A Multi-criteria Decision Framework for Marine Protected Area Policy

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Abstract

Marine Protected Areas have been shown to be effective policy tools that confer environmental, economic and socio-cultural benefits. However, as with any policy that affects multiple stakeholders, trade-offs must be made between agents with disparate interests and goals. This paper utilises Multi-Attribute Utility Theory to develop a multi-criteria framework intended to inform decision makers of optimal policies based on their subjective preferences. Using an Ecosystem Based Management approach where multiple uses, knowledge types and interactions between ecological components are considered, the user is presented with utilities generated through simulation across ecological, economic and social dimensions that demonstrate how optimal policies may change with their weighting preferences. Novel to applications in marine policy, this paper explores how these utilities change with temporal consumption preferences and time spans under consideration. An application of this framework to a theoretical study area illustrates the relevance of such a tool for marine spatial planning.

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Chapter 1

Introduction

New Zealand is a world leader in protecting its marine environment, establishing its first Marine Protected Area (MPA), the Cape Rodney-Okakari Point Marine Reserve, in 1975 (Davies et al., 2018). This small no-take MPA was implemented under the Marine Reserves Act 1971, and, for the greater part of half a century, most MPAs in New Zealand were introduced under this legislation (Rovellini and Shaffer, 2020). These MPAs were implemented with the purpose of preserving marine organisms and their environment for scientific study (Rovellini and Shaffer, 2020; Davies et al., 2018). However, developments in conservation science and the adoption of international agreements such as the United Nation's Convention on Biological Diversity (CBD) has seen the scope of MPA implementation widen significantly.

Today, greater emphasis is placed on the creation of MPA networks that cover representative ecosystems, protect ecosystem functions and services, are legally and socially viable, and facilitate human enjoyment (Convention on Biological Diversity, 2004). Thus, in order to meet its CBD obligations, New Zealand developed the New Zealand Biodiversity Strategy in 2000. Its latest iteration, *Te Mana O Te Taiao* Aoteroa New Zealand Biodiversity Strategy, sets ambitious conservation targets for 2030 and 2050 (Department of Conservation, 2020).

These frameworks aim to incorporate socio-cultural and economic elements into ecological goals. Consequently, New Zealand's 44 Marine Reserves have increasingly been implemented under a mixture of imperatives including scientific, recreational, educational, cultural, fishery value and ecosystem recovery objectives (Rovellini and Shaffer, 2020). However, the inclusion of multiple stakeholders with different, often conflicting, objectives makes the decision to implement an MPA, as well as an MPAs size and location, a complex issue for policy makers.

All decisions involve a decision maker's beliefs and values. While science can and should inform these beliefs, it is difficult to convey complex issues in a manner that is both understandable but informative (von Winterfeldt, 2013). Cost benefit analysis is often utilised as a tool that allows decision makers to evaluate between alternatives, but the reduction of advantages and disadvantages of regulatory policies to the monetary dimension results in the severe underestimation of social and environmental aspects (Department of Conservation, 2020; Hwang, 2016; Ackerman and Heinzerling, 2002). Coupled with the growing recognition that our socio-economic systems are embedded within functional ecosystems and habitats rather than independent sectors, governing bodies are increasingly adopting alternative methodologies to address these concerns.

This paper develops a multi-criteria decision framework intended for users to explore an array of MPA policies, presenting Pareto efficient outcomes (an outcome where one agent cannot be made better off without being at the expense of another). Using a spatio-temporal model, we track a theoretical marine habitat across ecological, economic and social dimensions. These outcomes are presented to the user as utility surfaces, where all possible combinations of the weightings are depicted, demonstrating how optimal policy decisions may change when components are weighted differently. Furthermore, other parameters are able to be altered, including discount rates, time horizons and delays to implementation, all of which affect decision making.

This framework provides decision makers with a tool that allows for easier comparisons to be made when implementing policy, and in future could be applied to existing locations, incorporating environmental and economic data. Its flexibility can allow changes to be made to the functional form of the relationships, additional components to be easily integrated and weightings elicited through expert opinion or stakeholder consultation.

Chapter 2

Background

2.1 Multi-Criteria Analysis

Decision-makers in the environmental field require methodologies that are able to incorporate non-market valuations (Melià, 2017). As mentioned in the introduction, many objections have been raised with the application of cost benefit analysis to policy decisions, particularly in the environmental sphere (Hansson, 2007; Ackerman and Heinzerling, 2002). Most of these issues stem from the distillation of a multi-dimensional problem to a uni-dimensional one, which, in the case of most cost benefit analyses, is the attempt to convert the incommensurable to dollars and cents. Known as scalarisation, this reduction often under-values environmental and social elements, and, at worst, the complexities in their estimation may lead to their omission.

Economists often rely on contingent valuation—a method of eliciting willingness to pay—in order to place monetary values on non-market goods and services. This can lead to somewhat awkward assertions, such as Jakobsson and Dragun (2001) estimating that local residents are on average willing to pay \$30 (AUD) per annum to prevent the extinction of the Leadbeater's possum in Victoria, Australia. This measurement was in turn converted into a \$40 million (AUD) lower bound on the conservation value of this species (Jakobsson and Dragun, 2001). While valuations such as these are certainly better than nothing, the implicit assumption that the sum of survey responses of local residents (that likely exhibit imperfect information, low levels of risk aversion, a high incidence of the free rider effect in addition to a high discounting of future benefits (Hwang, 2016; Hansson, 2007; Ackerman and Heinzerling, 2002)) determines the existence value of a species or an ecosystem leaves much to be desired.

In contrast, Multi-Criteria Analysis (MCA) is a framework that allows for the comparison of objectives that are not scalarised to a single dimension (Melià, 2017; Zionts, 1979). Since its formalised introduction in the field of operations research in the 1960s, the applications of MCA has expanded to the fields of engineering, information technology, economics and natural science (Melià, 2017; Hajkowicz, 2008). Emerging as a popular tool for evaluating alternative policies that involve multiple stakeholders, its applications to MPA policy are apparent.

There are many methods of 'solving' MCA problems, which vary widely in scope and technique.[1] They can be broadly categorised into the following: compensatory and outranking methods. These methods differ in that the former tend to quantify performance under each criteria and aggregate them into a single output for each decision alternative. As a consequence, poor performance in one outcome can be diminished by high performance in another. The latter do not allow for the perfect substitutability of criterion and instead evaluate alternatives pair wise, constructing a family of binary relationships between every combination of alternatives studied.

There are pros and cons to both of these approaches. By aggregating criteria into a single output, compensatory methods allow for the identification of an optimal action and a complete ranking of the action set. However, the assumptions of perfect substitutability and independence of criteria do not often hold in reality

[1] See Greco et al. (2016) for a comprehensive review of approaches.

(Matarazzo, 1991). On the other hand, outranking methods avoid the issue of substitutability, but as a result, are only able to discern between acceptable and unacceptable actions (Melià, 2017). In addition, outranking is highly sensitive to the initial action set, where the addition or subtraction of actions may change the relations dramatically.

The following section details Multi-Attribute Utility Theory (MAUT), the compensatory method used as a baseline for this project. We give an overview of this approach, its applications to environmental policy, criticisms of the method and our modifications applied to the framework to address these concerns.

2.2 Multi-Attribute Utility Theory

Most MAUT methods assume there exists an agent that makes decisions in the best interests of the public, and that this decision maker exhibits a utility function U that is comprised of sub-utilities that stem from the consequences of a decision (Greco et al., 2016). The utility associated with decision j (U_j), and its i sub-utilities ($u_{i,j}$) are cardinal measures with weak order preference relations defined by the following axioms:

- Preferences are *complete*:
  For every pair of options x and y, the decision maker either weakly prefers x (denoted x $\succeq$ y), weakly prefers y (y $\succeq$ x) or is indifferent (denoted $x \sim y$).
- Preferences are *consistent*:
  There are no pairs of outcomes such that outcome x is strictly preferred to outcome y (denoted $x \succ y$) AND outcome y is preferred to outcome x.
- Preferences are *transitive*:
  If $x \succ y$ and $y \succ z$, then $x \succ z$.

When these axioms are satisfied, our agent exhibits rational preference relations and is consequently able to rank all decisions in a unique order where decision a is preferred to decision b if and only if $U_a \succ U_b$. We then assume that the decision-maker chooses an alternative that maximises their expected utility.

The sub-utility functions arise from 'indicators' that measure the performance with respect to one of the objectives under consideration. These utilities are typically normalised between zero and one in order to allow for perfect substitutability and comparability. While linear utility functions are often used due to their simplicity, the functional forms of the utilities are flexible, and non-monotonic or piecewise functions can be employed. Another important consideration is the concavity of the function, as this can represent risk tolerance and introduce diminishing marginal utility.[2] Having utility functions that are catered to specific indicators adds to the realism of the model framework (Melià, 2017).

These sub-utilities are typically aggregated using a weighted sum to form the overall utility of the decision maker. This is represented as:

$$U_j = \sum_{i=1}^{n} u_{i,j} w_i \ , \qquad \text{such that} \ \sum_{i=1}^{n} w_i = 1 \tag{2.1}$$

where U_j is the utility of the decision maker caused by action j, $u_{i,j}$ is the sub-utility associated with the action j's impact on objective i, and w_i, is the weight given to the sub-utility u_i.

Combining these sub-utilities into a single measure necessitates the inclusion of subjective weights, which is one of the main criticisms of the MAUT framework (Nussbaumer et al., 2012; Munda et al., 1994). However, this is also touted as one of the strengths of MCA by its advocates. As mentioned previously, the act of decision making inherently involves one's subjective beliefs and thus the formalised inclusion of said beliefs allows a decision maker to explore how their optimal actions change with them (Hwang, 2016; von Winterfeldt, 2013; Munda et al., 1994).

[2]Diminishing marginal utility refers to the concept that the utility gained from each additional unit of consumption declines. It is a common and often realistic component of utility functions. For example, the utility one gains from eating their second cheese burger is greater than their fourteenth one.

2.3 Applications to Environmental Policy

There is a relatively large literature on the application of MCA to issues of environmental policy due to its ability to consider conflicting objectives in a less reductive way than traditional monetary valuation and research in this area has seen substantial growth over the last 20 years (Greco et al., 2016; Huang et al., 2011; Munda et al., 1994).

Underpinning most environmental MCA frameworks are three main objectives to be simultaneously maximised: ecological, economic, and socio-cultural system goals. Given that all three dimensions are often conflicting, with the concepts of ecological and economic sustainability oftentimes diametrically opposed, studies tend to explore acceptable Pareto-efficient compromises. In this context, emphasis tends to be placed on MCA developing a framework through which policy options can be evaluated and compared in a transparent and rigorous manner, rather than providing a single output that determines 'best' practice (Hajkowicz, 2008).

Due to the relative simplicity, flexibility, and the robustness of its approach in comparison to other MCA techniques, MAUT has emerged as a popular method to assess environmental policy (Cinelli et al., 2014; Huang et al., 2011). In a review of 312 papers that apply MCA to environmental sciences, Huang et al. (2011) found studies that applied the MAUT framework to a range of scenarios including air quality, water management, energy, emissions and waste management. Of the papers that applied multiple MCA methods to the same decision problem, they found that the rankings of the top alternatives were relatively robust (Huang et al., 2011).

While all of these studies address multiple objectives, and most conduct sensitivity analysis of the weightings and indicators, few address the time preferences of the decision maker, which can have drastic impacts on decision making (Greco et al., 2016). It is standard practice in economic analysis of the environment to incorporate time preferences in the form of discount rates (Pearce et al., 2006).[3] However, in a study examining forestry management policies in Finland, Pukkala and Miina (1997) develop a simulation-based forest stand model where—in addition to addressing multiple objectives—their MAUT framework accomodates the risk and time preferences of the decision maker.

The results of MAUT analysis need not be simple numeric outputs based on the overall utility of a policy either. Evaluating a rural landscape in southern Australia, Bryan et al. (2011) explored how social and ecological value were related spatially. Using a suite of indicators to measure the ecological and social value of the area, two spatially explicit layers were created for the respective objectives in order to see whether they exhibited any correlation. This spatially explicit presentation allows for the clear communication to decision makers of priority areas for conservation management (Bryan et al., 2011).

Applications of MCA to marine policy are scarce, though there exist a handful of examples of MAUT applied to other forms of fishery management and the identification of conservation strategies (Melià, 2017).

Exploring alternative fishery management policies in the Mediterranean, Rossetto et al. (2015) created a MAUT framework that assesses the ability of alternative policies to achieve a range of social, economic and ecological objectives. Eight indicators were selected to represent socio-economic and biological objectives: two economic (maintaining short and long term profits), two social (maintaining employment and job attractiveness), two about biological conservation (avoiding overfishing and maintaining spawning stocks) and two about biological production (maintaining yield and reducing discard rates). After constructing utility functions for these indicators, the authors used another MCA technique

[3]Discount rates, typically expressed as a percentage, represent how much an agent prefers consumption today versus a future period. While applying a discount rate to ecosystems or biodiversity may be problematic, it is an essential component of economic decision making. As a thought experiment, consider how many people would be indifferent between $100 today versus $100 in 50 years (an illustration of a 0% discount rate)?

(called the Analytic Hierarchy Process) to elicit weightings for the relative importance of each indicator through pairwise comparisons gathered from stakeholder groups.

Noticeably absent from these objectives are cultural values such as aesthetics, and it could be argued that the social and biological production measures lean more towards the economic dimension. Furthermore, the study examined a period of 14 years and did not conduct sensitivity analysis with respect to the time span (Rossetto et al., 2015). This is an important consideration with regards to intergenerational sustainability as shorter time spans favor extractive actions that may reduce the future viability of an ecosystem (Greco et al., 2016).

Drawing from novel approaches to MAUT analysis in other contexts such as the spatially explicit presentation of utilities from Bryan et al. (2011) and the incorporation of time preferences, uncertainty and simulation in Pukkala and Miina (1997) while also addressing the shortcomings of prior applications of MCA to marine policy, the following chapter details our methodological framework for evaluating MPA policy.

Chapter 3

Methodology

For a multi-attribute analytic framework to be successfully applied as a tool for decision makers, trade-offs must be made between model complexity and simplicity in order to balance realism with interpretability. Without a clear understanding about the procedures applied to arrive at a result, users may be apprehensive about using or simply reject a framework's conclusions (Hajkowicz, 2008; Bojórquez-Tapia et al., 2005). Thus, the contruction of a usable framework requires transparency and active steps to minimise the cognitive burden for the user in order to avoid being perceived as a 'black box' operation.

Consequently, the assumptions made by the creators of MCA frameworks with regards to the inclusion, exclusion and interactions between objectives must be clearly presented to the user and, while still maintaining accuracy, minimise its complexity.

Thus, we begin the discussion of our framework with its theoretical underpinnings. As depicted in Figure 3.1, we recognise that our social and economic systems are nested within the environmental system and as such are subject to its biophysical constraints. This conceptual framework of the economy was developed in the field of ecological economics, and is built upon the notion of strong sustainability. Strong sustainability—as opposed to weak sustainability—posits that man-made capital is not a substitute for natural capital, and as such they are non-compensatory (Greco et al., 2016; Daly, 2005).

