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# Mapping Cumulative Impacts of Human Activities on Marine Ecosystems

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# ABSTRACT

Given the diversity of human uses and natural resources that converge in coastal waters, the potential independent and cumulative impacts of those uses on marine ecosystems are important to consider during ocean planning. This study was designed to support the development and implementation of the 2009 Massachusetts Ocean Management Plan. Its goal was to estimate and visualize the cumulative impacts of human activities on coastal and marine ecosystems in the state and federal waters off of Massachusetts.

For this study, regional ecosystem experts were surveyed to gauge the relative vulnerability of marine ecosystems to current and emerging anthropogenic stressors. Survey results were then combined with spatial information on the distribution of marine ecosystems and human stressors to map cumulative impacts in Massachusetts waters.

The study resulted in an ecosystem vulnerability matrix and human impacts maps, which together yield insights into which ecosystems and places are most vulnerable and which human uses, alone and in combination, are putting the most stress on marine ecosystems. These products can be used in a number of ways, including to help clarify ocean planning decisions, identify areas of potential conflict among ocean users and areas that may merit conservation, and assess ecological, economic and social values of particular places.



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SeaPlan initiated and participated in this effort to advance the scientific basis of coastal and marine spatial planning.

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# Mapping cumulative impacts of human activities on marine ecosystems

A SeaPlan funded project to support the development and implementation of the Massachusetts Ocean Management Plan

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## Executive Summary

More and more human activities depend upon and compete for coastal and marine ecosystem goods and services. This intensification of use is necessitating a shift toward more comprehensive and integrated approaches to management – a shift which is already underway via approaches like ecosystem based management and coastal and marine spatial planning. Given the diversity of human uses and natural resources that converge in coastal waters, understanding the potential independent and cumulative impacts of those uses and associated stressors on marine ecosystems can be very challenging. Few empirical data are available to weigh the relative vulnerability of the range of ecosystem types to the full set of human stressors, and robust methods for quantifying cumulative impacts have been lacking. Nevertheless, decision makers require scientific input in order to proceed with the priority setting, spatial planning and zoning of various human uses of the marine environment they are increasingly being called to undertake.

The state of Massachusetts (USA) passed the Massachusetts Oceans Act in 2008, requiring the Executive Office of Energy and Environmental Affairs (EEA) to implement a comprehensive ocean management plan for most of Massachusetts state waters (0.3 to 3 nm from shore), the first of its kind in the US. This plan is intended to address ocean uses or development that are incompatible with each other; uses or development that are incompatible with natural resources; and the overall balance of use, protection and development. To inform this effort, we first conducted a survey of regional experts in each of 15 different marine ecosystem types in order to gauge the relative vulnerability of each ecosystem to each of 58 different current and emerging anthropogenic stressors (Kappel et al. *in press*). Scores from the ecosystem vulnerability assessment were then combined with spatial information on the distribution of marine ecosystems and the distribution and intensity of human stressors to map cumulative impacts in the marine environment. Spatial data for all 58 stressors were not available; however, we synthesized, aggregated, and in some cases modeled a wide array of data to produce twenty-one human stressor data layers that represent many of the most important human uses of the waters

off Massachusetts. The resulting maps allow managers to visualize for the first time the pattern of human impact in state and federal waters.

Together these products yield insights into which ecosystems and places are most vulnerable and which human uses, alone and in combination, are putting the most stress on marine ecosystems. Because the cumulative impact framework we have developed is designed to be flexible, transparent, and easily updatable, it represents a powerful tool in a manager's toolbox for comprehensive ocean planning.

Our results reveal that ecological experts rank subtidal benthic habitats as most vulnerable to disturbance by human activities (especially hard bottom shelf and nearshore hard and soft bottom). They rank ocean warming, ocean acidification, invasive species, increased ultraviolet radiation, and ocean pollution among the worst threats to New England marine ecosystems. Maps of cumulative impacts highlight areas of intense use, especially within the coastal zone, where as many as twenty and no fewer than five different human stresors co-occur over the course of a year. The importance of ecosystem context can be seen from these maps, as the highest cumulative impacts are found in areas where many human stressors co-occur with particularly vulnerable marine ecosystems. In addition, differences in the spatial footprint of different activities can be understood from maps of individual stressors and subsets of stressors, e.g., the broad scale signal of climate impacts versus the watershed driven dynamics of land-based stressors.

The cumulative impact model, which combines ecosystem vulnerability, ecosystem distribution, and distribution and intensity of human stressors, has been vetted at global (Halpern et al. 2008b) and regional scales (Halpern et al. 2009, Selkoe et al. 2009). Cumulative impacts are modeled at each location in a 250m grid by adding up the combined impacts of the suite of human stressors that occur there, weighted by the average vulnerability of the ecosystem(s) found in that location to each stressor. This weighting accounts for the fact that the same activity or stressor may have different impacts in different ecosystems.

The weights are the ecosystem vulnerability scores derived from the survey of regional ecological experts, which was based on methods developed elsewhere (Halpern et al. 2007, Neslo et al. 2009, Teck et al. 2010). These scores allow us to compare very different stressors and ecosystems using a common scale. The expert survey also revealed important gaps in our knowledge of marine ecosystems of the region. In particular, expertise in algal zone, bathyal, and deep pelagic habitats was poorly represented in our survey, at least in part because few scientists study these habitats in this region. In addition, experts reported relatively high uncertainty about the effects of some stressors, in particular light pollution, noise pollution, military activity, atmospheric pollution, inorganic pollution, and ocean acidification.

Marine ecosystems (also known as habitats) were mapped using existing data from the Massachusetts Office of Coastal Zone Management. Maps of ecosystems were based on the best available data, but for some ecosystem types and some places, these maps may have important, but poorly known gaps. In particular, because of the lack of good side scan sonar data for much of the study region, hard bottom habitat is likely to be under-estimated. The algal zone, which we have modeled as being everywhere between 0-10m depth (except where eelgrass is known to occur), will be over-estimated. We have chosen a habitat classification system that takes advantage of the best available data, but a more finely subdivided classification that takes into account benthic biology as well as substrate type might be appropriate when more/better data become available. Because our method is dependent on the relative vulnerability of different ecosystem types, accurate data on the distribution of those ecosystems is critical to the accuracy of the final maps.

Next, though most of the major human stressors were included, we were not able to obtain data on all uses of the marine environment. We were not able to include potentially important impacts like changes in freshwater runoff and sedimentation, some sources of nutrient addition, or direct human disturbance from coastal visitation at this time, because existing data and models were inadequate. Other drivers were mapped using preliminary or partial data. For example, state fishing data is known to be incomplete and captures only a (unknown) portion of total fishing activity in state waters. Recreational fishing, like many other recreational uses of the marine environment, could not be mapped at all due to a lack of data. In addition, the impacts of certain activities have been modeled using simple methods (e.g., assuming diffusive spread of pollutants away from sources or using simple proxies when empirical data are lacking), which could be improved upon in the future. The impacts of some human activities are likely to be affected by oceanographic and ecological dynamics that are currently not captured by our mapping framework, which is static. Finally, our method captures a snapshot in time based on recent/current conditions (using data from the past 5 years). It does not incorporate historical changes to marine ecosystems in the study region, nor does it forecast future changes.

Despite these caveats, much can be learned from both our results and the process of developing cumulative impact maps. First, given the numbers of overlapping human uses we observed, it is clear that multiple use is the rule, not the exception in Massachusetts waters. Second, comparing cumulative impact maps to the “footprint” of human uses provides critical new insights into how we are impacting coastal and oceanic ecosystems: ecosystem context matters. Integrating ecological and human use data has yielded new insights and fostered collaboration among a network of data providers who might otherwise never have connected. Finally, a flexible, repeatable and transparent approach is necessary for buy-in, iteration, and adaptive management. Both the survey and cumulative impact model can be easily updated to account for new and emerging human stressors or to take advantage of new data. As new data become available, managers can produce updated maps to evaluate possible management decisions and monitor change through time. Improvements in habitat and human use mapping will serve to make the tool even more robust.

# Introduction

As the coastal zone becomes increasingly crowded, more and more human activities depend upon and compete for coastal and marine ecosystem goods and services. This intensification of use is one factor catalyzing a shift toward more comprehensive and integrated approaches to management like ecosystem based management and coastal and marine spatial planning (McLeod et al. 2005; Crowder et al. 2006; Day 2002; Douvere et al. 2007; Douvere 2008; Executive Order, 75 FR 43023 2010). Given the diversity of human uses and natural resources that converge in coastal waters, understanding and quantifying the potential independent and cumulative impacts of those uses on marine ecosystems can be very challenging. Few empirical data are available to weigh the relative vulnerability of the range of ecosystem types to the full set of human stressors (Halpern et al. 2007), and robust methods for quantifying cumulative impacts have been lacking (Halpern et al. 2008a). Nonetheless, decision makers require scientific input in order to proceed with the priority setting, spatial planning and ocean zoning they are increasingly being called to undertake (Leslie and McLeod 2007; Ehler and Douvere 2009).

The Commonwealth of Massachusetts (USA) passed the Massachusetts Oceans Act in 2008, requiring the Executive Office of Energy and Environmental Affairs (EEA) to develop and implement a comprehensive ocean management plan for most of Massachusetts state waters (0.3 to 3 nm from shore) to serve as the basis for long term protection and sustainable use of the state's coastal and ocean resources. The intent of the plan is to address ocean uses or development that are incompatible with each other; uses or development that are incompatible with natural resources; and the overall balance of use, protection and development. The plan must balance ocean protection not only with existing ocean uses, but also new and emerging ocean uses that have been proposed for Massachusetts waters, such as renewable energy, deepwater aquaculture, and offshore sand mining. Among other directives, the Act requires that EEA's plan "value biodiversity and ecosystem health" and "identify and protect special, sensitive or unique estuarine and marine life and habitats." Accordingly, the plan identifies special, sensitive and unique (SSU) marine resources, establishes marine resource management areas, and establishes management measures for those areas that both protect SSU resources and allow for permitting and siting of appropriate ocean uses within designated areas.

We identified two key knowledge gaps that our work might fill and which would support the development and implementation of the plan. First, comprehensive information on the relative vulnerability of marine ecosystems (aka habitats) to the full suite of human ocean uses was lacking, but such information could be critical to understanding compatibility. Second, no methods or data for visualizing the cumulative impact of the myriad human activities occurring in Massachusetts' waters were available to ocean managers, though current cumulative impacts provide the necessary context for considering any proposed future development.

To address these important scientific needs, we first conducted a survey of regional experts in each of 15 different marine ecosystem types in order to gauge the relative vulnerability of each ecosystem to each of 58 different current and emerging anthropogenic stressors (Kappel et al. *in press*). The Massachusetts Office of Coastal Zone Management (CZM) helped us to classify and map the 15 ecosystem types. The 58 current and emerging human stressors were developed based on our previous work, refined with input from SeaPlan and CZM. Scores from the ecosystem vulnerability assessment were then combined with spatial information on the distribution of marine ecosystems and the distribution and intensity of human stressors to map cumulative impacts in the marine environment, using a cumulative impacts model we developed and have tested at global (Halpern et al. 2008b) and regional scales (Selkoe et al. 2009, Halpern et al. 2009). Spatial data for all 58 stressors were not available; however, we synthesized, aggregated, and in some cases modeled a wide array of data to produce 21 human stressor data layers that represent many of the most important human uses of the waters off Massachusetts. The resulting cumulative impact maps allow managers to visualize for the first time the pattern of human impact in state and federal waters.

Together these products give us insight into which ecosystems and places are most vulnerable and which human uses, alone and in combination, are putting the most stress on marine ecosystems in the waters off Massachusetts. They also highlight important knowledge gaps that could hamper future management efforts if not addressed. Because the cumulative impact framework we have developed is designed to be flexible, transparent, and easily updatable, it represents a powerful tool in a manager's toolbox for comprehensive ocean planning.

In the remainder of this report, we describe the framework and methods used to develop ecosystem vulnerability scores, habitat maps, human use maps, and cumulative impact maps, and we discuss our results. We consider how these findings might help to inform and support the implementation of the Massachusetts Ocean Management Plan and outline ways that the process could be applied by state agencies for future analysis, decision making and monitoring in connection with the plan.

## Overview of the cumulative impact framework

In 2008, we published the first ever synthesis of the impact of human activities on marine ecosystems at a global scale, using global datasets for 17 different human stressors ranging from fishing to commercial shipping to climate change (Halpern et al. 2008b). The accompanying map contradicts the commonly held notion that much of the world's ocean is too vast or remote to be affected by humans (Figure 1). In contrast, over 40% of the world's oceans are heavily influenced by stresses associated with human activities, less than 4% can be considered relatively pristine, and no single square mile is untouched by human impact. Most parts of the globe, but especially coastal areas, are affected by a multitude of human uses.

We have since applied the same analytical framework for mapping cumulative impacts at the regional scale, in places where more and better data are available and can provide a more detailed picture of cumulative impacts (Halpern et al. 2009, Selkoe et al. 2009). While the global analysis can inform large-scale conservation and management priority setting, these regional analyses better match the scale of ocean management decisionmaking. These results and the cumulative impacts framework have generated significant interest in the marine spatial planning community (including among academics, policymakers and managers). We are currently adapting the model for use in the Great Lakes and discussing its application in other US states.

The analytical framework for calculating cumulative impact scores ($I_C$) is described elsewhere (Halpern et al. 2008b). Briefly, the cumulative impact model requires three inputs: maps of the distribution of marine ecosystems, maps of the distribution and intensity of human stressors and ecosystem by stressor vulnerability scores that essentially act as spatial weighting factors, either increasing or decreasing the relative influence of a given stressor, depending on the vulnerability of the ecosystems found in a particular location. The impact score, $I_C$ is calculated for each 0.0625 km$^2$ pixel (250m grid) by summing across all the human stressors and averaging across the ecosystems found in that pixel; because our model incorporates both pelagic and benthic ecosystem types, there can be more than one ecosystem in a given pixel.

$$I_C = \sum_{i=1}^{n} \frac{1}{m} \sum_{j=1}^{m} D_i * E_j * \mu_{i,j} \quad (1)$$

where $D_i$ is the log-transformed and normalized value (scaled between 0-1) of intensity of anthropogenic stressor $i$ of $n$ stressors (aka drivers of ecosystem change in Halpern et al. 2008b), $E_j$ is presence or absence of ecosystem $j$ of $m$ ecosystems, $\mu_{i,j}$ is the impact weight for anthropogenic driver $i$ and ecosystem $j$, and $1/m$ averages across the ecosystems found in a particular location.

We have used expert judgment to estimate the vulnerability scores or impact weights ($\mu_{i,j}$) because empirical data on many, if not most, ecosystem by stressor combinations are lacking. As described in the section below, experts were asked to quantify five different ecological components of the vulnerability of ecosystems to human activities (spatial extent, frequency, trophic impact, percent change in biomass, and recovery time) (Table 1). They assessed the vulnerability of 15 marine ecosystem types to a comprehensive list of 58 current and emerging human stressors found in the waters off Massachusetts (Table 4). A previously developed model was used to combine the five vulnerability criteria into a single vulnerability score (Neslo et al. 2008; Teck et al. 2010). We synthesized or modeled a wide array of data to produce 21 human stressor data layers. Cumulative impact to an individual ecosystem ($I_E$) was calculated as

$$I_E = \sum_{i=1}^{n} D_i * E_j * \mu_{i,j} \quad (2)$$

Impact of individual drivers across all ecosystem types ($I_D$) was calculated as

$$I_D = \sum_{j=1}^{m} D_i * E_j * \mu_{i,j} \tag{3}$$

And the footprint (unweighted by ecosystem vulnerability) of a driver ($F_D$) was calculated as

$$F_D = \sum_{i=1}^{n} D_i \tag{4}$$

All major ecosystems and nearly all major human stresses to them were captured, including locations of positive 'stresses' where extractive activities are prohibited (i.e. marine protected areas).

## Expert survey of ecosystem vulnerability

This section is adapted from Kappel et al. (*in press*). For further details on the methods and results of the expert survey, please see the full paper.

### Background on ecosystem vulnerability and expert elicitation

Previous efforts to assess threats to species and the environment and prioritize actions to mitigate them have tended to focus on single species, habitats or stressors (e.g., Mace and Lande 1991; Master 1991; Bryant et al. 1998; Roberts et al. 2002; Burke et al. 2002; Wilson et al. 2005; Vié et al. 2009). Few examine threats at the ecosystem scale, and even fewer integrate multiple stressors or multiple ecosystem types (but see community-level methods reviewed in Nicholson et al. 2006, and integrated ecosystem assessments, e.g., Wickham et al. 1999, Noss et al. 2002, and Tran et al. 2002). Though a few studies have compared a suite of different stressors (e.g., Wilcove et al. 1998, Kappel 2005), contrasting very different stressors (e.g., ocean acidification versus recreational fishing), especially at the ecosystem level, is challenging. In addition, many conservation priority setting exercises, (e.g., Noss et al. 2002), have been perceived as "black box" processes because they have relied on expert judgment collected behind closed doors (Regan et al. 2004, Beazley et al. 2010). Expert elicitation requires a transparent and clearly documented process so that the results will be reliable and repeatable (Tversky and Kahneman

1982; Plous 1993; Burgman 2001; Keith 1998; Rush and Roy 2001; Regan et al. 2004; Aspinall 2010).

We developed a tool for expert elicitation that addresses many of these issues. This well vetted and documented too, which has been applied previously with global and regional pools of experts, provides for transparency and repeatability (Halpern et al. 2007, Neslo et al. 2008, Selkoe et al. 2009, Teck et al. 2010). The structured framework for assessing ecosystem vulnerability to human stressors allows us to compare the effects of multiple stressors across different ecosystems on the same measurement scale and account for the fact that the same activity may have different effects in different ecosystems.

With 15 different ecosystem types and 58 different human uses and associated stressors, there are 870 possible stressor-by-ecosystem combinations, most of which have not been investigated scientifically. For this reason, empirical data could not be the sole source of information used to weigh relative vulnerability of ecosystems. Furthermore, a review of the scientific literature was unlikely to provide comprehensive information specific to the region. Therefore, we turned to regional experts to help us judge ecosystem vulnerability.

We used the elicitation framework referred to above to assess vulnerability of marine and coastal ecosystems (or habitats) of Massachusetts, such as beaches and dunes, seagrass beds, rocky reefs, and pelagic waters. We define an *ecosystem* as a complex system made up of a community of organisms together with their physical environment. We focus here on the vulnerability of ecosystems because this level of biological organization is important ecologically, economically and sociologically. At the ecosystem level, relationships among organisms and their environment underpin ecological structure and function. These interconnected ecological systems also support human systems by supplying valuable ecosystem goods and services like seafood production, clean water, and coastal protection. Recent approaches to management such as ecosystem based management and comprehensive marine spatial planning emphasize ecosystem level processes and interconnections and target management actions at an ecosystem scale.

Using a structured survey, we asked regional experts with experience studying each ecosystem to assess its specific vulnerability to a list of different human stressors associated with human activities. A *stressor* is defined as anything that may perturb an ecosystem beyond its natural limits of variation. For example, sea surface temperature rise is a stressor associated with anthropogenic climate change, and seafloor habitat destruction, biomass removal and bycatch are associated with demersal habitat-modifying fishing. Whether a stressor affects a particular ecosystem depends on that ecosystem's *vulnerability*. Vulnerability is dictated by *exposure*, or the chance that the ecosystem encounters a given stressor, *sensitivity*, or the degree to which the ecosystem is affected by the stressor, and *resilience*, the ability of the affected ecosystem components to recover from the stressor's disturbance (Millenium Ecosystem Assessment 2005).

To capture these various aspects of vulnerability, we use five vulnerability criteria: spatial scale in $km^2$ of a single occurrence of the stressor, frequency in days per year that the stressor occurs at a given location, trophic impact from single species up to entire community, percent change in biomass of the affected ecosystem component, and recovery time in years required for the ecosystem to return to natural conditions (Table 1). These criteria described were developed previously in a workshop at the National Center for Ecological Analysis and Synthesis that convened conservation scientists and ecologists (Halpern et al. 2007). The first two criteria quantify exposure to the stressor of interest. Trophic impact and percent change address which component(s) of the ecosystem are sensitive to a given activity or stressor and how sensitive they are. The final criterion, recovery time, measures an aspect of ecosystem resilience by asking how long it would take for the system to recover following removal of the stressor. Each expert scored the five criteria for each stressor's effects on their ecosystem of expertise. We then averaged the criteria scores for all experts in a given ecosystem type and combined them into a single vulnerability score, which can stand on its own as an index of ecosystem vulnerability to a particular stressor, but which is also used as the "impact weight" in the cumulative impact model.

Requiring the experts to evaluate ecosystem vulnerability using the same set of criteria and the same measurement scales aids them in formalizing their knowledge and improves transparency and repeatability (Regan et al. 2004). A separate task in the survey allowed us to quantify the importance or weight the experts gave to each of the five criteria when making their decisions about ecosystem vulnerability. This means that were we were not limited to equal weighting when we summed the criteria into a single vulnerability score. For example, experts may feel that percent change in biomass is more important to vulnerability than a stressor's spatial extent. We used methods from the field of decision theory to determine the relative importance or weight of each criterion to expert judgment of vulnerability and test how weights varied across experts. One goal of the survey of New England experts was to assess whether this pool of experts perceive the criteria similarly to experts previously surveyed in the California Current region, (along the west coast from the US-Canada border south to Baja California Sur), and thereby validate the generality of our model of ecosystem vulnerability. The main output of the survey is a matrix of vulnerability scores across all ecosystems and human stressors. Those scores can be used to rank stressors or rank ecosystems to guide management decisionmaking and prioritization efforts.

## Expert elicitation methods

### Experts

We defined experts as academic, agency, nongovernmental organization or private scientists or managers with expertise in the ecology and/or management of fifteen different regional coastal and marine ecosystems (Table 2) and experience with one or more of the 58 human stressors (Table 4). Each expert had worked in the waters of New England for two or more years. We identified experts via Google Scholar searches using combinations of the ecosystem types and human stressors. We further refined the pool of experts by limiting it to authors of published, peer reviewed papers that addressed one or more stressors within relevant marine ecosystems of the region and who had significant experience in the region as determined from their curriculum vitae or websites (e.g., working at a New England institution, publishing multiple relevant papers and/or participating in major research projects in the area). We identified other experts, especially government scientists, through recommendations of Massachusetts Executive Office of Energy and Environmental Affairs (EEA) and SeaPlan. We also asked respondents to recommend other potential experts (a snowball sampling procedure, *sensu* Goodman 1961; Meyer 2001).

## Survey instrument and data collection

The Massachusetts marine ecosystem vulnerability survey was based on and refined from previous instruments deployed globally (Halpern et al. 2007), in the Northwest Hawaiian Islands (Selkoe et al. 2009), and in the California Current (Neslo et al. 2008, Teck et al. 2010). The survey instrument was pre-tested with a group of seven experts, none of whom participated in the final expert pool. Kim Starbuck (SeaPlan) contacted potential experts by email or telephone and invited them to participate. Willing participants were sent up to three reminder messages or calls until they returned their surveys or were classified as non-respondents. Respondents filled out a survey for each of the ecosystems (one or more) in which they had expertise. We collected expert knowledge using a spreadsheet-based survey instrument with pull-down menus. We provided clear instructions for the survey through written documentation and a video tutorial. Survey materials were distributed via the web and returned anonymously online.

The survey was composed of two sections. The purpose of the first section was to collect information that would help us to derive the vulnerability weights for our model of ecosystem vulnerability. In this section, we asked experts to rank a set of human stressor scenarios, identifying which represent the highest vulnerability for a hypothetical ecosystem based on given values for the vulnerability criteria. For example, we asked them to compare a scenario in which a stressor is known to occur at a spatial scale of 10 km$^2$ with a frequency of once a year, which impacts the entire community (trophic level=4) with a 25% change and a recovery time of 1 year, to another scenario with spatial scale of 1 km$^2$ and frequency of 365 days/year, impacting a single species with a 80% decline in biomass and six month recovery time. We asked each person to choose the five "worst" of these stressor scenarios for the hypothetical ecosystem and rank them 1 to 5 in decreasing order of vulnerability. Our intent was to elicit how important each of the five criteria is for experts' ranking of vulnerability. This was accomplished by comparing the distribution of criteria values in the scenarios to the experts' rankings of those scenarios, using a mathematical technique called probabilistic inversion to fit a multicriteria decision model (see Kappel et al., in press for details).

The second section of the survey was used to gather quantitative estimates of vulnerability for every ecosystem–stressor combination. However, because experts could only be expected to comment in detail on ecosystems for which they had knowledge, a single survey addressed one ecosystem type only. For each of the list of 58 human stressors, the expert considered their ecosystem of expertise and estimated a value for each of the five vulnerability criteria from a pull-down menu of ranges (see Table 1) or stated that they did not know what the value should be. These values were averaged across replicate surveys for each ecosystem (e.g., all beach surveys were combined to get vulnerability criteria values for beach habitat for each stressor). In the next section, we explain how these average criteria values were combined into a single score.

## Ecosystem vulnerability model

We treat vulnerability as the weighted sum of the five vulnerability criteria described above (Table 1), represented mathematically as:

$$\text{Vulnerability}\left(\text{driver } i, \text{ecosystem } j\right) = \sum_{k=1,\ldots,5} \mu_k D_{i,k}^{j} \tag{5}$$

where $D_{i,k}^{j}$ is the value of criterion *k* for stressor (aka driver) *i* in ecosystem *j*, and $\mu_k$ is the weight assigned to criterion *k*, such that $\mu_{k\geq 0}$, $\sum_{k=1,\ldots,5} \mu_k = 1$. We use an additive, linear model with positive weights because we expect vulnerability to be monotonic with respect to all five criteria, (i.e. higher values of the criteria should be associated with greater vulnerability of the ecosystem). A linear model is the simplest, most easily interpreted model form, and it allows us to compute scores for new scenarios not included in section one of the survey by simply supplying values for the five criteria, multiplying them by the model weights and summing them. We assume that the criteria weights are consistent across all stressors and ecosystems; this allows us to use a single model for all ecosystem-by-stressor combinations and to compare them directly. The methods for deriving the model weights are detailed in Kappel et al. (in press).

Prior to all analyses, spatial scale and frequency values were transformed to bring them within a similar range of values to the other vulnerability criteria (scale = ln[scale×100] and freq = ln[freq×360]. This was necessary to avoid these criteria unduly biasing the results simply because they have larger ranges. Once weights for each of the criteria were determined using probabilistic inversion, we multiplied them by the average values for each criterion, which were computed by averaging across replicate surveys within each ecosystem type. The five weighted average criteria values were then summed to create a final vulnerability score for each ecosystem–stressor combination. This resulted in a matrix of scores for all possible combinations, from which we calculated average scores by stressor (across all ecosystems) and for each ecosystem (across all stressors), allowing comparison among stressors or ecosystems and identification of important knowledge gaps.

### Comparison of Massachusetts and California Current models

We compared model weights from the Massachusetts pool of experts to those from the California Current to test how generalizable our model of ecosystem vulnerability might be across different regional pools of experts. We interpreted similar model weights between the two pools of experts as evidence that they have a shared conception of ecosystem vulnerability and the relative importance of the five vulnerability criteria. This suggests that the model can be used in other regions and applied to other stressors.

### Gap filling

Gaps in the matrix of vulnerability scores point to understudied ecosystems and/or stressors and yield insights into future research needs. For the purposes of the cumulative impact model, however, we require a full matrix of scores. When necessary, we filled gaps in the matrix using data from our previous work in the California Current. To do so, we calculated new average scores for missing ecosystem by stressor combinations using the vulnerability criteria weights derived from the Massachusetts survey (see Model Results below). We then inserted these new weighted scores from the California Current (CC) survey into the Massachusetts survey gaps, matching habitats. In most cases, we only needed to fill a few combinations where no data were available from the Massachusetts survey. However, for the bathyal and deep pelagic habitats, we had so few respondents that we added in the overall average scores from the CC for all stressors, either directly, if there were no Massachusetts responses, or by averaging them with the MA response(s). For hard bottom bathyal (>200m), we used hard bottom slope (200-2000m) results, and for soft bottom bathyal (>200m), soft bottom slope (200-2000m). Gaps in the nearshore hard bottom were filled with results from the CC rocky reef ecosystem type, and gaps in nearshore soft bottom were filled using CC shallow soft substrate results. Tidal flat gaps were matched to CC mud flat responses. All of these ecosystems were defined in the same way in terms of depth and substrate type, but were given different names in the two surveys. Algal zone gaps were the most difficult to fill, because this habitat type is less directly comparable to those on the west coast, though it has some overlap with both rocky reefs and kelp forests. For algal zone, we used a literature search to fill gaps for ocean acidification, sea temperature change, UV change, coastal engineering, demersal habitat-modifying fishing, pelagic high bycatch fishing, pelagic low bycatch fishing, invasive species, nutrient input, ocean pollution, atmospheric pollution, light pollution, organic pollution, coastal power plants, inorganic pollution, and whale watching.

## Results of expert survey

### Survey response rate

We invited 332 potential experts to take the survey. Twenty-one self-identified as non-experts, and 112 did not respond. Of the remaining 199 potential experts, 57 agreed to participate, yielding a participation rate of 28.6%. Some experts returned surveys for more than one ecosystem, resulting in a total of 87 completed surveys for the ecosystem vulnerability section of the survey. We discarded one survey because the expert did not specify an ecosystem type and only provided information on a single stressor. We removed an additional survey for the algal zone habitat that was identified as an outlier based on extremely high criteria values (more than four standard deviations from the mean for that ecosystem). As no expert evaluated hard bottom bathyal habitat, we eliminated this ecosystem from further analyses. Though our target was three to five survey responses per ecosystems type, in some cases, we received fewer than three responses. We included results for these ecosystems for comparison's sake, but our confidence in these results is lower than for better-sampled ecosystems.

Section one, the ranking section, was added to the survey instrument in a second round of sampling, so not all experts completed this portion of the survey: 35 ranking sections were returned – 26 from coastal habitat experts and 9 from offshore habitat experts.

### Demographics of survey respondents

We received completed surveys from 37 men and 20 women. Respondents had an average age of 47.1±1.6 years (mean ± standard error henceforth), with an average of 18.9±1.4 years of experience working in the region and an average of 19.1±1.6 years of experience in their ecosystem of expertise. Most respondents (65%) were PhD-level scientists, but 25% had a Master's degree and 10% had a B.S. or other degrees. The majority of respondents were employed by academic institutions (35%) or government agencies (33% federal, 23% state), while 7% came from NGOs and 2% from private firms. Expertise came from throughout the region: 63% of respondents indicated that their answers applied to the entire New England region, 21% said their answers applied to the Acadian biogeographic province north of Cape Cod and 16% said their answers applied to the Virginian province, south of the Cape. Tests for bias in survey results with respect to gender, affiliation or years of experience were negative, indicating that this was a fair sample of the expert pool (Kappel et al., in press).

## Model results

Kappel et al. (in press) found that both coastal and offshore experts ranked scenarios similarly. Both groups relied most heavily on trophic impact and percent change in biomass of the affected ecosystem component(s) in making ranking decisions (weights of 0.466±0.074 and 0.345±0.059, respectively, for coastal experts and 0.542±0.103 and 0.283±0.077, for offshore experts). The authors found that New England experts' responses to the ranking section were broadly, but not wholly consistent with a linear, monotonic model of vulnerability based on our five criteria. Experts agreed that vulnerability increases with the number of species and trophic levels affected, the magnitude of change in biomass in these affected species or trophic levels, and the length of time required for recovery, as well as the spatial extent and frequency of stressor events. New England results supported the generalizability of the model developed in the California Current: in both regions, experts placed a combined weight of 81 to 89% on trophic impact and percent change in biomass when determining ecosystem vulnerability (Table 3).

