ingegneria sismica
International Journal of Earthquake Engineering
Anno XLIII - Num. 2 - 2026

Construction and Comprehensive Evaluation of Green and Low-Carbon Consumption Indicator System in the Context of "Double Carbon" Goal

Huihui Tian[1,*]

[1] Department of Economics and Management, Taiyuan Institute of Technology, Taiyuan, Shanxi, 038000, China

SUMMARY: *Against the backdrop of the "dual carbon" goals, practicing green and low-carbon consumption has become a crucial component of national strategic objectives. However, the exploration of its implementation still faces a series of new challenges and issues.For the purpose of executing an unbiased and all-round quantitative evaluation of green low-carbon consumption, this research has constructed an index system that is prepared for environment-friendly low-carbon consumption. After that, this research uses the fuzzy analytic hierarchy process, which is called AHP, to build the weights of these indices.Furthermore, the spatial autocorrelation analysis is utilized by us to measure the spatial mutual connection of eco-friendly and low-carbon consumption, revealing its spatial distribution patterns and regional disparities. Spatial econometric models are then utilized to explore the factors influencing green and low-carbon consumption. The regression coefficients for technological innovation and talent introduction reached 0.015 and 0.162 respectively, demonstrating significant positive spatial spillover effects at the 1% confidence level. Conversely, the regression coefficients for industrial structure and urbanization level were both negative, tutting forward a restraining function for the promotion of environment-protective and low-carbon consumption degrees.*

KEYWORDS: *Fuzzy Analytic Hierarchy Process; Spatial Autocorrelation Model; Spatial Econometric Model; Green and Low-Carbon Consumption*

1 Introduction

One after another, high-level design papers about carbon peaking and carbon neutrality have been issued out. These files clearly point out that controlling carbon emissions which come from family consumption is a key component in reaching the "dual carbon" goals.These written materials put forward that we should increase the supply and use of ecological protection, low-carbon goods. They also give encouragement to the accepting of eco-friendly, low-carbon life styles and thus push forward a whole-nation green movement, low-carbon actions [1-3]. It is obvious that the consumption which is oriented by environmental protection and low carbon constitutes a key path that China uses to push forward energy saving and emission cutting, and also to reach its "dual carbon" goals. Furthermore, it plays an important function in promoting the transformation and promotion of consumption and achieving the high-quality development.

Global warming has become a severe challenge, with frequent extreme weather events, melting glaciers, and rising sea levels posing serious threats to the human living environment. Green and low-carbon consumption behaviors—such as choosing energy-efficient appliances, using public transportation, and reducing single-use plastics—can effectively reduce

*tianhuihui0810@126.com
https://doi.org/10.65102/is2026582
Published: 30 April, 2026

greenhouse gas emissions and serve as crucial measures to mitigate climate change [4-7]. Furthermore, green and low-carbon consumption advocates resource conservation, promotes the use of resource-efficient tools, enhances resource utilization efficiency, reduces consumption of high-energy-consuming and high-polluting products, and simultaneously encourages resource recycling and reuse. This contributes to advancing resource circularity and sustainable development [8-11]. Furthermore, the promotion of environmental friendliness and low-carbon consumption patterns will hence push forward the development of related green industries. This scope contains many aspects, from the research, innovation, making of new-energy vehicles to the exploration and development of sustainable energy resources. It moreover contains the building of ecology-aware constructions and the making and selling of environment-friendly goods. These economic branches therefore will bring into being extensive industrial groupings.This will create new employment opportunities, contribute to the optimization and upgrading of economic structures, and enhance national economic competitiveness [12-16].

The green consumption philosophy holds that consumers bear environmental responsibilities. It discourages the use of products that negatively impact the environment during production, use, or disposal, urging consumers to engage in consumption activities that satisfy personal needs while minimizing natural resource depletion [17-19]. Promoting the enhancement of evaluation methods for environment-protective low-carbon consumption is an important tool for pushing forward the sustainable development. For letting every region find methods that fit their own situation, very many countries have started low-carbon city experiment projects. China has step by step built 81 this kind of experiment cities, and 95% of these cities have finished very big cuts to carbon intensity. [20, 21]. Therefore, the Evaluation Report about the Advancement of the State Low-Carbon City Pilot Plan puts forward the proposal of perfecting organization systems. These structures include rules, policies, standards, and evaluation indexes, and the promotion must be conducted in line with the features of regional development.Therefore, establishing a comprehensive evaluation system covering all aspects of green consumption in residential life holds significant importance.

Green and low-carbon consumption behavior includes two aspects: reducing carbon sources and increasing carbon sinks. This document places stress on cultivating green life styles, and explicitly indicates that controlling energy consumption and carbon discharge in the consumption course is of key importance for addressing non-sustainable consumption from the perspective of carbon discharge [22 - 24]. Therefore, Reference has put forward methods for the low-carbon conversion of family consumption patterns. These aspects include strengthening residents' consciousness on low-carbon consumption, establishing and completing supervision systems, and prompting enterprises to carry out low-carbon production for reducing the harm to the ecological environment.Realizing the transformation of residents toward green and low-carbon consumption is a key component for reaching the "dual carbon" goals.

For measuring the development degree of green and low-carbon consumption, one must establish an appraisal indicator system which is based on its basic principles.The existing research body which is about indicator systems for green and low-carbon consumption is still rather insufficient. By comparison, a great number of studies have put attention on connected notions like environment-protective consumption, carbon-cutting consumption, and consumption for environmental-friendly sustainable development.Literature [26] observes that current green consumption is primarily driven by developed nations centered around the United States and developing nations led by China, exhibiting rapid overall growth. Reference [27] employs text mining to analyze the subjects covered by 308 Chinese green consumption policies, establishing a policy consistency evaluation framework. We use the Policy Modeling Consistency (PMC) index model to carry out the evaluation on policy coherence. This research makes known that China's green consumption policies put emphasis on advocating environment-protective products and promoting energy use efficiency. By comparison, green service items and cyclic utilization programs have been given relatively fewer attentions from people. Reference [28] developed a three-tiered indicator system for China's green consumption development. Under the Analytic Hierarchy Process (AHP), indicator weights were calculated, followed by fuzzy comprehensive evaluation-based scoring and comparison. The study revealed that China's green consumption development most significantly impacts high-tech enterprise revenue generation and local government environmental expenditure across multiple provinces. Reference [29] employed four primary indicators—environment, energy, economy, and health—along with eight sub-indicators: and eight sub-indicators: population density, carbon dioxide emissions, the total sum of natural resource income, electric power produced by renewable energy sources, the value added by the farming, forestry, and fishing industries, every person's gross domestic product, population birth rate, and population death rate. Using the ideal solution similarity ranking method, it evaluated the sustainable consumption status of green growth in 10 countries, highlighting the critical roles of added value in agriculture-forestry-fisheries industries and GDP per capita in development. Literature [30] used the regression discontinuity method to assess the effect of the social media-broadcast “Guiding Opinions for Promoting Green Consumption” policy on residents’ willing degree for green consumption. The carrying out of this policy has caused a rise in the desire of residents to take part in consumption that is friendly to the ecology, which acts as an indicator that points to sustainable development. Four different consumption fields, that is to say eating, moving, living, and goods for using, have gotten more obvious influences.Reference [31] designed evaluation indicators for China's green energy consumption revolution across economic, social, energy, and environmental dimensions. Using entropy-weighted approximation to ideal solution ranking to compute and analyze these indices, it revealed nationwide stagnation and regression in green energy consumption, with regional disparities observed. Reference [32] proposed a comprehensive metric for measuring green consumption behavior, focusing on three dimensions: health, resources, and society. This metric was validated through multiple regression analysis.

One [33] thorough and well-arranged evaluation method for low-carbon energy utilization in country areas of China has been formulated by Reference. This approach addresses the limitations of traditional evaluation methods, such as insufficient exploration of relevance, poor applicability, and limited policy coordination. It demonstrates strong adaptability to scenarios with scarce baseline data and incomplete consumption statistics. Reference [34] developed a comprehensive evaluation index for low-carbon energy consumption performance in the Yangtze River Delta region from economic, energy, and environmental perspectives, employing the Approximation to Ideal Solution Ranking Method and the Full-Aligned Polygon Graphical Indicator Method for assessment. Reference [35] conducted data mining, measurement modeling, and evaluation index system construction for sustainable consumption research within a big data context, exploring pollution and carbon emissions issues during the product life cycle of cities and enterprises. Reference [36] assessed products' entire lifecycles using life cycle assessment across five consumption domains—food, transportation, housing, household goods, and appliances—from a consumer footprint perspective, exploring environmental impacts of sustainable production and consumption. One sustainability [37] assessment index which centers on the ecological energy footprint for the consumption of Chinese city inhabitants has been proposed by Reference. The research result points out that in regions with developed economy there exist quite big differences in ecological aspect. These areas include the Beijing-Tianjin-Hebei region, the Yangtze River Delta region, and the Pearl River Delta region.

