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ORIGINAL RESEARCH ARTICLE

Ecological indicator system construction for water resources and pollution governance in Guangxi (2004–2022) and coupling-coordination assessment

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Abstract: Guangxi's rapid urbanization and rising environmental pressures have made balanced water–ecology governance a core regional policy concern. Using annual data for prefecture-level cities in Guangxi, China, from 2004 to 2022, this study constructs an ecological indicator system encompassing "water resources–pollutants–clean governance" and conducts a comprehensive evaluation with a coupling-coordination diagnosis. Data sources included the *Guangxi Statistical Yearbook*, the *China Environmental Statistical Yearbook*, and relevant editions of the *Guangxi Statistical Bulletin of National Economic and Social Development*. Methodologically, indicators were first standardized via minimum–maximum scaling. Using the driver–pressure–state–impact–response framework, indicators were selected. Objective weights were determined through the criteria importance through the intercriteria correlation method. The technique for order preference by similarity to the ideal solution method was used to compute composite scores for the three subsystems. We then established models for the coupling degree (C) and coupling-coordination degree (D). Across 2004–2022, the D ranged from 0.458 to 0.798, indicating predominantly low-to-moderate coordination with discernible phase fluctuations rather than extreme imbalance. In 2022, the headline metrics were measured at 0.958 for C and 0.798 for D, representing the upper end of the observed coordination level over the sample period. Overall, urban ecological governance in Guangxi remained only partially coordinated during 2004–2022, although with episodic improvements. Policy pathways should prioritize high-weight, high-dispersion dimensions to enhance subsystem matching and raise coordination.

Keywords: Water resources management; Pollution control; Ecological governance; Urban sustainability; Guangxi; Indicator system; Wastewater treatment

1. Introduction

Global urbanization is accelerating, resulting in unprecedented pressure on urban ecosystems. Major obstacles to sustainable urban development include strained water resources, excessive contaminant emissions, and insufficient refuse treatment capacity. Particularly in a diverse ecological region such as Guangxi, the effects of urbanization and industrialization on water resources and the environment have become increasingly significant. Consequently, the urgent and realistic issue of scientifically and effectively assessing and managing water resources, pollutants, and clean governance in urban ecological governance has arisen.

Despite the abundance of water resources in southern China (Figure 1), Guangxi's water resources management, pollution management, and ecological environment construction are confronted with numerous challenges, including irrational resource allocation and uneven regional development. In particular, the conventional ecological governance model is inadequate to address the requirements of contemporary urban development due to the imbalance between water supply and demand, as well as the substantial increase in pollutant emissions. Current governance measures are frequently hindered by issues such as incomplete data acquisition and insufficient cross-disciplinary synergy, causing challenges in evaluating the efficacy of ecological governance and an inadequate foundation for decision-making.

The objective of this study is to develop a comprehensive ecological indicator system that encompasses a variety of aspects, including water resources management, pollutant emission management, and clean governance. The study evaluated urban ecological governance in Guangxi using quantitative indicators and investigated the coordination between these indicators. It also established a scientific foundation for ecological governance in Guangxi and encouraged the enhancement of the ecological management system by conducting a comprehensive analysis of key data, including total water resources, water supply, water management, wastewater discharge, air pollution management, waste treatment, and ecological greening.

Simultaneously, this investigation focused on the matter of data coordination, assessed the association between data from various domains, and suggested effective strategies for cross-domain data sharing and integration to provide more accurate policy support to decision-makers. It may significantly enhance the effectiveness of policy implementation and the level of precise management of urban ecological governance, as well as guarantee the sustainability of the ecology during the urbanization process, through data unification and coordination. To conclude, this study not only offers quantifiable assessment tools for urban eco-governance in Guangxi and other regions but also serves as a critical reference for the government and related departments in the formulation of eco-environmental policies. This reference is of significant theoretical and practical importance.

2. Literature review

2.1. Overview of typicality in China and abroad

Globally, accelerated urbanization presents unprecedented challenges to urban ecological governance. Water

Figure 1. Map of the Guangxi province

resources, pollution control, ecological conservation, and related policy formulation have become focal research areas. Scholars from diverse regions have proposed distinct perspectives and research outcomes to address these issues. The viewpoints and relevant research findings from Chinese and Western scholars are summarized in Table 1 and in the following sections.

2.1.1. Research perspectives from Chinese scholars

These include:

(i) Water resources management and pollution control: Chinese scholars generally believe that effective water resources management and pollution control are central to advancing sustainable urban ecological development. Zhao[1] noted in her research that although China's urban water resources rank among the world's largest in total volume, geographical distribution imbalances, overexploitation in economically intensive areas, and severe pollution have led to water supply-demand conflicts. Water scarcity and pollution are particularly severe in central and western regions. Consequently, she emphasized the need to strengthen regional collaborative management and to optimize water resources allocation, alongside introducing modern water resources scheduling technologies.

(ii) Construction of ecological indicator systems: Addressing the multidimensional challenges of ecological governance, Jiang *et al*.[2] proposed a comprehensive ecological indicator system designed to evaluate the effectiveness of governance measures across multiple domains, including water resources, wastewater discharge, air pollution, and solid waste management. They contended that ecological governance should commence with "quantitative

Table 1. Comparison of the views of Chinese and foreign scholars

Serial number	References	Scholars' views
1	Zhao[1]	Focuses on water resources management and pollution control, emphasizing the need to strengthen regional collaborative management and optimize water resources allocation, while incorporating modern water resources scheduling technologies.
2	Jiang *et al*.[2]	Proposes a comprehensive ecological indicator system, employing a "water–air–soil" interaction model to enhance data coordination in urban ecological governance.
3	Yang and Cao[3]	Explores the impact of data synergy on urban ecological governance outcomes, proposing an optimization model for urban ecological governance based on big data and cloud computing.
4	Wang *et al*.[4]	Focusing on green development principles, this study proposes a policy framework based on ecological compensation mechanisms to advance the implementation of environmental protection measures.
5	Wang[5]	Emphasizes that pollution control is not only the responsibility of government and enterprises but also a shared task for all sectors of society, proposing that the public and non-governmental organizations should participate in pollution control.
6	Pires *et al*.[6]	Proposes integrated water resources management, emphasizing the coordination of water use, conservation, and governance in the face of diverse water demands and pollution challenges.
7	Khan *et al*.[7]	Highlights innovations in water pollution control technologies, proposing membrane techniques and constructed wetlands to address wastewater treatment and water reuse requirements.
8	Amann *et al*.[8]	Investigates economic approaches to urban pollution control, proposing tools such as emissions trading and environmental taxes to promote environmental protection.
9	Mathey *et al*.[9]	Proposes that green urban development should enhance resource utilization, pollution control, and ecological conservation while incorporating ecological compensation mechanisms and public participation.
10	Makumbura *et al*.[10]	In pollution control and water-quality management, the approach increases predictive accuracy and interpretability, enabling anomaly alerts, identification of key pollutants, and evidence-based decisions for urban ecological governance.

indicators," employing more refined standards to assess the efficacy of various governance measures. The research proposed an interactive "water–air–soil" relationship model to better coordinate data across urban ecological domains, thereby enhancing the precision and efficiency of governance.

(iii) Data coordination and governance decision-making: Yang and Cao[3] examined the impact of data coordination on urban ecological governance outcomes. They contended that significant data silos currently exist within urban ecological governance, particularly in water resources management, pollutant control, and waste disposal. This severely hampers decision-makers' ability to accurately assess governance outcomes and formulate policies. Consequently, they proposed a big data-driven urban ecological governance model emphasizing cross-domain data sharing and integration, aimed at dismantling data silos and enhancing governance efficacy.

(iv) Green development and ecological compensation mechanisms: Scholars such as Wang *et al*.[4] focused on applying the "green development" concept to urban ecological governance, proposing a policy framework based on ecological compensation mechanisms. They contended that ecological compensation mechanisms should be introduced during water resources and pollutant management processes to incentivize enterprises and local governments to adopt more environmentally sustainable measures. Concurrently, governments should strengthen policy guidance and rationally allocate environmental resources, particularly by enhancing research, development, and promotion of green technologies for water pollution control and wastewater treatment.

(v) Pollutant emissions and social responsibility: Addressing pollutant discharge issues in China's major cities, Wang[5] contended that pollution control is not solely the responsibility of the government and enterprises, but a shared task for all sectors of society. She observed that with advancing urbanization, pollutant emissions are increasing, particularly in regions experiencing rapid industrial development, making the balance between economic growth and environmental protection a significant challenge. She proposed that, beyond governmental policy guidance and corporate environmental responsibility, the general public and non-governmental organizations should actively participate in monitoring and advocating for pollution control.

2.1.2. Perspectives from foreign scholars

These include:

(i) Integrated water resources management (IWRM): IWRM has emerged as a primary research focus within academia and governmental policy. Pires *et al*.[6] noted that rational coordination of water resources utilization, conservation, and governance is essential, particularly when confronting diverse water demands and the challenge of water pollution. They contended that water resources management should be integrated into a sustainable development framework, balancing economic, social, and environmental considerations to promote equitable and efficient water resources allocation.

(ii) Water pollution control and technological innovation: Research on water pollution control has increasingly focused on technological innovation. Khan *et al*.[7] emphasized the continuous advancement of pollution treatment technologies, noting that accelerated industrialization and urbanization have rendered traditional wastewater treatment methods inadequate for meeting increasingly stringent environmental standards. Consequently, novel pollutant removal techniques, membrane technologies, and ecological engineering solutions, such as constructed wetlands, are being widely deployed to address urban wastewater treatment and water reuse requirements. They contended that technological advancement is pivotal to resolving urban water pollution issues, yet it is equally important to balance economic costs with societal acceptability.

(iii) Environmental economics and pollutant management: Environmental economics methodologies have found extensive application in pollution control. Amann *et al*.[8] indicated that urban pollution control is not merely a technical issue but fundamentally an economic one. They proposed adopting market-based approaches to urban pollutant management, utilizing policy instruments, such as emissions trading schemes and environmental taxes, to incentivize enterprises towards more environmentally sound production processes and technologies. These economic measures can effectively reduce pollutant emissions while sustaining economic growth and development.

(iv) Green cities and ecological compensation mechanisms: Green city development has become a crucial direction for advancing sustainable development. Mathey *et al*.[9] proposed that green cities extend beyond architectural design to encompass innovative measures in resource utilization, pollution control, and ecological conservation. They contended that urban ecological governance should strengthen ecological compensation mechanisms, incorporating social participation and public oversight to establish a virtuous cycle of multi-stakeholder co-governance.

(v) Application of artificial intelligence (AI) in pollution and water quality assessment: For water quality assessment and prediction in urban and watershed contexts, Makumbura *et al*.[10] integrated machine learning models with explainable AI (XAI) for water quality evaluation. They utilized a weighted arithmetic water quality index to construct and compare models, including random forest, lightGBM, and XGBoost. Simultaneously, they employed Shapley additive explanations to interpret the "black-box" models, identifying key water quality factors and quantifying their marginal contributions to prediction outcomes. Within the pollution control and water quality management contexts, this approach enhances both predictive accuracy and interpretability. It facilitates anomaly early warning, pinpoints key pollutants, and underpins governance decisions, offering data-driven technical solutions for urban ecological governance.

