

# A Study of Sustainable Tourism Development Modeling Based on Multi-Objective Optimization and Machine Learning

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**Abstract.** This paper aims to promote sustainable tourism by developing a multi-objective optimization-based sustainable tourism model and a visitor flow balancing model, addressing over-tourism challenges in destinations such as Juneau, Yellowstone National Park, Venice, and the Maldives. The first model integrates ARIMA and EMA for forecasting tourist volumes and environmental indicators, employs multiple linear regression to evaluate resident satisfaction, and incorporates a feedback mechanism linking carbon footprint and tourism revenue. The paper further conducted a sensitivity analysis on tourist volume, carbon tax rate, and resident satisfaction, confirming the robustness and adaptability of the sustainable tourism model. The second model utilizes a probabilistic framework to balance visitor flow, exemplified through 12 attractions in Yellowstone. Seasonal patterns are predicted using the SARIMA model, and a variance-mean ratio is minimized to optimize distribution. The models demonstrate strong scalability and practical value for real-world tourism management.

**Keywords:** Sustainable tourism model, Visitor flow balancing model, Tourist management, Multi-objective optimization.

## 1. Introduction

With the global rise in tourism, ecologically sensitive destinations are increasingly threatened by over-tourism, leading to environmental degradation, infrastructure strain, and reduced resident satisfaction [1]. Juneau, Alaska exemplifies this tension, where rapid tourist inflows have intensified carbon emissions, traffic congestion, and glacier retreat. While tourism remains a key economic driver, its hidden environmental and social costs challenge long-term sustainability. Previous studies have proposed various sustainable tourism frameworks, but many lack a quantitative integration of carbon footprint, resident sentiment, and tourist flow distribution [2]. Moreover, existing models often fall short in capturing the complex trade-offs under real-world policy constraints. This study addresses these gaps by developing a data-driven, multi-objective optimization model that incorporates time series forecasting, multiple linear regression, and machine learning to evaluate and balance tourism growth with environmental impact [3]. The use of the Kaya identity and a carbon tax mechanism introduces a feedback loop connecting tourism activity to carbon costs [4]. Additionally, a probabilistic visitor flow balancing model is established to improve spatial and temporal distribution efficiency. Together, these innovations offer adaptable, evidence-based tools for sustainable tourism management in ecologically vulnerable regions. (Data Source: <https://www.comap.com/contests/mcm-icm>)

## 2. Sustainable Tourism Model

To maintain both applicability and tractability, the model rests on the following assumptions: a stable socioeconomic and epidemiological context with no major disruptions; tourism revenue proportional to visitor numbers under a constant per-capita expenditure; carbon emissions taxed at USD 55 per ton with a fixed share of proceeds reinvested in environmental protection; daily arrivals capped by ecological and infrastructural capacity limits; and resident satisfaction driven jointly by tourism intensity and government investment.

Study data—tourist numbers, carbon emissions, infrastructure capacity, and resident satisfaction across times and locations—were cleaned (normalized types, imputed missing values, removed outliers) and distilled to key sustainability features (daily visitor counts, environmental metrics, government spending). Correlation checks and visual reviews confirmed data validity, forming the input for the subsequent models [5].

### 2.1. Multi-objective Optimization Model

The paper establishes a multi-objective optimization model with tourism profit, carbon footprint, and resident satisfaction as the optimization objectives.

(1) Profit Maximization: Tourism is the most important economic pillar of Juno City. Under the sustainable tourism model, profit maximization remains the primary objective of the tourism industry.

$$Max\{W\} \tag{1}$$

(2) Carbon Footprint Minimization: Tourists increase the carbon footprint in environmentally sensitive areas, exacerbating ecological degradation. To develop a sustainable tourism industry, there is a general expectation to minimize carbon footprint emissions and implicit costs as much as possible. Among them,  $E_{ep}$  represents equivalent environmental governance and  $C$  represents implicit expenditure in tourism, both of which are functions of  $V$ , that is the number of tourists[6].

$$Min\{E_{ep}(V) + C(V)\} \tag{2}$$

(3) Resident Satisfaction: Resident satisfaction with the tourism industry largely determines the changes in tourism policies. Due to excessive hidden burdens, most residents have successfully voted for legislation to limit tourists. If resident satisfaction is too low, the number of tourists will be further restricted or even "banned"[7]. If sustainable tourism leads to widespread resident satisfaction, it will reflect a balance between increased income and environmental improvement.

