A Study on Sustainable Tourism Optimization Based on a Logistic-Driven RTS Model

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Abstract. As one of the fastest-growing industries in the world, tourism has become an important driver of economic development. However, its rapid expansion has also brought about serious environmental degradation and social unrest, especially in regions facing overtourism. Therefore, sustainable tourism has become a global priority. This study proposes an RTS tourism optimization model to balance economic benefits, environmental impacts, and social well-being. The three optimization factors of the model are total tourism revenue (R), tourism carbon footprint (TCF), and social happiness index (SH), which represent the economic, environmental, and social dimensions, respectively. The economic revenue (R) is modeled using a logistic model to simulate the initial growth and subsequent saturation stages of tourism development, thereby obtaining the RTS optimization model. The model is applied to overtourism cities (Juneau). The Pareto optimal solution is selected based on the entropy weight method (EWM) using the NSGA-II and NSGA-III algorithms combined with actual data. The results show that the proposed model can significantly reduce the environmental burden and improve the well-being of residents while ensuring an acceptable level of tourism revenue, which provides a flexible and scalable framework for local governments to design evidence-based sustainable tourism development policies.

Keywords: Sustainable Tourism, Logistic Model, Multi-Objective Optimization, NSGA-II Algorithm, EWM.

1. Introduction

As the world's third-largest export category and one of the world's fastest-growing industries before the epidemic, tourism has been an important source of foreign exchange and jobs for countries around the world, and has been closely linked to their economic and environmental development [1]. Although the epidemic had a huge impact on the tourism industry, the world tourism industry has shown an extremely rapid recovery since 2021. However, this rapid growth has led to problems such as overtourism, which causes overcrowding in cities, distress among local residents during peak seasons, and permanent changes in lifestyle, infrastructure, and well-being. These issues, known as hidden costs, have burdened many cities, leading to rising housing prices, traffic congestion, ecological damage, and other challenges that undermine residents' quality of life, turning tourism from a development driver into a hazard.

To tackle the challenges of sustainable tourism, researchers have developed a variety of models based on multi-objective optimization and multi-criteria decision-making. These approaches commonly integrate environmental, economic, and social dimensions into unified analytical frameworks. Notably, NSGA-II has been widely applied to address complex sustainability goals. Tan (2023) improved the algorithm to balance economic returns and environmental constraints in urban tourism [2], while Akbari et al. (2024) used NSGA-II and MCE to map ecotourism suitability based on spatial and socio-ecological data [3]. Hybrid evaluation models have also gained attention. Liang et al. (2017) combined PCA, entropy weighting, and TOPSIS to assess scenic area sustainability [4], and Heydari et al. (2025) introduced a spatial MCDM framework for ecological park planning under uncertainty [5]. Other studies focus on practical decision support. Arbolino et al. (2021) built a model to optimize tourism project investments across sustainability metrics [6], and Pitakaso et al. (2024) proposed a multi-objective trip design system balancing tourist preferences and environmental impacts using artificial intelligence [7].

Despite these contributions, existing models often lack an integrated framework that balances environmental, economic, and social objectives. Many are confined to static case studies or specific regions, limiting their adaptability. Furthermore, few incorporate dynamic feedback between government interventions and tourism system responses, which is essential for realistic policy evaluation.

To address these gaps, this study proposes the RTS optimization model based on Logistic economic forecasting. The model incorporates a comprehensive set of indicators across economic, environmental, and social dimensions, and integrates policy decision variables with dynamic feedback loops [8]. It is applied to both over-touristed cities. Using the Entropy Weight Method (EWM), the optimal solutions are identified to support local governments in making timely decisions and formulating long-term strategies for sustainable tourism development.

2. RTS Tourism Optimization Model

From the perspective of the present and the future, sustainable development encompasses three main dimensions: economic, social and environmental sustainability. For the tourism industry, the realization of sustainable development must pay attention to the impact of tourism on the economy, environment and society. By analyzing the relationship between various factors under the influence of the three dimensions, we can solve problems such as over-tourism and realize sustainable tourism.

