

Article

An Empirical Framework for Evaluating Environmental Sustainability Through the Circular Economy and Eco-Innovation: A Nudge-MCDM Approach for Chinese Provinces

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Abstract

As the world focuses more on the Sustainable Development Goals, there is a growing need to assess applied environmental improvement actions across regions. In this research, we suggest that policymakers prioritize the Circular Economy (CE) and Eco-Innovation (EI) to enhance decision making in response to environmental sustainability challenges. Our research offers a groundbreaking framework that integrates CE and EI concepts, providing an innovative lens for monitoring and comparing improvements in environmental sustainability. This approach not only identifies provinces excelling in environmental sustainability strategies but also sheds light on the ones going through demanding situations in regions like uneven improvement and environmental aid control. Considering the provinces of China as a macro-case study, the proposed framework precisely integrates nudge theory with the simultaneous assessment of criteria and options (SECA) methodology, enriched by professional insights and a comprehensive literature review. The findings show that Guangdong, Jiangsu, and Shandong are the most environmentally sustainable provinces for growth. Other provinces and areas that struggle with inconsistent growth and ecological aid management due to difficult circumstances include Tibet, Qinghai, and Hainan. Our findings make appreciable contributions to the discourse on environmental sustainability.

Keywords: environmental planning assessment; environmental sustainability development; eco-innovation; circular economy; empirical framework; Nudge theory; China



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1. Introduction

1.1. History and Motivation

The United Nations (UN) structured the Sustainable Development Goals (SDGs) to defend and enhance the environment and nations [1,2]. Among other things, the UN urges states to be open and quick to adopt environmental sustainability development policies and assessments in order to prevent the appearance of nations with a singular focus on development. But, accomplishing the SDGs presents essential challenges, along with global resource shortage, climate change, waste era, and environmental pollution [3]. The circular economy (CE) is a powerful solution aimed at addressing those issues. The concept

of CE involves advancing environmental control practices by imposing eco-design principles to facilitate the disassembly and reuse of products, using recyclable substances, and restoring natural resources from waste streams [4].

The aim of CE, in fact, is to enhance efficiency to achieve a waste-free and zero-emission system, and thus to play an important role in sustainable development [5]. Sustainability is generally assumed to be a crucial triple of harmonizing the three elements of the economy, environment, and society. The development of CE methods requires careful evaluation of these three pillars of sustainability [6]. As a result, CE effectively helps all three dimensions of sustainable development [7]. Therefore, organizing a comprehensive evaluation system to assess CE practices in relation to the SDGs is vital for green and applicable techniques. To this end, constructing an assessment machine for enforcing CE practices is vital for analyzing environmental sustainability development (SD) strategies. This research presents a complete framework for promoting this technique.

1.2. Problems and Solutions

The importance of a CE system, which emphasizes the critical use of finite sources [8], is further underscored by the life of indices for assessing it at macro, meso, and micro ranges, highlighting its multifaceted impact and significance in sustainable resource management [9]. Preceding studies have particularly centered on evaluating the impact of CE practices on SDGs at the micro and meso stages, along with the contribution of small and medium-sized businesses (SMEs) [10], and at the meso level [11]. However, there is a lack of evidence in the recent literature on critical CE practices aligned with the SDGs at the macro level. Moreover, even though Eco-Innovation (EI) is a key driver of the SDGs, as it makes environmentally friendly product improvements less complicated [12], only a few studies have investigated the role of EI in CE and the SDGs [13].

Empirical investigations into how EI and CE practices can advance the SDGs at the country level hold great potential. However, assessing the SD level based on CE and EI presents a variety of competing evaluation criteria. To address this issue, the multi-criteria decision-making (MCDM) approach has been widely used and is considered a fundamental analytical tool [14]. Despite its usefulness, several concerns need to be addressed in the study of SD-level evaluation based on MCDM technology. Firstly, evaluation criteria are often unable to reflect comprehensive real-life conditions. Secondly, modern solutions that efficiently address environmental sustainability development challenges are often ignored. Finally, MCDM methodologies are heavily reliant on decision-maker (DM) judgements, and the decision-making environment can significantly influence the final results.

Overall, while a robust body of empirical literature has investigated macro-level sustainability indicators and circular economy metrics across Mainland Chinese provinces, a distinct gap remains in how these evaluations address data uncertainty. Existing macro-level tools often assess circular patterns or eco-innovative milestones as separate, parallel streams, frequently relying on arbitrary weight allocations that fail to capture the high correlation and data volatility inherent in provincial inputs. This study does not suggest a complete absence of regional macro frameworks in China; rather, it identifies a clear need to move beyond isolated assessments. By introducing an optimization framework that dynamically weights interconnected circular and innovative dimensions under a unified mathematical lens, this paper provides a more precise and objective diagnostic tool for macro-level regional monitoring.

1.3. Contribution and Innovation

This study evaluates the SD level of China's provinces, which has theoretical and practical implications. Firstly, the framework uses the nudge theory (NT) to gather indicators

and construct an evaluation system, which helps DMs make more informed and beneficial choices. Secondly, the proposed framework considers two modern solutions for SD challenges, namely, CE and EI practices. The framework includes various indicators that reflect various aspects of SD assessment adequately. Next, the developed SECA methodology is utilized to determine integrated weights of indicators and to rank alternatives in terms of SD implementation. Finally, the suggested framework is employed in provinces of China as a significant case study to determine the SD level because it faces significant challenges of climate change [15]. While China has developed wide-ranging ambitions to cope with environmental challenges, the amount of garbage being disposed of in China has soared, as displayed in Figure 1 [16]. Therefore, CE and EI practices can facilitate China's combat against these challenges while keeping economic goals intact.

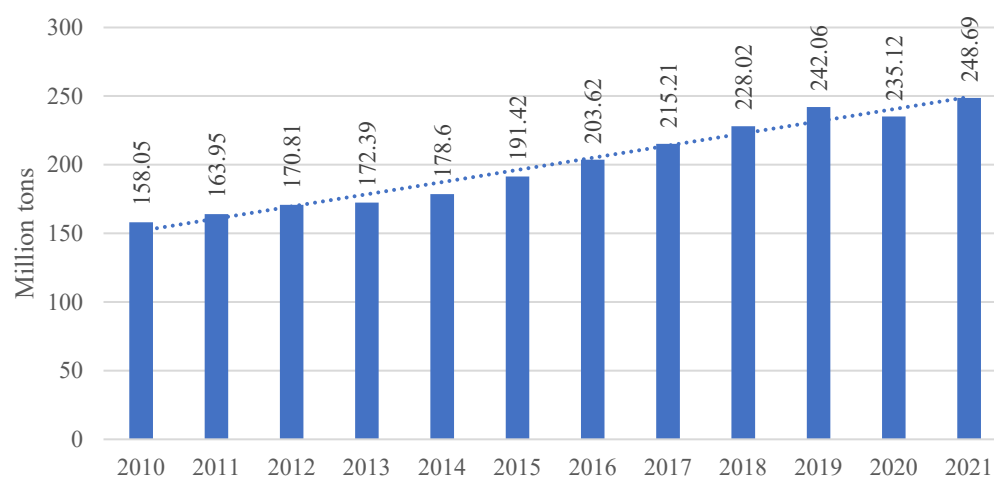


Figure 1. The increasing volume of disposed garbage in China from 2010 to 2021.

Unlike conventional macro-level sustainability indexes that rely solely on retrospective, static environmental footprints (such as raw carbon-emission tallies or ecological indices), the novelty of our proposed framework lies in its active tracking of implementation. Specifically, our model introduces two unprecedented structural dimensions: (1) it measures the readiness of localized infrastructure for resource life-cycle loops (such as repair labor and industrial waste-treatment capabilities) rather than merely recording pollution; and (2) it mathematically integrates behavioral economics (Nudge Theory) directly into an objective multi-criteria decision-making model (SECA). This prevents the cognitive bias and arbitrary weighting common in previous macro frameworks, establishing a verifiable and actionable blueprint for regional sustainable development.

The key benefits of our new algorithm include: (1) We introduce innovative dimensions of CE and EI, derived from their practices, to assess SD levels. Our framework outlines three main criteria for CE and two for EI, encompassing all aspects of SD evaluation based on CE and EI practices. (2) We developed a novel application of NT in decision making. This approach helps DMs make more precise judgments while maintaining flexibility in individual decisions. We compared the results with various well-known MCDM methods to confirm our framework's effectiveness. (3) Our study focuses on the provincial level, unlike existing research that mainly examines micro and meso levels.

The remainder of the study is organized as follows: Section 2 provides a review of related literature on the topic. Section 3 presents the basics of the methods considered. In Section 4, the proposed evaluation framework is introduced. The findings are shared in Section 5, followed by a discussion and policy implications in Section 6. Finally, Section 7 outlines the study's results and limitations and suggests future research approaches.

