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Citation to Publisher Version: Cheung, William W. L., Frölicher, Thomas L., Asch, Rebecca G., Jones, Miranda C., Pinsky, Malin L., Reygondeau, Gabriel, Rodgers, Keith B., Rykaczewski, Ryan R., Sarmiento, Jorge L., Stock, Charles & Watson, James R. (2016). Building confidence in projections of the responses of living marine resources to climate change. *ICES Journal of Marine Science 73*(5), 1283-1296.http://dx.doi.org/10.1093/icesjms/fsv250.

Citation to *this* Version: Cheung, William W. L., Frölicher, Thomas L., Asch, Rebecca G., Jones, Miranda C., Pinsky, Malin L., Reygondeau, Gabriel, Rodgers, Keith B., Rykaczewski, Ryan R., Sarmiento, Jorge L., Stock, Charles & Watson, James R. (2016). Building confidence in projections of the responses of living marine resources to climate change. *ICES Journal of Marine Science 73*(5), 1283-1296. Retrieved from doi:10.7282/T3154KVW.

Building confidence in projections of the responses of living marine resources to climate change

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Keywords: Climate change, projection, uncertainty, multi-model ensembles, marine resources, fisheries

Abstract

The Fifth Assessment Report of the Intergovernmental Panel on Climate Change highlights that climate change and ocean acidification are challenging the sustainable management of living marine resources (LMRs). Formal and systematic treatment of uncertainty in existing LMR projections, however, is lacking. We synthesize knowledge on how to address different sources of uncertainty by drawing from climate model inter-comparison efforts. We suggest an ensemble of available models and projections, informed by observations, as a starting point to quantify uncertainties. Such an ensemble must be paired with analysis of the dominant uncertainties over different spatial scales, time horizons and metrics. We use two examples, (1) global and regional projections of Sea Surface Temperature and (2) projection of changes in potential catch of sablefish (*Anoplopoma fimbria*) in the 21st century, to illustrate this ensemble model approach to explore different types of uncertainties. Further effort should prioritize understanding dominant, under-sampled dimensions of uncertainty, as well as the strategic collection of observations to quantify, and ultimately reduce, uncertainties. Our proposed framework will improve our understanding of future changes in LMR and the resulting risk of impacts to ecosystems and the societies under changing ocean conditions.

Living marine resources projections under climate change

The Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC AR5) highlights that changes in ocean temperature, oxygen, carbonate system, and other ocean properties are contributing to the challenges of sustainable ocean management (IPCC, 2014). The importance of a comprehensive assessment of the impact of climate change on the ocean is highlighted by two new ocean-specific chapters within the IPCC AR5 Working Group II (WGII) on impacts, adaptation and vulnerability (IPCC, 2014). In relation to living marine resources (LMR), the IPCC Report concludes with medium to high confidence that marine species have been shifting their ranges, seasonal activities and periodicities, migration patterns, abundances and inter-/intra- specific interactions that result in changes in trophodynamics in response to changing ocean conditions (Pörtner *et al.*, 2014). These changes are projected to lead to altered patterns of ocean productivity, biodiversity and fisheries catch potential in the 21st century (Kirby and Beaugrand, 2009).

One of the advances in assessing the impacts of climate change on LMR in the IPCC AR5 WGII over previous assessment reports is the wider availability and use of ecosystem model projections. These quantitative model projections include shifts in net primary productivity, the distribution of exploited populations and changes in potential fisheries production and ecosystem structure at local and global scales (Pörtner *et al.*, 2014). Projections have been generated from modelling approaches that range from global coupled atmosphere-ocean-biogeochemistry earth system models (e.g., Bopp *et al.*, 2013), to species distribution models (e.g., Cheung *et al.*, 2009), single-species population dynamic models (e.g., Lehodey *et al.*, 2010), and whole ecosystem models (e.g., Ainsworth *et al.*, 2011; Griffith *et al.*, 2011). The scope, objectives, assumptions, scales (spatial and temporal) and degree of validation with empirical data vary widely across these models, and approaches range from highly empirical to highly mechanistic (Barange *et al.*, 2010; Fulton, 2010; Plagányi *et al.*, 2011; Stock *et al.*, 2011).

Statements of confidence concerning the impacts of climate change on LMRs within the IPCC-AR5 WGII report were based on a qualitative assessment of observational evidence and individually published projections encompassing the diversity of LMR models described above. While this is a necessary starting point, more quantitative confidence estimates for projections can increase their utility for policy formulation and evaluation. There is therefore a need for a quantitative framework for systematically exploring uncertainties in LMR projections. Such a framework would also help identify where investment in further theoretical development, observational measurements, and model development are needed, ultimately improving the reliability of climate-LMR projections (Cheung *et al.*, 2013a; Brander, 2015). Systematic exploration of uncertainties have been undertaken for climate and oceanographic projections (e.g., the Atmospheric Model Intercomparison Project (Gates, 1992) and the Coupled Model Intercomparison Project (Meehl *et al.*, 2000; Taylor *et al.*, 2011) and for impact assessments of selected sectors (e.g., Agricultural Model Intercomparison and Improvement Project (Rosenzweig *et al.*, 2013)). Exploration of uncertainties are also an important component in traditional fisheries resource assessment, while the increasing demand for ecosystem-based fisheries management raises additional challenges to systematically understanding projection uncertainties (e.g., Hill *et al.*, 2007; Link *et al.*, 2012). More recently, initiatives on comparing fisheries models (e.g., Fisheries Model Intercomparison Project, ICES-PICES Strategic Initiative on Climate Change Impacts on Marine Ecosystems) have also been started.

While challenges in quantifying uncertainty in climate-LMR projections for global change assessment parallel those considered in modelling other complex natural systems such as climate, there are additional sets of complexity that are specific to LMRs. Climate-LMR projections require linking physical, biological and human sub-systems across different temporal and spatial scales. Such inter-linkages lead to additional uncertainties that originate from particular systems or scales (Planque, 2015). In addition, the behavior of some components of LMR systems is difficult to predict, such as the responses of fishing activities to changes in climate and fisheries resources). Moreover, many LMR models require large number of input parameters relative to the available observational data that are available to calibrate and validate the model outputs. Techniques for assessing model uncertainties that are commonly applied to conventional fisheries assessment (e.g., Bayesian estimates of process and observation errors) are thus difficult to apply to climate-LMR projections.

This paper aims to synthesize our knowledge of the uncertainties of LMR projections under climate change and propose a framework to systematically assess such uncertainty. Our paper complements that of Payne *et al*. (this volume), which reviews existing approaches in addressing uncertainties in LMR. Here, we focus on the following: firstly, we characterize different types of uncertainty in climate and LMR projections, highlighting the challenges of the large uncertainty space; secondly, drawing from the experience of physical climate model inter-comparisons, we explore how multi-model comparison and ensemble frameworks can be used to systematically identify and quantify uncertainties in LMR projections. Through an example, we highlight the relative roles of uncertainty linked to climate variability, climate model uncertainty and future emissions scenarios as a function of time horizon and spatial scale. This is followed by a discussion of the role of observations in refining uncertainty estimates. Finally, we discuss how outcomes from this model-assessment framework can be used to evaluate the risk of climate change to LMRs and inform the design of management and conservation measures to reduce such risk.

Sources of uncertainty

Climate-LMR models that estimate the impacts of climate change generally have three model components that are linked to describe the responses of marine resources, fisheries, and human society to climate systems. These components generally include an atmosphere-ocean-biogeochemical and lower-trophic level models, a fish or upper-trophic level model (Holt *et al.*, 2014), and a model for the extraction and availability of ecosystem services from marine ecosystems (see Fulton, 2010; Plagányi *et al.*, 2011; Stock *et al.*, 2011). The three components are either related "off-line", where each model component is run separately with the outputs from one component used as inputs for another (Cheung *et al.*, 2011; Blanchard *et al.*, 2012; Christensen *et al.*, 2015), or dynamically (i.e., "on-line") with the models incorporating fully interactive processes and, in some cases, feedbacks among the three components (Fulton, 2010; Lefort *et al.*, 2015).

Research on physical climate projections, biodiversity and ecological modelling has recognized numerous topologies of uncertainties (Regan *et al.*, 2002; Link *et al.*, 2012). Modelling of physical and biogeochemical properties of atmospheric and ocean systems in climate change assessments have commonly categorized uncertainties, for any time horizon and spatial scale, into three components: (1) internal variability, (2) model uncertainty, and (3) scenario uncertainty (Table 1) (Hawkins and Sutton, 2009). In our discussion of the uncertainties associated with climate-LMR projections, we adopt this terminology to leverage the knowledge and experience of the climate modelling communities.

Internal variability is caused by natural physical and ecological processes that are intrinsic to climate and ecological systems. It arises in both temporal and spatial dimensions, even in the absence of any external (e.g., anthropogenic) perturbations and includes phenomena such as the El Niño Southern Oscillation (ENSO), the North Atlantic Oscillation (NAO), the Atlantic Multidecadal Oscillation (AMO), variations in gyre boundaries not correlated to major climate models, and predator-prey cycles etc. (Day, 1982). Century-scale climate change projections developed in association with the IPCC realistically resolve many modes of internal climate variability, but these simulations are not designed to simulate a specific observed event or predict a future event, and will not capture all aspects of spatial and temporal scales of these modes (Guilyardi *et al.*, 2009). For ecological systems, natural fluctuations that are driven by environmental variability and dynamics of ecological interactions are often difficult to predict (Beckage *et al.*, 2011; Deser *et al.*, 2012), causing systematic or seemingly random variations in ecological states that may persist for a decade or more (Deser, 2013; Stocker *et al.*, 2014). Different initial conditions of the climate or LMR models, representing different realizations of the climatic and ecological systems, will generate different patterns of internal variability. Thus, one method to explore internal variability is to analyze simulation results generated from ensemble members of climate and ecological models that have different initial conditions.