To illustrate this approach, Figure 1 presents the overall structure and workflow of the RTS tourism optimization model, highlighting the relationships between decision variables, evaluation metrics, and the multi-stage optimization process applied across different regional contexts.

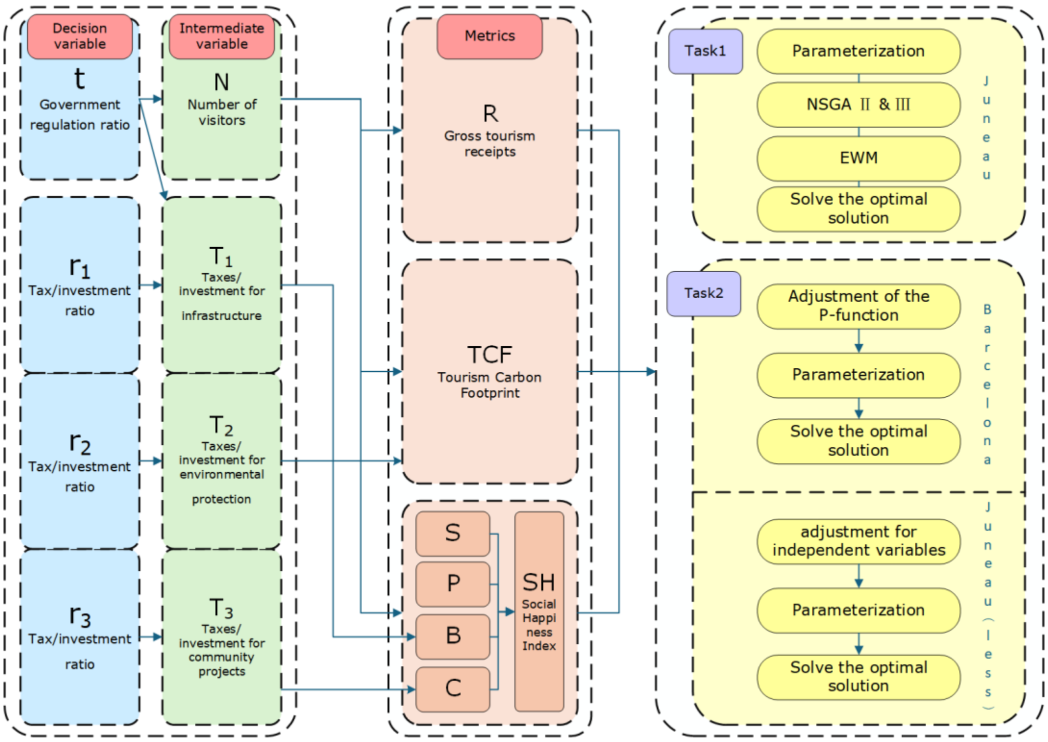

Figure 1. The flow chart of our work

2.1. Decision variables

In order to reflect whether the government adopts an absorption policy or a restriction policy for tourists, we set the government regulation ratio (t) as a decision variable. t is positive for additional tax revenue and t is negative for government investment. At the same time, we divided the additional tax revenue into three parts: the part for infrastructure (r_1), the part for environmental protection (r_2), and the part for community programs (r_3). By allocating the additional tax revenues, we achieve a specific regulation of tourism and feed the results back into the measurement indicators.

2.2. Intermediate variable

For the specific calculation of the objective function, we also need to express the number of visitors per day and the amount of tax revenue. These two as independent variables after the calculation of the results, directly reflecting the results of the regulation of measures, the impact of the indicator factors.

