Using Available Data and Information to Identify Offshore Wind Energy Areas Off the California Coast

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Updated Report to the California Ocean Protection Council

March 15th, 2024

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Executive Summary

The goal of this project is to assess and complete an analysis using updated existing spatial data for representing marine species, the marine environment, and human uses of ocean waters to: 1) examine the existing offshore Wind Energy Areas (WEAs) and the sea space for potential future development identified under the AB525 process, and 2) identify areas for potential offshore wind energy development that balance impacts and benefits. Existing data and information will help identify areas that maximize energy generation potential while preserving existing ocean uses and protecting the marine and coastal environments. To do this, we combined data on the spatio-temporal abundance of species, habitats, and human activities in the U.S. Exclusive Economic Zone (EEZ) off California, Oregon and Washington with expert-derived information on the likely sensitivity of those components to negative impacts from offshore wind installations. Given that California offshore wind development has advanced ahead of the other two states, we specifically analyze waters offshore from California in the context of federal and California state wind energy development plans and gigawatt targets.

We have developed a spatial model that evaluates the potential impacts of offshore wind energy development on wildlife, habitats and human uses of the ocean. The model is evaluated for four seasons (spring, summer, fall and winter) and for construction and operation phases of development. In order to ensure transparency, the model is constructed using open-source R programming language running in the cloud and has been parameterized with a combination of data from several scientific institutions (National Oceanographic and Atmospheric Administration (NOAA), Bureau of Ocean Energy Management (BOEM), United States Geological Survey (USGS)), other existing publicly accessible data (e.g., FishBase, IUCN Red List), restricted access data stored in the Conservation Biology Institute Wind Energy Gateway, and data collected by Point Blue. From the existing data sets we compiled for this project, we covered 180 species, habitats, and human uses. Our general modeling approach is summarized in Figure 1. In addition to the data sets compiled by this project, we received 191 responses to our expert surveys to quantify sensitivity to offshore wind impacts for all species.

We added new datasets since the first version of this report, representing 17 new species, 2 new habitats and improving data quality for 69 model components. Updated model runs identify priority wind energy installation areas off Punta Gorda, Humboldt County, Point Arena, Mendocino County and Point Conception, Santa Barbara County. The updated selections were similar to areas identified in prior prioritizations before updated data were added; improved data did not significantly alter model outcomes. The models were configured to maximize wind energy benefit while allowing for simulations resulting in no more than 10% of the possible cumulative detrimental impacts to seabirds, marine mammals and turtles, fish, benthic habitats and existing human uses. When model constraints are relaxed to include areas encompassing up to 50% of cumulative impacts, broad areas north of San Francisco and mostly south of Morro Bay are prioritized for installation siting. In this second scenario, parts of the Humboldt and Morro Bay WEAs areas also identified by BOEM

are included, suggesting that these areas are of intermediate priority for development if biodiversity conservation is an important consideration.

When considering trade-offs between wind energy development and impacts to individual species, habitat or human use categories, the patterns differ significantly across space. However, some areas of low conservation impact overlap consistently across groups, including a region near the Oregon border and some of the waters off Cape Mendocino that were also identified by two different prioritization algorithm approaches. The results of the equal weight trade-off analysis we used indicate that the existing WEAs will present moderate impact levels that are strongest for fish and marine mammals but lower for seabirds and human uses. For the Humboldt WEA, seabird and fish impacts were on the higher end when compared to the whole coastal region. In contrast, marine mammal impacts were higher than other coastal regions in the Morro Bay WEA. The optimizations also provide initial indications of other areas that are likely to be high-priority development regions for future planning and that will maximize energy production in the most sustainable manner. It is important to note that the detailed optimal selected areas would shift if the weighting of impacted species and human uses was changed.

When performing optimizations for areas with installation potential between 25 and 30GW, the most commonly included regions were southwest of Punta Gorda, west of Point Conception and the northern Channel Islands and in the offshore waters near the Oregon border. Following the findings derived directly from assessment of impact patterns, the existing WEAs were selected in a moderate number of these GW-target optimizations, suggesting they are of moderate priority when balancing energy-production goals and minimal impacts while still achieving the AB525 2045 goals. This analysis also showed that offshore waters are preferred for optimal space choice solutions that allow 25GW of energy production, suggesting that the potential development of deep-water floating wind deployment technologies could be a boon to sustainable offshore wind planning.

To date, the model provides a variety of outputs, including a spatial optimization that accounts for trade-offs between wind energy generation and predicted impacts to wildlife and human uses. The Point Blue model can accommodate numerous optional formulations to capture different valuations of economic, cultural, and ecosystem services. These optional formulations provide valuable outputs to guide decision making.

Based on the combined results of our modeling, Point Blue recommends that among the six areas feasible for offshore wind development by AB525 strategic plan the Mendocino Area_1 sea space region be identified as the highest priority area for the next phases of wind development offshore of California. In addition, portions of the Mendocino Area_2, and both Humboldt Area sea space regions should be considered high-priority for development plans to meet the AB525 2045 goals. These areas comprise waters with high energy production, balanced and minimized combined impacts to species, habitats and existing human uses and reasonable access to grid interconnection.

Important improvements for future work include the evaluation of sensitivity of model outputs to data uncertainties and data gaps, proper evaluation of species' needs (e.g., differential use of the marine space between breeding and non-breeding seasons), and inter-annual variability in the energy generation and human uses. The Point Blue model was constructed with the capacity to incorporate these improvements.

Using Available Data and Information to Identify Offshore Wind Energy Areas

Background

The importance of offshore wind as a key renewable resource capable of meeting targets for decarbonizing energy production has been demonstrated in Europe, but approval and installation of offshore wind turbines in the U.S. has been much slower (Methratta et al. 2020). In part, this has been due to concerns for impacts to wildlife, conflicts with human uses like fishing, and both novel and complex approval processes. Challenges regarding the approval process stem from legal requirements to consider the potential cumulative environmental effects of development of offshore wind facilities when the data to determine these effects do not exist (Goodale & Milman 2016). Indeed, the lack of reliable cumulative effects assessment has been identified as a barrier to stakeholder buy-in and successful project approval in the past (Durning & Broderick 2019; Ryan et al. 2019). Now that projects on the east coast are underway and the planning process is advancing on the west coast, it is important to consider the multiple potential impacts in a collective way to best ensure a successful and responsible U.S. offshore wind industry.

In 2016, with tests of floating turbines beginning elsewhere in the world, Trident Wind submitted an unsolicited proposal for development of an area offshore from Morro Bay, California. After public comments, input from other federal agencies and a request to identify areas of development interest from the industry, the Bureau of Ocean and Energy Management (BOEM) defined two Wind Energy Areas (WEAs) for potential initial lease sales: Morro Bay WEA and the Humboldt Bay WEA in northern California. BOEM filed a Notice of Intent to prepare NEPA studies for the Humboldt call area and a modified Morro Bay area in January of 2021, and in 2022, the lease auctions for Humboldt and Morro Bay were completed. Also in 2021, the Biden administration announced a major initiative to deploy 30 gigawatts (GW) of offshore wind generation in the U.S. by 2030 and AB525, a California bill to develop the state's offshore wind development plan, was signed into law. The AB525 draft report set goals for wind generation offshore from California of 2-5GW by 2030 and 25GW by 2045. Future development of the Humboldt and Morro Bay Wind Energy Areas (WEAs) is expected to reach 4.6GW of installed capacity, meeting the 2030 goal and planning for areas that can meet the 2045 GW target is underway. There is rapid progress toward offshore wind development along the U.S. west coast and science-based decision support tools will be key in deciding the timeline, locations and requirements necessary to ensure a sustainable plan that make comparisons across the whole area of potential development and incorporate as many trade-offs and expected impacts as possible while maximizing energy generation.

As the BOEM continues the process toward future marine renewable energy developments, it is imperative that planning, research and monitoring be guided by the best available data, in an open and transparent decision-making environment that accounts explicitly for uncertainty and data gaps (Masden et al., 2015). Offshore from California, Oregon and Washington, the U.S. west coast marine environment is home to economically and biologically important fish, wildlife, and benthic organisms, while also encompassing areas of significant renewable energy potential and a suite of other human uses. However, research on established renewable energy installations has shown potentially significant impacts to marine habitats and wildlife (Bailey et al. 2014). Those impacts and the data available to assess them vary significantly at different locations and times. The assessment is further complicated by the fact that the marine environment is variable, with daily to decadal cycles combining with long-term environmental change. In addition, the narrow continental shelf of the U.S. west coast precludes the use of most potential wind energy development technologies, favoring the use of floating turbines, a rapidly developing technology that has only been minimally studied to determine environmental impacts. Therefore, it is crucial that we design a transparent research and planning process for marine renewable energy siting that allows for the streamlined ability to update the decision-making process as new or revised datasets become available (Masden et al. 2009).

Project Framing

The goal of this project was to assess and analyze the existing spatial data for representing marine species, the marine environment, and human uses, use key data sets to identify areas for potential offshore wind energy development that balance impacts and benefits and examine the offshore wind energy areas identified by BOEM and the CEC. Existing data and information will help identify areas that maximize energy generation potential while preserving existing ocean uses and protecting the marine and coastal environments. To do this, we combined data on the spatio-temporal abundance of species, habitats, and human activities in the U.S. west coast Pacific waters with expert-derived information on the likely sensitivity of those components to negative impacts from offshore wind installations. The model structure and methods are covered in detail in the Methods section below, but we clarify here the broader approach and strategy for this project.

This analysis has three different study areas, corresponding to different components. First, the broadest study area covers the entire U.S. Exclusive Economic Zone (EEZ) off California, Oregon, and Washington (also referred to here as the California Current). The EEZ includes waters between the U.S. national boundaries and out to 200 nm from shore. We target data and species that represent this entire area to provide models and results that can be used in the future to evaluate holistic strategies and management decisions for the entire U.S. west coast. We divided this largest analysis domain into a study grid that aligns with the BOEM lease aliquots which measure 1200 by 1200 meters. Most spatial model data are standardized to, and analyses are performed on, a raster version of this grid. The second study area is restricted to the California EEZ where we have full data representation and provide assessment of impacts. Finally, we limit the trade-off and optimization results to a domain extending from the California Coast out to approximately 70 nautical miles, an area for which we have data representing the economic value and potential energy production of wind energy development. While our study area extends to shore, our focus is on the impacts resulting directly from the site development where turbines may be installed. The results do not address potential impacts to species and habitats in the nearshore coastal zone from activities where the transmission cable comes ashore.

The overall strategy of the project was to design the models and optimization analyses to incorporate as many important factors as possible as derived from past similar efforts (e.g., Bailey et al. 2014; Bergström et al. 2014a, 2014b; Masden et al. 2015, 2021; Fox & Petersen 2019) and through careful consideration of the problem and needs for management and decision-making. This approach contrasts with models that only include components that can be parameterized with existing data. The advantages of our approach are that it provides a framework that is easily updated and adapted as new and revised data become available to enhance the models and fill in current gaps in data availability. In addition, the approach enables us to explore and highlight those existing data gaps and provide basic metrics of uncertainty. Where data are lacking for model components, uniform values are used as placeholders or assumptions are made to ensure impacts are not underestimated (e.g., when a species' seasonal presence/absence is unknown, it is assumed to be present). Where such assumptions or placeholders are used, they are noted and the reasoning explained. In addition, we clearly identify places in the modeling and optimization processes that require parameterization based on subjective judgements or value sets.

Finally, we provide a few examples of optimization approaches that demonstrate the capacity of our models to identify preferred siting for development based on a set of value assumptions. These results are intended to identify places where minimization of impacts and maximization of energy production may satisfy the priorities of multiple stakeholder groups. These examples cannot be exhaustive but provide the basis for how Point Blue may create a future interactive tool to enable managers, industry, the public, and other stakeholders to provide inputs and receive model results specific to their preferences and valuations. Interactive model use would empower stakeholders to negotiate development proposals transparently using the best available data.

Outputs

This phase of the project provides static model results that fall into two main outputs: 1) mapping of projected impacts to species, habitats, and human uses, and 2) three distinct approaches to optimizing high-benefit, low impact areas for wind farm installation. Each of these outputs is evaluated and discussed at the study-wide level (EEZ waters offshore from California), at the scale of the two WEAs, Morro Bay and Humboldt and for the areas of interest and sea space identified in the AB525 Draft Report. In addition to these results, the project also produced open-source R language software code that can be accessed from a GitHub software repository. This enables researchers, managers, and users to directly evaluate the methods we employed in our models, ensuring transparency of our work, trust and confidence in the outputs, and full repeatability.

Methods

The first step of the project process was to determine the model framework, followed by an evaluation of the available data and how it could inform the model. The overall model structure follows a cumulative adverse effects (CAE) approach (Bailey et al. 2014; Goodale & Milman 2016, 2019; Ecology and Environment Engineering 2017; Morandi et al. 2018) which combines the pressures (sources of potential negative interaction, e.g., turbine blades present collision risk for birds), exposure (overlap in space and time) and sensitivity (the combined factors that determine effects on individuals and populations given exposure to pressures) to determine cumulative impact estimates (the combined negative outcome for exposed species, habitats or human activities). Because in this study we evaluate multiple sectors that may be impacted by the development of offshore wind energy, we use the generic term 'receptor' to refer inclusively to any of the wildlife species, habitats and human uses evaluated in this analysis. While there are some potential positive outcomes for species and habitats from wind energy development (e.g., *de-facto* exclusion of fishing pressures benefitting fish populations), we do not include those due to the difficulty in evaluating and integrating positive and negative effects.

To identify species of seabirds, marine mammals, turtles, and fish present in the study area, we combined species lists from research surveys, federal and state management agencies and international species authorities such as Birds of the World and Fishbase. We also included several benthic habitat types that marine ecologists consider to be both highly productive and especially vulnerable to disturbance and impacts. Finally, based on past similar risk and impact assessments (Goodale & Milman 2016; Ecology and Environment Engineering 2017; Morandi et al. 2018), we included commercial fisheries and shipping as human uses with a focus on fisheries. While fisheries and marine transport have been identified as the most significant and economically valuable uses potentially impacted by offshore wind, other uses such as recreation, cultural sites and viewsheds have been previously identified. While these latter components could be added to our model framework in the future, they have not been included here due to lack of data to sufficiently represent them.

With a comprehensive list defined, we then set about to identify groupings of receptors that would be likely to experience a similar set of pressures and have related sensitivity to those pressures. We first broadly divided receptors into three wildlife categories (seabirds, marine mammals and turtles, and fish), one inclusive benthic habitat category and one human use category, which we refer to as Super Groups. We then subdivided the five Super Groups into 10 seabird Groups, 8 marine mammal and turtle Groups, 9 fish Groups, 5 benthic habitat Groups, and 8 human use Groups (Appendix A; Table A1). For each of the 27 wildlife Groups, we compiled lists from literature and reports of the potential offshore wind development pressures that each was likely to experience (Appendix B; Table B1). The pressures identified through this process were used to design expert elicitation surveys to gather data on specific impact metrics which we combined into a cohesive metric of impact used in our models. The survey design and functional form of the impact metric calculations are described below in detail. In addition to incorporating the expert survey responses, the impact formula also incorporates modifiers that weight vulnerabilities according to factors that increase spatial and temporal exposure, such as breeding behaviors and movement speed and extent, specific to each wildlife group. To make our model as temporally explicit as possible, we evaluated these functions with data specific to four seasons (spring, summer, fall and winter) and both operation and construction phases of development. In cases where distribution, presence/absence or breeding data were available on a monthly time-scale, we averaged the monthly data by season prior to use in the model. Differences in presence of receptors across seasons and intensity or effect of pressures between construction and operation result in variation in the predicted impact for each of season/phase combinations. We refer to the model processing for each of the 8 season/phase combinations as a 'track'.

Another key aspect of the modeling process is that the input data components, model formulas and calculations are the same for all species within a Group and for all Groups within a Super Group, allowing us to combine the resulting metrics up to the Super Group level. That is, the impact metrics, while providing relative measures among species and Groups, all have the same component structure and mathematical treatment so they can reasonably be combined mathematically at the Group or Super Group level (Figure 2). Our model structure allows for weighting the contribution of some receptors within a Group more than others (for example, to increase the representation of impacts on IUCN Red List or Endangered Species Act endangered species more than others) (Figures 3 and 4).

Further, across Super Group levels (e.g., Seabirds vs. Human Uses), the impact metrics are not directly comparable. Thus, to use Super Groups for the optimization analysis, there must be explicit weighting of each Super Group relative to others. This weighting incorporates the relative value that represents the perspective of a stakeholder or interested group. Weightings may be equal, implying that a solution should strive equally to avoid the cumulative adverse effects to each of the Super Groups. These are the results presented in this report. Alternatively, as an example, the optimization may be run searching for solutions that prioritize energy value most, seek to avoid impacts to seabirds most stringently, but are more lenient for marine mammal and turtle, habitat and human use impacts. Therefore, our model allows stakeholders to provide their own valuations of Super Groups to customize their energy development proposals. The formulation of the model provides an ideal basis for an interactive tool that allows stakeholders to select their own value weightings which can inform discussions and negotiations that may identify priority development sites meeting the needs of multiple stakeholder perspectives. While we plan to build such a publicly accessible tool, for this project we represent only a selection of value weights that we defined *a priori* - specifically, all Super Groups weighed equally.

Model input data

Distributions and density

Three main categories of data serve as inputs into the impact models: 1) distribution and abundance of receptors (per unit area); 2) metadata for receptors to help quantify sensitivity, weight Group members when combining into a single Group measure and add information on spatial and temporal exposure; and 3) expert elicitation survey responses used to develop relative sensitivity scores. All data used to represent distributions of receptors were provided by experts either directly or compiled from various sources (Appendix A; Table A1), while receptor impact metadata and survey responses were collected and collated as part of this project. Since we compare our results to the AB525 selected sea space areas, it is useful to note some key differences in source data and modeling between this work and the Conservation Biology Institute (CBI) models that were used as part of the sea space identification process. Many of the same spatial distribution data sets were used by the CEC, though treatment of those in the modeling carried out by CBI was significantly different. Specifically, the CBI models did not include sensitivity or expert elicitation data or model impacts. Instead, the models created a metric indicative of 'environmental concerns' for different receptors based largely on spatial use datasets. In addition, the CEC sea space identification placed more restrictions on potential locations based on technical feasibility and space-use conflicts than we did in our analysis.

Two final data sources used in the optimization analyses provide information about the profitability of energy developments and the potential energy production per area. We used the estimates of Levelized Cost of Energy (LCOE), which was predicted from the National Renewable Energy Laboratory LCOE models (Beiter et al. 2020 - see Wind energy benefit below) as a representation of economic benefit of development (Appendix A; Figure A1). To evaluate the potential energy production per area, we used Net Capacity predictions also derived from National Renewable Energy Laboratory models (Zuckerman *et al.* 2023 - see Wind energy benefit below) (Appendix A; Figure A2). Both LCOE and Net Capacity were evaluated out to approximately 70nm from shore, meaning the datasets were largely limited to waters shallower than 1300m.

Once the complete list of receptors was created and Groups were defined, we searched for distribution and abundance data that would best represent each receptor. We first examined the existing data in the Conservation Biology Institute Offshore Wind Energy Gateway, followed by online searches, literature searches and inquiries with relevant experts. We classified the available datasets in terms of type, temporal coverage, spatial coverage, spatial resolution and quality. We then selected the most appropriate dataset for each receptor so that coverage and quality assessments were maximized. First, the dataset had to cover the entire California EEZ at a minimum and ideally extend to Oregon and Washington waters. Next, more recent data and data representing a longer time-series were prioritized. Finally, statistical models of species density and habitat preference were considered highest quality, followed by environmental envelope distribution models, followed by density metrics (such as utilization density), and simple data on species ranges considered lowest quality. An ideal data set would be density predictions with a resolution close to 1-2 km^2 representing seasonal patterns derived from observations spanning the most recent two decades and with extensive model validation. The selected data sets for each Group are listed in Appendix A; Table A1.

Most receptor density data was simply standardized to the 1.414 km^2 (1200 m x 1200 m) study aliquot grid via resampling and reprojection. In a few cases, pre-processing to combine multiple source datasets into a single representation of a receptor was necessary before conversion to the common data grid. For data from Brodie *et al.* (2018) and Muhling *et al.* (2019), monthly model predictions were averaged for each of our defined seasons (spring, summer, fall, winter) to provide seasonal distribution data. For both hydrothermal vents and methane seeps, two different point location datasets were merged and then the points were buffered by 1000 m prior to rasterizing the data on the study grid. For seamounts, the features were weighted by the inverse of the depth (in m) prior to raster conversion such that shallower seamounts were a higher value than deeper ones. Finally, we used two main sources of fishery distribution data: densities of observed fishing that were created by NOAA based on observer records (Somers et al. 2020), and fisheries catch evaluated based on landings data (Miller et al. 2016). The Miller *et al.* data separately evaluated groundfish fisheries and other marine fisheries, while the Somers *et al.* data only assessed groundfish but did so in finer categories and is of higher-quality and resolution. In order to combine both datasets, we calculated a scaling factor relating the sum of all the Somers *et al.* groundfish data and the Miller *et al.* data. We then scaled values in the individual Somers *et al.* data layers such that they provided a spatial representation of groundfish fishing effort but had a distribution and range that matched the corresponding groundfish catch data from the Miller *et al.* analysis.

Expert elicitation sensitivity surveys

We chose to utilize expert elicitation to quantify aspects of sensitivity and impact rather than using literature sources alone because of the novel nature of floating offshore wind development in the California Current. While some aspects of impact are likely to be generalizable from fixed offshore wind, across locations and to different taxa, others invariably are not. Not only does floating offshore wind present a novel subset and intensity of stressors, but the California Current ecosystem is quite distinct from the locations where impacts have most been studied like the North Sea. For these reasons, we believed expert elicitation was the most suitable method to accurately quantify the novel combinations of risk, receptors and setting while allowing some measures of uncertainty which simply would not be possible through literature surveys alone.

We chose to conduct our expert surveys for wildlife sensitivity metrics at the Group level (e.g. Albatrosses, Larids) because we explicitly designed our Groups such that patterns of sensitivity were roughly similar across member species in a Group but differ notably among Super Groups (e.g. Seabirds, Marine Mammals and Sea Turtles, and Fish). In addition, this approach provided a manageable level of complexity for the design, deployment, and targeted response rate of the surveys.

In our initial survey, we identified 16 or more subject matter experts for each Group from our professional contacts, searches of relevant journal article and report authors, and related working group members or agency staff. In addition to explicitly requesting survey responses from these lists of identified experts, we distributed the survey to the Pacific

Seabird Group e-mail list, the MARMAM marine mammal listserv and the American Fisheries Society e-mail list. We required a minimum of 3 but targeted 5 or more expert responses per species/pressure combination to enable assessment of uncertainty in responses. We collected 119 responses from 98 individuals across all the groups included. Six seabird Groups (fulmars and shearwaters, grebes and loons, pelicans, petrels, phalaropes, and storm-petrels), two marine mammal Groups (killer whales and sperm whales), and four fish Groups (billfish, lingcod and greenling, salmonids, and tuna and mackerel) did not receive enough expert responses at the time.

Two reasons for the response shortage were a lack of understanding about how survey results would be used in the model, and the context and intention of the survey questions. To resolve these matters, we issued invitations to two workshops to responders and additional experts in each of the three wildlife Super Groups. The first workshop focused on clarifying questions generated during the initial round of surveys and provided definitions and guidance for the various vulnerability metrics. After this workshop, respondents were asked to complete the survey for their preferred group(s); in some cases, individuals who participated in the initial survey completed the survey again. A second workshop was held two weeks after the first, presenting general summaries of the survey results and how those results would be used to inform the sensitivity scores for each threat. Metrics where scoring had low consensus across respondents were reviewed, and workshop attendees were polled to align responses across the Group. The second survey effort gathered 191 responses from 133 respondents across all the groups included. In this effort, the same two marine mammal groups (killer whales and sperm whales) and three of the four previously underrepresented fish groups (lingcod and greenling, salmonids, and tuna and mackerel) again did not receive enough expert responses. Although we did not receive at least 3 expert responses for these groups, we included these species groups in our analyses. A review of variance in expert responses shows that the responses for these groups are similar to those for groups with more expert responses. The six previously deficient seabird groups and billfish received sufficient responses to include in our modeling.

According to experts, threats are potentially the most impactful to pelicans, cormorants, and phalaropes (Figure 5). The mean scores of the response impact metrics show that the highest average scores were given to birds, followed by marine mammals, and least to fish. The variance (Figure 6) in response scores was lower for fishes, and generally the same across birds and mammals and turtles. Low scores (excepting those for fishes) show the larger range of variance values (Appendix B; Figure B1), even though the average variance (see yellow line in Appendix B; Figure B1) does not increase with mean impact score. Experts concurred more on the score for a threat when the potential impact was higher, suggesting that there was more certainty on the impact of a threat when it was high and not so much when impact was low.

Receptor metadata for sensitivity, spatial and temporal weighting

We collected additional data types related to each receptor or Group to parameterize quantitative modifiers of sensitivity and to weight species when combining impact across receptors to quantify Group-level impacts. For each receptor Super Group, we collected data to represent inherent relative risk of impacts not captured in the expert survey responses, as described in detail below. For species Super Groups (seabirds, marine mammals and turtles, and fish), we compiled endangerment rankings from global, regional, and local assessments. Global status was collected from the IUCN, while regional and local rankings were from U.S. and state agency assessments. We combined these metrics into a single 'endangerment' metric by giving sequential categories numeric scores that increased by one unit for each increase in level, then weighting local ranks by four times, and regional ranks by two times, before summing across all three status types. For the habitat Super Group, weights were calculated as the inverse of the proportional total area coverage within the study area and then re-scaled so that the maximum to minimum matched the species endangerment range. Finally, for human uses, we combined two datasets into a single metric: 1) we calculated the recent (past 10 years) ex-vessel value of each fishery based on data from the PacFIN database, and 2) we collected from California Department of Fish and Wildlife reported estimates of the number of vessels participating in each fishery. We then re-scaled each of these datasets to match the species endangerment range and averaged them to reach a single weighting metric. By combining these two components, we more heavily weighted economically valuable fisheries, and those that support a greater number of individual fishers.

Modeling output is specific to season (fall, winter, spring, summer). To address that specificity, we compiled data from a variety of sources on the monthly presence/absence and breeding status of each species and the active months for each fishery where available. In some cases, we had seasonally explicit predictions of density and distribution for receptors while most receptors were represented by a single average distribution dataset without any intra-annual information. Therefore, we used the data on presence/absence to weight the density rasters so that each model season accounted for the proportion of months with that receptor present or absent. When quantitative data were available, we considered months with less than 10% of peak study area abundance to be absent. If information available from the literature or reports was qualitative, we only considered a receptor absent if it was described as very rare relative to peak abundance periods. If no information on presence/absence was available, we took a conservative approach in assuming the receptor was present.

We also incorporated information on breeding activity during the year, to account for greater impact specifically associated with breeding for some species. We included a weighting factor for species groups that are central place foragers during the breeding season, such as pinnipeds and seabirds, as described below. This factor reflects greater exposure at the local level due to increased foraging behavior at a restricted spatial scale.

Finally, because our calculation of impact is explicitly performed at the scale of each 1200 m grid cell, we developed spatial scalars to account for pressures that only act on receptors within an area smaller than the cell, decreasing the probability of co-occurrence relative to those pressures that act over the full cell area. For example, habitat or fishing exclusion within wind farms will act at the scale of the cell and beyond while electromagnetic field effects only extend meters around the length of each cable. To account for these differences, we calculated the approximate proportion of a cell likely to be affected by the pressure (Appendix A; Table A2).

Detailed model structure

The theoretical basis of CAE models is to account for spatial and temporal overlap between pressures and receptors, scale those according to the exposure, sensitivity, and the level of impact each receptor is likely to experience for a given pressure and combine the total resulting impact metrics to produce a single metric of cumulative impact for each receptor. This model calculation is performed for each grid cell of the study area. The resulting metrics represent relative impacts, assuming offshore wind development to occur in that cell. The model is calculated for 8 different “tracks” – or season/phase permutations – a track for each season (Spring, Summer, Fall and Winter) and wind energy project phase (construction and operation) combination. This allows us to evaluate any permutation of seasons and phases independently or in combination. When combining across seasons, we equally weight the seasonal components because they represent the same time-span. Thus, seasons contribute to the total impact according to their calculated weighted impact rasters without other modification. In contrast, when combining across phases, operation impacts are weighted 20 times greater than construction, since industry estimates and past projects suggest construction is likely to last 1-3 years while wind farm lifespan is projected to be 20 years or more (Beiter et al. 2020).

In addition to combining the temporal and phase model tracks to quantify whichever phase and time components a user desires, the impact models can also produce results at three levels: Group, Super Group, and impacts combined across all Super Groups to represent the total expected impacts. While the basic model unit is a receptor, in most cases there are multiple receptors (e.g., species) in each Group.

Several additional aspects of our model structure should be noted. First, the model is explicitly a CAE model, so it does not include any potential *positive benefits* of wind energy development such as reef effects or *de facto* protection from fishing. Second, we explicitly assume additive effects across pressures and do not include any potential antagonistic or synergistic cumulative effects. For example, if an animal or fishery exhibits avoidance or displacement from wind farm areas, then the exposure to collision or entanglement would be mitigated; we do not incorporate such effects. Future model versions could include these types of interactions if there is sufficient evidence to quantify the effects.

Impact calculation

The calculation of impact using the density and distribution, exposure, sensitivity, and modifier data is the core of the model. We start with a threat (we have 10 identified threats), for example: "impact of collision with turbines." For each threat, there are risk components quantified through the expert survey responses and four additional factors reflecting exposure and sensitivity not addressed by the survey but incorporated as well. These impact modifiers, as described below, include the spatial footprint of a threat within a grid cell, impact of spatial movement on encounter probability, increased impact due to breeding activity, and difference in risk due to phase (construction vs. operation).

The five risk components that were quantified through the expert survey responses were: fecundity impact, recovery time from fecundity impact, lethality impact, frequency of exposure, and proportion of population impacted (Appendix B; Table B2). Within a Group, and for each threat, we average the expert responses to each risk component and then combine them as described below, to obtain a Response per Group, f(R). We refer to f(R) as a "Lethality Score": as described below it includes lethality effects as well as fecundity effects that have been scaled to be commensurate with lethality.

The risk components for which respondents were queried consider both lethality risks and fecundity risks. Impacts to fecundity are categorized into three levels: low (quality of offspring reduced), medium (reduced offspring production per breeding season), and high (mortality of reproductive adults). A second aspect of fecundity impact that respondents quantified is the time needed to recover from such an impact. Because mortality both decreases a population directly and eliminates all future reproduction of individuals that are killed, the effect of mortality is much greater than sublethal effects which can at most only decrease current and future fecundity. We scaled fecundity effects (level and time to recovery) in relation to lethality as shown in Table 1.

To understand the values in the table, we must first note that the lethality risk scores from our expert surveys are 1, 3, and 5 for low, medium, and high lethality effects, respectively. We weight the fecundity effects relative to the mortality effects as shown in Table 1. The maximum "low fecundity-level effect" (an effect on the quality of offspring that persists a long time) is 5/8, equating to 1/8 of the maximum mortality impact. Similarly, the maximum medium fecundity effect (i.e., reduced offspring production and with a long recovery) is 1/3 of the maximum mortality effect. At the same time, decreased fecundity of intermediate to long duration is scored higher than "low" lethality, but less than "medium" lethality. Because we assess mortality as a separate risk component, any "high fecundity impacts" (mortality of reproductive individuals) are instead assessed through the mortality impact. Thus, we use the table above to translate each expert's response on fecundity impacts (none, low, medium, high) and time to recover (short, intermediate, or long) into a comparable lethality impact value. The fecundity scores (as in Table 1) were subsequently averaged across surveyors for each threat/Group combination and combined with the lethality metric (Eq. 1). The summed fecundity + lethality score is then multiplied by the product of the other two components scored by respondents that reflect increased exposure or sensitivity: frequency of exposure and proportion of population affected, as shown in Eq. 1.

Eq. 1: $f(R) = (FecundityEquivalents + Lethality) \times IncidenceFrequency \times PropPopulation$

A review of lethality scores across groups and threats (Figure 7) shows that marine mammals and turtles, and fish, all had relatively low response scores (indicating low sensitivity/exposure), while bird groups showed the highest scores.

The respondent scores were then modified by four additional components to yield a group- and threat-specific impact (Eq. 2). The first component considers the spatial footprint of each threat relative to the grid cell. Because our calculation of impact is explicitly performed at the scale of each 1200 m grid cell, we developed spatial scalars to account for those pressures that only act on receptors within an area smaller than the cell, decreasing the probability of co-occurrence relative to those pressures that act over the full cell area. For example, habitat or fishing exclusion within wind farms will act at the scale of the cell and beyond while electromagnetic field effects only extend meters around the length of each cable. To account for these differences, we calculated the approximate proportion of a cell affected by the pressure (Appendix A; Table A2).

