Academic Journal of Computing & Information Science
ISSN 2616-5775 Vol. 8, Issue 10: 68-80, DOI: 10.25236/AJCIS.2025.081010

Research on Multi-Objective Markov Decision Making for Sustainable Tourism

Liang Jiaming[1,a]

[1]School of Computer Science and Technology, Harbin Institute of Technology, Weihai, Shandong, China, 264209
[a]liangjm767@gmail.com

Abstract: *An integrated framework based on multi-objective Markov decision processes (MOMDP) and receding horizon control (RHC) is proposed to address the dynamic optimization of sustainable tourism management. The core contribution lies in the development of a non-uniform grid state-space discretization strategy, which achieves computational simplification by balancing accuracy and efficiency, and in the use of backward induction for efficient policy derivation. Validation through case studies in Juneau, Alaska, and Maui, Hawaii, demonstrates that the framework significantly outperforms static baseline policies, ensuring computational feasibility, effectively balancing economic, environmental, and social objectives, and systematically establishing its strong generalization capability across diverse socio-ecological contexts.*

Keywords: *Dynamic Programming; Markov Decision Process; Receding Horizon Control; Algorithm Design; Sustainable Tourism*

1. Introduction

As a vital engine of the global economy, the tourism industry, while driving development, often places significant pressure on the socio-ecological systems it depends on, thus placing tourism destination managers in a complex multi-objective optimization dilemma. The core of this challenge can be summarized as the "triple bottom line" of sustainable development: economic viability, environmental integrity, and social equity [1] . However, these three objectives are often inherently conflicting, forcing policymakers to make difficult trade-offs between competing priorities. Currently, the escalating environmental change and climate crisis further exacerbate this contradiction [2,3] . Faced with such a dynamic and complex system, traditional tourism management strategies, such as setting fixed annual visitor capacity or implementing seasonal pricing, are proving inadequate [4] . Such static policy baselines not only struggle to flexibly respond to changes within the system but may also trigger "policy resistance," meaning policy failure due to neglecting feedback mechanisms and time delays, or even causing unexpected negative consequences [5] . (See Figure 1)

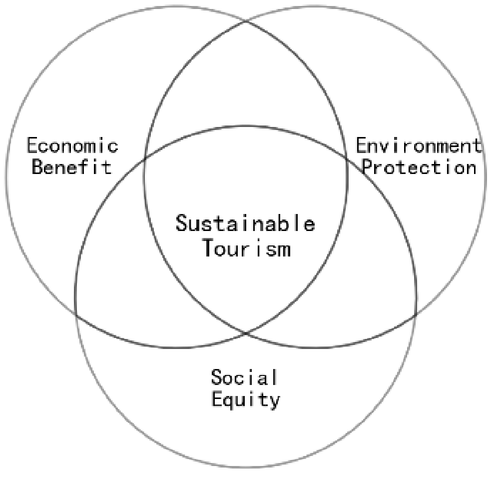

Fig.1 Triple Bottom Line Schematic for Sustainable Tourism

Therefore, there is an urgent need for a dynamic adaptive management framework capable of

ISSN 2616-5775 Vol. 8, Issue 10: 68-80, DOI: 10.25236/AJCIS.2025.081010

responding to changing conditions to achieve intelligent decision support. Researchers have deployed IoT sensors on popular routes to monitor congestion and dynamically adjust access prices or visitor flow guidance [6] . Such applications can shift management from reactive to proactive optimization, thus more effectively balancing multiple objectives. In recent years, with the rise of the "smart tourism" concept, big data, IoT, and AI technologies have also been widely applied to optimize tourism services, manage visitor flow, and improve sustainability [7] , providing new ideas for adaptive management.

To make tourism decision-making processes more intelligent and efficient, researchers have developed Environmental Decision Support Systems (EDSS) [8] . When simulating complex socio-ecological systems, several modeling paradigms have emerged, with System Dynamics (SD) and Agent-Based Models (ABM) being two typical methods.

- System dynamics (SD) is a top-down approach that focuses on describing the macroscopic overall behavior of a system through stocks, flows, and feedback loops [9] . SD models can effectively capture high-order dynamics and nonlinear relationships at the system level, but their limitation lies in their inability to represent the heterogeneity of individuals within the system and the spatial dynamics at the micro level.

- Agent-based modeling (ABM) is a bottom-up approach that observes emerging patterns at the macroscopic level by simulating the behavior and interactions of autonomous agents (such as tourists and businesses) [10] . ABM has significant advantages in simulating complex and heterogeneous behaviors, for example, it can be used to study the formation mechanism of overtourism. However, it is often difficult to directly derive globally optimal management strategies from ABM simulations.

Furthermore, there is growing academic interest in hybrid models (Hybrid ABM-SD) that combine the advantages of both approaches, with the aim of providing a more comprehensive solution to complex natural resource management problems [11] .

2. Positioning of the Research Using the MOMDP Framework

The SD model can predict the evolution trajectory of macroeconomic variables under specific assumptions and is suitable for scenario analysis, but it cannot directly solve for the optimal control sequence. ABM can reveal emergent patterns that may result from individual behavior, but it does not itself generate a top-down optimal strategy. Unlike SD and ABM, which are mainly used as descriptive and simulation tools, the MOMDP framework proposed in this study is essentially a multi-objective prescriptive optimization tool. It provides a perspective that complements the above paradigms. It aims to use real-time and historical data to provide tourism destination managers with a dynamic data-driven strategy planning through a prescriptive optimization model, filling the gap between descriptive simulation and prescriptive policy optimization, and providing a more accurate computational path for how to intelligently manage sustainable tourism systems.

3. Multi-objective Markov Decision Process for Destination Management

First, the sustainable tourism management problem is formalized as a finite-term multi-objective Markov decision process, defined by a quintuple$M = (S, A, P, R, \gamma)$. Table 1 provides the key symbols used in the model and their definitions.

