Selection of planning unit size in dynamic management strategies to reduce human-wildlife conflict

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Selection of planning unit size in dynamic management strategies must consider environmental variability and data latency.

Abstract

Conservation planning traditionally relies upon static reserves, however there is increasing emphasis on dynamic management (DM) strategies that are flexible in space and time. Due to its novelty, the field of DM lacks best practices to guide design and implementation. We assess the effect of planning unit (PU) size within the context of an applied DM tool designed to reduce entanglements of protected whales in a lucrative U.S. crab fishery. We find that smaller PUs avoided up to $47M of revenue loss and reduced entanglement risk by up to 25% compared to the large PUs currently in use by avoiding the incidental closure of lose-lose areas with low biodiversity value and high fisheries revenue. However, larger PUs were more buffered against the effects of an unprecedented marine heatwave in 2014-16, and were less affected by delays in data availability. Our findings suggest that novel and adaptive management solutions - rather than a one-size-fits-all approach - are needed to separate wildlife from their threats under a changing climate.

1. Introduction

The "single large or several small" (SLOSS) debate over reserve size has persisted in the conservation planning community since the 1970s (Simberloff & Abele, 1976). Proponents of single large reserves argue that large, continuous reserves protect more species and reduce edge-effects, while proponents of several small reserves posit that the multiple smaller reserves protect wider ranges of biodiversity while providing insurance against disturbance. More recently, the SLOSS debate has deepened to consider planning units (Cheok et al., 2016; Hamel et al., 2013; Richardson et al., 2006; Van

Wynsberge et al., 2015) - subdivisions of a planning region that are assessed by cost and biodiversity value and then selected to design a reserve (Pressey et al., 2007). While multiple trade-offs can influence the choice of planning unit size, smaller units are generally more efficient, flexible, and require less area to achieve conservation targets compared to larger units (Mills et al., 2010).

Thus far, SLOSS has been investigated with respect to static reserves, i.e., protected tracts of land or ocean that remain fixed in space and time such as national parks and marine protected areas. However, increasing awareness of environmental variability and availability of real-time data streams on animal and human movements has led to the development of dynamic management. Dynamic management (DM) is an emergent strategy in which management boundaries and recommendations are updated in near-real time to reflect changing environmental conditions, wildlife-human interactions, socio-economic factors, and/or management priorities (Lewison et al., 2015; Maxwell et al., 2015; Welch, Hazen, Bograd, et al., 2019). For example in the U.S., the marine DM tool 'EcoCast' produces daily maps delineating areas that are better and poorer to fish (Hazen et al., 2018), while on land, the Active Fire Mapping Program produces sub-daily maps of fire activity to delineate evacuation areas (Quayle et al., 2004).

With increasing attention and implementation of DM strategies, the SLOSS debate reemerges within a new context. The effect of planning unit size on DM performance (i.e., ability to achieve desired management outcomes) has not been explored, with DM tools typically using the original resolution of environmental data as planning units (Abrahms et al., 2019; Eveson et al., 2015; Hazen et al., 2017). However, this question begs reinvestigation because the choice of planning unit size in DM may be impacted by factors that do not influence static reserve design, including: 1) rapidly shifting conservation targets, 2) episodic and extreme environmental events, and 3) information delays. While static reserves are designed to protect a fixed level of biodiversity (e.g. Aichi target 11 specifies the protection of 10% marine and coastal areas (CBD, 2020)), targets for biodiversity protection in DM can change with environmental and socio-economic conditions (Hazen et al., 2018), e.g. policies providing legal protection for threatened species may require decision makers to increase restrictions following a ship strike event. DM tools therefore need to be flexible enough to accommodate a range of biodiversity targets, and smaller planning units have been found to increase the flexibility of static reserves (Mills et al., 2010). DM tools' near real-time planning unit selection may be impacted by episodic and extreme environmental events like heatwaves, coldwaves, storms, and floods, all of which may redistribute biodiversity value and cost across planning units. Lastly, the near real-time datastreams frequently used to inform DM tools can be delayed. Socio-economic and ecological data may take time to compile and process, and real-time planning unit selection may actually be based on spatial information from last week or last month (Welch, Hazen, Bograd, et al., 2019). Information delay could be problematic if the environment, biodiversity, and/or cost is highly dynamic, causing management actions to lag behind a moving target (Ingeman et al., 2019).

To evaluate the effect of planning unit size on DM tool performance, we used a case-study of blue and humpback whale entanglement in California's commercial Dungeness crab fishery. In this fishery, crab are caught using traps attached to surface buoys by vertical ropes, which can result in entanglement, injury, and mortality for large whale species. Dungeness crab is one of California's most lucrative fisheries (Santora et al., 2020), while blue and humpback whales are ESA-listed and federally protected in U.S. waters under the Marine Mammal Protection Act, creating steep trade-offs between supporting fisheries revenue and whale conservation. A prolonged marine heatwave from 2014-16 spatially and temporally redistributed both the fishery and whales (Santora et al., 2020), leading to a 10-fold increase in entanglement and a diminished ability for management strategies to navigate these trade-offs (Free et al., 2023; Samhouri et al., 2021). During this marine heatwave, a domoic acid outbreak resulted in a delayed opening of the Dungeness crab fishery, causing the peak of the fishing season to coincide in space and time with the arrival of foraging whales. In addition, the distribution of prey species was compressed along the coast, resulting in greater density of foraging whales into inshore waters also targeted by the crab fishery (Santora et al., 2020). Thus, the heatwave exacerbated management trade-offs between whale entanglement reduction and avoiding losses in fisheries revenue (Samhouri et al., 2021). In response to elevated entanglements during the heatwave, a Risk Assessment and Mitigation Program (RAMP) was established in 2020 to mitigate entanglement risk using a suite of tools, including the ability to dynamically close one or more of seven large fishery zones.

We use a decade-long retrospective analysis to compare the utility of the seven RAMP zones and six increasingly smaller planning unit sizes at reducing blue (*Balaenoptera musculus)* and humpback (*Megaptera novaeangliae)* whale entanglements while avoiding losses in fisheries revenue. The effect of planning unit size was evaluated (1) across a suite of conservation targets, (2) during the 2014-16 marine heatwave, and (3) under multiple lengths of information delay (i.e. delays in information on fishery and whale distributions). This work serves to better contextualize knowledge and best practices from static reserve design within dynamic management, improving our ability to navigate human-wildlife conflicts under climate variability.

