Wildlife Conservation Planning for Habitat Protection

MGSC 662: Decision Analytics

Professor Rob Glew

December 8th, 2024

Group 6

Alexandra Guion – 261207375
Nandini Sankarabukta – 261194419
Berly Brigith Biju – 261208805
Tehreem Nasir – 261196987

Executive Summary

This report presents an optimization framework for wildlife conservation planning aimed at maximizing biodiversity impact under real-world constraints, such as budgets, labor, and logistical limitations. The project leverages advanced optimization techniques and data-driven insights to prioritize conservation actions efficiently. Key highlights include:

1. A robust optimization model incorporating deterministic and stochastic elements to account for uncertainties in biodiversity impacts and costs.
2. Practical recommendations emphasizing stakeholder engagement, adaptive planning, and alignment with global sustainability goals.
3. Analytical insights through Pareto front visualizations, illustrating cost-impact trade-offs for informed decision-making.

The findings demonstrate the model's effectiveness in driving impactful, scalable, and adaptive conservation strategies, ensuring a balance between ecological priorities and resource constraints.

1 Introduction

The conservation of wildlife habitats is one of the most pressing challenges in achieving environmental sustainability today. Over the past 40 years, global populations of mammals, birds, fish, and reptiles have declined by 60%, signaling an alarming loss of biodiversity (WWF, 2020). The threat to biodiversity is compounded by habitat loss, climate change, invasive species, pollution, and deforestation. These interconnected issues pose extensive risks not only to ecosystems but also to human health, economic stability, and societal resilience.

This project addresses the urgent need for effective resource allocation in conservation planning, where financial, labor, and logistical limitations challenge organizations like the World Wildlife Fund (WWF) to deliver impactful conservation strategies. Drawing on frameworks such as **Priority Threat Management (PTM)**, this project develops an optimization model to help prioritize conservation actions and maximize biodiversity outcomes under resource constraints.

Why this Problem?

Biodiversity loss is more than an environmental issue; it disrupts supply chains, threatens economic stability, and undermines natural defenses against climate change. According to the **World Health Organization**, biodiversity loss has direct implications for human health, while the **BMO Climate Institute** reports that over half of global GDP is nature-dependent, making biodiversity essential for economic resilience.

This project seeks to answer a critical question: *How can we optimize the allocation of conservation resources to maximize biodiversity preservation?*

Key Reasons for Addressing This Problem:

1. **Global Relevance:** Biodiversity loss is a universal crisis impacting ecosystems, economies, and communities worldwide. Addressing it through efficient conservation planning offers significant environmental and societal benefits.

2. **Complex Decision-Making:** Conservation planning involves balancing multiple objectives, such as ecological priorities, financial constraints, and political considerations. Optimizing these systematically through a robust model can improve decision-making processes.

3. **Data-Driven Insights:** The project leverages proven frameworks like PTM, which have demonstrated success in regions like Australia and Canada by prioritizing conservation actions based on cost-effectiveness and biodiversity outcomes.

Project Goals

The project's goals align with tackling biodiversity loss through practical, actionable approaches:

1. **Maximize Biodiversity Impact:** Identify and prioritize the most impactful areas and conservation actions.

2. **Incorporate Constraints:** Develop an optimization model that reflects real-world limitations, such as budget, labor, and material resources.

3. **Provide Actionable Recommendations:** Deliver insights that guide policymakers and conservation practitioners in effectively allocating resources to maximize biodiversity outcomes.

This model draws from credible data sources, including the **IUCN Red List**, **WWF**, and the **Global Biodiversity Information Facility (GBIF)**, to ensure data accuracy and relevance. By combining biodiversity priorities with operational constraints, the project provides a powerful framework for addressing one of the most critical environmental challenges of our time.

The intersection of advanced optimization techniques and ecological science presents an exciting opportunity to develop innovative, impactful solutions. This project not only contributes to wildlife conservation but also demonstrates the potential of decision analytics to address complex global challenges, ensuring a sustainable future for both nature and society.

2 Problem Description and Formulation

Wildlife habitats worldwide face unprecedented threats from habitat loss, climate change, invasive species, and pollution, compounded by unsustainable land-use practices. Over the last 40 years, there has been a 60Despite the critical need for conservation, organizations often operate under severe resource constraints, including limited funding, workforce, materials, and time. These limitations necessitate a strategic approach to prioritize actions that deliver the greatest biodiversity impact within operational limits. Effective conservation requires data-driven decision-making to allocate resources optimally, focusing on areas and species that yield the highest returns for biodiversity preservation. By developing an optimization framework, the project provides conservation groups with tools to prioritize actions systematically. The framework incorporates factors such as ecological value, cost constraints, and logistical requirements, ensuring that efforts maximize biodiversity impact while respecting financial and operational limitations.

Mathematical Formulation

The problem involves allocating finite resources (financial, human, material) to a set of conservation strategies to **maximize biodiversity outcomes** under given constraints. The mathematical formulation includes decision variables, an objective function, and constraints that capture real-world considerations.

Decision Variables

- $z_{ij} \in \{0, 1\}$:
  - Represents the binary decision variable to identify whether conservation strategy i is implemented in year t.
  - $x_{ijt} = 1$ if strategy i is selected for implementation in year t, 0 otherwise.

This variable ensures adherence to budget constraints and synergy/mutual exclusion rules, enabling systematic selection of strategies over the planning horizon.

