IOP Publishing
Journal Title
Journal **XX** (XXXX) XXXXXX
https://doi.org/XXXX/XXXX

Viability Of Forest Landscapes for Carbon Credit Generation in Papua New Guinea

Zane Bowser[1]

[1] Faculty of Science, Queensland University of Technology, Brisbane, Australia

E-mail: n10996541@qut.edu.au

Received xxxxxx
Accepted for publication xxxxxx
Published xxxxxx

Executive Summary

The Nature Conservancy (TNC) is an environmental organisation working to protecting forests within Papua New Guinea (PNG). Their initiatives support local communities and governments in promoting sustainable land use and conservation efforts. By utilising carbon credits generated when preserving land, TNC can protect biodiversity, and produce funding for future conservation projects. Despite this, not everything can be conserved, and choices must be made as to where is the most valuable when prioritising. The purpose of this report is to present the methods of a preliminary model designed to prioritise Intact Forest Landscapes (IFLs) in PNG. The model aims to help TNC determine where conservation efforts should be directed and how resources should be allocated.

This investigation takes into consideration several key factors relating to each IFL, including accessibility, carbon density and its change over time, relative safety and region stability to justify the allocation of carbon credits as required by TNC. For this purpose, the data for each factor is first sourced and prepared in MATLAB.

Each of these factors is considered in an expected cost effectiveness function to rank each IFL using a preliminary static optimisation model. This model considers each influencing factor in its computations to identify the IFLs that would provide the greatest benefit from immediate conservation investment. From this model, a ranking is determined for each IFL that describes its significance. This can be used to develop some initial conclusions. Additionally, possible model improvements including the consideration of partial protection of IFLs are discussed.

As conservation efforts must also adapt to changes over time, the implementation of the dynamic optimisation model is proposed. This model is designed to consider how protection decisions can impact the future conditions of surrounding IFLs over time.

A planned uncertainty analysis discusses which elements of uncertainty are present in the model, and methods to minimise their effects. Proposed are several improvements to the way factors such as travel time are calculated and incorporating uncertainty datasets into the model.

Keywords: Intact Forest Landscapes (IFL's), Carbon Credits, Biodiversity, Habitat Loss, Conservation

1. Introduction and Background

The Asia Pacific region is rapidly urbanising, which is putting significant strain on natural resources and leading to increased deforestation. Papua New Guinea (PNG), home to some of the world's largest tropical rainforests, has been significantly impacted. These rainforests are crucial to maintaining biodiversity and act as natural carbon sinks, helping to reduce the effects of climate change. However, they are under threat from logging and agricultural activities [1].

The Nature Conservancy (TNC) is an environmental organisation that has been working to protect these forests. Their initiatives aim to support local communities and governments in sustainable land use and conservation efforts. In recent years, programs including Reducing Emissions from Deforestation and forest Degradation (REDD+) have emerged that provide financial incentives to preserve forests [2]. This provides a pathway that aligns environmental conservation with economic benefits, which TNC aims to achieve in PNG.

The primary aim of this project is to assist TNC in identifying the best areas, known as Intact Forest Landscapes (IFLs), for community conservation efforts and carbon-based project within PNG. It involves analysing the ecological, economic and social factors to prioritise IFLs for protection.

Mathematical models are built to guide this decision-making process. The purpose of this report is to detail the prioritisation approaches. It involves the integration of key PNG datasets and the development of a static and dynamic optimisation model. The datasets are related to various factors within PNG including carbon storage, biodiversity, safety and costs. The static model uses this data to conduct a cost effectiveness analysis, helping to prioritise areas for conversation efforts. The dynamic model then allocates funding over time across IFLs accounting for changing conditions. This helps TNC allocate resources to maximise long term benefits. This report documents the mathematical approach used to create the models, presents the relevant data for each IFL and includes a planned uncertainty analysis, along with future recommendations for IFL prioritisation.

2. Data Sources, Purpose and Preparation

Various data resources are taken into consideration in the prioritisation model. These include: IFL locations, carbon stores, biodiversity, accessibility and safety. Data relevant to PNG is extracted and mapped out across all IFLs.

Data preparation involves different techniques depending on the required measures. Spatial data is typically in the form of shape defined by longitude and latitude arrays. These locations define spatial perimeters which can be processed as polygons using the *Polyshape* function in MATLAB.

2.1 IFL Loss Rate

The ***Intact Forested Landscape*** database serves as the spatial framework upon which all subsequent elements of analysis can be overlayed. Once filtered to contain only PNG landscapes by determining the geographical bounds, this database provides an exhaustive list of PNG IFLs including their: location; shape; size; number and name identifiers. Figure 1 shows a map of PNG with the relevant IFLs identified in green for data from a 2020 survey.

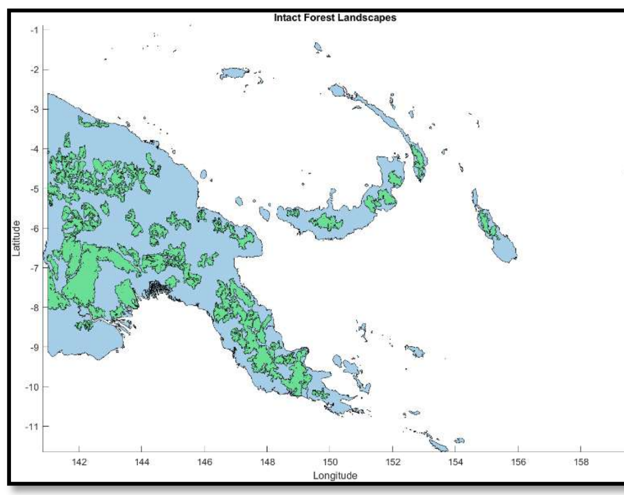

Figure 1 – Map of Intact Forest Landscapes (IFLs) in Papua New Guinea, highlighting the geographical distribution and spatial boundaries used as the foundation for conservation prioritisation.

This survey identified 63 separate IFLs, each of which must be considered when building the prioritisation models. In addition to the 2020 data, datasets from 2013 and 2016 were also reviewed to calculate deforestation rates for each of the identified IFLs. Understanding the total land area and deforestation rates is essential for determining the feasibility of financing projects through carbon credits.

The subsequent datasets are prepared to align with each extracted IFL highlighted in Figure 1. This is achieved by cross checking the location assigned to the datapoints with the IFL polygons; The *inpolygon* MATLAB function enables the crosschecking of polygon (*Polyshape* type) data. The data is segmented and organised to describe characteristics of the forest landscapes.

2.2 Above Ground Carbon Storage

Another key factor determining the feasibility of financing projects through carbon credits is the amount of above ground carbon stored in the IFLs. The carbon storage data sourced from NASA's high resolution **Earth Data Carbon Map** dataset, describes the above-ground carbon storage in forests, highlighting high carbon density areas as shown in Figure 2.

