Sustainable Future and Tourism Development: Building a Resilient Path for Tourism Sustainability

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Abstract: Rising living standards and global mobility have increased tourism demand, often causing overtourism, environmental degradation, resource pressure, and social disruption, which threaten community well-being and destination competitiveness. Achieving sustainable tourism requires balancing economic, environmental, and social objectives. This study develops a Sustainable Tourism Management Model based on System Dynamics and Multi-Objective Optimization to address these challenges. Tax allocation ratios serve as control variables, while Particle Swarm Optimization (PSO) and NSGA-II are applied to identify Pareto optimal solutions, enabling effective management of tourist flows, infrastructure, and community development. Case studies demonstrate the model's capability to guide policy, mitigate environmental pressure, and optimize resource allocation. The framework can be extended to other multi-objective domains, such as urban planning and regional resource management, and its adaptability is enhanced through field-specific indicators, real-time data, and intelligent forecasting. By combining methodological rigor with dynamic optimization, the model provides a practical tool for policymakers and planners to manage overtourism and promote sustainable tourism across diverse regions.

1. Introduction

In recent years, the global tourism industry has expanded rapidly alongside rising living standards, becoming a key driver of economic growth for destinations ranging from culturally rich Venice to ecologically sensitive Yellowstone National Park and economically tourism-dependent areas like Juneau, Alaska. However, this growth has brought cascading challenges: overtourism strains infrastructure and disrupts resident life[1][2], environmental degradation such as Juneau's accelerating Mendenhall Glacier retreat linked to tourism-related carbon emissions[3][4] undermines natural attractions, and social equity gaps widen as local needs are sidelined for short-term economic gains[5][6]. Traditional single-objective management models, which prioritize revenue over ecology or community well-being, have proven inadequate to address these interconnected issues, highlighting an urgent need for integrated, multi-dimensional solutions[7][8].

To address this, the study constructs a multi-objective optimization framework that transcends the limitations of single-objective models. This framework integrates three core dimensions economic benefits, environmental quality, and social satisfaction to maximize comprehensive gains, with objective weights dynamically adjusted to match destination traits: Venice prioritizes cultural heritage and groundwater protection[5][9], Yellowstone focuses on ecological preservation[1][3], and Juneau balances glacier conservation with community needs[4][8]. Constraints are embedded to avoid extreme optimization, ensuring coordinated sustainable development[10][11]. Complementing this, global sensitivity analysis identifies key passive design parameters like window-to-wall ratio (WWR) and envelope thermal transmittance (U-value) for rural tourism buildings (RTBs) in China's

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southeastern coastal areas to enhance model adaptability[2]. For instance, RTBs in Zhejiang Province, a hub for rural tourism, require tailored adjustments to WWR and shading systems to balance energy efficiency and indoor comfort, demonstrating the framework's ability to account for regional specifics[2][12].

The study further leverages intelligent algorithms to enhance optimization precision. Particle Swarm Optimization (PSO) is used to solve multi-objective problems, with tax allocation as a key decision variable: PSO simulates global searches to avoid local optima, efficiently converging to Pareto optimal sets[3][5]. It integrates the NSGA-II enhanced with hill-climbing to boost search ability[1] to refine solutions, such as calculating accurate tax ratios for Juneau that balance revenue with environmental protection[3]. Sensitivity analysis validates the model's robustness, confirming that infrastructure investment and ecological input are primary drivers of tourism dynamics[1][4]. The model's adaptability is further demonstrated in two scenarios: for China's rural tourism buildings, it quantifies regional traits via a matrix of environmental sensitivity, cultural protection, and economic dependence, adjusting parameters like shading systems and insulation materials[2]; for hotel recommendation systems in tourism management, it uses linguistic neutrosophic sets to handle uncertain user feedback, converting vague terms into quantifiable data to guide strategy selection[5]. This flexibility ensures targeted strategies for diverse destinations, from RTBs in Zhejiang to hotels in hill stations, supporting sustainable tourism across varied contexts[5][9][12].

The main contribution of our work is summarized as follows:

- A multi-objective optimization framework is established to overcome the limitations of single-objective models. It integrates economic, environmental, and social dimensions, with dynamic weights reflecting local characteristics as cultural and environmental priorities in Venice and ecological emphasis in Yellowstone. Built-in constraints safeguard against extreme outcomes, ensuring balanced and sustainable development.
- The study applies PSO combined with NSGA-II to optimize tax allocation, using global search to avoid local optima and generate efficient Pareto sets. Tax distribution serves as the decision variable, producing precise policy ratios, further validated through sensitivity analysis.
- The model adapts to diverse destinations by mapping environmental, cultural, and economic traits, adjusting parameters such as tax policies, and substituting core indicators, enabling tailored strategies from cultural cities to ecological zones.

2. Methods

2.1 Multi-Objective Optimization

2.1.1 Multi-Objective Optimization Framework

We created a sustainable tourism model using system dynamics and multi-objective optimization, identifying key interconnected factors via a Sustainable Dynamic Interaction Network (SDIN). This method optimizes configurations to ensure long-term sustainability in Juneau's tourism across environmental, economic, and social aspects.

Therefore, our objective function is optimized by incorporating multiple factors.

$$\text{Maximize}Z = \alpha_1 \int_0^T R(t)e^{-\rho t}dt - \alpha_2 \int_0^T E(t)dt - \alpha_3 \int_0^T \big(1-S(V,D,A)\big)dt - \alpha_4 \int_0^T \left|\frac{dA(t)}{dt}\right| dt \tag{1}$$

The objective function balances factors such as tourism revenue, environmental pressure, res ident satisfaction, and glacier area change by introducing four parameters: α_1, α_2, α_3, and α_4. It ensures the coordinated development of each objective within a unified optimization framework. With this framework, the model can comprehensively assess and promote the sustainable development of tourism in Juneau.

2.1.2 Critical Constraints

Changes in infrastructure capacity are influenced by a combination of factors. Its dynamic adjustment follows the relationship outlined below:

$$\frac{dC}{dt}=\eta_2 l_i(t)T_a(t)-\mu C(t) \tag{2}$$

Among them, η_2 is the infrastructure construction efficiency coefficient; $l_i(t)$ is the infrastructure expansion investment, allocated proportionally from tax revenue; $T_a(t)$ is the technological progress factor, reflecting the improvement effect of technological progress on infrastructure construction and utilization efficiency; and μ is the natural aging rate of infrastructure.

Accordingly, we present all the constraints.

$$\begin{cases} 0\le V(t)\le V_{limit} \\ E(t)\le E_{max} \\ S(V,D,A)\ge S_{min} \\ A(t)\ge A_{min} \\ V(t)\le C(t) \end{cases} \tag{3}$$

2.2 Particle Swarm Optimization Algorithm

2.2.1 Glacier Area Change Simulation

Quantifying glacier volume is challenging due to the limited availability of data, often relying on preconditions or assumptions. As a result, volumetric measurements may be biased and fail to accurately reflect actual changes in glacier volume. Through our in-depth analysis of the glacier recession process, we have identified several key factors that influence glacier change.

(1) Preliminary Model for Glacier Area Change

To model glacier area change, we introduced the following equations.

$$\begin{cases} \frac{dA(t)}{dt}=\alpha E(t)+\beta T_a(t)+\gamma V(t_0)+\delta_2 A(t) \\ V(t_0)\le 20000\times 30 \end{cases} \tag{4}$$

Where α is the coefficient for carbon emissions, β is the coefficient for temperature changes, γ is the coefficient for tourism activities, and δ_2 is the coefficient for natural glacier changes.