2.3. The Establishment of RTS Model

2.3.1. Intermediate variable

a. Number of visitors:

$$N = -\alpha t + N_0 \tag{1}$$

Where t is positive, α is the marginal negative impact coefficient of taxation on the number of tourists, which is used to indicate the degree of negative impact of the tax regulation ratio; when t is negative, α is the marginal positive side of the impact coefficient of investment on the number of tourists, which is used to indicate the degree of positive impact of the investment regulation ratio. The larger the value, the more sensitive the impact of the increase in tax revenue on the reduction of tourists. N_0 is the average value of the number of tourists before the regulation is implemented.

b. Tax revenue:

Total tax revenue:

$$T = t \cdot R \tag{2}$$

Taxes for infrastructure:

$$T_1 = T \cdot r_1 \tag{3}$$

Taxes for environmental protection:

$$T_2 = T \cdot r_2 \tag{4}$$

Taxes for community projects:

$$T_3 = T \cdot r_3 \tag{5}$$

Where t is the proportion of government regulation, R is the value of tourism revenue, N is the number of tourists. r_i is the proportion of additional tax allocation.

2.3.2. Objective function determination

a. Gross tourism receipts

Economic income is mainly considered as macro income, and the disposable income factor of residents is related to the happiness of residents, so the disposable income factor of residents is attributed to the social level. Economic growth and the number of tourists have the characteristics of rapid growth in the early stage and over-saturation in the later stage, which is consistent with the logistic model, and the use of the model to establish a relationship can well illustrate the changes in tourism revenue in over-tourism areas and areas with low tourism numbers, so as to find out the total tourism revenue.

$$R(N) = (t+1) \cdot \frac{R_{\max}}{1+e^{-k(N-N')}} \tag{6}$$

Where t is the government regulation percentage, N is the number of tourists, $Rmax$ is the maximum economic revenue, and N' is the turning point describing the number of tourists at the moment of the fastest growth in tourism revenue.

b. Tourism Carbon Footprint

Environmental pollution is mainly caused by the carbon footprint, and the impact of water pollution and solid pollution is mainly on residents' lives, so when determining the carrying capacity, water pollution and solid pollution are attributed to the social level calculation. From the above, only the carbon footprint of the tourism and transportation sector is considered [9]. According to the relevant literature model, we take the product of the number of people, the distance and the average carbon emission as the base, and add the equivalence factor and the proportion of transportation modes as the coefficients, so as to find the total carbon footprint.

$$TCF = \sum_{i=1}^{k}(N\, L_i\, D_i\, \beta_i\, \varepsilon_i)$$
$$\beta_i = \beta_{i0} - c \cdot T_2 \tag{7}$$

Where N is the number of tourists, L_i is the transportation mode share of category i, D_i is the operating distance (km), β is the CO2 emission intensity, ε_i is the equivalence factor, and k is the total number of transportation modes.

c. Social Happiness Index

Social well-being index is a reflection of residents' satisfaction and is directly related to the environmental carrying capacity of tourism. The limit of the number of tourists that a tourist area can accommodate is called the environmental carrying capacity of tourism, which consists of four kinds of carrying capacity: the spatial carrying capacity of resources ($REBC$), the economic carrying capacity ($DEBC$), the waste treatment capacity ($EEBC$), and the psychological carrying capacity of residents ($PEBC$). When the number of tourists exceeds the limit value, it means that the carrying capacity is insufficient, which will cause negative impacts on the local economy, environment and society, thus affecting the satisfaction of the residents.

$$SH = w_1 \cdot S + w_2 \cdot P + w_3 \cdot B + w_4 \cdot C \tag{8}$$

Where w_1-w_4 are the weights of the factors, S is the spatial factor, P is the factor of disposable income of residents, B is the factor of infrastructure, and C is the factor of community activities.

Spatial factor:

$$S = \begin{cases} 1 - \gamma_1(\mathrm{N} - REBC), N \geq REBC \\ 1, N < REBC \end{cases}$$
$$REBC = \frac{daily\ turnover\ rate \times Total\ resource\ space}{Standard\ area\ of\ basic\ space\ per\ capita} \tag{9}$$

Where $REBC$ is the spatial carrying capacity of resources and γ_1 is the overcrowding factor.