The second component reflects the encounter probability of an organism with the threat given that it intersects a specified grid cell. For each threat, we evaluated whether this encounter probability is increased for a flying or swimming animal compared to a completely sessile individual. For a sessile individual, the encounter probability simply reflects the spatial footprint as described above. However, the entanglement probability of baleen whales traversing the grid cell, for example, is high relative to the spatial footprint of the cable itself. On the basis of simple simulations of flying and swimming animals, drawing on assumptions of turning behavior and multiple encounters during the relevant period, we estimated the probability of encounter. For a swimming animal, this is reflected in a score of 6 for entanglement (i.e., a six-fold increase compared to the spatial footprint of the cable). Comparable simulations yielded a score of 10 for flying birds relative to infrastructure collision. In contrast, habitat displacement is no greater for a swimming species than a sessile one, hence this component is 1. The encounter probability is zero where the threat is not applicable, e.g., infrastructure collision for baleen whales. Details are shown in Appendix A; Table A4.

The third component reflects any additional impact specific to the breeding period. We start with a "baseline" impact with respect to exposure and sensitivity, but we include a modifier (an inflation) adjustment to account for increased foraging activity during the breeding season for central-place foraging animal groups (birds, pinnipeds). This accounts both for elevated potential exposure because of restricted distributions during breeding (to and from breeding colonies) and the greater energetic needs of breeding animals (feeding young, nursing, etc.). For each species group, we scored that group as 1, 2, or 3, depending on whether there was no increased impact (score = 1; e.g., for fish) or moderate increase (score = 2, e.g., for pinnipeds) or strong increase (score = 3, e.g., for cormorants and many other seabirds). Species that do not breed in the study area at all are scored 1. Details are provided in Appendix A; Table A5.

The last of the four weighting components is for the phase. Phase-specific weights modify exposure due to phase-specific impacts, comparing construction and operation. They are specific to the phase and to the group and vary from 0 to 2, indicating relative effect. If the threat is not applicable to the group at all, then weighting is zero for both phases. If the threat impact is the same for both phases, then the weighting is 1 for both. If the impact only applies to one of the phases, then that phase is scored 1 and the other zero. If the impact is stronger for one phase than the other, then that phase is scored 2 and the other scored one. Details are provided in Appendix A; Table A6.

To summarize, for each Group and Threat we use the lethality score, f(R), whose calculation is described above, and multiply by the appropriate four weighting components. The impact for the Group is then summed over all threats, as shown in Eq. 2, yielding I_{gr}, which we refer to as Group Impact Weight:

Eq. 2 $I_{gr} = \sum_{threats} (f(R) \times W_{ia} \times T_{ep} \times Breed_P \times W_{pgp})$,

where W_{ia} is the spatial footprint (proportion of a cell) and is threat-specific, $Breed_P$, reflects increased impact due to breeding and is group-specific, T_{ep} reflects modification of encounter probability due to flux and is group- and threat-specific, and W_{pgp} is phase-specific weighting and is group- and threat-specific. I_g is thus a single scalar for the group (Figure 4).

Adjustments to threat exposure by seasons

When evaluating impacts for a particular season, we consider the number of months within the season that the species is present in the California offshore environment and in how many of these it is breeding. Thus, species presence adjustments to the foraging behavior weight for a particular season can vary between 0 (species absent that season), 0.33 (present 1 month), 0.66 (present two months out of three), and 1 (present all three months). The breeding behavior adjustment in Eq. 2, $Breed_P$, follows the same rubric depending on how many months of the chosen season the species is breeding (Appendix A; Table A3).

Weighting species within a group

Ideally, we would like to have all the data on abundance in the seascape for each receptor in a Group, and for each season of the year. That is not the case, unfortunately. We have a fraction of the species represented, and this representativity may be skewed toward including the common species. To address this, we could weight some species more than others to increase their representativity. For example, if 30% of the species in the Group are endangered, or 20% are deep divers, and yet only 5% of these types are among the ones with data, we may want to inflate their representation with weights. We call these the "species representativity weights", denoted by W_{sr}. These weights are species-specific, resulting in a vector with length equal to the number of species with data in the group. This vector is scalar-multiplied by each species' density (D_s), a vector of equal length, a calculation done on a grid cell by grid cell basis. For now, we take the naive approach and assign each species the same representativity weight, but that can be altered if well-justified.

As discussed above, we also developed a scale of weights representing robustness of each receptor, which we denote by W_e. For species receptors, the weights are derived from endangerment listings, for habitats they represent relative spatial coverage and for human uses they represent a combination of economic value and the size of the population participating in the use.

Aggregating across species

The next step is to aggregate the impact indices at each grid cell. I_{gr} is already aggregated across threats. For each grid cell, we then sum across all species, for each season and phase, to the group level weighting by:

- Species density (D_s)
- Species representativity (W_{sr}), and
- Species endangerment level (W_e)

W_{sr}, D_s, and W_e are single values that are species-specific. K is the combined group-specific impact of all threats, calculated for each cell as shown in Equation 3.

Eq. 3: $K = \sum_{species} (I_{gr} \times W_{sr} \times D_s \times W_e)$

Normalizing impact values

Because we have calculated impact for four seasons in a year, and two impact phases (construction and operation), we can weight each season and each impact phase separately (dependent on, or independent of, Group). We denote these weights as W_{gs}, and W_{ph} respectively. Thus, we can define the total impact, T_w, of all threats on a group across seasons and phases as:

Eq. 4: $T_w = \sum Season \sum Phase\ (K * W_{gs} * W_{ph})$ (eq. 4)

For the current model, seasonal weights are set to be equal while phase weights are set at 1 to 20 for construction and operation, respectively, as discussed above. We can then re-scale the Group-specific T_w values to 0-100 by using the maximum T_w value in the entire landscape.

Wind energy benefit

To quantify the benefit of developing offshore wind installations for each cell within our study area, we use the LCOE model predictions created by the National Renewable Energy Laboratory (Beiter et al. 2020). This model incorporates many components of development cost including available wind energy resource, wind wake losses, transmission losses, capital costs for infrastructure, system down time, maintenance and repair costs and grid connection costs. Many of these cost components vary across space due to distance from construction and operation ports, distance to grid connection points, water depth, and weather and sea conditions. Using all these components, the LCOE model predicts the cost per megawatt-hour over the lifetime of a windfarm under assumptions of 15 megawatts (MW) floating turbines with semi-submersible substructure spaced at 7-rotor diameter intervals with a total energy production capacity of 1,000 MW. The LCOE model predictions only extend to approximately 70 nm (~130 km) from shore, so all our optimization analyses are currently limited to this area. The model is predicted on a 10.6 km resolution grid, so to prepare the LCOE data, we kriged the model predictions to our 1.2 km study grid. Since our goal is to prioritize locations with high energy potential at the lowest cost, we rescaled the

LCOE from 0-100 and subtracted this from 100 to invert the metric for the study area.

To evaluate optimizations that incorporate the AB525 25GW goal for 2045, we used Net Capacity estimates calculated as a basis for Zuckerman et al. 2023. Net Capacity is the power generation for a given area based on assumptions about turbine size, spacing and operational losses. The data set uses the Renewable Energy Potential Model (reV; Maclaurin *et al.* 2019) to estimate energy production using the Wind Integration National Dataset Toolkit. The model includes a capacity density of 5.3MW/km^2 derived using expected trajectories for upsizing of turbines, with associated adjustments to turbine spacing and capacity factors. Based on consultation with the authors, we also applied a more conservative (i.e. lower energy production) scenario of 4MW/km^2. To produce the low scenario Net Capacity raster, we simply used the underlying Net Capacity Factor data produced by Zuckerman et al. 2023 and multiplied by the lower 4MW/km^2 power density and the area for each grid cell. This lower scenario allows optimization model runs that target sufficient development area if installation was unable to reach the 5.3MW/km^2 density assumed by the NREL analysis. Similar to the LCOE dataset, the predictions were done on 10.6 km resolution grid. Thus, to prepare the dataset for use in our optimizations, we also used ordinary krigging to calculate Net Capacity estimates on our model grid.

Optimizations

Once the rasters of impacts are calculated for each Group, we use those data as inputs for three trade-off analyses. The first approach is used to produce a simple continuous metric that simultaneously accounts for wind energy benefit and impacts, and which can be visualized as a heat map. This benefit/cost metric is calculated by using the re-scaled LCOE data, rescaling Group, Super Group, or total combined impact metrics to 0-100 and subtracting the impact metric from the LCOE. Because this approach provides a continuous metric, it allows relative assessment of site suitability across space. We calculate this metric independently for each Super Group and for the total combined cumulative impact so that trade-offs can be evaluated specific to each set of impact receptors. The metric can be calculated at the Group level, but for simplicity, we focus on the Super Group level in this report.

We then performed two approaches using a mathematical optimization algorithm to identify priority development locations. For these optimization analyses, we excluded the existing National Marine Sanctuaries since current regulations do not allow wind development within their boundaries. Note that the proposed Chumash Heritage NMS was not excluded. The second optimization approach is to use the statistical package *'prioritizr'* (Hanson et al. 2022) available for the R statistical programming language (R Core Team 2022). *Prioritizr* is a conservation prioritization software that searches for the optimized solution of a conservation trade-off problem using integer linear programming. We formulate the optimization such that the solver maximizes the LCOE metric while ensuring that a maximum proportional impact should not be exceeded (relative to total possible impact across the study domain) for each input impact metric. Linear integer programming uses solving algorithms to narrow the potential mathematical solution space and ultimately compares all viable solutions, guaranteeing the optimal solution is reached. We run example optimizations and report results here for three scenarios that equally weight across Super Groups but set the maximum proportional impact to 10, 30 and 50 percent, respectively. These optimizations represent a progressive relaxing of limits on the adverse effects of offshore wind development and identify increasingly large areas of higher priority for development.

Since the specific areas chosen for the above solutions depend on the combination of estimated impacts for each of the Super Groups, they provide a good indication of optimal location for development assuming each respective impact constraint, but do not allow evaluation of better or worse locations across the available area. To provide a continuous metric for optimal development priorities, we ran a series of optimizations with proportional impact limits set from 2% to 50%, stepped every 2%. Running this specific series of optimizations provided sufficient to visualize the patterns of selected areas clearly without performing an excessively computing- and time-intensive analysis; a smaller impact limit step or greater range did not change the resulting patterns. This resulted in 25 optimal area selections. We then summed these selections such that the resulting raster represents the number of times a particular grid cell was chosen as part any of the 25 optimization runs. Thus, cells with values close to 25 are locations that are of the highest priority for balanced trade-offs.

Finally, in addition to optimizations that set varying limits on impacts, we wanted to perform analyses to identify the optimal areas that can meet the AB525 2045 25GW target while minimizing impacts. For this assessment, we used the inverted Net Capacity as a “cost” metric. Thus, the optimization prioritized areas based on higher Net Capacity (lower inverted Net Capacity) and lower proportional Super Group Impacts. We switched to Net Capacity from LCOE here for two reasons: 1) we wanted to prioritize maximum power production without the weight that LCOE gives to developer costs and 2) we needed to be able to calculate the total Net Capacity of the optimized solutions while minimizing the area of those solutions. We developed an algorithm to iteratively decrement the target maximum impacts, run an optimization process and calculate the total Net Capacity within the selected optimum area. We started with the 10% maximum impact as used in the conservative LCOE optimization and initially used a decreasing step of 1%. Once a result was found that encompassed less than 30GW, we increased the starting impact back up 1% and ran a series of optimizations with 0.01% step until 10 results comprised less than 25GW. We saved all solutions that resulted in 25-30GW of potential installed wind energy and summed these solutions to provide a raster where higher values indicated more frequent inclusion in optimal solutions, as done with the LCOE optimization sequence above. We chose to include all solutions between 25 and 30 GW for two reasons: 1) If we optimized for exactly 25GW, there would be only a single solution that was much less informative than a range of solutions, particularly given uncertainties in our model data and 2) within any area offered for development, there will need to be some room for selection to avoid conflicts and impacts – including solutions up to 30 GW identifies priority areas while enabling some flexibility in final lease offerings and development. This iterative analysis was done for four scenarios: Low or High power density assumption and either the existing leases assumed to be developed or not.

Results

Data quality and coverage

There is significant variation in the quality and availability of distribution data for the range of receptor Groups and Super Groups in our model. At the highest level, distribution data for fish and habitats are the poorest. For fish, only 7 of 88 species are represented by high-quality species distribution models with fine spatial resolution and seasonal predictions. While there are distribution data for all fish species, the majority (78/88) are represented by AquaMaps data which is based on limited observations, is not rigorously validated or reviewed by experts, and is predicted to a coarse 0.5-degree grid with no seasonal resolution. For habitats, data quality varies with reasonable identification of seamounts, a reasonable-quality combination of two datasets for deep-sea corals, and incomplete datasets for methane seeps and hydrothermal vents. Vents and seeps have been shown to be much more widespread than represented in the available EEZ-wide datasets used (Beaulieu & Szafranski 2020; Merle et al. 2021). Human use data is of high quality for shipping but of varying quality for the different fisheries represented. Much of the fisheries data is derived from observer records, which represent only a portion of the fleets of each fishery, or VMS data which can be biased regarding the vessel population covered and inaccurate in identification of fishing activity.

On the other end of the data quality spectrum, the seabirds Super Group has distribution data for 50 of 60 species but all the data is modeled based on extensive long-term observational datasets with high-quality and validated statistical approaches, a relatively fine resolution, and seasonally explicit predictions for all those species included (Dick 2016; Leirness et al. 2021). Thus, all but one Group of seabirds (Petrels) have high-quality distribution data to represent more than 80% of the species within each Group. Unfortunately, three seabird Groups (Pelicans, Phalaropes and Storm-Petrels) lacked sufficient expert survey responses to be included. Similar to habitats, data for marine mammals and turtles varied in quality with three cetacean Groups having good coverage and quality data sets, two single-species cetacean Groups (killer and sperm whales) having lower quality data, while pinniped, sea otter and sea turtle data were all lower quality. These patterns suggest that research efforts to improve baseline distribution information should focus on fish species, pinnipeds, sea turtles, sea otters, benthic habitats, and fisheries. Prioritization of these groups could use endangerment scores in combination with the likelihood of spatial overlap with development. For example, remedying the lack of inclusion of the endemic and endangered ashy storm-petrel should be a high-priority.

Group- and Super Group-level impacts

Across the 34 Groups included in the impact models, several broad patterns emerged. First, with the exceptions of shipping, fishing for highly pelagic species, sea mounts, hydrothermal vents and a few highly oceanic species of marine mammals, seabirds and fish, receptor densities and calculated impacts were higher over the continental shelf than offshore (Appendix C; Figure C1-C5). In addition, many Groups showed north-south patterns of impact, though there was variation across Groups whether higher impact occurred in the north or south of the study area. Among seabirds, the albatross and alcid Groups had the highest impact scores; albatross impact was offshore while alcid impact most strikingly concentrated over the continental shelf (Appendix C; Figure C1).

Baleen whales showed the greatest impact for the marine mammal and turtle Super Group and were also more evenly distributed but with an elevated area offshore from Point Conception and the Southern California Bight (Appendix C; Figure C2). Sea turtles, and small cetaceans also showed higher impact metrics off southern California while beaked whales had broad impacts north-south but generally off the shelf and pinniped impacts were concentrated on the shelf.

Rockfish had the highest impact scores within the fish Super Group, though tuna and mackerel had the most widely distributed high impacts. All seven groups were more evenly balanced in terms of maximum impacts than the other Super Groups (Appendix C; Figure C3). Groups differed in whether impacts occurred predominantly on the shelf and whether the highest impact areas were concentrated in the north or south. While rockfish impacts were patchy and slightly skewed toward the north coast from the San Francisco Bay to beyond Punta Gorda, tuna and mackerel, chondrichthyes and forage fish had the most significant offshore impacts.

Neither vents nor seeps were prevalent enough to be easily visible on the maps of the whole study area, and seamounts and marine canyons dominated the Benthic Habitat Super Group (Appendix C; Figure C4). Unsurprisingly, seamount impact was mostly concentrated offshore, so despite their sparse distribution, impacts to seeps, vents and corals may play a key role for benthic habitat impacts in local areas near and on the shelf.

Finally, among the human uses Super Group, the marine non-groundfish, bottom trawl and shipping sectors had the highest impact metrics as well as the broadest distributions, especially the former (Appendix C; Figure C5). Refinement of the non-groundfish representation with more specific categories and high-quality data sources will be a worthwhile improvement for this model component. In our updates to model input data, we represented multiple fishery types within the marine non-groundfish Group, but separate analysis of these categories will also require development of weighting and risk data to match.

At the Super Group level, fish have elevated predicted impacts in the north while marine mammal and turtle impacts were elevated toward the south, but most broadly distributed (Figure 8). Seabird impacts were mostly over the shelf especially in the southern region and were especially high north of Point Conception, while human uses were concentrated close to the coast and especially patchy. The irregular and offshore distribution of benthic habitats is dominated by the seamount and canyon impacts layers but also shows elevated risk on and near the shelf from deep-sea corals. At the Super Group level, the disparity in data quality between the receptors of each group is also apparent, with high-resolution seabird data clear in the impact map while course resolution data dominate the patterns for marine mammals, and fish. These differences are important to note since the extensive use by seabirds of the shelf break and oceanographic features that lead to high productivity are clearly quantified, but any similar fine-scale patterns are missing for the coarser Group data. This highlights the current value of these model outputs for broader scale planning use with only some application for finer scale decisions that must be made at the level of individual wind energy areas. Improving the quality of input distribution data will significantly enhance the usefulness of this cumulative impacts approach at smaller scales.

Trade-off and optimization results

The benefit/impact metric, calculated as the difference between the normalized energy benefit metric and the normalized impact metric of each Super Group (Figure 8), can help understand which Super Group impacts contribute to patterns of more- or less-desirable development locations. Since most of the Super Group impact metrics are relatively high in the Southern California Bight and wind energy benefit is correspondingly low, all metrics show a pattern of low benefit/impact trade-off there (Figure 9). Marine mammals and turtles, and human use metrics are largely driven by the patterns of energy benefit except for along the coast where higher impacts for the two Super Groups lower the trade-off metric. Fish benefit/impact metrics were the lowest across the greatest area, deriving from the relatively even and broad spatial distribution of impact on the shelf, in the trade-off analysis domain. Small areas farther offshore as well as one coastal area off the Bay Area have higher trade-off values for fish, but those should be treated with some caution because of the coarser resolution and lower quality of much of the fish distribution data.

Across all but the fish trade-off results, similar areas fell into the top 10th percentile of the scoring (Figure 99). Those areas are near the Oregon border and southwest from Punta Gorda/Cape Mendocino. One additional area was highlighted southwest of Point Arena for benthic habitats and human uses and marine mammals and turtles but not for seabirds or fish. While the selection of the 10th percentile is arbitrary, it helps to visualize the overlap of higher-priority areas across the different Super Groups. The divergent patterns of the fish trade-off metric suggest that conflicts and concerns for impacts might be especially challenging for that group while there may be more consensus among the other Super Group results as to where higher priority locations fall.

The series of optimization analyses we performed with the conservation algorithms of the *prioritizr* R software package provide a preliminary demonstration of what can be assessed with a more rigorous algorithmic approach to prioritization (Figure 10). When the optimization is run under the most restrictive scenario which targets a maximum of 10% of the total impacts for each Super Group, there are two areas selected that broadly align with the top regions from the trade-off metric: southwest from Punta Gorda/Cape Mendocino, and offshore from Point Conception. Only a very small area near the Oregon border is selected, likely because while impacts are lower offshore for seabirds, benthic habitat and human uses, the only areas with low marine mammal and turtle impacts are closer to shore while fish impacts are generally high in that region. However, as we allow for up to 30% of the impact for each Super Group, the areas initially selected expand and an offshore region near the Oregon border is added. For this scenario, small areas of the Humboldt WEA and approximately half the Morro Bay WEA are also included. Finally, when further relaxing the constraints on impacts to 50% allowable, much of the north coast offshore area is selected, including a larger portion of the Humboldt WEA. With this scenario, part of the Morro Bay WEA is also selected along with an adjacent area to the northeast. This last 50% scenario is actually most useful in identifying the lowest-priority areas for development which are not selected; these areas fall offshore of the southern California bight, offshore from the excluded NMSs in central California and in a patch to the north of the Humboldt WEA. Additional information to help prioritize within the selected areas comes from an 'irreplaceability' score that ranks the importance of each selected cell to achieving the optimization solution (Appendix C; Figure C6). This metric helps to know what sub-regions within the optimal selected area are most valuable to ensuring development minimizes impact across all Super Groups.

Though there have been conflicts with the Department of Defense over the prospect of development offshore and south of Point Conception, a large area is prioritized in that region as well. It is interesting to note that when prioritizations are run that do not exclude the NMSs, more than half of the Greater Farallones, and most of Cordell Bank and Monterey Bay National Marine Sanctuary (NMS) areas are still not selected, even in the more development-friendly 50% scenario (Appendix C; Figure C21). That suggests that the extraordinary marine productivity and natural resources which those NMSs were designated to protect would likely experience high impacts from development, excluding them from selection.

These three scenarios lie along a spectrum that moves from weighting protection of wildlife and current human uses to emphasizing the benefits of wind energy production more heavily. They provide information that could help guide the staged process of offshore wind development as California seeks to meet renewable energy targets while protecting wildlife and important human uses of the ocean. It is important to note that though the existing WEAs are not fully selected with the 10 and 30% optimizations, this is not an indication that they are poor areas for development that will result in high impacts. Instead, this is explicitly a prioritization tool and the specific scenarios that we ran highlight other regions as meeting the balance between development benefits and impacts somewhat better than the WEAs. The specifics of the selected areas, however, rely on the quality of the data currently used in the model and the explicit equal weighting across impacted sectors. With different value weights applied across Super Group impact measures, the pattern of optimized areas may change.

To help understand the drivers behind the optimization results discussed above and to allow consideration of site selection based on each Super Group in isolation, we ran optimizations that traded off each Super Group's impact scores with LCOE independently (Figure 11). These optimizations were performed with maximum proportion of impact set to 10%. The optimal locations for marine mammals and turtles most closely align with the selection from the combined optimization runs. Seabirds, by contrast, have optimal areas selected closer to shore, though they still include regions offshore from Punta Gorda and Point Conception. The only location selected for fish lies off Punta Gorda, while optimal locations are smaller for benthic habitat and the main areas are located north and south of Punta Gorda. These results also contrast somewhat with the results from the Benefit/Impact metric analysis (Figure 9). The optimal areas selected for each group generally have moderate (yellow) Benefit/Impact scores. This is because while the optimization accounts for all impacts and benefits simultaneously and uses Mixed Integer Linear Programming to find the mathematically minimized solution, the Benefit/Impact is a simple difference between normalized summed impact and normalized benefit (inverted LCOE). Extremely high Benefit or extremely low Impact could lead to a high metric score. This moderate discrepancy highlights the value and importance of using multiple approaches to identifying priority locations for offshore wind. Finally, it is important to note that the Super Group Optimization could not be performed for Human Uses. That is because the distribution of Human Use impact scores is heavily skewed with only a handful of cells with high impact and the vast majority having low impacts. This type of distribution makes the mathematical optimization intractable because the solution space becomes very flat leading to failure to solve the optimization problem.

The LCOE optimization series results (Figure 12) clarify the conclusions above with added information. The most-selected areas fall offshore from Punta Gorda, Point Conception and the northern Channel Islands. An additional area in the offshore waters near the Oregon border is also frequently selected as part of the optimal solutions. This raster-based output provides a more nuanced assessment of where to prioritize development and thus has benefits in use for decision-making, allowing selection of higher priority areas within the optimized solutions.

Finally, our optimization analyses to find the areas most suitable to fulfill the AB525 2045 25GW target provide a third approach to prioritizing areas for development (Figures 13 and 14). The approach suggests that the highest-priority areas for development lie to the southwest of Punta Gorda with additional areas offshore near the Oregon border, just north of Greater Farallones NMS and a few scattered locations west of the northern Channel Islands. As expected, the areas selected by the 'high' power density optimizations (Figure 14 panels B and D) are smaller since more power can be produced per unit area. For the solutions that assume the existing WEAs are developed (panels A and B), the areas selected also contract (since much of the target is met by the existing WEAs) in size. In addition, those solutions give less priority to some of the offshore areas that are frequently selected when existing WEAs are not 'locked-in' to the optimizations (panels C and D). On the other hand, compared to the LCOE optimizations, all the gigawatt target optimization areas are further offshore and far fewer locations near Point Conception are identified. This is in part because LCOE penalizes offshore areas due to their cost for development and maintenance while Net Capacity most prioritizes areas with high power generation potential.

These findings both highlight the importance of holistic and science-driven evaluations of siting priorities early in the process as well as the significance of using and continuing to develop the highest quality input data for such models. In addition, since certain components necessitate value-driven decisions and weighting, our tool is most useful as a dynamic, updateable, and modifiable means to inform decision making. If key stakeholders can use these models to produce results according to their needs and priorities, those outputs can serve as a way for invested parties to discuss trade-offs and find commonly selected areas that meet the needs of a broad array of people and natural resources.

Wind Energy Area results

We plotted and evaluated the cumulative and Super Group impact results of the Humboldt and Morro Bay WEAs to see if any patterns of interest arose to inform development at the lease level (Appendix C; Figure C7-C10), while recognizing the above-stated limitations. We also show the distributions of impact scores for cells within each WEA as compared to scores in the optimization area and across the whole EEZ (Figure 15 and Appendix C; Figures C11-C15). Key results show that the cumulative impacts for the Humboldt WEA fall in the higher range of impacts within the coastal optimization area, while the impacts for Morro Bay are on the lower end of the optimization area range. This suggests that the Morro Bay WEA minimizes impacts more than most other feasible locations while the Humboldt area will be more impactful to species, habitats and human uses than the other potential sites (Figure 15). Among the Super Groups, fish had the greatest impact level in the Humboldt WEA while impact was greatest for benthic habitats in the Morro Bay WEA (Appendix C; Figures C7 and C13). Several areas of elevated benthic habitat impact exist in the Humboldt WEA from the presence of a few known seeps, but otherwise, the areas covered by the WEAs have low human use and benthic habitat impacts relative to the remainder of the EEZ (Appendix C; Figures C7, C14 and C15). Seabird impacts were moderate in both WEAs (Appendix C; Figures C7 and C12) while marine mammal and turtle impacts were moderate in the Humboldt WEA but higher in the Morro Bay WEA (Appendix C; Figures C11 and C12). The reverse pattern was true for fish, which had significantly higher impacts in the Humboldt WEA compared to Morro Bay (Appendix C; Figures C13). The other broad pattern that emerges from these zoomed-in evaluations of the WEAs is that for seabirds and fish and thus for the cumulative impacts, offshore areas have higher impact values than closer to shore. This onshore-offshore gradient holds true in most broader patterns as well.

AB525 sea space results

We also assessed the distribution of impacts within the sea space areas identified by the AB525 evaluation process (Figure 16 and Appendix C; Figures C16-C20). Of the selected areas, the Mendocino Area_1 covers the lowest combined impact cells which are significantly lower than the distribution of impact cells within the optimization area. By contrast, the Del Norte Area_1 sea space has impacts that are moderate relative to other potential development areas as does the Monterey Area_1. The latter has a much wider variability in scores, suggesting there might be opportunity to prioritize lower impacts within that selected sea space. Bi- or multi-modal distributions of combined impact in Humboldt Area_1, Humboldt Area_2, Mendocino Area_1 and Mendocino Area_2 also suggest there may be sub-regions within this sea space that are higher or lower impact.

With regard to specific impacts to each SuperGroup (Appendix C; Figures C16-C20), Mendocino Area_1 stands out as consistently lower than scores across the optimization area and than all the other sea space areas. In contrast, Monterey Area_1 has highest impact scores for Seabirds, Benthic Habitats, and Marine Mammals and Turtles, suggesting it may be less suitable for low-impact development.

Conclusions

The methods and results presented in this report exemplify the status of our siting model efforts to-date. Our recent updates to the input data significantly expanded and improved the coverage of impacted species, habitats and human uses. The seabird Super Group has excellent coverage with the highest-quality data and will further expand as expert vulnerability assessments are added so that three additional Groups can be included in the models. Marine mammals input data is of mixed quality that also varies among the Groups. Baleen whales, killer whale, pinnipeds, sea otter and sea turtles would especially benefit from improved model quality and better seasonal coverage. Fish species are well-represented, but with low-quality data, making this the Super Group that would best benefit from developing and including high-resolution, expert models. Despite these remaining gaps, our data updates added 17 new species and 2 habitats and improved the quality of data for 69 model components.

We also found significant differences in estimated impacts both at the cumulative level and for individual Super Groups between the two existing WEAs and among the identified AB525 sea space areas. These differences can help prioritize development planning as well as guide how mitigation and monitoring requirements area established for each location. Patterns of scores in these regions compared to the optimization area and the full EEZ highlight that offshore areas tend to be lower-impact in aggregate, though there are exceptions for specific Groups. The offshore declining trend in impacts also was evident in the areas selected by both optimization approaches. Areas selected by the optimizations using LCOE, which incorporates industry costs of development and operation were closer to shore than those selected using Net Capacity, which does not include those costs. This pattern suggests that evolving technology and associated reductions in cost to install wind energy further offshore could be a significant boon to future development plans. Among the AB525 sea space areas, the Mendocino Area_1 may be of highest priority for future development. Both combined impacts and those for most of the SuperGroups were lower than the other sea space areas and lower than the coastal waters potentially available for development. In addition, that area was selected and highlighted by all of the optimization analyses we performed.

Based on the combined analyses done here, multiple distinct approaches to optimal siting converged on a priority area for development to the west and southwest of Punta Gorda. While some of the identified region is in waters too deep for current development, portions include some of the sea space areas identified for development by the AB525 process. Based on the combined results of our modeling, Point Blue recommends that the Mendocino Area_1 sea space region be identified as the highest priority area for the next phases of wind development offshore of California. In addition, portions of the Mendocino Area_2, and both Humboldt Area seaspace regions should be considered high-priority for development plans to meet the AB525 2045 goals. These areas comprise waters with high energy production, balanced and minimized combined impacts to species, habitats and existing human uses and reasonable access to grid interconnection. Development of these regions would help balance benefits and impacts and likely require significantly less stringent mitigation efforts to avoid negative impacts.

We have developed a robust modeling framework that includes many key factors for quantitatively analyzing cumulative adverse impacts and using those to understand trade-offs with offshore wind energy development. The models and analysis have been developed with open-source software which are available for use and inspection on a public repository. The models are also built to be easily updated with new data, an important capability given the many ongoing research efforts to advance the data on distributions and vulnerabilities across a number of receptors. As we continue to develop this modeling system, we will refine the visualizations and types of outputs to better meet the needs of stakeholders and managers. In addition, there is great potential for the optimization component of this model to be modified so that it can identify siting solutions that meet specific total energy production targets, such as those that will be developed as part of AB 525.

Related Work, Next Steps and Opportunities

We have built a robust CAE model and optimization analyses in an open-source framework and using the collated datasets available during the development of the analysis. We also collected and created a large database of information from primary sources and the literature to parameterize many of the components in our models. We have now added and updated most of the data sets that became available during the first phase of this project, significantly improving quality and coverage of distribution data. Potential new data sets that could be included in the future are models for benthic macrofauna, improved fishery data from NOAA Northwest Fishery Science Center, and high-quality and resolution fish models in development. There were several model weights (e.g., breeding range for central place foragers) that could not be incorporated due to lack of readily available data. Future data collation efforts could provide sufficient information to parameterize and include these weighting factors.

We also conducted expanded surveys and expert elicitation workshops to improve sensitivity formulation, allowing us to include 8 additional receptor Groups in our model runs. The purpose of the models continues to be to identify areas that maximize energy generation potential while preserving existing ocean uses and protecting the marine and coastal environments.

Additionally, Point Blue collaborated extensively with the technical assistance team at the Patrick J. McGovern Foundation as part of the 2022 global Data to Climate Action Cohort. Through this collaboration, we increased our capacity around data use and processing, computing infrastructure and data management. During that project, we significantly improved the efficiency in adding and processing new data for the siting models, developing an automatic cloud-based data pipeline that prepares input spatial data for model use. We also decreased offshore wind energy model and optimization processing times and with a software deployment workflow in the Amazon Web Services cloud ecosystem that allows efficient processing of siting model and optimization runs and has the potential to be automatically scaled for numerous simultaneous runs concurrently. This related project moved our offshore wind modeling process and platform significantly closer to potential deployment as a web-accessible tool for planners and/or the public if that were to become a priority for offshore wind planning.