2. Methods

2.1. Case-study background

The RAMP evokes zone closures and additional management actions using near real-time information on entanglement reports and whale presence as triggers. Reported entanglements are investigated by the National Marine Fisheries Service to determine the entangling gear type. Whale presence is determined using quantitative whale count thresholds based on a combination of aerial and vessel surveys. Using information on entanglements and whale presences, risk assessments are undertaken every two weeks during the fishing season to determine if management action such as zone closures are needed.

However, there is motivation to explore a dynamic management (DM) framework. Many whale entanglements are unreported, or reporting is delayed such that the location and timing of the entangling event is unknown. Aerial surveys are costly and patchy in space and time, and observations from whale watching vessels are biased inshore near areas with high levels of tourism. A predictive DM framework could provide information on the distribution of whales and entanglement risk at fine spatio-temporal resolutions to allow more areas to stay open to fishing while still reducing entanglement risk at whale hotspots. In order for any management program, including the RAMP, to transition to a DM framework, the effect of planning unit size will need to be explored to ensure management outcomes are achievable. Planning unit size has not been explicitly explored for the RAMP, and the relatively large zones used in practice were selected to safeguard against incomplete information on the distribution of whales and the fishery.

An operational model for blue whales produces new predictions of blue whale distribution each day (https://coastwatch.pfeg.noaa.gov/projects/whalewatch2/about_whalewatch2.html). There does not yet exist an operational model for humpback whales or an operational pipeline for spatially explicit fisheries revenue, but both are possible (Welch, Hazen, Bograd, et al., 2019). As such, our purpose is to investigate how planning unit size affects DM tool performance using the RAMP as a case-study, rather than to provide explicit guidance to the RAMP on planning unit size. This study uses historical 5km data on monthly modeled humpback and blue whale distributions and monthly observed fisheries effort produced by Samhouri et al. (2021). We conducted a retrospective analysis using these data to evaluate the ability of DM tools to navigate trade-offs between risk and revenue, if the tools had been operational during that time (the RAMP first went into effect in the 2020-21 fishing season). Our study explores a decision-making framework in which closures are updated monthly, as finer time-steps are not possible due to the resolution of the existing humpback whale model output. Time-steps of one month are likely too coarse to be relevant to RAMP risk assessments, which are conducted every two weeks. We test 5 km planning units because this spatial scale is substantially smaller than one which is practical for on-the-water implementation of Dungeness crab fishery management measures given existing information and technology. Therefore, it provides an idealized scenario for comparison against those that are more realistic.

2.2. Data

Monthly whale and fisheries model output (Supporting Information 1.) from 2009-2019 used in this present study were the same generated for Samhouri et al. (2021). Regulations allowing for RAMP zone closures did not come into effect until the 2020-21 fishing season, and so the 2009-2019 time-series allows for the investigation of status quo conditions controlled for the effect of management actions. In brief, model-derived predictions of blue and humpback whale distributions were hindcast for each month over a 5 x 5 km grid using species distribution models (Abrahms et al., 2019; Samhouri et al., 2021). Fisheries effort was redistributed following closures using the methods in Samhouri et al. (2021). Fishery effort and revenue (USD value of landings per grid cell) were calculated for each month over the 5 x 5 km grid using vessel monitoring system data linked to California landings receipts registered to Dungeness crab (Feist et al., 2021). Monthly humpback and blue whale risk in each grid cell was calculated by multiplying fishery effort by blue and humpback whale habitat distribution, respectively.

2.3. Prioritizr and zones

For each month in the time-series, fisheries closure scenarios (i.e. sets of planning units) were simulated using the RAMP zones (hereafter: zones) and the spatial prioritization software Prioritizr (hereafter: prioritizr; Supporting Information 2.).

We used prioritizr to solve the min-set problem; that is, what is the minimum set of planning units that must be closed to meet user-defined conservation targets at the cheapest possible cost? In the context of this analysis and setting a conservation target of 10%, prioritizr finds the scenario that avoids at least 10% of each whale's entanglement risk (the target), while protecting as much fisheries revenue as possible (the cost). We tested 17 conservation targets: 1%, 10%, 20%, 30%, 40%, 45%, 50%, 55%, 60%, 65%, 70%, 75%, 80%, 85%, 90%, 95%, 99%. Prioritzr was run using the data's original resolution as planning units, i.e. the 5 x 5 km grid, and five increasingly coarse planning unit sizes (Fig. 1A-F).

The seven zones (Fig. 1G) are coarse, with an average latitudinal breadth of 198 km. We tested all possible zone closure combinations for a total of 126 scenarios: single zone closures (n=7), two zone closures (n=21), three zone closures (n=35), four zone closures (n=35), five zone closures (n=21), and six zone closures (n=7). When zones 1-6 are closed, the entire study domain is closed to fishing (Fig. 1G). This configuration effectively allows zones to run like prioritizr - testing all possible scenarios before selecting the optimal scenario.

2.4. Effect of planning unit size on performance

The effect of planning unit size on DM tool performance was evaluated using two metrics: 1) hypervolume - a measure of the quality of spatial management opportunities for navigating trade-offs between avoiding bycatch and protecting fisheries revenue (Fig. 2), and 2) the realized change in avoided whale entanglement risk and protected fisheries revenue under three types of objectives. These metrics were used to understand overall performance, and the effect of a prominent marine heatwave and data latency on performance.

2.4.1. Hypervolume

Hypervolume (Guerreiro et al., 2021) is a measure of the quality of sets of management opportunities, with bigger and smaller hypervolumes indicating better and worse opportunities, respectively (Supporting Information 3.1.). In DM, the best single scenario to enact will depend on the decision-maker. For example, the best scenario, i.e., combination of planning units to close, may depend on the minimum reduction in whale risk required under protected species policies, or the minimum amount of fisheries revenue decision makers can protect in order to sustain fishers' livelihoods, or it may be the scenario that simultaneously maximally optimizes both avoided whale risk and protected fisheries revenue (see Section 2.4.2.). In lieu of assuming an arbitrary objective, hypervolume is calculated across a full set of possible scenarios to evaluate the overall quality of management opportunities. Hypervolume thereby captures overall performance across all possible objectives, and could be applied in diverse trade-off contexts such as (Lester et al., 2010, 2013; Watson et al., 2009).