Model uncertainty is comprised of two sub-categories: parameter and structural uncertainty (Tebaldi and Knutti, 2007). Parameter uncertainty relates to the specific parameter values used in the formulae that influence the behavior of a model (Tebaldi and Knutti, 2007; Knutti *et al.*, 2010). For parameters that are estimated from observations, parameter uncertainty stems from our limited ability to precisely measure or estimate specific physical or ecological processes and quantities (Link *et al.*, 2012), as well as from the inherent variability in certain processes (e.g. growth rates that vary across individuals) that are not resolved within the models.

Structural uncertainty relates to the spatial, temporal, and mathematical resolution employed by a model and the types of processes that are represented. Structural uncertainty includes the function forms of equations used to describe mechanistic processes and the types of interactions assumed to influence climate-LMR processes. Such uncertainties cannot be explored via parameter perturbations. For example, explicit trophic relationships that are not described by size-structured interactions are not represented in size-based trophodynamic models (e.g., Blanchard *et al.*, 2012; Watson *et al.*, 2014), while such relationships may be included in functional-group type food web models (e.g., Christensen and Walters, 2004).

Scenario uncertainty relates to the many possible futures comprising different socio-economic policies and technological developments likely occurring over the course of a model projection (e.g., Moss *et al.*, 2010; Nakicenovic *et al.*, 2014). Climate-LMR model drivers include the spatial and temporal changes in greenhouse gas and aerosol concentrations, fishing effort, and other human social-economic activities. Scenario uncertainty is not completely independent of internal variability in the climate-LMR system, as future decisions on the utilization and conservation of resources are sensitive to natural variation in the availability and distribution of LMR (e.g., the fishing quota decided on for the next management cycle are dependent on the productivity and abundance of the resources, as well as on how neighboring countries or regions are managing their resources).

The full range of possible future states for a given LMR reflects contributions from all of the sources of uncertainty outlined above, with potential cascades of uncertainties interacting and accumulating over components of the climate-LMR models (Figure 1). For any particular scenario, LMR models that differ in their structure and parameter values will simulate a range of future changes in ocean biogeochemistry, fish and fisheries. Additionally, an individual model with a fixed set of parameters will display variability in projections as a result of the internal variability associated with natural fluctuations of the climatic or ecological systems. Uncertainties that originate from different climate-LMR model sub-components may be additive or multiplicative. Thus, the final scope of uncertainties of LMR projections is expected to be different from the uncertainty scope of each model sub-component.

[Figure 1.]

The width of the envelope of uncertainty is dependent on the nature of interactions between linked models; the types of interactions include linearity of the linkages, existence of threshold responses, and positive/negative feedbacks (Peters and Herrick, 2004). When the processes linking two or more models are non-linear, uncertainties may be dampened or magnified through model linkages, for example, through attenuation or amplification of changes in higher trophic level production in marine ecosystems driven by climate change (Chust *et al.*, 2014; Stock *et al.*, 2014a). Feedbacks in social-ecological systems can be positive or negative, and uncertainties propagated in models that are linked dynamically with feedbacks resulting in emergent dynamics are difficult to predict.

Here, we draw experience from the large body of research on exploring uncertainties of climate projections to propose that the envelope of uncertainties of climate-LMR projection can be explored by systematically quantifying the three categories of uncertainty that we discussed above: internal variability, model uncertainty and scenario uncertainty. Review on specific techniques to explore each source of uncertainties can be found in Payne *et al*. (this volume).

Experiences from quantifying uncertainty of climate projections

For ocean-atmospheric general circulation models and biogeochemical models, the Coupled Model Intercomparison Project Phase 5 (CMIP5) multi-model database allows assessment of uncertainty in climate change projections across the dimensions illustrated in Fig. 1. Climate change projections were produced from more than 30 models, developed by different modelling groups with a standard set of scenario experiments (Flato *et al.*, 2013). The CMIP5 database allows some exploration of uncertainty, but comprehensive categorization of uncertainty into structural uncertainty, parameter uncertainty, and internal variability is not possible. The main challenges include the limited number of modeling groups that were able to contribute ensembles of runs, some models are fully independent of one another, and a lack of exploration of parameter uncertainty. Ideally, the ensemble should consist of a random sample across the uncertainty components in Fig. 1. For complex inter-linked models such as climate or climate-LMR models, exploring their full scope of uncertainty would require substantial computational time and other resources. Thus, a systematic approach is needed to efficiently explore the envelope of uncertainties.

To further explore the uncertainty contributed by internal variability for each model, ensembles of climate simulations have been run under identical forcing, but with each simulation initialized with slightly different, but equally plausible, conditions (Rodgers *et al.*, 2015). The chaotic nature of climate variability quickly produces different climate trajectories in each ensemble member (Wittenberg *et al.*, 2014). By considering each of the trajectories as a plausible outcome, the ensemble can be used to isolate that part of projection uncertainty due to internal variability (Frölicher *et al.*, 2009; Deser *et al.*, 2012).

Hawkins and Sutton (Hawkins and Sutton, 2009) analyze CMIP3 (i.e., the precursor of CMIP5) projections to explore the contribution of internal variability and model and scenario uncertainties to climate projections at global and regional scales. They showed that the dominant sources of uncertainty in surface air temperature projections vary with spatial scale and time horizon, noting the importance of model uncertainty and internal variation for mid-21st century regional projections. To further illustrate the application of the framework used by Hawkins and Sutton (2009) in the oceanic realm, we analyzed the projection uncertainties for sea surface temperature by combining CMIP5 projections and a large ensemble projections from the Earth System Model of the Geophysical Fluid Dynamic Laboratory (GFDL ESM2M model; Dunne *et al.*, 2012; Dunne *et al.*, 2013; Rodgers *et al.*, 2015).

We used the projection of SST as an example of exploring the sensitivity of model projections to different sources of uncertainties. Scenario uncertainty is estimated to be the difference between the multi-model mean of projections from 15 CMIP5 models of two 21st century emissions scenarios: the low-emissions scenario RCP2.6 with an increased radiative forcing that peaks at approximately 3 W/m^2 before 2100 and then declines to 2.6 W/m^2 by 2100, and the high-emissions scenario RCP8.5, with an increased radiative forcing of >8.5 W/m^2 by year 2100 (Meinshausen *et al.*, 2011). Model uncertainty is estimated as the standard deviation of changes in SST (10-year running mean) from each model projections. The internal variability is estimated as the standard deviation of projections from 30 ensemble member simulations of GFDL ESM2M (Rodgers *et al.*, 2015).

[Figure 2.]

Globally, the analysis shows that model uncertainty is dominant in the medium term SST projection (2030 - 2050), while the long-term (2080 - 2100) projection is dominated by scenario uncertainty (Fig. 2). The large model uncertainty over the medium term reflects the large variations in regional scale biases in the models. Although the importance of internal variability is second to model uncertainty in near term projection (2010 – 2030), its relative importance decreases rapidly further into the future.

The relative importance of different uncertainty sources varies between different regions. In the Northeast Atlantic (North Sea Large Marine Ecosystem, (Pauly *et al.*, 2008)), the importance of scenario uncertainty is smaller compared to those projections at the global scale, while model uncertainties and internal variability become the dominant uncertainty sources. The internal variability in the Northeast Atlantic may represent known properties of interannual and multidecadal climate and oceanographic variability such as North Atlantic Oscillation (NAO) and Atlantic Multidecadal Oscillation (AMO) (Viles and Goudie, 2003; Beaugrand and Kirby, 2010). In the Northeast Pacific (Gulf of Alaska Large Marine Ecosystem), internal variability becomes a dominant source of uncertainty representing properties, such as ENSO and Pacific Decadal Oscillation (PDO). In both basin scale examples, the internal variability of SST is a bigger contribution to projection uncertainty than in the global scale projection (Fig. 3). Moreover, in the short to medium term, the projected increase in SST is not sensitive to different emission scenarios, both globally and in the NE Atlantic and NE Pacific (Fig. 3). However, long-term warming is much more sensitive to different emission scenarios, particularly at the global scale. We anticipate the increased importance of internal variability observed at the basin scale may be even more prominent when examining even smaller spatial scales.

[Figure 3.]

In addition to highlighting the relative contribution of different sources of uncertainty, this exploration of uncertainty suggests strategies to prioritize investment in order to improve our understanding of specific types of uncertainties. In the example presented here, the large model uncertainties in the projections of SST in the Northeast Atlantic call for better understanding of key processes that may be represented differently among models. In the Northeast Pacific, where large internal variability is difficult to reliably predict, the medium term effects of greenhouse gas emission will be difficult to separate from natural variability. This further highlights the need for better understand inter-annual variability and thus the need for longer-term observational records.

Systematic exploration of climate-LMR projection uncertainties

Systematic exploration of the components of uncertainty in both space and time dimensions in a manner analogous to examples from physical climate model projections (Figure 3) is critical for moving quickly toward refined uncertainty bounds on climate-LMR projections. Thus, exploration of uncertainties within climate-LMR projections would include: (1) making projections from ensemble members of models with different properties of intenral temporal or spatial variability; (2) making projections from ensemble members of models with different model structure and parameter values, and (3) generating projections that are based on different climate and fishing scenarios.