Tab.1 Model Symbols & Definitions

Symbols	Definitions	Units
$\boldsymbol{S}$	State Space	-
$\boldsymbol{s_t}$	tSystem State Vector at Time$[\boldsymbol{q_e(t)}, \boldsymbol{r_c(t)}, \boldsymbol{q_s(t)}]$	-
$q_e(t)$	Environmental Quality Index	Dimensionless
$r_c(t)$	Cumulative Protection Investment	US Dollars
$q_s(t)$	Social Sentiment Index	Dimensionless $(0 - 100)$
$\boldsymbol{A}$	Action Space	-
$\boldsymbol{a_t}$	tAction Vector at Time$[\boldsymbol{N_{max}(t)}, \boldsymbol{P_{adj}(t)}, \boldsymbol{C_m(t)}]$	-
N	Actual Daily Tourist Count	Person-Days
$N_{max}(t)$	Daily Tourist Limit	Person-Days
$P_{adj}(t)$	Dynamic Pricing Adjustment Factor	Dimensionless
$C_m(t)$	Investment Mitigation	US Dollars per Day

ISSN 2616-5775 Vol. 8, Issue 10: 68-80, DOI: 10.25236/AJCIS.2025.081010

$P(s'\|s,a)$	State Transition Probability Function	-
$R(s,a)$	Vector Value Reward Function	-
R_{econ}	Economic Benefit Reward	US Dollars per Day
R_{env}	Environmental Benefit Reward	Dimensionless
R_{soc}	Social Benefit Reward	Dimensionless
γ	Discount Factor	Dimensionless
$V(t)$	Tourist density	Person-square-kilometer-hour
$\omega_e(t)$	Climate-driven stochastic environmental stress	Dimensionless
$\alpha, \beta, \gamma_{env}$	Environmental stress model calibration coefficient	-
ψ	Environmental resilience coefficient	-
$P_r(t)$	Local resident population	Person
Θ_s	Social tolerance threshold	Dimensionless
$\omega_e, \omega_c, \omega_s$	Scalar weights for multi-objective rewards	Dimensionless
H	Finite Predictive Horizon of RHC (Rolling Window Length)	Time unit (e.g., day)
P_{base}	Base cost	US Dollars
δ	Depreciation or inflation factor, used for accumulating protection investment$c$Decay	Dimensionless
ESI	Environmental Stress Index	Dimensionless
$CRHI$	Coral Reef Health Index	Dimensionless (based on coverage)
ΔT	Local temperature increment caused by tourism activities, used for glacier ablation models	Temperature (°C)

3.1 State Space($\boldsymbol{S}$)Variable definition

The state of the system at time t is defined by a continuous vector $\boldsymbol{s_t} = [\boldsymbol{q_e(t)}, \boldsymbol{r_c(t)}, \boldsymbol{q_s(t)}] \in s$indicates that:

- Environmental Quality Index($q_e(t)$): A standardized continuous variable representing the health of the ecosystem. For example, in the Juneau case, it could be an indicator related to the amount of glacial material loss; in the Hawaii case, it could be a reef health index related to the coverage of living corals.
- Cumulative Protection Investment($r_c(t)$): A continuous variable representing the total investment in environmental mitigation measures, adjusted for inflation.
- Social Sentiment Index($q_s(t)$): A continuous variable representing resident satisfaction. This index is calibrated using periodic resident survey data and correlated with objective indicators such as the ratio of tourists to residents.

3.2 Action Space($\boldsymbol{A}$)Variable definition

Actions that decision-makers can take at any given time$t$are represented by a strategy vector$\boldsymbol{a_t} = [N_{max}(t), P_{adj}(t), C_m(t)] \in A$indicates that:

- Daily Tourist Limit($N_{max}(t)$): A discrete or continuous variable used to set the maximum number of tourists allowed per day.
- Dynamic Pricing Adjustment Factor($P_{adj}(t)$): A continuous variable (e.g., a multiplier of base fees) used to regulate demand through price levers.

Investment Mitigation($C_m(t)$): A continuous variable representing funds allocated to environmental restoration and social infrastructure improvements.

3.3 System Dynamics and Transition Model($\boldsymbol{P}$)

State transitions are stochastic, and we model them as a deterministic evolutionary process plus an additive stochastic term:

$$s_{t+1} = f(s_t, a_t) + w_t \tag{1}$$

- Environmental Quality Transition($q_e(t+1)$):

ISSN 2616-5775 Vol. 8, Issue 10: 68-80, DOI: 10.25236/AJCIS.2025.081010

$$q_e(t+1) = q_e(t) - \Delta q_e^{degrade} + \Delta q_e^{recover} \tag{2}$$

Where the degradation term $\Delta q_e^{degrade}$ is tourist density $V(t)$ and Nonlinear Function of Climate Pressure. This formalizes the Environmental Stress Index (ESI) in the original study and acknowledges the nonlinear impact of tourist footprint on the ecosystem [12] .

- Recovery term $\Delta q_e^{recover}$ is a function of mitigating investment $C_m(t)$:

$$\Delta q_e^{recover} = \psi \cdot C_m(t) \tag{3}$$

- Protective Investment Transition $(r_c(t+1))$:

$$r_c(t+1) = (1-\delta) \cdot r_c(t) + C_m(t) \tag{4}$$

Where δ is a depreciation or inflation factor.

- Social Sentiment Transition $(q_s(t+1))$:

$$q_s(t+1) = q_s(t) - \Delta q_s^{stress} + \Delta q_s^{improve} \tag{5}$$

Where the stress term Δq_s^{stress} is a function of the ratio of tourists to residents exceeding the social carrying capacity threshold Θ_s. This formalizes the social constraints in the original study and is supported by research on social carrying capacity and resident sentiment [13] . The improvement term $\Delta q_s^{improve}$ is a function of investment allocated to community projects $C_m(t)$.