In this research work, an indicator system for environment-friendly and low-carbon consumption has been constructed. For reaching this target, measuring indicators are firstly selected from four different domains: low-carbon city traffic, low-carbon family consume, use of public establishments, and low-carbon business consume.Each primary indicator encompasses ten secondary indicators, including urban public transportation systems and social low-carbon transportation consumption. The blurry hierarchical method is employed to assign weight values to the indexes at each level inside the green and low-carbon consumption index framework. After this developed indicator framework is integrated, a comprehensive assessment on China’s green low-carbon consumption level has been carried out. Employing spatial autocorrelation analysis models, global and local Moran's I indices are calculated to measure China's spatial agglomeration levels of green low-carbon consumption and explore its spatiotemporal evolution characteristics. By the utilization of spatial econometric models, the determining factors of green low-carbon consumption levels are being accurately located out. After that, the spatial autoregression coefficients which belong to every determinant are gotten through calculation. Then we carry out a spatial econometric regression analysis upon these determinant factors. At last, according to the results got from this research, policy advices are put forward by us for pushing environmental protection and low-carbon consumption.

2 Study Design

2.1 Research Background

Addressing climate change and promoting green, low-carbon consumption development represent a global trend and historical imperative. To encourage localities to explore green, low-carbon development pathways tailored to their specific conditions, China issued the Guidelines for Establishing a Carbon Peaking and Carbon Neutrality Standards System in April 2023. This article puts forward the construction of a completely completed standards system for reaching carbon peaking and carbon neutrality (hereafter called “dual carbon”). It puts focus on doing basic preparation through foundational general norms, and satisfying the demands that rise from the growth of carbon-reduction work, carbon removal, and carbon markets. China's consumer behavior is currently undergoing a pivotal transformation in consumption patterns.Quite obvious progress has been achieved in environment-protective low-carbon consumption styles, thus our country has made beginning steps in its whole green low-carbon transformation. Under the background of the “double carbon” goals, enhancing the evaluation standards for green low-carbon consumption is a key method to push forward continuous development. Embracing green and low-carbon consumption has become an integral part of national strategic objectives. However, both practical exploration and theoretical research face a series of new challenges and emerging issues.

2.2 Research Objectives

Under the background of China’s double carbon goals, this research paper has the objective to build a more overall and usable evaluation system for environmental protection and low-carbon consumption. This framework shall be built upon the basic tenets of green and low-carbon consumption. The weight values of key indicators inside this framework will be given the determination. Through using spatial autocorrelation and spatial econometric methods, this article evaluates the current condition of green and low-carbon consumption in China. According to this assessment, therefore, it puts forward concrete strategies and suggestions for the promotion of the development of green low-carbon consumption.

2.3 Data Sources

The data which this research needs are got from yearbooks, reports, and other publications which are issued by already-established authoritative organizations. The main origin of data include the below: China's Statistical Yearbook, which is published by the National Bureau of Statistics of the People's Republic of China; the Chinese Energy Statistics Yearbook, which is together compiled by the National Bureau of Statistics of People's Republic of China and the Ministry of Ecology and Environment; and the government-intersected official websites of the Intergovernmental Panel on Climate Change (IPCC) and the International Energy Agency (IEA), Besides, data which come from the National Bureau of Statistics of China have been utilized by this study. Because there is not any related statistical data that can be obtained for Tibet, therefore it is got rid of from this analysis. This research only concentrates on evaluating the degrees of green and low-carbon consumption development among 30 provinces, municipalities directly under central government, and autonomous regions in China.

2.4 Research Methods

2.4.1 Fuzzy Analytic Hierarchy Process

Fuzzy Hierarchical Analysis Process (FHAP) is a fuzzy extension method proposed based on the traditional Analytic Hierarchy Process (AHP). The basic core idea is that triangular fuzzy numbers are used by us to replace the 1–9 scale that the traditional Analytic Hierarchy Process (AHP) uses. Through this method, one fuzzy judgment matrix may be built up, which effective handles the fuzziness and uncertainty that exist in the process of assessing the importance degree of indexes.[38].The basic difference between the fuzzy judgment matrix and the traditional judgment matrix lies in that the former gives a fuzzy judgment scope to every index. This interval expresses a concrete grade of expert judgment results and, to some degree, can be considered as the “confidence interval” in mathematical statistics.A bigger time gap shows a lower degree of belief, hence a smaller gap indicates a higher degree of belief. The FAHP method puts the idea of confidence into the Analytic Hierarchy Process. This method enables us to carry out a quantitative evaluation of the whole characteristics of site-choice places and also to show how the uncertainty of information influences the outcomes of judgment.

The triangular fuzzy number $\tilde{M}$ can be represented by a triplet (l,m,u), and its membership function $\mu_M(x)$ can be expressed as:

$$\mu_M(x)=\begin{cases}\dfrac{x-l}{m-l}, & x\in[l,m]\\ \dfrac{x-u}{m-u}, & x\in[m,u]\\ 0, & x\in(-\infty,l)\cup(u,+\infty)\end{cases} \tag{1}$$

In the formula, $l\le m\le u, x\in R, \mu_{\tilde{M}}(x): x\to[0,1]$, l, and u represent the upper and lower bounds of $\tilde{M}$, respectively, while m denotes the median of $\tilde{M}$. Generally, the triangular fuzzy number $\tilde{M}$ can be expressed as (l,m,u).

The fuzzy analytic hierarchy process which depends on triangular fuzzy numbers usually includes the following steps:

1) Establish the site selection evaluation indicator system

The structural model of AHP is commonly made up of three layers in hierarchy. The topmost layer, which people frequently call the goal level, it contains only one single element. In common cases, this element represents the pre-established goal of the object which is being analyzed. The middle layer, which is also named the normal rank, includes the middle steps which are required to reach the target or perfect condition. This contains standards and sub-standards that must be considered, hence it may be formed of many sub-layers. The most low layer, sometimes called the measure level or the scheme level, contains many different targets or schemes which can be utilized to reach the target or ideal. The level-shaped framework which is built by the top-to-bottom control connections inside the structure model is named as a "recursive level framework."

2) Calculate indicator weights

(1) Constructing a triangular fuzzy judgment matrix

Invite several domain experts to conduct pairwise comparative evaluations of factors at the criterion level and solution level based on a predetermined hierarchical structure. In the process of assessment work, professional personnel are required not only to confirm the comparative importance of one element relative to another but also to consider the fuzziness and unpredictability which are inherent to their appraisals. To this end, the triangular fuzzy number (l, m, u) is used to quantitatively represent the results of experts' comparative judgments regarding the importance of two indicators, where l and u denote the degree of fuzziness in the judgment. The importance of indicator j relative to indicator i is represented by the triangular fuzzy number a_{ij}^{-1}. After providing $[n(n-l)/2]$ fuzzy judgments, a fuzzy judgment matrix $A=(a_{ij})_{n\times n}$ composed of triangular fuzzy numbers is obtained, where $a_{ij}=(l_{ij}, m_{ij}, u_{ij})$, and a_{ij} is a closed interval with m_{ij} as its median.

(2) Consistency Test for the Median Matrix M

Since experts may exhibit logical inconsistencies when pairwise comparing the importance of factors, the logical consistency of the judgment matrix must be verified. In fuzzy AHP, the middle values of the fuzzy judgment matrix are typically approximated as a standard judgment matrix from traditional AHP. The consistency index (CI) is then calculated by determining its maximum eigenvalue $\lambda_{\max}$. After that, the Consistency Index (CI) is put into comparison with the average random consistency index (RI) of the corresponding order to compute the consistency ratio (CR). The consistency proportion is defined as the division result that CI is divided by RI, that is, CR = CI/RI. When the numerical value of CR is smaller than 0.10, therefore the judgment matrix is by people regarded as possessing an acceptable degree of consistency. This therefore indicates that the judgments which are done by experts show a high level of whole logical consistency. If the value exceeds this threshold, the expert ratings should be re-examined and the judgment content adjusted to enhance the model's reliability.

The value of the median m is determined based on the AHP 1–9 scale method. The lower bound l and upper bound l of the triangular fuzzy number can be determined according to the degree of fuzziness: the larger $(u-l)$ is, the more ambiguous the judgment; the smaller $(u-l)$ is, the clearer the judgment. When $u-l=0$, the judgment is non-fuzzy, and at this point $l=m=u$, it is identical to the judgment scale value in the general sense.

