FATE PROPOSAL COVER SHEET
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1. Title:

# Incorporating climate into distribution and abundance indices for stock assessment: looking into the past and planning for the future

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**Incorporating climate into distribution and abundance indices for stock assessment: looking into the past and planning for the future**

***Principal Investigators:*** *Tim Miller, NOAA NE Fisheries Science Center; Christine N. Meynard, David M. Kaplan &Robert Latour, Virginia Institute of Marine Science, College of William & Mary*

**Background:** Climate is one of the main drivers in determining species distributions. Species range shifts related to climate change have been well documented in many contexts, with marine systems showing higher rates of shifts than terrestrial systems (Cheung et al. 2009, Doney et al. 2012, Pinsky et al. 2013). Predicting species distributions from climate data has become a major tenet in ecology, and one of the few areas that has developed concise statistical strategies in the context of predictive ecology (Dawson et al. 2011, Bellard et al. 2012). One of the most common tools in this field is statistical species distribution models (SDMs) that correlate species occurrence data (presence-absence) with environmental factors such as temperature and salinity. This strategy usually involves collecting opportunistic presence-absence data from different sources, sometimes meaning loss of information, such as when abundance data are converted into presence-absence to fit into the modeling framework, or to be combined with other sources of data. This step is often necessary given the lack of systematic and standardized survey data across a large portion of a species range. Presence-absence data are then correlated to environmental gradients to characterize the species range, and the resulting output of these models is a spatially-explicit estimation of either a probability of occurrence or a suitability index, either of which can be translated into a simplified range map (i.e., a map of predictions of presences and absences; Guisan and Thuiller 2005). These simplifications allow locating range shift patterns at large scales, but do not show abundance patterns within the range. This approach has become incredibly useful as a forecasting tool since it allows studying the potential effects of different climate change scenarios on individual species and on biodiversity at large (Cheung et al. 2009, 2010, Albouy et al. 2014). For example, Robinson et al. (2015) used SDMs to study how different climate change scenarios would affect nine large pelagic species in eastern Australia, and found that the trailing edge is likely to shift at a faster rate than the leading edge. Cheung et al. (2010) used an SDM framework in which the relative abundances of more than a thousand globally important commercial fishes and invertebrate species were translated into a suitability scale and related to environmental gradients to predict the potential effects of climate change scenarios on their distribution. They showed that these important fisheries are going to suffer large redistributions across the globe affecting food security in vulnerable areas and requiring the adaptation of fisheries to such changes. More recently, Albouy et al. (2015) used SDMs to forecast the changes in distribution of 230 coastal Mediterranean fish species, including many of commercial importance, and look at the potential effects of such shifts on phylogenetic and functional diversity, which may in turn affect ecosystem services.

Despite their centrality to predicting the effects of climate change on marine biota, results from SDMs are rarely integrated in fish stock assessments. This is in part because these correlative models usually ignore abundance patterns and predict a probability of occurrence that is not easy to relate to either abundance or to a concept of the species range that involves sustainable

populations (Ehrlen and Morris 2015). Some authors have also argued that looking at simple range shifts under climate change might not be enough. For example, Bell et al. (2015) argued that changes in fishing pressure throughout the range of a species could confound changes in distributions that are expected from temperature increases towards the poles, pointing out to the importance of relative abundance and size-frequency distributions across the range. In this context, they used the location of the center of biomass for different fish species as a better indicator of climate-related range shifts. Although this is an improvement over using simple presence-absence maps, since it would detect a poleward shift in the areas of higher abundance even in the absence of extinction and colonization of parts of the range, this is still a large simplification of reality where the whole abundance pattern is reduced to a single center of abundance. Understanding how abundance is distributed throughout the range of a species and what is likely to happen to that distribution is therefore important for developing a better understanding of the potential effects of climate change on availability of resources and on the fate of total biomass on important commercial fisheries. Spatially-explicit estimates of abundance over time can also help locate areas where populations are decreasing, increasing, or stable, but such information cannot be gathered using simple presence-absence SDMs (Ehrlen and Morris 2015). Therefore, for realistic management applications, knowledge of the distribution of abundance within the species range is of very high priority. Knowing that the range is going to shift directionally is often not enough.

