Dynamic Analysis of Ecological Efficiency in Urban Tourism Industry Based on DEA-Malmquist Model

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The development of urban tourism has to some extent driven urban economic growth. However, it involves multiple industries such as transportation, accommodation, entertainment, and catering, which can generate significant carbon emissions. To promote the tourism economy and environment's coordinated development, tourism ecological efficiency is proposed. Its measurement methods have also attracted attention. Therefore, the city tourism ecological efficiency measurement model based on tourism carbon emissions and DEA-Malmquist was proposed. Then, the accuracy of measuring tourism ecological efficiency can be improved. This study first constructed a mixed model of least absolute shrinkage and selection operator-genetic algorithm-support vector regression to measure the carbon emissions of urban tourism industry. Subsequently, the DEA-Malmquist measurement means was constructed to evaluate urban tourism's ecological efficiency. The relative error and absolute error of the proposed intelligent model were 2.005% and 2.005%, respectively, which were significantly better than the comparison models. The average carbon emission from leisure vacation activities, sightseeing, business trips, and visiting relatives and friends was 171100, 126700, 72300, and 61200 tons. The overall tourism ecological efficiency of this province showed a fluctuating trend. The technical efficiency decreased from its highest point of 0.774 in 2019 to its lowest point of 0.706 in 2020, and then gradually rebounded to 0.759 in 2023. Therefore, this proposed method can effectively measure the carbon emissions and tourism ecological efficiency of cities. It has practical operability and can provide an effective path for promoting tourism economy and ecological environment's balanced development.

Povzetek: Algoritem za dinamično analizo ekološke učinkovitosti v mestni turistični industriji temelji na DEA-Malmquistovem modelu in omogoča zmanjšanje ogljičnih emisij in analizo turizma.

1 Introduction

China's tourism industry is developing rapidly and has grown into the world's largest domestic tourism marketplace [1]. The rapidly developing tourism industry is bound to cause environmental pressure. Currently, 4.4% of the global Carbon Emission (CE) comes from the tourism industry. This proportion will continue to grow [2]. China has clearly stipulated that a spatial pattern of resource conservation and environmental protection must be formed. Therefore, the focus of academic attention includes coordinating the contradiction between tourism development and CE and finding low-carbon tourism development paths [3-4]. Tourism Ecological Efficiency (EE) is a measure method using the ratio between economic benefits and environmental impacts. In accounting, CE represents environmental impact and tourism revenue represents economic benefits. Therefore, CE accounting is important for measuring the urban tourism industry EE [5]. Tourism EE is evaluated by the ratio of tourism revenue to CE, reflecting how tourism activities affect the environment. The tourism industry's negative impact on the environment can be objectively evaluated by calculating CE, thereby guiding the formulation of low-carbon tourism development strategies.

Nowadays, scholars have discussed the relevant methods of CE accounting in the tourism industry. Yıldırım et al. proposed an analytical method aimed at evaluating the impact of tourists and tourism revenue in Mediterranean countries on CE. This study used econometric means to test the hypothesis and measure the tourism industry CE. This study took data from 15 countries from 2001 to 2017 as an example. The increase in tourists led to an increase in CE before reaching a certain threshold. However, exceeding this threshold reduced CE, providing a new perspective and evidence for tourism CE impact assessment [6]. Zhang et al. used a vector error correction means and other methods to measure the tourism industry CE. They explored the causal relationship between tourism, economic growth, et al. in 30 provinces of China from 2000 to 2017. This proposed method confirmed the long-term equilibrium relationship between variables through panel cointegration testing. GDP and the tourism industry had a bidirectional short-term and long-term causal correlation. Energy consumption had a one-way long-term and short-term impact on other variables [7]. Razzaq et al. proposed a moment quantile regression method. This experiment evaluated the impact of green technology innovation on tourism economic growth and carbon dioxide emissions. This method addressed the non-normality of data and constructed a suitable statistical framework. International tourism promoted tourism economic growth but increased carbon dioxide emissions. Its effectiveness varied depending on national development and environmental pollution [8]. Selvanathan et al. used autoregressive distributed lag model, panel framework, and other method to measure the tourism industry CE. Meanwhile, they explored the interaction between South Asia's tourism industry, energy consumption, et al. Through in-depth analysis of long-term data, this study revealed the positive contribution of the tourism industry to GDP. However, its CE had a certain negative impact. This result laid a theoretical foundation for subsequent research on the tourism industry EE [9]. Razzaq et al. developed a new composite index that used quantile auto-regressive distribution lag method and Granger quantile causality to measure tourism industry CE. This experiment explored the correlation between tourism development, technological innovation, and CE. This proposed model effectively measured the tourism industry CE. In addition, the environmental Kuznets curve hypothesis existed for a long time. There was an asymmetric bidirectional causal relationship between tourism, technology, and CE [10].

The measurement method of the tourism industry EE is always a hot research topic in the academic community. Many scholars are committed to it. Li et al. used location quotient index and other methods to evaluate the relationship between the agglomeration of China's provincial-level tourism industry and its EE from 2011 to 2016. This proposed method effectively measured the clustering trend of the tourism industry in various regions and its impact on efficiency. Ultimately, the eastern region of China had the highest agglomeration. The tourism industry efficiency in this region was also relatively high. In addition, industrial agglomeration significantly improved the efficiency of the tourism industry nationwide, including overall, pure technical, and scale efficiency [11]. Liu et al. used a relaxation measurement model and a spatial Durbin model to evaluate China's tourism industry EE and explore spatial spillover effects and their influencing factors. This study analyzed 30 regions. Technological innovation, urbanization rate, and government support affected carbon efficiency positively. Economic growth and transportation infrastructure had a negative impact. This result also verified the applicability of the proposed model for evaluating tourism industry EE [12]. Huang et al. utilized a method using super efficiency relaxation and three spatial econometric models. They evaluated the tourism EE of 30 provinces and explored the influence of technological innovation and industrial structure upgrading. Based on empirical modeling, technological innovation alone affected tourism EE negatively. When combined with industrial structure upgrading, it showed a significant positive effect [13]. Du et al. constructed a mixed triangle envelope analysis ideal solution means to assess 248 cities' tourism EE over a 14-year period. This method combined the advantageous features of various models. This method allowed for the analysis of synergistic effects between relevant standards. The tourism EE of the selected cities was generally low. However, low-carbon pilot city policies significantly improved tourism EE through green technology innovation. This result also verified the proposed model's effectiveness [14]. Filipiak et al. explored the tourism development and GDP growth's correlation and proposed a tourism industry EE measurement method based on three variables: ICT, SDG, and E&T. This method effectively revealed the relationship between digital tourism and tourism industry development and the correlation between tourism industry development and sustainability factors. The digitization of the tourism industry significantly improved operational efficiency and supported the implementation of sustainable tourism, verifying the applicability of the proposed model [15].

Table 1 is a summary of the related works to this study.

Table 1: Summary of related works

Researcher	Method	Dataset	Performance index	Key finding
Yıldırım et al. [6]	Econometric model	Data for 15 Mediterranean countries, 2001-2017	Carbon emission impact	The increase in the number of tourists causes carbon emissions to rise before reaching the threshold, and then decrease after the threshold
Zhang and Zhang [7]	Vector error correction model, Granger	Data from 30 provinces in China, 2000-2017	Balanced causality in the long run	There is a two-way short-term and long-term causal relationship between

	causality			GDP and tourism. Energy consumption has a one-way long-term and short-term impact on other variables
Razzaq et al. [8]	Moment quantile regression	Data for the top 10 GDP countries from 1995 to 2018	The impact of green technologies on carbon emissions	International tourism promotes the growth of tourism economy but increases carbon emissions. The effect varies according to the level of national development and environmental pollution
Selvanathan et al. [9]	Autoregressive distributed lag model	South Asian countries	Energy consumption and GDP	Tourism contributes positively to GDP but negatively to carbon emissions
Razzaq et al. [10]	Quantile autoregressive distribution lag, Granger causality	Global tourism data	The impact of tourism carbon emissions	The environmental Kuznets curve hypothesis has existed for a long time. There is an asymmetric bidirectional causal relationship between tourism, technology, and carbon emissions
Li and Liu [11]	Location quotient index, three-stage data envelopment analysis	Chinese provincial data, 2011-2016	Tourism agglomeration and ecological efficiency	Eastern China has the highest tourism agglomeration, which significantly improves tourism efficiency
Liu et al. [12]	Relaxation measure model, spatial Durbin model	Data from 30 provincial levels in China from 2008 to 2019	Spatial spillover effect and influencing factors	Technological innovation, urbanization rate, and government support have a positive impact on carbon efficiency. Economic growth and transport infrastructure have a negative impact
Huang et al. [13]	Excess efficiency relaxation measurement model, spatial econometric model	Data from 30 provincial levels in China from 2008 to 2017	Ecological efficiency assessment	Technological innovation alone has a negative effect on tourism eco-efficiency. It has a positive effect when combined with industrial structure upgrading
Du et al. [14]	Hybrid triangular envelope analysis ideal solution model	Data of 248 cities in China in 2014	Tourism ecological efficiency	The low-carbon pilot city policy significantly improves the ecological efficiency of tourism through green technology innovation
Filipiak et al. [15]	Measurement of ICT group, SDG group and E&T group variables	Global tourism data	Tourism digitization and eco-efficiency	The digitization of the tourism industry significantly improves operational efficiency and supports the realization of sustainable tourism

In summary, there have been many research results on the accounting methods for the tourism industry CE and the measurement methods for it. However, the above research methods often rely on historical data and economic models when calculating CE and EE in the tourism industry. They may not fully consider the impact of regional environmental policy changes, rapid technological progress, and global economic fluctuations. The accuracy of the final measurement results needs further improvement. Therefore, the study focuses on the factor of tourism CE to more accurately measure the urban tourism industry EE and provide reference value for the urban tourism industry's low-carbon development. The city tourism EE measurement model based on tourism CE and DEA-Malmquist is proposed by combining computer intelligence algorithm models and economic models.