The set of scenarios used to calculate hypervolume is termed the Pareto frontier (Fig. 2). Pareto frontiers are the set of scenarios that optimize trade-offs between avoided whale risk (y-axis) and protected fisheries revenue (x-axis). The concept of pareto frontiers originated in the field of production theory, but in recent years, pareto frontiers have been adopted into conservation science to navigate conflicting trade-offs (Lester et al., 2013; Nelson et al., 2008; White et al., 2012).

Hypervolume is affected by three features of the Pareto frontier (Cao et al., 2015): 1) trade-off optimality: how close the frontier is to the theoretical optimal scenario, i.e. 100% avoided whale risk and 100% protected fisheries revenue; 2) set evenness: how balanced the spread of scenarios is along the Pareto frontier; and 3) set range: how big a span the scenarios cover with respect to the objectives (x and y axes).

For each month and planning unit size, hypervolume was calculated across the full set of scenarios for each planning unit size (Fig. S5). Average monthly hypervolume was compared across the full time-series to understand relative management opportunity quality, and a Cox-Stuart test was used to test for a significant trend in hypervolume as planning unit size increased.

2.4.2. Objectives

While hypervolume is a useful metric to evaluate the quality of management opportunities, it does not capture trade-offs between avoided whale risk and protected fisheries revenue once a closure has been enacted. To evaluate trade-offs between avoided whale risk and protected fisheries revenue, we used three hypothetical objective types to select scenarios in each month across the time-series (Supporting Information 3.2). The first objective ("optimal objective", Fig. S6) was to select the scenario in each month with the closest Euclidean distance to the theoretical optimal scenario (100% avoided whale risk and 100% protected fisheries revenue)(Bre & Fachinotti, 2017; Lin et al., 2016). The theoretical optimal scenario is impossible to achieve because of the conflicting nature of fisheries revenue and entanglement risk; if it were possible to achieve, it would indicate that these features were not conflicting and an analysis of trade-offs would not be necessary (Bre & Fachinotti, 2017). Using the theoretical optimal scenario to choose scenarios in each month selects for scenarios that simultaneously maximize avoided whale risk and protected fisheries revenue to the greatest possible extent.

The second objective ("avoided whale risk objective") was to select the scenario in each month that protects the most fisheries revenue while avoiding at least 40, 50, 60, and 70% of whale risk. This objective prioritizes avoiding whale risk first, and protecting fisheries revenue second. The third objective ("protected revenue objective") was to select the scenario in each month that avoids the most whale risk while protecting at least 40, 50, 60, and 70% of fisheries revenue. While these exact objectives are unlikely to be used in the real-world, they allow us to understand the relative performance of DM tools using the types of objectives that might be employed.

2.4.3. Marine heatwave impact

Monthly hypervolumes were compared during the 2014-16 marine heatwave versus more 'normal conditions' (2009-14 and 2016-19) to understand how the heatwave impacted opportunities for navigating trade-offs between avoiding bycatch and protecting fisheries revenue. Kolmogorov-Smirnov-Tito's tests were used to test for significant differences in hypervolume between marine heatwave and normal conditions.

2.4.4. Information delay

Data latency is important to consider when working with social-ecological data. While blue whale distributions are currently predicted at daily time-steps, the humpback whale model is not operational. The latency of modeled data is affected by delays in environmental data dissemination (e.g. satellite data streams may be delayed due to technical issues with the sensor), or pipeline breakages with regard to acquiring environmental data or disseminating model outputs (Welch, Hazen, Bograd, et al., 2019). Spatial data on fisheries effort and revenue are also not yet produced operationally, but latency will be affected by how quickly vessel monitoring system data and landing recipes can be acquired, quality controlled, merged, and disseminated. Latency is particularly important to consider in the contexts of species' motility; for example, for wide-ranging species such as large whales, data delays could lead to concerningly incorrect inferences on the distributions and risk to bycatch species, whereas this may be less of an issue with more sedentary species.

Using the optimal objective, we tested how the performance of the seven planning unit sizes decayed as delays in information on the distribution of whales and fisheries effort increased. We tested how the performance of the seven planning unit sizes decayed as delays in information increased. For each month, information delays were evaluated at one, two, and three months; e.g., February 2010 was managed using the selected closure scenario for January 2010 (one month lag), December 2009 (two month lag), and November 2009 (three month lag). Information was delayed within-season, e.g selected scenarios from the end of one season in July were not used to manage the beginning of the next season in November. Instead, the selected scenario for the beginning of a season was used to manage the beginning of the next season, e.g. for a two month delay, the first two months of season two (November and December 2010) were managed using the selected scenarios for the first two months of season one (November and December 2009). Due to the seasonality of the fishery and whale migrations (Fig. S3), when information is unavailable, the best option for managers may be to make inferences from the same time the previous year (although alternative options may be more useful in practice). Performance decay at each information delay was measured as the Euclidean distance from the selected closure with no information delay (black line, Fig. S7). For each delay length, Kolmogorov-Smirnov tests were used to test for significant differences in decay between the smallest planning unit (5 km) and the largest planning unit (198 km).

3. Results

We found that better management opportunities (i.e., larger hypervolumes) emerged with smaller planning units relative to larger planning units (Fig. 3A). Hypervolume had a significantly decreasing trend as planning unit size increased (p-value <0.05), with the largest planning unit (198 km) having a median hypervolume 35% smaller than the smallest planning unit (5 km). While all planning unit sizes had similar set ranges, smaller planning units better optimized trade-offs and had a more even distribution of scenarios with respect to avoided whale risk (Figs. 2, S4, S5). At smaller planning unit sizes, selected scenarios were always closer to optimal (Fig. 3B), protected more fisheries revenue (Fig. 3C), and avoided more whale risk (Fig. 3D). On average under the optimal objective (Fig. 3B), the smallest planning unit (5 km) protected ~$1M more revenue and avoided 1.2% more entanglement risk than zones (198 km). Across the avoided whale risk and protected revenue objectives (Fig. 3C,D), the smallest planning unit avoided $31-$47M of revenue loss and reduced entanglement risk by 22-25% compared to the largest planning unit.

