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

Report to the California Ocean Protection Council

April 28, 2022

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Conservation science for a healthy planet

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Table of Contents

Executive Summary

The goal of this phase of the project was to assess and complete a preliminary analysis the existing spatial data for representing marine species, the marine environment and human uses of the ocean, use key data sets to examine the offshore wind energy areas identified by BOEM, and 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.

To date, 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. In order to ensure transparency and trust, the model is constructed using open-source R programming language running in the cloud and has been parameterized with a combination of data from the 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 Wind Energy Gateway, and data collected by Point Blue. From the existing data sets we compiled for this project, we covered 131 species, habitats and human uses. Our general approach is summarized in Figure 1. In addition to the data sets compiled by this project, we received 120 responses to our expert surveys to quantify sensitivity to offshore wind impacts for all species.

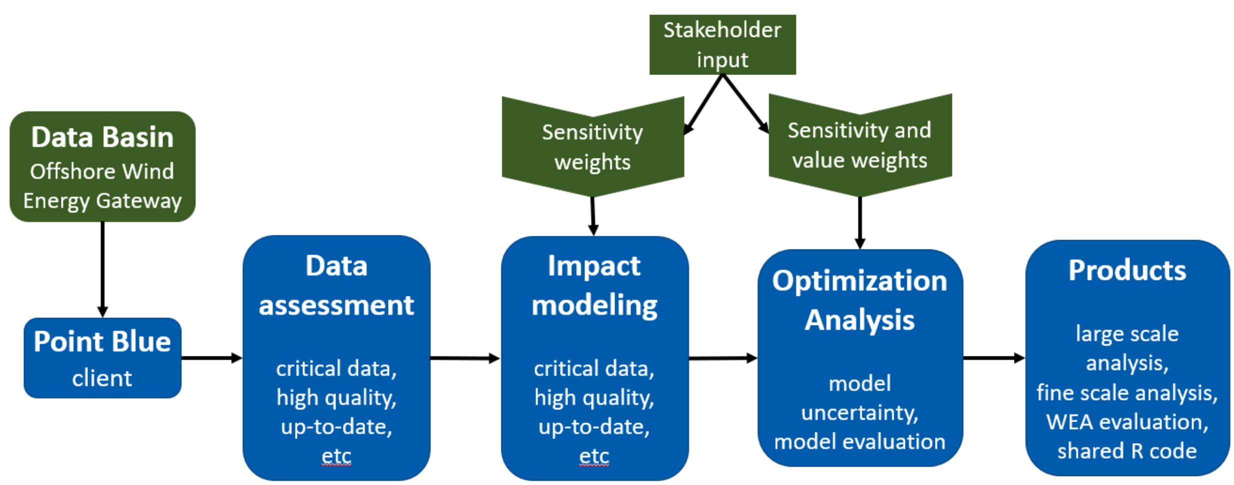

Figure 1 - Overview of methods and project approach.

Preliminary model runs identify priority wind energy installation areas off Punta Gorda, Humboldt County, Point Arena, Mendocino County and Point Conception, Santa Barbara County. These preliminary 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 Wind Energy Areas (WEAs) also identified by BOEM are included, suggesting that these areas are of intermediate priority for development if biodiversity conservation is a priority; while still avoiding the worst impact regions for wildlife and current human uses.

From our preliminary analyses, 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 Point Conception that were also identified by the prioritization algorithm. While detailed conclusions are likely to shift as improved and additional data are incorporated, these results provide preliminary indications that the existing WEAs will present moderate impact levels that are strongest for fish and marine mammals but lower for seabirds and human uses. They also provide initial indications of other areas that are likely to be high-priority development regions for future planning that will maximize energy production in the most sustainable manner.

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 a variety of optional formulations to capture different valuations of economic, cultural, and ecosystem services. These optional formulations provide valuable outputs to guide decision making.

Important improvements 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. Phase II of this project targets some of these improvements, primarily addressing enhancements in data quality.

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 past 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 leasing 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 (BEOM) 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, moving the west coast process forward toward lease offers. Also in 2021, the Biden administration announced a major initiative to deploy 30GW 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. 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 prepares to provide leases for 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 notoriously 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 but largely untested and unstudied technology. Therefore, it is imperative 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 phase of the 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 examine the offshore wind energy areas identified by BOEM, and 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. 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 extents and species lists 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 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 component that can be parameterized with existing data. The advantages of this approach are that it provides a framework that is easily updated and adapted as new and revised data become available to enhance the models. In addition, the approach enables us to explore and highlight existing data gaps and provide basic metrics of uncertainty. Where data are lacking for model components, uninformative or uniform values are used as placeholders or assumption 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 place-holders are used, we clearly highlight those. 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 in the future an interactive tool to enable managers, industry, the public, and other stakeholders to provide inputs and receive model results specific to their preferences and valuations, thereby empowering them 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 impacts to species, habitats and human uses, and 2) A limited subset of optimization analyses that identify high-benefit, low impact areas for wind farm installation. Each of these outputs is evaluated and discussed both at the study-wide level (EEZ waters offshore from California) and at the scale of the two WEAs, Morro Bay and Humboldt. 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 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 exposed 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 species, habitats and human uses evaluated in this analysis.

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 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 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 types, and 8 human use Groups (Appendix A; Table 2). For each of the 27 species Groups, we compiled lists from literature and reports of the potential offshore wind development pressures that each was likely to experience (Appendix B; Table 4). The pressures identified through this process were used to design expert elicitation surveys to gather data on specific sensitivity metrics which we combined into a cohesive metric of sensitivity used in our models. The survey design and functional form of the sensitivity metric calculation 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 speeds.

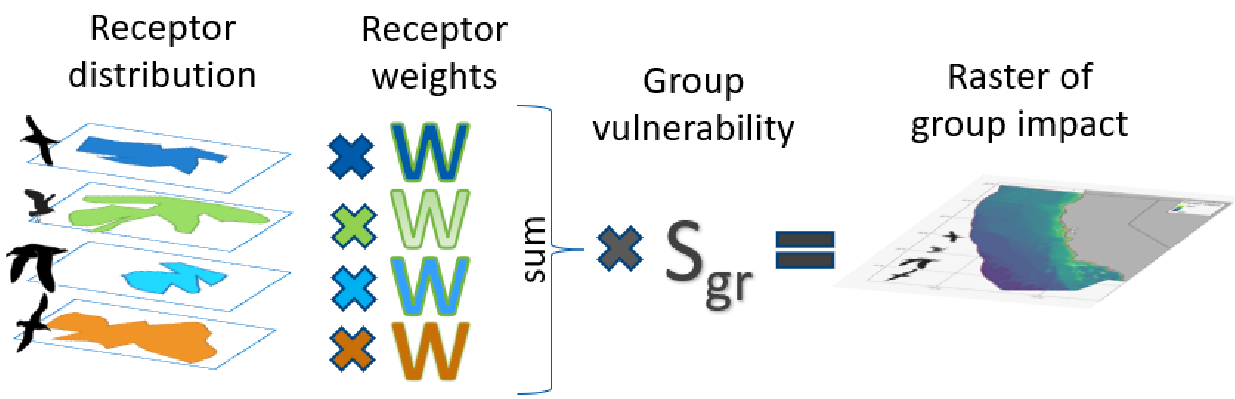

Figure 1. Diagram depicting the calculation of Group-level impact rasters. Raster data representing each receptor (left column) are multiplied by receptor-specific weights (second column) which include endangerment level for species receptors, spatial prevalence for habitat receptors and economic/social importance for human use layers. Seasonal presence and breeding behavior are also included in W for species receptors. The resulting weighted distributions are summed and then multiplied by the Group-specific sensitivity, S_{gr}. Group sensitivity is derived from expert surveys, impact-specific spatial footprint scalars and movement multipliers. The resulting raster is representative of the Group cumulative impact metric (right column and figure).

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 (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). In the results presented here, we weigh all receptors equally. 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. Alternately, 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 species in Groups and 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 density 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 quantify relative sensitivity scores. All data used to represent distributions of receptors were existing data provided by experts either directly or compiled from various sources (Appendix A; Table 2), while receptor metadata and survey responses were collected and collated as part of this project. A final data source used in the optimization analyses provides information about the profitability of energy developments. 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).

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 and 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 finally by simple data on species ranges. 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 2.

Most receptor density data was simply standardized to the 1200 m^2 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 1000m prior to rasterizing the data on the study grid. For seamounts, the features were weighted by inverse of the depth (in m) prior to raster conversion such that shallower seamounts were a slightly 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 higher-quality and resolution data. In order to combine use of 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 conduct our expert surveys for wildlife sensitivity metrics at the Group level because we explicitly designed our groupings such that patterns of sensitivity were roughly similar across member species in a Group but differ notably among Super Groups. In addition, this approach provided a manageable level of complexity for the design, deployment, and targeted response rate of the surveys. For each Group, we identified 10 or more subject matter experts 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 listserve 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. Two seabird Groups (pelicans and storm petrels), two marine mammal Groups (killer whales and sperm whales) and one fish Group (salmonids) did not receive enough expert responses and were therefore excluded from the current model runs. Additional effort to gather more expert survey responses for these groups will enable their inclusion in future model runs. For the surveys, we collected a total of 120 responses across all the included Groups.

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 weight species when combining impact across receptors to quantify Group-level impacts. For each receptor Super Group, we collected different data types to represent inherent relative risk of impacts not captured in the expert survey responses. 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, 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 reports 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 weight economically valuable fisheries, as well as those that support a greater number of individual fishers.

We also 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 an 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. In addition to data on presence/absence, we also used monthly information on known breeding activity to inflate impacts given the likely increase in sensitivity of species during breeding periods. These breeding season weights were increased for species that are central-place foragers during breeding and thus most restricted spatially, such as pinnipeds and seabirds.

Finally, because our calculation of impact is explicitly performed at the scale of each 1,200 m^2 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 3).

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 MW floating turbines with semi-submersible substructure spaced at 7-rotor diameter intervals with a total energy production capacity of 1,000 MW. The model is only predicted out to approximately 70 nm (~130 km) from shore, so all of our trade-off and optimization analyses are currently limited to this area. The model is predicted on a ~10 km resolution grid, so to prepare the LCOE data, we krigged the model predictions to our study grid. Since our goal is to prioritize locations with high energy potential at the lowest cost, we inverted the LCOE and rescale it 0-100 for the study area, corresponding to minimum and maximum LCOE values.