The innovation of this research lies in: (1) A mixed model of Least Absolute Shrinkage and Selection Operator-Genetic Algorithm-Support Vector Regression (Lasso-GA-SVR) is constructed to calculate the CE of urban tourism industry. (2) EE evaluation indicators and DEA-Malmquist index model are constructed to measure the urban tourism industry EE. The main contribution of this study is utilizing a Lasso-GA-SVR hybrid model to accurately measure the urban tourism industry CE. Furthermore, a comprehensive evaluation of urban tourism industry EE is conducted using the DEA-Malmquist index model. This comprehensive model can elevate the evaluating accuracy and reliability. This can offer a scientific basis for formulating low-carbon development strategies for the urban tourism industry. This can promote tourism and environmental protection's sustainable development.

2 Methods and materials

This study first constructs an urban tourism CE measurement model based on the Lasso-GA-SVR hybrid model. Subsequently, a city tourism EE measurement model based on tourism CE and DEA-Malmquist is constructed. Firstly, this study combines the feature selection ability of Lasso regression, the optimization ability of GA, and the predictive ability of Support Vector Regression (SVR). This can optimize model parameters, reduce measurement errors, and address the limitations of traditional intelligent measurement models in complex data processing. This study conducts the urban tourism EE measurement after obtaining the urban tourism CE.

2.1 Methods for calculating carbon emissions

The calculation of tourism EE relies on an accurate evaluation of economic benefits and environmental costs' correlation. CE is a core indicator for measuring environmental costs. Therefore, CE measurement in the tourism industry is a key link in ensuring the tourism EE assessing effectiveness. Through precise CE data, the environmental impact of tourism activities can be analyzed in depth. The existing calculation methods can provide effective predictions in specific scenarios. However, they typically perform less stably in complex and highly variable data environments, which are more sensitive to outliers and noise [16]. In contrast, the combination calculation model can elevate the model's generalization ability and accuracy by integrating multiple calculation methods. This study proposes a Lasso-GA-SVR that can elevate CE calculation's accuracy and stability. Lasso-GA-SVR combines the feature selection ability of Lasso regression, optimization ability of GA, and prediction ability of SVR to optimize model parameters and reduce prediction errors [17]. Lasso evaluates the importance of explanatory variables by compressing estimated values and generating sparse solutions. Lasso can solve various problems such as multicollinearity and model overfitting. In Figure 1, the tourism industry has complexity and industry relevance. Tourism activities involve multiple fields, such as transportation, accommodation, catering, and entertainment, each with a different source of CE [18]. From the perspective of tourist consumption, it should comprehensively consider factors such as transportation mode, accommodation type, dietary habits, and entertainment activities. These factors have both direct and indirect impacts on tourism CE [19].

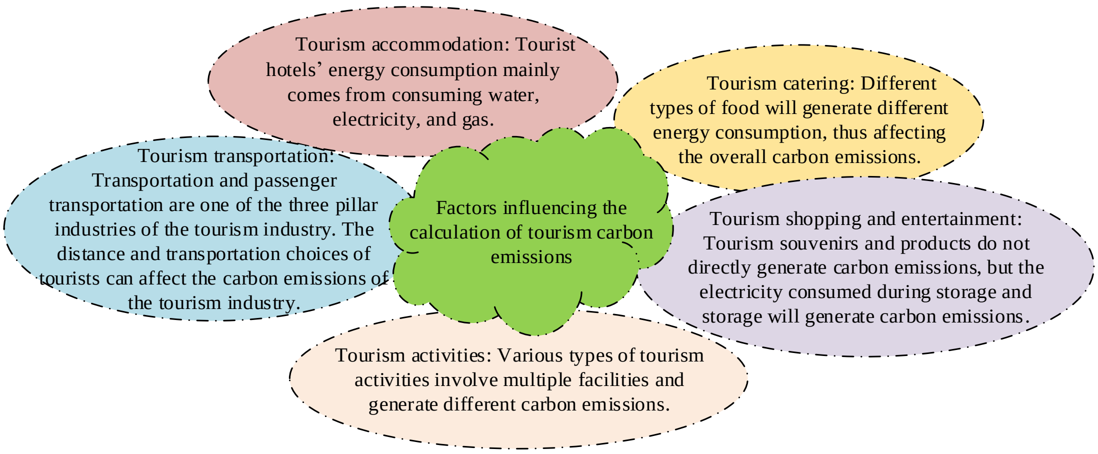


Figure 1: Relevant factors affecting carbon emissions measurement in the tourism industry

Given the strong multicollinearity among the tourism industry CE's various affecting factors, Lasso regression analysis is used to select characteristic variables, represented by equation (1).

$$\hat{\beta} = \arg_{\beta} \min \| y - x\beta \|^2 + \lambda \sum_{j=1}^{p} \left| \beta_j \right| \quad (1)$$

In equation (1), β represents the coefficient vector estimated by Lasso regression. y represents a dependent variable. β_j represents the coefficient of the independent variable. p represents the quantity of independent variables. x represents a characteristic value. λ represents a regularization parameter. $\lambda \sum_{j=1}^{p} \left| \beta_j \right|$ is a parameter penalty term. When λ is large, that is, when the penalty for parameters is large, the non-zero variables in the regression coefficients are smaller, and the retained variables are smaller. When λ is small, more variables are retained. SVR minimizes the error between the model and real data by finding an optimal function [20-21]. The basic idea is to map data to a high-dimensional space and find the optimal hyperplane to achieve regression. This method is suitable for complex nonlinear regression problems and has high prediction accuracy. Assuming the training sample is $D = \{(x_1, y_1), \ldots, (x_n, y_n)\}$, SVR is to find a function $f(x)$ that minimizes the predicted value $f(x)$ and the error of the true value y, represented by equation (2).

$$f(x) = \langle w, x \rangle + b \quad (2)$$

In equation (2), w represents a weight vector. b represents a bias term. $\langle \square \rangle$ refers to the inner product operation. SVR trains models by minimizing the sum of intervals and errors [22]. The interval is defined as the absolute difference between y and $f(x)$. The loss function is represented by equation (3).

$$\min imize \left(\frac{1}{2} \| w \|^2 + C \sum_{i=1}^{n} \left(\xi_i + \xi_i^* \right) \right) \quad (3)$$

In equation (3), $\| w \|^2$ represents the weight vector's norm. C represents a regularization parameter. ξ represents a relaxation variable. The optimization of SVR can be expressed as equation (4).

$$\begin{aligned} &\left[\min imize \left(\frac{1}{2} \| w \|^2 + C \sum_{i=1}^{n} \left(\xi_i + \xi_i \right) \backslash \ right \right) \right] \\ &[\ subject\ to\ y_i - \langle w, x_i \rangle - b \leq \int + \xi_i, \backslash\ quad\ \ \backslash\ langle\ w_1 x_i \rangle + b - y_i \leq \int + \xi_i \Big] \\ &\xi_i, \xi_i^* \geq 0 \end{aligned} \quad (4)$$

In equation (4), ò represents the set tolerance value used to determine the range of support vectors. The optimal w and b are found by solving the above optimization problem, thus obtaining SVR.

SVR significantly depends on selecting kernel functions and setting regularization parameters. Improper selection of these parameters may lead to overfitting or underfitting [23]. GA can enhance the model's adaptability to complex data and overall prediction accuracy by simulating natural selection and selecting the optimal parameter combination. This further enhances the model's accuracy and robustness in CE calculation in the tourism industry. Therefore, this study introduces the GA to optimize the parameter selection of SVR. The fitness function is $g(m)$, represented by equation (5).

$$g(m) = accuracy(SVR(m)) \quad (5)$$

In equation (5), m represents the parameter vector. Based on the fitness function, individuals with better performance are selected for crossover and mutation. Then, the new parameter combination is generated to explore the parameter space and find the optimal solution, represented by equation (6).

$$\begin{aligned} m_{new} &= crossover\left(m_{parent1}, m_{parent2} \right) \\ m_{new} &= mutate\left(m_{new} \right) \end{aligned} \quad (6)$$

This process simulates natural selection and improves the accuracy and adaptability of SVR by continuously iterating and optimizing until the optimal parameter combination is found. Therefore, the constructed Lasso-GA-SVR can predict the tourism industry CE [24-25]. The tourism industry CE reflects the total carbon dioxide generated by the industry in energy consumption. Given that the tourism industry covers a wide range of sectors, the CE generated includes both direct and indirect sources, which increases the complexity of CE measurement. It is necessary to clearly define the constituent sectors of the tourism industry to accurately measure. In Figure 2, the tourism industry is usually divided into three levels: direct, indirect, and related tourism. When estimating CE, four main sources of CE, namely tourism transportation, accommodation, catering, and activities, are selected to generate significant CE.