Finding a relationship between SDM outputs (probability of occurrence or suitability) and abundance would help the integration of SDMs into many management applications, including fisheries stock assessments. In terrestrial systems, several comparative studies have tried to build on this relationship, but the results are mixed and often show idiosyncratic relationships (Jimenez-Valverde et al. 2009, Thuiller et al. 2014). For example, VanDerWal et al. (2009) modeled the relationship between suitability (as predicted by a presence-absence SDM approach) and local densities in 69 different species of vertebrates in Australia, and found predicted suitability could only relate to maximum densities. However, most communities showed values below this theoretical maximum, meaning that SDMs could not be used to estimate local densities. This is an important management shortcoming of SDMs and greatly reduces their applicability to advance management efforts in fisheries science. Although reliable information on species relative abundances over large geographic areas is rare, many long-term systematic survey efforts exist and have been under-studied with respect to spatial and temporal abundance trends. The time seems ripe to use such large-scale abundance data to understand not only species range shifts, but also spatial abundance patterns and how they have changed over time. This will also help us prepare for the future, particularly if we can understand how climate change is likely to affect the distribution of resources for relevant exploited species.

Here we will adopt a pragmatic approach where abundance will be corrected by fishing pressure and used in a correlative modelling framework to understand its spatial variation, its relationship to different environmental gradients, and the likely effects of climate change scenarios on spatial and temporal variations. The main objectives of this project will be to investigate relationships of environmental gradients (e.g., sea-surface and sea-bottom temperatures, salinity, topography, distance to coast and to the Gulf Stream, productivity, currents) to abundance, and generate

temporally- and spatially-explicit predictions of abundance-at-size for five commercially important fish stocks on the United States northeast continental shelf. For stocks found to have abundance correlated to environmental gradients, we will also use the models to predict long-term changes in distributions of abundance. Models will be developed and validated using past and present data, and used to predict long-term changes in distributions using different climate change scenarios. We will focus on yellowtail flounder, scup, black sea bass, red hake and Atlantic cod, as these are species that are regularly assessed, are reasonably well studied, and have different life history strategies. Furthermore, these species have been shown to have shifted their range in response to climate change (Nye et al. 2009, 2011, Bell et al. 2015).

**Approach:**

We will adopt a correlative approach to estimating annual spatial distributions of abundance-at-size for each of the species considered. We will aim to identify major environmental drivers of the distribution of each species while controlling for fishing effects and will generate maps of estimated species abundances over time. The statistical relationships generated in this effort will be used to project into the future the potential impacts of climate change on species' distributions. We will then study areas of consensus and uncertainties between approaches, and draw management implications from them by relating current and past patterns and results from stock assessments for each species.

*Data processing*

The NOAA Northeast Fisheries Science Center (NEFSC, Woods Hole, MA) annual surveys (1963-present) on the continental shelf from Nova Scotia to Cape Hatteras, NC, are ideal to develop and test such approaches. The surveys have extensive spatial and temporal coverage and use standardized methods that are independent of fisheries, thereby providing a rich dataset with which species relative abundances can be related to large-scale environmental gradients and temporal variability in those gradients. Furthermore, the surveys include species of wide economic interest for which an annual stock assessment is performed.

We will divide the study area in an equal-area grid of 10 km x 10 km resolution. Survey data will be overlaid and averaged at this resolution for each season and year, and grid cells with little or no temporal or spatial sampling will be eliminated from the analysis for model calibration. This will filter out spatial locations with poor data (few sampling locations or few temporal replicates) and use only the best available information for model calibration. However, for model projections (hind-casting or forecasting), all grid cells will be considered unless they are located in areas with unique environmental conditions that are not represented by the survey (this is unlikely to eliminate a large number of grid cells due to the extremely long time-series and extensive spatial coverage of the survey). Notice that this grid-based spatial aggregation will provide a finer visualization of abundance patterns throughout the survey area, as compared to the strata used in stock assessments. However, for comparison purposes, grid cells can be aggregated by survey stratum. Environmental data will be summarized for each trawl survey at the same spatial resolution. Additional environmental data will be downloaded from the web, including from the Bio-ORACLE environmental dataset. This dataset includes current

conditions, as well as future climate change scenarios (Tyberghein et al. 2012). Other sources of environmental data include the MODIS Ocean website; NOAA's world ocean database; NOAA's GFDL and the IPCC data portal. Variables that can be obtained and have been previously used in the oceans to model species under climate change scenarios include sea surface temperature, bottom temperature, salinity, bathymetry, and ocean advection (Cheung et al. 2010, Albouy et al. 2012). Climate change scenarios considered will include the extreme cases where technology and people become aware and change their behavior to reduce climate change (optimistic B1 scenario), as well as the opposite extreme of little and slow global technological change and continued increase in population growth (pessimistic A2 scenario). Different temporal scales will be considered so that we can get an understanding of the importance and effects of environmental variability in the region. For example, the analysis of yearly data will be valuable for understanding the effects of temporal variability on abundances, whereas aggregating data by 5 or 10-year periods can help ignore transient dynamics and focus on the more general long-term trends in species distributions and abundances (e.g., poleward shifts in species ranges, centers of biomass, and changes in abundances across the range).