## Ecosystem vulnerability

Experts judged coastal and offshore benthic habitats, specifically hard bottom shelf, nearshore soft bottom, soft bottom shelf, algal zone, nearshore hard bottom, and tidal flats to be most vulnerable to human impacts in this region (see score means, Table 4). Intertidal and pelagic habitats received lower vulnerability scores. One should treat these results with caution however, as overall sample sizes and average score sample sizes for some ecosystems were quite low

(Table 5). It is especially problematic that one of the most vulnerable habitats, algal zone, and one of the least vulnerable, soft bottom bathyal, had overall sample sizes of two or fewer experts, average score sample sizes below two, and missing vulnerability scores for many stressors.

Top stressors include climate change impacts from rising ocean temperatures and ocean acidification, invasive species, increased ultraviolet radiation exposure, and ocean pollution (e.g., chemical and oil spills from ships and ports). This ranking of stressors is similar to that observed in the California Current, where ocean acidification, ocean warming, and invasive species were also seen as top threats by regional experts (Table 6). There were differences in perceived ecosystem vulnerability, though, both in terms of specific stressors and the overall level of vulnerability, which was generally lower in the eyes of California Current experts (mean 0.7±0.07 SE) than New England experts (mean 1.9±0.1 SE). However, the difference in overall mean scores was partly driven by differences in model weights between the two regions. If California Current vulnerability scores are re-calculated using the Massachusetts model weights, the overall range and mean are comparable to that in Massachusetts (MA range: 0.3-4.5; CA range: 0-4.2, mean 1.4±0.12 SE) (Table 6). The Massachusetts model likely results in greater overall scores because it gives greatest weight to trophic impact, which is an integer from 1-4, whereas the CC model gives greatest weight to percent change, which ranges from 0 to 1.

# Discussion

## Model results

As in the California Current region, New England experts emphasize trophic impact and percent change in biomass of affected ecosystem components in ranking ecosystem vulnerability. By weighting these two criteria heavily, experts have focused mainly on the *sensitivity* of an ecosystem to particular stressors when determining vulnerability.

Previous investigations of this model have shown strong internal model validity (Neslo et al. 2008, Teck et al. 2010). The Massachusetts results add further support for the model by demonstrating consistent results for coastal and offshore expert groups within the region and similar model weights to those derived from the California Current expert pool, (i.e., across regions). In combination, these results suggest that this is a reliable model of experts' perceptions of ecosystem vulnerability, which may be used in a variety of settings across a wide array of marine ecosystem types.

## Ecosystem vulnerability and stressor ranking

The top threats identified by New England experts (climate change stressors, invasive species, ocean pollution) correspond to a certain degree with important stressors identified in the literature (e.g., Harris & Tyrell 2001, Scavia et al. 2002, Stachowicz et al. 2002, Lotze et al. 2006). Historical overfishing, nutrient input, pollution, and habitat destruction through various means are generally emphasized as the major drivers of change in ecosystems of the region (Howarth et al. 1996, Short & Burdick 1996, Steneck 1997, Jackson et al. 2001, Lotze et al. 2006, Steneck et al. 2004). While some of the stressors that rank high in our results correspond to this list (especially pollutants), others, like fishing, ranked surprisingly low. In part, these differences may result from the fact that our model looks only at recent impacts (last five years), rather than historical change. Many of the higher ranked stressors are more recent or emerging threats, such as climate change and energy development. This disparity may also reflect the difference between theoretical vulnerability and actual impact, which depends not only on vulnerability, but also on the intensity and extent of disturbance by the stressor. The latter is depicted by our cumulative impact model (results discussed later in this report).

Ecosystem vulnerability ranks also ran somewhat counter to common perceptions. Eelgrass is frequently cited as a critically threatened ecosystem in the region (e.g., Stuart & Burdick 1996), yet its overall vulnerability score was intermediate among the 15 ecosystems. Other intertidal ecosystems such as salt marshes and tidal flats that are also typically cited as at risk had moderate average vulnerabilities (e.g., Scavia et al. 2002, Lotze et al. 2006). This may be because the survey does not take into account historical alterations to these ecosystems or overall impacts, which depend not only on vulnerability but also the distribution and intensity of stressors. Alternatively, it may reflect differences in how experts rank ecosystems "off the cuff" versus how they rank them when using our structured approach. Other ecosystem rankings were more in keeping with standard notions of vulnerability. Hard bottom shelf was rated as highly vulnerable, in keeping with the general perception of this as a habitat that is highly vulnerable to fishing, climate change, and other stressors (e.g., Watling and Norse 1998, Hall 2002, Drinkwater 2005).

## Data needs

The expert elicitation framework we described here filled a critical need for objective and quantitative ways to compare the relative vulnerability of a diversity of ecosystem types to a broad suite of human stressors. The resulting data help to fill many important data gaps for understudied ecosystems and stressors and provide useful information on potential incompatibilities between particular ecosystems and human uses, which may help to inform ocean management and planning in Massachusetts.

The survey also helped to identify knowledge gaps and uncertainties for the region that even expert knowledge is hard pressed to fill. For example, despite our efforts, very few experts filled out surveys for several ecosystem types, (especially algal zone (n= 2, after outlier removed) and soft bottom bathyal (n= 1)). These and other ecosystems are also plagued by gaps for individual stressors, where all experts answered, “don’t know”. Even ecosystems with decent sample sizes, (e.g., nearshore soft bottom and soft bottom shelf), sometimes have large numbers of understudied stressors, for which no experts were able to score our vulnerability criteria.

Though a very large number of experts were contacted and agreed to participate in the survey, we still ended up with small sample sizes for some ecosystems, because the expert pool must be divided among so many different ecosystem types. Lack of experts for particular ecosystems may be due to a real dearth of expertise for those ecosystem types in this region and/or reluctance on the part of such experts to participate. Targeted funding may be necessary to address knowledge gaps highlighted by this work and increase our understanding of the impact of certain stressors in marine environments.

In order to use vulnerability scores from the survey in the cumulative impacts model, values were required for all of the mapped ecosystems and stressors. We filled in missing values using vulnerability scores from our previous work in the California Current (Table 7). Because vulnerability scores on average were lower in the California Current than in Massachusetts, this may lead to underestimation of the importance of the stressors for which values were substituted.

### Potential survey redeployment

Once the matrix of vulnerability scores has been populated, there is no need to repeat the survey unless one has reason to believe that vulnerability for one or more ecosystem by stressor combination has changed fundamentally or unless one wants to attempt to fill gaps or consider new ecosystem types or human stressors. There were some challenges associated with this expert elicitation approach including the time and labor costs associated with deploying the survey, a rather time-intensive survey instrument, reluctance on the part of some scientists to participate, and survey fatigue within the expert pool. However, given the robustness of the model and its validation across very disparate groups of experts, it may be used in novel settings and to address emerging stressors without having to redeploy the entire survey. Ecosystem vulnerability to new and emerging human stressors could be evaluated with a smaller group of experts and much shortened survey instrument (restricted to the new stressors and relevant ecosystems).

## Conclusions

Ecosystem based management and other forms of comprehensive ocean management require robust methods for assessing the impacts of human activities on marine ecosystems (Leslie and McLeod 2007; Halpern et al. 2008a; Ehler and Douvere 2009). Unfortunately, few tools exist to easily and robustly assess the impacts of the myriad human uses that compete for space in coastal waters. Even worse, data that could help us to understand the relative threat to marine ecosystems from the cumulative impacts of these various activities are fragmentary. Approaches that can aggregate the collective expert knowledge of the people who know these ecosystems best will be necessary in order to move forward with marine spatial planning in the face of such pervasive and severe data gaps. We provide one framework for doing so – one that is flexible enough to be applied in a variety of settings and easily transferred to new situations. The framework is ecologically grounded, flexible, transparent, and easily updated to accommodate emerging stressors. The framework is objective-neutral, meaning that it does not have as its end goal informing a particular kind of management action, like marine protected area design. Instead, the results of this expert elicitation approach can be used to inform a variety of conservation and management prioritization and planning exercises. In Massachusetts, it can specifically inform the assessment of compatibility between ocean uses and resources and feed into spatial maps of the cumulative impact of human stressors on marine ecosystems. Future work might expand this approach to evaluating anthropogenic stressors by assessing management criteria like feasibility of addressing a particular stressor, enforceability, and cost. Finally, marine spatial planning may benefit from expanding our definition of the "expert," for example our survey could be tailored to elicit information from traditional ecological knowledge holders like fishermen (Murray et al. 2006; St. Martin et al. 2007; Johannes et al. 2008).

## Cumulative impact mapping

### Background

As noted in the introduction, few quantitative methods for understanding cumulative impacts to marine (or terrestrial) systems have been developed. This may reflect gaps in our empirical understanding of individual impacts to particular systems, the challenges of combining information measured in very different ways, and/or the lack of cumulative impact frameworks. We have conceived and tested a novel technique for comparing and combining the impacts of a wide range of very different stressors to the full gamut of different marine ecosystem types (Halpern et al. 2008a). The method takes into account the importance of ecosystem context, namely that the same stressor can have very different effects depending upon the ecosystem in which it occurs. It uses results of the vulnerability assessment described above to yield "apples-to-apples" comparisons of diverse stressors. And it relies on transformation and normalization of overall stressor intensities to allow comparison of relative impacts and combination across different units and measurement scales.

As stated earlier, there are three inputs to the cumulative impact model: vulnerability scores, habitat maps, and maps of the distribution and intensity of human stressors. Details of habitat and human stressor mapping are given in the Ecosystem Mapping and Human Stressor Mapping sections below. In the Methods section below we detail the steps required for preparing data layers for entry into the model and running the model. A narrative description of each of the resulting maps is also included, followed by discussion and conclusions.

## Methods

All data layers and model outputs were produced on a 250m grid (0.625 $km^2$ grid cells), matching the management unit planning grid used by EEA in the Ocean Management Plan. The study region extends from the Massachusetts shoreline through state waters out to the boundary of the US exclusive economic zone (the outer limit of federal waters) (Figure 2). The northern and southern boundaries are extensions of Massachusetts state lines.

All data layers were converted to 250m grid ArcGIS raster files in ArcGIS 9.3.1. Habitat data layers were expressed as binary rasters representing the presence (1) or absence (0) of each habitat type in each 250 m grid cell. Before input into the cumulative impact model, each human stressor raster was log transformed to reduce the influence of extreme values. It should be noted that for some stressors (e.g., noise pollution), these extreme values may actually be of particular interest because it is only at these levels that there are impacts on species or ecosystems (e.g, sound levels so loud they cause injury to cetaceans within range). Nevertheless, for most stressors, log transformation just reduces the influence of outliers. It is possible to apply a different transformation to the data layers and re-run the model, should that be desired. After transformation, each raster was normalized so that its values ranged from zero to one. This allowed comparison of intensities measured in different units and prevented stressors with higher magnitudes from dominating the analysis. Weighting of the stressor layers is accomplished via the vulnerability scores, as described above in the Overview of the Cumulative Impact Framework section.

Pre-processed rasters (contained in UCSB_model_inputs_2010 geodatabase) were then imported into the open source GIS software GRASS v. 6.3, along with a matrix of vulnerability scores covering the 315 ecosystem by stressor combinations represented by the 15 ecosystems and 21 stressors. The cumulative impact model runs in GRASS using a series of Python scripts. The resulting maps are exported back to ArcGIS for display and cartography.

## Results and narrative description of maps

This section of the report comprises results from cumulative impact mapping for Massachusetts. These take the form of spatial maps with a grid resolution of 250 m (cells of 0.0625 $km^2$ in area) accompanied by a brief narrative describing features of each. Maps are shown for two spatial extents – one set encompassing the entire study region out to 200nm and one set zoomed in to focus on state waters. We present maps of the distribution of overall cumulative impact and maps of the impact of subsets of stressors (climate-related, land-based, fishing, and other commercial activities). We also show maps of the number of stressors occurring in each pixel and maps of the footprint of stressors (i.e. just their summed intensities, without accounting for ecosystem vulnerability).

When interpreting these maps, please keep in mind that the cumulative impact scores are only meaningful relative to each other; they are not absolute scores. In addition, because appropriate groundtruthing data that could be used to pin the cumulative impact score scale to empirical measures of ecosystem condition (as was done in the global project, Halpern et al. 2008b) are not available for the region, we are not able to say what a particular score "means" in terms of level of impact. There may be an opportunity to compare our impact scores to monitoring data and other measures of ecosystem condition for the particular ecosystem types and locations where they exist (e.g., MWRA outfall). For this report, the color scale of each map is based solely on standard deviations of the distribution of impact score values, and while red areas of the map are more impacted than orange, yellow, or blue areas, we cannot say that red represents heavy impact or that blue represents no impact because of the lack of groundtruthing data. The color scales for all maps except Figures 10 and 11 (Number of human uses) are stretched over four standard deviations. The number of human uses scale is stretched over two standard deviations.

### Cumulative impacts (Figure 6)

This map shows the cumulative impact of all 21 human stressors on 15 marine ecosystems in the waters off of Massachusetts. The highest cumulative impact scores (yellow to red colors) can be seen in coastal waters – especially within and offshore of Boston Harbor, down through the Great South Channel and north of Gloucester. Watershed plumes are visible in parts of the nearshore, and many coastal pixels have high (orange to red) values because of these and other land-based sources of stress (e.g., light pollution). Nearshore areas are red both because of higher stressor levels, larger numbers of co-occurring stressors, and because of the relatively high vulnerability of nearshore habitats to many stressors.

A number of habitat effects can be seen in this map. The 10m, 30m, 60m, and 200m isobaths that define different habitat types (algal zone, shallow pelagic, nearshore soft and hard substrate, shelf, bathyal and deep pelagic) are visible in various places in the map. Differential vulnerability of these habitats leads to clear boundaries in some locations (e.g., the irregular yellow-blue boundary offshore, which defines the start of deep pelagic habitat, and the blue area around the islands beyond which shallow pelagic habitat begins). As noted in the description of pelagic habitats, we assumed that benthic and pelagic habitats are fully coupled in waters <30m deep, so we do not map a separate pelagic habitat within this depth range. Beyond 30m, we treat the photic zone (0-200m) as an additional habitat overlying benthic habitats, and average their vulnerability scores. Once you get out to waters >200m deep, there are three habitat layers: benthic, deep pelagic (or aphotic), and shallow pelagic (photic).

Other spatial patterns are due to underlying human use data. Blockiness evident in the upper portion of the map and elsewhere comes from the ten-minute square fishing blocks used to map the distribution of fishing intensity in NMFS Vessel Trip Report data. High fishing intensity and commercial vessel traffic contribute to high impact scores off of Massachusetts' northern shore and down through the Great South Channel. Larger blocks evident offshore result from ultraviolet radiation and ocean acidification, which are both mapped at the one degree scale (especially visible in some parts of the map, for example, the horizontal line across the lower corner of the map, where the colors change from yellow to blue). Shipping lanes are visible as orange or red lines coming in and out of Boston Harbor, to Gloucester, and through the Great South Channel. Ferry routes can be seen connecting the Cape and Islands. Land-based impacts derive from watershed processes and human population density and show up as small red plumes close to shore.

### Nearshore cumulative impacts (Figure 7)

This figure displays the same data as Figure 6, zoomed in to allow closer examination of coastal patterns. At this scale, the coastal patterns of land-based impacts are easier to see. Fishing impacts and commercial vessel traffic patterns are quite visible, including the ferry routes between the Cape and Islands. The effects of ecosystem vulnerability can be seen as well, e.g., in Nantucket Sound where the <30m deep waters where no pelagic habitat was mapped generally have lower impact scores than deeper waters beyond the islands, where shallow pelagic habitat begins. Banding around the Cape and Islands and elsewhere within state waters results from the state Statistical Reporting Areas for fisheries. The red patch visible inland on the western edge of the map is the upper reach of Narragansett Bay (Mt. Hope Bay) around Fall River. It is disconnected from ocean waters within the mapped study extent, though it was treated as continuous for all watershed plume modeling.

### Relative intensity of human use (Figures 8 and 9)

The footprint is the sum of the intensity of all stressors. It does not take into account ecosystem vulnerability. Consequently, there is no evidence of habitat effects in the map (such as isobath lines; see other map narratives for comparison). The offshore blockiness is due to the NMFS fishing data, which is reported in ten-minute blocks. Yellow values in the southwestern part of the map are due to higher atmospheric deposition of nitrogen and sulfur (nutrients and atmospheric pollution layers) and the major shipping route that connects Europe to New York City. Yellow to red stripes around Cape Cod represent the commercial shipping routes into Boston and the ferry routes connecting the islands. Red spots nearshore: the largest of these are centered around the major ports, which have multiple ocean based stressors at high levels and many land-based stressors that plume out from the large watersheds that connect to these harbors. The red area off of Boston and Gloucester represents high levels of commercial vessel traffic, fishing, light pollution, ocean warming and other ocean stressors.

### Number of human uses (Figures 10 and 11)

The count is the number of stressors in any given pixel. As for the footprint, ecosystems are not included, so there is no evidence of habitat effects in the map. Again, offshore blockiness is due to NMFS fishing data, reported in ten-minute blocks and the UV and ocean acidification data, reported in one degree cells. Many of the land-based stressors are mapped at 250m resolution, so the zoomed in nearshore map looks smoother and the ten-minute and one degree blocks are less evident. In some places, land-based plumes can be clearly seen.

### Climate stressors' contribution to cumulative impacts (Figures 12 and 13)

These maps include ocean warming (sea surface temperature or SST increase), ocean acidification, and increased ultraviolet (UV) radiation and allow one to visualize how climate stressors, in particular, contribute to the overall pattern of cumulative impacts. As mentioned above, UV and ocean acidification are mapped in one degree blocks that are visible in many places in the map. Both ocean acidification and ocean warming have high values in the southern part of the study region, which contributes to the yellow and orange values in the southern part of this map. Other patterns are due to variation in ecosystem vulnerability as well as variation in the intensity of these three stressors. In general, the deeper habitats were less vulnerable to these stressors. Moderately high vulnerability scores for nearshore soft bottom habitats (especially for SST and UV) lead to the yellow band that extends across the middle of the map from west to east through Nantucket Shoals and Georges Bank. Hard bottom shelf has high vulnerability scores for all three climate stressors, so a patch of hard bottom shelf in the center of the map (Great South Channel) and some smaller hard bottom shelf and bathyal hard bottom patches to the east show up in orange to red.

### Fishing activities' contribution to cumulative impacts (Figures 14 and 15)

Inputs to this map are the five categories of commercial fishing: demersal habitat-modifying, demersal non-habitat-modifying low bycatch, demersal non-habitat-modifying high bycatch, pelagic low bycatch, and pelagic high bycatch. Highest values are seen along the north shore, northern Massachusetts Bay, and through the Great South Channel. Shapes of the state statistical reporting areas (SRAs) and the ten-minute squares are visible throughout the map (e.g., inside the arm of Cape Cod). The outlines of marine protected areas that limit demersal habitat-modifying fishing can also be seen as darker blue areas with low to no impact. Differential vulnerability of habitats to the stressors again leads to clear boundaries between ecosystems in some parts of the map. Low values nearshore are generally due to the low vulnerabilities of many intertidal habitats, which are mapped in the first 250m pixel adjacent to the coastline.

### Land-based stressors' contribution to cumulative impacts (Figures 16 and 17)

This map includes pollution from nutrient, organic, inorganic, atmospheric and light sources; coastal power plants; and coastal engineering. Watershed plumes, including the location of the Deer Island sewage outfall pipe, are visible in the nearshore as red plumes. This map appears smoother than the others because all land-based stressors inputs had data that could be mapped at 250m resolution (most ocean-based stressors have 1km$^2$ or coarser resolution). Higher values in offshore waters in the southwest corner are due to atmospheric pollution, which is highest in the Mid-Atlantic region and tapers off as one moves northeast across the map. Nearshore areas are red (high impact) both because of much higher stressor levels and because some intertidal and shallow subtidal habitats are more vulnerable to these stressors. Soft and hard bottom shelf habitats have higher vulnerabilities than soft and hard bottom habitats in either nearshore or bathyal depths, resulting in higher impact scores down the Great South Channel and across the middle of Figure 17.

### Other commercial activities' contribution to cumulative impacts (Figures 18 and 19)

This map includes shellfish aquaculture, ocean-based pollution, invasive species, marine debris, commercial vessel traffic, and whale watching. The blue ring represents the transition between the two sources of commercial vessel traffic data: our global layer (offshore waters) and AIS radar stations (nearshore). The radar picks up ships well up to 25 miles, and less well between 25 and 75 miles. Beyond 75 miles, the AIS signal is lost. To create a single shipping layer, we blended the two datasets within the range from 25-75 miles from shore, using the linear decay rate in the AIS dataset. Past 75 miles, we use solely the global dataset, and one can see a much more dispersed pattern of ship tracks. This dataset is noisier, but also, ships follow less regular routes as you get further offshore; these two factors account for the difference in the pattern of traffic beyond 75 miles. The wide swath of yellow heading east-west across the middle of the map is the huge shipping route connecting northern Europe to New York City, which also coincides with the 60-200m depth zone, which has higher average vulnerability scores (across shallow pelagic and soft and hard bottom shelf) for some of these stressors than adjacent habitats (deep pelagic and soft and hard bathyal). The lines in Nantucket Sound are the ferry routes that connect Cape Cod to the islands. This layer includes aquaculture, but the locations are too small to see at this scale (they are all nearshore and generally only a single pixel in size). This layer also includes ocean-based pollution that comes from ship traffic and ports. The impact of ports can be seen as red bubbles around the major ports in Massachusetts, particularly Boston Harbor.

### Ecosystem histograms (Figure 20)

The distribution of impact scores varied by ecosystem, depending both upon that ecosystem's vulnerability and its overlap with the suite of human ocean uses. The mean cumulative impact score across all ecosystems and all pixels was 11.1. Some individual ecosystems experienced much lower average impact scores (e.g., bathyal soft bottom 6.9, beach dune complex 8.6, deep pelagic 9.7), while others experienced much higher scores (hard bottom shelf 16.7, tidal flat 15.6, shallow pelagic 13.6). In general, soft bottom habitats had lower cumulative impacts than hard bottom in the same depth range. Deep water habitats (>200m) had some of the lowest impact scores.

## Discussion

Mapping human uses and their impacts reveals much about the waters off Massachusetts. First, maps of the number of human uses found in any given location demonstrate that multiple use is the rule, not the exception. Every single cell in the study area is affected by five or more different human activities over the course of an average year. Coastal waters, in particular, are subject to a large number of uses. This lends weight to the argument for comprehensive marine spatial planning, which aims to account for the needs and impacts of all ocean uses. Next, it is clear from both maps of the footprint of impacts and maps of cumulative impacts that take into account ecosystem vulnerability, that the coastal zone is being intensely used. The waters adjacent to land are orange to red along much of the coast in both of these maps (Figures 6 and 8), pointing to high intensity of human use and high cumulative impacts. Much of this is driven by land-based impacts. However, the waters beyond Boston Harbor (even into federal waters) also light up as red because of high commercial vessel traffic and fishing in this area.

The differences between maps of human use intensity and cumulative impact are driven by ecosystem vulnerability. As explained above, the cumulative impact model accounts for the fact that different ecosystems or habitats have different vulnerabilities to the same stressor. You can see the importance of ecosystem context by comparing these two sets of maps. In figures 8 and 9 (relative intensity of human use, aka the "footprint" of human use), the distributions of particular stressors are readily apparent: ferry routes and shipping lanes show up clearly, as do plumes of land-based inputs and fishing blocks. By contrast in figures 6 and 7 (cumulative impacts), the distribution and vulnerability of ecosystems is combined into the picture, and the patterns become more subtle and complex. In some places, an underlying habitat with high vulnerability results in higher impact scores and warmer colors. For example, south of Gloucester and in spots along the Great South Channel, patches of hard bottom shelf habitat stand out in red. In other places, habitat(s) with relatively low vulnerability reduce the perceived importance of an area of high relative intensity of use, e.g., at the mouth of Boston Harbor where shipping, fishing and other stressors have high levels, but the underlying soft bottom habitat is relatively insensitive to these stressors (yellow to red in Figure 9, patch of light green in Figure 7). The importance of ecosystem vulnerability to the model means that ecosystem mapping is critical to the accuracy and utility of the model outputs. As we discuss below in the ecosystem mapping section, the habitat classification scheme and data used here have some limitations. In particular, mapping of hard substrate data is inconsistent across the region. If this model is going to be used increasingly in management decisionmaking and monitoring (particularly fine scale decisions like siting or permitting), we recommend further investments in habitat mapping.

Both the ecosystem vulnerability survey and cumulative impact maps reveal that ecosystems in this region vary in the degree to which they are impacted by human uses of the ocean. Both analyses pointed to hard bottom shelf as being particularly at risk. Similarly, nearshore hard and soft bottom had high vulnerability scores and high overall cumulative impacts. Tidal flats, on the other hand, had moderately high mean vulnerability in the expert survey (mean 2.2, n=6 experts), but very high mean cumulative impact scores (mean 15.6), suggesting that this ecosystem is exposed to particularly high stressor levels. Similarly, salt marsh had moderate average vulnerability (mean 1.7, n=15 experts), but relatively high cumulative impacts (mean 12.4). Given the intensity of land-based inputs into coastal marshlands in the region, this is not surprising.

Interestingly, eelgrass, which has been recognized as a special, sensitive and unique marine resource in Massachusetts and is widely acknowledged as threatened in the Atlantic, had lower than average cumulative impact scores (mean 10.2) and moderate average vulnerability (mean 1.7, n=10 experts). We are not sure of the reason for this difference, however it may relate to the fact that our survey does not include historical impacts to this (or any) ecosystem. Eelgrass throughout the region succumbed to wasting disease impacts in the 1930s and the system is still trying to recover (Muehlstein 1989, Fonseca and Uhrin 2009). The current distribution of eelgrass is much curtailed from its historical distribution. Our model will only map impacts to an ecosystem where it is currently found, so human stresses that limit the recovery and expansion of eelgrass or other habitats are not taken into account. Additionally, there may be some aspect of either the vulnerability of this ecosystem type or the threats to it that our model and/or data have missed. One critical stressor to eelgrass is sediment runoff from land, which we have not included here. Also, as we acknowledge in the description of our model of nutrient runoff, more sophisticated techniques might produce more accurate maps of the distribution and intensity of nutrient runoff into eelgrass and other coastal habitats.

## Future directions

The datasets we have compiled here and the cumulative impact model provide a robust platform for a variety of future applications. Simple scenario analysis could be developed using the ecosystem vulnerability matrix and the cumulative impact model as a basis. For example, one could examine different siting or management action scenarios by examining how changes in particular ocean uses affect the pattern of overall cumulative impact scores. Alternatively, one could map the distribution of ecosystem vulnerability to a particular human use that is subject to management action and see how changes in its spatial distribution would affect ecosystem vulnerability. For example, maps of the vulnerability of marine ecosystems to wind energy could be examined to look for hotspots of vulnerability that should be avoided when permitting new facilities. More sophisticated scenario analysis could be achieved by incorporating dynamic models of the tradeoffs in ecosystem services associated with different human uses and the ways in which they are managed spatially. Our group is developing just such models under a separate contract with SeaPlan in support of the Ocean Management Plan.

It is our hope that these datasets, methods, and models are taken up by the state and used in future implementation and monitoring of the management measures included in the Ocean Management Plan. Our products should also be useful to ongoing revision of the plan. To make this more feasible, we have made our data publicly available and produced an ESRI Model Builder ArcGIS model, delivered to the Office of Coastal Zone Management, to allow managers to implement the model themselves. This will allow managers to alter data inputs and assumptions of the model to meet their own needs. With this ability, the model becomes completely portable, updatable, and customizable to the state's ocean management process.

## Conclusions

The process of developing a cumulative impact model to support ocean management in Massachusetts has been instructive in many ways. Though this should be treated as a first generation model, it can tell us many things. Data gaps revealed by the effort point to important information needs for ocean management in Massachusetts and for coastal and marine spatial planning in the region. We identified significant human use and ecosystem mapping data gaps. Some of these gaps were filled as a result of this study, e.g., a comprehensive map of shellfish aquaculture beds in Massachusetts did not previously exist. Others, like recreational boating and cables and pipelines, are now in development, in part because they were identified as significant gaps by this project.

There are also significant gaps in our knowledge of the vulnerability of ecosystems that were revealed by this work. This demonstrates the need to either identify additional experts or invest research dollars in a better understanding of certain ecosystems. The vulnerability survey provides a transparent and repeatable means for eliciting expert judgment, something that will likely continue to be part of the process of ocean management decision making moving forward, given the pervasive gaps in our understanding of these systems. Indeed expert advice is nearly always used to inform decision making, but not often documented or made transparent in this way.

Though the details of cumulative impact maps might change in subtle ways as our knowledge of human uses and marine ecosystems expands, there are some results that are unlikely to be altered by refinements of the data inputs. First, multiple use is the rule. All parts of the study area experience at least five stressors a year, and most places are subject to many more than five. This kind of data helps to quantify the potential for human use conflicts and negative impacts on ecosystems in our busy coastal and marine environment, and provides a clear argument for more comprehensive (cross sector) management. In addition, by accounting for the relative vulnerability of marine ecosystems as well as the distribution of human uses, we show clearly that some areas are likely to be much more impacted than others and will be much more vulnerable to increased existing or new uses.

While the gaps are significant and the results should be used with a clear understanding of existing gaps and limitations, this model presents a framework for a quantitative analysis of cumulative impacts. This represents a valuable opportunity to complement or replace the qualitative analyses of cumulative impacts that are currently used in project review, permitting, and large scale planning. If adopted, maintained and advanced by the State, this framework will become an even more powerful tool for managers. It can only improve as data and model inputs are improved.

This framework has the potential to help organize and streamline data acquisition and use. It identifies data products (and data purveyors) for each stressor. For example, we now have a framework for integrating different datasets into a combined vessel traffic layer, a framework for using fishery landing data, a framework for modeling nutrient input into coastal waters, and others. In addition, the interim products developed along the way are often just as useful as the final products. In some cases interim datasets were aggregated and analyzed for the first time for this project, e.g., AIS data for large commercial vessel traffic.

The supporting outputs that accompany the cumulative impact map that is the model's ultimate output are also quite useful in and of themselves. The number of human stressors by pixel map confirms multiple use and supports arguments for cross sector and land/sea interface management. The footprint of human stressors map demonstrates the relative contribution of different activities and aids in interpretation of the cumulative impact map. Theme-specific impact maps, such as those for climate-related impacts or fisheries impacts, help identify ecosystems and locations that are highly impacted by a suite of related stressors. Ecosystem histograms can further indicate areas that should be the focus of management attention.

We feel that this model, supporting methods, and outputs have great potential for use in ocean management. We have perhaps learned as much about the potential uses of a model like this and its outputs as we have about vulnerability and cumulative impacts. We briefly mention a few potential applications here, but a more complete discussion of this topic will be the subject of a forthcoming paper.

