Research on Sustainable Tourism Management Model Based on Multivariable Dynamic Optimization Algorithm

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Abstract: With the rapid expansion of tourism in Juneau, Alaska, environmental degradation, infrastructure pressure and community welfare damage caused by the surge in tourists have become increasingly prominent. To this end, this paper, guided by the theory of sustainable development, proposes and establishes a dynamic system optimization model covering multiple variables such as market demand, resource consumption and policy intervention. The model uses differential equations to simulate the complex interaction between the number of tourists, tourism income, environmental carrying capacity and social benefits, and clearly takes maximizing tourism revenue, minimizing environmental impact and social equity as the optimization goals to achieve dynamic balance under specific constraints. Through empirical data calibration, parameter sensitivity analysis and numerical simulation, the threshold effect of income and tourist scale and the nonlinear growth characteristics of environmental impact are systematically revealed, highlighting the key role of policy regulation in sustainable tourism management. The model is highly adaptable and transferable, and can provide scientific decision-making support and theoretical reference for other destinations facing the dilemma of overtourism. The research results provide a quantitative basis for the tourism management department of Juneau to optimize resource allocation and formulate effective sustainable tourism policies, and enrich the mathematical modelling research method system in the field of tourism sustainability.

1. Introduction

Juneau, Alaska, has a permanent population of about 30,000 and will receive 1.6 million cruise tourists in 2023, bringing in about $375 million in economic revenue. However, the large number of tourists has put ecological pressure on scenic spots such as the Mendenhall Glacier, which has retreated about eight football fields since 2007, mainly due to climate change and the impact of tourism activities. If the glacier disappears completely, it will weaken the main local tourist attraction. Despite this, Juneau can still achieve tourism sustainability by developing other natural resources such as whale watching and rainforest ecology. In order to ease the pressure on the environment and infrastructure, many places have adopted management measures such as tourism taxes and tourist flow restrictions, and part of the revenue is used for environmental protection and infrastructure construction.

In recent years, the sustainable development of the tourism industry has become a topic of widespread concern in the global academic community. Streimikiene et al. pointed out through a systematic literature review that the sustainability of the tourism industry is not only related to economic competitiveness, but also to resource protection and long-term social welfare [1]. Hardy and Beeton emphasized that true sustainable tourism management should go beyond short-term resource consumption, focus on optimizing long-term overall interests, and achieve resource "maintainability" [2]. In order to characterize the inherent dynamic relationship of the complex system of the tourism industry, the system dynamics method has been widely used. Ran first systematically introduced the system dynamics model to analyze the interaction of multiple factors

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in the tourism system, emphasizing the important role of feedback mechanism in policy deduction and scenario simulation [3]. Some scholars further combined system dynamics with decision support systems. For example, Tan et al. integrated coastal zone integrated management with tourism sustainability in the case of Taiwan (China) and achieved the optimization of multi-objective decision-making [4]. Sjaifuddin took Indonesian wetland ecotourism as an example and explored the dynamic balance between tourism and ecological environment through system dynamics modelling, providing a new methodological perspective for ecosystem management [5]. In addition, Khan et al. analyzed the dynamic relationship among tourism growth, economic development and environmental pollution through empirical research, and pointed out that effective sustainable tourism policies play a coordinating role between alleviating environmental pressure and promoting economic growth [6].

Overall, the existing research not only enriches the theoretical framework of sustainable tourism, but also verifies the applicability and effectiveness of modelling and decision-making algorithms based on system dynamics in tourism management practice, providing a solid theoretical and methodological reference for this study to construct an algorithm optimization model for sustainable tourism development in Juneau.

2. Model building and solving

2.1. A dynamic model that considers market demand, price adjustments, and resource consumption

Juneau, Alaska, has a permanent population of about 30,000 and will receive 1.6 million cruise tourists in 2023, bringing in about $375 million in economic revenue. However, the large number of tourists has put ecological pressure on scenic spots such as the Mendenhall Glacier, which has retreated about eight football fields since 2007, mainly due to climate change and the impact of tourism activities. If the glacier disappears completely, it will weaken the main local tourist attraction. Despite this, Juneau can still achieve tourism sustainability by developing other natural resources such as whale watching and rainforest ecology. In order to ease the pressure on the environment and infrastructure, many places have adopted management measures such as tourism taxes and tourist flow restrictions, and part of the revenue is used for environmental protection and infrastructure construction.

Market demand is influenced by several factors, with price being the most critical. Other determinants include consumer preferences, income levels, technological advancements, and external economic conditions. To reflect the changes in market demand accurately, we introduce a demand function that not only depends on price $P_i(t)$ but also incorporates external variables $\mathbb{Z}_i(t)$ which represent factors such as economic cycles, government policies, or technological changes.