The conditions to systematically explore uncertainties within climate-LMR projections already exist. For fish and fisheries models, attempts to explore the full matrix of uncertainties (particularly model uncertainty with scenario uncertainty) have been made for a limited number of fisheries or stocks (Table 2). Existing examples mainly involve Management System Evaluations in which the performance of different models is assessed under different management scenarios (Link *et al.*, 2012). Methods such as Monte Carlo simulation, Bayesian statistical frameworks, and a plethora of quantitative methods also provide a basis for exploring both the parameter and structural components of model uncertainty (Hill *et al.*, 2007; Hollowed *et al.*, 2013). Moreover, various statistical approaches are available to analyze the properties of different components of uncertainty, and how they contribute to the full scope of uncertainty (Saltelli *et al.*, 2000). Furthermore, initiatives such as the fisheries component of the Inter-Sectoral Impact Model Intercomparison Project (ISI-MIP) (Warszawski *et al.*, 2014), which aim to develop LMR projection databases for climate-fisheries assessment that are similar in nature to CMIP now been established. Such a database would facilitate collaborative efforts of LMR research communities to explore the full scope of uncertainties.

A remaining knowledge gap in climate-LMR uncertainty exploration is the limited understanding of uncertainties arising from internal variations in the ecological system or fishing scenarios in projecting LMR changes, as well as their interactions with internal variability at different temporal and spatial scales. The linkages between physical and biogeochemical ocean changes and ecosystem responses are likely to be non-linear and may also involve thresholds; thus the resulting pattern of internal variability of climate-LMR model projections are likely to be more complex. For example, the actual response of LMRs to a particular level of environmental change may be limited by predator – prey interactions, or altered by species-specific sensitivity and adaptability to environmental fluctuations (Foden *et al.*, 2013).

Exploration of internal variability in climate-LMR projections can be done by comparing projections from ensemble members of a single model with different sets of initial conditions. For example, we used three versions of Dynamic Bioclimate Envelope Model (DBEM) (Cheung *et al.*, 2011; Cheung *et al.*, in review) to project changes in maximum potential catch of sablefish (*Anoplopoma fimbria*) in the Northeast Pacific (Gulf of Alaska Large Marine Ecosystem) from

2000 to 2060 (Figure 4). Specifically, we explored the effects of internal variability of ocean conditions using 20 different ensemble member projections from the GFDL ESM2M (Rodgers *et al.*, 2015). We also compared the relative contribution of uncertainties from internal variability of ocean conditions, structural uncertainties of DBEM, and uncertainty from different climate scenarios (RCP 2.6 and 8.5).

The results suggest that internal variability is a dominant source of uncertainty for sablefish in the Northeast Pacific (Gulf of Alaska Large Marine Ecosystem) by 2060 relative to 2000, followed by the structural uncertainties of DBEM. Scenario uncertainty contributes less than 10% of the total uncertainty. This is broadly consistent with the projected SST changes in this region, with internal variability contributing around 40% to 70% of the total uncertainty over the time frame of 2000 - 2060 (Figure 2). However, model uncertainty is substantially lower for sablefish projections relative to SST projections, possibly because the structural difference between CMIP5 models (used in SST projection) is much larger than those between the three versions of DBEM (used in sablefish projection). Also, in addition to SST, DBEM projections are driven by other ocean biogeochemical variables, such as oxygen and net primary production (Cheung *et al.*, 2011). Internal variability of multiple oceanographic properties may have magnified the internal variability of the DBEM projections.

[Figure 4.]

Since DBEM outputs represents mainly long-term trend of potential catches, inter-annual variation of reported catches is substantially higher than the internal-variability of the projections (Fig. 5). DBEM does not represent some processes that contribute to inter-annual variability of catches such as recruitment variability and changes in fishing effort. Besides spawning stock abundance, recruitment variability could be dependent on both physical (temperature, wind, current) and/or biological (primary productivity, predation pressure) at different spatial and temporal scales (Houde, 2008). The relative importance of these factors and the processes contributing to recruitment vary between species. In addition, catches are also dependent on changes in fishing effort which can be dependent fisheries management (e.g., quota), social-economics factors (e.g., price of fish and cost of fishing), and fishers' behavior. DBEM does not resolve many of these processes and does not have species-specific recruitment sub-model. Therefore, DBEM is not expected to represent the actual inter-annual variability of the catch. On the other hand, DBEM is structured to represent the long-term trends of resource productivity. The long-term trend (20-year running mean) of the reported catch of sablefish falls within the range of trajectories of the projections (Fig. 5).

[Figure 5]

The example of the sablefish highlights the need to carefully consider the actual processes that are represented by the sample of LMR models in quantifying uncertainty from model ensembles. This challenge applies to both ocean biogeochemical and LMR models. For instance, the relatively coarse-resolution Earth System Models do not capture potentially large random variability associated with submesoscale and mesoscale ocean features such as fronts, eddies and filaments (Stock *et al*. 2011).

A standardized set of climate-LMR scenarios is needed to quantify scenario uncertainty for climate-LMR projections. These scenarios must be reconciled with a range of different realizations of future emission (e.g., IPCC AR5's Representative Concentration Pathways, or RCPs) (Moss *et al.*, 2010) and social-economic development (e.g., Shared Socio-economic

Pathways or the Sustainable Development Goals) (Griggs *et al.*, 2013; Hunter and O'Neill, 2014). However, emissions scenarios only describe broad-brush societal changes in the 21st century. Fishing sector-specific storylines concerning management, aquaculture and technological development, and demand for fish in countries across the economic development spectrum at global and regional scales are also needed. Such factors would ultimately affect the magnitude and distribution of fishing effort. Trajectories of other human marine-related activities that drive changes in marine ecosystems should also be included (Figure 6). Development of these scenarios requires interdisciplinary collaboration between natural and social scientists (Österblom *et al.*, 2013). Although, there are currently independent efforts to develop such scenarios at global and regional scales (e.g., Barange *et al.*, 2014; Jones *et al.*, 2014), community-wide effort in developing standardized sets of scenarios would facilitate consistent comparison of LMR projections.

[Figure 6]

Building confidence and constraining the scope of plausible projections with observations

Observations across different scales are critical for building confidence in projections and reducing the scope of LMR uncertainty by constraining parameters, model structures, and eliminating implausible solutions. Model metrics are observations that can be compared to model outputs in order to obtain a quantitative assessment of model skill. Model metrics that are of particular interest for LMR models include species distributions, and the composition and abundance of fisheries catches (Table 3). These data are generally available for broad-scale evaluation.

Different LMR models may vary in their ability to represent seasonal cycles, inter-annual variability and/or long-term (decadal or longer) trends, with skill at one scale not always implying skill at others (Table 3). To assess confidence in the temporal properties of climate-LMR projections, we suggest three possible tiers of evaluation that involve the use of observational data to assess consistency with: (1) mean observed spatial patterns or seasonal climatologies across the scale of interest; (2) previously observed responses to climate variability; and (3) observed long-term trends attributable to climate change, fishing and other human drivers. In practice, the ability to assess models across all three tiers is often limited by data availability, particularly the paucity of the long-term, comprehensive, and high-quality data sets required to assess models against the often subtle trends in tier 3 (see next section). Comparisons between LMR data and model projections are also challenging due to issues of consistency between timeframe and spatial scales, as well as the confounding effects of multiple human pressures, such as climate and fishing (McOwen *et al.*, 2014). These challenges should not, however, preclude improving confidence in LMR-climate projections.

Confidence in climate-LMR model projections can arise from model evaluation across a subset of tiers, as well as the reliance of models on robust physiological and ecological principles (Stock *et al.*, 2011). Real caveats, however, are needed. Observational limitations also suggest that great care should to be taken eliminating particular projections from consideration within an ensemble framework. That is, a coarse culling of grossly inconsistent simulations (Overland *et al.*, 2011) is suggested rather than attempting to finely weight models based on nuanced differences in model-data fit. Even if model projections fit well with observational data, it does not guarantee that the model can accurately predict future changes, particularly when future conditions (environmental conditions or human activities) lie outside the bounds of historical conditions. In addition, a good fit between model projections and observational data could, on occasion, be more indicative of over-parameterization rather than prediction skill.