$$Max\{S(V)\} \tag{3}$$

(4) Constraints: Juno has reached an agreement with major cruise companies, limiting the number of tourists to 16,000 from Sunday to Friday, and 12,000 on Saturdays.

$$0 \leq N \leq \begin{cases} 16000, t \neq \text{Saturday} \\ 12000, t = \text{Saturday} \end{cases} \tag{4}$$

Additional income refers to the indirect revenue created by the tourism industry through driving related industries. Juno can obtain additional income by imposing tourism taxes, hotel taxes, airport taxes, etc., thereby increasing economic benefits. In this paper, the average tax rate for additional income is set as  $r$ .

$$0 \leq r \leq 1 \tag{5}$$

### 2.2. Expenditure Plan for Additional Income

Additional charges limit tourist numbers while generating significant revenue. This income can support environmental protection, infrastructure improvements, and community projects, reducing carbon footprints and increasing resident satisfaction, creating a positive feedback loop. However, higher taxes may reduce tourist numbers. Let  $r$  represent the average tax rate, and a linear model will describe the relationship between tax rate and tourist numbers. Among them,  $N_0(t)$  represents the benchmark value of the number of tourists.

$$N(t) = N_0(t)(1 - \bar{r}) \tag{6}$$

Additional expenditures improve resident satisfaction and the ecological environment. To quantify the positive feedback loop, the paper introduces the carbon tax as a "bridge."

$$C_{tax} = 55 \tag{7}$$

(Price of 1 ton of carbon = 55 USD)

The carbon tax serves a dual purpose: it converts the carbon footprint  $E(V)$  into implicit expenditure  $C(V)$ , representing environmental management costs, which are included in the total profit calculation; and it transforms public construction expenditure  $C_1(V)$  and corporate subsidy expenditure  $C_2(V)$  into reduced carbon footprints  $E(V)$  [8]. The carbon tax acts as a proportional constant in the model, quantitatively describing the relationship between carbon footprint and income (expenditure).

### 2.3. Final Model

(1) Resident Satisfaction: Spearman’s correlation coefficient indicates that resident satisfaction is highly correlated with infrastructure, corporate subsidies, additional income, and the number of visitors. Therefore, the paper establishes a multiple linear regression model to fit resident satisfaction. Here,  $R(V)$  and  $T(V)$  respectively represent total income from tourism and carbon tax amount, and  $\beta_i$  is the weight coefficient of each variable.

$$S(t) = \beta_1 C_1(V) + \beta_2 C_2(V) + \beta_3 R(V) + \beta_4 T(V) + \beta_5 N(t) + \varepsilon_0 \tag{8}$$

(2) Carbon Footprint: The Kaya formula is a crucial tool for analyzing the relationship between carbon emissions and economic activity. It decomposes the carbon footprint into several key factors, facilitating the identification of the driving forces behind carbon emissions.

$$E(V) = P \left( \frac{G}{P} \right) \left( \frac{E}{G} \right) \left( \frac{C}{E} \right) = P_{gpc} = G \cdot \frac{C}{G} = G \cdot h \tag{9}$$

In the first equation,  $C$  is the total carbon emissions,  $P$  is the total population,  $G$  is the total GDP, and  $E$  is the total energy consumption. In the second equation,  $g$  denotes GDP per capita,  $e$  is the energy consumption per unit of GDP, and  $c$  represents the carbon footprint per unit of energy consumption. In the final equation,  $h$  signifies the carbon emission intensity per unit of GDP, which can be equated to the carbon footprint corresponding to the carbon tax amount.

$$\begin{cases} E_{ep}(V) = C_{tax} \cdot E(V) \\ \Delta E(V) = C_{tax} \cdot (\Delta A_1 + \Delta C_2) \end{cases} \tag{10}$$

(3) Total Profit: Tourism revenue includes both direct and indirect revenues from the tourism sector.

$$R(V) = \bar{w} \cdot N(t) + \bar{w} \cdot \bar{r} \cdot N(t) \tag{11}$$

The paper calculates the per capita spending of tourists  $\bar{w}$  by dividing the total tourism revenue from the Juno Fiscal Report by the total number of visitors.