The demand model is given by:

$$X_i(t) = \alpha_i \cdot \left(P_i(t)^{\beta_i} \cdot e^{-\lambda_i z_i(t)}\right) \cdot (1 + \sum_{k=1}^{M} \gamma_{ik} \cdot \mathbb{Y}_k(t)) \quad (1)$$

Where, α_i is the baseline coefficient for demand, β_i represents price elasticity,λ_i is the coefficient for external economic variables' impact on demand, $\mathbb{Y}_k(t)$ is an influencing factor related to other market behaviors (e.g., competitor products, advertising effects, etc.). The exponential term $e^{-\lambda_i \cdot \mathbb{Z}_i(t)}$ effectively models the negative impact of external disturbances on demand. Figure 1 shows a schematic diagram of nonlinear dynamics and delay effects.

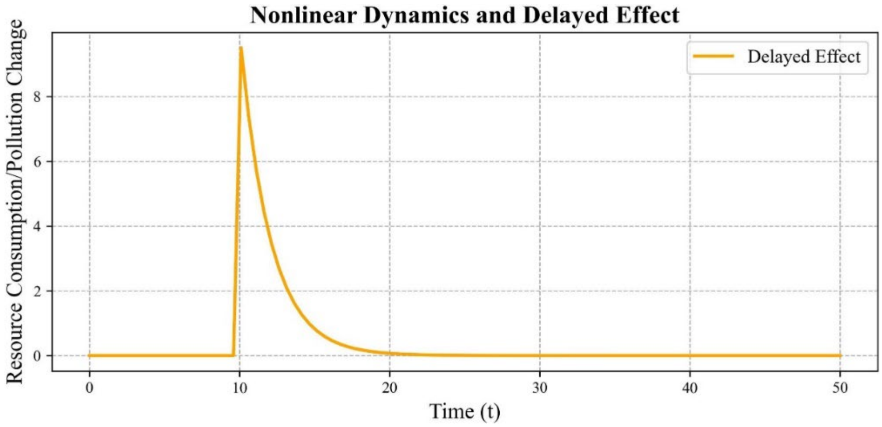

Figure 1 Nonlinear Dynamics and Delayed Effect

Price dynamics are not only influenced by market demand but also by production costs, competitor pricing, and market sentiment. Price changes often exhibit delayed responses, which we model as a feedback system with delays. The price dynamics are expressed as:

$$\frac{dP_i(t)}{dt} = \gamma_i \cdot (P_i(t) - P_i(t-1)) + \sum_{j \neq i} \theta_{ij} \cdot (P_j(t) - P_j(t-1)) + \epsilon_i(t) \tag{2}$$

Where: γ_i is the self-adjustment coefficient of price for market i; θ_{ij} is the cross-market influence of market i; $\epsilon_i(t)$ represents a random disturbance term that models the uncertainty in the price changes.

This model captures both gradual price adjustments and fluctuations resulting from market interactions.

Resource consumption is influenced by demand, technological efficiency, and resource renewability. We model resource consumption as a self-regulating dynamic system with nonlinear characteristics. The resource consumption model is given by:

$$\frac{dR(t)}{dt} = \sum_{i=1}^{N} \alpha_i \cdot X_i(t) - \beta \cdot R(t) \cdot (1 - \frac{R(t)}{R_{max}}) - \lambda \cdot (\int_0^t X_i(\tau) d\tau) \tag{3}$$

Where: $\alpha_i \cdot X_i(t)$ reflects the impact of demand on resource consumption, $\beta \cdot R(t) \cdot (1 - \frac{R(t)}{R_{max}})$ captures the nonlinear resource depletion process, with R_{max} being the maximum resource capacity.

The external influence term $\lambda \cdot (\int_0^t X_i(\tau) d\tau)$ models the cumulative impact of historical demand on current resource consumption. Figure 2 shows the relationship between market demand and price.

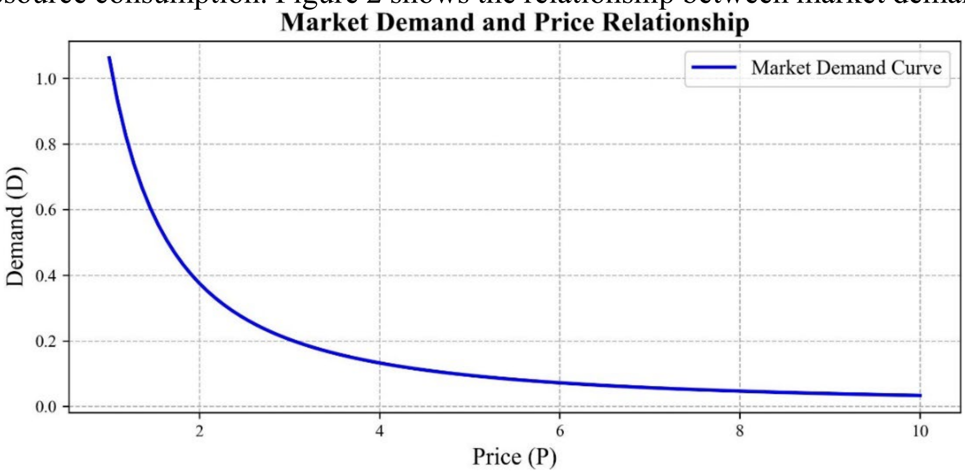

Figure 2 Market Demand and Price Relationship

Environmental pollution diffusion is a dynamic process influenced by resource consumption and other factors, such as spatial location and time. To simulate this diffusion process, we use a Partial