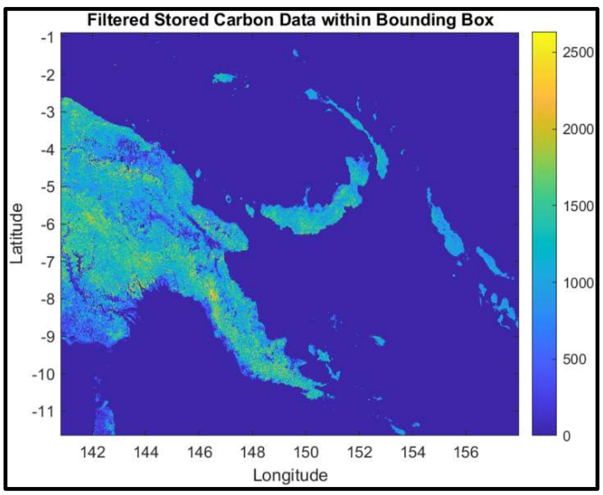

Figure 2 - Above-ground carbon storage data for Papua New Guinea's forests, sourced from NASA's Earth Data carbon map. This map highlights areas with high carbon density, guiding the prioritisation of IFLs that contribute significantly to carbon sequestration.

The key metric extracted from this dataset is the average carbon density (measured in Megagrams of Carbon per Hectare, MgC/ha). This information is crucial in identifying which IFLs store the highest amounts of carbon, helping prioritise forests that play a significant role in reducing atmospheric carbon and mitigating climate change.

This metric also plays an essential role in assessing whether investment in an IFL will be viable. The amount of carbon present affects the potential for local support for conservation, as it directly influences the benefits that can be derived from carbon credits. These factors are integrated into the utility function, along with deforestation rates, to guide the prioritisation and decision-making process.

2.3 Biodiversity

Another key consideration for IFLs is the number of threatened species and overall biodiversity they contain. The IUCN's Rare and Threatened Species database contains species habitat information for mammals, reptiles and amphibian's native to PNG. This data is visualised in Figure 3, which highlights areas of species concentration across the region's IFLs.

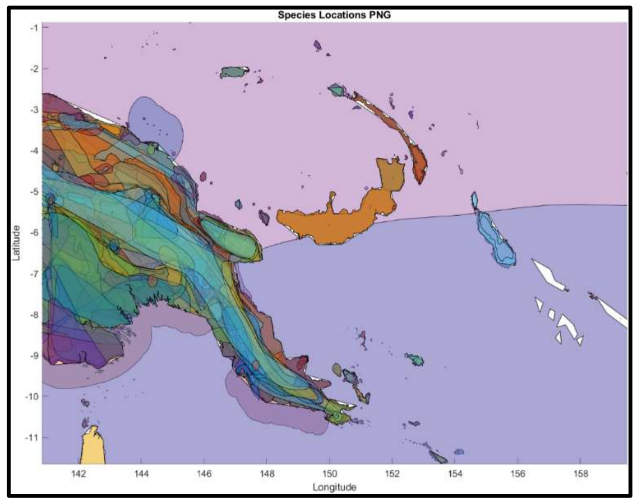

Figure 3 - Map showing biodiversity within Papua New Guinea's IFLs. This map highlights the regions where species inhabit with large overlaps corresponding to higher concentrations of biodiversity.

This map consists of polygons representing the habitats of individual species in PNG. Areas with significant overlap indicate high levels of species biodiversity, which directly influences the prioritisation of conservation investments. Protecting these biodiversity-rich IFLs becomes a priority, as preserving diverse ecosystems is crucial for long-term environmental sustainability.

To ensure biodiversity considerations are integrated into the prioritisation models, the numbers of species inhabiting each IFL is extracted from the data. This metric plays an essential role in the allocation of conservation efforts and funding, guiding the decision-making process to maximise ecological impact.

2.4 Accessibility

To ensure practical conservation management, IFL accessibility is a key component considered in the proposed model. NASA's **Global Roads Map** in conjunction with an **Airport List** created by the Mission Aviation fellowship in PNG. This information is visualised in Figure 4, which highlights the primary transportation infrastructure across the region.

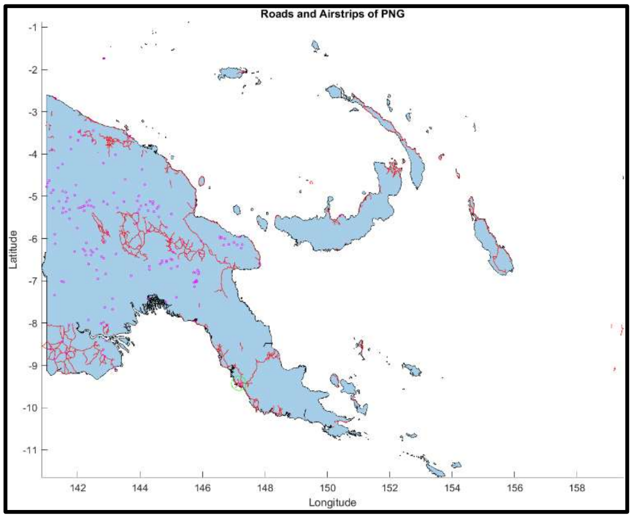

Figure 4 - Map of PNG containing all major roads represented in red. It also contains a list of all airstrips represented by the purple dots.

This data is used to calculate a cost value for each IFL based on the time required to travel to and from each location. All trips are measured from Port Moresby and travel times are calculated using average speeds:

- Road travel: 30 km/h
- Off-road travel: 4 km/h
- Boat travel: 20 km/h
- Airline travel:

The shortest travel time corresponds to the lowest cost value, with these times serving as arbitrary cost measures for comparison across IFLs. Geodesic distance calculations were used to estimate these travel times accurately.

Accessibility is a critical factor in determining conservation priorities, as IFLs that are easier to access are often more at risk of deforestation due to increases logging activity. Conversely, remote IFLs may be more suitable for preservation projects. Incorporating accessibility into the model ensures that conservation investments are both feasible and strategically aligned to reduce deforestation risks.

2.5 Threat Levels

As site visits to the IFLs are required to obtain carbon financing, the relative safety of each IFL is the final metric considered when creating our models. The Expert Map of Safety Across PNG, provided by TNC, offers an overview of threat levels throughout the region. This information is visualised in Figure 5, showing the varying likelihood of safety incidents in different areas.

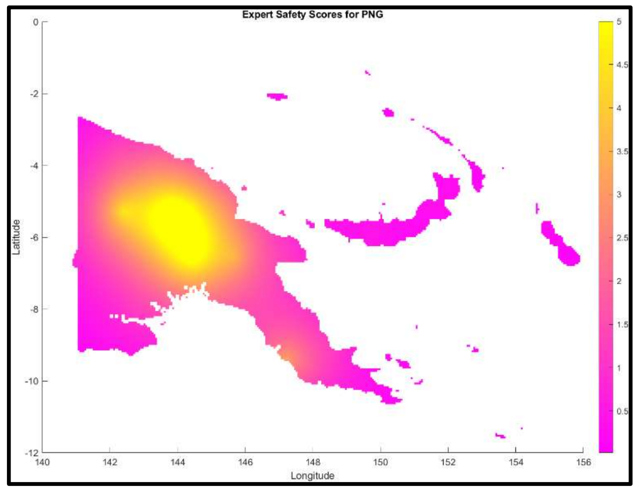

Figure 5 - Map illustrating safety ratings across different areas of PNG. Higher values indicate a greater likelihood of safety incidents occurring in those regions.