Disposable income factor:

$$P = \delta_1 P_1 + \delta_2 P_2 \tag{10}$$

Where δ_1,δ_2 are the number of non-tourism-related residents and the percentage of tourism-related residents, respectively.

For the non-tourism-related general population, the factor is P_1:

$$P_1 = \begin{cases} 1 - \gamma 2(\mathrm{N} - \mathrm{DEBC1}), N \geq \mathrm{DEBC1} \\ 1, N < \mathrm{DEBC1} \end{cases} \tag{11}$$

Where N is the number of non-tourism-related residents, γ_2 is the housing supply and cost factor.

For tourism-related residents, the factor is P_2:

$$P_2 = \frac{R}{Np \cdot rmax} \tag{12}$$

Where $rmax$ is the income maximum and N_r is the number of tourism-related residents.

The economic carrying capacity $DEBC$ includes hotel beds ($DEBC1$), water supply capacity ($DEBC2$), electricity supply capacity ($DEBC3$), and transportation capacity ($DEBC4$), where hotel beds ($DEBC1$) are considered to be provided to tourists. Take the value according to the local specific situation.

Infrastructure factor:

$$B = \frac{B_1+B_2}{2} \tag{13}$$

For drinking water supply, the factor is B_1:

$$B_1 = \begin{cases} 1-\gamma 4(N-DEBC2), N \geq DEBC2 \\ 1, N < DEBC2 \end{cases}$$
$$DEBC2 = d_2 \cdot T_1 + N_1 \tag{14}$$

Where $DEBC2$ is the water supply capacity, γ_4 is the drinking water supply shortage factor, and N_1 is the number of people based on the basis of local environmental support for water supply.

For waste disposal, the factor is B_2:

$$B_2 = \begin{cases} 1-\gamma 5(N-EEBC), N \geq EEBC \\ 1, N < EEBC \end{cases}$$
$$EEBC = d_1 \cdot T_1 + N_1 \tag{15}$$

Where $EEBC$ is the waste treatment capacity, d_1 is the tax effect coefficient, γ_5 is the pollution coefficient for waste treatment, and N_2 is the base carrying capacity of the local environment to support waste treatment.

Community activity factor:

$$C = \begin{cases} 1-\gamma 6(N-PEBC), N \geq PEBC \\ 1, N < PEBC \end{cases}$$
$$PEBC = d_3 \cdot T_3 + N_3 \tag{16}$$

Where $PEBC$ is the psychological carrying capacity of residents, which refers to the number of tourists (persons per day) that the residents of a tourist destination can accept from the psychological perception. γ_6 is the community tourist carrying coefficient, and N_3 is the base number of tourists that local residents can accept.

The above γ_1-γ_6 are all coefficients, which need to be decided according to the base number of local tourists and the living conditions of the residents; d_1, d_3, c are the coefficients of the tax effect, reflecting the degree of influence of the tax on the change of the carrying capacity.

2.3.3. Model feedback

In our model, the additional government spending will be used to improve infrastructure, environmental protection and social activities, which will form the internal feedback of the model; the specific flow is shown in Figure 2.

