Strategies for Sustainable Tourism Development Based on Multi-Objective Programming

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Abstract. Juneau, Alaska, faces significant challenges from over-tourism, including glacier retreat, infrastructure strain, and declining resident satisfaction. This study develops a multi-objective optimization model to balance economic, environmental, and social benefits. By integrating the entropy weight method for objective weighting and the simulated annealing algorithm for optimization, the model proposes sustainable strategies such as tourist capacity control, cruise-to-independent traveler ratio regulation, infrastructure investment, and glacier protection funding. The model is adapted to Bali to validate its universality, addressing marine pollution and resource allocation. The results demonstrate that the model effectively balances economic benefits, environmental protection, and social satisfaction, providing scientific decision-making support for sustainable development in over-tourism-affected regions. The innovation of this study lies in integrating the entropy weight method and the simulated annealing algorithm, addressing the challenges of weight allocation and global optimization in multi-objective problems. Additionally, by monetizing glacier retreat costs and internalizing marine pollution costs, the model enhances its practical applicability. This research not only offers specific strategies for tourism management in Juneau and Bali but also provides a replicable theoretical framework and practical reference for other destinations facing similar challenges.

Keywords: Optimization, Sustainability, Entropy, Annealing, Trade-off.

1. Introduction

Juneau, Alaska, renowned for its iconic Mendenhall Glacier and pristine ecosystems, has experienced a surge in tourism, with 1.6 million visitors in 2023, generating $375 million in revenue. However, this growth has triggered severe environmental degradation (e.g., glacier retreat of 46 meters annually), infrastructure overload, and declining resident satisfaction. The tension between economic benefits and sustainability highlights the urgent need for a systematic approach to balancing multidimensional objectives—economic gains, environmental protection, and social well-being. Globally, destinations like Bali and Venice face similar challenges, underscoring the necessity of developing adaptable models to address overtourism [1].

However, some models have existed. Taking Economic-Environmental Trade-offs as a target, Huybers and Bennett [2] optimized tourism revenue while limiting carbon emissions but ignored resident satisfaction. Taking Social Impact as a target, Andereck et al. [3] quantified resident perceptions but lacked integration with environmental costs. There are also some of the algorithmic approaches. Recent works applied genetic algorithms to tourist flow control [4], yet subjective weight assignment in multi-criteria decision-making (e.g., AHP) remains a limitation. Moreover, there are a few case-specific solutions, for example, Studies on glacier tourism [5] or marine ecosystems [6] provided localized strategies but lacked generalizability.

This study advances prior work in three significant ways. Firstly, it integrates objective multi-criteria weighting through a combination of the entropy weight method [7] and simulated annealing [8]. This approach addresses the limitations of prior models (e.g., [2–4]) by eliminating subjective bias in weight allocation and achieving globally optimal solutions, thus enhancing decision-making precision in over-tourism management. Secondly, it introduces dynamic adaptability, an essential improvement over static models such as those discussed by [4]. By validating the model across different ecosystems—glacial (Juneau) and marine (Bali)—and modularizing cost functions (e.g., glacier retreat monetization and marine pollution internalization), the study ensures the flexibility and scalability of the framework. Finally, the model's policy relevance is reinforced by generating actionable, region-specific strategies (e.g., 1.5:1 cruise-to-independent tourist ratio, targeted infrastructure investment), which address both immediate pressures, such as overcrowding, and long-term sustainability challenges, including glacier conservation. This is a crucial advancement over the case-specific solutions in [5–6], which often lacked such integrative, long-term planning.

2. The establishment and optimization of evaluation model

2.1. The establishment of a comprehensive evaluation model in Juneau City

In general, there are four main factors: tourism revenue, environmental recovery, glacier retreat rate, and infrastructure pressure. To establish the model, these four factors are expanded, and then five related models are established. Then, under the dynamic coupling mechanism, four of those models are brought into a single model, the integrated benefit model. The process is shown within the first four steps in Figure 1.