After obtaining the median matrix (i.e., M) of the fuzzy judgment matrix, the CI value is calculated using Equation (2):

$$CI=\frac{\lambda_{\max}-n}{n-1} \tag{2}$$

In the formula:

$\lambda_{\max}$ — The maximum eigenvalue of the median matrix M. Consult the RI table for the corresponding order to obtain the RI value,

then calculate CR = CIRI. If CR < 0.1, the consistency test passes.

(3) Construct the matrix which is used for fuzzy evaluation factors E.

$$E=(e_{ij})_{n\times n}=\begin{bmatrix} 1 & 1-\frac{u_{12}-l_{12}}{2m_{12}} & \cdots & 1-\frac{u_{1n}-l_{1n}}{2m_{1n}} \\ 1-\frac{u_{21}-l_{21}}{2m_{21}} & 1 & \cdots & 1-\frac{u_{2n}-l_{2n}}{2m_{2n}} \\ \vdots & \vdots & \ddots & \vdots \\ 1-\frac{u_{n1}-l_{n1}}{2m_{n1}} & 1-\frac{u_{n2}-l_{n2}}{2m_{n2}} & \cdots & 1 \end{bmatrix} \tag{3}$$

In the formula:

$e_{ij}=\frac{u_{ij}-l_{ij}}{2m_{ij}}$ — Standard deviation rate, representing the degree of uncertainty in expert evaluations. The larger the value of e_{ij}, the more high the uncertainty level in assessment work, the more low the reliability degree; the smaller the value of e_i, the lesser the uncertainty in the evaluation and the higher the reliability.

(4) Calculate the adjusted judgment matrix Q

$$Q=M\times E=\begin{bmatrix} m_{11} & m_{12} & \cdots & m_{1n} \\ m_{21} & m_{22} & \cdots & m_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ m_{n1} & m_{n2} & \cdots & m_{nn} \end{bmatrix} \times\begin{bmatrix} 1 & 1-\frac{u_{12}-l_{12}}{2m_{12}} & \cdots & 1-\frac{u_{1n}-l_{1n}}{2m_{1n}} \\ 1-\frac{u_{21}-l_{21}}{2m_{21}} & 1 & \cdots & 1-\frac{u_{2n}-l_{2n}}{2m_{2n}} \\ \vdots & \vdots & \ddots & \vdots \\ 1-\frac{u_{n1}-l_{n1}}{2m_{n1}} & 1-\frac{u_{n2}-l_{n2}}{2m_{n2}} & \cdots & 1 \end{bmatrix} \tag{4}$$

(5) Adjust the judgment matrix Q by column-wise transformation to obtain the judgment matrix Q' with a diagonal of 1.

(6) Calculate the weights of each indicator using the square root method to compute the fuzzy judgment matrix A by taking the nth root of all elements in each row:

$$\bar{\omega}_i = \left(\prod_{j=1}^{n} a_{ij} \right)^{\frac{1}{n}}, i = 1, 2, \cdots, n \tag{5}$$

In the formula:

$\bar{\omega}_i$ - The nth root of all elements in row i of the fuzzy judgment matrix A.

Normalize to $\bar{\omega}_i$:

$$\omega_i = \frac{\bar{\omega}_i}{\sum_{i=1}^{n} \bar{\omega}_i}, i = 1, 2, \cdots, n \tag{6}$$

In the formula:

ω_i — Weight value of the ind indicator.

Final weight:

$$W = [\omega_1, \omega_2, \cdots, \omega_n] \tag{7}$$

(7) Calculate the weights for each indicator at each level

Perform weight calculations and ranking analysis for indicators at each level. This step comprises two phases: At the first step, carry out a one-layer ranking for each judgment matrix. This procedure is conducted by us for the calculation of the local weight numerical values of every element. These numerical values reflect the connection of every element to the elements which come from the prior level in the identical tier. Then, propagate weights top-down through the hierarchical structure to perform a comprehensive ranking, ultimately yielding the overall weights of each alternative at the lowest level relative to the target level.

2.4.2 Spatial Autocorrelation Models

This research study uses spatial autocorrelation analysis methods, that is global and local spatial autocorrelation analyses. The spatial autocorrelation analysis carries on the quantitative evaluation to the spatial connection of the green low-carbon consumption. By means of this, it discovers the spatial distributing rules and district differences of green low-carbon consumption behaviors. The whole world space self-correlation is calculated by utilizing the whole world Moran's I exponent, and its formula is given as [39]:

$$I = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij} \sum_{i=1}^{n} (x_i - \bar{x})^2} \tag{8}$$

Among them, n represents the number of research units (county-level regions); W_{ij} is the spatial weight matrix, representing the spatial adjacency relationship between units i and j. Units x_i and x_j represent the carbon emission intensities of the i th and j th units respectively. $\bar{x}$ represents the average carbon emission intensity of all units. The value range of Moran's I is [-1, 1]: When $I > 0$, it indicates that the carbon emission intensity has a positive correlation in space (that is, similar values cluster in space); When $I<0$, it indicates a negative correlation in space (i.e., the aggregation of different values). When $I=0$, it indicates a random distribution.

For carrying out deeper discussion on spatial heterogeneity and accurately finding out spatially related rules in specific regions, this research adopts local spatial autocorrelation analysis. The partial space self-related index is utilized by people to assess the space connection of green low-carbon consume inside each area. The computation of this index is in the following way:

$$I_i = \frac{n(x_i-\overline{x})\sum_{j=1}^{n} W_{ij}(x_j-\overline{x})}{\sum_{i=1}^{n}(x_i-\overline{x})^2} \tag{9}$$

Among these, I_i represents the local spatial autocorrelation coefficient for the i unit. When $I_i>0$, it indicates positive spatial correlation in the surrounding area, encompassing both “high-to-high” and “low-to-low” clustering patterns. When $I_i<0$, this result points out a negative space connection, which includes the “high to low” and “low to high” gathering arrangement forms. This mirror gives out obvious differences in the strength of green low-carbon consumption among areas which are next to each other.

2.4.3 Spatial Measurement Model

The economic increase of one specific region does not take place by itself; On the contrary, it is influenced by the development of adjacent regions.Spatial econometric models incorporate spatial interactions into traditional regression models, not only resolving the error issues inherent in traditional models when handling spatial data but also providing a theoretical foundation and technical support for quantifying spatial effects and spatial linkages. Based on this, this paper establishes a spatial econometric model using basic panel data, considering the role of spatial correlation to measure the factors influencing economic development. Space economic metric models mainly include Spatial Autoregressive Models (SAR), which are also called Spatial Lag Models (SLM), Spatial Autoregressive Error Models (SAEM), which people usually name as Spatial Error Models (SEM), and Spatial Durbin Models (SDM) [40, 41].

1) Spatial Lag Model:

$$y=\rho W_y + X\beta + \varepsilon \tag{10}$$

Among them, y is the dependent variable of $n\times 1$, ρ is the spatial autoregressive coefficient to be estimated, W is the spatial weight matrix of $n\times n$, X is the independent variable of $n\times k$, β is the coefficient of the independent variable to be estimated of $k\times 1$, and ε is the error term of $n\times 1$.

2) Spatial error model:

$$\begin{cases} y = X\beta + \varepsilon \\ \varepsilon = \lambda W\varepsilon + v \end{cases} \tag{11}$$

Among these, λ represents the spatial autoregressive coefficient, and v denotes the error term of the exogenous variable.

3) Spatial Durbin Model

$$y = \rho W_y + X\beta + WX\theta + \varepsilon \tag{12}$$

Among these, θ represents the estimated lagged coefficient of the independent variable space for $k \times 1$.

3 Establishing a Green and Low-Carbon Consumption Indicator System

For carrying out a reasonable evaluation upon green low-carbon consumption degrees in different areas, hence it is necessary to construct an overall and academic system for measuring their total advancement. This frame, which is called a green and low-carbon consumption index system, needs to be built on the clear understanding of the core of a low-carbon economy.In the present chapter, one indicator system shall be constructed through following the principles of scientific accuracy, impartiality, systematic property, comprehensiveness, truthfulness, and comparability. The fuzzy analytic hierarchy process (AHP) is going to be utilized by us for the purpose of assigning weights to the indicators.

3.1 Establishment of the Indicator System

This present research work has designed a green low-carbon consumption target index system. This paper chooses measurement targets from four big aspects: city low-carbon traffic, family low-carbon consume, public facility use, and enterprise low-carbon consume. Table 1 gives detailed description of the concrete index system which is for green and low-carbon consumption.