Thus, the total profit is:

$$W = R(V) - E_{ep}(V) + T(V) - C(V) \tag{12}$$

### 2.4. Model Summary

To summarize the formulas, The paper establishes the optimization model as follows:

The optimization goal is the sum of total profit, carbon footprint, implicit costs, and resident satisfaction.

$$\begin{cases} \max \{M\} \\ \min \{E_{ep}(V) + C(V)\} \\ \max \{S(V)\} \end{cases} \quad (13)$$

The constraints are shown in formula (14), where the constraints are the number of tourists and the average tax rate of additional taxes.

$$\begin{cases} 0 \leq N(t) \leq \begin{cases} 16000, t \neq \text{Saturday} \\ 12000, t = \text{Saturday} \end{cases} \\ 0 \leq r \leq 1 \end{cases} \quad (14)$$

The remaining auxiliary formulas supporting the model are listed together in formula (17).

$$\begin{cases} W = R(V) - E_{ep}(V) + T(V) - C(V) \\ R(V) = \bar{w} \cdot N(t) + \bar{w} \cdot r \cdot N(t) \\ N(t) = N_0(t) \cdot (1 - \bar{r}) \\ E(V) = P \cdot \left(\frac{G}{P}\right) \cdot \left(\frac{E}{\alpha}\right) \cdot \left(\frac{C}{E}\right) = P_{gec} = G \cdot h \\ S(t) = \beta_1 C_1(V) + \beta_2 C_2(V) + \beta_3 R(V) + \beta_4 T(V) + \beta_5 N(t) + \varepsilon_0 \\ \begin{cases} E_{ep}(V) = C_{tax} \cdot E(V) \\ \Delta E(V) = C_{tax} \cdot (\Delta \Delta_1 + \Delta C_2) \end{cases} \end{cases} \quad (15)$$

### 2.5. Model Results

Combined with the data in recent five years and solved by genetic algorithm, the optimal profit  $W$  is 266,374,765.7 dollars, the minimum expenditure  $E(V) + C(V)$  is 80,192,809 dollars, and the optimal satisfaction  $S$  is 0.4976. At this point, the daily average number of visitors  $N(T) = 1,5083$  person, and the additional tax rate  $r = 0.0739$ . This not only limits the number of visitors but also increases the net profit, demonstrating that the model is correct and effective.

### 2.6. Sensitivity Analysis

Collected data confirms that tourist volume drives both profits and resident satisfaction. To evaluate this relationship, a single-factor sensitivity analysis was performed by systematically varying the daily visitor cap within  $\pm 80\%$  of its baseline in increments of 10%. For each scenario, optimal profit and resident satisfaction were recalculated and visualized through Figure 1. Results indicate that changes in tourist volume significantly impact profits, particularly as visitor caps are relaxed. Resident satisfaction, however, remains relatively stable, though it shows a declining trend when the visitor cap increases beyond a 20% threshold, suggesting a critical point at which tourism begins to negatively affect local satisfaction.

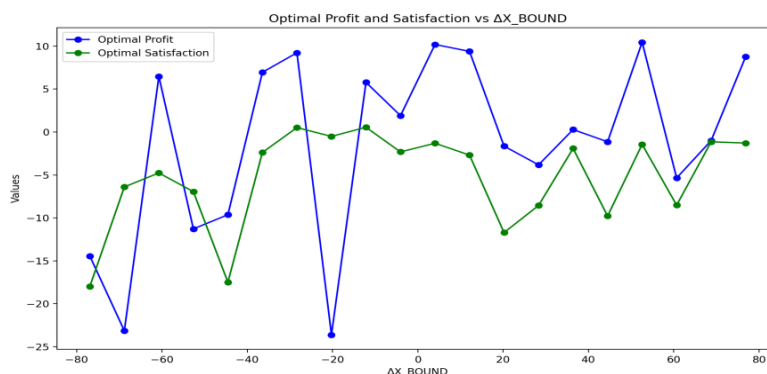
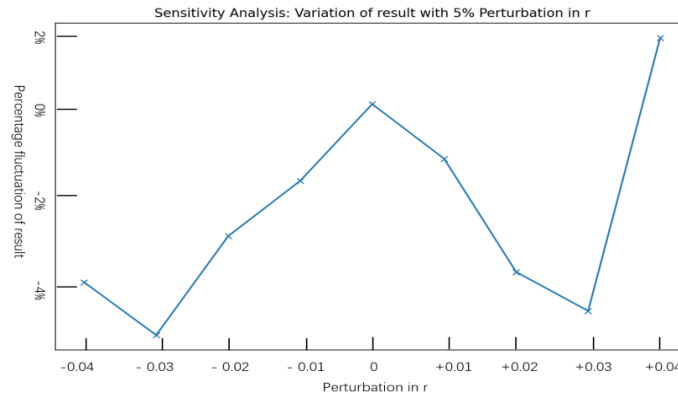