Hypervolume was on average 13-16% lower during the marine heatwave compared to normal conditions for each planning unit size (Fig. 4). However, this effect was only significant for planning units smaller than or equal to 40 x 40 km (p-value < 0.05, black asterixis Fig. 4), whereas the difference at larger planning units (>=80 x 80 km) was not significant (p-value $>=0.1$). Smaller planning units had a significant marine heatwave effect due to larger differences in hypervolume between the heatwave and normal conditions (on average, 7% greater than differences for larger planning units) and smaller interquartile ranges (on average, 24% less than larger planning units).

All planning unit sizes were negatively affected by information delay (Fig. 5). However, smaller planning units were most strongly affected, with steeper performance decays (measured as distance from the scenario selected by the optimal objective at no delay) as information delay lengthened. Across all delay lengths, the largest planning unit (zones) had 28-32% less decay compared to the smallest planning unit (5 km), which was significant for all delay lengths. At the smallest planning unit size, an information delay of three months resulted in an average of 20% less whale risk avoided and 5% more fisheries revenue protected than with no information delay. Although smaller planning units have steeper performance decays under information delays and greater performance loss during the marine heatwave relative to larger planning units (Figs. 4 and 5), they outperform larger planning units across time (including both normal and marine heatwave periods) at all information delay lengths (e.g. selected scenarios are always closer to optimal, Figs. 3B and S7).

4. Discussion

We found there was no silver bullet solution to the choice of planning unit size, ushering the "the single large or several small" debate into the field of dynamic management. Ultimately, the choice of planning unit size will require decision makers and fishers to navigate trade-offs between multiple social-ecological and logistical considerations (Fig. 6). We found that smaller planning units had the highest performance, providing better spatial management opportunities relative to larger planning units (Fig. 3A), and avoiding more whale risk and protecting more fisheries revenue regardless of objective type or conservativeness (Fig. 3B-D). This result emerged because smaller planning units can align with distributions of biodiversity and cost with more spatial precision, avoiding the incidental closure of low biodiversity, high cost waters (i.e. lose-lose areas) that occurs with large planning units. Critically, smaller planning units avoided up to $39M of revenue loss and reduced entanglement risk by up to 23% compared to the large zones that are currently in use.

However this precision can be disadvantageous during extreme and episodic environmental events, information delay, or distribution uncertainty (Fig. 6). Even if closures had been part of the management toolbox during the 2014-2016 marine heatwave, spatial management opportunities to navigate the tradeoffs between avoiding bycatch and protecting fishery revenue were worse during the heatwave relative to historical conditions, regardless of planning unit size. However, this difference was more severe for smaller planning units (Fig. 4). Spatial overlap between the fishery and whales increased during the heatwave due to a compression of prey and a delayed fishery opening (Santora et al., 2020), reducing the prevalence of win-win areas to close (waters with high whale entanglement risk and low fisheries revenue, Samhouri et al., 2021). Larger planning units were more buffered by this increase in overlap, because they have inherently less precision to find and close win-win waters. This consideration is very important from a management perspective, and a substantial part of the rationale for creating relatively large zones (CDFW, personal communication). Similarly, larger planning units were more buffered against performance decay as information delay increased compared to smaller planning units (Fig. 5), because their less-precise alignment with whale and fishery distributions at any given point in time provides an incidental safeguard against changing distributions across time. We explored the effect of information delays (lags in distributional information on whales and the fishery), however delays due to the time it takes to make and communicate decisions, and implement these decisions, on-the-water are also possible. We hypothesize that larger planning units will be more buffered against performance decay across all types of delay, but we note this as an avenue for future research. Lastly, the precision of smaller planning units is beneficial if the exact and complete distribution of whales and the fishery are known. Social-ecological data will always have gaps and uncertainties (Pressey, 2004), particularly model-derived distributions (Beale & Lennon, 2012), and the lower precision of larger planning units provides risk-averse accommodation of uncertainty.

The choice of planning unit size will also be influenced by the authority given to and the ability of fishery managers to communicate and effectively enforce closures (Fig. 6). DM scenarios are more challenging to manage than static reserves because of their temporal complexity, i.e., the spatial orientation of closures changes over time. The greater spatial complexity of closures designed using smaller planning units (i.e., patchier closures and more complex boundaries, Fig. S6), will exacerbate this challenge. However, larger planning units may disproportionately impact specific communities of resource users, for example scenarios that close all waters to fishing near a specific port or region (Seary et al., 2022). The patchiness of smaller planning units is likely to distribute impacts more equitably across communities.

Lastly, planning unit size will depend on the spatial and temporal footprint of the features being managed. While crab pot gear is small enough to be contained within a 5 x 5 km planning unit, a 45 km long drifting longline is not. Planning unit size will also depend on fleet mobility - while big, high-powered vessels may be able to move outside of larger planning units following a closure, smaller vessels may not. Over the temporal frequency (Welch, Hazen, Bograd, et al., 2019) of the DM tool (one month in our case-study), lower-mobility species like crab may remain in the same 5 x 5 km planning unit, however highly mobile species like whales are less likely to do so. Low temporal durability of distributional information could reduce the protective benefit of closures during their phase of operation. In practice, information delay and distribution uncertainty likely interact with species' and fleet mobility such that each is more impactful for highly mobile species/fleets than for sedentary species/fleets. In our case-study, which involved a highly mobile bycatch species (blue and humpback whales) and a relatively sedentary target species (Dungeness crab), it is likely that information delay and distribution uncertainty have more negative impacts on whale conservation than on fisheries revenue. In a converse scenario involving a relatively sedentary bycatch species and a mobile target species (e.g. bycatch of relatively sedentary groundfish while targeting relatively mobile Pacific whiting; (Holland & Martin, 2019)), fisheries revenue is more likely to be negatively affected by information delay and distribution uncertainty.