1) Index System for Appraisement of City Low-Carbon Traffic Transportation. These mainly measure the development condition of city underground railways (track traffic). When the subway system gets more progress, a bigger quantity of people have the tendency to choose green and low-carbon travel choices. Building a convenient and effective public traffic net is an indispensable key component in the development of green and low-carbon consumption.

2) Low-Carbon Household Consumption Evaluation Indicators. As economies develop and living standards rise, household energy consumption will continue to expand. Therefore, building low-carbon households forms the foundation and building blocks of green low-carbon consumption. This study places significant emphasis on evaluating indicators for low-carbon households.

3) Assessment Norms for Business Low-Carbon Usage. Business type low-carbon consumption is the most direct expression that green and low-carbon consumption shows. In current cities, with economy development and living standard raise, business actions and consumption have increased both in size and range. Therefore, putting focus on business low-carbon consumption is the most direct measurement for pushing forward green and low-carbon consumption. Therefore, this thing is included in the indicator research system of the present paper.

4) Indexes for Evaluating Public Use Utility Expenditure. The consumption of public utilities constitutes the fundamental domain of green low-carbon consumption. The low-carbon advancement of public service domains includes many different aspects. This this encompasses the supply of important society resources, for example city electric power, water, and gas. It

also includes the low-carbon transformation of public establishment, for instance, city illumination and the green plants in constructed zones. Furthermore, it contains public joining into energy-saving and carbon-reduction undertakings, and the modern low-carbon logistics, for example the reutilization of abandoned domestic electric appliances and automobiles, is both the basic foundation and the newly arising front-edge region for evaluating green and low-carbon consumption.

Table 1: Green low-carbon consumption index system

Index system	First level indicators	Secondary indicators
Green low-carbon consumption index system	Low-carbon urban transportation	Urban public transport system
		The society uses the low-carbon transportation
	Sustainable family consumption behaviors under the background of low-carbon life	Evaluation on families with low carbon discharge
		Evaluation of household consumption
	Low-carbon consumption of commercial activities	Low-carbon hotel evaluation
		Evaluation of low carbon shopping malls
		Low-carbon evaluation of catering industry
	Low-carbon consumption of public utilities	Evaluation of urban resource supply and consumption
		Evaluation of low-carbon public facilities
		Urban low-carbon logistics

3.2 Determination of Indicator Weights

We have used the fuzzy hierarchical selection method to give weights to the indicators on each level inside the green low-carbon consumption index framework. The concrete weighting results are given in Table 2. Regarding the main indices, when we arrange them from the biggest weight to the smallest weight, the sequence is like this: Low-Carbon Consumption in Public Utilities (0.3763) is bigger than Low-Carbon Transportation in Urban Regions (0.2909), which is bigger than Low-Carbon Consumption in Commercial Behaviors (0.2063), and this is bigger than Low-Carbon Consumption in Families (0.1265). Among the secondary indicators, the sub-indicator “Urban Resource Supply and Consumption Evaluation” under Public Utilities Low-Carbon Consumption received the highest weight of 0.7821. The secondary indicators under Urban Low-Carbon Transportation and Household Low-Carbon Consumption were assigned relatively balanced weights, both close to 0.5.

Table 2: Weighting results based on FAHP

First - grade indices	Weight	Secondary indicators	Weight
Low-carbon urban transportation	0.2909	Urban public transport system	0.4962
		Social low-carbon transport consumption	0.5038
Family low-carbon consumption	0.1265	Low carbon family evaluation	0.4458
		Evaluation of household consumption	0.5542
Low-carbon consumption of commercial activities	0.2063	Low-carbon hotel evaluation	0.2829
		Evaluation of low carbon shopping malls	0.4542
		Low-carbon evaluation of catering industry	0.2629
Low-carbon consumption of public utilities	0.3763	Evaluation of urban resource supply and consumption	0.7821
		Evaluation of low-carbon public facilities	0.1654
		Urban low-carbon logistics	0.0525

4 Evaluation and Analysis of China's Green and Low-Carbon Consumption Levels

In the foregoing part, this research article has constructed an index system for environment-friendly and low-carbon consumption. Through the integration of the already determined index weights with the pre-processed numerical values of each individual index, this chapter will employ a linear weighted synthesis method to calculate the green and low-carbon consumption level indices for each region, along with their respective sub-indices. This approach will first provide a comprehensive evaluation of China's green and low-carbon consumption level.

4.1 Comprehensive Evaluation Analysis

The 30 provinces and regions of China are numbered from A1 to A30, with the corresponding codes shown in Table 3.

Table 3: Number the provincial areas.

Provincial regions	Numbering	Provincial regions	Numbering
Beijing	A1	Liaoning	A16
Guangdong	A2	Anhui	A17
Shanghai	A3	Jilin	A18
Zhejiang	A4	Henan	A19
Jiangsu	A5	Shaanxi	A20
Fujian	A6	Heilongjiang	A21
Tianjin	A7	Yunnan	A22
Jiangxi	A8	Hebei	A23
Guangxi	A9	Qinghai	A24
Hainan	A10	Inner Mongolia	A25
Hunan	A11	Gansu	A26
Shandong	A12	Xinjiang	A27
Chongqing	A13	Shanxi	A28
Sichuan	A14	Ningxia	A29
Hubei	A15	Guizhou	A30

When employing the fuzzy AHP method, the assigned weights carry a degree of subjectivity due to research limitations. Considering this, this paper utilizes indices such as urban low-carbon transportation, household low-carbon consumption, public utility consumption, and low-carbon commercial consumption for cluster analysis. The resulting cluster tree diagram is shown in Figure 1. According to what the diagram shows, the data has been completely divided into three big kinds, that is, the low-carbon zone, the medium-carbon zone, and the high-carbon zone.

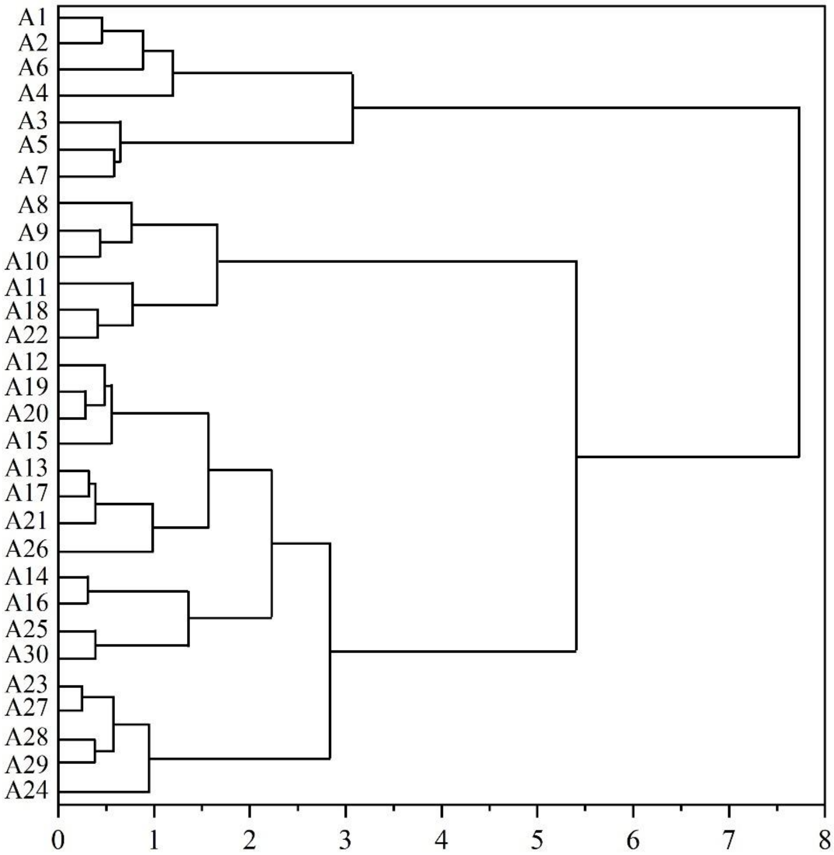


Figure 1: Clustering tree

The specific clustering results for the three categories—low-carbon, medium-carbon, and high-carbon regions—are shown in Table 4. The low-carbon region includes seven areas: Beijing, Shanghai, Guangdong, Jiangsu, Zhejiang, Tianjin, and Fujian. The medium-carbon region comprises six provinces: Jiangxi, Hainan, Hunan, Guangxi, Sichuan, and Yunnan. All other regions fall into the high-carbon category.