Such an approach is particularly apt in the context of the marine environment, as human benefits such as tourism, fisheries, aquaculture, aesthetics and cultural appreciation derived from it are all directly linked to the health of the surrounding ecosystem (Department of Conservation, 2020; Greco et al., 2016). Daly (2005) illustrates a relevant example stating "strong sustainability recognises that more fishing boats are useless if there are too few fish in the ocean and insists that catches must be limited to ensure maintenance of adequate fish populations for tomorrow's fishers."

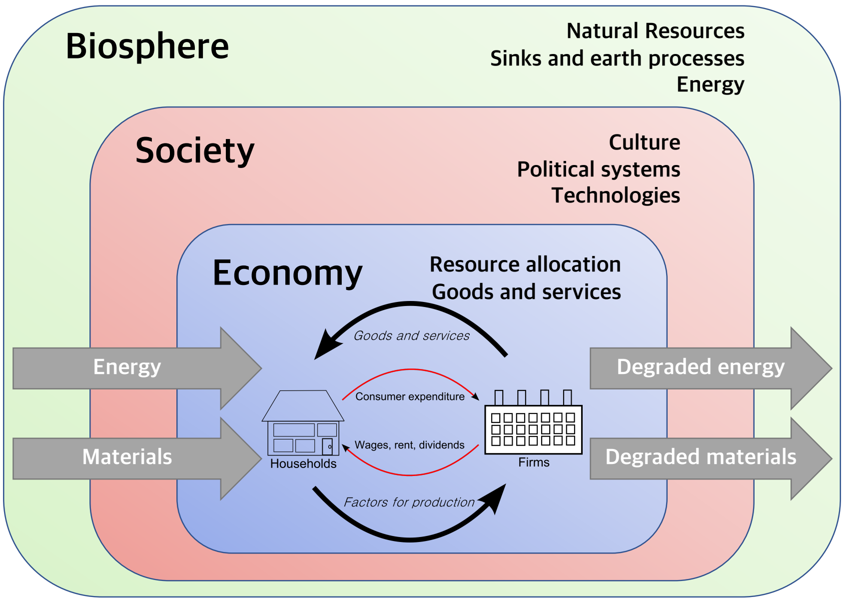

Figure 3.1: Depiction of an ecological-economic approach to the economy, where the human and economic systems are subsets of the biosphere, and as such are subject to its finite resource and energy constraints and capacity to handle their wastes. This figure features the image "Circular flow of goods and income" by Irconomics, licensed under CC BY-SA 3.0.

Thus, our MAUT framework considers distinct utilities for ecological, economic and social dimensions that are not aggregated. Instead, users are presented with three-dimensional utility surfaces for each policy under consideration. These surfaces represent all possible combinations of weights for each of the three dimensions and allow the user to identify policies that yield the highest utilities given their preferences.

The sub-utilities for each dimension are a mixture of spatially explicit and non-explicit indicators that are tracked over 100 simulations of the study area with a given policy intervention. Using a user-specified time span and discount rate, annual values are added, normalised and then combined into their respective dimensions.

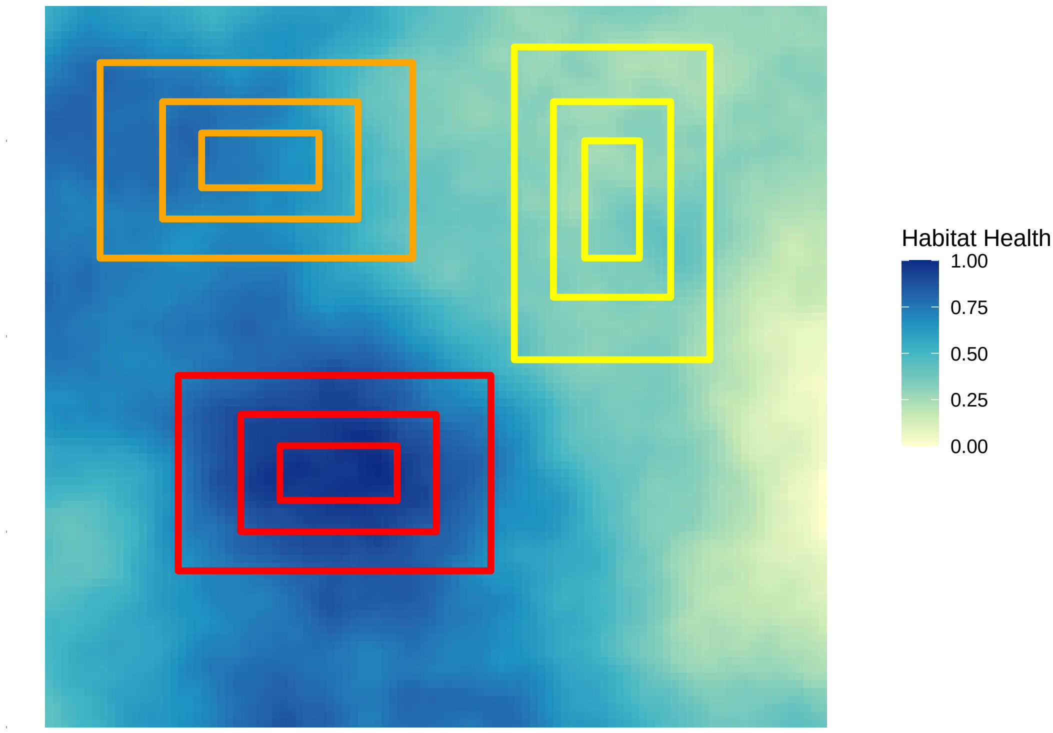

Figure 3.2: Depiction of our study site with the MPA locations and sizes. Yellow, orange and red boxes denote MPAs in locations of low, medium and high habitat health respectively.

In order to demonstrate how this framework may be applied, we explore a theoretical marine habitat encompassing an array of ecosystems that contributes to its local economy, supports socio-cultural values and provides important ecosystem services, all of which affect the well-being and quality of life in the wider area. Spatially explicit measures are tracked across a 100x100 unitless grid, but—given that we are considering the effects at a fisheries scale—can be thought of as representing a 100km^2 area.

This framework is used to explore eleven scenarios: small, medium and large no-take Marine Reserves that protect areas of high, medium and low levels of habitat health, in addition to MPA designation of the entire study site and no protections (see Figure 3.2). The small, medium and large Marine Reserves cover 105, 375 and 1000 square units representing a 1.05%, 3.75% and 10% protection of the study area respectively. No-take Marine Reserves prohibit any extractive activities within their boundaries such as commercial or recreational fishing and have been shown to be the most effective form of MPA protection (Sala and Giakoumi, 2018). However, the flexibility of this MAUT framework allows for other forms of MPA or fishery restrictions to be introduced in future analyses.

The following sections detail the indicators for objectives within the ecological, economic and social dimensions. These sub-utilities were chosen with consideration given to stakeholder goals as well as data quality and availability for data that often span different spatial scales, temporal ranges and resolutions.

3.1 Ecological Dimension

Habitat Health

Habitat health is a spatially explicit indicator that represents the ecosystem functionality of a grid cell. This measure is a proxy for the biotic and abiotic elements of an ecosystem which support fish populations and biodiversity. Examples may include benthic epifauna and flora, water clarity and oxygen levels. It takes values between zero and one, with one denoting full habitat health and zero representing a completely degraded ecosystem. This indicator forms the baseline of our ecological-economic model and was generated using a 2-D Perlin noise algorithm in order to create spatially auto-correlated values that appear representative of real world marine ecosystems. As Figure 3.3 illustrates, there are patches of high and low habitat health that represent areas with varying levels of productivity, nutrient availability and seafloor habitat structure, which may have been shaped by ocean currents or past disturbance.

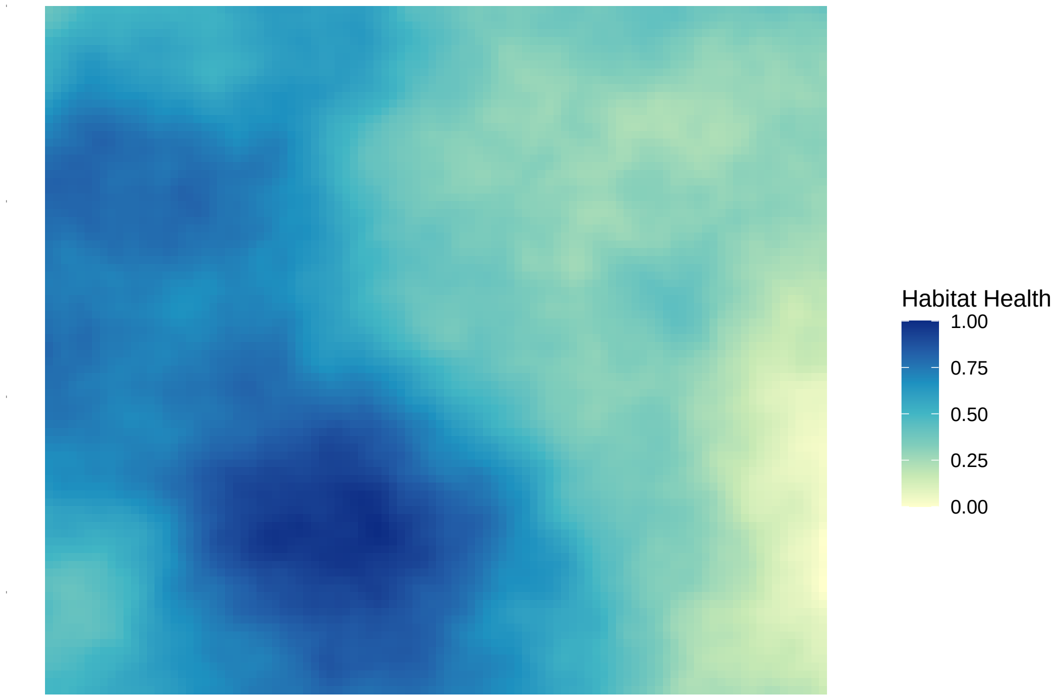

Figure 3.3: Habitat health of the study site at time zero. This layer was generated using a 2-d Perlin noise algorithm to emulate the spatial auto-correlation of real-world ecosystems.

In our model, the habitat health of a given cell is affected by the values of neighbouring cells in addition to the level of commercial fishing that occurred within it. This interaction was included as the most common method of commercial fishing in New Zealand is bottom trawling, which—due to its contact on the seafloor—has one of the largest anthropogenic impacts on benthic ecosystems and particularly on the epibenthos (Althaus et al., 2009; Thrush and Dayton, 2002).

Given the complexities of ecosystem dymamics, there is significant year-to-year variation in most biological measures. Therefore, to adequately reflect this inherent variability, the habitat health for each cell in subsequent periods is sampled from a normal distribution with standard deviation σ_{hh_t} that increases with habitat health, and mean μ_{hh_t} described by the following logistic growth model:

$$\mu_{hh_t} = \widetilde{hh}_{t-1} \cdot \left(1 + \left(\frac{1 - \widetilde{hh}_{t-1}}{20}\right)\right), \qquad 0 < \widetilde{hh}_{t-1} < 1 \tag{3.1}$$

$$hh_t \sim N\left(\mu_{hh_t}, \sigma_{hh_t}\right)$$

here, $\widetilde{hh}_{t-1}$ is the weighted mean[1] of neighbouring cells after the impact of commercial fishing during period $t-1$ has been incorporated.

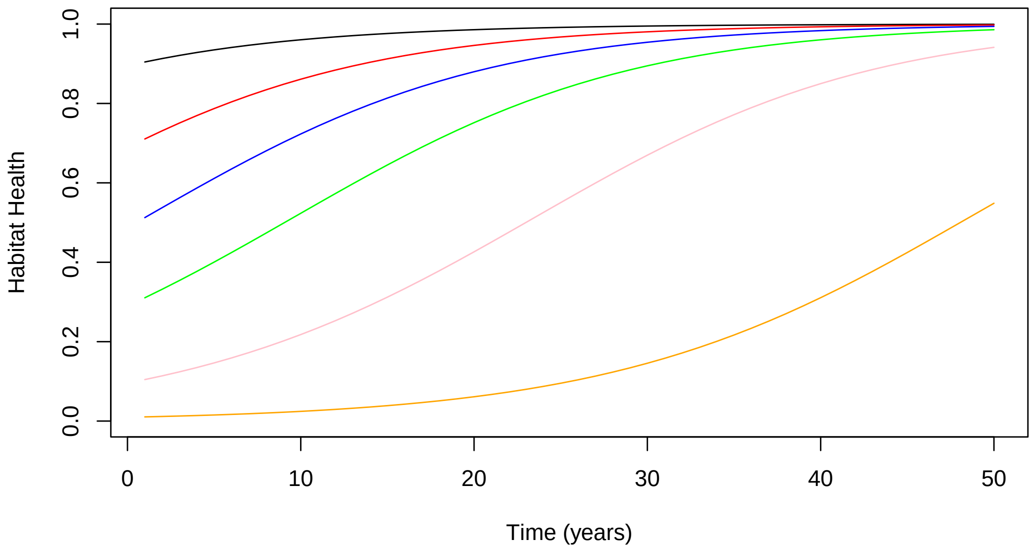

Figure 3.4: A non-stochastic demonstration of how habitat health changes through time with different starting values and no disturbance.

Logistic growth models are commonly used for modelling population dynamics or other biological properties of interest (Tsoularis and Wallace, 2002). Their

[1]With consideration given to edge effects, we constructed a function that determines the weighted mean of neighbouring cells in a 5x5 area surrounding the cell of interest. Cells closer to the centroid have higher weightings, with the centroid having the highest weighting. This function was applied to many of the spatially explicit indicators in this model. See the documentation for further details.

attractiveness lies in the fact that rates of growth are slow for low values, increase with intermediate values, then taper off as a maximum value is approached. Given that habitat recovery is sensitive to the extent of initial degradation and may take decades to centuries, in our model, annual increases are proportional to one minus the current habitat health divided by 20, capping the maximum possible annual increase at 5% (Duarte et al., 2020). These values are subsequently capped between zero and one.

Biodiversity

Biodiversity is another spatially explicit indicator that represents the number of species that can be observed in a grid cell. It is an integral component of environmental health and sustainability, as well as for human activities such as tourism, fishing and aesthetic appreciation (Feary et al., 2007). It is another measure that ranges between zero and one, with one representing the highest possible biodiversity. Given the positive association between biodiversity and habitat health (Thrush et al., 2002, 2001), starting values for the biodiversity layer were sampled from a normal distribution with a mean of the habitat health plus 0.1 (as even in the poorest conditions, some species are likely to be observed (Norkko et al., 2012)) and subsequently smoothed using the weighted mean of neighboring cells (see Figure 3.5).