To control for fishing mortality, we will include indices of fishing pressure as covariates in the statistical models. Fishing information is not available with the same precision and resolution as the environmental information. We will therefore use a coarse relative exploitation index as a proxy for fishing pressure (Nye et al. 2011). The spatial scale for the index may depend on the species investigated, but is essentially the catch data divided by the relative biomass estimated from the surveys. Although we recognize the limitations of this index, it is intended to use the best available estimates of fishing pressure without using assessment model output in subsequent analyses (e.g., Brooks and Deroba 2015).

*Correlative approach*

We will use a two-step process to model species relative abundances within each species' range. In a first step, we will use presence-absence data to model the range of each species in the study area. This will delimit the external envelop within which relative abundances will be modeled, and will serve to minimize zero-inflation in the dataset used later for abundance modeling by eliminating areas of very marginal habitat or areas in which the species is always absent. At this stage we will use standard species distribution modeling techniques with an ensemble forecasting approach (Araujo and New 2007, Thuiller et al. 2009, Meynard et al. 2013). In this context, 70% of the presence-absence data will be used to calibrate different types of statistical models (GLM, GAM, classification trees, boosted regression trees, MAXENT and random forests are among some of the most common approaches). Model outputs will be checked for their performance in terms of classification rates (i.e., how well they predict presence-absence data) using the remaining 30% of the data and applying a threshold that maximizes classification rates on the probabilities of occurrence to generate presence-absence predictions. The best models will be retained for a consensus prediction that will be used as the perimeter of the species range, within which species relative abundances will be modeled in the next step. These distribution models will also be used to detect species distribution shifts over time.

In a second step, within each species range we will consider relative abundances by size as a response variable in a multiple regression approach. A mixed model (e.g., a generalized additive mixed model using *mgcv* in the statistical package R) will be used to consider temporal and spatial dependencies, as well as effects of environmental gradients, such as sea surface temperature, bottom temperature, salinity, topography (i.e., depth and heterogeneity), on species relative abundances by size. Since the surveys provide for temporal and spatial replication, we will use partial regressions to separate the effects of temporal variability versus spatial variability to obtain an understanding of their relative importance. This work will also allow us to identify the most relevant environmental gradients determining species abundances. We will also compare trends of annual aggregated predictions of relative abundance with the predicted relative abundance indices from assessment models to determine whether the predictions using the two approaches are correlated. Weak correlations of the currently used indices would suggest considering the environmentally driven indices, or other ways of incorporating the effects of these environmental gradients on distributions, within the assessment models.

**Benefits:**

This project would allow us to (1) develop a general modeling framework to integrate yearly abundance and catch data with environmental variables; (2) use hind-casting to test the models using the long-term time series into the past; (3) produce predictions into future climate change scenarios which are based on stages that can be compared to current stock assessment outputs; and (4) compare the results from this framework to the results of the respective stock assessments. Once the framework has been developed for a species, it can provide for a powerful forecasting tool to predict vulnerability and consequences of climate change on commercially important marine resources. Model outputs (relative abundances by size) could be used in fisheries stock assessments, potentially improving estimated population trends and productivity and subsequent management strategies in the face of different climate change scenarios. This work responds to the objectives of the NEFSC Strategic Science Plan to (1) improve the quality of stock assessments and other science-based advice and (2) improve understanding of the influence of climate on living marine resources in order to provide integrated scientific advice to managers. It also responds to several of the FATE RFP research objectives (Topics 1, 2, 4) by evaluating tools to investigate mechanisms driving interactions between fisheries and climate (Topic 1), developing spatial and temporal models to investigate climate effects on population distribution (Topic 2), and examining climate effects and fishing effects on commercially important fish stocks with an ability to forecast climate impacts on distribution (Topic 4).

**Deliverables:** This project will produce at least one scientific publication on the effect of environmental gradients on abundance of important commercial fisheries into past trends and another one looking into future climate change scenarios. We will produce a report for FATE highlighting the management and assessment implications, especially as they relate to planning ahead for climate change. This work will also be presented at the FATE annual conference, as well as in other relevant international conferences (possibly at ICES, AFS or ESA annual science conferences). Model outputs will be available by request, and the maps and models will be published as part of the scientific publications.

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