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 sensitivity and 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 were offshore wind development to occur in that cell. The model is calculated for 8 different "threads" – or season/phase permutations – a thread for each season (Spring, Summer, Fall and Winter) and wind energy project phase (construction and operation) combination. This allows us to evaluate any combination of seasons and phases independently or in combination. When combining across seasons, we equally weight the model components. 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 life-span is projected to be 20 years or more (Beiter et al. 2020).

In addition to combining the temporal and phase model threads to quantify whichever phase and time components a user desires, the impact models also can produce results at three different levels: Group, Super Group or cumulative combined impacts. While the basic model unit is a receptor, in most cases there are multiple receptors 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. Future model versions could include such interactions if sufficient evidence shows that they occur.

Impact calculation

The calculation of impact using the distribution, exposure, sensitivity, and modifier data is the core of the model. We start with a threat (we have 10 identified threats), for example:

"threat of mortality due to collision with turbines". Each threat has five risk components that were quantified through the expert survey responses: fecundity impact, recovery time, mortality impact, frequency of exposure, and proportion of population impacted (Table 5). Within a Group, we average the expert responses to each risk component and then combine them as follows, to obtain an impact value per Group (I_{gr}).

The risk components come in two classes: mortality 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). 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 only decrease future fecundity at most. For this reason, we scaled fecundity effects (level and time to recovery) in relation to mortality as shown in Table 1.

Table 1. Weighting 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

To understand the values in the table, we must first note that the mortality risk scores from our expert surveys are 1, 3, and 5 for low, medium, and high effects, respectively. We weight the fecundity effects relative to the mortality effects using the table. The maximum low fecundity effect (effects on the quality of offspring that persist a long time) is no greater than 5/8, equating to 1/8 of the maximum mortality impact. Similarly, the maximum medium fecundity effect (i.e., that which has the longest recovery) is 1/3 of the maximum mortality effect. Because we assess mortality as a separate risk component, any high fecundity impacts are instead assessed through the mortality impact. Thus, we use the table above to translate each expert's response on fecundity impacts (low, medium, high) and time to recover (short, intermediate, or long) into a mortality impact value that is subsequently averaged across surveyor responses for a specific sensitivity/Group combination to give a single expert-elicited mortality sensitivity metric.

In our model impact formulation, fecundity effects are modulated by the extent of exposure to the pressure and the recovery time after exposure, while both mortality and fecundity risks are modulated by the frequency of exposure and proportion of the population affected. Further, we must also consider the size of a single cell, 1.44 km^2. Because of the nature of each threat, some are more pervasive throughout the cell area and some are more localized. Animal foraging behavior also increases risk to exposure, where those animals traversing the cell more frequently (e.g., birds) are exposed more often to the threat. We add a weight to account for these behavioral differences. Lastly, the exposure to the threat is also not homogeneous in time throughout the year. We have strived to capture a "baseline" impact with the values of frequency of exposure and behavior, 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 and the greater energetic needs of breeding animals. We scale each pressure by multiplying by these additional weights. The formulation of Group sensitivity thus becomes the sum of fecundity impact weights and the mortality weights, multiplied by the weights of frequency of exposure, precent of the population exposed, impact area adjustment, foraging behavior adjustment, and breeding behavior adjustment:

f() = ((Fecundity ∪ LengthRecovery) + Mortality) * Frequency * PercentExposed * ImpactArea * ForagingBehavior * BreedingBehavior (eq. 1)

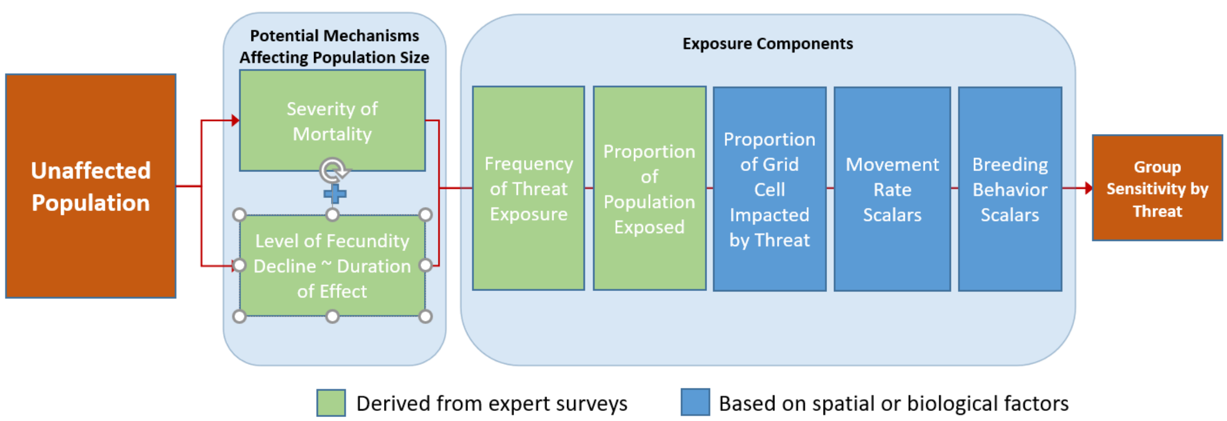

Figure 2. Diagram of the calculation of Group sensitivity. The formula is based in a population model framework such that the change in population size is determined by both death and birth rate and modeled pressures affect those components through mortality (for death rate) and the combination of mortality and fecundity decline (for birth rate).

Adjustments to threat exposure by phases and seasons

As mentioned above, we add a modifier to the threat (Eq. 1) based on breeding behavior. When requesting an evaluation of 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. 1 follows the same rubric depending on how many months of the chosen season the species is breeding.

Some pressures will also vary in their intensity or even their presence between the construction and operation phases of offshore wind projects. For example, turbine collision is not a threat to birds during the construction phase but is a significant concern during operation. We use a set of 0/1 weights to activate or nullify threats by animal group depending on the phase. Thus, Equation 1 is modified based on these adjustments by phases and species presence and breeding behavior within the season selected.

Threats

Per expert responses, within a species Group (e.g., baleen whales), threats are not equally weighted (for example, mortality due to collision with turbines would be a much more important threat for alcids than for baleen whales). We did not ask experts to provide weights of threats relative to one another. A naive approach is to consider that all threats are equally important for each group. In this model formulation, we use a set of weights for the threats based on Point Blue's expertise on the ecology of each group.

We denote the vector of weights for threats for the species group as W_{gt}. We denote the matrix of (numerical) expert responses on weights to risk components for each threat as R. Since we are considering 10 threats and 5 risk components for each, the matrix has dimension 10 x 5. We apply equation 1 above to R and end up with 10 values, one for each threat. The resulting R values are combined by multiplying each by the area-adjusted threat weights and adding them. Note that this is a vector multiplication of the results of function *f()* in eq. 1 above, a 1 x 10 vector, and the vector of threat weights, 10 x 1. So, for each group we calculate the threat sensitivities as:

$S_{gr} = f(R)$ %*% (W_{gt}) (eq. 2)

S_{gr} is a single scalar value of sensitivities for a given group.

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 to 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. 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 inherent resilience 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. These are receptor-specific weights and of equal length to W_{sr} and D_s. We combine the threat risk score with density, representativity, and endangerment weights for a group as follows:

$K = S_{gr} * ([W_{sr} * D_s]^t \text{ \%*\% } W_e)$ (eq. 3)

where K is a single value representing the combined group impact value of all threats within the cell. If D_s is the vector of values of each species' density within each cell, we could think of this vector as a scaled vector, where the density for each species is divided by the maximum density of that species in the entire landscape. This would result in D_s being a vector of values between 0 and 1.

Normalizing impact values

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

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

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

Optimizations

Once the rasters of impacts are calculated for each Group, we use those data as inputs to two optimization 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 also 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 for these results.

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 targeting that a maximum proportional impact should not be exceeded (relative to total possible impact across the study domain) for each input impact metric. We run example optimization and report results here for three scenarios that equally weight across Super Groups but vary the maximum proportional impact between 10, 30 and 50 percent. 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.

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 relatively few 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 dataset for deep-sea corals which does not cover more coastal areas of the study region and thus can't be used in optimization analyses, and very incomplete datasets for methane seeps and hydrothermal vents. Vents and seeps have been shown to be much more widespread than shown in the available EEZ-wide datasets (Beaulieu & Szafranski 2020; Merle et al. 2021). Human uses 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.

On the other end of the data quality spectrum, the seabirds Super Group has distribution data for 33 of 60 species but all the data is modeled based on extensive long-term siting datasets with high-quality and validated statistical approaches, a relatively fine resolution and seasonally-explicit predictions for all those species included (Dick 2016). Thus, all but one Group of seabirds (Petrels) have high-quality distribution data to represent more than a third 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 also varied in quality with three cetacean Groups having good coverage with 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 of 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 39 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 more oceanic species of marine mammals, seabirds and fish, receptor densities and calculated impacts were higher over the continental shelf than offshore (Appendix C; Figures 7-11). 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 cormorant group had the highest impact scores which were also the most strikingly concentrated over the continental shelf with low values offshore (Appendix C; Figure 7). In contrast, the albatross Group had the most evenly-distributed impact risk with only a mild gradient increasing toward the north.

Baleen whales showed the greatest impact for the marine mammal and turtle Super Group and was also more evenly distributed but with an elevated area offshore from Point Conception and the Southern California Bight (Appendix C; Figure 8). Sea turtles, beaked whales and small cetaceans all also showed higher impact metrics off southern California.

Rockfish were the most impacted within the fish Super Group, though all four groups were more evenly balanced than the other Super Groups (Appendix C; Figure 9). While rockfish impacts were patchier and slightly skewed toward the north coast from the San Francisco Bay to beyond Punto Gordo, the predicted impacts to Chondrichthyes were the most wide-spread both latitudinally and onshore/offshore.

Neither vents nor seeps were prevalent enough to be easily visible on the maps of the whole study area, and seamounts dominated this Super Group (Appendix C; Figure 10). Unsurprisingly, seamount impact was mostly concentrated offshore, so despite their sparse distribution, impacts to seeps and vents may play an important role for benthic habitat impacts in local areas near and on the shelf.

Finally, among the human uses Super Group, the marine non-groundfish and bottom trawl sectors had the highest impact metrics as well as the broadest distributions, especially the former (Appendix C; Figure 11). Refinement of the non-groundfish representation with more specific categories and improved data sources will be a worthwhile improvement for this model component.