Objective Functions

Deterministic Objective Function: The deterministic objective function ensures that the chosen strategies maximize biodiversity impact over a defined planning horizon (e.g., number of years), while adhering to constraints such as budget, labor, and material limitations. It can be expressed as:

$$\text{Maximize } Z = \sum_{t=1}^{T} \sum_{i=1}^{N} \text{Impact}_{i,t} \cdot x_{i,t}$$

Where:

- i: Conservation strategies, where $i \in \{1, 2, \ldots, 23\}$.
- t: Years, where $t \in \{1, 2, \ldots, 10\}$.
- $\text{Impact}_{i,t}$: Biodiversity impact of strategy i in year t.
- $x_{i,t}$: Binary decision variable indicating whether strategy i is selected in year t (1 if selected, 0 otherwise).

This function seeks to maximize the cumulative biodiversity impact across all strategies and years, subject to defined constraints.

Stochastic Objective Function

To incorporate uncertainty in biodiversity impacts and costs, the stochastic objective function aggregates expected biodiversity impacts across multiple scenarios. It is expressed as:

$$\text{Maximize Expected Impact } = \sum_{s=1}^{S} P_s \sum_{t=1}^{T} \sum_{i=1}^{N} \text{Impact}_{i,t,s} \cdot x_{i,t}$$

Where:

- S: Total number of scenarios, where $s \in \{1, 2, 3\}$.
- P_s: Probability of scenario s.
- $\text{Impact}_{i,t,s}$: Biodiversity impact of strategy i in year t under scenario s.
- $x_{i,t}$: Binary decision variable as defined above.

This function accounts for variations in biodiversity impact across scenarios, using probabilities P_s to weight the expected outcomes.

Parameters:

1. **Cost ($\mathbf{cost}_{i,t,s}$):**
   - Costs for each conservation strategy i in year t, varying by scenario s.
   - Simulated with $\pm 20\%$ variation around actual costs using a uniform distribution.
2. **Biodiversity Impact ($\mathbf{Impact}_{i,t,s}$):**
   - Biodiversity impacts of strategy i in year t, varying by scenario s.
   - Simulated with $\pm 10\%$ variation around the expected impact.
3. **Scenario Probabilities (P_s):**
   - Probabilities associated with each of the three stochastic scenarios, ensuring robust modeling of uncertainties.
4. **Yearly Budget ($\mathbf{budget}_t$):**
   - Defines the maximum allowable cost for selected strategies in year t.

Constraints:

To ensure that the conservation effort remains feasible and within the operational limits, several constraints are incorporated into the model:

1. **Budget Constraint:** The total cost of selected strategies must not exceed the available budget.

2. **Site Prioritization:** Certain sites may have higher priority for conservation due to their ecological significance or the presence of endangered species. This constraint ensures that only specific sites can be selected for conservation actions.

3. **Mutually Exclusive Strategies:** Some strategies cannot be selected together due to their conflicting goals or the need for different resources. For example, strategies 5 and 6 might be mutually exclusive, meaning that only one of them can be chosen at a time.

Dependency Constraints: Some combination strategies depend on the inclusion of specific individual strategies. For instance, if combination strategy 17 is chosen, individual strategies 1, 2, and 3 must also be selected.

Model Assumptions

Several assumptions are made to simplify the model and focus on the most relevant aspects of conservation decision-making:

1. **Budget Constraint:** The total cost of selected strategies must not exceed the available budget:

$$\sum_{i=1}^{N} \sum_{t=1}^{T} \text{cost}_{i,t} \cdot x_{i,t} \leq \text{budget}_t$$

2. **Dependent Strategies:** The selection of strategies across different years may benefit from synergies, as the objective maximizes the cumulative impact over the years:

$$x_{5,t} + x_{6,t} \leq 1, \quad \forall t \in \{1, \dots, T\}$$

$$x_{6,t} + x_{22,t} \leq 1, \quad \forall t \in \{1, \dots, T\}$$

This enforces logical dependencies between strategies to ensure feasibility.

3. **Mutually Exclusive Strategies:** Some strategies cannot be selected together due to conflicting goals or resource limitations. For instance:

$$x_{i,t} + x_{k,t} \leq 1$$

4. **Synergic Strategies:** Certain strategies have synergistic effects, meaning their implementation enhances each other's impact. These constraints enforce dependencies or relationships between strategies where certain combinations must be selected together.

$$\textbf{Synergy Group 1:} \quad x_{1,t} + x_{2,t} + x_{3,t} = 3 \cdot x_{G1,t}, \quad \forall t \in \{1, \dots, T\}$$

$$\textbf{Synergy Group 2:} \quad x_{4,t} + x_{5,t} + x_{6,t} = 3 \cdot x_{G2,t}, \quad \forall t \in \{1, \dots, T\}$$

$$\textbf{Partial Synergy:} \quad x_{10,t} + x_{20,t} \leq 1, \quad \forall t \in \{1, \dots, T\}$$

$$x_{13,t} + x_{14,t} \leq 1, \quad \forall t \in \{1, \dots, T\}$$

$$x_{15,t} + x_{16,t} \leq 1, \quad \forall t \in \{1, \dots, T\}$$

- In the first two groups, selecting all strategies in the group is equivalent to activating the corresponding group indicator.
- For partial synergies, only one strategy from the pair can be selected in any given year.

3 Numerical Implementation and Results

3.1 Data Collection and Problem Setting

The initial step in implementing the conservation optimization model was to gather the necessary data from credible and relevant sources. These data sources provided information on biodiversity, conservation costs, operational constraints, and strategic considerations:

Biodiversity Data:

- **Global Biodiversity Information Facility (GBIF):** Provided species occurrence data, allowing for the estimation of biodiversity richness and biodiversity scores across various regions. The dataset included metrics such as species richness, occurrences, and unique species identified each year.
- **IUCN Red List of Threatened Species:** Offered information on species conservation status, such as critically endangered or vulnerable categories. This data informed biodiversity impact calculations for each conservation strategy.