First, these analyses could help to inform large area planning. They could easily provide a basis for simple scenario analyses, in which alternative management scenarios are evaluated, comparing changes in individual or cumulative impacts that might result. Maps of the distribution of human stressors could help to inform use-use compatibility discussions, e.g., by examining spatial overlap among uses. Outputs of both the expert survey and the cumulative impact model could also serve to inform analysis of use-resource compatibility, allowing managers to identify particular ecosystem–stressor combinations that lead to especially high (or low) vulnerability.

Second, our results could help to support project review and the environmental impact statement process. For example, potential spatial planning decisions, like siting of a pipeline or cable, could be evaluated against maps of ecosystem vulnerability to that particular use. Proposed routes for the structure could be compared to see which travels through the least vulnerable seabed types. If integrated as a GIS tool, this could allow managers to easily review, compare and identify preferred alternatives.

Third, this project helps to set a research agenda for science to support the ocean management process in Massachusetts. As described above, this project revealed important knowledge and data gaps that currently limit our understanding of ecosystem vulnerability and cumulative human impacts in this region. Addressing these gaps will help to further ocean management. The top stressors identified by our project represent critical threats to the region and major coastal management issues, which should be the focus of redoubled research effort. Finally, managers or scientists could use our cumulative impact maps to identify areas of particular concern for monitoring and study. Similarly, these maps may help to identify or select sites for ecological restoration and/or protection (e.g., relatively un-impacted areas, or areas that are threatened by a small number of easily mitigated stressors).

A fourth benefit of this approach is that it may inform coastal land use and land use planning. Because the approach that we use integrates land- and ocean-based human uses, our results help us to understand the relative contribution of land-based inputs to ocean condition. They also highlight the importance of integrated management at the land-sea interface. Land use planners could use our maps to both identify problem hotspots and consider alternative scenarios to address land-based inputs.

The maps can also help managers, stakeholders and the public to visualize the connection between land and sea. As such, these maps can be powerful educational tools, helping teach the public about how upstream decisions ultimately affect ocean ecosystems. Understanding the implications of land use decisions is just one way in which we can learn from this model. There are many ways it can be used to engage stakeholders and managers to learn and think about how we depend on marine ecosystems, how we affect them through our activities, and how we might better manage them. We are just at the beginning of learning all the possible ways this tool might be applied to coastal and marine spatial planning, education, outreach and research.

# Appendix 1 – Ecosystem mapping

## Background

There are many different marine ecosystem or habitat classification schemes, based on geological, oceanographic or biological characteristics or some combination of these (e.g., Greene et al. 1999, Mumby and Harborne 1999, Sherman and Duda 1999, Auster et al. 2001, Zacharias and Roff 2000, Tyrell 2005). The choice of classification scheme will influence results of any habitat-based analysis and their scientific and management utility. Because our cumulative impact model is dependent on the relative vulnerability of different ecosystem types, ecosystem classification affects spatial patterns of the resulting maps, and accurate data on ecosystem distributions are critical to the maps' accuracy.

## Methods

Massachusetts Office of Coastal Zone Management (CZM) developed the ecosystem/habitat classification scheme we use here and mapped the habitat classes using existing data. The 15 ecosystem types included represent fairly coarse, but readily recognized and mapped classes (Table 2, Figures 2-4).

### *Intertidal ecosystems*

Intertidal habitats were derived from the MassGIS Department of Environmental Protection (DEP) Wetlands dataset (1:12,000). Barrier beach system combined all DEP barrier categories except barrier-salt marsh. Coastal beach/dune complex combined DEP beach, dune, barrier-beach system, barrier-beach coastal bank, barrier-beach coastal dune, coastal dune, and coastal beach. DEP rocky intertidal was used directly to map rocky intertidal shore. Salt marsh was represented by DEP salt marsh and barrier beach-salt marsh categories. Tidal flats were mapped using DEP tidal flat data. Developed and/or filled shorelines were not included as an intertidal habitat type in this classification.

### *Nearshore subtidal ecosystems*

Eelgrass habitat was mapped using DEP's seagrass dataset. Algal zone (or shallow rocky subtidal dominated by algae) was assumed to exist everywhere in waters less than 10m deep except where eelgrass is found. This assumption was made because comprehensive data on the actual distribution of this ecosystem are not currently available. Waters less than 10m deep were delineated using the MassGIS 30m bathymetry. Nearshore soft bottom was delineated in waters 10-60m deep where silt, mud or sand substrate was found. This mapping was based on the MassGIS bathymetry (30m) and CZM/Division of Marine Fisheries (DMF) interpolated seabed sediment size for coastal Massachusetts derived from USGS sediment survey data. Similarly, nearshore hard bottom was based on the same datasets and comprised areas of cobble, boulder or bedrock substrate between 10-60m depth.

### *Offshore subtidal ecosystems*

All offshore habitats were mapped using the MassGIS bathymetry (30m) and USGS Continental Margin Mapping sediment grain size (CONMAPSG) distribution for the US East Coast continental margin. Areas of cobble, boulder or bedrock in depths of 60-200m were classified as hard bottom shallow shelf (CONMAPSG codes for gravel-sand, gravel, and bedrock). The same bottom type in deeper water (>200m) was considered hard bottom bathyal shelf. Mud, silt or sand substrates in 60-200m depths were classified as soft bottom shallow shelf, while soft sediments in waters >200m deep were classified as soft bottom bathyal shelf (CONMAPSG codes for clay, sand, and silt).

### *Pelagic ecosystems*

In waters >30m deep, we also delineated pelagic habitats (Figure 4). We assume that in waters shallower than that depth, benthic and pelagic habitats are sufficiently coupled to consider them as a single interconnected ecosystem. MassGIS Bathymetry (30m) and USGS Open File Report 98-01 were used to classify pelagic habitats. We designated the water column from 0 to 200m depth in waters >30m deep as shallow pelagic habitat (i.e. the photic zone). Shallow pelagic ecosystem was delineated horizontally between the 30 and 1000m depth contours. In waters >200m deep, we also considered a deep (aphotic) pelagic zone. This zone was delineated horizontally between 200 and 1000m depth contours. Thus, in waters <30m deep, there is only one ecosystem type. In waters 30-200m deep, there are two – a bottom type plus the shallow pelagic. In waters >200m deep, there are three ecosystem types – a benthic habitat, plus both shallow and deep pelagic zones.

## Caveats and data needs

Maps of ecosystems were based on best available data, but for some ecosystem types and some places, these maps may have important, but poorly known gaps. In particular, because of the lack of good side scan sonar or other fine-scale substrate mapping data for much of the region, hard bottom habitat is likely to be under-estimated. The CONMAPSG dataset was chosen because it is comprehensive for the entire shelf area, however it is fairly coarse. Better substrate mapping data exist for parts of, but not the entire study region. Improved benthic substrate mapping is a research priority for the state. The algal zone, which we have modeled as being everywhere between 0-10m depth, will be over-estimated since its actual distribution is restricted to hard bottom. Again, better data on the distribution of rocky substrate could greatly improve the mapping of this ecosystem type.

Pelagic habitat mapping could also be made more sophisticated with the addition of long-term oceanographic data. Such data could be used to identify important pelagic zones based not only on depth, but also relatively stable long-term patterns of productivity and ocean currents.

The simple habitat classification system we have chosen takes advantage of available data, however a more finely subdivided classification (e.g., one which splits up benthic habitats according to substrate grain size or which combines substrate information with biological community data) might be appropriate in the future if and when more/better data become available. Drawing upon complementary habitat mapping efforts by the State, The Nature Conservancy (Northwest Atlantic Marine Ecoregional Assessment), Woods Hole Oceanographic (Habcam), and others could lead to improved classification schemes in the future.

# Appendix 2 – Human stressor mapping

## Background

The final input to the cumulative impact model is information on the spatial distribution and intensity of human activities (both land- and ocean-based) that affect marine ecosystems. Human use data can be scarce for the oceans, and existing datasets are often spotty. Obtaining comprehensive datasets for our entire study region often meant aggregating and synthesizing data from multiple sources. In some cases, we developed models or proxies to represent the distribution and intensity of a given activity or its associated stressor(s) when direct empirical data were lacking. The resulting data layers are useful both as standalone products and as inputs to the model. In the methods section below, we describe the data sources and methods for mapping each of 21 human stressors.

## Methods

### Supporting data: watershed boundaries and pour points

Many of the land-based stressors that affect marine ecosystems depend upon watershed processes, for example the transport of water-borne pollutants like fertilizers and pesticides from land to coastal waters via streams and rivers. To map these kinds of stressors, we calculated watershed level loads and then plumed them out into coastal waters using a diffusive plume model. This method depends on accurate mapping of coastal watershed boundaries and locations of watershed mouths or pour points. For most of New England very high resolution coastal watershed boundaries were not available at the time of this project. To delineate watershed boundaries and assign coastal pour points, we used methods developed as part of the global project (Halpern et al. 2008b). Briefly, we used an automated flow-accumulation process (Jenson and Domingue 1988) based on US EPA’s National Hydrography Dataset Plus (NHD+) hydrologically corrected 30m digital elevation model to assign watershed boundaries from Rhode Island to Maine (to include all watersheds that drain into Massachusetts’ waters) (Figure 5). In the Buzzards Bay region, we used watersheds developed by the Buzzards Bay Estuary Program rather than those created using the NHD+ model, because these high-resolution coastal watershed boundaries have been well groundtruthed. Watershed boundaries in this area were replaced and snapped to NHD+ boundaries where necessary. Finally, watersheds were prepared for use in land-based stressor modeling by (1) combining any watersheds that had land-based pour points so that all watersheds drained to the sea; and (2) eliminating very small watersheds by combining any coastal watersheds less than 4-250m pixels in size (250,000 $m^2$) with adjacent watersheds or removing them if they represented small islands/rocks. A raster of watershed pour points was created for use in plume models by locating the point of highest flow accumulation within the watershed in an automated ArcGIS process, then manually cleaning up watersheds with multiple pour points and making sure all pour points were snapped to the coastline.

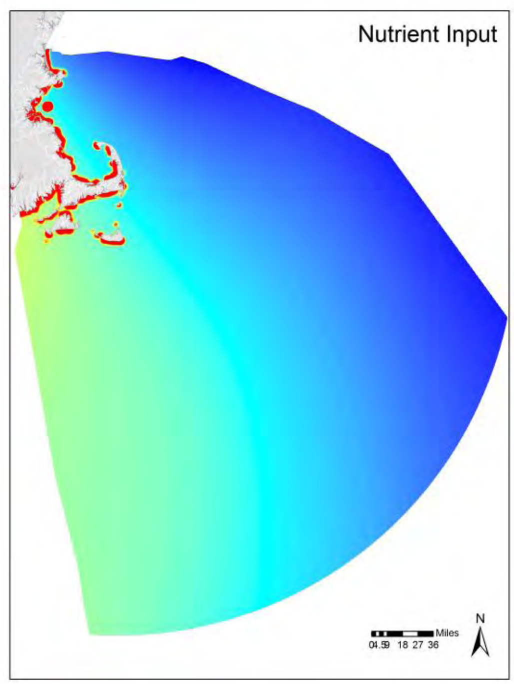
## Land-based stressors

Data for watershed process-driven stressors (nutrient input, inorganic pollution, and organic pollution) was distributed to watersheds using ancillary data, summed using raster statistics (i.e. aggregation by watershed), and then assigned to coastal pour points. A least cost path diffusive plume model was used to spread stressor levels out from each pour point as for the global and California Current projects (Halpern et al. 2008b, Halpern et al. 2009). The cost-path surface uses a decay function that assigns a fixed percentage of the stressor to the first cell at the watershed's mouth (in this case, 0.5% of the value in the previous cell) and then distributes the remainder of the pour point stressor level evenly across all adjacent, unvisited cells. This process repeats until a minimum threshold (0.05% of global maximum) is reached. This simple diffusive model allows the plume to wrap around headlands and islands. It does not account for nearshore advection, however, so in some regions the actual pattern of spread could vary from that modeled here, depending on local nearshore oceanography.

### *Nutrient input*

Nutrient input into coastal waters can lead to algal blooms, eutrophication, and major shifts in community structure (Vitousek et al. 1997, Carpenter et al. 1998, Beman et al. 2005). Sources of nutrients include fertilizers, manure, sewage, wastewater, and atmospherically deposited nitrogen, among others (Valiela et al. 1997, Vitousek et al. 1997, Caraco and Cole 1999). We developed a simple model of nitrogen (N) input as a proxy for overall nutrient input into coastal waters. Though our model focuses solely on inputs of N and does not account for losses, previous validation against empirical data and more sophisticated models shows that it captures spatial patterns of relative N loading reasonably well (Halpern et al. 2009). Other work has also shown that total nitrogen inputs correlate well with nitrogen fluxes from coastal rivers (Howarth et al. 1996). Nitrogen sources in our model include land-based fertilizer application, upstream and coastal wastewater treatment plant discharge, coastal septic tanks, combined sewer overflows, sewer outfall pipes, and atmospheric nitrogen deposition. These disparate sources, each measured in lbs N/yr, were summed to create a single N input layer. Data sources and methods for each follow.

**Upstream farming** can be a major source of N input into coastal waters via runoff of N-based fertilizers and manure from confined animal operations (Carpenter et al. 1998, Beman et al. 2005). We used county-level fertilizer application data from USGS, which report average annual N input from 1976-1985 in lbs/hectare, to estimate average annual fertilizer inputs by watershed. Dasymetric mapping was used to distribute county level N levels to the landscape: GeoSTAC tools were used to map N levels within each county to 2001 USGS National Land Cover Dataset land cover classes. Cropland received 93% of total N levels; cropland/shrubland/woodland/mixed received 6% of total N; and the remainder was distributed across the remaining land. Nitrogen from fertilizer was then summarized by watershed and assigned to the watershed pour point. Confined animal manure (primarily from dairy farms) is from the USGS for the years 1992 and1997 (http://water.usgs.gov/GIS/metadata/usgswrd/XML/gwava-s_conf.xml, Nolan and Hitt 2006). Nolan and Hitt assigned the original county level data, averaged across 1992 and 1997, to agricultural land classes within watersheds. We then summed manure-derived N at the watershed level and assigned those values to watershed pour points.




**Sewage input** is generally difficult to document across large scales, but an important source of nutrient addition into coastal waters (Valiela et al. 1997). We include several different sources of treated and untreated sewage in an attempt to capture patterns of relative N-input from this source: treated wastewater releases from coastal and upstream wastewater treatment plants, combined sewer overflows (CSO), sewage outfall pipes, and a proxy for leaky septic systems based on coastal population density and the proportion of each coastal town that is served by sewer systems. Discharge rates and average concentration of nitrogen were used to estimate average annual nitrogen loads from these sources.

Wastewater treatment plant locations in watersheds upstream of Massachusetts coastal waters (in Rhode Island, Massachusetts, New Hampshire, and Maine), average annual flows, and average N concentration came from the EPA's database of Water Discharge Permits (PCS) (http://www.epa.gov/enviro/html/pcs/pcs_query_java.html). Nitrogen concentration was not reported for most facilities; in these cases, a conservatively estimated average concentration of 15 mg/L was used (TetraTech Inc. 2004). Upstream wastewater treatment plant releases were aggregated by watershed and assigned to pour points. Coastal wastewater treatment plants were assumed to discharge treated wastewater directly into coastal waters and so were plumed from their locations rather than from watershed pour points. In some cases, wastewater treatment plant locations had to be shifted slightly to be directly adjacent to ocean pixels.

Data on combined sewer overflow locations (CSO), discharge rates, and average nitrogen concentrations came from the Massachusetts Water Resource Authority (MWRA) for 2007. Discharge volumes were estimated using "typical year rainfall" under 2007 system conditions. Nutrient input was calculated using the overall mean concentrations for $NH_4$, $NO_3$ and $NO_2$ reported by MWRA (Alber and Chan 1994). Nutrient loads in lbs/yr were summarized by watershed and assigned to the watershed pour point.

There are 51 sewage outfall diffuser pipe locations associated with the Deer Island wastewater treatment facility outfall tunnel in western Massachusetts Bay. These locations and data on average annual N input (which was divided evenly among the 51 pipe openings) came from MWRA.

Many coastal communities in Massachusetts depend upon septic systems for some or all of their wastewater treatment. In adjacent coastal waters, eutrophication due to nutrient runoff has been documented as an ongoing problem (Valiela et al. 1997, Valiela and Costa 1998, Bowen and Valiela 2001). This is especially true in the communities of Cape Cod and the Islands, where seasonal vacationers swell summer populations and most towns have incomplete sewer system coverage. Comprehensive data on septic system discharges into coastal waters were not available, so we developed a simple modeling approach to capture this source. We scale nitrogen input to the number of houses in the unsewered and partially sewered coastal towns in Massachusetts and adjacent states (including the first few towns over the border). Valiela et al. (1997) provide a model for estimating nitrogen input from coastal septic systems, among other sources, to Waquoit Bay on Cape Cod. We applied their parameters and a modified form of their approach. We calculated nitrogen delivery as the amount of nitrogen contributed per person on an annual basis, times the number of people, which is derived from the number of houses on sewer times the average occupancy rate:

Nitrogen delivery = per capita N release/yr × ave number of people/household × number of houses in watershed

We use 4.8 kg/yr per capita input rate (from Valiela et al. 1997) and 1.8±0.6 people/house occupancy rate. The number of houses on sewer we estimated by applying the proportion of houses on sewer in the town (reported by the towns) within a given US census block, multiplied by the number of houses per block from census block data. If the proportion of the town on sewer was not available, we assumed a 50:50 ratio. We calculated nitrogen loads for each block centroid using this approach and then snapped the block centroids to the nearest ocean cell to represent nitrogen input into coastal waters.

Valiela and colleagues apply several loss terms to capture the loss of nitrogen in the septic tank, in the leach field, in the plume leaving the leach field, and in the aquifer. To be comparable to the approach we have used with other nitrogen sources, wherein we do not account for losses on the landscape, we modeled nitrogen leaving the septic system and not nitrogen losses to soil and aquifers. Therefore, we applied only the loss terms for within the septic tank and the leach field, which total 40% (Valiela et al. 1997). Nitrogen input into coastal waters is then nitrogen delivery minus nitrogen loss. These values were applied to the nearest ocean cell and later summed with all other nitrogen inputs for the final nutrient layer.

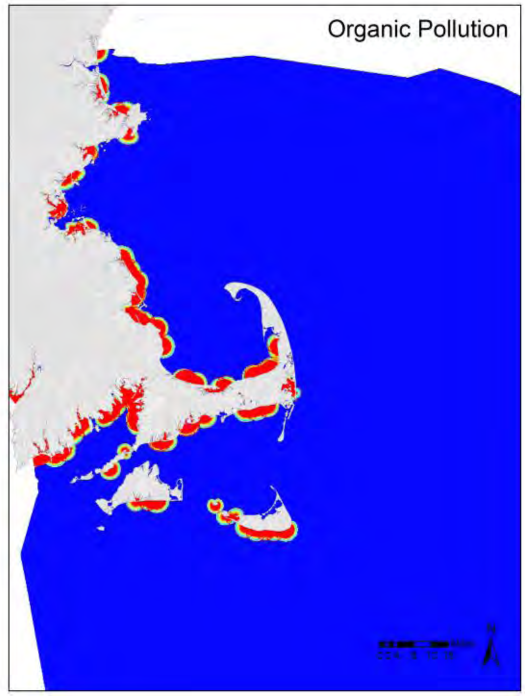
**Atmospheric deposition** is another important source of nitrogen to coastal and marine areas. Atmospheric wet deposition of pollutants is recorded at over 100 stations within the U.S. as part of the National Atmospheric Deposition Program (http://nadp.sws.uiuc.edu/); we used data on nitrate and ammonium deposition from the 27 stations in New England, and spatially kriged values between the stations over the landscape and onto the waters of the study region to provide estimates of atmospheric wet deposition of nitrogen to all pixels. Similarly, we used kriging to estimate dry deposition of nitrogen (nitrate, ammonium and nitric acid) from the 11 stations in New England that are part of the Clean Air Status and Trends Network (CASTNET, http://www.epa.gov/castnet/). These two layers were then summed to give a total atmospheric nitrogen deposition data layer for the region. Atmospheric nitrogen deposition onto land was combined with the other land-based nitrogen input layers (fertilizer, manure, inland wastewater treatment plants, and CSOs), summing them by watershed (in lbs N/watershed). Atmospheric deposition onto water was treated separately.

The **final nutrient data layer** was created by (1) pluming watershed values (in lbs. N) into coastal waters using the plume model developed for the global project (Halpern et al. 2008b), (2) pluming N values from the sewage outfall pipe and coastal wastewater treatment plants, (3) log transforming both of the preceding data layers and (4) summing these two layers with the log transformed septic data layer. The summed data layer was then normalized from 0 to 1.

### *Organic pollution*

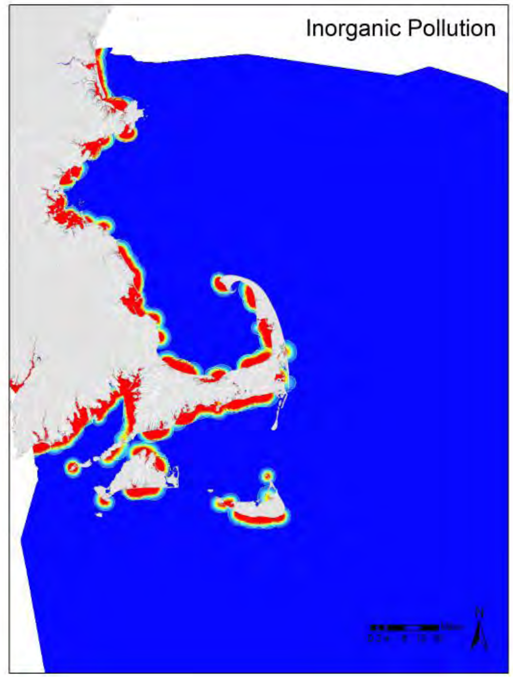
A wide variety of organic (carbon-containing) pollutants run off into coastal waters. Some of these pollutants persist and biomagnify in marine food webs and can cause mutations, disease, and endocrine disruption in marine organisms. We mapped organic pollution using two sources: EPA's Toxic Releases Inventory (TRI) for point sources and the National Pesticide Use Database for non-point source pesticide use.

The Toxic Releases Inventory contains data on annual estimated releases of toxic chemicals to air, water or land by the manufacturing industry. We extracted release location and discharge amount (in lbs.) for all known surface water discharges of organic chemicals for Maine, New Hampshire, Massachusetts and Rhode Island from the TRI database for 2006. Individual chemicals were weighted by their known toxicity as in Halpern et al. (2009), summed by watershed, and assigned to the watershed pour point. Chemicals whose toxicity was not listed in Halpern et al. (2009) were weighted using the average toxicity for their chemical class.




Because fine scale data on pesticide application rates were not available, we used a dasymetric mapping approach to allocate statewide application rates to cultivated crop land cover. Coastal Change Analysis Program (CCAP) data were used to extract cultivated crop land cover for New England for 1995/1996 and 2005/2006. Pesticide data from 1997 came from the National Pesticide Use Database (2000). Statewide pesticide application rates were extrapolated to 2006 levels by using the change in crop class land cover from 1995/1996 to 2005/2006. The Pesticide Allocation Tool was used to allocate extrapolated pesticide values to cropland. Pesticide loads were then summed by watershed and assigned to pour points. The two organic pollutant layers were log transformed and normalized to a scale from 0 to 1 before being summed. The final organic value at each pour point was re-normalized from 0 to 1. Total organic pollutant values were then spread from pour points using the diffusive plume model described above.

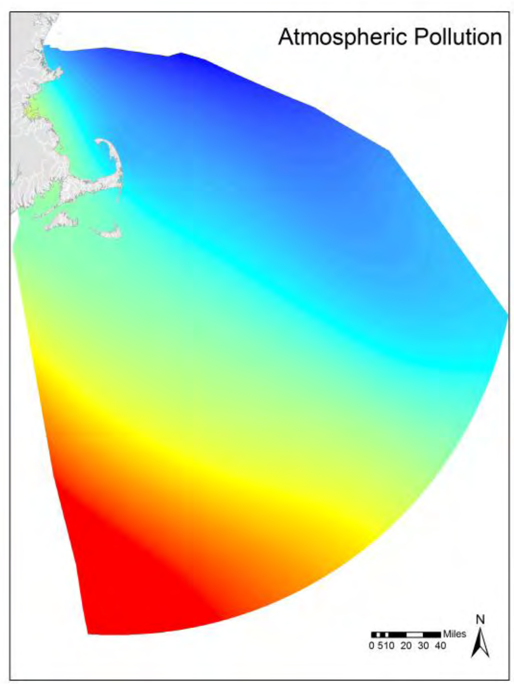
### *Inorganic pollution*




Inorganic pollutants (e.g., heavy metals) were estimated from two sources: EPA's Toxic Releases Inventory for point source releases and impervious surface area, which was used as a proxy for nonpoint sources. As for organic pollutants, inorganic releases to surface waters (in lbs.) were extracted from the TRI database and weighted by their toxicity. Values were then summed by watershed and assigned to watershed pour points.

Nonpoint sources of inorganic pollutants include cars, roads, and urban areas. Using impervious surface area as a proxy for these sources is a widely used approach (Arnold & Gibbons 1996; Gergel et al. 2002). We obtained impervious surface area data from the National Land Cover Database 2001, which provides percent imperviousness per pixel. Percent cover was summed by watershed and assigned to watershed pour points.

### *Atmospheric pollution*

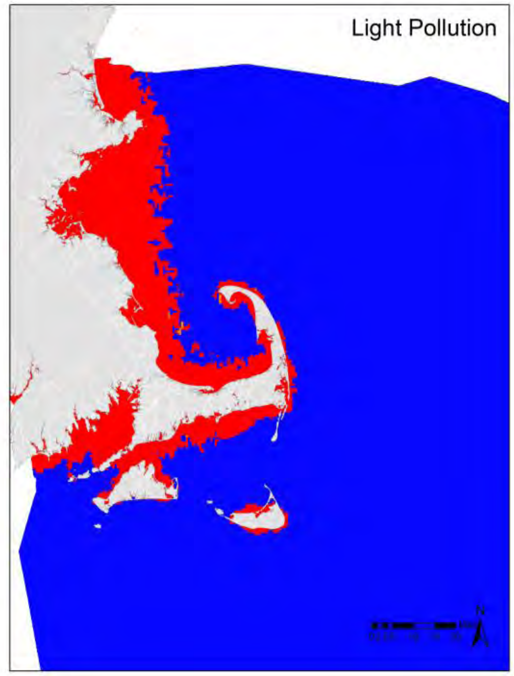



Various chemical pollutants may be dispersed atmospherically. We used data on wet and dry atmospheric deposition of sulfate as a proxy for other atmospherically derived pollutants. Dry deposition data come from the Clean Air Status and Trends Network program (CASTNET) http://www.epa.gov/castnet/ and wet deposition from the National

Atmospheric Deposition Program (NADP) http://nadp.sws.uiuc.edu/. Sulfate data were processed in the same manner as described above for atmospheric deposition of nitrogen.

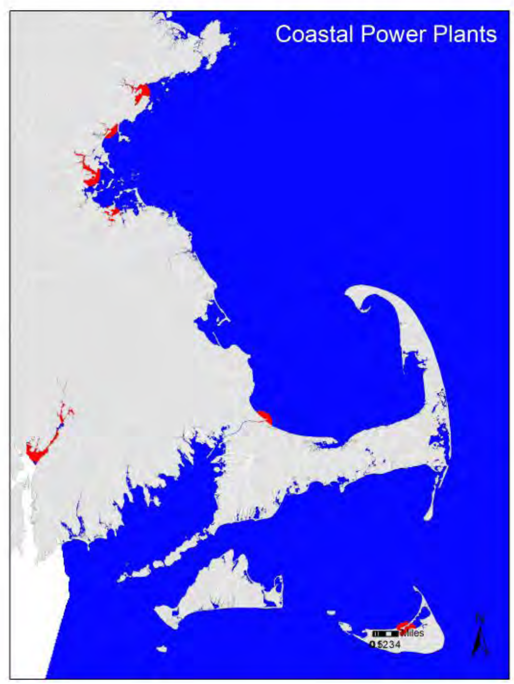
### *Light pollution*

We used NOAA's Stable Lights at Night database to map the distribution of light pollution from coastal development (http://www.ngdc.noaa.gov/dmsp/global_composites_v2.html). This dataset allows one to map the light that can be seen in coastal ocean pixels. The dataset is mapped on a 30 arc second grid, which we converted to a 250m grid raster.




### *Coastal power plants*

Coastal power plants draw in water for cooling, entraining larvae and small plants from an area around the intake pipes. Entrainment 'plumes' vary in size and shape depending on the size of the plant and local ocean currents. We used a 3 km buffer as an estimate of the scale of impact of the entrainment plume.

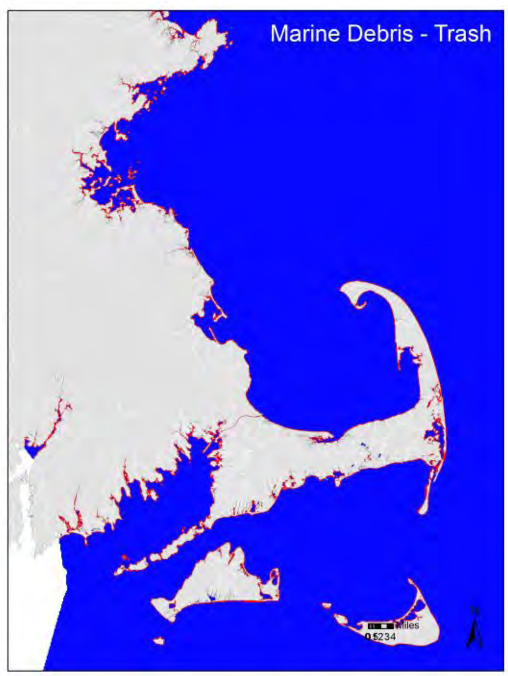


### *Coastal engineering*

Coastal engineering leads to various kinds of shoreline hardening, including riprap, sea walls, groins, jetties and piers. These structures modify and/or destroy habitat and can significantly alter surrounding ecosystems through changes in nearshore circulation and sediment transport. We extracted data on hardened shorelines from NOAA's Environmental Sensitivity Index (ESI) dataset [http://response.restoration.noaa.gov/book_shelf/855_MASS.pdf](http://response.restoration.noaa.gov/book_shelf/855_MASS.pdf). This database classifies linear segments of coast into different ecosystem types and various types of human-modified shoreline, based on digitized aerial imagery. We extracted the coastal engineering shoreline types, identified by codes 1B, 6B, and 8C and classified the first ocean pixel adjacent to these shoreline segments as "impacted" in the coastal engineering data layer (presence/absence data only).