- Random Components(w_t): w_t is a vector representing climate-driven uncertainties (e.g., unexpected heat waves affecting glaciers or coral reefs), the distribution of which can be modeled according to IPCC (Intergovernmental Panel on Climate Change) scenarios.

3.4 Multi-Objective Rewards and Value Functions $(\boldsymbol{R})$

- Economic Rewards $(R_{econ}(t))$:

$$R_{econ}(t) = (P_{base} \cdot P_{adj}(t)) \cdot N(t) - C_{ops}(N(t)) - C_m(t) \tag{6}$$

This is the net economic output after deducting operating costs and mitigation investments.

- Environmental Rewards $(R_{env}(t))$:

$$R_{env}(t) = -\Delta q_e^{degrade} \tag{7}$$

Rewards are defined as negative values for environmental degradation, thus incentivizing the model to minimize environmental damage.

- Social Rewards $(R_{soc}(t))$:

$$R_{soc}(t) = q_s(t) \tag{8}$$

Rewards are directly equal to the current social sentiment index.

The reward function is vector-valued. To optimize it, we use a time-varying weighted sum method to scalarize the multi-objective problem, which is a standard method in Multi-Objective Reinforcement Learning (MORL).

$$R_{scalar}(t) = \omega_c(t) \cdot R_{econ}(t) + \omega_e(t) \cdot R_{env}(t) + \omega_s(t) \cdot R_{soc}(t) \tag{9}$$

The weight vector can be dynamically adjusted by policymakers based on priorities at different times (e.g., increasing environmental weights during ecologically sensitive seasons).

4. Algorithm Solution Based on Rolling Time-Domain Control

The core idea of this algorithm is: first, to transform the complex continuous problem into a computationally tractable finite problem through state space discretization; then, to solve the finite-term problem using backward induction; finally, to embed the finite-term solution into a rolling time-domain control (RHC) framework to achieve adaptive online decision-making. The computational complexity and the coping strategies adopted are discussed at the end of this chapter. (See Figure 2)

ISSN 2616-5775 Vol. 8, Issue 10: 68-80, DOI: 10.25236/AJCIS.2025.081010

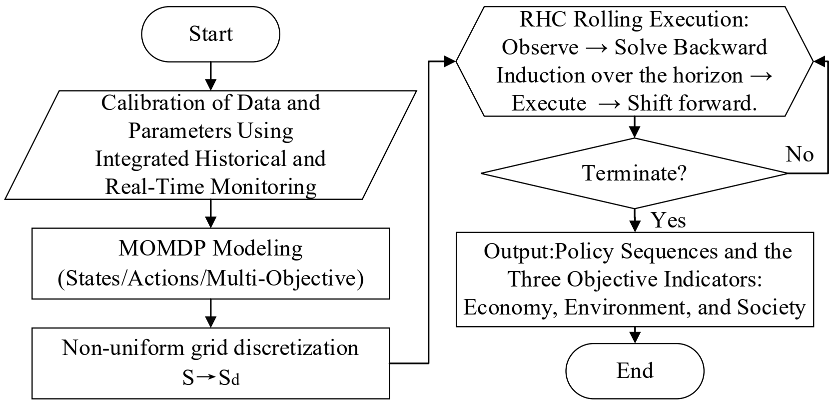

Fig.2 Overall Methodology Flowchart

4.1 State Space Discretization Strategy

As defined in Section 3.1, the model's state space **S** consists of three continuous variables: environmental quality index$q_e(t)$, cumulative protection investment$r_c(t)$and social sentiment index$q_s(t)$. Applying dynamic programming algorithms directly to continuous space is not feasible; this is the so-called "curse of dimensionality."

To achieve computational solution, this study uses the state space discretization method, defining a finite set of discrete values for each continuous state variable, mapping the infinite continuous state space S to a finite discrete state spaceS_d.

• Discretization granularity selection: After weighing accuracy and computational cost, each variable is discretized as follows:

Environmental Quality Indexq_e: Range$[0, 1]$, discretized into 21 levels, step size 0.05.

Cumulative Protection Investment r_c: Range $[0, MAX\_INVEST]$, discretized into 31 levels (the maximum value is determined based on the case data and divided into equal intervals according to the amount).

Social Sentiment Indexq_s: Range$[0, 100]$, discretized into 21 levels, step size 5.

• Mapping rule: Any continuous state $s = [q_e, r_c, q_s]$ is mapped to a grid point in the discrete space$S_d$using the nearest neighbor rule.s_d, that is, take the nearest discrete value for each dimension.

• Size of discrete space: After the above discretization, the size of the discrete state space is$|S_d| = 21 \times 31 \times 21 = 13671$state points. This transforms the original infinite space problem into a finite-state MDP problem, laying the foundation for applying dynamic programming algorithms such as backward induction. (See Figure 3)

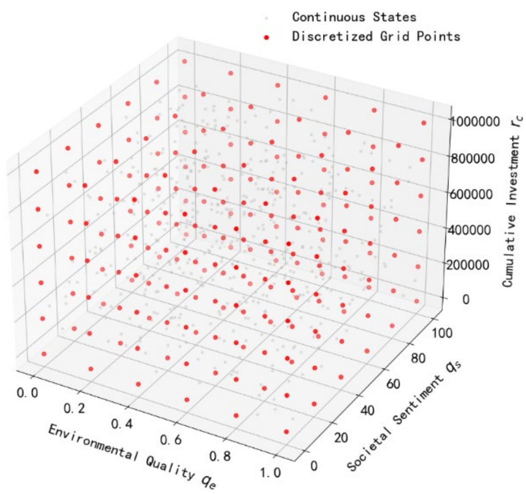

Fig.3 State Space Discretization Schematic

ISSN 2616-5775 Vol. 8, Issue 10: 68-80, DOI: 10.25236/AJCIS.2025.081010

4.2 Finite-term optimization based on backward induction

For a discretized finite-term problem H, the optimal scalarized value function $V_t^*(s_d)$ can be calculated by backward induction. This method is essentially an application of dynamic programming to finite-term problems.