The potential applications of our model are many, ranging from more refined optimization runs that exclude more locations where development is technically infeasible and include future development as it occurs, to deeper analysis of impacts and associated uncertainties to inform monitoring and mitigation requirements. The model can also become more accurate and useful by adding newly available data with higher-quality distribution data, or revised impacts based on even greater expert surveys or empirical studies done as installations become operational. The most valuable application of the model would be in close collaboration with managers and industry as they evaluate more realistic combinations of potential WEAs with constraints based on technical feasibility limitations. Point Blue could achieve this with direct partnership or by developing a web-based version of our modeling platform to allow stakeholders to run analyses based on their specific needs. Ultimately, this impact and optimization model has the potential to play an important role in guiding future planning for offshore wind development that meets the ambitious California renewable energy targets while minimizing negative impacts to wildlife, habitats and existing human uses.

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Figures

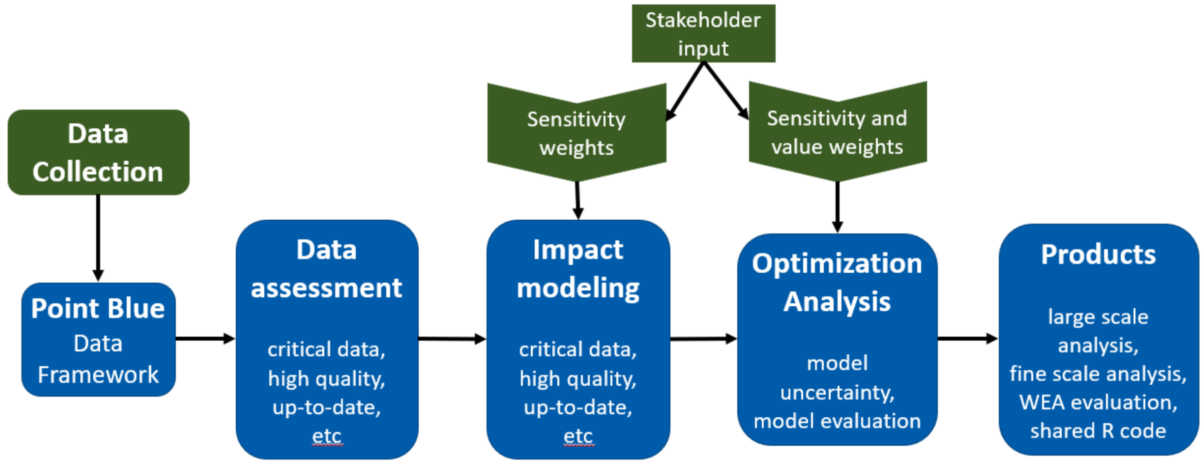

Figure 1. Overview of methods and project approach.

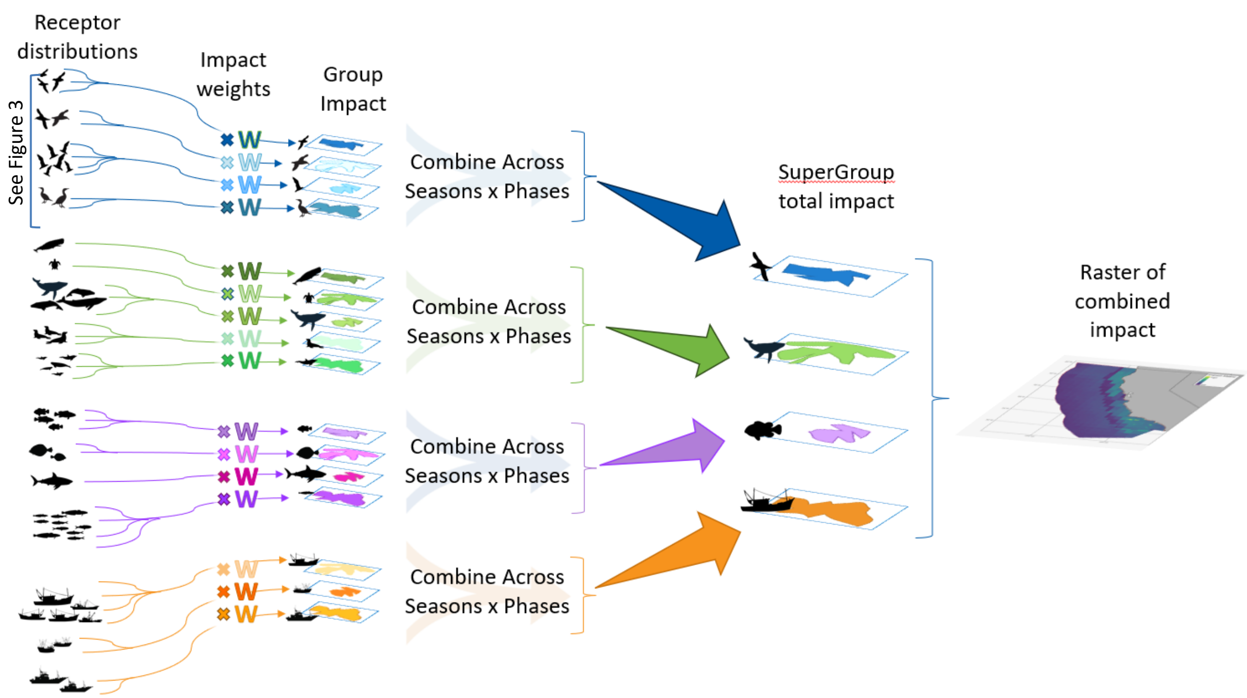

Figure 2. Diagram of the full impact model. Inputs to the model include species-level distribution and population data (left column) and empirical data and expert-opinion survey data that are combined to provide weights representing the level of impact a receptor is expected to experience if exposed to offshore wind development (Impact weights column). See figures 3 and 4 for more detail on the formulation and components of these weights. Impact is calculated for each of the 8 combinations of season and phase and for each Group within a Super Group. These Impact rasters are then combined with a temporally-weighted sum between Construction

and Operation phases to represent the total expected impact to a Super Group. Finally, Super Groups are summed to give a single representation of total expected impact.

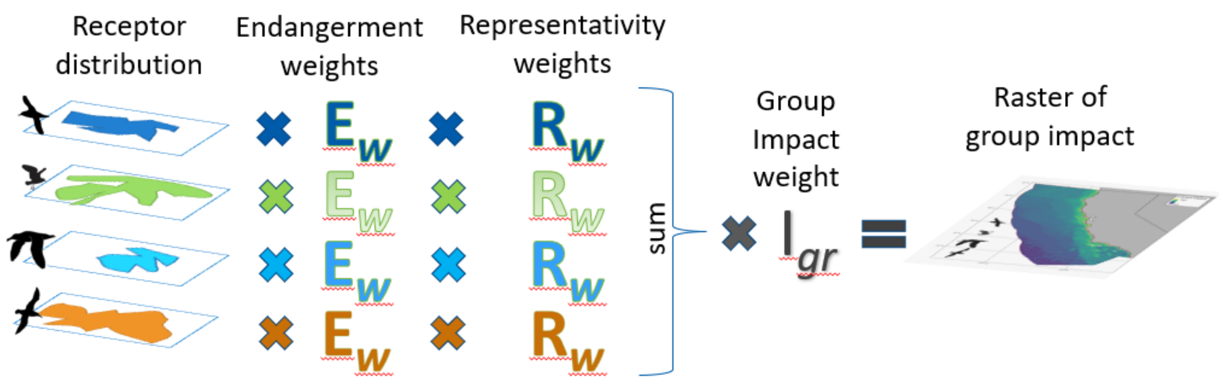

Figure 3. Diagram depicting the calculation of Group-level impact rasters. Each row represents a constituent receptor (species, habitat or human activity) within the Group. Raster data representing the distribution of each receptor (left column) is multiplied by receptor-specific weights (second and third columns) which include endangerment level and group representation weights for species receptors, spatial prevalence for habitat receptors and economic/social importance for human use layers. The resulting weighted distributions are summed and then multiplied by the Group-specific Impact weight, I_{gr}. Group-specific Impact weight is derived from expert surveys, impact-specific spatial footprint scalars and movement multipliers and is dependent on seasonal presence and breeding behavior (see Figure 4 for more detail). The resulting raster is representative of the Group cumulative impact metric (right column and figure).

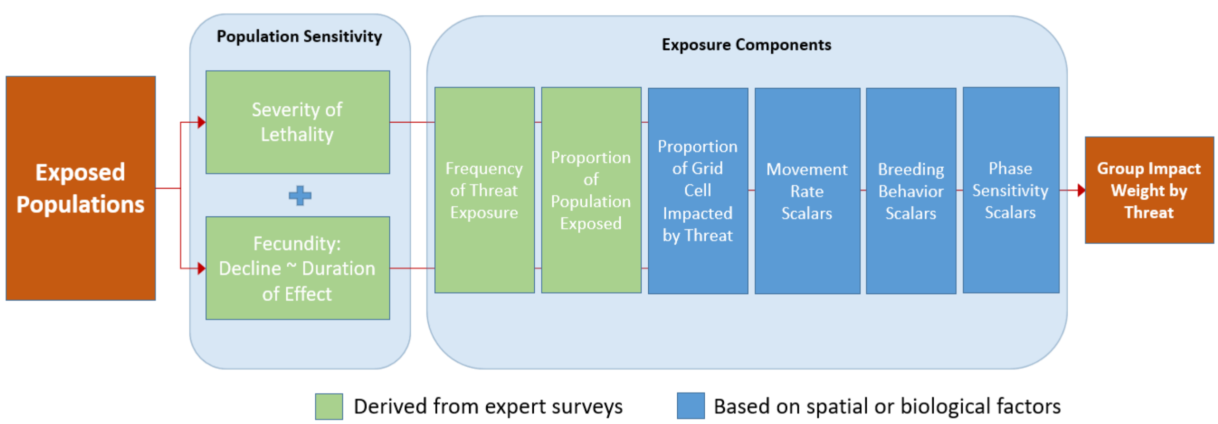

Figure 4. Visual representation of the formula for calculating Group Impact weights. This calculation is done for each combination of Group and threat and separately for each season and phase. The formula is based in a population model framework such that the impact weight depends on both threats that are expected to result in mortality and threats that will have sub-lethal effects on fecundity. Effects on fecundity are discounted relative to lethal threats and also

discounted for shorter duration of effect. Components of the formula in green are derived from expert opinion surveys, while components in blue are from empirical information about the receptor and impact.

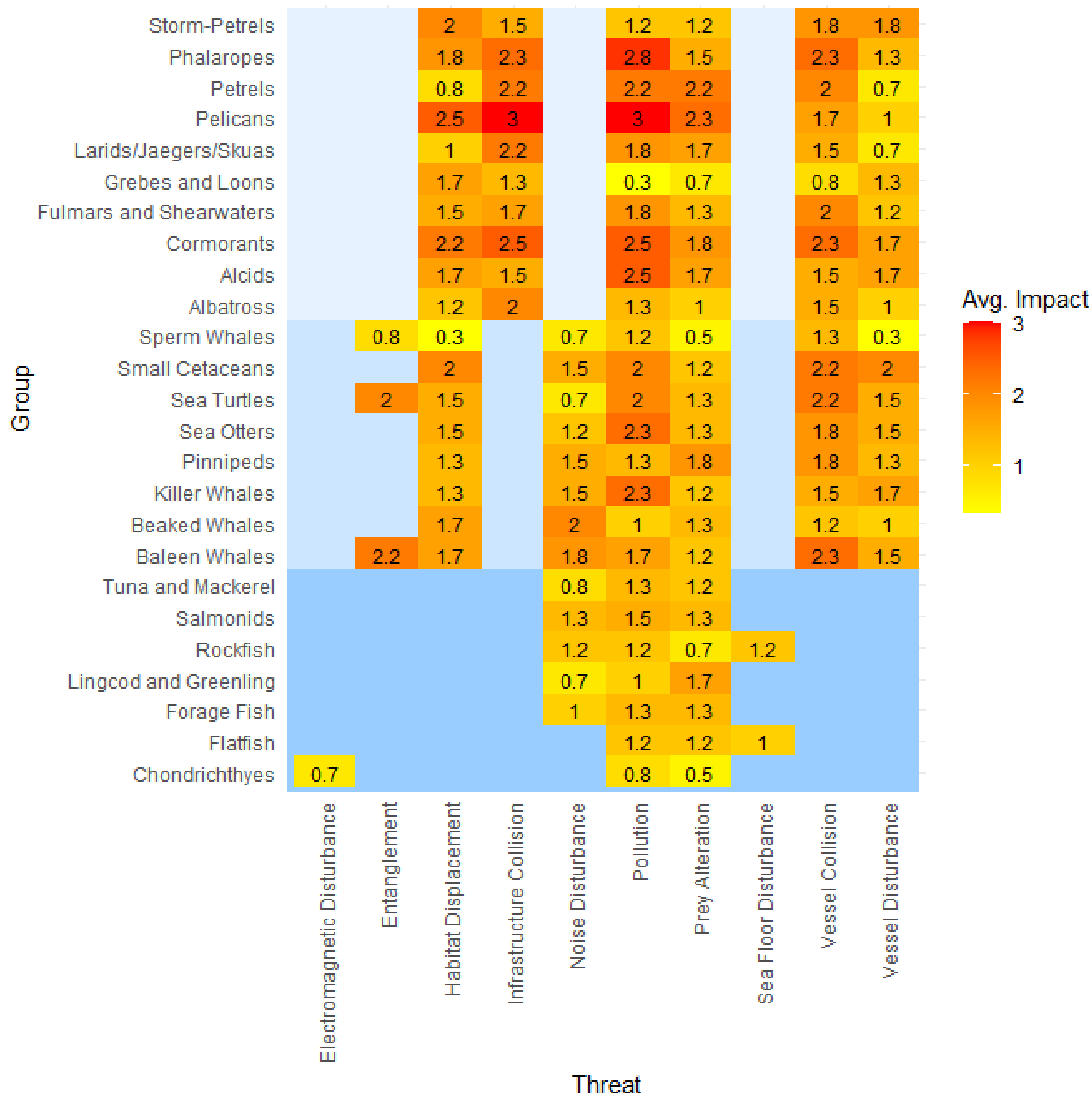

Figure 5. The average score of expert responses for each threat and species group. The number inside the cell is the average across all respondents and values of fecundity and lethality effects, frequency of exposure and proportion of population exposed. Null cells indicate threats that were not considered for the given species group.

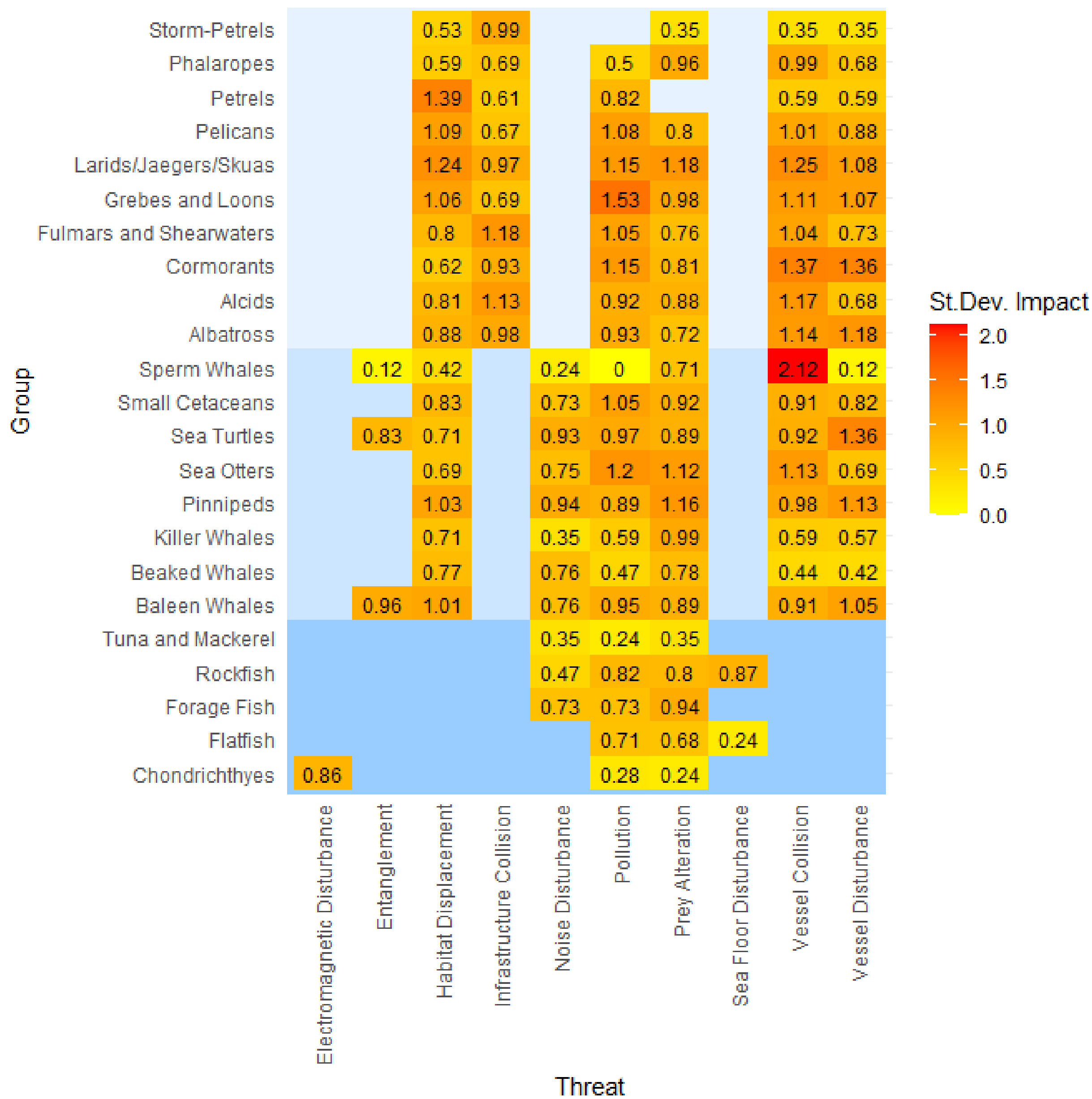

Figure 6. The standard deviation of the score of expert responses for each threat and species group. The number inside the cell is the standard deviation of the score across all respondents and values of fecundity and lethality effects, frequency of exposure and proportion of population exposed. Null cells indicate threats that were not considered for the given species group.

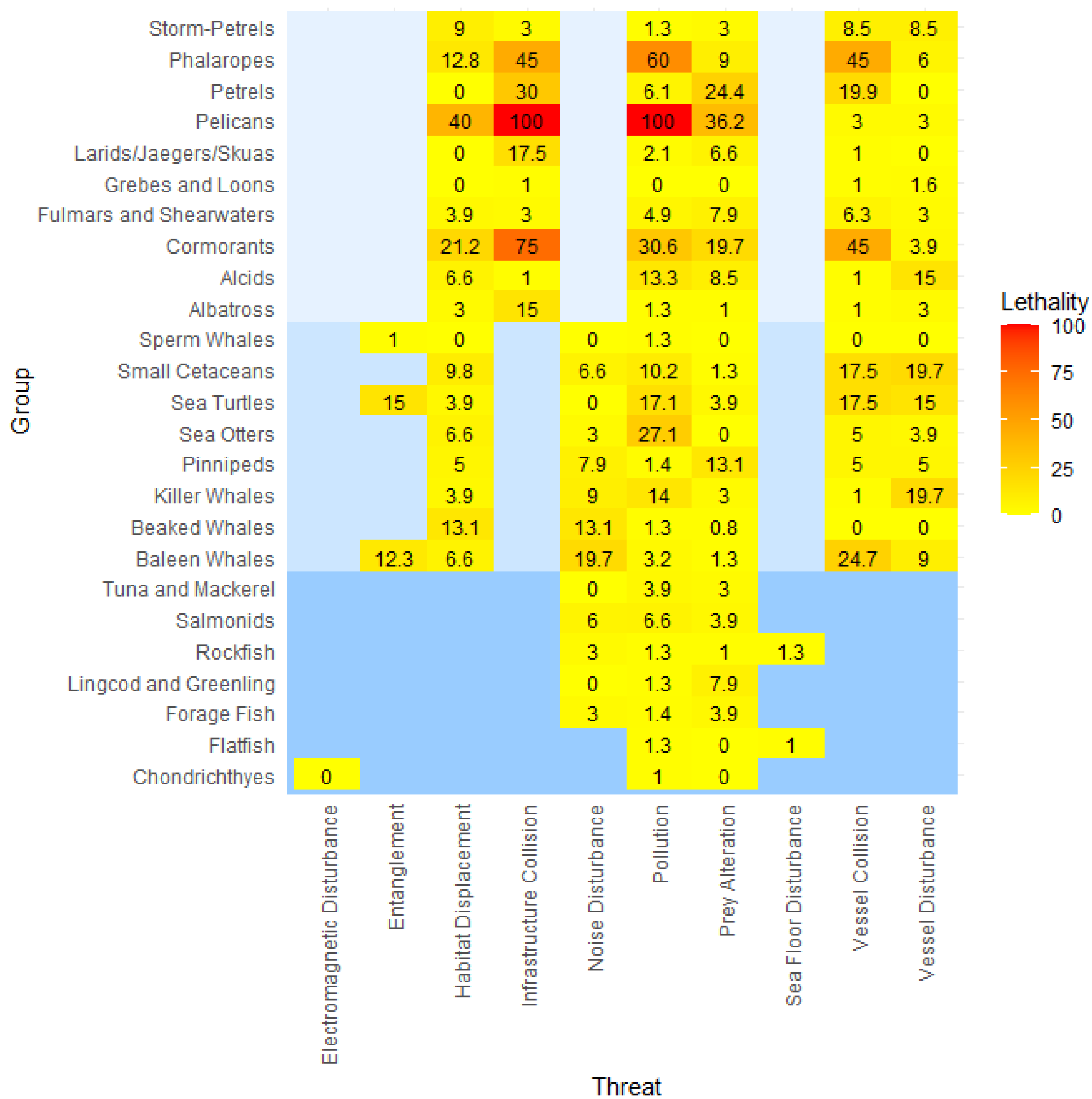

Figure 7. The lethality score calculated from expert responses for each threat and species group. See Equation 1 for details. The number inside the cell is the lethality score. Null cells indicate threats that were not considered for the given species group.

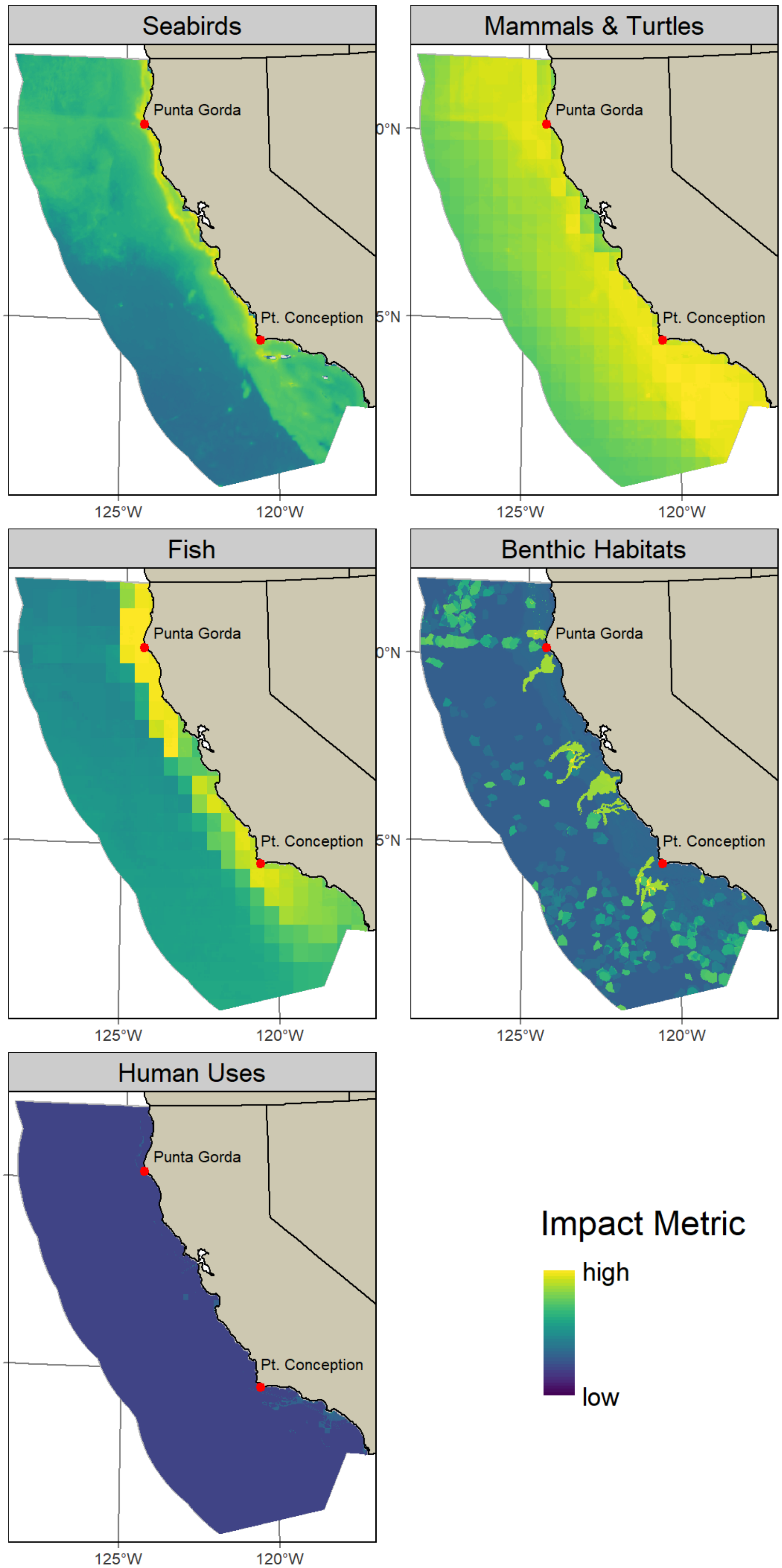

Figure 8. Supergroup cumulative impact maps for seabirds, marine mammals and turtles, fish, benthic habitats and human uses. Yellow values indicate high impacts while blue represent areas with the lowest relative impact. Punta Gorda and Point Conception are added as landmarks referenced throughout the results.

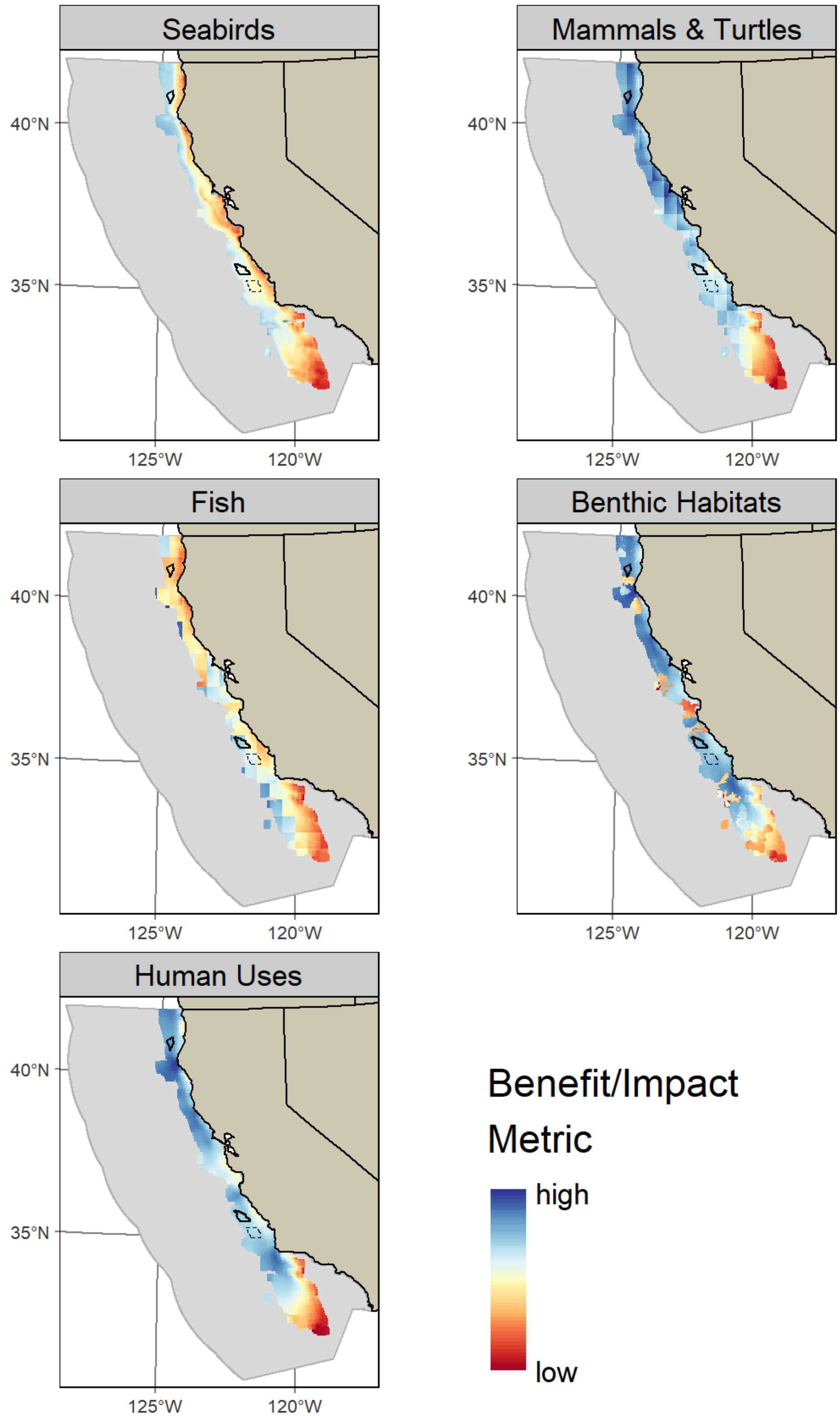

Figure 9. Benefit/Impact Metric for seabirds, marine mammals and turtles, fish, benthic habitats and human use. Warmer colors represent a low value of the trade-off metric, signaling locations that are less desirable for development. Cooler colors are areas more desirable for development. The existing WEAs are outlined in black. The Diablo Canyon Call Area is outlined in dashed black.

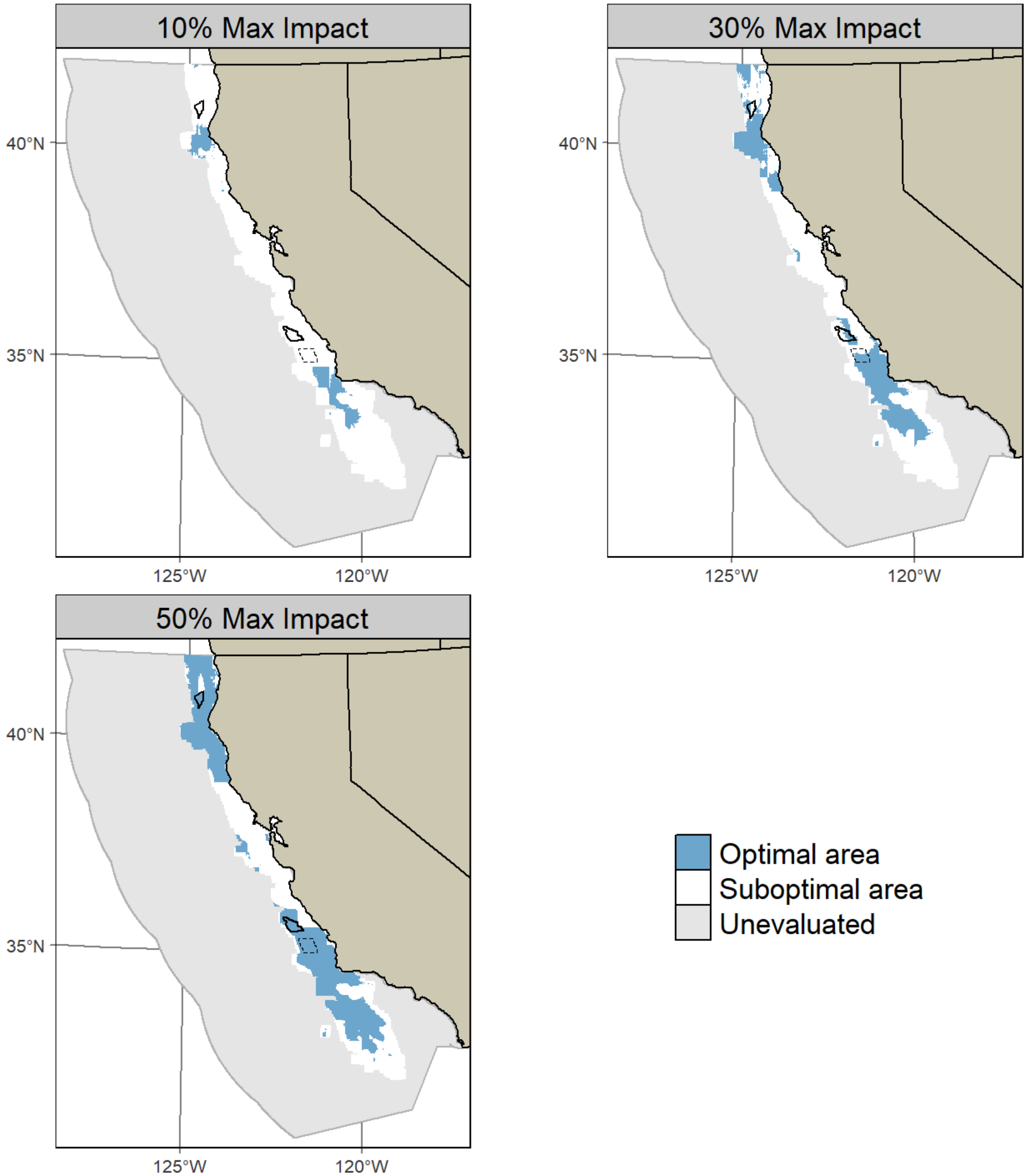

Figure 10. Three optimization scenarios representing a spectrum of relative value trade-off between energy development benefit (as quantified by the LCOE metric) and solving for areas that do not exceed cumulative proportional impact for any of the Super Group impacts. The targeted maximum total impact is set so as not to exceed 10%, 30%, or 50% of the total impact across the entire study domain. The existing WEAs are outlined in black. The Diablo Canyon Call Area is outlined in dashed black. Areas in gray were unevaluated because LCOE data was not available for these regions.

