Frenken, K. (2019). "Proximity, innovation and networks: a concise review" in A research agenda for new economic geography. eds. A. Torre and D. Gallaud. Cheltenham, UK: Edward Elgar Publishing), 143–165.
- Barbier, E. B. (2012). The green economy post Rio+20. *Science* 338, 887–888. doi: 10.1126/science.1227360
- Barbier, E. B. (2016). Is green growth relevant for poor economies? *Resour. Energy Econ.* 45, 178–191. doi: 10.1016/j.reseneeco.2016.05.001
- Barbier, E. B., and Burgess, J. C. (2020). Sustainability and development after COVID-19. *World Dev.* 135:105082. doi: 10.1016/j.worlddev.2020.105082
- Borel-Saladin, J. M., and Turok, I. N. (2013). The green economy: incremental change or transformation? *Environ. Pol. Gov.* 23, 209–220. doi: 10.1002/eet.1614
- Chen, A., and Partridge, M. D. (2013). When are cities engines of growth in China? Spread and backwash effects across the urban hierarchy. *Reg. Stud.* 47, 1313–1331. doi: 10.1080/00343404.2011.589831
- Chen, Y., Rong, J., and Li, X. (2019). Evaluation and research on the driving factors of the green growth level in the three northeastern provinces. *Ecol. Econ.* 35, 50–56. Available online at: https://kns.cnki.net/kcms2/article/abstract?v=ZHE1803t14vCX58uO4_kCUhmL_GodMn0atGpmE1RyVBtsVUBzeKus0TJTUB9-6gAnZSZCGcoEBT18PMBSsaKQpFfgtb1Q-KRSLQxL0COBCTFW3anjTY8rCBa_zYJGipMbDYIgiu6qfjhmNAufFH2JlY_QVht8UZaZnJTMk7bcb29hxeYFs6Ig==&uniplatform=NZKPT&language=CHS
- Coenen, L., Bennenworth, P., and Truffer, B. (2012). Toward a spatial perspective on sustainability transitions. *Res. Policy* 41, 968–979. doi: 10.1016/j.respol.2012.02.014
- Coenen, L., Hansen, T., and Rekers, J. V. (2015). Innovation policy for grand challenges. An economic geography perspective. *Geogr. Compass* 9, 483–496. doi: 10.1111/gec3.12231
- Cosbey, A. (2011). "Trade, sustainable development and a green economy: benefits, challenges and risks" in The transition to a green economy: benefits, challenges and risks from a sustainable development perspective. New York, NY: United Nations Department of Economic and Social Affairs. 40–61. Available online at: https://scholar.google.com/scholar?q=Trade,+sustainable+development+and+a+green+economy:+benefits,+challenges&hl=zh-CN&as_sdt=0&as_vis=1&oi=scholar
- Demirel, P., Li, Q. C., Rentocchini, F., and Tamvada, J. P. (2019). Born to be green: new insights into the economics and management of green entrepreneurship. *Small Bus. Econ.* 52, 759–771. doi: 10.1007/s11187-017-9933-z
- Derkzen, M. L., van Teeffelen, A. J., and Verburg, P. H. (2017). Green infrastructure for urban climate adaptation: how do residents' views on climate impacts and green infrastructure shape adaptation preferences? *Landsc. Urban Plan.* 157, 106–130. doi: 10.1016/j.landurbplan.2016.05.027
- Fan, P., Chen, J., and John, R. (2019). Urbanization and environmental change during the economic transition on the Mongolian plateau: Hohhot and Ulaanbaatar. *Environ. Res.* 144, 96–112. doi: 10.1016/j.envres.2015.09.020
- Fotheringham, A. S., Crespo, R., and Yao, J. (2015). Geographically and temporally weighted regression (GTWR). *Geograph. Analysis*, 47, 215–229. doi: 10.1111/gean.12071
- Gao, L., and Bryan, B. A. (2017). Finding pathways to national-scale land-sector sustainability. *Nature* 544, 217–222. doi: 10.1038/nature21694
- Geels, F. W. (2011). The multi-level perspective on sustainability transitions: responses to seven criticisms. *Environ. Innov. Soc. Transit.* 1, 24–40. doi: 10.1016/j.eist.2011.02.002
- Geels, F. W. (2014). Reconceptualising the co-evolution of firms-in-industries and their environments: developing an inter-disciplinary triple embeddedness framework. *Res. Policy* 43, 261–277. doi: 10.1016/j.respol.2013.10.006