### *Marine debris*

Marine debris or trash from both ocean and land-based sources was mapped using Massachusetts Office of Coastal Zone Management CoastSweep (http://www.coastsweep.umb.edu/) data from 2002-2008. Volunteers in the CoastSweep program spend one day each year cleaning up Massachusetts' beaches. We have used the

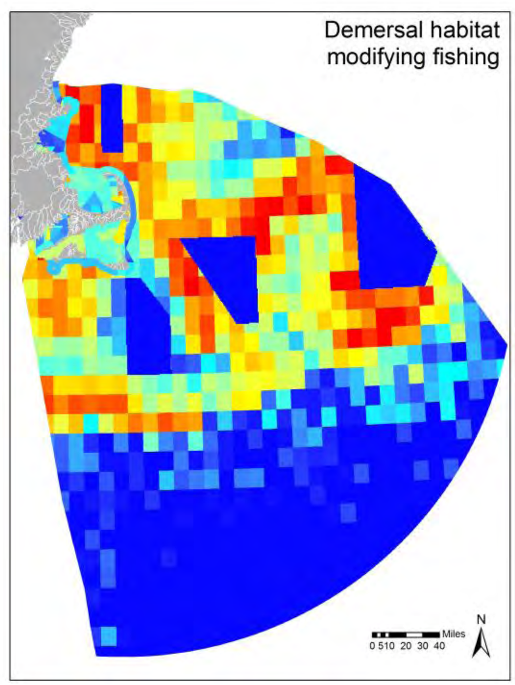


average annual weight of trash (standardized by effort) as a proxy for the amount of marine debris in coastal habitats of Massachusetts. Coastsweep data were summarized by county in average lbs./person/mile/year and then distributed evenly along the shoreline of the county.


## Ocean-based stressors

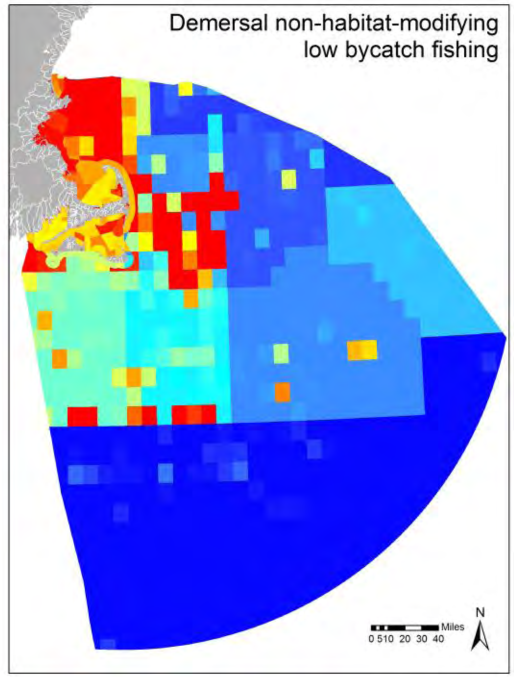
### *Aquaculture – shellfish*

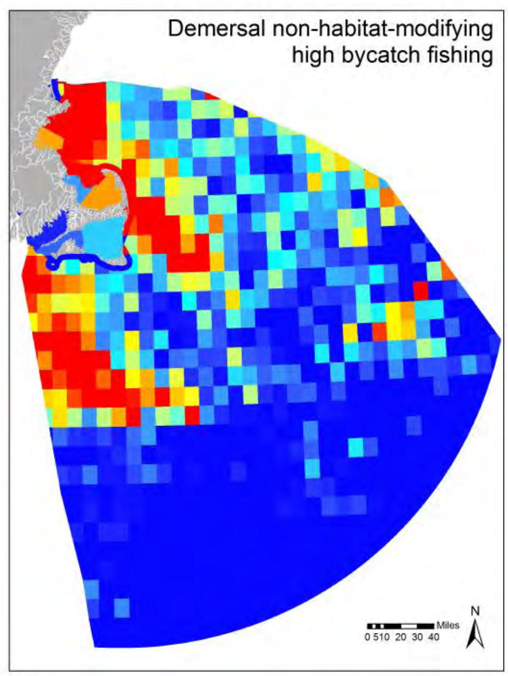
Locations of shellfish aquaculture beds were digitized by Stone Environmental and MA Division of Marine Fisheries from Google Earth 2009 images. Locations were verified in 2009 by staff of the MA Department of Agricultural Resources and the coastal towns that issue shellfish aquaculture permits, and additional bed locations were added from these sources. Because reliable information on how much shellfish is harvested from these beds is not available, this is merely a presence/absence data layer. Shellfish harvest from aquaculture operations is subsumed into the shellfish records supplied by MA Division of Marine Fisheries and so is included in the fishing data layers (demersal habitat-modifying or demersal non-habitat-modifying low bycatch, depending on the gear used to harvest the species).



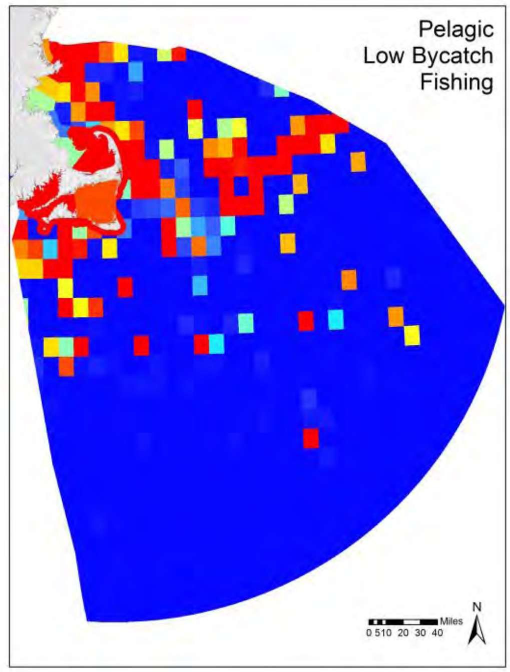

### *Fishing – five types*

We identified 5 different categories of commercial fishing gear on the basis of whether or not the gear modifies habitat, if it incurs bycatch, and if it occurs in pelagic or benthic areas (Watson et al. 2006, Halpern et al. 2008b). Since habitat-modifying fishing is by definition high-bycatch and habitat-modifying methods for pelagic fishing do not currently exist, five categories of fishing emerge: pelagic low-bycatch, pelagic high-bycatch, demersal habitat-modifying, demersal non-habitat-modifying low-bycatch, and demersal non-habitat-modifying high bycatch.

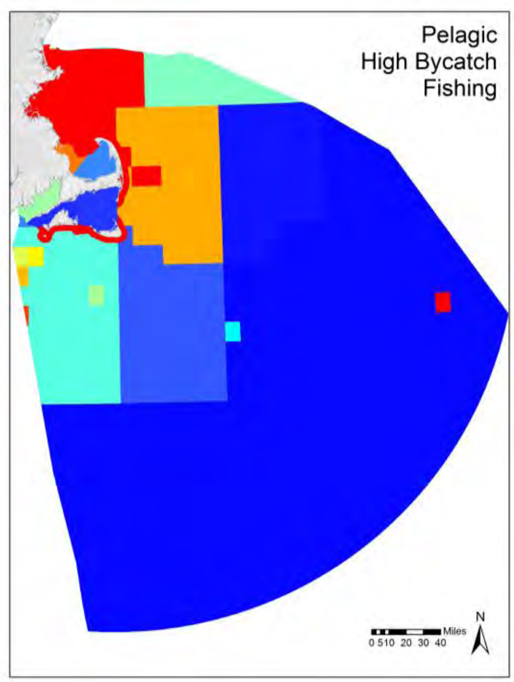



We used commercial catch data from the MA Division of Marine Fisheries (DMF) for state-regulated finfish fisheries within statistical reporting areas (SRAs) in state (SRAs 1-14) and federal waters (SRAs 15-25) and for federally-regulated fisheries within state waters (SRAs 1-14) from 1988-2007. Data were given to us as average annual landings; actual length of the time series varies by fishery, encompassing some or all of the years from 1988-2007. The federally regulated fishery data originated with NMFS vessel trip reports and were processed by DMF and combined into their dataset. This dataset provides average annual pounds landed per reporting area. Additional data on shellfish landings were supplied by DMF in average annual pounds shell weight harvested per shellfish growing area. These data include both wild caught and aquaculture harvested shellfish. All DMF records were classified into the five fishing categories based on gear type and supplemental information from Micah Dean at DMF. Landed pounds were then standardized to catch per unit area (lbs./$km^2$) by dividing by the area in $km^2$ of the reporting area in which they were caught.



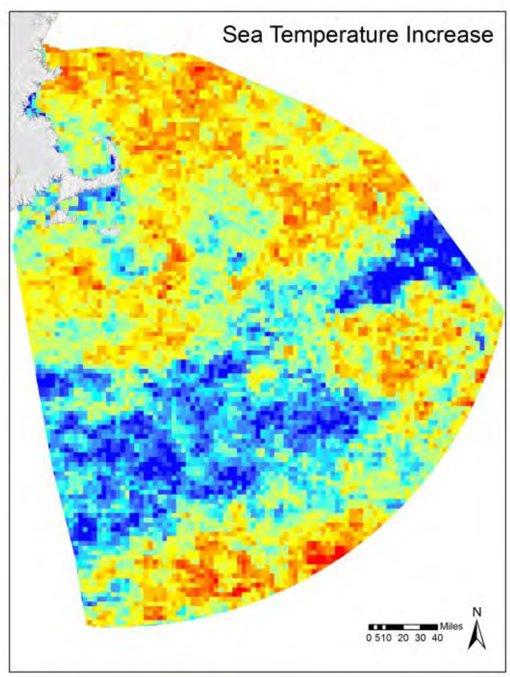

For federally regulated fisheries in federal waters, we used NOAA National Marine Fisheries Service vessel trip report (VTR) data. The VTR dataset provides gear type, species caught, and total kept catch (in lbs.) by ten-minute square for all reported fish for 2003-2008. Individual species-gear combinations were classified into the five commercial fishing categories by Carrie Kappel (NCEAS) based on gear type and supplemental information about fishery impacts from NMFS fishery management plans, MA DMF, Blue Ocean Institute, and SeafoodWatch. Average annual landings for each fishing category were then calculated for each 250m cell.



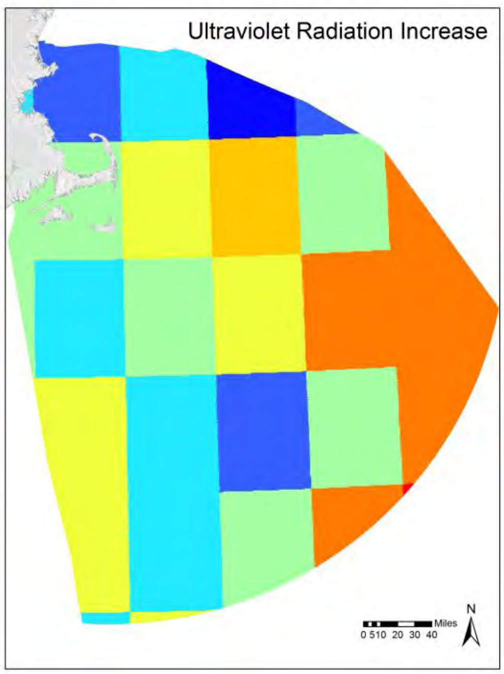

Shapefiles for marine protected areas (MPAs) that affect fisheries in Massachusetts were obtained from the National Marine Protected Areas Center's Marine Managed Areas Inventory (http://mpa.gov/helpful_resources/inventory.html). There are ten federal MPAs that affect some or all Massachusetts fisheries via permanent, year-round restriction of fishing activity. We used associated documentation (http://maps7.msi.ucsb.edu/metadata/explorer.jsf, http://www.nwr.noaa.gov/Groundfish-Halibut/Groundfish-Fishery-Management/Groundfish-Closed-Areas/Index.cfm, http://mpa.gov/helpful_resources/inventory.html) for each MPA to determine which types of fishing were prohibited within the boundaries. Demersal habitat-modifying fishing is prohibited in all of these MPAs, and the two coastal MPAs (Mashpee National Wildlife Refuge and Nomans Land Island National Wildlife Refuge restrict all fishing, though only along the shore. MPA polygons were combined to form an MPA mask (provided in UCSB_IntermediateData_2010.gdb). Values for prohibited fishing layers were set to zero when overlapped by the MPA mask (i.e. within an MPA's boundaries).

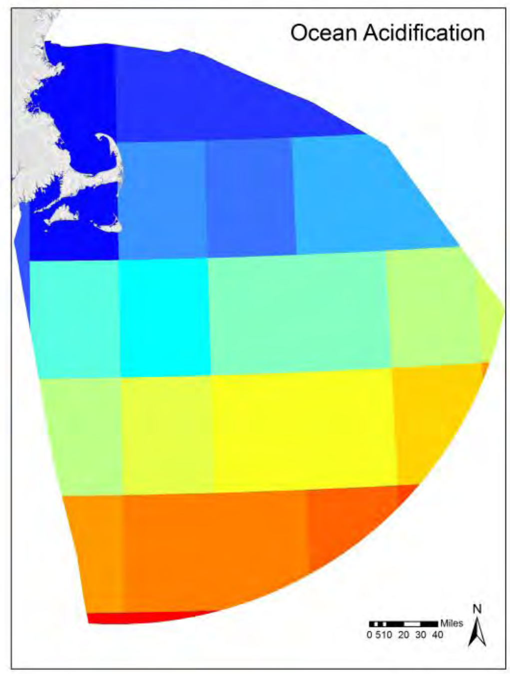
### *Climate change (SST, UV, ocean acidification)*

Data for the three climate change stressors (sea surface temperature (SST) anomalies, UV radiation anomalies, and ocean acidification) were taken from global data described elsewhere (Halpern et al. 2008b), clipped to the Massachusetts study region. Ocean warming was described by the difference in the number of sea surface temperature anomalies from the start to the end of the Advanced Very High Resolution Radiometer (AVHRR) Pathfinder Version 5.0 SST time series (NOAA), 1985-2005 (4.6km, nominally 21km$^2$ at the equator). SST anomalies were defined as weeks when the average SST exceeded the long-term standard deviation in average temperature for a given location and week of the year, based on a climatology developed from the whole time series. We then calculated the difference in frequency in anomalies between the last five years in the database (2000-2005) and the first five (1985-1990).




The number of UV radiation anomalies (defined as for SST) was calculated for 2000-2004, relative to the 1996-2004 climatology. Because the UV time series, which comes from the (one degree) GSFC TOMS EP/TOMS satellite program at NASA, is shorter than the SST series, we did not calculate a difference in number of anomalies.

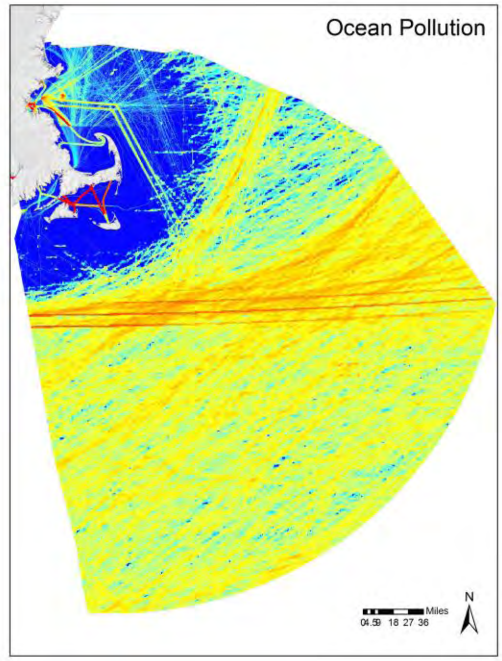



Rising seawater $CO_2$ concentration (i.e. ocean acidification) is affecting the aragonite saturation state of the oceans, which in turn, affects the ability of calcifying species such as corals and mollusks to create calcium carbonate shells or skeletons (Kleypas et al. 1999). Guinotte et al. (2003) have modeled global aragonite saturation state at 1-degree resolution for pre-industrial and modern times. We represent ocean acidification stress as the change in modeled aragonite saturation state from pre-industrial times (1870) to modern times (2000-2009) at each location.

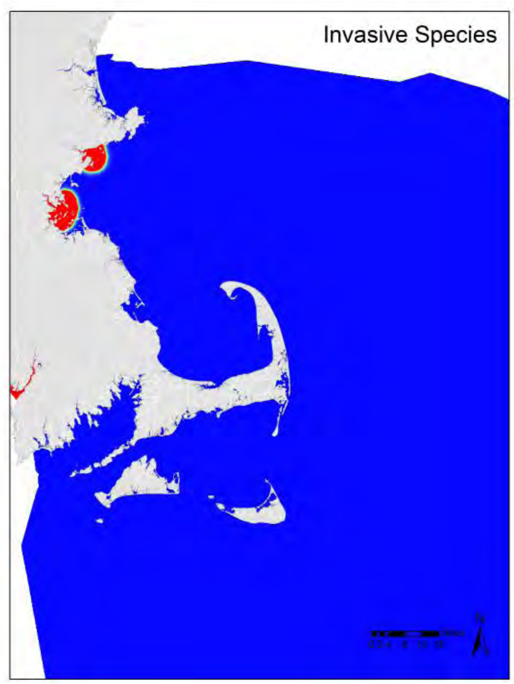
### *Ocean-based pollution*

We mapped pollution from ocean-based sources using the distribution and volume of large commercial vessel traffic and ports as proxies. We recognize that the oil, anti-fouling paints, debris and other contaminants that enter the ocean from these sources may be redistributed and dispersed or concentrated by ocean currents and wind. However, the ports and shipping lanes are known to have higher concentrations of pollutants than surrounding waters (Long et al. 1996, Bothner et al. 1998, Gade and Alpers 1999, Strand et al. 2003, Hunt and Slone 2010), so we use these as a first order approximation of ocean-based pollution. Commercial vessel traffic is mapped as described above, with a 1km buffer. Pollutants from the ports are described using a diffusive plume, as described above for invasive species. These two separate sources were log-transformed and normalized from 0 to 1 before being summed and re-normalized from 0 to 1.



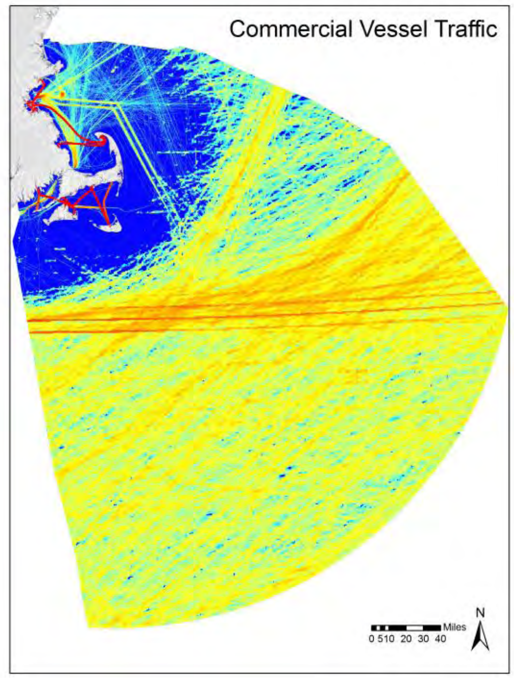

### *Invasive species*

Empirical data on the distribution and spread of invasive species have not been collated for Massachusetts' waters. Many invasive species introductions have been traced to ballast water and the fouled bottoms of ships (Carlton 1985). We use port volume as a proxy for the potential for invasive species introductions as we did for the global and California Current projects (Halpern et al. 2008b, 2009). Port volume data came from the Principal Port file, which contains USACE port codes, geographic locations, names and commodity tonnage summaries for Principal USACE ports. Invasive spread is modeled using a diffusive least cost path surface model as for the land-based stressors.



### *Commercial vessel traffic*

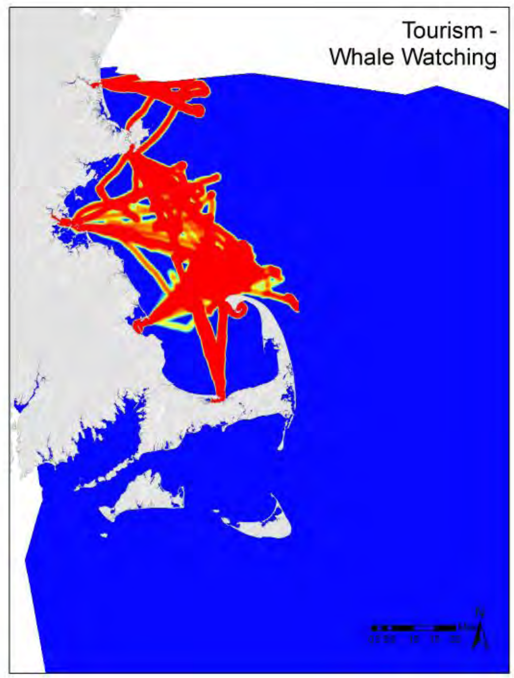
Commercial vessel traffic can impact species and ecosystems through noise and light pollution and direct impacts like vessel strikes. Empirical data on the distribution and intensity of vessel traffic is limited to larger vessels in the Massachusetts area, consequently smaller ships like recreational boats and fishing boats are not included in this data layer. We map average annual density of ship tracks (i.e. number of passes/year) for regional ferry traffic and large commercial shipping traffic, using two sources. Vessels over 299 gross tons are required to carry Automatic Identification System (AIS) transponders by the International Maritime Organization. The AIS system records position and course information using GPS. The transponders then send out a signal over two VHF channels, which is tracked by land-based radio receivers. Data for this analysis were collected by the US Coast Guard and processed by Applied Science Associates (ASA). Within the range of the receivers (average ~25km), this represents a very high-resolution source of information on vessel positions. Receivers in the study area are in Gloucester, Scituate, and Provincetown in MA and at unknown locations in RI. We received AIS data covering Massachusetts and Rhode Island waters for January to April 2008. We multiplied these data by 3 to represent a full year's density. We acknowledge the fact that there may be seasonal variability that affects whether these four months are representative of the annual average.




Beyond the range of the receivers, the AIS data begins to degrade. We calculated a linear decay rate of the AIS signal starting from 25km from shore and moving out. This decay rate was used to "blend" in global shipping data from the global project (Halpern et al. 2008b). Please see the Halpern et al. 2008b supplementary online methods for details on how these October 2004 to

September 2005 data, collected as part of the World Meteorological Organization Voluntary Observing Ships Scheme, http://www.vos.noaa.gov/vos_scheme.shtml, were originally processed. Because about 10% of large commercial vessels participate in this program, we rescaled the density of tracks in the global dataset by ten. Ferry route data came from the MA Executive Office of Transportation, Office of Transportation Planning. We added data on number of passes per year for each ferry route derived from published ferry schedules. The ferry routes and all commercial vessel tracks were buffered to 1km to represent the spread of impacts beyond the exact path of travel.

### *Tourism – whale watching*




We received data from Stellwagen Bank National Marine Sanctuary on average number of transits by whale watching vessels per grid cell. The data started out as an aggregate of GPS data points from whale watching vessels gathered in the 2003-2004 Whale Watching Guidelines Study and 2008 and 2009 Whale Watching tracks by the United States Coast Guard Auxiliary. The dataset contains 111 total transits, with accompanying information about port of origin. Because the dataset was biased by which ports observers worked out of, the number of transits per port was normalized by research effort. Density of transits per 250 m grid cell was then calculated and mapped.

## Caveats and data needs

Though most of the major drivers of change in Massachusetts' waters were included, we were not able to obtain data on all uses of the marine environment. We were not able to include potentially important impacts like noise pollution or changes in freshwater runoff and sedimentation because we did not have sufficient time or resources within the project to develop models for these stressors. However, existing approaches could be adapted to map these stressors' intensities across the study region, given more time. For other stressors, existing models and/or data were inadequate. This is particularly true for recreational uses of marine ecosystems: no good comprehensive datasets exist for recreational fishing, recreational boating, direct human disturbance from coastal visitation, or other uses like surfing and scuba diving at this time. Future efforts to collect data on these human uses could facilitate their inclusion in the model. Similarly, data were scarce for disease, scientific research activities, ocean dumping, dredging, mining, and bottom infrastructure like cables and pipelines (including liquefied natural gas pipelines), though some of these datasets may have become available since our analysis was completed. Impacts of sea level rise were not included at this time because high-resolution models that separate climate change driven sea level rise from natural changes in sea level were not available for the region.

Other drivers were mapped using preliminary or partial data. For example, state fishing data is known to be incomplete and captures only an unknown portion of total fishing activity. The state fishing data are somewhat coarse in resolution and biased by the irregularly shaped statistical reporting areas. Similarly, the federal data are aggregated to ten-minute blocks, which do not allow exact pinpointing of where landings occur. Because our approach depends so heavily on ecosystem vulnerability, and ecosystems were mapped at a much finer scale than the fishing data, this spatial mismatch may lead to inaccuracies in the mapping of cumulative impacts. In addition, logbook fishing data can be prone to inaccuracies and deliberate misreporting, particularly of the locations of catches. The degree to which such problems hamper the state and federal datasets we have used here has not been quantified. Finally, changes in fishing policies and quotas as well as changes in the distribution of harvested species can mean that even a recent annual average is not an accurate representation of current fishing patterns. Nonetheless, these data represent the best available source of information on fishing for the region. Improvements in data collection, data quality and availability could enhance the fishing data layers in the future.

The impacts of certain activities have been modeled using simple methods (e.g., assuming diffusive spread of pollutants away from sources or using simple proxies when empirical data are lacking), which could be improved upon in the future. Invasive species' impacts could be mapped more accurately if/when empirical data on their distribution become available. Nutrient input could be modeled in more sophisticated ways, taking into account both inputs and losses and incorporating biogeochemical processes that affect nitrogen cycling (e.g., Smith et al. 1997, Alexander et al. 2002, Seitzinger et al. 2005). Finally, some human stressors' impacts are likely to be affected by oceanographic and ecological dynamics (like advection and migration) that are not currently captured by our mapping framework, which is static. Future work could improve upon this.

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# Tables

Table 1. Description of the five vulnerability criteria used to assess ecosystem vulnerability to each stressor and the values provided to survey respondents as choices when scoring each criterion in section two of the survey. Values for vulnerability scenarios in section one of the survey were chosen to span these same ranges. Values for these five criteria are weighted and combined to calculate a single vulnerability score for each stressor by ecosystem combination.

Table 2. Marine ecosystem types assessed in New England waters, with brief descriptions. These represent the categories of experts that were consulted through the survey as well as the ecosystem types that were included in the cumulative impacts model.

Table 3. Mean weights for vulnerability criteria based on model results from this project and the California Current (Teck et al. 2010).

Table 4. Vulnerability scores for 58 stressors in 15 ecosystems. Ecosystem abbreviations: *b* = beach; *bb* = barrier beach; *ri* = rocky intertidal; *salt* = salt marsh; *tide* = tidal flat; *eel* = eelgrass; *alg* = algal zone; *nh* = nearshore hard bottom; *ns* = nearshore soft bottom; *h sh* = hard bottom shelf; *s sh* = soft bottom shelf; *bath* = soft bottom bathyal; *sp* = shallow pelagic; *dp* = deep pelagic. Combinations with no survey responses are indicated with *nd* for no data. Ecosystem-by-stressor vulnerability scores are derived from experts' average criteria values from the vulnerability portion of the survey, weighted and summed using the model of ecosystem vulnerability. We use weights derived from the coastal experts' ranking sections given its greater sample size and similarity to offshore experts' values. Scores are color-coded into four bins, dividing the range equally: 0-1.6 in white, 1.6-3.2 in light gray, 3.2-4.6 in dark gray, and 4.6-6.4 in black with white letters. Mean scores for each stressor across all ecosystems and for each ecosystem across all stressors are reported in the "Score mean" column and row, respectively. Sample size means (±SE) were calculated by averaging across the number of responses provided for each vulnerability criterion (this number differs from the overall sample size by ecosystem given at top because not all experts filled out values for every criterion and every stressor).

Table 5. Sample sizes (i.e. number of experts) for vulnerability scores matrix.

Table 6. Comparison of Massachusetts and California Current results for overall vulnerability score mean, shown in order of decreasing rank for Massachusetts. We show both the original California Current scores, and scores that were re-calculated using weights from the Massachusetts model

Table 7. Matrix of vulnerability scores used for cumulative impacts model with gaps in Massachusetts survey results filled using values from the California Current project (Halpern et al. 2009) or from the literature. Carrie Kappel conducted a literature review of known impacts to fill in the values shown in red. Values from the California Current are given in bold. We re-weighted all California Current scores using model results from Massachusetts.

Table 8. Data details for human stressors included in our analyses. Further information can be found in the metadata accompanying data layers.

## Table 1

| Spatial scale | Frequency | Trophic impact | Percentage change in biomass | Recovery time |
|---|---|---|---|---|
| The spatial scale ($km^2$) at which a single instance of an activity or stressor impacts the ecosystem, both directly and indirectly | The mean annual frequency (days per year) of the stressor at a particular location within a given region | The primary extent of marine life affected by a stressor within a given ecosystem and region (i.e. single or multiple species, single or multiple trophic levels, or the entire ecosystem) | The degree to which the species, trophic level or levels, or entire ecosystem's "natural" state is affected by the stressor | The mean time (in years) required for the affected species, trophic level or levels, or entire ecosystem to return to its former, "natural" state following disturbance by a particular stressor |
| 0 | 0 | 0 | 0% | 0 |
| <1 $km^2$ | once every 100 years | 1 (1 or more species) | 1 to 10% | <6 months |
| 1 to 10 $km^2$ | once every 50 years | 2 (1 trophic level) | 11 to 20% | 6 months to 1 year |
| 10 to 100 $km^2$ | once every 20 years | 3 (>1 trophic level) | 21 to 30% | 1 to 5 years |
| 100 to 1000 $km^2$ | once every 10 years | 4 (entire community) | 31 to 40% | 6 to 10 years |
| 1000 to 10 000 $km^2$ | once every 5 years | Don't know | 41 to 50% | 11 to 25 years |
| >10 000 $km^2$ | once every 2 years | | 51 to 60% | 26 to 50 years |
| Don't know | 1 to 7 days per year | | 61 to 70% | 51 to 75 years |
| | 7 to 14 days per year | | 71 to 80% | 76 to 100 years |
| | 15 to 31 days per year | | 81 to 90% | >100 years |
| | 31 to 90 days per year | | 91 to 100% | Don't know |
| | 91 to 180 days per year | | Don't know | |
| | 181 to 364 days per year | | | |
| | 365 days per year | | | |
| | Don't know | | | |

**Table 2**

| | Ecosystem | Description |
|---|---|---|
| Intertidal | Beach | Sandy shoreline habitat within the tidal zone |
| | Barrier beach | Sandy intertidal habitat parallel to and separated from shore by a body of water |
| | Rocky intertidal | Rocky shoreline habitat within the tidal zone |
| | Salt marsh | Vegetated marine or estuarine habitat within the tidal zone |
| | Tidal flats | Un-vegetated sand or mud habitat within the tidal zone |
| Subtidal coastal | Eelgrass | Nearshore subtidal habitat dominated by *Zostera marina* |
| | Algal zone | Nearshore subtidal habitat <10 m deep dominated by algal cover * |
| | Nearshore soft bottom | Nearshore subtidal habitat 10-60 m deep with silt, mud, or sand substrate |
| | Nearshore hard bottom | Nearshore subtidal habitat 10-60 m deep with cobble, boulder, or bedrock substrate |
| Offshore | Hard bottom shelf | Subtidal habitat 60-200 m deep with cobble, boulder or bedrock substrate |
| | Soft bottom shelf | Subtidal habitat 60-200 m deep with silt, mud, or sand substrate |
| | Hard bottom bathyal | Subtidal habitat >200 m deep with cobble, boulder or bedrock substrate |
| | Soft bottom bathyal | Subtidal habitat >200 m deep with silt, mud or sand substrate |
| | Shallow pelagic | Water column above 200 m in all areas >30 m deep** |
| | Deep pelagic | Water column below 200 m in all areas >200 m deep |

* Mapped as being everywhere except where eelgrass is found, in waters <10 m deep
** Pelagic habitat in waters <30 m deep was considered as part of the benthic habitat, i.e. fully coupled.