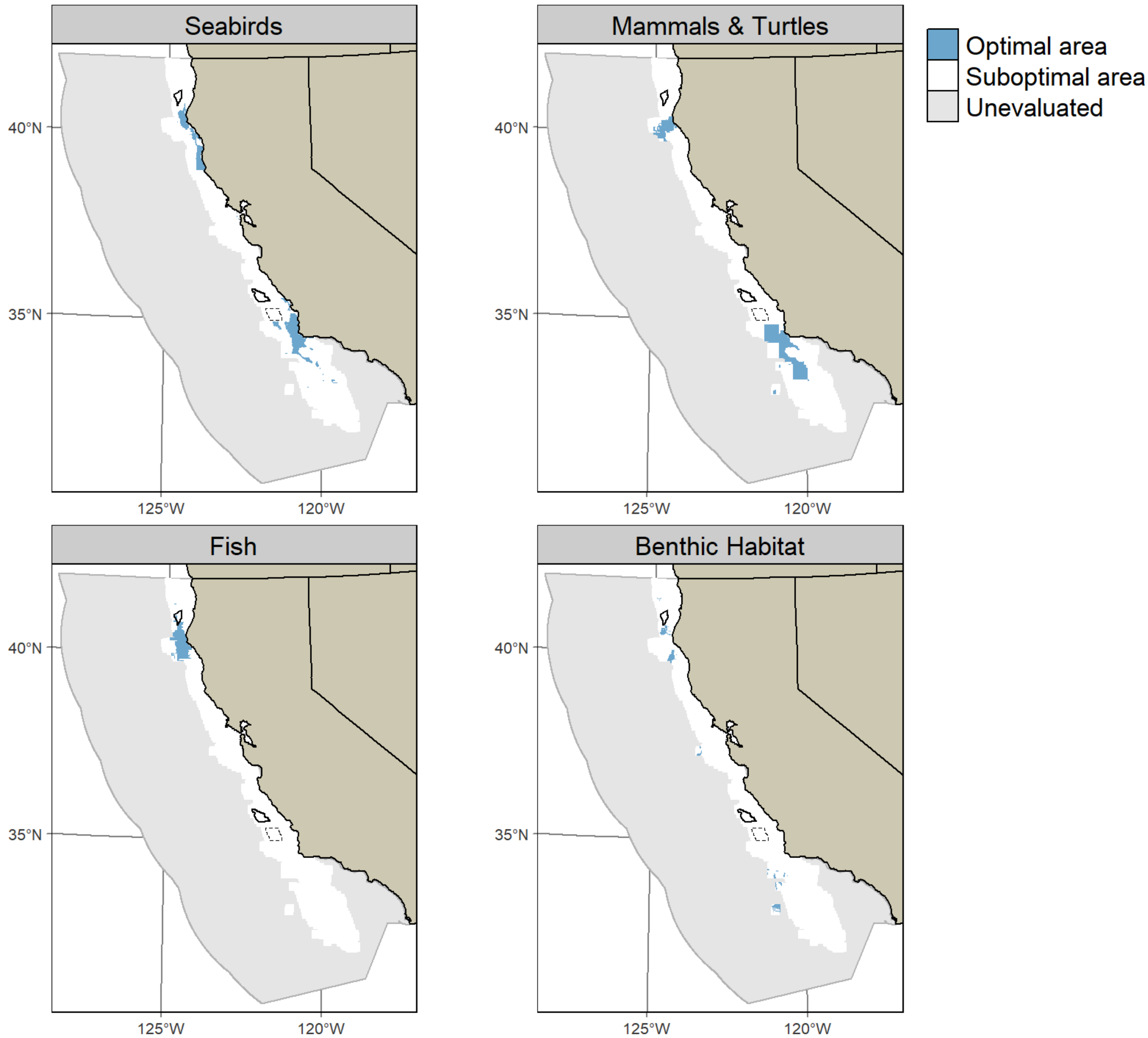

Figure 11. Super Group-specific optimizations representing relative value trade-off between energy development benefit (as quantified by the LCOE metric) and solving for areas that do not exceed 10% cumulative proportional impact to that Super Group. Seabirds, Marine Mammals and Turtles, Fish and Benthic Habitat. Human Use impacts are greatly concentrated in small areas along the coast, making the data unsuitable for Super Group-level optimization, so no analysis was done on that Super Group. The existing WEAs are outlined in black. The Diablo Canyon Call Area is outlined in dashed black. Areas in gray were unevaluated because LCOE data was not available for these regions.

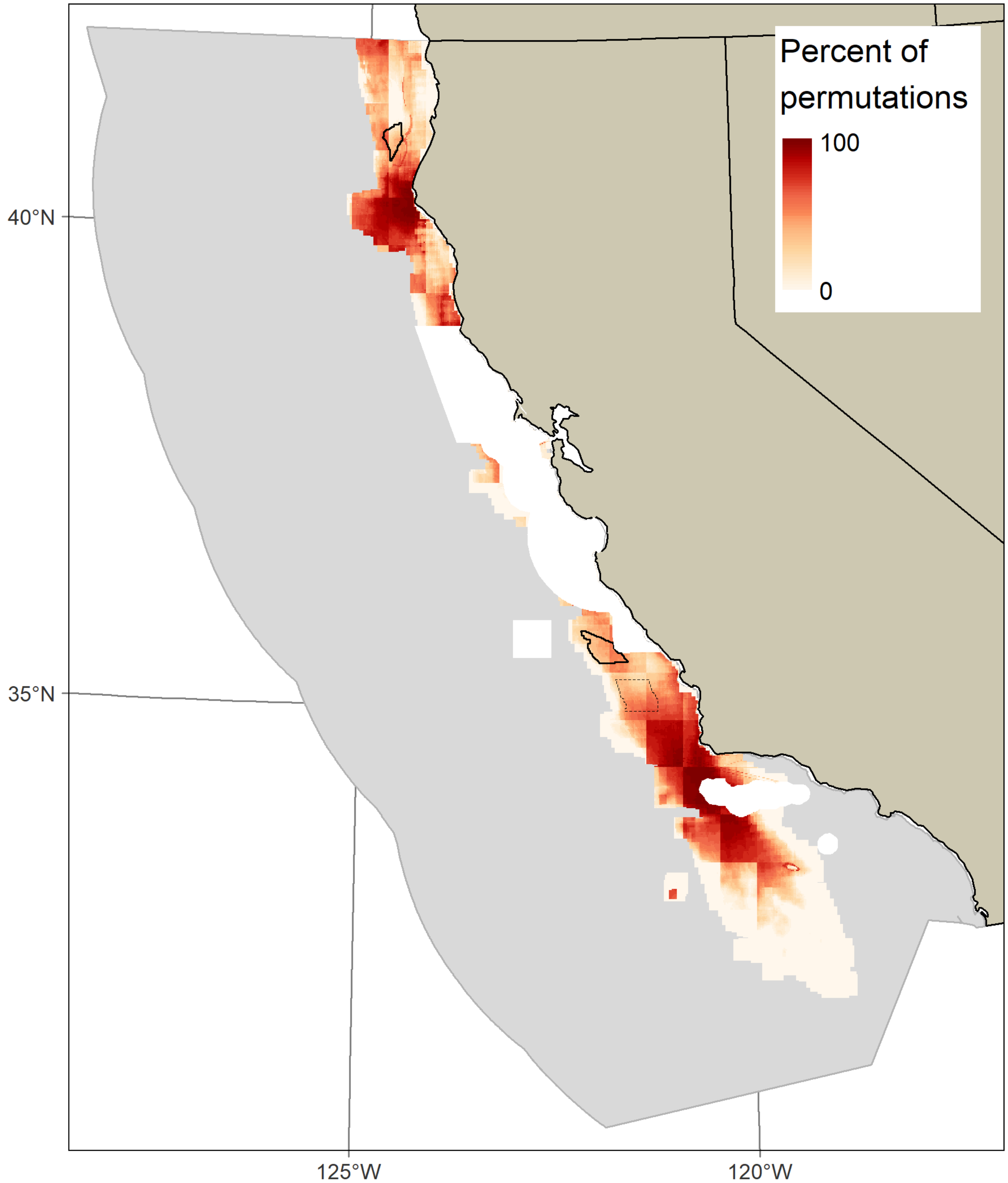

Figure 12. Map of frequency that each aliquot cell is selected by optimizations with maximum allowed impact ranging from 2% to 50% in two percent increments. Areas shown in the darkest red are chosen in all 25 optimization permutations, while areas in lighter colors were chosen less frequently. Areas in white are the National Marine Sanctuaries which were excluded from the optimizations. Areas in grey could not be analyzed due to lack of LCOE data.

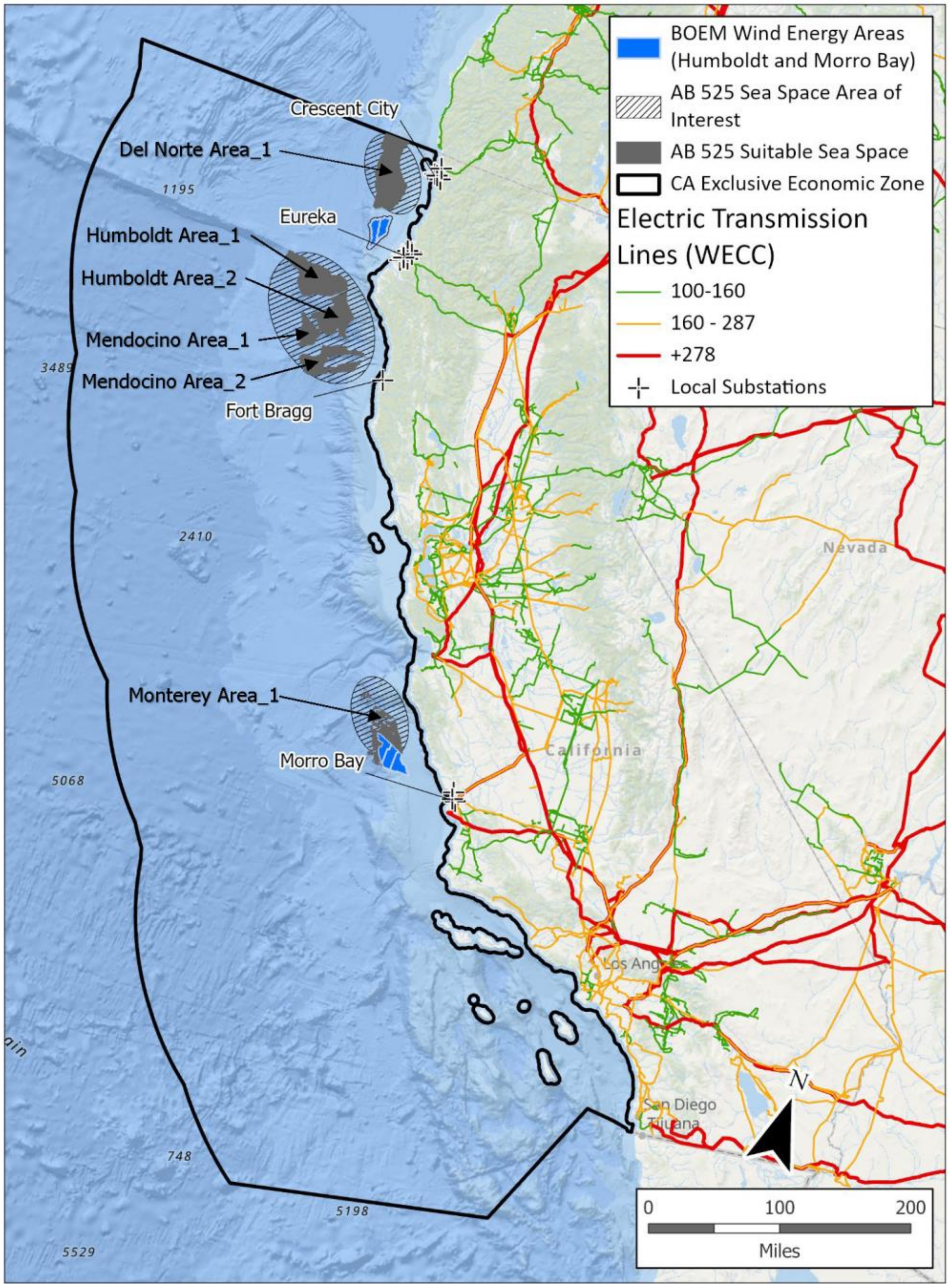

Figure 13. Map of AB525 Areas of Interest (hashed ellipses) and selected sea space (grey labeled areas). Also shown are the existing Humboldt and Morro Bay WEAs (blue) and the onshore transmission and grid connection infrastructure. Source: CEC 2023.

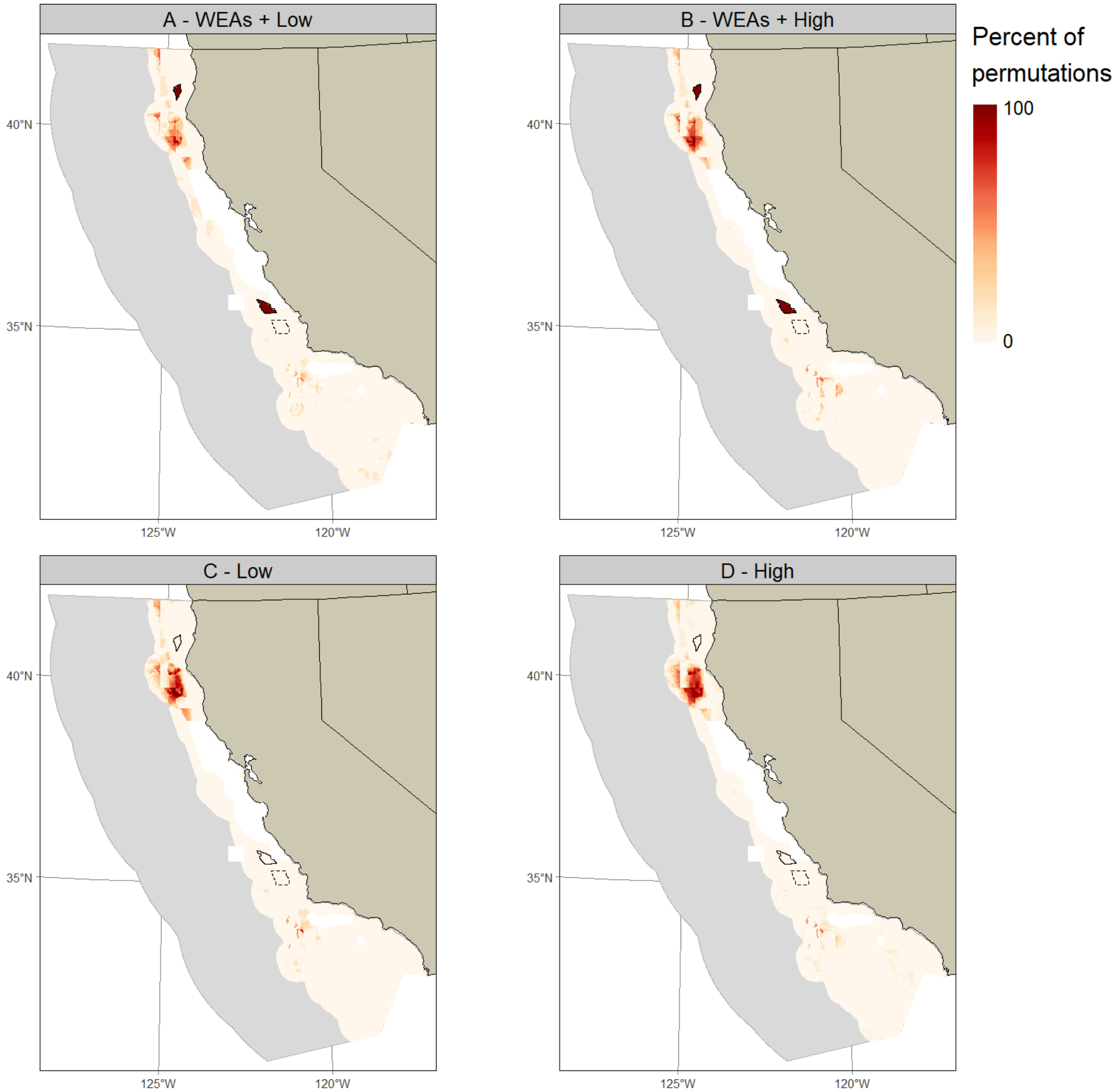

Figure 14. Rasters of the percent of optimization permutations in which each cell is included that allow 25-30GW of installed Net Capacity while minimizing impacts and area selected. Scenarios shown are for existing WEAs 'locked-in' to the solution with low (A) and high (B) power density and for WEAs not 'locked-in' with low (C) and high (D) power density. Darker red areas are more frequently selected as part of the optimal solutions that meet all targets.

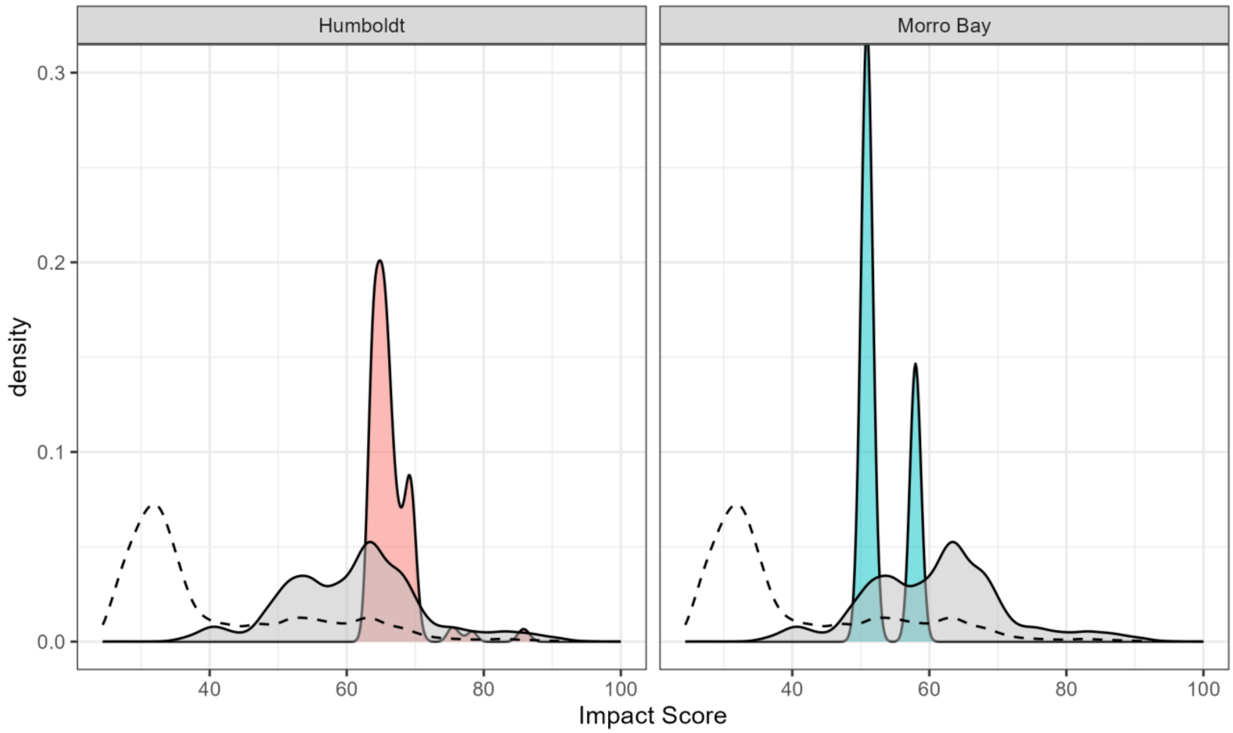

Figure 15. Density of combined impact scores (impacts summed across all Super Groups) for the cells within each existing WEA (colored curve), LCOE optimization area (grey curve), and full California EEZ area (dashed curve).

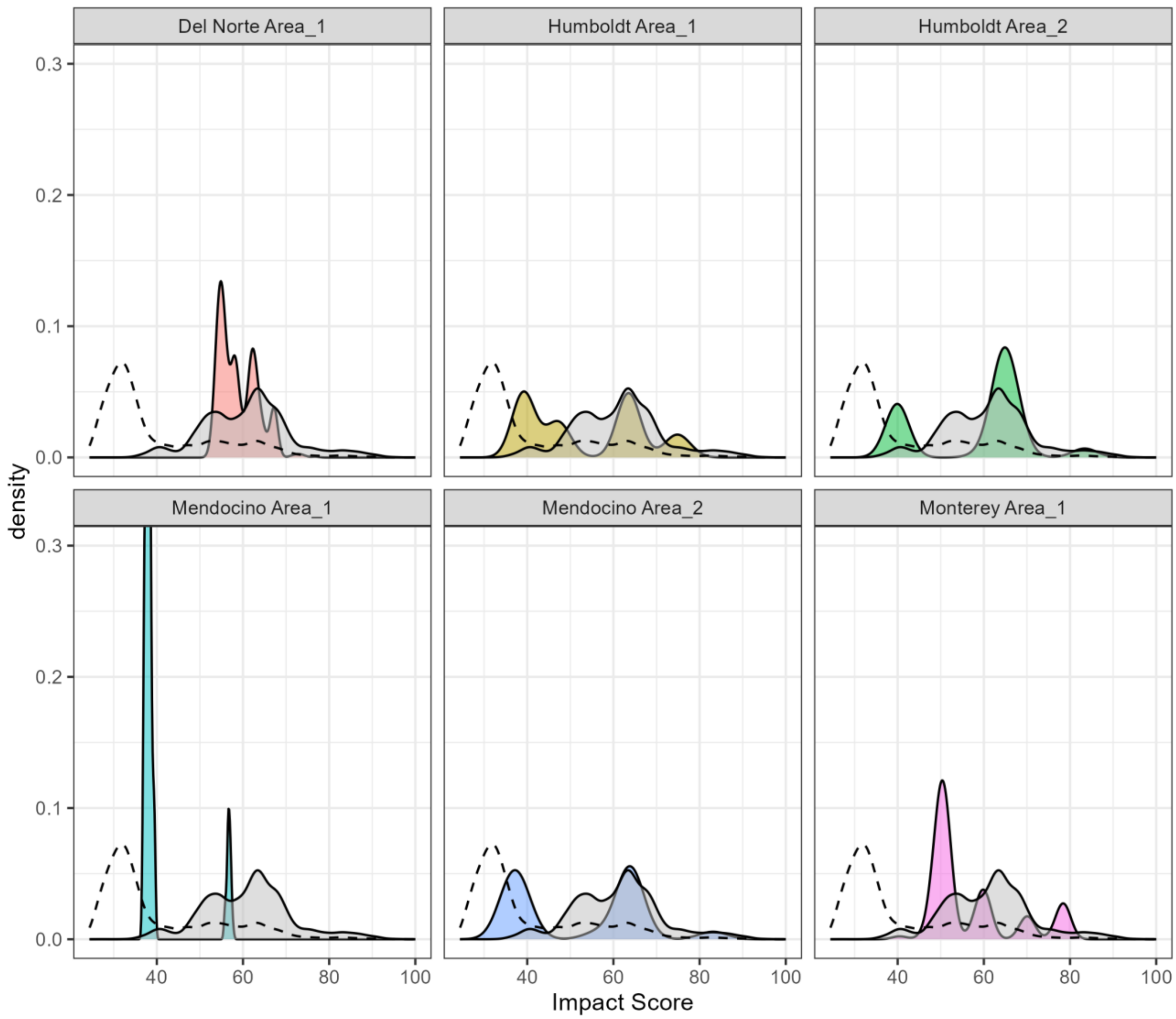

Figure 16. Density of combined impact scores (impacts summed across all Super Groups) for the cells within each AB525 sea space area (colored curve), LCOE optimization area (grey curve), and full California EEZ area (dashed curve).

Tables

Table 1. Lethality equivalent rubric for combinations of fecundity effect and recovery time expert responses.

		Recovery Time			
		None	Short	Intermediate	Long
Fecundity Effect	None	0	0	0	0
	Low quality offspring	0	5/16	5/12	5/8
	Decreased fecundity	0	5/6	10/9	5/3

Appendices

Appendix A – Data

Table A1. Spatial distribution datasets representing receptors in each Group. Values in parentheses in the Data Sets column represent the number of receptors that derive data from the listed data source out of the total number of receptors in the Group. The right column summarizes the representation numbers across the whole Super Group. Groups marked with asterisks (*) did not meet the minimum target of 3 survey responses and thus relied on fewer expert opinions.

<table>
<tr><th></th><th>Group</th><th>Data Sets (Spp. Represented/Total Spp.; Seasons/Total seasons)</th><th>Total Spp. Represented</th></tr>
<tr><td rowspan="8">Marine Mammals and Turtles</td><td>Beaked whales</td><td>Becker 2020a (1/4; 2/16); Becker 2020b (3/4; 6/16)</td><td rowspan="8">Overall: (33/34)
Becker 2020a: (2/34)
Becker 2020b: (14/34)
Welch: (2/34)
Aquamaps: (15/34)</td></tr>
<tr><td>Baleen Whales</td><td>Becker 2020b (3/7; 8/28); AquaMaps (4/7; 16/28)</td></tr>
<tr><td>Small Cetaceans</td><td>Becker 2020b (8/10; 16/40); AquaMaps (2/10; 8/40)</td></tr>
<tr><td>Killer whale*</td><td>AquaMaps (1/1; 4/4)</td></tr>
<tr><td>Sperm whale*</td><td>Becker 2020a (1/1; 2/4)</td></tr>
<tr><td>Pinnipeds</td><td>Welch 2020 (1/6; 4/24); AquaMaps (5/6; 20/24)</td></tr>
<tr><td>Sea otter</td><td>AquaMaps (1/1; 4/4)</td></tr>
<tr><td>Sea turtle</td><td>Welch 2020 (1/4; 4/16); AquaMaps (2/4; 8/16)</td></tr>
<tr><td rowspan="10">Seabirds</td><td>Albatrosses</td><td>Leirness 2021 (2/3; 6/8); Dick 2016 (1/3; 2/8)</td><td rowspan="10">Overall: (50/60)
Leirness: (46/60)
Dick: (19/60)</td></tr>
<tr><td>Alcids</td><td>Leirness 2021 (10/10; 20/40); Dick 2016 (7/10; 18/40)</td></tr>
<tr><td>Cormorants</td><td>Leirness 2021 (3/3; 10/12); Dick 2016 (1/3; 2/12)</td></tr>
<tr><td>Fulmars & Shearwaters</td><td>Leirness 2021 (6/7; 20/28); Dick 2016 (1/7; 1/28)</td></tr>
<tr><td>Grebes and Loons</td><td>Leirness 2021 (2/3; 6/12); Dick 2016 (1/3; 4/12)</td></tr>
<tr><td>Larids, Jaegers & Skuas</td><td>Leirness 2021 (16/19; 52/76); Dick 2016 (6/19; 10/76)</td></tr>
<tr><td>Pelicans</td><td>Leirness 2021 (1/1; 4/4)</td></tr>
<tr><td>Petrels</td><td>Leirness 2021 (2/6; 4/24)</td></tr>
<tr><td>Phalaropes</td><td>Dick 2016 (2/2; 8/8)</td></tr>
<tr><td>Storm-Petrels</td><td>Leirness 2021 (4/6; 14/24)</td></tr>
</table>

	Group	Data Sets (Spp. Represented/Total Spp.; Seasons/Total seasons)	Total Spp. Represented
Fish	Forage Fish	Muhling 2019 (2/10; 8/40); AquaMaps (6/10; 24/40)	Overall: **(84/88)** Muhling: **(3/88)** Brodie: **(4/88)** Aquamaps: **(77/88)**
	Chondrichthyes	Brodie 2018 (3/14; 12/56); AquaMaps (9/14; 36/56)	
	Flatfish	AquaMaps (13/13; 52/52)	
	Lingcod and Greenling*	AquaMaps (4/4; 16/16)	
	Tuna and Mackerel	Muhling 2019 (1/8; 4/32); AquaMaps (7/8; 28/32)	
	Salmonids*	AquaMaps (7/7; 28/28)	
	Rockfish	AquaMaps (30/30; 120/120)	
	Billfish	Brodie et al. 2018 (1/2; 4/8); AquaMaps (1/2; 4/8)	
Benthic Habitat	Deep sea coral	Poti 2020; Yesson 2012	
	Hydrothermal vent	InterRidge Vents Database (2020); Kitchingman 2004	
	Methane seeps	Merle et al. 2021; Kitchingman 2004	
	Sea mounts	Yesson 2011	
	Marine canyon	BOEM Submarine Canyon Atlas	
Human Uses	Midwater Trawl - Industrial	CalPoly VMS	
	Midwater Trawl - Hake	CalPoly VMS	
	Midwater Trawl - Rockfish	NOAA Observed Effort (2011-2017)	
	Bottom Trawl	CalPoly VMS	
	Hook and Line	NOAA Observed Effort (2011-2017)	
	Trap	NOAA Observed Effort (2011-2017)	
	Other Marine Fisheries	CalPoly VMS; NOAA Dungeness; CA Sea Cucumber Logbook; CA Albacore Troll Logbook; PSMFC Gill Net VMS; Miller et al. 2016	
	Shipping	Marine Cadastre AIS (2019-2020)	

Table A2. Area scalars for each pressure type to account for effects that occur at a smaller scale than the study grid. Scalars represent an estimate of the proportion of a cell effected by a pressure assuming development in that cell.

Pressure	Cell Proportion Scalar	Explanation of assumptions for scalar calculation
Infrastructure Collision	0.017	Assuming a 1-2 km turbine spacing (100 to 200-m rotor with 10 rotor-diameter spacing), there would be 0.5 to 1 turbine per km^2. As a simplification, we consider the area of likely collision to be an equilateral triangle with base equal to rotor diameter. Thus, the risk area ranges from 0.0085 km^2 to 0.017 km^2
Entanglement	0.1	Assuming a single cable pass (1 km) with an entanglement risk 'halo' of 100 m, the risk area is 10% of the total grid cell area.
Noise Disturbance	1	Construction and operation noise will extend 1km or more. (Maxwell et al. 2022)
Sea Floor Disturbance	0.0075	Assuming 3 anchors per turbine with 50x50 m disturbance for each placement totals 7500 m^2 of disturbance, or 0.75% of the total area.
Electromagnetic Disturbance	0.006	Electromagnetic fields extend several meters on each side of cables (Hutchinson et al. 2020). If we assume a cable passes across the entire cell, and influences a 6 m swath of sea floor, that equates to 0.6 % of the grid cell area.
Habitat Displacement	1	Avoidance of wind turbine infrastructure may vary by species group but can extend for many kilometers (Cook et al. 2018).
Vessel Disturbance	0.5	Avoidance of vessels may vary by species group but can extend for several kilometers due to visual or sound cues (Velando et al 2011).
Vessel Collision	0.05	Assuming service vessels have average beams of 50m and transit each affected cell regularly, potential collision covers 5% of the grid cell area.
Prey Alteration	1	Prey alteration may extend for multiple kilometers in the case of changes in water and wind flow or may have a smaller footprint due to floating objects or hard surfaces.
Pollution	1	Pollution can impact many square kilometers.

Table A3 – Species data, endangerment and representativity weights, and seasonal presence (_ = no data, 0 = not present, 1 = present, B = present and breeding).