Here, we explored how a major environmental perturbation - the 2014-16 northeast Pacific marine heatwave - reshuffled opportunities for bycatch protection and fisheries revenue. In this case, the heatwave created an unprecedented "perfect storm" of whale entanglements, but dynamic management regulations were not yet accessible to fisheries managers until the 2020-21 fishing season. Moreover, heatwaves that occurred in the region during 2019 and 2020 (Weber et al., 2021) did not result in the marked increase in entanglements of the 2014-16 event. There is wide variation in the drivers, evolution, and characteristics of marine heatwaves and other climate shocks (Holbrook et al., 2019; Schlegel et al., 2017), which likely leads to wide variation in species and industry response (e.g. Cavole et al., 2016; Li et al., 2019). While the heatwave in this present study increased overlap between target and bycatch species and reduced the prevalence of win-win waters to close, the converse outcome is also possible. Similar investigations into the effect of PU size in other regions should explore how past environmental perturbations redistributed risk and revenue, ideally across multiple perturbation events to capture how physical differences between events may lead to differences in ecological and economic impact. Evidence from diverse social-ecological systems indicates that climate change and associated environmental perturbations are amplifying human-wildlife conflict globally (Abrahms et al., 2023), increasing the demand for climate-ready management solutions to navigate trade-offs (Meyer-Gutbrod, E.L. et al., 2021; Welch, Hazen, Briscoe, et al., 2019).

The practice of spatial management is under constant evolution, at each advancement translating lessons learned from past iterations to meet new objectives. Following historical forest conservation practices in India and Africa, and later the proclamation of Yellowstone, the world's first National Park, reserves moved into the coastal seas (Ramp et al., 2006), and eventually pelagic oceans, requiring novel ideas about how to accommodate ocean dynamics into conservation planning (Carr et al., 2003; Hyrenbach et al., 2000). Planning unit selection evolved from the theoretical SLOSS debate, to simple algebra (Kirkpatrick, 1983), to advanced optimization algorithms (Ball et al., 2009; Brito-Morales et al., 2022; Hanson et al., 2020) guided by a systematic approach to designing reserves (Margules & Pressey, 2000). The volume of data available for decision-making from satellite earth observation, animals as environmental sensors, and human mobility data has changed a social-ecological problem into one of data analytics, where the solution space is outside the historically available tools. As the field of dynamic management matures, inferences from static reserve design will need to be re-examined, revised, and re-implemented to ensure robust strategies that can accommodate our increasingly dynamic world.

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Glossary

Dynamic management (DM) tool: *A family of management tools in which spatial boundaries and recommendations are updated in near-real time to reflect changing environmental conditions, wildlife-human interactions, socio-economic factors, and/or management priorities*

RAMP: *The Risk Assessment and Mitigation Program used to support management of the Dungeness crab fishery in California. The RAMP has multiple management tools to mitigate entanglements, e.g. zone closures, depth restrictions, and gear reduction*

Zones: *Seven large fishery zones that can be dynamically closed to fishing by the RAMP to reduce whale entanglement*

Prioritizr: *A software designed to help decision makers solve conservation planning problems*

Planning unit: *An individual area that can be closed to fishing*

Conservation target: *quantitative targets for the minimum amount of whale risk to avoid (e.g. 10%)*

Scenario: *A series of planning units that are closed together*

Pareto frontier: *the set of scenarios that optimize trade-offs between protected fisheries revenue and avoided whale risk*

Hypervolume: *a metric to compare performance across two or more pareto frontiers*

Management opportunities: *the ability of a set of scenarios to navigate trade-offs between avoiding bycatch and protecting fisheries revenue, indicated by hypervolume (larger and smaller hypervolumes indicate better and worse management opportunities, respectively)*

Entanglement risk: *the product of fishery effort and blue or humpback whale habitat distribution*