At the Super Group level, fish and fisheries have elevated predicted impacts in the north while marine mammal and turtle and seabird coastal impacts were elevated toward the south (Figure 3). The patchy and offshore distribution of benthic habitats is dominated by the seamount impacts layer and will be significantly improved when the impact prediction for deep-sea corals can be added. 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, fish and human uses. 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 data. This highlights the current value of these model outputs for broader scale planning use with only some application for finer scale decisions must be made at the level of individual wind energy areas. Improving the quality of input distribution data to will significantly enhance the usefulness of this cumulative impacts approach at smaller scales.

WEA results

We plotted and evaluated the Super Group impact results at the scale of the Humboldt and Morro Bay WEAs to see if any patterns of interest arose to inform development at the lease level (Figure 12 and 14), while recognizing the above-stated limitations. We also discuss the benefit/impact tradeoff metric and optimization results at the scale of the WEAs in the next section. Among the Super Groups, fish had the greatest impact level in HWEA while impact was greatest for marine mammals and turtles in MBWEA. Several areas of elevated benthic habitat impact exist in HWEA from the presence of a few known seeps, but otherwise, the areas covered by the WEAs have low seabird, human use and benthic habitat impacts relative to the remainder of the EEZ. The other broad pattern that emerges from these zoomed in evaluations of the WEAs is that for those marine mammals and turtles and fish and thus for the cumulative impacts, offshore areas have higher values than closer to shore. This onshore-offshore gradient holds true in most broader patterns as well.

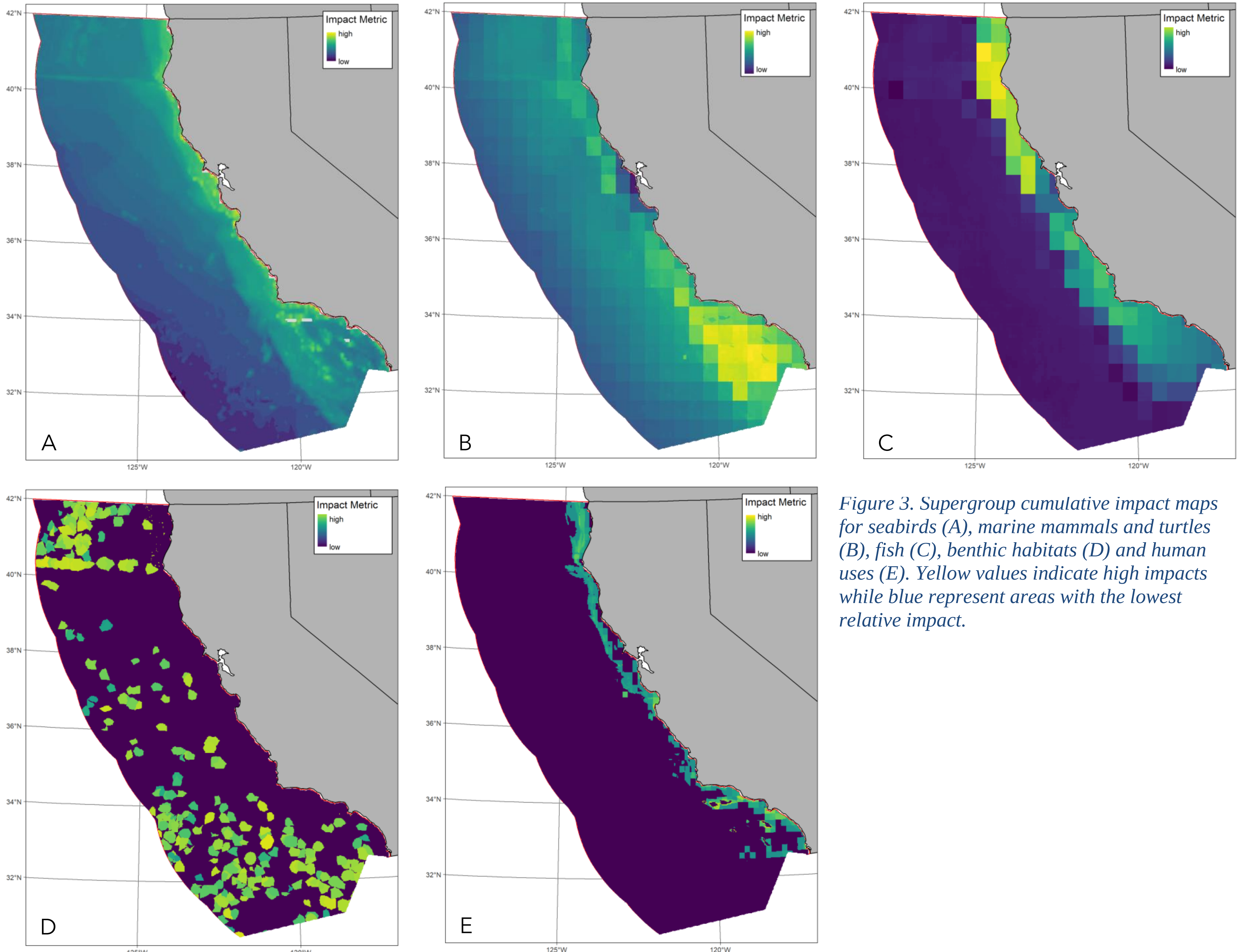

Figure 3. Supergroup cumulative impact maps for seabirds (A), marine mammals and turtles (B), fish (C), benthic habitats (D) and human uses (E). Yellow values indicate high impacts while blue represent areas with the lowest relative impact.

Optimization results

The benefit/impact metric, calculated as the difference between the normalized energy benefit metric and the normalized impact metric (Appendix A; Figure 6), 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 (Figure 4). Seabird, 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 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, but those should be treated with some caution because of the courser resolution and lower quality of much of the fish distribution data.

Across all but the fish trade-off results, similar areas were highlighted as falling into the top 10^{th} percentile of the scoring (Figure 4). Those areas are near the Oregon border, southwest from Punta Gorda/Cape Mendocino, and offshore from Point Arena. One additional area was highlighted southwest of Point conception for seabirds, benthic habitats and human uses but not for marine mammals and turtles. While the selection of the 10^{th} 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 may fall.

Finally, 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 5). 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 three areas selected that broadly align with the top regions from the trade-off metric: southwest from Punta Gorda/Cape Mendocino, and offshore from Point Arena. Interestingly, no 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 HWEA area 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 HWEA. With this scenario, part of the MBWEA is also selected along with an adjacent area to the northeast.

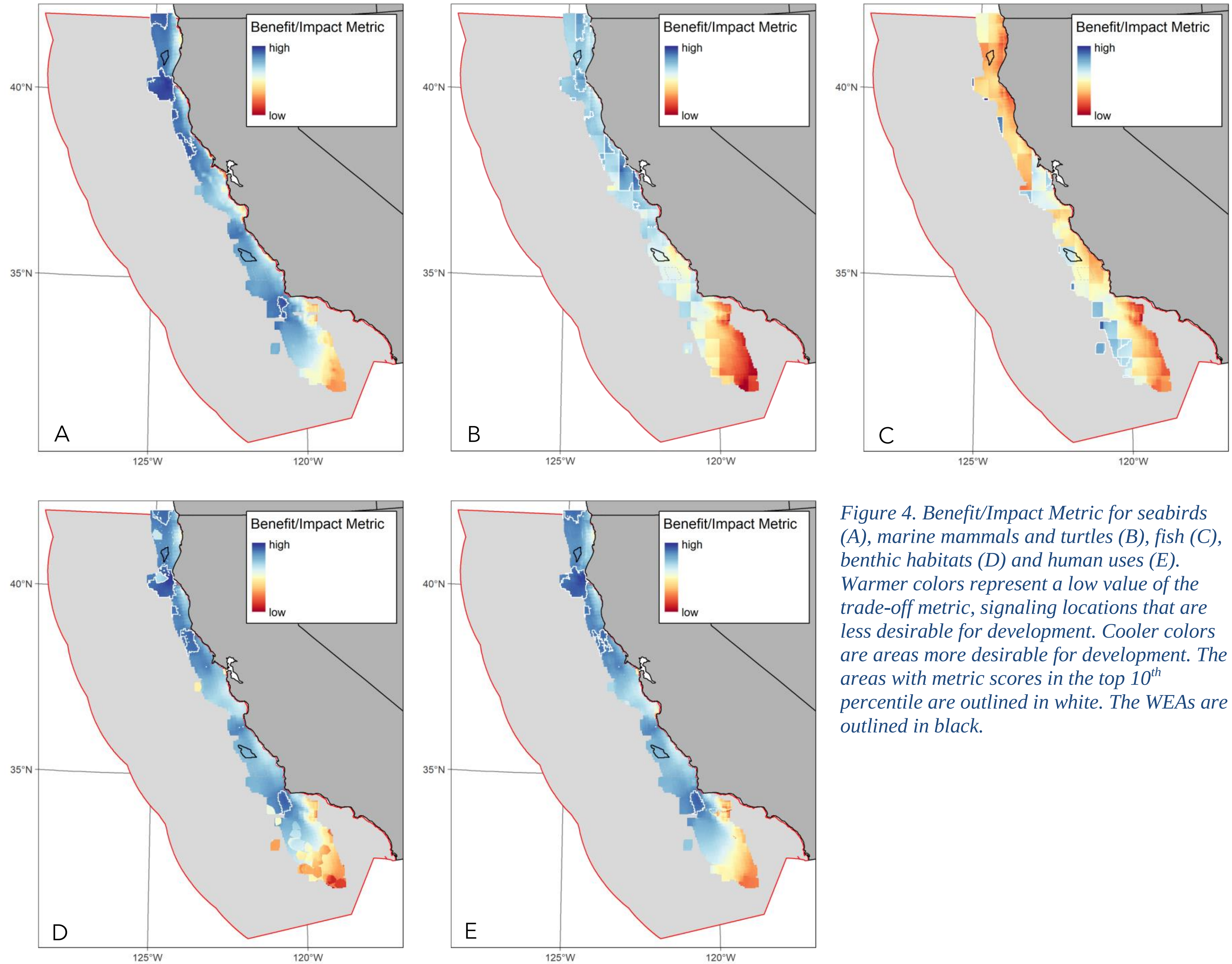

Figure 4. Benefit/Impact Metric for seabirds (A), marine mammals and turtles (B), fish (C), benthic habitats (D) and human uses (E). Warmer colors represent a low value of the trade-off metric, signaling locations that are less desirable for development. Cooler colors are areas more desirable for development. The areas with metric scores in the top 10th percentile are outlined in white. The WEAs are outlined in black.