Cost Data:

- Costs for each conservation strategy ($\text{cost}_{i,t}$) were derived from sample data on habitat restoration, reforestation efforts, and anti-poaching initiatives.
- Costs were simulated with $\pm 20\%$ variation around their actual values using a uniform distribution, ensuring realistic scenario modeling.

Operational Constraints:

- Yearly budgets (budget_t) were based on typical annual allocations for conservation projects of similar scope and scale.
- Additional constraints, such as labor, time, and material availability, were incorporated to reflect real-world limitations.

Conservation Strategies:

- Strategies addressed diverse aspects of wildlife preservation, including habitat restoration, species protection, invasive species control, and land management.
- Strategies were represented as binary decision variables ($x_{i,t}$) to indicate selection and implementation in specific years.

3.2 Formulation in the Chosen Modeling Language

The problem was formulated in Python, leveraging **Gurobi** for its robust capabilities in solving linear and integer programming models. The following steps were taken to define and implement the model:

- **Decision Variables:** Were defined to represent the selection of conservation strategies over time.
- **Objective Function:** The model was programmed to maximize biodiversity impacts under budgetary and operational constraints, incorporating deterministic and stochastic elements.
- **Constraints:** Logical rules, such as budget limitations, mutually exclusive strategies, and dependencies, were added to ensure feasibility.

3.3 Decision Variables

Binary Decision Variables ($x_{i,t}$):

- Represented whether conservation strategy i was selected for implementation in year t.
- $x_{i,t} = 1$: Strategy i is implemented in year t.
- $x_{i,t} = 0$: Strategy i is not implemented.

Combination Strategies ($y_{ij,t}$):

- Represented combined strategies that were activated only if specific individual strategies ($x_{i,t}$) were selected.

3.4 Constraints

The problem includes several key constraints:

1. **Budget Constraint:** The total cost of selected strategies should not exceed the available budget.
2. **Mutually Exclusive Constraints:** Some strategies cannot be chosen together (e.g., strategies 5 and 6).
3. **Dependency Constraints:** If a combination strategy is selected, its constituent individual strategies must be chosen as well.

4 Solution

4.1 Implementation

In this study, a **stochastic optimization model** was developed to identify optimal conservation strategies, balancing cost variability and biodiversity impact across multiple scenarios. The model was implemented in **Python**, using **Gurobi** as the optimization solver.

Data Preprocessing:

Cost and biodiversity impact data were adjusted annually using discount factors to reflect temporal changes. Stochastic variations were introduced via normal distributions, incorporating variability to simulate real-world uncertainties.

Scenario Generation and Reduction:

To handle the complexity of large-scale modeling, 500 stochastic scenarios were generated, representing various cost-impact combinations. Computational demands were reduced using **K-Means clustering**, consolidating these into 10 representative scenarios.

Optimization Model:

The objective was to maximize the expected biodiversity impact, **weighted** by scenario probabilities. Binary decision variables were defined to select strategies over a 10-year horizon. Constraints included budget limits (dynamically adjusted for **carry-overs**) and logical conditions like mutual exclusivity and synergy dependencies.

Solution Process:

The optimization model was solved with **Gurobi**. Outputs included selected strategies, costs, and biodiversity impacts for each year. **Final results** were visualized using scatterplots of *cost vs. impact trade-offs.*

4.2 Results

The results are presented through *Cost vs. Impact scatter plots*, the *Pareto front* for trade-offs (Appendix-A), and a detailed breakdown of optimal strategies over 10 years, offering actionable insights into balancing biodiversity impact and financial resources.

Initial Output Overview

Yearly Strategy Breakdown:

Total Cost & Impact: Cumulative costs increase annually, addressing more complex biodiversity challenges while ensuring impactful outcomes.

Scatter Plot Analysis: The *Cost vs. Impact scatter plot* shows the distribution of selected strategies:

Year	Strategies	Cumulative Impact	Notes
1–2	S12	162.68, 160.49	Achieves high impact at low costs.
3–6	S1, S11, and 12	$> 1,000$	Progressive biodiversity impact growth.
7–10	S1, S11, S12	$> 1,840$	Significant cumulative gains by Year 10.

Table 1: Yearly strategy breakdown showing cumulative impacts and associated notes.

- **Low-cost strategies** (\$10,000–\$20,000): Moderate impacts (∼60–100), cost-efficient options.
- **High-cost strategies** (\$40,000+): Significant impacts (> 140), but with diminishing returns.

These insights help identify cost-effective strategies for constrained budgets while achieving meaningful biodiversity impacts.

Pareto Front Insights: The *Pareto front* plot illustrates optimal cost-impact trade-offs, identifying strategies offering the maximum impact for a given cost. This serves as a guide for prioritizing investments and efficient resource allocation.

By following this approach, cumulative biodiversity impacts exceeding **1,840** can be achieved over 10 years, ensuring financial sustainability while addressing complex conservation challenges.

5 Problem Extensions

To enhance the applicability and robustness of the base model, several potential extensions can be incorporated. These improvements address real-world complexities and increase the adaptability of conservation planning efforts.