Overall, scholars globally concur that water resources management and pollutant control constitute pivotal elements of urban ecological governance. In China, researchers predominantly focus on optimizing urban ecological governance through refined ecological indicator systems and data coordination. Conversely, Western nations have extensively explored technological innovation, market mechanisms, and cross-sectoral data sharing. Regardless of geographical context, advancing the sustainability of water resources and pollutant management necessitates collaborative efforts among policymakers, academia, and society at large.

Drawing upon these international research findings and contextualized within Guangxi's specific circumstances, this study explores ecological governance models suited to Guangxi's regional characteristics, thereby providing scientific grounds for relevant policy formulation.

2.1.3. Comparative analysis of domestic and international cases

Domestically, the "sponge city + integrated watershed management" approach has evolved under conditions of high-intensity urbanization and spatially and temporally uneven water resources. This approach forms a comprehensive strategy centered on "pollution source control and interception–ecological absorption–non-conventional water utilization." Taking the Pearl River Delta and Yangtze River Delta as examples, local governments have reduced non-point source loads through dual sewer system upgrades, stormwater storage and retention, and reclaimed water reuse. They have advanced cross-regional collaborative water management with sectional compliance as a hard constraint. Their success rests upon precise identification of the coupled dynamics between "increasing pollution–water scarcity–regional imbalance."[11] Concurrently, horizontal ecological compensation integrates upstream/downstream and left/right riverbanks within a unified incentive framework, mitigating administrative boundary-induced free-riding and governance fragmentation.[12]

Certain prefecture-level cities further embedded public participation and transparent evaluation into the river and lake chief system, as well as black and odorous water body remediation, forming a dual-drive model of "engineering foundation + social co-governance:" Community river patrols, public reporting, and performance disclosure enhanced compliance pressure and maintenance frequency, proving particularly effective for monitoring small water bodies and discharge outlets. Complementary district-level performance evaluations and ecological product valuation mechanisms create a closed-loop system integrating fiscal investment, social capital, and ecological benefits, thereby promoting coordinated urban-suburban non-point source pollution control.[12]

Internationally, IWRM, as the overarching framework, focuses on systemic coupling across "supply–demand–ecology–risk." Case studies such as those in Singapore integrate catchment management, reclaimed water, and desalination into a unified portfolio, employing distributed online monitoring, zoned reuse, and resilient water allocation to mitigate systemic vulnerability during extreme weather events. Within the context of advanced wastewater treatment, synergistic upgrades of membrane processes, adsorption/advanced oxidation, and reuse standards enhance dual efficiency in resource recovery and compliance, while dynamically balancing costs against societal acceptability.[13]

Initiatives such as Philadelphia's "Green City, Blue Water" program replace portions of grey infrastructure with distributed green infrastructure. Leveraging differential stormwater fees, compliance incentives, and permitting systems, these projects mobilize private landowners to construct infiltration and detention facilities, concurrently reducing stormwater runoff and improving thermal environments.[14,15] Their governance emphasizes iterative support through closed-loop cost–benefit assessments. Concurrently, machine learning and XAI are deployed for water quality anomaly alerts, critical factor identification, and facility operation optimization, enhancing precision and accountability.[10]

Comparative analysis reveals that domestic cases excel in achieving baseline improvements through government coordination and mandatory compliance targets in the short term, gradually refining collaborative governance via ecological compensation and public participation. International cases, conversely, demonstrate greater emphasis on institutionalized division of labor under IWRM frameworks, price signals, and the long-term performance of distributed green infrastructure, leveraging data intelligence for refined operations.[16] The implications for Guangxi are to maintain coordinated planning and mandatory compliance while calibrating incentive structures through horizontal ecological compensation and pricing instruments, integrating reclaimed water and nature-based solutions into the portfolio. This should be complemented by an XAI-driven closed-loop system of monitoring, early warning, and optimization, forming a composite governance pathway of "engineering foundation + institutional incentives + data intelligence."

2.2. Review of literature search studies

The effectiveness and scientific rigor of ecological governance largely depend on a rational ecological indicator system.[17] Within Guangxi's ecological governance framework, water resources management, pollutant control, and the implementation of clean governance measures constitute key components. In recent years, both domestic and international scholars have increasingly focused on how ecological indicator systems can be employed to evaluate and optimize these governance measures, thereby advancing the sustainable development of the environment. This study conducted a literature review using the keywords "clean governance" and "ecological indicators" across two major databases: China National Knowledge Infrastructure (CNKI) and PubMed. It summarized the current status and development trends within these two research domains.

2.2.1. Examination of the literature search findings

Figure 2 illustrates the literature search analysis chart. The details are as follows:

(i) Research review on clean governance: A total of 517 documents related to "clean governance" were obtained from CNKI using the keywords. According to the search results, the research topics of clean governance encompass a diverse range of areas, including "ecologically clean small watersheds," "integrated management," and "ecological cleanliness." The objectives include "ecologically clean watersheds," "integrated management," "cleaner production," and other similar objectives. The core disciplines include "basic agricultural science," "agronomy," "industrial economics," and "agricultural economics." The primary fields include "basic agricultural science," "environmental science and resource utilization," "agronomy," "industrial economics," and "agricultural economics." The research levels are "engineering research" and "technology development." More attention has been given to research on ecologically clearer sub-watersheds and cleaner production, particularly for industrial and agricultural applications. By optimizing production processes and decreasing pollutant emissions, these studies underscore the objective of cleaner management.

Searching the term "clean governance" in the PubMed database yielded 2,802 articles. In contrast to the CNKI-sourced literature, these articles primarily concentrate on the past decade and encompass broader research fields, including biomedical sciences, environmental sciences, and ecology. The majority of the research delves into the implementation of clean governance in various environments, particularly in water pollution and soil remediation. They also discuss relevant topics, including ecological sanitation and health, clean energy, and environmental pollution mitigation measures. Specifically, the application of pollutant control and environmental restoration is closely linked to public health and ecosystem health, as evidenced by these studies.

(ii) Review of ecological indicator research: A search on CNKI identified a total of 5,105 documents that are relevant to the keyword "ecological indicators." These documents primarily address the subjects of "ecological civilization," "ecological environment," "evaluation indicator system," and "indicator system research." They primarily concentrate on "research on the indicator system," "evaluation indicator system," "ecological civilization," and "ecological environment." The disciplines that are addressed include "environmental science and resource utilization," "building science and engineering," "forestry," "agricultural economics," and "biology." The primary research directions

Figure 2. Literature search analysis map
Abbreviation: CNKI: China National Knowledge Infrastructure.

are applied fundamental research and engineering research. These articles emphasize the utilization of eco-indicator systems to evaluate the health of ecological environments, establish ecological civilizations, and manage water resources. They particularly pertain to the development of effective eco-indicator systems in various regions and fields to facilitate decision-making and governance. The primary objective of ecological indicators research is to quantitatively evaluate the condition of the ecological environment, improve the efficacy of ecological governance, and develop scientific environmental governance policies.

Searching for the term "ecological indicators" on PubMed yielded 6,491 articles. These articles also address the subjects of "ecological indicator system" and "ecological environment evaluation." However, the literature from PubMed focuses more on the role of ecological indicators in biomedicine, disease prevention, and health impacts, particularly the connections between environmental contamination, public health, and disease control. Over the past 5 years, various studies have emphasized the critical role of ecological health indicators in assessing the impact of climate change, biodiversity monitoring, and the effects of pollutant exposure. Additionally, PubMed-sourced studies have emphasized the integrated assessment and application of ecological indicators in the fields of public health, environmental protection, and biodiversity conservation.

2.2.2. Future directions and research trends

Analyzing the literature on CNKI and PubMed reveals the following characteristics of the research trends in sustainable governance and ecological indicators:

(i) Among CNKI-sourced articles, clean governance research predominantly centers on engineering and technological development, such as clean production techniques, pollutant treatment, and ecological restoration. Conversely, PubMed-sourced studies emphasize the health effects of clean governance, particularly within biomedical and public health domains. Recent years have seen increased emphasis on the long-term ecological impacts of clean governance, exploring its effects on human health and ecosystem services.[18]

(ii) The study of ecological indicators has garnered significant attention nationwide and internationally. Studies from CNKI focus on the development and implementation of ecological indicator systems, with a particular emphasis on the role of assessment in the construction of ecological civilizations, ecological environments, and water resources. Conversely, PubMed-sourced studies are predisposed to the fields of biomedicine and eco-health, with a particular emphasis on the correlation between ecological indicators, human health, and environmental pollution. Given the escalation of environmental pollution and global climate change, it is crucial to investigate the ecological indicator system, particularly in the context of multi-dimensional and multi-level environmental assessments, to facilitate the decision-making process of ecological governance.

As data technology continues to evolve, the coordination and sharing of ecological data have emerged as a critical concern. The accuracy and operability of assessing the effects of ecological governance are becoming a growing concern among researchers. These are achieved by integrating multi-source data under a standardized ecological indicator system. For ecological governance, data coordination research can offer more precise and scientifically sound decision support.

Research on water resources, contaminant control, and clean governance in ecological governance has garnered significant attention both domestically and internationally, demonstrating a diversified development trajectory. A critical area of academic research is the clean governance and ecological indicator system, which serves as a critical instrument for evaluating the character of the ecological environment and the impact of governance. With the ongoing advancement in data technology and ecological assessment methodologies, it is crucial to establish a scientific ecological indicator system and achieve data coherence to enhance the quality and efficacy of ecological governance in Guangxi.

3. Data modelling

3.1. Construction of the evaluation index system

The proposed evaluation indicator system scientifically assesses the efficacy of governance and data coordination from multifaceted perspectives of water resources management, pollution management, and resource treatment, in accordance with the comprehensive requirements of water resources, pollutant management, and clean management in Guangxi's ecological governance. Table 2 presents a systematic framework of this indicator system.

Water resources management is addressed using the evaluation indicator system, which encompasses four levels: total water resources, water supply management, water use management, and water resources availability and efficacy. The first-level indicators encompass the total water resources, which are subsequently partitioned into second-level indicators, including the quantities of surface water resources and groundwater resources, to represent the natural endowment and fundamental reserves of regional water resources. Water supply management is divided into the total quantities of surface water, groundwater, and other water sources, reflecting the structure and balance of the water supply. The primary objective of water use management is to monitor the total volume of water consumed for agricultural, industrial, domestic, and ecological purposes. It also helps to optimize water use efficiency and allocate resources rationally. Simultaneously, it assesses the overall performance of water resources management by assessing the availability and efficacy of water resources through indicators such as the duplication of surface and groundwater resources, per capita water resources, and water consumption levels.