Figure 1. Sensitivity of Tourist Volume

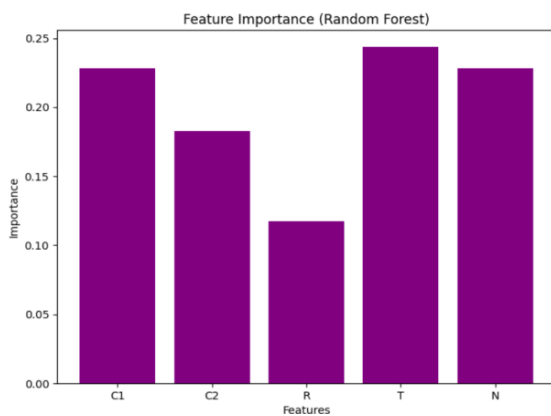
Because carbon tax rates vary and fluctuate with policy (e.g., post-Paris Agreement withdrawal), a sensitivity analysis was conducted by perturbing the carbon tax coefficient  $\pm 5\%$  around the baseline value, with increments of 1%. The resulting percentage fluctuations in the combined objective function (integrating both profit and environmental cost) are plotted in Figure 2. The analysis reveals a nonlinear response, with a notable positive impact on the objective function at +4% perturbation, highlighting an optimal range for balancing economic and environmental goals. Conversely, reducing the carbon tax rate results in diminishing returns, suggesting limited benefit from lower taxation.



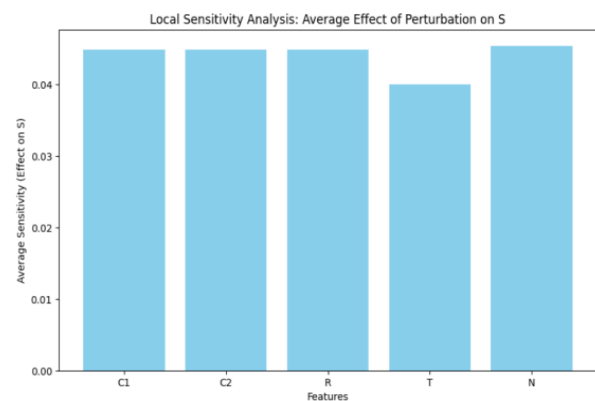
**Figure 2.** Sensitivity of Carbon tax

Resident-satisfaction drivers were probed with global and local sensitivity analyses. A random-forest model highlighted  $C_1$  and  $N$  as dominant features, with  $R(V)$  less influential. Refer to Figure 3. A  $\pm 5\%$  perturbation of each input quantified local impacts on  $S$ . Refer to Figure 4. The resulting sustainable-tourism model remains robust and readily transferable to similar regions.

In conclusion, the sustainable tourism model demonstrates strong robustness and can be easily adapted to other countries or regions with similar situations.



**Figure 3.** Global sensitivity analysis



**Figure 4.** Local sensitivity analysis

### 3. A balanced model of tourist diversion

Considering the necessity of narrowing the economic income gap and the reality that the carrying capacity of the ecological environment in different places is limited, this model focuses on Yellowstone Park and allocates seasonal visitor caps — 20% in spring, 40% in summer, 25% in autumn, and 15% in winter—to prevent over-tourism [10]. These proportions reflect summer’s peak travel and wildlife activity, U.S. holiday timing, and winter access restrictions due to heavy snowfall.

Besides, Carbon emissions generated by visitor activities vary depending on the mode of transportation. The paper assumes that private cars emit 0.2 kg of carbon dioxide per kilometer per person, buses emit 0.05 kg per kilometer per person, and walking or cycling produces no carbon emissions [11].

Based on the above two indicators, the paper selects 12 scenic spots below Yellowstone Park as research objects, and marked the peak season of tourism and the use of transportation in each place. Refer to Table 1.