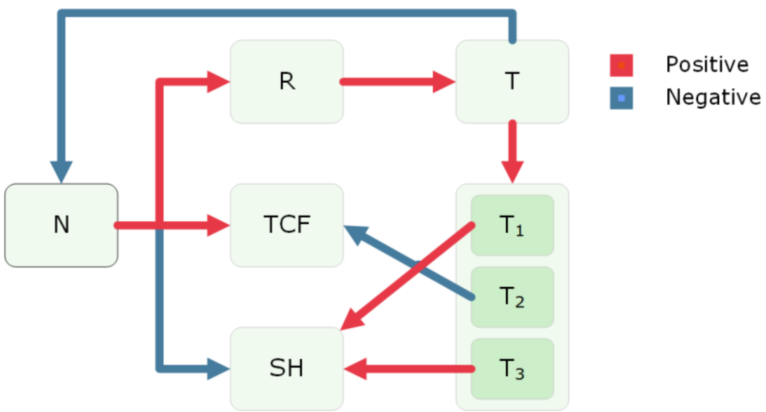

Figure 2. Feedback schematic

3. Results

The data utilized in this paper were collected from https://juneau.org/, https://www.delta-foundation.org.tw/blogdetail/8553?utm_source=chatgpt.com, https://www.akbizmag.com/monitor/travel-juneau-releases-results-of-convention-and-visitor-surveys/

3.1. A Model-Based Solution for Sustainable Tourism Development

3.1.1. Parameterization

The initial values of all parameters are shown in the following Table 1.

Table 1. Initial Parameter Value of Juneau

Parameters	Value	Parameters	Value	Parameters	Value
N_0	20000	α	40000	t	10%
R_{max}	6000000	N'	7000	k	2.26*10^(-5)
L_1	0.7	L_2	0.2	L_3	0.1
D_1	500	D_2	10	D_3	10
β_1	0.07	β_2	0.018	β_3	0.075
ε_1	1.05	ε_2	1.05	ε_3	1.05
W_1	0.35	W_2	0.25	W_3	0.2
W_4	0.2	γ_1	6*10^(-5)	γ_2	6*10^(-5)
γ_3	0.067	γ_4	4*10^(-5)	γ_5	4*10^(-5)
γ_6	4*10^(-5)	N_1	15000	N_2	15000
N_3	15000	δ_1	15%	δ_2	75%
d_1	0.025	d_2	0.025	d_3	0.025

According to the above table, assuming all independent variables are 0, substituting these values into the model yields the initial solution. The initial data set for the city shows that the initial number of tourists is 20,000. The initial economic income is $56,981,626.The initial carbon emission is 739,305 kg. The initial social well-being index is 0.53923681. This initial dataset reflects a situation where economic income is nearing saturation, carbon emissions are high, and social well-being is low, which aligns with the actual conditions of the area.

3.1.2. Equation solving

NSGA-III improves upon NSGA-II by focusing on multi-objective optimization problems with a large number of objectives and introducing reference points to enhance the algorithm's performance. While NSGA-II uses non-dominated sorting for selection and ranking, it struggles with the effectiveness of sorting and selection pressure when the number of objectives increases, leading to uneven solution distribution, especially when the objectives are greater than or equal to 3.

NSGA-III addresses this issue by introducing reference points, which are predefined, usually equidistant points in the target space. These reference points are incorporated into congestion calculations, enabling a more uniform division of the target space and a more even distribution of solutions, making it ideal for problems with many objectives.

3.1.3. Result of the Simulation

Based on the above solution method, we use NSGA-II and NSGA-III algorithms to solve the model and the obtained Pareto solution set is shown in Figure 3.