2. Literature Review

This section affords a brief overview of the literature on CE and sustainability, EI and sustainability, and, in the end, we summarize the gaps that our empirical research has addressed.

2.1. Circular Economy and Environmental Sustainability Development

The traditional linear economy, which comprises consuming, producing, and discarding goods, has been harshly criticized [17]. Businesses typically fail to evaluate the environmental effect of a product throughout its life cycle, contributing to negative ecological repercussions [18]. The CE concept, in contrast, calls for sustained efforts to advance ecological sustainability in business operations. According to [19], this entails implementing regulations that cover waste management, reducing energy usage, limiting pollutants, and encouraging reuse.

According to Schroeder et al., (2019) [20], Rodríguez et al., (2019) [21], putting CE methods into practice can enhance the SDGs. The importance of CE practices on the direction of SD at the micro and meso levels was assessed in several studies. These assessments were reached in diverse industries. Additionally, some academics have merged CE with Industry 4.0 to evaluate the amount of sustainability of various authorities towards reaching the SDGs [22].

CE practices may be classified into four categories. The first category consists of replacing traditional sources with renewable resources. All CE hints suggest using renewable resources. The energy sector in CE primarily focuses on renewable energy (RE) resources consisting of wind and solar PV energy [23]. Preceding studies have proven that RE performs an essential role in SD. The second category includes mending and reusing goods rather than discarding them. Repairing is a key cyclical practice that may assist us in remaining within our planet's limits while also reducing our ecological impact [24,25]. The third category is recycling, which is important to boosting CE ideals. It completes the cycle and decreases primary resource exploitation. Recycling makes extra restrained use of limited resources by converting end-of-life goods into valuable materials [26]. The fourth category is sharing and second-hand practices. These practices can help reduce the demand for new items and natural resources. These four CE strategies have a great impact on all dimensions of SD. Therefore, using these indicators may enhance results.

2.2. Eco-Innovation and Environmental Sustainability Development

Making an investment in sustainability and adopting green practices is a clever decision for SD as it promotes social development, environmental neutrality, and financial increase [27]. EI is a central strategy for accomplishing sustainability and presents organizations with an aggressive advantage. EI refers to using technological innovation to preserve assets and power, thereby preventing, reducing, or mitigating environmental pollution or damage [28]. The adoption of EI speeds up SD. Technological innovations that result in medical patents enhance a country's global role and attract investment via other countries' acquisition of patents [29].

Numerous researchers have set up a connection between environmental sustainability, pollution, and the adoption of EI. As an instance, in a research comparing the relationship between EI and CO₂ emissions, Lin & Ma, (2022) [30] it was observed that the development of green techniques can extensively lessen climate change situations in recent times. Sun et al., (2023) [29] evaluated the significance of environmental innovation in the top ten greenest economies between 1980 and 2019, and found that financial depth and environmental innovation can greatly reduce carbon emissions and minimize ecological impact. The results showed that monetary intensity and EI dramatically lower carbon

emissions and ecological effects. Lisha et al., (2023). [31] tested the interplay among environmental sustainability, EI, economic technology, financial improvement, and natural resources in BRICS countries between 2000 and 2019. The results confirmed that EI and economic development can guide environmental sustainability.

It has been discovered via several studies that there may be a strong link between sustainability and EI. This is, in general, measured via factors which include research and development (R&D) expenses, the number of researchers in the R&D sector, patent offers, and patent programs. However, those studies no longer examine the level of SD. On the other hand, it is essential not to forget the synergy between CE and EI. Studies suggest that CE can supply superb results whilst blended with EI [32]. Consequently, the contemporary look at uses those measurements to research the rating of SD regarding CE and EI.

From a strict epistemological standpoint, Eco-Innovation (EI) and the Circular Economy (CE) operate at structurally distinct levels of analysis: CE defines the normative, structural loops and systemic boundaries of resource preservation, whereas EI serves as the primary technical mechanism and operational vehicle for executing individual R-strategies. In this framework, they are not positioned as parallel theoretical constructs; rather, they are evaluated as interdependent operational dimensions of regional capacity. The circular economy indicators (C1 to C7) measure a province's physical scaling and existing capacity for material looping, recycling, and clean energy inputs. Concurrently, the eco-innovation metrics (C8 and C9) track the ongoing flow of technological assets and financial investments that fuel future loop refinements. Evaluating them within a single matrix is methodologically crucial because structural waste loop capacity (CE) remains static and sub-optimal without an active technological engine (EI) to drive efficiency transformations across macro-regions continually.

2.3. Research Gaps

The literature review's investigation of the importance of CE and EI practices in relation to the SD at the macro level uncovered several gaps. Firstly, the simultaneous function of CE and EI practices in achieving SD is neglected, especially with the life cycle approach. In order to provide more guidance to governments' decision making, research is needed to quantify the degree of SD through CE and EI practices from their points of view. To aid in decision making, countries must be aware of how their policies in expanding CE and EI practices affect sustainable performance. Therefore, further research is required to provide an evaluation system of SD level considering CE and EI approaches. Secondly, while suggested frameworks in the existing literature emphasize micro and meso levels, evaluating the SD level on the macro level (countries) is neglected. At present, no framework provides a comprehensive evaluation system for the SD level at the national level. A critical review of the existing methodologies exposes two deep architectural flaws that render them inadequate for macro-level governance. First, previous micro and meso frameworks rely heavily on localized, firm-specific indices that fail to scale up to regional administrative bodies due to complex cross-jurisdictional data boundaries. Second, existing national-level assessment tools suffer from severe subjectivity, relying heavily on uniform averaging or arbitrary Delphi weightings that ignore the complex correlations and high statistical volatility among different provincial data inputs. Consequently, prior models often misclassify a region's static environmental state as active sustainable progress. There is an urgent methodological need for an integrated framework that captures macro-level operational scale while mathematically adjusting for localized data discrimination, thereby validating the development of our proposed CE-EI model.

This study aims to improve the decision-making process and behavior of DMs by incorporating nudge theory (NT), which has proven to be effective in improving helpful

knowledge and actual behavior. By conducting a comprehensive assessment, the impact of the decision-making process on DM's behavior is considered to develop the existing literature. The study also integrates well-known multiple criteria decision-making (MCDM) approaches to assess the success of provinces in China in adopting CE and EI practices towards SD. Table 1 compares the considered criteria, scale, and study regions. It declares the priorities of our research clearly.

Table 1. The characteristics of literature concerning CE and EI evaluation systems.

Reference	Considered Indicators		Scale			Study Region/Scope
	Circular Economy (CE)	Eco-Innovation (EI)	Micro	Meso	Macro	
[33]	✓	-	✓	-	-	Agri-food Supply Networks
[34]	✓	-	✓	-	-	Manufacturing Sectors
[22]	✓	-	✓	-	-	The leather industry
[35]	✓	-	✓	-	-	The construction industry
[13]	✓	✓	✓	-	-	Small and Medium Enterprises
[36]	✓	✓	✓	-	-	Pharmaceutical industry
[37]	✓	✓	✓	-	-	10 Countries
[38]	✓	✓	✓	-	-	EU frms
[39]	✓	-	✓	-	-	3 Manufacturing sectors in Iran
[40]	✓	-	✓	-	-	Small manufacturing firms in OECD
[6]	✓	-	✓	-	-	Small and Medium-sized Enterprises in Vietnam
[11]	✓	-	-	✓	-	255 Chinese manufacturing firms
[41]	✓	-	-	✓	-	Urban-industrial symbiosis
[42]	✓	-	-	✓	-	Industrial Symbiosis
[23]	✓	-	-	-	✓	BRI countries
[3]	✓	✓	-	-	✓	European Regional Panel Analysis
[43]	✓	-	-	-	✓	52-Country Comparative Panel
Our study	✓	✓	-	-	✓	Chinese Provinces

To bridge these macro-level deficits, this study addresses two core research questions: (1) How can a combined evaluation framework based on both Circular Economy (CE) and Eco-Innovation (EI) practices effectively capture the uneven sustainable performance across different administrative regions? (2) How can behavioral insights from Nudge Theory be practically embedded into empirical multi-criteria optimization to help poli-

cymakers make more precise and less subjective choices? By answering these questions, this study moves beyond the single-dimensional metrics that currently dominate macro-sustainability literature.

3. Preliminaries

In this study, we developed an integrated framework that uses NT, the SECA approach, and nonlinear programming to evaluate a region's environmental sustainability performance and provide realistic outcomes. The strategy intends to improve the decision-making environment by identifying the most relevant evaluation indicators using the SECA method and ranking the options using nonlinear programming. This section gives an overview of various techniques and their main ideas.

3.1. Essential Principle of the Nudge Theory

The nudge theory (NT) permits professionals to conduct more informed assessments. According to NT, giving nudges to help great picks is a good strategy for improving DMs' judgments [44]. NT is a novel concept in behavioral economics that subtly influences DMs' behavior without forcing them to choose certain options or limiting their freedom [45]. This study aims to incorporate NT's benefits in creating a more specific environment for DMs and supporting their professional behavior into the evaluation method for SD-level evaluation. This integration is expected to improve selection accuracy, which will lead to more rational and meaningful consequences.