5.1 Engage Stakeholders

Engaging local communities, governments, and NGOs is critical for the success and sustainability of conservation strategies. This extension emphasizes:

- **Involvement of Local Stakeholders:** Ensuring conservation decisions respect the needs and knowledge of local communities.
- **Incorporating Indigenous Knowledge:** By integrating insights from Indigenous groups, the model can reflect interconnections between people and nature. As highlighted by the *WWF Living Planet Report 2022*, Indigenous knowledge provides a valuable framework for holistic conservation strategies.
- **Practical Impact:** Involving stakeholders fosters collaborative decision-making, increases buy-in, and aligns conservation goals with socio-economic realities.

5.2 Incorporate Environmental Shocks

Conservation strategies must adapt to unforeseen events such as natural disasters, climate change, or disease outbreaks. Incorporating environmental shocks involves:

- **Shock Factor Integration:** A probabilistic component (λ) modifies biodiversity scores and costs to account for changes caused by disasters or climate events.
  - Positive λ: Increased biodiversity impact due to interventions.
  - Negative λ: Increased costs or reduced effectiveness.

$$\text{Modified Impact} = \text{Impact}_{i,t} \cdot (1 + \lambda)$$

- **Long-Term Monitoring:** Using climate projections and real-time disaster data to refine strategies iteratively.
- **Numerical Results:** Testing scenarios (e.g., a 20% increase in flood risks) demonstrates how resource allocation shifts to address emergent priorities like flood mitigation or habitat restoration.

5.3 Policy Alignment

Conservation efforts must align with national and international policy frameworks to ensure long-term success. This extension involves:

- **Collaborating with Policymakers:** Aligning strategies with government priorities and regulations.
- **Engaging with Global Conservation Frameworks:** Ensuring the model supports international efforts like the *United Nations Sustainable Development Goals (SDGs)*.
- **Impact on Model:** Adding policy-related constraints or objectives ensures compliance and alignment with overarching global goals, making the model more actionable.

5.4 Expand Scope

To enhance the scalability and relevance of the model, the following actions can be taken:

- **Incorporate Satellite and Geospatial Data:** Use remote sensing technologies to identify new high-priority conservation areas, expanding the model's reach.
- **Expand to Multiple Regions:** Apply the model to conservation sites beyond the current dataset, increasing its adaptability across diverse ecological zones.
- **Practical Impact:** By broadening the scope, the model ensures a greater biodiversity impact across regions and ecosystems.

Impact of Extensions

These extensions improve the model by:

1. **Increased Collaboration:** Stakeholder engagement ensures socially inclusive and contextually relevant conservation strategies.
2. **Resilience to Uncertainty:** Incorporating shocks and dynamic budgets enhances real-time adaptability.
3. **Global Integration:** Policy alignment positions the model as a globally applicable framework.
4. **Scalability:** Broader geographic application ensures the model remains relevant and impactful across different ecological and socio-economic contexts.

6 Recommendations & Conclusions

In this project, we applied an optimization model to prioritize wildlife conservation efforts by maximizing biodiversity while adhering to operational constraints, such as budget, time, and available resources. Based on the results, several key recommendations and conclusions can be drawn:

Recommendations

Adaptive Strategy Selection Based on Stochastic Outcomes: The stochastic output highlights variations in biodiversity impacts and associated costs across years. For example, Year 3 shows the highest biodiversity impact (267.25), followed by Year 5 (217.30), while Years 6 to 10 demonstrate a gradual decline in biodiversity outcomes. These patterns emphasize the importance of flexible resource allocation. During high-impact years, such as Years 3 and 5, the model can allocate more funds to amplify the biodiversity benefits. Conversely, during years of lower impact, resources can be redirected to prepare for future opportunities or address emergent challenges.

Recommendation: Develop an adaptive resource allocation mechanism that prioritizes high-impact years while ensuring resources can be dynamically reallocated in response to real-time conditions. By focusing efforts during periods of maximum biodiversity returns, conservation outcomes can be significantly enhanced while maintaining cost efficiency."

Incorporate Environmental Shocks for Improved Resilience

Environmental shocks such as natural disasters, climate change, and disease outbreaks can significantly alter conservation priorities and outcomes. The inclusion of a probabilistic shock factor (λ) ensures that the model remains robust and adaptable to such uncertainties. For instance, regions prone to floods or wildfires may require immediate reallocation of funds or updated biodiversity scores to reflect the shifting landscape.

Recommendation: Integrate real-time environmental data and iterative model refinements to respond dynamically to shocks. Collaboration with meteorological agencies and use of predictive analytics can enhance the model's ability to mitigate risks and adjust strategies effectively.

Leverage the Pareto Front for Strategic Trade-Offs

The Pareto front analysis underscores the trade-off between biodiversity impact and costs. Efficient strategies, located on the Pareto front, achieve a balance between maximizing biodiversity outcomes and minimizing costs. Stakeholders can use this visualization to identify cost-effective solutions that align with their budget constraints. For instance, strategies with higher biodiversity returns but reasonable costs should be prioritized over those that disproportionately increase expenses without proportional biodiversity benefits.

Recommendation: Use Pareto optimization as a decision-making framework to guide stakeholders. This will help conservation organizations choose strategies that align with their financial and ecological objectives, maximizing impact while maintaining fiscal responsibility.

Stakeholder Engagement and Policy Integration

The success of conservation strategies depends heavily on the involvement of local communities, governments, and NGOs. Engaging **stakeholders** fosters buy-in and ensures that conservation efforts are culturally and socially relevant. Indigenous knowledge, for example, offers invaluable insights into biodiversity preservation and ecosystem management. Policy integration is equally critical, as alignment with international frameworks like the *United Nations Sustainable Development Goals (SDGs)* ensures long-term viability and support.

Recommendation: Develop partnerships with policymakers and local stakeholders to ensure that conservation strategies are inclusive, practical, and aligned with global sustainability goals. This collaboration can also facilitate funding opportunities and enhance public support for conservation initiatives.