The safety rating is measured on a scale from 1 to 5, with each value representing the probability of a safety event occurring:

- 1: Probability is 1 in 100
- 2: Probability is 1 in 50
- 3: Probability is 1 in 25
- 4: Probability is 1 in 10
- 5: Probability is 1 in 3

This metric is critical for the feasibility of IFL projects, as conservation efforts are likely to fail if two or more safety incidents occur during the project. Site visits are planned to occur every three months over a five-year period, meaning that even a moderate risk could jeopardise project success. Incorporating these safety considerations into the model ensure that prioritised

IFLs align not only with ecological goals but also with practical implementation constraints.

2.6 Data Preparation Summary

Following the visualisation of these datasets, they were rescaled using the *interp* function in MATLAB to ensure consistent resolution across all datasets for seamless integration into a unified model. The resolution was aligned with the IFL map shown in Figure 1 and set to a resolution of (resolution value). To isolate data within IFLs, all cells corresponding to the mapped IFL areas were retained, while all other values were set to zero. This allowed the datasets to be multiplied by the IFL map, ensuring that the only data contained within each IFL was extracted. Using the extracted data, key metrics were calculated, including the IFL forest loss rate, the average safety rating, and the average carbon density per hectare.

All the data used in the prioritisation model has been summarised in Table 1, which outlines the datasets, and the specific information extracted from each. This summary ensures clarity on how each dataset contributes to the model and highlights the key metrics used for decision making.

Table 1– Provides a summary of the data sets used in the model and the relevant information extracted from these datasets.

Dataset	Data Extracted	Processed Form
Intact Forested Landscape	IFL Polygon Latitudes & Longitudes	IFL Polygons
Earth Data Carbon Map (NASA)	Average Carbon Density [MgC/ha]	Average Carbon Density [MgC/ha] for each IFL
IUCN's rare and Threatened Species	Species Areas Latitudes & Longitudes describing some area a species inhabits.	Species Polygons & total number of species per IFL
Global roads map (NASA)	PNG road locations (Longitudes & Latitudes)	Geodesic travel times. Polyshape list of each road and airstrip containing latitude and longitude coordinates
Airport list (PNG Mission Aviation fellowship)	PNG Airports location (Longitudes & Latitudes)	
Expert Map of Safety across PNG (TNC)	Likelihoods of safety incidents to occur within regions of PNG	Coordinate-spaced matrix of average safety values (values from 1-5).

Using the values extracted from the datasets, a comprehensive table was created to summarise all relevant metrics for each of the 63 IFLs. Appendices A provides an example of this collation, displaying key data for ten representative IFLs from the complete dataset. This sample offers a clear view of the final data structure, which includes metrics such as forest area, carbon density, safety rating, accessibility, and annual forest loss rate.

3. Static Prioritsation

In assessing the viability of various Intact Forest Landscapes (IFLs) in Papua New Guinea for carbon credit investment, we have employed two static prioritization methods. The first approach involved an initial ranking of the IFLs based on key factors stated in Table 2. Building upon this, the second method partially allocates resources to a selection of IFLs, taking into account their individual rankings and potential for maximizing conservation impact. These methodologies aim to guide targeted investment in the most promising IFLs to support both environmental and economic objectives.

3.1 IFL Ranking

The static prioritisation model aims to identify the most critical IFLs for immediate conservation investment. This method involves two main steps. First, the IFLs in PNG are ranked based on several ecological, economic, social, and logistical factors outlined above in the data collected. The goal is to compute the expected cost effectiveness value for each IFL, which takes the general form:

$$E_i = \frac{p_i B_i}{c_i} \tag{1}$$

With,

- E_i – The expected cost-effectiveness of any given IFL i, and will be used to determine the ranking. A higher value is indicative of an IFLs ability to provide greater benefits, adjusted by the probability of the IFL being successful.
- p_i – The probability of a given IFL i being successful.
- B_i – The total benefits the project will deliver if deemed successful.

- c_i – The cost to undertake the project at any given IFL i.

These parameters are representative of the data collected for each of the IFLs in PNG. However, the problem is more complex and defined by additional factors that must be considered in the ranking process. The entire static prioritisation model can be redefined using the below parameters:

- B_i – The ecological importance of the IFL and is based on the contained biodiversity.
- c_i – The cost of undertaking the project. This is proportional to the minimum travel time required to reach the IFL.
- K_i – The community-based carbon benefits, quantified by the average carbon density measured in tonnes of carbon per hectare [tC/ha].
- δ_i – Defines the rate of carbon loss in each IFL.
- s_i – The Safety metric for each IFL is measured using a 'risk mean', which represents the average safety rating across the IFL on a scale from 1 to 5. For a project to be considered safe, a site visit must occur every three months over a five-year period, if two safety incidents occur during this period the project is abandoned.
- q_i – The probability of an IFL having less than two safety events in the 5yr period. The probability of the project not being abandoned was found using a binomial probability distribution.

$$P(X = x) = \binom{n}{x} p^x (1-p)^{n-x}$$

$$q_i = P(X = 0) + P(X = 1)$$

n – The total number of site visits over the 5-year period (20).

x – The number of incidents over the 5-year period

p – The probability of an incident occurring at each visit, this differs based on the average safety rating of the IFL:

- Safety Rating of 1 has a probability of 1 in 100.
- Safety Rating of 2 has a probability of 1 in 50.
- Safety Rating of 3 has a probability of 1 in 25.
- Safety Rating of 4 has a probability of 1 in 10.
- Safety Rating of 5 has a probability of 1 in 3.

p_i – The probability of success based on the carbon benefits of the project and can be defined by the relationship:

$$p_i = 1 - \exp\left[-25 \cdot \delta_i \cdot K_i\right] \qquad (2)$$

All these parameters are considered when calculating the expected cost effectiveness; crucial for ranking the IFLs from the highest to the lowest priority. By incorporating these additional parameters, we can refine the general form of the expected cost-effectiveness formula to:

$$E_i = \frac{q_i p_i B_i}{c_i} \qquad (3)$$

3.1.1 IFL Ranking Results

Taking the data from Appendices A, the appropriate calculations were applied to find the probability of success based on safety and the probability of success based on carbon benefits which is known as the local support. Using these values Equation 3 was used to rank the IFLs in terms of cost effectiveness and sorted. Table 3 shows the top five and bottom five ranked IFLs along with all the values calculated to produce this ranking system.

Table 2- Shows the top 5 and bottom 5 ranked IFLs along with the data used to calculate these ranking values.