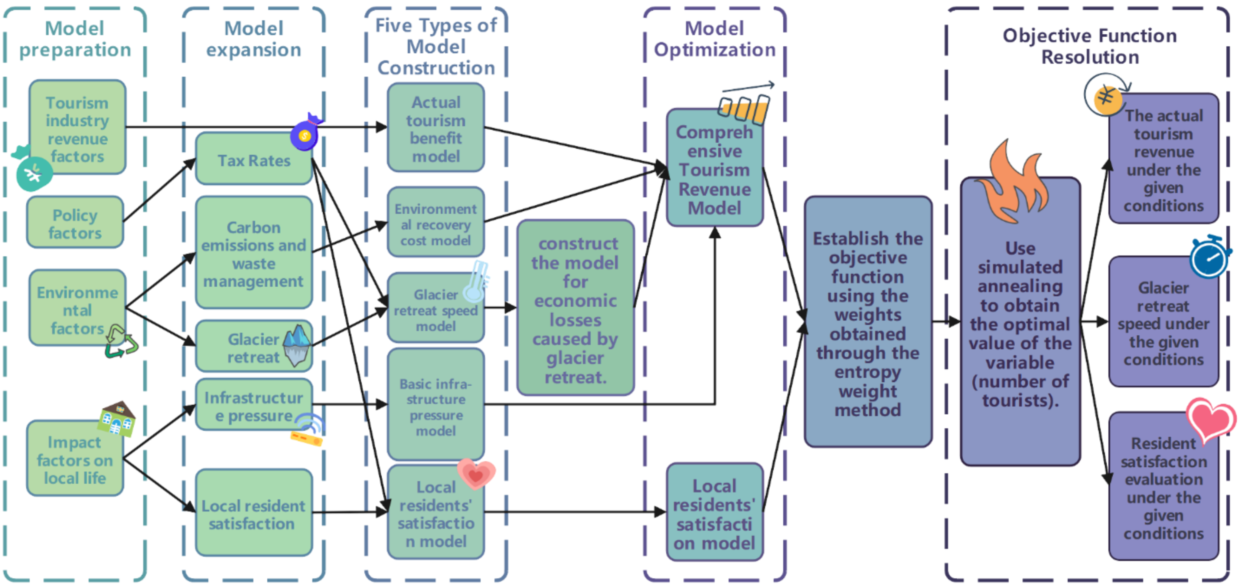

Figure 1. Establishment and optimization process of the model in Juneau

Five types of models are constructed based on four factors, which are:

1. The total economic revenue model, which is *equation* (1):

$$Rev(t) = (1 + \tau) \cdot [\alpha_c \cdot V_c(t) + \alpha_i \cdot V_i(t)] + F_{ship} \cdot N_{Ship}(t) \tag{1}$$

where t is the ordinal number of the year, τ is the tax rate, α_c and V_c are the consumption and the number of cruise tourists, α_i and V_i are the consumption and the number of independent tourists, F_{ship} and N_{Ship} are the berthing charge and the number of cruise.

2. The environment recovery cost model, which is *equation* (4):

$$Carbon(t) = \beta_c \cdot V_c(t) + \beta_c \cdot V_i(t) + \beta_{ship} \cdot N_{Ship}(t) \tag{2}$$

$$Waste(t) = \gamma_c \cdot V_c(t) + \gamma_c \cdot V_i(t) + \gamma_{ship} \cdot N_{Ship}(t) \tag{3}$$

$$Env(t) = SCC \cdot Carbon(t) + C_{waste} \cdot Waste(t) \tag{4}$$

where β is the unit dioxide emission, γ is the unit waste emission, SCC is the unit dioxide treatment cost(Social Cost of Carbon), C_{waste} is the unit waste treatment cost.