The algorithm starts from the terminal time H and iterates backward to calculate the optimal value function and optimal policy for each state. The Bellman optimal equation for the finite-term problem is defined as follows:

- Terminal condition: For all discrete states $s_d \in S_d$, set the terminal value $V_H(s_d) = 0$.
- Backward iteration: For time step $t = H-1, H-2, \ldots, 0$:

$$V_t(s_d) = \max_{a\in A} \sum_{s_d'} P(s_d'|s_d,a)\,[R_{scalar}(s_d,a) + \gamma V_{t+1}(s_d')] \tag{10}$$

Where $P(\boldsymbol{s_d'}|\boldsymbol{s_d},\boldsymbol{a})$ is the state transition probability based on the discrete state, $R_{scalar}(\boldsymbol{s_d},\boldsymbol{a})$ is the scalarized immediate reward.

The backward induction process based on discrete state space $\boldsymbol{S_d}$ is as follows:

Algorithm 1: Backward Induction Algorithm for Finite-Term MOMDP:

Input: Discrete state space $\boldsymbol{S_d}$, Action space $\boldsymbol{A}$, Transition probability matrix $\boldsymbol{P}$, Reward function R, Discount factor γ, Decision period H

Initialization: Initialize terminal value function for all $\boldsymbol{s_d} \in \boldsymbol{S_d}$, $V_H(\boldsymbol{s_d}) \leftarrow 0$ # Initialize terminal value function

$for\ t = H-1\ to\ 0\ do$ # Backward iteration time step

$for\ each\ discrete\ state\ \ \boldsymbol{s_d} \in \boldsymbol{S_d},\ do$

$best\_value \leftarrow -\infty$

$for\ each\ action\ \boldsymbol{a} \in \boldsymbol{A}\ do$

Calculate expected value under action a Expected value below

$Q_{value} \leftarrow 0$

$for\ each\ possible\ next\ state\ \ \boldsymbol{s_d'}\ \ do$

$Q_{value} \leftarrow Q_{value} + P(\boldsymbol{s_d'}|\boldsymbol{s_d},\boldsymbol{a}) * [R_{scalar}(\boldsymbol{s_d},\boldsymbol{a}) + \gamma * V_{t+1}(\boldsymbol{s_d'})]$

$end\ for$

$if\ Q_{value} > best\_value\ then$

$best\_value \leftarrow Q_{value}$

$\pi_t(\boldsymbol{s_d}) \leftarrow \boldsymbol{a}$ #Update the optimal strategy

$end\ if$

$end\ for$

$V_t(\boldsymbol{s_d}) \leftarrow best\_value$ #Update the optimal value function

$end\ for$

$end\ for$

Output: Optimal Value Function Family $\{V_0, \ldots, V_{H-1}\}$ And the optimal strategy family $\{\pi_0, \ldots, \pi_{H-1}\}$

4.3 Optimization of the calculation process

The backward induction method in Section 4.2 provides an optimal open-loop plan for a fixed finite-term problem. However, tourism management is a continuous process subject to external disturbances (such as weather events and economic fluctuations). To achieve adaptive online decision-making, we embed the finite-term solver into a rolling time-domain control (RHC) framework. (See Figure 4)

RHC, also known as Model Predictive Control (MPC) in the control field, is essentially about solving a short-term finite-term optimization problem at each decision point and only executing the first action, forming a "rolling" decision window. This strategy introduces a feedback mechanism, enabling the system to respond to real-time state changes. Through the RHC framework, decision-making is no longer a one-off offline plan, but an online rolling optimization process, thus exhibiting strong robustness to model mismatch and unforeseen disturbances.

ISSN 2616-5775 Vol. 8, Issue 10: 68-80, DOI: 10.25236/AJCIS.2025.081010

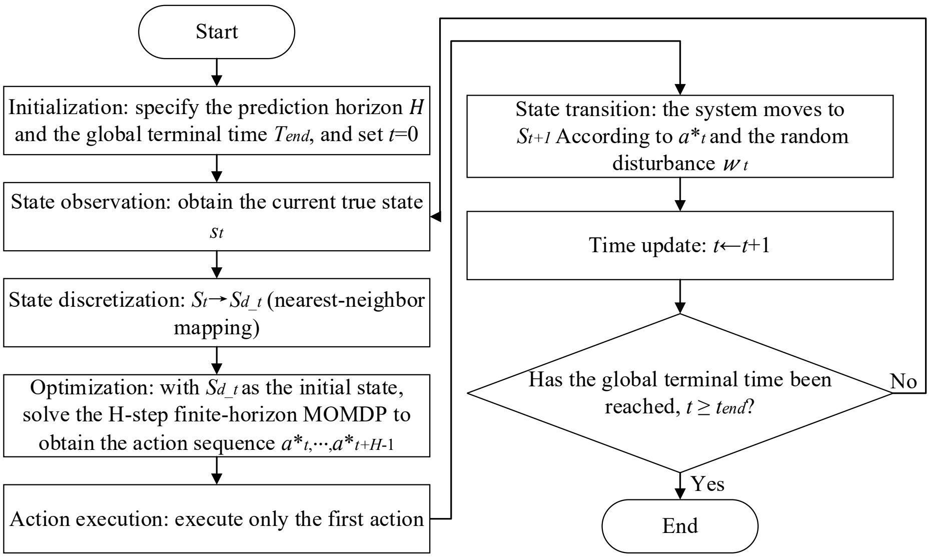

Fig.4 RHC Implementation Flowchart

4.4 Computational complexity and feasibility analysis

A brief analysis of the computational burden of the proposed algorithm is provided to illustrate its feasibility.