(2) Optimization of the Formula

The glacier's natural retreat rate δ_2 is 1.5%[13]. We have constructed two datasets. First, based on several studies[14]-[18], provides data on glacier area changes with temperature. Second, also based on several studies[19]-[23], provides data on glacier area changes with atmospheric greenhouse gas concentrations. We then fitted and adjusted the data to derive the exact formula, as shown below.

$$\frac{dA(t)}{dt}=\alpha E(t)+\beta T_a(t)^2+\gamma T_a(t)+D+\delta_2 A(t) \tag{5}$$

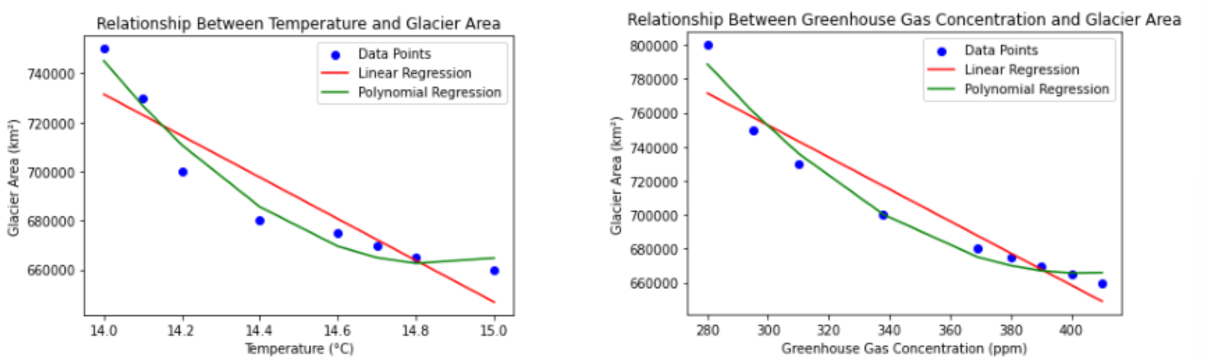

Fig. 1. Glacier Area Regression with Temperature and Greenhouse Gas Concentrations

The relationship between glacier area, temperature, and greenhouse gas concentration was analyzed using Polynomial Regression and linear regression. Polynomial Regression provides a better fit and more accurately captures the nonlinear trends in the data, while linear [Fig. 1] regression performs relatively poorly.

Based on fitting and unit conversion, $\alpha = 0.002$, $\beta = 0.003$, $\gamma = -0.033$, and $D = 0.008$ are the coefficients that influence glacier area change rate due to temperature changes.

2.2.2 Nonlinear Environmental Pressure

To study the evolution of tourism in Juneau, nonlinear environmental pressures are introduced. $E(t)$ represents the environmental pressure, quantifying the negative impacts of tourism activities on the city's environment and reflecting the burden tourism places on it.

$$\frac{dE}{dt}=k_2V(t)S_s(t)-k_4T(t)-\delta_1E(t) \tag{6}$$

$k_2=R(t)\times 1.02$ represents the impact of maritime tourism on environmental pressure[24]. k_4 is defined as 0.2, reflecting the tax's role in mitigating environmental stress, according to the 2023 City of Juneau sales tax data.$S_s(t)$ is the seasonal influence factor, fluctuating within a range of values according to seasonal changes. Specifically, $S_s(t)$ is 1.25 during the peak season and 1.0 during the off-season. δ_1 is the environmental self-repair coefficient, reflecting the inability of the environment to self-repair without external intervention. When the environmental pressure $E(t)$ exceeds the critical value Ecrit, the recovery coefficient δ_1 adjusts according to $\delta_1 = \delta_0 - \lambda(E(t)-E_{crit})$, where δ_0 represents the recovery rate under normal conditions, and λ is the adjustment coefficient.

2.2.3 Resident Satisfaction

To assess resident satisfaction in the City of Juneau, several key factors closely linked to well-being and quality of life were considered. Based on these factors, the following formula was used to describe their relationship with resident satisfaction.

$$S(V,D,A)=S_0+\eta_1\cdot\ln(1+V(t))-\zeta_1V(t)-\zeta_2D(t)+w_1A(t)+\xi_3I_c(t) \tag{7}$$

where S_0 represents the baseline satisfaction of residents without external disturbances; η_1 is the positive impact coefficient of tourist numbers on resident satisfaction; and $I_c(t)$ represents the effect of changes in community welfare investment on resident satisfaction.

We applied the Analytic Hierarchy Process (AHP) [Fig. 2] to solve the problem and analyzed the key factors, as shown in the following AHP hierarchy diagram.

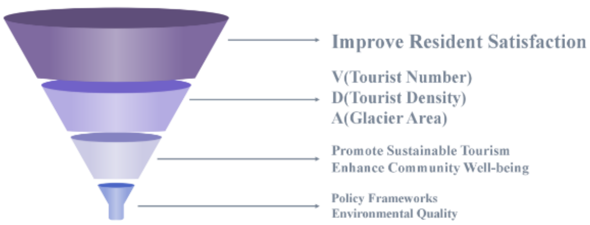

Fig. 2. AHP Hierarchy Diagram

Based on the factorsζ_1, ζ_2, w_1, ξ_3, we constructed the judgment matrix to evaluate the relative importance of different factors, as shown below:

$$A=\begin{bmatrix}1 & 3 & 0.5 & 1\\ \frac{1}{3} & 1 & \frac{1}{7} & \frac{1}{2}\\ 2 & 7 & 1 & 3\\ 1 & 2 & \frac{1}{3} & 1\end{bmatrix} \tag{8}$$

After calculating the eigenvalues and eigenvectors of the judgment matrix, we determined the maximum eigenvalue and its corresponding eigenvector. These were normalized to derive the weight vector. Next, we calculated the consistency index(CI) and the random consistency index(RI), and performed a consistency check using the consistency ratio(CR).

The CR value of 0.0087, which is well below the threshold of 0.1, confirms the model's strong consistency. Therefore, the final weight values were determined as follows: $\zeta_1 = 0.5135$, $\zeta_2 = 0.2241$, $\xi_3 = 0.0793$,and $w_1 = 0.1872$.

2.2.4 Tourism Revenue

Tourism revenue is the key indicator and is influenced by factors such as the number of tourists and the structure of consumption. The following equation outlines the dynamics of tourism revenue.

$$R(t)=k_1 V(t)\cdot\left(1-\frac{V(t)}{V_{sat}}\right)\sum_{i=1}^{n} C_{s,i}(t)P_i(t)(1-C_c(t))\cdot f(A(t)) \tag{9}$$

Taking into account the local consumption tax rate of 5%, k_1, the tourism revenue coefficient, quantifies how the number of tourists V(t) influences tourism revenue. Its value is set to 0.95. When the number of tourists V(t) approaches the maximum capacity V_{sat} = 600000, the marginal contribution to revenue decreases, consistent with the principle of diminishing returns. $C_{s,i}(t)$ represents the expenditure structure at time t, with the i-th item's share of total expenditure. $P_i(t)$ is the price of the i-th item at time t, and $C_c(t)$ denotes Juno's competitiveness in the tourism market at time t, ranging from 0 to 1, where smaller values indicate higher competition. The correction function $f(A(t)) = A(t)/A_{max}$ represents the impact of glacier area A(t), another key factor in the Network, on tourism revenue. As the glacier area decreases, the correction function and, consequently, tourism revenue decline.