3.2. Essential Principle of the SECA Technique

The Simultaneous Evaluation of Criteria and Alternatives (SECA) technique [46] is a robust new technique. Its objective is to determine the importance of the assessment gadget and rank research options primarily based on a weighted evaluation machine. What sets SECA apart from other comparable methods for alternative ranking is its simultaneous determination of each burden of criteria and the ranking of options, which complements accuracy and leads to higher results. Furthermore, the SECA method accepts qualitative and quantitative criteria as input, making it more flexible. The following are the steps involved in this approach [46]:

Step 1. Normalization of the decision matrix: Here, the positive and negative measurements in the decision matrix are normalized. Positive measurements (PM) are those that have a gain issue, while negative measurements (NM) are those that have a cost issue.

$$X_{ij}^N = \begin{cases} \frac{X_{ij}}{\max_k X_{kj}} & \text{if } j \in PM, \\ -\frac{\min_k X_{kj}}{X_{ij}} & \text{if } j \in NM, \end{cases} \quad (1)$$

Step 2. Building the optimization model: To obtain information between measurements in the choice matrix, the correlation between each pair of measurements has to be calculated. The normalized values (σ_j) and (π_j) are defined as reference factors for measurement weights as follows:

$$\pi_j = \sum_{l=1}^m (1 - r_{jl}) \quad (2)$$

$$\sigma_j^N = \frac{\sigma_j}{\sum_{l=1}^m \sigma_l} \quad (3)$$

With the provided explanations, an optimization model is formulated and solved to examine the importance of the criteria.

$$\text{Max } S_i = \sum_{j=1}^m W_j X_{ij}^N, \quad \forall_i \in \{1, 2, \dots, n\} \quad (4)$$

$$\text{Min } \lambda_b = \sum_{j=1}^m (W_j - \sigma_j^N)^2 \quad (5)$$

$$\text{Min } \lambda_c = \sum_{j=1}^m (W_j - \pi_j^N)^2 \quad (6)$$

$$\text{s.t. } \sum_{j=1}^m W_j = 1 \quad (7)$$

$$0 \leq W_j \leq 1, \forall j \in \{1, 2, \dots, m\} \quad (8)$$

where n is the number of alternatives, m is the number of indicators, and W is the weight of indicators.

Step 3. Summarizing the results: In this step, the results obtained from solving the optimization model are summarized. In this model, for different values of β , different weights for criteria and different scores for options are obtained. The optimal β gain where the results converge is determined. The outcomes of the optimization model using the optimal β are the final results.

4. The Proposed Empirical Framework to Analyze CE-EI Environmental Sustainability

It is currently doubtful how to assess the environmental sustainability level based on the use of CE and EI techniques. However, it is essential to conduct research in this sector to build a reasonable assessment system. This will help evaluate policies that are currently in place and improve future policies. In Figure 2, a CE-EI criterion system is developed using a two-phase process. The first phase involves the formation of an expert committee. The committee then reviews and filters the criteria one by one. They also replace and augment the criteria based on the real circumstances of selecting CE and EI methods. In the second phase, the study area is evaluated using CE and EI procedures. The full illustration of each stage's associated steps is provided below. From an operational standpoint, each stage of the framework functions as a practical step for regional governance. Phase I (Stages 1.1 to 1.3) serves as a qualitative filtering system, using expert insights and behavioral nudges to develop a localized indicator menu that aligns with the study region's specific socio-economic realities. Phase II (Stages 2.1 to 2.3) serves as an active decision-making tool. By constructing the decision matrix and applying the SECA methodology, the framework translates raw, volatile provincial performance metrics into steady indicator weights and performance scores. This objective mapping removes personal bias and allows policymakers to pinpoint exactly where regional vulnerabilities lie, shifting sustainability monitoring from an abstract concept into an actionable evaluation system.

This article aims to establish a set of evaluation criteria that can be used to determine the level of environmental sustainability development. Phase I involved forming an expert panel consisting of ten members, all of whom were academic or industrial executives meeting the following requirements: (i) an average age of 35 years; (ii) at least six years of experience in related industries; and (iii) preferably holding at least an MSc degree. Specifically, the ten-member committee comprised four senior academic researchers specializing in environmental planning, three industrial executives from waste management and recycling sectors, and three public policy consultants with extensive experience in regional circular economy frameworks. Next, the nudge theory was employed to provide supporting data to the expert team. The nudges addressed various aspects of the subject matter, with the aim of assisting specialists from different professions and educational backgrounds to make informed decisions. The consultation process was conducted in three successive rounds, using a structured feedback loop guided by Nudge Theory. In the first round, experts were provided with an initial list of 15 indicators derived from the literature. To improve the decision-making environment without restricting expert

judgment, ‘informational nudges’, consisting of standardized data summaries of provincial data availability and life-cycle relevance, were presented to the panel. In the second round, indicators receiving less than 70% approval were filtered out. In the final round, a complete consensus (full agreement) was reached on the final considered indicators (nine indicators), eliminating the need for traditional statistical consistency tests by achieving unanimous qualitative alignment. Then, the proposed CE-EI evaluation framework was constructed. We collected three criteria for the CE category, including repair, recycling, and renewable sources. Repair and recycling boost the fundamental principle of the CE of reimbursing the value of products and materials as much as possible [47]. While one indicator can reflect the repair criterion properly, several indicators are required to measure the recycling criterion. Examining these indicators broadened the information on various variables representing recycling. This approach is rational because it was not accurate to consider the entire scope of recycling with a single indicator. Numerous studies have shown that renewable energy, particularly solar and wind energy, boosts CE and thus decreases environmental challenges [48]. To demonstrate the overall contribution of the EI on the SD level, green patent and R&D expenditure were employed. Several scholars have confirmed that green patents and R&D expenditure play a crucial role in boosting innovation, and innovation improves the SD level dramatically [49]. Accordingly, based on these criteria and available data, nine indicators were developed to measure the mentioned criteria, as shown in Table 2. For the CE domain, C1 (repair services labor) directly reflects the regional capacity to prolong product lifetimes and minimize upstream waste, while C2 (water conservancy labor) represents the structural human capital required to build secure, closed-loop water resource loops. Indicators C3, C4, and C5 measure the physical outputs and investments of waste loop execution, whereas C6 and C7 capture renewable resource capacity. For the EI domain, green patents (C8) and R&D expenditure (C9) serve as inputs and outputs of technological infrastructure. Together, these metrics move past static ecological measures by focusing entirely on the active implementation scale of regional circular systems.

Table 2. The proposed CE-EI evaluation indicators to measure the environmental SD level.

Category	Criteria	Indicator	Code	Unit
Circular Economy	Repair	Person works in repair and other related services	C1	Person
		Person works in handling water conservancy	C2	Person
	Recycling	Integrated reuse share	C3	%
		Volume of local garbage harmlessly treated	C4	Ton
		Investment completed in the industrial pollution treatment	C5	Yuan
	Renewable resource	Wind energy usage	C6	Kwh
		Solar energy usage	C7	Kwh
Eco innovation	Green patent	Number of patent applications	C8	Piece
	R&D	Expenditure on R&D	C9	Yuan