Observation data and model metrics

In the paragraphs that follow, we review available LMR data and their potential use as model metrics for evaluating LMR projections across the three tiers of evaluation described previously. We focus on the utility of three broad categories of LMR observations: fisheries dependent data, scientific surveys, and species occurrence records. Similar efforts focusing on metrics for physical climate models (Knutti and Sedláček, 2013) and biogeochemical/plankton food web models (Stock *et al.*, 2014b) are also being undertaken. We also identify key uncertainties associated with such observational data, as these would complicate their use in assessing the reliability of LMR projections.

a. Fisheries dependent data

Fisheries catch data are particularly useful for Tier 1 and 2 evaluations as they are of direct relevance to LMRs and their broad spatial, temporal and taxonomic coverage. Total catch potential can be estimated from the maximum catch of historical time-series, under certain assumptions concerning fishing effort (Cheung *et al.*, 2008; Friedland *et al.*, 2012). Moreover, spatial patterns and temporal changes in catch volume (Cheung *et al.*, 2013c) and functional and taxonomic composition (Cheung *et al.*, 2013b) of fisheries catch can be obtained from global fisheries databases. Species composition can be aggregated by body size-classes (for size-based LMR models (Blanchard *et al.*, 2012)), functional role (for functional group trophodynamic models (Christensen and Walters, 2004)), and by species (for species distribution models

(Cheung *et al.*, 2011)). Fisheries catch data can be obtained from the Sea Around Us project (SAU) (www.seaaroundus.org), which provides spatially explicit estimates of global catches from 1950 onward. In addition, the recent effort of SAU to reconstruct catches that are not reported in the United Nations Food and Agriculture Organization (FAO) landings statistics further improves the utility of such data for use as a metric for model comparisons (e.g., Zeller *et al.*, 2006). For example, in the Northeast Atlantic, fisheries catch and effort data since the early 20th century can be used to understand the ability of LMR models to reproduce changes driven by the Atlantic Multi-decadal Oscillation and the North Atlantic Oscillation (Kerby *et al.*, 2013). Similar examples of the potential use of long-term series of fish and fisheries data are also available in the Northeast Pacific (Lindegren *et al.*, 2013), and large pelagic long-line catch data are also available for ocean basins. As such datasets are spatially-explicit, the estimated catch-per-unit-effort can be used as an indicator of the distribution of large pelagic fishes, including tunas, billfishes, and sharks (Myers and Worm, 2003). Annual and decadal patterns of catches and their compositions can be assessed to understand the ability of the model to reproduce interannual and long-term changes in fisheries catches. Interpretation of fisheries catch data, however, must be done with care as changes or differences in fishing effort, gear, regulations, taxonomic identification, economics, or human behavior can strongly affect the quantity, composition, and location of catches (Pinsky and Fogarty, 2012). For this reason, determining whether observed changes in catch data are caused by climate, ecology, or human behavior can be complicated. Fisheries dependent data have substantial uncertainties because of inconsistent data quality and biases in sampling methods, timing and location. Fisheries catches and landings data may be under-reported (Zeller *et al.*, 2006), over-reported (Watson and Pauly, 2001) or mis-reported (Pascoe *et al.*, 2001), and the reliability and accuracy of the data may change over time. Also, biases in the location and timing of fishing activities render it challenging to standardize and use fisheries dependent catch-per-unit-effort data as an index of abundance (Maunder *et al.*, 2006). There may therefore be biases in using such data to interpret resource abundance and distribution (Walters, 2003).

b. Scientific survey data

Scientific surveys are useful across all three tiers of evaluation. They can provide spatial and temporal patterns of abundance, biomass, biodiversity and distribution. Among the benefits of scientific surveys is the use of standardized and repeatable methods, stratified random or fixed design to facilitate statistical inference, and documented survey locations so that both species presence and absence can be known. These properties make it more likely to attribute observed changes to particular drivers, such as fishing, pollution and climate change, compared to fisheries data. For example, data from the California Cooperative Oceanic Fisheries Investigations (CalCOFI) (Bograd *et al.*, 2003) for the California Current Large Marine Ecosystem, which is strongly affected by decadal to multidecadal atmospheric oscillations, such as ENSO and PDO, provide detailed documentation of ecological changes since 1951. The CalCOFI data describe the abundance of plankton, including larval fishes. A time series of larval fish abundance provide a useful proxy for adult fish abundance (Koslow *et al.*, 2013). Some surveys further record information on oceanographic conditions, which might be useful for simultaneously assessing the skill of the climatic and ecological components of LMR models. Although a number of surveys available have been sampling for more than four decades, care must be taken to ensure that large changes in survey methods have not biased the time-series. A common standardization is to ensure that the same region has been surveyed consistently through time. Also, bias correction factors may be available to account for changes in survey methods (e.g., Ohman and Smith, 1995).

Although survey data can provide estimates of large-scale changes in the distribution of relative abundance or biomass of LMR (e.g., Pinsky *et al.*, 2013), they are regional in scale, typically conducted during a certain season, and are designed to sample a specific set of species or size-classes (e.g., large groundfishes). Different surveys also vary in timeframe, and availability of long time-series survey data is limited. On the other hand, survey data are available for a range of ecosystem types (from the tropics to high latitudes), thereby allowing the examination of model performance across ecological gradients.

c. Species occurrence records

A major biological response to ocean changes is a shift in the distributions of marine species (Pinsky *et al.*, 2013; Poloczanska *et al.*, 2013), which can have further implications for marine ecosystems and LMR (Cheung *et al.*, 2010; Cheung *et al.*, 2013b). It is thus desirable for LMR models to realistically predict distributions for a wide range of species. A range of species distribution models have been applied to model LMRs under climate change (e.g., Jones and Cheung, 2015). The reliability of predicted species distributions are often examined using geo-referenced species occurrence records and test statistics, such as the Area Under Curve (AUC) of the Receiver Operating Characteristics (ROC). These records are collated from a range of sources including museum collections, scientific expeditions and surveys, and fisheries records. Many are now publicly accessible through databases, such as the Global Biodiversity Information Facility (GBIF) (Robertson *et al.*, 2014) and the Ocean Biodiversity Information System (OBIS) (Costello *et al.*, 2007), and have frequently been standardized for taxonomy and checked for quality. Species occurrence records have the advantage in having a much broader spatial and taxonomic coverage than any single data source (e.g., from scientific survey only). However, problems with taxonomic misidentification, common names, synonyms, and errors in geo-referencing are still present. Confidence in species occurrence data may also be reduced due to sampling bias (Webb *et al.*, 2010). Specifically, information on locations where unsuccessful sampling has occurred is not always available, making it difficult to determine the areas where specific species are absent and therefore to interpret test statistics such as the AUC (Pearce and Boyce, 2006).

To help inform the use of uncertain observational data in assessing model projections, a framework has been proposed to systematically assess the level of uncertainty associated with observational data particularly for climate change impact assessment (O'Connor *et al.*, 2015). This framework is based on evidence combined from theory, experiments and historical data with statistical analysis being undertaken to attribute any signals in observational data to climate change, thereby building confidence in the model. Such a framework will help identify cases where observational data are too uncertain to help assess model outputs e.g., with insufficient temporal and spatial coverage of observational data to reveal underlying trends and patterns.

Post-processing of LMR model outputs is generally needed before they can be compared to empirical data, as there will inevitably be differences between LMR models due to variations in model structure and other factors. For example, output from species-based LMR models will be more directly comparable to empirical data. However, species-based LMR models may only include a subset of species or taxonomic groups that are included in the empirical data. In contrast, output from size-based models can easily be compared with aggregated LMR production. However, the lack of explicit representation of taxonomic identity in size-based models makes their output difficult to compare to species- or population-specific data. Approximations can be made in some cases to convert information from size- or trophic- based models into taxonomic-based data. For example, the abundance and production of organisms at size > 1 m can be assumed to represent adult large pelagic fishes and can thus be compared to data from pelagic long-line catches. Functional group-based LMR models are intermediate between species-based and size-based models, and their outputs can be approximately converted to both taxonomic- or size-based aggregations. Thus, having identified the dominant taxonomic groups in a functional group, the dynamics of that functional group can be assumed to be representative of that taxonomic group. Functional groups that represent specific taxonomic groups of interest can also be included explicitly in the model (deYoung *et al.*, 2004; Griffith and Fulton, 2014).

From quantifying uncertainty to assessing risk

Given the large sources of uncertainty discussed in previous sections, a systematic exploration of potential future LMR states and the associated uncertainties is an important step towards a full risk assessment that would allow us to understand the potential impact of climate change on human societies through, for example, diminished food security, income or other ecosystem services. In general, risk consists of two components: (1) the magnitude of potential changes, and; (2) the probability of occurrence of such changes. Previous climatic risk assessments have involved both quantitative risk-based approaches and more qualitative, social vulnerability approaches (Dessai and Hulme, 2004), or a combination of both (Brown *et al.*, 2012).

Quantitative assessment generally involves identifying climate hazards and their probability of occurrence. For example, Li *et al.* (2009) assessed the drought risk for world crop production under climate change based on ensemble results from 20 GCM and six emission scenarios. The ensemble of projections was used to estimate probability density functions of drought disaster frequency. Their results show a consistent increase in drought risk in the middle and end of the 21st century under climate change, leading to significant reductions in yield for major crops. In our case study of projecting changes in potential catches of sablefish in the Northeast Pacific (Figure 4), the probability of projecting a decrease in catch could be quantified by systematically exploring the envelope of uncertainty. Thorough estimates of risk can facilitate policy discussion for mitigation and/or adaptation in LMR management through the exploration of the potential for regrets/no-regrets policies and the associated costs and benefits (Polasky *et al.*, 2011). This approach to risk-based, ecosystem-based management has been developed for certain marine systems, for example in Australia (Hobday *et al.*, 2011). One area of risk assessment that remains particularly difficult to accurately quantify and yet important for guiding societal choices, is an understanding of “tail risk”, or risk from extreme and high-impact, but low-probability, events (Weitzman, 2011).

Future direction of climate-LMR projections

The many sources of uncertainty in climate-LMR projections and computational cost will always limit our ability to fully explore uncertainty in climate-LMR projections. However, the framework described here provides a basis for concerted effort to improve estimation of uncertainty ranges for climate-LMR projections and, eventually, reduce these ranges. As was the case for physical climate projections, a climate-LMR ensemble offers a starting point. Systematic exploration of uncertainty space to identify prominent components for a given spatial scale, time horizon and variable of interest can guide research investment and accelerate progress toward more accurate estimates of uncertainty bounds. More rigorous and standardized comparison with observations (i.e., model metrics) must also play a central role in building confidence in projections. In combination, these steps should produce more robust risk estimates for policy formulation that will promote LMR sustainability in a changing climate.