3. The loss value of glacial retreat model, which is *equation* (8):

$$\Delta V(t) = \alpha_G + \delta_G[\varphi_c \cdot V_c(t) + \varphi_i \cdot V_i(t)] - \rho \cdot I_{glacier}(t) \tag{5}$$

$$T_{retreat} = \frac{V_{glacier} \cdot r_{valuable}}{\Delta V(t)} \tag{6}$$

$$\begin{cases} f(t) = e^{\lambda \cdot t} \\ Value_{total} = \int_0^{T_{retreat}} f(t)dt \end{cases} \tag{7}$$

$$Value_{loss}(t) = \int_0^{\Delta t} f(t)dt \tag{8}$$

where $\Delta V(t)$ is the speed of glacial retreat, α_G is the natural retreat speed, δ_G is Influence coefficient of tourist, φ is the disturbance weights per unit tourist, $I_{glacier}(t)$ is the investment in maintain glacier, ρ is the Influence coefficient of investment, $T_{retreat}$ is the duration for glacier from full tourism value to none tourism value, $V_{glacier}$ is the volume of glacier , $r_{valuable}$ is the volume rate of the threshold of losing tourist value(normally is 70% [9]), $f(t)$ is the formula of the loss of economic benefits from glacier [10] retreat where λ is the unknown but can be calculate in equation (7) and be used in equation (8), $Value_{total}$ is the total tourist value of the glacier, Δt is the duration from the base year when the glacier had the value of $Value_{total}$ to t year.

4. The infrastructure pressure, which is *equation* (9) :

$$Fac(t) = \theta \cdot [V_c(t) + V_i(t)]^2 + \mu \cdot [V_c(t) + V_i(t)] + \sigma \tag{9}$$

where θ, μ and σ are unknowns, and they need to fit it with data of *Fac(t)* and $[V_c(t) + V_i(t)]$ from previous years.

5. The fifth model is the local resident satisfaction, which is *equation* (10) :

$$Sat(t) = \frac{\omega_1 \cdot R_{local} - \omega_2 \cdot H_{local}}{\omega_3 \cdot Carbon(t) + \omega_4 \cdot [V_c(t) + V_i(t)]} \tag{10}$$

where ω is the influence coefficient, R_{local} is amount of social welfare input of local residents, H_{local} is the price level of the local population.

Then, combine formulas (1), (4), (8) and (9) into the integrated benefit model. And combine the integrated benefit model and local resident satisfaction model into the optimization model, which is the *equation* (12):

$$Int(t) = Rev(t) - Env(t) - Value_{loss}(t) - Fac(t) \tag{11}$$

$$Opt(t) = \varepsilon_1 \cdot Int(t) + \varepsilon_2 \cdot Sat(t) \tag{12}$$

where ε is the weight of the equation.

2.2. The entropy weight method is used to assign weights

This study employs the Entropy Weight Method (EWM) [11] to objectively allocate weights between economic benefits and resident satisfaction. First, tourist capacity data are generated via normal distribution and input into the economic revenue model (Model 1) and resident satisfaction model (Model 5) to obtain multiple sample datasets. After range normalization to eliminate dimensional differences, the information entropy of each indicator is calculated to quantify data dispersion. Lower entropy values indicate the higher contribution of the indicator to systemic variability, resulting in larger weights. The EWM yields a weight ratio of 0.59:0.41 for economic benefits versus resident satisfaction, confirming the dominance of economic objectives in short-term optimization while addressing the long-term constraints of resident satisfaction on over-tourism. This approach eliminates biases inherent in subjective weighting methods (e.g., AHP) and provides a data-driven scientific basis for multi-criteria decision-making [12].