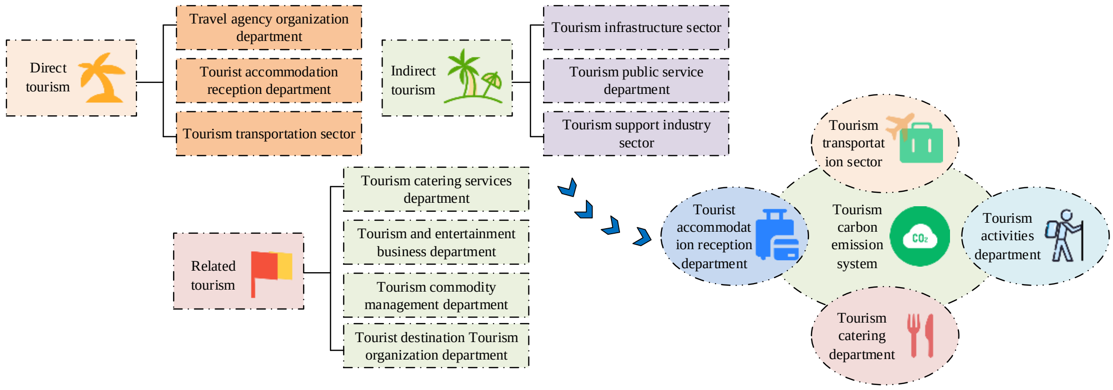


Figure 2: Specific sectors of the tourism industry and their main components of carbon emission systems

Models are established to measure four main sources of CE. The tourism transportation CE is represented by equation (7).

$$\begin{cases} C_j^T = \sum i\alpha_i F_i C_{ij} \\ E_j^T = \sum l\alpha_i G_i C_{ij} \end{cases} \tag{7}$$

In equation (7), i represents the mode of transportation. α_i means the proportion of tourism in the i th transportation mode. F_i represents CE. G_i represents energy consumption. C_{ij} means the i th passenger transportation mode's passenger turnover in region j. The calculation for tourism accommodation CE is represented by equation (8).

$$\begin{cases} C_j^H = n\beta N_j \tau_j \\ E_j^H = n\gamma N_j \tau_j \end{cases} \tag{8}$$

In equation (8), N_j and τ_j represent the occupancy rates of beds and rooms in a hotel in region j, respectively. β and γ represent the unit CE and unit energy consumption values per bed per night, respectively. n represents a constant. The tourism activity CE is represented by equation (9).

$$\begin{cases} C_j^A = n\sum M\eta_k P_{jk} \\ E_j^A = n\sum M\sigma_k P_{jk} \end{cases} \tag{9}$$

In equation (9), k means the type of tourism activity. M means the quantity of tourists received. η and σ represent the average CE and average energy consumption generated by a tourist participating in the k th tourism activity, respectively. P_{jk} represents the proportion of regional j tourists participating in the k th category tourism activity. The CE of tourism catering is represented by equation (10).

$$\begin{cases} C_j^C = n \cdot D\sum_{i=1}^{n}\left(E_i p_i \mu_i\right) \\ E_j^C = n \cdot D\sum_{i=1}^{n}\left(E_i p_i\right) \end{cases} \tag{10}$$

In equation (10), n means the quantity of tourists. D means the average day that tourists travel. E_i is the i th energy consumed by each tourist for daily dining. p_i is the i th energy source's heat conversion coefficient. μ_i is the CE coefficient of the i th energy source. Therefore, the tourism industry's CE and energy consumption are represented by equation (11).

$$\begin{cases} C_j = C_j^T + C_j^H + C_j^A + C_j^C \\ E_j = E_j^T + E_j^H + E_j^A + E_j^C \end{cases} \tag{11}$$

Therefore, Figure 3 shows the tourism industry CE measurement model based on Lasso-GA-SVR constructed in the study. Firstly, an analysis of influencing factors is conducted to identify various factors that affect the tourism industry CE, providing a foundation for subsequent model construction. Subsequently, data collection is carried out to collect data related to the tourism industry CE, providing data support for model training. In the model construction stage, Lasso regression is used for feature selection. GA optimizes the parameter selection of SVR. SVR is used for CE prediction. The prediction accuracy and robustness can be improved by iteratively optimizing model parameters. Finally, the trained model is used to predict the tourism industry's CE.

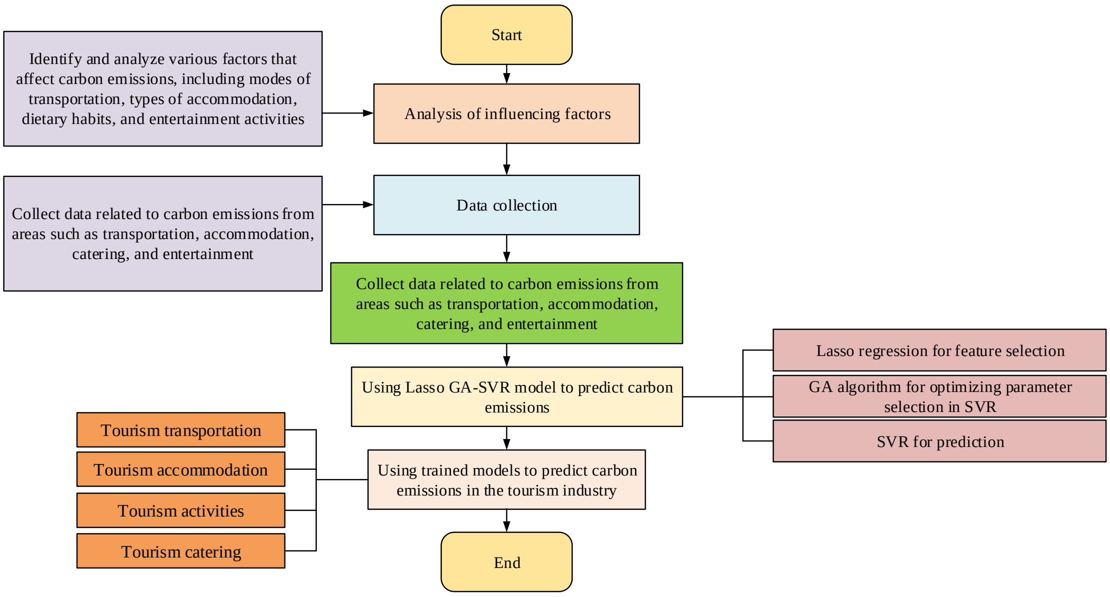


Figure 3: Model for measuring carbon emissions based on Lasso-GA-SVR

2.2 Construction of an urban tourism ecological efficiency measurement model based on tourism carbon emissions and DEA-Malmquist

The calculation of urban tourism CE provides important data support for the evaluation of tourism EE. Firstly, a calculation model for tourism CE and energy consumption is established. Quantitative analysis is conducted through actual data to accurately assess how urban tourism affects the environment. Next, the DEA-Malmquist productivity index model is utilized to dynamically analyze cities' tourism EE to reveal the efficiency changes in the tourism industry [26]. The Data Envelopment Analysis (DEA) model is an efficiency evaluation means using mathematical programming, especially suitable for dealing with efficiency problems in multi-input and multi-output situations. Figure 4 shows the categories and characteristics of DEA [27]. In the measurement of urban tourism EE, DEA can evaluate and compare the tourism resource consumption and environmental effects of different cities. DEA identifies decision-making units with relatively low efficiency by setting various inputs and outputs for the tourism industry. DEA points out potential directions for efficiency improvement.