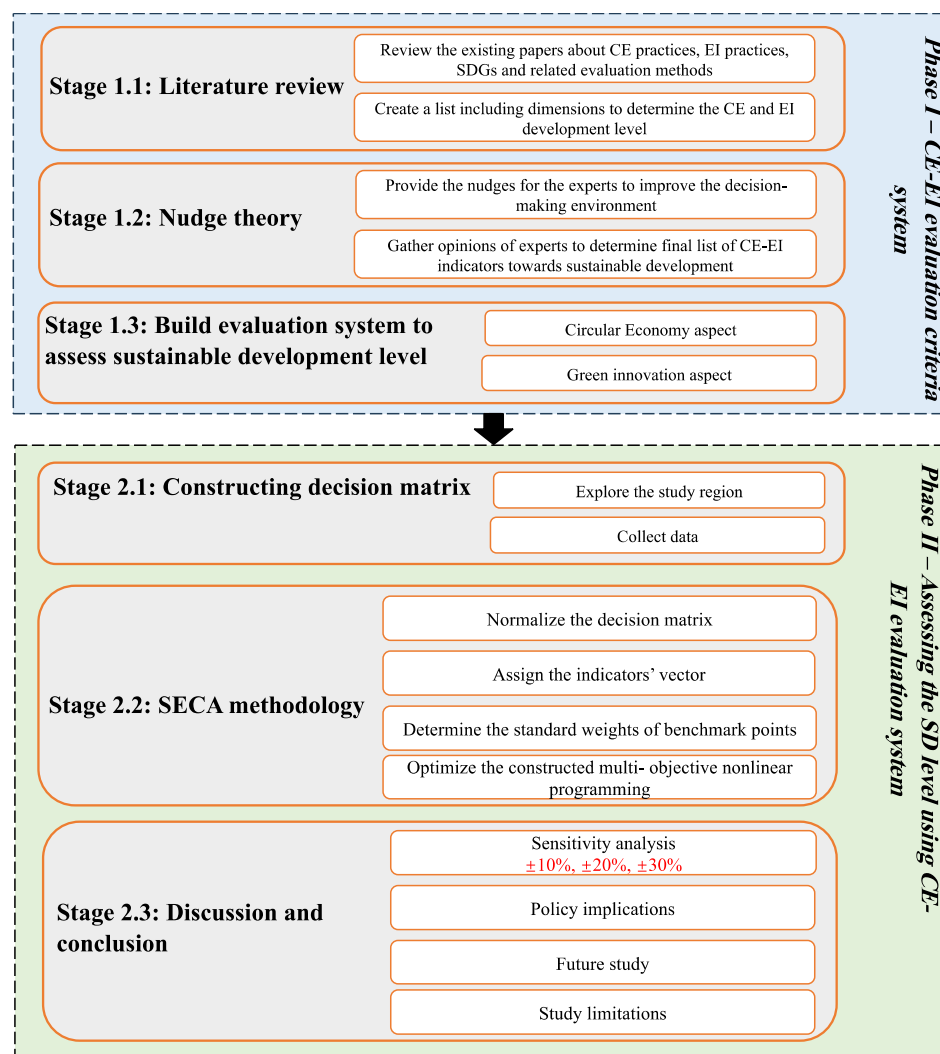


Figure 2. The proposed research framework used to assess the environmental SD situations.

The selection of the specific indicators and their corresponding units of measurement in Table 2 is tightly governed by data accessibility and life-cycle relevance within Chinese official statistical reporting systems. Under the Circular Economy category, human labor units ('Person') were selected for C1 (repair) and C2 (water conservancy) to serve as stable structural proxies for evaluating a province's active, localized operational capacity to retain assets and manage water looping, avoiding the price distortions common in monetary units. Metric C3 uses a normalized percentage ('%') to track resource reuse efficiency, while C4 ('Ton') and C5 ('Yuan') use raw volume and capital dimensions to monitor waste treatment output and industrial pollution inputs, respectively, directly from national statistical monitoring databases. For clean energy inputs, C6 and C7 rely on kilowatt-hours (kWh) to capture actual physical utility scale across regional electrical grids. Finally, within the Eco-Innovation domain, C8 uses 'Piece' to record the absolute physical volume of successful patent outputs, while C9 relies on 'Yuan' to track the raw monetary scale invested in provincial research and development. This multi-unit setup allows the SECA methodology to evaluate data discrimination across diverse physical and economic scales without forcing arbitrary dimensional conversions.

During Phase II of the study, a decision matrix is created to rank the problem options. The decision matrix is a matrix with rows and columns, where the columns represent decision criteria, and the rows represent the problem options. Each cell in the matrix is used to evaluate each option with respect to each criterion. To begin Phase II, the study region is

explored to analyze the current conditions of the considered indicators. Then, the required data for the period of 2010 to 2021 is collected using official databases, such as the China Statistical Yearbook 2022. The SECA methodology is used to rank all alternatives. In this method, the indicators are weighted based on the gathered data, and then scores are assigned to the alternatives using the nonlinear programming approach. Finally, based on the obtained results, policy implications are provided.

5. Results

5.1. The Study Region

Climate challenges and development have been the most critical challenges in China for the last few decades. Tackling these challenges is one of the most significant Chinese national government strategies to improve environmental quality [43,50]. Jiangsu's high ranking. The province's performance is supported by its natural potential and social capacities, which have contributed to the long-term development of both its rural and urban communities [51]. Furthermore, China is a high-priority case study to analyze its environmental sustainability considering CE and EI approaches, which effectively combat climate change and assist China in meeting the environmental sustainability level targets in this study. The study encompasses all six urban regions of mainland China, which include North China, Northeast China, East China, Central and Southern China, Southwest China, and Northwest China. Table A1 presents critical factors of the study area, showcasing the economic, environmental, social, and energy consumption conditions.

5.2. Building and Normalizing the Decision Matrix

After reviewing the existing literature and consulting with an expert group, we developed the proposed CE-EI indicators (refer to Table A1). The CE-EI framework comprises nine metrics, and we gathered data on the performance of China's provinces using the SECA methodology. The descriptive statistics of the considered variables are provided in Table 3. We then created a decision matrix with one row for each alternative and columns corresponding to the CE-EI framework. Using Equation (1), we calculated the normalized decision matrix for both positive and negative criteria. The resulting matrix is shown in Table A2.

Table 3. The descriptive statistics of the considered variables.

Variables	C1	C2	C3	C4	C5	C6	C7	C8	C9
Mean	8.15	2.77	0.63	1.00	108,140.74	5,649,756.68	45,277.77	112.39	1831.32
Median	7.10	1.70	0.55	1.00	95,548.00	3,196,867.00	20,104.00	74.40	1411.40
Maximum	21.70	12.40	1.00	1.00	380,607.00	29,021,849.00	340,935.00	578.60	5138.07
Minimum	0.70	0.10	0.09	0.97	10	24,782.00	100	0	58.96
Std. Dev.	4.69	2.81	0.22	0.01	96,650.30	7,224,153.33	71,701.24	122.89	1401.98
Skewness	0.85	2.03	−0.01	−4.75	1.76	2.20	2.99	2.28	0.88
Kurtosis	1.11	4.60	−0.49	24.04	3.13	4.77	9.84	6.42	−0.15
Observations	31	31	31	31	31	31	31	31	31

5.3. Constructing and Solving the Nonlinear Optimization Model

Following the calculation of the π_j and σ_j values using Equations (2) and (3), a nonlinear optimization model is constructed using Equations (4) to (6) and solved using Lingo 11.0 software. The model is executed for values of β ranging from 0.1 to 9, and in each run, the weights of the criteria and the values of the alternatives are obtained. It is also possible

to select suitable outcomes from this process. The values of the criteria weights (W) and option scores (A) for various β values are presented in Figures 2 and 3, respectively.

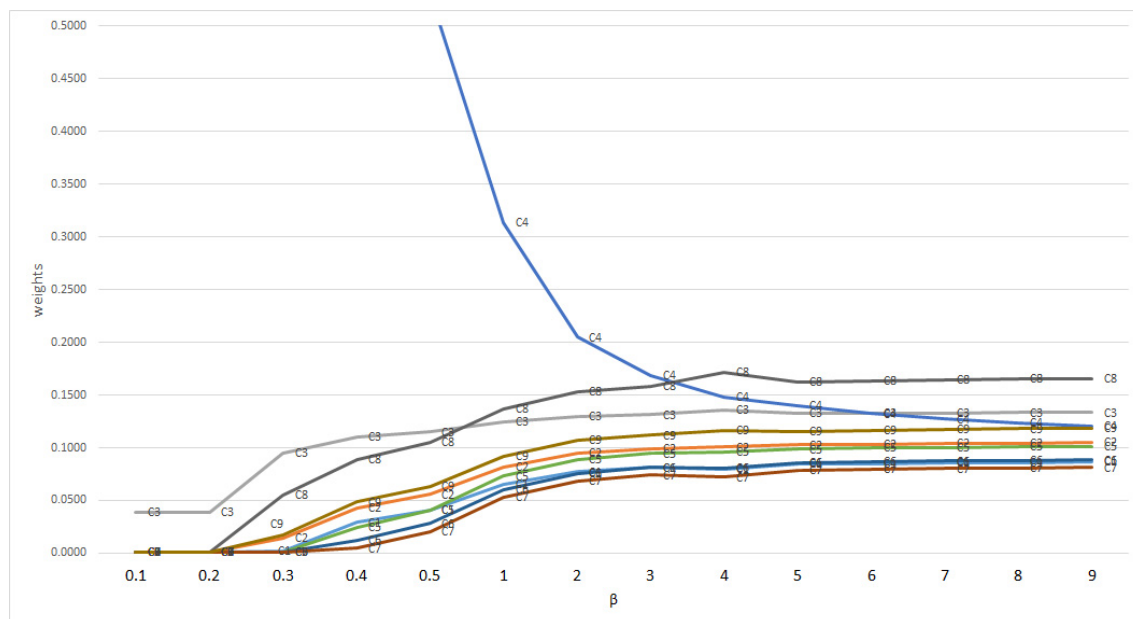


Figure 3. Illustration of the variations in the weights of the indicators for different scores of β .