Differential Equation (PDE) to describe the spatial and temporal variation of pollution concentration $E(t,x)$:

$$\frac{\partial E(t,x)}{\partial t} = D \cdot \nabla^2 E(t,x) + \gamma_0 \cdot X(t)^\theta + v(t) \cdot (\frac{R(t)}{R_{max}}) \tag{4}$$

Where: $D \cdot \nabla^2 E(t,x)$ describes the diffusion of pollution in space, $\gamma_0 \cdot X(t)^\theta$ models the nonlinear impact of market demand on pollution concentration, $v(t) \cdot (\frac{R(t)}{R_{max}})$ simulates increased environmental stress due to resource scarcity. Figure 3 shows the trend diagram of the pollution diffusion model.

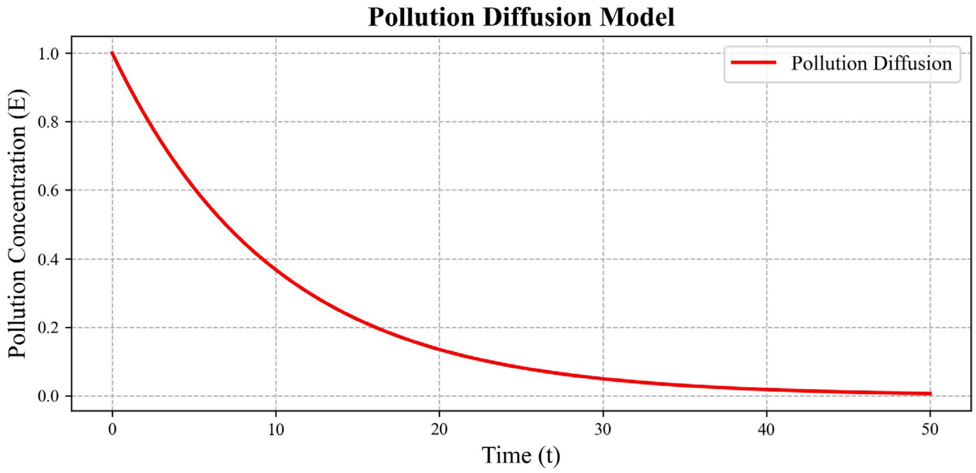

Figure 3 Pollution Diffusion Model

2.2. A multi-factor dynamic model considering environmental pollution, technological progress and social welfare

Social welfare dynamics depend on market demand, technological progress, resource consumption, social inequality, wealth distribution, and public policies. In the social welfare model, we consider the negative impact of wealth inequality on welfare and the effect of environmental pollution on public health. The social welfare function is expressed as:

$$S(t) = \int_0^t (\alpha_1 \cdot \log(H(t)) + \alpha_2 \cdot \log(T(t)) + \alpha_3 \cdot \log(W(t)) - \lambda_t \cdot G(t) + \theta \cdot E(t))dt \tag{5}$$

Where: $H(t)$ represents health levels, $T(t)$ represents technological progress, $W(t)$ represents wealth distribution, $G(t)$ is the social inequality index, $E(t)$ is the environmental pollution level.

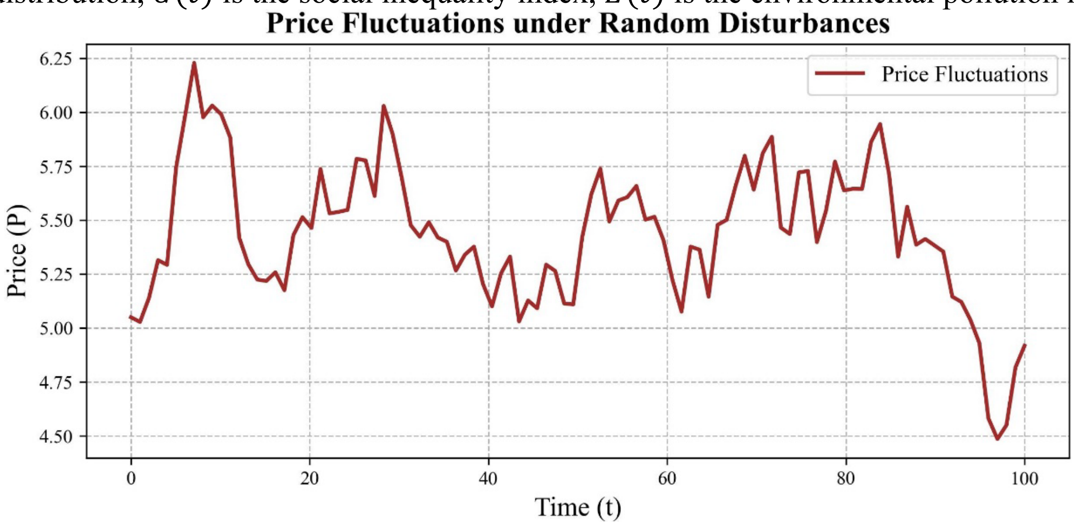

Figure 4 Price Fluctuations under Random Disturbances

This function allows us to analyze the long-term effects of various policies on social welfare.