Ranking	IFL ID	Average Safety	Avg Safety	Travel Time	Species	Average Carbon	Loss Rate	Local Support	Ranking Value
1	SEA_16	1.287	0.973	40.132	108	11.924	0.006	0.834	122.992
2	SEA_9	1.957	0.942	10.766	99	14.05	0.007	0.937	122.648
3	SEA_37	1.768	0.951	40.569	95	12.171	0.009	0.948	120.285
4	SEA_21	1.422	0.967	5.895	177	12.808	0.002	0.473	113.685
5	SEA_26	2.952	0.817	52.829	84	13.148	0.025	0.999	96.251
59	SEA_22	1.929	0.943	23.848	34	12.719	0.00008	0.0253	1.14
60	SEA_41	5	0.003	53.047	85	11.49	0.0029	0.57	0.245
61	SEA_46	5	0.003	56.045	86	9.335	0.001	0.217	0.094
62	SEA_49	5	0.003	50.149	91	11.096	0.00049	0.127	0.058
63	SEA_64	5	0.003	50.969	81	10.323	0.0002	0.067	0.027

In terms of safety, the chance of success is significantly higher for the top-ranked IFLs. Conversely, the lowest ranking IFLs have near-zero values suggesting that projects in these areas would not be viable. Higher ranked IFLS also tend to have a higher number of species which would increase the biodiversity benefit. While the average carbon remains similar across higher and lower ranked IFLs, the loss rate is much higher for the top-ranked IFLs. This highlights the prioritisation of areas with greater risks of carbon loss.

While this ranking provides a great staring point to see which IFLS should be further researched, a more complex model might look at partial allocation.

3.2 Partial Allocation

The initial ranking assumes that IFLs are either fully prioritised or not at all. While this provides a useful starting point, it is often more effective to consider partial investment across several IFLs to maximise biodiversity benefits. The biodiversity benefit of an IFL can be determined using the 'species-area' relationship, which describes the benefit as a function of the total protected area:

$$\beta_i(P_i) = B_i\left(\frac{P_i}{T_i}\right)^z \tag{4}$$

Where,

- P_i – The area of IFL i that is protected.
- T_i – The total area of the IFL.
- z – Is an empirically estimated constant (typically equal to 0.3)

This equation is effective however, it must account for a constrained budget. To optimise the allocation of investments, the total budget I is divided into investments u_i for each IFL. This must be considered in the overall biodiversity benefit β across all IFLs, with the goal being to maximise β:

$$\max_{0\le u_i\le 1} \beta = \sum_i B_i\left[\frac{p_i \cdot q_i \cdot u_i \cdot I}{c_i \cdot T_i}\right]^z \tag{5}$$

This is subject to the constraint:

$$\sum_i u_i \le 1 \tag{6}$$

To solve this problem, a vector u_i must be found that maximises β. This is achieved using a Lagrange multiplier to effectively handle the constraint, which converts the constrained optimisation problem into a form where derivative tests (typically applied in unconstrained problems) can be used. This creates the following system:

$$\nabla f = \lambda \cdot \nabla g \tag{7}$$

Where, λ is known as the Lagrange multiplier and represents the relative gradient of the functions at the optimum. As such, the constrained problem must be transformed into a system of equations for f and g.

$$\begin{aligned} &f(u_1, u_2, \dots, u_n) \\ &= B_1\left(p_1 q_1 \frac{u_1 I}{c_1 T_1}\right)^z + B_2\left(p_2 q_2 \frac{u_2 I}{c_2 T_2}\right)^z \\ &+ \dots + B_n\left(p_n q_n \frac{u_n I}{c_n T_n}\right)^z \end{aligned}$$

If we let $k_i = \frac{p_i\, q_i}{c_i\, T_i}\, I$, we can express f as:

$$f = \sum_{i=1}^{n} B_i\left(p_i q_i \frac{u_i I}{c_i T_i}\right)^z = \sum_{i=1}^{n} B_i (k_i u_i)^z$$

Subject to the constraint:

$$g(u_1, u_2, \dots, u_n) = u_1 + u_2 + \dots + u_n = \sum_{i=1}^{n} u_i = 1$$

This formulation enables the partial protection of IFLs while optimising the biodiversity benefit based on the available budget and other the other constraints of the problem.

We now implement the condition

$$\nabla f = \lambda \cdot \nabla g$$

Where

$$\nabla f = \begin{bmatrix} \frac{\partial}{\partial u_1} \sum_{i=1}^{n} B_i (k_i u_i)^z \\ \vdots \\ \frac{\partial}{\partial u_n} \sum_{i=1}^{n} B_i (k_i u_i)^z \end{bmatrix} = \begin{bmatrix} z B_1 k_1 (k_1 u_1)^{z-1} \\ \vdots \\ z B_n k_n (k_n u_n)^{z-1} \end{bmatrix}$$

$$\nabla g = \begin{bmatrix} \frac{\partial}{\partial u_1}(u_1) \\ \vdots \\ \frac{\partial}{\partial u_n}(u_n) \end{bmatrix} = \begin{bmatrix} 1 \\ \vdots \\ 1 \end{bmatrix}$$

We now substitute these into the Lagrangian formula:

$$\nabla f = \lambda \cdot \nabla g$$

$$\begin{bmatrix} zB_1 k_1 (k_1 u_1)^{z-1} \\ \vdots \\ zB_n k_n (k_n u_n)^{z-1} \end{bmatrix} = \lambda \begin{bmatrix} 1 \\ \vdots \\ 1 \end{bmatrix}$$

So, for $i \in \{1,2, \dots, n\}$

$$[z\, B_i k_i (k_i u_i)^{z-1}] = \lambda$$

We then rearrange this to find in terms of u_i

$$(k_i u_i)^{z-1} = \frac{\lambda}{z\, B_i k_i}$$

$$k_i u_i = \left(\frac{\lambda}{z\, B_i k_i}\right)^{1-z}$$

$$u_i = \frac{1}{k_i}\left(\frac{\lambda}{z\, B_i k_i}\right)^{1-z}$$

We apply the condition:

$$\sum_{i=1,\dots n} u_i = 1$$

To get

$$\sum_{i=1,\dots n} \frac{1}{k_i}\left(\frac{\lambda}{z\, B_i k_i}\right)^{1-z} = 1$$

And rearrange for λ

$$\lambda = \left(\sum_{i=1,\dots n} \frac{1}{k_i}\left(\frac{1}{z\, B_i k_i}\right)^{1-z}\right)^{\frac{1}{z-1}}$$

Estimate z from empirical 'species-area' relation

$$z = 0.3, B_i, k_i\ known$$

Substitute back into

$$u_i = \frac{1}{k_i}\left(\frac{\lambda}{z\, B_i k_i}\right)^{1-z}$$

This provides the final form of the partial allocation problem and solving for u_i, will provide a vector that contains the amount of allocation that should be provided to an IFL to reach a maximum biodiversity benefit.

3.2.1 *Partial Allocation Results*

The partial allocation model was applied to determine the optimal distribution of investments across IFLs, with the goal of maximising biodiversity benefits while adhering to the budget constraints as outlined above. This model generated optimal allocation values u_i for each IFL. These values represent the proportion of the total investment that should be allocated to each IFL to achieve the greatest biodiversity gain.

For this analysis, we focused on the top 10 ranked IFLs from the initial ranking since maintaining partial investments across all IFLs is unrealistic. This narrowed focus allowed us to assess how partial investments across several high-priority IFLs could provide more effective conservation outcomes compared to a binary, all-or nothing approach. To visually demonstrate the optimal allocation strategy, Figure 6 present a pie chart that highlights the proportion of investment allocated to each of the top 10 IFLs.