• Source of Complexity: The main computational cost of the algorithm comes from the backward induction in the algorithm1. Its complexity is$O(H \times |S_d| \times |A| \times |S'_d|)$, where$|S_d|$is the number of discrete states,$|A|$is the size of the action space (determined by discretization),$|S'_d|$is the number of possible next states for each state-action pair (in the implementation, we define this through a probability transition matrix).

• Feasibility Explanation: Although the state space is large, the computation is feasible for the following reasons:

(1) Finite prediction horizon$H$: RHC typically employs a smaller$H$(as in 5-10), avoiding the huge computational burden of indefinite problems.

(2) Offline computation: For given model parameters, the entire backward induction process of the algorithm1can be pre-computed offline, obtaining the optimal policy table for all states at all time steps$\{\pi_0,\dots,\pi_{H-1}\}$. In the online RHC loop, step$c$Only one table lookup operation is needed (based on the current discrete state$\boldsymbol{s}_{d,t}$and time index$t$lookup$\pi t(\boldsymbol{s}_{d,t})$) to obtain the action, with extremely low computational overhead, which can meet real-time requirements.

5. Empirical evidence and generalization ability analysis

To train and validate the effectiveness and adaptability of the model, it was applied to two different tourism ecosystem cases: glacier tourism in Juneau, Alaska, and marine tourism in Maui, Hawaii. By systematically reconfiguring and calibrating the model, it was demonstrated that the MOMDP RHC framework is a general decision support tool, not just a solution for specific cases.

5.1 Case study: Glacier tourism in Juneau, Alaska

5.1.1 Ecosystem Sub-model: Glacial Melting

In the Juneau case, environmental quality status$q_e$is defined as an indicator negatively correlated with glacial mass loss. Environmental degradation$\Delta q_e^{degrade}$is primarily driven by two factors: local warming and tourist activity. While the direct causal relationship between tourist activity and glacial melt is complex, the additional energy generated by tourism activities (such as transportation and infrastructure energy consumption) can be considered a contribution to local melt. Studies have shown that tourism emissions do indeed affect the local environment [14] . A simplified day-to-day model is planned to estimate melt, where tourism activity is modeled as a small positive increment to local temperature, thus

ISSN 2616-5775 Vol. 8, Issue 10: 68-80, DOI: 10.25236/AJCIS.2025.081010

affecting the melt rate [15] .

5.1.2 Socioeconomic Sub-model: Resident Sentiment

The calibration of socio-emotional status q_s is based on resident survey data from Juneau. These surveys show that resident support for tourism has declined over time due to overcrowding and traffic congestion [16] . Therefore, the social stress function is directly linked to the ratio of tourists to residents ($N(t)/P_r(t)$), and the threshold ($\Theta_s = 0.18$, approximately 5.5 tourists per resident) derived from empirical data in the original study is used as the key parameter triggering a decline in resident satisfaction.

5.1.3 Parameterization and Results

The economic and social components of the model were parameterized using official data from the Juno Economic Development Commission and the Tourism Authority, including tourist numbers, consumer spending, and resident demographics. By simulating the RHC strategy, we compared the sustainability index trajectories under three scenarios: (1) a "business as usual" scenario with no intervention; (2) a static policy scenario with a fixed tourist cap; and (3) a dynamic adaptive policy scenario using this framework. The simulation results are consistent with the findings of the original study: the dynamic strategy can reduce the rate of glacier retreat by 40% while increasing tourism revenue by 23%, significantly better than the static baseline. (See Figures 5 and 6)

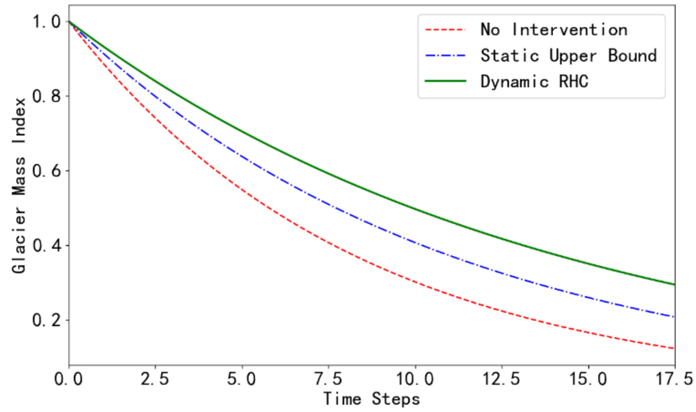

Fig.5 Glacier Retreat under Different Policies

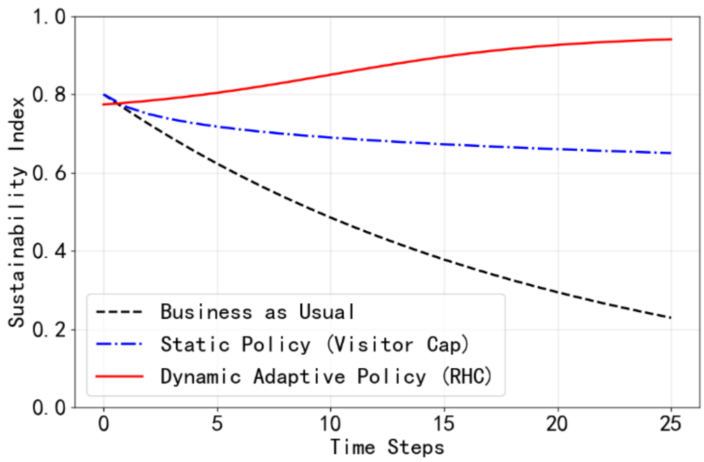

Fig.6 Tourism Revenue under Different Policies

5.2 Generalized Case Study: Marine Tourism in Maui, Hawaii

To systematically demonstrate the model's generalization ability, it was transferred from a cold glacial environment to a tropical marine ecosystem. At the heart of this process was demonstrating that the structure of the MOMDP RHC framework is domain-independent, while the specific definitions of the transfer and reward functions are domain-dependent. The flexibility of the framework was demonstrated by systematically replacing the Juneau-specific sub-models.