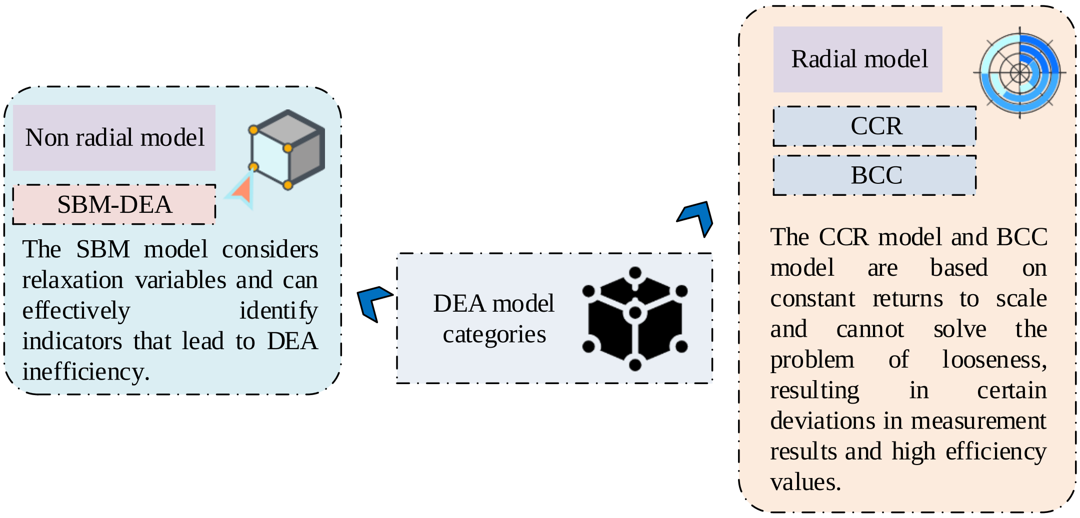


Figure 4: Types and characteristics of DEA models

In Figure 4, DEA can be divided into two categories, namely radial and non-radial models. However, traditional DEA cannot reflect decision-making units' dynamic efficiency changes at different times. Therefore, the Malmquist index is introduced in this study [28]. The Malmquist index can calculate total factor productivity. It does not require price information, which can measure panel data based on time series. It can identify the reasons for changes in total factor productivity. It contains Technical Efficiency Change (TEC) and Technical Progress Change (TPC). The Malmquist index model is shown in equation (12).

$$TFP = M^{t,t+1} = \left[M^t \times M^{t+1}\right]^{1/2} = \left[\frac{D^t\left(x^{t+1}, y^{t+1}\right)}{D^t\left(x^t, y^t\right)} \times \frac{D^{t+1}\left(x^{t+1}, y^{t+1}\right)}{D^{t+1}\left(x^t, y^t\right)}\right]^{1/2} \quad (12)$$

In equation (12), $\left(x^t, y^t\right)$ and $\left(x^{t+1}, y^{t+1}\right)$ mean the input-output relationship of the t and $t+1$ periods, respectively. The change from $\left(x^t, y^t\right)$ to $\left(x^{t+1}, y^{t+1}\right)$ is the change in EE. D^t and D^{t+1} are the output distance functions for the t and $t+1$ periods, respectively. If $TPE > 1$, productivity rises. If $TPE < 1$, productivity shows a downward trend. On the foundation of Fixed Scale Return (CRS), the Malmquist index can be decomposed into TEC and TPC. TEC measures whether output is approaching the optimal production boundary. If TEC>1, the Decision-Making Unit (DMU) efficiency increases from t to $t+1$, which decreases if TEC<1 [29]. Whether the TPC measurement technology improves or not, that is, whether the forefront of EE moves. If TPC>1, it indicates progress in DMU technology. On the contrary, it indicates a technological retreat. Equation (12) is further decomposed to obtain equation (13).

$$\begin{aligned} M_c^{t,t+1} &= \frac{D_c^{t+1}\left(x^{t+1}, y^{t+1}\right)}{D_c^t\left(x^t, y^t\right)} \times \left[\frac{D_c^t\left(x^t, y^t\right)}{D_c^{t+1}\left(x^t, y^t\right)} \times \frac{D_c^t\left(x^{t+1}, y^{t+1}\right)}{D_C^{t+1}\left(x^{t+1}, y^{t+1}\right)}\right] \\ &= TEC \times TPC^{1/2} \end{aligned} \quad (13)$$

Since equation (13) is decomposed under CRS conditions, it is not possible to determine the contribution of economies of scale to productivity. Under the condition of Variable Returns to Scale (VRS), a technical efficiency index can be degraded into Pure Technical Efficiency Index (Pech) and Scale Efficiency Index (Sech), as shown in equation (14) [30].

$$\begin{aligned} M_{v,c}^{t,t+1} &= \frac{D_v^{t+1}\left(x^{t+1}, y^{t+1}\right)}{D_v^t\left(x^t, y^t\right)} \times \left[\frac{D_v^t\left(x^t, y^t\right)}{D_c^t\left(x^t, y^t\right)} / \frac{D_v^{t+1}\left(x^{t+1}, y^{t+1}\right)}{D_c^{t+1}\left(x^{t+1}, y^{t+1}\right)}\right] \\ &\times \left[\frac{D_c^t\left(x^t, y^t\right)}{D_c^{t+1}\left(x^t, y^t\right)} \times \frac{D_c^t\left(x^{t+1}, y^{t+1}\right)}{D_c^{t+1}\left(x^{t+1}, y^{t+1}\right)}\right]^{\frac{1}{2}} \\ &= Pech \times Sech \times TPC \end{aligned} \quad (14)$$

In equation (14), if Pech > 1, pure technical efficiency increases. Otherwise, it indicates a decrease. If Sech > 1, scale efficiency increases. On the contrary, it indicates a decrease.

This study selects prefecture level cities as DMU, mainly based on their high autonomy and representativeness in tourism resource allocation and management. This choice enables research to measure and compare the tourism industry EE of provincial capital cities at the prefecture level (city level) scale. This helps to identify differences in resource utilization and environmental protection among cities. The tourism industry has strong industry relevance and comprehensiveness. Therefore, when selecting EE indicators, it should comprehensively reflect the tourism industry's core characteristics. It should meet the requirements of DEA to ensure accurate reflection of its input-output situation. When constructing an indicator system, multi-dimensional input and output indicators that can represent the basic operation of the tourism industry should be selected. Meanwhile, it is necessary to follow the usage conditions of DEA for data to ensure the scientific and accurate evaluation. This indicator setting helps to deeply analyze the tourism industry EE and provides a basis for sustainable development strategies in the tourism industry. Figure 4 shows the relevant principles that should be followed when selecting indicators.

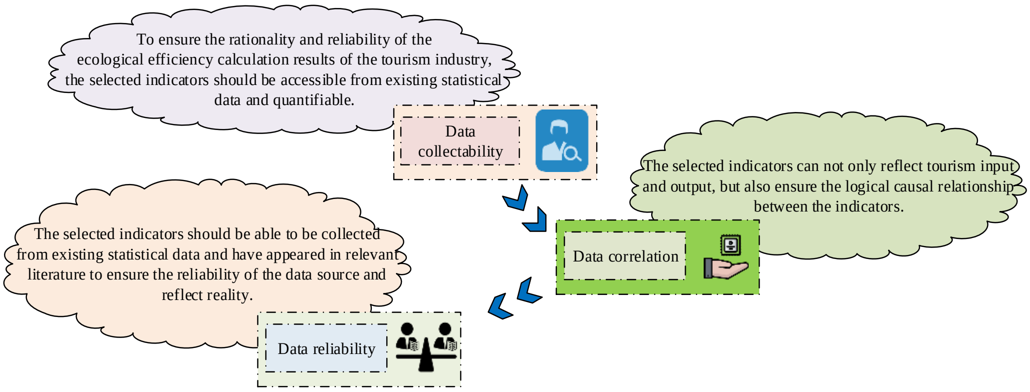


Figure 5: Principles for constructing tourism ecological efficiency indicators

According to the principles in Figure 5, this study adjusts the tourism EE indicators to ensure the evaluating scientificity and accuracy. In general, the more indicators selected, the more accurately the efficiency value can be reflected. However, when using DEA, the ratio of indicators to decision-making units needs to be controlled below 1/3. Therefore, this study selects 3 input and 2 output indicators, covering 12 decision-making units (excluding sub-provincial cities), in accordance with DEA standards. These three types of indicators include input, expected output, and unexpected output to comprehensively evaluate the tourism industry's EE in Figure 6.

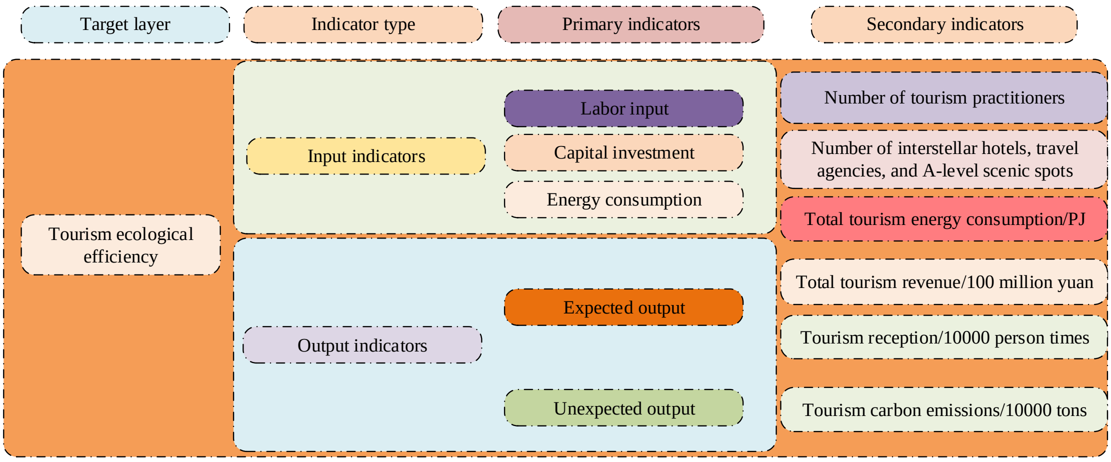


Figure 6: Tourism ecological efficiency indicator system

In Figure 6, labor input, capital input, and energy consumption are selected as the main input indicators to comprehensively reflect the resource allocation and environmental burden of the tourism industry. Total tourism revenue (including domestic and inbound tourism revenue) and the quantity of tourists received are regarded as expected output indicators. Tourism CE is used as an unexpected output indicator. The total tourism revenue and visitors can effectively measure the economic performance and attractiveness of the regional tourism industry. However, CE reflects the tourism industry’s environmental impact, especially the CE situation dominated by the four major sectors of tourism transportation, accommodation, catering, and activities. These indicator settings meet the proportion requirements of DEA for data quantity. That is, indicators should not exceed one-third of the decision-making units, ensuring a comprehensive evaluation of the tourism industry's EE.