While adoption of the framework described herein will improve climate-LMR projections, numerous challenges must still be overcome. Various unknowns pose a major challenge to exploring the real scope of uncertainties. Particularly, adaptive responses in nature to climate change, and by society to changes in LMRs, are difficult to predict and are poorly understood (Pinsky and Fogarty, 2012). There are also "unknown-unknowns", such as ecological tipping points, which contribute to uncertainties and that cannot be assessed with our current knowledge. This problem could be partly addressed by developing scenarios that aim to explore the sensitivity of outputs to such uncertainties, such as a scenario incorporating high levels of biological and social adaptation. Additionally, when exploring structural uncertainty of the models, the sample of model structures is often assembled opportunistically based on existing models rather than strategically based on a systematic sampling of all plausible model structures. Furthermore, different climate-LMR models may not be entirely independent from one another as the models may be parameterized with similar datasets. This may result in biases in assessing the effects of model uncertainties on projections (Hawkins and Sutton, 2009). On the other hand, an ensemble of opportunities would be the most practical way to tackle the challenge of quantifying climate-LMR projection uncertainties and would help examine whether there is a need for large-scale cooperative initiatives that provide substantial resources and facilities to address these challenges.

Observational data that are available for comparison with LMR models generally only cover a short period of time and a limited number of regions. This magnifies the issues regarding uncertainties associated with observation errors, making it more challenging to attribute the reasons for any discrepancies between observations and model predictions. Moreover, many LMR models use available observational data for parameterization, thus the scope of using additional data for model testing is limited. Careful selection of statistical and cross-validation techniques can help mitigate this problem (Arlot and Celisse, 2010). Further discussion and consensus amongst LMR modelers is needed to develop criteria to identify unrealistic models (i.e., what type and how many discrepancies are needed before a model is excluded from an ensemble). These challenges reiterate the need to improve the sharing of observational data between scientists, institutes and countries and develop data facilities to support their use in testing climate-LMR projections (Hollowed *et al.*, 2013).

Scenario development has not matured for LMR assessment. Scenarios specifically tailored for marine-related sectors are very limited, while existing assessments adopt scenarios that are used for more general purposes (Millennium Ecosystem Assessment, 2005). These scenarios may not account for key uncertainties in the projected pathways of LMRs. In relation to this, fisheries models linking fishing to changes in LMRs, and the socio-economic conditions that are used to generate LMR scenarios are only starting to be developed for global- and basin- scale LMRs, although much effort has focused on regional- and local- scale fishing fleet dynamic models (van Putten *et al.*, 2012) and management strategy evaluation (MSE) models. All existing global- or basin-scale LMR models either do not have explicit fisheries components or have simple assumptions of stock- or region- specific fishing mortality rates. Only recently has a global scale LMR model study included a spatially-explicit fishing dynamics model to simulate changes in fishing effort (Christensen *et al.*, 2015). However, there is a need to improve efforts such as this to develop additional LMR-specific scenarios representing human activities before meaningful comparison of scenario uncertainties can be undertaken.

Understanding where uncertainty comes from and how it interacts with model components is necessary to improve the interpretation of model projections and to inform policy. Improving the quantification of uncertainties will therefore be a major area of development in climate-LMR projections to inform global and regional assessments of climate change impacts, vulnerability and adaptation on marine ecosystems and related sectors.

Acknowledgement

We thank Y. Ota, D. Pauly and J. Dunne for their inputs into the discussions that contributed to the content of this manuscript. This is a contribution to the Nippon Foundation – University of British Columbia Nereus Program. The present article is a product of Nereus' international and interdisciplinary effort towards improving global sustainable fisheries. All authors contributed to the design and writing of the manuscript. T L Frölicher acknowledges financial support from the SNSF (Ambizione grant PZ00P2_142573).

Table 1. Summary of different types of uncertainties in LMR models.

Types of uncertainties	Description	Examples	
		Coupled atmospheric, ocean and biogeochemical models	**Fish and fisheries models**
Internal variability	Natural variations of physical, biogeochemical and ecological processes that contribute random variability to projections of LMRs	El Niño-Southern Oscillation (ENSO) and Pacific Decadal Oscillation (PDO), North Atlantic Oscillation (NAO), Atlantic Multidecadal Oscillation (AMO), locations of gyre boundaries	Predator-prey dynamics, spatial and temporal variations in fish populations not arising from deterministically modeled climate change signal.
Model uncertainty			
a. Parameter	Specific parameter values used in the formulae determining the behavior of the models	Parameters controlling sub-grid scale oceanographic processes, phytoplankton growth, zooplankton grazing, biogeochemical transformations, and detritus remineralization.	Values of the parameter describing diet composition, dispersal rate, production and consumption rates, trophic interactions and other ecological/anthropogenic processes represented in the models. If variations in parameter values reflect an alteration of model architecture or design, it

			should belong to the structural uncertainty category.
b. Structure	Differences in abstraction, understanding and representation of the system through different model architecture, design and assumptions, the method of representing space/time,and the kinds of ecological processes, human and natural drivers included.	Size-based vs functional group based approaches, grid resolution; the number of nutrients included in biogeochemical models; the number of functional groups included in a lower trophic level or fish model; differences in representing food web structure, fish movement, and different life history stages in fish models.	
Scenario uncertainty	Differences in the natural and/or anthropogenic forcing that drive the model simulation	Representative Concentration Pathways (RCPs)	Shared Socio-economic Pathways (SSPs), spatial and temporal changes in fisheries, and how all of these influence model components directly or indirectly

Table 2. Selected case studies that explored different aspects of uncertainties in projections of aquatic (marine and freshwater) biological resources under climate change.

Spatial scale	**Selected case studies**	**Explored uncertainties and conclusions**
Global	Variability of projections of distribution and patterns of species turnover across three different species distribution models for over 800 commercially exploited fishes and invertebrates in the world under two greenhouse gas emission scenarios (Jones and Cheung, 2015).	- Structural uncertainties of species distribution models; - Scenario uncertainties of greenhouse gas emission pathways. - Larger variability in projections exists between greenhouse gas emission scenarios (RCP2.6 and RCP8.5) than between three different species distribution models.
Regional (UK waters)	Projecting changes in maximum catch potential and profitability from fishing 31 key commercially targeted fish species primarily inhabiting UK waters using different climate models, species distribution modelling approaches and socio-economic scenarios (Jones *et al.*, 2014). Three fisheries and socio-economic scenarios were designed based on key	- Structural uncertainties of species distribution models and climate models; - Scenario uncertainties of greenhouse gas emission, fisheries and socio-economics pathways; - Scenario (climate, fisheries and socio-economic) uncertainty

	variables identified in the Alternative Future Scenario for Marine Ecosystems (AFMEC) scenarios.	dominates over structural uncertainty of climate and biological models.
Regional (Central North Pacific Ocean)	Uncertainty of a trophodynamic model (Ecopath with Ecosim) was explored using Monte Carlo simulation. Confidence limits of key input parameters were set based on the reliability of the data, as indicated by the data type. Results from 500 dynamic simulations (each involving up to several thousand iterations to find a balanced model) were used to construct 95 % confidence intervals for the derived biomass time series (Kearney *et al.*, 2012).	- Parameter uncertainty of the ecological models.
Regional (Eastern U.S. coast)	Using experimentally-derived thermal tolerance limits to project range shift of gray snapper (*Lutjanus griseus*) in estuaries along eastern US coast. Projections were driven by temperature simulated from 23 different climate models, two thermal tolerance metrics under three different emission scenarios (Hare *et al.*, 2012).	- Parameter uncertainty of range shift model; - Structural uncertainties of climate models; - Scenario uncertainties of greenhouse gas emission pathways. - Different species distribution models contributed the largest

		variation in projections, followed by different General Circulation Models (GCMs). The contribution of variability from different GCMs increased over time and to a level that is comparable to variability from different species distribution models for end of 21st century projections. Different observation datasets had a small influence on the overall variability of the projections.
Regional (freshwater ecosystems in France)	Projection of distribution shifts of 35 species of freshwater fishes in France across 100 random subsets of observation data, seven species distribution models and climate projections from 12 climate models, resulting in 8400 different potential futures projections (Buisson *et al.*, 2010).	- Parameter uncertainty of species distribution models; - Structural uncertainties of species distribution models and climate models; - Scenario uncertainty of greenhouse gas emission pathways. - Uncertainty about thermal limits of the species dominates over model or scenario uncertainties

Table 3. Examples of observation datasets and the model metrics for comparison with LMR model outputs.