- Ghisellini, P., Cialani, C., and Ulgiati, S. (2016). A review on circular economy: the expected transition to a balanced interplay of environmental and economic systems. *J. Clean. Prod.* 114, 11–32. doi: 10.1016/j.jclepro.2015.09.007
- Gómez-Calvet, R., Conesa, D., Gómez-Calvet, A. R., and Tortosa-Ausina, E. (2014). Energy efficiency in the European Union: what can be learned from the joint application of directional distance functions and slacks-based measures? *Appl. Energy* 132, 137–154. doi: 10.1016/j.apenergy.2014.06.053
- Gu, W., and Ge, Y. (2018). Research on the temporal and spatial evolution and influencing factors of China's provincial greening pattern. *Ecol. Econ.* 34, 80–85. Available online at: https://kns.cnki.net/kcms2/article/abstract?v=ZHE1803t14tc9dWKupkh2cS9VQm-BwZ3CG2-SetADhZ5yoH4BRZ0AJb67pX0cyZzaU8eUa2lqvoJROUWNS07Ovx0DD0Yfezx_kUOQzWdlC9kZmud57zhm6wJltpqR-V-voivrbh8oyJD-5zkNBTYbce52KXrXsnkz7uR_Csq3m9nibUlwTayQ==&uniplatform=NZKPT&language=CHS
- Halkos, G. (2023). Economic analysis and policies for the environment, natural resources, and energy. *Energies* 16:6578. doi: 10.3390/en16186578
- Hansen, T., and Coenen, L. (2015). The geography of sustainability transitions: review, synthesis and reflections on an emergent research field. *Environ. Innov. Soc. Transit.* 17, 92–109. doi: 10.1016/j.eist.2014.11.001
- Hickel, J. (2020). The sustainable development index: measuring the ecological efficiency of human development in the Anthropocene. *Ecol. Econ.* 167:106331. doi: 10.1016/j.ecolecon.2019.05.011
- Hickel, J., and Kallis, G. (2020). Is green growth possible? *New Polit. Econ.* 25, 469–486. doi: 10.1080/13563467.2019.1598964
- Hou, C., Chen, H., Long, R., Zhang, L., and Zhu, Y. (2021). Construction and empirical research on evaluation system of green productivity indicators: analysis based on the correlation-fuzzy rough set method. *J. Clean. Prod.* 279:123638. doi: 10.1016/j.jclepro.2020.123638
- Hu, L., Liu, J., and Zhang, J. (2024). Evaluation and spatio-temporal evolution of green tourism economic development efficiency in Tibet—an empirical study based on super-efficiency SBM model. *Bus. Econ. Res.* 12, 189–192. doi: 10.3969/j.issn.1002-5863.2024.12.044
- Huang, B., Wu, B., and Barry, M. (2010). Geographically and temporally weighted regression for modeling spatio-temporal variation in house prices. *Int. J. Geogr. Inf. Sci.* 24, 383–401. doi: 10.1080/13658810802672469
- Kivimaa, P., and Kern, F. (2016). Creative destruction or mere niche support? Innovation policy mixes for sustainability transitions. *Res. Policy* 45, 205–217. doi: 10.1016/j.respol.2015.09.008
- Larsen, G. (2018). "An inquiry into the theoretical basis of sustainability" in Routledge handbook of the history of sustainability. ed. J. L. Caradonna. (Abingdon, Oxon: Routledge), 15–31.
- Li, J., Zhao, M., and Han, R. (2021). Research on the spatial differentiation characteristics of urban comprehensive carrying capacity in Shandong Province and its influencing factors. *Ecol. Econ.* 37, 85–92. Available online at: <https://link.cnki.net/urlid/53.1193.F20210528.1102.002>
- Lin, X., Xu, W., and Yang, F. (2017). Temporal and spatial evolution and influence mechanism of green economic efficiency in old industrial bases in Northeast China—taking Liaoning Province as an example. *Econ. Geogr.* 37, 125–132. doi: 10.15957/j.cnki.jjdl.2017.05.017
- Loorbach, D., Frantzeskaki, N., and Avelino, F. (2017). Sustainability transitions research: transforming science and practice for societal change. *Annu. Rev. Environ. Resour.* 42, 599–626. doi: 10.1146/annurev-environ-102014-021340
- Loorbach, D., and Rotmans, J. (2006). "Managing transitions for sustainable development" in Understanding industrial transformation. X. Olshoorn and A. J. Wiczeorek. (Dordrecht: Springer), 187–206.