**Table 3**

| Model | No. top ranks included | Spatial extent ($km^2$) | Frequency (days/yr) | Trophic impact (level 1-4) | Percent Change (%) | Recovery time (yr) |
|---|---|---|---|---|---|---|
| Coastal (MA) | 2 | 0.0709±0.012 | 0.0964±0.023 | 0.466±0.074 | 0.345±0.059 | 0.0214±0.006 |
| Offshore (MA) | 2 | 0.0644±0.021 | 0.0848±0.029 | 0.542±0.103 | 0.283±0.078 | 0.0257±0.009 |
| Combined (CA Current) | 4 | 0.061±0.008 | 0.046±0.007 | 0.221±0.022 | 0.665±0.029 | 0.008±0.001 |

*Notes*: The second column gives the number of top stressor ranks used to fit the model. Standard error (±SE) is given for each weight. Weights for the coastal (MA) model were used for subsequent analyses.

**Table 4** (on following two pages)

| | Coastal ecosystems | | | | | | | | | Offshore ecosystems | | | | | Mean |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Human activity | b | bb | r int | salt | tide | eel | alg | nh | ns | h sh | s sh | bath | sp | dp | Score |
| Expert sample size (*n*) | 5 | 5 | 8 | 15 | 6 | 10 | 2 | 6 | 6 | 4 | 7 | 1 | 7 | 3 | 6.1 |
| Aquaculture: finfish (herbivores) | 0.0 | 0.0 | 1.9 | 0.8 | 0.3 | 0.6 | nd | 2.2 | 1.9 | 1.5 | 0.6 | 0.0 | 1.7 | 0.0 | 0.9 |
| Aquaculture: finfish (predators) | 0.0 | 0.0 | 1.9 | 0.9 | 0.2 | 0.6 | nd | 2.1 | 1.9 | 3.0 | 0.6 | 0.0 | 1.7 | 0.0 | 1.0 |
| Aquaculture: marine plants | 0.0 | 0.0 | 2.0 | 0.8 | 0.8 | 0.7 | nd | 1.0 | 1.8 | 1.5 | 0.6 | 0.0 | 1.0 | 0.0 | 0.8 |
| Aquaculture: shellfish | 0.9 | 1.7 | 2.5 | 1.4 | 2.0 | 2.0 | 1.7 | 2.1 | 2.5 | 2.4 | 0.6 | 0.0 | 1.0 | 0.6 | 1.5 |
| Benthic structures | 0.0 | 1.3 | 2.8 | 1.9 | 3.3 | 1.2 | 3.7 | 2.6 | 3.3 | 3.8 | 3.2 | 3.6 | 1.8 | 1.9 | 2.5 |
| Climate change: ocean acidification | 1.8 | 3.2 | 4.0 | 3.7 | 4.3 | 2.5 | nd | 3.0 | 1.5 | 5.0 | nd | nd | 4.7 | 3.8 | 3.4 |
| Climate change: sea level rise | 4.4 | 5.0 | 4.8 | 4.6 | 4.8 | 3.5 | nd | 2.4 | 2.0 | 4.7 | 1.0 | 0.0 | 2.5 | 1.1 | 3.1 |
| Climate change: sea temperature change | 4.3 | 5.5 | 3.9 | 4.2 | 6.1 | 2.8 | nd | 4.6 | 4.8 | 5.9 | 3.5 | 4.3 | 5.1 | 4.6 | 4.6 |
| Climate change: UV change | 2.1 | 2.5 | 3.6 | 3.9 | 5.3 | 4.2 | nd | 3.1 | 3.8 | 5.3 | nd | 0.0 | 3.8 | 3.3 | 3.4 |
| Coastal engineering: altered flow dynamics | 3.6 | 4.2 | 4.0 | 3.7 | 3.6 | 2.8 | nd | 1.2 | 3.2 | 1.4 | 1.3 | 0.0 | 1.2 | 1.5 | 2.5 |
| Coastal engineering: habitat alteration | 3.7 | 4.0 | 3.7 | 3.4 | 3.6 | 2.9 | nd | 1.6 | 4.2 | 1.6 | 1.4 | 0.0 | 1.3 | 1.3 | 2.5 |
| Direct human impact: trampling | 3.0 | 2.9 | 2.0 | 2.2 | 2.7 | 1.6 | 0.0 | 0.6 | 0.8 | 0.0 | 0.5 | 0.0 | 0.4 | 0.9 | 1.3 |
| Diseases and pathogens | 1.5 | 1.6 | 2.9 | 1.8 | 3.2 | 2.3 | nd | 2.5 | 1.8 | 2.5 | 6.1 | 2.3 | 2.8 | 2.8 | 2.6 |
| Dredging | 2.8 | 3.9 | 1.3 | 1.8 | 3.3 | 2.6 | 3.4 | 3.2 | 3.5 | 4.1 | 3.2 | 0.0 | 1.3 | 1.8 | 2.6 |
| Energy infrastructure: liquid natural gas | 1.2 | 2.1 | 3.3 | 1.3 | 3.1 | 2.5 | nd | 2.1 | 4.6 | 3.3 | 3.4 | nd | 2.8 | 2.4 | 2.7 |
| Energy infrastructure: tidal | 1.4 | 2.6 | 1.0 | 1.5 | 3.0 | 2.7 | nd | 2.6 | 5.9 | 3.0 | 2.2 | 0.0 | 2.6 | 0.7 | 2.3 |
| Energy infrastructure: wave | 1.4 | 2.7 | 1.0 | 0.5 | 3.1 | 2.5 | nd | 2.6 | 5.5 | 3.0 | 3.1 | 0.0 | 3.3 | 0.7 | 2.3 |
| Energy infrastructure: wind | 1.3 | 2.4 | 4.0 | 0.6 | 3.1 | 2.4 | nd | 2.8 | 4.7 | 3.4 | 3.5 | 0.0 | 3.4 | 1.8 | 2.6 |
| Fishing: aquarium | 0.0 | 0.6 | 0.3 | 0.3 | 0.0 | 0.0 | nd | 0.9 | 0.4 | 1.9 | 0.6 | 0.0 | 0.7 | 0.7 | 0.5 |
| Fishing: demersal habitat-modifying | 0.0 | 0.0 | 0.9 | 0.5 | 3.1 | 2.6 | nd | 3.5 | 3.8 | 3.5 | 3.4 | 3.4 | 2.2 | 2.8 | 2.3 |
| Fishing: demersal non-habitat-modifying high bycatch | 0.0 | 0.0 | 0.3 | 0.8 | 1.1 | 0.5 | 2.8 | 2.5 | 2.6 | 3.9 | 3.5 | 2.7 | 1.8 | 1.4 | 1.7 |
| Fishing: demersal non-habitat-modifying low bycatch | 0.0 | 0.0 | 1.4 | 0.7 | 1.1 | 0.8 | 2.5 | 2.2 | 2.1 | 2.3 | 2.2 | 0.0 | 2.5 | 1.7 | 1.4 |
| Fishing: habitat-modifying artisanal (subsistence) | 0.2 | 0.0 | 0.0 | 0.5 | 1.1 | 0.0 | nd | 1.3 | 0.6 | 1.7 | 0.7 | 0.0 | 1.1 | 0.0 | 0.5 |
| Fishing: non-habitat-modifying artisanal (subsistence) | 0.6 | 0.0 | 0.2 | 0.7 | 1.0 | 0.3 | nd | 2.0 | 0.0 | 2.3 | 1.0 | 0.0 | 0.3 | 0.0 | 0.6 |
| Fishing: pelagic high bycatch | 0.0 | 0.4 | 0.0 | 0.2 | 1.0 | 0.0 | nd | 1.6 | 1.5 | 3.0 | 2.9 | 0.0 | 3.2 | 2.9 | 1.3 |
| Fishing: pelagic low bycatch | 0.0 | 0.3 | 0.0 | 0.2 | 1.0 | 0.0 | nd | 1.3 | 1.5 | 2.3 | 2.6 | 0.0 | 2.8 | 1.1 | 1.0 |
| Fishing: recreational | 1.1 | 1.7 | 1.2 | 1.6 | 2.1 | 1.1 | 1.6 | 2.5 | 1.5 | 2.8 | 2.0 | 0.0 | 2.2 | 0.9 | 1.6 |
| Freshwater input: decrease | 0.2 | 0.0 | 1.7 | 2.6 | 0.2 | 1.8 | nd | 3.0 | 0.0 | 3.4 | 2.4 | 0.0 | 1.2 | 0.8 | 1.3 |
| Freshwater input: increase | 0.5 | 1.1 | 2.6 | 3.5 | 2.2 | 2.4 | nd | 3.0 | 1.9 | 3.4 | 2.7 | 0.0 | 2.4 | 0.8 | 2.0 |
| Invasive species (from ballast, etc.) | 3.6 | 3.5 | 3.8 | 3.5 | 1.8 | 2.6 | nd | 3.5 | 4.0 | 4.0 | 3.3 | nd | 3.2 | 3.1 | 3.3 |
| Military activity | 0.0 | 0.8 | 0.5 | 0.2 | 3.1 | 0.0 | nd | 2.2 | nd | 1.8 | nd | nd | 1.7 | nd | 1.1 |

| Human activity | b | bb | r int | salt | tide | eel | alg | nh | ns | h sh | s sh | bath | sp | dp | Mean |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Nutrient input: causing harmful algal blooms | 0.2 | 1.5 | 2.1 | 1.7 | 3.6 | 2.6 | nd | 2.7 | 1.5 | 3.5 | 2.9 | 0.0 | 3.1 | 1.2 | 2.0 |
| Nutrient input: causing hypoxic zones | 0.2 | 1.6 | 1.9 | 1.9 | 3.6 | 2.4 | nd | 3.2 | 3.7 | 3.2 | 3.0 | 0.0 | 1.5 | 1.1 | 2.1 |
| Nutrient input: into eutrophic waters | 0.2 | 1.8 | 1.3 | 2.9 | 4.0 | 2.9 | nd | 3.2 | 3.7 | 3.7 | 2.7 | 0.0 | 2.3 | 1.1 | 2.3 |
| Nutrient input: into oligotrophic waters | 0.2 | 1.7 | 0.5 | 2.5 | 2.4 | 2.3 | 2.9 | 1.6 | nd | 3.4 | 2.9 | 0.0 | 0.4 | 1.1 | 1.7 |
| Ocean dumping: lost fishing gear | 2.5 | 2.5 | 1.1 | 0.7 | 1.4 | 1.0 | 2.5 | 2.4 | 3.0 | 2.8 | 3.1 | 2.9 | 2.3 | 2.6 | 2.2 |
| Ocean dumping: marine debris (trash, etc.) | 3.6 | 4.2 | 2.2 | 1.6 | 2.7 | 0.8 | 3.1 | 2.4 | 3.3 | 2.8 | 3.7 | nd | 3.1 | 2.9 | 2.8 |
| Ocean dumping: shipwrecks | 0.5 | 2.7 | 1.6 | 0.3 | 1.2 | 0.5 | nd | 1.6 | 3.4 | 2.0 | 2.8 | nd | 1.3 | 1.5 | 1.6 |
| Ocean dumping: toxic materials | 1.9 | 2.2 | 2.6 | 1.5 | 3.4 | 0.7 | 3.7 | 2.2 | 2.2 | 3.9 | 4.3 | 5.2 | 2.3 | 2.6 | 2.8 |
| Ocean mining (sand, minerals, etc.) | 2.3 | 2.8 | 1.6 | 0.7 | 1.4 | 0.5 | nd | 2.3 | 3.8 | 3.7 | 3.3 | 0.0 | 2.0 | 2.9 | 2.1 |
| Ocean pollution (from ships, ports, etc.) | 3.4 | 3.3 | 3.3 | 2.9 | 3.2 | 1.8 | nd | 3.1 | 3.5 | 3.8 | 4.0 | 3.0 | 3.5 | 2.9 | 3.2 |
| Pollution input: atmospheric | 1.0 | 3.0 | 1.8 | 2.8 | nd | 1.8 | nd | 4.2 | nd | 4.0 | 4.7 | 0.0 | 3.4 | 2.8 | 2.7 |
| Pollution input: inorganic | 1.3 | 1.7 | 2.0 | 3.0 | 2.6 | 2.0 | nd | 3.5 | nd | 3.9 | 4.7 | 0.0 | 2.8 | 2.6 | 2.5 |
| Pollution input: light | nd | 2.1 | 1.0 | 0.7 | 0.0 | 0.0 | nd | 1.5 | nd | 1.8 | nd | 0.0 | 1.5 | 1.4 | 1.0 |
| Pollution input: noise | nd | 1.9 | 0.6 | 1.3 | 1.6 | 0.0 | nd | 1.7 | nd | 2.4 | nd | 0.0 | 2.7 | 2.9 | 1.5 |
| Pollution input: organic | 2.3 | 2.3 | 3.0 | 3.0 | 3.0 | 3.0 | nd | 3.4 | 3.8 | 3.6 | 3.8 | 0.0 | 3.5 | 3.2 | 2.9 |
| Pollution input: trash, etc. (urban runoff) | 3.1 | 3.3 | 2.1 | 2.7 | 2.7 | 1.9 | 3.6 | 3.1 | 4.1 | 2.4 | 3.2 | 0.0 | 2.8 | 2.1 | 2.7 |
| Power plants and desalination plants | 0.0 | 0.0 | 1.4 | 2.1 | 1.5 | 1.5 | nd | 2.6 | 3.1 | 3.2 | 1.3 | 0.0 | 1.5 | 1.1 | 1.5 |
| Scientific research: collecting | 0.6 | 1.4 | 1.7 | 2.1 | 1.3 | 0.4 | 0.5 | 0.9 | 1.3 | 1.5 | 1.8 | 0.0 | 0.9 | 1.6 | 1.1 |
| Scientific research: experiments/surveys | 0.6 | 1.9 | 1.6 | 2.3 | 1.4 | 0.6 | 0.5 | 0.6 | 1.3 | 2.2 | 2.1 | 0.0 | 0.4 | 0.6 | 1.2 |
| Sediment input: decrease | 2.7 | 4.3 | 1.3 | 4.1 | 2.0 | 1.4 | nd | 1.9 | 0.7 | 3.2 | 1.5 | 0.0 | 1.0 | 0.8 | 1.9 |
| Sediment input: increase | 3.1 | 3.8 | 2.4 | 2.4 | 3.6 | 2.2 | nd | 2.2 | 2.3 | 3.4 | 2.8 | 0.0 | 1.8 | 0.8 | 2.4 |
| Shipping (commercial, cruise, ferry) | 0.9 | 3.1 | 1.2 | 0.8 | 0.9 | 1.7 | 1.8 | 2.8 | nd | 3.2 | 1.7 | 0.0 | 2.7 | 0.8 | 1.7 |
| Tourism: kayaking | 0.7 | 1.5 | 1.1 | 1.2 | 0.8 | 0.5 | nd | 0.6 | 0.0 | 0.0 | 0.0 | 0.0 | 0.5 | 0.0 | 0.5 |
| Tourism: recreational boating | 1.4 | 2.1 | 1.6 | 2.0 | 2.3 | 2.8 | nd | 2.0 | 1.7 | 1.2 | 0.7 | 0.0 | 1.2 | 0.8 | 1.5 |
| Tourism: scuba diving | 0.5 | 0.8 | 1.1 | 0.1 | 0.6 | 0.7 | nd | 1.2 | 1.5 | 0.0 | 0.0 | 0.0 | 0.5 | 0.6 | 0.6 |
| Tourism: surfing | 1.2 | 1.7 | 0.6 | 0.1 | 0.0 | 0.0 | nd | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.4 | 0.0 | 0.3 |
| Tourism: whale watching | nd | 1.9 | 0.0 | 0.0 | 0.0 | 0.0 | nd | 0.6 | 0.0 | 1.9 | 0.0 | 0.0 | 2.3 | 1.1 | 0.7 |
| Mean score | 1.3 | 2.0 | 1.8 | 1.8 | 2.2 | 1.5 | 2.3 | 2.2 | 2.5 | 2.8 | 2.3 | 0.5 | 2.1 | 1.6 | 1.9 |
| Standard error of the mean score | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 | 0.2 | 0.1 | 0.1 | 0.1 | 0.1 | 0.2 | 0.1 | 0.1 | |
| Mean sample size | 2.7 | 2.5 | 5.3 | 8.5 | 2.5 | 6.6 | 0.6 | 3.7 | 2.4 | 1.9 | 3.8 | 0.9 | 4.0 | 2.4 | |
| Standard error of the mean sample size | 0.1 | 0.1 | 0.2 | 0.3 | 0.1 | 0.2 | 0.1 | 0.2 | 0.2 | 0.1 | 0.2 | 0.0 | 0.1 | 0.1 | |

## Table 5

| | Coastal ecosystems | | | | | | | | | Offshore | | | | | Mean |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Human activity | b | bb | r int | salt | tide | eel | alg | nh | ns | h sh | s sh | bath | sp | dp | n |
| Aquaculture: finfish (herbivores) | 3.0 | 2.0 | 6.8 | 9.2 | 2.2 | 6.2 | 0.8 | 3.0 | 2.0 | 2.0 | 5.0 | 1.0 | 5.8 | 2.0 | 3.6 |
| Aquaculture: finfish (predators) | 3.0 | 2.0 | 6.8 | 9.6 | 2.2 | 6.2 | 0.8 | 3.0 | 2.0 | 2.0 | 5.0 | 1.0 | 5.8 | 2.0 | 3.7 |
| Aquaculture: marine plant | 3.0 | 2.0 | 5.4 | 9.2 | 2.0 | 5.4 | 0.8 | 3.0 | 2.0 | 2.0 | 5.0 | 1.0 | 4.8 | 2.0 | 3.4 |
| Aquaculture: shellfish | 3.0 | 2.0 | 3.8 | 11.0 | 2.8 | 7.0 | 1.0 | 3.8 | 3.0 | 2.0 | 5.0 | 1.0 | 5.8 | 3.0 | 3.9 |
| Benthic structures (e.g. oil rigs) | 3.0 | 2.0 | 5.6 | 8.8 | 1.8 | 6.6 | 1.0 | 5.0 | 3.6 | 3.0 | 5.8 | 1.0 | 4.8 | 3.0 | 3.9 |
| Climate change: ocean acidification | 1.6 | 2.4 | 4.2 | 6.2 | 2.6 | 4.4 | 0.0 | 3.0 | 1.6 | 1.8 | 3.2 | 0.0 | 4.0 | 2.6 | 2.7 |
| Climate change: sea level rise | 3.6 | 4.4 | 5.8 | 11.2 | 3.6 | 7.6 | 0.4 | 4.0 | 3.0 | 2.0 | 4.0 | 1.0 | 3.6 | 2.6 | 4.1 |
| Climate change: sea temperature change | 2.8 | 2.6 | 5.6 | 9.6 | 3.6 | 6.2 | 0.0 | 3.8 | 2.0 | 2.4 | 4.4 | 1.0 | 4.0 | 2.6 | 3.6 |
| Climate change: UV change | 1.8 | 1.8 | 2.6 | 3.4 | 1.6 | 3.8 | 0.0 | 4.0 | 1.8 | 1.0 | 1.6 | 1.0 | 3.2 | 2.6 | 2.2 |
| Coastal engineering: altered flow dynamics | 3.8 | 3.8 | 5.8 | 11.6 | 3.6 | 8.0 | 0.8 | 3.6 | 1.6 | 1.8 | 4.6 | 1.0 | 4.0 | 2.8 | 4.1 |
| Coastal engineering: habitat alteration | 3.8 | 4.2 | 6.4 | 10.8 | 3.6 | 8.8 | 0.8 | 3.8 | 2.4 | 1.8 | 4.6 | 1.0 | 4.6 | 3.0 | 4.3 |
| Direct human impact: trampling | 4.0 | 4.8 | 8.0 | 12.8 | 3.8 | 8.0 | 1.0 | 5.0 | 3.6 | 2.0 | 3.4 | 1.0 | 5.6 | 2.8 | 4.7 |
| Disease/pathogens | 1.8 | 2.6 | 3.6 | 6.2 | 1.2 | 8.0 | 0.0 | 4.0 | 2.0 | 1.8 | 1.8 | 1.0 | 3.2 | 1.6 | 2.8 |
| Dredging | 3.2 | 4.0 | 7.8 | 9.2 | 3.0 | 8.0 | 1.0 | 5.0 | 3.8 | 3.8 | 5.4 | 1.0 | 5.6 | 3.0 | 4.6 |
| Energy infrastructure: liquid natural gas | 2.6 | 2.6 | 5.2 | 5.0 | 1.8 | 6.0 | 0.8 | 3.8 | 2.0 | 1.6 | 3.2 | 0.8 | 4.4 | 2.6 | 3.0 |
| Energy infrastructure: tidal | 2.0 | 1.2 | 2.4 | 4.2 | 1.6 | 5.0 | 0.0 | 3.0 | 1.4 | 1.0 | 3.2 | 1.0 | 4.8 | 3.0 | 2.4 |
| Energy infrastructure: wave | 2.0 | 1.8 | 2.4 | 4.8 | 1.6 | 4.0 | 0.0 | 3.0 | 1.4 | 1.0 | 2.2 | 1.0 | 3.8 | 3.0 | 2.3 |
| Energy infrastructure: wind | 2.6 | 2.6 | 3.8 | 6.0 | 1.6 | 5.0 | 0.8 | 3.8 | 2.2 | 1.6 | 2.8 | 1.0 | 4.8 | 3.0 | 3.0 |
| Fishing: aquarium | 2.0 | 2.0 | 5.8 | 9.0 | 2.0 | 6.8 | 0.8 | 4.0 | 1.6 | 2.0 | 5.0 | 1.0 | 3.2 | 2.0 | 3.4 |
| Fishing: demersal habitat-modifying | 2.0 | 1.0 | 6.8 | 8.2 | 2.6 | 8.2 | 0.8 | 4.8 | 3.6 | 3.0 | 6.0 | 1.0 | 4.0 | 1.6 | 3.8 |
| Fishing: demersal non-habitat-modifying high bycatch | 2.0 | 1.0 | 6.0 | 9.0 | 2.0 | 8.0 | 1.0 | 4.4 | 3.6 | 3.0 | 5.4 | 1.0 | 4.0 | 1.6 | 3.7 |
| Fishing: demersal non-habitat-modifying low bycatch | 2.0 | 1.0 | 5.6 | 9.0 | 2.0 | 9.0 | 2.0 | 5.4 | 4.6 | 2.0 | 4.6 | 1.0 | 4.0 | 1.6 | 3.8 |
| Fishing: habitat-modifying artisanal (subsistence) | 2.2 | 1.0 | 4.0 | 8.2 | 3.0 | 5.0 | 0.0 | 3.8 | 1.2 | 2.0 | 5.0 | 1.0 | 4.8 | 2.0 | 3.1 |
| Fishing: non-habitat-modifying artisanal (subsistence) | 2.8 | 1.0 | 4.8 | 9.0 | 3.0 | 7.0 | 0.0 | 2.8 | 1.0 | 2.0 | 5.0 | 1.0 | 4.8 | 2.0 | 3.3 |
| Fishing: pelagic high bycatch | 2.0 | 1.2 | 6.0 | 8.4 | 2.2 | 7.2 | 0.0 | 4.2 | 2.2 | 2.0 | 3.6 | 1.0 | 4.0 | 1.6 | 3.3 |
| Fishing: pelagic low bycatch | 2.0 | 1.2 | 6.0 | 8.4 | 2.2 | 7.2 | 0.0 | 4.2 | 2.2 | 2.0 | 3.6 | 1.0 | 5.0 | 1.6 | 3.3 |
| Fishing: recreational | 3.0 | 2.8 | 6.4 | 10.0 | 3.0 | 8.0 | 1.0 | 4.8 | 4.0 | 2.0 | 3.8 | 1.0 | 5.2 | 1.6 | 4.0 |
| Freshwater input: decrease | 1.2 | 1.0 | 4.4 | 9.8 | 2.2 | 6.0 | 0.2 | 2.0 | 1.0 | 1.0 | 2.8 | 1.0 | 3.6 | 3.0 | 2.8 |
| Freshwater input: increase | 1.2 | 1.6 | 5.0 | 9.6 | 2.8 | 4.8 | 0.6 | 2.0 | 1.8 | 1.0 | 3.4 | 1.0 | 3.6 | 3.0 | 3.0 |
| Invasive species (from ballast, etc.) | 2.0 | 2.0 | 5.0 | 10.4 | 2.6 | 5.2 | 0.8 | 3.8 | 4.4 | 3.6 | 4.8 | 0.0 | 3.4 | 2.8 | 3.6 |
| Military activity | 3.0 | 1.8 | 5.0 | 6.8 | 1.4 | 6.0 | 0.0 | 2.0 | 0.0 | 1.0 | 1.0 | 0.0 | 2.6 | 1.0 | 2.3 |

| Human activity | b | bb | r int | salt | tide | eel | alg | nh | ns | h sh | s sh | bath | sp | dp | Mean |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Nutrient input: causing harmful algal blooms | 1.2 | 2.0 | 5.4 | 9.2 | 2.0 | 9.0 | 0.4 | 3.4 | 2.4 | 2.0 | 4.0 | 1.0 | 4.6 | 2.0 | 3.5 |
| Nutrient input: causing hypoxic zones | 2.2 | 2.0 | 4.8 | 9.0 | 2.0 | 8.2 | **0.0** | 4.0 | 3.4 | 2.0 | 4.0 | 1.0 | 3.8 | 2.0 | 3.5 |
| Nutrient input: into eutrophic waters | 2.2 | 2.0 | 4.8 | 10.2 | 2.0 | 8.0 | **0.0** | 3.0 | 2.8 | 1.0 | 3.0 | 1.0 | 2.6 | 2.0 | 3.2 |
| Nutrient input: into oligotrophic waters | 2.2 | 1.8 | 4.6 | 10.6 | 2.2 | 7.0 | **0.0** | 2.0 | 1.0 | 1.0 | 3.8 | 1.0 | 2.4 | 2.0 | 3.0 |
| Ocean dumping: lost fishing gear | 2.8 | 2.8 | 6.0 | 10.2 | 2.0 | 8.0 | 2.0 | 6.0 | 3.8 | 2.8 | 5.2 | 1.0 | 5.0 | 1.6 | 4.2 |
| Ocean dumping: marine debris (trash, etc.) | 2.8 | 3.6 | 6.0 | 10.2 | 2.8 | 8.0 | 1.0 | 5.0 | 2.8 | 2.8 | 4.6 | 0.8 | 4.4 | 1.6 | 4.0 |
| Ocean dumping: ship wrecks | 3.6 | 2.6 | 5.6 | 10.0 | 3.6 | 6.8 | 1.0 | 4.0 | 1.6 | 2.0 | 3.2 | 0.8 | 3.6 | 2.6 | 3.6 |
| Ocean dumping: toxic materials | 1.8 | 2.8 | 5.6 | 8.2 | 2.4 | 4.0 | 0.8 | 3.8 | 2.6 | 2.0 | 2.6 | 1.0 | 3.6 | 2.4 | 3.1 |
| Ocean mining (sand, minerals, etc.) | 2.6 | 3.4 | 6.0 | 7.0 | 2.0 | 7.0 | 1.0 | 3.8 | 2.4 | 2.8 | 4.2 | 1.0 | 3.2 | 2.0 | 3.5 |
| Ocean pollution (from ships, ports, etc.) | 3.6 | 3.4 | 5.0 | 10.2 | 4.0 | 4.8 | 0.8 | 4.8 | 3.6 | 2.6 | 4.2 | 1.0 | 4.0 | 2.6 | 3.9 |
| Pollution input: atmospheric | 1.4 | 2.4 | 3.2 | 7.2 | 0.4 | 4.0 | **0.0** | 1.2 | 0.6 | 1.2 | 2.6 | 1.0 | 3.4 | 2.6 | 2.2 |
| Pollution input: inorganic | 1.6 | 2.0 | 3.4 | 6.2 | 2.4 | 5.0 | **0.0** | 2.8 | 0.6 | 1.8 | 2.4 | 1.0 | 3.6 | 2.6 | 2.5 |
| Pollution input: light | **0.0** | 1.0 | 3.0 | 3.0 | 2.0 | 1.0 | **0.0** | 3.0 | 0.6 | 1.0 | 0.6 | 1.0 | 2.0 | 2.0 | 1.4 |
| Pollution input: noise | **0.0** | 1.0 | 3.0 | 3.0 | 1.6 | 2.0 | **0.0** | 3.0 | 0.4 | 1.0 | 0.2 | 1.0 | 2.0 | 2.0 | 1.4 |
| Pollution input: organic | 2.2 | 2.4 | 4.2 | 5.0 | 2.6 | 5.0 | 0.8 | 3.8 | 1.8 | 2.6 | 3.2 | 1.0 | 3.6 | 2.6 | 2.9 |
| Pollution input: trash, etc. (urban runoff) | 3.4 | 3.6 | 5.8 | 7.6 | 2.4 | 8.8 | 1.0 | 3.0 | 1.0 | 2.6 | 4.8 | 1.0 | 3.2 | 2.6 | 3.6 |
| Power, desalination plants | 3.0 | 1.0 | 3.6 | 5.0 | 2.2 | 5.4 | 0.8 | 2.8 | 2.4 | 1.0 | 3.2 | 1.0 | 5.4 | 3.0 | 2.8 |
| Scientific research: collecting | 4.0 | 3.8 | 7.6 | 11.0 | 3.8 | 8.8 | 1.8 | 5.8 | 5.6 | 2.0 | 4.4 | 1.0 | 4.6 | 3.0 | 4.8 |
| Scientific research: experiments/surveys | 3.8 | 3.8 | 7.4 | 12.0 | 3.6 | 8.8 | 1.8 | 5.8 | 5.6 | 2.8 | 5.2 | 1.0 | 5.2 | 3.0 | 5.0 |
| Sediment input: decrease | 2.8 | 3.4 | 5.2 | 10.6 | 2.2 | 5.6 | 0.8 | 2.8 | 2.8 | 1.0 | 3.4 | 1.0 | 3.4 | 3.0 | 3.4 |
| Sediment input: increase | 3.6 | 4.2 | 6.4 | 10.0 | 2.8 | 7.0 | 0.8 | 2.8 | 2.8 | 1.6 | 4.4 | 1.0 | 3.4 | 3.0 | 3.8 |
| Shipping (commercial, cruise, ferry) | 3.6 | 2.6 | 7.8 | 9.0 | 1.6 | 8.8 | 1.0 | 2.6 | 1.4 | 2.0 | 4.2 | 1.0 | 4.2 | 3.0 | 3.8 |
| Tourism: kayaking | 4.6 | 4.6 | 7.6 | 12.0 | 3.6 | 9.0 | 0.8 | 5.0 | 4.0 | 2.0 | 5.0 | 1.0 | 5.6 | 3.0 | 4.8 |
| Tourism: recreational boating | 3.6 | 4.4 | 6.2 | 11.4 | 3.0 | 8.8 | 0.8 | 4.8 | 3.2 | 2.0 | 5.0 | 1.0 | 4.2 | 3.0 | 4.4 |
| Tourism: scuba diving | 3.0 | 4.0 | 7.0 | 10.0 | 2.8 | 8.0 | 0.8 | 4.8 | 3.4 | 2.0 | 5.0 | 1.0 | 4.6 | 3.0 | 4.2 |
| Tourism: surfing | 3.8 | 3.8 | 7.8 | 10.0 | 4.0 | 8.0 | 0.8 | 4.8 | 3.8 | 2.0 | 5.0 | 1.0 | 5.6 | 2.0 | 4.5 |
| Tourism: whale watching | **0.0** | 1.0 | 3.0 | 3.0 | 2.0 | 3.0 | **0.0** | 3.0 | 1.0 | 1.0 | 2.0 | 1.0 | 2.0 | 2.0 | 1.7 |
| Grand total | 141.4 | 138.8 | 295.2 | 476.6 | 138.8 | 368.0 | 34.6 | 211.4 | 136.0 | 107.8 | 213.6 | 52.4 | 226.4 | 134.8 | |
| Sample size mean | 2.5 | 2.5 | 5.3 | 8.5 | 2.5 | 6.6 | 0.6 | 3.8 | 2.4 | 1.9 | 3.8 | 0.9 | 4.0 | 2.4 | |
| Sample size standard error | 0.1 | 0.1 | 0.2 | 0.3 | 0.1 | 0.3 | 0.1 | 0.1 | 0.2 | 0.1 | 0.2 | 0.0 | 0.1 | 0.1 | |