Data type/ Model metric	Timeframe	Spatial aggregation	Taxonomic resolution	Examples of data sources
Fisheries data				
Total fisheries catch potential	Average from 1950 - 2010	Global and large marine ecosystems	Aggregated	Sea Around Us project
Species composition of catch (or the mean temperature of catch)	Annual from 1950 - 2010	Global and large marine ecosystems	Exploited taxa	Sea Around Us project
CPUE of large pelagic fishes	1970s to 2000s	Global	Large pelagic fishes (tunas)	Regional Fisheries Management Organizations for tunas and billfishes e.g., Myers and Worm (2003)
Survey data				
Rate of range shift of marine species	Average from 1970s to 2000s	Regional (North America continental shelf, North Sea)	By species of fishes and invertebrates	Pinsky *et al.* (2013), ICES's International Bottom Trawl Survey
Community composition	1960s to 2010s	Regional (continental	By species of	Worm *et al.* (2009)

		shelves around the world)	fishes and invertebrates vulnerable to bottom trawls	
Variability in abundance driven by large-scale oceanographic changes	1951 – Present	Regional: California Current	Larvae and eggs of exploited and unexploited fishes	CalCOFI (Moser *et al.*, 2001)
	1931 - Present	North Sea	Exploited and unexploited fishes	Continuous Plankton Recorder (CPR) Survey
	1970s – 2000s	North America continental shelf	By species of fishes and invertebrates	Pinsky *et al.* (2013)
Occurrence record				
Occurrence of marine species	Mostly since the 20th century	Global	All marine taxa	OBIS (Costello *et al.*, 2007)

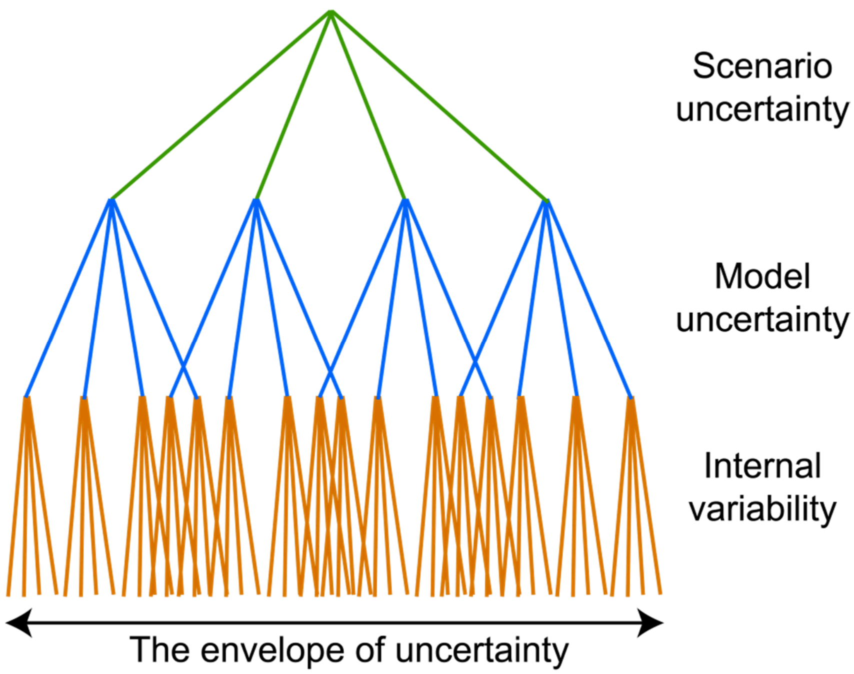


Figure 1. Schematic example illustrating cascades of uncertainties in LMR projection (modified from Wilby and Dessai (2010)). For a particular time horizon and spatial scale, the range, or envelope, of possible outcomes includes contributions from scenario uncertainty (green), model uncertainty (blue) and internal variability (orange). The cascades of uncertainties apply to each of the sub-components of climate-LMR models. Uncertainties from each model sub-component may be additive or multiplicative. In this schematic diagram, the width of each uncertainty level does not imply the magnitude of the uncertainty. E.g., internal variability may be larger than scenario uncertainty and *vice versa*.

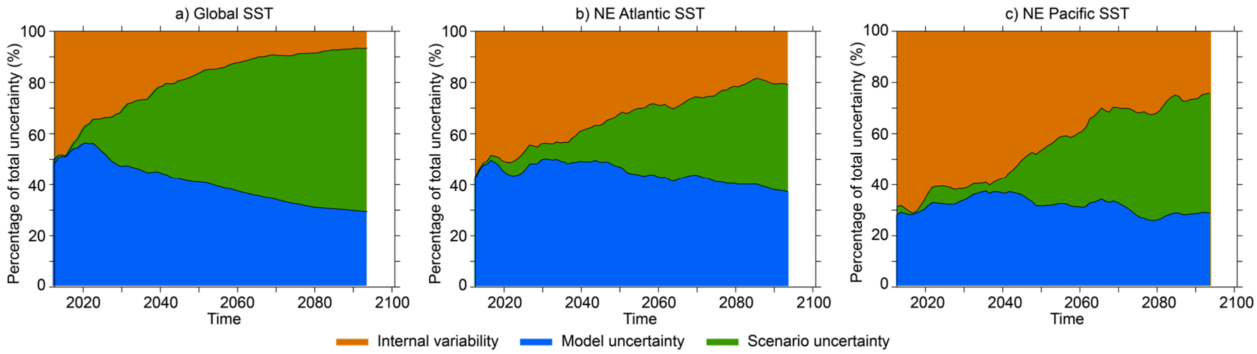


Figure 2. The relative importance of each source of uncertainty in annual mean sea surface temperature projection is shown by the fractional uncertainty for (a) global mean, (b) northeast Atlantic, and (c) northeast Pacific in the 21st century. Uncertainties are separated into three components: internal variability (orange), model uncertainty (blue), and scenario uncertainty (green). The percentage of total uncertainty is calculated from dividing the level of uncertainty from the specific component by the sum of the three types of uncertainties. For internal variability, the standard deviation of annual mean SST from the GFDL ESM2M ensemble is calculated year-by-year. The same procedure has been applied for model uncertainty, but a 10-yr running mean (longer than the typical ENSO period) is first applied to the individual CMIP5 model projections.

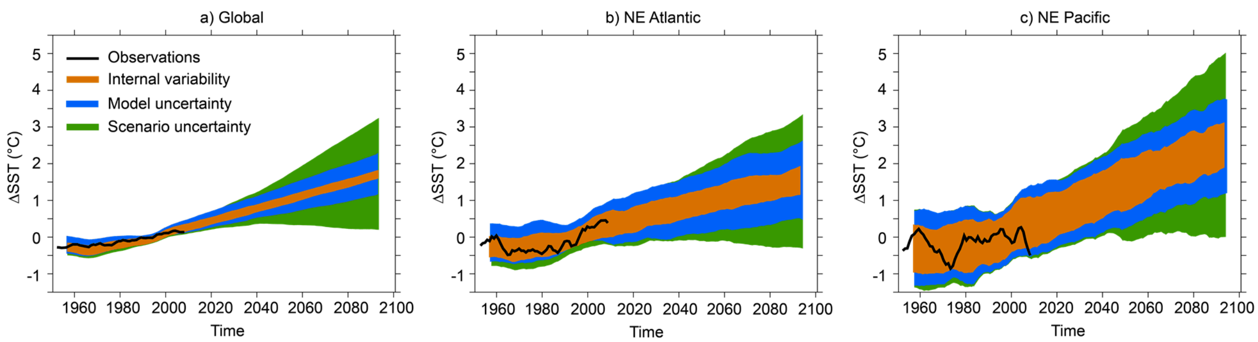
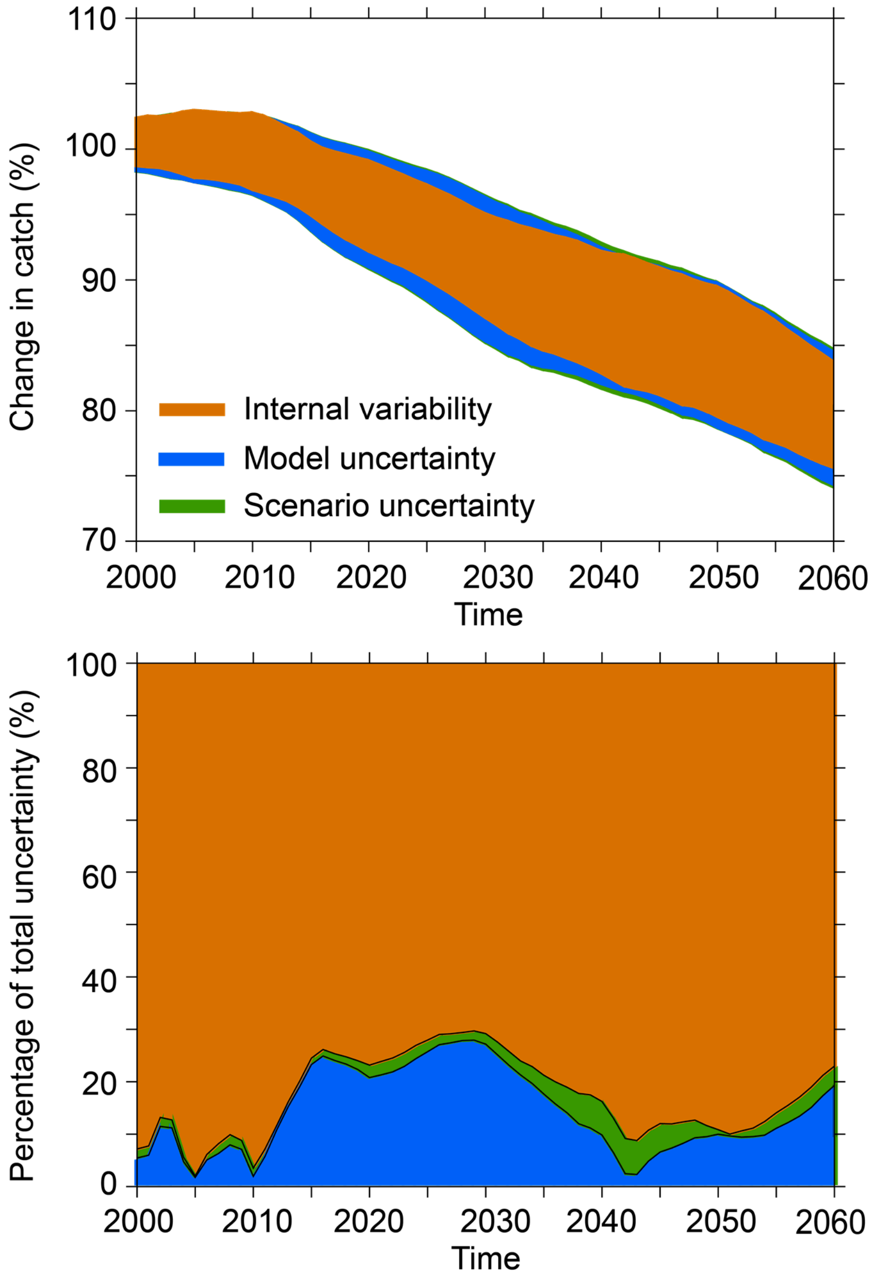