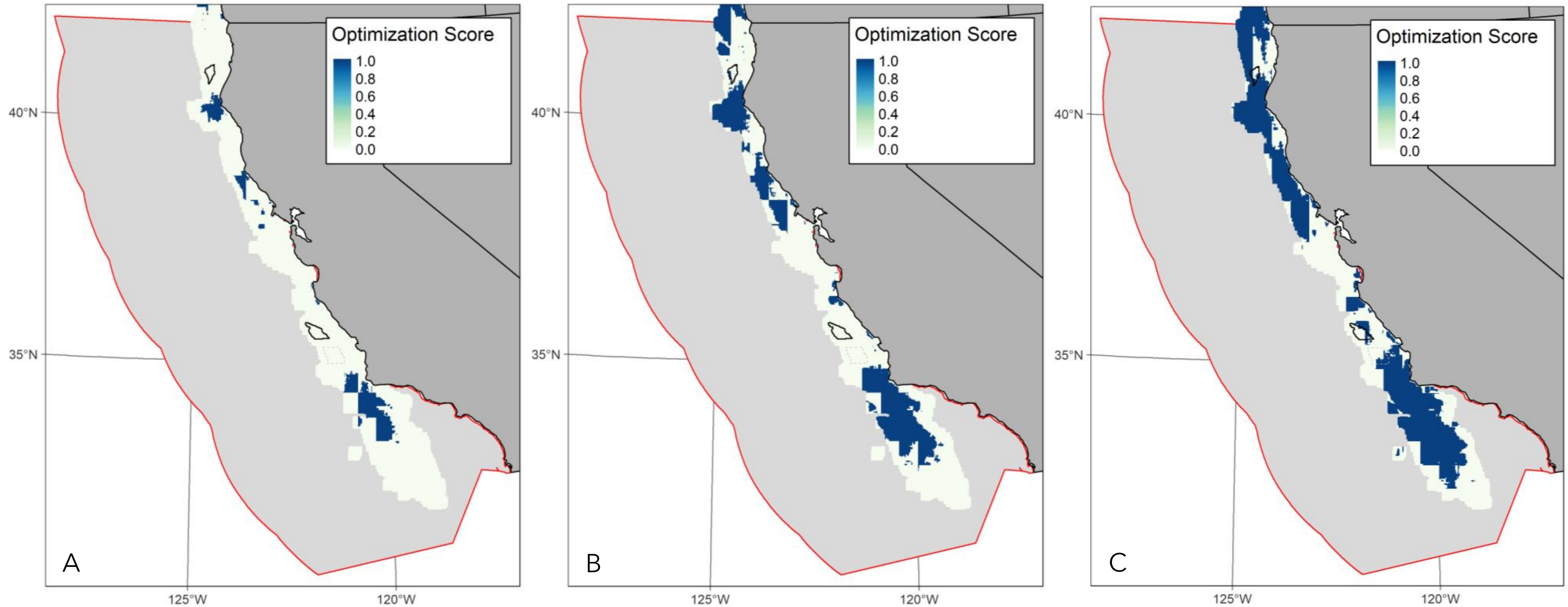

Figure 5. Three optimization scenarios representing a spectrum of relative value trade-off between energy development benefit (as quantified by the LCOE metric) and solving for areas that do not exceed cumulative proportional impact for any of the Super Group impacts. The targeted maximum total impact is set so as not to exceed 10% (A), 30% (B), or 50% (C) of the total impact across the entire study domain. The selection can identify cells which should be partially included in the development solution, with the proportion of cell area quantified by the optimization score and depicted by lighter green colors. Most cells are fully selected (optimization score = 1.0) and shown as dark blue.

Finally, 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 most of the Greater Farallones, Cordell Bank and northern Monterey Bay National Marine Sanctuary (NMS) areas are not selected, even in that more development-friendly scenario. 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 selected with these 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 run 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.

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, easily updated and modified 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.

Conclusions

The methods and results presented in this report exemplify the status of our siting model efforts to-date. 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.

Next Steps and Opportunities

During this phase of the project we have built a robust CAE model and optimization analyses in and open-source framework and using the collated datasets available during the development of the analysis. We also collected and created a sizeable database of information that enabled us to parameterize many of the components in our models. Because of limitations on the data available and the time to collect new data, there were a number of receptor components that were not included in the current model runs, but there are opportunities to remedy these deficiencies with newly released data, data we have discovered that were not hosted in the California Offshore Wind Gateway and through additional data collection tasks. In addition, 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.

At this stage of our work, there is an exciting opportunity to build on our existing efforts and improve our ability to guide science-based siting of offshore wind installations. We can leverage this opportunity by incorporating additional datasets, expanding the sensitivity assessments, getting feedback on the models, and publishing our work in a peer reviewed journal. 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.

Specifically, key opportunities have emerged highlighting the need to:

- Update and add newly available and key spatial datasets representing distribution of receptors previously not included in the model
- Conduct expanded surveys and expert elicitation workshops to improve sensitivity formulation and enable additional receptor Groups to be included in model runs

Additionally, Point Blue is collaborating 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 are increasing our capacity around data use and processing, computing infrastructure and data management. The key project goals are to improve efficiency in adding and processing new data for the siting models, decrease offshore wind energy model and optimization processing times and design a software deployment workflow that significantly decreases computing costs for large-scale deployment of our siting models. We expect this opportunity to help us produce improved data products to benefit decision makers.

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Appendices

Appendix A – Data

Table 2. Spatial distribution datasets representing receptors in each Group. Parenthesis 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 (*) were excluded due to insufficient survey responses while groups marked with pluses ($^{+}$) were excluded because distribution data was lacking.

	Group	Data Sets	
Marine Mammals and Turtles	Beaked whales	Becker et al. 2020 (4/4)	Totals - Becker et al. 2020 (16/34); Aquamaps (17/34)
	Baleen Whales	Becker et al. 2020 (3/7); AquaMaps (4/7)	
	Small Cetaceans	Becker et al. 2020 (8/10); AquaMaps (2/10)	
	Killer whale*	AquaMaps (1/1)	
	Sperm whale*	Becker et al. 2020 (1/1)	
	Pinnipeds	AquaMaps (6/6)	
	Sea otter	AquaMaps (1/1)	
	Sea turtle	AquaMaps (3/4)	
Seabirds	Albatross	Dick 2016 (2/3)	Totals - Dick (33/60)
	Alcids	Dick 2016 (9/10)	
	Cormorants	Dick 2016 (1/3)	
	Fulmars and Shearwaters	Dick 2016 (3/7)	
	Grebes and Loons	Dick 2016 (1/3)	
	Larids, Jaegers and Skuas	Dick 2016 (12/19)	
	Pelicans*	Dick 2016 (1/1)	
	Petrels*$^{+}$	(0/6)	
	Phalaropes*	Dick 2016 (2/2)	
	Storm-Petrels*	Dick 2016 (2/6)	
Fish	Forage Fish	Muhling et al. 2019 (2/9); AquaMaps (6/9)	Totals - Muhling (3/88); Brodie (4/88); Aquamaps (78/88)
	Chondrichthyes	Brodie et al. 2018 (3/14); AquaMaps (9/14)	
	Flatfish	AquaMaps (13/13)	
	Lingcod and Greenling*	AquaMaps (4/4)	
	Tuna and Mackerel	Muhling et al. 2019 (1/8); AquaMaps (7/8)	
	Salmonids*	AquaMaps (7/7)	
	Rockfish	AquaMaps (30/30)	
	Billfish	Brodie et al. 2018 (1/2); AquaMaps (1/2)	

Table 1. continued

	Group	Data Sets
Benthic Habitat	Deep sea coral	Yesson et al. 2012
	Hydrothermal vent	InterRidge Vents Database v.3.4 (2020); Kitchingman and Lai 2004
	Methane seeps	Merle et al. 2021; Kitchingman and Lai 2004
	Sea mounts	Yesson et al. 2011
	Marine canyon	–
Human Uses	Midwater Trawl - Industrial	NOAA observer densities (2011-2017)
	Midwater Trawl - Hake	NOAA observer densities (2011-2017)
	Midwater Trawl - Rockfish	NOAA observer densities (2011-2017)
	Bottom Trawl	NOAA observer densities (2011-2017)
	Hook and Line	NOAA observer densities (2011-2017)
	Trap	NOAA observer densities (2011-2017)
	Other Marine Fisheries	Miller et al. 2016 (Catch 1981-2005)
	Shipping	Marine Cadastre AIS (2019-2020)

Table 3. 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 km2. As a simplification, we consider the area of likely collision to be a equilateral triangle with base equal to rotor diameter. Thus, the risk area ranges from 0.0085 km2 to 0.017 km2
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.
Sea Floor Disturbance	0.0075	Assuming 3 anchors per turbine with 50x50 m disturbance for each placement totals 7,500 m2 of disturbance, or 0.75% of the total area.
Electromagnetic Dist.	0.006	Electromagnetic fields only extend several meters on each side of cables. 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.
Vessel Disturbance	0.5	Avoidance of vessels may vary by species group but can extend for several kilometers due to visual or sound cues.
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.