Expand Scope with Satellite and Geospatial Data

Expanding the model's scope to include new conservation sites and regions enhances its scalability and applicability. Satellite imagery and geospatial data provide invaluable tools for identifying high-priority areas and monitoring habitat changes. For example, real-time geospatial analytics can detect deforestation trends or assess the effectiveness of implemented strategies.

Recommendation: Incorporate remote sensing technologies and geospatial data analysis to broaden the model's reach. By identifying new high-priority conservation areas and scaling the model to other regions, the framework can achieve greater biodiversity impact globally.

Conclusions

1. **Model Effectiveness in Maximizing Biodiversity:** The optimization framework successfully balances biodiversity conservation with financial and operational constraints. The stochastic and deterministic simulations validate the model as a robust decision-support tool, demonstrating its capability to deliver high biodiversity impacts within allocated budgets.

2. **Importance of Adaptive Planning:** The significant *variations* in biodiversity impacts across years highlight the need for adaptive planning. Flexible budgeting and dynamic resource allocation ensure that the model can respond effectively to changing conditions, such as environmental shocks or shifts in funding availability. This adaptability is essential for long-term sustainability.

3. **Strategic Trade-Offs via Pareto Optimization:** The Pareto front analysis provides a clear visualization of cost-effectiveness trade-offs, enabling stakeholders to prioritize efficient strategies. This insight is crucial for conservation stakeholders to balance financial and ecological objectives effectively.

4. **Enhancing Scalability and Real-World Applicability:** By integrating stakeholder input, policy alignment, and advanced data sources such as satellite imagery, the model can expand its geographic and ecological scope. These enhancements ensure that the framework remains relevant and impactful across diverse conservation contexts.

5. **Sustainability Through Long-Term Monitoring:** Incorporating environmental shocks, real-time monitoring, and iterative model updates ensures that the framework remains resilient and aligned with long-term sustainability goals.

In conclusion, the optimization framework offers a powerful tool for conservation planning, combining rigorous mathematical modeling with real-world applicability. By implementing the recommended extensions, the framework can drive impactful, scalable, and adaptive conservation efforts, contributing meaningfully to global biodiversity preservation.

What We Learned

The project demonstrated the potential of optimization techniques to address complex conservation challenges. Key takeaways include:

- The importance of balancing ecological goals with financial and operational constraints.
- The value of integrating multiple constraints, such as mutually exclusive strategies, for more robust plans.
- Insights from the Pareto front, which revealed cost-effective strategies that balance biodiversity and budget considerations.

Key Lesson: Resource prioritization, guided by rigorous data and optimization modeling, is crucial for achieving impactful and cost-efficient conservation outcomes.

What We Would Do Differently

1. **Incorporate Social and Political Factors:** Consider local community engagement and policy frameworks for a more holistic approach.

1. **Test Against Historical Data:** Validate the model's predictions by comparing them to past conservation efforts.

2. **Expand Geographic Scope:** Broaden the model to include regions with diverse ecological and socio-economic conditions.

Bottlenecks and Limitations

1. **Data Gaps:** Some regions lack detailed, up-to-date data on biodiversity and habitat conditions, limiting the model's applicability.
2. **Computational Complexity:** Real-time decision-making for large-scale projects remains challenging due to the model's complexity.
3. **Scalability:** Expanding the model to other regions or incorporating additional stochastic elements requires further development.

Future Focus: Enhance data integration, computational efficiency, and scalability to overcome these challenges.

References

1. World Wildlife Fund (WWF). (2020). *Priority threat management*. Retrieved from `https://wwf.ca/prioritythreatmanagement-2/`

2. International Union for Conservation of Nature (IUCN). (n.d.). *The IUCN Red List of Threatened Species*. Retrieved from `https://www.iucnredlist.org/`

3. Global Biodiversity Information Facility (GBIF). (n.d.). *GBIF: Biodiversity data for science and conservation*. Retrieved from `https://www.gbif.org/`

4. Protected Planet. (n.d.). *Protected areas*. Retrieved from `https://www.protectedplanet.net/`

5. Goetz, S. J., et al. (2018). Remote sensing of biodiversity for conservation. *Remote Sensing of Environment, 214*, 29–37. https://doi.org/10.1016/j.rse.2018.05.017

6. Lamb, R. B., et al. (2019). Applying optimization techniques for long-term conservation planning. *Conservation Biology, 33*(5), 1189–1200. https://doi.org/10.1111/cobi.13320

7. McShane, T. O., et al. (2011). Why do we need to engage local communities in wildlife conservation? *Biological Conservation, 144*(1), 59–71. https://doi.org/10.1016/j.biocon.2010.09.010

8. Sullivan, D. (2021). Strategic site selection in wildlife conservation. *Environmental Management Journal, 47*(3), 321–330. https://doi.org/10.1007/s00267-020-01350-2