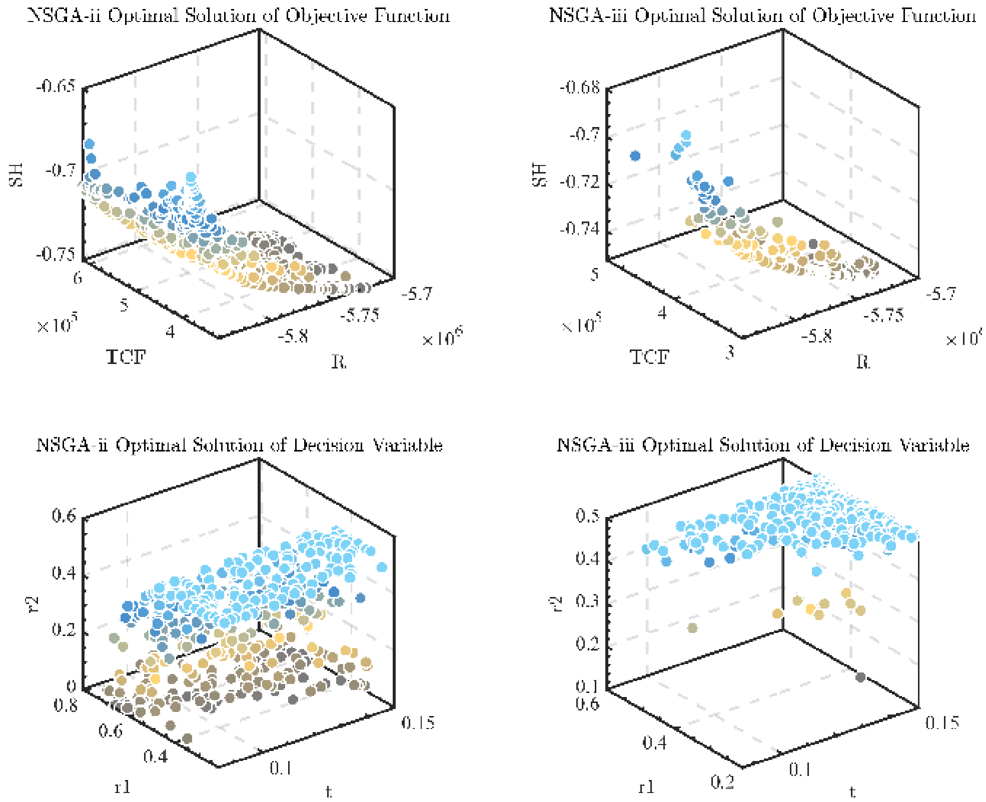

Figure 3. Pareto solution set of NSGA-II/NSGA-III

The two algorithms yield similar distributions, indicating reasonable solution sets. However, NSGA-II's solution set is more planar, while NSGA-III's is more curvilinear. NSGA-II shows a more uniform distribution of independent variables, while NSGA-III's solutions are concentrated in the higher r2r_2r2 region. This suggests that NSGA-II offers better diversity, possibly due to the lower dimensionality of the function. After obtaining the Pareto solution set, we use the entropy weighting method to rank the objectives and find the optimal solution. which aligns with recent research applying NSGA-II to manage visitor-related emissions and social outcomes [10].

The weights obtained are shown in Figure 4.

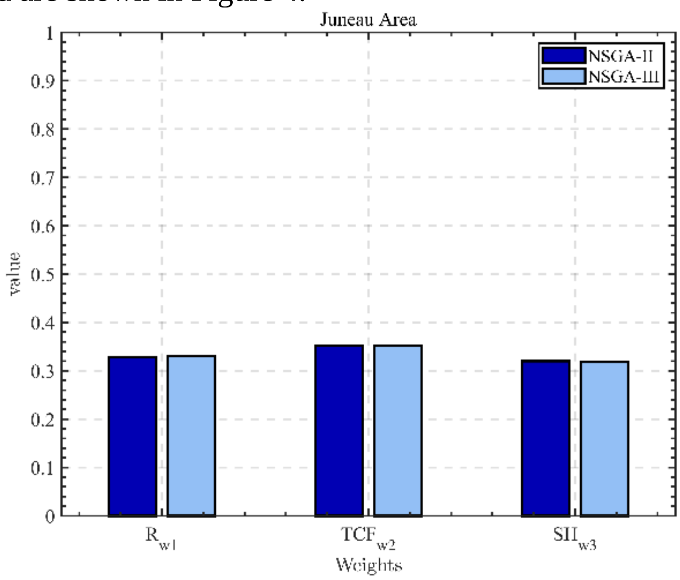

Figure 4. Entropy weights

The weights obtained by the two algorithms are basically the same, reflecting the consistency and convergence of NSGA-II and NSGA-III at the level of information entropy. Despite their differing distribution characteristics in the solution space—NSGA-II tending to produce more planar solutions and NSGA-III generating more curved, concentrated fronts—the calculated indicator weights remain nearly identical. This suggests that the entropy weight method offers a stable and algorithm-independent means of evaluating indicator importance. By applying these entropy-derived weights, the solutions in the Pareto front are ranked objectively, ensuring that the optimal solution selected reflects the most balanced trade-off among all indicators.

