Opportunities and precautions for the use of MPAs in bycatch reduction

Daniel Ovando

Darcy Bradley

Lennon Thomas

Echelle Burns

2021-10-11

# 1 Introduction

Marine protected areas (MPAs) are a growing part of the marine conservation toolbox, with 5.9% of the world’s oceans currently in implemented MPAs (Grorud-Colvert et al. 2021), and bodies such as the IUCN calling for 30% protection by 2030. One of the potential benefits of MPAs is their ability to provide protection to broad segments of an ecosystem at once, rather than requiring targeted management based on individual species that may be unfeasible in many parts of the world lacking in data or fisheries management capacity. Their ability to provide protection across a range of species with one policy has led them to be suggested as a tool to reduce problems around weak stock or “bycatch” species (Hastings, Gaines, and Costello 2017). We use the term “bycatch” here to generally refer to the capture of species within a fishery primarily targeting a different set of species.

While the effect of MPAs on fisheries yields is a continuously debated topic, the conservation impacts of MPAs are seemingly simpler, albeit challenging to detect in many cases (Ovando et al. 2021), due in part perhaps to the perceived obvious nature of their benefits: if you prevent fishing of a species within an area, there will be more of that species in that area, and so the conservation benefits of MPAs will increase with MPA size. Hastings, Gaines, and Costello (2017) clearly illustrates this idea. Using a two-species two-patch analytical model, they derive conditions under which MPAs can solve the “weak-stock” problem in which a less productive species is caught as bycatch by a fleet targeting a more valuable and productive stock.

However, as Hastings, Gaines, and Costello (2017) point out, their results depend on a very specific set of assumptions, namely that 1) adults are perfectly sedentary 2) the target and bycatch species overlap perfectly in terms of habitat and 3) recruits are perfectly mixed throughout the system. In this paper We build on Hastings, Gaines, and Costello (2017) to consider the role of MPAs in reducing bycatch while managing tradeoffs with fisheries under a more resolved model.

Specifically, the potential benefits of MPAs as a bycatch management are complicated by two key issues: effort displacement and technical interactions. One of the primary questions around MPAs is to what extent do MPAs remove versus displace fishing effort. If MPAs remove fishing effort, then their direct effects on target and bycatch species can only be positive. If however MPAs displace fishing effort evaluating their potential impacts becomes more complicated. The net conservation impact of MPAs becomes a balancing act between the effects of reduced fishing inside protected borders and increased fishing intensity outside MPAs. The outcomes of this displacement can be further complicated by technical interactions, i.e. the degree to which fishing effort for one species affects another, particularly when species have markedly different habitat distributions. For example, Abbott and Haynie (2012) demonstrated that an MPA designed to protect red king crab (*Paralithodes camtschaticus*) caused an unintended increase in bycatch of Pacific halibut (*Hippoglossus stenolepis*) by the displaced bottom-trawl fishery. Policy leakage is not a unique feature to MPAs, e.g. XX, but the potential impacts of MPAs on target and bycatch species taking into account the potential for these leakage effects has received relativelly little generalized attention in the literature (see Abbott and Haynie 2012; **savina2008?**; Elizabeth A. Fulton et al. 2011; Baum et al. 2003 for notable exceptions).

This study addresses this gap using a novel bio-economic simulation model that allows for efficient evaluation of the effects of MPAs on target and bycatch species across a range of ecological and economic dynamics, critically accounting for the potential impacts of effort displacement and technical interactions. We use this model first to explore general conditions that lead to positive and negative outcomes for target and bycatch species from MPAs. We then present a case study tuned to reflect the dynamics of the tuna, billfish, and shark populations and fisheries of the Western and Central Pacific Ocean (WCPO) to explore the value of optimal MPA design in managing tradeoffs between maximizing bycatch conservation and minimizing economic impacts. We chose the WCPO as a case study as the modern science of MPAs was largely developed around coastal ecosystems, often characterized by relatively static features such as coral reefs [citation]. However, large MPAs are increasingly being implemented and considered across pelagic ecosystems. These pelagic systems are characterized by highly mobile species and fishing fleets using a diverse mix of static and dynamic ocean features (Game et al. 2009; Lubchenco et al. 2003). These ecosystems are also home to combinations of relatively abundant species targeted by fishing, such as many tuna stocks (Pons et al. 2016), and highly threatened species caught as incidental “bycatch” in targeted fishing operations, such as oceanic whitetip sharks (Pacoureau et al. 2021). These dynamics, combined with the increased policy interest in large MPAs covering expanses of blue-water ecosystems, make pelagic systems such as the WCPO an ideal case study in bycatch management through MPAs. The goal of this paper is to provide a strategic evaluation of the sensitivity of bycatch populations and targeted fisheries to key unknowns and design choices in MPA planning.

# 2 Methods

Hastings, Gaines, and Costello (2017) employed an analytically tractable model to derive conditions under which MPAs would benefit bycatch species. However they also pointed out that even small increases in model complexity quickly make analytical solutions to the effects of MPAs intractable. As such, we employ a numerical simulation strategy in the form of a spatially explicit, multi-species, multi-fleet, bio-economic model we call [marlin](https://github.com/DanOvando/marlin). Models of MPAs span a wide range of complexity, from simple analytical tools to end-to-end ecosystem models (Elizabeth A. Fulton et al. 2015). marlin follows a “models of intermediate complexity” (MICE) philosophy (Plagányi et al. 2014) targeted specifically around the role of technical interactions across species. Many MPA models simulate the impacts of MPAs on a single-species level (Ovando et al. 2021). This can be useful for for example examining the ways in which species-specific life history traits interact with fleet dynamics to influence MPA outcomes. However, bycatch problems are driven by technical interactions, in which fishing effort for a target species incidentally captures another species. marlin accounts for this by allowing the user to simulate an arbitrary number of fleets capable of catching an arbitrary number of species in a spatial area. Different fleets can place different economic value on different species, while also having species-specific selectivity functions. This allows us to simulate bycatch dynamics of MPAs in pelagic ecosystems.

Below we provide a summary of the marlin model, as well as details of the generalized simulation exercises and case study analyses.

## 2.1 marlin

#### 2.1.0.1 Fleet Dynamics

The key feature of marlin for the purposes of this project is the ability to capture technical interactions across species. While marlin does not simulate species interactions, fishing fleets in marlin are capable of targeting and affecting multiple species simultaneously. This allows us to capture for example the potential impacts of displacement of effort from one area into another across multiple species.