1) Low-Carbon Zone

The leading green low-carbon consumption levels in Beijing, Shanghai, Guangdong, Jiangsu, Zhejiang, Tianjin, and Fujian are significantly influenced by their respective economic development levels. Higher economic development implies more advanced infrastructure such as urban subways (rail transit), resulting in outstanding low-carbon urban transportation performance. The relocation of traditional light and heavy industries alongside the upgrading of the tertiary sector has driven low-carbon consumption in both commercial activities and household spending.

2) Medium Carbon Zone

Green low-carbon consumption levels are closely tied to a region's stage of development. Jiangxi, Hainan, Hunan, Guangxi, Sichuan, and Yunnan all lag behind the national average in economic development. While they strive to reduce carbon emissions relative to economic growth, their green low-carbon consumption levels remain concerning. These zones display below-standard outcomes in city low-carbon traffic and also low-carbon use inside business activities. Urban resource allocation prioritizes industrial production and economic growth, with insufficient emphasis on green low-carbon consumption.

3) High-Carbon Zone

The regions that have obvious carbon discharge are mostly situated in the middle and west areas of this nation. The degree of green and low-carbon consumption is influenced by very many factors, for example the development situation and the energy constitution.The provinces like Shanxi and Inner Mongolia, which play the role of key energy suppliers for China, possess coal consumption that accounts for more than 80% of their total energy utilization. This therefore leads to a comparatively high degree of carbon emission discharge. Furthermore, both the low-carbon traffic in city zones and the low-carbon use in public service facilities are still comparatively comparatively not yet fully developed. It can be clearly seen that, the regions which have high carbon possess quite big potential which can be used to make improvement in the consumption of low carbon.

Table 4: The division results of green low-carbon consumption level

Category	Region
The first category	Beijing, Shanghai, Guangdong, Jiangsu, Zhejiang, Tianjin, Fujian
The second category	Jiangxi, Hainan, Hunan, Guangxi, Sichuan, Yunnan
The third category	Shandong, Chongqing, Anhui, Liaoning, Henan, Hubei, Jilin, Shanxi, Heilongjiang, Hebei, Inner Mongolia, Gansu, Qinghai, Xinjiang, Shanxi, Ningxia, Guizhou

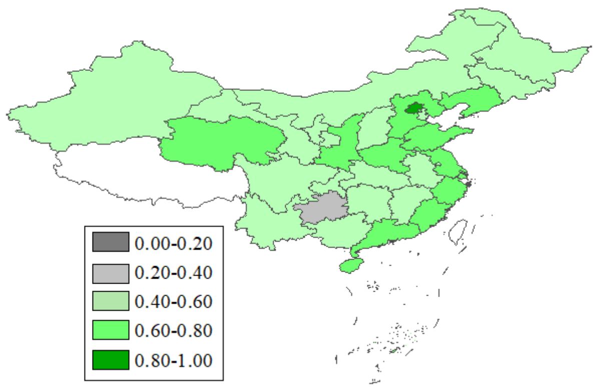
It is necessary to point out that currently, China is undergoing a rapid course of industrialization and urbanization. This progress requires that important support be obtained from high-carbon industries such as manufacturing industry, construction industry and transportation industry. Under these circumstances, the obtaining of absolute reference standards for ecological protection and low-carbon consumption still has difficulties. Therefore, the divisions of low-carbon, medium-carbon, high-carbon regions which this paper has divided only give a comparison assessment of the future situations of China's green low-carbon consumption increase. They are not capable of directly reflecting the real numerical values of the green and low-carbon consumption index for every single province or region.

4.2 Spatiotemporal Feature Analysis

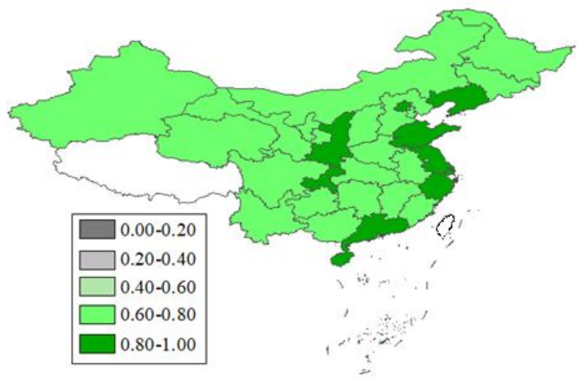
In this section, we use spatial autocorrelation analysis to inspect the spatial distribution trend of the green low-carbon consumption index. This index has been divided into five grades by us:

1) (0, 0.02), dark gray;
2) (0.2, 0.4), gray;
3) (0.4, 0.6), light green (transitional stage);
4) (0.6, 0.8), green (acceptable stage);
5) (0.8, 1), dark green (mature stage).

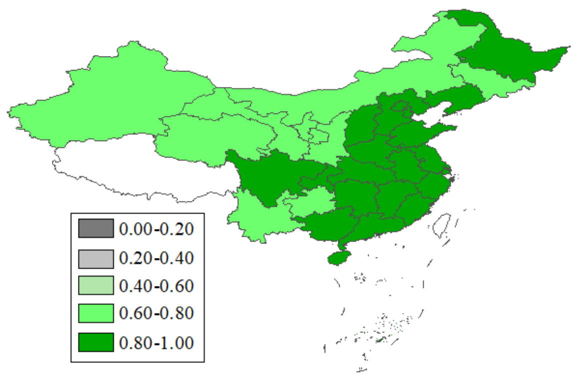
Figure 2 gives depiction of the spatial arrangement of China's Green and Low-Carbon Consumption Index which spans the time from 2011 to 2024, with panels (a) to (c) representing the years 2011, 2018, and 2024 respectively. In the year 2011, people could clearly see that Guizhou possessed the lowest degree of green development, which remained in the gray stage. By way of opposition, merely Beijing alone obtained the capability of arriving at the advanced deep-green mature phase. Furthermore, 14 provinces have reached the green-acceptable stage, hence another 14 provinces are located in the light-green transformation stage. Up to the year 2018, Gansu had the most unfavorable green development condition, therefore it had already advanced to the stage that its green development was considered as acceptable. On another hand, the provinces that have higher green development degree are Beijing, Shandong, Guangdong.A total of 20 provinces were in the green acceptable stage, while 10 provinces reached the deep green mature stage. From 2011 to 2018, provinces demonstrated rapid and substantial improvements in green development levels. By 2024, Xinjiang had the lowest green development level but still reached the green acceptable stage.Altogether eleven provinces have arrived at the green, satisfying stage, while nineteen provinces have achieved the dark-green, completely developed stage. In the time period from 2011 to 2024, the green development index of each province has maintained continuous improvement.The development degree of green low-carbon consumption inside China has shown an overall going-up track, which is accompanied by notable increasing, remaining in the green acceptable stage with considerable room for development. Following the year 2013, the speed of growth began to become slower. This shows that the whole development level of China's green low-carbon consumption has obtained promotion. Nevertheless, from the year 2018 onwards, it is obvious that the growth driving force has a clear shortage.



(a)2011



(b)2018



(c)2024

Figure 2: Spatial distribution of green low-carbon consumption index

4.3 Spatial Agglomeration Analysis

In the domain of environment-friendly and low-carbon consumption use, the geographic distribution of ecological resources, industries, and markets inside China’s administrative areas is not a separated occurrence. Elements such as labor force, technical level, capital fund, and environmental resource often get connected with the development of green low-carbon consumption spatial units. This mutual connection therefore has the potential to cause the forming of spatial group clusters.Carrying out a deep-going investigation on the influences of spatial gathering possesses very great importance for more effectively coordinating and promoting the cooperative progress of green and low-carbon consumption among different areas.

We employ the Moran's I index to measure the spatial gathering degree of green low-carbon consumption within China. By us, this index may be divided into two kinds: the global Moran's I and the local Moran's I.

4.3.1 Global Moran Index for Measuring Spatial Agglomerativity

Table 5 gives the detailed results of the Moran's I index concerning China's green low-carbon consumption which covers the years from 2011 to 2024.The result that our research got shows that, since 2013, the Moran's I index of green and low-carbon consumption has not had statistical significance. This indicates that during the time period from 2011 to 2013, the development progress of China's green low-carbon consumption has displayed a quite clear spatial connection. But, after the year 2013, this obvious space connection has already stopped existing.At the same time period, the Moran's Index which concerns green and low-carbon consumption has the decrease from 0.174 of the year 2011 to 0.101 of the year 2013. This descending tendency indicates that within this time interval, the regional gathering of green and low-carbon consumption gradually got weaker.A part of the decrease in the regional centralization inside the development of green and low-carbon consumption can be attributed to China's economic development, the increasing consciousness among the people about green and low-carbon consumption, and the gradual lessening of regional gaps in green and low-carbon consumption. Therefore, green and low-carbon consumption has step by step changed from a consumption pattern that is limited to few regions to a pattern that is widely accepted by more people.