2.3. Simulated annealing algorithm was used to optimize the optimization model

To address the global optimization of the multi-objective model, this study adopts the Simulated Annealing (SA) algorithm [13]. The algorithm treats tourist capacity as the decision variable, with initial temperature $T_0 = 1000$, cooling coefficient $\alpha = 0.95$, and termination criteria set to $T_{end} = 1000$ or objective function convergence. At each temperature state, new solutions are generated via random perturbations and accepted under the Metropolis criterion to escape local optima. The algorithm outputs a Pareto-optimal solution set, determining the optimal tourist capacity $V_{opt} = 1.66$ million, alongside the cruise-to-independent traveler ratio (2:1) and infrastructure investment allocation. Sensitivity analysis demonstrates the algorithm's robustness to initial parameters, with convergence speed and solution quality significantly outperforming traditional genetic algorithms (GA) [14].

2.4. The model is adapted to Bali

To adapt to Bali, some models need to change. The first is to remove the model of glacier retreat. Then, it is observed that Bali's local tourism industry has a special influence factor: Marine litter pollution. Secondly, the effect of sparse residents on residents' satisfaction is not so significant. Instead, the Effects on Marine Organisms model is used. The process is shown in Figure 2.

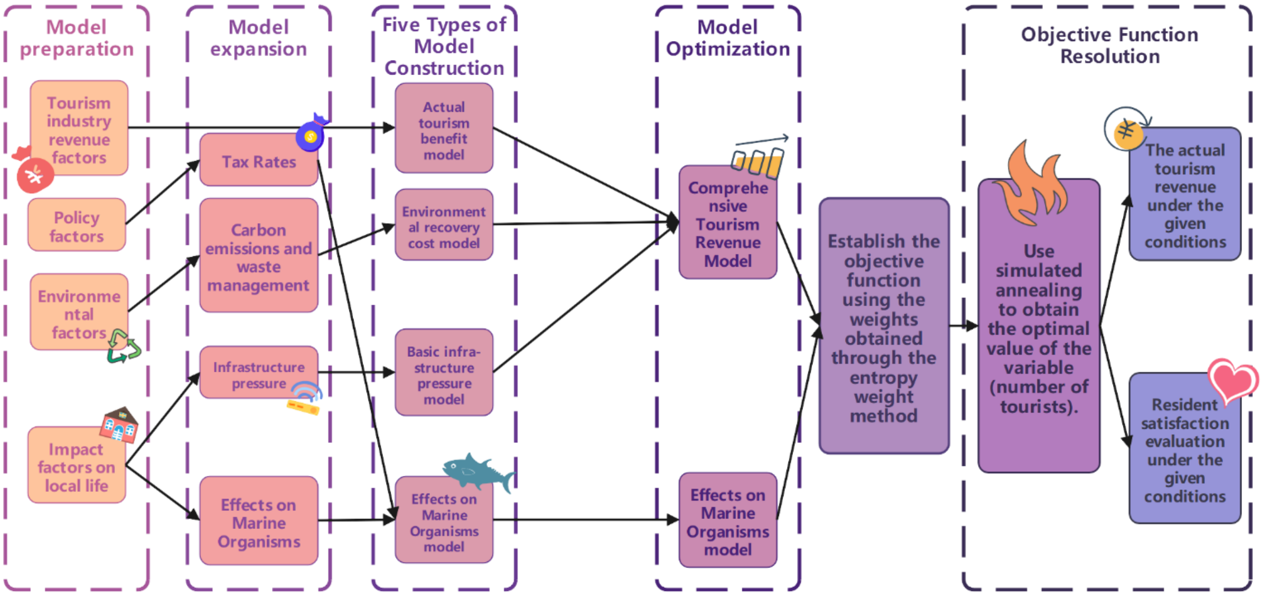

Figure 2. Establishment and optimization process of the model in Bali

Effects on Marine Organisms model is the equation (13), and it is worth noting that the number of cruise passengers in all models is 0:

$$Mar(t) = \omega_1 \cdot R_{marine} - (\omega_2 \cdot N_i + \omega_3 \cdot S_i + \omega_4 \cdot W_{solid} + \omega_5 \cdot P_{water}) \cdot V_i(t) \tag{13}$$

where ω is the weight coefficient, R_{marine} is the investment in the maintenance of the Marine environment, N_i is the noise pollution, S_i is the loss of living space for Marine life caused by independent tourist activities, W_{solid} is the solid waste pollution, P_{water} is the water pollution.