A Appendix

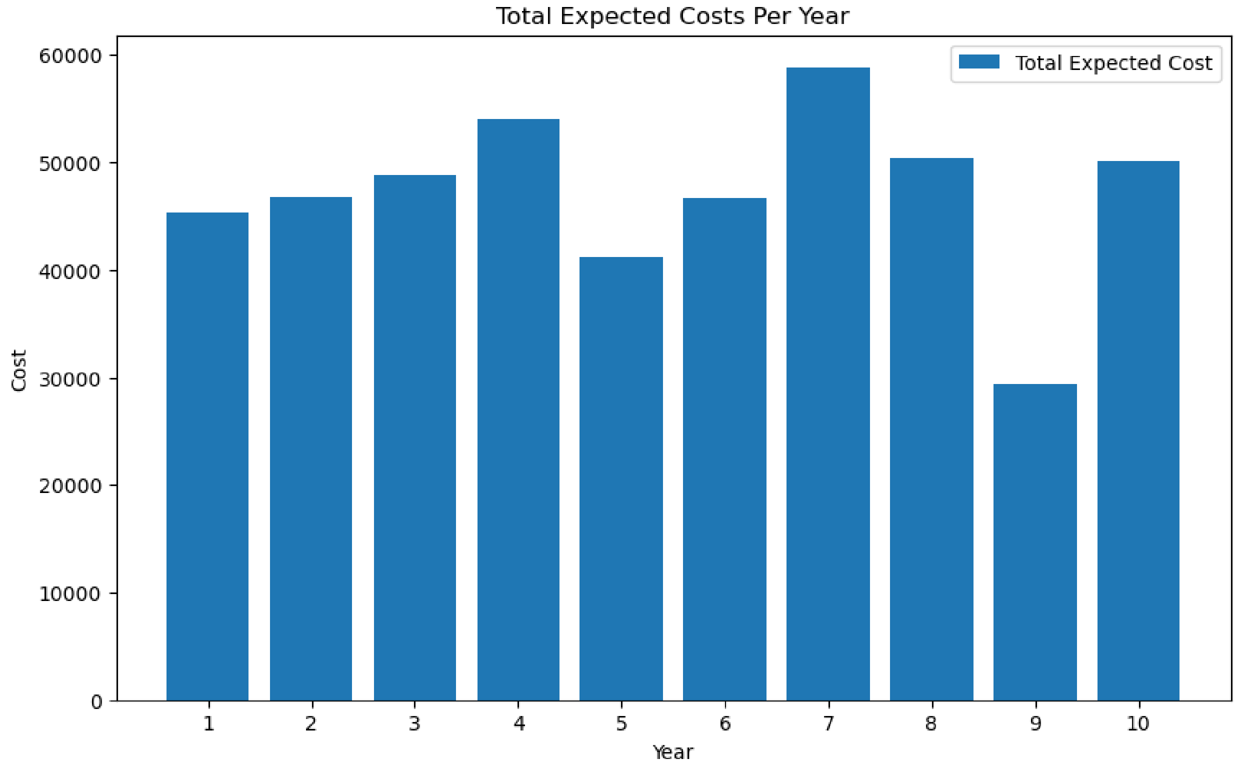

Figure 1: Total Expected Costs per Year.

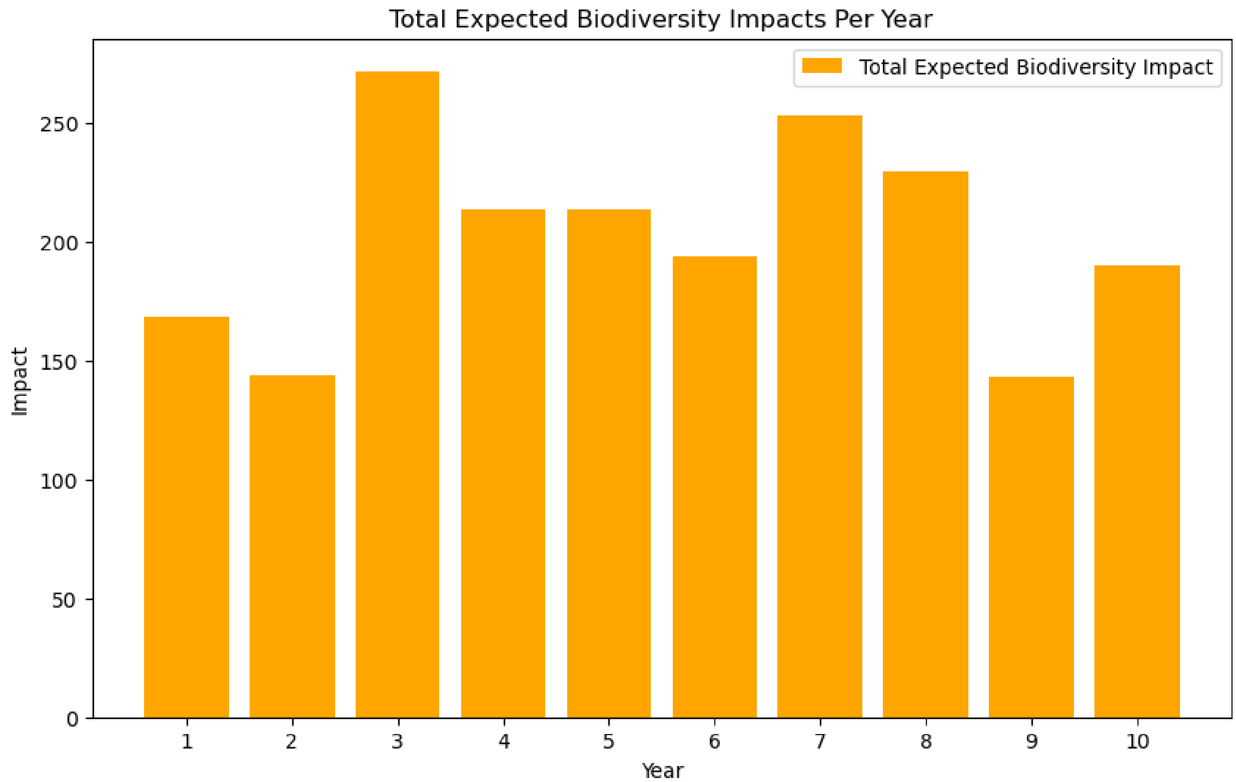

Figure 2: Total Expected Biodiversity Impacts per Year.