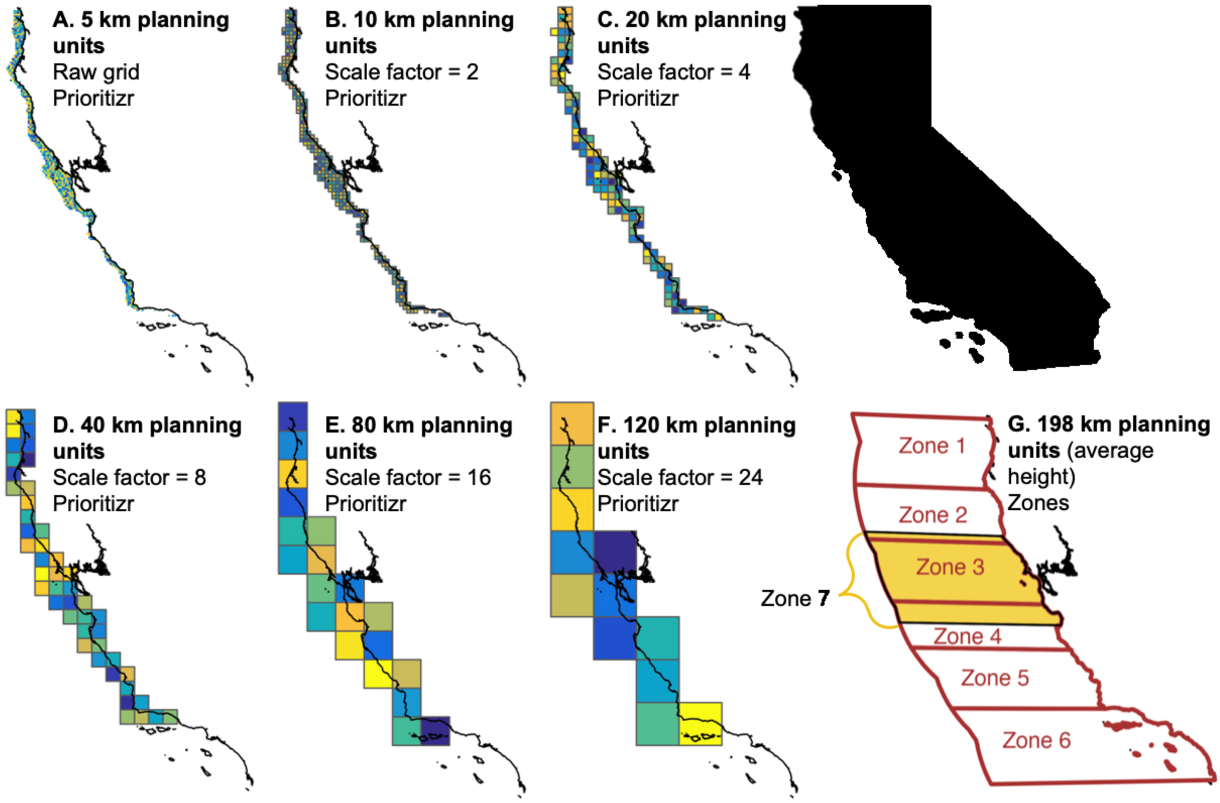

Figure 1. Prioritizr (A-F) and zones (G) configurations. For prioritizr, scale factors indicate how many times larger the latitudinal/longitudinal breath of planning units is than the original resolution (5 x 5 km), e.g. a scale factor of 16 indicates planning units that have latitudinal/longitudinal breadths 16 times larger (80 x 80 km) than the original resolution. Planning units in A-F are colored to aid visualization at the smaller sizes.

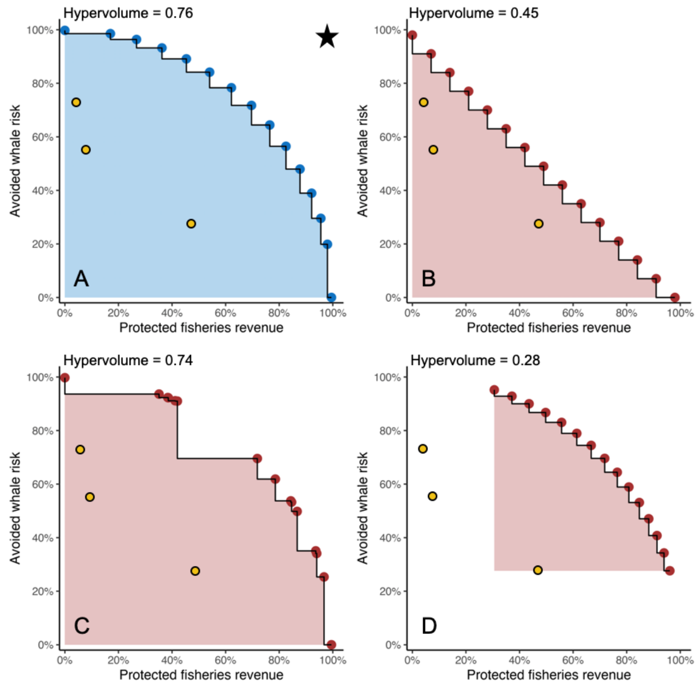

Figure 2. Four hypothetical examples of Pareto frontiers consisting of 15 spatial management scenarios (red and blue points) and hypervolumes (red and blue shading). Scenarios interior to the frontier (yellow points) are dominated by scenarios on the frontier, meaning they have less efficient trade-offs (fewer whales avoided per revenue protected). Hypervolume is the volume of the decision space between the minimum value of each objective (e.g. 0% avoided whale risk, 0% protected fisheries revenue) and a convex stepwise curve connecting each Pareto frontier scenario (black steps). Hypervolume therefore compares performance across two or more Pareto frontiers, where greater hypervolume represents better management opportunities. A. A high-performing pareto frontier with a large hypervolume (0.76): scenarios optimize trade-offs, are evenly distributed, and cover the full range of possible values on the x and y. B-D. represent lower performing Pareto frontiers with smaller hypervolumes due to: (B) less optimal trade-offs (hypervolume = 0.45), (C) uneven distribution of scenarios (hypervolume = 0.74), (D) small range of scenarios (hypervolume = 0.28). Black star indicates the theoretical optimal scenario, i.e. 100% avoided whale risk and 100% protected fisheries revenue.