The system has established a variety of dimensions in the areas of pollution management and resource treatment, including the management of effluent discharge, air pollution, the treatment of refuse and feces, capacity for waste treatment, facilities for waste treatment, and ecological greening. Among them, wastewater emission control focuses on the total volume of wastewater discharged, chemical oxygen demand, and ammonia nitrogen emissions, estimating the pollutant emission burden and control pressure. Sulphur dioxide emissions serve as the primary indicator for air pollution management, enabling the assessment of its efficacy. Quantitative evidence of the efficacy of treatment in the field of rubbish and feces treatment is provided through indicators such as the quantity of domestic rubbish removed, the rate of harmless

Table 2. Evaluation indicator system for water resources and pollution management and resource treatment in Guangxi

System level	Primary indicators	Secondary indicators (symbols)	Definition/scope	Unit	Per capita	Price/ currency
Ecological water resources management	Total water resources	Total water resources (H1)	Annual available water resources within Region I (integrated surface water and groundwater to avoid double-counting)	Billion cubic meters	No	-
		Surface water resources (H2)	Natural surface water runoff resources (e.g., river runoff)	100 Million cubic meters	No	-
		Groundwater resources (H3)	Exploitable groundwater resources (excluding portions overlapping with surface water resources counted under H1)	100 Million cubic meters	No	-
	Water supply management	Total water supply (H4)	Annual total water supply (including tap water, non-conventional water, and externally transferred water)	Billion cubic meters	No	-
		Total surface water supply (H5)	Water supply volume sourced from surface water	100 Million cubic meters	No	-
		Total groundwater supply (H6)	Water supply volume sourced from groundwater	100 Million cubic meters	No	-
		Total other water supply (H7)	Unconventional water sources (reclaimed water/recycled water, stormwater harvesting, desalination, etc.) and water transferred from external sources	Billion cubic meters	No	-
	Water management	Total water consumption (H8)	Annual total water withdrawal (including that used in agricultural, industrial, and domestic sectors)	100 Million cubic meters	No	-
		Total agricultural water use (H9)	Water used for agricultural production, including farming, forestry, animal husbandry, and fisheries	Billion cubic meters	No	-
		Total industrial water consumption (H10)	Water used for industrial production	Billion cubic meters	No	-
		Total domestic water consumption (H11)	Residential and public service water consumption	100 Million cubic meters	No	-
		Total ecological water use (H12)	Water for ecological environment maintenance (river and lake ecological base flows, ecological replenishment, etc.)	100 Million cubic meters	No	-
	Water resources availability and efficiency	Surface water and groundwater resource redundancy (H13)	Overlap between H2 and H3 (for deductions to avoid double-counting)	Billion cubic meters	No	-

(Cont'd...)

Table 2. ***(Continued)***

System level	Primary indicators	Secondary indicators (symbols)	Definition/scope	Unit	Per capita	Price/currency
		Per capita water resources (H14)	H1/Year-end resident population	Cubic meters per person	Yes	-
		Per capita water consumption (H15)	Permanent residents at year-end (H8)	Cubic meters per person	Yes	-
Pollution control and resource management	Pollutant emissions	Chemical oxygen demand (COD) emissions (K1)	Annual COD emissions from industrial and domestic sources	Ten thousand tons	No	-
		Ammoniacal nitrogen emissions (K2)	Annual industrial and domestic NH_3–N emissions	Ten thousand tons	No	-
		Sulphur dioxide emissions (K3)	Annual sulfur dioxide emissions	Ten thousand tons	No	-
	Waste and fecal matter treatment	Domestic waste collection volume (K4)	Annual volume of household waste collected and disposed of	Ten thousand tons	No	-
		Sanitary treatment rate of municipal solid waste (K5)	Harmonized treatment volume/collection volume×100	%	No	-
	Waste treatment capacity	Domestic waste harmless treatment capacity (K6)	Upper limit of society-wide domestic waste treatment capacity	Tons/day	No	-
		Sanitary landfill treatment capacity (K7)	Maximum sanitary landfill disposal capacity	Tons/day	No	-
		Waste incineration treatment capacity (K8)	Maximum incineration capacity	Tons/day	No	-
	Treatment facilities	Number of sanitizing treatment plants (K9)	Number of operational harmless treatment plants	Units	No	-
		Number of sanitary landfill disposal plants (K10)	Number of operational sanitary landfills	Site	No	-
		Number of waste incineration plants (K11)	Number of operational incineration plants	Units	No	-
	Ecological greening	Total afforestation area (K12)	Annual afforestation area achieved	Thousand hectares	No	-
		Area of artificial afforestation in the current year (K13)	Area of artificial afforestation in the current year	Thousand hectares	No	-
	Industrial pollution control investment	Industrial pollution control investment completed (K14)	Completed investment in pollution control within the industrial sector	Ten thousand yuan (CNY)	No	Nominal value (current prices)

(Cont'd...)

Table 2. ***(Continued)***

System level	Primary indicators	Secondary indicators (symbols)	Definition/scope	Unit	Per capita	Price/ currency
		Completed investment in wastewater treatment projects (K15)	Completed investment in industrial wastewater treatment projects	Ten thousand yuan (CNY)	No	Nominal value (current prices)
		Completed investment in waste gas treatment projects (K16)	Completed investment in industrial waste gas treatment projects	Ten thousand yuan (CNY)	No	Nominal value (current prices)

treatment, and the quantity of feces treated. The supply and operation capacity of facilities is assessed through the dimensions of harmless treatment capacity and the number of facilities. In contrast, the ecological greening indicators assess the efficacy of regional ecological restoration and green development, with the core being the total area of afforestation and the area of artificial afforestation in the current year.

Lastly, the investment in industrial pollution management is a critical component of this system.[11] This investment comprehensively reflects the resource input and effectiveness of pollution management in the industrial sector by incorporating the amount of completed investment in industrial pollution management and the detailed indicators of completed investment in wastewater and waste gas projects. In conclusion, the indicator system provides a comprehensive evaluation framework for water resources management and pollution management in Guangxi's ecological governance, as well as the groundwork for systematic analysis and data coordination.

The foundational data for this study (Table 3) were sourced from the *Guangxi Statistical Yearbook*,[19] the *China Environmental Statistical Yearbook,*[20] and the "Guangxi Statistical Bulletin" for relevant years.[21] The details include (Table 2):

- *Guangxi Statistical Yearbook (2004–2022)* by the Guangxi Zhuang Autonomous Region Bureau of Statistics and the Guangxi Survey Team of the National Bureau of Statistics (annual editions).
- *China Environmental Statistical Yearbook (2004–2022)* by the Department of Urban Socio-economic Surveys, National Bureau of Statistics (annual editions).
- "Guangxi Statistical Bulletin (2004–2022)" by the Department of Ecology and Environment of Guangxi Zhuang Autonomous Region (annual editions).

These sources represent the primary statistical standards employed in the main text; where data for specific years were missing, the most recent comparable standards from the same department's annual bulletins/ yearbooks were used to complete the data.

The price and currency definitions (K14–K16; Table 2) are as follows:

- Currency unit: Ten thousand Renminbi (CNY)
- Price basis: Current prices (nominal values) for the respective year.

Nominal values were used in the main text for standardization and evaluation. Robustness checks might be conducted in the appendix by converting K14–K16 to actual values for a base period using the fixed asset investment price index/environmental protection investment price index.

The per capita conversion methodology is as follows:

- Per capita indicators: H14 (per capita water resources) and H15 (per capita water consumption).
- Remaining indicators are presented as total volume/ capacity/quantity metrics and are not further per capita adjusted (e.g., K6–K8 represent treatment capacity in "tons per day").

3.2. Construction of the data analysis model

3.2.1. Dimensionless processing of indicators

To eliminate the dimensionality and physical significance of each indicator, this study employed a normalization method to perform dimensionless processing on the raw data. Equation (1) is as follows:

$$MMS\_C_i = \frac{x - x_{Min}}{x_{Max} - x_{Min}} \tag{1}$$

Where x_{Max} denotes the maximum value, x_{Min} denotes the minimum value, and MMS_C_i denotes the dimensionless processing results for the 11 secondary indicators. Normalization serves as a simplified

Table 3. Basic indicator data on water resources and pollution management and resource treatment in Guangxi

Year	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10	H11	H12	H13	H14	H15	
2004	1,604.5	1,604.5	321.5	290.8	277.4	11.5	1.9	290.8	210.1	41.6	36.0	3.1	321.5	3,281.9	594.8	
2005	1,720.8	1,720.8	365.7	312.9	298.4	12.0	2.4	312.9	225.4	45.0	38.9	3.6	365.7	3,703.8	673.4	
2006	1,881.1	1,881.1	453.2	314.4	298.3	13.1	3.0	314.4	222.3	46.5	41.9	3.7	453.2	4,011.3	670.5	
2007	1,386.3	1,386.3	341.3	310.4	293.9	13.5	3.0	310.4	208.4	47.8	48.6	5.6	341.3	2,922.4	654.4	
2008	2,282.5	2,282.5	504.8	310.1	296.1	11.5	2.6	310.1	202.9	51.7	50.0	5.5	504.8	4,763.1	647.1	
2009	1,484.3	1,484.3	256.8	303.4	289.0	11.6	2.7	303.4	195.3	54.0	48.4	5.7	256.8	3,069.3	627.3	
2010	1,823.6	1,823.6	355.8	301.6	289.3	11.1	1.1	301.6	194.6	55.2	46.5	5.3	355.8	3,852.9	637.2	
2011	1,350.0	1,350.0	271.2	301.8	286.9	10.8	4.1	301.8	193.2	57.3	45.7	5.6	271.2	2,917.4	652.2	
2012	2,087.4	2,086.4	587.3	303.0	291.4	11.0	0.6	303.0	211.9	51.5	36.6	3.0	586.3	4,476.0	649.8	
2013	2,057.3	2,056.3	478.1	308.2	295.9	11.6	0.7	308.2	209.4	57.4	38.3	3.0	477.1	4,376.8	655.6	
2014	1,990.9	1,989.6	403.0	307.6	295.2	11.6	0.8	307.6	209.2	56.8	39.2	2.4	401.7	4,203.3	649.4	
2015	2,433.6	2,432.2	467.3	299.3	286.4	11.7	1.2	299.3	201.7	55.5	39.7	2.4	465.9	5,096.5	626.8	
2016	2,178.6	2,176.8	529.2	290.6	278.0	11.5	1.1	290.6	198.3	49.8	39.7	2.7	527.4	4,522.7	603.3	
2017	2,388.0	2,386.0	446.6	284.9	273.1	10.5	1.4	284.9	195.8	46.0	40.2	3.0	444.6	4,912.1	586.0	
2018	1,831.0	1,829.7	440.9	287.8	276.1	10.0	1.8	287.8	196.4	47.6	40.8	3.0	439.6	3,732.5	586.7	
2019	2,105.1	2,103.8	445.0	283.4	272.1	9.3	2.1	283.4	189.9	49.0	41.2	3.3	443.7	4,258.7	573.3	
2020	2,114.8	2,113.7	445.4	261.1	249.8	9.1	2.2	261.1	186.9	34.7	35.4	4.1	444.3	4,229.2	522.1	
2021	1,541.2	1,540.5	349.2	268.5	258.2	7.1	3.2	268.5	189.6	36.5	36.1	6.3	348.5	3,065.2	534.0	
2022	2,208.5	2,207.6	436.9	264.0	253.7	6.6	3.8	264.0	190.0	31.6	36.1	6.3	436.0	4,380.2	523.6	
Year	**K1**	**K2**	**K3**	**K4**	**K5**	**K6**	**K7**	**K8**	**K9**	**K10**	**K11**	**K12**	**K13**	**K14**	**K15**	**K16**
2004	99.40	7.39	94.40	228.7	60.9	4,860	3,730	430	12	8	2	170.70	170.70	35,668	20,194	8,265
2005	107.00	8.94	102.40	204.7	61.4	4,170	3,040	430	12	7	2	124.00	124.00	103,730	33,678	56,863
2006	111.90	7.10	99.40	220.6	57.5	4,070	2,450	500	12	5	2	119.28	119.30	86,604	43,700	37,012
2007	106.30	6.10	97.38	246.4	68.4	3,880	2,980	500	13	9	2	135.20	120.60	181,940	61,803	101,154
2008	101.30	5.58	92.50	248.5	82.3	6,390	4,790	1,000	15	10	3	129.10	120.80	149,751	109,237	34,223
2009	97.60	4.80	89.05	240.2	86.3	7,482	6,262	820	17	14	2	139.40	119.00	117,118	75,922	28,286
2010	93.70	4.74	90.38	245.1	91.1	8,191	6,871	920	20	16	3	143.25	125.34	92,845	47,388	27,250
2011	79.33	8.39	52.10	255.8	95.5	8,241	7,061	600	21	17	2	147.81	132.21	86,230	45,998	34,460
2012	78.03	8.26	50.41	266.2	98.0	8,271	7,271	600	21	18	2	148.88	124.44	85,644	43,969	25,546
2013	75.94	8.10	47.20	302.3	96.4	8,891	8,291	600	20	18	2	149.88	133.51	183,218	66,235	110,217
2014	74.40	7.93	46.66	338.9	95.4	8,091	7,491	600	19	17	2	143.65	117.99	178,909	32,927	106,049