2.2.5 Taxation and Distribution

Taxation is a key tool used by governments to manage tourism revenues and promote the sustainable development of tourism.

$$T(t)=f(R(t)) \tag{10}$$

According to the 2023 One Percent Sales Tax Information from the City of Juneau, as stated on the official webpage of Juneau City and Borough, the city generates revenue through a 5% sales tax. Based on the collected data, we establish a linear relationship between the tax revenue, T(t), and the total revenue, R(t), given by

$$T(t)=0.05R(t) \tag{11}$$

T(t) is allocated as follows: the proportion of p_1 is used for environmental technology upgrades, the proportion of p2 is used for infrastructure expansion, and the proportion of p3 is used for community welfare, where $p_1+p_2+p_3=1$.

The values of p_1, p_2, and p_3 are derived by maximizing Z in a comprehensive model based on the Sustainable Dynamic Interaction Network, as detailed in Section 5. Through short-term and long-term simulations, we obtained two distinct sets of numerical results.

2.3 Adaptive Tourism Optimization

2.3.1 Quantification of Regional Characteristics

To adapt to the tourism characteristics of different regions, we define the regional feature matrix $M = [m_1,m_2,m_3]^7$, where m_1,m_2,m_3 represent the environmental sensitivity index, cultural protection intensity, and economic dependence, respectively (all within the range [0,1]). These variables are calculated using a weighted normalization method and influence the adjustment of parameters and the multi-objective optimization framework.

2.3.2 Parameter Adjustment

Parameter adjustments for factors in the Sustainable Dynamic Interaction Network are as follows:

$$k_1=k_{1original}\cdot(1+2a_1),k_2=k_{2original}\cdot(1+a_2) \tag{12}$$

The environment-related parameter k_2 is adjusted to $k_2 = k_{2original}\cdot(1+2m_1)$. In the resident satisfaction model related to social costs, some coefficients are adjusted as follows:

$$\xi_1^{new}=\xi_1^{original}\cdot(1+m_1) \text{ and } \xi_2^{new}=\xi_2^{original}\cdot(1+m_2) \tag{13}$$

The upper limit of tourist numbers Unimit is adjusted to Unter= Vtriginal,(1-0.5m $_3$).

2.3.3 Multi-Objective Optimization with Dynamic Weight Adjustment

The multi-objective optimization framework Maximize Z employs dynamic weighting, where the weight parameters α1,α2,α3 are calculated using the following normalization formulas:

$$\begin{cases} a_1=\dfrac{1+m_3}{4+m_1+m_2+m_3} \\ a_2=\dfrac{1+2m_1}{4+m_1+m_2+m_3} \\ a_3=\dfrac{1+m_2}{4+m_1+m_2+m_3} \end{cases} \tag{14}$$

The weight a_4 is dynamically adjusted using the following formula:

$$a_4=1-a_1-a_2-a_3 \tag{15}$$

3. Results and Analysis

3.1 Extra Income and Expenditure Plan

Based on our model, which maximizes the Z-function score, we predict tourism revenues after three years and calculate the tax revenue and its distribution under a 5% sales tax rate, as shown in Table 1.

Our model uses particle swarm algorithm to iteratively calculate and obtain the most reasonable allocation ratio for annual expenditures, that is, the income and expenditure plan.

Table 1. Tourism Revenue and Taxation Data Presentation (Tourism Revenue and Tax Revenue)

Year	Tourism Revenue	Tax Revenue
2024	22121512.36	1109721.97
2025	31509144.74	1586437.76
2026	46412421.22	2323492.98

Table 2. Tourism Revenue and Taxation Data Presentation (Investments)

Year	Environmental Tech Investment	Infrastructure Investment	Community Investment
2024	267788.47	536290.34	292813.75
2025	490236.58	823554.44	456123.58
2026	745421.38	1204537.86	687876.32

For example, tourism revenue in 2024 is 22121512.36 and its tax revenue is 1109721.97.The Government’s expenditure plan should be allocated as follows: Environmental Tech Investment at 267,788.47, Infrastructure Investment at 536,290.34, and Community Investment at 292,813.75, as shown in Table. 2.

As a result, the allocation ratio can be clarified each year, resulting in an income-expenditure plan.

- **How to Drive Model Dynamics**

Our review of the information shows that the City of Juneau spends 20% of its tax revenue on infrastructure. We have increased the rate of investment in infrastructure to 36.7%, which has increased the population carrying capacity of the region and thus the number of tourists that can be received. That is to say raising the capacity (C(t)) threshold. At the same time, we increased the local community investment (welfare) to 38.57%, which increased the regional satisfaction (S(t)) of the local people so that it can accept more tourists and increase the threshold of the acceptable number of people to promote the development of local tourism.

3.2 Pareto score

3.2.1 Visualization Based on the Pareto Frontier Algorithm

We consider both glacial and nonlinear environmental factors as the influence of environmental factors, and we visualize the dynamics of economic, social, and environmental factors with the number of iterations, and the following figures show the results after 100 and 500 iterations, respectively [Fig. 3].

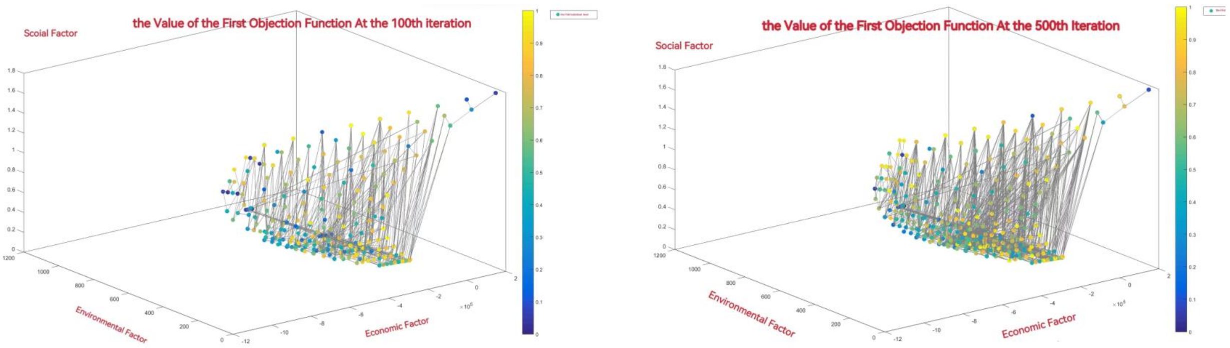

Fig. 1. Dynamics ater 100 and 500 Iterations

As can be seen from the figure, the optimization results are gradually shifted in the direction of larger objective weights as the number of iterations increases (300 and 500). In particular, Tourism Revenue 46.3% has the largest weight, so the optimization solution is gradually concentrated in this direction, while Glacier Area 36.9% has the second largest influence. Relatively small objectives such as Environmental Pressure 7.0% and Resident Satisfaction 9.7% have a weaker influence on the optimization solution, resulting in the solution being less skewed in these directions, and as the number of iterations increases, the solution will converge more closely in the direction of the objective with the larger weight.

3.2.2 Trends in Key Indicators

Based on the optimal weights obtained from the model, we visualized and rationalized the trends in the number of tourists, environmental impact, resident satisfaction, and glacier area from 2024 to 2026 [Fig. 4].