A fishing fleet or *metier* is defined in marlin by a total pool of effort that can have different catchability, prices, and selectivity for individual species within a simulation. For example, both a longline and purse seine fleet may capture bigeye (*Thunnus obesus*) and skipjack (*Katswamus pelamus*), but the longline fleet is much more likely to catch bigeye than skipjack, and *vice versa*. Each fishing fleet generates catches, revenues, and profits from individual species that it targets, and makes decisions based on its total objective function across all species.

Revenues *R* for fleet *f* in time step *t* are given by

where *p* is patch, *s* is species, *a* is age, is selectivity at age, *q* is catchability , *F* is total fishing mortality, is price per unit weight, and *Y* is total catches.

where *F* is total fishing mortality, given by

Selectivity is modeled through a logistic form per

where is length at age, is the length at 50% selectivity, and is the difference between the length at 50% selectivity and the length at 95% selectivity.

*z* is total mortality given by

Where *m* is natural mortality.

This means that each species experiences a total mortality at age in a time step in a patch, individual fractions of which are portioned off as catches and subsequently revenues for each fleet. Given revenues, we then calculate profits per

where *c* is cost per unit effort and, the 1.3 exponent is in the manner of Costello et al. (2016) . The addition of one to the total effort is to constrain the value to be greater than 1, preventing undesired behavior where fishing effort actually gets less expensive if total effort is less than 1.

The important feature here then is that the revenues and profits for a given fleet are a function of the prices and catchability of individual species, but that mortality itself is independent of price. So, a fleet that has selectivity and catchability greater than zero can exert fishing mortality on a species even if it obtains no value from that species.

Each fishing fleet then decides how to allocate its effort in space based on one of four possible spatial allocation strategies. The ideal free distribution (IFD) is the standard method for distributing fishing fleets in spaces (see Gillis (2003) and references therein). However, the IFD presents a number of complications for our study. First, in order to simplify the assessment of the impacts of different fishing mortality rates we simulate scenarios with a fixed total pool of effort. As MPAs change the spatial distribution of profits though, the total amount of effort required to satisfy the IFD may not equal the total amount of effort required by the model. Second, even if we were to implement the IFD for a single fleet, the model is capable of tracking multiple fleets at once. This means that the IFD for a single fleet would be a game-theoretic outcome of the actions of each of the individual fleet conditional on the actions of all other fleets. While possible to implement this would slow down our model runs to the point of practically preventing large-scale evaluation of the effects of MPAs on bycatch.

As such we explored a series of “next best” fleet distribution algorithms. While not the IFD in any individual time step, over time they start to approximate the IFD, as each assumes that fleets base their decisions for the current time step on the outcomes in the prior timestep, meaning that the impacts of the actions of other fishing fleets are somewhat internalized. The four possible fleet distribution algorithms are

1. Revenue per unit effort (RPUE): The fleet distributes itself in space based on revenue per unit effort
2. Revenue: The fleet distributes itself in space based on revenue
3. Profit per unit effort (PPUE): The fleet distributes itself in space based on profit per unit effort
4. Profit: The fleet distributes itself in space based on profit

Revenue based spatial distribution is not likely to be very realistic . However, due to the complexity of parameterizing cost functions fleet dynamics are often evaluated based on yield or revenue alone, and so we include those scenarios here to evaluate the potential implications of this choice. The decision on whether to allocate the fleet based on absolute or relative (per unit effort) is more complex. When effort represents the actions of separate and individual fishing actors (e.g. independent fishing vessels), a per-unit-effort strategy may be more realistic, in which fishers distribute themselves based on the expected catch of their individual efforts (Hilborn and Walters 1987). Conversely, a system defined by a sole owner seeking to maximize total profits might be better represented by a fleet model based on total profits

#### 2.1.0.2 Population Model

The underlying population model used is an age structured single-species model in the manner of Ovando et al. (2021).

For the population model, numbers *n* at time *t* for age *a* are given by

where *BH* is the Beverton-Holt recruitment function, *ssb* is spawning-stock-biomass.

where is the mean length at at age, is the length at which on average 50% of individuals are selected by the fishery, and are the additional units of length at which on average 95% of fish are selected by the fishery.

*ssb* is calculated by converting age to mean length, calculating weight at age, maturity at age, and then calculating spawning stock biomass as the sum of spawning potential at age in a given time step.

Biomass *b* at age is then given by

and maturity *mat* is calculated as

where is the length at which on average 50% of individuals are sexual maturity, and is the units of length beyond at which on average 95% of fish are sexually mature.

Spawning stock biomass at time *t* is then calculated as

##### Recruitment

Recruitment follows Beverton-Holt dynamics. We do however allow for three variants in the timing of density dependence:

1. Global density dependence: Density dependence is a function of the sum of spawning biomass across all patches, and recruits are then distributed according to habitat quality

where *hab* is a vector of recruitment habitat quality by patch degined by

2. Local density dependence: Density dependence occurs independently in each patch and recruits are retained in their home patch.

1. Local density dependence then disperse: Density dependence occurs independently in each patch and recruits are then dispersed.

where **dl** is the recruitment movement matrix

1. Post-dispersal density dependence: Larvae are distributed throughout the system, and then density dependence occurs based on the density of adult biomass at the destination patch.

##### Dispersal

Dispersal in the model is broken into two components: adults and recruits Both assume a Gaussian dispersal kernel of the form

where *i* is the source patch, *j* is the destination patch, *d* is the distance between patches *i* and *j* , and is the movement rate, in units of patches.

Along with distance, net movement is defined by habitat quality. Habitat quality defines the quailty for adults or larvae of a given patch. The net probability of movement from patch *i* to patch *j* is defined then by the product of distance and habitat quality, normalized to sum to one from each patch, such that all else being equal organisms will move the most to the closest patch with the best habitat. We allow for seasonal movement in the model, where years are broken into two seasons. Movement in season two is defined as the opposite of movement in season one, intended to reflect the behavior of seasonal migrations.

## 2.2 Rule-of-thumb MPA Design Strategies

MPA design is governed by two general parameters: the number of cells to place inside an MPAs, and the design strategy used to place the MPAs.

We consider 5 different MPA placement strategies.

1. Depletion: MPA locations are prioritized in proportion to the spawning stock biomass of the most depleted species pre-MPA. So, patches with high spawning biomass of highly depleted species are prioritized over patches with high spawning biomass of lightly depleted species.
2. Rate: MPAs are placed in based on the pre-MPA depletion-weighted catch relative to the total catch in a patch. So, patches with high rates of catch of depleted species relative to total catch are prioritized.
3. Avoid\_fishing: MPAs locations are prioritized inversely to fishery catches. So, patches with low catches are prioritized over patches with high catches.
4. Target\_fishing: MPAs locations are prioritized proportionally to fishery catches. So, patches with high total catches are prioritized over patches with low catches.
5. Area: For the “area” strategy, we simply assign patches in sequential order until the desired total MPA size is reached.