**Table 1.** Summary of Yellowstone Park attractions

Attractions	Rank	Peak season	Average distances	Car	Bus	Walk	Protection needs
Yellowstone Grand Canyon	1	Summer	10	60%	30%	10%	High
Lamar Valley	2	Spring	20	70%	20%	10%	Middle
Grand Prismatic Spring	3	Summer	15	65%	25%	10%	High
Old Faithful	4	Summer	5	50%	40%	10%	High
Yellowstone Lake	5	Summer	18	55%	35%	10%	Middle
Mammoth Hot Springs	6	All seasons	8	60%	30%	10%	High
Artist Point	7	Summer	12	60%	30%	10%	Low
Bisquit Basin	8	Summer	7	55%	35%	10%	Low
Upper Geyser Basin	9	Summer	14	65%	25%	10%	High
Hayden Valley	10	Spring	13	60%	30%	10%	Middle
Lower Falls of the Yellowstone River	11	Summer	17	55%	35%	10%	High
Grand Loop Road	12	Summer	20	70%	20%	10%	Low

### 3.1. Visitor Balance Model

(1) Objective Function: Variance of Comprehensive Scores. Let the comprehensive objective for the  $p$ -th attraction be denoted as  $Q$ .

$$Q_{(i,p)} = \alpha_1 N_{(i,p)} + \alpha_2 S_{(i,p)} + \alpha_3 E_{(i,p)} + \alpha_4 C_{(i,p)} + \alpha_5 \quad (16)$$

The parameters in the formula are consistent with the first model, where  $i$  represents the  $i$ -th quarter and  $p$  represents the attraction's sequence. Variance is a mathematical feature that reflects the degree of dispersion of a random variable. A smaller variance of the comprehensive objective indicates a more balanced distribution of visitor numbers between popular and less popular attractions. Due to the relationship between variance and mean.

$$D(S) = E(S^2) - E^2(S) \quad (17)$$

Considering the practical context of the problem, the objective function is:

$$\text{Min} \left\{ \frac{1}{12} \sum_{i=1}^4 \left( \sum_{p=1}^{12} Q^2(i,p) - \left( \frac{1}{12} \sum_{p=1}^{12} Q(i,p) \right)^2 \right) \right\} \quad (18)$$

(2) Constraints concerning Budget and Visitor Numbers: From the first model and the beginning of this chapter, it is known that budget allocation is seasonal. The constraints are as follows:

$$\begin{cases} N_{i,p} \leq N_{\max(i,p)} \\ E_i + C_i \leq M_i \\ 0 \leq r \leq 1 \end{cases} \quad (19)$$

$M_i$  is the budget for the  $i$ -th quarter.

(3) Optimization Model: There is no essential difference between Yellowstone Park and the Juno region, and the sustainable tourism model is equally applicable. Taking into account the seasonal factors of Yellowstone Park, some modifications are made to the optimization model, which is summarized as:

$$\left\{ \begin{array}{l} \max \{W\} \\ \min \{E(v) + C(v)\} \\ \max \{S\} \\ W = \sum_{i=1}^4 R_i(v) - E_i(v) + T_i(v) - C_i(v) \\ Ni(t) = N_{0,i}(t) \cdot (1 - \bar{r}) \\ E_i(V) = P_i \cdot \left(\frac{Gi}{Pi}\right) \cdot \left(\frac{Ei}{\alpha i}\right) \cdot \left(\frac{Ci}{Ei}\right) = Gi \cdot hi \\ Si(t) = \beta_{1i} C_{1i}(V) + \beta_{2i} C_{2i}(V) + \beta_{3i} R(V) + \beta_{4i} T(V) + \beta_{5i} N_i(t) + \varepsilon_0 \end{array} \right. \quad (20)$$

(4) Final Model: By combining the visitor balance model with the optimization model, the paper obtains the new model, which is also an extension of the sustainable tourism model from the first one.

$$\text{Min} \left\{ \frac{1}{12} \sum_{i=1}^4 \left( \sum_{p=1}^{12} Q^2(i,p) - \left( \frac{1}{12} \sum_{p=1}^{12} Q(i,p) \right)^2 \right) \right\} \quad (21)$$

$$\left\{ \begin{array}{l} N_{i,p} \leq N_{\max(i,p)} \\ E_i + C_i \leq M_i \\ 0 \leq \bar{r} \leq 1 \end{array} \right. \quad (22)$$

$$\left\{ \begin{array}{l} \max \{W\} \\ \min \{E(v) + C(v)\} \\ \max \{S\} \\ W = \sum_{i=1}^4 R_i(v) - E_i(v) + T_i(v) - C_i(v) \\ Ni(t) = N_{0,i}(t) \cdot (1 - \bar{r}) \\ E_i(V) = P_i \cdot \left(\frac{Gi}{Pi}\right) \cdot \left(\frac{Ei}{\alpha i}\right) \cdot \left(\frac{Ci}{Ei}\right) = Gi \cdot hi \\ Si(t) = \beta_{1i} C_{1i}(V) + \beta_{2i} C_{2i}(V) + \beta_{3i} R(V) + \beta_{4i} T(V) + \beta_{5i} N_i(t) + \varepsilon_0 \end{array} \right. \quad (23)$$

### 3.2. Result Analysis

Visualize the results, where Spot 1 – 12 represent the top 12 tourist attractions in Table 1 ranked as rank 1 – 12. As can be seen from Figure 5, the 12 scenic spots studied all give appropriate quarterly average tourist reception, quarterly average profit, average resident satisfaction and environmental governance expenditure according to the actual situation.