The weights of the indicators show sensitivity to the parameter β , as demonstrated in Figure 3. When $\beta < 6$, several indicators have identical weights; for example, at $\beta = 0.1$ and 0.2 , the weights for C1, C2, C5, C6, C7, C8, and C9 all converge to a uniform value of 0.001. Additionally, notable fluctuations occur for C3, C4, and C8 within this range. Specifically, the weight of C4 decreases from 0.954 at $\beta = 0.1$ to 0.132 at $\beta = 6$. As a result, values of $\beta < 6$ are excluded from the final weight determination due to this numerical instability. Convergence is reached at $\beta = 6$, where results are stable, confirmed by the consistency in alternative scores (Figure 4). While total criteria weights consistently equal 1 and stay positive, fulfilling Equations (7) and (8) scores obtained at $\beta < 5$ (near 1.0) were found to be statistically inconsistent with the expected distribution of alternatives.

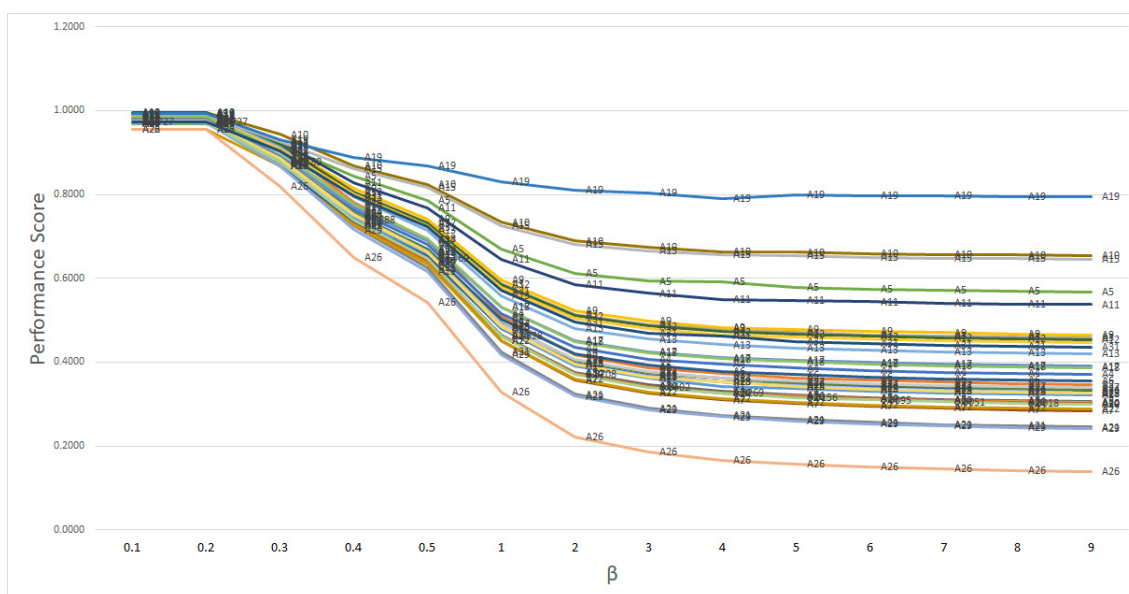


Figure 4. Demonstration of the variations in the alternatives ranking for various β values.

Based on this optimization ($\beta = 6$), the final weight of the indicators is provided in Figure 5. Accordingly, C6 is identified as the most significant indicator, followed by C3 and C4, while C9 has the least significance (as elaborated in Table 4). By monitoring labor inputs, C1 evaluates the regional operational capacity to maintain products within the functional economy, while C2 captures the institutional scaling of water infrastructure necessary to support industrial closed-loop recycling systems.

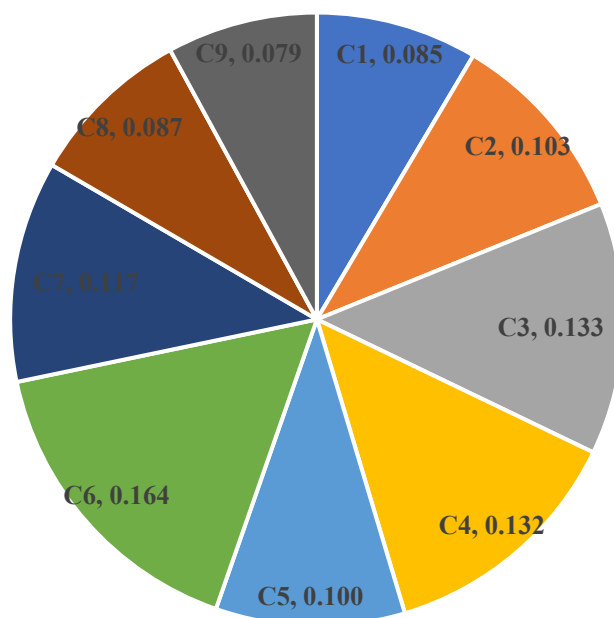


Figure 5. The significance of the considered CE-EI indicators.

Table 4. Categories and ranking of the CE-EI indicators.

Code	Weight	Rank	Category
C6	0.1638	1	Impressive
C3	0.1328	2	
C4	0.1323	3	
C7	0.1167	4	Middle
C2	0.1034	5	
C5	0.0997	6	
C8	0.0866	7	Low
C1	0.0852	8	
C9	0.0794	9	

Based on these optimal weights, the indicators were grouped into three clusters: high, middle, and low significance. Table 4 displays the specific rankings and classifications; C6 was identified as the most significant indicator, followed by C3 and C4, while C9 was the least significant, followed by C1 and C8.

Subsequently, the provinces of China were sorted (Figure 6 (Map reference: Ministry of Natural Resources of China, Standard Map/Public Map Content Representation Specification; reference map: 中华人民共和国版图, 审图号 GS(2019)1818.)) and categorized into three levels of environmental sustainability: high, middle, and low. As shown in Table 5, Guangdong stands out as the most sustainable province, followed by Jiangsu and Shandong. Conversely, Tibet exhibits the lowest level of environmental sustainability, with Qinghai and Hainan trailing closely behind.

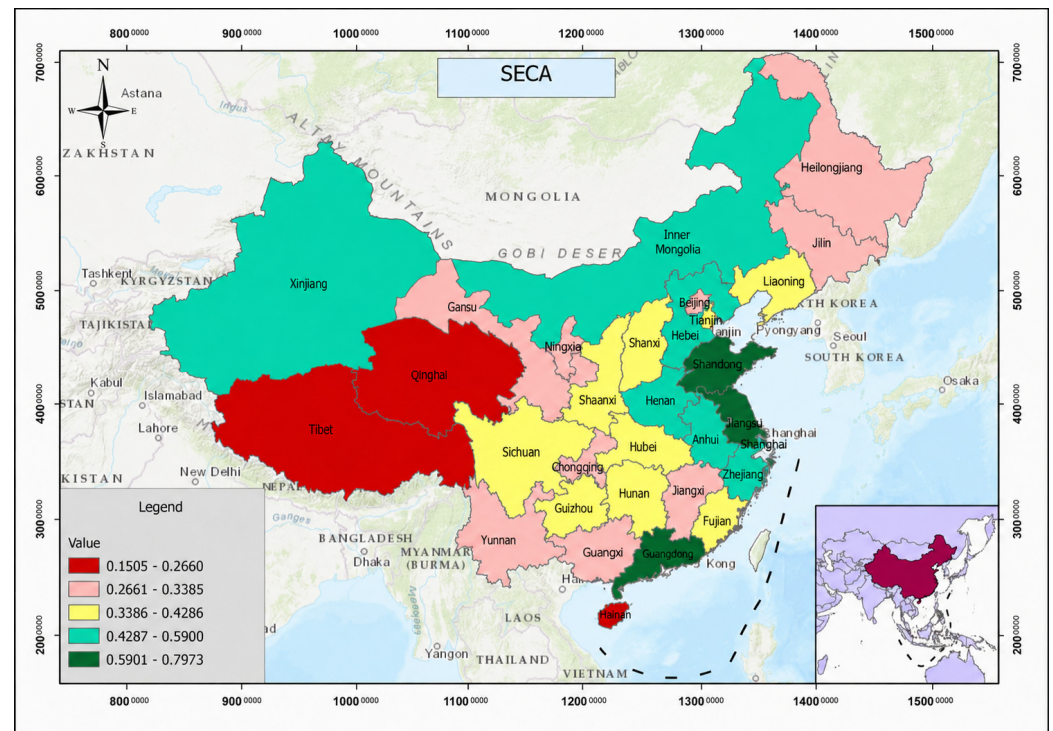


Figure 6. The obtained score of China provinces in terms of environmental SD analysis by the proposed model.

Table 5. Categories and ranking of the provinces in terms of environmental sustainability development.