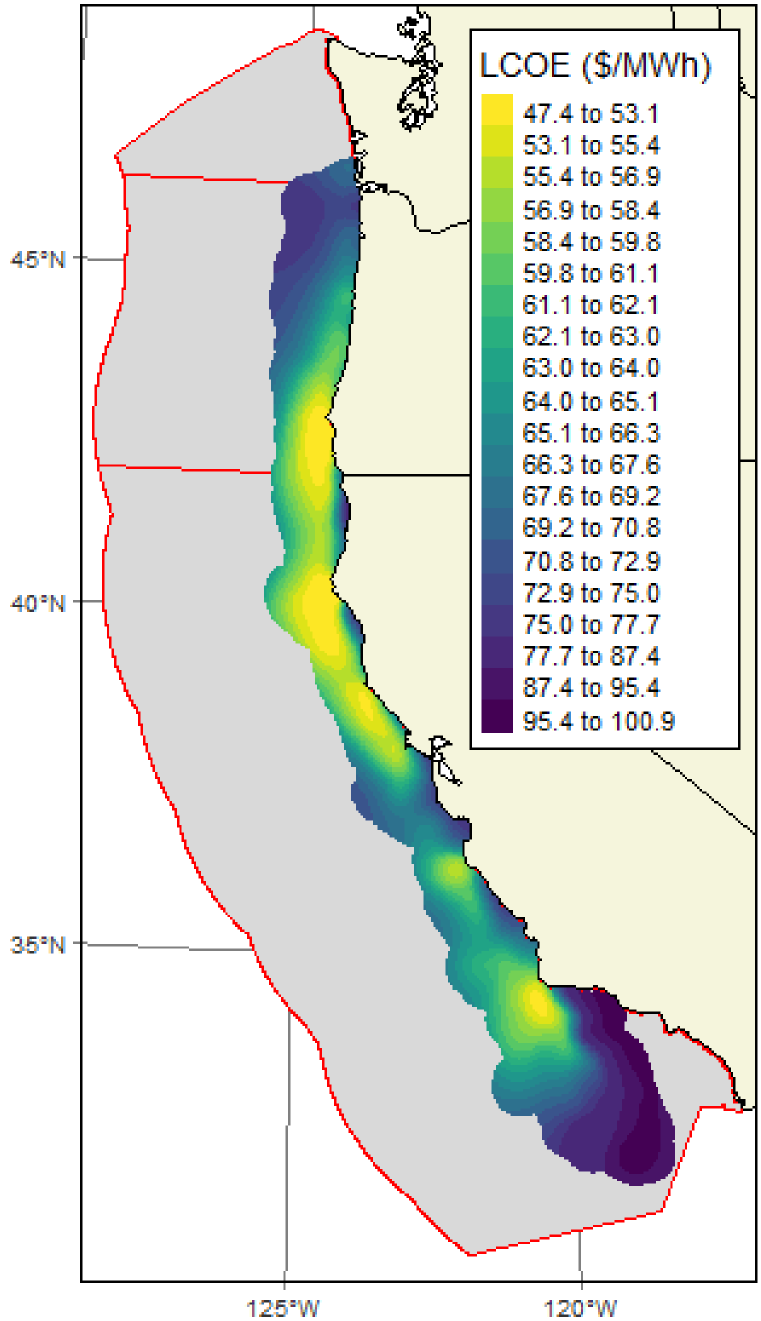

Figure 6. Map of the Levelized Cost of Energy metric produced from models in Beiter et al. 2020. Lower cost (yellow) represents more desirable locations for development while higher costs (blue) are less desirable. The LCOE values are inverted and standardized 0-100 prior to use in calculating our trade-off metrics and use in the optimization.

Appendix B – Expert survey data and structure

Table 4. Table derived from journal articles and reports of probable pressures that species groups are expected to experience as a result of offshore wind development.

	Group	Installation noise	Vessel traffic Disturbance	Vessel traffic Collision	Vessel noise	Antifouling chemicals	Chemical spills (oil etc.)	Anchors/ excavation	Cable excavation	Collision (blades)	Collision (towers)	Collision (moorings)	Entanglement (cables)	Electromagnetic field	Habitat displacement	Wind wake	Operational noise	Biofouling community	Hydrological wake	Floating objects
Seabirds	Albatross		Y	Y			Y			Y	Y				Y	Y		Y	Y	Y
	Alcids		Y	Y			Y			Y	Y				Y	Y		Y	Y	Y
	Cormorants		Y				Y			Y	Y				Y	Y		Y	Y	Y
	Fulmars and Shearwaters		Y				Y			Y	Y				Y	Y		Y	Y	Y
	Grebes and Loons		Y				Y			Y	Y				Y	Y		Y	Y	Y
	Larids, Jaegers, and Skuas		Y				Y			Y	Y				Y	Y		Y	Y	Y
	Pelicans		Y				Y			Y	Y				Y	Y		Y	Y	Y
	Petrels		Y	Y			Y			Y	Y				Y	Y		Y	Y	Y
	Phalaropes		Y				Y			Y	Y				Y	Y		Y	Y	Y
	Storm-Petrels		Y	Y			Y			Y	Y				Y	Y		Y	Y	Y
		0	**10**	**4**	**0**	**0**	**10**	**0**	**0**	**10**	**10**	**0**	**0**	**0**	**10**	**10**	**0**	**10**	**10**	**10**
Marine Mammals and Turtles	baleen whales	Y	Y	Y	Y		Y					Y	Y		Y		Y			
	beaked whales	Y	Y	Y	Y		Y								Y		Y			
	killer whale	Y	Y	Y	Y		Y						Y		Y		Y			Y
	pinnipeds	Y	Y		Y		Y						Y		Y			Y	Y	Y
	sea otters	Y	Y		Y		Y								Y					
	sea turtles		Y	Y			Y						Y		Y					Y
	small cetaceans	Y	Y	Y	Y		Y								Y		Y	Y	Y	Y
	sperm whale	Y	Y	Y	Y		Y						Y		Y		Y			
		7	**8**	**6**	**7**	**0**	**8**	**0**	**0**	**0**	**0**	**1**	**5**	**0**	**8**	**0**	**5**	**2**	**2**	**4**
Fish	Chondrichthyes						Y							Y						Y
	Flatfish					Y	Y	Y	Y									Y	Y	Y
	Forage Fish						Y												Y	Y
	Lingcod and Greenling					Y	Y											Y	Y	Y
	Other					Y												Y	Y	Y
	Rockfish					Y	Y	Y	Y									Y	Y	Y
	Salmonid						Y													Y
	Tuna and Mackerel						Y													Y
	Billfish						Y													Y
		0	**0**	**0**	**0**	**4**	**8**	**2**	**2**	**0**	**0**	**0**	**0**	**1**	**0**	**0**	**0**	**4**	**5**	**9**

Table 5. 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

Appendix C – Supplementary figures and results

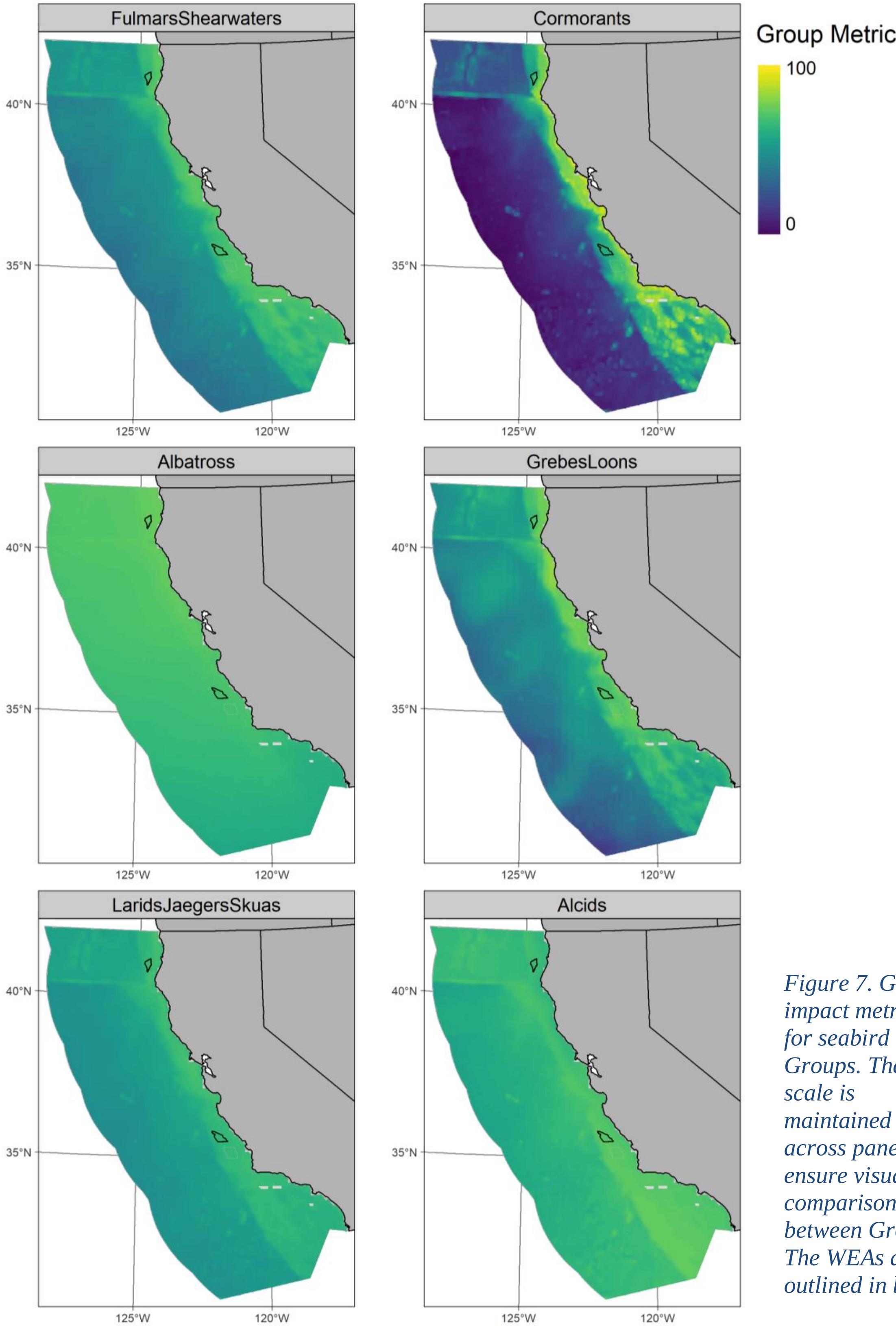

Figure 7. Group impact metrics for seabird Groups. The scale is maintained across panels to ensure visual comparison between Groups. The WEAs are outlined in black.