## 2.3 MPA Optimization

Our MPA optimization algorithm seems to create an MPA network that maximizes an objective function, given by

Where *scale* rescales the values to be between 0 and 1 such that the weight parameter is comparable between vectors. The algorithm works by first assigning every patch in the system to an MPA. For the first round, the algorithm then calculates the equilibrium objective function value resulting from sequentially removing each individual patch from the MPA network. The cell whose removal from the MPA produces the highest objective function value is then removed from the MPA network, and the marginal value of the objective function each of the remaining cells from the last steps are then stored. For the next steps, we sampled 25% of the remaining MPA cells with probability proportional to their marginal contribution to the objective function in the prior iteration, selecting the cell whose removal produces the highest total objective function as the cell to remove from the network, and updateing the marginal value of the sampled-but-not-selected cells. This in essence is a sampling-importance-resampling algorithm. The algorithm continues until no more cells are left in the MPA. This then provides for a given objective weighting value the near-optimal MPA network at every MPA size from 0 to 100%. We say “near” as they is some path dependency here, in that for example the network that maximizes the objective function with 40% of the MPAs does not necessarily contain the optimal network at 30%. However, the reversed nature of the algorithm, starting at 100% MPA coverage and working better, produces a more stable network with regards to this problem than starting at 0% and growing to 100%.

## 2.4 Generalized Experiments

Given the complexity of the operating model used here, a complete sensitivity analysis across all parameters is not practical. Instead, we focus on the role of life history, fishing pressure, and MPA design.

Each iteration uses one of three species: A stylized tuna modeled after skipjack tuna (), a stylized marlin modeled after (), and a stylized shark modeled after (). Each species has all life history parameters pulled from FishLife (Thorson (2020)), with the exception of steepness, set to XX, and fecundity. For the tuna and marlin species, fecundity is assumed to scale with weight modified by the hyperallometric exponent. For the shark species, we assume a constant value of six pups per year at all ages greater than the age at maturity. We assume that tunas have an unfished biomass of XX, marlins XX, and sharks XX, to reflect a large, medium, and small population.

For the generalized experiments we only include one fishing fleet. We asign a price per KG of $XX for tuna, intended to reflect a low value high volume fishery, $XX for marlin for a higher value low volume fishery, and $0 for sharks to reflect at true bycatch species. We assign a selectivity of 60% of length at maturity for skipjack to allow for some overfishing when F/M is high enough, 70% for mariln, and 90% for shark.

We ran 600 state experiments, varing the state of nature experienced by a simulation. The candidate states include

|  |  |  |
| --- | --- | --- |
| State | Distribution | Description |
|  |  | Standard deviation of habitat centroid |
|  |  | Standard deviation around centroid |
| Spatial catchability |  | Catchability varies in sapce |
| Spatial allocation |  | Fleet allocation strategy |
| F/M |  | Fishing mortality relative to natural mortality |
| Adult movement rate |  |  |
| Recruit movement rate |  |  |
| Hyperallometry |  | Presence of hyperallometric fec |
| DD timing |  | Timing of density dependence |
| Seasonal Movement |  | Seasonal Movement Present |

For each of these 600 state experiments, we then apply 210 placement experiments defined by an MPA size, an MPA placement strategy, and …XX

We simulate degrees of species overlap using two parameters, and . All species start with the assumption that the centroid of their preferred habitat occurs in the center-most patch of teh two dimensional system simulated by marlin. For our simulations, we then generated a random deviation from that default centroid for each species using in the manner

where *s* denotes species, and *center* is the coordinate of the central cell. In this way, the larger grows, the more variation there is betwen the centroid of the preferred habitat for each species.

We then control the spread of a creatures preferred habitat around that centroid per a Gaussian dispersal kernal in the manner

Where is the euclidian distance from the to patch and controls the dispersal of the habitat around that range.

## 2.5 WCPO Case Study Application

The purpose of the case study is to assess the value of optimization. Given the time constraints of optimization, rather than iterating over the 600, we fix the values from that table to values that best reflect the state of 9 species reported as caught in the WCPO.

Sigh. lots of details to add in here. This is the worst.

|  |  |
| --- | --- |
| Scientific Name | Common Name |
| prionace glauca | Blue Shark |
| carcharhinus longimanus | Oceanic Whitetip Shark |
| isurus oxyrinchus | Shortfin Mako Shark |
| carcharhinus falciformis | Silky Shark |
| thunnus albacares | Yellowfin Tuna |
| thunnus obesus | Bigeye Tuna |
| thunnus alalunga | Albacore |
| katsuwonus pelamis | Skipjack Tuna |
| kajikia audax | Striped Marlin |
| istiompax indica | Black Marlin |
| makaira mazara | Indo-Pacific Blue Marlin |
| xiphias gladius | Swordfish |

## 2.6 Assessing Performance

Each model run started at equilibrium conditions and was then run for 80 years (160 seasons. We assessed performance by comparing relevant metrics (e.g. depletion and profits) under a given scenario with MPAs relative to the values of those same metrics in the simulated counterfactual world identical in every way save for the presence of MPAs.

Degree of habitat difference was calculated as

xx will work out the notation for this xx

In order to weight habitat difference by cells where animals occur, not where they are not.

# 3 Results

Our simulation experiments allow us to examine the wide range of effects that MPAs can have on groups of target and bycatch species depending on combinations of ecological, economic, and design parameters. The goal of this exercise is not to assign any probability to the potential impacts of MPAs; we have not provided any explicit probabilities to the alternative states modeled here, and so it may be that a state that was only modeled on a few occasions in our simulations is in fact highly common in the real world.

What these experiments are designed to do is illustrate the range of outcomes that are possible from MPAs under the types of conditions evaluated here, and evaluate which drivers are potentially the most influential in affecting particular outcomes with regards to bycatch. Our case study of a WCPO-esque system is intended then to reduce the parameter space enough that we can examine the relative tradeoffs and value of optimization for economic and conservation objectives in a pelagic system.

One clear caveat across all of these results is that we have made two very strong assumptions around the behavior of the fishing fleet. The first is that we assume that effort is displaced, not removed, by the creation of MPAs. This is a widely debated question around MPAs, and the real impacts of MPAs on fishing effort will clearly be setting dependent. For example, large-scale pelagic fishing fleets already have high rates of vessel movement built into their economic models, and so may be more likely to move rather than exit the fishery in response to MPAs. In contrast, smaller scale coastal fishing operations may simply exit the fishery if their local fishing grounds are placed in MPAs. There is clear evidence of effort displacement in many fisheries though (citation), and moreover a motivation for this study was to evaluate the performance of MPAs in reducing bycatch given the potential for effort displacement and technical interactions. If MPAs do not produce increases in fishing effort outside their borders, then the direct conservation effects of MPAs have to be positive for all species concerned.