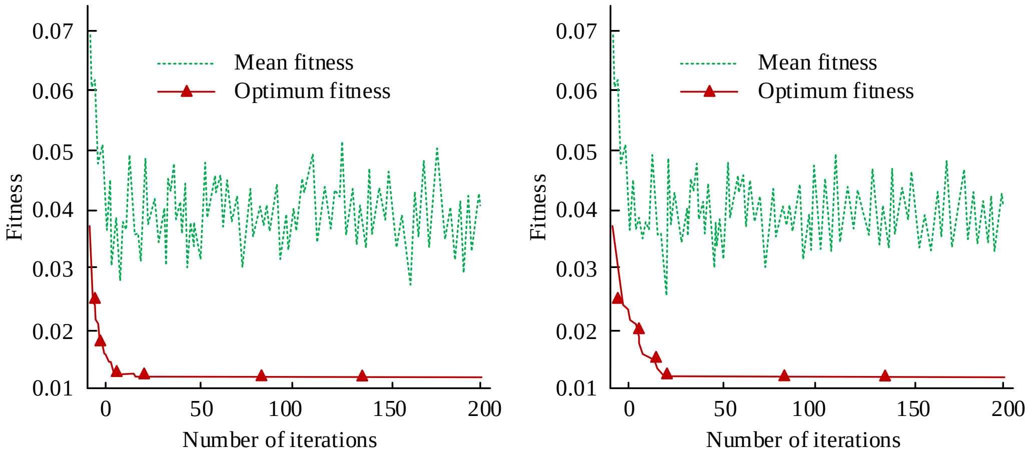
3 Results

First, this study validated the CE measurement performance of Lasso-GA-SVR, selecting CE data from a certain province as the dataset. Lasso-GA-SVR was compared and validated with the currently popular PCA-GA-SVR and GA-SVR. Subsequently, taking a certain province as an example, the DEA-Malmquist model was used to measure urban tourism EE.

3.1 Performance verification of carbon emission calculation models for the tourism industry

This study used CE data from a certain province from 2002 to 2022 as the research object to validate the proposed tourism industry CE calculation model. A Lasso-GA-SVR combined prediction model was established and used to calculate the tourism industry CE of the province in 2023. Meanwhile, the feasibility and effectiveness of this model were verified by comparing multiple combination models. This study selected time-series data from a certain province from 2002 to 2022 for empirical analysis. The CE factor data, energy consumption, energy conversion standard coal reference coefficient, and impact factor data were sourced from the China, China Energy, and provincial statistical yearbooks, respectively. This experiment was conducted on servers equipped with high-performance computing processors and large capacity memory. This study used 80% (2002-2017) of data as the model building and parameter optimization's training set. The remaining 20% (2018-2022) was utilized as the test set to validate the model's generalization ability and prediction accuracy. The experimental software environment included Python programming language, SVR implementation using Scikit learn library, and GA optimization using DEAP library, with Linux operating system.

This study set the penalty factor C and kernel function parameter g to have a value range of 0-100. Based on the complexity and target accuracy of the dataset, the population size was 20 individuals. The maximum iteration was 200 times, with a crossover probability of 0.7 and a mutation probability of 0.1. Through repeated selection, crossover, and mutation processes, the individual with the highest fitness was selected from the population and decoded. Then, the optimal hyper parameters C of 55.899 and g of 0.039301 were obtained. The mean square error of cross validation was 0.012251%. Figure 7 shows the population fitness curve. With the increase of genetic algebra, the optimum fitness and mean fitness gradually decreased and fluctuated within a small range, demonstrating good convergence.



(a) Fitness curve of training set (b) Fitness curve of test set

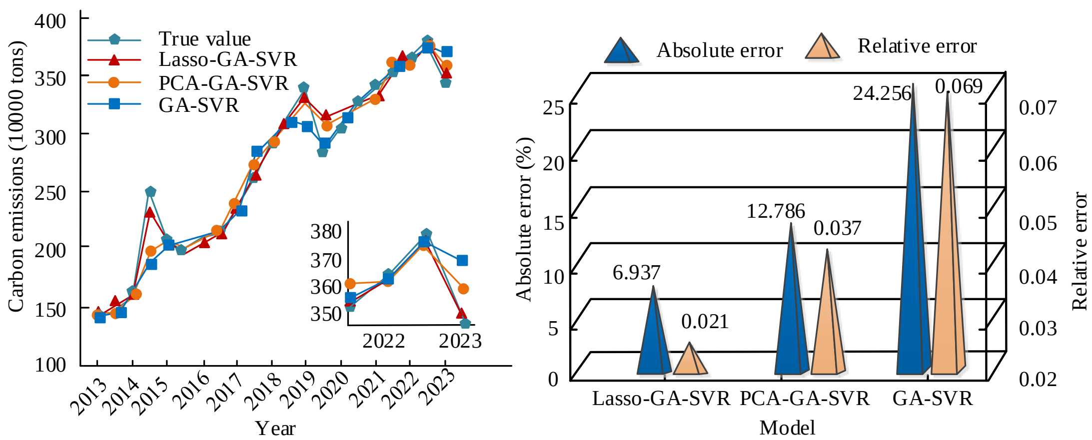
Figure 7: Population fitness curve

Parameter sensitivity analysis experiments were conducted to further understand the influence of regularization parameters and kernel function changes on model performance. The results are shown in Table 2. The results showed that the regularization parameters and kernel functions in different value ranges had significant effects on the model performance. In the range of 50-100 penalty factors, the mean square error of the model was the smallest (0.011678%). The prediction accuracy was the highest (95.12%). The mean square error of the model was 0.011945% and the prediction accuracy was 95.05% in the range of 50-100 kernel function. In the lower range of parameter values, although the calculation time was reduced, the prediction accuracy of the model was decreased. Appropriate adjustment of penalty factor and kernel function parameters could improve the accuracy of model prediction and optimize the training and test time.

Table 2: Experimental results of sensitivity analysis of parameters

Parameter	Value range	Optimal parameter	Mean square error (%)	Training time (s)	Test time (s)	Prediction accuracy (%)
Penalty factor	0-100	55.899	0.012251	45	5	93.56
Kernel function	0-100	0.039301	0.012251	43	4.8	93.65
Penalty factor	0-50	25.75	0.015345	30	4	90.43
Kernel function	0-50	0.02045	0.015786	29	3.9	90.32
Penalty factor	50-100	75.67	0.011678	55	5.5	95.12
Kernel function	50-100	0.05534	0.011945	53	5.3	95.05

Lasso-GA-SVR was compared and validated with PCA-GA-SVR and GA-SVR to validate the proposed Lasso-GA-SVR's computational effectiveness. Figure 8 presents the comparison results of the obtained combination model's prediction performance. Figure 8 (a) shows the predictive fitting performance of three models. From the zoomed in image, Lasso-GA-SVR had a better fit between the predicted and actual values compared to PCA-GA-SVR and GA-SVR. Therefore, Lasso-GA-SVR had a smaller error and better predictive performance in the tourism industry CE calculation in 2023. In Figure 8 (b), the relative error of Lasso-GA-SVR, PCA-GA-SVR, and GA-SVR was 2.005%, 3.701%, and 7.011%, respectively. The absolute error was 6.937%, 12.786%, and 24.256%, respectively. Lasso-GA-SVR performed the best due to its lower absolute and relative errors compared to the other two models. Therefore, the combination of Lasso feature variable selection and GA significantly improved the prediction accuracy of SVR.