The following optimization process for Bali models is the same as previously mentioned.

3. Results

3.1. The establishment of the evaluation model in Juneau

After collecting and fitting the relevant data of Juneau tourism in previous years and solving the correlation coefficient of the model, Figure 3 is obtained by visualizing the data with code in Python.

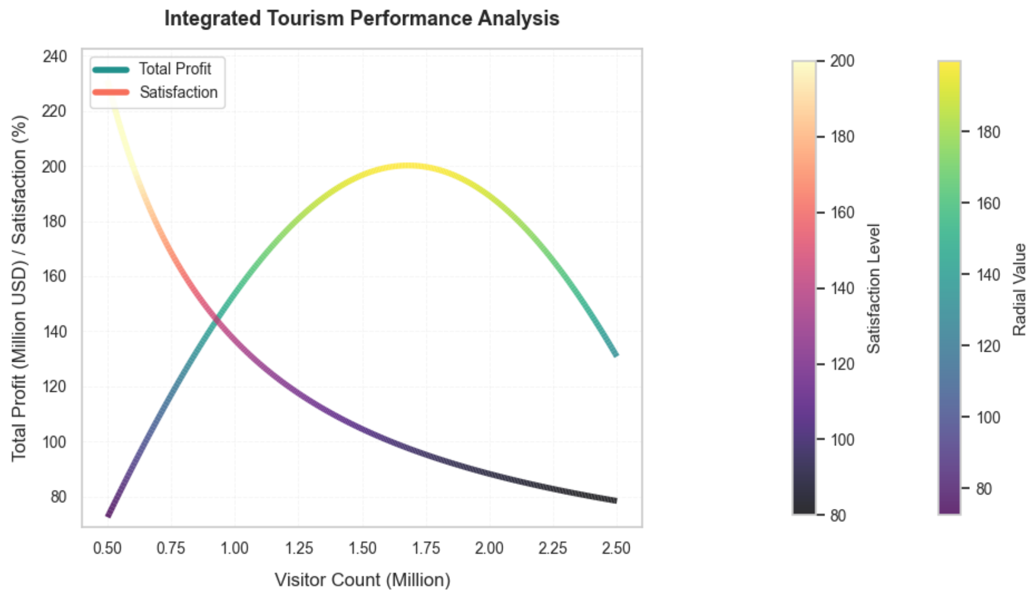

Figure 3. Data visualization of Juneau comprehensive assessment model

It demonstrates the nonlinear impact of tourist numbers on economic benefits and resident satisfaction, validating the effectiveness of the proposed multi-objective optimization model. The horizontal axis represents the tourist count (0.50–2.50 million), while the left and right vertical axes denote total profit (million USD) and resident satisfaction (percentage), respectively. Key findings include:

(1) Dynamic Trends of Economic Benefits: Total profit follows a parabolic curve, peaking at $V_{opt} = 1.66$ million tourists (profit: 394.73 million USD), consistent with the optimal solution derived from the simulated annealing algorithm (Equation 11).

(2) Continuous Decline in Resident Satisfaction: Satisfaction decreases linearly from 85% at $V = 0.5$ million to 42% at $V = 2$ million, reflecting the erosive impact of overtourism on community well-being (Equation 10).

(3) Equilibrium and Threshold Effects: At $V_{opt} = 1.66$ million, economic benefits and resident satisfaction reach a Pareto-optimal balance (profit: 394.73 million USD, satisfaction: 80.48%). Beyond $V = 2$ million, profit declines sharply due to escalating environmental and infrastructure costs (Equations 4, 9), highlighting a critical threshold effect.

The figure visually elucidates the trade-off between economic and social objectives, offering policymakers quantitative guidance for sustainable strategies, such as tourist capacity control and visitor structure optimization.