(Cont'd...)

Table 3. Basic indicator data on water resources and pollution management and resource treatment in Guangxi

Year	K1	K2	K3	K4	K5	K6	K7	K8	K9	K10	K11	K12	K13	K14	K15	K16
2015	71.12	7.67	42.12	385.5	98.7	8,851	7,651	1,200	21	18	3	197.58	100.76	247,152	15,940	187,490
2016	30.55	2.26	13.79	411.2	99.0	12,651	8,851	3,800	25	20	5	193.34	82.41	130,433	10,906	104,591
2017	32.64	2.29	10.52	438.3	99.9	13,206	8,206	4,800	26	19	6	176.08	54.58	75,847	9,019	43,792
2018	32.17	2.44	10.06	466.5	100.0	15,896	9,796	6,100	27	19	8	247.80	46.83	58,273	4,025	14,370
2019	32.73	2.47	9.51	497.7	100.0	16,546	7,296	9,250	29	18	11	220.07	34.54	48,620	14,708	17299
2020	103.04	7.25	8.78	519.6	100.0	18,972	7,172	11,650	33	18	14	211.01	21.00	35,534	7,644	20,387
2021	95.82	5.32	7.43	583.5	100.0	21,724	7,714	13,900	35	19	15	194.77	9.79	119,600	3,323	113,170
2022	93.44	4.78	6.16	601.4	100.0	30,459	8,159	19,950	43	19	18	119.18	5.95	22,841	132	22,456

computational method, transforming expressions with dimensions into dimensionless expressions, thereby rendering them as scalars.

Benefit-oriented indicators (where higher values are preferable) are processed directly using Equation (1). Cost-oriented indicators (where lower values are preferable) first undergo directional standardization (normalization) to convert them into equivalent measures where higher values are preferable (e.g., differences or ratios relative to upper limits/benchmarks that preserve monotonicity without altering rankings). These are then uniformly processed using Equation (1). When x_{Max} is equal to x_{Min}, to avoid a zero denominator, standard practice dictates treating this indicator as a constant (e.g., 0.5) for the period or excluding it from the evaluation. All normalized indicators fall within [0,1], with no negative or out-of-bounds values observed. Should subsequent supplementary data yield $MMS\_C_i < 0$ or $MMS\_C_i > 1$, boundary adjustments and corrections are implemented retrospectively via data verification procedures.

Furthermore, to understand the characteristics of the indicators, descriptive statistical analysis was conducted on the pre-normalized data, including the following metrics:

(i) Mean: Measures the central position of each indicator.

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{2}$$

(ii) Standard deviation: Measures the dispersion of data.

$$\sigma = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})} \tag{3}$$

(iii) Range: Examines the distribution span and provides boundaries for normalization.

$$R = x_{Max} - x_{Min} \tag{4}$$

(iv) Median: The median is the value occupying the middle position after data sorting, making it less susceptible to the influence of extreme values. When data is sorted in ascending order, the median is the middle value.

$$Median\begin{cases} x_{\frac{n+1}{2}} \\ \dfrac{x_{\frac{n}{2}} + x_{\frac{n}{2}+1}}{2} \end{cases} \tag{5}$$

Where the first expression applies when n is odd; the second when n is even.

3.2.2. Objective weights determination using the criteria importance through intercriteria correlation (CRITIC) method

The CRITIC method is an effective approach to objective weight allocation compared to entropy weighting and standard deviation weighting.[22] It comprehensively considers both the comparative strength and conflict potential among evaluation indicators to determine their objective weights. The CRITIC method not only addresses variability among indicators but also accounts for their interrelationships. This implies that it does not solely evaluate indicator importance based on numerical magnitude, but rather comprehensively considers the relationships between indicators for scientific assessment.

Within this framework, contrast strength represents the degree of divergence between different evaluation schemes for the same indicator, typically expressed as standard deviation. A larger standard deviation indicates greater divergence among evaluation schemes, thereby conferring higher weight to that indicator. Conflict indicators measure the correlation between different metrics, typically represented by correlation coefficients. Strong positive correlations indicate lower conflict between metrics, resulting in lower weights. When standard deviations are equal, metrics with lower conflict receive smaller weights; conversely, greater conflict leads to larger weights.[12] Furthermore, when two indicators exhibit a high positive correlation (where the correlation coefficient approaches 1), their conflict is minimal, indicating similarity in the information they convey regarding the relative merits of evaluation schemes. The specific equations are as follows:

(i) Indicator variability:

$$\begin{cases} \bar{x}_j = \dfrac{1}{n}\sum_{i=1}^{n} x_{ij} \\ S_j = \sqrt{\dfrac{\sum_{i=1}^{n}(x_{ij} - \bar{x}_j)^2}{n-1}} \end{cases} \tag{6}$$

Where S_j denotes the standard deviation of the j^{th} indicator. The CRITIC method employs standard deviation to represent the fluctuation in internal values across indicators. A larger standard deviation indicates greater numerical variation within the indicator, reflecting more information and thus conferring greater evaluative strength to that indicator, warranting a higher weight allocation.

(ii) Indicator conflict:

$$R_j = \sum_{i=1}^{p}(1 - r_{ij}) \tag{7}$$

Where the correlation coefficient (r_{ij}) denotes the relationship between the evaluation indicators i and j. The value of the correlation coefficient reflects the degree of association between indicators. If an indicator exhibits a high correlation with others, it suggests reduced conflict and significant overlap. Consequently, the indicator's uniqueness within the evaluation diminishes, warranting a reduction in its assigned weight.

(iii) Information content:

$$C_j = S_j \sum_{i=1}^{p}(1 - r_{ij}) = S_j \times R_j \tag{8}$$

As the C_j value increases, the influence of evaluation indicator j within the entire evaluation indicator system grows; consequently, a greater weight should be assigned to this indicator.

(iv) Objective weight determination for the j^{th} indicator:

$$W_j = \frac{C_j}{\sum_{j=1}^{p} C_j} \tag{9}$$

(v) Sensitivity testing:

To test weight robustness, the "standard deviation method" (i.e., normalizing weights solely by each indicator's standard deviation [σ_j]) was employed as a control scenario and compared with CRITIC weights through ranking. Results are as follows:

- 3 out of the top 5 rankings align with CRITIC (MMS_K3, MMS_H12, MMS_K1).
- Compared to CRITIC weights, the maximum absolute change in individual weights was approximately 0.41% (MMS_K11: 3.84% → 3.43%), with the remaining key indicators fluctuating within ±0.35% (e.g., MMS_K3: 4.35% → 4.19%; MMS_H12: 4.12% → 3.77%; MMS_K1: 3.89% → 3.65%).
- The Spearman rank correlation coefficient between the two weighting vectors was 0.81 (p<0.001), indicating strong overall consistency in the ranking.

Accordingly, the CRITIC weights demonstrated good robustness under the data of this study; the results were insensitive to minor perturbations in the weighting criteria.

3.3. System coupling-coordination model

Coupling is a physics concept characterizing the degree of interaction between two elements. Coupling strength reflects the interaction level within the "water resources, pollutants, and clean governance" system in ecological governance, but cannot truly measure the synergistic effects of their overall development. Consequently, this study introduced a more scientific coupling-coordination model:

$$D = \sqrt{C \times T} \tag{10}$$

Where C is calculated by $\left[\frac{c_1 c_2 c_3}{(c_1 + c_2 + c_3)^3}\right]^{1/3}$, representing the coupling degree (C); c_1, c_2, and c_3 denote the alignment progress of each subsystem; and T is calculated by $\alpha c_1 + \beta c_2 + \gamma c_3$ (c_1=U1, c_2=U2, and c_3=U3), constituting the comprehensive coordination index (T), where α, β, and γ denote the weights assigned to each subsystem via the CRITIC method. A higher coupling-coordination degree (D) indicates superior coordination and coupling.

This study followed the classification criteria proposed by Chengjun *et al*.[23] for determining coordination grades, classifying the coupled coordination levels into 10 subcategories (Table 4).