Table 5: Global moran's index

Year	I	E(I)	Z(I)	P-value*
2011	0.174	-0.038	1.047	0.034**
2012	0.043	-0.038	0.709	0.025**
2013	0.101	-0.038	1.327	0.081*
2014	-0.053	-0.038	0.131	0.44
2015	-0.132	-0.038	0.915	0.176
2016	-0.086	-0.038	0.398	0.346
2017	-0.011	-0.038	0.158	0.432
2018	-0.105	-0.038	0.544	0.282
2019	0.092	-0.038	1.112	0.125
2020	-0.062	-0.038	0.302	0.379
2021	0.056	-0.038	0.866	0.201
2022	-0.014	-0.038	0.271	0.406
2023	-0.02	-0.038	0.223	0.409
2024	-0.021	-0.038	0.156	0.443
Note: * * and * represent significant at 5 % and 10 % levels				

4.3.2 Local Moran's I Measure for Spatial Agglomerativity

Although the global Moran's I index possesses the capability to calculate the yearly concentration degree of green and low-carbon consumption, it cannot accurately reflect the spatial autocorrelation of green and low-carbon consumption between different provinces and regions. Therefore, it is not feasible to carry out the identification of the spatial gathering features of green and low-carbon consumption in every single province or region. Hence, therefore it is necessary to further employ the local Moran's I index to measure the particular spatial autocorrelation of green low-carbon consumption inside every administrative region. Figure 3 gives out the scatter diagrams of the local Moran's I index concerning green and low-carbon consumption that cover the years from 2011 to 2013. Figure a, figure b and figure c separately correspond to the year 2011, the year 2012 and the year 2013. Below is the explanation for the quadrants that are in the figure:

1) First Quadrant: High regional economic development level, high development level of surrounding areas

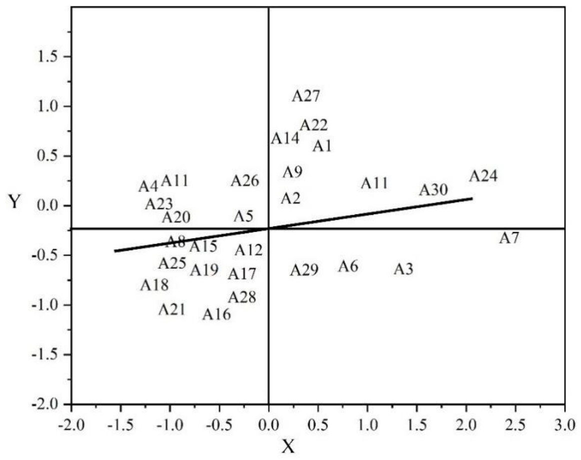
2) Second Quadrant: Low regional economic development level, low development level of surrounding areas

3) Third Quadrant: Low regional economic development level, high development level of surrounding areas

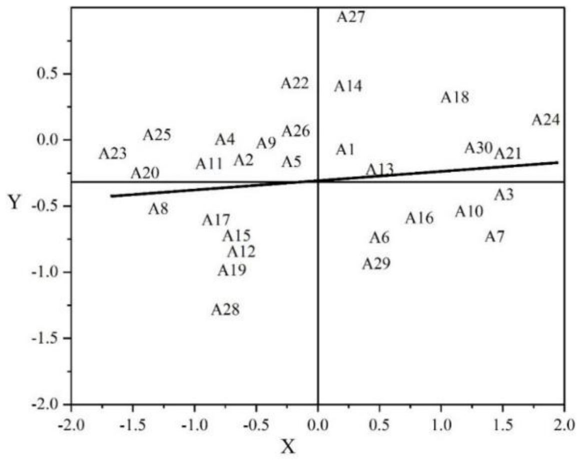
4) Fourth Quadrant: High regional economic development level, low development level of surrounding areas

4) Fourth Quadrant: Rise of regional economic progress degree, reduce of development degree in the around areas

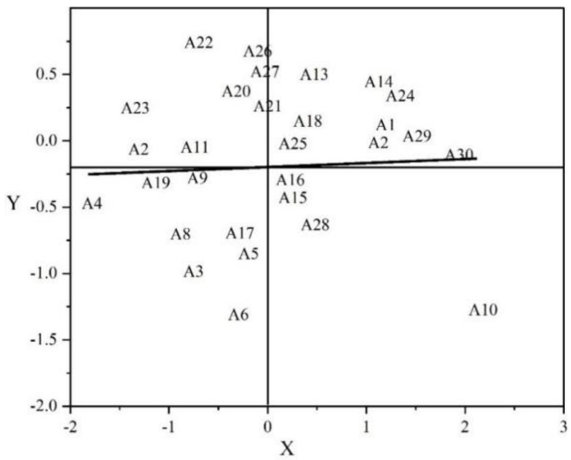
Just as what the figure shows, the quantity of points in the first and third quadrants of every diagram is obviously bigger than that which is in the second and fourth quadrants. Every one of the fitted lines has an upward slope from the position of bottom-left to the position of top-right. This points out that administrative districts which have “low-low” and “high-high” clusters of green and low-carbon consumption are more numerous than those which have “high-low” or “low-high” clusters.This result shows that areas which have a bigger degree of green and low-carbon consumption development, hence they have a higher probability to carry out spatial gathering, when compared with areas which have a lower level of this kind of development. During the 2011 to 2013 years, the advancement of green low-carbon consumption has manifested a certain degree of agglomeration effect. Low-level agglomeration was observed in the central region, where economic growth was relatively slower than in coastal areas and resource-environmental pressures were greater. High-level agglomeration was seen in several ecologically resource-rich areas in the west. However, overall agglomeration remained at a low level. This shows that the agglomeration effect of green and low-carbon consumption is, within a certain scope, dependent upon regional economy conditions, environment situations and resource supplies. Under the background of quick economy development and the continuous and wide acceptance of ecological environment ideas, the overall level of green low-carbon consumption has obtained continuous promotion. Nevertheless, the gathering feature of green and low-carbon consumption already became not so outstanding. This indicates that regions which have various resource gifts are able to cultivate green and low-carbon consumption through the use of their own superior points.Green and low-carbon consumption is neither exclusive to economically developed regions nor the sole domain of areas with inherent ecological advantages. Factors such as technological progress can compensate for shortcomings in economic development and ecological resources, therefore, this promotes the wide acceptance of environment-friendly and low-carbon consumption patterns and the growth of an economy which is based on eco-friendly and low-carbon consumption.



(a)2011



(b)2012



(c)2013

Figure 3: Local Moran index scatter plot

4.4 Analysis of Driving Factors

To reduce empirical bias caused by omissions in key variable selection, representative explanatory variables must be introduced to enhance the accuracy of results. Here, drawing upon existing research, this paper enriches and refines the factors influencing green and low-carbon consumption levels. Table 6 displays the final group of influence factors together with the results of their Variance Inflation Factor (VIF) examinations. From what we can observe, the factors that have been verified are the technological innovation ability, the industrial composition structure, the capability for attracting talent, the urbanization degree, and the urban greening degree. Since all VIF test results are below 7.5, these factors are deemed free of multicollinearity.

Table 6: Indexes for the Elements Which Influence the Degree of Green Low-Carbon Consumption

Variables	Indicators	Code	VIF
Technological innovation capability	Comprehensive measured value of technological innovation	Tec	2.74
Industrial structure	The proportion that the added value of the service sector accounts for in the gross domestic product	Ind	2.11
Talent introduction ability	The number of teachers introduced in colleges and universities that year	Tal	1.52
Urbanization level	Urbanization rate	Urb	2.36
Urban greening situation	Green coverage rate of built-up area	Gre	1.15

We utilized Stata 14.0 to carry out a spatial econometric regression analysis upon the explanatory variables which are related to the green low-carbon consumption level of China.The results obtained from this analysis are placed in Table 7. The outcome obtained by our study displays that the regression coefficient values for technique innovation and talent introduction are 0.015 and 0.162, each in turn. These coefficient values have statistics meaning at the 1% confidence level. This shows that technique creation has a very big effect on company modernization and change, and the getting of persons with ability helps to raise the level of green and low-carbon consumption. Furthermore, the regression coefficient values for their space lag items are 0.532 and 0.213 separately. The first one gets significance under 1% confidence level, the second one under 5% confidence level, which hence proves that there exists a positive spatial overflow effect. By opposite way, the regression coefficient values for industry structure and city development level are all negative and remarkable at the 1% confidence level.This point therefore illustrates that the industrial composition and the degree of urbanization hinder the promotion of green and low-carbon consumption levels. The variable which has relation with urban greening did not pass the significance test. This indicates that the green coverage ratio which belongs to provincial areas does not have a meaningful influence on the levels of green and low-carbon consumption.