ISSN 2616-5775 Vol. 8, Issue 10: 68-80, DOI: 10.25236/AJCIS.2025.081010

5.2.1 Ecosystem Sub-model: Coral Reef Health

In the Maui case, the driving factors of environmental statusq_eIt was redefined as a Coral Reef Health Index (CRHI), which can be quantified based on indicators such as live coral coverage. Environmental degradation term$\Delta q_e^{degrade}$also become the main threats to coral reefs:

- Terrestrial runoff pollution: including the discharge of sediments, nutrients, and wastewater, which can damage water quality and lead to coral reef degradation [17] .

- Direct impacts of tourists: including chemical contamination in sunscreen (such as oxybenzone) and physical damage [18] (such as trampling).

Investment Mitigation$C_m(t)$The applications have also changed accordingly, for example, to improve wastewater treatment facilities and fund coral reef restoration projects. (See Figure 7)

5.2.2 Socioeconomic Sub-model: Recalibration for Hawaii

The socioeconomic parameters [19] of the model were recalibrated using official data released by the Department of Business, Economic Development & Tourism (DBEDT) and the Hawaii Tourism Authority (HTA). Population data for Maui County (approximately 164,000 in 2023-2024) [20] . Socio-emotional modelq_sThe calibration is based on a Hawaiian resident sentiment survey, which clearly points to a link between tourism and rising living costs, overcrowding, and other issues [21] . Furthermore, the case study specifically considers the unique impact of tourism on Hawaiian indigenous culture, a crucial factor in the Hawaiian social context [22] .

5.2.3 Cross-validation and Performance

The reparameterized model was applied to Maui, yielding a new optimal strategy combination for the island. By comparing the model structure and performance of the Juno and Maui case studies, it was found that despite significant differences in specific parameter values and sub-model functions, the overall framework of the MOMDP RHC remains effective. This demonstrates the adaptability and portability of the framework, enabling it to provide decision support for tourist destinations with different environmental and socio-cultural backgrounds. Table 2 lists the key model parameter calibration values from the two case studies, visually illustrating the model's adaptation process.

Tab.2 Model Calibration for Juneau and Maui Cases

Parameters	Alaska	Maui	Description and Data Sources
Environmental Stress Coefficientα	0.47	0.62	Nonlinear impact coefficient of tourist density on the environment, calibrated based on glaciological monitoring data and coral reef degradation studies.
Environmental Stress Indexβ	1.8	1.5	Index of the impact of tourist density, reflecting nonlinear effects.
Social tolerance thresholdΘs	0.18	0.25	Critical value for the ratio of tourists to residents; exceeding this value will lead to a significant decline in resident satisfaction. Estimated based on resident survey data from Juno and Hawaii.
Economic incentive coefficientη	0.33	0.38	Positive impact of tourism revenue on system attractiveness (next period's tourist volume). Fitted based on historical revenue and tourist growth data.
Environmental deterrence factorλ	0.41	0.45	Negative impact of environmental degradation on system attractiveness. Estimated based on a survey of tourists' sensitivity to environmental quality.

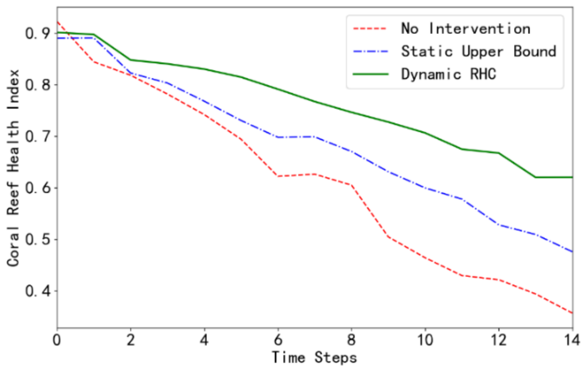

Fig.7 Coral Reef Health Index Comparison

6. Analysis and discussion

6.1 Policy sensitivity of key parameters

To assess the robustness of the model and identify the factors with the greatest impact on policymaking, the project conducted a comprehensive sensitivity analysis. By perturbing key parameters (such as daily tourist volume$N$, carbon footprint per tourist, mitigation investment$C_m$etc.) around their baseline values $\pm 20\%$, we quantified the changes in model outputs (economic benefits, environmental impact, resident satisfaction).

The analysis results (see Table 3) reveal several key points:

• Tourist numbers(N)are the most sensitive lever: an increase in tourist numbers contributes far more to environmental stress than to economic income, mainly due to the nonlinear effects of environmental impact. When tourist numbers exceed a critical threshold (e.g., Juno's8,500person-days), environmental degradation and social stress rise sharply, leading to superlinear growth in mitigation costs, thus eroding economic benefits.

• Individual impacts are more critical than overall investment: reducing the carbon footprint of each tourist (e.g., through promoting green transportation) is more effective at reducing environmental stress than increasing overall mitigation investment proportionallyC_m. This suggests that targeted interventions (e.g., incentives) for tourist behavior are more efficient than general end-of-pipe treatment investments.