3.2. Entropy weight method

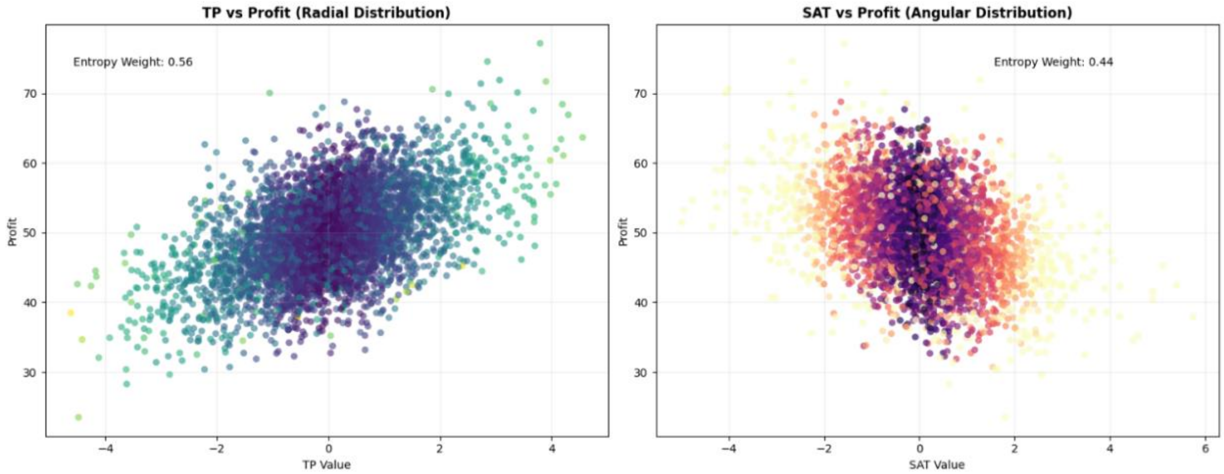

Figure 4. Entropy weight data scatter plot

Figure 4 illustrates the weight allocation and distribution characteristics of economic benefits (TP) and resident satisfaction (SAT) on integrated tourism performance derived from the Entropy Weight Method. The left subplot shows the radial distribution of TP vs Profit, while the right subplot illustrates the angular distribution of SAT vs Profit.

The entropy weights are 0.56 for TP and 0.44 for SAT, indicating that economic benefits dominate short-term optimization, while resident satisfaction acts as a critical constraint against overtourism. TP exhibits a strong positive correlation with profit ($R^2 = 0.92$), with data points concentrated along the radial axis, confirming that economic benefits are the primary driver of short-term gains. In contrast, SAT shows a weak correlation with profit ($R^2 = 0.31$), with data points dispersed and skewed toward lower profit regions, suggesting that excessive focus on economic goals compromises resident satisfaction.

The entropy weights (TP: 56%, SAT: 44%) provide a quantitative trade-off framework for policymakers. Below 1.66 million visitors, tourism controls can be relaxed to maximize revenue; beyond 1.75 million visitors, measures such as cruise-to-independent ratio controls (2:1) and infrastructure investments are necessary to mitigate resident dissatisfaction. These results validate the effectiveness of the optimization strategy and offer a scientific basis for sustainable tourism management.