Form 7: Outcome from Space Econometric Measuring Regression

Variable	OLS	SAR	SEM	SDM
Lntec	0.105***	0.015**	0.016**	0.015***
Lnind	0.212***	-0.024***	-0.032***	-0.048***
Lntal	0.255***	0.121***	0.125***	0.162***
Lnurb	0.538***	-0.043***	-0.044***	-0.035***
Llngre	0.072	-0.02	-0.01	-0.009
Llntec×W	-	-	-	0.532***
Lnind×W	-	-	-	-0.575*
Lntal×W	-	-	-	2.844**
Lnurb×W	-	-	-	0.213
Lngre×W	-	-	-	-0.071
R^2	0.695	0.811	0.824	0.815
Log-likelihood	-	1650.502	1650.448	1662.571
Individual effect	Control	Control	Control	Control
Time effect	Control	Control	Control	Control

5 Strategies and Recommendations for Promoting Green and Low-Carbon Consumption

For the purpose of efficiently deal with the shortcomings in environmental friendly low-carbon consumption and more effectively use its important function in guiding development under the framework of double carbon goals, this article proposes strategies and recommendations for pushing forward green low-carbon consumption on the basis of the outcomes of its study.

1) Enhance green and low-carbon transformation at the production end, strengthen supporting institutional frameworks, and safeguard the social and environmental conditions for consumption.

Regarding clothing, we must drive the low-carbon transformation of the textile industry to provide consumers with more green and low-carbon apparel options. For food, we should encourage the production and supply of green foods, enhance food quality and safety standards, and meet people's demand for healthy diets. In housing, we need to promote green building materials and technologies, improve building energy efficiency and comfort, and create green and low-carbon living environments. For transportation, we must advance innovation and adoption of new energy vehicles while providing efficient and convenient public transit services to reduce carbon emissions in the transportation sector. For daily consumption, we should promote energy-efficient and eco-friendly household goods, improve product energy efficiency and durability, and minimize energy waste and environmental pollution. In the field of travel industry, it is necessary to push the sustainable transformation of the tourism part. This thing includes putting out travel products and services which have low carbon discharge and are environment-protective.

3) Enhance green awareness campaigns for residents to foster a new ethos of green, low-carbon living.

At the beginning stage, strengthen the propagation of green ideas. This target can be reached through emphasizing the importance and practical methods of practicing a green, low-carbon life style by means of many kinds of channels and in many different forms. By means of these works, the environmental awareness and participation degree of residents can be effectively raised. Second, encourage residents to experience the joys and benefits of green, low-carbon living through practical activities, enhancing their sense of environmental responsibility and motivation for action. Third, establish green living model communities or green family selection mechanisms to set benchmarks and role models for green, low-carbon living, fostering a positive green lifestyle atmosphere. Fourth, strengthen policy guidance and support by formulating and refining relevant green, low-carbon living policies to create a more convenient and affordable green, low-carbon living environment for residents.

3) Strengthen investment and oversight to safeguard the natural environment for consumption.

Fortify ecological barriers, steadily increase vegetation resources, and accelerate the development of a well-planned, aesthetically pleasing urban greening system. Concurrently, continue implementing actions to protect drinking water sources, enforce a “zero-tolerance” approach against environmental violations, and improve air quality.

4) Explore new pathways for coordinated regional development in green and low-carbon consumption.

Leveraging new urbanization as a driving force, prioritize shaping a green image and protecting green resources. Focus on enhancing overall green quality and green development capabilities by strengthening regional cooperation in green and low-carbon consumption. Simultaneously, increase investment in environmental protection, appropriately convert economic advantages into ecological and environmental benefits, push energy use efficiency, reduce emission amounts, guard ecological security, and reach sustainable development.

Regions which possess relatively lower indices for green low-carbon consumption development should efficiently draw lessons from the experiences of socioeconomic development and resource-environment management of areas which possess higher indices.They should implement targeted shifts in consumption patterns, regulate consumption levels, and gradually establish rational consumption structures. Furthermore, they should actively cultivate comparative advantages in infrastructure development, ecological landscape clusters, and modern service industry growth to create favorable external conditions for advancing green and low-carbon consumption.

6 Conclusion

Guided by principles of scientific rigor, fairness, and systematic approach, a green low-carbon consumption indicator system was established with primary indicators encompassing low-carbon transportation, household low-carbon consumption, public utility consumption, and commercial low-carbon consumption. The order of the weightings, from high to low, is like this: public utilities low-carbon consumption (0.3763) is higher than urban low-carbon transportation (0.2909), which then is bigger than commercial low-carbon consumption (0.2063), and commercial low-carbon consumption hence is larger than household low-carbon consumption (0.1265). Our side have chosen 30 provinces and regions inside China to be the research objects. After that, a cluster analysis was conducted, it considered indices such as city low-carbon traffic, family low-carbon consume, public facility consume, and low-carbon business consume.In the present analysis, we have carried out a classification of regions into three different kinds: low-carbon zones, medium-carbon zones, and high-carbon zones. The low-carbon regions include Beijing, Shanghai, Guangdong, Jiangsu, Zhejiang, Tianjin, and Fujian. Six provinces, that is to say Jiangxi, Hainan, Hunan, Guangxi, Sichuan, Yunnan, are constituted as the medium-carbon areas. The leftover provinces and regions are divided into the group of high-carbon area. We employed spatial autocorrelation analysis to carry out exploration on the tendency of the spatial distribution of green low-carbon consumption indices.In the time period from 2011 to 2024, the progress of green low-carbon consumption in China on the whole displayed a trend that goes up. It possessed a prominent increment, and it has been kept in a permissible green condition.Beginning from the year 2013, the growth speeds have begun to become slower. We utilized the Moran's I index to carry out measurement on the spatial clustering degree of China's green low-carbon consumption. On the global Moran's I aspect, during the years 2011 to 2013, an obvious spatial connection existed in the development of China's green low-carbon consumption. But, this space connection disappeared after that time, hence the Moran's I index has a decrease to 0.101 in the year 2013. A deeper-level analysis, which utilizes the partial Moran's I index to measure the space self-correlation of green low-carbon consumption in all provinces of China, hence reveals that between 2011 and 2013, the increment of China's green low-carbon consumption presented a certain degree of gathering effect.After that, while the overall level of green and low-carbon consumption continued to rise, the agglomeration effect became less pronounced. To enrich and refine the factors influencing green and low-carbon consumption levels, technological innovation capacity, industrial structure, talent attraction capability, urbanization level, and urban greening conditions were identified as key indicators. The regression coefficients for technological innovation and talent attraction were 0.015 and 0.162, respectively, while those for spatial lag terms were 0.532 and 0.213. All coefficients were statistically significant at the 1% confidence level, indicating positive spatial spillover effects. Conversely, the regression coefficients for industrial structure and urbanization level were -0.014 and -0.043, respectively. Both were negative and statistically significant at the 1% confidence level, indicating that industrial structure and urbanization level exert a suppressing effect on the enhancement of green and low-carbon consumption levels. Urban greening status passed the significance test but showed no significant impact on green and low-carbon consumption. In the end, by utilizing the research results, strategies and proposals were put forward from the perspectives of residents and the government. These include the green and low-carbon transformation in the production link, input into environment-friendly and low-carbon consumption, and control measures. This provides reference materials and precious viewpoints for the development of local green and low-carbon consumption.

References

[1] Wang, Y., Guo, C. H., Chen, X. J., Jia, L. Q., Guo, X. N., Chen, R. S., ... & Wang, H. D. (2021). Carbon peak and carbon neutrality in China: Goals, implementation path and prospects. China Geology, 4(4), 720-746.

[2] Tan, X., Cai, X., Cheng, Y., & Yan, H. (2025). Critical policies for China's carbon neutrality:‘dual control’on energy consumption versus carbon emissions. Climate Policy, 1-16.

[3] Li, X., & Xing, H. (2024). Better cities better lives: How low-carbon city pilots can lower residents’ carbon emissions. Journal of Environmental Management, 351, 119889.

[4] Xiao, J., Zhen, Z., Tian, L., Su, B., Chen, H., & Zhu, A. X. (2021). Green behavior towards low-carbon society: theory, measurement and action. Journal of Cleaner Production, 278, 123765.