Table 4. Classification criteria for coupling-coordination levels

Interval of D-values for coupling coordination	Level of coordination	Degree of coupling coordination
(0.0–0.1)	1	Extreme disorder
(0.1–0.2)	2	Severe disorder
(0.2–0.3)	3	Moderate disorder
(0.3–0.4)	4	Mild disorder
(0.4–0.5)	5	On the verge of becoming dysfunctional
(0.5–0.6)	6	Sue for coordination
(0.6–0.7)	7	Primary coordination
(0.7–0.8)	8	Intermediate level coordination
(0.8–0.9)	9	Good coordination
(0.9–1.0)	10	Quality coordination

4. Evaluation and analysis of ecological governance and clean governance in Guangxi and their data coordination

4.1. Descriptive statistical analysis of raw data and standardized processed data

As an initial step, we examined the original data (Table 5). In this dataset, all indicators demonstrated relatively consistent ranges and variations. The raw data showed fluctuations in the minimum, maximum, mean, and standard deviation values; however, the majority of data points were within reasonable ranges, and there were no significant anomalies. Consequently, the standard deviation did not exceed the data's mean value, and the minimum and maximum values of indicators such as H1, H2, and H3 varied significantly within acceptable ranges.

After the normalization process (as illustrated in Table 6 and Figure 3), the data for each indicator were dimensionless. The [0,1] interval was used to normalize the data for all normalized indicators. The dataset remained stable due to the normalized data, which were equitably distributed within an interval with a minimum value of 0 and a maximum value of 1. As evidenced by the data in Table 6, the means of all indicators were comparatively equitably distributed, and the standard deviations did not deviate significantly after normalization. For example, the mean value of MMS_H1 was 0.526, with a standard deviation of 0.307, and the mean value of MMS_K2 was 0.543, with a standard deviation of 0.340. These values demonstrate consistency and lack extremes.

The fluctuations in the data were effectively controlled and normalized by combining the original data with the normalized data, yielding no anomalies outside the standard range. The [0,1] interval equitably distributed all of the normalized data, and no significant deviations or objectionable values were identified. This implies that the analytical conclusions were not influenced by any outliers in the original data, and the normalization procedure did not introduce any new anomalies, thereby guaranteeing the data's coherence and reliability.

In summary, the original and normalized data were both devoid of anomalies, and the standardization phase of data processing effectively eliminated the scale's impact, thereby improving the accuracy and comparability of the analysis.

4.2. Data weighting results of the CRITIC method

We computed the variability, conflict, and information content of each indicator, generating the weight of each indicator (Table 7). Weight allocation is predicated on these computations. The information content of each

Table 5. Basic indicators before data processing

Indicator	Sample size	Minimum value	Maximum value	Average	Standard deviation	Median
H1	19	1,350.000	2,433.600	1,919.447	332.452	1,990.900
H2	19	1,350.000	2,432.200	1,918.721	331.974	1,989.600
H3	19	256.800	587.300	415.747	86.030	440.900
H4	19	261.100	314.400	294.937	16.458	301.600
H5	19	249.800	298.400	282.063	15.147	286.900
H6	19	6.600	13.500	10.795	1.757	11.500
H7	19	0.600	4.100	2.089	1.048	2.100
H8	19	261.100	314.400	294.937	16.458	301.600
H9	19	186.900	225.400	201.647	11.061	198.300
H10	19	31.600	57.400	48.184	7.675	49.000
H11	19	35.400	50.000	41.016	4.651	39.700
H12	19	2.400	6.300	4.084	1.390	3.600
H13	19	256.800	586.300	415.021	85.624	439.600
H14	19	2,917.400	5,096.500	3,988.174	680.320	4,203.300
H15	19	522.100	673.400	614.079	48.727	627.300
K1	19	30.550	111.900	79.811	27.957	93.440
K2	19	2.260	8.940	5.885	2.272	6.100
K3	19	6.160	102.400	51.066	37.981	47.200
K4	19	204.700	601.400	352.689	131.128	302.300
K5	19	57.500	100.000	88.989	15.205	96.400
K6	19	3,880.000	30,459.000	11,096.947	6,978.247	8,271.000
K7	19	2,450.000	9,796.000	6,583.263	2,140.357	7,271.000
K8	19	430.000	19,950.000	4,086.842	5,657.408	920.000
K9	19	12.000	43.000	22.158	8.513	21.000
K10	19	5.000	20.000	15.211	4.814	18.000
K11	19	2.000	18.000	5.474	5.189	3.000
K12	19	119.180	247.800	163.736	37.489	148.880
K13	19	5.950	170.700	92.829	48.660	119.000
K14	19	22,841.000	247,152.000	107,366.158	59,823.804	92,845.000
K15	19	132.000	109,237.000	34,039.368	29,321.629	32,927.000
K16	19	8,265.000	187,490.000	57,520.000	48,437.838	34,460.000

indicator was assessed based on its variability and conflicts. The weight of an indicator is indicative of its significance in the overall evaluation. Normalization was employed to determine the variability and conflict of each indicator, both of which were subsequently integrated into the calculation of quantifying the information to generate the corresponding weights. For example, MMS_H12 was a heavily weighted indicator, with a weight of 4.12%. This is because it was more prominent in the data in terms of both variability and informativeness, and had a lower level of conflict, posing a greater impact on ecological governance. Similarly, MMS_K3 was the most weighted indicator (4.35%), and its information content was the highest among all indicators.

The increased weights of indicators such as MMS_K3, MMS_H12, and MMS_H7 suggest that they have more substantial effects on the management of water resources, pollutants, and sanitation in Guangxi's ecological governance. Although certain indicators with lower weights (e.g., MMS_H3 and MMS_K14) suggest that they have a lesser impact, they remain a significant component of the evaluation. These findings allow for the establishment of a foundation for decision-making.

Table 6. Basic indicators after data processing

Indicator	Sample size	Minimum value	Maximum value	Average	Standard deviation	Median
MMS_H1	19	0.000	1.000	0.526	0.307	0.591
MMS_H2	19	0.000	1.000	0.526	0.307	0.591
MMS_H3	19	0.000	1.000	0.481	0.260	0.557
MMS_H4	19	0.000	1.000	0.635	0.309	0.760
MMS_H5	19	0.000	1.000	0.664	0.312	0.763
MMS_H6	19	0.000	1.000	0.608	0.255	0.710
MMS_H7	19	0.000	1.000	0.426	0.299	0.429
MMS_H8	19	0.000	1.000	0.635	0.309	0.760
MMS_H9	19	0.000	1.000	0.383	0.287	0.296
MMS_H10	19	0.000	1.000	0.643	0.297	0.674
MMS_H11	19	0.000	1.000	0.385	0.319	0.295
MMS_H12	19	0.000	1.000	0.432	0.356	0.308
MMS_H13	19	0.000	1.000	0.480	0.260	0.555
MMS_H14	19	0.000	1.000	0.491	0.312	0.590
MMS_H15	19	0.000	1.000	0.608	0.322	0.695
MMS_K1	19	0.000	1.000	0.606	0.344	0.773
MMS_K2	19	0.000	1.000	0.543	0.340	0.575
MMS_K3	19	0.000	1.000	0.467	0.395	0.426
MMS_K4	19	0.000	1.000	0.373	0.331	0.246
MMS_K5	19	0.000	1.000	0.741	0.358	0.915
MMS_K6	19	0.000	1.000	0.272	0.263	0.165
MMS_K7	19	0.000	1.000	0.563	0.291	0.656
MMS_K8	19	0.000	1.000	0.187	0.290	0.025
MMS_K9	19	0.000	1.000	0.328	0.275	0.290
MMS_K10	19	0.000	1.000	0.681	0.321	0.867
MMS_K11	19	0.000	1.000	0.217	0.324	0.063
MMS_K12	19	0.000	1.000	0.346	0.291	0.231
MMS_K13	19	0.000	1.000	0.527	0.295	0.686
MMS_K14	19	0.000	1.000	0.377	0.267	0.312
MMS_K15	19	0.000	1.000	0.311	0.269	0.301
MMS_K16	19	0.000	1.000	0.275	0.270	0.146

4.3. Coordination analysis among ecological water management, pollution management, and resource treatment

4.3.1. Analysis of the evolutionary trajectory of data coordination

From the annual sequence between 2004 and 2022 (Table 8), the three ecological governance subsystems of Guangxi—indices U1 (water resources management), U2 (pollution control), and U3 (resource treatment/cleaning)—remained within the (0,1) interval. The T, aggregated using CRITIC weights, varied between 0.272 and 0.664. C fluctuated between 0.735 and 0.999, while D ranged from 0.458 to 0.798. The overall trajectory exhibited a pattern of "initially low levels followed by steady improvement," with distinct phased variations that corroborate the three curves depicted in Figure 4. The results in phases are as follows:

(i) 2004–2006: Low-level commencement with phased troughs. In 2004, U1 was 0.457, U2 was 0.124, and U3 was 0.187, with U2 being the lowest, resulting in a value of 0.858 for C, 0.300 for T, and 0.507 for D (barely coordinated). The subsequent

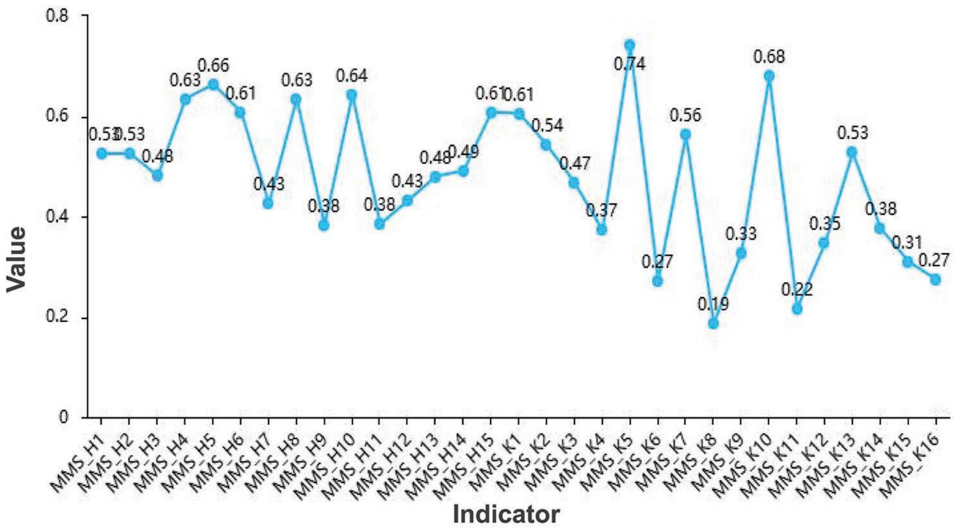

Figure 3. Mean values of all indicators after data processing

2 years formed a phase of trough: in 2005, U3 reached its lowest point (0.102), causing C to drop to 0.800, T to 0.272, and D to 0.466 (verging on imbalance); in 2006, U3 further declined to 0.069, with C falling to the lowest point within the sample period at 0.735, T to 0.286, and D to 0.458 (on the verge of imbalance). A common feature of this phase was the marked divergence among the three subsystems, with curves diverging in a fan-shaped pattern (Figure 4). The low-positioned U3 (or U2) constituted the dominant "weak link" in coupling, directly causing small values of C and D.