Similar to habitat health, biodiversity is affected by the values of neighbouring cells but is negatively impacted by both commercial and recreational fishing. While recreational fishing is generally much less intensive than commercial fishing and uses gear that itself does minimal damage to habitats (as the most common technique is angling), there is a growing recognition of its potential indirect impacts on biodiversity (Lewin et al., 2006), hence its inclusion.

In order to integrate inherent biological variation, the values for each cell in subsequent periods are sampled from a normal distribution with standard deviation σ_{biod_t} that increases with biodiversity and mean μ_{biod_t} given by the following logistic growth model:

$$\mu_{biod_t} = \widetilde{biod}_{t-1} \cdot \left(1 + \left(\frac{1-(hh_{t-1}+\widetilde{biod}_{t-1})/2}{20}\right)\right), \quad 0 < \widetilde{biod}_{t-1} < 1 \tag{3.2}$$

$$biod_t \sim N\left(\mu_{biod_t}, \sigma_{biod_t}\right)$$

where $\widetilde{biod}_{t-1}$ is the weighted average biodiversity of surrounding cells after commercial and recreational fishing impacts are incorporated and hh_{t-1} is the habitat health value of the same cell. Thus, the growth of biodiversity is dependent on the mean of the biodiversity and habitat health. Again, the growth rate is moderated in order to produce realistic values, yielding a maximum possible growth rate of 5%.

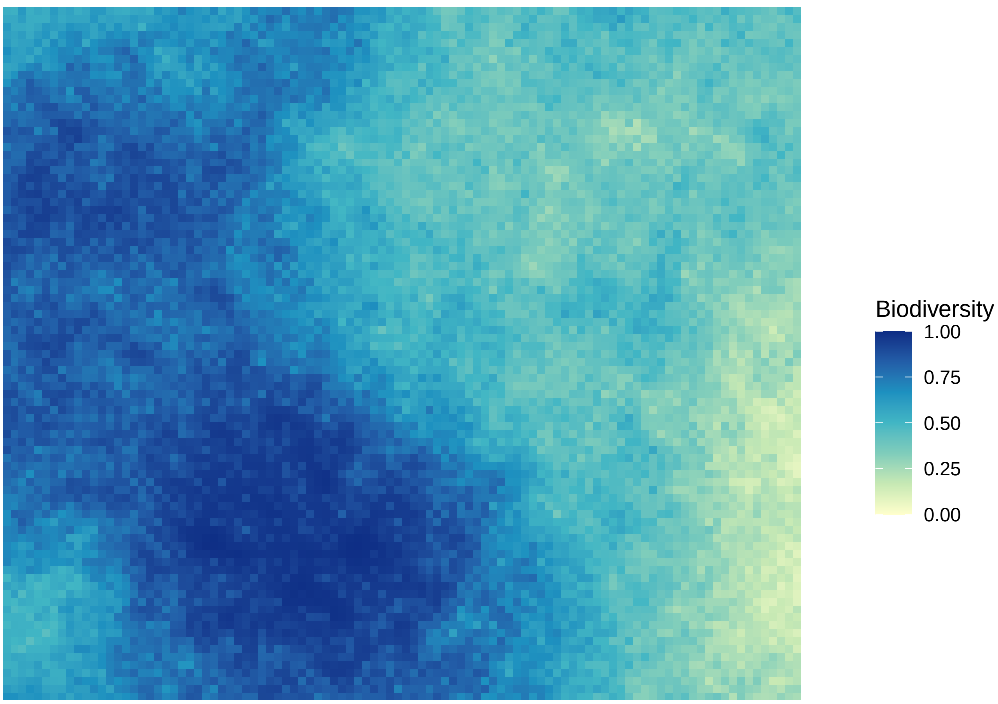

Figure 3.5: Biodiversity of the study site at time zero. Values were generated from the habitat health layer, but biodiversity in low habitat health regions are typically higher.

Adult Fish Biomass

Adult fish biomass is the final indicator in the ecological dimension. It is another spatially explicit layer that represents the weight of catchable fish in a grid cell. Its values range from zero to one, with one representing the carrying capacity for adult fish in a cell. It is an important proxy of ecosystem health given that a healthy ecosystem is required to support large fish populations. Moreover, adult fish are integral for the generation of spawning stock and juvenile fish that in turn sustain these populations.

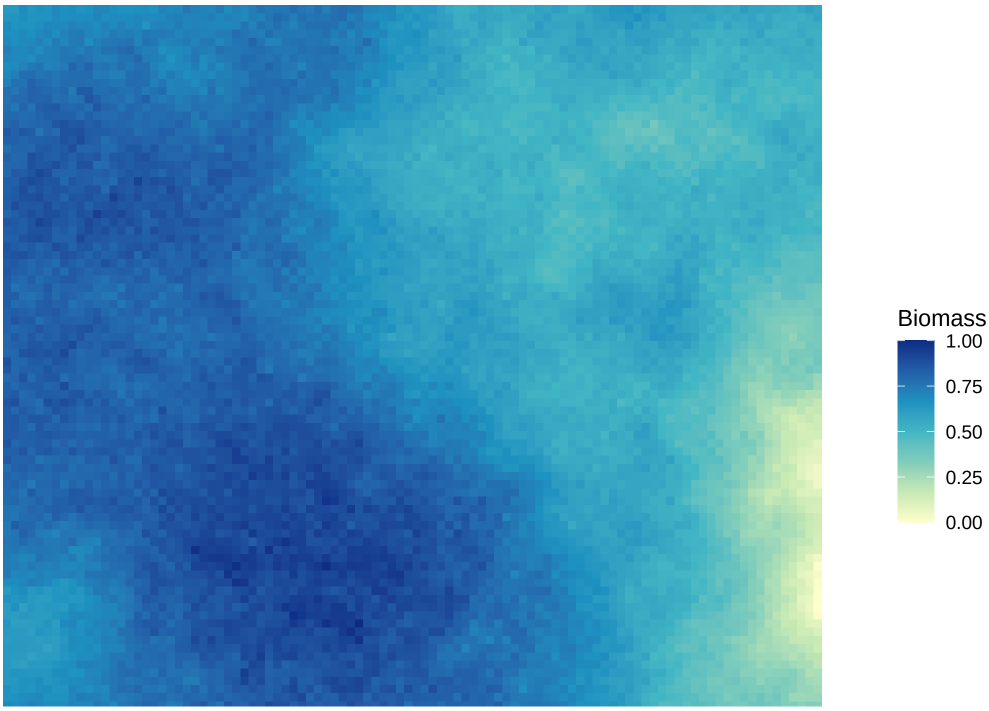

Figure 3.6: Adult fish biomass of the study site at time zero. Compared to the habitat health and biodiversity layers, it is more diffuse and uniform to represent their mobility.

Due to their dependence on healthy ecosystems, the initial values were sampled from a normal distribution centred at the log-transformed value of habitat health. These values were then smoothed using the weighted mean of neighbouring cells and re-normalised to fall between zero and one. The log transformation was chosen so that biomass first increases relatively sharply with habitat health, then begins to diminish with higher values. This results in more diffuse values in comparison to the habitat health and biodiversity layers (see Figure 3.6).

Fish tagging has shown that individuals can travel from 5 to 150km based on species behaviour (Di Lorenzo et al., 2016). Consequently, it is important to incorporate the weighted means to simulate the dispersion of individuals from high to low density cells. In addition, adult fish biomass is directly affected by both commercial and recreational fishing.

Given these considerations, the biomass of subsequent periods is drawn from a normal distribution with standard deviation σ_{biom_t} that increases with biomass and mean μ_{biom_t} from a modified version of the Gordon-Schaefer bio-economic logistic growth model typically used in fishery analyses:

$$\mu_{biom_t} = \widetilde{biom}_{t-1} + \frac{hh_{t-1}}{3} \cdot \widetilde{biom}_{t-1} \left(1 - \widetilde{biom}_{t-1}\right), \quad 0 < \widetilde{biom}_{t-1} < 1 \tag{3.3}$$

$$biom_t \sim N\left(\mu_{biom_t}, \sigma_{biom_t}\right)$$

where $\widetilde{biom}_{t-1}$ is the weighted mean of neighbouring cells after commercial and recreational fishing has been incorporated. Compared with the growth models for habitat health and biodiversity, biomass introduces an additional parameter; the intrinsic growth rate. Typically used to represent the generation times of particular species, in our model, the intrinsic growth rate is determined by the habitat health of a cell at time $t-1$. This results in higher rates of biomass growth in areas with high habitat health. In a study using fishery data as experiments to investigate bio-economic model parameters, Jensen et al. (2012) found that the intrinsic growth rate ranged from 0.06 to 1.33 with a mean of 0.38. Consequently, we divide the habitat health by three in order to moderate the growth rate to realistic levels.

3.2 Economic Dimension

Commercial Fishing

Commercial fishing is a spatially explicit layer representing the total biomass caught in a grid cell during one year. The fishing industry is New Zealand's fifth largest export commodity by value, generating \$1.2—\$1.5 billion annually from an average of 434 million kg of commercial catch and is consequently an important indicator for the economic dimension (Williams et al., 2017).

Fishers respond to incentives in terms of both changing conditions, such as the decline of certain fish stocks, and to regulatory changes, in order to maintain profitability (Stephenson et al., 2018). Consequently, well-documented phenomena such as displacement, which refers to the redistribution of fishing effort from MPAs to the surrounding area, and 'fishing the line' of MPA boundaries, must be incorporated into modelling fishing behaviour (Grüss, 2014; Kellner et al., 2007). In addition, reasonable assumptions about target catch rates over the time span under consideration must be made.

Hence, our commercial fishing behaviour model begins prior to a simulation being run. Firstly, an optimal target catch rate λ_C that maximises the present value of total catch over the user-specified time span and discount rate is calculated:

$$catchPV = \sum_{i=0}^{t} \frac{biom_t \cdot \lambda_C}{(1+\delta)^t} \tag{3.4}$$

where $catchPV$ is the present value of catch over the time span with discount rate δ, and $biom_t$ is the biomass at time t. This model incorporates imperfect information, with commercial fishers basing their decision on the behaviour of a single cell that follows the non-stochastic logistic growth model:

$$biom_t = biom_{t-1} + \frac{1}{3} biom_{t-1} \cdot (1 - biom_{t-1}) \tag{3.5}$$

here, the intrinsic growth rate does not depend on habitat health, and is at the higher end of the true adult fish biomass indicator.

Equipped with a target catch rate that maximises the present value of adult fish biomass harvested, commercial fishers in our model aim to harvest fish from above the 70^{th} percentile of adult fish biomass cells in a given year i.e. the commercial trawl footprint covers around 30% of the fishable area each period. Excluding the first year, the mean prior catch for each cell is also factored into this decision to fish making it more likely that activity will occur in areas in which they have previously found success (Stephenson et al., 2018). The 70^{th} percentile value only considers areas that are open to fishing, and thus cells within MPAs are excluded. As a result, fishing effort is mainly displaced outside of the MPA boundaries.

In cells that have been designated to be fished through the process described above, the commercial catch is sampled from a normal distribution with a mean of the biomass of the cell multiplied by the target catch rate λ_C and a variance that increases with the biomass.

The impacts of commercial fishing on the ecological dimension are manifold. Firstly, the catch for each cell is directly subtracted from the adult fish biomass indicator each period. Due to its aforementioned impacts on biodiversity and habitat health, the commercial catch for each cell divided by two is also subtracted from both of these layers. Given the slower growth rates of biodiversity and habitat health, this decision reflects the less immediate, but still consequential, impact commercial fishing has on them.

Fishing Industry

The fishing industry is a significant contributor to the world economy, with an estimated 260 million people involved both directly and indirectly in global marine fisheries and around 20% of the world population depending on fish as their primary source of protein (Teh and Sumaila, 2013). In our model it is a non-spatially explicit indicator that represents the multiple flow-on benefits of commercial fishing on the economic dimension. It reflects indirect economic contributions such as employment related to the processing and distribution of landed catch in addition to other industries such as fishing vessel contruction and maintentance (Barbera, 2012).

To represent the diminishing marginal benefits related to the amount of commercial catch, the values for our fishing industry indicator are generated from the log-transformed sum of total biomass caught per year.

Tourism Industry

Prior to the COVID-19 pandemic, tourism was New Zealand's largest export industry, with tourism and tourism-adjacent industries contributing to nearly 10% of the nation's gross domestic product in 2019 (Stats NZ, 2020). Nature-based tourists, referring to visitors that participate in at least one nature-based activity, comprise 70% and 22% of international and domestic tourists respectively (Barbera, 2012). Thus it is evident that this large sector of the economy is heavily reliant on the beauty and consequently the health of New Zealand's ecosystems.

Yet, economic valuations of marine ecosystems often overlook the contribution of tourism and as a result severely underestimate them (Lange and Jiddawi, 2009). In our model, the tourism industry is another non-spatially explicit indicator. Marine tourism encompasses many activities such as recreational fishing, sailing, SCUBA diving, whale watching and other scenic tours. Many other adjacent industries are also affected by these activities such as accomodation, retail and hospitality. To represent their dependence on the ecological dimension, values for the tourism industry indicator are composed of the mean values of the habitat health, biodiversity and biomass cells, the amount of recreational fishing catch (normalised between zero and one), and megafauna sightings for each year.

3.3 Social Dimension

Aesthetics

Aesthetic value forms some of our closest socio-cultural connections to our surroundings and is an important component of the non-material benefits of an ecosystem (Tribot et al., 2018; Swaffield and McWilliam, 2013). Yet, due to the inherent subjectivity and the difficulty of its characterisation, aesthetic preferences are often absent from our valuations of them. The aesthetics of pristine marine environments is an important source of tranquility, art inspiration, and, for many indigenous communities such as Māori, their wellbeing or vital essense (Department of Conservation, 2020; Fletcher et al., 2014).

Ultimately bounded by human perception, aesthetic appreciation of environmental and ecological phenomena occur on many scales, from seeing a single individual of a species, to hearing the rustling of leaves in a stand of trees, to the awe of staring at sunlight glistening in a bay (Tribot et al., 2018). Studies have shown that the aesthetic preferences of a landscape are correlated with proxies of ecological health, and that environmental degradation can have severe negative cultural impacts (Tribot et al., 2018; Fletcher et al., 2014; Junker and Buchecker, 2008).

Taking these factors into consideration, aesthetics is a non-spatially explicit indicator comprised of the mean of the habitat health and biodiversity indicators as well as the megafauna sightings for each year. Consequently, this indicator is adversely affected by the level of commercial and recreational fishing.

Megafauna Sightings

Marine megafauna, referring to large-bodied organisms such as whales, dophins, turtles and sharks, are species that exhibit disproportionate social, economic and cultural significance (Pimiento et al., 2020). They are often charismatic species that draw attention to and generate funding that supports marine conservation efforts (Krause and Robinson, 2017). In addition, they play a large role in the aesthetic appreciation of an ecosystem and consequently the tourism industry, where activities such as whale watching and recreational diving directly depend on their abundance.