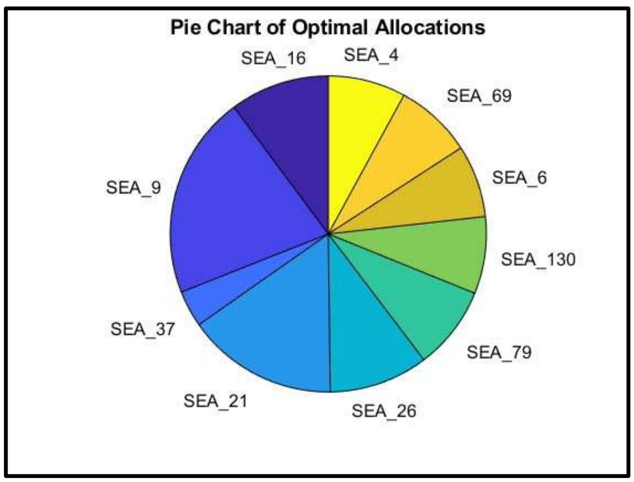

Figure 6 - Pie chart showing the optimal allocation of investment across the top 10 ranked IFLs.

Figure 6 shows the proportion of investment allocation across the top 10 ranked IFLs. Each slice represents the proportion of the total budget allocated to an individual IFL, with larger slices indicating areas that require greater investment to maximise biodiversity benefits.

From this chart, it is evident that SEA 9, SEA 21, and SEA 37 receive the most substantial portions of the budget, highlighting their importance in achieving the model's biodiversity objectives. These IFLs likely rank higher due to a combination of their ecological significance, accessibility, and cost effectiveness. In contrast, SEA 4 and SEA 16 receive smaller allocations suggesting that their conservation benefit may be limited by factors such as higher costs, lower carbon density, or smaller protected areas.

When compared to the original ranking, several notable shift emerge. One key observation is that SEA 16, initially ranked as the highest in cost-effectiveness, receives a smaller share of the budget than other IFLs under the partial allocation model. To further explore why this occurred, along with other ranking shifts, Table 3 presents the ranked order of optimal allocation, their investment amounts, and the changes in rank compared to the original prioritisation.

Table 3 - Shows a comparison between the partial allocation and the initial ranking models.

ID	Optimal Allocation	Biodiversity Benefit	Position Change
SEA_9	0.21	0.83	+1
SEA_21	0.15	0.61	+2
SEA_16	0.10	0.40	-2
SEA_26	0.10	0.40	+1
SEA_79	0.09	0.34	+1
SEA_4	0.08	0.31	+4
SEA_69	0.08	0.31	+2
SEA_130	0.08	0.31	-1
SEA_6	0.07	0.29	-1
SEA_37	0.04	0.15	-7

Table 3 provides a detailed breakdown of the optimal allocation values, biodiversity benefits, and position changes for the top 10 IFLs when applying the partial allocation model. One of the most notable findings is the shift in SEA 16's ranking. Despite being initially ranked highest in cost-effectiveness, it drops two positions and receives only 10% of the total budget, suggesting that other factors such as diminishing returns or higher costs may have reduced its priority in the partial allocation strategy.

Another key observation is the rise of SEA 4, which improves by four positions, despite receiving a relatively modest 8% allocation. This suggests that its combination of biodiversity benefit and investment efficiency becomes more favourable under a partial allocation model. Similarly, SEA 9 and SEA 21 rise to the top, receiving the largest allocations and generating the highest biodiversity benefits, with SEA 9 securing a benefit of 0.83 and improving by one position.

Conversely, SEA 37 experiences the largest drop, falling seven positions to the bottom of the list. This outcome indicates that, while SEA 37 may have initially seemed promising, it provides lower biodiversity benefit returns relative to other IFLs when considered in the partial allocation context.

To further understand the factors influencing optimal allocation in the partial investment model, key metrics were plotted to better visualise what's causing these variations. The first of these is looking at the number of species (B_i) and how it relates to the optimal allocation (u_i) as shown in Figure 7.

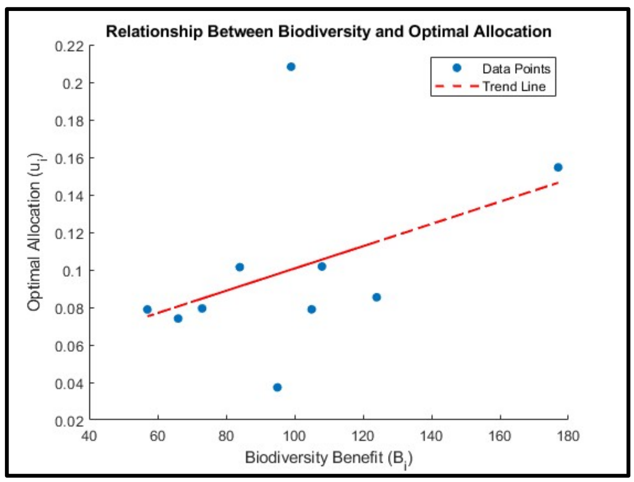

Figure 7 - Scatter plot showing the relationship between the number of species (B_i) and optimal allocation (u_i).

Figure 7 shows a clear positive trend between the number of species and the optimal allocation. This suggests that IFLs with a higher number of species tend to receive a greater share of the total investment. The trend line highlights this relationship, indicating that the model prioritises IFLs with richer biodiversity to maximise ecological benefits. However, some data points deviate from this trend, potentially due to the influence of other variables such as accessibility or cost constraints. This is why the relationship between the inverse cost and optimal allocation was also plotted to identify why these outliers may occur shown in Figure 8.

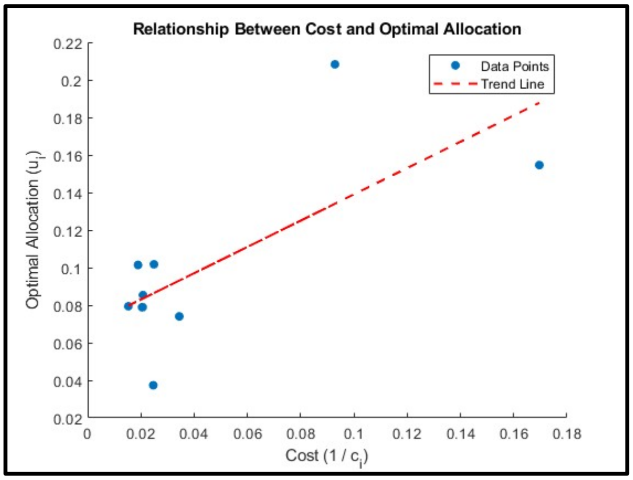

Figure 8 - Scatter plot showing the relationship between cost (1/c_i) and optimal allocation (u_i).

Figure 8 depicts the relationship between cost and optimal allocation. The positive correlation shown here suggest that IFLs with a more favourable cost-benefit ratio (lower cost per biodiversity gain) receive a higher proportion of investment. The trend line supports this, showing that cost-efficient IFLs are prioritised in the allocation strategy. Outliers in this plot may reflect IFLs that, despite having higher costs, still receive investment due to their significant ecological or strategic value. In both cases the key outlier is SEA 9 with the highest optimal allocation this is most likely due to a combination of land size and cost affecting the allocation of investment to that IFL as the initial ranking method doesn't consider the IFL land size.

