Research on Sustainable Tourism Development Based on Multi-Objective Optimization

Zhiyu Wang [1, *, #], Zhaodi Mu [2, #], Jianing Niu [1], Weixiang Wang [2], Ye Wang [1]

[1] School of Management, Shijiazhuang Tiedao University, Shijiazhuang, China, 050043

[2] School of Information Science and Technology, Shijiazhuang Tiedao University, Shijiazhuang, China, 050043

* Corresponding Author Email: zywang812@163.com

#These authors contributed equally.

Abstract. The global tourism industry has experienced significant growth in the aftermath of the COVID-19 pandemic. However, the rise of over-tourism and the surge in mass "revenge tourism" have presented substantial challenges to the sustainable development of the sector. This paper examines the phenomenon of over-tourism, using Juneau, Alaska, as a case study. It highlights that the number of tourists is the most crucial factor influencing sustainable tourism development. A multi-objective planning-based RC model was developed, which incorporates tourism revenue, environmental pressure, social pressure, and infrastructure strain. The weights for these pressures were effectively determined using the Analytic Hierarchy Process (AHP). Adaptive inertia weights were incorporated to enhance the efficiency and stability of the algorithm. Sensitivity analysis confirms that the number of tourists is the most critical factor influencing sustainable tourism, with tax levels and penalty coefficients also exhibiting significant sensitivity. Finally, this paper proposes a management strategy to achieve a balance between tourism-driven economic growth and the pressures associated with over-tourism.

Keywords: Over-tourism, Multi-objective planning, Tourist number optimization, Sustainable tourism.

1. Introduction

Juneau, Alaska, is a well-known tourist destination, and tourism has significantly boosted the region's economy. However, over-tourism has become an escalating challenge at the local level, with destinations such as Seychelles, Bhutan, and the Grand Cayman Islands lifting tourism restrictions, resulting in congestion and localized inflation. Academic research on over-tourism and sustainable tourism development has been increasing. Shi (2022) assessed the extent of over-tourism in cities using a comprehensive evaluation method; however, the study relied on a limited number of indicators, making the quantification somewhat simplistic [1]. Flyen (2023) examined the impact of tourism in the Svalbard archipelago through case studies and field surveys, yet the study lacked quantitative analysis of the indicators [2]. In the same year, Huang et al. (2023) investigated sustainable tourism in Aragon using an environmental-social-economic triad model, offering a well-structured interpretation. However, their choice of evaluation indicators limits the model's applicability to urban environments [3].

This paper uses Juneau as a case study to develop a model for sustainable tourism development based on multi-objective optimization. The model enhances its interpretability by incorporating a comprehensive set of indicators, including tourist numbers, tourism-related economic benefits, the city's carrying capacity, and environmental and social pressures. By employing multi-objective optimization, the model determines the optimal tourist flow and provides recommendations for effectively managing visitor numbers. This study on over-tourism in Juneau offers valuable insights into promoting the sustainable development of the local tourism industry.

2. Patronage, Economic Benefits, and Pressures on the City of Juneau

2.1. Analysis of Tourist Numbers

In the model developed in this paper, the growth in tourist numbers can be represented by an exponential model, assuming no constraints are placed on the number of tourists.

Table 1. Number of visitors to Alaska

Year	Number of Tourists (Million)
2000	1.4
2005	1.7
2010	1.9
2015	2
2019	2.26

This paper refers to the Alaska Travel Industry Association's report, which excludes data influenced by the global COVID-19 pandemic after 2020, as shown in Table 1.

$$N(t) = N_0 \times e^{r(t-t_0)} \tag{1}$$

Where $N(t)$ is the number of visitors in year t.