The optimal solutions obtained through this process are illustrated in Figure 5. Interestingly, although the weighting results are consistent, the optimal solutions from each algorithm are located in different regions of the solution set. This is the effect of algorithm-specific search behavior, while also reaffirming the significance of this study's entropy-based evaluation in guiding consistent decision-making.

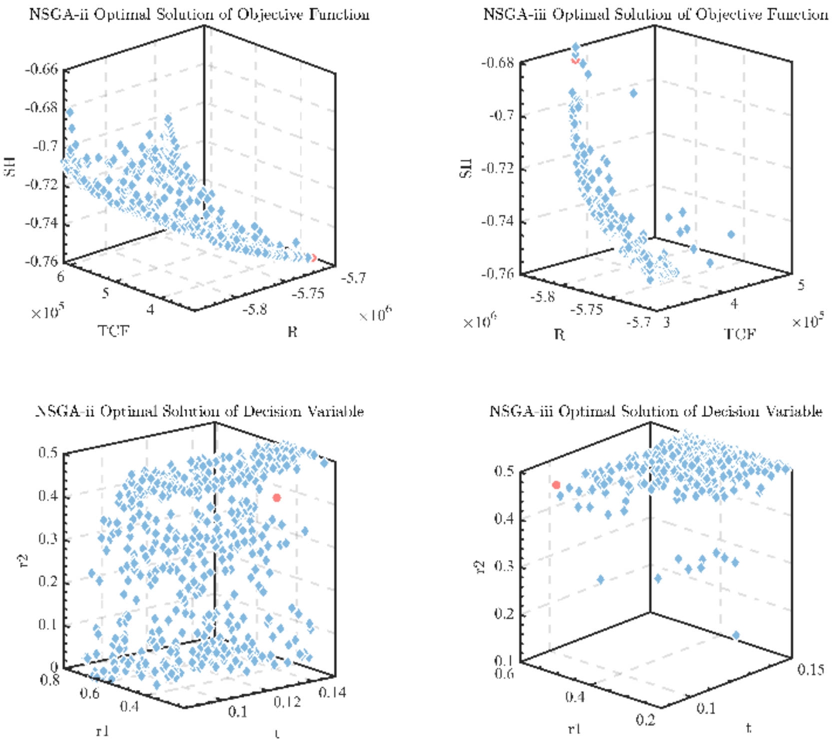

Figure 5. Optimal solution position

It can be seen that the optimal solutions of the two algorithms are distributed in the lower right and upper left of the solution set, respectively, which may be due to the principle of the entropy weight method using information entropy evaluation. In order to quantitatively analyze the degree of optimization of the model solutions to the indicators, we define the optimization rate (F):

$$F = \frac{F_1}{F_2} - 1 \tag{17}$$

Where F1 represents the amount of indicators after optimization, F2 represents the initial amount before optimization, a positive F represents positive optimization, and the absolute value of F represents the degree of optimization.