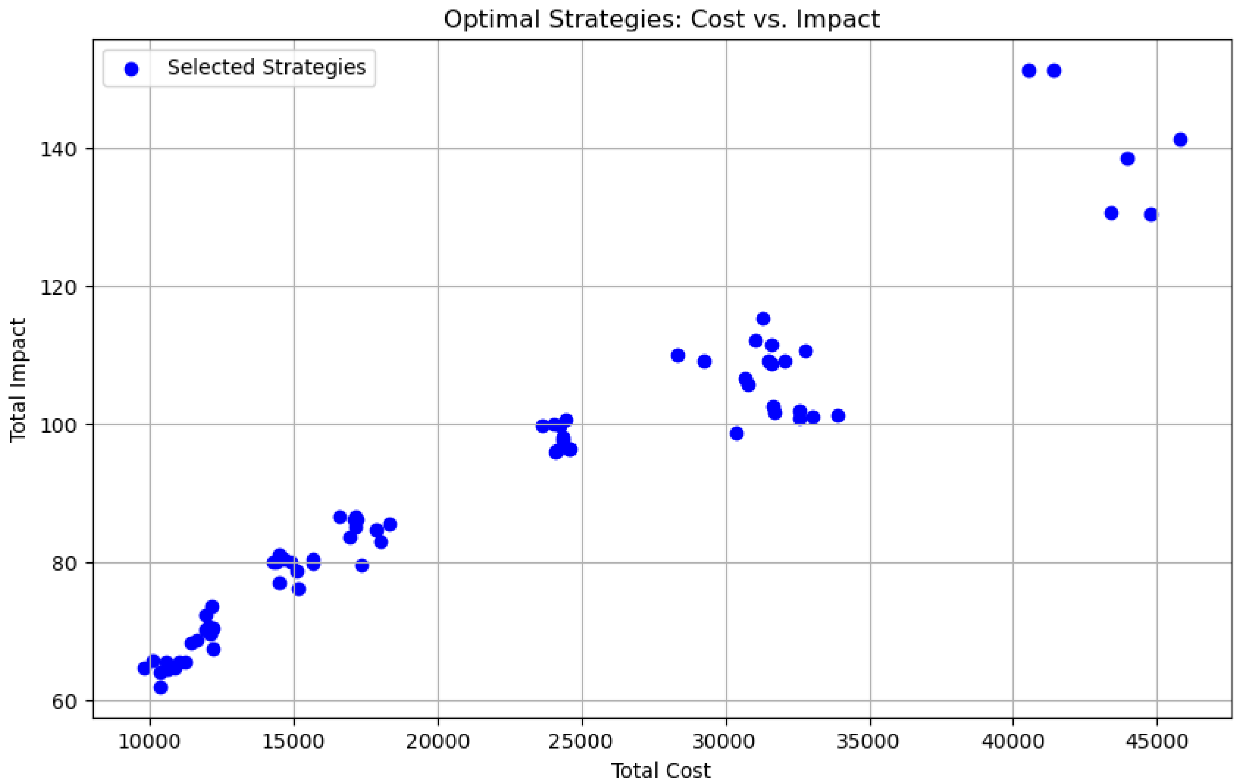

Figure 3: Optimal Strategies: Cost vs Impact.