• Trend Analysis of Tourist Arrivals

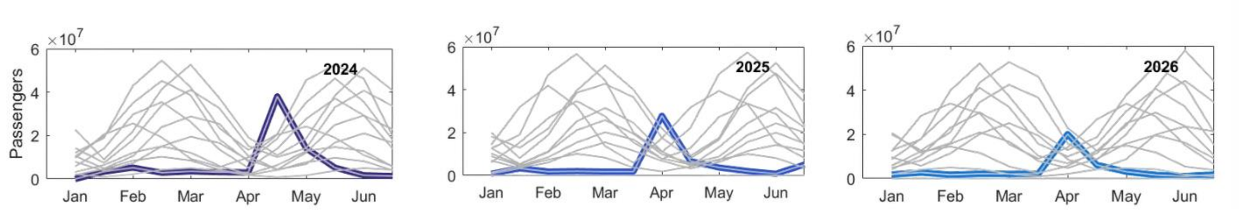

Fig. 2. Trends in visitor arrivals over three years

This set of graphs illustrates the trend between 2024 and 2026, reflecting the fact that the peak period of each year is concentrated between April and June in the late spring and early summer, in line with the peak tourist season. Although the peak months vary slightly from year to year, occurring in April and May respectively, this cyclical variation may be related to external factors. Overall, such seasonal fluctuations and changes in peak periods demonstrate the annual cyclical pattern of tourism, while the annual peak of tourists remains concentrated in the spring and summer seasons, highlighting the general pattern of the peak tourist season [Fig.5].

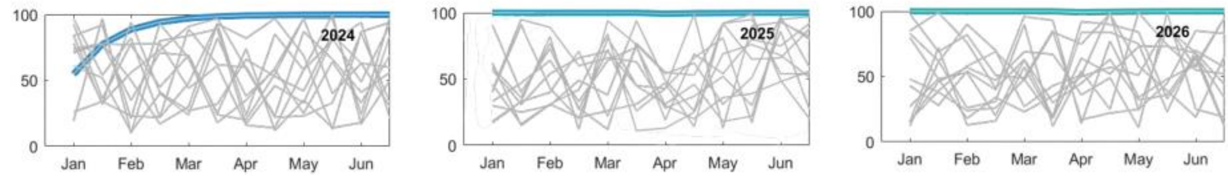

Fig. 5. Trends in environmental impact over three years

The graph shows that the environmental pressure fluctuates in 2024, especially during the peak tourist season, while it gradually smoothens out in 2025 and 2026. This indicates that the interventions undertaken were effective in mitigating the environmental pressure. According to the formula for nonlinear environmental pressure, the number of tourists and seasonal factors exacerbate the environmental pressure during the peak tourism season, while the role of taxes and environmental self-healing help to stabilize the environment, especially after the interventions are taken, the self-healing capacity is gradually increased, resulting in the leveling off of the environmental pressure [Fig.6].

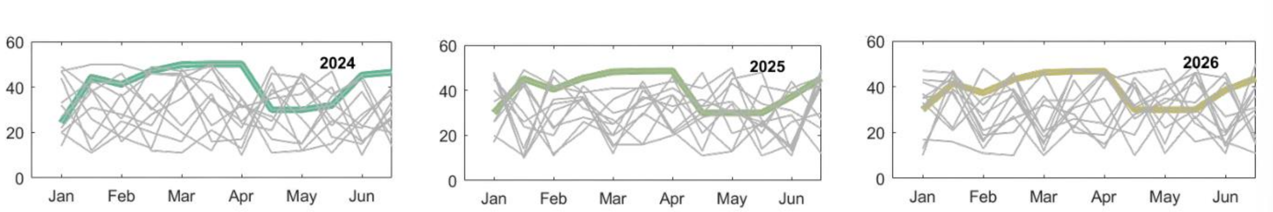

Fig. 6. Trends in resident satisfaction over three years

As the number of tourists increases during the peak season, resident satisfaction initially rises but begins to decline when the number becomes too large, leading to resource constraints and congestion. The formula for resident satisfaction indicates that the positive impact of tourist numbers is stronger initially, but the negative effects gradually increase as overcrowding occurs. On the other hand, community welfare investments play a positive role in improving residents' quality of life and infrastructure, which can enhance resident satisfaction in the long term [Fig. 7].

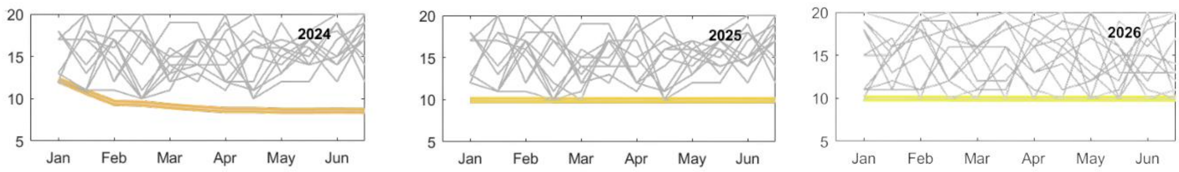

Fig. 7. Trends in glacier area over three years

The figure shows that the glacier area changes drastically in 2024 but flattens out in 2025 and 2026, which may be due to effective interventions such as emission reduction, climate regulation and tourism management. According to the formula for glacier area, the impacts of carbon emissions and temperature change on glacier area are mitigated by the interventions, while external interventions and increased glacier self-healing capacity help to slow down glacier retreat and ultimately stabilize glacier area.

3.3 Sensitivity Analysis

• Correlation Analysis of Model Inputs and Outputs

Sensitivity calculations were performed using a Monte Carlo sampling-based approach, which approximates the assessment of sensitivity by calculating the Pearson correlation coefficients between the input parameters and the model outputs.

Our sensitivity analysis found that for the influences on the Z-function, the effects of tourism industry expenditures and glacier recession were the strongest, suggesting that the absence of glacier breaching has greatly impacted the tourism industry in Juneau.

• Correlation Analysis of Tourism Revenue, Environmental Pressure, and Resident

Satisfaction Impact Factors

Based on Monte Carlo random simulations and Pearson correlation coefficients, we randomly generated the number of tourists to conduct a sensitivity analysis on the function R(t). The results show that time t and glacier area At are positively correlated factors in R(t), while the environmental carrying capacity C is a negatively correlated factor. Specifically, time t has the greatest impact on R(t), indicating that time plays a dominant role in influencing income. Meanwhile, the environmental carrying capacity acts as a constraint, limiting the expansion of the positive correlation, thus maintaining a dynamic equilibrium.

For the environmental factor E(t), both time and income have a positive effect. As income increases, tax revenues also rise, allowing the government to allocate these funds toward environmental protection. Therefore, tax revenue is a function of income and has a positive impact on the environment. Upon analyzing the function E(t), it becomes evident that although changes in certain factors, such as Ta, may counterbalance the positive correlation to some extent, the positive factors ultimately dominate. This leads to an increase in environmental pressure, which aligns with real-world observations. In other words, the mitigating effects do not fully offset the negative impacts.

In the analysis of the S(V, D, A) function, an interesting phenomenon is observed: all factors show a negative correlation. This is because there are two main factors affecting resident satisfaction. On one hand, the increase in the number of tourists leads to higher income. On the other hand, the growing number of tourists brings about negative impacts, such as pressure on accommodation and sewage systems. This result highlights that the environmental pollution and inconvenience caused by overcrowding have a significant impact on residents [Fig. 8].