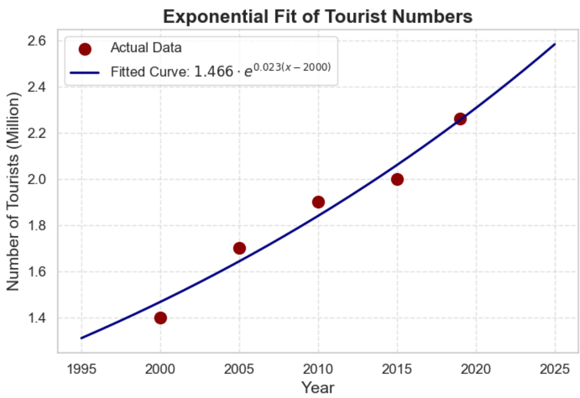

Figure 1. Fitted Curve for Tourist Arrival Growth

As shown in Figure 1, the number of tourists is growing exponentially at a rapid rate. While it is essential to increase the number of tourists to generate economic benefits for the city, this growth rate should not exceed the city's development pace. Otherwise, it could exacerbate the issue of over-tourism.

2.2. Tourism Economic Model of the City of Juneau

Tourism revenue is driven by tourism expenditures, and the economic impact of the cruise ship industry includes all spending by cruise ship visitors. In 2023, the cruise ship industry generated 3,150 direct jobs and 700 indirect jobs in the city of Juneau. Onyeabor (2020), in his assessment of the Obudu Hills Resort in Nigeria, identified employment as the primary contributor to economic growth[4]. Similarly, the value of jobs created by the cruise ship industry in Juneau must be considered when evaluating tourism development.

With cruise passengers spending approximately $320 million in Juneau during the summer of 2023—accounting for 85% of all direct spending—the cruise economy is the most significant contributor to the city's tourism revenue. This paper will model the cruise economy through an analysis of its impact on the local economy.

In the Economic Impact of Juneau's Cruise Industry report by McKinley Research Group (2023), the composition of the cruise economy in Juneau is categorized into direct income, indirect income, direct income from tourist spending, and indirect income from job creation[5]. The economic benefits$R(t)$are outlined below:

$$R(t) = N(t) \times p \times T + J(t) \times w \tag{2}$$

Where p represents per capita consumption, T is the proportion of government tax revenue, $J(t)$ denotes jobs, and w is the average wage. By analyzing the relevant data presented in Table 2, this paper shows a significant correlation between employment ($J(t)$), the number of tourists, and infrastructure investment.

Table 2. Data on Employment, Infrastructure Investment, and Tourist Arrivals

Year	Infrastructure Investment (Million)	Tourist Arrivals (10,000)	Employment
2015	2.3	2	343.35
2016	2.32	2.155	346.02
2017	2.35	2.205	348.69
2018	2.36	2.255	351.36
2019	4.69	2.26	354.03

Based on publicly available data, regression analysis was conducted using Stata 18, and the following regression equation was derived using the least squares method:

$$J(t) = 225.21 + 54.66 \times N(t) + 1.16 \times I \tag{3}$$

where I represents infrastructure investment.

2.3. Tourism Stress Model for the City of Juneau

The criteria for evaluating a tourist destination are not limited to the level of income generated by the tourism industry, but also need to consider the various pressures that the development of tourism brings to the local community[6].

$$C(t) = \sum_{i}^{n} C(t)_i \times \lambda_i \tag{4}$$

$C(t)$ represents the tourism pressure in year t, $C(t)_i$ denotes the i -th type of pressure,and λ_i is the penalty factor corresponding to the current pressure.

Considering the actual situation of Juneau, this paper classifies tourism pressure into three main components: environmental pressure, social pressure, and infrastructure pressure, which are respectively denoted by C_α、C_β、C_γ,The corresponding penalty coefficients are λ_α、λ_β、λ_γ.

The penalty coefficients are crucial for constructing the model. Given the specifics of the research subject, the setting of these coefficients requires careful discussion. The Analytic Hierarchy Process (AHP) is a decision-aid method used to determine the penalty coefficients in this paper. Drawing on the approach of Huang et al. (2023), experts in relevant fields—such as the economic, social, environmental, and infrastructure impacts—were invited to score the penalty coefficients. The resulting penalty coefficients are presented in the heat map shown in Figure 2.