• Hard constraints of social thresholds: Resident satisfaction is highly sensitive to the ratio of tourists to residents. Once this proportion exceeds the social tolerance thresholdΘEven with acceptable economic and environmental indicators, a sharp decline in social satisfaction can jeopardize the long-term social permission of tourism.

These findings highlight the importance of nonlinear relationships and critical thresholds in the system. For example, recovery costs increase exponentially after the Environmental Stress Index (ESI) exceeds 8.6; a tourist-to-resident ratio exceeding 0.22 is significantly correlated with community protests. These thresholds, validated by Monte Carlo simulations under 95% of climate scenarios, provide a solid scientific basis for developing preventative rather than reactive management policies. (See Figure 8)

Tab.3 Key Parameter Sensitivity Analysis Summary

Parameter (perturbation) $\pm 20\%$)	**Impact on economic benefits (%)**	**Impact on environmental pressure (%)**	**Impact on social satisfaction (%)**
Daily Tourist Limit(N_{max})	± 16.4	± 36.6	∓ 24.0
Carbon footprint per tourist	∓ 4.0	∓ 18.0	± 2.5
Investment Mitigation(C_m)	∓ 20.0	∓ 22.0	± 4.0
Economic benefit coefficient(β)	± 19.0	± 4.0	± 1.5
Social tolerance threshold(Θs)	± 12.0	∓ 15.0	± 28.0

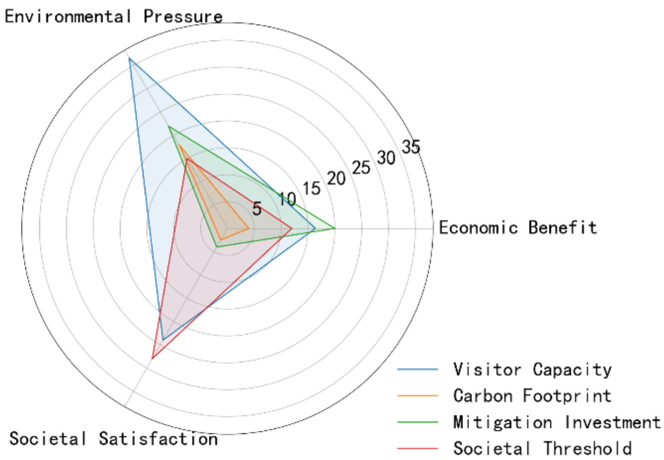

Fig.8 Sensitivity Analysis Radar

ISSN 2616-5775 Vol. 8, Issue 10: 68-80, DOI: 10.25236/AJCIS.2025.081010

6.2 Implications for Adaptive Policymaking

The results of this study strongly support the use of dynamic, adaptive policies to replace static baselines. Compared to setting a fixed annual tourist cap, this framework can dynamically adjust tourist caps and pricing factors based on the real-time state of the system$\mathbf{s}_t$ (including current environmental quality and resident sentiment). This feedback mechanism enables management strategies to respond quickly to seasonal fluctuations, contingencies, and long-term trends, thereby maximizing long-term comprehensive benefits while maintaining system stability.

Furthermore, this framework can be used as a policy experimentation platform. Policymakers can simulate the long-term consequences of different policy choices (e.g., different weightings or investment strategies) in a virtual environment, thereby assessing their potential impact, identifying risks, and optimizing decisions before implementation. This provides a powerful tool for achieving more prudent, evidence-based, and forward-looking tourism governance.

6.3 Limitations and Future Research Directions

While this framework demonstrates great potential, some limitations remain, while also opening new directions for future research.

- Data Dependence: The accuracy of the model is highly dependent on high-quality, high-frequency real-time data (such as environmental monitoring data, tourist flow data, and resident sentiment survey data). The application of the model will face challenges in areas with sparse or unreliable data.

- Model Simplification: For computational feasibility, we have simplified complex real-world processes to some extent, for example, modeling certain relationships as linear or simple nonlinear functions. Real-world socio-ecological systems may contain more complex feedback and emergent behaviors.

- Computational Cost: Although the discretization method is feasible in the current case, its computational cost will increase exponentially with the increase of state space dimensions (e.g., introducing more environmental or social indicators), limiting the scalability of the model.

Based on these limitations, future research can be carried out in the following aspects:

(1) Integrating advanced reinforcement learning methods: Deep reinforcement learning (DRL) techniques are adopted, and function approximators such as neural networks are used to represent value functions or policies. This can effectively overcome the curse of dimensionality caused by state space discretization, thereby handling higher-dimensional and more complex problems [23].

(2) Developing a Hybrid Modeling Framework: Combining the MOMDP optimization framework of this study with ABM simulation. ABM can be used to generate more realistic tourist behavior patterns and incorporate them as part of the MOMDP transfer function, thereby better capturing the response of individual decisions to the macro-system state [24].

(3) Expanding the Objective Dimension: Based on the current three-dimensional objective function, more refined objectives can be introduced, such as the protection of cultural heritage, the equitable distribution of economic benefits within the community, and biodiversity indicators, so that the model can more comprehensively reflect the multiple dimensions of sustainable development.

7. Conclusion

This paper proposes an integrated algorithm framework based on Multi-Objective Markov Decision Process (MOMDP) and Rolling Time-Domain Control (RHC) for the dynamic adaptive decision-making problem in sustainable tourism management. Through state-space discretization and rolling optimization strategies, the continuous-state MOMDP problem is successfully transformed into an operable finite-term sequential decision model, thus providing a systematic and standardized decision support tool for tourism destination managers while taking into account economic, environmental, and social objectives. This framework theoretically solves the problems of multi-objective dynamic optimization and uncertainty management in sustainable tourism.