Figure 4 shows the price fluctuation under random interference.

Nonlinear dynamics and delay effects play a significant role in economic models. To better capture these effects, we introduce nonlinearity and delay terms into resource consumption and environmental pollution models. Specifically, we include a nonlinear feedback mechanism in the resource consumption model:

$$\frac{dR(t)}{dt} = \sum_{i=1}^{N} \alpha_1 \cdot X_i(t) \cdot (1 + \beta_i \cdot R(t)^{\gamma}) - \beta \cdot R(t) \cdot (1 - \frac{R(t)}{R_{max}}) \tag{6}$$

Additionally, we incorporate time-delay terms $R(t-\tau)$ to model delayed responses to policy interventions and market adjustments. Figure 5 shows resource consumption and inventory dynamics.

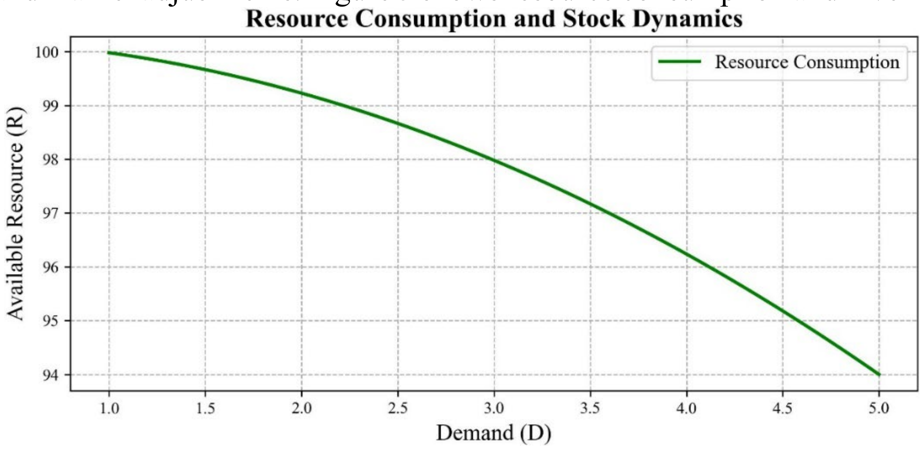

Figure 5 Resource Consumption and Stock Dynamics

Economic systems are subject to a variety of uncertainties, such as policy changes, market fluctuations, and natural disasters. To account for these random disturbances, we introduce stochastic factors into the model using Stochastic Differential Equations (SDEs):

$$dX(t) = f(X(t)) \cdot dt + \sigma(X(t)) \cdot dW(t) \tag{7}$$

Where: $\sigma(X(t))$ represents the noise intensity dependent on the system's state, $W(t)$ is standard Brownian motion, representing external random disturbances. Figure 6 shows the relationship between social welfare and health level.

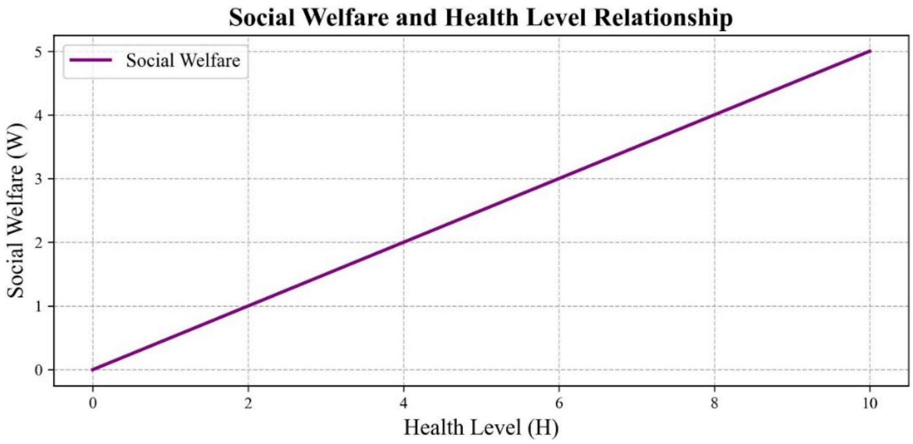

Figure 6 Social Welfare and Health Level Relationship

To maximize social welfare, we formulate an optimal control problem. The Hamilton-Jacobi-Bellman (HJB) equation is given by:

$$\frac{\partial V(t,\mathbf{y})}{\partial t} + \max_{u} (f(t,\mathbf{y},\mathbf{u}) + \nabla V(t,\mathbf{y}) \cdot g(t,\mathbf{y},\mathbf{u})) = 0 \tag{8}$$

Where: $f(t,y,u)$ is the objective function, which includes resources, pollution, and welfare,

$g(t, y, u)$ is the state transition function.