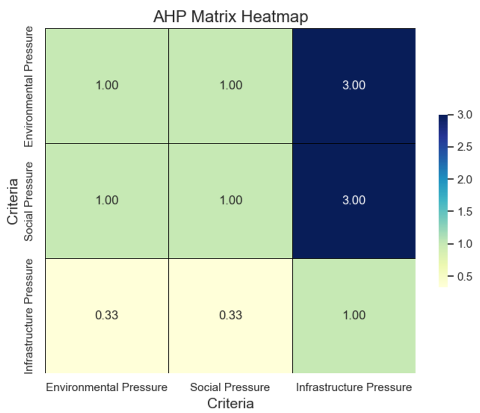

Figure 2. Heat Map of Penalty Coefficients

Finally, λ_α= 0.6 , λ_β= 0.2, λ_γ=0.2.

The city of Juneau is renowned for its glacial environment, and the condition of its glaciers serves as an indicator of the environmental impacts of tourism. Wang et al. (2020) used a shallow ice approximation model to describe glacier volume changes[7], while Flyen (2023) identified a negative correlation between environmental factors, such as greenhouse gas emissions, and the sustainability of tourism growth in his study on tourism-induced pressures and site degradation. In this paper, we examine the relationship between carbon emissions, temperature changes, and glacier volume changes by simplifying the shallow ice approximation model.

Relationship between temperature and carbon emissions:

$$\Delta T = \eta \times ln\left(\frac{C}{C_0}\right) \tag{5}$$

ΔT represents the temperature change relative to the initial state, λ is the climate sensitivity factor, and $C$and C_0 refer to the atmospheric CO2 concentrations for the current and base years, respectively.

Glaciers are affected by temperature:

$$V(t) = V_0 - \phi \times \Delta T \tag{6}$$

$V(t)$ is the glacier volume in year t, V_0 is the initial glacier volume, and ϕ is the coefficient of the effect of temperature change on the decrease in glacier volume. The glacier trend is shown in Figure 3.

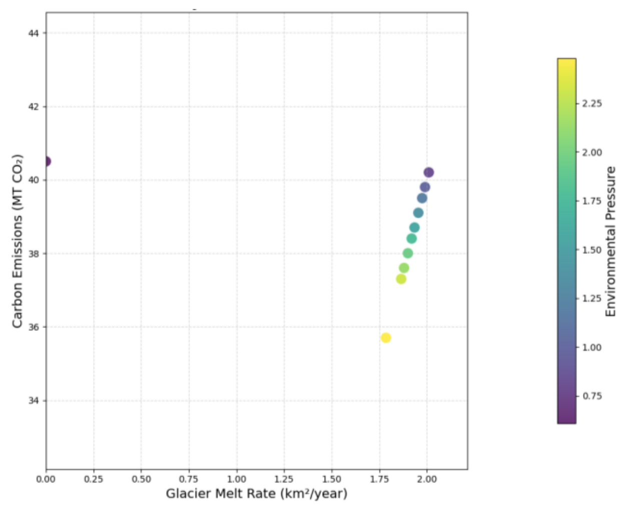

Figure 3. Glacier Change

Over-tourism has intensified social pressures in Juneau, including overcrowding, rising housing prices, and increased tax levels, which can lead to lower life satisfaction among local residents.

Crowding pressure is defined as follows:

$$\varphi(t) = \frac{N(t)}{P(t)} \tag{7}$$

$\varphi(t)$ represents the level of congestion, and $P(t)$ refers to the local population.

The social stress model is as follows:

$$C(t)_\beta = \Phi_1 \times \phi(t) + \Phi_2 \times T + \Phi_3 \times H + (\phi(t) - \phi(t)_{max})(T - T_{max})(H - H_{max}) \tag{8}$$

where T represents the tax level, H is the house price, and $\varphi(t)_{max}$, T_{max}, $H_{\max}$ are the corresponding thresholds.

Infrastructure is primarily under pressure in terms of water supply, waste disposal, and transportation, and the level of infrastructure is a crucial factor for tourism development [8].

The infrastructure stresses of the City of Juneau are modeled as follows:

$$C_\gamma(t) = \sum_{i=1}^{3} \Psi_i \times N(t) \times \pi_i \tag{9}$$

where Ψ_i represents the components of infrastructure stress, and π_i is the coefficient for each infrastructure stress factor.