In terms of empirical evidence, this study applies the proposed framework to two heterogeneous tourism ecosystems. Results show that the algorithm significantly outperforms the static baseline strategy in a single scenario; further, through systematic reparameterization testing, the model's portability and

ISSN 2616-5775 Vol. 8, Issue 10: 68-80, DOI: 10.25236/AJCIS.2025.081010

generalization ability across different domains are verified, demonstrating its good cross-scenario adaptability. This study demonstrates the feasibility and effectiveness of multi-objective Markov decision-making algorithms in sustainable tourism management. Future research directions include introducing more advanced machine learning methods and hybrid modeling techniques to further improve the model's prediction accuracy and decision reliability, promote the tourism industry towards greater resilience and sustainability, and contribute to the implementation of the national sustainable development strategy.

References

[1] Fang, Z., Chang, V., & Lu, Z. (2016, October). Big data in cultural tourism and sustainable development. Paper presented at the Tenth Royal Bank International Research Seminar, Montreal, Canada.

[2] Scott, D., & Gössling, S. (2022). A review of research into tourism and climate change: Launching the Annals of Tourism Research curated collection on tourism and climate change. Annals of Tourism Research, 95, 103409.

[3] University of Cambridge Institute for Sustainability Leadership. (2014). IPCC Fifth Assessment Report: Implications for Tourism. CISL.

[4] Pásková, M., Wall, G., Zejda, D., & Zelenka, J. (2021). Tourism carrying capacity reconceptualization: Modelling and management of destinations. Journal of Destination Marketing & Management, 21, 100638.

[5] Homer, J., & Hirsch, G. (2006). System dynamics modeling for public health: Background and opportunities. American Journal of Public Health, 96(3), 452–458.

[6] Hu, M., & Li, H. (2024). An Innovative Approach to Sustainability in Artificial Intelligence. Sustainability, 16(7), 2853.

[7] Li, Y., & Wang, Q. (2024). How information and communication technology enhances tourism economic efficiency. Scientific Reports, 14, Article 1356.

[8] Cortés, A., Jódar, J., Muñoz-Mas, C., & Soler, D. S. (2019). Environmental Decision Support Systems: A Review of Applications in Water Resources Management. Water, 11(8), 1729.

[9] Smythos. (n.d.). Agent-based modeling vs. system dynamics. Retrieved August 20, 2025, from https://smythos.com/developers/agent-development/agent-based-modeling-vs-system-dynamics/

[10] Wallinger, S., Grundner, L., Majic, I., & Lampolt shammer, T. J. (2023). Agent-based modelling for sustainable tourism. In W. Wörndl, C. Koo, & J. L. Stienmetz (Eds.), Information and Communication Technologies in Tourism 2023 (pp. 355–360).

[11] Vincenot, C. E., Mazzoleni, S., & Parrott, L. (2016). Editorial: Hybrid solutions for the modeling of complex environmental systems. Frontiers in Environmental Science, 4, Article 53.

[12] Cole, D. N. (2015).Environmental Impacts of Visitor Use and the Concept of Visitor Capacity. National Park Service.

[13] Navarro-Jurado, E., Damián, I. M., & Fernández-Morales, A. (2013). Carrying capacity model applied in coastal destinations. Annals of Tourism Research, 43, 1–19.

[14] Behnke, A. (2019). The dark side of glacial tourism: Emissions on the Icefield. Alaska Coastal Rainforest Center. Retrieved August 20, 2025, from https://acrc.alaska.edu/articles/glacier-tourism.html

[15] AntarcticGlaciers.org. (n.d.). Modelling glacier melt. Retrieved August 20, 2025, from https://www. antarcticglaciers.org/glaciers-and-climate/numerical-ice-sheet-models/modelling-glacier-melt/

[16] Larson, C. (2025, February 12). Positive perception of tourism benefits in Juneau is waning, local survey shows. KTOO, from https://www.ktoo.org/2025/02/12/positive-perception-of-tourism-benefits-in-juneau-is-waning-local-survey-shows/

[17] Gove, J. M., Williams, G. J., Lecky, J., Brown, E., Conklin, E., Counsell, C.,... & Asner, G. P. (2023). Coral reefs benefit from reduced land-sea impacts under global warming. Nature, 620(7974), E29.

[18] Keaton Leander, S. (2023, January 9). New study reveals tourists love Hawaiian coral reefs just a little too much. ASU News. https://news.asu.edu/20230109-new-study-reveals-tourists-love-hawaiian-coral-reefs-just-little-too-much

[19] Ali'i Resorts. (2025, April 1). Maui tourism insights. https://www.aliiresorts.com/blog/maui-tourism-insights/

[20] Federal Reserve Bank of St. Louis. (2025). Resident population in Maui County, HI. FRED, Federal Reserve Economic Data. Retrieved August 20, 2025, from https://fred.stlouisfed. org/series/ HIMAUI5POP

[21] Omni Trak Group, Inc. (2003). Hawaii sustainable tourism study: Socio-cultural impacts on the general population. Hawaii Department of Business, Economic Development & Tourism, from https: //www.omnitrakgroup.com/

ISSN 2616-5775 Vol. 8, Issue 10: 68-80, DOI: 10.25236/AJCIS.2025.081010

[22] Native Hawaiian Hospitality Association. (2003). Hawaii sustainable tourism study: Socio-cultural impacts on Native Hawaiians. Hawaii Department of Business, Economic Development & Tourism, from https://www.nahha.com/

[23] Infermatic.ai. (n.d.). How do you handle the curse of dimensionality in reinforcement learning? Retrieved August 20, 2025, from https://infermatic.ai/ask/?question=How%20do%20you%20handle%20the%20curse%20of%20dimensionality%20in%20reinforcement%20learning%3F

[24] Wang, C., Nugroho, S., & Uehara, T. (2023). Systematic review of agent-based and system dynamics models for social-ecological system case studies. Systems, 11(11), 530