The dynamic game theory model for different agents (government, firms, and consumers) is formulated by solving the following optimization problems for each agent:

Government:

$$U_{gov} = \mathbb{E}\left[\int_0^T (\omega_1 R_{net}(t) - \omega_2 E(t) + \omega_3 S(t))dt\right] \tag{9}$$

Firm:

$$U_{firm} = \mathbb{E}\left[\int_0^T (\pi(t) - \lambda \cdot E(t))dt\right] \tag{10}$$

Consumer:

$$U_{consumer} = \mathbb{E}\left[\int_0^T (log(C_{cons}(t)) - \eta \cdot E(t))dt\right] \tag{11}$$

In these expressions, $\pi(t)$ is the firm's profit, $C_{const}(t)$ is the consumer's consumption, and the integrals over time capture the long-term effects of decision-making. Each agent chooses its strategy over time to maximize its expected utility, leading to a Nash equilibrium.

Through the establishment of a comprehensive dynamic model, this paper successfully simulates the complex interactions between market demand, price adjustments, resource consumption, environmental pollution, and social welfare. The model highlights the significance of nonlinear feedback, delay effects, social inequality, and external random disturbances in economic systems. By incorporating these factors, we provide valuable insights for policy formulation aimed at sustainable development, resource optimization, and social welfare enhancement.

2.3. Data Calibration and Model Construction

To ensure the accuracy and relevance of our model, we calibrated its parameters based on real-world data from Juneau, Alaska, with a focus on tourist arrivals, revenue, and environmental impacts. Given the rapid growth of the tourism industry, particularly cruise tourism, the following models were constructed and validated using generated data.

We generated random data for tourist numbers (T), revenue (R), environmental impact (E), weather conditions (W), and policies (P), and then analyzed these variables with several visualizations. These simulations allowed us to visualize how seasonal patterns affect both revenue and environmental impacts.

A violin plot was used to visualize the distribution of revenue across different seasons. The mathematical model for revenue distribution by season can be expressed as:

$$R_{season} = \gamma_0 + \gamma_1 \cdot Season + \epsilon \tag{12}$$

Where: γ_0 is a constant, γ_1 is the seasonality coefficient for revenue, ϵ represents the error term or unexplained variance due to other factors (e.g., unaccounted external influences).

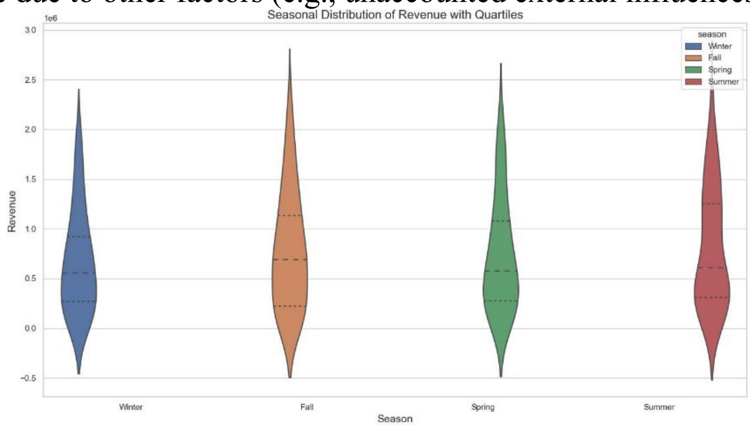

Figure 7 Seasonal Distribution of Revenue with Quartiles

This model helps us understand how the quartiles (inner distribution) vary within each season, providing insights into when Juneau's tourism industry experiences the most significant financial activity. Figure 7 shows the seasonal distribution of quartile income. The plot highlights that revenue peaks during certain seasons (e.g., summer), aligning with higher tourist arrivals.

A violin plot was used to show the relationship between environmental impact (E) and tourist numbers by season, incorporating weather conditions (W). The environmental impact can be modelled as:

$$E = \alpha_0 + \alpha_1 \cdot T + \alpha_2 \cdot W + \nu \quad (13)$$

Where: α_0 is a constant, α_1 represents the effect of tourist numbers on environmental impact, α_2 represents the effect of weather conditions, v is the error term accounting for other environmental factors not captured in the model.

This model emphasizes how environmental degradation increases with tourist numbers and how certain weather conditions (clear, cloudy, rainy, or stormy) may either exacerbate or mitigate the impact. Figure 8 shows a violin diagram of the effects of season and weather on the environment. The visualization helps highlight the importance of managing environmental sustainability, particularly in high-traffic seasons.