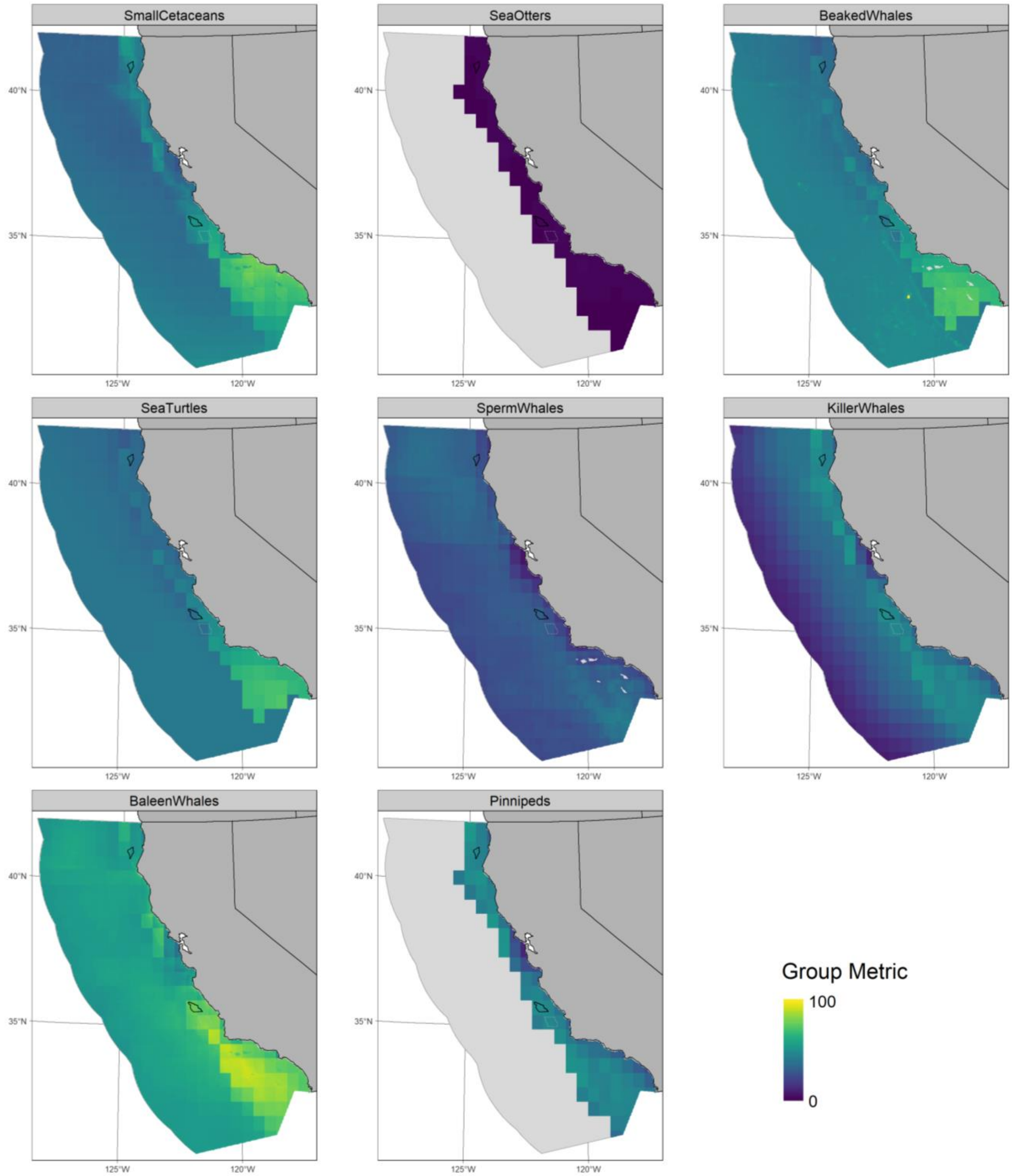

Figure 8. Group impact metrics for marine mammal and turtle Groups. The scale is maintained across panels to ensure visual comparison between Groups. The WEAs are outlined in black.

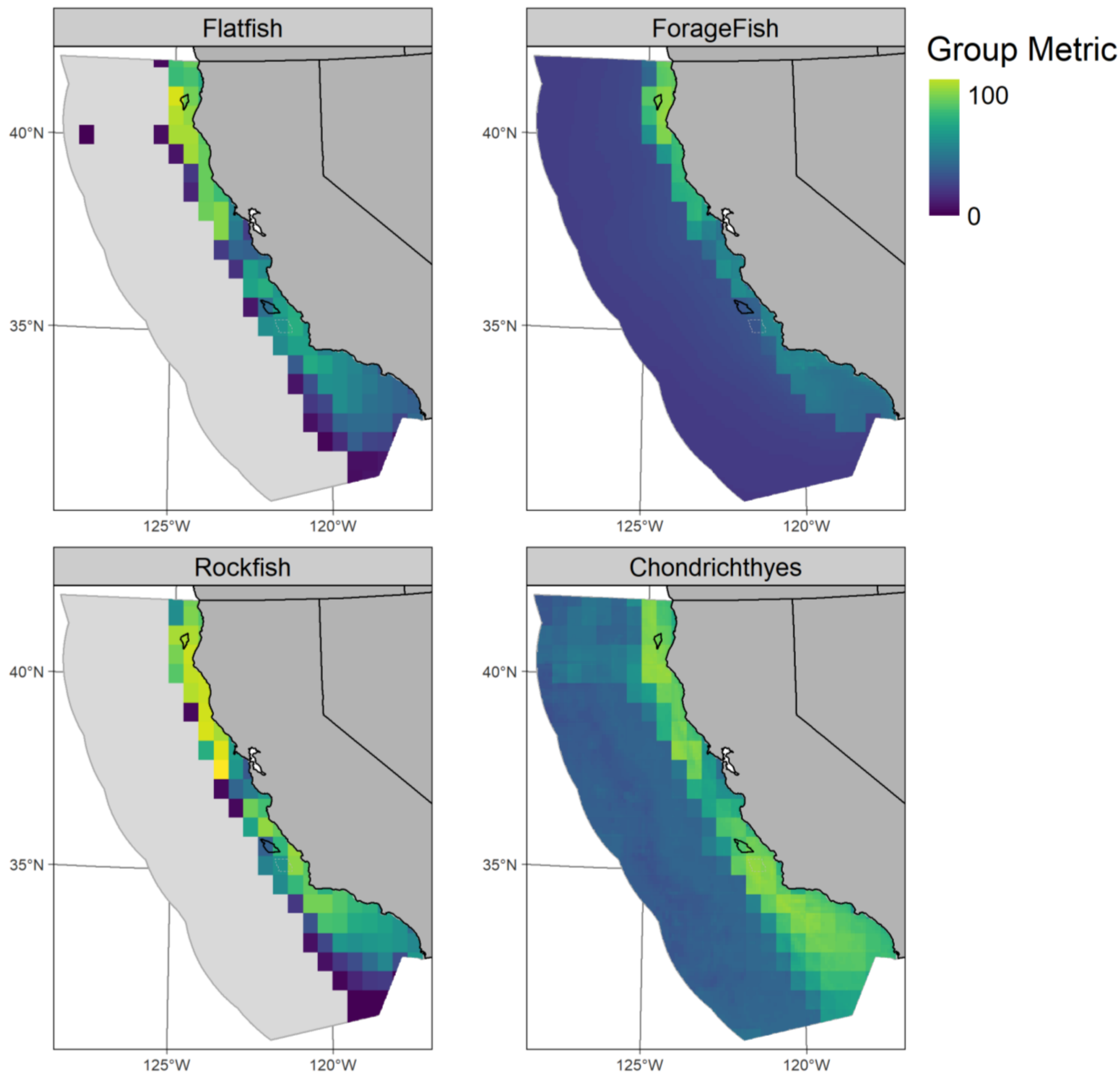

Figure 9. Group impact metrics for fish Groups. The scale is maintained across panels to ensure visual comparison between Groups. The WEAs are outlined in black.

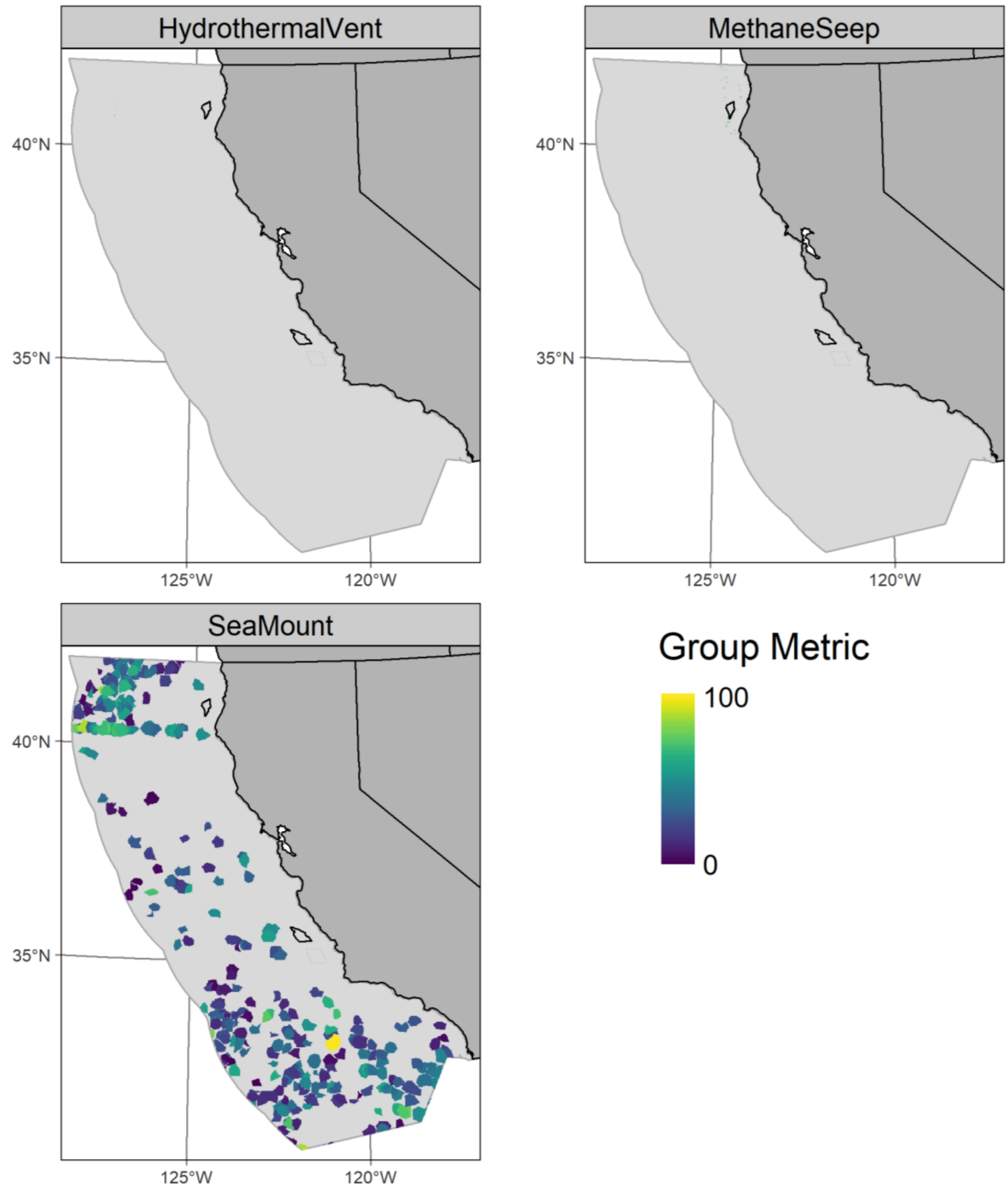

Figure 10. Group impact metrics for benthic habitat Groups. The scale is maintained across panels to ensure visual comparison between Groups. The WEAs are outlined in black.