The second is that we do not account for evolution of total effort. Our assumption is that while fleets can make economic decisions based around where to allocate their effort in space, the total pool of effort they exert is fixed (we would note that the underling marlin model does have capacity for more realistic fleet models such as open-access dynamics). This is clearly an incorrect assumption over the long term, but allows us to focus on the impacts of the other drivers considered here. A more through consideration of the impacts of fleet model structure on MPA outcomes is generally needed, and is critical for any tactical efforts at MPA modeling.

## 3.1 Generalized Experiments

We focused first on the range of impacts that MPAs can have on mature biomass of target and bycatch species across the range of variables explored. To illustrate, we pulled out two example simulations, one where MPAs provided relatively large benefits across all three species, and a second where MPAs actually produced substantial losses in some species. In the “best case” scenario, each of the three species shares a common habitat distribution, and so protection of the central habitat of one species results in protection for all species. In the “worst case” scenario, an MPA designed primarily around the tuna fishery displaces effort onto the marlin and shark habitats, increasing the tuna population while driving the other two species down (Fig.3.1).

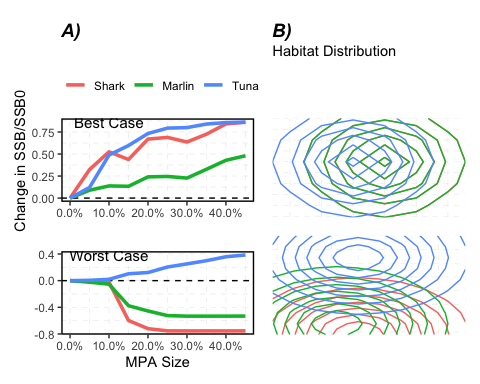


Figure 3.1: Illustrative example demonstrating how degrees of overlap can influence

Looking at the full 6000 experiments run, the results were highly variable. Across our simulations, gains were much more common than losses, with losses of any magnitude occurring in 19% of simulations with MPAs, but losses of 10% or greater of SSB in only 4% of simulations. However we stress again that we can assign no probabilities to any of these outcomes in the real world; this simply tells us that under the range of conditions, selected to represent plausible states of nature, there are many more ways for MPAs to provide a conservation effect greater than or equal to 0 than there are for them to provide a net loss for some species.

The question of interest then are which of the considered drivers appear to be the most influential in affecting the magnitude and direction of conservation effects of MPAs. Fishing mortality is the most obvious answer; if fishing mortality is zero in the absence of an MPA then clearly a no-take MPA will have no effect. As such we do not focus on that metric here, focusing instead on other key drivers identified by our simulation. Four visually prominent factors were MPA size, species, design strategy, and degree of habitat difference. The degree to which MPAs of a given size impact spawning biomass depends on a host of factors. Any potential for conservation losses are intuitively convex in MPA size: effects of any kind are low when MPA size is low, and conservation losses must be zero when MPA size is 100% (which this graph does not quite reach), with peak losses in our simulations occurring between MPA sizes of XX and XX. Life history plays a clear role our stylized with shark and marlin populations being much more likely to experience net conservation losses as a function of MPA placement than the more resilient tunas. High degree of habitat differences can lead to both to the potential for large conservation gains or losses depending on whether a more isolated species is located primarily inside or outside of MPAs (Fig.3.2).

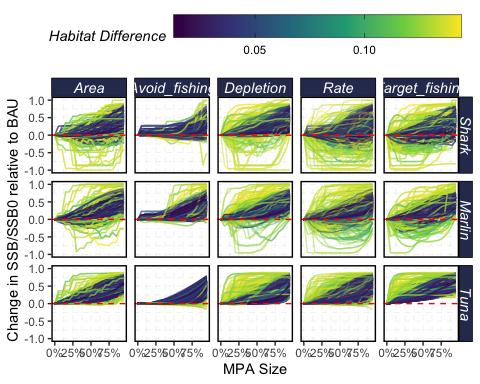


Figure 3.2: Trajectories of changes in SSB/SSB0 relative to BAU for each species across rule-of-thumb MPA design scenarios. Color indicates degree of habitat difference.

We can somewhat quantitatively evaluate the relative impact of these drivers using a regression, given that by construction variation in each of evaluated drivers are independent in our simulations. We fit a binomial regression to the presence or absence of of a net conservation loss per species as a function of the simulated experimental variables. The factors that according to this model most increase the probability of a net conservation loss occurring include habitat differences, a placement strategy of avoiding fishing areas, and the life history of the species (shark or marlin relative to tuna). The factors that most decrease the probability of a conservation loss from an MPA are MPA size, placement strategy based on local depletion, and somewhat interestingly fishing mortality rate (Fig.3.3-A).

However, this result is somewhat misleading (xx so should we just remove?xx). Fig.3.2 shows the clearly bimodal nature of for example habitat differences. This analysis helps inform us that habitat differences are a necessary but not sufficient condition for conservation losses induced by effort displacement. The regression based results require assuming that each of the effects are independent and linear in nature. In fact each of these factors can interact in complex and non-linear ways that may not be apparent visually or through this type of regression analysis. To address this, we ran a random forest using the ranger package (citation) in R (citation) and extracted the impurity corrected importance scores for each of the variables. While this does not tell us the expected marginal effect of individual drivers, it does tell us which variables are important if our goal is to accurately predict the potential for unintended consequences or magnitude of conservation gains in MPAs. Note here that variables that intuitively should have an impact but have no visually or statistically (in a linear model) clear impact on the probability of experiencing a conservation loss such as the dispersal distances of adults or larvae have importance scores comparable in magnitude to habitat differences when considered in the context of nonlinear effects and interactions with other variables (Fig.3.3-B).

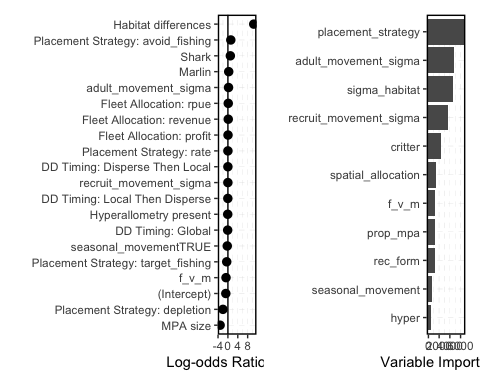


Figure 3.3: Things

## 3.2 WCPO Case Study

Our case study allows us to focus in on important questions around the relative performance of “rule of thumb” MPA design strategies relative to optimized networks. In particular, as any leakage induced losses from MPAs must be 0 if MPA size is 100%, an important question then is within this case study what tradeoffs are present between increasing the probability of a successful conservation outcome by increasing MPA size and the increasing probability of negative economic impacts with MPA size (xx phrase better xx).