Megafauna appear in the mythology, storytelling and beliefs of many cultures. For Māori, whales were seen as guardians of high ranking chiefs and are believed to be the children of Tangaroa, the god of the oceans (Fletcher et al., 2014; Gillespie, 1999). Moreover, whales and dolphins were an important source of food and provided prized materials for tools and ornaments. Consequently, they command a high cultural reverence, being deemed taonga or treasure (Department of Conservation, 2020).

As with many other marine species, industrial fishing, whaling and sealing beginning in the 19^{th} century saw the substantial decline of megafauna populations worldwide (Mazzoldi et al., 2019). While concerted conservation efforts beginning in the mid-20^{th} century have seen populations slowly recover, megafauna are still routinely caught as bycatch by commercial trawlers and are increasingly disrupted by vessel activities (Mazzoldi et al., 2019).

In our model, megafauna sightings is a non-spatially explicit indicator representing their observation frequency in the study area. Given that megafauna tend to be highly transient, this indicator does not directly depend on the ecological dimension. Instead, it is adversely affected by the amount of commercial fishing which reflects bycatch, boat strikes and disruptions to migratory patterns caused by vessel activities. Megafauna sightings takes a value between zero and one, with one denoting their maximum observation frequency. Values for each period are calculated as one minus the commercial fishing impact, a value sampled from a normal distribution centred at the total commercial catch divided by 1000.

Recreational Fishing

Recreational fishing is a popular pastime for New Zealanders, with an estimated 19.5% of the population participating annually (Barbera, 2012). Besides the direct benefit of harvesting food for consumption, there are a range of intangible benefits that individuals derive from fishing such as the sport of fishing itself as well as spiritual or cultural enrichment.

However, given population growth, the increasing affluence in developed countries resulting in greater leasure time, and technological advancements in fishing gear such as fish finders, the impact of recreational fishing on biodiversity and fish stocks is increasing (Holder et al., 2020; Lewin et al., 2006). Moreover, studies have documented that fishing pressure surrounding MPAs have resulted in the severe decline of populations both within and outside of their boundaries (Haggitt and Freeman, 2014).

Addressing these socio-cultural benefits while incorporating its impact on the ecological dimension, recreational fishing is a spatially explicit indicator representing the amount of adult fish biomass caught per year. In order to address time preferences, recreational fishing intensity utilises the optimal target catch rate from the commercial fishing indicator.

In our demonstration of the model framework, recreational fishing occurs on a much smaller scale than the commercial fishing industry, though this can vary based on the study site, with areas such as the Hauraki Gulf exhibiting roughly equal proportions of recreational and commercial catch (Barbera, 2012). As a result, the recreational optimal target catch rate λ_R is one tenth of the commercial target rate λ_C. The extent of recreational fishing is also smaller, aiming to harvest fish in areas that are above the 90^{th} percentile of adult fish biomass cells outside of MPA boundaries each period i.e. recreational fishing occurs in around 10% of fishable cells in a given year. As with the commercial fishing indicator, the mean prior catch in each cell is factored into this decision to fish in subsequent periods in order to reflect fisher behaviours.

Recreational catch in cells that are designated to be fished are drawn from a normal distribution with a mean of the adult fish biomass multiplied by the recreational catch rate λ_R, with a variance that increases with biomass. To represent the impact of recreational fishing on the ecological dimension, catch is subtracted from the biomass and biodiversity indicators. To reflect the less direct impact on the slower growing biodiversity values, recreational catch is halved before it is incorporated.

Thus, the weighted mean values for habitat health, biodiversity and adult fish biomass described in Equations 3.1, 3.2 and 3.3 are characterised as follows:

$$
\begin{aligned}
\widetilde{hh}_{t-1} &= \omega\left(hh_{t-1} - \frac{biom_{t-1}\cdot\lambda_C}{2}\right)\\
\widetilde{biod}_{t-1} &= \omega\left(biod_{t-1} - \frac{(biom_{t-1}\cdot\lambda_R) + (biom_{t-1}\cdot\lambda_C)}{2}\right)\\
\widetilde{biom}_{t-1} &= \omega\left(biom_{t-1} - biom_{t-1}\cdot\lambda_R - biom_{t-1}\cdot\lambda_C\right)
\end{aligned}
$$

where ω represents our weighted mean function. Commercial and recreational catch are computed in isolation, thus making it possible for these values to exceed the biomass in a given cell. To avoid this issue, recreational catch is first subtracted from the biomass cell. If this value is less than zero, recreational catch is replaced with the biomass value, completely depleting the biomass of the cell. Commercial catch is then subtracted from the remaining biomass and the same process is applied.

3.4 Simulation Model

Using the indicators described above, our framework evaluates policy alternatives through simulations of the study area using the user-specified time span and discount rate. This section describes how these indicators are combined to create the final outputs of the model and how they can be utilised to aid decision making.

Discount Rate and Time Horizon

As mentioned previously, these factors have important consequences on the behaviour of individuals and thus outcomes in the ecological, economic and social dimensions. Thus, our framework introduces novel applications of both discounting and time horizons to multi-criteria decision making for MPA policy.

The incorporation of discounting is necessary to realistically model economic behaviour, however, its application to environmental and social consequences can trivialise the long-term impacts of a decision (Hwang, 2016; Ackerman and Heinzerling, 2002). As Figure 3.7 depicts, the same utility received 50 years in the future with 8% discounting yields a benefit that is less than 2% of its value if received in the present, and even a 2% discount rate results in a 63% reduction.

What follows is that, as discount rates are increased, an agent's proclivity to over-exploit a resource also increases, given that the consequences which stem from such a decision contribute increasingly small amounts to their net present value being maximised. Moreover, since the impacts of conservation policy may take decades or even centuries to materialise, even if a policy were to benefit the agent in the long-run, the short-term benefits of harvesting a resource tend to outweigh any benefits that arise from reducing yields in the short-term.

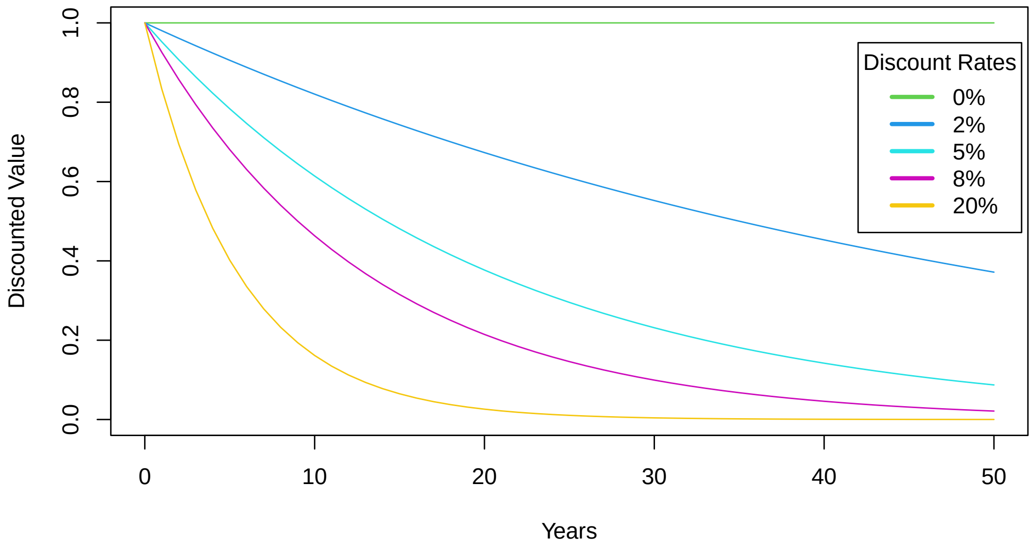

Figure 3.7: A demonstration of the effects of time and discount rates. In each period, the numeric value is 1, with the corresponding discount rate applied.

These issues are amplified by using short time horizons. Reducing the time period over which the costs and benefits of a policy are evaluated results in the undervaluing of ecological benefits and can overstate the negative impacts on stakeholders regardless of the discount rate involved (O'Mahony, 2021). Using our model indicators as an example, a cell within a Marine Reserve (and thus not subject to disturbance from commercial fishing) with a starting habitat health of 0.1 will take around 50 years to reach its maximum value of 1. Cutting our time horizon to 20 years, this cell is likely to reach a value around 0.4 due to its initial low growth rates and thus the full effect of protection will not be realised in the estimation of the policy's ecological benefits. Conversely, a Marine Reserve that reduces the fishable area by 10% immediately reduces commercial fishing but may lead to greater fish harvests after 25 years. When using a 20 year window, the positive benefits for the commercial fishing industry are completely excluded when estimating the impact stemming from this policy. Consequently, decision making based on shorter time spans also increase the propensity to act unsustainably as fewer future periods are considered.

With these factors in mind, our model simulations utilise the user-specified time horizon and discount rate in order to determine optimal target catch rates for recreational and commercial fishing, λ_R and λ_C, and values for the economic dimension are subsequently discounted according to this rate. For the reasons outlined above, for higher discount rates and shorter time horizons, target catch rates are higher, resulting in a greater rate of biomass depletion.

The decision to not discount the ecological and social dimensions was made to reflect the principle of intergenerational equity. Using a 0% discount rate ensures that the wellbeing of ecosystems and society in present and future periods are weighted equally and thus long-term effects are not undervalued. Given that the model presents distinct, non-compensatory utilities for the ecological, economic and social dimensions, the application of different discount rates allows for the inclusion of realistic consumptive behaviour without being at the expense of ecological and cultural objectives and thus better reflects conservation and societal goals.

Model Output

A user of this tool selects the MPA policy interventions they would like to investigate, such as small, medium and large MPAs over areas of high habitat health, and specify the discount rate and time horizon they wish to apply to the analysis.

For each policy scenario, 100 simulations of the study area are run in order to incorporate the variation within the ecological-economic model. In a single simulation, the total benefits associated with each indicator over the time span are stored, with discounting applied to indicators within the economic dimension. The mean value of each indicator across the 100 simulations is then calculated to reflect the average sub-utility incurred by the policy intervention and is subsequently normalised to fall between zero and one.

The values used to normalize the indicators were found by taking the maximum utility of each indicator from simulations over 50 years using a 0% discount rate for the economic dimension across every MPA policy. These theoretical maxima are utilised solely to allow for the indicators within dimensions to be compensatory, and thus the values themselves should not be overinterpreted.

The ecological, economic and social dimension values are then created by taking the mean of the normalised indicators in their respective dimensions. Thus, the final result for each policy with a given discount rate and time horizon are three values between zero and one representing the utilities for the ecological, economic and socio-cultural systems.

The values for a policy are presented to the user as three-dimensional utility surfaces that represent all possible combinations of weighting the three dimensions. This allows decision makers to identify optimal policies given their subjective preferences as well as illustrate how optimal policy may change when greater weight is given to one dimension over another. These surfaces are calculated by multiplying the ecological, economic and social dimension values of a given policy intervention by vectors that, in combination with one another, contain many possible combinations of the weightings, all of which add to one.

The utility surfaces provide an intuitive way to compare and evaluate policies. For example, Pareto dominated policies, referring to policies where all dimension scores can be improved without reducing another and will therefore not be chosen by a rational decision maker, will appear as surfaces that do not intersect and are therefore completely below the Pareto dominant policy. Boundaries where different policies intersect depict regions that yield different optimal policies. For example, as one places greater weight on the social dimension, the policy that yields the greatest combination of utilities may shift from a large marine reserve to the protection of the entire study area.

Chapter 4

Results and Discussion

Utilising the New Zealand Treasury's recommended 5% discount rate for general cost benefit analysis and a 50 year time horizon, we explore how our decision framework can be applied. For brevity, we investigate five policy scenarios: business as usual (where no MPA is implemented), small, medium and large Marine Reserves over an area of high habitat health, and designation of the entire study site as a Marine Reserve.

We use these results to demonstrate how this tool may be used to inform decision makers of optimal policy, as well as explore the impacts of these policies on the individual indicators. Later, we repeat the analysis using 10 and 30 year time horizons in addition to 0% and 12% discounting in order to explore the sensitivity of the model framework.

4.1 Optimal MPA Size

Figure 4.1 depicts the utility surfaces generated from our model simulations. The economic dimension values are significantly smaller than those of the ecological and social dimensions due to the 5% discounting applied and the normalisation values being derived from simulations with 0% discounting.

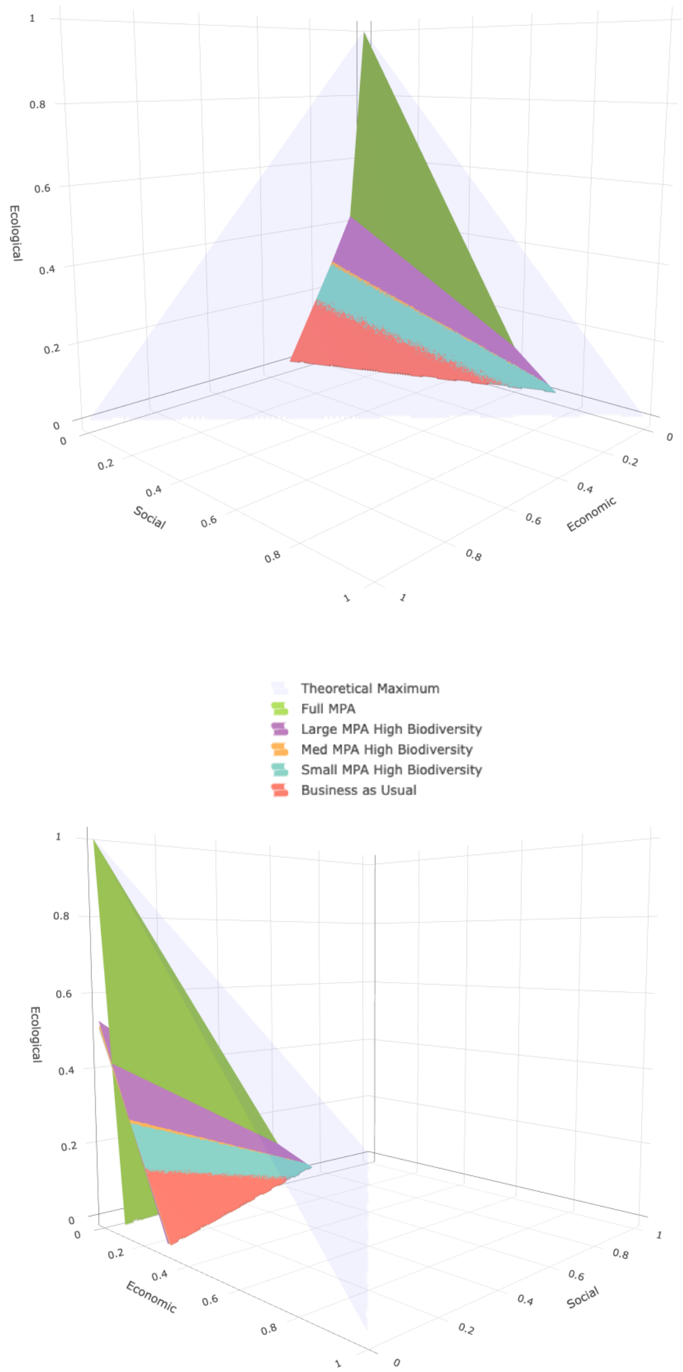

Figure 4.1: Utility surfaces comparing five policy scenarios with a 50 year time span and 5% discount rate from two angles. The axes of the graphs represent the ecological, economic and social dimension values associated with each policy multiplied by combinations of subjective dimension weightings.