(ii) 2007–2010: Recovery from low levels to "primary coordination." In 2007, U1 was 0.439, U2 was 0.340, and U3 was 0.154. Compared to the preceding 2 years, U2 showed a marked increase, with C rebounding to 0.914, T to 0.322, and D to 0.543 (barely coordinated). From 2008 onwards, the overall trend entered the "primary coordination" range: D was 0.627 in 2008, 0.610 in 2009, and 0.626 in 2010. During this phase, C remained at a high level around 0.94 (C=0.939–0.984 from 2008 to 2010), indicating a significant convergence in the divergence among the three subsystems. Concurrently, T steadily increased alongside the sustained improvement of U1 and U3 (T = 0.419 in 2008 and 0.398 in 2010, although U3 had risen from 0.154 to 0.361 over this period). In Figure 4, the spacing between the three curves noticeably narrowed, with the coupling state approaching "resonance."

(iii) 2011–2014: The stable plateau of "primary coordination." Between 2011 and 2014, D remained stable at 0.630–0.674, maintaining the "primary coordination" level for four consecutive years. During this period, C further approached 1: C was 0.998 in 2013 and 0.999 in 2014, indicating minimal internal variation within the three subsystems (2013: U1 = 0.465, U2 = 0.487, U3 = 0.425; 2014: U1 = 0.439, U2 = 0.449, U3 = 0.397). With all three subsystems nearly level, minor fluctuations in D were primarily driven by subtle variations in T. As shown in Figure 4, the three curves during this phase converged towards "parallel alignment," with coupling strength approaching full capacity and ceasing to be a limiting factor.

(iv) 2015–2019: Transition to "intermediate coordination" and further consolidation. From 2015, D crossed into the "intermediate coordination" range (D = 0.721 in 2015) and remained between 0.751 and 0.763 from 2016 to 2019. During this period, C remained largely stable between 0.988 and 0.997, indicating sustained equilibrium within the three subsystems. The overall improvement stemmed primarily from the rise in T (T = 0.570 in 2016, T = 0.584 in 2019). In Figure 4, U1 and U3 exhibited further upward trends with reduced volatility compared to 2011–2014, while U2 remained at moderately high levels (U2 = 0.731 in 2016, U2 = 0.654 in 2017, U2 ranged between 0.614–0.623 and 2018–2019), with stable relative relationships among the three driving a steady upward shift in D.

(v) 2020–2022: High-level "intermediate coordination" with optimal terminal performance. In 2020, U1 was 0.611, U2 was 0.308, and U3 was 0.679. Despite

Table 7. CRITIC weighting results

Indicator	Indicator variability	Conflicting indicators	Volume of information	Weights (%)
MMS_H1	0.307	27.301	8.376	3.00
MMS_H2	0.307	27.299	8.374	3.00
MMS_H3	0.260	27.070	7.046	2.52
MMS_H4	0.309	28.025	8.653	3.10
MMS_H5	0.312	27.806	8.666	3.10
MMS_H6	0.255	29.134	7.417	2.66
MMS_H7	0.299	33.523	10.035	3.60
MMS_H8	0.309	28.025	8.653	3.10
MMS_H9	0.287	29.675	8.526	3.05
MMS_H10	0.297	27.238	8.103	2.90
MMS_H11	0.319	29.458	9.385	3.36
MMS_H12	0.356	32.307	11.512	4.12
MMS_H13	0.260	27.063	7.033	2.52
MMS_H14	0.312	26.772	8.358	2.99
MMS_H15	0.322	27.975	9.009	3.23
MMS_K1	0.344	31.557	10.845	3.89
MMS_K2	0.340	29.709	10.103	3.62
MMS_K3	0.395	30.762	12.140	4.35
MMS_K4	0.331	31.990	10.574	3.79
MMS_K5	0.358	29.183	10.441	3.74
MMS_K6	0.263	32.254	8.468	3.03
MMS_K7	0.291	29.736	8.664	3.10
MMS_K8	0.290	32.919	9.541	3.42
MMS_K9	0.275	31.835	8.742	3.13
MMS_K10	0.321	29.838	9.576	3.43
MMS_K11	0.324	33.027	10.712	3.84
MMS_K12	0.291	32.534	9.483	3.40
MMS_K13	0.295	29.802	8.802	3.15
MMS_K14	0.267	26.151	6.974	2.50
MMS_K15	0.269	27.968	7.516	2.69
MMS_K16	0.270	27.353	7.392	2.65

a significant decline in U2, C reached 0.946, T to 0.575, and D to 0.737 (intermediate coordination) due to U1 and U3 remaining elevated. In 2021, the three values converged again (U1 = 0.557, U2 = 0.494, U3 = 0.726), yielding 0.987 for C, 0.602 for T, and 0.771 for D. 2022 achieved the optimal values within the sample period: U1 was 0.695, U2 was 0.391, U3 was 0.781, C was 0.958, T was 0.664, and D was 0.798 (upper threshold of "moderate coordination"). Figure 4 illustrates the overall upward shift of the three curves in the final phase with manageable relative gaps. Notably, the sustained thickening of U1 and U3 underpinned T's elevated position, thereby propelling D to its highest stage value.

(vi) Grade distribution overview: According to classifications in Table 4, among the 19 years from 2004 to 2022, 8 years fell in the "intermediate coordination" category (2015–2022); 7 years in "primary coordination" (2008–2014); 2 years in "barely coordinated" (2004, 2007), and 2 years in "near-dysfunctional" (2005, 2006). This reveals a clear phase structure: early low levels, mid-term "primary coordination," and late-stage "intermediate coordination," exhibiting an overall long-term trend of monotonic improvement. In summary, C approached 1 in most years, making the elevation of T the decisive factor for D's upward movement. The low D values in the early period were primarily triggered by the significantly low status of a single subsystem (see the "weakest link migration" diagnosis in Section 4.3.2), aligning perfectly with the relative positions depicted in Figure 4.

4.3.2. Analysis of underlying causes for data evolution stage types

Based on numerical values and curves, an experimental decomposition of the "coupling-coordination" formation mechanisms across each phase was conducted, focusing on examining the impact of the relative positions of the three subsystems and the annual migration of the "weakest subsystem" on C, T, and D. For clarity, the "weakest subsystem" here refers to the one with the lowest value among the three each year. Annual diagnostic tables from 2004 to 2022 revealed the bottleneck shifting sequentially from U2 → U3 → U1 → U2 across several phases (totaling 9 years with "U3 as bottleneck," 7 years with "U2 as bottleneck," and 3 years with "U1 as bottleneck"). Based on Figures 4 and 5, Table 8, the evolutionary phases between 2004 and 2022 and their underlying causes can be characterized as follows:

(i) Trough phase (2004–2006): The bottleneck significantly depressed C. In 2004, the bottleneck was U2 (0.124), forming a marked disparity with U1 (0.457) and U3 (0.187), resulting in a C of 0.858 and a D of 0.507. From 2005 to 2006, the weakest link shifted to U3, which plummeted to 0.069 in 2006. The relative disparity (maximum minus minimum) between the three components widened to 0.426 (U1 = 0.495 vs. U3 = 0.069),

Table 8. Coupling-coordination degree calculation results

Year	U1	U2	U3	C	T	D	Coordination level	Degree of coupling coordination
2004	0.457	0.124	0.187	0.858	0.300	0.507	6	Barely coordinated
2005	0.454	0.136	0.102	0.800	0.272	0.466	5	Borderline imbalance
2006	0.495	0.170	0.069	0.735	0.286	0.458	5	Borderline imbalance
2007	0.439	0.340	0.154	0.914	0.322	0.543	6	Barely coordinated
2008	0.572	0.369	0.239	0.939	0.419	0.627	7	Primary coordination
2009	0.449	0.342	0.300	0.986	0.377	0.610	7	Primary coordination
2010	0.468	0.300	0.361	0.983	0.398	0.626	7	Primary coordination
2011	0.445	0.323	0.386	0.991	0.401	0.630	7	Primary coordination
2012	0.479	0.324	0.401	0.987	0.422	0.645	7	Primary coordination
2013	0.465	0.487	0.425	0.998	0.455	0.674	7	Primary coordination
2014	0.439	0.449	0.397	0.999	0.427	0.653	7	Primary coordination
2015	0.540	0.553	0.478	0.998	0.522	0.721	8	Intermediate coordination
2016	0.515	0.731	0.552	0.988	0.570	0.751	8	Intermediate coordination
2017	0.569	0.654	0.536	0.996	0.574	0.756	8	Intermediate coordination
2018	0.468	0.614	0.648	0.990	0.558	0.743	8	Intermediate coordination
2019	0.530	0.623	0.636	0.997	0.584	0.763	8	Intermediate coordination
2020	0.611	0.308	0.679	0.946	0.575	0.737	8	Intermediate coordination
2021	0.557	0.494	0.726	0.987	0.602	0.771	8	Intermediate coordination
2022	0.695	0.391	0.781	0.958	0.664	0.798	8	Intermediate coordination

Notes: C indicates coupling degree; D indicates value for coupling coordination; T indicates coordination index.

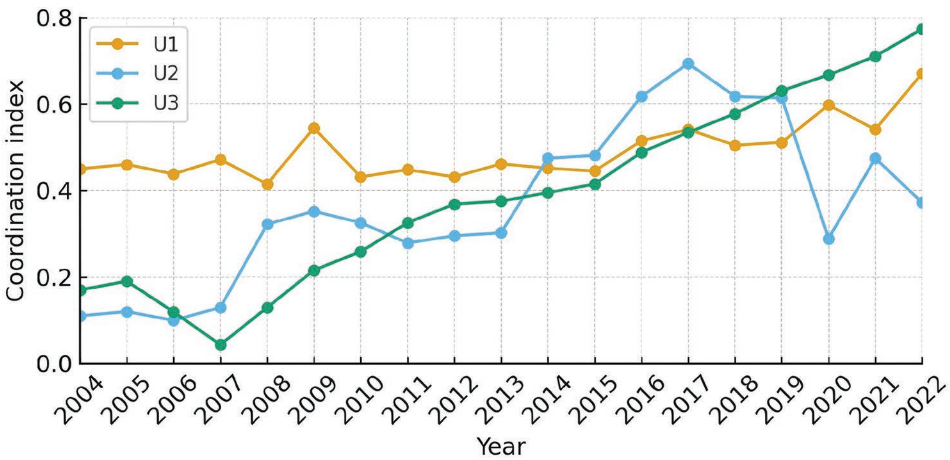

Figure 4. Time series diagram of the three subsystems: U1, U2, and U3

further reducing C to 0.735 and D to 0.458. This phase exhibited a distinctly bifurcated three-curve pattern: the low-level subsystem acts as a factor "dragging down the geometric mean," with C being sensitive to extreme relative differences, leading to periodic "collapses." As T was already at a low level of 0.27–0.30 during this phase, the combined effect of C and T being "double-low" ultimately resulted in a rating of "verging on imbalance."