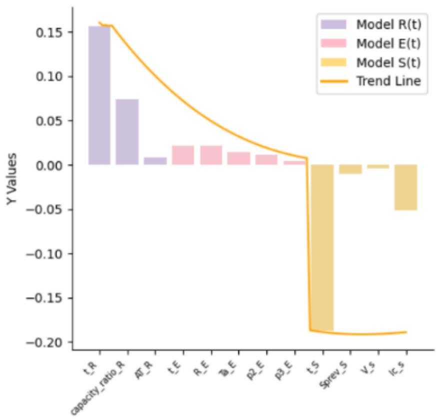

Fig.3.Tourism Revenue, Environmental Pressure, and Resident Satisfaction Sensitivity Analysis

- **Correlation analysis of Dynamic carrying capacity and Z-function impact factors**

For the sensitivity analysis of the infrastructure capacity function, we can see that the impact of the primitive facilities is the largest, while the positive and negative impacts of the artificial factors almost cancel each other out.

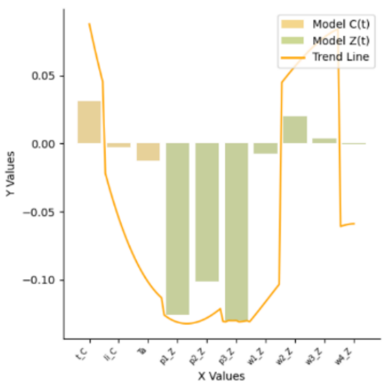

Fig.4. Dynamic Carrying Capacity and Z-function Sensitivity Analysis

For the Z-function, we introduce three additional unknown variables in the tax component, even though only four factors are involved in the equation. Even if the tax revenues are used for the corresponding infrastructure development, rapid rehabilitation may trigger a reverse effect and attract a large number of tourists. Through sensitivity analysis, we find that ecological preservation is the most critical factor, a result that is highly consistent with reality, as shown in Fig. 9.

4. Case Analysis

4.1 Effect of Cultural Protection Intensity on Tourism in Venice

4.1.1 Model Customization for Venice

Based on this, the model is able to dynamically reflect the specific characteristics of the target area. We selected Venice as a representative city with prominent cultural protection intensity. Due to its 22% sales value-added tax, the tourism revenue coefficient, k_1 is set to 0.18, which is derived from the calculation 1-22/122.Vsu= 200,000 per day represents the maximum capacity of Venice's reception; the average consumption per person is around 200 units of currency, similar to that of Juneau. C(t) = 0.2 is the carbon emission coefficient, set based on seasonality and activity intensity. k_2 = 1.06 is a coefficient used to measure environmental impact, indicating that Venice has a greater impact on carbon emissions and environmental protection compared to Juneau.

Since there are no glaciers in Venice, instead of using the glacier formula from the previous model, we introduced a formula for the change in groundwater level in our modeling to better reflect the environmental factors specific to Venice.

$$\frac{dW(t)}{dt} = n_1 \cdot P(t) - n_2 \cdot S(t) + n_3 \cdot I(t) \tag{16}$$

P(t) represents the precipitation, affecting the change in groundwater level; S(t) represents the sea level, influencing the long-term change in groundwater level; I(t) represents the groundwater extraction amount, related to the decline of groundwater level;n_1,n_2,n_3 are coefficients controlling the change in groundwater level, representing the impact of precipitation, sea level, and extraction on the groundwater level.

4.1.2 Results of Adapting the Model: Evaluating the Most Effective Measures

Based on the city characteristics, we assign the feature matrix as [0.3, 0.5, 0.2], yielding the following results.

Table 1. Percentage distribution of funds and fixed target weights

Category	Proportion
Tourism Maintenance	16.5%
Infrastructure	58.4%
Community Investment	25.1%
Tourism Revenue	24.0%
Environment Pressure	32.0%
Resident Satisfaction	30.0%
Groundwater Rights	14.0%
Comprehensive Optimization Index	Z = 0.14

Based on the model’s weighted allocation, when the overall evaluation is maximized over the three years, the government should allocate 58% of the funds to infrastructure,16% to environmental maintenance, and 25% to community welfare.

This chart indicates that environmental pressure (0.32) is the most prominent factor in the optimization process, making it the core objective. Reducing environmental pressure directly influences resident satisfaction (0.30) and tourism revenue (0.24). The key to optimization is balancing environmental protection with economic development, ensuring that tourism revenue growth does not lead to overdevelopment and negative environmental impacts, while simultaneously improving residents' quality of life and achieving sustainable development [Fig. 10] [Fig. 11].