Given these observed fluctuations, an uncertainty analysis was conducted to assess the reliability of the model and the accuracy of the allocations under changing data.

3.3 Uncertainty Analysis

To assess and evaluate how sensitive the prioritisation model is to changes in input data, an uncertainty analysis was conducted. This involved applying random variations between 1 and 5% to the optimal allocations over 100 trials. For each trial, the changes were applied and the resulting shift in IFL rankings were recorded. The mean rank change was then calculated to quantify the impact of data variability on the prioritisation outcomes. This analysis ensures that the model remains reliable under realistic variations in data and highlights any potential weaknesses that could affect decision-making. The outcomes of this analysis are shown in Table 4.

Table 4 - shows the results of the uncertainty analysis for the partial allocation.

IFL ID	Optimal Allocation	Mean Shifted Allocation	Mean Rank Change
SEA 9	0.21	0.22	0
SEA 21	0.15	0.17	0
SEA 16	0.10	0.13	-0.43
SEA 26	0.10	0.13	0.43
SEA 79	0.09	0.11	0
SEA 4	0.08	0.11	-0.61
SEA 69	0.08	0.11	-0.05
SEA 130	0.08	0.11	+0.66
SEA 6	0.07	0.10	0
SEA 7	0.04	0.09	0

The results of the uncertainty analysis, shown in Table 4, demonstrates the impact of random variations on the optimal allocation values and the corresponding investment that should be directed to each IFL. In most cases, the mean rank change is minimal, with values close to 0, indicating that the prioritisation model is robust to small changes in the input data. For example, IFLs such as SEA 9, SEA 21, SEA 79, SEA 6 and SEA 7 show no significant change in rank, suggesting that their allocations remain stable even under data variations.

However, some IFLs exhibit minor positive or negative shifts in rank. For instance, SEA 16 shows a small negative shift, meaning it drops slightly in priority across the trials. In contrast, SEA 130 experiences the largest positive shift, with a change of +0.66, indicating a moderate improvement in its prioritisation under certain conditions.

Overall, these results suggest that, while some variability in ranking occurs, the changes remain relatively small. This reinforces the reliability and robustness of the model under realistic levels of uncertainty, ensuring that the allocation recommendations remain consistent even when data fluctuates slightly.

4. Dynamic Optimisation

While the static optimisation focuses on a one-time allocation of resources to prioritise IFLs, dynamic optimisation addresses the more complex problem of distributing resources over time. Conservation efforts must adapt to changing conditions, where factors like habitat loss, budget availability, and project outcomes evolve over a given period.

4.1 Dynamic Optimisation Approach

The dynamic optimisation approach seeks to maximise the long-term biodiversity benefits by determining how resources should be allocated across IFLs over time. This method is necessary because investments in different IFLs do not yield immediate results but rather accrue benefits gradually as conservation projects progress. To effectively model the dynamic allocation of resources over time, we introduce several key variables that describe the evolving state of each IFL. These variables represent how conservation investments impact protected, degraded and available land areas as projects progress. The nature of this problem requires the use of coupled Ordinary Differential Equations (ODEs), to capture the evolving nature of the problem.

For each FIL i, the following variables are defined:

- $P_i(t)$ – The protected land area over time.
- $L_i(t)$ – The cleared land area over time.
- $A_i(t)$ – The available land over time.
- $u_i(t)$ – The proportion invested over time.

Using these variables a system of coupled ODEs can be created to describe the rate of change in protected, degraded, and available land.

$$\frac{dP_i}{dt} = \frac{p_i q_i u_i(t) I}{c_i T_i} \qquad (8)$$

$$\frac{dL_i}{dt} = \delta_i A_i \qquad (9)$$

$$\frac{dA_i}{dt} = -\frac{p_i q_i u_i(t) I}{c_i T_i} - \delta_i A_i \qquad (10)$$

This system of ODEs dynamically describes how over time the amount of each type of land in an IFL will change. They describe how the amount of protected land will increase by a factor of the probability of success, the amount of resources allocated to it divided by the cost and the total area. Additionally, it describes how each IFL will lose land according to the deforestation rate multiplied by the available land. Finally, the system describes that the available land will decrease in relation to the increase in protected and lost land exactly.

With this system of coupled ODEs, the equation for maximum biodiversity benefit (β) can now be defined in terms of time:

$$\beta(t) = \max_{u_i(t)} \sum_i B_i \left(\frac{A_i + P_i}{T_i}\right)^z \qquad (11)$$

Subject to the constraints,

$$\sum_i u_i(t) = 1\,, 0 \le u_i \le 1 \qquad (12)$$

To solve this dynamic optimisation, Pontryagin's Maximum Principle is applied, allowing the optimisation of control variables $u_i(t)$ over time by maximising an integral objective function defined as:

$$J = \Psi\big(\boldsymbol{x}(T)\big) + \int_0^T L(\boldsymbol{x}(t), \boldsymbol{u}(t), t) \cdot dt \qquad (13)$$

- $\psi\big(\boldsymbol{x}(T)\big)$ – Is the value of the systems state at a final time T.
- $L(\boldsymbol{x}(t), \boldsymbol{u}(t), t)$ – Is the objective function (β).

To maximise the integral objective function, a Hamiltonian is constructed, which combines the dynamics of the system with the objective function ($L(\boldsymbol{x}(t), \boldsymbol{u}(t), t)$), and a set of time varying costate variables ($\lambda(t)$), which act as Lagrange multipliers for the dynamic system. The Hamiltonian is defined as:

$$\begin{aligned} H(\boldsymbol{x}(t), \boldsymbol{u}(t), \boldsymbol{\lambda}(t), t) \\ = \boldsymbol{\lambda}(t) \cdot \boldsymbol{f}\big(\boldsymbol{x}(t), \boldsymbol{u}(t)\big) \\ + L(\boldsymbol{x}(t), \boldsymbol{u}(t), t) \end{aligned} \tag{14}$$

Where,

- $f(\cdot)$ – represent the dynamic state constraints (8), (9) and (10).

To optimise the allocation of investments over time, the Hamiltonian needs to be maximised at each point in time t, which ensures the integral objective is maximised. This leads to the following conditions: the optimal state trajectory $x^*(t)$, the optimal control $u^*(t)$, and corresponding Lagrange multipliers must satisfy:

$$\begin{aligned} H(\boldsymbol{x}^*(t), \boldsymbol{u}^*(t), \boldsymbol{\lambda}^*(t), t) \\ \geq H(\boldsymbol{x}(t), \boldsymbol{u}(t), \boldsymbol{\lambda}(t), t) \end{aligned} \tag{15}$$

This means, functions for $x^*(t), u^*(t)$, and $\lambda^*(t)$ that satisfy the first order conditions:

$$\frac{\partial H}{\partial u} = 0 \tag{16}$$

$$\frac{\partial H}{\partial \lambda} = \dot{x} \tag{17}$$

$$\frac{\partial H}{\partial x} = -\dot{\lambda} \tag{18}$$

Terminal boundary conditions must also be set these are known as transversality conditions and are defined as:

$$\lambda_i(T) = \frac{\partial \Psi(T)}{\partial x_i} \tag{19}$$

These conditions ensure that the investment strategy ($u_i(t)$), maximises the biodiversity benefit while considering the dynamic state of the problem. The Hamiltonian method enables the integration of both the immediate effects of resource allocation and the long-term evolution of each IFL, allowing for a dynamic and adaptive conservation strategy.