## Table 6

| Human activity | MA | CA-recalc | CA-orig | | Human activity (cont) | MA | CA-recalc | CA-orig |
|---|---|---|---|---|---|---|---|---|
| Climate change: sea temperature change | 4.5 | 2.9 | 1.5 | | Nutrient input: into eutrophic waters | 1.8 | 1.5 | 0.8 |
| Climate change: ocean acidification | 3.5 | 4.2 | 2.6 | | Fishing: demersal non-destructive high bycatch | 1.7 | 1.8 | 1.0 |
| Invasive species (from ballast, etc.) | 3.3 | 3.3 | 1.2 | | Ocean dumping: marine debris (trash, etc.) | 1.7 | 1.5 | 0.8 |
| Climate change: UV change | 3.3 | 1.8 | 0.9 | | Sediment input: increase | 1.6 | 1.7 | 0.8 |
| Ocean mining (sand, minerals, etc.) | 3.2 | 0.6 | 0.2 | | Pollution input: light | 1.6 | 0.9 | 0.4 |
| Climate change: sea level rise | 3.1 | 2.1 | 0.9 | | Fishing: recreational | 1.6 | 1.6 | 0.9 |
| Pollution input: noise | 2.9 | nd | nd | | Aquaculture: shellfish | 1.5 | 1.0 | 0.4 |
| Ocean dumping: ship wrecks | 2.8 | 2.7 | 1.6 | | Tourism: kayaking | 1.5 | 0.4 | 0.2 |
| Ocean dumping: lost fishing gear | 2.8 | 1.8 | 1.1 | | Pollution input: trash, etc. (urban runoff) | 1.5 | 1.9 | 0.9 |
| Energy infrastructure: liquid natural gas | 2.7 | nd | nd | | Fishing: demersal non-destructive low bycatch | 1.4 | 1.5 | 0.8 |
| Ocean pollution (from ships, ports, etc.) | 2.7 | 1.2 | 0.7 | | Freshwater input: decrease | 1.3 | 0.6 | 0.3 |
| Pollution input: organic | 2.6 | 2.7 | 1.3 | | Fishing: pelagic high bycatch | 1.3 | 0.3 | 0.3 |
| Disease/pathogens | 2.6 | 1.2 | 0.7 | | Direct human impact: trampling | 1.2 | 0.8 | 0.3 |
| Dredging | 2.6 | 1.2 | 0.5 | | Power, desalination plants | 1.2 | 1.2 | 0.6 |
| Pollution input: atmospheric | 2.5 | 1.4 | 0.8 | | Scientific research: collecting | 1.2 | 1.2 | 0.6 |
| Energy infrastructure: wind | 2.5 | nd | nd | | Marine component of forestry | 1.1 | 0.7 | 0.2 |
| Coastal engineering: habitat alteration | 2.5 | 2.1 | 0.8 | | Aquaculture: finfish (predators) | 1.1 | 0.5 | 0.3 |
| Benthic structures | 2.5 | 2.7 | 1.4 | | Pollution input: inorganic | 1.0 | 2.3 | 1.2 |
| Coastal engineering: altered flow dynamics | 2.5 | 1.8 | 0.7 | | Fishing: pelagic low bycatch | 1.0 | 0.3 | 0.2 |
| Sediment input: decrease | 2.4 | 1.5 | 0.6 | | Aquaculture: finfish (herbivores) | 0.9 | 0.0 | 0.0 |
| Fishing: demersal destructive | 2.3 | 1.8 | 1.3 | | Aquaculture: marine plant | 0.9 | 0.3 | 0.1 |
| Nutrient input: into oligotrophic waters | 2.2 | 1.6 | 0.9 | | Fishing: non-destructive artisanal | 0.7 | 0.6 | 0.3 |
| Nutrient input: causing hypoxic zones | 2.2 | 1.8 | 1.0 | | Fishing: destructive artisanal | 0.6 | 0.6 | 0.2 |
| Energy infrastructure: tidal | 2.2 | nd | nd | | Tourism: whale watching | 0.6 | nd | nd |
| Ocean dumping: toxic materials | 2.2 | 1.8 | 1.2 | | Tourism: surfing | 0.6 | 0.2 | 0.1 |
| Energy infrastructure: wave | 2.2 | nd | nd | | Tourism: recreational boating | 0.6 | 0.6 | 0.3 |
| Nutrient input: causing harmful algal blooms | 2.0 | 1.8 | 1.0 | | Shipping (commercial, cruise, ferry) | 0.5 | 0.4 | 0.2 |
| Freshwater input: increase | 2.0 | 1.1 | 0.5 | | Fishing: aquarium | 0.5 | 0.3 | 0.1 |
| Military activity | 1.9 | 1.3 | 1.0 | | Tourism: scuba diving | 0.3 | 0.3 | 0.1 |
| Scientific research: experiments/surveys | 1.9 | 1.4 | 0.8 | | | | | |

## Table 7

| Human Activity | b | bb | r int | salt | tide | eel | alg | nh | ns | h sh | s sh | h ba | s ba | sp | dp |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Aquaculture: shellfish | 0.9 | 1.7 | 2.5 | 1.4 | 2.0 | 2.0 | 1.7 | 2.1 | 2.5 | 2.4 | 0.6 | **0.0** | **0.0** | 1.0 | **0.6** |
| Climate change: ocean acidification | 1.8 | 3.2 | 4.0 | 3.7 | 4.3 | 2.5 | **3.2** | 3.0 | 1.5 | 5.0 | **4.4** | **4.7** | **4.4** | 4.7 | **3.7** |
| Climate change: sea temperature change | 4.3 | 5.5 | 3.9 | 4.2 | 6.1 | 2.8 | **3.8** | 4.6 | 4.8 | 5.9 | 3.5 | **3.1** | **4.3** | 5.1 | **4.6** |
| Climate change: UV change | 2.1 | 2.5 | 3.6 | 3.9 | 5.3 | 4.2 | **3.6** | 3.1 | 3.8 | 5.3 | **0.0** | **0.0** | **0.0** | 3.8 | **3.3** |
| Coastal engineering: habitat alteration | 3.7 | 4.0 | 3.7 | 3.4 | 3.6 | 2.9 | **3.5** | 1.6 | 4.2 | 1.6 | 1.4 | **0.0** | **0.0** | 1.3 | **1.3** |
| Fishing: demersal habitat-modifying | 0.0 | 0.0 | 0.9 | 0.5 | 3.1 | 2.6 | **3.1** | 3.5 | 3.8 | 3.5 | 3.4 | **2.8** | **3.4** | 2.2 | **2.8** |
| Fishing: demersal non-habitat-modifying high bycatch | 0.0 | 0.0 | 0.3 | 0.8 | 1.1 | 0.5 | 2.8 | 2.5 | 2.6 | 3.9 | 3.5 | **2.2** | **2.7** | 1.8 | **1.4** |
| Fishing: demersal non-habitat-modifying low bycatch | 0.0 | 0.0 | 1.4 | 0.7 | 1.1 | 0.8 | 2.5 | 2.2 | 2.1 | 2.3 | 2.2 | **1.7** | **0.0** | 2.5 | **1.7** |
| Fishing: pelagic high bycatch | 0.0 | 0.4 | 0.0 | 0.2 | 1.0 | 0.0 | **2.6** | 1.6 | 1.5 | 3.0 | 2.9 | **0.0** | **0.0** | 3.2 | **2.9** |
| Fishing: pelagic low bycatch | 0.0 | 0.3 | 0.0 | 0.2 | 1.0 | 0.0 | **1.7** | 1.3 | 1.5 | 2.3 | 2.6 | **0.0** | **0.0** | 2.8 | **1.1** |
| Invasive species (from ballast, etc.) | 3.6 | 3.5 | 3.8 | 3.5 | 1.8 | 2.6 | **3.5** | 3.5 | 4.0 | 4.0 | 3.3 | **2.6** | **1.2** | 3.2 | **3.1** |
| Nutrient input | 0.2 | 1.7 | 0.5 | 2.5 | 2.4 | 2.3 | 2.9 | 1.6 | **3.7** | 3.4 | 2.9 | **2.1** | **0.0** | 0.4 | **1.1** |
| Ocean pollution (from ships, ports, etc.) | 3.4 | 3.3 | 3.3 | 2.9 | 3.2 | 1.8 | **1.7** | 3.1 | 3.5 | 3.8 | 4.0 | **1.7** | **3.0** | 3.5 | **2.9** |
| Pollution input: atmospheric | 1.0 | 3.0 | 1.8 | 2.8 | **2.1** | 1.8 | **2.1** | 4.2 | **0.0** | 4.0 | 4.7 | **2.0** | **0.0** | 3.4 | **3.8** |
| Pollution input: inorganic | 1.3 | 1.7 | 2.0 | 3.0 | 2.6 | 2.0 | **2.0** | 3.5 | **1.4** | 3.9 | 4.7 | **1.9** | **0.0** | 2.8 | **2.6** |
| Pollution input: light | **2.1** | 2.1 | 1.0 | 0.7 | 0.0 | 0.0 | **2.1** | **1.5** | **1.0** | 1.8 | **0.0** | **1.8** | **0.0** | 1.5 | **1.4** |
| Pollution input: organic | 2.3 | 2.3 | 3.0 | 3.0 | 3.0 | 3.0 | **2.0** | 3.4 | 3.8 | 3.6 | 3.8 | **2.3** | **0.0** | 3.5 | **3.2** |
| Pollution input: trash, etc. (urban runoff) | 3.1 | 3.3 | 2.1 | 2.7 | 2.7 | 1.9 | **3.6** | 3.1 | 4.1 | 2.4 | 3.2 | **0.7** | **0.0** | 2.8 | **2.1** |
| Power, desalination plants | 0.0 | 0.0 | 1.4 | 2.1 | 1.5 | 1.5 | 3.2 | 2.6 | 3.1 | 3.2 | 1.3 | **0.0** | **0.0** | 1.5 | **1.1** |
| Shipping (commercial, cruise, ferry) | 0.9 | 3.1 | 1.2 | 0.8 | 0.9 | 1.7 | 1.8 | 2.8 | **0.0** | 3.2 | 1.7 | **0.0** | **0.0** | 2.7 | **0.8** |
| Tourism: whale watching | **0.0** | 1.9 | 0.0 | 0.0 | 0.0 | 0.0 | **0.0** | 0.6 | 0.0 | 1.9 | 0.0 | **0.0** | **0.0** | 2.3 | **1.1** |

## Table 8

| | Anthropogenic Driver | Brief description | Source | Native resolution |
|---|---|---|---|---|
| Land-based | Nutrient input | | | |
| | Fertilizer and manure input | Fertilizer use for crops and confined manure from livestock | USGS | 0.0625 $km^2$ |
| | Wastewater | Coastal wastewater treatment plants, combined sewer overflows, and sewage outfalls | Massachusetts Wastewater Regional Authority (MWRA) | point, converted to 0.0625 $km^2$ |
| | Septic systems | Leaky septic systems of non-sewered households | MassGIS, US Census | 1:100,000 |
| | Atmospheric N deposition | Wet and dry deposition of ammonium, nitrate, and nitric acid | CASTNET and NADP | point, kriged to 0.0625 $km^2$ |
| | Atmospheric deposition of pollutants | Wet and dry deposition of sulfate | CASTNET and NADP | point, kriged to 0.0625 $km^2$ |
| | Inorganic pollution | | | |
| | Non-point source | Impervious surface area (urban areas) | National Land Cover Database | 0.0625 $km^2$ |
| | Point source | Factories, mines and other point sources | EPA Toxic Release Inventory | point, converted to 0.0625 $km^2$ |
| | Organic pollution | | | |
| | Non-point source | Pesticide use on agricultural land | National Pesticide Use Database, Coastal Change Analysis Program | 0.0625 $km^2$ |
| | Point source | Factories, mines and other point sources | EPA Toxic Release Inventory | point, converted to 0.0625 $km^2$ |
| | Light pollution | Satellite nighttime images of light intensity | NGDC Stable Lights at Night | 1 $km^2$ |
| | Coastal engineering | Linear extent of hardened shoreline (riprap, jetties, seawalls) | NOAA's Environmental Sensitivity Index (ESI) | 1:25,000 |
| | Coastal power plants | Cooling water entrainment from power plants | EPA | point, converted to 0.0625 km2 |

| | Anthropogenic Driver | Brief description | Source | Native resolution |
|---|---|---|---|---|
| Fishing | Demersal habitat-modifying | Ave annual catch for all gear types in class | MA DMF & NMFS | variable (DMF SRAs) and 10' blocks (NMFS) |
| | Demersal non-habitat-modifying high bycatch | Ave annual catch for all gear types in class | MA DMF & NMFS | variable (DMF SRAs) and 10' blocks (NMFS) |
| | Demersal non-habitat-modifying low bycatch | Ave annual catch for all gear types in class | MA DMF & NMFS | variable (DMF SRAs) and 10' blocks (NMFS) |
| | Ppelagic high bycatch | Ave annual catch for all gear types in class | MA DMF & NMFS | variable (DMF SRAs) and 10' blocks (NMFS) |
| | Pelagic low bycatch | Ave annual catch for all gear types in class | MA DMF & NMFS | variable (DMF SRAs) and 10' blocks (NMFS) |
| Other | Aquaculture: shellfish | Shellfish aquaculture facility locations | Stone Environmental, MA DMR | 0.0625 km2 |
| | Invasive species | Modeled as a function of ballast water release in ports | Stone Environmental | 0.0625 $km^2$ |
| | Marine debris (trash) | Coastline trash removed in annual beach clean-up | CoastSweep | county level |
| | Ocean-based pollution | Pollution derived from commercial ships and ports | AIS, Halpern et al. 2008, Stone Environmental | 0.0625 $km^2$ and 1 $km^2$ |
| | Commercial vessel traffic | Commercial shipping and ferry routes and traffic | AIS, Halpern et al. 2008, Stone Environmental | 0.0625 $km^2$ and 1 $km^2$ |
| | Whale watching | Density of whale watching traffic | Stellwagen Bank National Marine Sanctuary | 0.0625 km2 |
| Climate | Ocean acidification | Recent anomalously high sea surface temperature | Halpern et al. 2008 | 21 $km^2$ |
| | Sea temperature increase | Modeled patterns of recent changes in ocean acidity | Halpern et al. 2008 | 1 degree |
| | UV radiation increase | Recent anomalously high surface UV irradiance | Halpern et al. 2008 | 1 degree |

# Figure Legends

Figure 1. Adapted from Halpern et al. 2008b. Cumulative impacts of human activities on global marine ecosystems.

Figure 2. Map of the study region extent and benthic ecosystem types (aka habitats). Beach and barrier beach are shown as one category here – beach dune complex – but for running the model, they were split into two exclusive categories. Pelagic ecosystems, which overlap benthic habitats in all waters >30m deep are shown in Figure 3.

Figure 3. A zoomed-in view of the benthic ecosystem types in the nearshore. Note that even at this scale, most intertidal habitats are difficult to see because they are generally only a single coastal pixel wide (i.e. 250m).

Figure 4. Map of pelagic ecosystems for the study region. In waters <30m deep (white areas on map), we assume that benthic and pelagic habitats are strongly coupled. For this reason, we do not map pelagic habitats separately in this depth zone. Beyond 30m, shallow pelagic habitat occupies the top 200m of the water column, which is generally equivalent to the photic zone (aqua areas on map). In waters >200m deep, we also map a deep pelagic, aphotic zone (dark blue green areas on map). Therefore in depths of 0-30m there is no pelagic habitat, in 30-200m there is only shallow pelagic habitat, and in >200m there is both shallow and deep pelagic. As noted in the description of the model, in any pixel where more than one habitat is found, vulnerability scores for each stressor are averaged across those ecosystems.

Figure 5. Map of the watersheds that influence Massachusetts' coastal waters. Watersheds from Rhode Island north through Maine are included. Watershed boundaries were developed for this project using an automated flow accumulation process, as described in the text.

Figure 6. The cumulative impact of 21 different human stressors on 15 marine ecosystems. Cumulative impact is a function of the intensity of each human stressor modified by the vulnerability of the underlying habitats. See methods documents for the full list of datalayers that

were included. Colors are ramped by the standard deviation of the data, with red as high cumulative impact and blue as low cumulative impact.

Figure 7. A zoomed-in view of the cumulative impact to Massachusetts state waters. See legend for full-view map for details.

Figure 8. The summed intensity of all human stressors without accounting for ecosystem vulnerabilities. All 21 human stressor data layers are included. Colors are ramped by the standard deviation of the data, with red as high cumulative impact and blue as low cumulative impact.

Figure 9. A zoomed-in view of the summed intensity of all stressors within Massachusetts state waters. See legend for full-view map for details.

Figure 10. The number of co-occurring human stressor data in each 250m$^2$ pixel regardless of the intensity of the stressor. All 21 human stressor data layers are included. Colors are ramped by the number of co-occurring stressors, with red as high cumulative impact and blue as low cumulative impact.

Figure 11. A zoomed-in view of the number of co-occurring human stressors to Massachusetts state waters. See legend for full-view map for details.

Figure 12. The cumulative impact of climate stressors only (UV, SST anomalies, and ocean acidification). Cumulative impact is a function of the intensity of each human stressor modified by the vulnerability of the underlying habitats. Colors are ramped by the standard deviation of the data, with red as high cumulative impact and blue as low cumulative impact.

Figure 13. A zoomed-in view of the cumulative impact of climate stressors only (UV, SST anomalies, and ocean acidification) to Massachusetts state waters. See legend for full-view map for details.

Figure 14. The cumulative impact of fishing stressors only (5 categories of commercial fishing). Cumulative impact is a function of the intensity of each human stressor modified by the vulnerability of the underlying habitats. Colors are ramped by the standard deviation of the data, with red as high cumulative impact and blue as low cumulative impact.

Figure 15. A zoomed-in view of the fishing impact to Massachusetts state waters. See legend for full-view map for details.

Figure 16. The cumulative impact of land-based sources of stress only (pollution from nutrient, organic, inorganic, atmospheric and light sources; coastal power plants; and coastal engineering). Cumulative impact is a function of the intensity of each human stressor modified by the vulnerability of the underlying habitats. Colors are ramped by the standard deviation of the data, with red as high cumulative impact and blue as low cumulative impact.

Figure 17. A zoomed-in view of the land-based pollution impact to Massachusetts state waters. See legend for full-view map for details.

Figure 18. The cumulative impact of other sources of stress only (commercial shipping, invasive species, marine debris, aquaculture, and ocean-based pollution). Cumulative impact is a function of the intensity of each human stressor modified by the vulnerability of the underlying habitats. Colors are ramped by the standard deviation of the data, with red as high cumulative impact and blue as low cumulative impact.

Figure 19. A zoomed-in view of the cumulative impact of other sources of stress only (commercial shipping, invasive species, marine debris, aquaculture, and ocean-based pollution) to Massachusetts state waters. See legend for full-view map for details.

Figure 20. Histograms of the frequency of cumulative impact scores by ecosystem and for the final model, (averaged across all ecosystems). Each histogram displays number of cells in cumulative impact score bins of size 0.1. Note the very different y-axis scales.

## Figure 1.

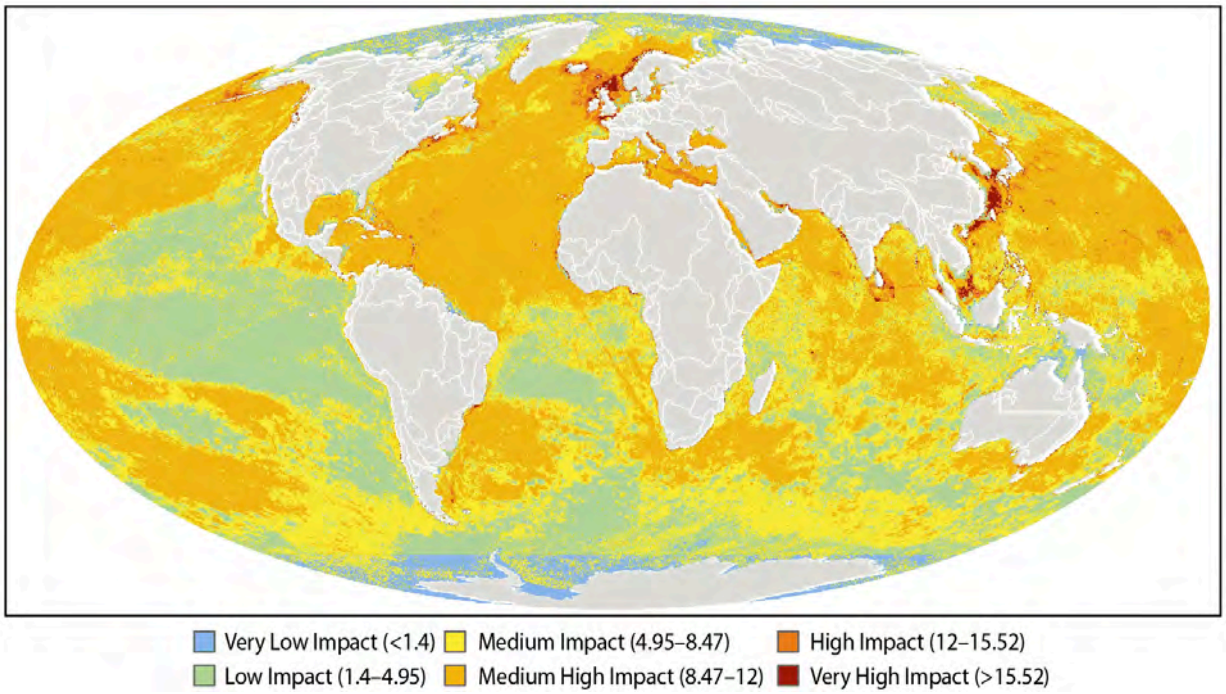
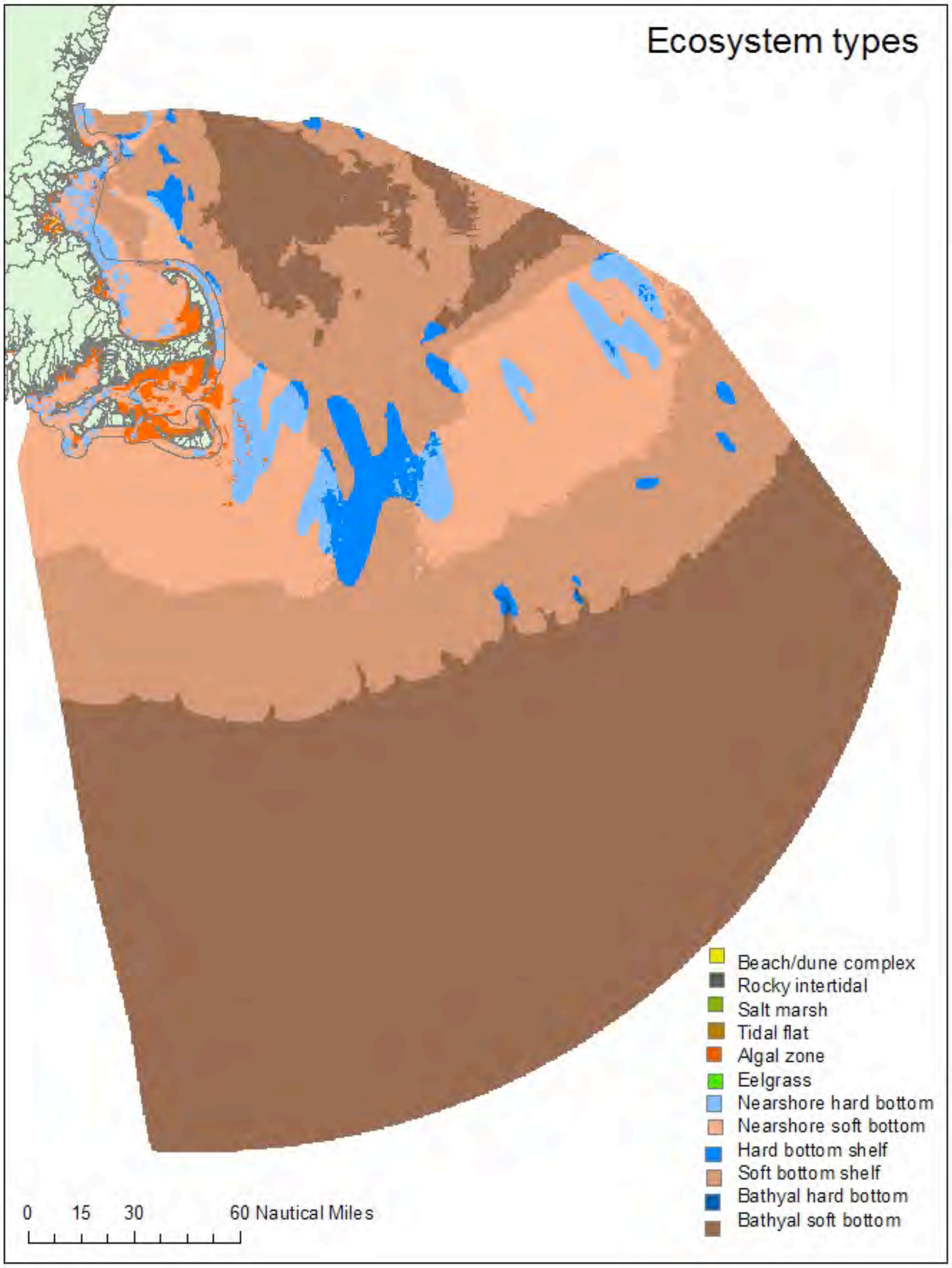
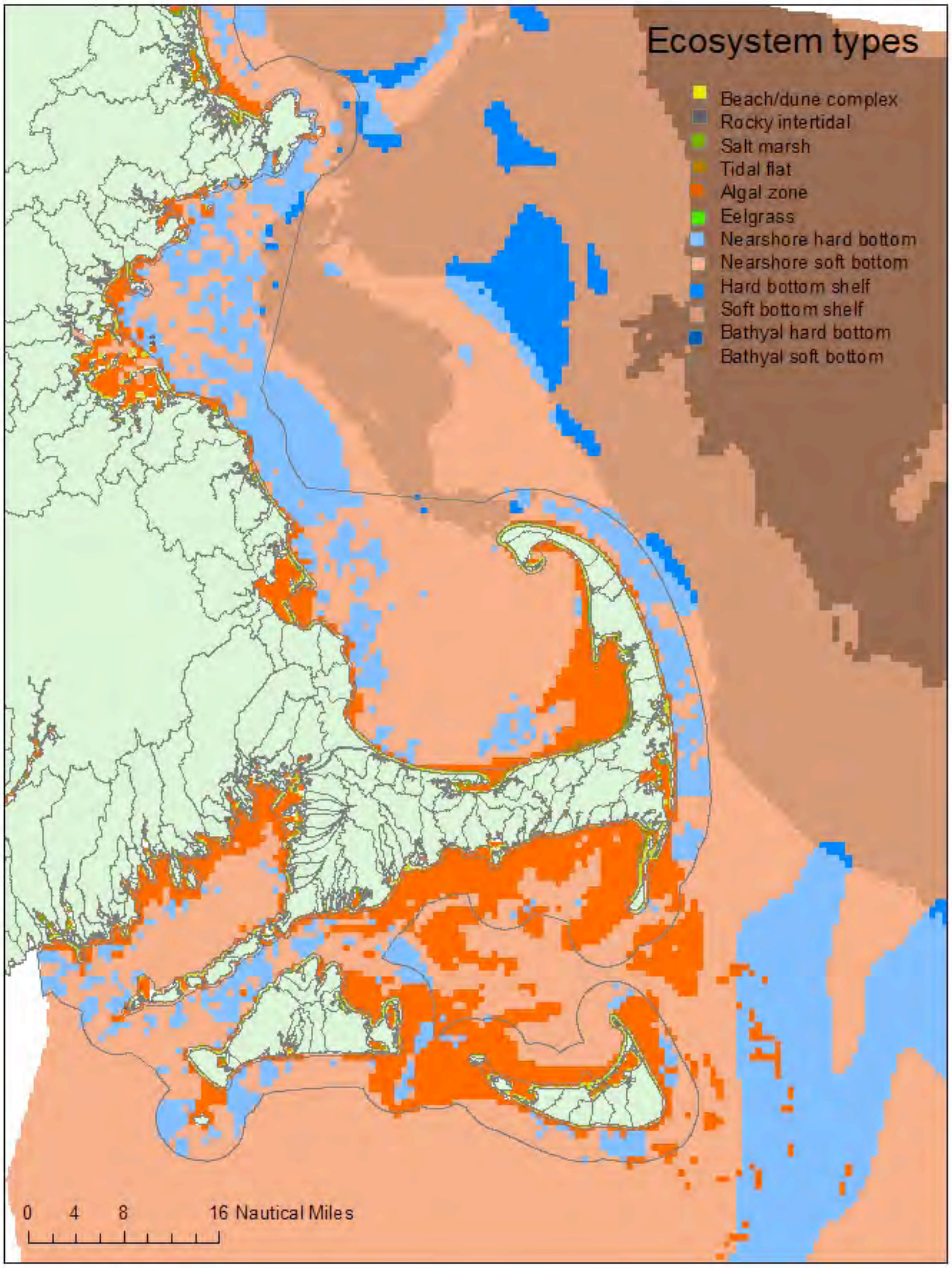

Very Low Impact (<1.4)
Medium Impact (4.95–8.47)
High Impact (12–15.52)
Low Impact (1.4–4.95)
Medium High Impact (8.47–12)
Very High Impact (>15.52)

**Figure 2.**


Ecosystem types
Beach/dune complex
Rocky intertidal
Salt marsh
Tidal flat
Algal zone
Eelgrass
Nearshore hard bottom
Nearshore soft bottom
Hard bottom shelf
Soft bottom shelf
Bathyal hard bottom
Bathyal soft bottom
0 15 30 60 Nautical Miles

## Figure 3.



Ecosystem types
Beach/dune complex
Rocky intertidal
Salt marsh
Tidal flat
Algal zone
Eelgrass
Nearshore hard bottom
Nearshore soft bottom
Hard bottom shelf
Soft bottom shelf
Bathyal hard bottom
Bathyal soft bottom
0 4 8 16 Nautical Miles