3. Key Factors and Future Directions for Sustainable Tourism

3.1. Construction and Solution of the RC Model

The core of sustainable tourism development is to achieve the harmonious integration of economy, society, and environment. The establishment of a sustainable tourism model must consider a variety of factors, with the ultimate goal of achieving multi-objective optimization to maximize economic benefits while minimizing pressure on environmental and social infrastructure. Building on the previous cruise economy model and pressure model, all models are standardized and processed to construct the RC model as follows:

$$Objective(t) = R(t)_{norm} - C(t)_{norm} \tag{10}$$

$$\begin{cases} C(t)_\alpha \le max\, C\,(t)_\alpha \\ C(t)_\beta \le max\, C\,(t)_\beta \\ C(t)_\gamma \le max\, C\,(t)_\gamma \\ 0 \le r \le 1 \\ 0 \le T \le 1 \\ 0 \le I \le max\, I \end{cases} \tag{11}$$

where $R(t)_{norm}$, $C(t)_{norm}$ is the normalized result.

In the RC model, the optimization decision variables—population growth rate, tax level, and infrastructure investment—are interrelated, and the solution space is relatively large. As a result, the overall solution space can be highly complex. The particle swarm optimization (PSO) algorithm itself has certain limitations, particularly the tendency to converge prematurely to local optima when its parameters are not appropriately set[9]. To enhance the efficiency and accuracy of the algorithm, we introduce adaptive inertia weights [10]. The formula for the adaptive inertia weights is as follows:

$$w(t) = w\left(wmin_{max} \times \frac{t}{n_{iter}}\right)_{max} \tag{12}$$

Where $w(t)$ is the inertia weight of the t -th generation, w_{max} and w_{min} correspond to the maximum and minimum inertia weights, t is the current iteration number, and n_{iter} is the maximum number of iterations. As the iterations progress, the inertia weight decreases from w_{max} to w_{min}, allowing the particle to gradually shift towards local search, which can lead to better solution outcomes. The effect of adaptive inertia weighting compared to other weighting methods is shown in Table 3.

Table 3. Comparison of various weight models

Name	Optimum value	Average value	Number of suboptimal solutions	Number of near-suboptimal solutions
Linear decrease inertia weight	0.266	0.253	34	66
Adaptive inertia weight	0.267	0.261	8	92
Stochastic inertial weight	0.267	0.261	14	86

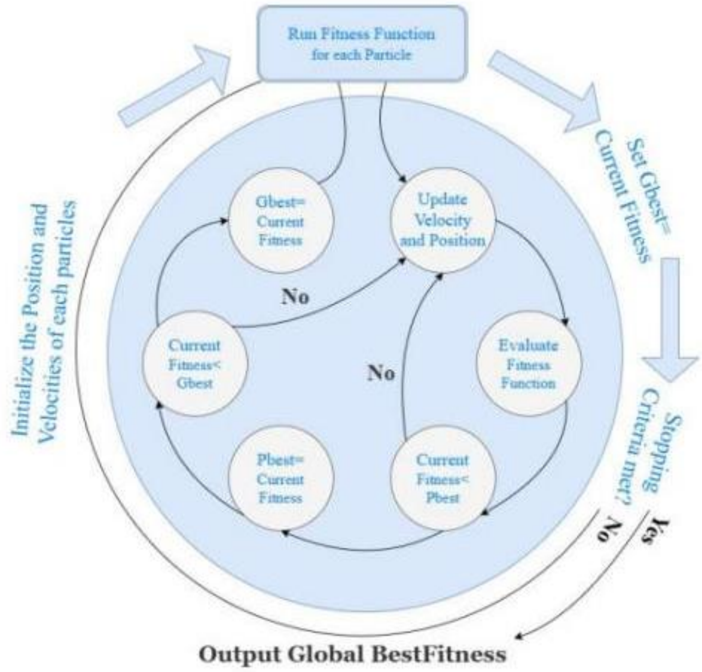

Figure 4. PSO algorithm flowchart

The solution process is shown in Figure 4, the PSO optimization algorithm produced the following results: the optimal population growth rate is 0.076, the optimal tax ratio is 0.0834, and the optimal infrastructure investment is $325 million. Since heuristic algorithms generate different results with each run, we performed multiple iterations to determine the ideal range for the number of tourists, which was found to be [142, 146] million.