SuperGroup	Group	Species	ScientificName	Endangerment	Representativity	Breed/Migr.	Winter	Spring	Summer	Fall
Seabirds	Albatross	Short-tailed Albatross	Phoebastria albatrus	13	1	Migrant	___	__1	111	11_
Seabirds	Storm-Petrels	Black Storm-Petrel	Hydrobates melania	9	1	Breeding	11_	_BB	BBB	B11
Seabirds	Storm-Petrels	Wilson's Storm-Petrel	Oceanites oceanicus	1	1	Migrant	___	___	__1	111
Seabirds	Alcids	Marbled Murrelet	Brachyramphus marmoratus	23	1	Breeding	111	BBB	BBB	__1
Seabirds	LaridsJaegersSkuas	Parasitic Jaeger	Stercorarius parasiticus	1	1	Migrant	111	111	___	111
Seabirds	Petrels(Procellariidae)	Cook's Petrel	Pterodroma cookii	9	1	Migrant	___	111	111	11_
Seabirds	GrebesLoons	Common Loon	Gavia immer	1	1	Migrant	111	1__	___	_11
Seabirds	Petrels(Procellariidae)	Parkinson's Petrel	Procellaria parkinsoni	9	1	Migrant	___	___	___	___
Seabirds	FulmarsShearwaters	Northern Fulmar	Fulmarus glacialis	1	1	Migrant	111	111	___	_11
Seabirds	Alcids	Rhinoceros Auklet	Cerorhinca monocerata	1	1	Breeding	111	1BB	BB1	111
Seabirds	LaridsJaegersSkuas	Black-legged Kittiwake	Rissa tridactyla	9	1	Migrant	111	111	111	111
Seabirds	Alcids	Ancient Murrelet	Synthliboramphus antiquus	9	1	Migrant	111	___	000	_11
Seabirds	Pelicans	Brown Pelican	Pelecanus occidentalis	1	1	Breeding	111	BBB	BBB	BB1
Seabirds	FulmarsShearwaters	Wedge-tailed Shearwater	Ardenna pacifica	1	1	Migrant	11_	___	__1	111
Seabirds	Storm-Petrels	Wedge-rumped Storm-Petrel	Hydrobates tethys	1	1	Migrant	___	___	_11	11_
Seabirds	FulmarsShearwaters	Sooty Shearwater	Ardenna grisea	8	1	Migrant	___	_11	111	11_
Seabirds	Petrels(Procellariidae)	Mottled Petrel	Pterodroma inexpectata	8	1	Migrant	___	___	___	___

SuperGroup	Group	Species	ScientificName	Endangerment	Representativity	Breed/Migr.	Winter	Spring	Summer	Fall
Seabirds	FulmarsShearwaters	Black-vented Shearwater	Puffinus opisthomelas	8	1	Breeding	111	11B	BBB	111
Seabirds	Cormorants	Pelagic Cormorant	Phalacrocorax pelagicus	1	1	Breeding	11B	BBB	BB1	111
Seabirds	Alcids	Guadalupe Murrelet	Synthliboramphus hypoleucus	22	1	Breeding	11B	BBB	B_1	111
Seabirds	Alcids	Pigeon Guillemot	Cepphus columba	1	1	Breeding	111	11B	BBB	111
Seabirds	GrebesLoons	Western Grebe	Aechmophorus occidentalis	1	1	Migrant	111	___	___	__1
Seabirds	LaridsJaegersSkuas	Glaucous Gull	Larus hyperboreus	1	1	Migrant	111	___	___	_11
Seabirds	Storm-Petrels	Ashy Storm-Petrel	Hydrobates homochroa	10	1	Breeding	B11	BBB	BBB	BBB
Seabirds	LaridsJaegersSkuas	Arctic Tern	Sterna paradisaea	1	1	Migrant	___	__1	111	111
Seabirds	LaridsJaegersSkuas	Least Tern	Sternula antillarum	23	1	Breeding	___	1BB	BBB	B11
Seabirds	LaridsJaegersSkuas	Sabine's Gull	Xema sabini	1	1	Migrant	___	_11	111	111
Seabirds	Cormorants	Brandt's Cormorant	Phalacrocorax penicillatus	1	1	Breeding	111	BBB	BB1	111
Seabirds	LaridsJaegersSkuas	Caspian Tern	Hydroprogne caspia	1	1	Breeding	___	1BB	BBB	1__
Seabirds	LaridsJaegersSkuas	California Gull	Larus californicus	1	1	Breeding	111	11B	BBB	111
Seabirds	Phalaropes	Red Phalarope	Phalaropus fulicarius	1	1	Migrant	111	___	___	111
Seabirds	LaridsJaegersSkuas	Elegant Tern	Thalasseus elegans	8	1	Breeding	111	BBB	BB1	111
Seabirds	Petrels(Procellariidae)	Murphy's Petrel	Pterodroma ultima	1	1	Migrant	___	_11	1__	___
Seabirds	FulmarsShearwaters	Buller's Shearwater	Ardenna bulleri	9	1	Migrant	_00	0__	111	111

SuperGroup	Group	Species	ScientificName	Endangerment	Representativity	Breed/Migr.	Winter	Spring	Summer	Fall
Seabirds	Alcids	Cassin's Auklet	Ptychoramphus aleuticus	9	1	Breeding	1BB	BBB	BBB	111
Seabirds	LaridsJaegersSkuas	Common Tern	Sterna hirundo	1	1	Migrant	11_	___	00_	_11
Seabirds	Petrels(Procellariidae)	Stejneger's Petrel	Pterodroma longirostris	9	1	Migrant	___	___	_11	111
Seabirds	Cormorants	Double-crested Cormorant	Phalacrocorax auritus	1	1	Breeding	111	1BB	BBB	111
Seabirds	Alcids	Scripps's Murrelet	Synthliboramphus scrippsi	22	1	Breeding	11B	BBB	BBB	111
Seabirds	Petrels(Procellariidae)	Juan Fernandez Petrel	Pterodroma externa	9	1	Migrant	___	___	___	___
Seabirds	FulmarsShearwaters	Pink-footed Shearwater	Ardenna creatopus	9	1	Migrant	100	__1	111	111
Seabirds	LaridsJaegersSkuas	Short-billed Gull	Larus brachyrhynchus	1	1	Migrant	___	___	___	___
Seabirds	Storm-Petrels	Fork-tailed Storm-Petrel	Hydrobates furcatus	9	1	Breeding	111	BBB	BBB	111
Seabirds	Albatross	Laysan Albatross	Phoebastria immutabilis	8	1	Migrant	111	111	___	_11
Seabirds	FulmarsShearwaters	Flesh-footed Shearwater	Ardenna carneipes	8	1	Migrant	___	_11	111	111
Seabirds	Alcids	Tufted Puffin	Fratercula cirrhata	9	1	Breeding	111	1BB	BBB	B11
Seabirds	Phalaropes	Red-necked Phalarope	Phalaropus lobatus	1	1	Migrant	___	_11	111	11_
Seabirds	LaridsJaegersSkuas	Pomarine Jaeger	Stercorarius pomarinus	1	1	Migrant	111	111	111	111
Seabirds	Alcids	Craveri's Murrelet	Synthliboramphus craveri	9	1	Migrant	__0	00_	_11	1__
Seabirds	LaridsJaegersSkuas	Herring Gull	Larus argentatus	1	1	Migrant	111	___	___	__1
Seabirds	LaridsJaegersSkuas	Heerman's Gull	Larus heermanni	1	1	Migrant	1_0	0_1	111	111
Seabirds	GrebesLoons	Pacific Loon	Gavia pacifica	1	1	Migrant	111	111	__1	111

SuperGroup	Group	Species	ScientificName	Endangerment	Representativity	Breed/Migr.	Winter	Spring	Summer	Fall
Seabirds	LaridsJaegersSkuas	Glaucous-winged Gull	Larus glaucescens	1	1	Migrant	111	___	___	__1
Seabirds	Storm-Petrels	Leach's Storm-Petrel	Hydrobates leucorhous	9	1	Breeding	___	BBB	BBB	B11
Seabirds	LaridsJaegersSkuas	South Polar Skua	Stercorarius maccormicki	1	1	Migrant	_00	001	111	11_
Seabirds	LaridsJaegersSkuas	Iceland Gull	Larus glaucoides	1	1	Migrant	111	___	000	__1
Seabirds	LaridsJaegersSkuas	Bonaparte's Gull	Chroicocephalus philadelphia	1	1	Migrant	111	111	___	_11
Seabirds	Alcids	Common Murre	Uria aalge	1	1	Breeding	111	11B	BBB	111
Seabirds	Albatross	Black-footed Albatross	Phoebastria nigripes	8	1	Migrant	111	111	111	111
Seabirds	LaridsJaegersSkuas	Western Gull	Larus occidentalis	1	1	Breeding	111	1BB	BBB	111
Marine Mammals & Turtles	SmallCetaceans	Dall's Porpoise	Phocoenoides dalli	3	1	Breeding	___	___	___	___
Marine Mammals & Turtles	KillerWhales	Killer whale	Orcinus orca	8	1	Migrant	___	___	___	___
Marine Mammals & Turtles	SmallCetaceans	Northern Right Whale Dolphin	Lissodelphis borealis	3	1	Breeding	___	111	BBB	111
Marine Mammals & Turtles	SeaTurtles	Green turtle	Chelonia mydas	10	1	Migrant	___	___	___	___
Marine Mammals & Turtles	BaleenWhales	Humpback Whale	Megaptera novaeangliae	9	1	Migrant	___	___	___	___
Marine Mammals & Turtles	BeakedWhales	Baird's Beaked Whale	Berardius bairdii	3	1	Unknown	___	___	___	___
Marine Mammals & Turtles	BeakedWhales	Stejneger's Beaked Whale	Mesoplodon stejnegeri	4	1	Unknown	___	___	___	___
Marine Mammals & Turtles	BaleenWhales	Blue Whale	Balaenoptera musculus	12	1	Migrant	___	___	___	___
Marine Mammals & Turtles	SpermWhales	Sperm Whale	Physeter macrocephalus	11	1	Unknown	___	__1	111	1__
Marine Mammals & Turtles	BaleenWhales	Minke Whale	Balaenoptera acutorostrata	3	1	Migrant	___	___	___	___
Marine Mammals & Turtles	SeaTurtles	Olive Ridley turtle	Lepidochelys olivacea	11	1	Migrant	___	___	___	___

SuperGroup	Group	Species	ScientificName	Endangerment	Representativity	Breed/Migr.	Winter	Spring	Summer	Fall
Marine Mammals & Turtles	SmallCetaceans	Harbor Porpoise	Phocoena phocoena	3	1	Breeding	___	___	___	___
Marine Mammals & Turtles	SmallCetaceans	Striped Dolphin	Stenella coeruleoalba	3	1	Unknown	___	___	___	___
Marine Mammals & Turtles	Pinnipeds	Guadalupe Fur Seal	Arctocephalus townsendi	19	1	Breeding	___	___	___	___
Marine Mammals & Turtles	BeakedWhales	Cuvier's Beaked Whale	Ziphius cavirostris	3	1	Unknown	___	___	___	___
Marine Mammals & Turtles	BeakedWhales	Perrin's Beaked Whale	Mesoplodon perrini	6	1	Unknown	___	___	___	___
Marine Mammals & Turtles	SmallCetaceans	Risso's Dolphin	Grampus griseus	3	1	Breeding	BBB	___	___	BBB
Marine Mammals & Turtles	BaleenWhales	North Pacific Right Whale	Eubalaena japonica	12	1	Migrant	___	___	___	___
Marine Mammals & Turtles	SmallCetaceans	Short-finned Pilot Whale	Globicephala macrorhynchus	3	1	Unknown	___	___	___	___
Marine Mammals & Turtles	SmallCetaceans	Bottlenose Dolphin	Tursiops truncatus	3	1	Breeding	___	___	___	___
Marine Mammals & Turtles	Pinnipeds	Steller Sea Lion	Eumetopias jubatus	16	1	Breeding	___	___	___	___
Marine Mammals & Turtles	Pinnipeds	Northern Elephant Seal	Mirounga angustirostris	3	1	Breeding	___	___	___	___
Marine Mammals & Turtles	BaleenWhales	Sei Whale	Balaenoptera borealis	12	1	Migrant	___	___	___	___
Marine Mammals & Turtles	BaleenWhales	Gray Whale	Eschrichtius robustus	3	1	Migrant	___	___	___	___
Marine Mammals & Turtles	SmallCetaceans	Short-Beaked Common Dolphin	Delphinus delphis	3	1	Breeding	BB1	111	111	11B
Marine Mammals & Turtles	Pinnipeds	Harbor Seal	Phoca vitulina	3	1	Breeding	111	1BB	BB1	111
Marine Mammals & Turtles	SeaTurtles	Leatherback Sea Turtle	Dermochelys coriacea	31	1	Migrant	___	___	___	___
Marine Mammals & Turtles	SeaOtters	Sea Otter	Enhydra lutris	22	1	Breeding	___	___	___	___
Marine Mammals & Turtles	SmallCetaceans	Long-beaked Common Dolphin	Delphinus capensis	3	1	Breeding	___	BBB	___	___

SuperGroup	Group	Species	ScientificName	Endangerment	Representativity	Breed/Migr.	Winter	Spring	Summer	Fall
Marine Mammals & Turtles	SmallCetaceans	Pacific White-sided Dolphin	Lagenorhynchus obliquidens	3	1	Breeding	111	11B	BBB	BBB
Marine Mammals & Turtles	Pinnipeds	Northern Fur Seal	Callorhinus ursinus	5	1	Breeding	___	___	___	___
Marine Mammals & Turtles	Pinnipeds	California Sea Lion	Zalophus californianus	3	1	Breeding	___	___	___	___
Marine Mammals & Turtles	BaleenWhales	Fin Whale	Balaenoptera physalus	11	1	Migrant	___	___	___	___
Marine Mammals & Turtles	SeaTurtles	Loggerhead turtle	Caretta caretta	15	1	Migrant	___	___	___	___
Fish	TunaMackerel	Skipjack Tuna	Katsuwonus pelamis	6.1	1		___	___	___	___
Fish	Rockfish	Quillback Rockfish	Sebastes maliger	10.29	1		___	___	___	___
Fish	OtherFish	Surf Smelt	Hypomesus pretiosus	4.92	1		___	___	___	___
Fish	Rockfish	Grass Rockfish	Sebastes rastrelliger	8.51	1		___	___	___	___
Fish	Rockfish	Speckled Rockfish	Sebastes ovalis	11.16	1		___	___	___	___
Fish	Rockfish	Chilipepper Rockfish	Sebastes goodei	8.3	1		___	___	___	___
Fish	Flatfish	Rock Sole	Lepidopsetta bilineata	10.52	1		___	___	___	___
Fish	Rockfish	Rosy Rockfish	Sebastes rosaceus	9.26	1		___	___	___	___
Fish	Rockfish	Deacon Rockfish	Sebastes diaconus	9.33	1		___	___	___	___
Fish	TunaMackerel	Jackmackerel	Trachurus symmetricus	6.13	1		___	___	___	___
Fish	Chondrichthyes	Sevengill Shark	Notorynchus cepedianus	13.04	1		___	___	___	___
Fish	Chondrichthyes	Longnose Skate	Beringraja rhina	12.54	1		___	___	___	___
Fish	Salmonids	Steelhead	Oncorhynchus mykiss	16.47	1		___	___	___	___
Fish	Rockfish	Brown Rockfish	Sebastes auriculatus	9.28	1		___	___	___	___

SuperGroup	Group	Species	ScientificName	Endangerment	Representativity	Breed/Migr.	Winter	Spring	Summer	Fall
Fish	Rockfish	Redstripe Rockfish	Sebastes proriger	9.23	1		___	___	___	___
Fish	LingcodGreenling	Lingcod	Ophiodon elongatus	10.16	1		___	___	___	___
Fish	Chondrichthyes	Spiny Dogfish	Squalus acanthias	14.87	1		___	___	___	___
Fish	Salmonids	Coho Salmon	Oncorhynchus kisutch	19.16	1		___	___	___	___
Fish	Chondrichthyes	Salmon Shark	Lamna ditropis	10.81	1		___	___	___	___
Fish	Rockfish	Black and Yellow Rockfish	Sebastes chrysomelas	7.58	1		___	___	___	___
Fish	OtherFish	Pacific Hake	Merluccius productus	10.92	1		___	___	___	___
Fish	Chondrichthyes	White Shark	Carcharodon carcharias	17.72	1		___	___	___	___
Fish	Flatfish	Dover Sole	Microstomus pacificus	12.74	1		___	___	___	___
Fish	OtherFish	Dolphin	Coryphaena hippurus	7.61	1		___	___	___	___
Fish	Chondrichthyes	Pacific Sleeper Shark	Somniosus pacificus	16.86	1		___	___	___	___
Fish	LingcodGreenling	Kelp Greenling	Hexagrammos decagrammus	9.08	1		___	___	___	___
Fish	Rockfish	Widow Rockfish	Sebastes entomelas	10.32	1		___	___	___	___
Fish	LingcodGreenling	Whitespotted Greenling	Hexagrammos stelleri	6.21	1		___	___	___	___
Fish	Salmonids	Chinook Salmon	Oncorhynchus tshawytscha	21.43	1		___	___	___	___
Fish	Chondrichthyes	Sixgill Shark	Hexanchus griseus	16.11	1		___	___	___	___
Fish	Billfish	Swordfish	Xiphias gladius	12.85	1		___	___	___	___
Fish	Flatfish	English Sole	Parophrys vetulus	8.29	1		___	___	___	___
Fish	OtherFish	Ocean Sunfish	Mola mola	14.66	1		___	___	___	___

SuperGroup	Group	Species	ScientificName	Endangerment	Representativity	Breed/Migr.	Winter	Spring	Summer	Fall
Fish	Rockfish	Tiger Rockfish	Sebastes nigrocinctus	11.28	1		___	___	___	___
Fish	Rockfish	China Rockfish	Sebastes nebulosus	8.99	1		___	___	___	___
Fish	Chondrichthyes	Leopard Shark	Triakis semifasciata	14.1	1		___	___	___	___
Fish	Salmonids	Sockeye Salmon	Oncorhynchus nerka	15.76	1		___	___	___	___
Fish	Chondrichthyes	California Skate	Beringraja inornata	8.3	1		___	___	___	___
Fish	Salmonids	Pink Salmon	Oncorhynchus gorbuscha	5.92	1		___	___	___	___
Fish	Flatfish	Sand Sole	Psettichthys melanostictus	7.32	1		___	___	___	___
Fish	Rockfish	Gopher Rockfish	Sebastes carnatus	7.58	1		___	___	___	___
Fish	ForageFish	Pacific Sardine	Sardinops sagax	6.84	1		___	___	___	___
Fish	Billfish	Striped Marlin	Kajikia audax	6.94	1		___	___	___	___
Fish	OtherFish	Spotted Ratfish	Hydrolagus colliei	9.28	1		___	___	___	___
Fish	OtherFish	Green Sturgeon	Acipenser medirostris	23.46	1		___	___	___	___
Fish	ForageFish	Eulachon	Thaleichthys pacificus	13.23	1		___	___	___	___
Fish	OtherFish	Finescale Triggerfish	Balistes polylepis	9.96	1		___	___	___	___
Fish	OtherFish	Pacific Pomfret	Brama japonica	8.22	1		___	___	___	___
Fish	OtherFish	White Sturgeon	Acipenser transmontanus	15.31	1		___	___	___	___
Fish	Chondrichthyes	Common Thresher Shark	Alopias vulpinus	15.66	1		___	___	___	___
Fish	Rockfish	Vermilion Rockfish	Sebastes miniatus	10.1	1		___	___	___	___
Fish	OtherFish	Sablefish	Anoplopoma fimbria	8.92	1		___	___	___	___

SuperGroup	Group	Species	ScientificName	Endangerment	Representativity	Breed/Migr.	Winter	Spring	Summer	Fall
Fish	Flatfish	Pacific Sanddab	Citharichthys sordidus	6.92	1		___	___	___	___
Fish	Flatfish	Starry Flounder	Platichthys stellatus	9.42	1		___	___	___	___
Fish	OtherFish	Yellowtail	Seriola lalandi	12.34	1		___	___	___	___
Fish	Rockfish	Yellowmouth Rockfish	Sebastes reedi	10.08	1		___	___	___	___
Fish	Rockfish	Copper Rockfish	Sebastes caurinus	9.29	1		___	___	___	___
Fish	TunaMackerel	Bluefin Tuna	Thunnus orientalis	14.51	1		___	___	___	___
Fish	OtherFish	Pacific Tomcod	Microgadus proximus	5.04	1		___	___	___	___
Fish	Rockfish	Canary Rockfish	Sebastes pinniger	9.94	1		___	___	___	___
Fish	Rockfish	Blue Rockfish	Sebastes mystinus	9.04	1		___	___	___	___
Fish	Chondrichthyes	Blue Shark	Prionace glauca	14.91	1		___	___	___	___
Fish	Flatfish	Rex Sole	Glyptocephalus zachirus	11.65	1		___	___	___	___
Fish	OtherFish	Striped Bass	Morone saxatilis	11.04	1		___	___	___	___
Fish	Flatfish	California Halibut	Paralichthys californicus	11.63	1		___	___	___	___
Fish	Rockfish	Silvergray Rockfish	Sebastes brevispinis	10.86	1		___	___	___	___
Fish	TunaMackerel	Bigeye Tuna	Thunnus obesus	12.88	1		___	___	___	___
Fish	Rockfish	Greenstriped Rockfish	Sebastes elongatus	10.15	1		___	___	___	___
Fish	Flatfish	Petrale Sole	Eopsetta jordani	10.16	1		___	___	___	___
Fish	TunaMackerel	Pacific Bonito	Sarda chiliensis	7.03	1		___	___	___	___
Fish	Salmonids	Chum Salmon	Oncorhynchus keta	15.81	1		___	___	___	___
Fish	ForageFish	Night Smelt	Spirinchus starksi	2.49	1		___	___	___	___

SuperGroup	Group	Species	ScientificName	Endangerment	Representativity	Breed/Migr.	Winter	Spring	Summer	Fall
Fish	Salmonids	Cutthroat Trout	Oncorhynchus clarkii	7.67	1		___	___	___	___
Fish	OtherFish	Monkeyface Prickleback	Cebidichthys violaceus	10.19	1		___	___	___	___
Fish	OtherFish	Pacific Cod	Gadus macrocephalus	8.03	1		___	___	___	___
Fish	LingcodGreenling	Rock Greenling	Hexagrammos lagocephalus	10	1		___	___	___	___
Fish	OtherFish	Rock Prickleback	Xiphister mucosus	9.18	1		___	___	___	___
Fish	Flatfish	Pacific Halibut	Hippoglossus stenolepis	15.1	1		___	___	___	___
Fish	Rockfish	Black Rockfish	Sebastes melanops	10.56	1		___	___	___	___
Fish	Rockfish	Rosethorn Rockfish	Sebastes helvomaculatus	10.57	1		___	___	___	___
Fish	ForageFish	Topsmelt	Atherinops affinis	6.47	1		___	___	___	___
Fish	Chondrichthyes	Shortfin Mako Shark	Isurus oxyrinchus	18.57	1		___	___	___	___
Fish	Rockfish	Redbanded Rockfish	Sebastes babcocki	8.68	1		___	___	___	___
Fish	ForageFish	Jacksmelt	Atherinopsis californiensus	0	1		___	___	___	___
Fish	OtherFish	Cabezon	Scorpaenichthys marmoratus	5.98	1		___	___	___	___
Fish	Rockfish	Olive Rockfish	Sebastes serranoides	7.39	1		___	___	___	___
Fish	ForageFish	Longfin Smelt	Spirinchus thaleichthys	5.79	1		___	___	___	___
Fish	Flatfish	Curlfin Sole/Turbot	Pleuronichthys decurrens	8.23	1		___	___	___	___
Fish	OtherFish	Walleye Pollock	Theragra chalcoramma	0	1		___	___	___	___
Fish	ForageFish	Pacific Herring	Clupea pallasii	4.49	1		___	___	___	___
Fish	OtherFish	Opah	Lampris guttatus	10.94	1		___	___	___	___

SuperGroup	Group	Species	ScientificName	Endangerment	Representativity	Breed/Migr.	Winter	Spring	Summer	Fall
Fish	OtherFish	Kelp Bass	Paralabrax clathratus	12	1		___	___	___	___
Fish	Rockfish	Yellowtail Rockfish	Sebastes flavidus	8.99	1		___	___	___	___
Fish	Chondrichthyes	Big Skate	Beringraja binoculata	13.76	1		___	___	___	___
Fish	Rockfish	Yelloweye Rockfish	Sebastes ruberrimus	19.75	1		___	___	___	___
Fish	Rockfish	Cowcod	Sebastes levis	11.13	1		___	___	___	___
Fish	ForageFish	Pacific Saury	Cololabis saira	5.18	1		___	___	___	___
Fish	ForageFish	Whitebait Smelt	Allosmerus elongatus	5.1	1		___	___	___	___
Fish	TunaMackerel	Albacore	Thunnus alalunga	10.68	1		___	___	___	___
Fish	Flatfish	Arrowtooth Flounder	Atheresthes stomias	11.51	1		___	___	___	___
Fish	Rockfish	Bocaccio	Sebastes paucispinis	10.05	1		___	___	___	___
Fish	TunaMackerel	Pacific Mackerel	Scomber japonicus	6.85	1		___	___	___	___
Fish	TunaMackerel	Yellowfin Tuna	Thunnus albacares	9.44	1		___	___	___	___
Fish	Rockfish	Pacific Ocean Perch	Sebastes alutus	8.88	1		___	___	___	___
Fish	Chondrichthyes	Soupfin Shark	Galeorhinus galeus	11.84	1		___	___	___	___
Fish	ForageFish	Northern Anchovy	Engraulis mordax	4.73	1		___	___	___	___
Fish	Flatfish	Butter Sole	Isopsetta isolepis	6.91	1		___	___	___	___
Fish	Rockfish	Greenspotted Rockfish	Sebastes chlorostictus	9.82	1		___	___	___	___
Fish	OtherFish	Wolf Eel	Anarrhichthys ocellatus	14.9	1		___	___	___	___
Benthic	Benthic	Marine canyon		5	1		111	111	111	111
Benthic	Benthic	Deep sea coral		18	1		111	111	111	111
Benthic	Benthic	Methane seep		28	1		111	111	111	111
Benthic	Benthic	Hydrothermal vent		22	1		111	111	111	111

SuperGroup	Group	Species	ScientificName	Endangerment	Representativity	Breed/Migr.	Winter	Spring	Summer	Fall
Benthic	Benthic	Sea mount		8	1		111	111	111	111
Human Uses	TrawlRockfish	MidwaterTrawlRockfish			1		_00	0_1	___	___
Human Uses	HookAndLine	HookandLine_CS			1		1__	___	_11	111
Human Uses	TrawlLargeVessel	MidwaterTrawlMothership			1		___	__1	111	11_
Human Uses	MarineNonGroundfish	MarineFisheries			1		111	111	111	111
Human Uses	Trap	Pot_NCS			1		__0	00_	___	11_
Human Uses	TrawlHake	MidwaterTrawlHake			1		_00	001	111	___
Human Uses	Shipping	Shipping			1		111	111	111	111
Human Uses	HookAndLine	HookandLine_NCS			1		1__	___	_11	111
Human Uses	TrawlBottom	BottomTrawl_CS			1		111	111	111	111
Human Uses	TrawlLargeVessel	MidwaterTrawlCatcherProcessor			1		___	__1	111	11_
Human Uses	Trap	Pot_CS			1		__0	00_	___	11_

Table A4 – Encounter weights by threat and group. Weights are multipliers reflecting probability of encounter with the threat given spatial overlap and flux of the wildlife Group (flying or swimming compared to sessile organisms). Zero indicates threat not applicable. Weights were based on simple simulations of flying and swimming animals, drawing on assumptions of turning behavior and multiple encounters during the relevant period. Weights for vessel disturbance, vessel collision, and pollution disturbance reflect conditional probability of encountering the threat.

Group	Infrastr. Collision	Entanglement	Noise Disturb.	Sea Floor Disturb.	Electromag. Disturb.	Habitat Displac.	Vessel Disturb.	Vessel Collision	Prey Alteration	Pollution Disturb.
Albatross	10	0	0	0	0	1	0	0	1	0.1
Alcids	10	0	0	0	0	1	0	0	1	0.1
Cormorants	10	0	0	0	0	1	0	0	1	0.1
FulmarsShearwaters	10	0	0	0	0	1	0	0	1	0.1
GrebesLoons	10	0	0	0	0	1	0	0	1	0.1
LaridsJaegersSkuas	10	0	0	0	0	1	0	0	1	0.1
Pelicans	10	0	0	0	0	1	0	0	1	0.1
Petrels (Procellariidae)	10	0	0	0	0	1	0	0	1	0.1
Phalaropes	10	0	0	0	0	1	0	0	1	0.1
Storm-Petrels	10	0	0	0	0	1	0	0	1	0.1
Deep Sea Coral	0	0	0	1	0	1	0	0	1	0
Hydrothermal Vent	0	0	0	1	0	1	0	0	1	0
Marine Canyon	0	0	0	1	0	1	0	0	1	0
Methane Seep	0	0	0	1	0	1	0	0	1	0
Sea Mount	0	0	0	1	0	1	0	0	1	0
Chondrichthyes	0	0	1	0	1	1	0	0	1	0
Flatfish	0	0	1	1	0	1	0	0	1	0
Forage Fish	0	0	1	0	0	1	0	0	1	0
LingcodGreenling	0	0	1	0	0	1	0	0	1	0
Rockfish	0	0	1	0	0	1	0	0	1	0
Salmonids	0	0	1	0	0	1	0	0	1	0
TunaMackerel	0	0	1	0	0	1	0	0	1	0
Hook And Line	0	0	0	0	0	1	0	0	0	0
Marine Non Groundfish	0	0	0	0	0	1	0	0	0	0
Shipping	1	0	0	0	0	1	0	1	0	0
Trap	0	0	0	0	0	1	0	0	0	0
Trawl Bottom	0	0	0	0	0	1	0	0	0	0
Trawl Hake	0	0	0	0	0	1	0	0	0	0

Group	Infrastr. Collision	Entanglement	Noise Disturb.	Sea Floor Disturb.	Electromag. Disturb.	Habitat Displac.	Vessel Disturb.	Vessel Collision	Prey Alteration	Pollution Disturb.
Trawl Large Vessel	0	0	0	0	0	1	0	0	0	0
Trawl Rockfish	0	0	0	0	0	1	0	0	0	0
Baleen Whales	0	6	1	0	1	1	0.1	0.1	1	0.1
Beaked Whales	0	6	1	0	1	1	0.1	0.1	1	0.1
Killer Whales	0	6	1	0	1	1	0.1	0.1	1	0.1
Pinnipeds	0	0	1	0	1	1	0.1	0.1	1	0.1
Sea Otters	0	0	1	0	1	1	0.1	0.1	1	0.1
SeaTurtles	0	6	1	0	0	1	0.1	0.1	1	0.1
Small Cetaceans	0	6	1	0	1	1	0.1	0.1	1	0.1
Sperm Whales	0	6	1	0	1	1	0.1	0.1	1	0.1

Table A5 – Breeding behavior weights (i.e., multipliers). Note that a score of 1 has no effect.

Group	Breeding Behavior Weight
Albatross	2
Alcids	3
Cormorants	3
FulmarsShearwaters	2
GrebesLoons	3
LaridsJaegersSkuas	3
Pelicans	3
Petrels (Procellariidae)	2
Phalaropes	3
Storm-Petrels	2
Deep Sea Coral	1
Hydrothermal Vent	1
Marine Canyon	1
Methane Seep	1
Sea Mount	1
Chondrichthyes	1
Flatfish	1
Forage Fish	1
LingcodGreenling	1
Marine Non-Groundfish	1
Other Fish	1
Rockfish	1
Salmonids	2
TunaMackerel	1
Hook And Line	1
Shipping	1
Trap	1
Trawl Bottom	1
Trawl Hake	1
Trawl Large Vessel	1
Trawl Rockfish	1
Baleen Whales	1
Beaked Whales	1
Killer Whales	1
Pinnipeds	2
Sea Otters	2
Sea Turtles	1
Small Cetaceans	1
Sperm Whales	1

Table A6 – Construction vs. operation phase weights by group.