Figure 3. Changes in annual average sea surface temperature (10-year running mean) for (a) global mean, (b) northeast Atlantic, and (c) northeast Pacific relative to the 1986-2005 mean. SST observations (black line) are based on Smith *et al*. (2008). The uncertainty area was calculated by adding and subtracting the errors from each uncertainty source (internal variability: orange, model uncertainty: blue, scenario uncertainty: green) to and from the ensemble-mean projection of 15 CMIP5 models. Errors from different uncertainty sources are assumed to be additive.

A

B


Change in catch (%)
110
100
90
80
70
Internal variability
Model uncertainty
Scenario uncertainty
2000
2010
2020
2030
2040
2050
2060
Time
Percentage of total uncertainty (%)
100
80
60
40
20
0
2000
2010
2020
2030
2040
2050
2060
Time

C

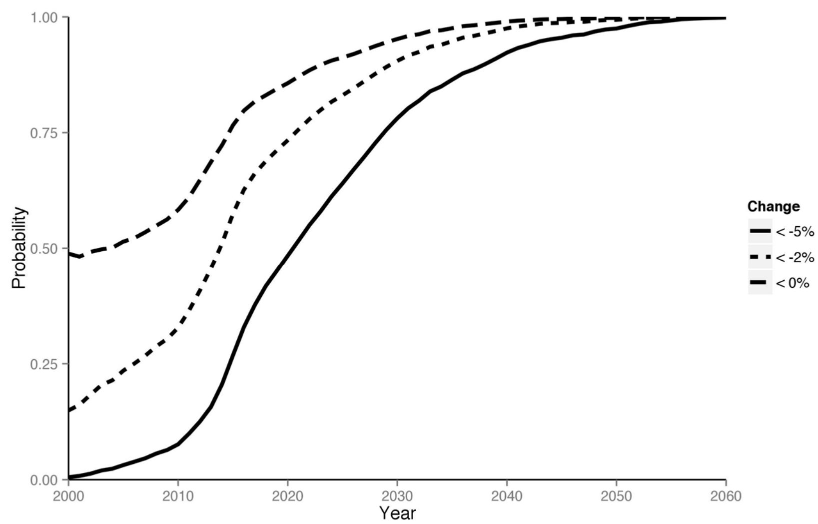


Figure 4. Projected changes in maximum potential catches of *Anoplopoma fimbria* from 2000 to 2060 under climate change. The projections were generated from using three versions of Dynamic Bioclimate Envelope Models (DBEM) (Cheung et al. under review), driven by outputs from GFDLESM2M. Internal variability was estimated from projected changes in catch potential driven by outputs from 20 ensemble members of GFDL ESM2M (Rodgers *et al*. 2015). (A) Projected changes in maximum potential catch and their standard deviation resulting from the three different types of uncertainties. (B) the relative contribution of each type of uncertainty, expressed as the proportion of total uncertainty, and (C) the probability of projecting a decrease in catch potential of more than 0% (dashed line), 2% (dotted line) and 5% (solid line).Model uncertainty represents variation of projections from the three versions of DBEM. Scenario uncertainty represents variations in projections between RCP2.6 and RCP8.5.

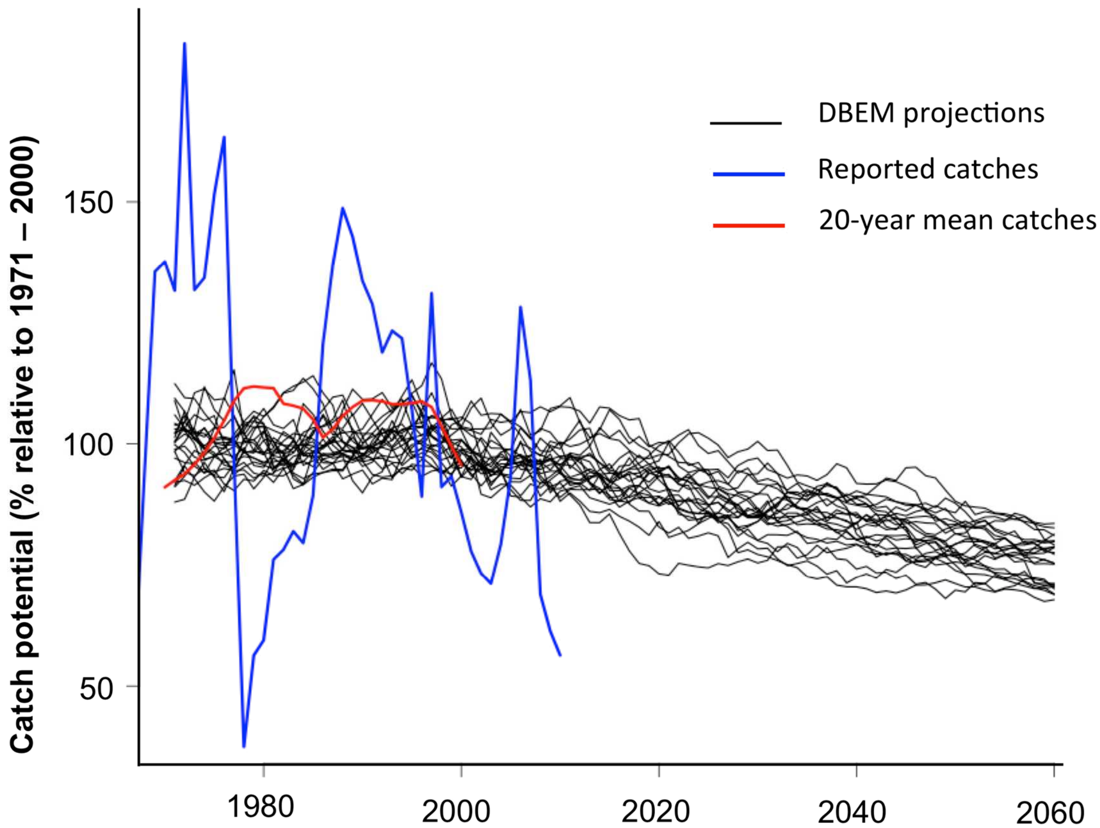


Figure 5. Comparison between projected changes in annual mean catch potential (relative to 1971 – 2000) using the three versions of DBEM and 20 GFDL ESM2M ensemble members under the RCP8.5 scenario (grey lines) with the reported catches (from Sea Around Us: www.seaaroundus.org) of sablefish in the Northeast Pacific (Gulf of Alaska Large Marine Ecosystem) (blue line). Reported catches are also smoothed by a 20-year running mean (red line).

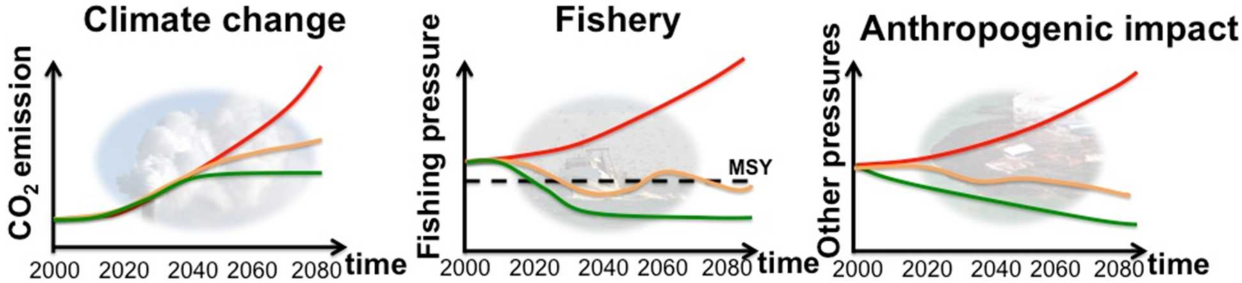


Figure 6. Schematic diagram showing an example of potential standardized sets of scenarios to be developed to explore scenario uncertainties. The red, yellow and green lines represent different scenario pathways to be explored by climate-LMR models. Anthropogenic impacts may include contaminant level, invasive species and habitat change.

References

Ainsworth, C. H., Samhouri, J. F., Busch, D. S., Cheung, W. W. L., Dunne, J., and Okey, T. A. 2011. Potential impacts of climate change on Northeast Pacific marine foodwebs and fisheries. ICES Journal of Marine Science, 68: 1217-1229.

Arlot, S., and Celisse, A. 2010. A survey of cross-validation procedures for model selection. Statistics surveys, 4: 40-79.