(a) The fitting results of the four models (b) Prediction errors of the four models

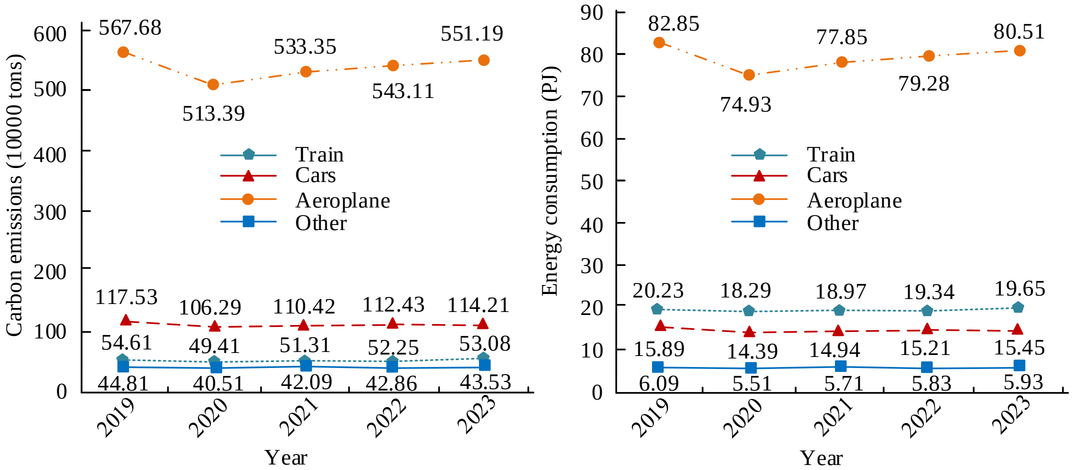
Figure 8 Comparison results of the predictive performance of the combination model

Other datasets were selected for testing to further verify the robustness of the Lasso-GA-SVR model. Several datasets were used to test the experiment, including energy consumption, traffic flow, and industrial production data. The same parameter settings were used for model training and testing. The performance of different models was compared by statistical significance test. The experimental results are shown in Table 3. Lasso-GA-SVR showed higher prediction accuracy and lower mean square error on different datasets. In the energy consumption dataset, the mean square error of Lasso-GA-SVR was 0.012251%, and the prediction accuracy was 93.56%, which was significantly better than PCA-GA-SVR and GA-SVR models. Experimental results on traffic flow and industrial production dataset also showed that the prediction performance of Lasso-GA-SVR model was superior to other models, especially on industrial production dataset, Lasso-GA-SVR model had the lowest mean square error (0.010978%) and the highest prediction accuracy was 95.45%. Through the statistical significance test of t test, the P-values were all less than 0.05, indicating that the prediction performance of Lasso-GA-SVR model was significantly better than other models on different datasets. Therefore, the model combined with Lasso feature variable selection and GA optimization had high robustness and showed stability. The model maintained high precision prediction results under different datasets.

Table 3: Robustness test results

Dataset	Model	Mean square error (%)	Training time (s)	Test time (s)	Prediction accuracy (%)	t test /P-value
Energy consumption	Lasso-GA-SVR	0.012251	45	5.1	93.56	/
	PCA-GA-SVR	0.013456	47	5.2	92.43	0.03
	GA-SVR	0.015678	50	5.5	90.12	0.04
Traffic flow	Lasso-GA-SVR	0.011345	43	4.8	94.23	/
	PCA-GA-SVR	0.012567	45	5.3	93.12	0.02
	GA-SVR	0.014789	48	5.3	91.45	0.03
Industrial production Dataset Energy consumption	Lasso-GA-SVR	0.010978	42	4.5	95.45	/
	PCA-GA-SVR	0.012345	44	4.8	94.32	0.01
	GA-SVR	0.013789	46	5.7	92.78	0.02

Figure 9 shows the CE and energy consumption of various transportation modes in the tourism industry in the province, calculated using Lasso-GA-SVR. In Figure 9 (a), the average CE of trains, cars, and airplanes was 521300, 1132300, and 5417400 million tons. In Figure 9 (b), the average energy consumption of trains, cars, and airplanes was 15.23, 19.85, and 79.88 PJ. As a result, the CE and energy consumption of airplanes were significantly higher than other transportation, becoming the main source of CE. With the improving living standards, airplanes have become the most convenient means of transportation for tourism. In contrast, although trains consume more energy than cars, their CE is lower than cars. Cars have become people's travel choices due to their flexibility, with CE ranking second. In addition, the CE and energy consumption of aircraft in 2020 decreased by 10% compared to the previous year, while from 2021 to 2023, it showed an annual growth rate of 7%. These data indicated that tourism transportation affected the environment significantly and pointed out potential key areas for future emission reduction measures.

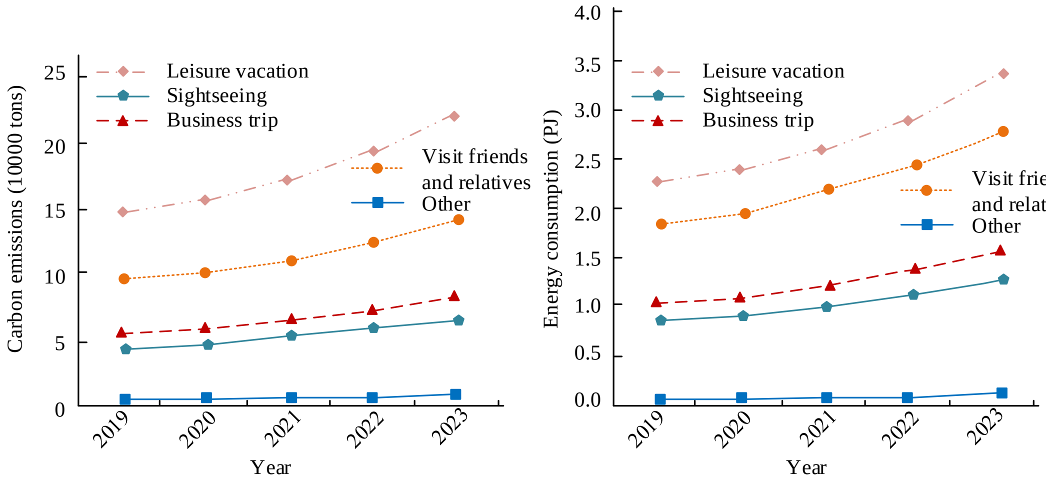


(a) Carbon emissions from tourism transport in the province

(b) Energy consumption for tourism transportation in the province

Figure 9 The carbon emissions and energy consumption of various transportation modes in the tourism industry of the province

Figure 10 shows the CE and energy consumption of different tourism activities in the province calculated using Lasso-GA-SVR. In Figure 10 (a), the average CE for leisure vacation activities, sightseeing, business trips, and visiting relatives and friends was 171100, 126700, 72300, and 61200 tons. In Figure 10 (b), the average energy consumption for these indicators was 2.82, 2.35, 1.23, and 1.12 PJ. According to the above data, the tourism CE and energy consumption generated by leisure vacation activities were both the highest and showed an increasing trend year by year. High income groups usually meant higher demands for tourism services quality, which prompted tourist destinations to improve service facility standards, thereby increasing energy use and CE. Meanwhile, the economic development of the province was slow. The motivation for most outbound tourism was to visit family and friends.



(a) Carbon emissions from different tourism activities in the province

(b) Energy consumption of different tourism activities in the province

Figure 10 Different tourism activities' carbon emissions and energy consumption

According to the data calculated using Lasso-GA-SVR, Figure 11 shows the trend of total tourism CE and energy consumption in the province from 2019 to 2023. Although the tourism CE and energy consumption in the province decreased significantly in 2020, both indicators increased year by year since 2020. Especially in 2021, the year-on-year growth rate of CE reached 5%, indicating the fastest growth year. The change in total energy consumption was roughly consistent with CE and also showed an upward trend. These data confirmed that over time, the energy dependence and CE pressure on the tourism industry in the province continued to increase.

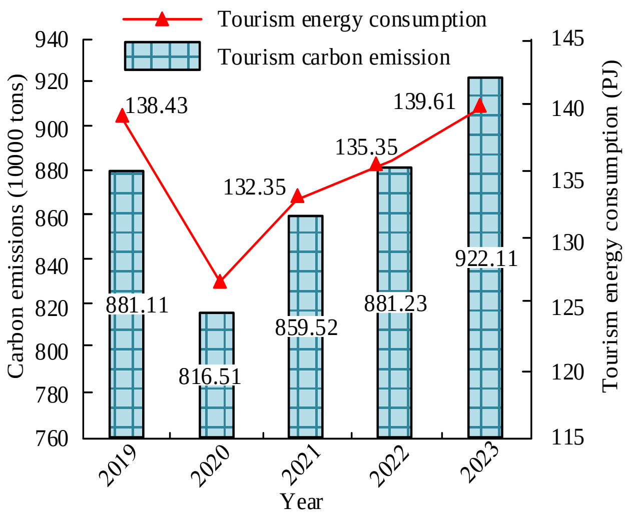
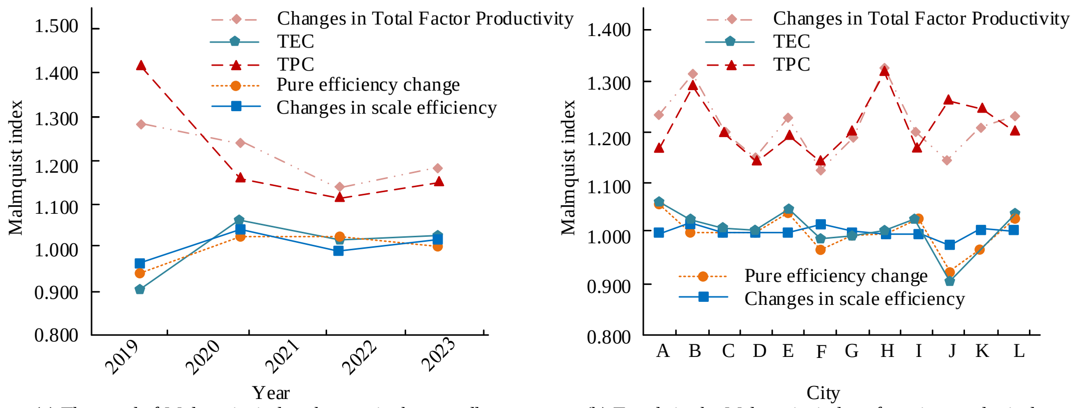