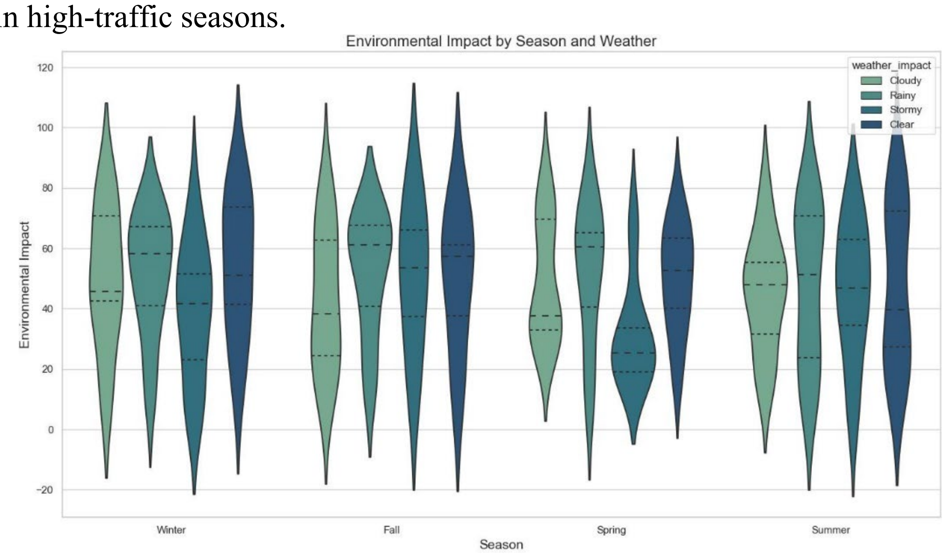

Figure 8 Environmental Impact by Season and Weather

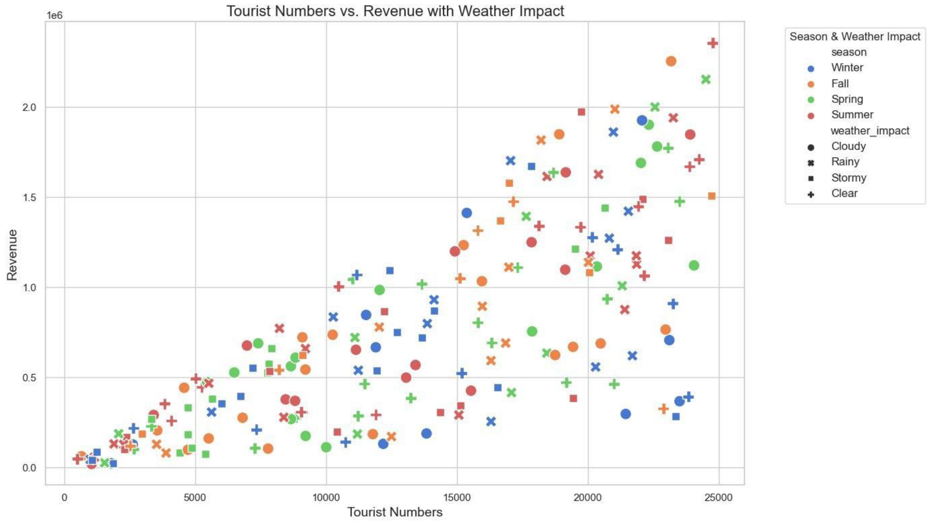

Figure 9 Tourist Number vs. Revenue with Weather Impact

As shown in Figure 9, a scatter plot is used to illustrate the relationship between the number of tourists and revenue (R), while taking into account weather conditions (W). The mathematical model of this relationship can be expressed as:

$$R = \beta_0 + \beta_1 \cdot T + \beta_2 \cdot W + \zeta \tag{14}$$

Where: β_0 is a constant, β_1 is the coefficient for tourist numbers, β_2 is the coefficient for weather impact, ξ is the error term.

This equation illustrates how extreme weather conditions influence the relationship between tourist numbers and revenue, offering insights into maximizing revenue by managing weather-driven fluctuations.

As shown in Figure 10, a heatmap was created to visualize how different policies (e.g., visitor caps or taxes) affect revenue across different seasons. The impact of policies on revenue can be modelled as:

$$R_{policy} =_0 +_1 \cdot P +_2 \cdot Season + \theta \tag{15}$$

Where: _0 is a constant, _1 is the coefficient for the effect of policies on revenue, _2 is the coefficient for seasonality, θ is the error term.

This helps assess the effectiveness of various policy interventions in enhancing seasonal revenue stability, especially in off-peak periods, indicating that moderate policies, such as taxes, can stabilize revenues.