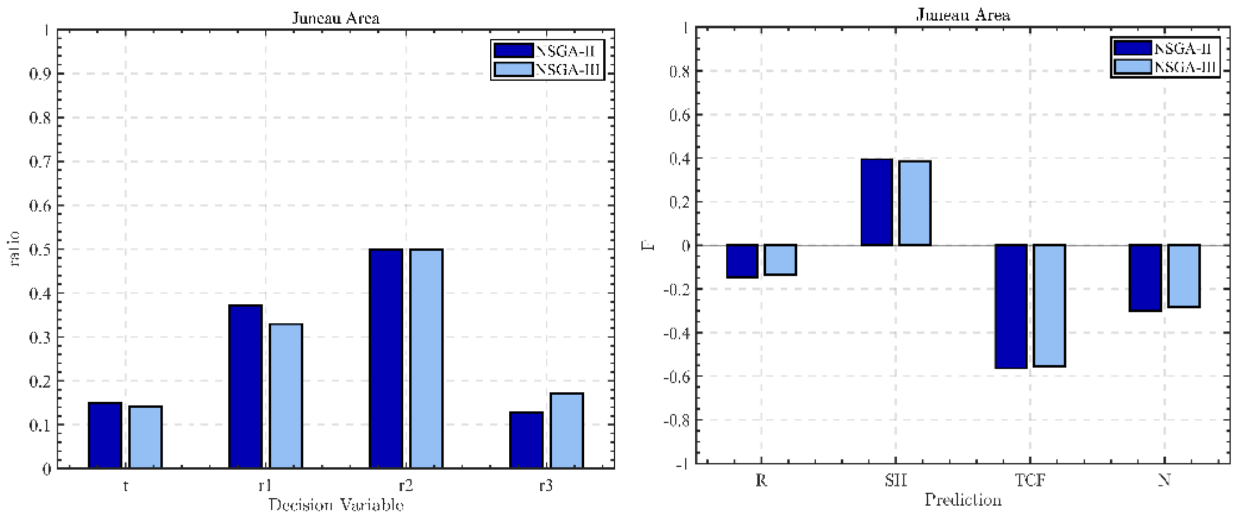

Figure 6. Independent variables (left) and optimization ratea (right) of the optimal solution

The independent variables and optimization rates of the two sets of optimal solutions are shown below.

From Figure 6, we can observe that the optimization rates of the independent variables and indicators of both solution sets are similar, indicating that the two algorithms yield nearly identical results, and the model exhibits a certain degree of stability.

Based on the actual situation in Juneau, we believe that environmental and social indicators are more critical for the development of sustainable tourism in Juneau, so we choose the NSGA-II algorithm's optimal solution. The optimal solution involves collecting a 15% tourism tax (including hotel tax, tourist fees, etc.), with 37% of the additional tax used for infrastructure, such as water supply and waste treatment systems; 50% for environmental protection, such as using clean energy to reduce carbon emissions; and 13% for community activities, supporting cultural, educational, and social service projects. This plan reduces the tourism carbon footprint by 56.32% and increases social well-being by 39.45%, but it results in a 30% decrease in tourists and a 14.62% reduction in tourism revenue, with a tourist count of 14,000. According to local information, the Juneau government will limit the number of tourists starting in January 2026, with a daily cap of 16,000 cruise tourists from Sunday to Friday, and 12,000 on Saturdays. The model's optimization results align closely with this policy, indicating that the solution is feasible and consistent with local conditions.

4. Conclusions and outlooks

This paper developed an RTS tourism optimization model to aid sustainable tourism development, with optimal solutions derived using the NSGA-ii&iii algorithm and entropy weight method:

Juneau: A 15% tourism tax is proposed, with 37% allocated for infrastructure (e.g., water and waste systems), 50% for environmental protection (e.g., clean energy to reduce carbon emissions), and 13% for community activities (e.g., cultural and social programs). This is expected to reduce the tourism sector's carbon footprint by 56.32%, enhance societal well-being by 39.45%, but could decrease visitor numbers by 30% and tourism revenue by 14.62%, resulting in about 14,000 visitors.

These results highlight the broader applicability of the RTS model as a practical decision-support tool for governments and planners. Its ability to adapt across different tourism contexts—ranging from over-touristed cities to emerging destinations—makes it a scalable framework for guiding sustainable tourism development in diverse regional settings.

Future work may focus on improving the accuracy of social well-being measurements by incorporating more comprehensive local data and refined indicators. Additionally, refining indicator selection methods and enhancing model adaptability to broader contexts will further strengthen the applicability and precision of sustainable tourism planning tools.

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