Figure 11: The carbon emissions and energy consumption of the tourism industry in the province

3.2 Empirical analysis of urban tourism ecological efficiency measurement model based on tourism carbon emissions and DEA-Malmquist

This study used prefecture level cities in the province as decision-making units to validate the proposed tourism industry EE measurement model. On the foundation of the prefecture level (city level) scale, the tourism industry EE of the province's prefecture level cities was calculated and compared. The static efficiency of each prefecture level city from 2019 to 2023 was evaluated. A longitudinal analysis was conducted on the dynamic changes of tourism EE in various prefecture level cities in the province from 2019 to 2023. The overall tourism EE status and individual development situation in the province were evaluated.

Figure 12 shows the annual Malmquist index trend of tourism EE in the province and its prefecture level cities. In Figure 12 (a), the overall tourism EE of the province showed a fluctuating trend from 2019 to 2023. The technical efficiency dropped from its maximum point of 0.774 in 2019 to its minimum point of 0.706 in 2020 and gradually rebounded to 0.759 in 2023. Pure technical efficiency and scale efficiency also showed similar fluctuations, experiencing a decline and slow recovery after reaching their peak in 2019. This indicated that after a period of adjustment, the tourism EE in the province gradually recovered and showed a positive development. In Figure 12 (b), from 2019 to 2023, in the tourism EE assessment of 12 prefecture level cities C, D, and H in the province all achieved ideal values of 1 in terms of technology, pure technology, and scale efficiency. This indicated that these cities were at the industry's forefront for tourism ecological management and scale. In contrast, cities A, B, and J had higher technological and scale efficiency, but room for improvement still existed. Especially, the scale efficiency of city G was 0.513, which was much lower than other cities, indicating its obvious disadvantage in the scale of tourism ecology.

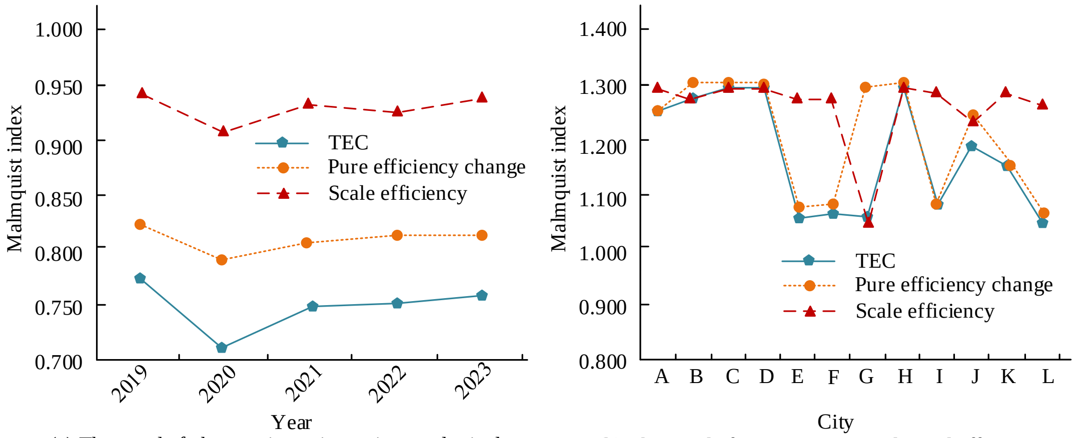


(a) The trend of Malmquist index changes in the overall tourism ecological efficiency

(b) Trends in the Malmquist index of tourism ecological efficiency

Figure 12: The annual trend of Malmquist index changes in tourism ecological efficiency of the province and its prefecture level cities

Figure 13 shows the average trend of static tourism EE in the province and its prefecture level cities. In Figure 13 (a), from 2019 to 2023, the total factor productivity of the province showed a V-shaped fluctuation. It dropped from its maximum point of 1.281 to its minimum point of 1.135, and then rebounded to 1.181, achieving an average growth rate of 20.98% over the past five years. TEC's average annual growth rate was 0.3%, far lower than TPC's average annual growth rate of 21.3%. Technological progress was a main driving force behind improving tourism EE in this province. In Figure 13 (b), from 2019 to 2023, 12 prefecture level cities' total factor productivity showed an increasing trend, with an average growth rate of 20.97%. City H had the largest growth rate, at 32.35%. TPC showed that some cities such as F, G, J, and K experienced negative growth, while cities A and B achieved positive growth. TPC achieved double-digit growth in all cities, with an average growth rate of 21.28%. The above data indicated that although some cities experienced a decline in technological efficiency, technological progress was still the main factor when improving tourism EE.

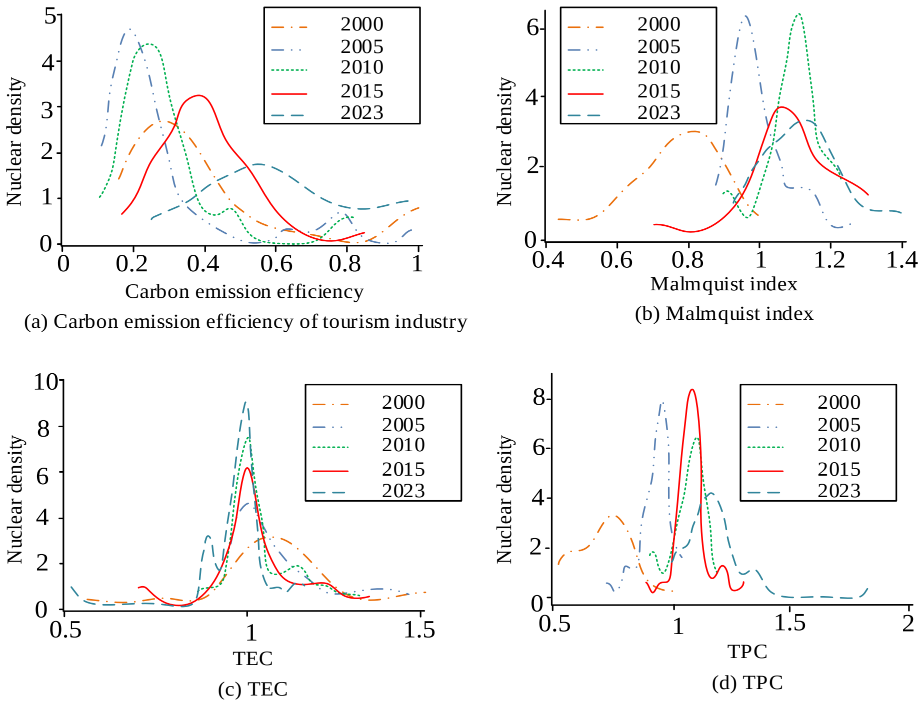


(a) The trend of changes in static tourism ecological efficiency in the province

(b) The trend of static tourism ecological efficiency changes in various cities in the province

Figure 13: The average trend of static tourism ecological efficiency in the province and its prefecture level cities

Figure 14 shows the kernel density calculation results of the tourism industry's CE efficiency in this province. This study selected 2000, 2005, 2010, 2015, and 2023 as the study time periods. Firstly, from the perspective of the evolution trend of CE efficiency, the nuclear density curve shifted to the right, showing a characteristic of increasing CE efficiency year by year. The nuclear density curve's right tail in 2000 showed obvious clustering characteristics. The following years showed a multi-peak distribution. This indicated that the efficiency improvement between cities was relatively fast. However, the efficiency gap was also widening. Secondly, the kernel density curve of tourism EE changed (Malmquist index) generally drifts to the right except for 2019, indicating a positive growth trend in tourism EE. Between 2005 and 2010, the curve shifted to the right and the peak narrowed, indicating a significant improvement in efficiency growth rate and a narrowing of inter regional disparities. The evolution trend of TEC indicated that the distribution of technological efficiency in various provinces and regions developed towards equilibrium since 2015. The nuclear density curve of TPC showed a clear right shift trend. This indicated that the technological progress of the tourism industry was significant. There are more cities with high levels of technological innovation. Overall, the improvement of the tourism industry's CE efficiency was primarily driven by technological progress. The efficiency differences between cities were gradually narrowing. However, there was also a phenomenon of slow or even regression in the growth of CE efficiency in some cities.