Given the set of parameters simulated here, we find little intrinsic risk for large-scale unintended losses in total spawning biomass caused by MPA effort displacement for the species included in our WCPO case study. Each of the design scenarios produced at least some small loss in biomass for one or more species at some MPA size. However, these losses were generally small and isolated to a subset of species within a small MPA size range, with the exception of the “Avoid\_fishing” MPA placement strategy that resulted in net losses for most species at large MPA sizes (though simply minimal impact at smaller sizes). All design strategies except “Avoid\_fishing” and “Rate” resulted in relatively rapid declines in profits for the three main tuna fisheries (skipjack, yellowfin, and bigeye). Both “Avoid\_fishing” and “Rate” maintained profits close to business as usual up to a large MPA size, but did so at the expense of conservation benefits (Fig.3.4). Results for yield rather than profits are qualitatively similar, see SI.

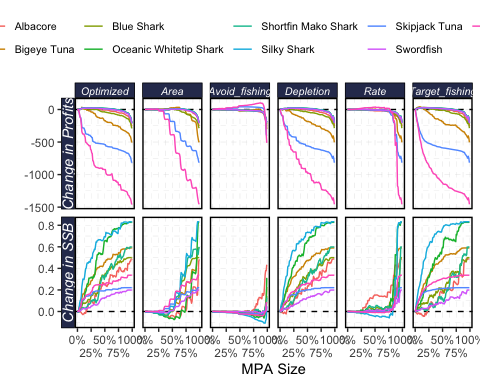


Figure 3.4: Simulated trajectories of changes in profits and spawning stock biomass (SSB) for selected species caught in the WCPO. Each column represents a different MPA design strategy. ‘Optimized’ refers to an MPA network optimized to maximize total SSB across all species.

Viewed as totals, we found a small parameter space under the “Area” and “Avoid\_fishing” design strategies where MPAs were capable of causing a net decrease in total spawning stock biomass across all evaluated species. However, the efficiency frontier indicates that these points are not Pareto efficient, and MPA design configurations exist that achieve the same levels of economic performance while producing a net gain in spawning biomass. Optimal MPA design was able to slow the tradeoff between total profits and bycatch spawning biomass, but for any conservation weighting any increases in total biomass of bycatch species came at a decrease in total profits. However we also found limited need for optimized networks, with the “Depletion” design scenario essentially following the Pareto efficiency frontier (Fig.3.5).

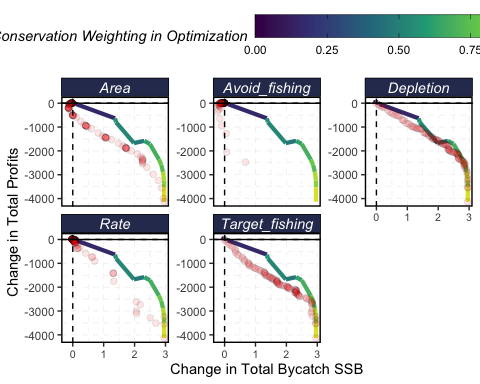


Figure 3.5: Efficiency frontiers for changes in total profits and total bycatch spawning stock biomass (SSB). Color gradient line shows optimized pareto frontier, with color showing weighting of conservation (total spawning stock biomass) in the objective function. Red points show outcomes of ‘rule of thumb’ MPA design strategies.

# 4 Discussion

MPAs can be a powerful tool for providing conservation benefits across large swaths of species and space. Under the appropriate circumstances they can also provide benefits to food security and economic outcomes. However, while spatial closures are simple in concept, predicting the likely effects of MPAs across groups of species and fishing fleets becomes increasingly complicated as the systems being studied deviate from assumptions of homogenously distributed species with perfectly selective fleets. In this paper we used a new bio-economic model to demonstrate how a range of variables often omitted in MPA modeling can act to influence the outcomes of MPAs on conservation and economic objectives, particularly with regards to protecting bycatch species. We demonstrate that unintended conservation losses to both target and bycatch species are possible, but only under a range of specific conditions, and under most simulated cases did not occur. MPAs were capable of causing small losses in biomass for the WCPO case study, but only for a subset of design strategies and species, most of which could be overcome by optimized design.

Our results indicate that as suggested by theory (citation) and empirical evidence (citation), MPAs can indeed have unintended consequences for conservation if they result in effort displacement rather than attrition. However, our model found these to be a minority of the simulations tested. This does not suggest that leakage may not a problem for specific MPA. But, it also indicates that across the range of plausible parameter combinations that we explored it was much more common for MPAs to provide net conservation benefits even if effort is displaced. This suggests then that we should of course not dismiss the conservation benefits of MPAs in the presence of effort displacement, but also that users must be aware of the potential for unintended consequences that can indeed occur. While many different factors interact in complex ways to affect the potential for unintended conservation consequences, the most obvious is the degree of difference in the habitats utilized by the species within an ecosystem in which an MPA is to be placed. As a starting point, it is critical that communities engaged in marine spatial planning create a localized assessment of the degree of habitat overlap across potentially affected species to assess the potential risk of unintended consequences.

The MPA literature is highly dominated by modeling studies (citation). What then is the added value of the model and results presented here? Our model contains many features missing from many general MPA models, including size structure, seasonal movement, larval and adult habitats and dispersal, and critically technical interactions xx clearer term for this xx across species. A reader might reasonably ask about a range of other factors not included, such as time-varying parameters and species interactions. One could of course continue to add features to the model until it reaches the complexity of an end-to-end model such as Atlantis (citation). While such models have tremendous value, our goal here is to present a model that can help provide closer to tactical advice for users without the data or capacity for such high resolution models. One justification for simpler MPA models is often computational tractability: tracking the full age structure of multiple species and the economic outcomes of multiple fleets dynamically across a high resolution spatial grid can quickly become computationally expensive. Faster implementations completely written in languages such as C++ however become inaccessible to many users. Our model seeks to fill a middle ground here, with the core operations run in C++ while providing a relatively user-friendly front end in the open-source and commonly used R programming language. This allows users to ask the sorts of questions addressed in this paper that require a more realistic model, without requiring inordinate amounts of data, programming expertise, or computational time.