Unsuprisingly, when the ecological dimension is given the highest weighting, protection of the entire study site yields the highest overall utility. This is due to the fact that this policy prohibits any recreational or commercial fishing and thus the ecological dimension indicators are undisturbed (see Figures 4.3, 4.4 and 4.5). However, this yields very low values for the economic dimension as the commercial fishing and fishing industry indicators are reduced to zero. Given that the tourism industry benefits from the health of the ecosystem, under full MPA protection this indicator increases continually over the 50 year period, though it is moderated by the fact that recreational fishing—another component of this indicator—is also zero under this policy. Full MPA protection yields high social dimension values due to the aesthetics and megafauna indicators both benefitting from the absence of fishing. However, the fact that recreational fishing is prohibited under this policy results in lower values in comparison to more compromising alternatives.

As the weighting of the economic dimension is increased, the optimal policy shifts from large, medium, and small MPAs to finally business as usual. This is directly linked to the reductions in fishable area caused by these policies. As mentioned above, the increase in values for the tourism industry indicator that directly result from MPA protection are only realised as the ecosystem recovers. In the absence of fishing pressure, adult fish biomass approaches its carrying capacity in about 20 years, however, biodiversity and habitat health take considerably longer, reaching their maxima around the end of the 50 year window (see Appendix, Figure A.1). As a result, the benefits of MPA protection are not fully realised until the end of the study period. By this time, the utilities are heavily discounted in the calculation of net present value and thus have a minimal impact on the overall utility of the economic dimension (see Figure A.4).

When greater weight is placed on the social dimension, both the small and large MPAs yield the highest utilities. This is likely due to the fact that the social dimension contains the extractive activity of recreational fishing in addition to the more passive indicators aesthetics and megafauna sightings, and thus the ability to both preserve the ecosystem and recreationally fish is preferred. Optimal policies for high weightings of the social dimension are more sensitive to the weightings given to the other dimensions as demonstrated in Figure 4.1. Compared to the ecological and economic dimensions where high weightings point to full MPA protection and business as usual as optimal policies regardless of the other (low) dimension weights, the optimal utility surfaces are much narrower for the social dimension, leaning towards large and full MPA protection when the ecological dimension has a high weighting, and conversely small and business as usual policies for higher economic weightings.

The fact that the orange utility surface in Figure 4.1 is almost completely obscured by the other policies demonstrates that the medium sized MPA is nearly Pareto dominated. This suggests that any of the alternatives lead to better outcomes regardless of ones weighting preferences. However, we can also see that the business as usual, small, medium and large MPA policies yield very similar utilities in comparison to full MPA protection. We explore in further detail the possible reasons for this by examining the individual indicators.

Figure 4.2 shows the distribution of indicator values from simulations under each policy treatment. The large MPA tends to have substantially different indicator values, whereas there is considerable overlap amongst the other policies. Differences between the large MPA and the other policies are most distinct in the habitat health, commercial fishing, fishing industry, tourism industry and recreational fishing indicators, where the distribution of the large MPA's simulation values are often several standard deviations away from the other policies. On the other hand, the medium, small and business as usual policies are almost indistinguishable in the adult fish biomass and megafauna indicators.

Given that the small and medium MPAs protect 1.05% and 3.75% of the study area respectively, this may suggest that the sizes of these smaller MPAs are

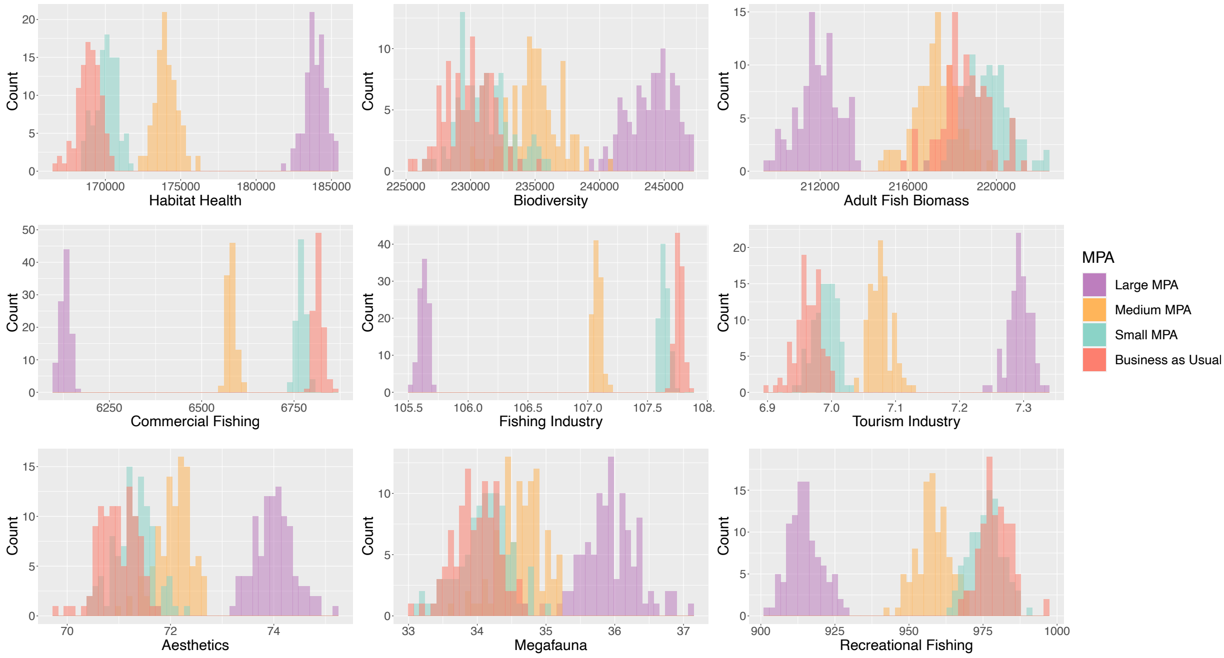

Figure 4.2: Histograms comparing the distributions of indicator values for the policies, each drawn from 100 simulations of the study site. Full MPA protection was excluded as its values far exceed the others.

insufficient to protect marine ecosystems. This is particularly the case with the small MPA, where, with the exception of the economic dimension, the distribution of indicator values are nearly identical to the business as usual policy. To explore this further, we investigate the temporal trends in these indicators over the 50 year period.

Figures 4.3, 4.4 and 4.5 depict spatio-temporal trends of the ecological dimension indicators. Evident from the business as usual policy, recreational and commercial fishing activity have severe impacts across all three indicators, causing relatively uniform reductions in values across the entire study site. Biodiversity (Figure 4.4) in particular shows the lasting impact of fishing, where the region that exhibited the highest ecological dimension values at time zero exhibits the lowest biodiversity at 50 years.

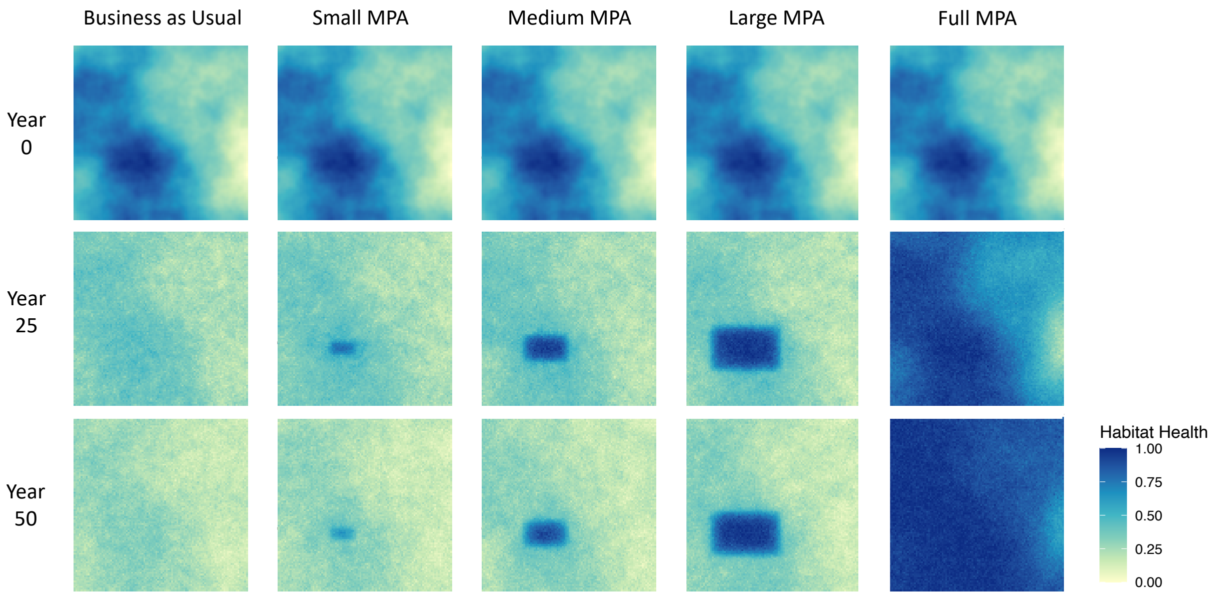

Figure 4.3: Habitat health values taken from simulations under the policy interventions examined. Each row presents the spatially explicit habitat health values at a certain point of time, while columns denote different policies.

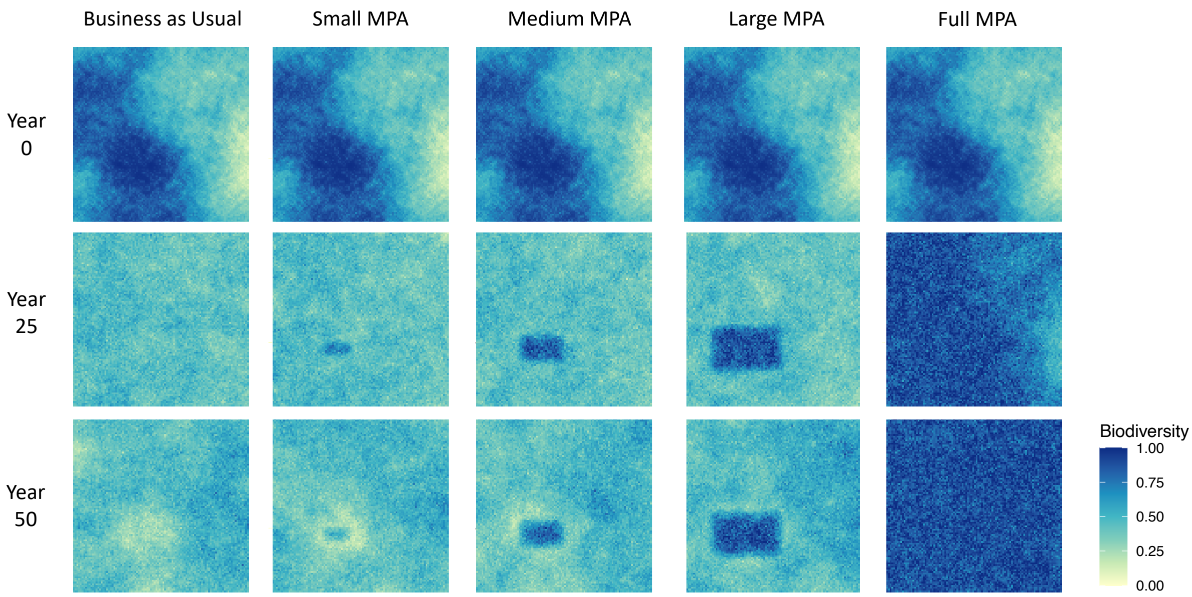

Figure 4.4: Biodiversity values taken from simulations under the policy interventions examined. Each row presents the spatially explicit biodiversity values at a certain point of time, while columns denote different policies.

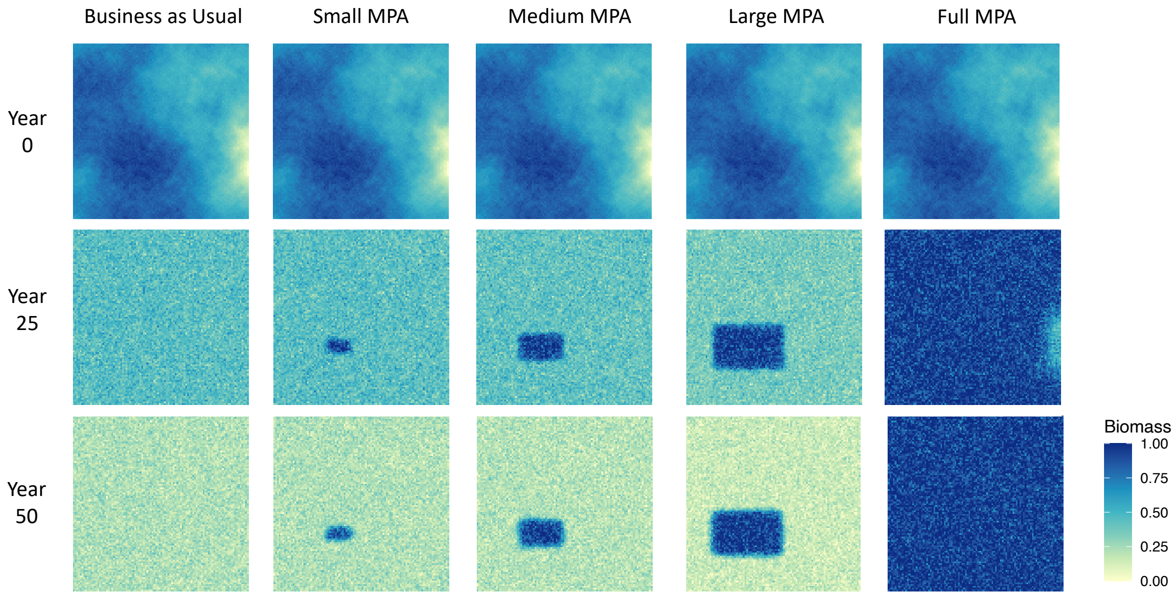

Figure 4.5: Adult fish biomass values taken from simulations under the policy interventions examined. Each row presents the spatially explicit biomass values at a certain point of time, while columns denote different policies.