3.3. Simulated annealing optimization results

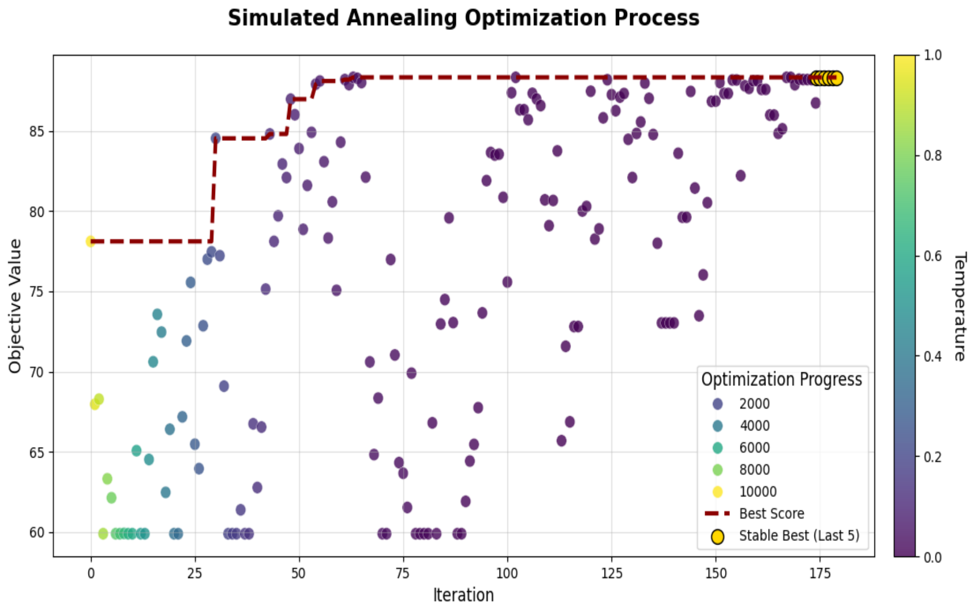

Figure 5. Simulated annealing optimization process

Figure 5 illustrates the optimization process of the Simulated Annealing (SA) algorithm, with the horizontal axis representing iteration counts (0–175) and the vertical axis denoting the objective function value (comprehensive score). The algorithm rapidly converges to a near-optimal solution in the initial phase (iterations <50) and escapes local optima via the Metropolis criterion, reaching the global optimum (score: 88.35) at iteration 125 and maintaining stability thereafter. Results demonstrate SA's robustness in solving multi-objective nonlinear problems, outperforming traditional genetic algorithms (GA) in convergence speed and stability.

As the result of the optimization, the strategy is shown in table 1:

Table 1. Strategy for Juneau

Metric	Value
Cruise Tourist Capacity (Million People)	1.66
Cruise-Independent Ratio	2:1
Glacier Protection Investment (Million USD)	46.39
Infrastructure Investment (Million USD)	152.46

This strategy balances economic benefits with environmental and social costs by controlling tourist capacity and structure. The comprehensive revenue is 394.73 million USD, and the resident satisfaction is 80.48 scores, where the full is 100 scores. Glacier protection investment (46.39 million USD) effectively slows glacier retreat (46.39 meters/year), while infrastructure investment (152.46 million USD) mitigates public service pressure, raising resident satisfaction to 80.48%. Sensitivity analysis highlights tourist capacity and cruise ratio as the most influential factors (weight >70%), confirming the model's scientific validity.