By solving the Hamiltonian and its associated ODEs numerically, we find the optimal trajectory ($u_i(t)$) that maximises the biodiversity benefits across all IFLs over the entire project duration.

In order to implement this for our problem, we first note that we are only attempting to optimise for the final time, without any running cost. As such, we can define J in terms of our area:

$$J = \Psi\big(x(T)\big) = \sum_i B_i \left(\frac{A_i(T) + P_i(T)}{L_i}\right)^z$$

Additionally, we can define our three state variables, and the remaining parameters

$$\boldsymbol{x} = \begin{matrix} A \\ P \\ L \end{matrix}, \dot{\boldsymbol{x}} = \begin{matrix} \frac{dA}{dt} \\ \frac{dP}{dt} \\ \frac{dL}{dt} \end{matrix}$$

Thus, we can define the Hamiltonian.

$$\begin{aligned} H(x(t), u(t), \lambda(t), t) \\ = \lambda(t) \cdot f(x(t), u(t)) \\ + L(x(t), u(t), t) \end{aligned}$$

Given $\dot{x} = f\big(x(t), u(t)\big), L = 0$ since there is no running cost, we can find an equation for H

$$H = \sum_i \lambda_{Ai} \frac{dA_i}{dt} + \lambda_{Pi} \frac{dP_i}{dt} + \lambda_{Li} \frac{dL_i}{dt}$$

$$\begin{aligned} H = \sum_i -\lambda_{Ai}(\alpha_i u_i + \delta_i A_i) + \lambda_{Pi}(\alpha_i u_i) \\ + \lambda_{Li}(\delta_I A_i)\,, \alpha_i = \frac{p_i q_i I}{c_i T_i} \end{aligned}$$

$$H = \sum_i (\lambda_{P_i} - \lambda_{A_i})\alpha_i u_i + \sum_i (\lambda_{L_i} - \lambda_{A_i})\delta_i A_i$$

From the condition equations, we can calculate the derivatives of the costate variables.

$$\dot{\lambda_{A_i}} = -\frac{\partial H}{\partial A_i} = \big(\lambda_{A_i} - \lambda_{L_i}\big)\delta_i$$

$$\dot{\lambda_{P_i}} = -\frac{\partial H}{\partial P_i} = 0 \ \rightarrow \lambda_{P_i}(t) = const$$

$$\dot{\lambda_{L_i}} = -\frac{\partial H}{\partial L_i} = 0 \rightarrow \lambda_{P_i}(t) = const$$

Additionally, we have the end state conditions

$$\lambda_{A_i}(T) = \frac{\partial \Psi(T)}{\partial A_i} = \frac{\partial \beta(T)}{\partial A_i}$$

$$= zB_i \left[\frac{A_i(T) + P_i(T)}{T_i}\right]^{z-1} \cdot \frac{1}{T_i}$$

$$\lambda_{P_i}(T) = \frac{\partial \Psi(T)}{\partial P_i} = \frac{\partial \beta(T)}{\partial P_i}$$

$$= zB_i \left[\frac{A_i(T) + P_i(T)}{T_i}\right]^{z-1} \cdot \frac{1}{T_i}$$

$$\lambda_{L_i}(T) = \frac{\partial \Psi(T)}{\partial P_i} = \frac{\partial \beta(T)}{\partial P_i} = 0$$

Thus, from this, we can define the three costate variables across all time.

$$\lambda_{P_i}(t) = \lambda_{P_i}(T) = zB_i \left[\frac{A_i(T) + P_i(T)}{T_i}\right]^{z-1} \cdot \frac{1}{T_i}$$

$$\lambda_{L_i}(t) = \lambda_{L_i}(T) = 0$$

Since $\lambda_{L_i} = 0, \dot{\lambda}_{A_i} = \lambda_{A_i}\delta_i$

$$\lambda_{A_i}(t) = \lambda_{A_i}(T)e^{\delta_i(t-T)}$$

Finally, we can use the optimality condition to determine which IFL to prioritise at any given time. By calculating delta for each IFL, we can identify the largest Δ, and allocate all the resources to that delta at that time, repeating the process for each timestep, ensuring that the optimal allocation of resources is done at each time.

$$\frac{\partial H}{\partial u} = 0$$

$$\Delta = \frac{\partial H}{\partial u} = \sum_i \alpha_i(\lambda_{P_i}(t) - \lambda_{A_i}(t))$$

Thus, at each timestep, the IFL i with the largest Δ will be given $u = 1$ resources, while the remainder will not be allocated resources for conservation at that time. By applying this equation at each timestep, we can optimise the solution of allocation over time.

4.1.1 Dynamic Optimisation Results

By implementing an iterative method, it is possible to find increasingly optimal allocations of resource over time, according to the costate variables defined in the model. By iterating through the steps of the model, calculating updated costate variables and areas, and then determining the optimal allocation area, we can produce a set of $u_i(t)$ that describes the optimal IFL to allocate all the resources I to at each timestep. Based on these results, we can calculate and plot the three types of land for each IFL, how they change over time, in relation to when the allocation of u changes. Based on the IFL properties derived from the datasets, the following allocation solution was produced.

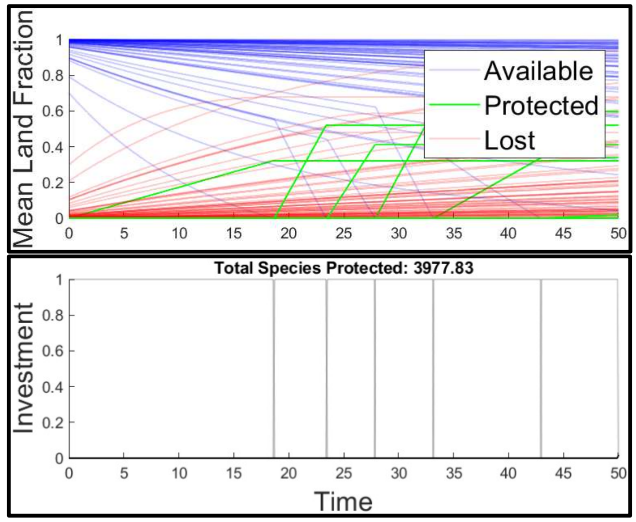

Figure 9 - Changing land values based on resource allocation and ODE models.

Figure 9 shows how the protected land of one IFL will increase as it is allocated resources until it either runs out of land to protect or another IFL becomes more beneficial to conserve. The cumulative allocation of u over time can be seen in Figure 10.