The absence of disturbance associated with the cessation of commercial and recreational fishing within MPA boundaries leads to distinctly higher values for the habitat health, biodiversity and adult fish biomass indicators compared to their surroundings. However, the benefits that stem from this protection are clearly scale-dependent, with the habitat health and biodiversity indicators in particular having higher values within the large and full MPAs in comparison to the small and medium MPAs. Due to the impact of neighbouring cells on the values of all three indicators as detailed in the methodology, the spillover damage in the surrounding areas adversely affects the MPAs themselves, with their boundaries exhibiting lower values than the centres. The benefits of the small MPA are unable to compensate for these spillover effects and its habitat health and thus its biodiversity indicator values are barely higher than the unprotected area.

These scale-dependent effects are amplified through time, with the benefits of MPA protection in the small MPA becoming negligible for the habitat health and biodiversity indicators (Figures 4.3 and 4.4). Perhaps due to the faster regeneration of adult fish biomass, this effect is less noticable for this indicator. This phenomenon is also visible within the medium MPA, though the size of the large MPA appears sufficient to sustain habitat health, biodiversity and biomass indicators near their maxima within its boundaries throughout the entire study period.

Despite these protections, total adult fish biomass declines over the study period across all policies except for the full protection of the study area (see Appendix, Figures A.1, A.2 and A.3). In addition, Figure 4.2 shows that total biomass is in fact lower for the large MPA than the other policies despite also exhibiting lower commercial and recreational catch. To understand why this occurs, we turn to the distribution of commercial and recreational fishing effort under the different policy interventions.

Given that commercial and recreational fishers aim to harvest from above the 70^{th} and 90^{th} percentiles of biomass in fishable areas respectively, Figures 4.6 and 4.7 demonstrate how the spatial autocorrelation of biomass values at the onset of the simulation leads to commercial and recreational catch being highly clustered. Since the small, medium and large MPAs protect areas of high habitat health, they also prohibit fishing in the region that exhibits the highest adult fish biomass. Consequently, the displaced fishing effort becomes spread over areas with increasingly low initial biomass values as the size of the MPA is increased. This likely explains why total adult fish biomass is lower in the large and medium MPAs, as commercial and recreational fishers continually harvest from these low biomass regions without allowing them to recover. However, as fish stocks rapidly decline in subsequent periods, biomass in the study area becomes homogenised resulting in fishing activity becoming more dispersed.

Due to the high biomass within the MPA boundaries, there are clear 'fishing the line' behaviours that can be observed as the biomass spills over into neighbouring areas. This phenomenon is more apparent as the size of the MPA increases sug-

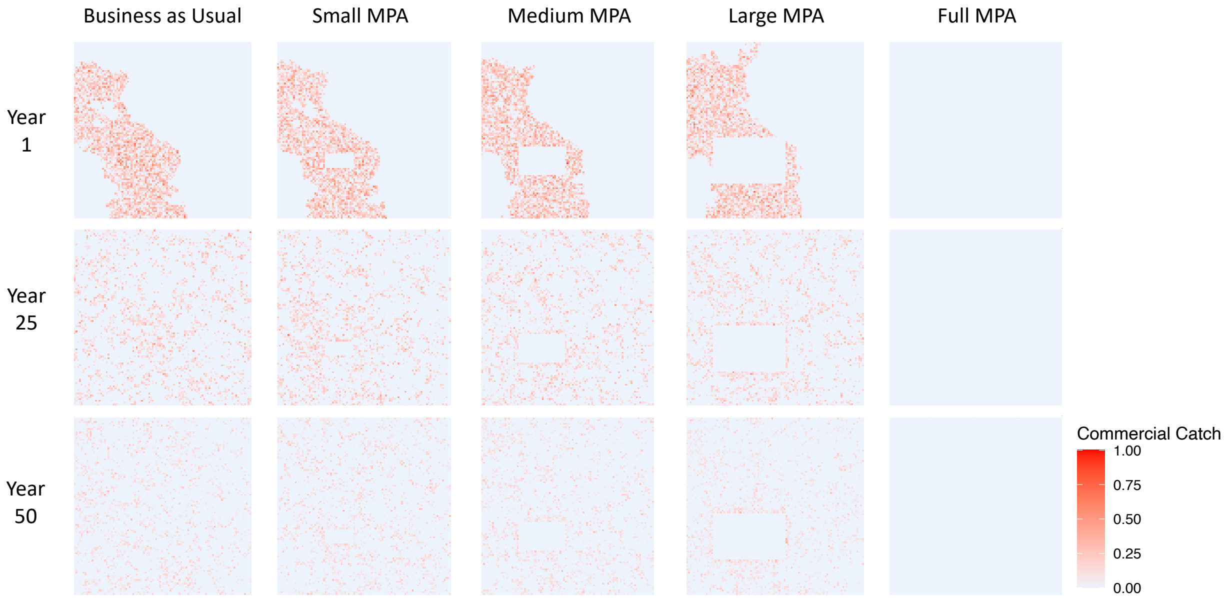

Figure 4.6: Commercial catch values taken from simulations under the policy interventions examined. Each row presents the spatially explicit catch values at a certain point of time, while columns denote different policies.

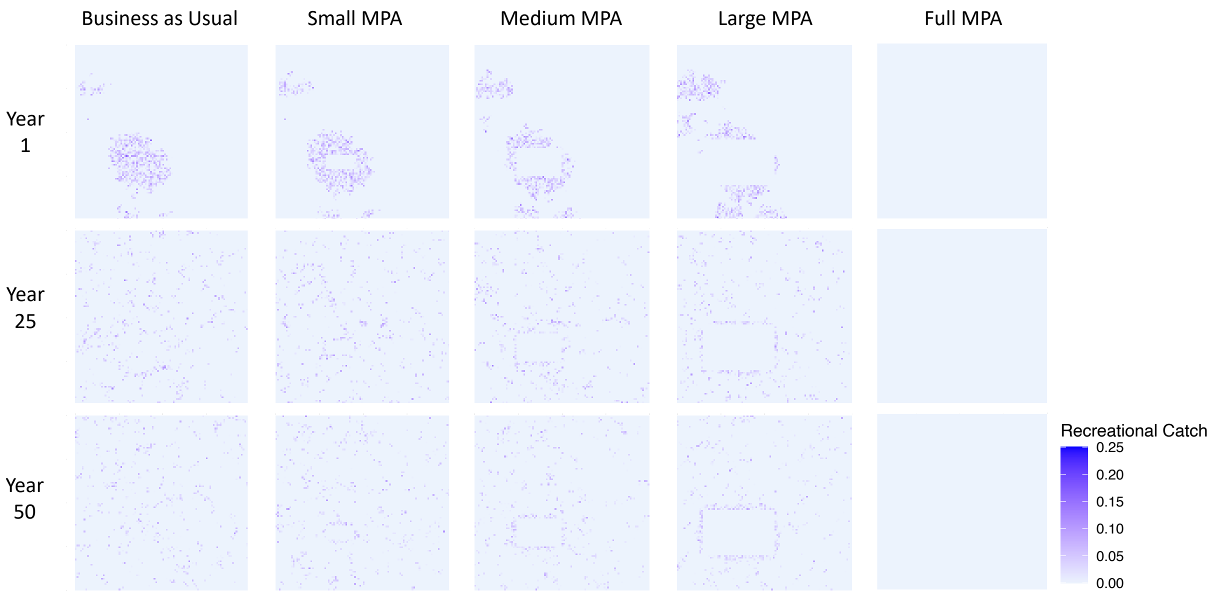

Figure 4.7: Recreational catch values taken from simulations under the policy interventions examined. Each row presents the spatially explicit catch values at a certain point of time, while columns denote different policies.

gesting that larger MPAs exhibit greater positive spillover effects. As mentioned previously, the ecological dimension values within the small MPA are substantially lower than the medium and large MPAs, and this is due to the fact that entire area within its boundaries is negatively affected by the fishing activity surrounding it whereas most areas within the larger MPAs are able to remain unaffected by this same phenomenon.

The impact of the increased fishing activity on the borders of the MPAs is most evident in the biodiversity indicator. Figure 4.4 depicts a ring of particularly low biodiversity values in the region immediately surrounding the MPAs. This effect is intensified as the size of an MPA decreases presumably because the higher biodiversity values within the larger MPAs compensate for these losses. Interestingly, for the small MPA this phenomenon leads to a region that exhibits lower biodiversity values than the business as usual policy, likely due to the fact that fishing activity is more uniformly distributed in the absence of an MPA.

In addition, 'fishing the line' appears to explain why biodiversity begins to increase in some regions under the MPA policy interventions. Figure A.2 shows that biodiversity declines for the first 20 years of the study period, after which it begins to level out and increases around 40 years. Given that adult fish biomass continually decreases throughout this period, commercial and recreational yields decrease, thus reducing disturbance to the ecological indicators. It is likely that this, coupled with fishing around the MPA boundaries leading to reduced fishing effort in other areas, allows for habitat health and biodiversity to recover. Using longer time horizons, we see that eventually habitat health also increases, albeit at a slower rate.

Again, this effect appears to be scale-dependent, with larger MPAs having higher biomass within them that leads to greater spillover at the boundaries. This in turn leads to more concentrated fishing effort surrounding the MPA and consequently less activity in other regions. Figures 4.6 and 4.7 show less fishing activity occurring in the northeast quadrants of the small, medium and large MPA scenarios, and in year 50, the cumulative effect of reduced fishing in this area is shown by higher biodiversity values in Figure 4.4.

4.2 Sensitivity Analysis

Having thoroughly explored these policies using a 50 year time horizon and 5% discount rate, we now demonstrate how the outcomes are affected by varying these parameters. Figure 4.8 depicts the utility surfaces for the same policies using a 30 year time horizon and 5% discount rate.

Given that the normalisation values for the dimensions were generated from simulations using a 50 year horizon, the surfaces are substantially smaller than those found in Figure 4.1. Nevertheless, this change also had a significant impact on optimal policies. As mentioned previously, shortening the time horizon diminishes the benefits of MPA implementation. Due to the gradual increase in ecological health, the full benefits stemming from protection are not accounted for when using a 30 year time span. As a consequence, both the medium and large MPAs are completely Pareto dominated by the business as usual, small MPA and full MPA protection policies. Additionally, the small MPA is only the optimal policy for a small region of weightings, again, likely due to the fact that the small MPA will not exhibit benefits substantially different from business as usual.

For high weightings of the ecological dimension, full protection of the study site remains the optimal policy, though the steepness of its utility surface compared to the other policies is less pronounced. Since the tourism industry indicator benefits that arise from full MPA protection are not fully realised in the 30 year time span, it contributes an even smaller amount to the economic dimension utility even before discounting is incorporated. This reduces the region of weightings in which the full MPA protection indicator is the optimal policy.

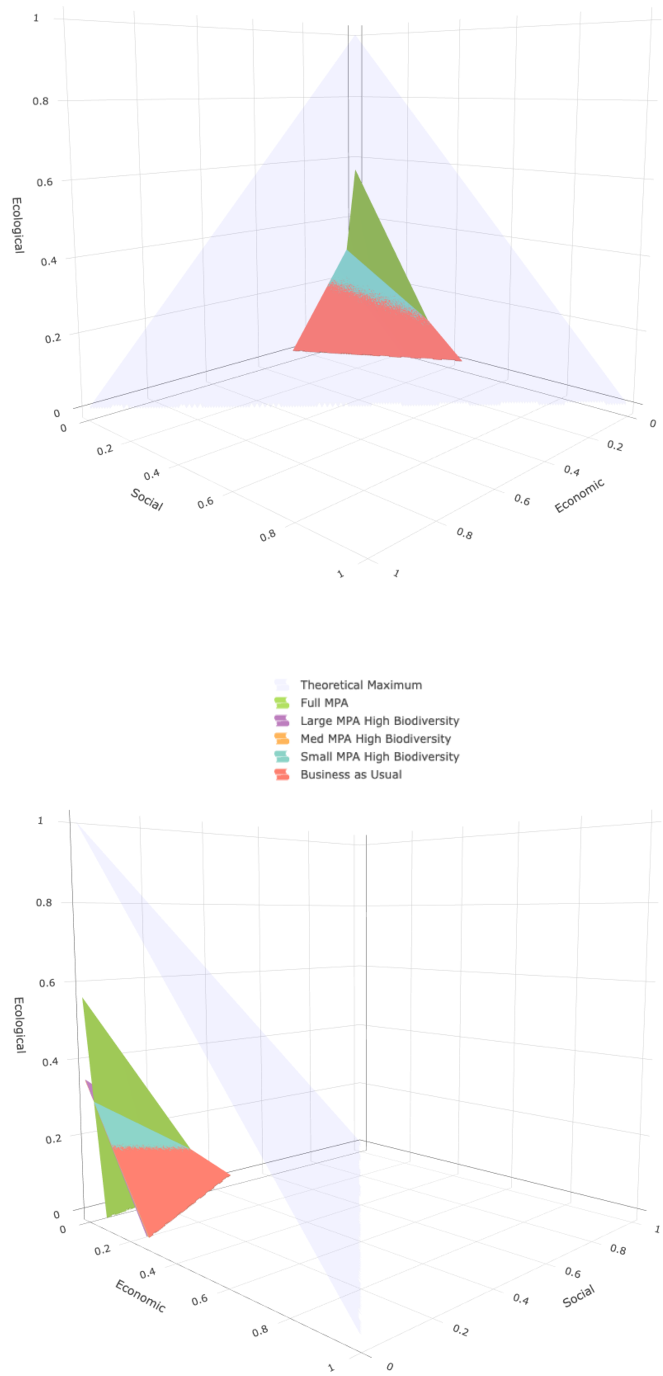

Figure 4.8: Utility surfaces comparing five policy scenarios with a 30 year time span and 5% discount rate from two angles. The axes of the graphs represent the ecological, economic and social dimension values associated with each policy multiplied by combinations of subjective dimension weightings.

When the economic and social dimensions are given high weightings, the business as usual policy dominates. This is in stark contrast to the results using the 50 year time horizon, where the social dimension was sensitive to the weightings of the other dimensions. Despite aesthetics and megafauna sightings benefitting from greater ecological health, the marginal increases in the ecological dimension afforded by the MPAs during the 30 year period appear to be outweighed by greater recreational catch. Thus, unlike the 50 year time horizon, neither the medium or large MPA become optimal policies for the highest weightings of the social dimension.

The optimal policies become more extreme when the time horizon is shortened to 10 years. Figure 4.9 depicts the utility surfaces generated from simulations using a 10 year time span and 5% discount rate. We can see that even the benefits conferred by full protection of the study site are minimal, only being the optimal policy for extremely high weightings of the ecological dimension. Again, the benefits for the tourism industry within the economic dimension are even smaller, reducing the region of weightings where the full MPA protection is optimal.

For the 10 year time span, the business as usual policy is nearly the sole Pareto dominant policy. Again, for high weightings of both the economic and social dimensions it is the optimal policy regardless of the weightings of the other dimensions. This is due to the fact that any indicators benefitting from protection are not substantially different than the business as usual policy in the initial 10 years following their implementation.