[5] Ye, H., Ren, Q., Hu, X., Lin, T., Xu, L., Li, X., ... & Pan, B. (2017). Low-carbon behavior approaches for reducing direct carbon emissions: Household energy use in a coastal city. Journal of Cleaner Production, 141, 128-136.

[6] Dubois, G., Sovacool, B., Aall, C., Nilsson, M., Barbier, C., Herrmann, A., ... & Sauerborn, R. (2019). It starts at home? Climate policies targeting household consumption and behavioral decisions are key to low-carbon futures. Energy Research & Social Science, 52, 144-158.

[7] Trivedi, S. K., Yadav, S. S., Awasthi, K., & Singh, S. (2025). Driving sustainable consumption of energy-saving appliances: an in-depth qualitative text analysis of consumer perceptions. Smart and Sustainable Built Environment.

[8] Mi, L., Zhu, H., Yang, J., Gan, X., Xu, T., Qiao, L., & Liu, Q. (2019). A new perspective to promote low-carbon consumption: The influence of reference groups. Ecological Economics, 161, 100-108.

[9] Zhao, C., Zuo, Q., Ma, J., Zang, C., & Wu, Q. (2023). Measurement of green water resource utilization efficiency for carbon neutrality: a multiple water use sectoral perspective considering carbon emission. Water, 15(18), 3312.

[10] He, M., Sun, Y., & Han, B. (2022). Green carbon science: efficient carbon resource processing, utilization, and recycling towards carbon neutrality. Angewandte Chemie,

134(15), e202112835.

[11] Armutcu, B., Zuferi, R., & Tan, A. (2024). Green product consumption behaviour, green economic growth and sustainable development: unveiling the main determinants. Journal of Enterprising Communities: People and Places in the Global Economy, 18(4), 798-819.

[12] Li, C., Wang, Y., Li, C., & Wang, L. (2025). Exploring the Coupling Coordination Mechanism of Green Governance and Low-Carbon Consumption in Enterprises: An Empirical Analysis of China. International Journal of Environmental Research, 19(3), 85.

[13] Xing, X., & Ye, A. (2022). Consumption upgrading and industrial structural change: A general equilibrium analysis and empirical test with low-carbon green transition constraints. Sustainability, 14(20), 13645.

[14] Shi, Z., & Cheng, J. (2023). How do government subsidies and consumers' low-carbon preference promote new energy vehicle diffusion? A tripartite evolutionary game based on energy vehicle manufacturers, the government and consumers. Heliyon, 9(3).

[15] Hanna, R., Heptonstall, P., & Gross, R. (2024). Job creation in a low carbon transition to renewables and energy efficiency: a review of international evidence. Sustainability Science, 19(1), 125-150.

[16] Zhang, S., Wang, J., & Guan, J. (2024). How does the energy consumption structure affect the green economic development? A spatial impact analysis. Frontiers in Environmental Science, 12, 1412612.

[17] Sivapalan, A., von der Heidt, T., Scherrer, P., & Sorwar, G. (2021). A consumer values-based approach to enhancing green consumption. Sustainable Production and Consumption, 28, 699-715.

[18] Leyva-Hernández, S. N., Arango-Ramírez, P. M., & Gaviria-Marin, M. (2024). Analysis green consumption concept from a bibliometric. Cogent Business & Management, 11(1), 2422168.

[19] Zhao, G., Geng, Y., Sun, H., Tian, X., Chen, W., & Wu, D. (2020). Mapping the knowledge of green consumption: a meta-analysis. Environmental Science and Pollution Research, 27(36), 44937-44950.

[20] Zeng, S., Jin, G., Tan, K., & Liu, X. (2023). Can low-carbon city construction reduce carbon intensity? Empirical evidence from low-carbon city pilot policy in China. Journal of Environmental Management, 332, 117363.

[21] Huo, W., Qi, J., Yang, T., Liu, J., Liu, M., & Zhou, Z. (2022). Effects of China's pilot low-carbon city policy on carbon emission reduction: a quasi-natural experiment based on satellite data. Technological Forecasting and Social Change, 175, 121422.

[22] Ma, H., & Chen, Q. (2025). Social environment, low-carbon cognition and low-carbon consumption behaviors of youth groups: evidence from Xizang, China. Frontiers in Psychology, 16, 1494761.

[23] Nematchoua, M. K., Sadeghi, M., & Reiter, S. (2021). Strategies and scenarios to reduce

energy consumption and CO2 emission in the urban, rural and sustainable neighbourhoods. Sustainable Cities and Society, 72, 103053.

[24] Di, K., Chen, W., Shi, Q., Cai, Q., & Liu, S. (2024). Analysing the impact of coupled domestic demand dynamics of green and low-carbon consumption in the market based on SEM-ANN. Journal of Retailing and Consumer Services, 79, 103856.

[25] Wang, Z., Chi, Y., Peng, R., & Yang, Y. (2023). Research on the Traditional and Low-Carbon Consumption Modes. Recent Patents on Engineering, 17(6), 177-183.

[26] Huang, H., Long, R., Chen, H., Li, Q., Wu, M., & Gan, X. (2022). Knowledge domain and research progress in green consumption: a phase upgrade study. Environmental Science and Pollution Research, 29(26), 38797-38824.

[27] Jiang, Z., & Gao, X. (2024). Text mining and quantitative evaluation of China’s green consumption policies based on green consumption objects. Environment, Development and Sustainability, 26(3), 6601-6622.

[28] Li, T. (2025). Research on the Green Consumption Development Based on Fuzzy Comprehensive Evaluation—A Case Study of the Middle and Lower Reaches of the Yangtze River. In SHS Web of Conferences (Vol. 215, p. 01001). EDP Sciences.

[29] Tam, P. M., Hang, D. T., Thuy, P. T., & Dat, L. Q. (2023). Comprehensive evaluation of sustainable consumption towards green growth based on an interval valued Neutrosophic TOPSIS approach. Environmental Science and Pollution Research, 30(38), 89838-89858.

[30] Liu, J., Long, R., Chen, H., Qin, L., Huang, H., Li, Q., & Ye, X. (2025). Assessing the effectiveness of green consumption policy in China: Evidence from social media data. Journal of Environmental Management, 376, 124500.

[31] Zou, T., Guo, P., & Wu, Q. (2023). Applying an entropy-weighted TOPSIS method to evaluate energy green consumption revolution progressing of China. Environmental Science and Pollution Research, 30(14), 42267-42281.

[32] Kim, S. Y., Yeo, J., Sohn, S. H., Rha, J. Y., Choi, S., Choi, A. Y., & Shin, S. (2012). Toward a composite measure of green consumption: an exploratory study using a Korean sample. Journal of family and economic issues, 33(2), 199-214.

[33] Zhang, M., Zheng, Q., & Xia-Bauer, C. (2024). A systematic assessment of low-carbon energy consumption by an integrated approach in rural China. Energy Reports, 12, 5704-5711.

[34] Sun, C., & Miao, B. (2022). Performance Evaluation of Reducing Consumption of Energy in the Yangtze River Delta under the Background of Low-Carbon Economy. Journal of Mathematics, 2022(1), 3235776.

[35] Wang, Z., Xue, M., Wang, Y., Song, M., Li, S., Daziano, R. A., ... & Zhang, B. (2019). Big data: New tend to sustainable consumption research. Journal of Cleaner Production, 236, 117499.

[36] Sala, S., & Castellani, V. (2019). The consumer footprint: Monitoring sustainable

development goal 12 with process-based life cycle assessment. Journal of Cleaner production, 240, 118050.

[37] Qu, Y., Liu, Y., Wang, W., & Cang, Y. (2021). Sustainability assessment of urban residential consumption in China megacity. Environment, Development and Sustainability, 23(5), 7509-7523.

[38] Moawiah Alnsour. (2025). An assessment-support model for measuring microscale public transport sustainability in Jordan: application of fuzzy AHP. Innovative Infrastructure Solutions,10(9),436-436.

[39] Thomas Lemmerz,Stefan Herlé & Jörg Blankenbach. (2023). Geostatistics on Real-Time Geodata Streams—High-Frequent Dynamic Autocorrelation with an Extended Spatiotemporal Moran's I Index. ISPRS International Journal of Geo-Information,12(9),350-.

[40] Sutikno,Purhadi,Fachrunisah & Fajar Dwi Cahyoko. (2025). Estimation of parameters and hypothesis testing of multivariate spatial autoregressive model. MethodsX,14,103294.

[41] Raveena Begum & Sanjeeva Kumar Jha. (2025). Maximum Likelihood Estimation of Spatial Error Model with Second-Order Neighborhood Structure. Journal of Agricultural, Biological and Environmental Statistics,(prepublish),1-21.