Group	Phase	Infrastruct. Collision	Entanglement	Noise Disturb.	Sea Floor Disturb.	Electromag. Disturb.	Habitat Displac.	Vessel Disturb.	Vessel Collision	Prey Alteration	Pollution Disturb.
Albatross	Construction	0	0	1	1	0	1	1	1	0	1
Alcids	Construction	0	0	1	1	0	1	1	1	0	1
Cormorants	Construction	0	0	1	1	0	1	1	1	0	1
FulmarsShearwaters	Construction	0	0	1	1	0	1	1	1	0	1
GrebesLoons	Construction	0	0	1	1	0	1	1	1	0	1
LaridsJaegersSkuas	Construction	0	0	1	1	0	1	1	1	0	1
Pelicans	Construction	0	0	1	1	0	1	1	1	0	1
Petrels(Procellariidae)	Construction	0	0	1	1	0	1	1	1	0	1
Phalaropes	Construction	0	0	1	1	0	1	1	1	0	1
Storm-Petrels	Construction	0	0	1	1	0	1	1	1	0	1
DeepSeaCoral	Construction	0	0	0	2	0	1	0	0	0	1
HydrothermalVent	Construction	0	0	0	2	0	1	1	0	0	1
MarineCanyon	Construction	0	0	0	2	0	0	0	0	0	1
MethaneSeep	Construction	0	0	0	2	0	0	0	0	0	1
SeaMount	Construction	0	0	1	1	0	1	0	0	0	1
Chondrichthyes	Construction	0	0	1	1	0	1	1	1	0	1
Flatfish	Construction	0	0	1	2	0	1	0	0	0	1
ForageFish	Construction	0	0	1	1	0	1	1	0	0	1
LingcodGreenling	Construction	0	0	1	2	0	1	1	1	0	1
MarineNonGroundfish	Construction	0	0	0	0	0	1	1	1	0	0
OtherFish	Construction	0	0	1	1	0	1	1	1	0	1
Rockfish	Construction	0	0	1	1	0	1	1	1	0	1
Salmonids	Construction	0	0	1	1	0	1	1	1	0	1
TunaMackerel	Construction	0	0	1	1	0	1	1	1	0	1
HookAndLine	Construction	0	0	0	0	0	1	1	1	0	0
Shipping	Construction	1	0	0	0	0	1	1	1	0	0
Trap	Construction	0	0	0	0	0	1	1	1	0	0
TrawlBottom	Construction	0	0	0	0	0	1	1	1	0	0
TrawlHake	Construction	0	0	0	0	0	1	1	1	0	0
TrawlLargeVessel	Construction	0	0	0	0	0	1	1	1	0	0
TrawlRockfish	Construction	0	0	0	0	0	1	1	1	0	0
BaleenWhales	Construction	0	0	2	1	0	1	1	1	0	1
BeakedWhales	Construction	0	0	2	1	0	1	1	1	0	1
KillerWhales	Construction	0	0	2	1	0	1	1	1	0	1

Group	Phase	Infrastruct. Collision	Entanglement	Noise Disturb.	Sea Floor Disturb.	Electromag. Disturb.	Habitat Displac.	Vessel Disturb.	Vessel Collision	Prey Alteration	Pollution Disturb.
Pinnipeds	Construction	0	0	2	1	0	1	1	1	0	1
SeaOtters	Construction	0	0	1	1	0	1	1	1	0	1
SeaTurtles	Construction	0	0	1	1	0	1	1	1	0	1
SmallCetaceans	Construction	0	0	2	1	0	1	1	1	0	1
SpermWhales	Construction	0	0	2	1	0	1	1	1	0	1
Albatross	Operation	1	1	1	0	1	2	1	1	1	1
Alcids	Operation	1	1	1	0	1	2	1	1	1	1
Cormorants	Operation	1	1	1	0	1	1	1	1	1	1
FulmarsShearwaters	Operation	1	1	1	0	1	1	1	1	1	1
GrebesLoons	Operation	1	1	1	0	1	1	1	1	1	1
LaridsJaegersSkuas	Operation	1	1	1	0	1	1	1	1	1	1
Pelicans	Operation	1	1	1	0	1	1	1	1	1	1
Petrels(Procellariidae)	Operation	1	1	1	0	1	1	1	1	1	1
Phalaropes	Operation	1	1	1	0	1	1	1	1	1	1
Storm-Petrels	Operation	1	1	1	0	1	1	1	1	1	1
DeepSeaCoral	Operation	0	0	0	1	1	1	0	0	1	1
HydrothermalVent	Operation	0	0	0	1	1	1	1	0	1	1
MarineCanyon	Operation	0	0	0	1	0	0	0	0	1	1
MethaneSeep	Operation	0	0	0	1	1	0	0	0	1	1
SeaMount	Operation	1	1	1	1	1	1	0	0	1	1
Chondrichthyes	Operation	1	1	1	0	1	1	1	1	1	1
Flatfish	Operation	1	1	1	0	1	1	0	0	1	1
ForageFish	Operation	1	1	1	0	1	1	1	0	1	1
LingcodGreenling	Operation	1	1	1	0	1	1	1	1	1	1
MarineNonGroundfish	Operation	1	0	0	0	0	1	1	1	0	0
OtherFish	Operation	1	1	1	0	1	1	1	1	1	1
Rockfish	Operation	1	1	1	0	1	1	1	1	1	1
Salmonids	Operation	1	1	1	0	1	1	1	1	1	1
TunaMackerel	Operation	1	1	1	0	1	1	1	1	1	1
HookAndLine	Operation	1	0	0	0	0	1	1	1	0	0
Shipping	Operation	2	0	0	0	0	2	1	1	0	0
Trap	Operation	1	0	0	0	0	1	1	1	0	0
TrawlBottom	Operation	1	0	0	0	0	1	1	1	0	0
TrawlHake	Operation	1	0	0	0	0	1	1	1	0	0
TrawlLargeVessel	Operation	1	0	0	0	0	1	1	1	0	0
TrawlRockfish	Operation	1	0	0	0	0	1	1	1	0	0

Group	Phase	Infrastruct. Collision	Entanglement	Noise Disturb.	Sea Floor Disturb.	Electromag. Disturb.	Habitat Displac.	Vessel Disturb.	Vessel Collision	Prey Alteration	Pollution Disturb.
BaleenWhales	Operation	1	1	1	0	1	1	1	1	1	1
BeakedWhales	Operation	1	1	1	0	1	1	1	1	1	1
KillerWhales	Operation	1	1	1	0	1	1	1	1	1	1
Pinnipeds	Operation	1	1	1	0	1	1	1	1	1	1
SeaOtters	Operation	1	1	1	0	1	1	1	1	1	1
SeaTurtles	Operation	1	1	1	0	1	1	1	1	1	1
SmallCetaceans	Operation	1	1	1	0	1	1	1	1	1	1
SpermWhales	Operation	1	1	1	0	1	1	1	1	1	1

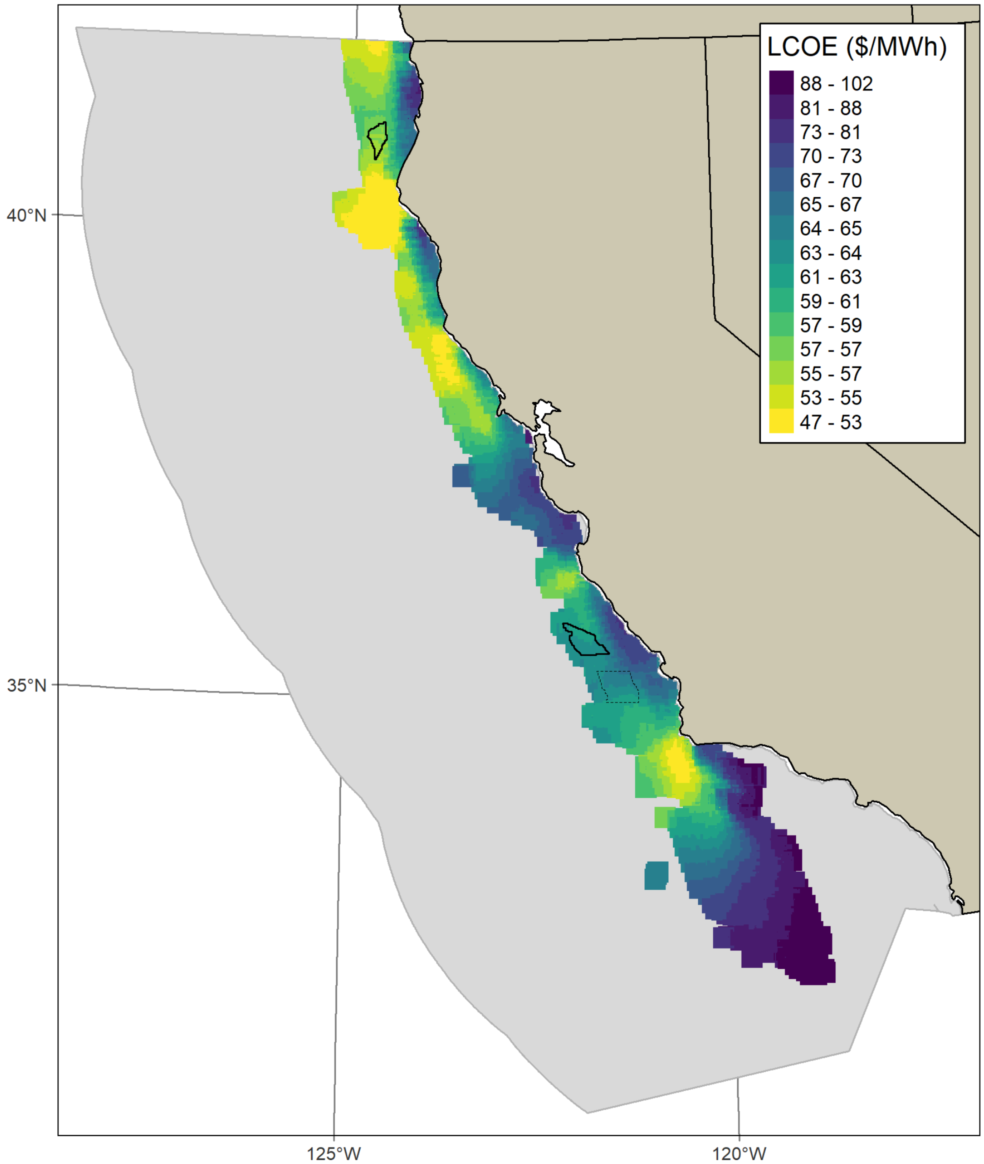

Figure A1. Map of the Levelized Cost of Energy (LCOE) metric produced from models in Beiter et al. 2020. Lower cost (yellow) represents more desirable locations for development while higher costs (blue) are less desirable.

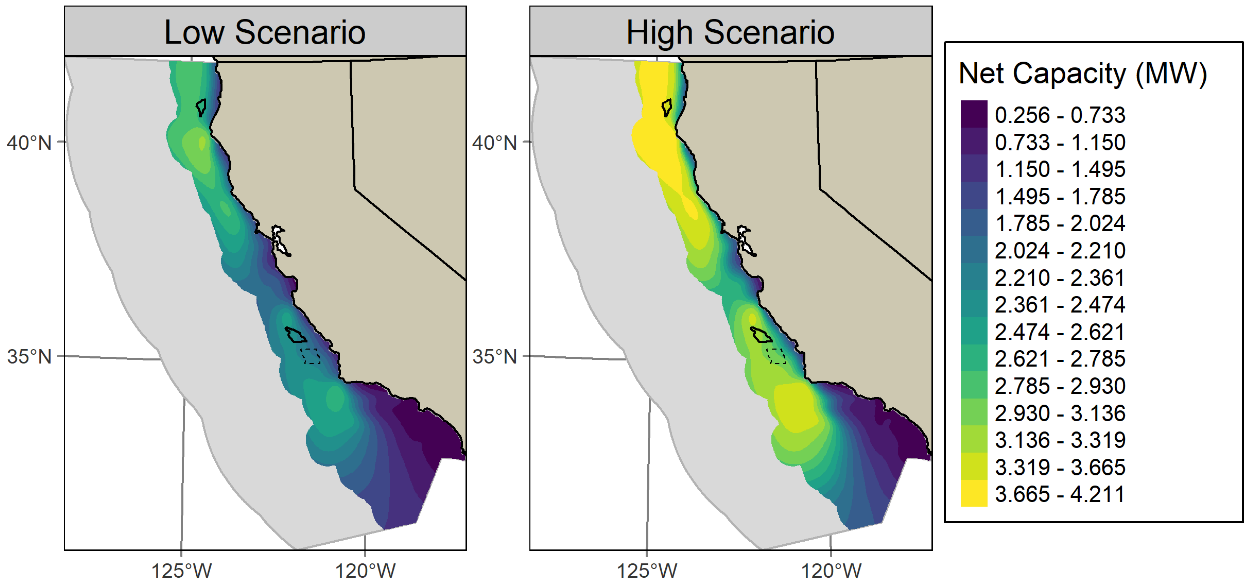

Figure A2. Low and high power density scenarios for estimated Net Capacity of installed energy along the California coast. Net Capacity represents the megawatts of power that would likely be produced from a given aliquot grid cell accounting for wind resource potential and operating losses. The low scenario uses a power density of 4 MW/km^2 while the high scenario uses 5.3 MW/km^2.

Appendix B – Expert survey data and structure

Table B1. Table derived from journal articles and reports of probable pressures that species groups are expected to experience as a result of offshore wind development. Sources include: Maxwell et al. 2022, Southall et al. 2019, Thompson et al. 2010, Cook 2017, Bailey et al. 2014 and many others. Group and pressures with "Y" that are filled red are those likely to occur and that were included in the expert surveys and modeling.

Group	Noise Disturbance	Vessel Disturbance	Vessel Collision	Prey Alteration	Pollution Disturbance	Sea Floor Disturbance	Infrastructure Collision	Entanglement	Electromagnetic Disturbance	Habitat displacement
Albatross		Y	Y	Y	Y		Y			Y
Alcids		Y	Y	Y	Y		Y			Y
Cormorants		Y		Y	Y		Y			Y
Fulmars and Shearwaters		Y		Y	Y		Y			Y
Grebes and Loons		Y		Y	Y		Y			Y
Larids, Jaegers, & Skuas		Y		Y	Y		Y			Y
Pelicans		Y		Y	Y		Y			Y
Petrels		Y	Y	Y	Y		Y			Y
Phalaropes		Y		Y	Y		Y			Y
Storm-Petrels		Y	Y	Y	Y		Y			Y
baleen whales	Y	Y	Y	Y	Y		Y	Y	Y	Y
beaked whales	Y	Y	Y	Y	Y			Y	Y	Y
killer whale	Y	Y	Y	Y	Y			Y	Y	Y

pinnipeds	Y	Y		Y	Y			Y	Y	Y
sea otters	Y	Y		Y	Y				Y	Y
sea turtles	Y	Y	Y	Y	Y			Y		Y
small cetaceans	Y	Y	Y	Y	Y			Y	Y	Y
sperm whale	Y	Y	Y	Y	Y			Y	Y	Y
Chondrichthyes	Y			Y					Y	Y
Flatfish	Y			Y		Y			Y	Y
Forage Fish	Y			Y						Y
Lingcod & Greenling	Y			Y						Y
Rockfish	Y			Y		Y				Y
Salmonid	Y			Y						Y
Tuna & Mackerel	Y			Y						Y
Billfish	Y			Y						Y

Table B2. Sensitivity metrics and possible impact scores used to determine relative sensitivity of each species Group to the relevant pressures they may face from offshore wind development. Expert survey questions were derived from these metrics and options.

Sensitivity Measure	Category	Value	Description
Frequency	Never	0	
How often does an individual encounter this threat? Consider the characteristics of the threat and disregard geographic co-occurrence.	Rare	1	Less than twice per generation time.
	Regular	2	Two or more times per generation time. Often seasonal or cyclic; episodic.
	Chronic	3	Consistently present and lasting over years to decades
Direct/Indirect	No threat	0	
How many steps removed is the driver of the threat from the impact of the threat?	Removed	1	Acting on fecundity through multiple links such as trophic cascades
	Indirect	2	Affecting the health, behavior, or fecundity of the individual, but without immediate mortality
	Mortality	3	Direct mortality
Lethality (likelihood of mortality)	None	0	
How likely is the individual to experience mortality from an encounter with the threat?	Low	1	Unlikely (1-33% of individuals encountering the threat die)
	Moderate	2	Moderate likelihood of death (34-66% die)
	High	3	High likelihood of death (67-100% die)
Time to Recovery	None	0	
How long after exposure to the threat will symptoms and impacts cease, on average?	Short	1	Less than 1/2 the generation time
	Intermediate	2	Between 1/2 and 1 generation
	Long	3	Greater than 1 generation
Effect on fecundity	None	0	
What is the impact on the potential reproductive output of the individual?	Low	1	Impacts multi-generational fecundity by decreasing the quality of offspring
	Moderate	2	Decreases reproductive rate
	High	3	Direct mortality eliminates future reproduction
Proportion of population affected	None	0	
What proportion of the population experiences the threat?	Low	1	Affects 1-10% of population
	Moderate	2	Affects 11-50% of population
	High	3	Affects >50% of population

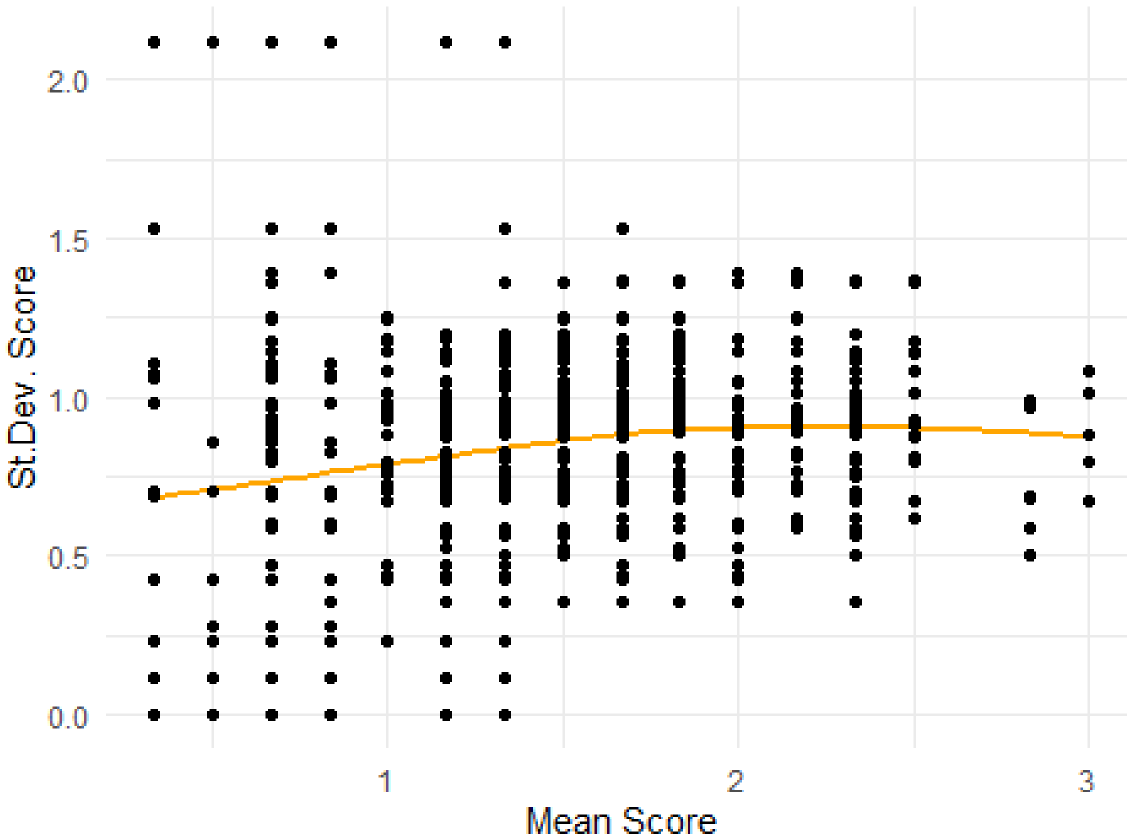

Figure B1. Relationship between average expert score for each threat and group, and its standard deviation. The average is calculated across all expert votes for the threat and group, and across all components of threat (see Equation1 for details). Note that there is no relationship between the mean and standard deviation of scores, and that higher scores had lower dispersion and overall standard deviation values, suggesting that experts were more confident of their scoring when the threat was more impactful, and less so when they expected it was not.

Appendix C – Supplementary figures and results

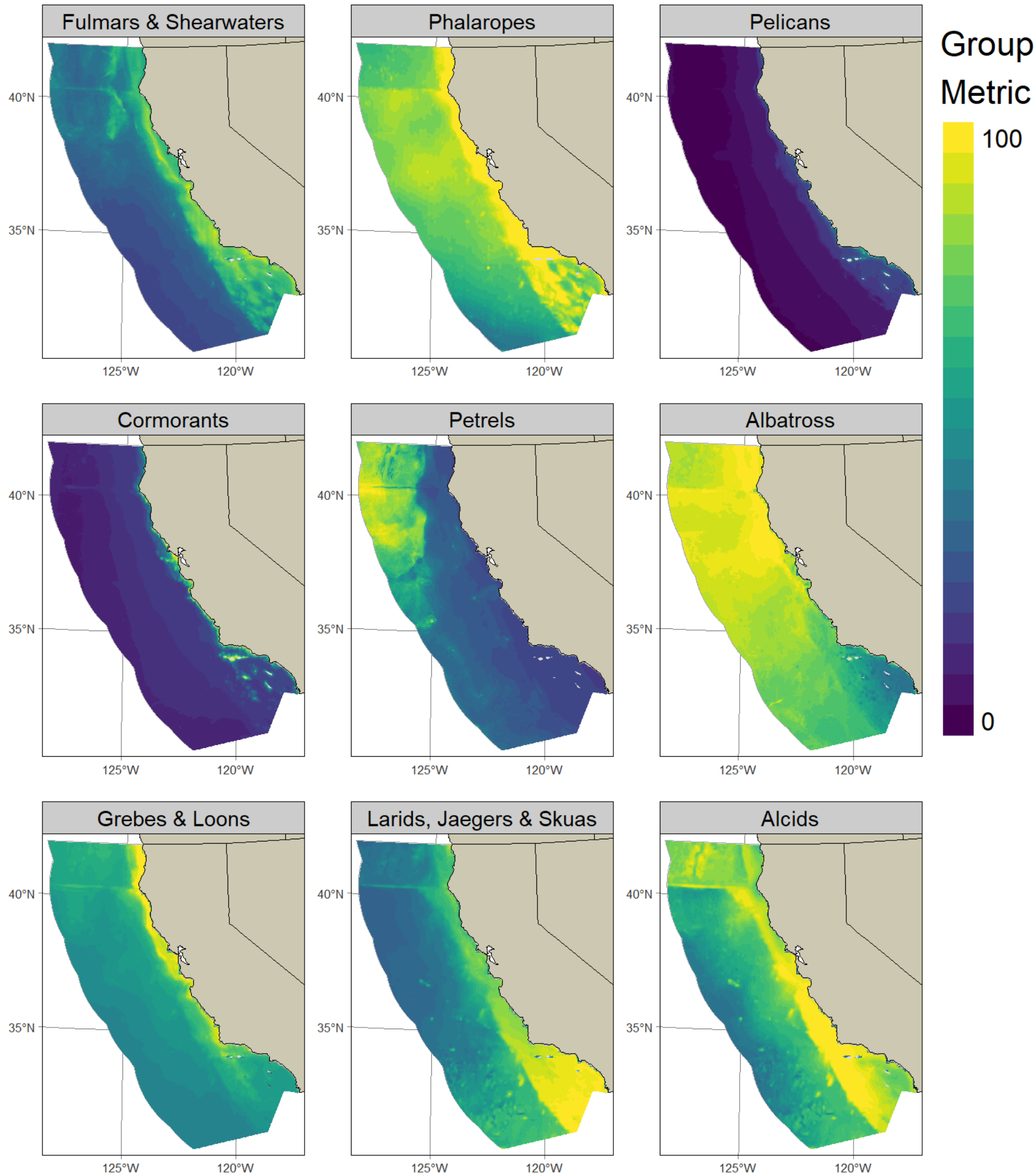

Figure C1. Group impact metrics for seabird Groups. The scale is maintained across panels to ensure visual comparison between Groups. Groups are: Fulmars and Shearwaters, Phalaropes, Pelicans, Cormorants, Petrels, Albatross, Grebes and Loons, Larids, Jaegers and Skuas, and Alcids. Higher impact/benefit metric is represented by yellow shades, while lower metric scores are represented by darker blue.

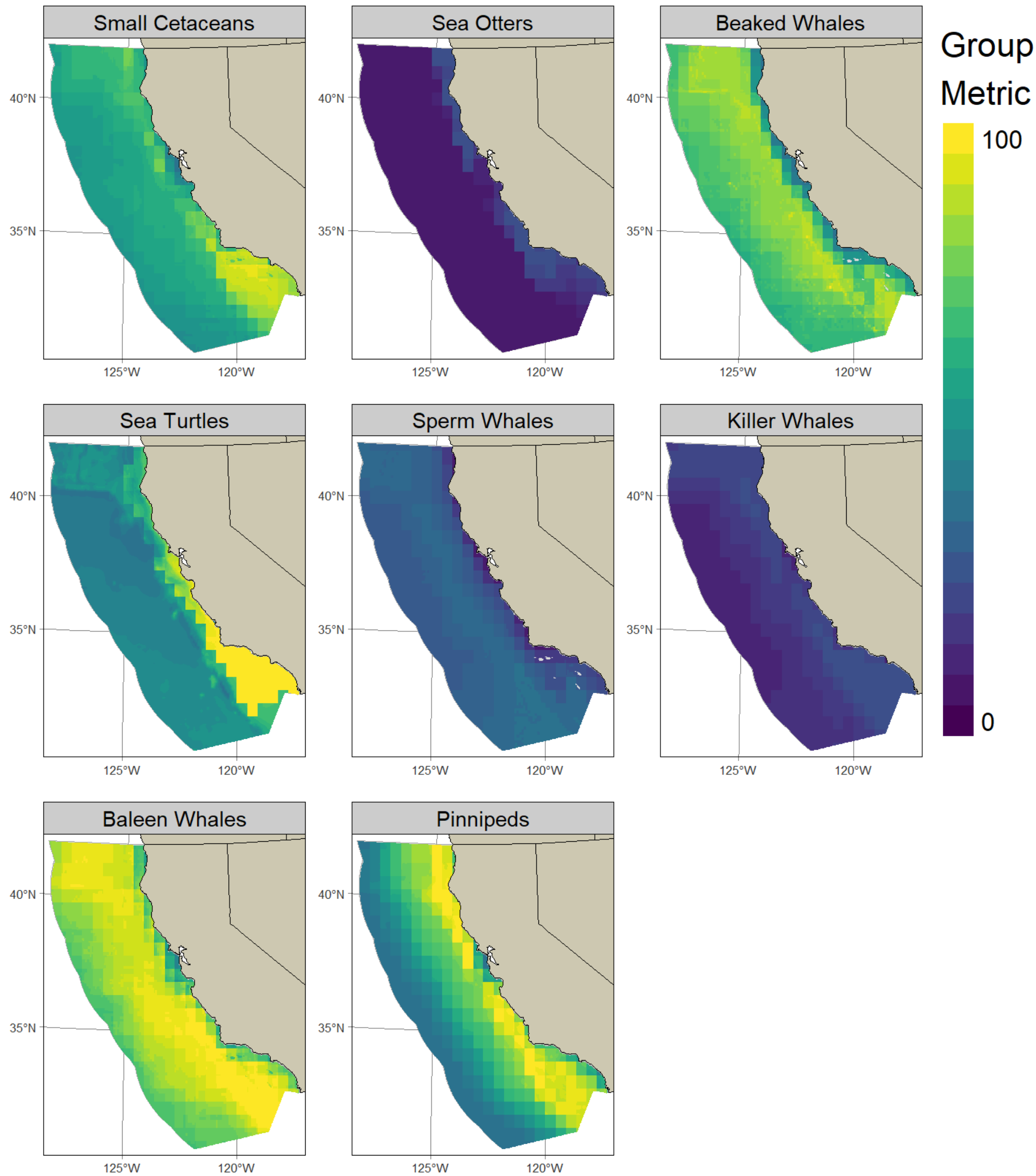

Figure C2. Group impact metrics for marine mammal and turtle Groups. The scale is maintained across panels to ensure visual comparison between Groups. Groups are: Baleen Whales, Beaked Whales, Killer Whales, Pinnipeds, Sea Otters, Sea Turtles, Small Cetaceans, and Sperm Whales. Higher impact/benefit metric is represented by yellow shades, while lower metric scores are represented by darker blue.

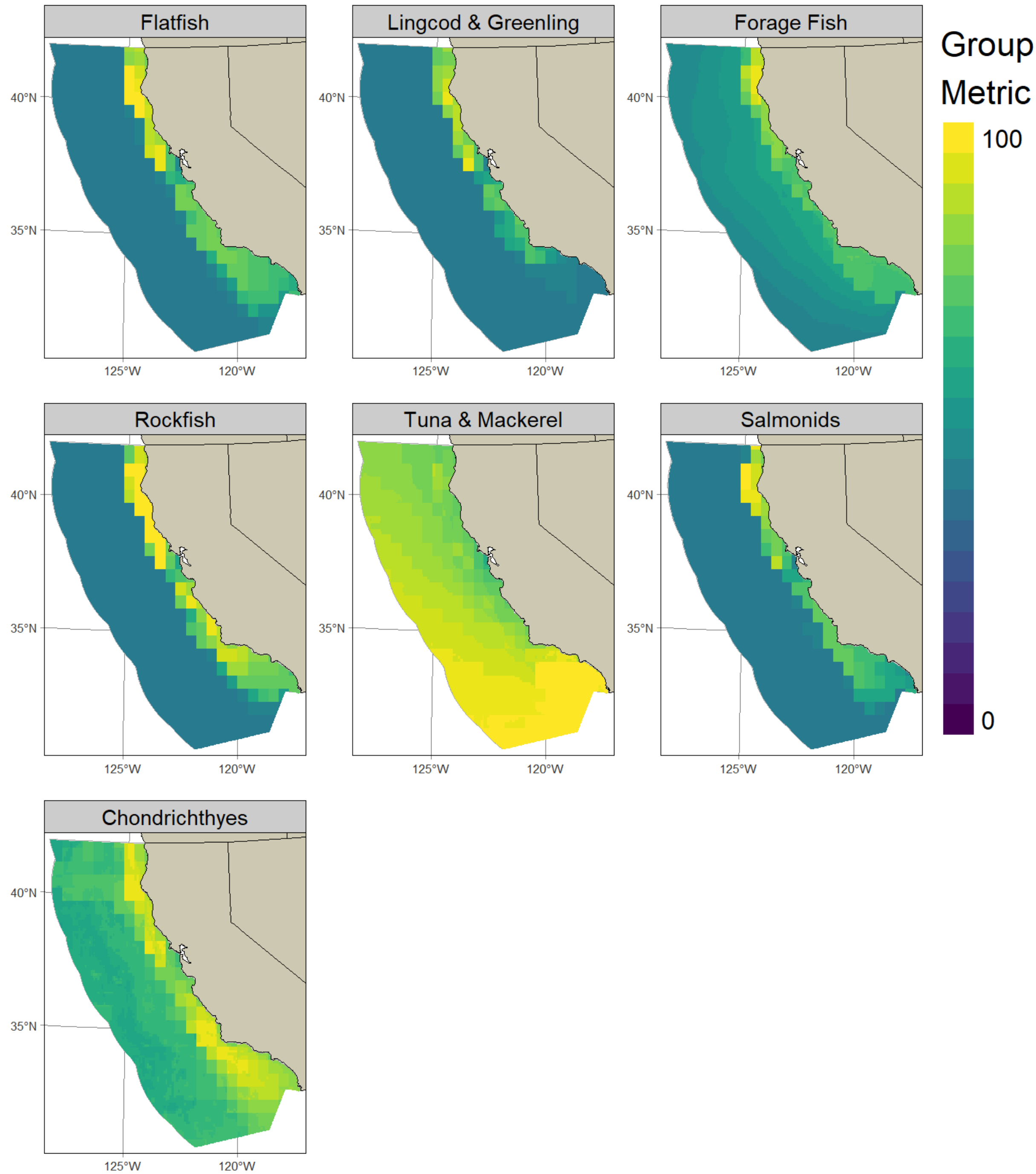

Figure C3. Group impact metrics for fish Groups. The scale is maintained across panels to ensure visual comparison between Groups. Groups are: Flatfish, Lingcod and Greenling, Forage Fish, Rockfish, Tuna and Mackerel, Salmonids, and Chondrichthyes. Higher impact/benefit metric is represented by yellow shades, while lower metric scores are represented by darker blue.