**Figure 4.**

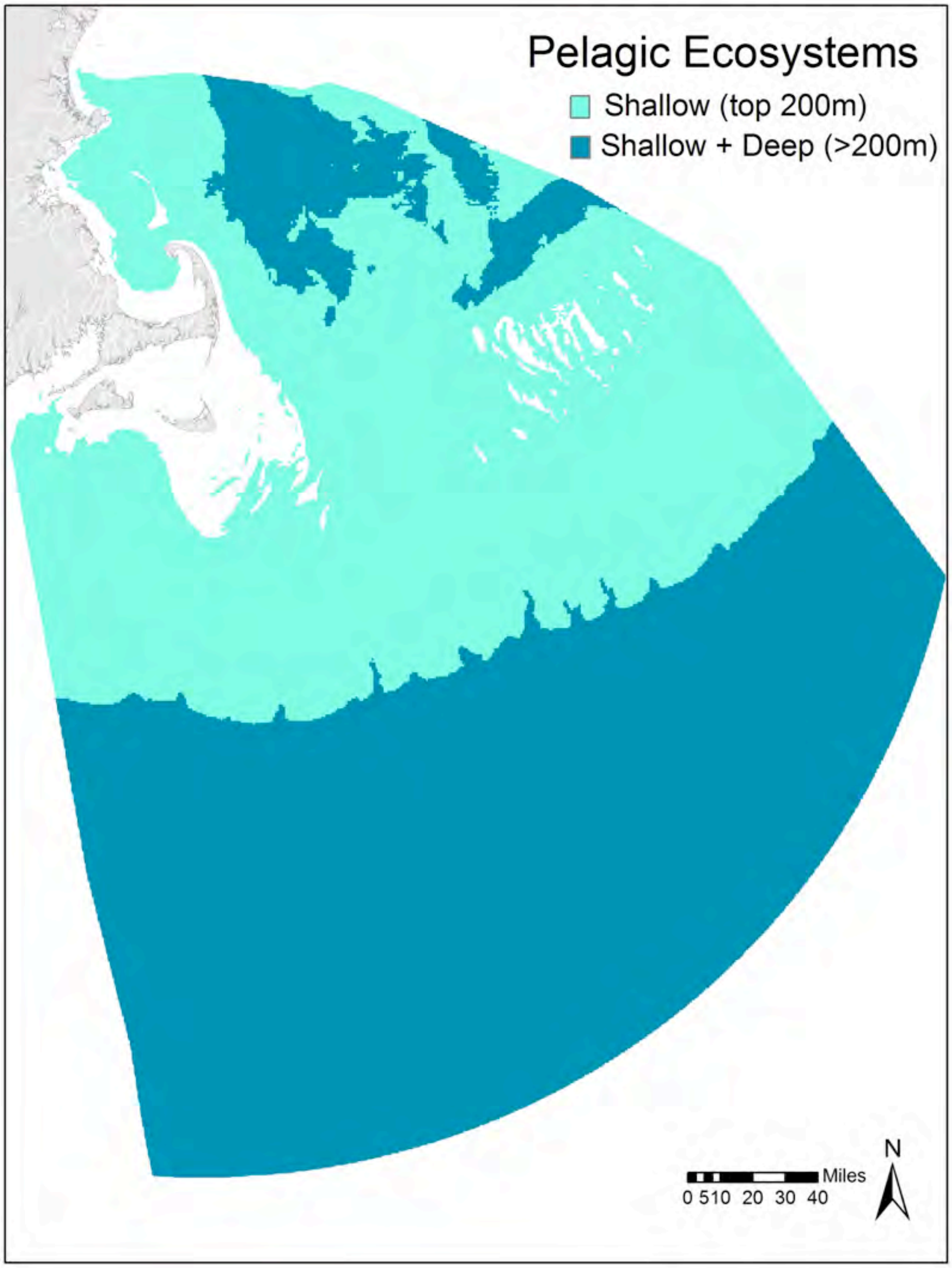
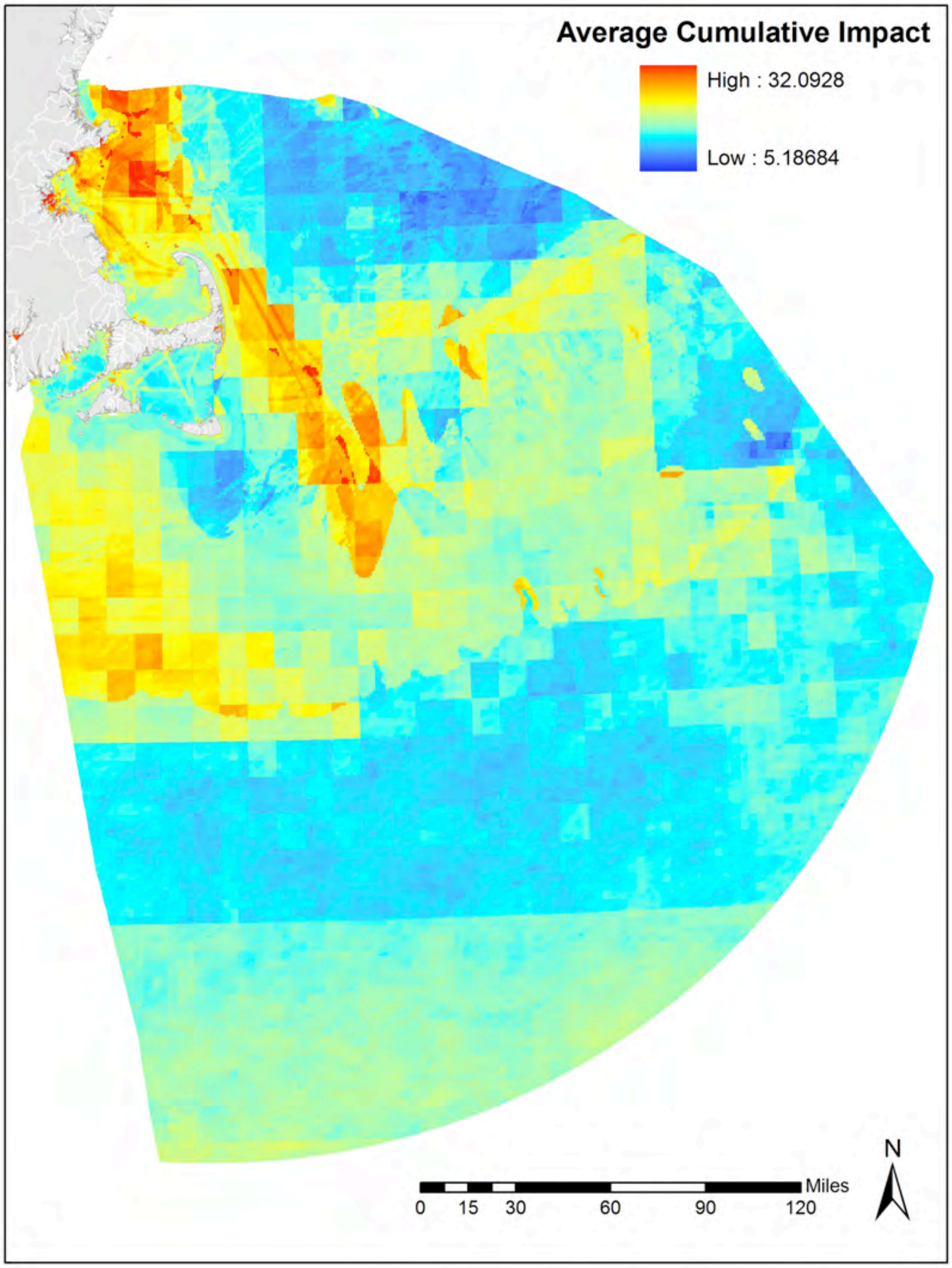
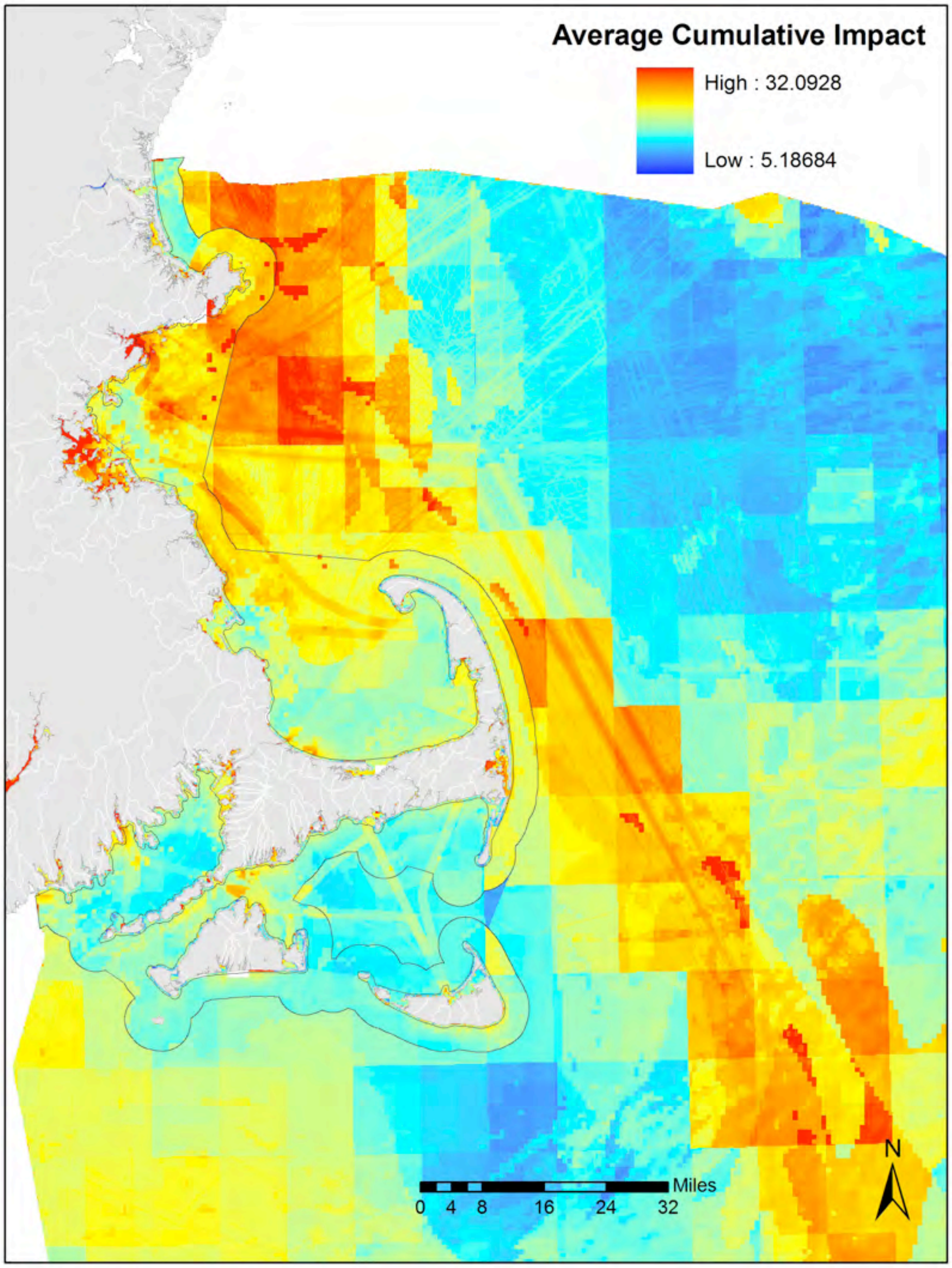

Pelagic Ecosystems
Shallow (top 200m)
Shallow + Deep (>200m)
Miles
0 5 10 20 30 40
N

**Figure 5.**

**Figure 6.**

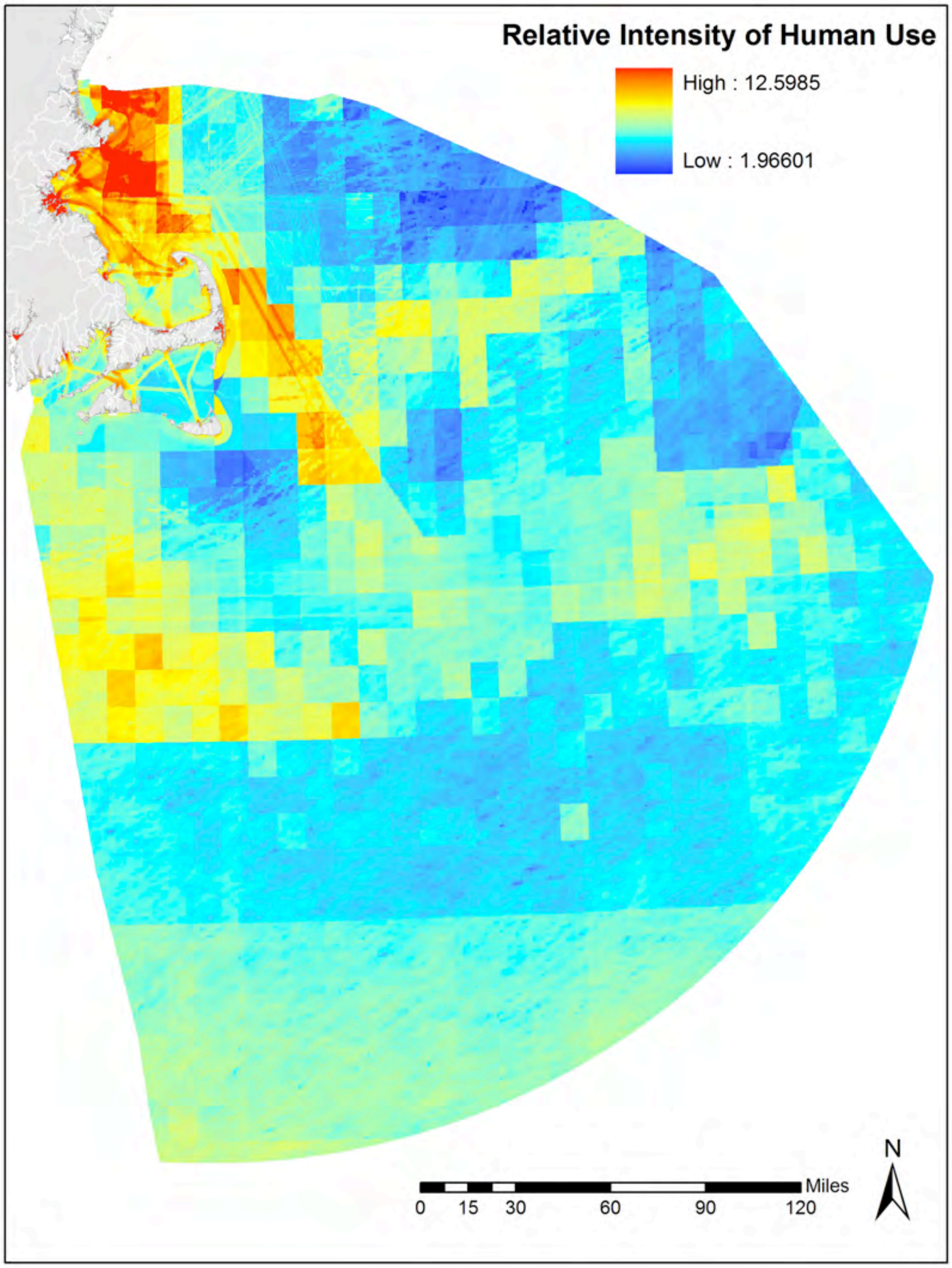

Average Cumulative Impact
High : 32.0928
Low : 5.18684
Miles
0
15
30
60
90
120
N

## Figure 7.



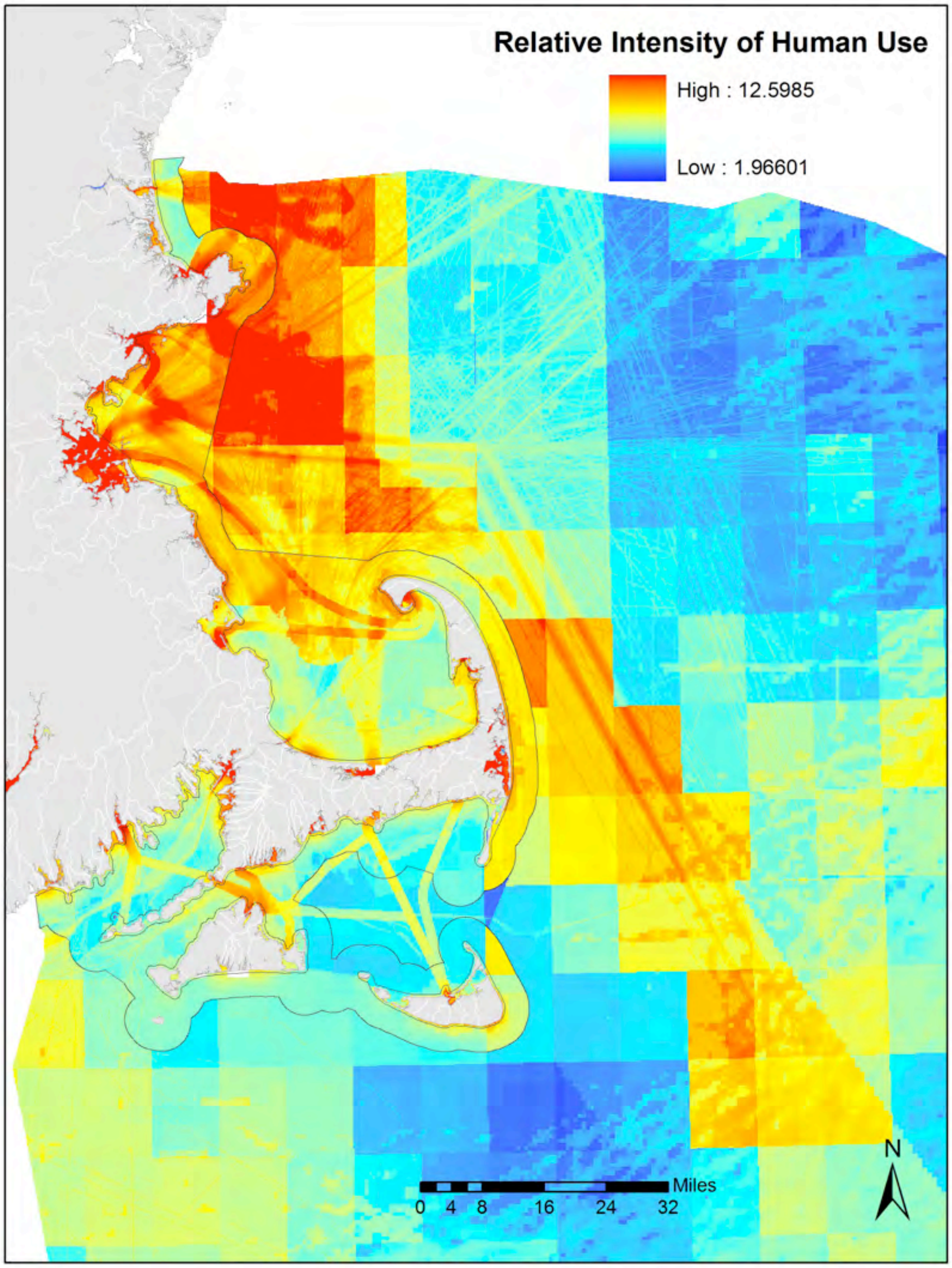
Average Cumulative Impact
High : 32.0928
Low : 5.18684
Miles
0 4 8 16 24 32
N

## Figure 8.



Relative Intensity of Human Use
High : 12.5985
Low : 1.96601
N
Miles
0
15
30
60
90
120

## Figure 9.



Relative Intensity of Human Use
High : 12.5985
Low : 1.96601
Miles
0 4 8 16 24 32
N

## Figure 10.

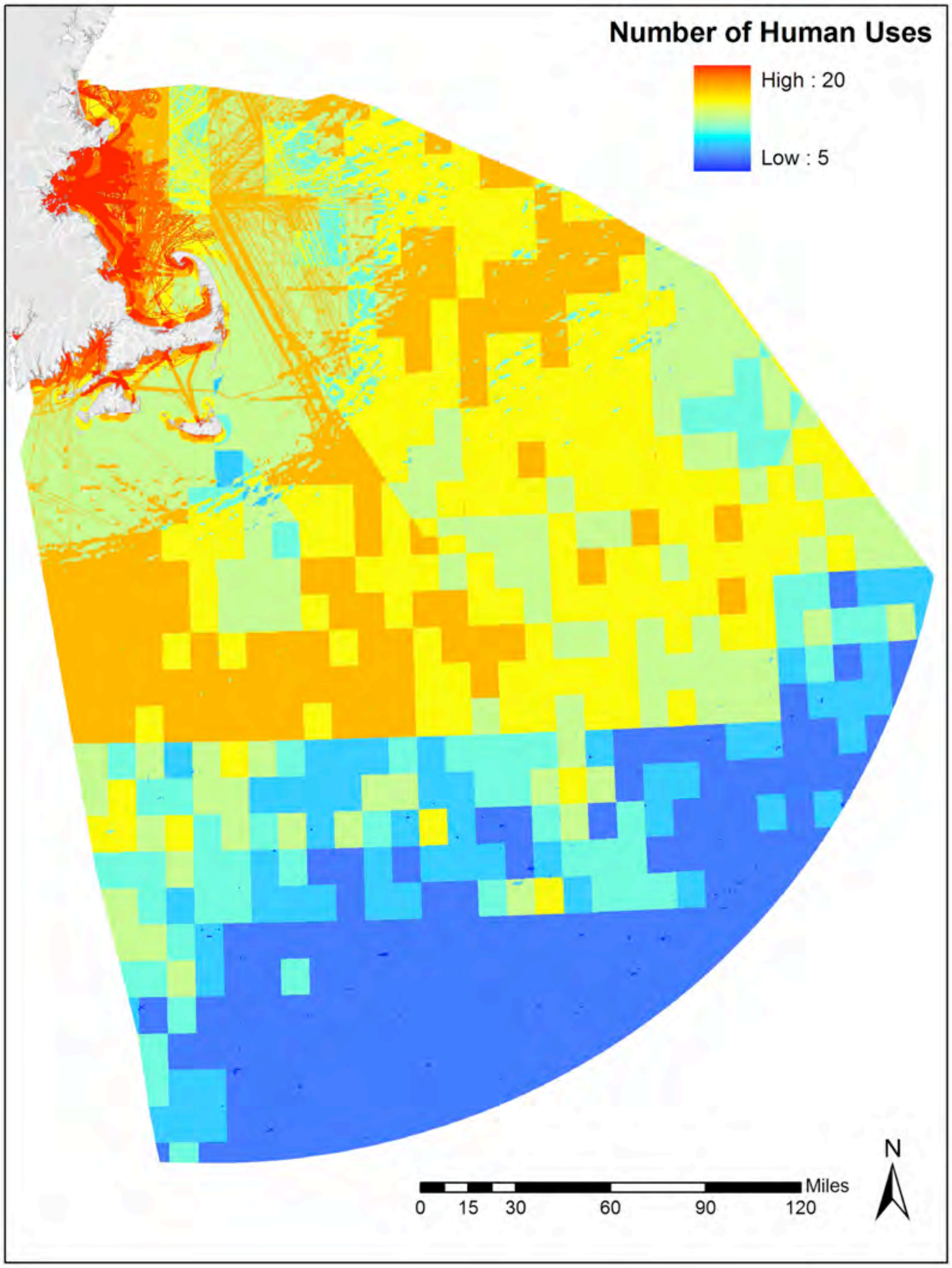


**Figure 11.**

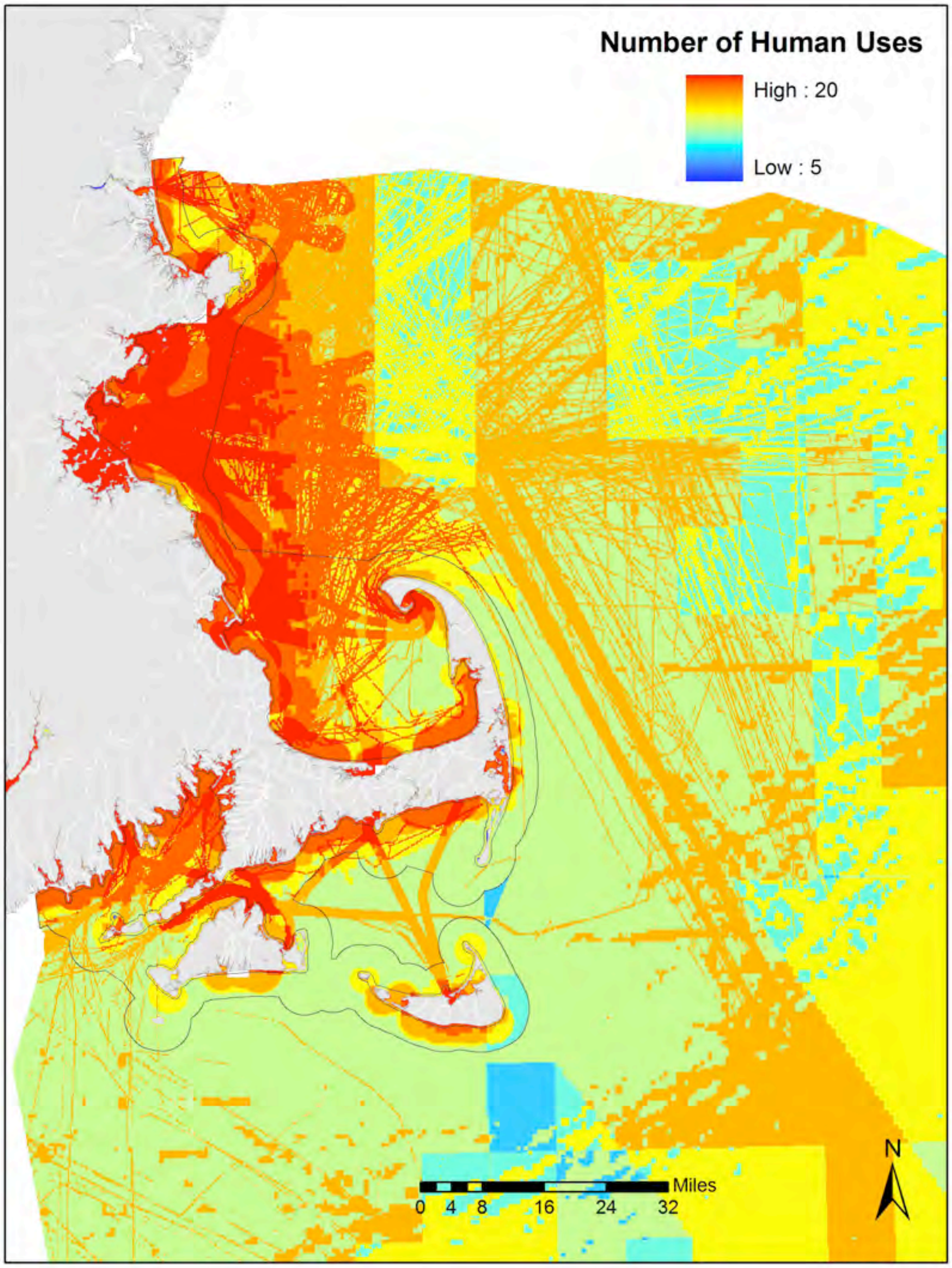
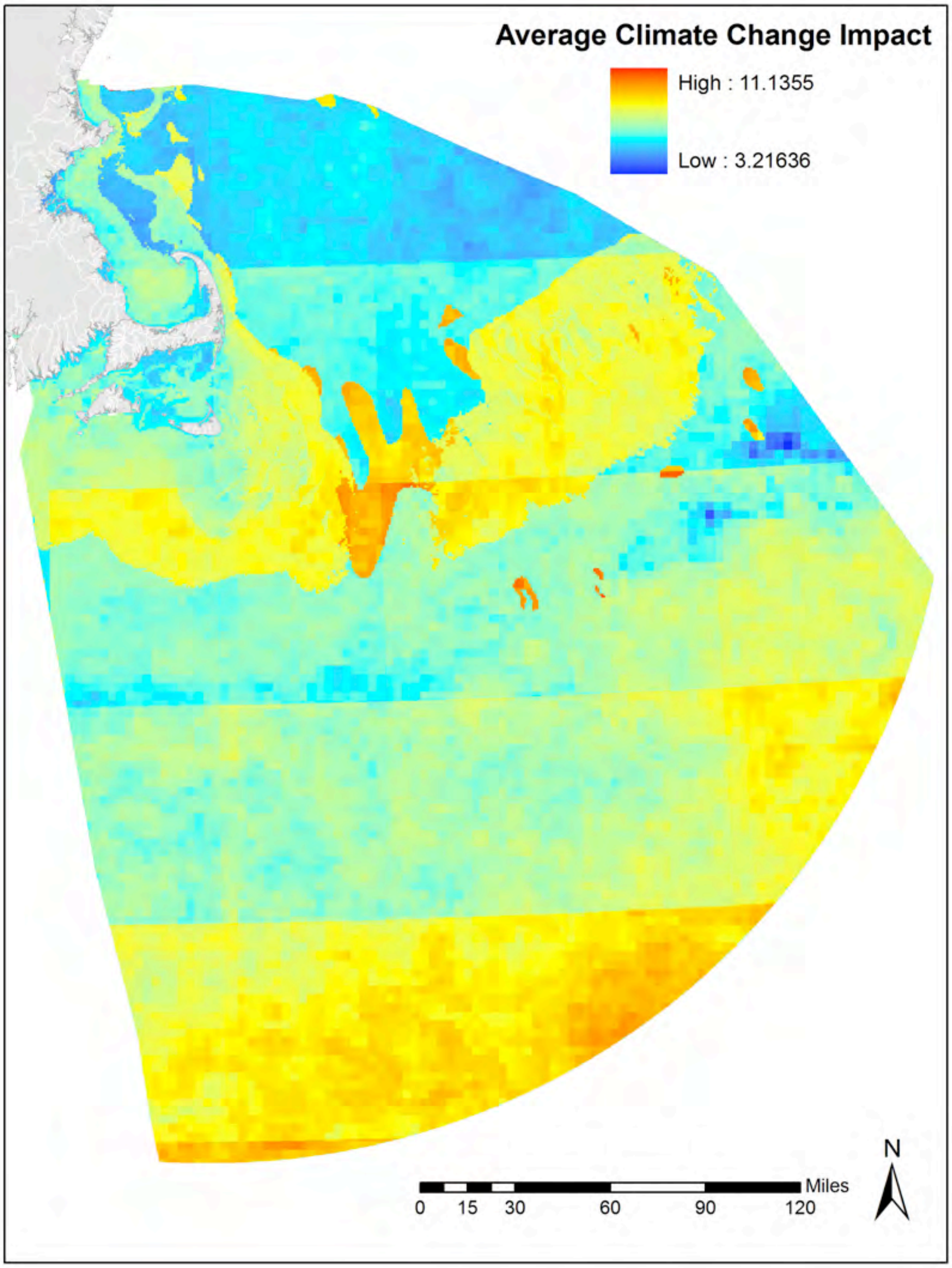
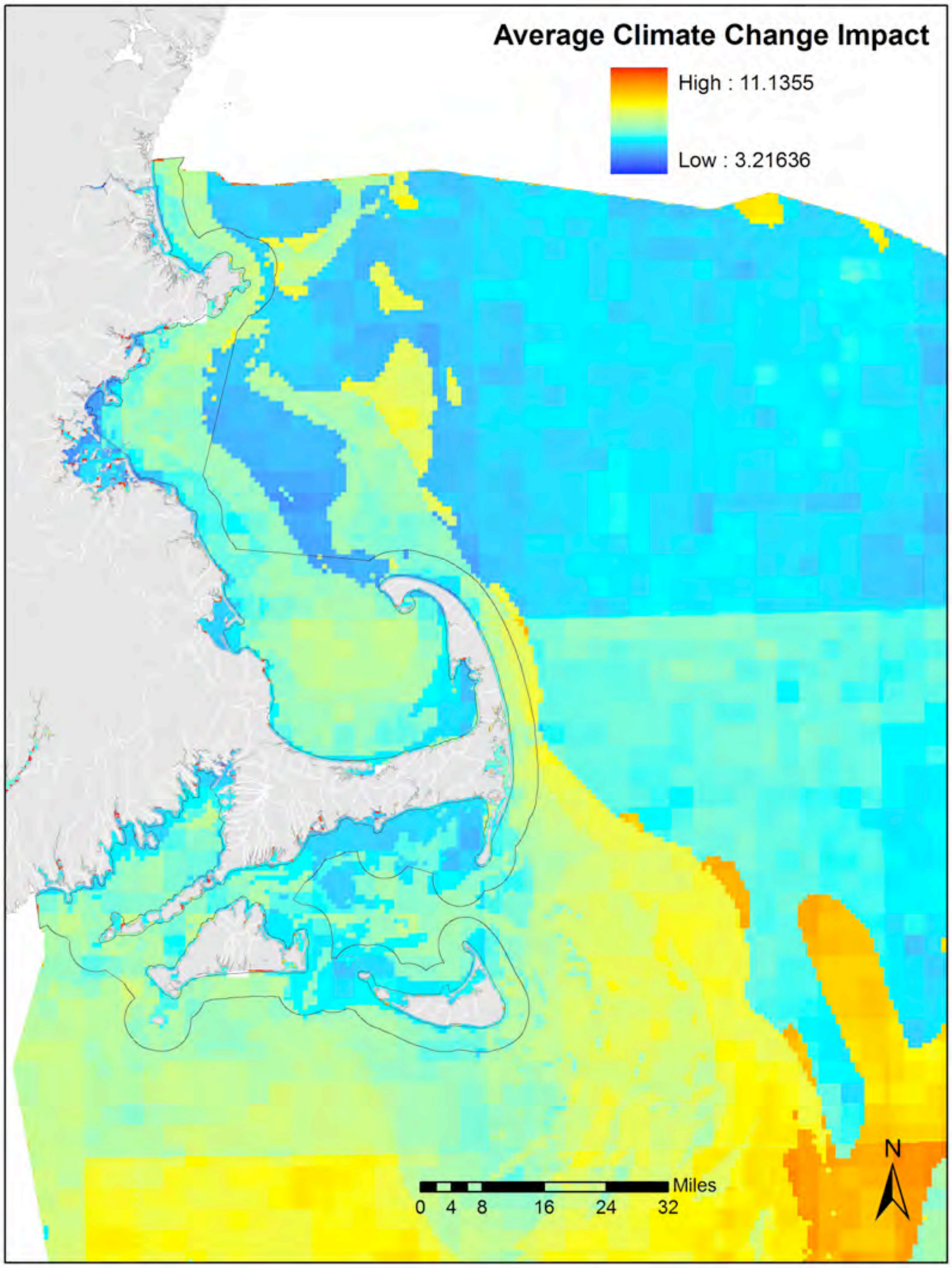