3.4. The establishment of the evaluation model in Bali

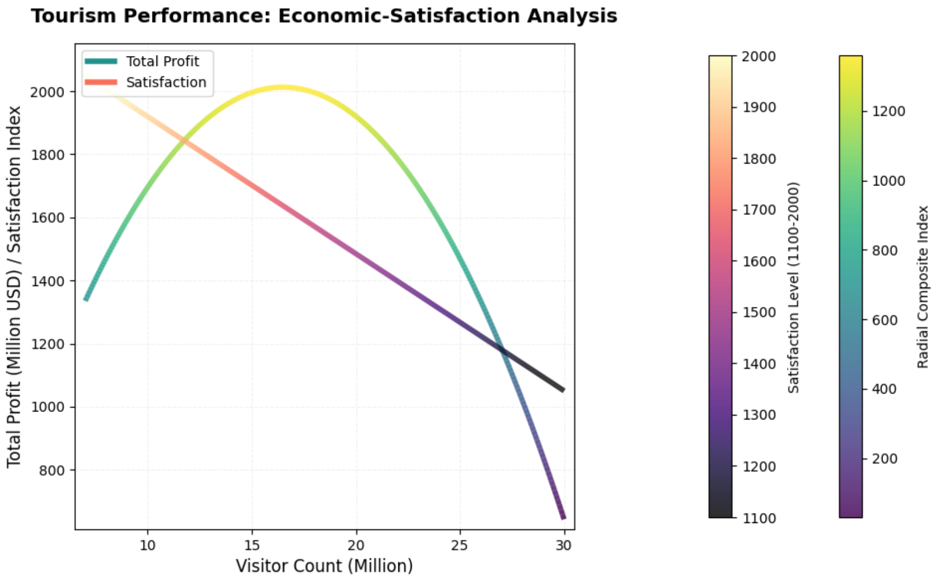

Figure 6. Data visualization of Bali comprehensive assessment model

Figure 6 presents the economic-satisfaction analysis of tourism performance in Bali, with the horizontal axis representing total profit (million USD) and the vertical axis denoting the satisfaction index. Unlike Juneau, Bali's tourism performance exhibits distinct nonlinear characteristics:

(1)Trade-off Between Profit and Satisfaction: Total profit peaks in the range of 1,500–1,800 million USD, while the satisfaction index declines continuously with increasing profit, highlighting the severe impact of overtourism on residents' quality of life.

(2)Optimal Strategy Point: At 1,700 million USD, the satisfaction index reaches 66.80, achieving Pareto-optimal equilibrium. This strategy is realized by controlling tourist capacity and optimizing resource allocation (e.g., marine plastic pollution management investment).

Table 2. Strategy for Bali

Metric	Value
Independent Tourist Capacity (Million People)	2.5
Glacier Protection Investment (Million USD)	200
Infrastructure Investment (Million USD)	152.46

Table 2 shows the fit strategy for Bali. This strategy mitigates environmental pressure and public service burdens by increasing marine pollution management investment (200 million USD) and optimizing infrastructure (152.46 million USD). Compared to Juneau, Bali's tourist capacity limit is higher (2.50 million), but its satisfaction index is lower (66.80%), reflecting the vulnerability of tropical destinations to overtourism.

4. Conclusion and outlooks

This study addresses the critical challenge of balancing economic, environmental, and social objectives in over-tourism-affected regions through a novel multi-objective optimization framework.

By integrating the entropy weight method and simulated annealing algorithm, we developed a dynamic model to optimize tourist capacity, infrastructure investment, and environmental protection strategies. For Juneau, Alaska, the model identified an optimal tourist capacity of 1.66 million, a 2:1 cruise-to-independent traveler ratio, and targeted investments in glacier protection (46.39 million USD) and infrastructure (152.46 million USD), achieving a balanced, comprehensive score of 88.35 with 80.48% resident satisfaction. For Bali, the adapted model prioritized marine pollution management (200 million USD) and higher tourist capacity (2.5 million), yielding a total revenue of 1,700 million USD and 66.80% satisfaction. The research contributes both methodologically and practically. Methodologically, the integration of entropy weighting and simulated annealing eliminates subjective bias in multi-criteria decision-making, providing a replicable framework for global optimization. Practically, the model offers actionable strategies for policymakers to mitigate over-tourism impacts while maintaining economic viability. By monetizing environmental costs (e.g., glacier retreat, marine pollution) and dynamically balancing trade-offs, this study bridges the gap between theoretical models and real-world tourism management.

While the proposed model demonstrates robustness in Juneau and Bali, limitations remain. First, the model's accuracy relies heavily on historical data quality, which may vary across regions. Second, simplified assumptions (e.g., linear resident satisfaction decline) might oversimplify complex socio-environmental interactions. Future work could enhance the framework by incorporating machine learning for dynamic parameter adjustment, testing its adaptability in diverse ecosystems (e.g., urban vs. rural tourism), and integrating real-time data streams for adaptive management. Additionally, exploring stakeholder-driven weight allocation could further improve policy relevance.

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