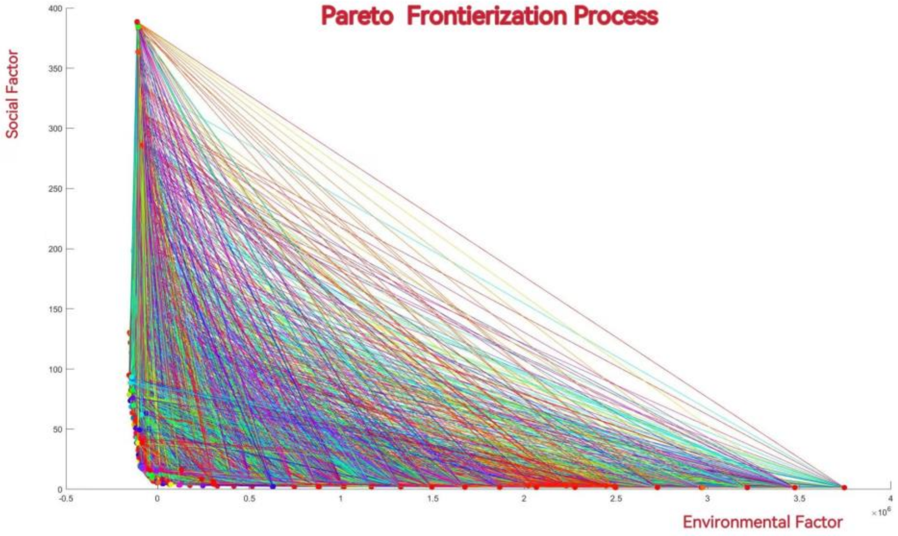

Fig.5. 2D Representation of Pareto Front for the Last 500 Generations

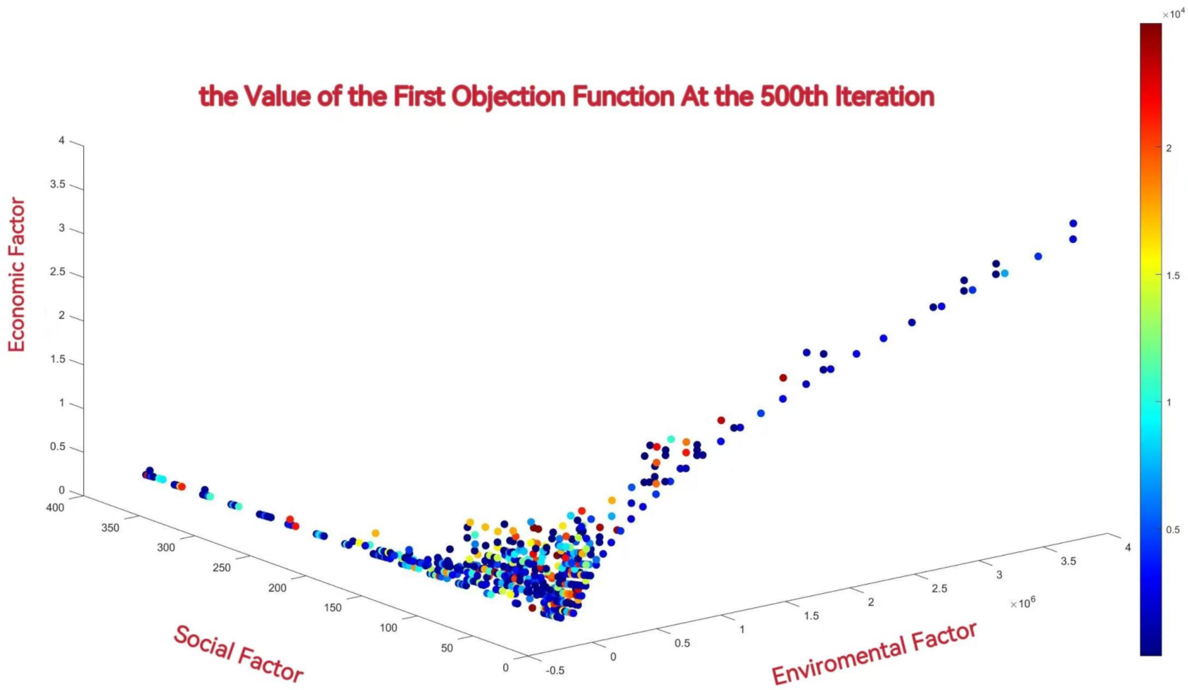

Fig.6. 3D Representation of Pareto Front for the Last 500 Generations

4.2 Effect of Economic Dependence on Tourism in Tokyo

4.2.1 Model Customization for Tokyo

k_1 is assigned a value of 0.91, reflecting Tokyo's high economic dependence on tourism. Vsar is set to 100,000/day, representing Tokyo's maximum visitor capacity, with an annual visitor limit of 3,000,000. The per capita expenditure is 300 units of currency, representing the average expenditure of each tourist. $C_c(t)$ is 0.05, representing the carbon emission coefficient of tourism activities. $S_s(t)$ is set to 1, indicating that Tokyo's tourism seasonality is not significant. $C_c(t)$ is set to 0.1, indicating that Tokyo's carbon emission coefficient is higher. E_0 is 70, reflecting the higher environmental pressure in Tokyo. c_0 is 20 million, representing Tokyo's infrastructure capacity, which is much greater than Juneau's. Ecrit is 75, indicating that Tokyo's environmental threshold is higher, in line with its modernization level. δ_1 is 0.004, which is lower than Juneau's natural recovery rate. k_2 is 1.06, indicating that Tokyo's environmental impact coefficient is slightly higher than Juneau's. η_1 is 0.05, reflecting the higher resident satisfaction in Tokyo. These values take into account Tokyo's tourism volume, infrastructure, modernization level, and environmental impact factors.

4.2.2 Results of Adapting the Model: Evaluating the Most Effective Measures

We selected the feature values as [0.3,0.1,0.6], yielding the following results.

Table 2. Percentage distribution of funds and fixed target weights

Category	Proportion
Tourism Maintenance	16.5%
Infrastructure	47.3%
Community Investment	36.2%
Tourism Revenue	32.0%
Environmental Pressure	32.0%
Resident Satisfaction	22.0%
Air Pollution	14.0%
Comprehensive Optimization Index	Z = 0.14

As a model for promoting regional tourism through economic development, it is important to focus on infrastructure development in order to further increase comprehensive revenue. The government should increase funding for infrastructure development, while also maintaining its focus on and support for private business investment.

4.3 Effect of the Environmental Sensitivity Index on Tourism Yellowstone National Park

4.3.1 Model Customization for Yellowstone National Park

Temperature: The average monthly temperature in Yellowstone Park ranges from -8.35℃ to 17.9℃, reflecting significant seasonal variations. Monthly Visitors: The number of visitors to Yellowstone each month ranges from 64,390 to 620,000, reflecting the seasonal fluctuations in tourism. Maximum Visitor Capacity: Yellowstone's maximum daily visitor capacity is 40,000, resulting in an annual total of 1.2 million visitors. Infrastructure Capacity: The total infrastructure capacity of Yellowstone is 1,500,000, indicating a high potential for tourism accommodation. Resident Satisfaction: Due to the lack of residents in Yellowstone, the satisfaction level is defined based on nearby residents, with an initial value of 50. This value increases as the local economy benefits from tourism, which in turn stimulates consumption. Seasonality Factor: Yellowstone exhibits significant seasonal influence, with a factor of 1.5 during peak seasons and 0.9 in off-seasons.Carbon Emission Coefficient $C_c(t)$: During peak seasons, $C_c(t)$ is 0.005, while during off seasons it is 0.2, reflecting the vast seasonal difference in tourism numbers and carbon emissions. Environmental Impact Factor k_1 : The environmental impact factor for Yellowstone is 0.96, which indicates a relatively low environmental impact compared to other regions.

4.3.2 Results of Adapting the Model: Evaluating the Most Effective Measures

The weight values for the region are assigned as m= [0.9,0.1,0.1], as it is a typical tourist area and a pure natural conservation zone, which is crucial for optimization and planning, yielding the following results.

Local governments should increase their investment in infrastructure development and maintenance of tourist sites in order to cope with the growing demand for tourism. It is understood that tourism activities have led to significant carbon dioxide emissions, which have put significant pressure on local ecosystems.

Table 5. Optimization Results for Funds Allocation

Category	Proportion
Tourism Maintenance	36.5%
Infrastructure	49.9%
Community Investment	13.6%
Tourism Revenue	22.0%
Environmental Pressure	54.0%
Resident Satisfaction	22.0%
Environment Impact	2.0%
Comprehensive Optimization Index	Z = 0.15

According to our general analysis of the selected tourist areas, these areas generally face high environmental pressures and their characteristics are all in line with the actual situation.

4.4 Balance of Tourist Flow

The attractiveness of tourism resources is crucial for tourist flows. Especially under the influence of over-tourism, rational allocation of tourist flows and optimization of attractions' attractiveness become key issues. To this end, we propose a multifactor-based attraction function for tourism resources.

$$\text{Attraction}(t)=\theta_1 A(t)+\theta_2 Q(t)+\theta_3 C_s(t) \tag{17}$$

θ_1, θ_2, and θ_3 are the corresponding weight coefficients; Q(t) represents the quality of tourism services, ranging from 0 to 100; and $C_s(t)$ represents the uniqueness of the tourism product, also ranging from 0 to 100.

We assigned weight coefficients and assumed that service quality is the most important factor, while attractiveness and product distinctiveness vary over time. The following figure shows its visualization [Fig. 12].