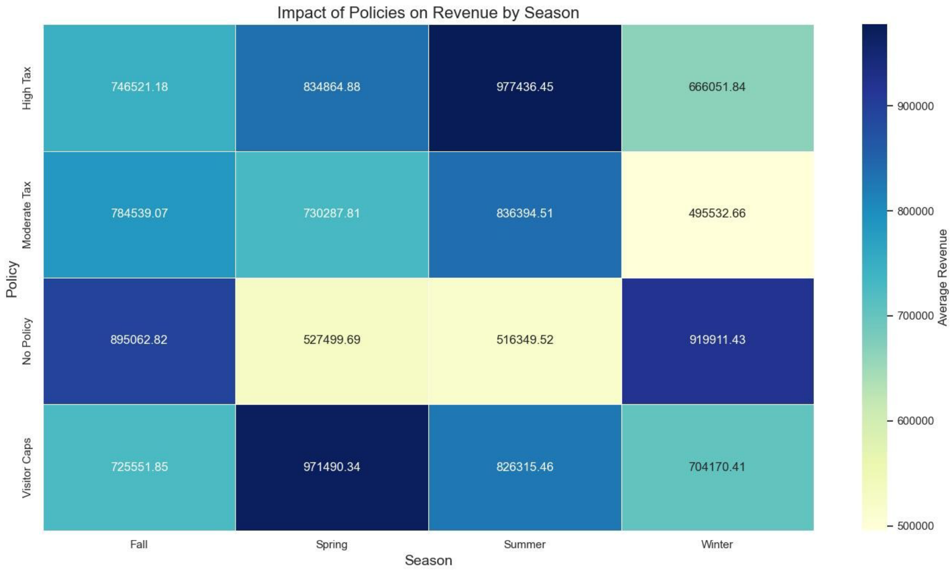

Figure 10 Impact of Policies on Revenue by Season

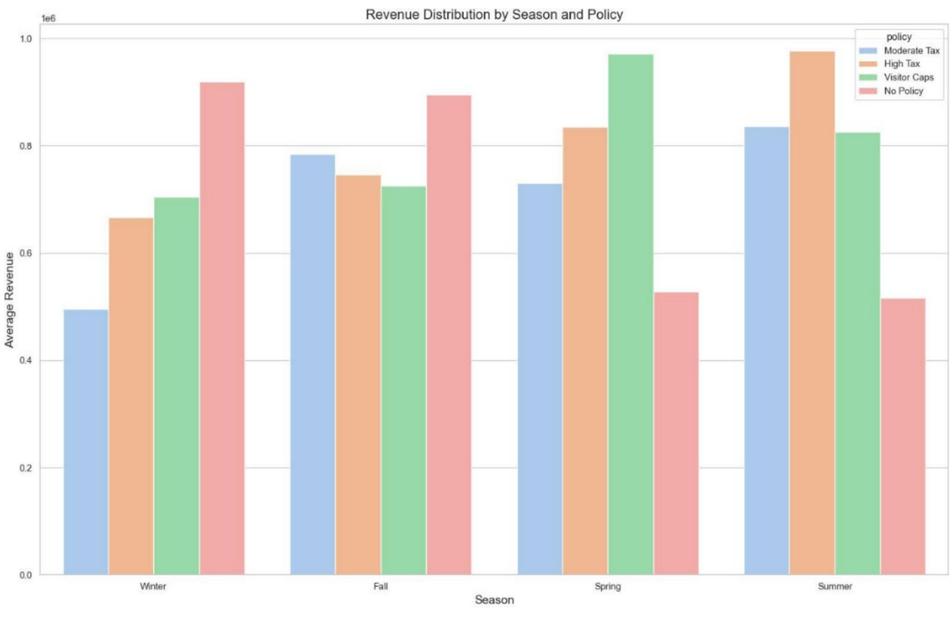

Figure 11 Revenue Distribution by Season and Policy

As shown in Figure 11, A bar plot was used to show the impact of various policies on revenue distribution across different seasons. The policy effect on revenue by season can be modelled by:

$$R_{policy,season} = \eta_0 + \eta_1 \cdot P + \eta_2 \cdot Season + \xi \tag{16}$$

Where: η_0 is the constant term, η_1 is the coefficient for policy impact, η_2 is the coefficient for seasonality, ξ represents unexplained variation.

This analysis helps determine which policy combinations lead to optimal outcomes for sustainable tourism, balancing both revenue and environmental preservation.

Finally, a line plot was used to depict the trends in both revenue and environmental impact across seasons. The trends can be described with the following equations:

$$\begin{aligned} R_{trend} &= \theta_0 + \theta_1 \cdot Season + \theta_2 \cdot Season^2 + \omega \\ E_{trend} &= \phi_0 + \phi_1 \cdot Season + \phi_2 \cdot Season^2 + \nu \end{aligned} \tag{17}$$

Where: θ_0 and $\phi_0$are constants, θ_1 and ϕ_1 represent the linear effects of seasonality on revenue and environmental impact, θ_2 and ϕ_2 represent the quadratic effects (capturing non-linear seasonal trends), ω and ν represent error terms.