**Figure 12.**



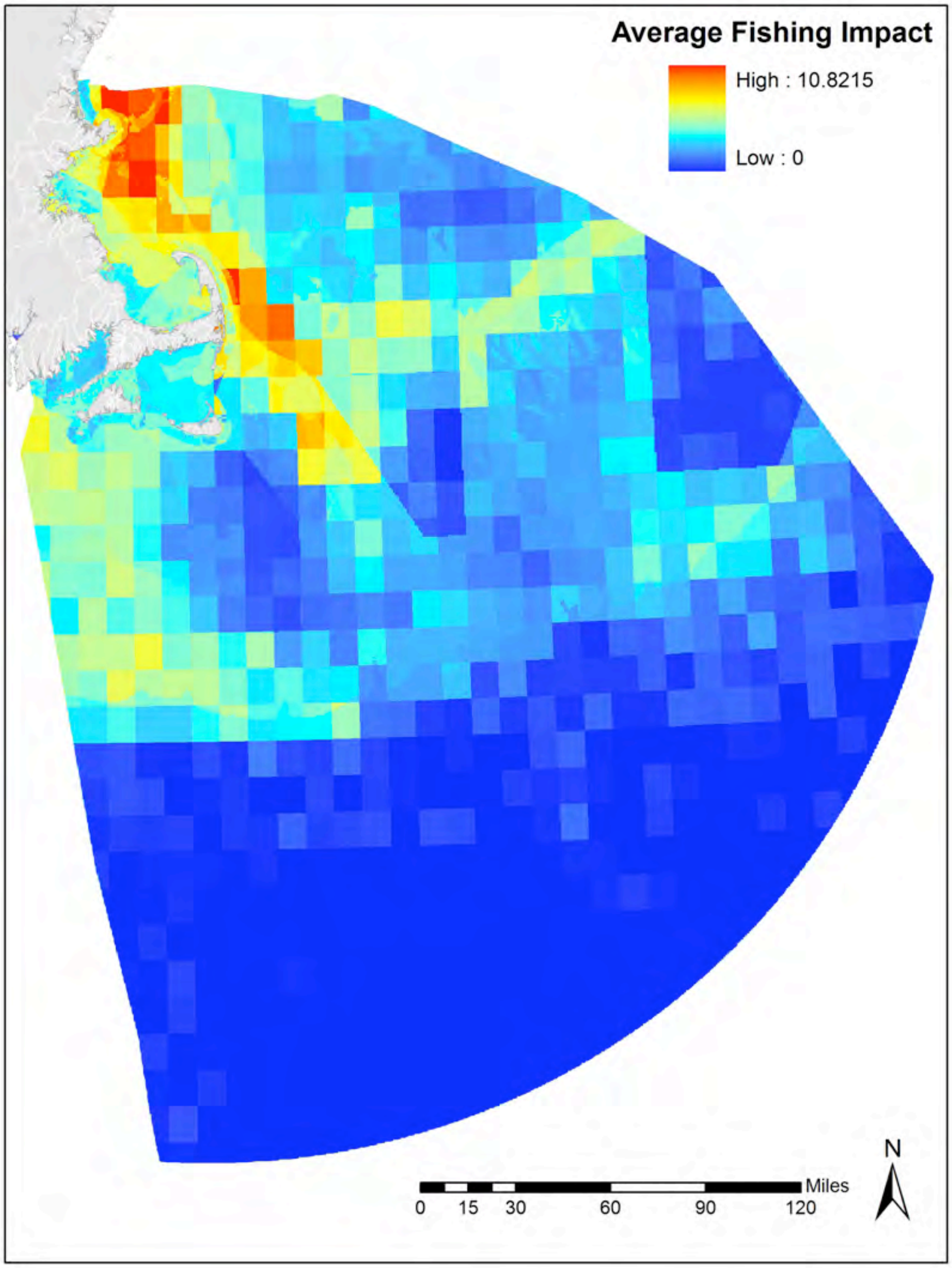
Average Climate Change Impact
High : 11.1355
Low : 3.21636
N
Miles
0 15 30 60 90 120

Figure 13.



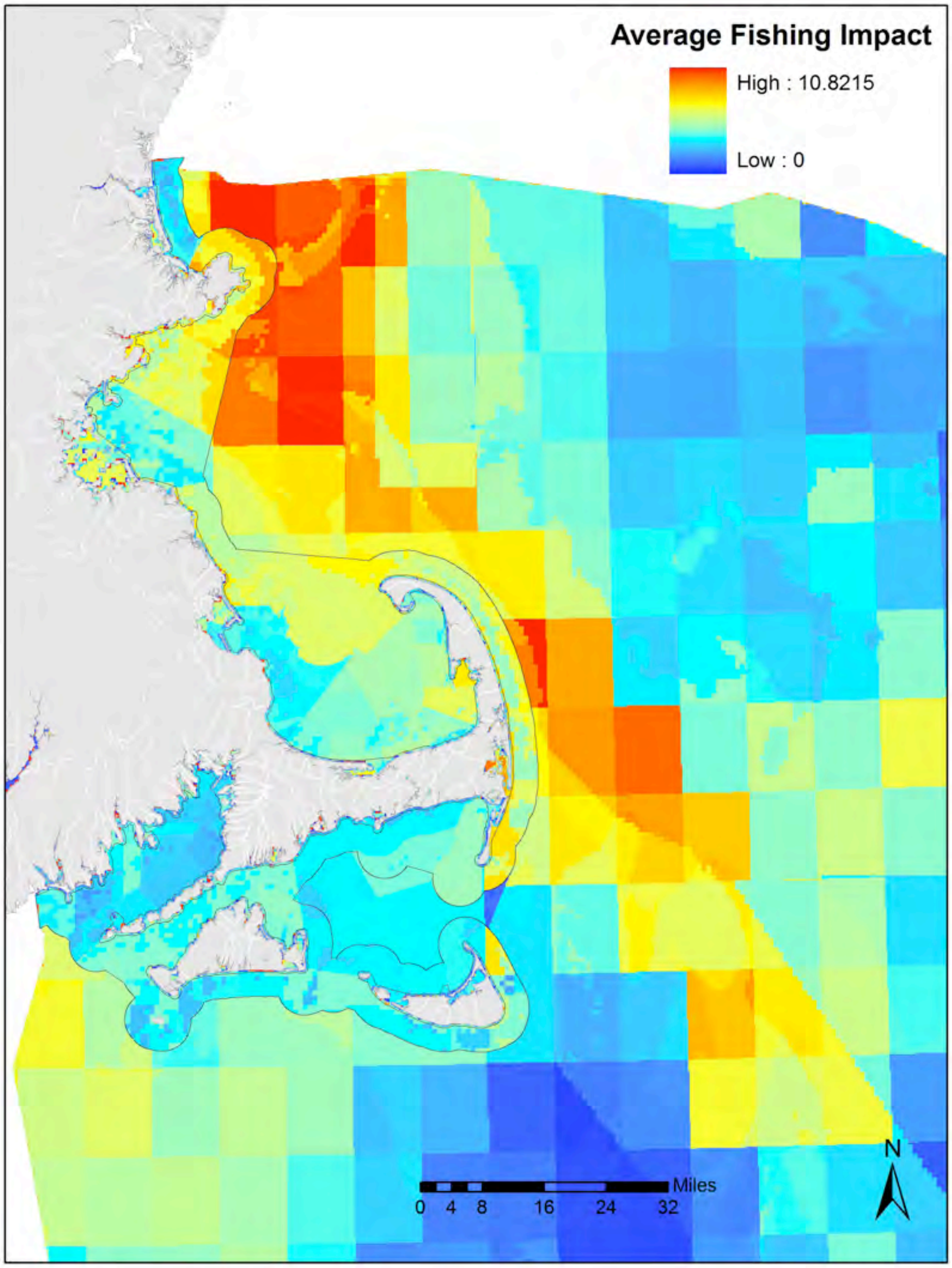
Average Climate Change Impact
High : 11.1355
Low : 3.21636
Miles
0 4 8 16 24 32
N

## Figure 14.

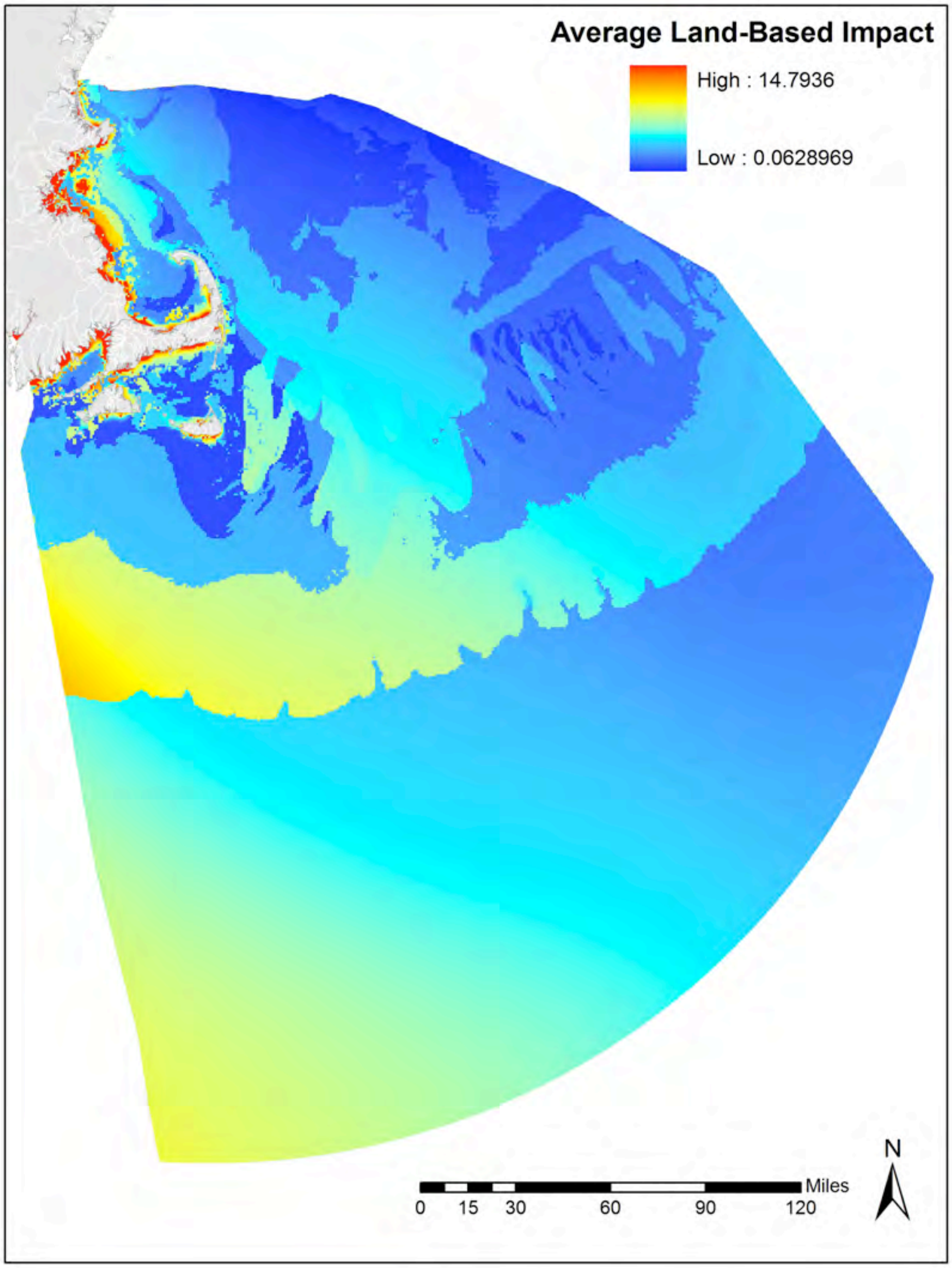


Average Fishing Impact
High : 10.8215
Low : 0
0
15
30
60
90
120
Miles
N

## Figure 15.

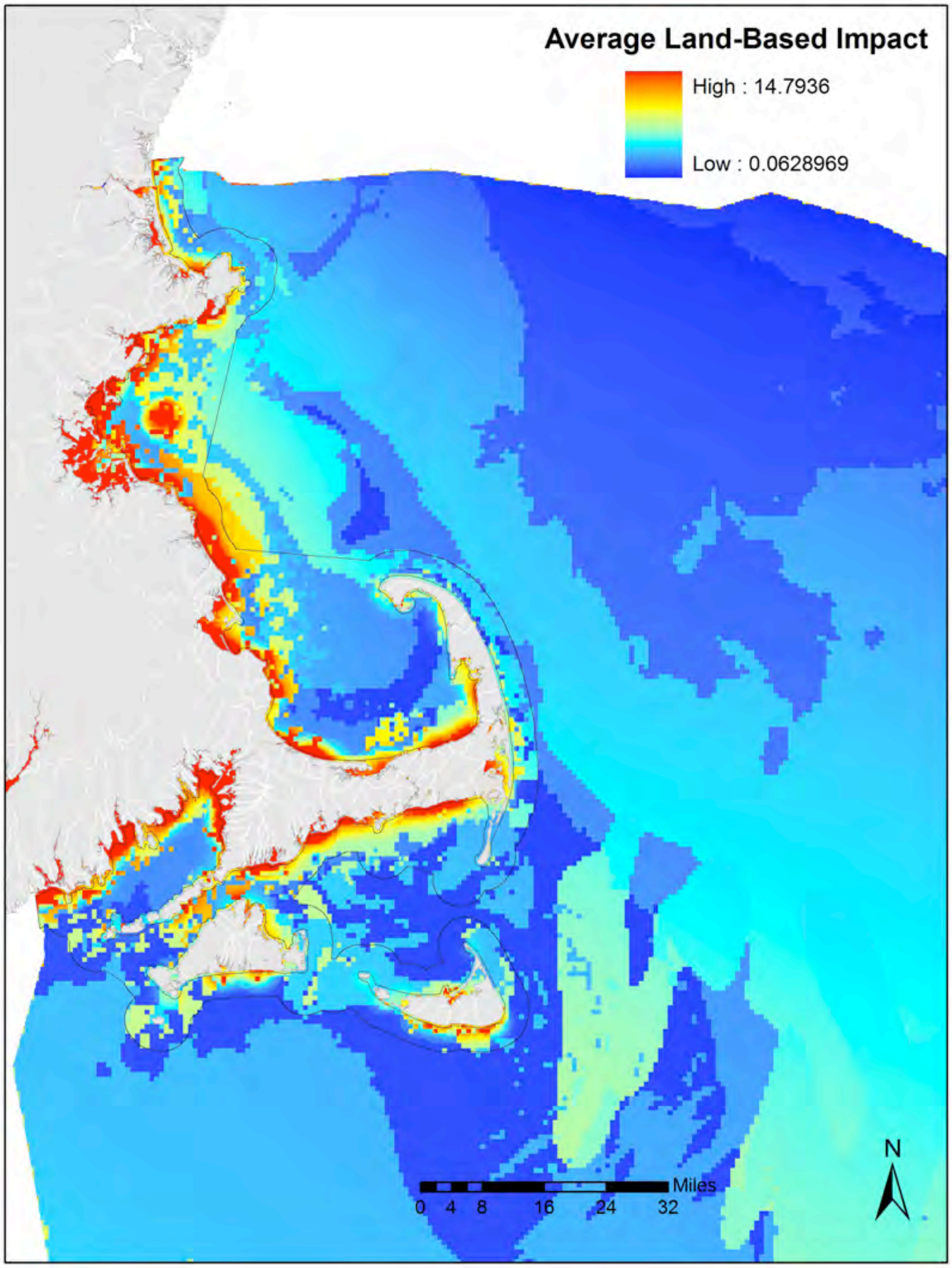


## Figure 16.

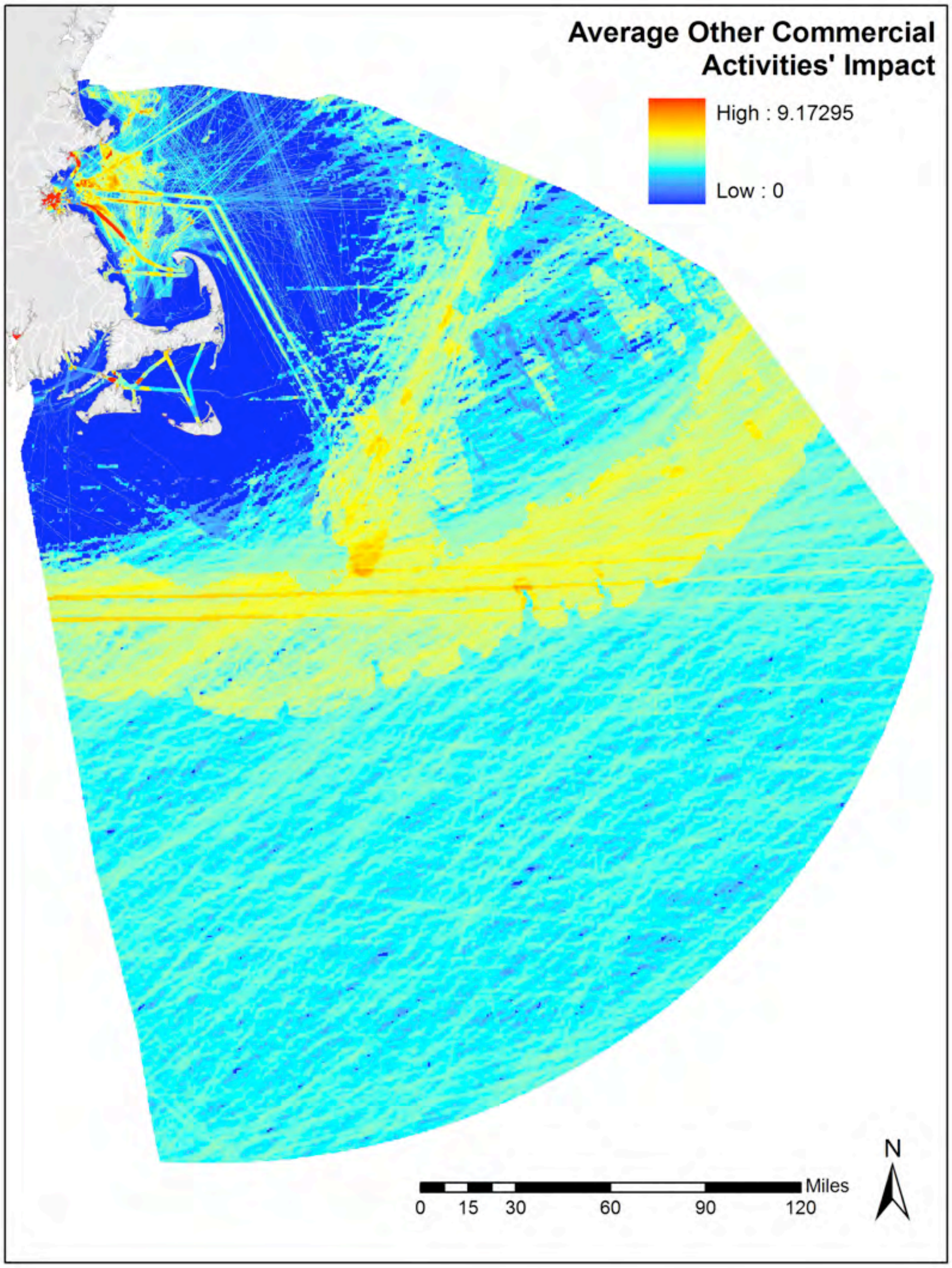


Average Land-Based Impact
High : 14.7936
Low : 0.0628969
N
Miles
0
15
30
60
90
120

**Figure 17.**

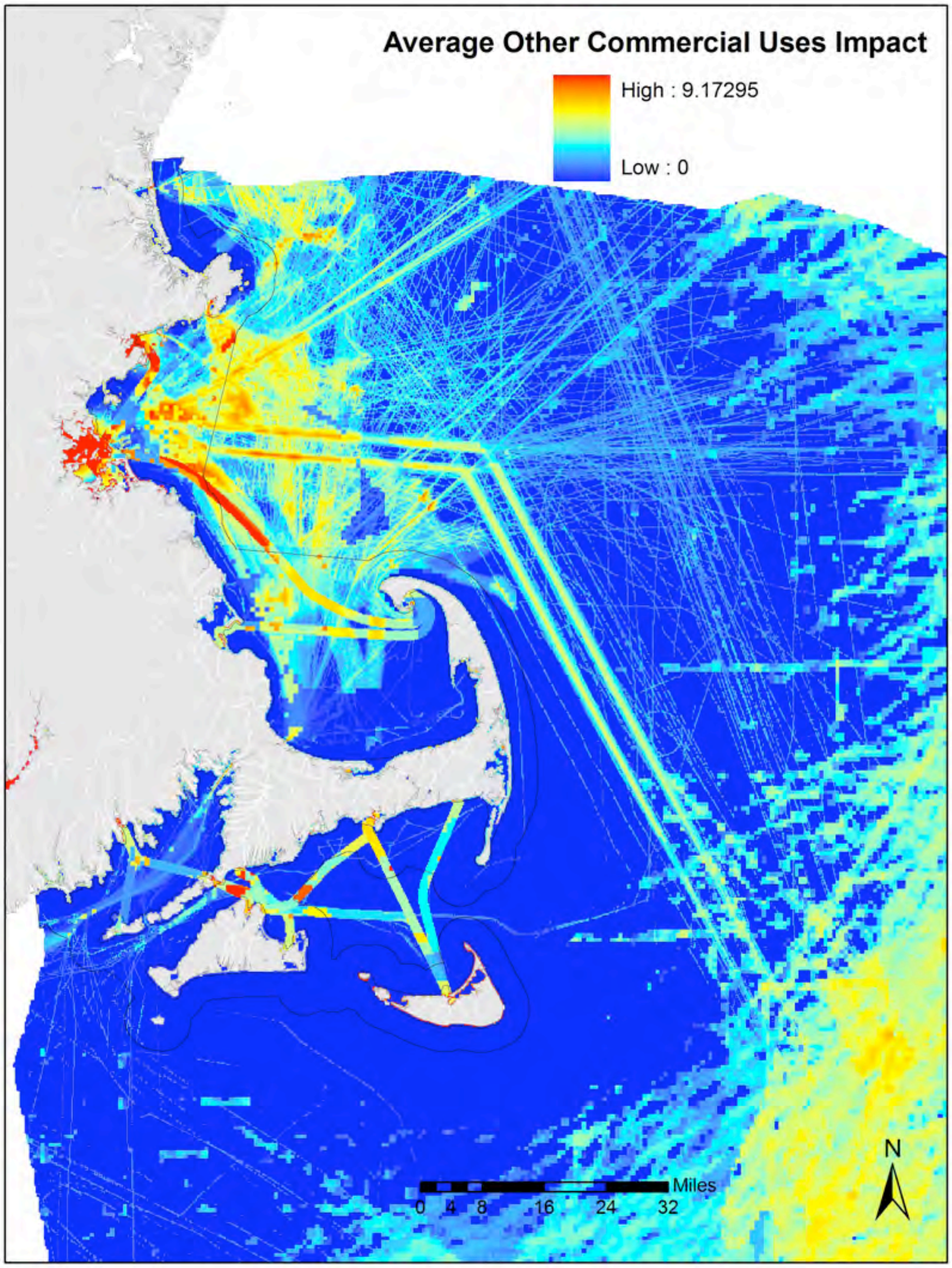

Average Land-Based Impact
High : 14.7936
Low : 0.0628969
Miles
0 4 8 16 24 32
N

## Figure 18.



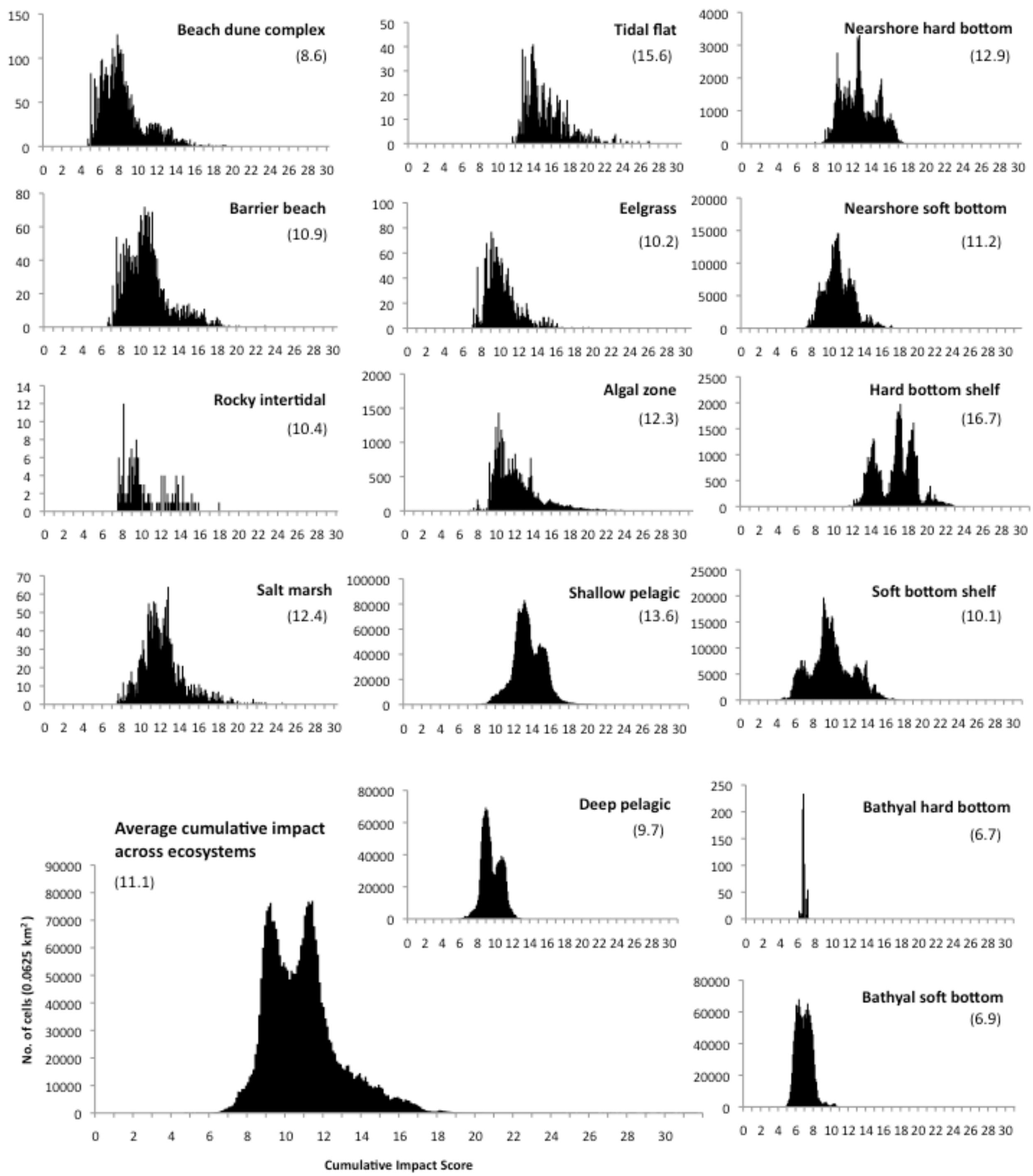
Average Other Commercial Activities' Impact
High : 9.17295
Low : 0
0 15 30 60 90 120
Miles
N

### Figure 19.



Average Other Commercial Uses Impact
High : 9.17295
Low : 0
Miles
0 4 8 16 24 32
N

## Figure 20.



Beach dune complex
(8.6)
Tidal flat
(15.6)
Nearshore hard bottom
(12.9)
Barrier beach
(10.9)
Eelgrass
(10.2)
Nearshore soft bottom
(11.2)
Rocky intertidal
(10.4)
Algal zone
(12.3)
Hard bottom shelf
(16.7)
Salt marsh
(12.4)
Shallow pelagic
(13.6)
Soft bottom shelf
(10.1)
Average cumulative impact across ecosystems
(11.1)
Deep pelagic
(9.7)
Bathyal hard bottom
(6.7)
Bathyal soft bottom
(6.9)
No. of cells (0.0625 km²)
Cumulative Impact Score