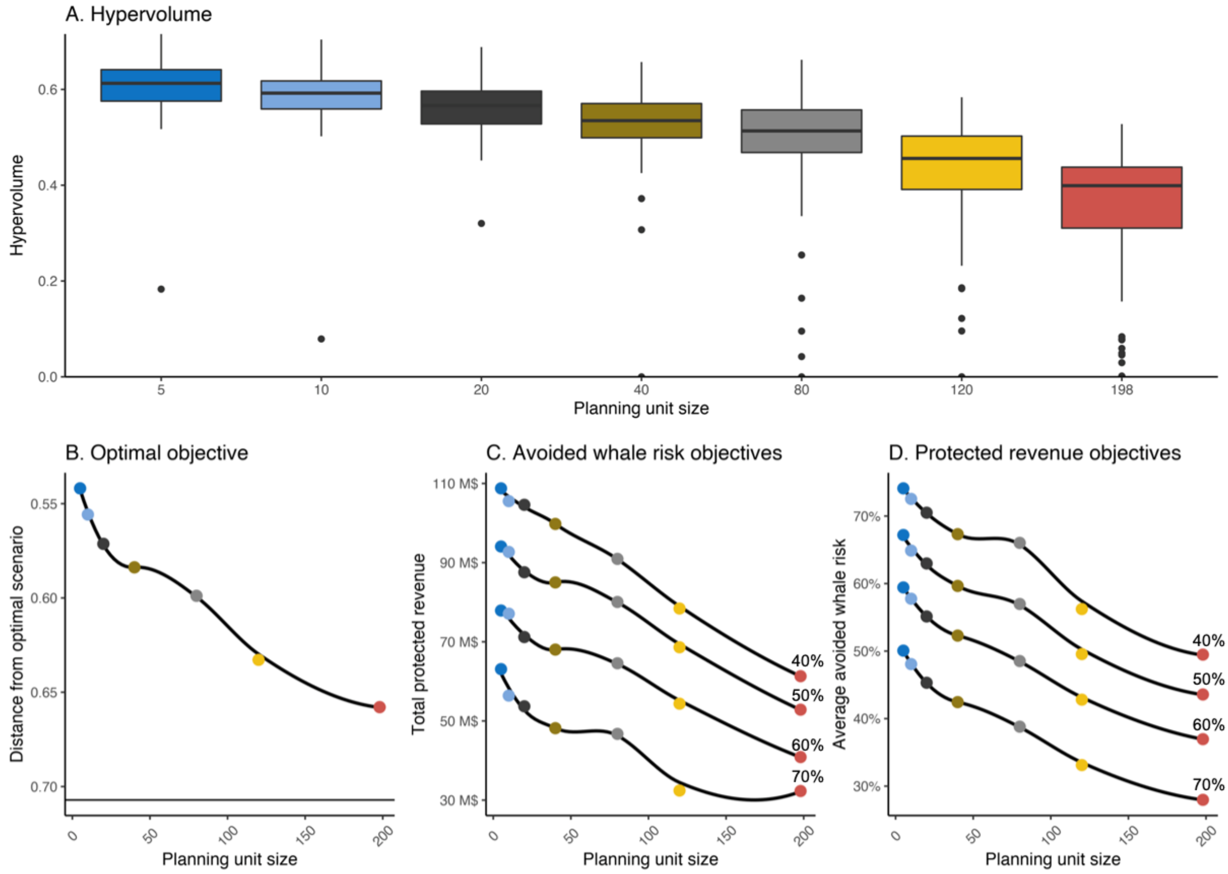

Figure 3. Boxplots of monthly hypervolumes for the seven planning unit sizes (A). Three hypothetical objective types to select scenarios in each month across the time-series (B-D) demonstrate that larger hypervolumes lead to better trade-offs between avoided whale risk and protected fisheries revenue. Horizontal line in (B) shows the Euclidean distance from optimal of a scenario that avoids 50% of whale risk and protects 50% of fisheries revenue. (C) Includes four sub-objectives of avoiding 40, 50, 60, and 70% of whale risk, while (D) includes four sub-objectives of protecting 40, 50, 60, and 70% of fisheries revenue. The y-axis in (B) is inverted so that panels (B-D) have consistent directionality in performance, i.e. all panels range from lowest performance at the axis origin to highest performance at the axis extreme.

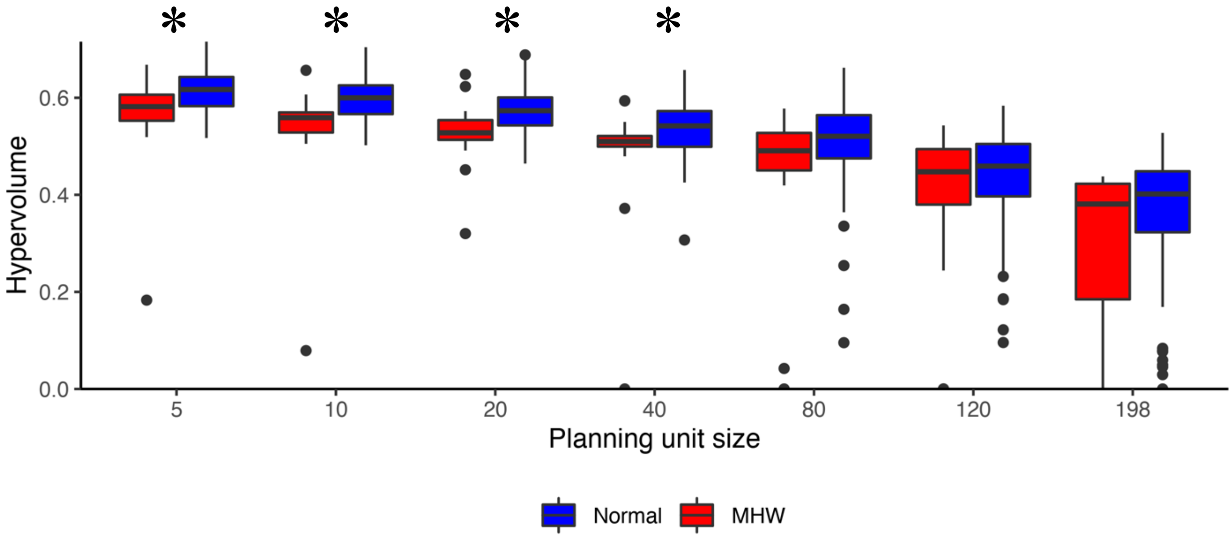

Figure 4. Boxplots of monthly hypervolumes for the six prioritizr configurations and zones during marine heatwaves (MHW) versus normal conditions. Black asterixis indicate statistically significant differences between MHW and normal conditions via Kolmogorov-Smirnov tests.