These models help us understand how tourism trends evolve over the year, showing the relationship between revenue and environmental costs, which is key to implementing policies that minimize environmental burdens while optimizing economic benefits. Figure 12 shows the seasonal trends of income and environmental impacts.

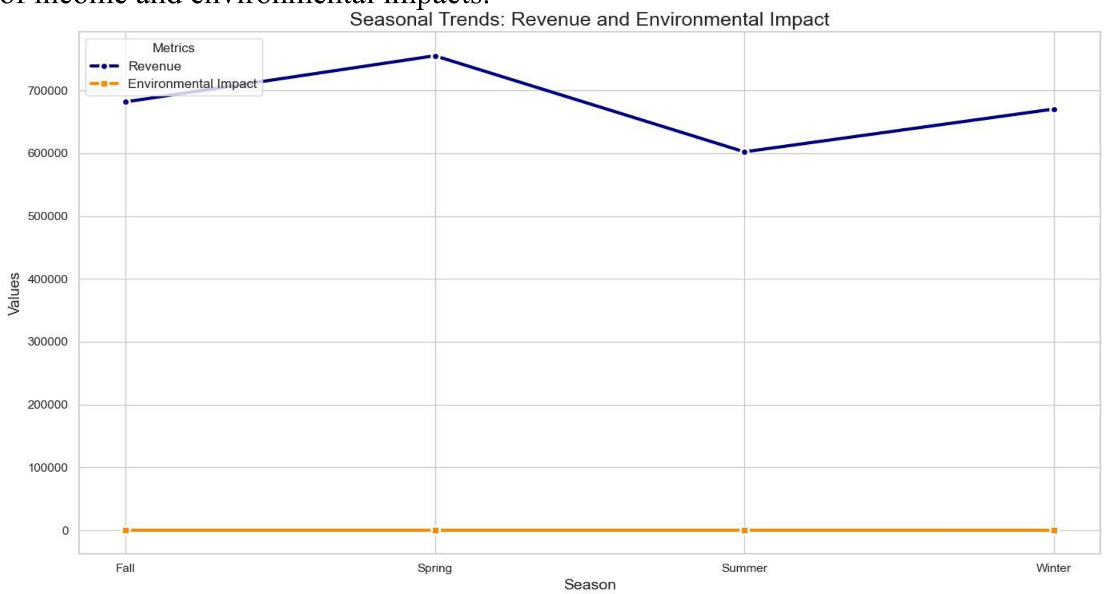

Figure 12 Seasonal Trends: Revenue and Environmental Impact

The numerical simulations and associated visualizations reveal that:

Revenue and Tourist Numbers: Revenue increases with tourist numbers, but after a certain threshold, diminishing returns are observed. A possible model for this relationship could be:

$$R = \alpha_0 + \alpha_1 \cdot T + \alpha_2 \cdot T^2 \tag{18}$$

Where α_2 represents the diminishing returns with increasing tourist numbers.

Environmental Impact and Tourist Numbers: Environmental impact increases non-linearly with the number of tourists. The scatter and violin plots confirm this, indicating substantial environmental strain during peak tourist seasons. The environmental impact model could be expressed as:

$$E = \beta_0 + \beta_1 \cdot T + \beta_2 \cdot T^2 \tag{19}$$

Weather and Seasonality Effects: Visualizations of the effects of weather and seasonality help identify periods where visitor numbers can be reduced or where infrastructure support needs to be increased. The impact of weather conditions can be factored into the revenue and environmental models above.

Policy Simulations: Simulations of policies like visitor caps or taxes show that moderate restrictions can reduce environmental impact while maintaining steady revenue, promoting sustainable tourism. The policy impact on revenue can be expressed as:

$$R_{policy} = \_0 + \_1 \cdot P \tag{20}$$

These findings provide actionable insights for balancing tourism growth with environmental protection, ensuring Juneau's tourism industry remains viable and sustainable in the long run.

By incorporating these mathematical models into the text, we quantify relationships between variables like tourist numbers, revenue, environmental impact, and policies, providing a more rigorous foundation for the insights derived from the visualizations.

3. Conclusion

Aiming at the environmental, economic and social challenges brought about by the rapid development of tourism in Juneau, Alaska, this paper constructs a multivariable dynamic optimization mathematical model based on the concept of sustainable development, and uses algorithms to simulate and analyze the interaction of core factors such as the number of tourists, tourism revenue and environmental impact. Through empirical data calibration and sensitivity analysis, the study reveals the threshold effect and nonlinear feedback mechanism in tourism development, and points out that moderate policy regulation is crucial to balancing tourism revenue and environmental protection. The model in this paper not only has high adaptability and promotion value, but also can provide scientific policy decision-making support for Juneau, and also provides theoretical innovation and methodological reference for other tourist destinations to deal with the problem of overtourism. Future research can further improve the model structure, incorporate more uncertain factors, and combine big data with intelligent algorithms to enhance the dynamic response and fine decision-making capabilities of the model, so as to better serve the global tourism sustainable development goals.

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