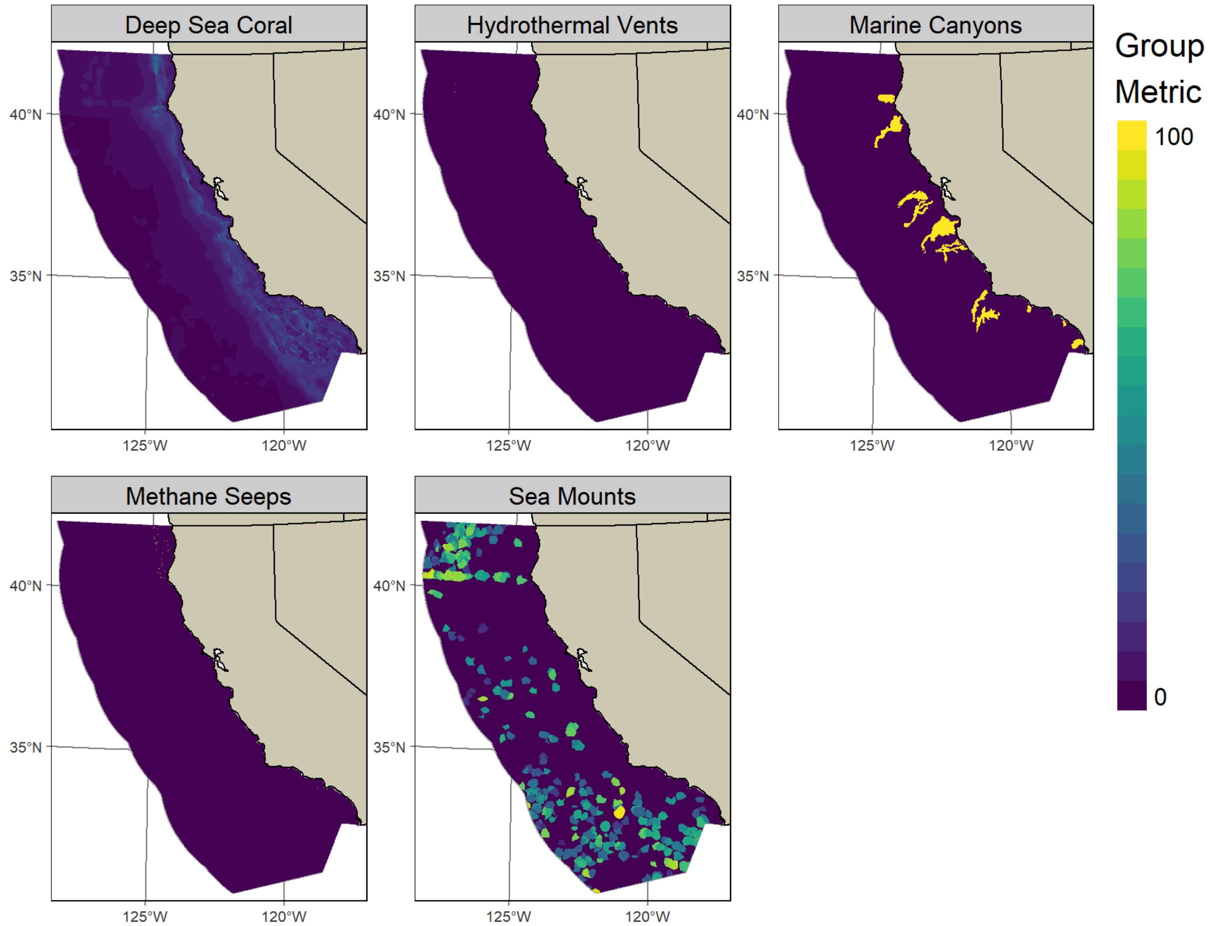

Figure C4. Group impact metrics for benthic habitat Groups. The scale is maintained across panels to ensure visual comparison between Groups. Groups are: Deep Sea Coral, Hydrothermal Vents, Marine Canyons, Methane Seeps, and Sea Mounts. Higher impact/benefit metric is represented by yellow shades, while lower metric scores are represented by darker blue.

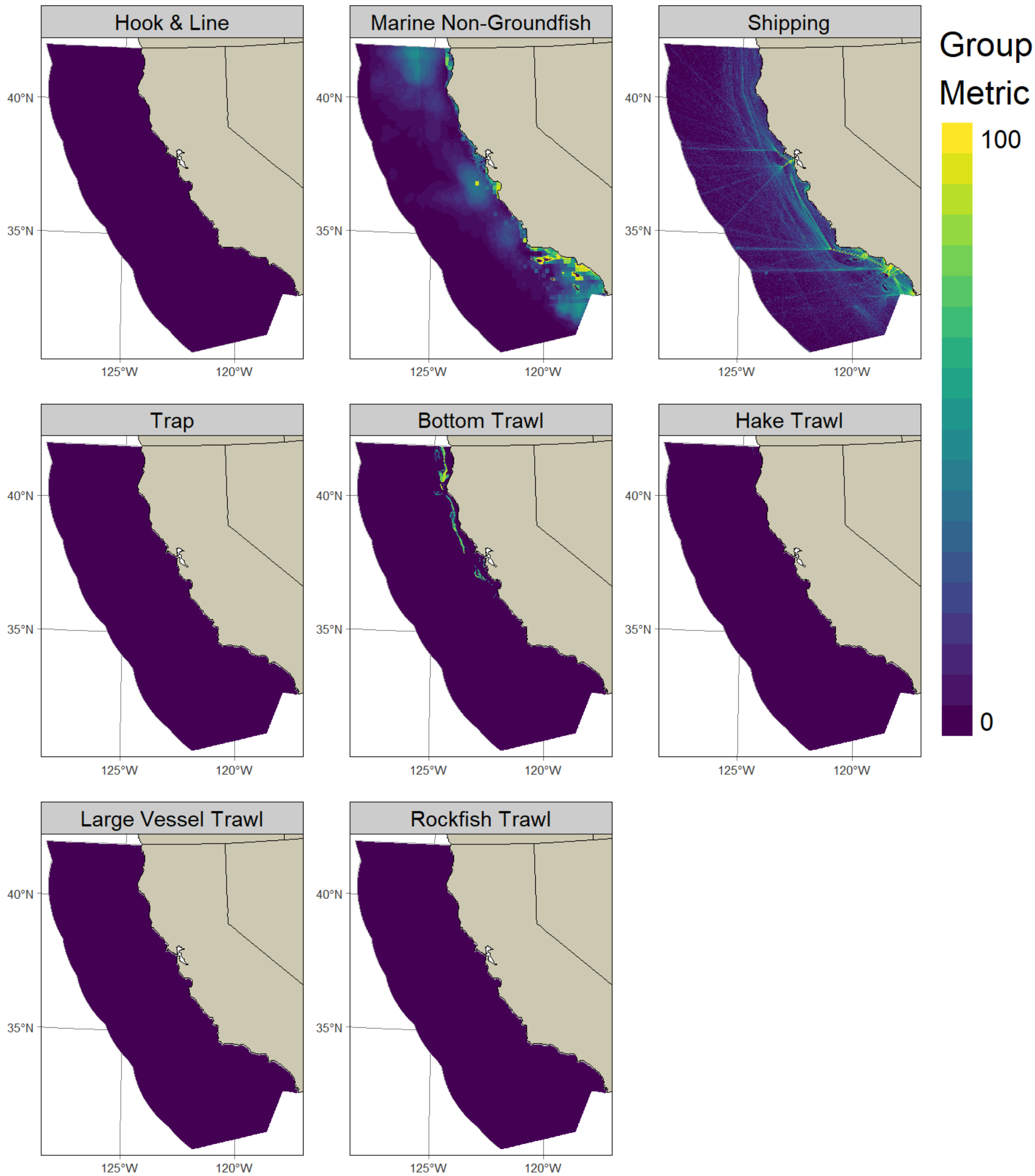

Figure C5. Group impact metrics for human use Groups. The scale is maintained across panels to ensure visual comparison between Groups. Groups are: Hook and Line, Marine Non-Groundfish, Shipping, Trap, Bottom Trawl, Hake Trawl, Large Vessel Trawl, and Rockfish Trawl. Higher impact/benefit metric is represented by yellow shades, while lower metric scores are represented by darker blue.

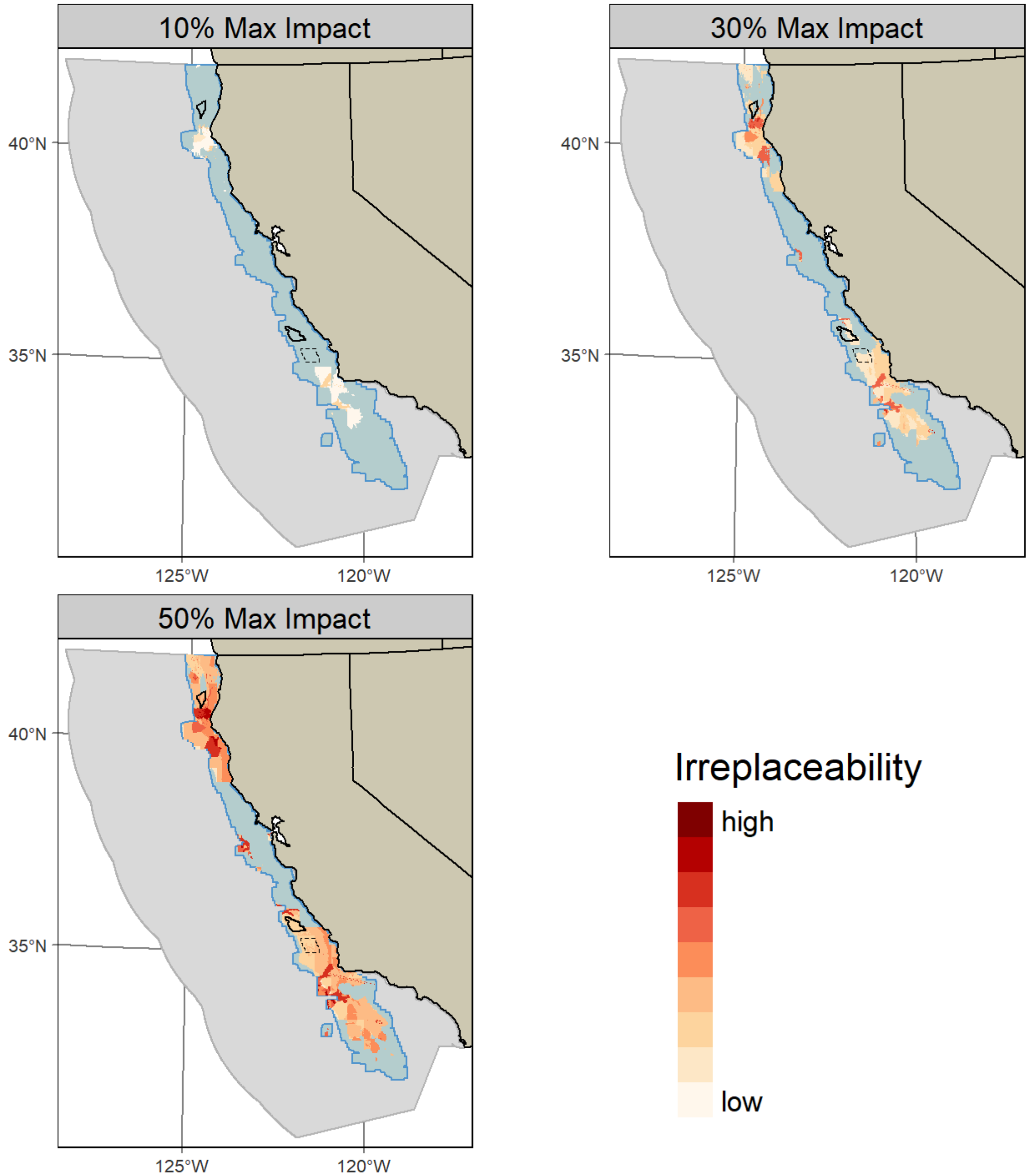

Figure C6. Irreplaceability scoring for three optimization scenarios representing a spectrum of relative value trade-off between energy development benefit (as quantified by the LCOE metric) and solving for areas that do not exceed cumulative proportional impact for any of the Super Group impacts. The targeted maximum total impact is set so as not to exceed 10%, 30%, or 50% of the total impact across the entire study domain. The irreplaceability metric ranks the importance of a particular cell to achieving the optimization solution. Thus, darker red areas serve a key role in each solution, while lighter colors are more likely to have alternatives that could meet the optimization goal. Areas in blue represent planning aliquots that were not selected as part of the optimized solution. Areas in light grey were not included in the optimization analysis.

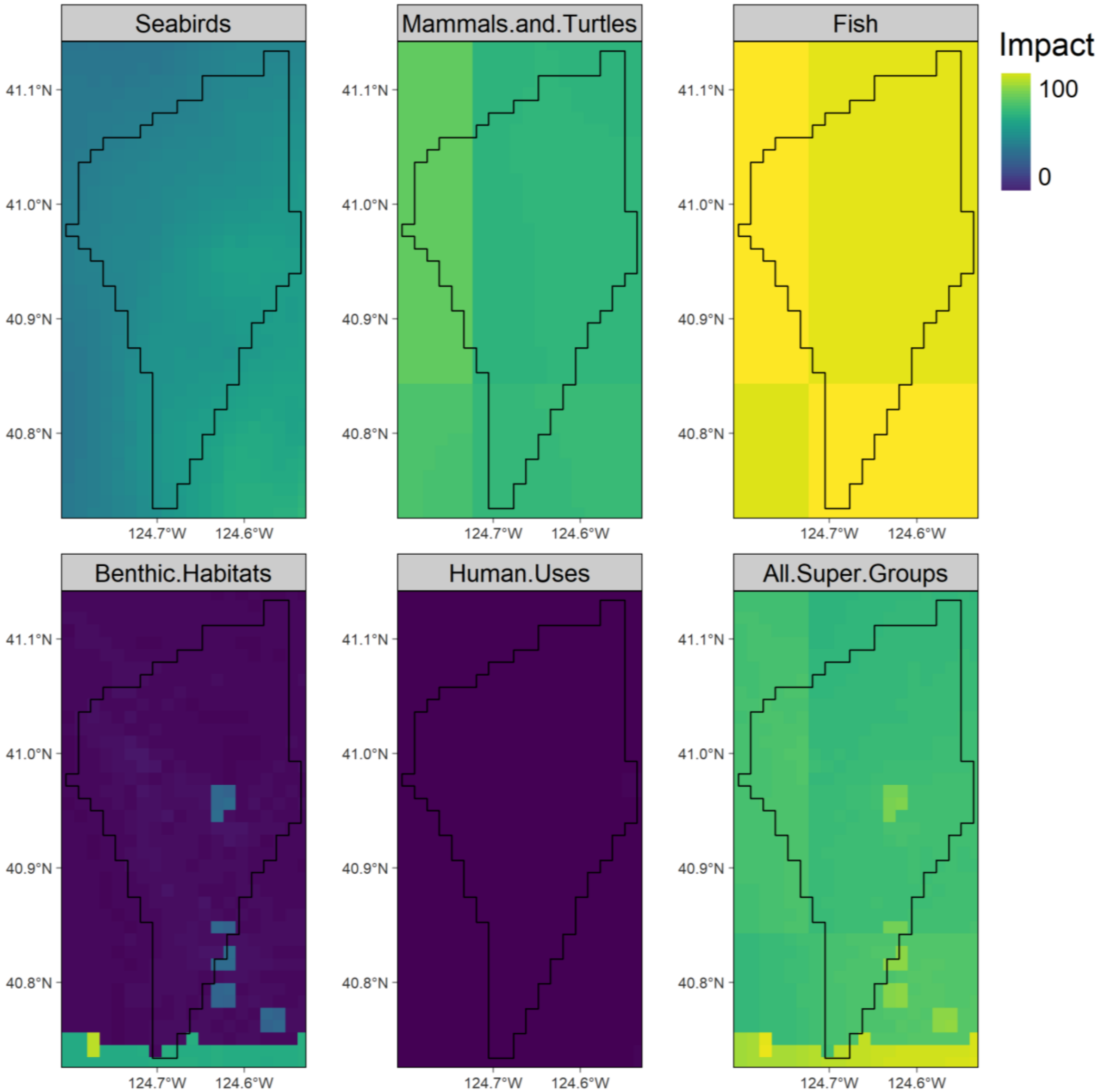

Figure C7. Maps of Super Group and combined cumulative impacts inside and around the Humboldt WEA. Higher impacts are in yellow while lower impacts are shown in darker blue.

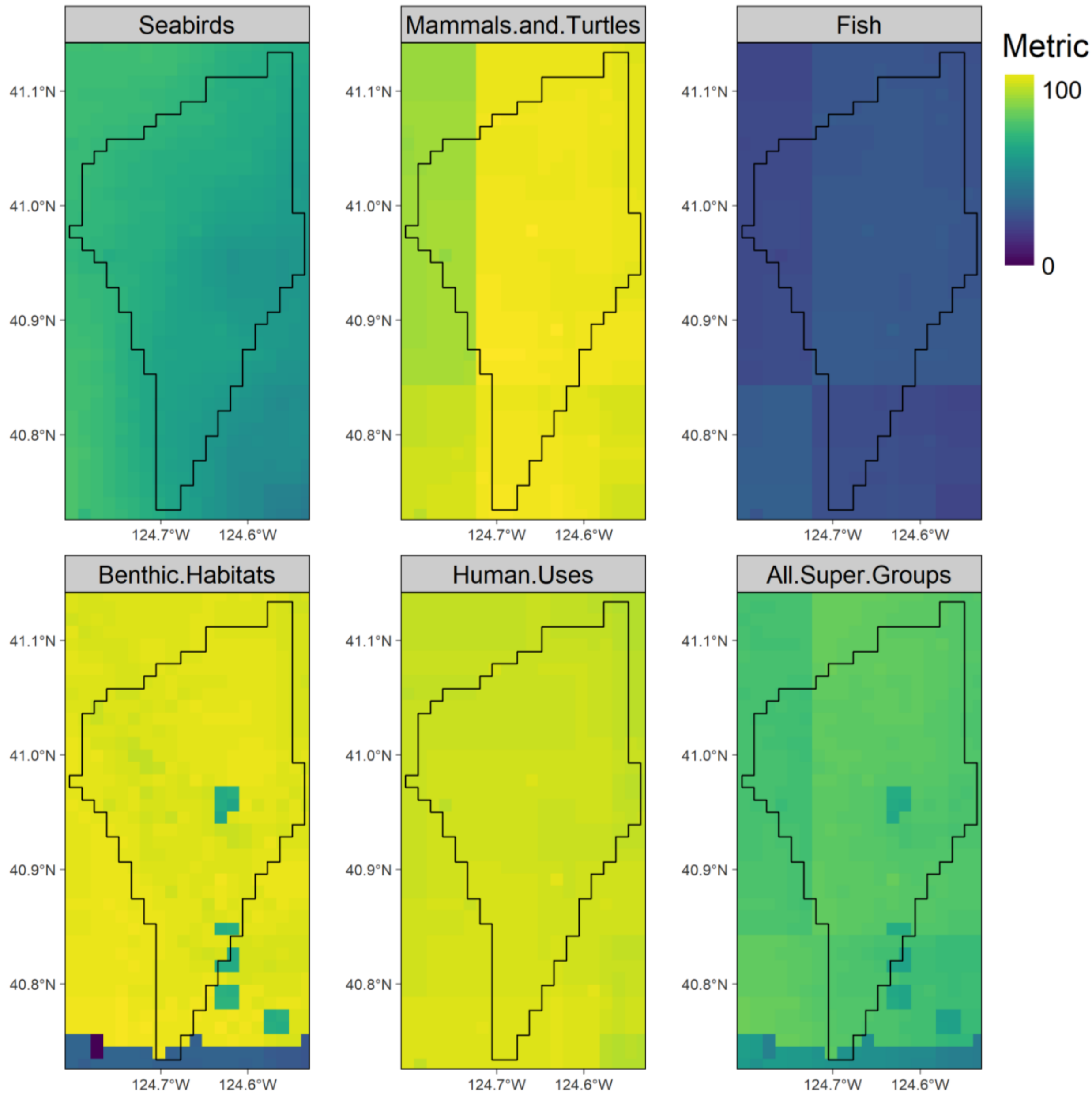

Figure C8. Maps of Super Group and combined benefit/impact trade-off metric inside and around the Humboldt WEA. Higher scores for the metric are in yellow while lower impacts are shown in darker blue and represent more desirable areas for development.

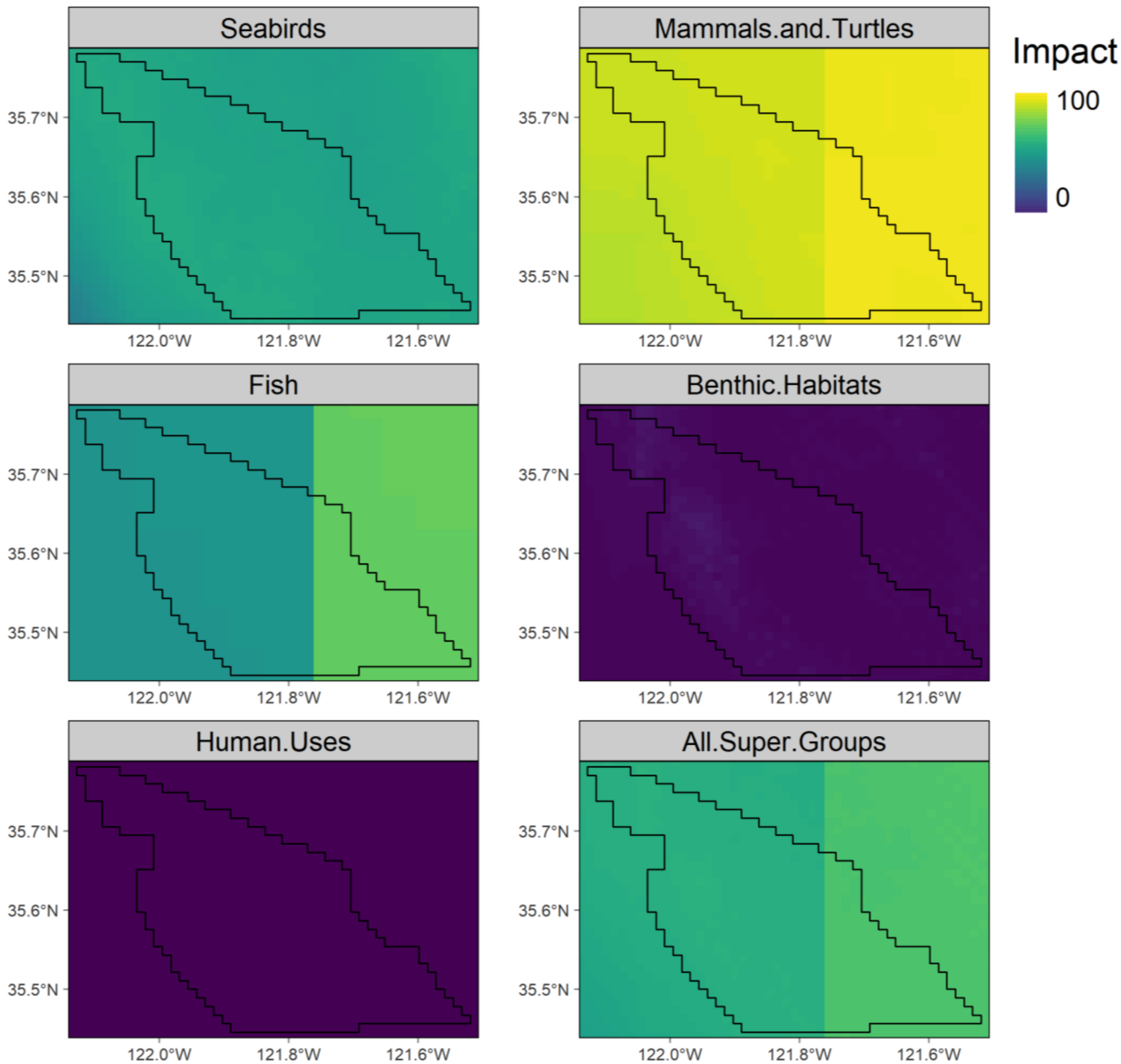

Figure C9. Maps of Super Group and combined cumulative impacts inside and around the Morro Bay WEA. Higher impacts are in yellow while lower impacts are shown in darker blue.

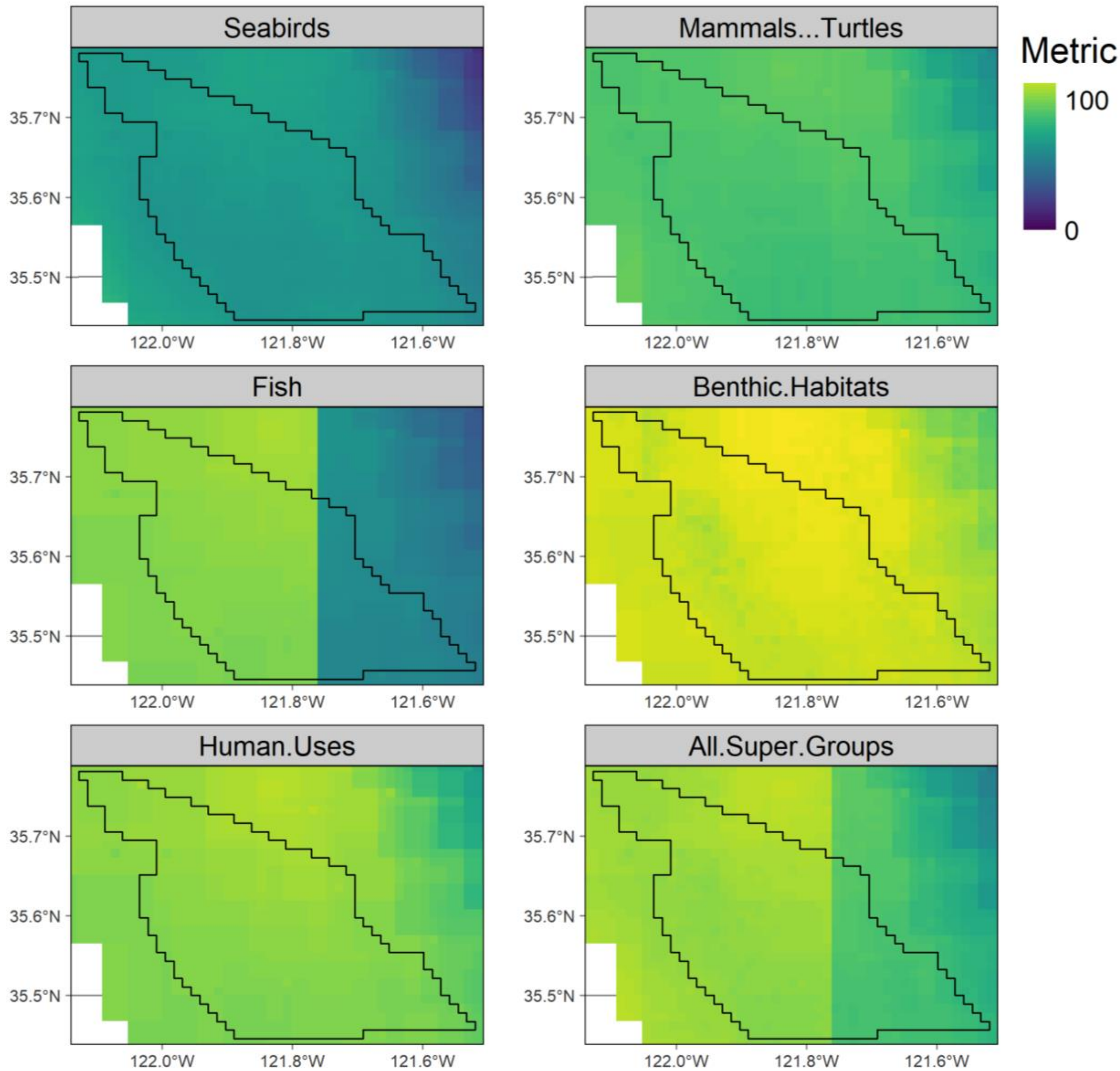

Figure C10. Maps of Super Group and combined benefit/impact trade-off metric inside and around the Morro Bay WEA. Higher scores for the metric are in yellow while lower impacts are shown in darker blue and represent more desirable areas for development.

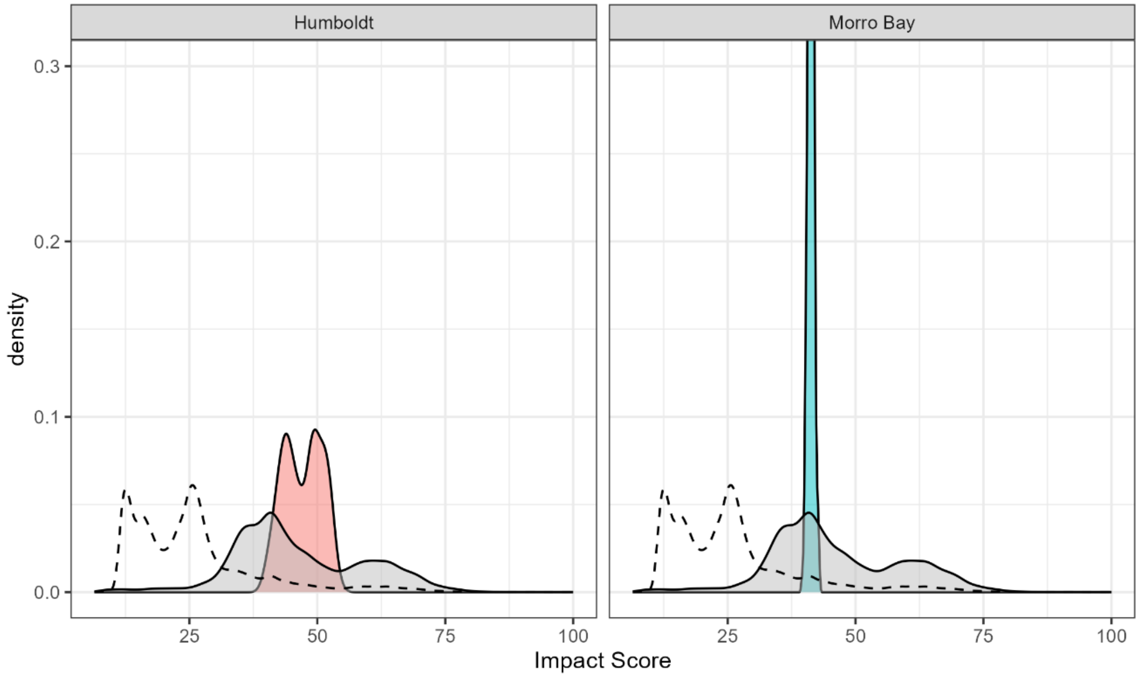

Figure C11. Density of Seabird impact scores for cells within each WEA (colored curve), LCOE optimization area (grey curve), and full California EEZ area (dashed curve). To best show distributions of impacts scores, the maximum density is limited to 0.3 but some distributions may exceed this value.