Province	Score	Rank	Category
Guangdong	0.7973	1	High
Jiangsu	0.6591	2	
Shandong	0.6505	3	
Inner Mongolia	0.5738	4	
Zhejiang	0.5438	5	
Shanghai	0.4736	6	Middle
Hebei	0.4654	7	
Anhui	0.4611	8	
Henan	0.4552	9	
Xinjiang	0.4443	10	
Fujian	0.4286	11	
Hubei	0.3987	12	
Hunan	0.3954	13	
Shanxi	0.38	14	
Liaoning	0.3641	15	
Tianjin	0.3566	16	
Shaanxi	0.3485	17	
Guizhou	0.3457	18	
Sichuan	0.3412	19	
Yunnan	0.3371	20	

Table 5. Cont.

Province	Score	Rank	Category
Gansu	0.3353	21	Middle
Beijing	0.3313	22	
Heilongjiang	0.3155	23	
Jiangxi	0.3129	24	
Guangxi	0.3123	25	
Ningxia	0.3095	26	
Chongqing	0.2981	27	
Jilin	0.2943	28	
Hainan	0.2562	29	Low
Qinghai	0.2522	30	
Tibet	0.1505	31	

6. Discussion

The results indicated that within the CE-EI evaluation system, wind energy consumption (C6), integrated reuse (C3), and the volume of domestic waste safely treated (C4) are the most important factors. Wind energy consumption (C6) emerged as the main indicator, probably because of its renewable nature, operational accessibility, and cost-effectiveness [52]. These weights showed that developing renewable energy should remain a key part of provincial sustainability policies. Integrated reuse (C3) is the second most important factor, as it directly affects material costs and waste production [53]. Additionally, the safe treatment of domestic waste (C4) is a crucial measure for evaluating environmental impact within a circular economy, helping to support wider sustainability goals. It is crucial to clarify that the high weight assigned to wind energy usage (C6) by the SECA methodology reflects its high degree of inter-provincial data discrimination rather than a normative assertion of its theoretical superiority over other sustainable practices. Because SECA derives weights from objective data volatility across the study region, the prominence of C6 demonstrates that wind energy deployment is the most unevenly distributed asset across Chinese provinces. Therefore, this weight serves as a practical macro-level policy signal, highlighting structural regional disparities in clean energy adoption rather than discounting the intrinsic value of lower-weighted criteria.

Guangdong is China's most prosperous economic province, contributing significantly to national growth. Considering the fast growth of the economy and urbanization, Guangdong has made environmental sustainability development (SD) a top priority and has enacted different policies to achieve this goal. The SD journey in Guangdong Province highlights the mutual relationship between economic growth and environmental protection. At the beginning, similar to many other regions, Guangdong primarily relies on resource-intensive growth [54]. However, with the evolution of social values, a visible change has formed towards equity between the economy and environmental growth. Such a transformation demonstrates a shift from involving basic material needs towards a wide perspective of life quality. With progress in science and technology, this province takes action towards rational consumption of resources and increases its own ecological carrying capacity. Nowadays, Guangdong, as an instance of the integration of economic growth and environmental responsibility, evolves with a sustainable approach [55]. The superior position of this province as a sustainable province demonstrates its success in implementing and retaining sustainable approaches, which can be attributed to its long-standing commit-

ment to environmentally friendly policies or its investments in green industries. Jiangsu ranks as the second most sustainable province, reflecting the impact of its regional development strategies. The province has experienced significant industrialization and urbanization, with a GDP in 2021 exceeding that of Australia by approximately 15% [16]. Despite its industrial prominence and high agricultural productivity, contributing 5.6% of national food output on only 3.3% of cultivated land, Jiangsu has successfully initiated a transition toward renewable energy sources [56]. These initiatives have been instrumental in Jiangsu achieving its high environmental sustainability ranking. Shandong province similarly ranks among the top performers, which aligns with its status as a participant in China's National Sustainable Development Pilot Zones (NSDPZs). In recent decades, Shandong has accelerated its development across economic, environmental, and social dimensions [57,58]. The province's performance is supported by its natural potential and social capacities, which have contributed to the long-term development of both its rural and urban communities [57,59].

In contrast, provinces with the bottom stage of environmental sustainability development include Hainan, Qinghai, and Tibet. Despite the fact that Hainan is a coastal province, it possesses the lowest level, which shows that it failed to harness its ecological potential sufficiently. This finding appears to be in line with [60]. Utilizing a comprehensive approach, such as CE, will be beneficial in enhancing environmental sustainability. Coastal provinces such as Guangdong, Shandong, and Jiangsu have achieved a high level of sustainable development.

On the other hand, Qinghai and Tibet encounter numerous challenges to achieving environmental sustainability. The results of this research indicate that CE and EI possess better space for improvement in such areas. This region, compared with other provinces, calls for extra interest to address its unique environmental and social characteristics [61]. Despite their natural resource wealth, these regions underperform in SD, potentially due to inadequate climate change mitigation, an urgent issue considering that the regional warming rate is twice the global average [62]. Provinces like Guangdong, Jiangsu, and Shandong score highly because they possess the massive financial capital, R&D budgets, and waste management infrastructure required to execute circular economy transformations actively. Conversely, despite their beautiful natural states, Hainan, Qinghai, and Tibet score lower due to severe geographical constraints, infrastructure gaps, low baseline green investment, and a warming rate that complicates climate adaptation. This paradox arises because our framework evaluates active circular-economy capacity and infrastructure deployment rather than static, untouched ecological states. While Hainan possesses vast coastal potential, it lacks the concentrated green capital, waste loop infrastructure, and industrial eco-innovation networks seen in major economic hubs like Guangdong. Similarly, Qinghai and Tibet face severe geographical constraints, infrastructure development gaps, and a regional warming rate that is double the global average. This model reveals a crucial policy reality: a province cannot rely solely on its natural ecological gifts to achieve sustainable development goals; it requires active green investment, infrastructure transformation, and technological eco-innovation to build a true circular economy.

The lower performance in these regions may be due to geographical difficulties and outdated industrial processes, infrastructure gaps, and limited investment in environmental quality. While measures have been proposed to improve these areas [63], the results suggest that additional policies are needed to promote social and technological progress. Without prioritizing disaster prevention and climate adaptation, these provinces may struggle to attract green investment. Therefore, enhancing sustainable development and climate resilience in mountainous regions remains a key priority for national policy.

The empirical provincial rankings must be interpreted alongside the unique socio-economic landscape of contemporary China. Top-tier provinces like Guangdong, Jiangsu, and Shandong are national economic pillars with immense fiscal resources, massive industrial output, and dense urban centers. Consequently, their high rankings reflect their heavy financial capacity to establish large-scale infrastructure, absorb R&D costs, and process large volumes of domestic waste. Conversely, provinces like Tibet, Qinghai, and Hainan are characterized by pristine ecological environments but possess lower active scores within this specific model. This lower performance is a direct consequence of structural geographical constraints, infrastructure development gaps, low baseline green investment, and rapid regional warming, which complicates climate adaptation. This highlights a key socio-economic reality: having a clean natural environment does not automatically translate into proactive circular-economy infrastructure, which requires significant capital accumulation and active green investment.

6.1. Sensitive Analysis

To evaluate and justify the consistency and effectiveness of the proposed approach for ranking alternatives, four additional MCDM methods (COPRAS, TOPSIS, SAW, and MABAC) were employed. Figure 7 displays the ranking of provinces generated by the proposed model and other widely recognized methodologies. Subsequently, the resulting orderings are compared to the proposed model in Figure 8.