(ii) Recovery and plateau (2007–2014): Weaknesses elevated, relative gaps converged (C→1). In 2007, the weakest link remained U3 (0.154), while U2 rose to 0.340, significantly narrowing the three-way gap as C rebounded to 0.914. From 2008 to 2010, U3 continued to recover within the 0.239–0.361 range, markedly diminishing the shortfall effect. Concurrently, U1 rose to 0.572 in 2008, while U2 stabilized between 0.300 and 0.369. Consequently,

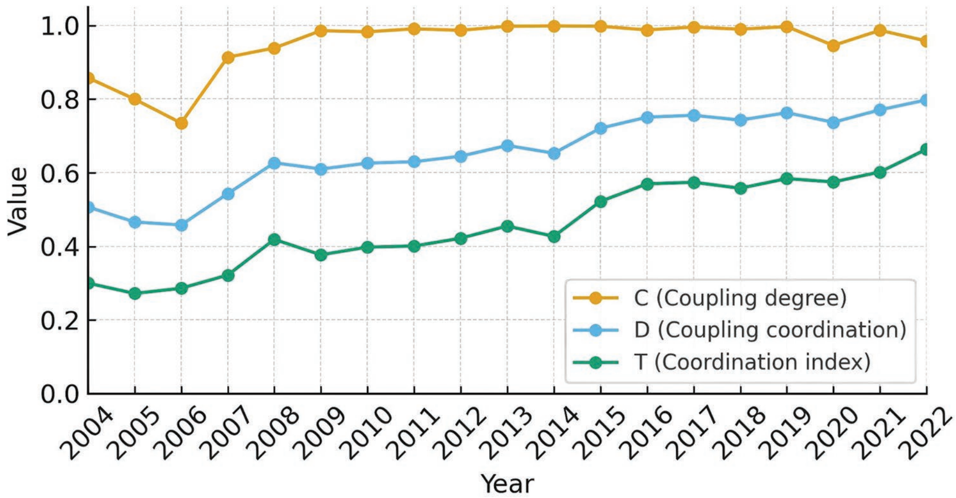

Figure 5. Line chart of coupling-coordination coefficients

the central levels of T entered the 0.38–0.42 range, with D entering a state of "initial coordination." From 2011 to 2014, the three subsystems advanced in unison, exhibiting a classic near-equivalence state in 2013–2014 (e.g., 2013: U1 = 0.465, U2 = 0.487, U3 = 0.425; 2014: U1 = 0.439, U2 = 0.449, U3 = 0.397), virtually eliminating relative disparities. Consequently, C surged and stabilized within the exceptionally high range of 0.998–0.999. During this phase, D's minor fluctuations were predominantly attributable to slight adjustments in T, indicating that once the "weakest link effect" was mitigated, T became the dominant factor.

(iii) Cross-level advancement (2015–2019): The bottleneck temporarily shifted to U1, yet T rose across the board. From 2015 to 2019, the system entered the "intermediate coordination" phase, during which C scarcely imposed constraints (0.988–0.998). However, the bottleneck shifted to U1 in specific years: in 2016, U1 (0.515) was the lowest among the three (corresponding to U2 of 0.731 and U3 of 0.552), and remained the lowest in 2018 (0.468) and 2019 (0.530). Nevertheless, as all three values remained within the medium-to-high range with relatively small differences, geometric equilibrium was not disrupted, and C remained elevated. Conversely, U2 maintained a moderately high range of 0.614–0.731 from 2016 to 2019, while U3 fluctuated between 0.536 and 0.648. This sustained upward pressure on the weighted T, elevating it to 0.57–0.58, while ultimately stabilizing D at 0.751–0.763. During this phase, the three curves, as shown in Figure 4, collectively ascended a step-like trajectory, with only occasional annual shifts in relative dominance over the weakest link occurring without significantly impacting C.

(iv) Late high phase (2020–2022): The weak link shifted back to U2, with T and D supported by U1 and U3. In 2020, the weak link returned to U2 (0.308), markedly lower than U1 (0.611) and U3 (0.679). Aggregated with weights α (0.463), β (0.197), and γ (0.340), T remained at a relatively high level of 0.575. With both U1 and U3 at elevated positions, C (0.946) was not significantly depressed, and D (0.737) was maintained at "intermediate coordination." In 2021, U2 rebounded to 0.494, narrowing the gap between C (0.987), T (0.602), and D (0.771). In 2022, the U2-as-the-weak-link structure reappeared (U2 = 0.391), but the high levels of U1 (0.695) and U3 (0.781) sufficiently propelled T to 0.664. Combined with C (0.958), D ultimately reached its highest point within the sample period at 0.798. This phase demonstrates that even when a single subsystem exhibits "low-level drag," provided the other two provide sufficient support in both weighting and level, the product of T and C can remain elevated, consequently preventing D from being reduced by the weakest link.

(v) Weakest link migration and C's response mechanism: Analysis of 19 sample years revealed three patterns: First, when the smallest subsystem lagged significantly behind the other two (>0.3), C showed a marked downward trend (e.g., during 2005–2006). Second, when all three subsystems were at medium-to-high levels with small differences (<0.15), C approached 1 (e.g., during 2013–2015). Third, when the weakest subsystem was at a low-to-medium level but the other two were high and carried greater weight, D was maintained or reached new highs (e.g., during 2020–2022). This aligns perfectly with the relationship between "geometric equilibrium" and "mean comparison" in the definition of C: extremely low values exert the most pronounced suppression on the geometric term of the subsystem, while relative convergence can rapidly eliminate this suppression.

(vi) Quantitative basis for tier transitions: Tier classification was determined monotonically using D. Progression occurred from "near-disharmony" (2005–2006) to "tenuous coordination" (2004, 2007), then "primary coordination" (2008–2014), ultimately reaching "intermediate coordination" (2015–2022). Each tier transition corresponds to: shortfall elevation (minimum subsystem advancement), relative gap convergence (C increase), or weighted T elevation (greater advancement in high-weight subsystems). Notably, the period 2013–2014 (characterized by C≈1) served as a prototypical prelude to structural equilibrium-driven progression. Post-2015, advancement stemmed from synergistic enhancement, combining structural equilibrium with central tendency uplift.

In summary, recalculated findings revealed that the phase-specific trough (2005–2006) originated from extremely low values in a single subsystem coupled with substantial relative disparity. Subsequently, short-board elevation and relative gap convergence propelled C rapidly towards 1, shifting D's dominant factor to T. In the final phase (2020–2022), although the short board shifted back to U2, the high levels of U1 and U3, coupled with the weighting structure, jointly supported T's upward movement and D's new peak. This quantitative conclusion is directly derived from the annual values in Table 8 and the curve morphology in Figure 4, fully demonstrating the intrinsic logic linking "weakest link effect–relative difference–coupling degree–coordination degree."

4.4. Analysis of experimental results

Based on the analysis of D calculations, the evolution of coordination among water resources, pollutant management, and clean governance during each phase of Guangxi's ecological governance can be quantitatively summarized. Annual sequences of C, T, and D represented these changes. Overall, between 2004 and 2022, D ranged from 0.458 to 0.798, following a trajectory of "relatively low in the early period–stable and gradual increase in the middle period-moderate coordination and upward trend in the later period"; C predominantly at a higher range (0.735–0.999); while T gradually rose from low levels (0.27–0.30) to high levels (approximately 0.66), indicating that in the later period, T played a more critical role in contributing to D. When analyzed by phases:

(i) 2004–2007: From a low starting point to "barely coordinated" recovery.

Contrary to the earlier assessment of "extreme imbalance (C=0, D≈0)," recalculations revealed that 2004–2007 did not represent "extreme imbalance" but rather a period of "near imbalance to barely coordinated": D was 0.507 in 2004 (barely coordinated), 0.466 and 0.458 in 2005 and 2006, respectively (both verging on imbalance), and 0.543 in 2007 (barely balanced). During this period, C was not at zero but ranged between 0.735 and 0.914 (with C=0.735 in 2006 being the lowest point of the phase, rising to 0.914 in 2007). This indicates that although significant disparities existed between the three subsystems, no coupling "breakdown" occurred. T remained at a low level (0.272–0.322), limiting the upward movement of D. Considering the relative positions of the three curves in Figure 4, it is evident that during this phase, either U2 or U3 frequently acted as the weakest subsystem, occupying a low position. For example, between 2005 and 2006, U3 reached a relatively low point within the sample period (U3 = 0.07 in 2006), significantly suppressing geometric equilibrium, thereby lowering C and indirectly inhibiting D. Similarly, U2's low position in 2004 created a "short-board effect." Thus, the direct quantitative cause for D's initial low levels was the single subsystem being substantially below the combined "system core level" of the other two subsystems.

(ii) 2008–2014: Entry into and stabilized within the "primary coordination" phase.

From 2008 onwards, D rose and remained within the "primary coordination" range: during 2008–2010, D was 0.610–0.627; during 2011–2014, D was 0.630–0.674. During this period, C rose significantly, approaching 1: C was 0.939–0.984 from 2008 to 2010, and reaching exceptionally high levels of 0.998–0.999 in 2013–2014. This reflects a marked convergence in the disparities between the three subsystems, with their coupling state approaching near-resonance. T steadily increased in tandem (0.398–0.454), stabilized with the elevated C to drive a sustained rise in D. Figure 4 illustrates the narrowing gaps and convergence of the three subsystem curves during this phase: U1 and U3 showed marked improvement over earlier periods, while U2 maintained a median trajectory. The convergence of their relative differences drove C closer to 1 from around 0.9. T's incremental growth, meanwhile, determined D's gradual ascent within the "primary coordination" range. The quantitative characteristics of this phase can be summarized as the combined effect of "shortfall elevation + relative gap convergence (C→1) + slight central tendency elevation (T↑)."

(iii) 2015–2019: Transition to "intermediate coordination" and steady-state maintenance.

In 2015, D was 0.721, signaling the transition from "primary coordination" to "intermediate coordination." Subsequently, from 2016 to 2019, D remained stable within the narrow range of 0.751–0.763, exhibiting pronounced steady-state characteristics. During this phase, C generally ranged between 0.988 and 0.998, indicating sustained high equilibrium within the three subsystems. Concurrently, T rose to the 0.57–0.58 range, becoming the decisive factor enabling D to sustain at "intermediate coordination" and a steady upward trajectory. Figure 4 further illustrates that although the weakest subsystem temporarily shifted to U1 (e.g., 2016 and 2018–2019), the relative disparity among the three subsystems remained contained, as the lagging subsystem itself resided within the mid-to-upper range, thus exerting minimal influence on C. In other words, D's robust performance post-2015 primarily stemmed from the combined effect of "elevated C (approaching 1) + sustained elevation of central T."

(iv) 2020–2022: High-level "intermediate coordination" with optimal end-period performance.