As these results show, the time span under which policies are evaluated has a strong impact on the optimal level of protection. The use of short time horizons fails to capture the long-term gains and losses associated with MPA implementation and as a result there is bias towards inaction that maximises extractive activities that harm ecosystems (O'Mahony, 2021).

Turning to how the discount rate affects optimal policy, we evaluate the same

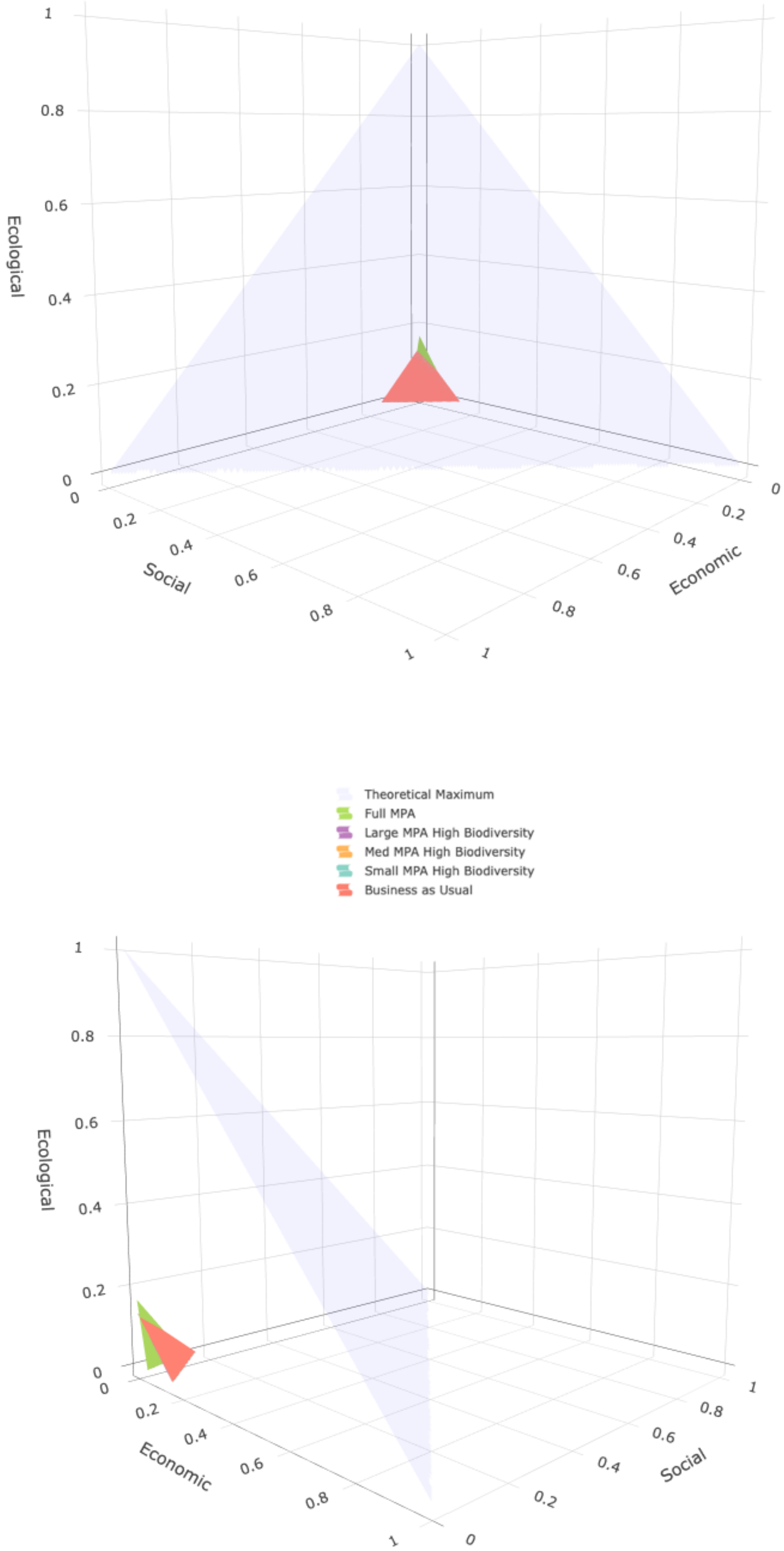

Figure 4.9: Utility surfaces comparing five policy scenarios with a 10 year time span and 5% discount rate from two angles. The axes of the graphs represent the ecological, economic and social dimension values associated with each policy multiplied by combinations of subjective dimension weightings.

MPAs using a 50 year time horizon with 0% and 12% discount rates. These represent the range of discount rates used by OECD countries when exploring the sensitivity of cost benefit analyses (Parliamentary Commissioner for the Environment, 2021).

Figure 4.10 presents the utility surfaces using the 0% discount rate. Given that the economic dimension values now approach the theoretical maximum due to the 0% rates used in simulations to generate them, the spread of utility surfaces is now greater than in previous analyses. Consequently, there are no Pareto dominated policies as demonstrated by five regions where each policy's utility surface yields the optimal policy, although the medium and large MPAs only cover small regions.

In contrast to the results using a 50 year time span and 5% discount rate, high weightings for each of the indicators point to single, distinct policies. For the ecological and economic dimensions this is the full MPA protection and business as usual respectively, as before. However, for the social dimension, the small MPA yields the highest utility and is much less sensitive to the low relative weights of the other dimensions.

When the economic dimension is not discounted, policies that allow for larger fish yields comprise a larger proportion of the optimal policy space. This is in spite of the long term benefits that the tourism industry draws from greater ecosystem protections now being fully realised. Though the tourism industry indicator nearing its maximum value does push the utility surface for full MPA protection closer towards the economic dimension, it is important to note that the components of each dimension were aggregated given equal weighting. Consequently, two of the three components in the economic dimension are directly linked to commercial fishing yields, implicitly weighting the economic dimension in favour of fishing interests rather than the tourism industry. Given our prior investigations highlighting that the small and medium MPAs are inadequate to protect the wider ecosystem, perhaps through exploring a wider range of MPA sizes and locations

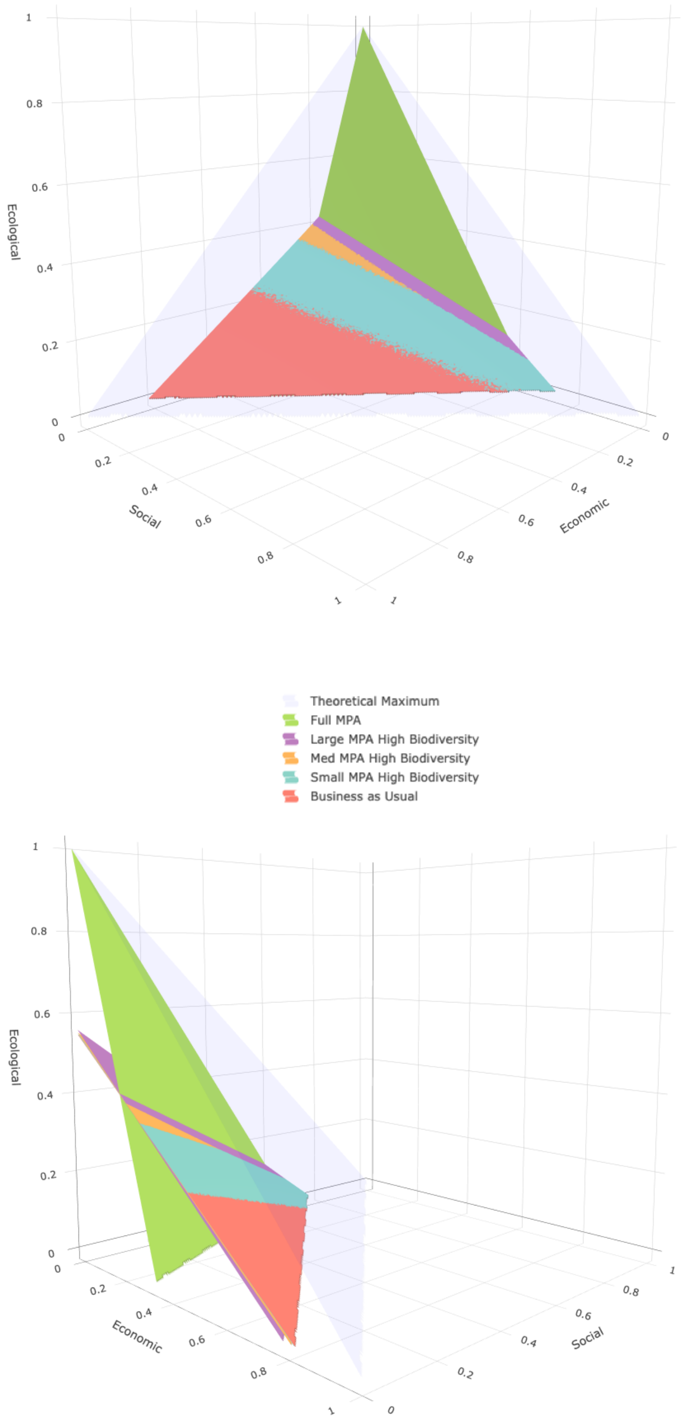

Figure 4.10: Utility surfaces comparing five policy scenarios with a 50 year time span and 0% discount rate from two angles. The axes of the graphs represent the ecological, economic and social dimension values associated with each policy multiplied by combinations of subjective dimension weightings.

the disparate interests within the economic dimension could reach a compromise. This also holds true for indicators within the social dimension, where recreational fishing is at odds with the aesthetics and megafauna indicators.

Altering the discount rate affects the optimal target catch rates for commercial and recreational fishers. Figures A.5 and A.6 show how this affects fishing yields for 0%, 5% and 12% discount rates using simulations under the business as usual policy. We can see that when fishers place equal weighting on future catch, they reduce the amount of fishing in the initial periods in order to maintain adult fish biomass. However, due to the imperfect information used to determine the optimal target catch rate, yields still decline through time due to overfishing. As the discount rate is increased, fishers trade off future yields for higher present catch and as a result, biomass is increasingly overexploited leading to substantial declines for both commercial and recreational catch in later periods. Consequently the total yield over the 50 years is lower for the 12% and 5% discount rates than when the 0% discount rate is used.

When the 12% discount rate is applied, the normalised values for economic dimension are substantially reduced. As Figure 4.11 depicts, the utility surfaces become compressed along the ecological and social axes. Consequently, the full protection of the study site and large MPAs comprise a larger proportion of the optimal policy space. As with 0% discounting, high weightings in each dimension propose distinct optimal policies, with the ecological, economic and social dimensions proposing full MPA protection, business as usual and large MPAs respectively.

The small and medium sized MPAs are nearly Pareto dominated by other policies, with the medium MPA barely visible. This contributes to the large sized MPA's dominance of optimal policy for high weightings of the social dimension. Given that the high discount rate increases the extent of ecosystem disturbance, the increased commercial yields associated with the policies that allow larger fish-

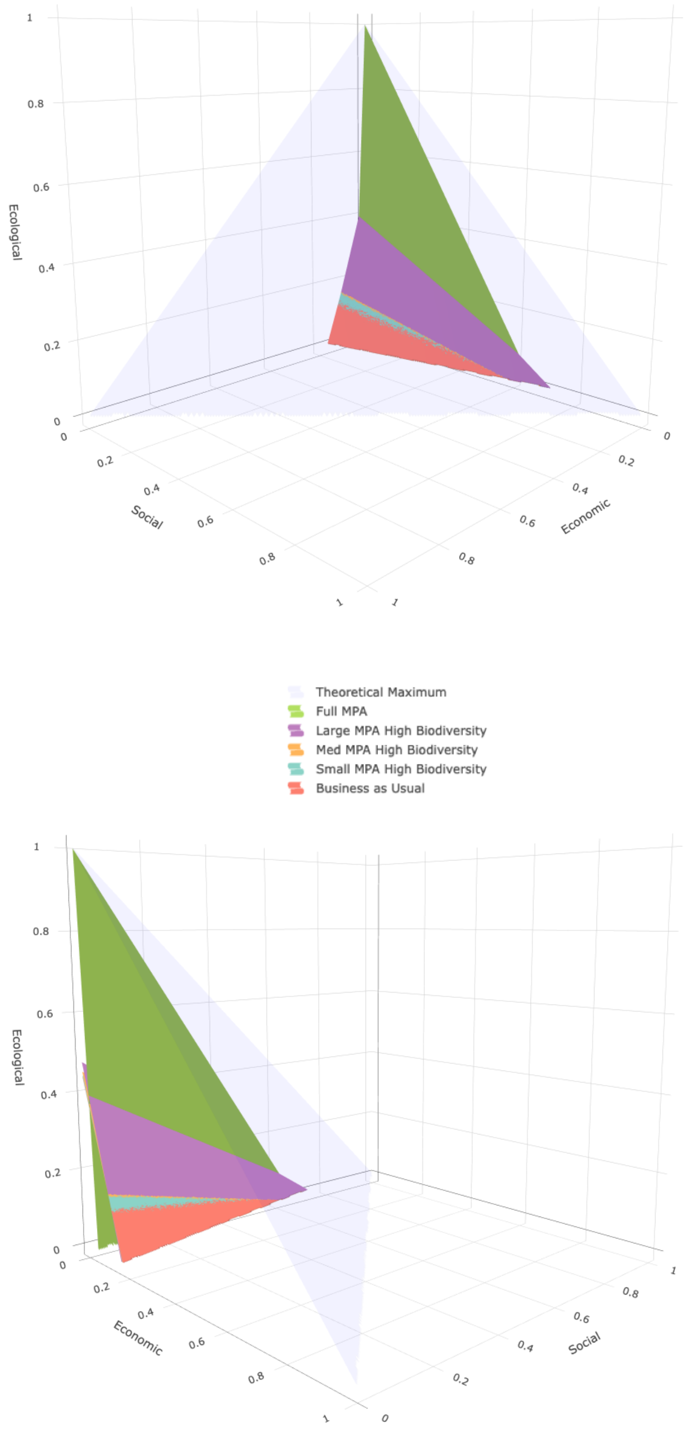

Figure 4.11: Utility surfaces comparing five policy scenarios with a 50 year time span and 12% discount rate from two angles. The axes of the graphs represent the ecological, economic and social dimension values associated with each policy multiplied by combinations of subjective dimension weightings.

able areas have a greater negative impact on the aesthetics and megafauna indicators within the social dimension. Consequently, these effects outweigh the gains associated with greater recreational catch and thus the large MPA becomes preferred to the other policies in contrast to the 5% and 0% discounting.

4.3 Summary

Utilising the decision making framework developed in this paper, we were able to evaluate five policy scenarios: full MPA protection, large, medium and small MPAs over areas of high habitat health, and business as usual. Through simulation of the study site under each policy intervention using a 50 year time horizon and 5% discount rate for the economic dimension, we generated utility surfaces that helped identify optimal policies given the user's subjective weighting of the ecological, economic and social dimensions. Additionally, these surfaces were used to examine how the optimal policies changed when greater weight was given to each dimension and identified that the medium MPA was nearly Pareto dominated by the other policies and as such would lead to sub-optimal outcomes.