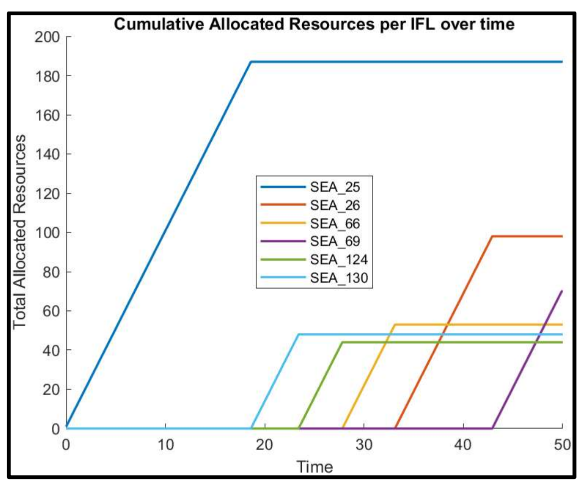

Figure 10 - Shows the allocated investment in each IFL over the project life-span.

From this figure, we can identify that according to the model, it is most beneficial to begin by allocating resources to IFL SEA_25, as protecting the land there will produce the most benefit. From Figure 9, we can see that at approximately 19 years into the project, as a result of protection and loss, there will be no more land to conserve. As such, it becomes more beneficial to allocate resources to SEA_130.

To extend on identifying the suitability of the model, we can run the same iterative process using only the top 10 IFLs as identified in the partial allocation. By doing this, we can clearly see that an efficient portion of the results were selected.

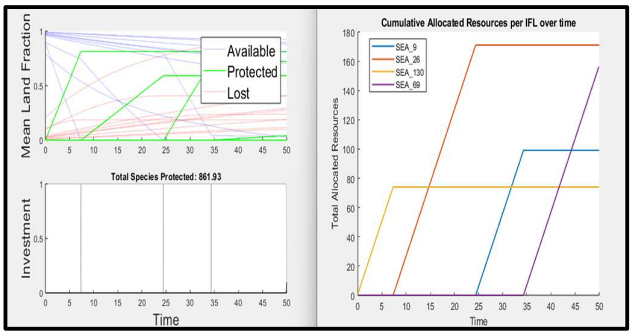

Figure 11 - Dynamic allocation of top IFLs identified in partial allocation.

4.2 Uncertainty Analysis

When considering the reliability of the model, it should first be noted that the number of resources allocated per timestep when calculating the solution is arbitrary. This can be seen by performing the model on the same datasets but reducing the available resources I by a factor of 10.

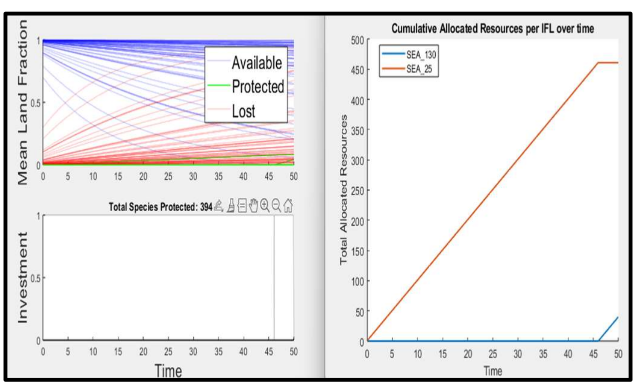

Figure 12 - Dynamic allocation with reduced resources I.

As can be seen in this figure, the dynamic allocation produces a different result, providing allocation resources to only two IFLs, and in fact starting with a different one than the previous iteration did. By considering the impact over time, the reduced resources lead to a different system. As such, the number of resources used in this system is arbitrary.

This leads to a limitation in the model when considering fluctuating resources, or control over a period.

Additionally, this model is limited in accuracy by the reliability of the data. As explored below, while the data sources are reliable, the methods used to extract and determine the properties for each IFL is limited, thus leading to restrictive and unreliable approximations.

Most notably in the calculations is the numerical approximations used when calculating each timestep. As the system cannot be modelled by a clear function, each time step in the iteration is estimated using a forward Euler approximation. Using this when calculating available areas and combining that by the approximation in calculating the costate variable for available leads to a slightly uncertain system. While it seemingly functions correctly, by increasing the number of steps too much, or reducing the accuracy of the data, the resultant time stepping solution could diverge from the expected model significantly.

Finally, several assumptions and approximations are made when determining which IFL to allocate resources to. Given enough resources it would be possible to allocate some to multiple IFLs at each timestep. Despite this, our system assumes that only one IFL can be allocated resources at a time. This assumes instant start up and shut down, which reduce the reliability of each area. For a more reasonable approximation, multiple IFLs would be given resources on a scaling amount as needed to produce even more benefit. Finally, when calculating Delta to determine how much each IFL would benefit from an allocation, it is directly assumed that any IFL with zero available land is to be ignored. This does not account for IFLs with a very small amount of land that would benefit the most mathematically, but it would not make sense to allocate resources to such a small parcel of remaining land. A more reliable system would consider the size of each preservation at each step to aim for a more realistic system.

5. Conclusions

5.1 Limitations

The carbon storage of IFLs was sourced from NASA's 2010 above-ground carbon biomass dataset. Consequently, any environmental changes in biomass since 2010 are not reflected in the carbon storage data used in the models. As a result, some IFLs may have less carbon stores than indicated from the data, affecting the accuracy of the IFL prioritizations.

Similarly, the Global roads open access data set utilised data from 1980-2010, meaning that in 2024, some paths for transportation may have been rendered infeasible, along with new paths of transportation opening up. Such changes in paths to reach IFLS could result in inaccurate prioritization of IFLs as their logistical feasibility is outdated, with some IFLs over-prioritized due to the assumption of easy or cheap access, whereas now they are much more costly to reach, or underprioritized due to new paths of transport that have been established since 2010.

The IFL forest cover over time was used to estimate rates of degradation within each IFL. This was sourced from Google Earth images and LandSat. The Google images are not taken synchronously. As the images may be taken at different times, images labelled for a specific year may include photos from different years, potentially not accurately reflecting the current forest conditions and resulting in inaccurate assessments of forest loss or regrowth in the IFL.

The times to reach IFLs from Port Moresby were found by taking a plane to the closest airstrip and travelling off road, or by taking a geodesic path that varies depending on whether the path is on land (off road) or sea. It is approximated that the travel times are the smaller of these values. This oversimplifies the complexities of actual travel routes, which may potentially require multiple modes of transportation along with unforeseen logistical issues.

The dynamic model assumes a fixed budget over time. Funding may fluctuate due to many numbers of reasons. The model can be re-evaluated with new data and an updated budget in the future; however, this assumption of a fixed budget may cause sub-optimal prioritizations if such funding issues occur suddenly in the future.

5.2 Recommendations

The project supports TNC in optimising the protection of IFLs within PNG while considering ecological, economic and social factors. The report outlines the mathematical approaches used to create a static and dynamic optimisation model. These models integrate key datasets on carbon storage, biodiversity, cost and safety to guide prioritisation and allocation of resources.

While the models are still under development, they lay a foundation for future work. Upcoming work will focus on solving a system of ODEs to predict the degradation of IFLs with and without intervention, and consequently assess the optimal allocation of resources to maximise the ecological and sustainability benefits of forest land within PNG.

Ultimately, this project seeks to aid TNC's goal of aligning environmental conservation with economic benefits. This contributes to the preservation of PNG's rainforests, minimising the effects of climate change and supporting sustainable development.

6. References

7. Appendices