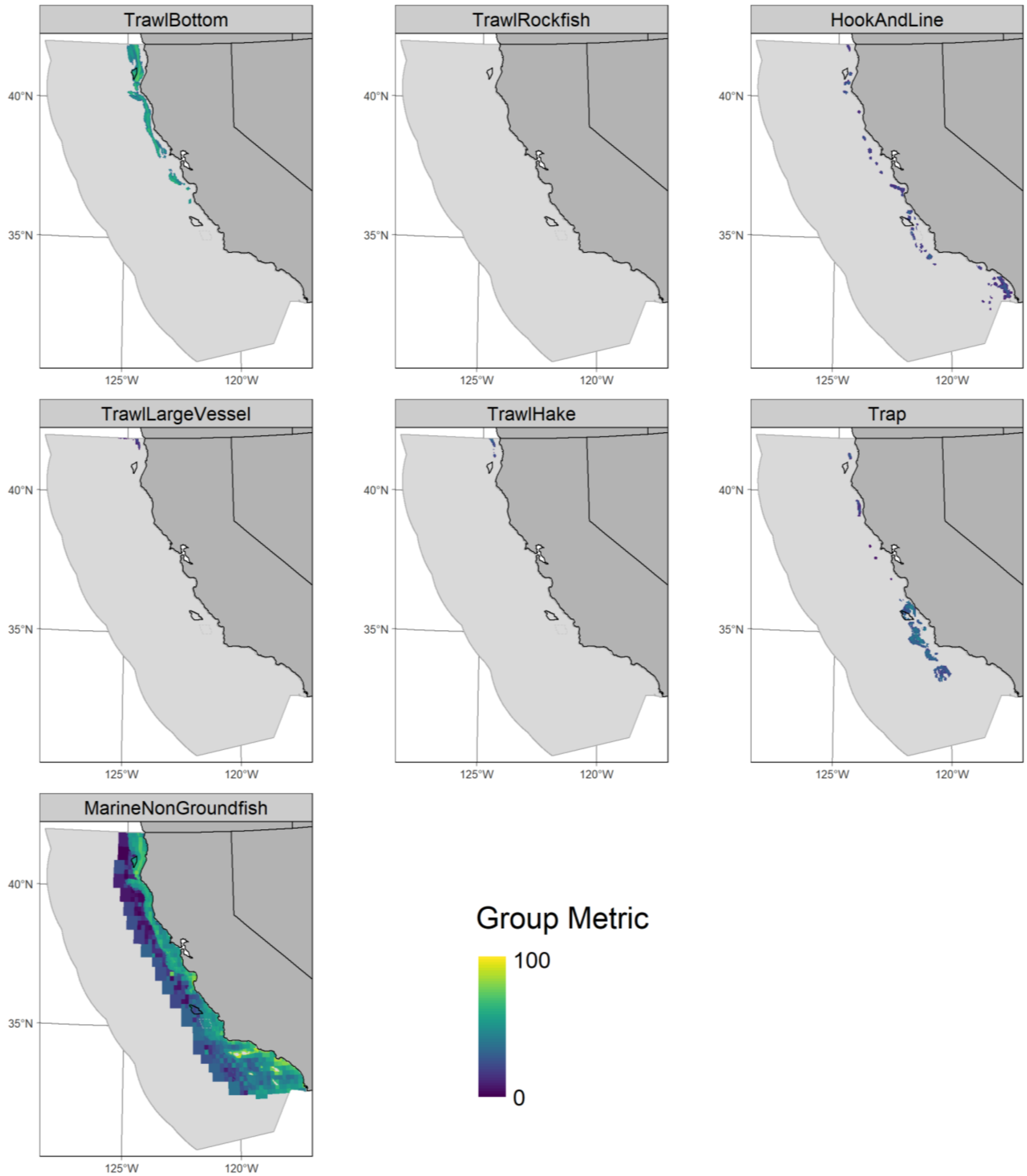

Figure 11. Group impact metrics for human use Groups. The scale is maintained across panels to ensure visual comparison between Groups. The WEAs are outlined in black.

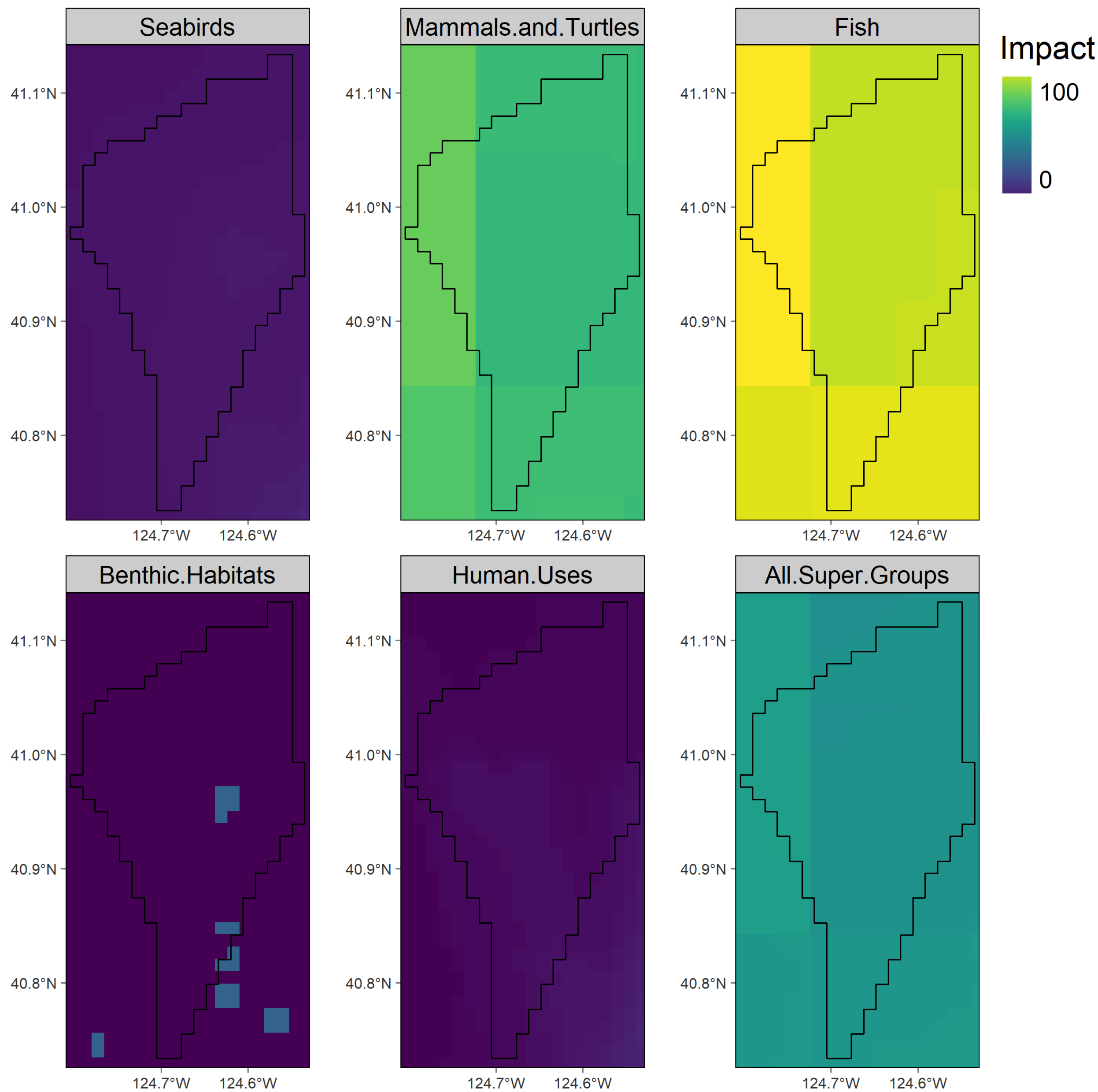

Figure 12. Maps of Super Group and combined cumulative impacts inside and around the Humboldt WEA. Higher impacts are in yellow while lower impacts are shown in darker blue.