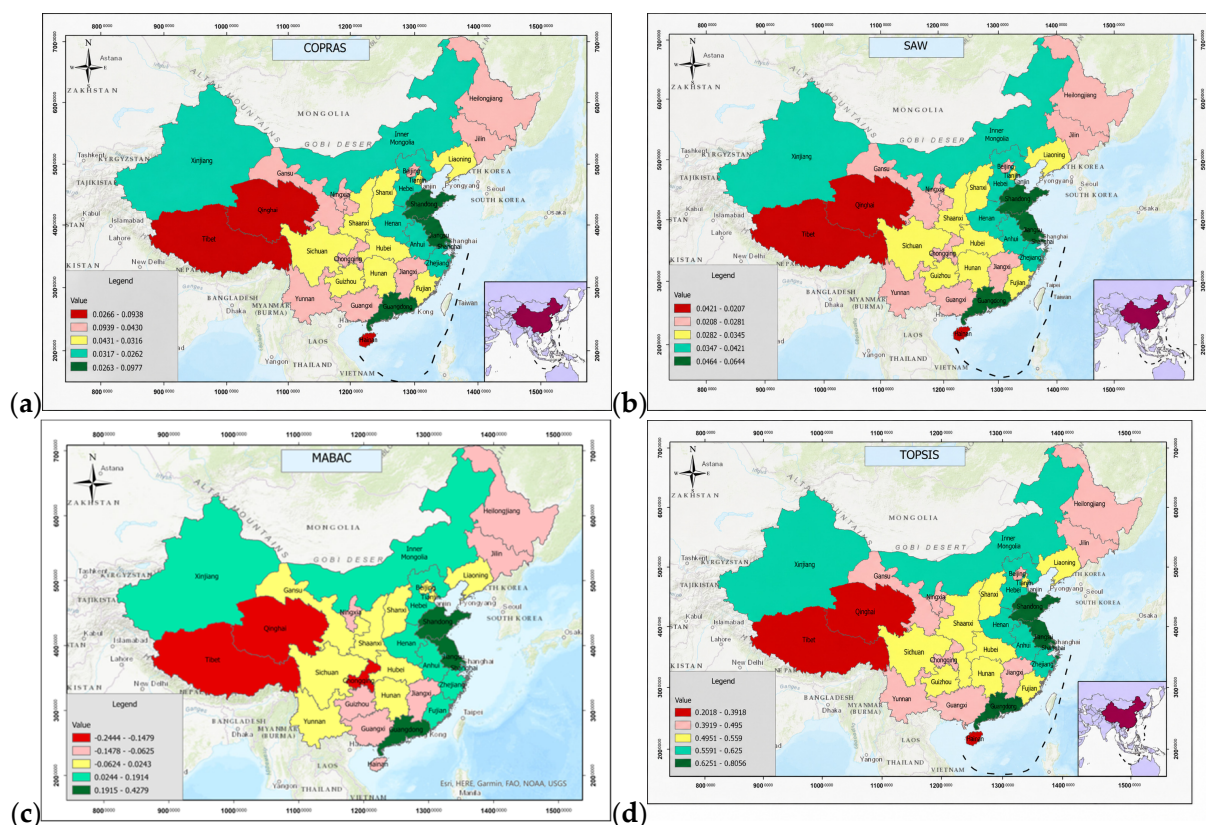


Figure 7. The sorting results of alternatives using MCDM methods such as (a) COPRAS, (b) SAW, (c) MABAC, and (d) TOPSIS.

As shown in Figure 8, the alternative sorting results from the proposed method are almost close to the other methods. Consequently, the validity of the suggested framework is strongly confirmed.

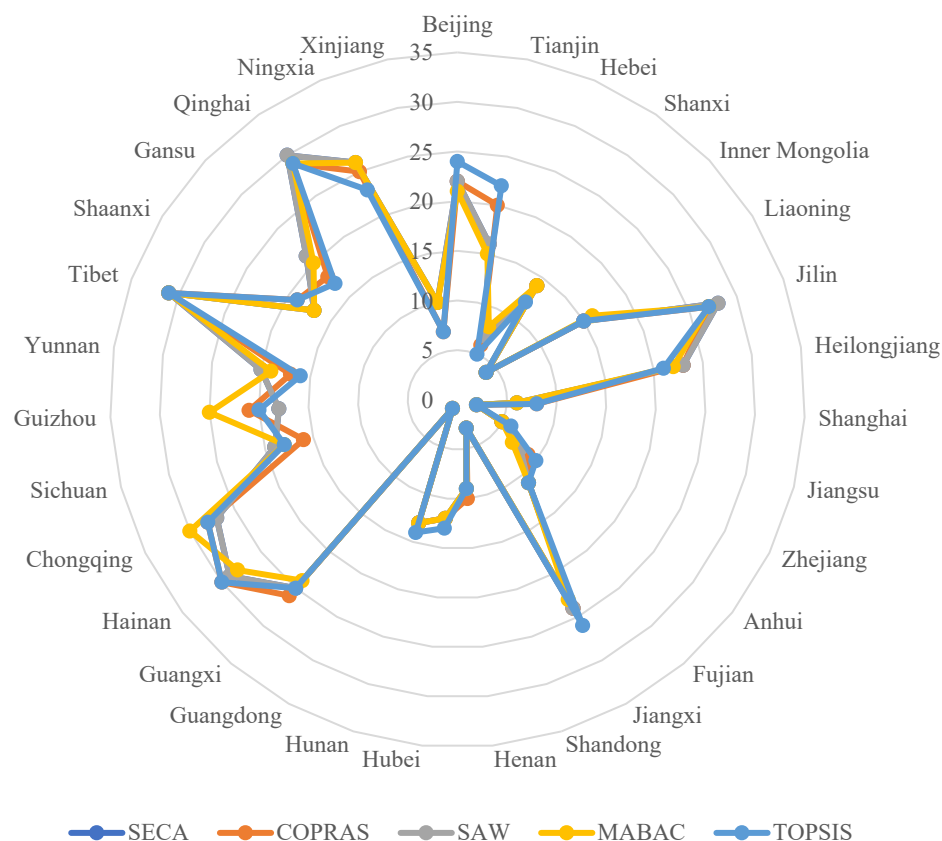


Figure 8. The sorting results of alternatives using MCDM methods compared to the proposed method.

6.2. Research Implications

6.2.1. Theoretical and Practical Implications

From a theoretical perspective, this study advances the behavioral decision-making literature by demonstrating that Nudge Theory can be successfully integrated with mathematical optimization models such as SECA. By using structured informational defaults in expert indicator selection, we demonstrate that behavioral nudging can minimize individual subjectivity before quantitative data modelling begins. Furthermore, this study bridges the gap between the Circular Economy (CE) and Eco-Innovation (EI) frameworks, providing a macro-level dual paradigm. This dual focus expands upon traditional urban system optimization approaches that model renewable utility policy paths independently [64], proving that sustainable development level assessments must track physical implementation capacity alongside eco-technological advancement.

Practically, our model provides actionable benchmarks for lagging provinces to improve their specific low-performing indicators. Because wind energy usage (C6) and integrated reuse share (C3) carry the highest weights, middle- and low-tier provinces can directly improve their environmental development scores by modernizing their regional grid distribution systems to absorb volatile wind energy loads and building municipal eco-industrial sorting parks to scale up the volume of treated local garbage.

6.2.2. Managerial and Policy Implications

Managerially, our framework serves as an objective monitoring dashboard for national and regional policymakers. Rather than enforcing uniform, top-down mandates, national administrators should apply a differentiated governance strategy tailored directly to the specific performance tiers identified by the model:

- For High-Capacity Clusters (Guangdong, Jiangsu, Shandong): Policy should prioritize cross-provincial technology transfer networks, advanced industrial symbiosis, and pioneering green patent commercialization markets. These economically developed provinces obtain high scores because they have the fiscal capacity to lead active green investment.
- For Middle-Tier Provinces (such as Inner Mongolia and Zhejiang): The target should shift toward expanding clean energy consumption limits, particularly wind energy use, which our model identified as the most sensitive indicator (C6) and as having high inter-provincial volatility.
- For Lower-Tier Ecological Priority Zones (Tibet, Qinghai, Hainan): National policy must move away from expecting raw industrial scale. Instead, the central government should establish specialized green infrastructure funds, close localized waste-treatment gaps, and build long-term climate resilience, allowing these regions to protect their natural ecological assets while steadily adopting tailored circular practices.

7. Conclusions, Research Limitations and Future Studies

This study proposes an integrated Circular Economy–Environmental Impact (CE–EI) framework to assess environmental sustainability at the national scale. This research did not consider political issues, which are completely out of scope in this research. China’s provinces serve as the empirical setting, partly because they offer clear contrasts in development pathways and partly because provincial data allow life-cycle considerations to be examined in a concrete way. By integrating circular-economy and environmental-impact concepts with the SECA method and drawing on nudge theory, the study seeks to move sustainability assessment beyond the conventional one-dimensional metrics that still predominate in the literature. The indicator system was developed through a combination of a systematic literature review and expert input, which helped narrow the set to items that were both theoretically grounded and practically measurable. When applied to provincial-level data, the framework highlights that certain indicators carry greater weight than others and reveals notable variation in sustainability performance across regions. Rankings produced using the SECA approach broadly align with those generated by other multi-criteria decision-making methods. This overlap does not prove correctness, of course, but it does suggest a degree of internal coherence in the results.

The analysis indicates that combining circular economy practices with environmental impact measures can illuminate regional sustainability patterns that might otherwise be missed. Provinces that score well under the CE–EI framework often appear to have higher shares of renewable energy use and more developed waste treatment and recycling systems. Still, these rankings should be read with some caution. They are model-based outputs, not direct evidence of policy success, administrative capacity, or governance quality. At best, they offer signals, useful ones, perhaps about relative strengths and areas that may deserve closer attention. The main contribution of the study is arguably the construction and empirical application of a holistic CE–EI framework at the national level, examined through a life-cycle lens. This approach may be helpful for policymakers and researchers who need comparative insights rather than definitive judgments. That said, sustainability assessment is rarely static or universal. Indicators that make sense in one socio-economic or institutional context may be less informative in another. For this reason, the CE–EI framework is probably best understood as adaptable rather than fixed, with its relevance depending on how carefully it is tailored to local conditions.