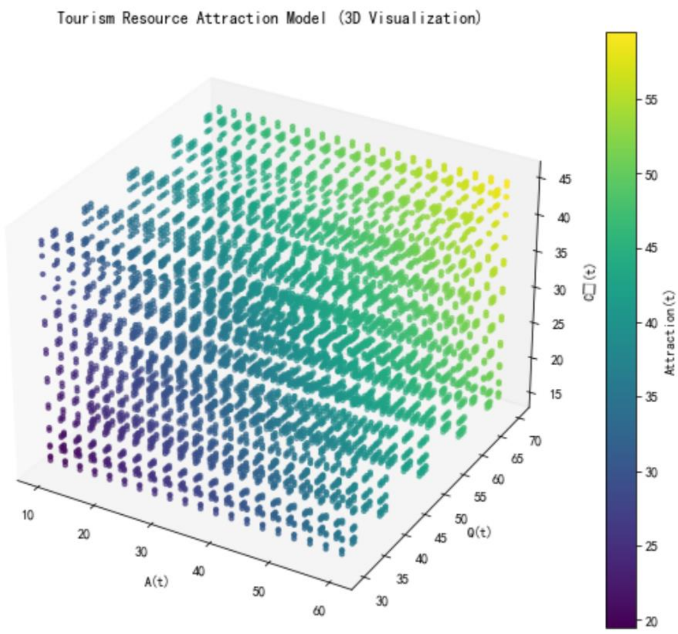

Fig.7. 3D Visualization of Tourist Attraction Dynamics

• Initiatives for Venice [Fig. 13]

According to our model, we define Venice as a historical and cultural city, so we define the characteristic matrix as [0.3,0.5,0.2], that is, the historical and cultural score is greater than the environmental score and greater than the economic score, we derive from the model the weights of the various local influencing factors in Venice, as shown in the table 3.

• We have come to the conclusion that: For the city of Venice, the environment has the greatest impact on his urban development at 32%. Therefore, in order to reduce the burden on the local environment, we optimized that we should reduce the number of their tourists by at least 13.76% to Isola di Malamocco, thus increasing the share of tourism revenue in the local development model, in order to promote the sustainable development of the local tourism industry.

• We therefore make this recommendation to the Government: Increase the original 20% of Venice's spending on infrastructure to 56.5%. This money can be used for the construction of the city's groundwater flooding system and the maintenance of the canals, in order to maximize the local population capacity C(t), thus reducing the pressure on the environment and increasing the satisfaction of the inhabitants with their lives and improving the overall score of the formation of a normal optimization circle. In this way, the sustainable development of the city can be ensured.

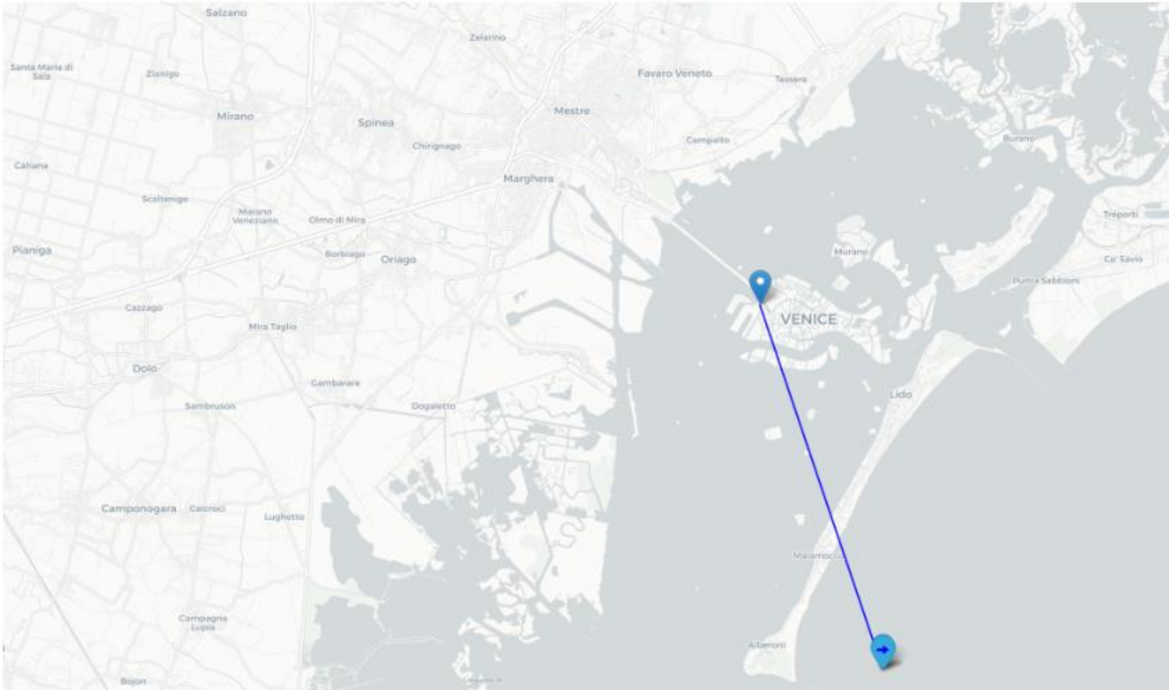

Fig.8. Venice transfers tourist arrivals

• Initiatives for Tokyo [Fig.14]

Based on the model we built, we define Tokyo as an economic characteristic type city, and therefore define the characteristic matrix as [0.3,0.2,0.6], i.e., the economic development score is greater than the environment score and greater than the culture score. We derive the weights of each local influencing factor in Tokyo from the model, as shown in Table 4.

• For Tokyo as an economic city, tourism revenue and the environment have the greatest impact on his development, both at 32%. As a local government, when the weights of both are equal, it should increase the income and reduce the environmental pressure at the same time. Therefore, in order to reduce the burden on the local environment and increase the local tourism income, under this condition, we optimize that we should reduce the number of their tourists by at least 9.18% to Kawasaki, and increase the local prices and house prices. This will increase the local tourism income and reduce the permanent population.

• 47.3% of tax revenues should be used for infrastructure development, such as wastewater treatment, air treatment, etc., to stabilize local environmental pressures and avoid excessive environ mental pressures that could affect sustainable development. Only 16.5% of tourism revenues should be used for tourism maintenance to reduce the number of long-term local tourists and yet maintain the stability of the tourism industry.

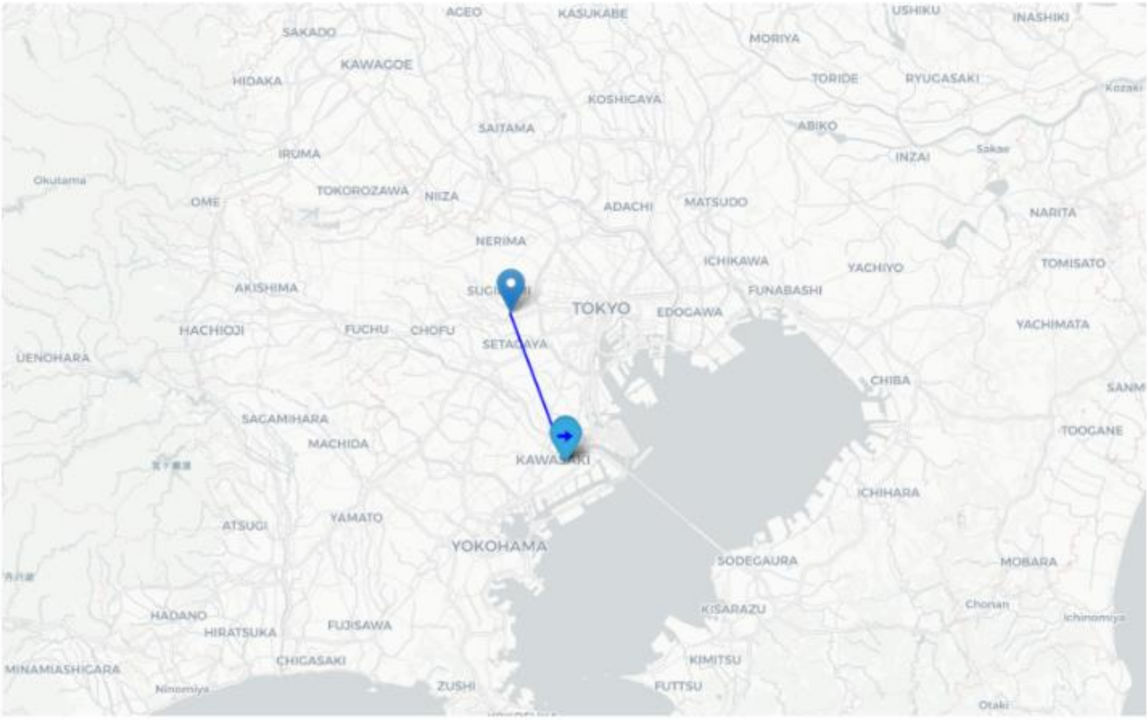

Fig.9. Tokyo transfers tourist arrivals

• Initiatives for Yellowstone National Park [Fig. 15]