Several results from our model may seem counterintuitive based on existing literature. We found little effect of the timing and spatial structure of density dependence in our model. Other studies have pointed out that decisions about whether density dependence is local or global can have major implications for fishery outcomes of MPAs (citations). The difference here is that our model is fully age structured. As such, yields are separated from recruitment, the location of density dependent processes in our model, by growth, natural mortality, and adult movment. In contrast biomass dynamics models assume that density dependence occurs on a net “growth” parameter combining both recruitment and biomass growth, and that this growth is instantly available to the fishery. As such we suspect that the timing of density dependence plays a much bigger role in the expected outcomes of MPAs when biomass dynamics models are used as opposed to when it is included as an effect on recruitment in an age structured model.

Marshall et al. (2021) pointed out that many fisheries models assume that fecundity is simply proportional to spawning biomass, when in fact there is ample empirical evidence that fecundity follows a hyperallometric pattern, i.e. that fecundity increases faster than weight. In that study the authors found that the presence of hyperallometric growth substantially amplified the predicted benefits of spatiao-temporal closures such as MPAs, relative to an assumption of allometric fecundity. In contrast, we find that the presence of hyperallometric fecundity, even at levels greater than the mean values reported in Marshall et al. (2021), had little effect on the expected conservation outcomes of MPAs (Fig.3.3, see SI for additional analyses). The key distinction here is that Marshall et al. (2021) evaluated the effect of MPAs under different assumptions of management, e.g. management based on spawning potential ratio values calculated assuming allmetric fecundity when in fact the relationship was hyperallometric. Our study holds effort constant, and so reflects more the isolated effect of hyperallometric on MPA outcomes independent of management actions.

Rassweiler, Costello, and Siegel (2012) and Rassweiler et al. (2014) both demonstrated the potential importance of optimized MPA planning over more “rule of thumb” MPA designs. In contrast, we found little value of optimization, with the “Depletion” MPA allocation strategy more or less following the Pareto efficiency frontier (Fig.3.5). As pointed out in Rassweiler et al. (2014), the value of optimization (at least if the objective function depends on both fishery yields and fish biomass) depends on the degree of overfishing present. In our WCPO case study, best available evidence is that none of the major tuna stocks that provide the bulk of yield, revenues, and profits to the WCPO fleets are overfished or experiencing overfishing (citations, need to update with assessments since pons is out of date now). Our results then are consistent with Rassweiler et al. (2014), and evaluations of our model on stocks experiencing overfishing will likely find much higher value of optimization.

Value of information and fleet dynamics are two critical areas for future study in this realm. Our study assumes perfect information in the design of MPAs. We feel this is a useful benchmark for isolating the potential impacts of key ecological and economic drivers of MPA effects. However it is clearly not a realistic assumption, particularly for pelagic ecosystems where species inhabit a complex, dynamic, and hard to observe mosaic of habitats. This is likely to be particularly true for rarer bycatch species such as sharks that may be the impetus behind many pelagic MPA designs. Further research is needed to examine how the types of dynamics explored here are affected by varying degrees of information quality.

We focused our efforts on modeling the spatial distribution of a fishing fleet conditional on a fixed pool of fishing effort. As discussed previously, the outcomes of MPAs depend critically on the reaction of fishing fleets to new spatial protections. In reality neither perfect attrition nor perfect redistribution are likely to be realistic scenarios. Instead individual fishing operations will adjust their behavior according to their own objective functions. More realistic models of total effort could include simple open-access dynamics in the manner of Cabral et al. (2019), to more complex dynamics reflecting combinations of policies such as effort controls, spatial closures, and rights based fisheries management.

As demonstrated here there though there is a possibly endless list of refinements and realism that could be added to simulation based studies. While efforts such as this can help illustrate which drivers may be the most important in particular circumstances in many cases as demonstrated here the effect of specific variables are likely to be so context dependent as to defy easy classification of “important” or “not.” We feel these models are better viewed as a foundation for empirical action. In terms of planning, models such as this can be used as tool for answering “what if” rather “what will be.” Helping community members visualize the potential impacts of alternative states of nature, such as debates around life history or habitat distribution, can help set expectations and guide data collection. Models such as this can also serve as hypotheses for expected effects that can ideally be confronted with data as MPAs are actually implemented.

# 5 Conclusions

The bluntness of MPAs as a tool is both their strength and weakness. Targeted fisheries management is often focused on the assessment and management of individual stocks. While this has worked well in many cases (Hilborn and Ovando 2014; Hilborn et al. 2020; Worm et al. 2009), it is an unrealistic and perhaps undesirable model to replicate in many parts of the world, where data limitations and fishery complexity make this sort of highly targeted management untenable. In contrast, MPAs can provide protection to entire portions of an ecosystem with minimal need for targeted interventions. As a result and as shown by Hastings, Gaines, and Costello (2017), MPAs can provide an effective solution to bycatch problems under the right circumstances. We extend the spirit of that analysis here, but expanding the model used to assess the impact of MPAs on bycatch under broader range of scenarios. As predicted by Hastings, Gaines, and Costello (2017), as conditions deviate from the stylized nature of their model the effects of MPAs on bycatch become more nuanced. While we similarly find a large parameters space where MPAs provide clear benefits to the conservation status of both target and bycatch species, we also identify a smaller subset of enabling conditions, such as degrees of habitat overlap, that can lead to MPAs producing net reductions in bycatch biomass. As increasing numbers of MPA networks are implemented around the world, tools such as this can help communities both design and evaluate the performance of MPA networks with the goal of better outcomes for marine ecosystems and the human communities that depend on them.

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# 7 SI

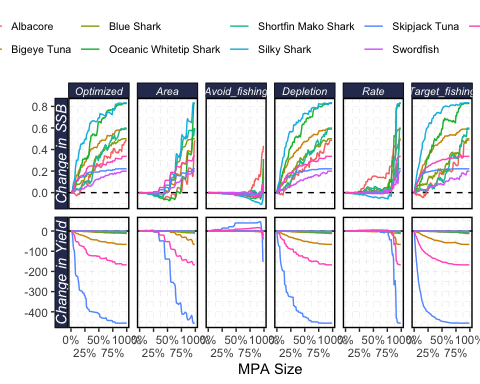


Figure 7.1: Simulated trajectories of changes in yields and spawning stock biomass (SSB) for selected species caught in the WCPO. Each column represents a different MPA design strategies. Optimized refers to an MPA network optimized to maximize total SSB across all species.