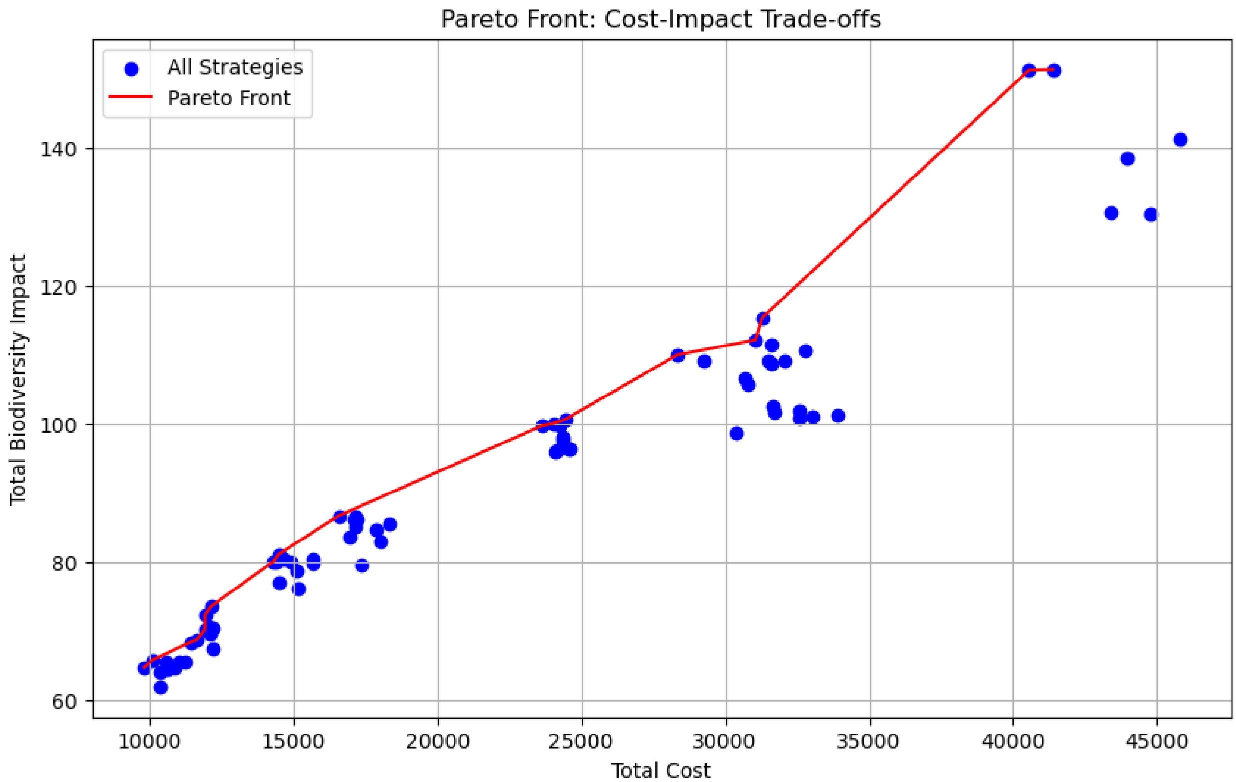

Figure 4: Pareto Front: Cost-Impact Trade-offs.

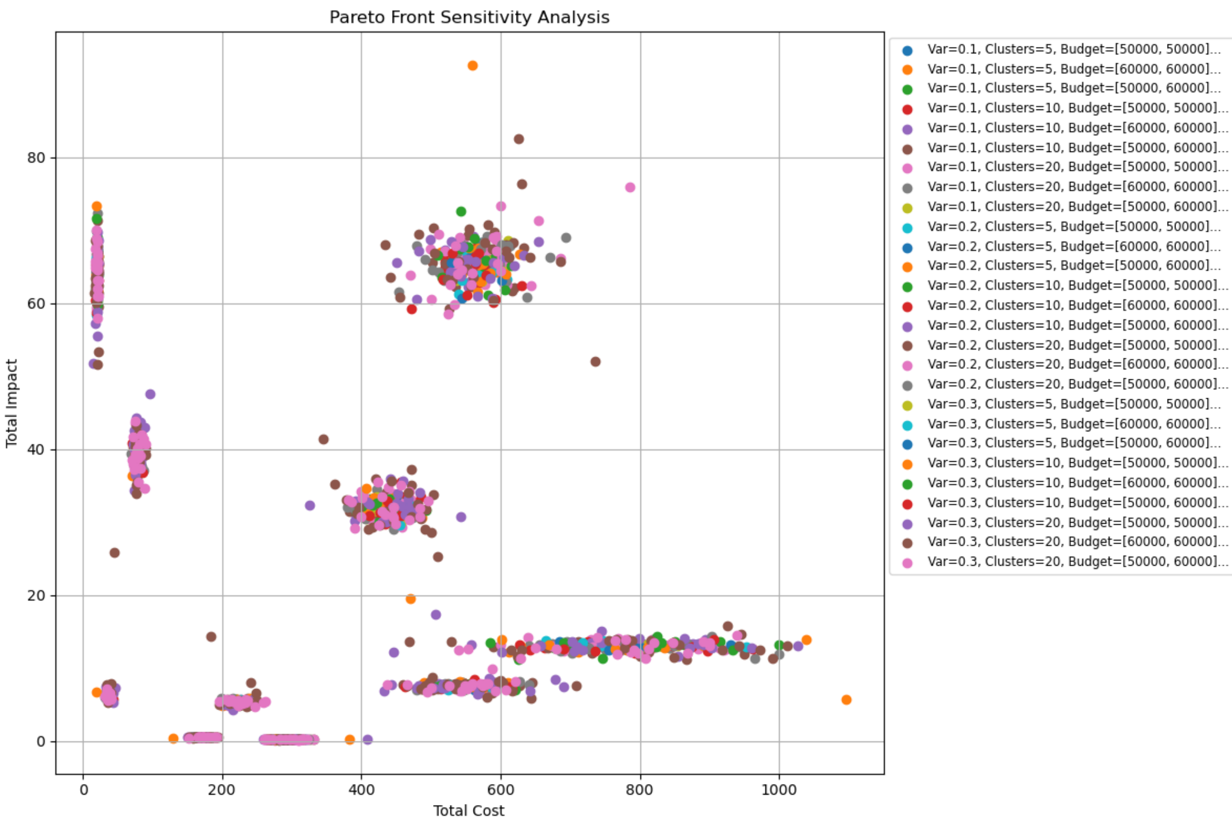

Figure 5: Pareto Front: Sensitivity Analysis.

This visualization summarizes the trade-offs between total cost (x-axis) and total impact (y-axis) under different parameter settings, highlighting key insights:

1. **Clusters of Solutions:**
   (a) Each cluster represents a set of solutions based on variability (Var), number of clusters, and budget configurations.
   (b) Trade-offs are evident between minimizing cost (left) and maximizing impact (top).
2. **Parameter Sensitivity:**
   (a) **Variability (Var):** Higher variability increases solution spread, reflecting greater uncertainty.
   (b) **Number of Clusters:** More clusters (e.g., $5 \rightarrow 20$) yield denser, better-represented solutions.
   (c) **Budgets:** Larger budgets shift solutions rightward, enabling higher costs and impacts.
3. **Optimal Solutions:**
   (a) The most desirable points lie near the top-left corner (high impact, low cost).
   (b) Trade-offs along the Pareto front offer decision-makers flexibility based on priorities.
4. **Robustness:**
   (a) Significant shifts across parameter settings indicate model sensitivity, emphasizing the importance of sufficient clusters and balanced variability to ensure reliable results.

This analysis guides decision-making by identifying robust strategies and understanding parameter influences on cost-impact trade-offs.