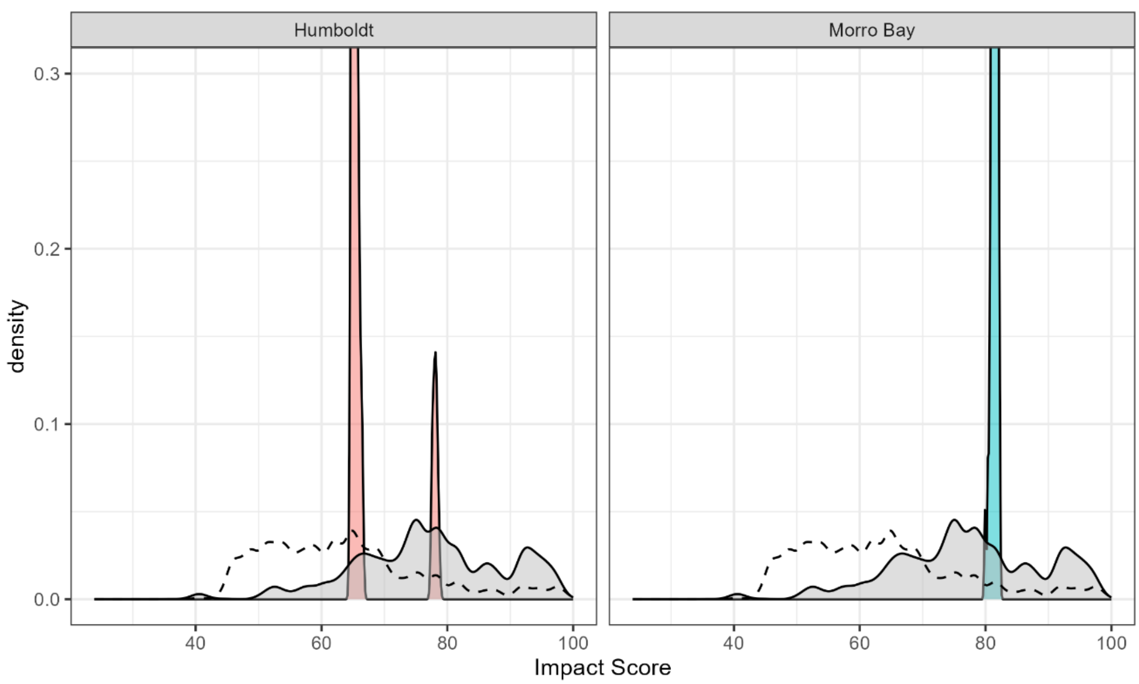

Figure C12. Density of Marine Mammal and Turtle impact scores for cells within each WEA (colored curve), LCOE optimization area (grey curve), and full California EEZ area (dashed *curve). To best show distributions of impacts scores, the maximum density is limited to 0.3 but some distributions may exceed this value.*

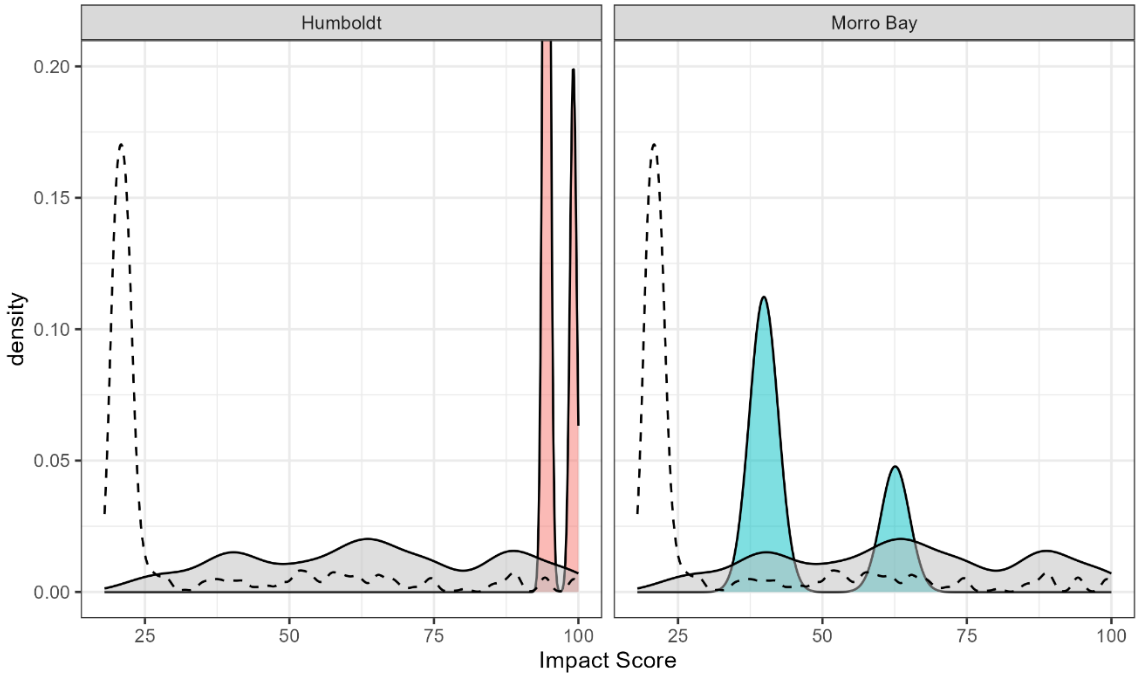

Figure C13. Density of Fish impact scores for cells within each WEA (colored curve), LCOE optimization area (grey curve), and full California EEZ area (dashed curve). To best show distributions of impacts scores, the maximum density is limited to 0.3 but some distributions may exceed this value.

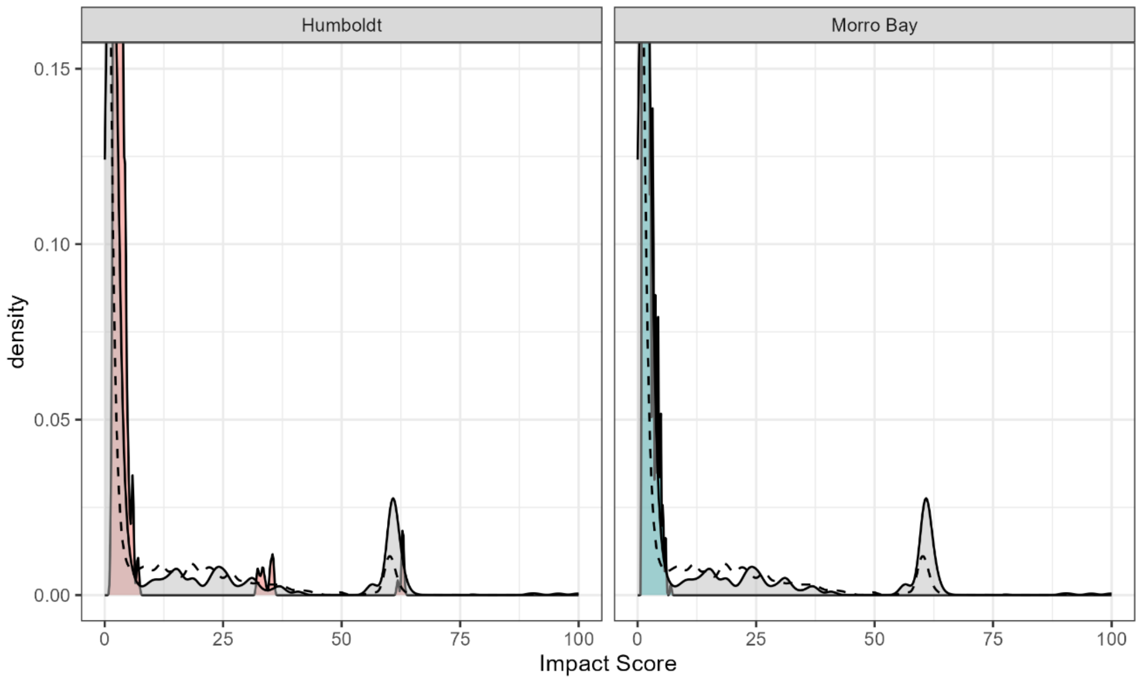

Figure C14. Density of Benthic Habitat impact scores for cells within each WEA (colored curve), LCOE optimization area (grey curve), and full California EEZ area (dashed curve). To best show distributions of impacts scores, the maximum density is limited to 0.3 but some distributions may exceed this value.

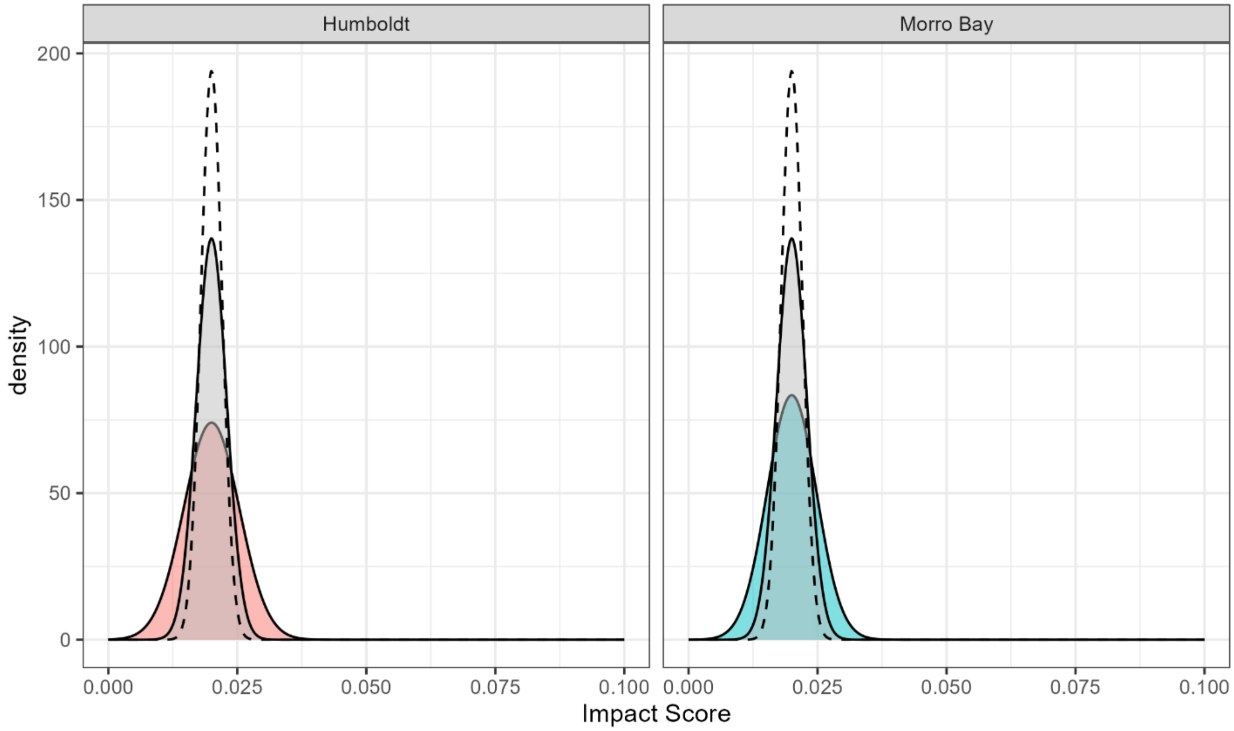

Figure C15. Density of Human Uses impact scores for cells within each WEA (colored curve), LCOE optimization area (grey curve), and full California EEZ area (dashed curve). To best show distributions of impacts scores, the maximum density is limited to 0.3 but some distributions may exceed this value.

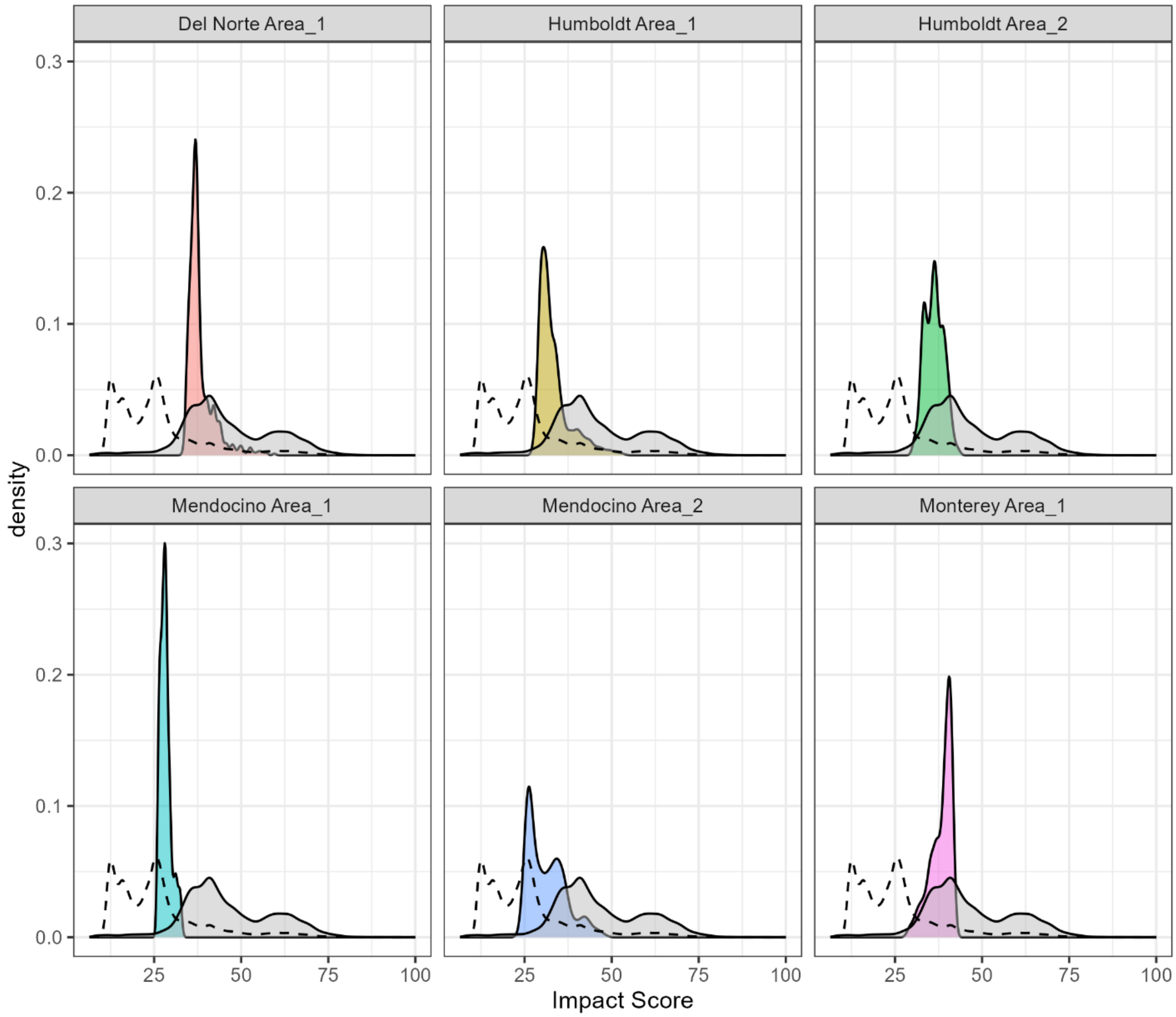

Figure C16. Density of Seabird impact scores for the cells within each AB525 sea space area (colored curve), LCOE optimization area (grey curve), and full California EEZ area (dashed curve). To best show distributions of impacts scores, the maximum density is limited to 0.3 but some distributions may exceed this value.

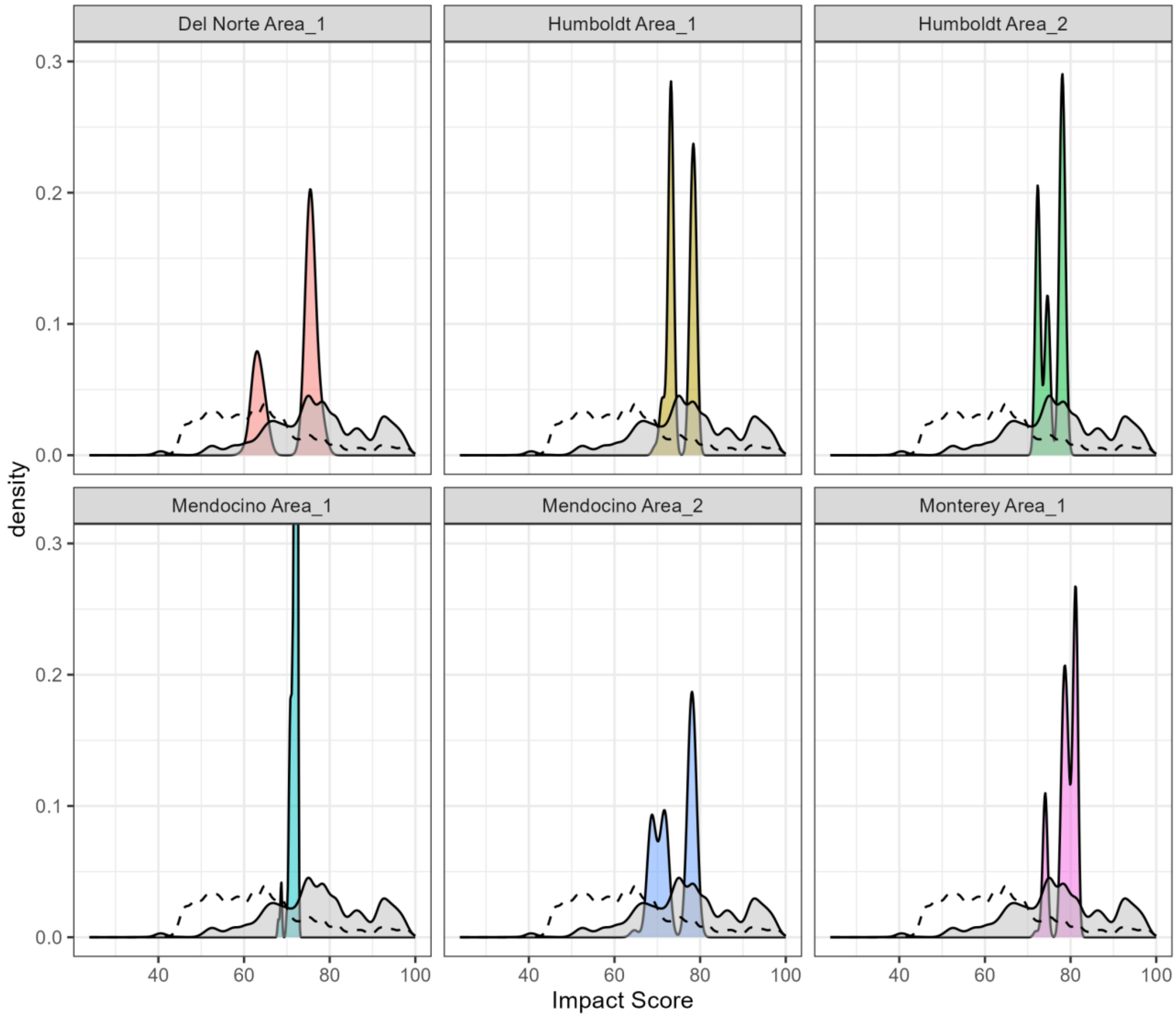

Figure C17. Density of Marine Mammal and Turtle impact scores for the cells within each AB525 sea space area (colored curve), LCOE optimization area (grey curve), and full California EEZ area (dashed curve). To best show distributions of impacts scores, the maximum density is limited to 0.3 but some distributions may exceed this value.

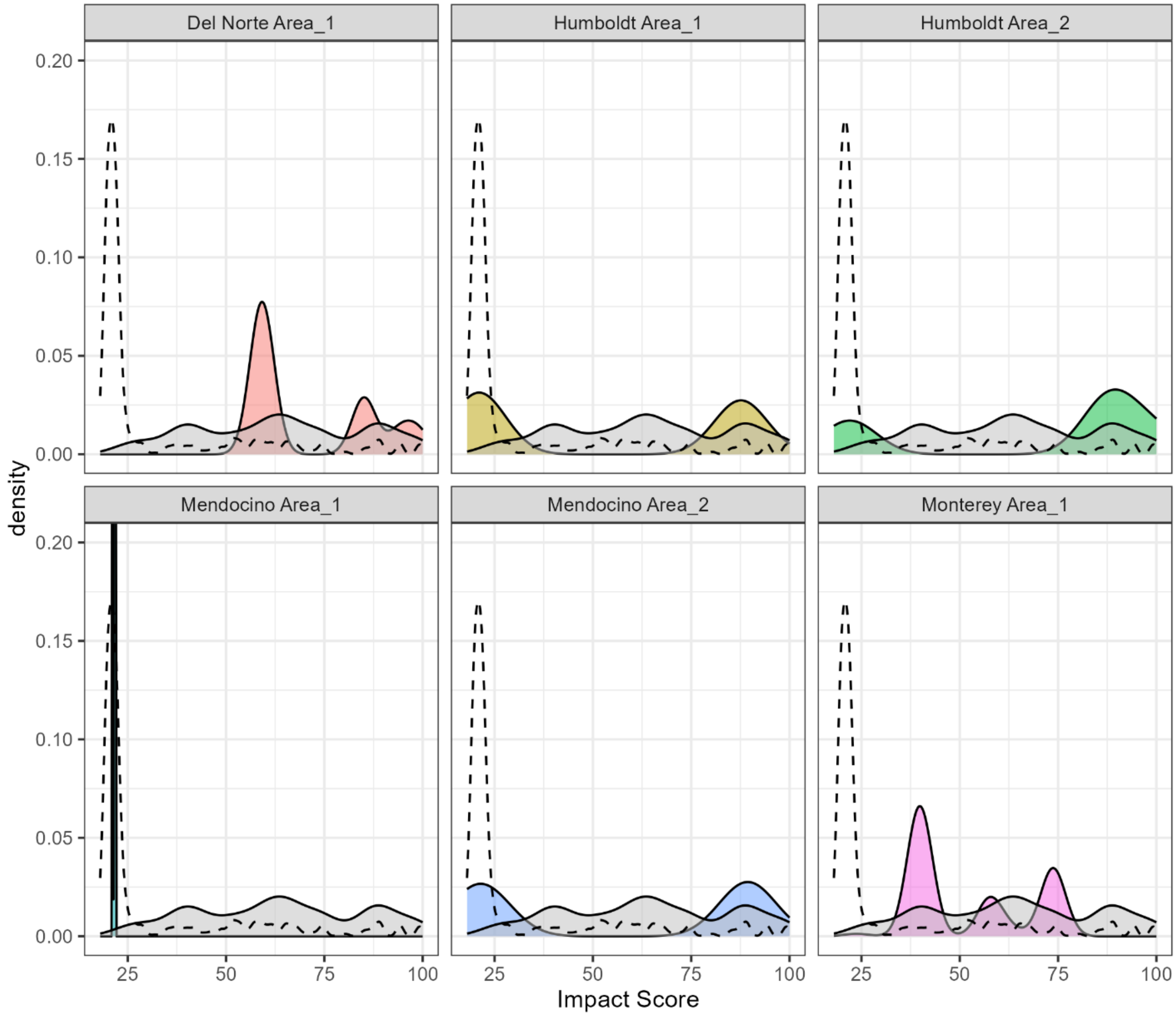

Figure C18. Density of Fish impact scores for the cells within each AB525 sea space area (colored curve), LCOE optimization area (grey curve), and full California EEZ area (dashed curve). To best show distributions of impacts scores, the maximum density is limited to 0.3 but some distributions may exceed this value.

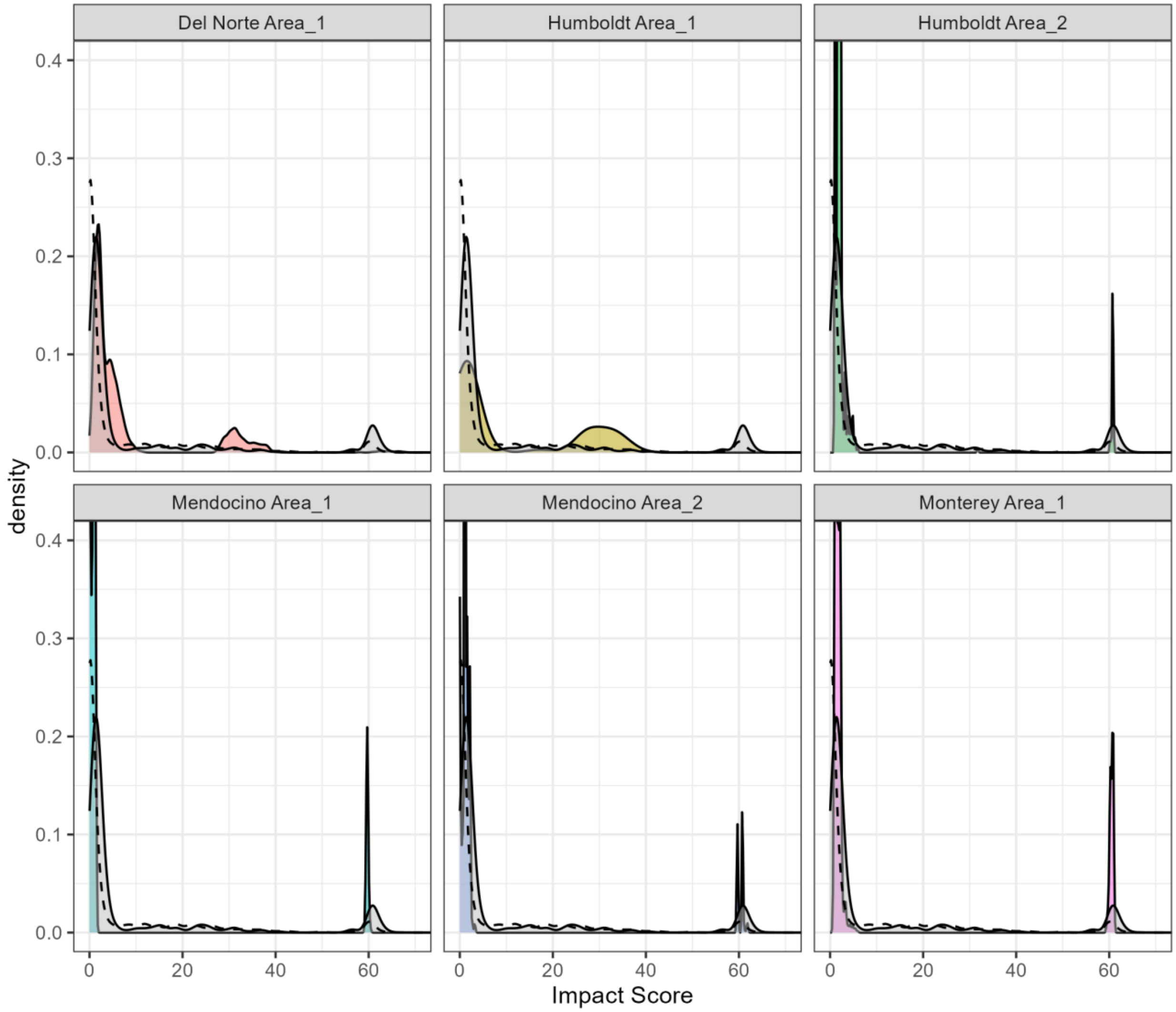

Figure C19. Density of Benthic Habitat impact scores for the cells within each AB525 sea space area (colored curve), LCOE optimization area (grey curve), and full California EEZ area (dashed curve). To best show distributions of impacts scores, the maximum density is limited to 0.3 but some distributions may exceed this value.

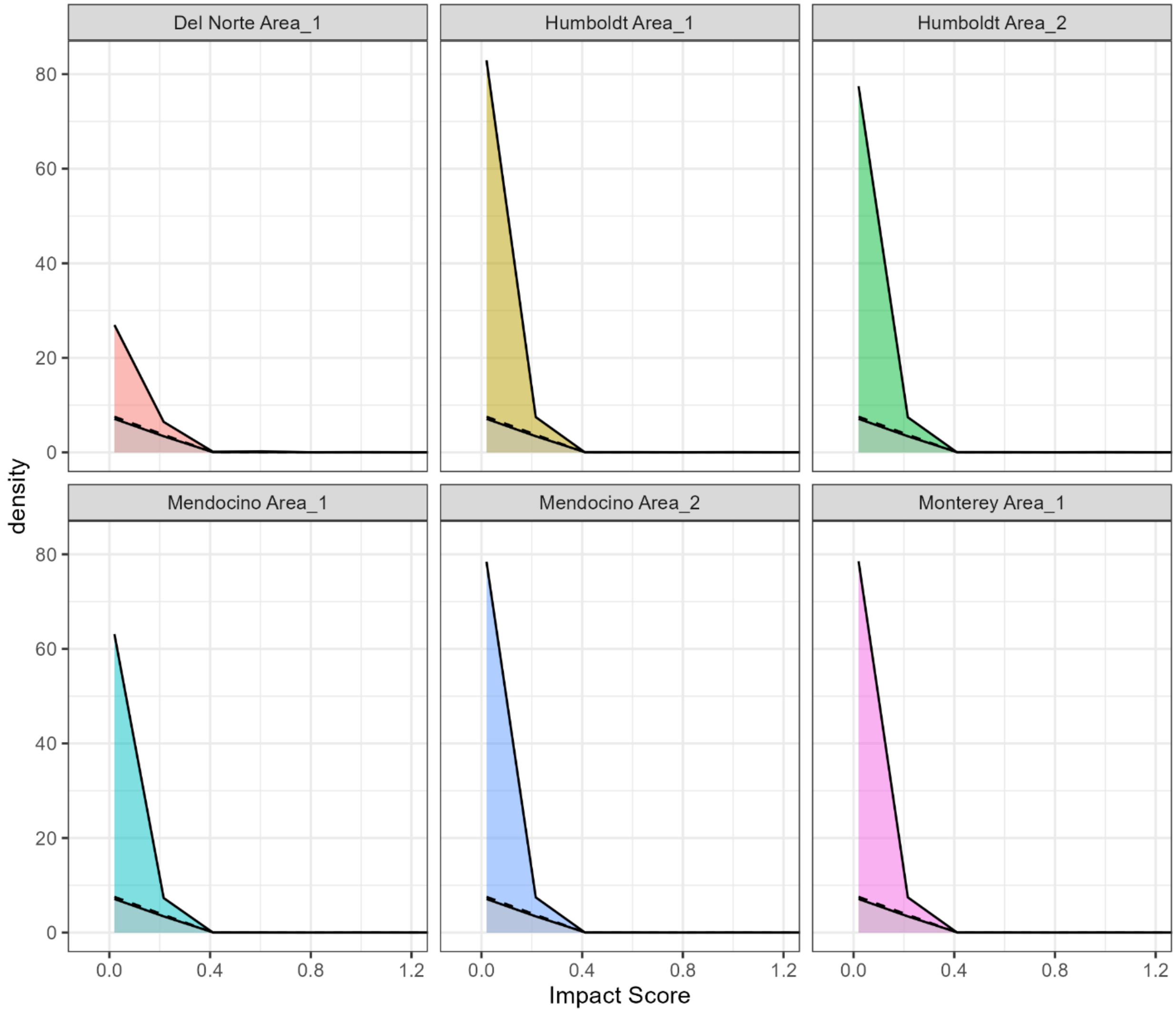

Figure C20. Density of Human Uses impact scores for the cells within each AB525 sea space area (colored curve), LCOE optimization area (grey curve), and full California EEZ area (dashed curve). To best show distributions of impacts scores, the maximum density is limited to 0.3 but some distributions may exceed this value.

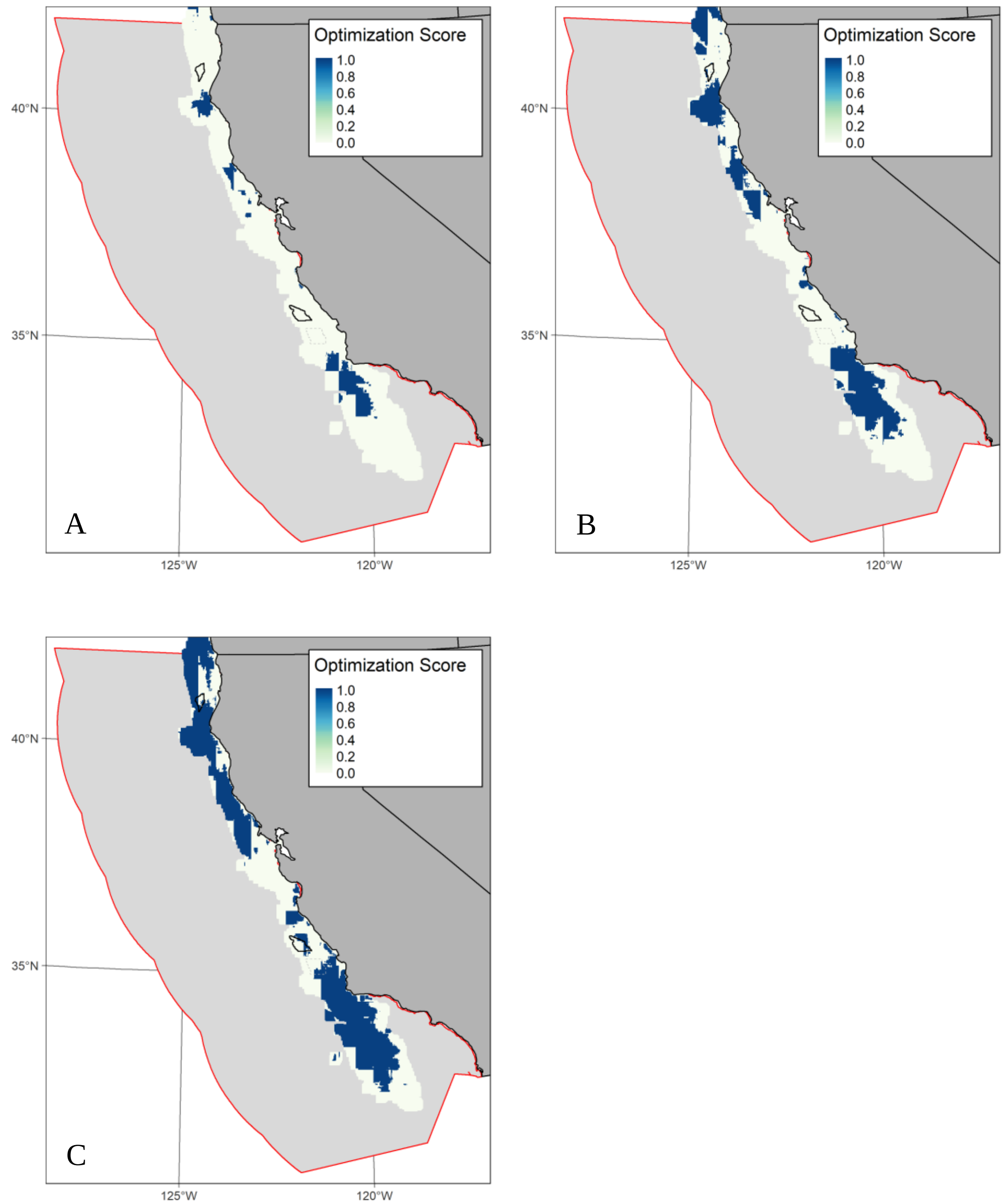

Figure C21. Three optimization scenarios that <u>do not</u> exclude NMSs. *The targeted maximum total impact is set so as not to exceed 10% (A), 30% (B), or 50% (C) of the total impact across the entire study domain. The existing WEAs are outlined in black. The Diablo Canyon Call Area is outlined in dashed black.*

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