# 8 Scraps

There two general results beg some important questions. First, are unintended consequences inevitable given the kinds of technical interactions explored here, or can optimized MPA networks reduce or eliminate these unintended consequences. Second, one clear solution to the problem of unintended consequences is to simply make the MPAs large: if MPAs cover 100% of the area there can be no direct unintended conservation consequences. The potential for negative impacts on economic fishery outcomes increases as MPAs reach large size though. What then are the tradeoffs between reducing the potential for unintended conservation consequences and fishery revenues?

To address these questions, we ran a more limited “case study” set of simulations, based on the dynamics of the WCPO tuna fisheries. Rather than iterating over different movement dynamics and habitat configurations, we fix habitat layers based on reported CPUE for the species in question, and xx other things we fix xx.

The general experiments conducted show two general insights

1. Even conditional on fishing exploitation and general life history strategy, the effects of MPAs on a group of species with technical interactions is highly variable and dependent on habitat distribution, design decisions, and data quality. xx make this more explicit.
2. Some degree of unintended conservation consequences occured across nearly all of our simulations below MPA coverage near 100%, though small losses were much more common than large. Different design strategies are better suited to avoiding unintended consequences.

Thinking through the “naive” MPA design strategies to compare against the optimized outcomes. Thoughts at the moment below. These can be run in a few seconds each, so we cab be be pretty liberal in coming up with combinations if there are other ideas people want to try, but also if some of these seem pointless can drop as well! 6:11 Design strategies 1. Assign protection by SSB / SSB0 weighted abundance in space (protect the highest concentrations of the most threatened species) 2. Assign protection by bycatch rates (distribution of biomass bycatch / biomass target) 3. Assign protection by targeting fishing effort 4. Assign protection by avoiding fishing effort Knowledge states 1. Degrees of accuracy over the thing being measured (i.e. error in the design strategy) 2. Number of species considered (e.g. design aronnd only 2 bycatch species instead of all) 3. über naive: just close off random patches up to a specified size We then plot these points in objective function space and compare to the efficiency frontier / consider frequency and magnitude of conservation and economic tradeoofs The question all this is answering: how sensitive are conservation and economic outcomes to design strategy / uncertainty when there are technical interactions and heterogeneity in habitat? The first stage is teeing up the idea that beyond conservation / yield tradeoffs, as you increase habitat heterogeneity with technical interactions you increase the potential for conservation tradeoffs. But, the degree is going to be super context dependent, so to dive in a bit we then focus on this case study of the particular species / habitat overlap in the WCPO. Further work might reveal more generalities in this, but htis is basically getting a sense for the potential magnitude of the challenge.

XX stress a key difference: may other papers on this are static, in that they just some up displacement on different layers, rather than addressing dynamic respones over tim xx

We show…. - sensitivity of both conservation and fishery outcomes to pelagic realism and design choices - compared to targeted / dynamic intervention… - value of information would be great…

Contrast to coastal MPA theoretical work - Hastings, Gaines, and Costello (2017) - (**ovando2021?**) - (**white2010?**) - not quite sure what to do about points raised in Elizabeth A. Fulton et al. (2011) - to what extent has this been done…

The paragraph from Elizabeth A. Fulton et al. (2011) that broke me…

" Spatial management was insufficient as the dominant management lever because it proves quite difficult to strike the balance between protecting areas that are of a size sufficient to produce any conservation benefit and providing sufficient fishing grounds to sustain an econom- ically viable industry (which is not possible in many fisheries if closures on the order of 70–80% or more are imposed, Fulton et al. 2007). More- over, Savina etal. (2008) found that effort displaced by closures potentially undermines any benefits coming from the zoning. For instance, strong improvements in diversity (by nearly 20%) under heavy fishing pressure occurred if effort outside a marine protected area (MPA) was controlled. However, without effort control, there was a significant (>20%) drop in overall diversity. Fulton et al. (2007), Savina et al. (2008), Smith et al. (2010) and unpublished work associated with Horne et al. (2010) all found that while spatial management appears to be an effective means of satisfying conservation objectives con- cerning habitat and restoring age-structures of less mobile species, benefits from closures for individual species depend on its trophic position, degree of mobility, geographical distribution and extent of ontogenetic shifts in habitat use and depth (highly mobile or prey species do not benefit in the way that more site attached or predatory species do)."

Lots of studies have shown that lots of things matter, can we provide guidance on which things are priorities?

Where does this fit in context of Smith et al. (2021)? One important difference is that they point out differences in effectiveness, where effectiveness is still almost always positive, since they just measure leatherbacks. So their fig 5, there are a few cases where leatherback catches actually go up, but it’s rare. So, extending to multiple species and keeping track off all of them shows it’s even harder

How does this contrast with the the large and growing dynamic ocean management lit? - By definition, with perfect information dynamic static spatial controls - DOM literature is mostly static, tracks displacement onto static abundance / risk layers - Doesn’t allow for dynamic impacts, for example fleet adjustments based on updated economic surface, or short-term costs for long-term benefits (can overstate costs?) - Dynamic model allows for delta between dynamic policies, e.g. Fmsy vs DOM - analytical models a la hastings have value but do / don’t stand up to realism

Presentation of the model as a MICE model for MSP - reasonable parameterizable - flexible - fast

Focus of debate has been on fisheries and yields. As MPAs move to pelagic systems though, we show that conservation outcomes also depend on correctly identifying ecological state / design decisions etc.

What are the considerations of protection you need to make good decisions. It’s not always obvious how to design things to get the outcome you want. If we could make the case that something like closing the high seas is insufficient conservation management without conservation management inside EEZs / what is the

Need to do an optimization here, calculate the marginal value of added cells.

What’s this about? Pointing out a problem, which to make impactful would require making the case that there is a problem with current design strategies. e.g.. “MPAs are often designed like this (simple dispersive models with constant habitat, or MARXSAN style things), and doing that does/does not create problems A tactical evaluation. Picking a handful of high profile MPAs, parameterizing all the knowns as well as possible, iterating over unknowns, and see what the range of outcomes are. Cleaner, more impactful, but also opens it up (depending on the results) to a details fight about very specific modeling choices How plausible are losses? Maybe we drill down on this a bit. From a purely bycatch perspective, the usual questions of fisheries tradeoffs aren’t on the table (but can add to the discussion considerations of how much target fishing you give up). Given that then, while it’s possible that”targeted" interventions would work better (ignoring costs/enforcement, etc), there’s really no reason not to do MPAs. Unless, you actually end up concentrating fishing pressure outside on populations. So, we consider how plausible is it for that to really happen. Issue here is that seems likely to be pretty hand-wavey. Most likely that the vast majority of simulations will show positive impacts, but have no way of assigning probabilities to any one state of nature.

The Role of Blue-Water Marine Protected Areas in Bycatch Reduction

What’s the question: How effective are Blue-Water MPAs in reducing fishing mortality of important pelagic bycatch species?