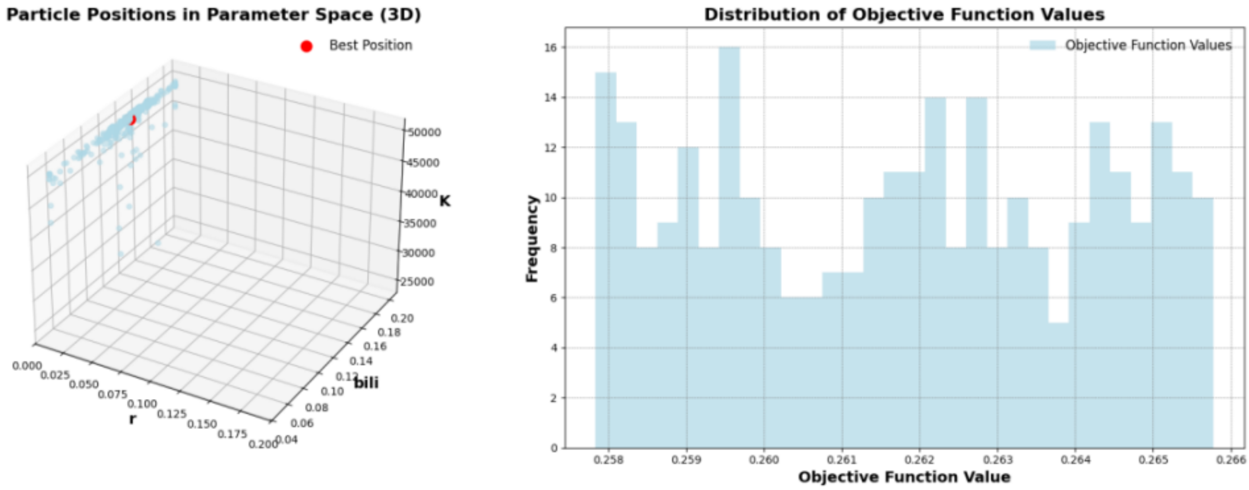

Figure 5. Particle Positions in Parameter Space and Distribution Objective Functon Values

In Figure 5, the three-dimensional scatter plot on the left shows the distribution of the particles in three-dimensional space. It can be observed that the particles are distributed relatively evenly,indicating that they do not fall into the local optima solution. Introducing adaptive inertia weight is a suitable approach. The histogram on the right displays the distribution of the objective function during the solving process. The distribution of the objective function values are relatively uniform, with the frequencies in each objective function range are relatively uniform. This suggests that the particles have explored the solution space comprehensively, validating the correctness of the model, and the convergence diagram of and particle optimization is shown in Figure 6.

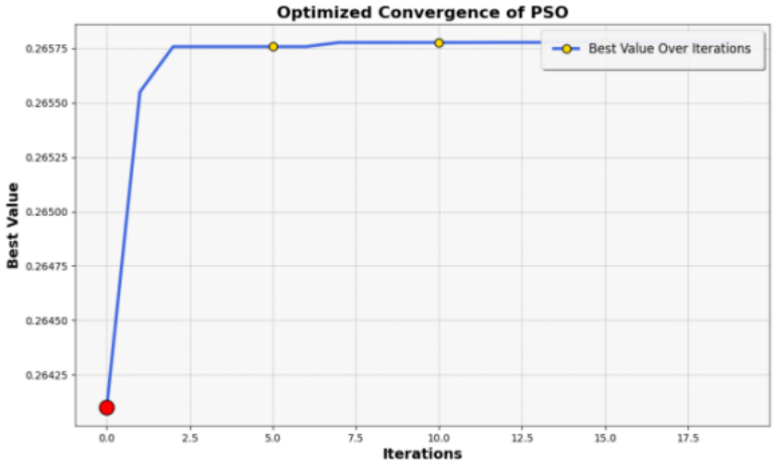

Figure 6. Optimized Convergence of PSO

3.2. Sensitivity Analysis and Evaluation

To identify effective measures for mitigating over-tourism in the City of Juneau, we conducted a sensitivity analysis of the RC model, primarily focusing on optimized parameters and penalty coefficients.