Furthermore, by incorporating seasonal demand patterns at Yellowstone National Park and differentiating travel modes (private car, bus, walking) according to their respective carbon-emission profiles, the multi-objective optimization effectively balances visitor distribution across all sites. Figure 5 illustrates the optimized outcomes: sites initially experiencing higher visitor numbers  $N$  and associated economic returns  $W$  in peak seasons are strategically offset by redirecting a proportion of visitors toward under-visited locations. Consequently, this redistribution ensures a balanced expenditure on environmental governance  $C$  and maintains elevated resident satisfaction  $S$  across all attractions. Notably, spots with higher initial congestion (such as Spots 1, 2, and 12) experience moderated visitation pressures, demonstrating the model’s effectiveness in managing tourism flows to optimize economic, environmental, and community objectives simultaneously. Refer to Figure 5.

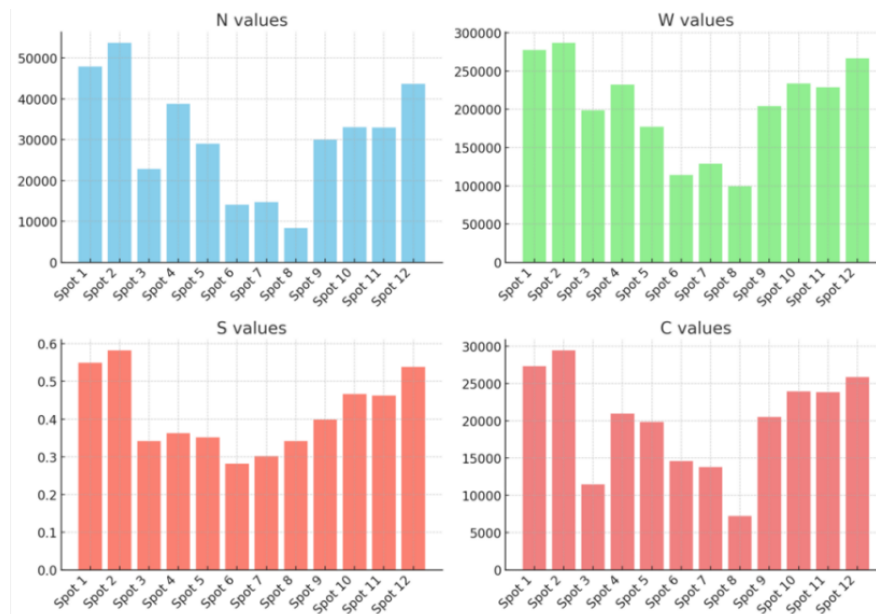


Figure 5. Results analysis

#### 4. Conclusions

In this study, the paper has developed and validated a comprehensive multi-objective optimization framework tailored to sustainable tourism management and visitor – flow equilibrium across two distinct contexts: the economy-centric setting of Juneau and the ecologically sensitive environment of Yellowstone National Park. By integrating genetic algorithms with empirical data spanning five years, the sustainable tourism model achieved an optimal profit of \$266.37 million, minimized combined expenditures to \$80.19 million, and secured a resident satisfaction index of 0.4976 under a daily average visitation of 15,083 and an ancillary tax rate of 7.39%. Concurrently, the visitor distribution model demonstrated its capacity to harmonize quarterly tourist loads, economic returns, community welfare, and environmental governance expenditure across twelve prime attractions. Crucially, the incorporation of seasonal demand dynamics and modal carbon-emission profiles (private car, bus, walking) enabled targeted redirection of peak-season visitors to underutilized sites, thereby sustaining elevated levels of profit, governance investment, and resident satisfaction without overtaxing any single locale.

Future research will explore advanced heuristic and exact algorithms to enhance computational efficiency and solution granularity, extend the framework to incorporate real-time visitor data streams, and examine the interplay between local stakeholder engagement and adaptive policy mechanisms. Such developments will further bridge the gap between theoretical modeling and dynamic, on-the-ground tourism management.

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