Another angle. There’s going to be a lot of unknowns in designing BWMPA. How much does not fully understanding a few key life history (e.g. movement) matter, and how much does the role that the species plays in the broader fleets portfolio matter

Could simulate habitat from a multivariate normal, where you use the sigma to control how similar rasters are across species

Marine protected areas are increasingly proposed to protect biodiversity in pelagic systems. However, maby paradigms of mpa design come from coastal systems. Here we ask, how likely are blue-water MPAs to provide conservation benefits to bycatch species, and what are the key uncertainties underlying these outcomes? We begin with a general discussion of the ways in which traits of open-ocean systems might influence the conservation performance of BWMPAs. Given the massive parameter space, we then constrain ourselves to a styulized version of the western central pacitic ocean to ask, how feasible is it to provide broad protection of bycatch species through common MPA design paradigms in the context of this system. Our results demonstrate the critical importance of XX and XX in designing MPAs in pelagic systems, and highlight the potential risks of not accounting for XX. Introductionhere

Bycatch is a significant driver of population declines for many pelagic species Sharks, seabirds, mammals, etc MPAs increasingly turned to as a solution for conservation problems, etc. MPA science is largely based on dynamics of coastal systems. Open-ocean ecosystems have very different dynamics that require dedicated research Burgess et al. (2018) estimated the reductions in fishing mortality needed to halt declines for a number of bycatch species Here we ask, what are the key drivers of bycatch conservation outcomes from MPAs? There are all of these species; you reduce fishing mortality. You can either do fisheries management, or you can do MPAs, let’s focus in on the MPA side. This could reduce fishing mortality, or it could do, and it depends on the dynamics of the species and the fleets. When can MPAs reduce fishing mortality enough for bycatch species? And where can you go wrong?

It doesn’t make any sense to ask “do MPAs help bycatch”: the question is obviously it depends. To quickly make this case, we’ll assume that a species is in need of recovery. We then do the simple mako example to show that effects of spatial closure depend on the overlap of habitat and the assumption of fleet dynamics, and provide some empirical evidence that in particular effort redistribution is not unlikely.

Determining the effect of an MPA network on bycatch then will also depend on trying to get close to a tactical model. But, this creates a problem for blue water systems in particular. Can make the argument that given the centrality of relatively static habitat features in coastal MPAs “protect the key habitats” might not be a bad strategy from a conservation strategy. But in highly mobile pelagic systems there (may be) a lot more variables in play. Where should researchers direct their attention?

To reduce the parameter space, we constrain ourselves to a system where 1) we know the species involved 2) we have some sense of the relative depletion and value of the different species and 3) some basic life history of the species. We then vary commonly unknown parameters, particularly preferred habitats, spatial catchability, movement rates etc, and pair these simulations with different MPA designs, and examine the conservation outcomes for bycatch species.

What i don’t like about this

There isn’t an “answer” to this: baring something like “changing the type of density dependence never had any effect greater than XX%,” for anything that on occasion has an impact the answer of “how much” will almost always depend on what else is going on.

So, it seems like there are two real angles of attack here

Pointing out a problem, which to make impactful would require making the case that there is a problem with current design strategies. I.e. "MPAs are often designed like this (simple dispersive models with constant habitat, or MARXSAN style things), and doing that does/does not create problems A tactical evaluation. Picking a handful of high profile MPAs, parameterizing all the knownns as well as possible, iterating over unknowns, and see what the range of outcomes are. Cleaner, more impactful, but also opens it up (depending on the results) to a details fight about very specific modeling choices

Methods

Collect life history for key bycatch species and target species, cite Bradley et al. pulling together species distribution and threats etc. Introduce marlin Parameterize marlin runs with “knowns” from life history of bycatch and target species Highlight key “unknowns” that we will iterate over, e.g. fleet models, density dependent movement, timing of density dependence etc Simulate effects of MPAs given reasonably realistic situations but iterating over key unknowns Evaluate the range of outcomes and key drivers of MPA effects I’m thinking we try and avoid a really specific case study but hard not to accidentally do one without making everything up….

Results Range of likely changes in fishing-induced mortality for the species selected Key drivers of uncertainty in those outcomes, focusing on things that switch states from reduction to increase in mortality How common are conservation tradeoffs between bycatch species? Fishery impacts

Discussion What does this say about BWMPAs and bycatch? Not going to get into design decisions here, depending how common tradeoffs are I think that will be the main focus Highlight any species that frequently induced tradeoffs Tee up future research MPAs in context of other management MPAs as risk reduction strategy Etc.

We do not focus into the individual effects of particular variables as we found them to be highly dependent on the exact question asked and the set of data included, and since we cannot ascribe any actual likelihood to any individual state of nature simulated here.

However, three important features do emerge. The first is that life history plays an important role in the potential for unintended conservation consequences from MPAs. All else equal, MPAs were much less likely to produce losses in spawning biomass for our tuna-like species than the marlin or shark-like species. Given that within the broad life history traits we do vary adult and larval movement, fishing mortality, as well as the timing of density dependence, we believe this result is mostly due to the high resilience (high steepness, low age at maturity, fast growth) of the tuna-like species relative to the marlin and shark-like species.

The second is that design matters…

The third is that extreme outcomes (both positive and negative), particularly at lower MPA sizes, are largely driven by the presence of small range sizes interacting with seasonal migrations. Across species, simulations without seasonal migrations and small ranges were much more likely to produce extreme results than those with seasonal migrations and/or larger ranges. Presence of seasonal migrations acts as a dilutant: As a given static MPA only provides protection, or displaces fishing effort, onto a particular area in only half of the year, both the benefits and costs of MPAs are smaller. When seasonal migrations are not present and the species range is small, MPAs are more capable of providing either large benefits or large losses.

\Big message: even constrained by the same initial depletion and core biology (e.g. movement rates), a wide range of outcomes are possible for each species for a given MPA size, dependent on the design strategy, habitat overlap, migrations, quality of information, etc. Across the board as MPA size increases the ratio of positive to negative outcomes increases, until all species achieve their maximum conservation potential in every iteration at 100% MPA. HOwever, every species experienced a set of simulations, roughyl xx%, that resulted in net losses in SSB/SSB0 relative to BAU. Losses were smaller than potential gaines, but reached meaningful levels in some species, and interestingly peaked in many cases right before max MPA (reflecting concentration of fishing in small amounts of habitat in habited by the species).Important to stress in here that there are no probabilities in this, no way of knowing which state is more probable than others, just given the range of things simulated more ways for a bigger positive effect. Also make clear though, biggish losses (10% or more) possible, but rare.