- Lu, J., Sun, N., and Liu, S. (2016). Study of the implementation strategy for promoting pollution prevention and control in industrial sectors. *Environ. Protec.* 38, 112–124. doi: 10.16803/j.cnki.issn.1004-6216.2016.04.013
- Mardani, A., Streimikiene, D., Zavadskas, E. K., Cavallaro, F., Nilashi, M., Jusoh, A., et al. (2017). Application of structural equation modeling (SEM) to solve environmental sustainability problems: a comprehensive review and meta-analysis. *Sustainability* 9:1814. doi: 10.3390/su9101814
- Markard, J., Raven, R., and Truffer, B. (2012). Sustainability transitions: an emerging field of research and its prospects. *Res. Policy* 41, 955–967. doi: 10.1016/j.respol.2012.02.013
- Mathews, J. A. (2012). Green growth strategies—Korean initiatives. *Futures* 44, 761–769. doi: 10.1016/j.futures.2012.06.002
- Mathews, S. A., and Yang, T. C. (2012). Mapping the results of local statistics: using geographically weighted regression. *Demogr.* 26, 151–166. doi: 10.4054/DemRes.2012.26.6
- McCauley, D., and Heffron, R. (2018). Just transition: integrating climate, energy and environmental justice. *Energy Policy* 119, 1–7. doi: 10.1016/j.enpol.2018.04.014
- Mo, J., Sun, P., Gong, Q., Liu, Q., and Shen, D. (2024). Spatio-temporal differentiation of urban green spaces and influencing factors: A case study of the Yangtze River Economic Belt. *J. Mountain Sci.* 42, 196–209. doi: 10.16089/j.cnki.1008-2786.000816
- Pearce, D., Markandya, A., and Barbier, E. (2013). Blueprint for a green economy. London: Routledge.
- Ren, C., Wang, T., Wang, Y., Zhang, Y., and Wang, L. (2023). The Heterogeneous Effects of Formal and Informal Environmental Regulation on Green Technology Innovation—An Empirical Study of 284 Cities in China. *Intern. J. Environ. Res. Public Health*, 20:1621. doi: 10.3390/ijerph20021621
- Robaina-Alves, M., Moutinho, V., and Macedo, P. (2025). A new frontier approach to model the eco-efficiency in European countries. *J. Clean. Prod.* 103, 562–573. doi: 10.1016/j.jclepro.2015.01.038
- Rodrik, D. (2014). Green industrial policy. *Oxf. Rev. Econ. Policy* 30, 469–491. doi: 10.1093/oxrep/gru025
- Sandmann, L., Bülbül, E., Castano-Rosa, R., Hanke, F., Großmann, K., Guyet, R., et al. (2024). The European green Deal and its translation into action: multilevel governance

- perspectives on just transition. *Energy Res. Soc. Sci.* 115:103659. doi: 10.1016/j.erss.2024.103659
- Sanye-Mengual, E., Orsini, F., and Gianquinto, G. P. (2018). Revisiting the sustainability concept of urban food production from a stakeholders' perspective. *Sustainability* 10:2175. doi: 10.3390/su10072175
- Schmalensee, R. (2012). From "green growth" to sound policies: an overview. *Energy Econ.* 34, S2–S6. doi: 10.1016/j.eneco.2012.08.041
- Schot, J., and Geels, F. W. (2008). Strategic niche management and sustainable innovation journeys: theory, findings, research agenda, and policy. *Res. Policy* 37, 583–603. doi: 10.1016/j.respol.2008.01.010
- Shahbaz, M., Loganathan, N., Muzaffar, A. T., Ahmed, K., and Jabran, M. A. (2016). How urbanization affects CO₂ emissions in Malaysia? The application of STIRPAT model. *Renew. Sust. Energ. Rev.* 57, 83–93. doi: 10.1016/j.rser.2015.12.096
- Shang, S., and Xu, D. (2022). Measurement of green economy at China's provincial level and analysis of influencing factors. *Bus. Econ. Res.*, 160–165. doi: 10.3969/j.issn.1002-5863.2022.08.041
- Shu, X., Min, Z., Guo, X., He, Y., and Zhang, Q. (2024). Provincial digital economy and tourism industry high-quality development coupling coordination and driving factors. *Econ. Geogr.* 44, 197–208. doi: 10.15957/j.cnki.jjdl.2024.01.020
- Spirandelli, D. (2015). Patterns of wastewater infrastructure along a gradient of coastal urbanization: A study of the Puget Sound region. *Land*, 4, 1090–1109. doi: 10.3390/land4041090
- Stern, N., and Stiglitz, J. E. (2021). The social cost of carbon, risk, distribution, market failures: an alternative approach. Cambridge, MA (National Bureau of Economic Research): NBER Working Paper.