In 2020, D was 0.737, 0.771 in 2021, and 0.798 in 2022, all of which fell within the "intermediate coordination" range, with 2022 recording the highest value within the sample period. Corresponding C values were 0.946, 0.987, and 0.958, while T values were 0.575, 0.602, and 0.664. As shown in Figure 4, U2, again, became the weakest link in 2020. However, the relatively high levels of U1 and U3, coupled with their weighting contributions within T, enabled T to remain above 0.57. This prevented D from suffering an early "weakest link collapse" effect. By 2022, U1 and U3 further increased with a manageable relative gap, driving T to 0.664. Even though U2 remained the weakest link that year, C maintained a high level of 0.958, and D ultimately reached a peak value of 0.798 for the entire period. The quantitative characteristics of this phase indicate that when two strong and one weak subsystem exist with moderate disparities, C does not decline significantly; if the contributions of the two strong elements increase and the weighting structure is favorable, the rise in T can offset the drag from the weak link, thereby propelling D to new heights.

In summary, "intermediate coordination" spanned 8 years (2015–2022), "primary coordination" 7 years (2008–2014), "barely coordinated" 2 years (2004, 2007), and "near-dysfunction" 2 years (2005, 2006). This distribution aligns with the combined trajectory of C and T: early-stage dual lows in C and T resulted in suboptimal D; mid-stage elevated C coupled with a modest T increase propelled D into "primary coordination"; late-stage sustained high C and markedly rising T drove D into and consolidated it within the "intermediate coordination" range. The key lies in the elevation of the weakest subsystem and relative convergence of disparities, alongside the sustained upward shift in T. Contrary to the earlier conclusion that C and D were zero in most years, recalculations showed C and D were >0 for all years, with C approaching 1 in most years. This indicates the "zero-score issue" has been eliminated through normalized metrics and strict positive value constraints.

5. Discussion: Future ecological governance and indicator coordination strategies in Guangxi

To avoid utilization assertions, this study proposes two quantifiable policy levers directly linked to indicators, based on the 2004–2022 indicator and D sequences:

(i) Policy lever one: Expansion and structural optimization of sewage treatment capacity targeting U3 (linked to K6–K8). This policy aims to enhance the resource processing and clean governance subsystem (U3) by expanding and utilizing domestic waste/sewage treatment capacity, thereby elevating T and stabilizing C. Historical data indicate significant capacity expansion during 2008–2010 (e.g., K6: 6,390 t/day → 8,191 t/day; K7: 4,790 t/day → 6,871 t/day; K8 fluctuating around 1,000 t/day), aligning with the upward shift in D from 0.610 to 0.626. This corresponds to the elevation of U3 and the convergence of relative disparities among the three subsystems, indicating that quantitative and structural improvements in treatment capacity (achieved through a rational proportion of landfill/incineration and regionally balanced distribution) constitute an operational lever driving the upward trajectory of D. This can be achieved by:

- Quantified target trajectories (using 2022 as baseline): While maintaining structural equilibrium (C=0.96–0.98), K6 shall achieve ≥32,000 t/day by 2025 and ≥36,000 t/day by 2030; K7 shall reach ≥8,500 t/day by 2025 and ≥9,500 t/day by 2030; and K8 shall reach ≥21,000 t/day by 2025 and ≥23,000 t/day by 2030. Accordingly, the utilization panel value for U3 is expected to approach higher levels, thereby pushing T towards 0.70 (2025)/0.75 (2030). Assuming C is 0.97, the corresponding D will be 0.82 (2025)/0.85 (2030), continuing to rise at the upper end of the current "intermediate coordination" range.
- Structural and regional dimension: Prioritize allocating K6–K8 units to node cities/basin units with relatively high U2 load and weaker U3 capacity, maximizing local consumption and coordinated disposal to minimize transfer losses. Dynamically calibrate panel boundaries to prevent technical deviations whereby incremental capacity is diluted through rolling utilization.
- Integration of AI (supporting lever one): Incorporate machine learning-based water quality assessments (e.g., anomaly detection, short-term inflow/load forecasting, and optimal operating condition search) into integrated plant-network scheduling. This enables advanced matching of capacity to peak loads, reduces overflow and bypass risks, indirectly increases U3, and underpins T growth.[10]

(ii) Policy lever two: Total pollutant constraints and process optimization for U2 (linked to K1–K3). This policy aims to reduce chemical oxygen demand (K1) and ammonia nitrogen (K2) while consolidating sulfur dioxide (K3) control achievements. These enhance the pollution control subsystem (U2), thereby elevating T and mitigating the adverse impact of the relative disparity among the three subsystems on C. Historical data indicate that low levels of U2 often constitute a "bottleneck," significantly suppressing D in the early stages. Post-2015, the stabilization of U_2 at medium-to-high levels became a key factor enabling D to enter a "mid-level coordination" phase. This policy can be achieved by:

- Quantified target trajectory: Setting phased emission caps based on 2022 levels: K1 ≤850,000 t (2025)/≤700,000 t (2030); K2 ≤40,000 t (2025)/≤30,000 t (2030); and K3 maintained at ≤80,000 t (from 2025 onwards). Using the panel-normalized U2 metric for estimation, these pathways may yield U2 improvements of approximately 0.03 (2025)/0.06 (2030). Under C ≥ 0.97 conditions, these correspond to a T of 0.70 (2025)/0.75 (2030) and a D of 0.82 (2025)/0.85 (2030), creating a synergistic effect with policy lever one.
- Process-level interventions: Differentiated limit values and performance-based payments at river discharge sections and key industrial sectors, alongside deep denitrification and phosphorus removal with recovery technology upgrades, plus refined governance through storm-sewer separation and non-point source interception, directly influence K1–K2.
- Integration of AI (supporting lever two): Supervised/semi-supervised learning models utilize multi-source water quality monitoring and operational data to identify abnormal events, forecast short-term loads, and generate real-time control recommendations. Prediction outcomes are translated into discharge throttling, peak shaving, and process parameter adjustments to optimize U2's monthly and annual performance.[10]

Capacity expansion and structural utilization in resource processing and clean governance, alongside total pollutant constraint policies for pollution control, constitute two policy pathways directly aligned with the indicators. Historical data revealed a synchronous increase in treatment capacity growth and coupling coordination between 2008 and 2010, indicating that when treatment capacity and its structure become more balanced within a region, inter-system disparities converge, T improves, and D steadily rises. By extension, future efforts can establish target trajectories for municipal solid waste treatment capacity, sanitary landfill capacity, and incineration capacity by 2025/2030, while maintaining structural equilibrium. These trajectories should be integrated with phased total control measures for chemical oxygen demand, ammonia nitrogen, and sulfur dioxide. Through annual rolling assessments, the two pathways could be consolidated into a unified evaluation framework, directly mapping annual improvements in subsystem performance and coordination indices. To mitigate implementation uncertainties, AI may be integrated into pollution and water quality management. Machine learning models, utilizing multi-source monitoring data, can perform anomaly detection, short-term load and water quality forecasting, and operational control optimization. This transforms stable compliance with key pollutant standards and efficient utilization of treatment capacity into verifiable process outcomes, thereby achieving higher and more stable coordination with reduced variability.

6. Conclusion

This study constructed and evaluated an ecological indicator system for water resources, pollutants, and clean governance within Guangxi's ecological management. It explored data coordination among ecological indicators and analyzed the evolution of coupling coordination from 2004 to 2022. Results indicate that Guangxi's ecological governance exhibits distinct phases: overall coupling intensity remains high yet converges annually, the system's overall coordination level steadily improves, and D follows an evolutionary pattern of "initially low-mid-term stable ascent-later intermediate coordination with upward trend."

Based on recalculated metrics, the period 2004–2006 generally fell within the borderline imbalance/barely coordinated range (with the lowest annual value of D = 0.458). From 2008 to 2014, it stabilized within the primary coordination range (D = 0.63–0.67), and from 2015 to 2022, it entered and remained within the intermediate coordination range, reaching the highest values within the sample period by 2022 (C = 0.958, T = 0.664, D = 0.798). This quantitative outcome aligns with the time series of the three subsystem indices U1/U2/U3: the early phase exhibited pronounced weaknesses (primarily low U2 or U3 values), the mid-phase saw convergence in the gaps between the three indices with C approaching 1, and the late phase maintained high coupling while driving sustained upward momentum in D through elevating T.

Additionally, this study established a multi-dimensional ecological indicator system encompassing water resources, wastewater discharge, air pollution control, waste disposal, ecological greening, and industrial pollution treatment investment. Data analysis revealed structural disparities in Guangxi's water supply–demand balance and wastewater/solid waste treatment capacity. Within the coupling-coordination framework, the increase in D from 2008 to 2010 aligns with improvements in "capacity and structure for non-hazardous treatment of domestic waste" (K6/K7/K8 correspond to U3). Conversely, the relatively low levels of U2 in 2020 and 2022 represent key constraints limiting further increases in both T and D.

To enhance the overall effectiveness of ecological governance in Guangxi, this study translates policy recommendations into two measurable policy levers directly linked to indicators:

(i) Resource treatment capacity expansion and structural optimization (anchoring K6/K7/K8 to U3): Establish annual hard targets for total capacity and disposal structure share, extending and amplifying the capacity improvement effect observed during 2008–2010 that synchronized with D growth. This will drive sustained elevation of U3 while maintaining C at elevated levels.

(ii) Pollutant dual-control plan (anchoring K1/K2 to U2): Implement dual constraints of "total volume × intensity" for chemical oxygen demand and ammonia nitrogen, as well as enhance U2 through annual quotas and intensity red lines, thereby elevating T. The combined leverage of these two measures can steadily elevate T while maintaining high coupling (C sustains at 0.95–0.99), enabling D to consistently surpass 0.80 from its 2022 level of 0.798 and converge towards higher levels. Here, the target trajectory for resource processing (K6/K7/K8) consolidates and replicates the 2008–2010 experience chain driving D's ascent, while dual pollutant controls (K1/K2) mitigate the later-stage constraints imposed by U2.

Overall, Guangxi's ecological governance must prioritize overcoming bottlenecks in data coordination and cross-departmental collaboration. It should establish a closed-loop "indicator–action–outcome" system around these two leveraged policy indicators: K6/K7/K8→U3 underpins geometric equilibrium and maintains high C; and K1/K2→U2 drives central uplift and increases T. Both jointly facilitate D's sustained improvement. Furthermore, by integrating the aforementioned data and modelling systems, decision support platforms may embed water quality data-trained machine learning models for short-term forecasting and threshold alerts of indicators such as chemical oxygen demand and NH_3–N. Linking prediction deviations with quota/capacity scheduling enables rolling corrections at weekly-to-monthly intervals, ensuring annual targets remain on track. This research delivers quantifiable assessment tools and decision-support pathways for Guangxi's ecological governance, while providing transferable analytical frameworks and operational levers for urban ecological management elsewhere.

Subsequent studies may refine elasticity coefficient estimates between U1/U2/U3 and sector-specific indicators, as well as conduct scenario comparisons under varying target trajectories, thereby enhancing the quantitative characterization of coupling-coordination mechanisms and stabilizing governance outcomes.

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Conflict of interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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Availability of data

The data used to support the findings of this study are included within the article.

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