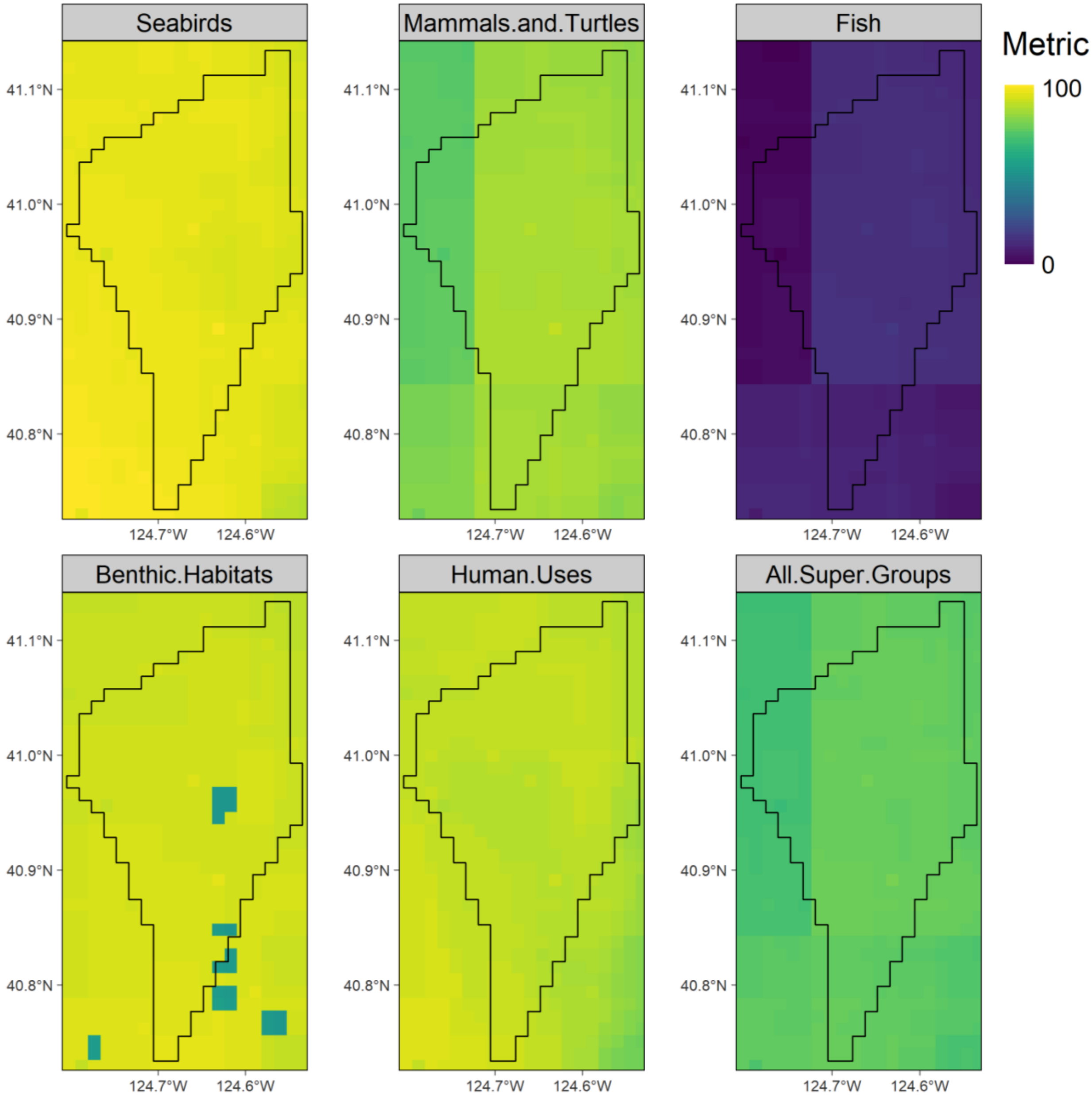

Figure 13. Maps of Super Group and combined benefit/impact trade-off metric inside and around the Humboldt WEA. Higher scores for the metric are in yellow while lower impacts are shown in darker blue and represent more desirable areas for development.

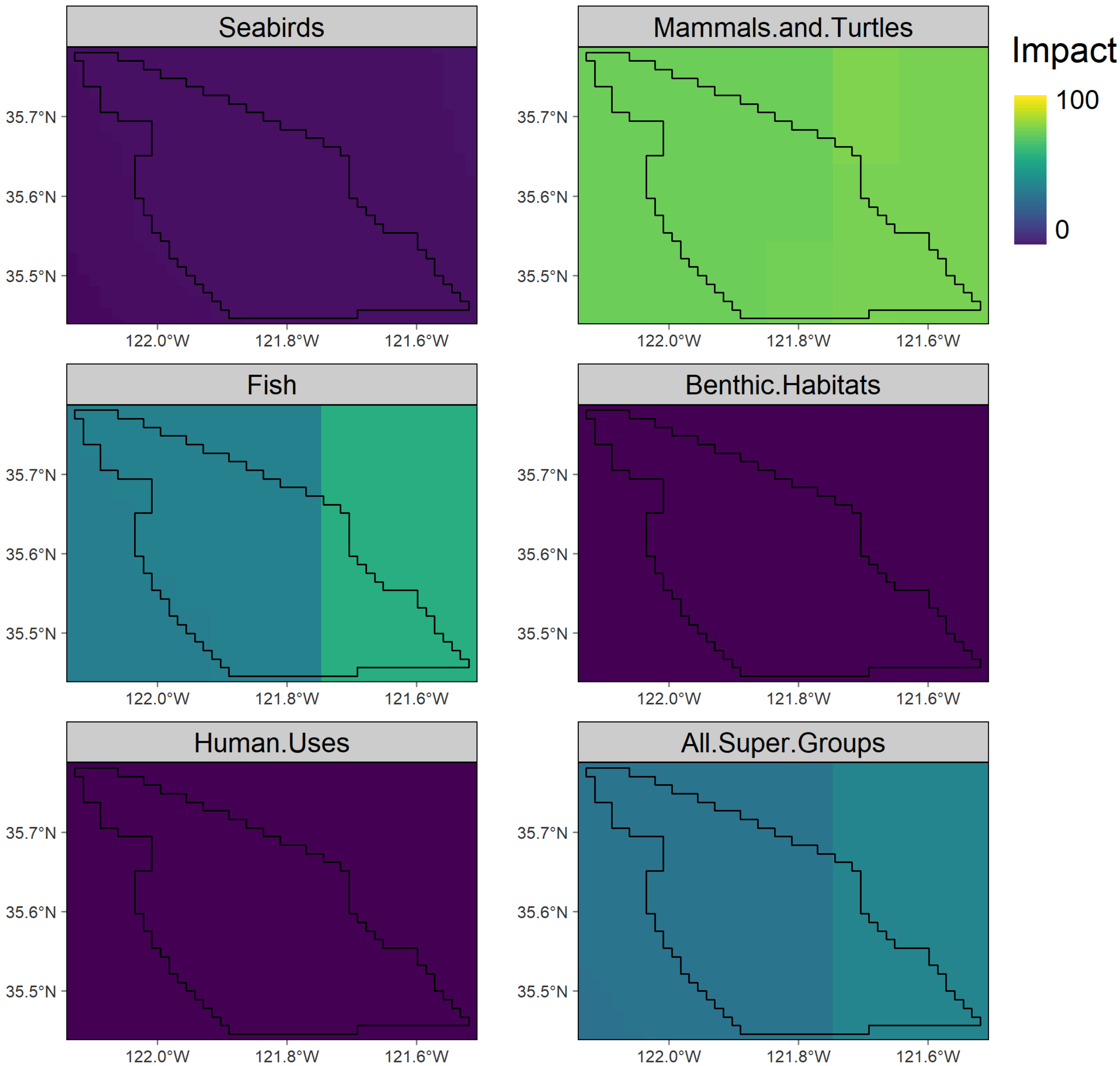

Figure 14. Maps of Super Group and combined cumulative impacts inside and around the Morro Bay WEA. Higher impacts are in yellow while lower impacts are shown in darker blue.

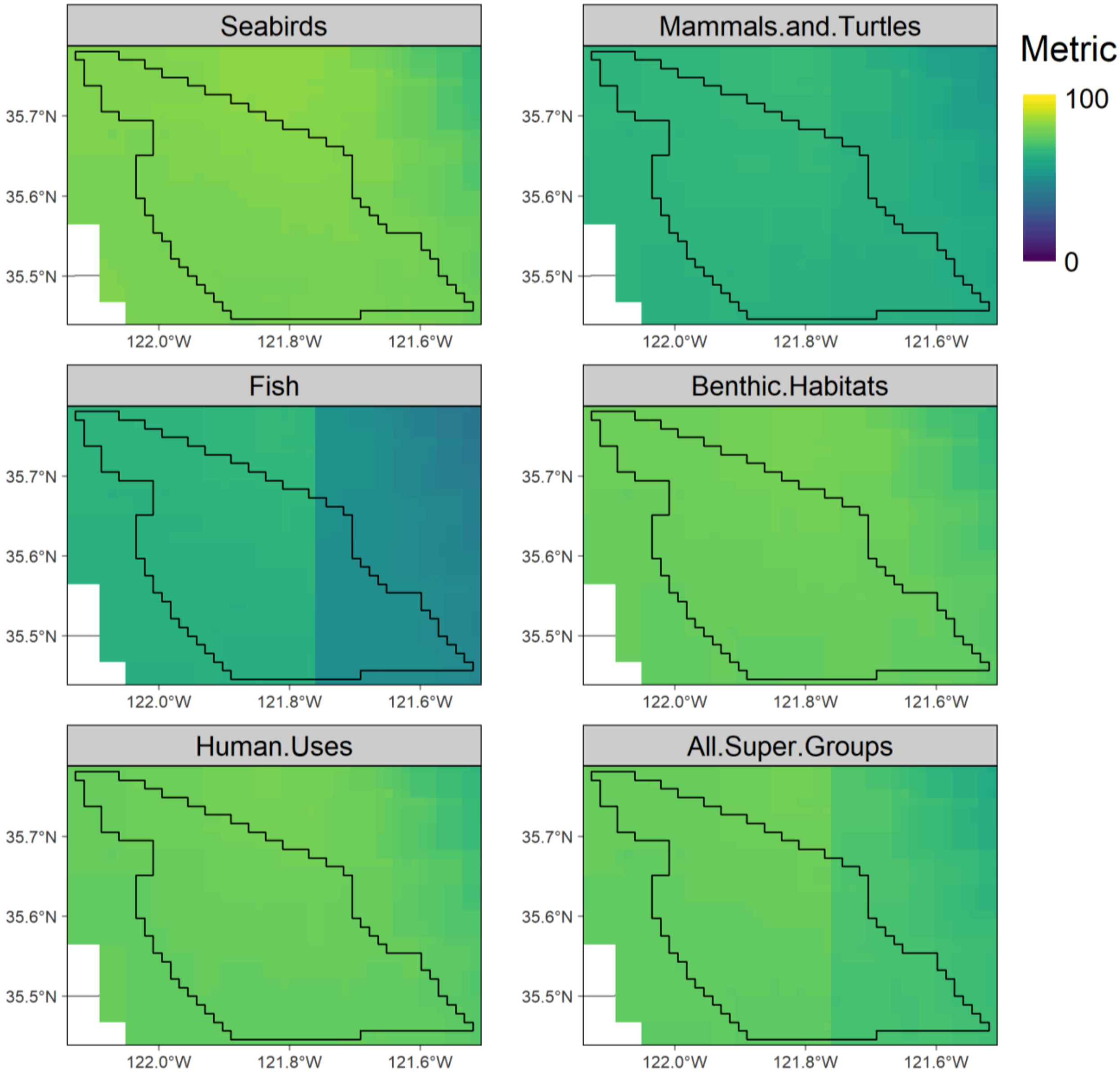

Figure 15. Maps of Super Group and combined benefit/impact trade-off metric inside and around the Morro Bay WEA. Higher scores for the metric are in yellow while lower impacts are shown in darker blue and represent more desirable areas for development.