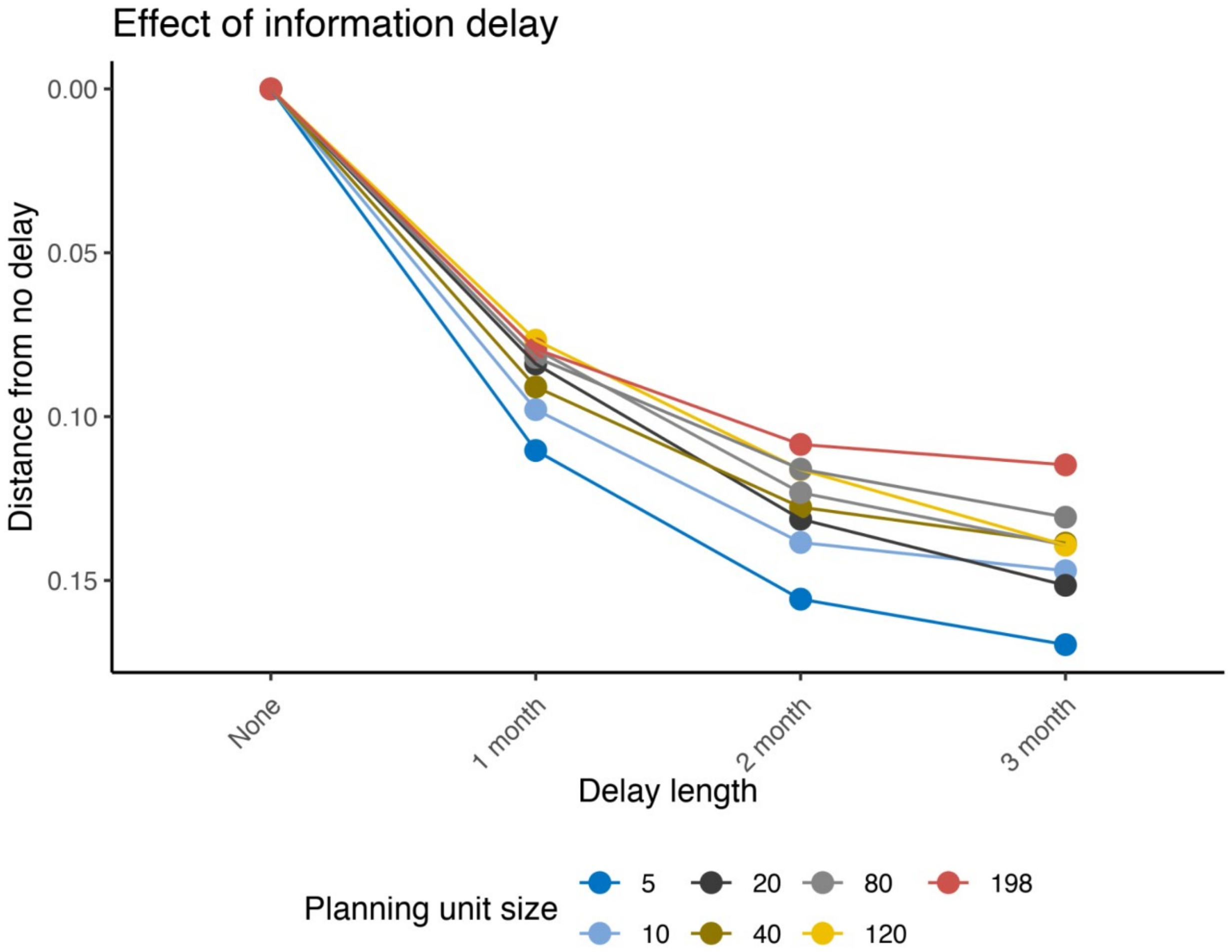

Figure 5. Average monthly performance decay under delays in information on fishery and whale distributions for the seven planning unit sizes. Y-axis measures the Euclidean distance from the closure selected by the optimal objective at no information delay. Black asterixis indicate statistically significant differences in distributions between the smallest and largest planning units via Kolmogorov-Smirnov tests.

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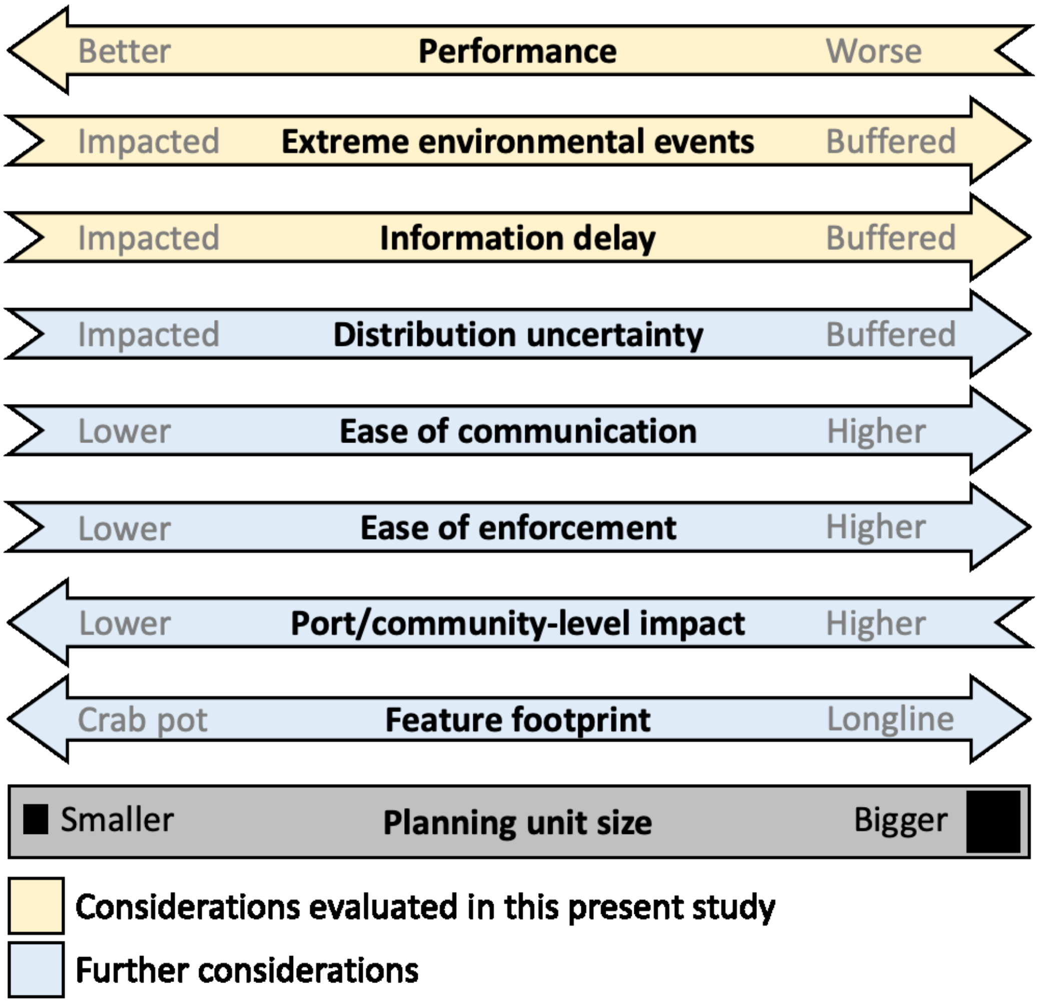

Figure 6. Social-ecological and logistical considerations regarding planning unit size that may affect the choices of decision makers. Arrow direction indicates positive management outcomes. Performance (the quality of management opportunities, indexed by hypervolume, and the the ability to navigate trade-offs between avoiding whale entanglement risk and protecting fisheries revenue under different types of management objectives), extreme environmental events (marine heatwaves), and information delay (latent data on the distribution of whales and the fishery) were evaluated in this present study.

Feature footprint captures the spatio-temporal distribution (e.g. size, mobility) of the features being managed (e.g. whales, the fishery)