Examining full MPA protection, we saw that the economic dimension was severely impacted due to the cessation of fishing. This was further amplified by the discount rate, as long term benefits in the tourism industry indicator are greatly diminished in calculating the net present value.

Further examination of the distributions of simulated indicator values suggested that the size of the small and medium MPAs may be insufficient to adequately protect the ecosystem of the study site. Delving into the spatio-temporal trends of these indicators we were able to clearly see the interactions between them and how phenomenon such as fishing along the boundaries of MPAs contributed to the scale-dependent effectiveness of these policies. Given that aggregate adult fish biomass continually declined even for large MPAs, these findings support the notion that larger MPAs or the introduction of additional fishery management policies such as quotas may be required to support ecosystem health of the study site.

These findings seem to align with the literature. In a review of bioeconomic models examining the efficacy of MPAs finds that many papers suggest a minimum of 15% to upwards of 50% of the fishable area being designated as an MPA is required to sustain fish populations (Pelletier and Mahevas, 2005). This suggests in further iterations of the decision making framework, a greater distribution of MPA sizes is required to explore effective alternative policies.

Chapter 5

Conclusion

Cognizant of the increasing number of disparate conservation objectives in Marine Protected Area policy implementation and the shortcomings of conventional cost-benefit analysis in valuing non-market goods, this project developed a multi-criteria decision framework as a tool to aid policy makers. Utilising Multi-Attribute Utility Theory, simulations from our ecological-economic model were used to generate sub-utilities for indicators within ecological, economic and social dimensions without reducing them to monetary values. Maintaining distinct dimensions highlights their non-compensatory nature, following the concept of strong sustainability and emphasising socio-cultural values.

The graphical depiction of three-dimensional utlity surfaces for each policy, in addition to the presentation of spatially explicit indicator values, aims to inform decision makers while minimising their cognitive burden. Exploring how scenarios vary with time horizons and discount rates demonstrate how these parameters have significant impacts on the behaviour of the indicators within the model framework and thus for determining optimal policies. Not only are these factors important in order to adjust for the decision makers preferences, the graphical depiction of how outcomes change with these parameters may prove to be informative for marine spatial planners.

The results explored using the decision framework on a theoretical marine habitat are purely illustrative, demonstrating how it may be applied to real-world marine ecosystems. One of the strengths of this framework is its flexibility, and thus through expert opinion model parameters such as the rate of biodiversity or biomass growth could be adjusted and functional forms of the indicators altered to reflect specific marine habitats and regions. Additionally, stakeholder engagement is another key component that must be integrated to ensure the successul implementation of marine policy, with indicators incorporated into the model that address specific iwi and other local community values. Moreover, weightings could be assigned to indicators within dimensions that better reflect stakeholder preferences and expert opinion.

The New Zealand government is requesting the development of tools that improve the presentation and communication of environmental information for senior officials and ministers in order to improve decision making (Parliamentary Commissioner for the Environment, 2021). Thus, tools that utilise multi criteria analysis are needed now more than ever. The framework developed in this paper, as well as its novel incorporation of time horizons and discounting, demonstrate how useful a multi-criteria approach may be for informed policy making.

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Chapter 6

Appendix[1]

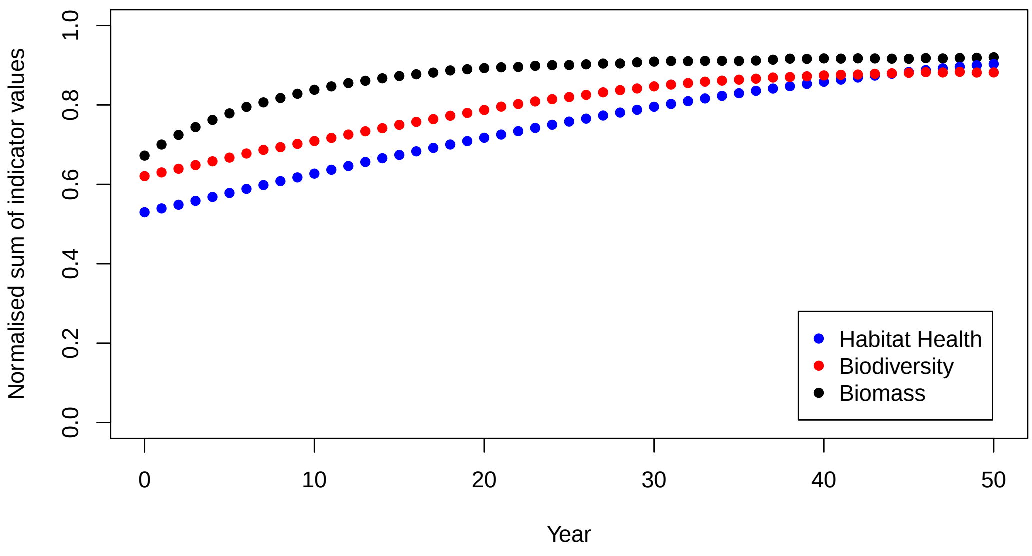

Figure A.1: Values of the ecological dimension indicators from a simulation under full MPA protection. The values were normalised between zero and one.

[1] Code documentation is available upon request. Contact: tloh305@aucklanduni.ac.nz.

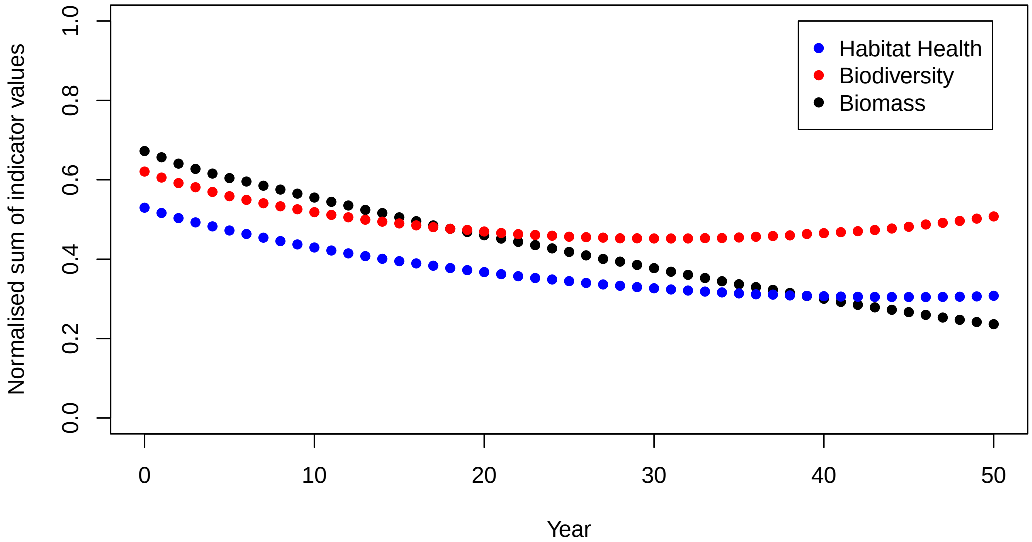

Figure A.2: Values of the ecological dimension indicators from a simulation with a large MPA over high habitat health. The values were normalised between zero and one.

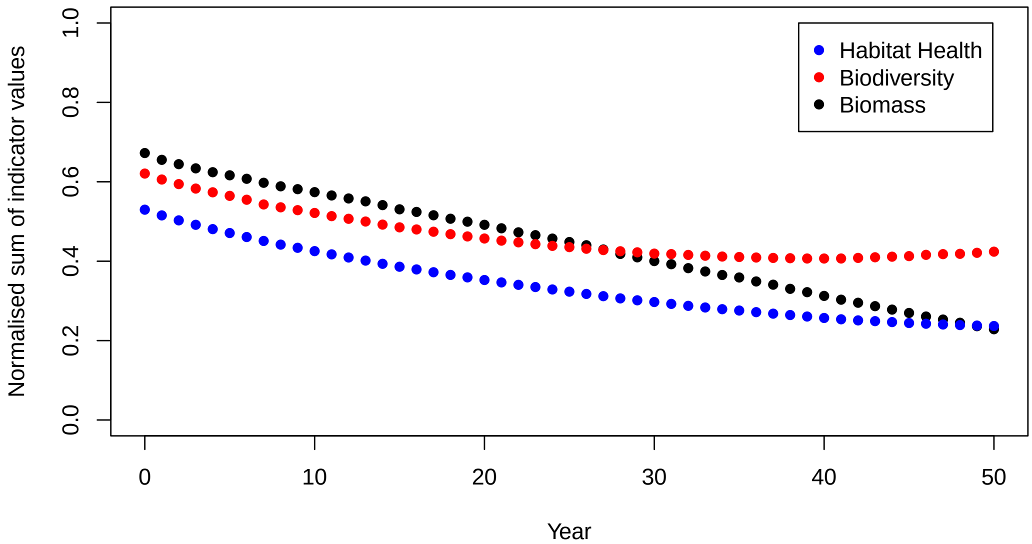

Figure A.3: Values of the ecological dimension indicators from a simulation with business as usual (no MPA). The values were normalised between zero and one.

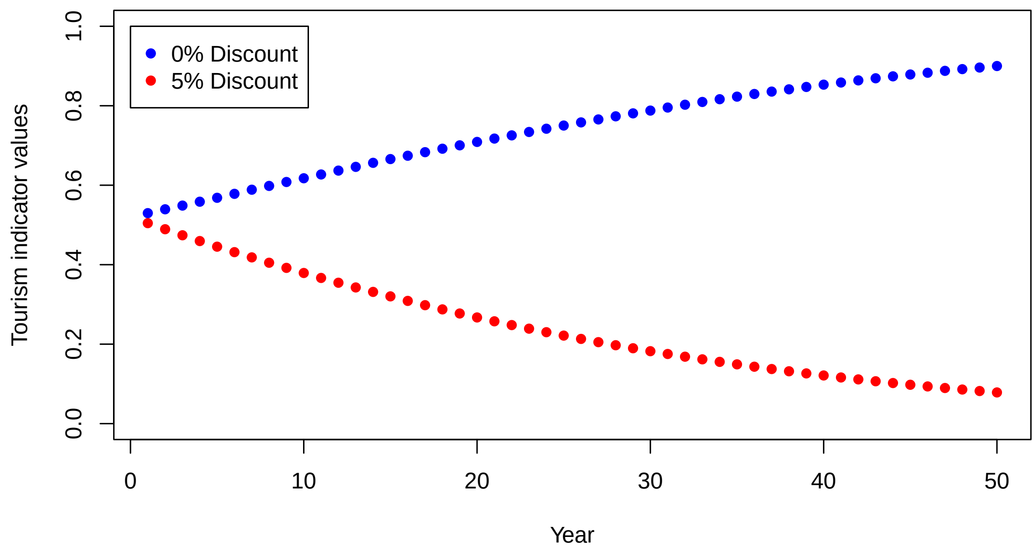

Figure A.4: Values of the tourism indicator from a simulation under full MPA protection presented with 0% and 5% discounting.

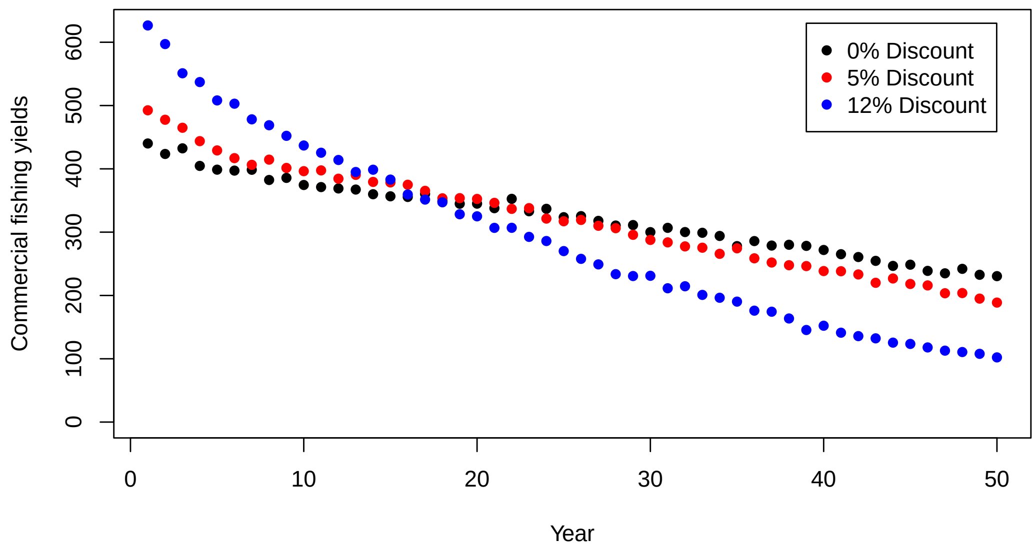

Figure A.5: Values of the commercial fishing indicator from simulations under business as usual with 0%, 5% and 12% discount rates affecting the optimal target catch. Note that the values themselves are not discounted.

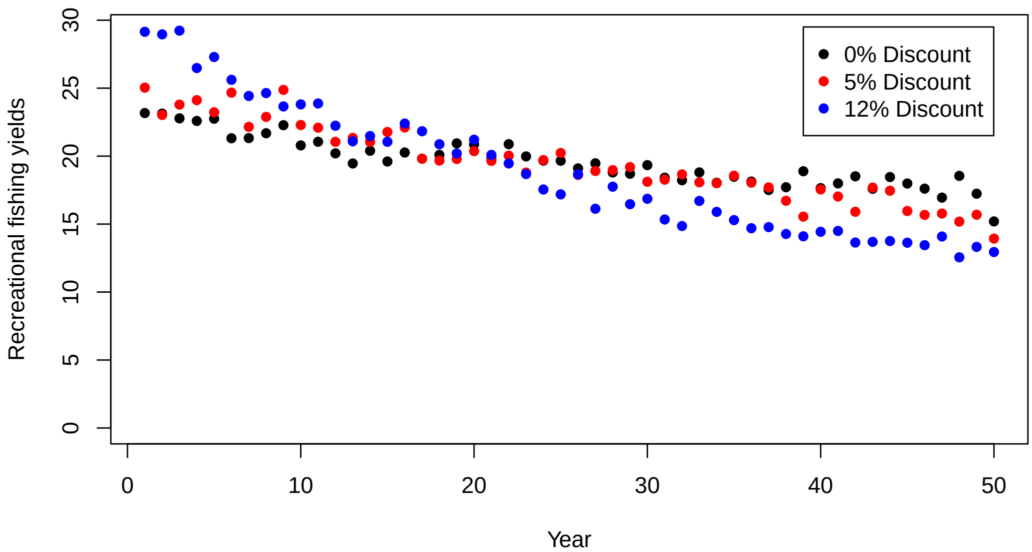

Figure A.6: Values of the recreational fishing indicator from simulations under business as usual with 0%, 5% and 12% discount rates affecting the optimal target catch. Note that the values themselves are not discounted.