Research Limitations and Future Studies

While the results align with current development trends, several limitations must be acknowledged. First, relying on publicly available provincial data may overlook intra-provincial disparities. Second, the expert panel approach and the use of fuzzy numbers introduce some subjectivity and uncertainty into the evaluation process. Third, the unique context of the COVID-19 pandemic may affect the applicability of these findings to future non-pandemic scenarios. Moreover, there are several key areas that could be explored in future research. Firstly, it is important to acknowledge that our examination of China's provinces may not have adequately accounted for the diverse regional and cultural variations, thereby limiting the generalizability of our findings. Additionally, the utilization of fuzzy numbers in our methodology may introduce uncertainties in the evaluation process. Lastly, it is worth noting that our study primarily relied on publicly available data, potentially overlooking certain intra-provincial nuances.

Furthermore, our current indicator selection primarily captures the capacity, scale, and structural inputs of circular economy and eco-innovation frameworks at the provincial level. A limitation of this approach is that it does not directly incorporate variables reflecting pure resource output rates or carbon emission intensity. Future research should integrate these efficiency-based metrics to balance the scale-heavy focus of the current model. While cross-algorithmic stability is validated here, more complex sensitivity tests represent the next logical step in refining this macro-framework and have been framed as essential objectives for upcoming methodological papers. Additionally, a key limitation of this study is its cross-sectional design, which focuses primarily on cumulative baseline performance over the target period. While this approach effectively highlights major regional disparities across China's provinces, it does not explicitly capture the year-over-year dynamic trajectories or long-term longitudinal trends of circular transition paths. Future research should look to integrate multi-period dynamic decision-making indices or time-series forecasting models to complement this static assessment and track how provincial performance evolves. Another limitation of this research stems from the chosen temporal boundary (2010–2021). Because our quantitative data streams rely on consolidated historical entries, our current empirical scores do not capture major macro-level green policy adjustments enacted after that period. Consequently, while our model provides a highly stable historical baseline of provincial capacity, it serves as a static cross-sectional diagnostic and cannot adapt instantly to real-time policy updates. To address this temporal boundary, future research must prioritize integrating dynamic time-series metrics or post-2021 data streams to assess how these foundational rankings shift in response to newly implemented regional regulations.

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Institutional Review Board Statement: Ethical review and approval were waived for this study by the Medical Ethics Committee Constitution of Shenzhen University as per <https://sugh.szu.edu.cn/Html/News/Articles/2939.html> (accessed on 20 December 2025). According to Article 4 of this document, the ethics committee explicitly limits its scope of review to: “Human biomedical research projects undertaken and implemented by the hospital,” including drug trials, medical devices, assisted reproductive technology, human-subject research projects, new medical technologies, and other similar cases requiring ethical review. Our study uses expert judgment in a multi-criteria

decision-making context within the field of management/economics. It does not involve clinical interventions, biomedical procedures, or sensitive personal data. Therefore, it falls outside the mandatory review scope defined by SZU's institutional guidelines.

Informed Consent Statement: All participants were informed about the purpose of the study, and their participation was voluntary. Informed consent was obtained from all participants prior to their involvement.

Data Availability Statement: The entry data utilized in this study are accessible at the National Bureau of Statistics of China on <https://data.stats.gov.cn/dg/website/page.html#/pc/national/en/home> (accessed on 20 December 2025).

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. GDP, population, CO₂ emission and electricity consumption of the case study [16].

Region	Province	GDP (USD)		Population (10 ⁴)		CO ₂ Per Capita (Ton)		Electricity (10 ⁸ kW.h)	Consumption
North	Beijing	36,102	121,404	2189	16,933	13,214	274,862	1140	12,191
	Tianjin	14,083		1387		18,314		875	
	Hebei	36,206		7464		94,739		3934	
	Shanxi	17,651		3490		60,741		2342	
	Inner Mongolia	17,359		2403		87,854		3900	
Northeast	Liaoning	25,114	51,124	4255	9825	63,175	116,095	2423	4242
	Jilin	12,311		2399		23,003		805	
	Heilongjiang	13,698		3171		29,917		1014	
East	Shanghai	38,700	387,437	2488	42,383	24,399	392,497	1576	26,258
	Jiangsu	102,718		8477		90,763		6374	
	Zhejiang	64,613		6468		49,169		4830	
	Anhui	38,680		6105		50,823		2428	
	Fujian	43,903		4161		32,866		2483	
	Jiangxi	25,691		4519		29,493		1627	
	Shandong	73,129		10,165		114,984		6940	
Central and Southern	Henan	54,997	278,672	9941	40,986	57,279	234,365	3392	16,420
	Hubei	43,443		5745		35,047		2144	
	Hunan	41,781		6645		34,374		1929	
	Guangdong	110,760		12,624		73,874		6926	
	Guangxi	22,156		5019		28,536		2029	
	Hainan	5532		1012		5255		363	
Southwest	Chongqing	25,002	117,852	3209	20,526	18,816	109,933	1186	7744
	Sichuan	48,598		8371		32,359		2865	
	Guizhou	17,826		3858		32,522		1586	
	Yunnan	24,521		4722		25,302		2025	
	Tibet	1902		366		934		82	
Northwest	Shaanxi	26,181	55,922	3955	10,360	35,616	145,312	1741	7996
	Gansu	9016		2501		21,092		1376	
	Qinghai	3005		593		7663		742	
	Ningxia	3920		721		24,262		1038	
	Xinjiang	13,797		2590		56,679		3099	

Table A2. The normalized decision matrix.

Province	C1	C2	C3	C4	C5	C6	C7	C8	C9
Beijing	0.553	0.4677	0.5876	1	0.0167	0	0.0674	0.108	0.0828
Tianjin	0.1429	0.4597	0.9969	1	0.0265	0.0168	0.1267	0.0866	0.0556
Hebei	0.4608	0.2097	0.5457	1	0.251	0.4841	0.6107	0.1965	0.0885
Shanxi	0.3733	0.0645	0.4049	1	0.1999	0.3232	0.6395	0.0642	0.0298
Inner Mongolia	0.2166	0.0484	0.3352	0.9989	0.8693	1	1	0.0533	0.0226
Liaoning	0.3871	0.129	0.4956	0.9983	0.3173	0.2437	0.2795	0.1266	0.059
Jilin	0.2765	0.121	0.5255	1	0.1036	0.1398	0.158	0.0296	0.0233
Heilongjiang	0.3134	0.121	0.434	1	0.3443	0.1727	0.1672	0.0306	0.0196
Shanghai	0.6267	0.8226	0.9392	1	0.2915	0.0204	0.1301	0.2406	0.1215
Jiangsu	0.6452	0.4274	0.9463	1	0.2581	0.29	0.8511	0.9361	0.6082
Zhejiang	0.4931	0.3871	1	1	0.4612	0.0455	0.5004	0.5484	0.4691
Anhui	0.3272	0.1935	0.937	1	0.4343	0.0672	0.5363	0.2547	0.2202
Fujian	0.3318	0.2984	0.8384	1	0.3163	0.1657	0.2747	0.2659	0.1512
Jiangxi	0.2719	0.0968	0.4843	1	0.2293	0.0707	0.2507	0.1371	0.0949
Shandong	0.7281	0.2823	0.7937	1	0.9903	0.2741	0.9283	0.5394	0.288
Henan	0.7465	0.2661	0.7846	1	0.1971	0.1115	0.4818	0.2633	0.1331
Hubei	0.424	0.2016	0.6698	1	0.3639	0.1085	0.2741	0.2493	0.1608
Hunan	0.4332	0.2177	0.7809	1	0.2774	0.1307	0.159	0.264	0.119
Guangdong	1	1	0.8415	1	1	0.1267	0.6695	1	1
Guangxi	0.3272	0.0968	0.4577	1	0.3142	0.1286	0.1894	0.0472	0.0341
Hainan	0.235	0.0484	0.6702	1	0.0291	0.0083	0.0405	0.0049	0.0047
Chongqing	0.1751	0.0726	0.8311	0.9663	0.0543	0.0194	0.0939	0.1463	0.0652
Sichuan	0.4977	0.3145	0.4261	1	0.2128	0.1134	0.1163	0.1655	0.1209
Guizhou	0.235	0.1371	0.7174	0.9901	0.257	0.1289	0.2819	0.0417	0.0246
Yunnan	0.3226	0.1452	0.5153	1	0.1878	0.3313	0.1142	0.0608	0.0278
Tibet	0.0323	0.0242	0.0891	0.9971	0	0	0.0115	0.0009	0.0003
Shaanxi	0.424	0.121	0.4952	1	0.1692	0.1224	0.441	0.1102	0.0478
Gansu	0.2258	0.0726	0.4775	1	0.1413	0.3635	0.3096	0.0222	0.0136
Qinghai	0.0461	0.0242	0.5319	0.9942	0.0311	0.093	0.2102	0.0048	0.004
Ningxia	0.0691	0.0081	0.4525	1	0.1717	0.258	0.4156	0.0178	0.0115
Xinjiang	0.3041	0.0565	0.4187	1	0.2914	0.6638	0.7198	0.0187	0.0152

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