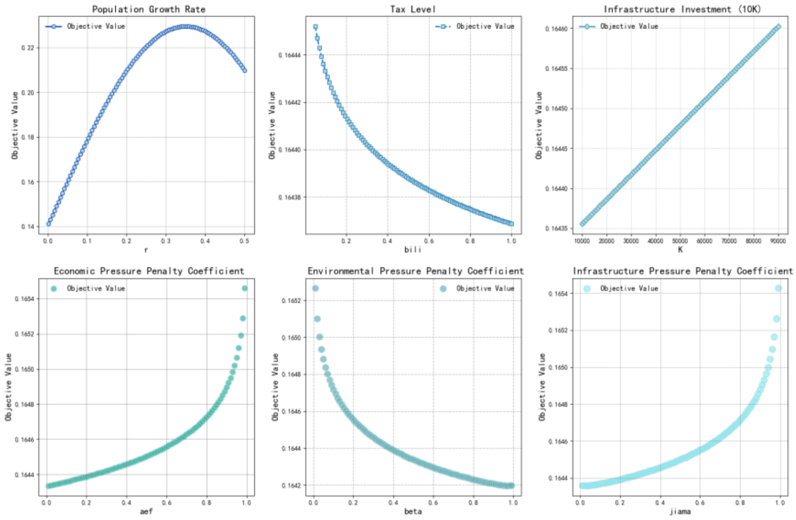

Figure 7. Sensitivity Analysis Chart

By analyzing the results shown in Figure 7, it is evident that the tourist growth rate, or the number of tourists, is the most sensitive factor. The tax level and penalty coefficient exhibit varying degrees of sensitivity, while infrastructure investment responds the slowest.

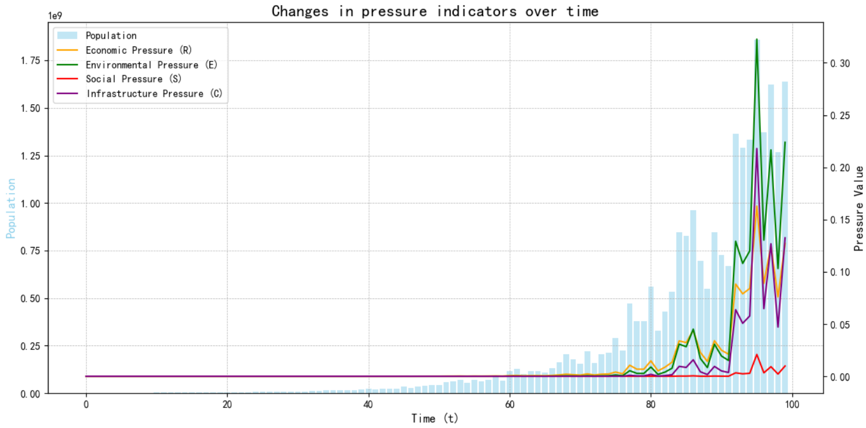

Figure 8. Changes in pressure indicators over time

In Figure 8, by modeling the changes in Juneau's stress indicators over time, it was found that controlling the number of visitors is the most effective measure.

4. Conclusions

Benefiting from its cruise ship economy and natural beauty, Juneau is a city with a particularly high level of tourism and over-tourism. Year after year, the number of tourists has increased, placing significant environmental, social, and infrastructural pressures on the city. Controlling the number of tourists has become urgent, and increasing taxes can help regulate visitor numbers while enhancing overall tourist satisfaction. Social pressures exhibit a lagging effect, are not highly responsive to short-term changes, and require long-term investments for meaningful reduction. Environmental pressure remains the most pressing concern, with Juneau’s glacier volume declining at an accelerated rate compared to previous years. This issue demands urgent attention from the government.

In constructing the model presented in this paper, an effort was made to account for as many factors as possible that influence the sustainable development of urban tourism. However, the reality is that these influencing factors are numerous and ever-evolving alongside urban development. While the RC model provides strong interpretability in the current context and can be adapted to similar tourism-dependent cities, it has inherent limitations and time sensitivity. Additionally, certain indicators are challenging to quantify, and obtaining relevant data can be difficult. Further refinement is needed, particularly in determining indicator weights. Future research should focus on expanding field studies and conducting extensive public surveys to enhance the model’s accuracy and applicability.

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