(a) Carbon emission efficiency of tourism industry

(b) Malmquist index

(c) TEC

(d) TPC

Figure 14: The nuclear density calculation results of carbon emission efficiency in the tourism industry of the province

This study used Moran scatter plots to analyze tourism EE's spatial agglomeration in 2005, 2010, 2015, and 2023, as shown in Figure 15. In 2005, there were 7 cities with tourism EE located in the first and third quadrants, accounting for 60% of the total sample, showing a strong spatial agglomeration effect. Subsequently, in 2010, cities in the first quadrant (high-high agglomeration) decreased by one, while cities in the third quadrant (low-low agglomeration) increased by one. By 2015, cities in the third quadrant decreased by 2. Cities in the first quadrant remained unchanged. In 2023. Cities in the first quadrant increased by 2. Cities in the third quadrant remained unchanged. Therefore, the high-high agglomeration trend of tourism EE in this province went through a process of first weakening and then strengthening. The low-low agglomeration showed a trend of first strengthening and then weakening. Overall, the decrease in low-low agglomeration cities indicated a trend towards high efficiency agglomeration in tourism EE in the province.

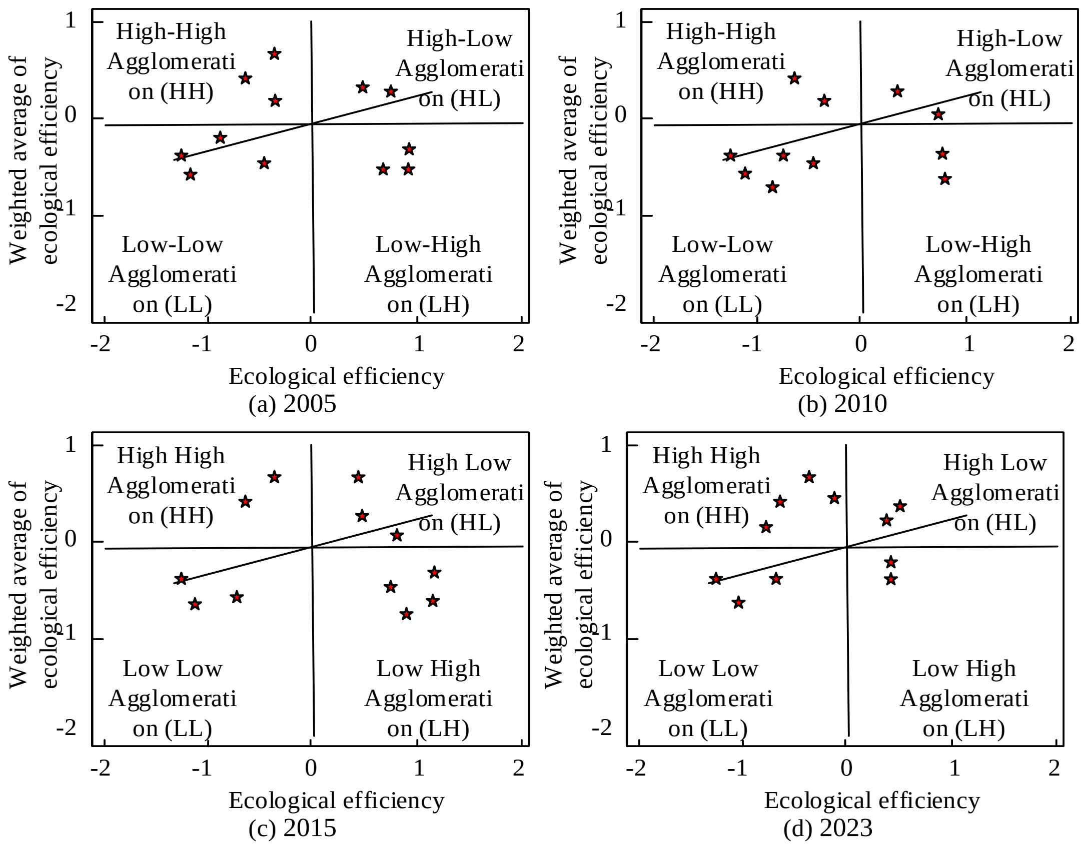


Figure 15: Moran scatter plot of ecological efficiency of tourism industry in the whole province

4 Discussion

The LASSO-GA-SVR model combined Lasso feature selection with GA-optimized SVR. The prediction accuracy and computational efficiency of the model were improved by reducing irrelevant features. Compared with PCA-GA-SVR and GA-SVR, Lasso-GA-SVR had lower mean square error and higher prediction accuracy on multiple datasets, indicating that the model was more robust and adaptive. The mean square error of Lasso-GA-SVR model was 0.011678%. The prediction accuracy was 95.12%, which was much better than the error and accuracy of PCA-GA-SVR and GA-SVR. In addition, experimental results on datasets such as energy consumption, traffic flow and industrial production further validated the superiority of Lasso-GA-SVR model. Lasso-GA-SVR had the lowest mean square error and the highest prediction accuracy. The novelty of LASSO-GA-SVR was that Lasso feature selection effectively reduced the complexity of the model and improved the computational efficiency. The introduction of genetic algorithm optimized the hyperparameter selection of SVR model and improved the prediction accuracy and robustness of the model. Compared with PCA-GA-SVR and GA-SVR, Lasso-GA-SVR model showed higher stability and applicability when dealing with complex datasets. The performance difference of Lasso-GA-SVR was due to the reduction of redundant information through feature selection, which improved the generalization ability of the model. In addition, the superior performance of GA in hyperparameter optimization enabled the model to better adapt to different datasets. Different methods were used in the CE accounting framework proposed by J. Zha et al., and H. Mishra et al. 's literature metrology review on tourism CE. Both pointed out the importance of feature selection and model optimization [31-32]. In contrast, Lasso-GA-SVR was better at improving prediction accuracy and handling complex datasets.

LASSO-GA-SVR performed well in feature selection and hyperparameter optimization. However, Lasso required more computing time and resources on large-scale datasets. The diversity of data in different geographic regions might introduce new features and variables, increasing the difficulty of model training and adaptation. These limitations can be further optimized in the future.

5 Conclusion

This study proposes a tourism CE measurement model based on Lasso-GA-SVR and an urban tourism EE measurement model based on DEA-Malmquist. This can more accurately measure the urban tourism industry EE and be conducive to the urban tourism economy and ecological environment’s coordinated development. Relevant validation was conducted to verify the proposed model’s effectiveness. The mean square error of cross validation for Lasso-GA-SVR was 0.012251%. With the increase of genetic algebra, the optimum and mean fitness exhibited good convergence. In comparative validation, the relative error of Lasso-GA-SVR, PCA-GA-SVR, and GA-SVR was 2.005%, 3.701%, and 7.011%, respectively. The absolute error was 6.937%, 12.786%, and 24.256%, respectively. Taking a certain province as an example, using Lasso-GA-SVR to calculate CE, the average CE of trains, cars, and airplanes was 521300, 1132300, and 5417400 tons. The average energy consumption was 15.23, 19.85, and 79.88 PJ. The average CE from leisure vacation activities, sightseeing, business trips, and visiting relatives and friends in tourism activities was 171100, 126700, 72300, and 61200 tons. The average energy consumption was 2.82, 2.35, 1.23, and 1.12 PJ. The empirical analysis results of DEA-Malmquist showed that the overall tourism EE in the province showed a fluctuating trend. The highest technical efficiency point was 0.774, the lowest point was 0.706, and then gradually rebounded to 0.759 in 2023. Different cities had different tourism EE. The proposed strategy can effectively measure CE and the urban tourism industry's EE. The limitation of this research lies in the tourism industry's strong comprehensiveness, which has not taken into account various departments. Future research can start from here.

The effectiveness of Lasso-GA-SVR is verified through experimental analysis. This model has accuracy and reliability in predicting and evaluating CE and energy consumption in the tourism industry in practical applications. By measuring and evaluating the EE of the tourism industry, this study further expands the model’s application fields and provides reference value for the tourism industry’s sustainable development. According to empirical analysis, the tourism industry CE and total energy consumption in the studied province continue to grow. Among various departments, tourism transportation has the largest proportion of CE, which has a decisive impact on overall CE and energy consumption. Therefore, this province needs to optimize its transportation structure and develop energy conserving and emission reducing technologies. Meanwhile, the tourism and catering industry has a significant increase in CE and energy consumption related to activities. People need to focus on developing tourism activities with low resource consumption and low energy demand to slow down the growth trend of energy consumption and CE. These experimental data indicate significant differences in tourism EE among the 12 prefecture level cities in the province. Each city should deeply analyze its own advantages and limitations, implement targeted improvement measures, and enhance tourism EE. For cities with lower scale efficiency, it is necessary to expand their scale, improve their intensification level, reduce CE, and achieve economies of scale. For cities with insufficient technological efficiency, attention should be paid to improving management and technological levels and promoting the comprehensive improvement of tourism EE.

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