- Stjepanovic, S., Tomic, D., and Skare, M. (2022). A new database on green GDP: 1970–2019: a framework for assessing the green economy. *Oecon. Copernic.* 13, 949–975. doi: 10.24136/oc.2022.027
- Sun, Y., and Jing, P. (2012). A study on green transition mode and transition path of resource-based regions. *China Soft Sci.* 12, 152–161. doi: 10.3969/j.issn.1002-9753.2012.12.015
- Tang, X., and Zhang, Y. (2020). Evaluation of China's provincial environmental quality and analysis of influencing factors based on DPSIR model. *J. Guangxi Normal Univ.* 56, 60–83. doi: 10.16088/j.issn.1001-6597.2020.04.007
- Thi, D., and Do, T. (2024). The interrelationships between economic growth and innovation: International evidence. *J. Appl. Eco.* 27:2332975. doi: 10.1080/15140326.2024.2332975
- Tong, C. (2000). Review on environmental indicator research. *Res. Environ. Sci.* 13, 53–55. Available online at: <https://www.hjkxyj.org.cn/en/article/id/20000415>
- Troian, A., Gomes, M. C., Tiecher, T., Berbel, J., and Gutiérrez-Martín, C. (2021). The drivers–pressures–state–impact–response model to structure cause–effect relationships between agriculture and aquatic ecosystems. *Sustainability* 13:9365. doi: 10.3390/su13169365
- UNEP (2011). Towards a green economy: Pathways to sustainable development and poverty eradication. Nairobi: UNEP.
- Varis, O., and Kumm, M. (2019). The demanding quest for harmony: China's polarizing freshwater resilience map. *Environ. Res. Letters*, 14:054015. doi: 10.1088/1748-9326/ab1040
- Velenturf, A. P., and Jopson, J. S. (2019). Making the business case for resource recovery. *Sci. Total Environ.* 648, 1031–1041. doi: 10.1016/j.scitotenv.2018.08.224
- World Bank (2019). Disclosing and valuing the benefits of resilience investments: a guide for utilities. Washington, DC: World Bank.
- Yang, W., Hu, Y., Ding, Q., Gao, H., and Li, L. (2023). Comprehensive evaluation and comparative analysis of the green development level of provinces in eastern and western China. *Sustaina.* 15:3965. doi: 10.3390/su1505396
- Yao, C., Teng, Y., and Huang, L. (2015). Construction and empirical analysis of China's food security evaluation index system. *Trans. Chin. Soc. Agric. Eng.* 31, 1–10. doi: 10.3969/j.issn.1002-6819.2015.04.001
- York, R., Rosa, E. A., and Dietz, T. (2003). Footprints on the earth: the environmental consequences of modernity. *Am. Sociol. Rev.* 68, 279–300. doi: 10.2307/1519769
- Zhang, W. (2021). Construction and empirical study of China's green economy evaluation index system. *Stat. Decis.* 37, 126–129. doi: 10.13546/j.cnki.tjyc.2021.16.028
- Zhang, Q., and Crooks, R. (2012). Toward an environmentally sustainable future: Country environmental analysis of the People's Republic of China. Mandaluyong, Philippines: Asian Development Bank.
- Zhang, B., Xie, Z. X., Gao, J. X., and Yu, X. L. (2021). Assessment on the cooling effect of urban green spaces in Shanghai. *Res. Sci.* 43, 1004–1015. doi: 10.31497/ZZZYXB.20210518
- Zhao, C., Han, N., Zhou, Q., Li, S., and Shi, B. (2024). Evaluation of water resource carrying capacity in Shanxi Province based on combined weighting-TOPSIS model. *J. Tianjin Agric. Univ.* 31, 74–80. doi: 10.19640/j.cnki.jtau.2024.04.013
- Zhao, W., Li, X., and Wang, Z. (2024). Measurement and spatial-temporal evolution analysis of China's green low-carbon circular economy system development level. *Statist. Decis.* 40, 109–114. doi: 10.13546/j.cnki.tjyc.2024.11.019
- Zhao, J., Zhang, H., Zeng, C., et al. (2023). Research on the spatial and temporal heterogeneity of influencing factors of green efficiency of water resources in Tuojiang River basin. *China Rural Water Hydropower* 45, 110–118. doi: 10.12396/znsd.221185
- Zhi, X., and Liu, C. (2022). Research on high-quality development of industrial economy in Xinjiang from the perspective of resource and environment carrying capacity. *Xinjiang State Farms Econ.* 11, 30–38. doi: 10.3969/j.issn.1000-7652.2022.11.005
- Zournatzidou, G., Sklavos, G., Ragazou, K., and Sariannidis, N. (2024). Anti-competition and anti-corruption controversies in the European financial sector: examining the anti-ESG factors with entropy weight and TOPSIS methods. *J. Risk Financial Manag.* 17:492. doi: 10.3390/jrfm17110492