Based on our modeling, we define Yellowstone National Park as an environmentally characterized city, and therefore define the characterization matrix as [0.9,0.1,0.1], i.e., the environment score is greater than the economic development score and greater than the culture score. We derive the weights of each local influencing factor in Tokyo from the model, as shown in Table 5.

• For an area like Yellowstone National Park in the United States, environmental pressures have the greatest impact on his development at 54%. Therefore, in order to reduce the burden of local environmental pressures, we optimized that we should reduce the number of their tourists by at least 5.37% to Bighorn Mountains, thus reducing the local environmental pressures, increasing the share of tourism revenues to the development model of the place, and improving the sustainability of the tourism industry.

• Increase the cost of tourism maintenance to 36.5%, increase the number of supervisory staff in local ecological reserves, and reduce the harm caused by tourism to local ecological reserves. Increase investment in infrastructure development to 49.9% to build a comprehensive set of tourist trails and habitats to separate human activities from flora and fauna and reduce human impacts on the natural environment.

A combined look at the performance of the three models in three areas with different characteristics. For the weighting of the development models, local environmental pressures are the most heavily weighted. This may be a common feature of being a tourist area or a city. For areas with different characteristics, we have different proportions of tax distribution, mainly in the distribution of different proportions of the distribution used for tourism maintenance and investment by community residents. This has to do with the local development model and the current state of development. And the development status also determines the characteristics of the city. Therefore, we believe that our model is more adaptable and in line with the development status of most cities.

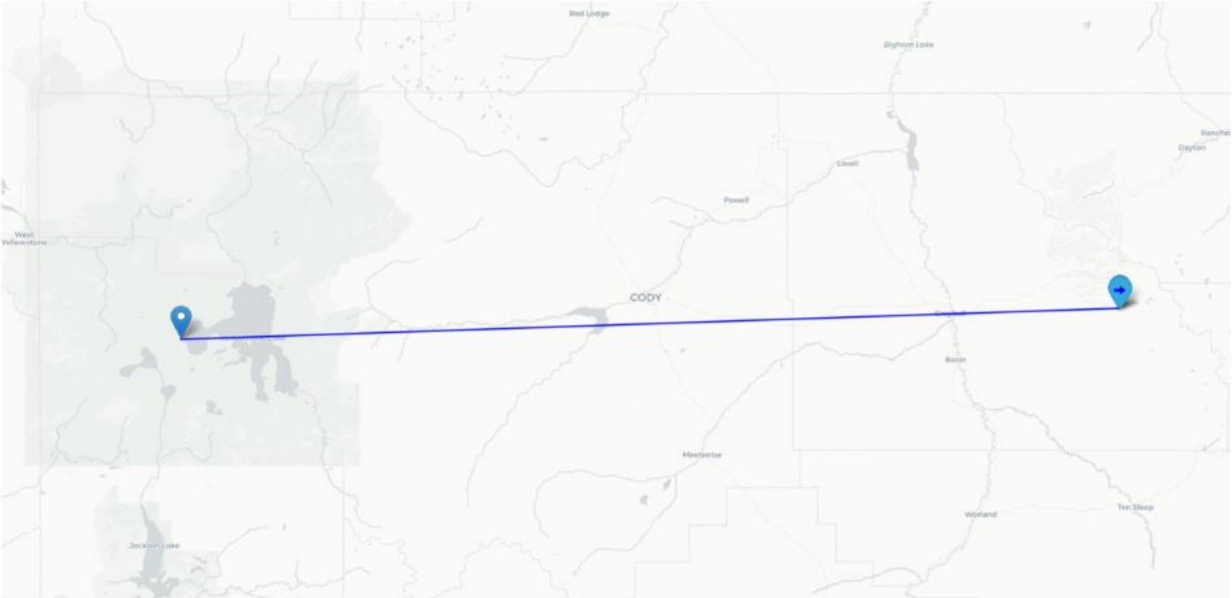

Fig.10. Yellowstone National Park transfers tourist arrivals

5. Conclusion

The study, which aims to address the issues of overtourism, environmental degradation, and social imbalance faced by global tourist destinations, constructs a sustainable tourism management model that integrates System Dynamics and Multi-Objective Optimization, and this model covers a multi-dimensional framework including economic, environmental, and social dimensions while incorporating intelligent algorithms such as Particle Swarm Optimization (PSO) and NSGA-II. Guided by the Sustainable Dynamic Interaction Network (SDIN), the model identifies key influencing factors, builds quantitative equations for the dynamic relationships between these factors, and takes tax allocation as the core variable to effectively avoid local optima, refine Pareto optimal solutions, and achieve balanced resource allocation, which has been verified through case studies in different types of destinations. For ecologically sensitive areas like Yellowstone National Park, the model can stabilize ecological indicators; for cultural areas such as Venice, it prioritizes the protection of cultural heritage; and for economically dependent regions like Tokyo, it optimizes infrastructure configuration, all of which demonstrate that the model outperforms single-objective approaches in various scenarios. Sensitivity analysis further confirms the robustness of the model, and the dynamic weight mechanism it adopts ensures that strategies can be tailored to the characteristics of different destinations, while the model also has flexible parameters and compatibility with real-time data, allowing it to be extended to fields such as urban planning.

Nevertheless, the model still has certain limitations, as its validation relies on specific destinations like Venice, Tokyo, and Yellowstone National Park and has not covered small- and medium-sized tourism regions or regions with mixed cultural, ecological, and economic characteristics, which means its applicability in more diverse scenarios needs further verification; in addition, the quantification of social factors such as resident satisfaction only uses the Analytic Hierarchy Process (AHP) and limited on-site survey data and does not integrate multi-source social information like social media feedback and real-time livelihood data, making it difficult to fully and dynamically reflect the real changes in the social dimension. Future research will expand the scope of case studies to include small- and medium-sized tourism regions and regions with mixed characteristics to further verify and improve the universality of the model, and it will also integrate multi-source social data such as social media public opinion and livelihood service feedback with objective social indicators like the coverage rate of public service facilities to optimize the quantification method of social factors and enhance the accuracy of the model in depicting the social dimension, while developing a real-time data integration module to connect with IoT sensors such as environmental pollutant monitoring sensors and traffic system data like real-time tourist flow monitoring data, so as to strengthen the model’s ability to respond to dynamic changes in the tourism system.

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