Barange, M., Cheung, W. W. L., Merino, G., and Perry, R. I. 2010. Modelling the potential impacts of climate change and human activities on the sustainability of marine resources. Current Opinion in Environmental Sustainability, 2: 326-333.

Barange, M., Merino, G., Blanchard, J. L., Scholtens, J., Harle, J., Allison, E. H., Allen, J. I., Holt, J., and Jennings, S. 2014. Impacts of climate change on marine ecosystem production in societies dependent on fisheries. Nature Climate Change, 4: 211-216.

Beaugrand, G., and Kirby, R. R. 2010. Climate, plankton and cod. Global Change Biology, 16: 1268-1280.

Beckage, B., Gross, L. J., and Kauffman, S. 2011. The limits to prediction in ecological systems. Ecosphere, 2: art125.

Blanchard, J., Jennings, S., Holmes, R., Harle, J., Merino, G., Allen, J., Holt, J., Dulvy, N. K., and Barange, M. 2012. Potential consequences of climate change for primary production and fish production in large marine ecosystems. Philosophical Transactions of the Royal Society B: Biological Sciences, 367(1605): 2979-2989.

Bograd, S. J., Checkley Jr, D. A., and Wooster, W. S. 2003. CalCOFI: a half century of physical, chemical, and biological research in the California Current System. Deep Sea Research Part II: Topical Studies in Oceanography, 50: 2349-2353.

Bopp, L., Resplandy, L., Orr, J. C., Doney, S. C., Dunne, J. P., Gehlen, M., Halloran, P., Heinze, C., Ilyina, T., Séférian, R., Tjiputra, J., and Vichi, M. 2013. Multiple stressors of ocean ecosystems in the 21st century: projections with CMIP5 models. Biogeosciences, 10: 6225-6245.

Brander, K. 2015. Improving the reliability of fishery predictions under climate change. Current Climate Change Reports, 1: 40-48.

Brown, C., Ghile, Y., Laverty, M., and Li, K. 2012. Decision scaling: Linking bottom-up vulnerability analysis with climate projections in the water sector. Water Resources Research, 48: W09537.

Buisson, L., Thuiller, W., Casajus, N., Lek, S., and Grenouillet, G. 2010. Uncertainty in ensemble forecasting of species distribution. Global Change Biology, 16: 1145-1157.

Cheung, W. W., Pauly, D., and Sarmiento, J. L. 2013a. How to make progress in projecting climate change impacts. ICES Journal of Marine Science, 70: 1069-1074.

Cheung, W. W., Watson, R., and Pauly, D. 2013b. Signature of ocean warming in global fisheries catch. Nature, 497: 365-368.

Cheung, W. W. L., Close, C., Lam, V., Watson, R., and Pauly, D. 2008. Application of macroecological theory to predict effects of climate change on global fisheries potential. Marine Ecology Progress Series, 365: 187-197.

Cheung, W. W. L., Dunne, J., Sarmiento, J. L., and Pauly, D. 2011. Integrating ecophysiology and plankton dynamics into projected maximum fisheries catch potential under climate change in the Northeast Atlantic. ICES Journal of Marine Science, 68: 1008-1018.

Cheung, W. W. L., Jones, M. C., Reygondeau, G., and Lam, V. W. Y. in review. Structural uncertainty in projecting global fisheries catches under climate change. Ecological Modelling.

Cheung, W. W. L., Lam, V. W. Y., Sarmiento, J. L., Kearney, K., Watson, R., and Pauly, D. 2009. Projecting global marine biodiversity impacts under climate change scenarios. Fish and Fisheries, 10: 235-251.

Cheung, W. W. L., Lam, V. W. Y., Sarmiento, J. L., Kearney, K., Watson, R. E. G., Zeller, D., and Pauly, D. 2010. Large-scale redistribution of maximum fisheries catch potential in the global ocean under climate change. Global Change Biology, 16: 24-35.

Cheung, W. W. L., Sarmiento, J. L., Dunne, J., Frolicher, T. L., Lam, V. W. Y., Deng Palomares, M. L., Watson, R., and Pauly, D. 2013c. Shrinking of fishes exacerbates impacts of global ocean changes on marine ecosystems. Nature Clim. Change, 3: 254-258.

Christensen, V., Coll, M., Buszowski, J., Cheung, W. W. L., Frölicher, T., Steenbeek, J., Stock, C., Watson, R. A., and Walters, C. J. 2015. The global oceans is an ecosystem: stimulating marine life and fisheries. Global Ecology and Biogeography.

Christensen, V., and Walters, C. J. 2004. Ecopath with Ecosim: methods, capabilities and limitations. Ecological Modelling, 172: 109-139.

Chust, G., Allen, J., Bopp, L., Schrum, C., Holt, J., Tsiaras, K., Zavatarelli, M., Chifflet, M., Cannaby, H., and Dadou, I. 2014. Biomass changes and trophic amplification of plankton in a warmer ocean. Global Change Biology, 20: 2124-2139.

Costello, M., Stocks, K., Zhang, Y., Grassle, J., and Fautin, D. 2007. About the Ocean Biogeographic Information System.

Day, R. H. 1982. Irregular growth cycles. The American Economic Review: 406-414.

Deser, C. 2013. A century of North Atlantic data indicates interdecadal change. Life, 50.

Deser, C., Knutti, R., Solomon, S., and Phillips, A. S. 2012. Communication of the role of natural variability in future North American climate. Nature Climate Change, 2: 775-779.

Dessai, S., and Hulme, M. 2004. Does climate adaptation policy need probabilities? Climate Policy, 4: 107-128.

deYoung, B., Heath, M., Werner, F., Chai, F., Megrey, B., and Monfray, P. 2004. Challenges of Modeling Ocean Basin Ecosystems. Science, 304: 1463-1466.

Dunne, J. P., John, J. G., Adcroft, A. J., Griffies, S. M., Hallberg, R. W., Shevliakova, E., Stouffer, R. J., Cooke, W., Dunne, K. A., and Harrison, M. J. 2012. GFDL's ESM2 global coupled climate-carbon Earth System Models. Part I: Physical formulation and baseline simulation characteristics. Journal of Climate, 25: 6646-6665.

Dunne, J. P., John, J. G., Shevliakova, E., Stouffer, R. J., Krasting, J. P., Malyshev, S. L., Milly, P., Sentman, L. T., Adcroft, A. J., and Cooke, W. 2013. GFDL's ESM2 Global Coupled Climate–Carbon Earth System Models. Part II: Carbon System Formulation and Baseline Simulation Characteristics*. Journal of Climate, 26: 2247-2267.

Flato, G., Marotzke, J., Abiodun, B., Braconnot, P., Chou, S. C., Collins, W., Cox, P., Driouech, F., Emori, S., Eyring, V., Forest, C., Gleckler, P., Guilyardi, E., Jakob, C., Kattsov, V., Reason, C., and Rummukainen, M. 2013. Evaluation of Climate Models.

Foden, W. B., Butchart, S. H., Stuart, S. N., Vié, J.-C., Akçakaya, H. R., Angulo, A., DeVantier, L. M., Gutsche, A., Turak, E., and Cao, L. 2013. Identifying the world's most climate change vulnerable species: a systematic trait-based assessment of all birds, amphibians and corals. PLoS ONE, 8: e65427.

Friedland, K. D., Stock, C., Drinkwater, K. F., Link, J. S., Leaf, R. T., Shank, B. V., Rose, J. M., Pilskaln, C. H., and Fogarty, M. J. 2012. Pathways between Primary Production and Fisheries Yields of Large Marine Ecosystems. PLoS ONE, 7: e28945.

Frölicher, T., Joos, F., Plattner, G. K., Steinacher, M., and Doney, S. C. 2009. Natural variability and anthropogenic trends in oceanic oxygen in a coupled carbon cycle–climate model ensemble. Global Biogeochemical Cycles, 23.

Fulton, E. A. 2010. Approaches to end-to-end ecosystem models. Journal of Marine Systems, 81: 171-183.

Gates, W. L. 1992. AMIP: The Atmospheric Model Intercomparison Project. Bulletin of the American Meteorological Society, 73: 1962-1970.

Griffith, G. P., and Fulton, E. A. 2014. New approaches to simulating the complex interaction effects of multiple human impacts on the marine environment. ICES Journal of Marine Science, 10.1093/icesjms/fst196.

Griffith, G. P., Fulton, E. A., and Richardson, A. J. 2011. Effects of fishing and acidification-related benthic mortality on the southeast Australian marine ecosystem. Global Change Biology, 17: 3058-3074.

Griggs, D., Stafford-Smith, M., Gaffney, O., Rockström, J., Öhman, M. C., Shyamsundar, P., Steffen, W., Glaser, G., Kanie, N., and Noble, I. 2013. Policy: Sustainable development goals for people and planet. Nature, 495: 305-307.

Guilyardi, E., Wittenberg, A., Fedorov, A., Collins, M., Wang, C., Capotondi, A., Van Oldenborgh, G. J., and Stockdale, T. 2009. Understanding El Niño in ocean-atmosphere general circulation models: Progress and challenges. Bulletin of the American Meteorological Society, 90 325-340.

Hare, J. A., Wuenschel, M. J., and Kimball, M. E. 2012. Projecting Range Limits with Coupled Thermal Tolerance - Climate Change Models: An Example Based on Gray Snapper (Lutjanus griseus) along the U.S. East Coast. PLoS ONE, 7: e52294.

Hawkins, E., and Sutton, R. 2009. The Potential to Narrow Uncertainty in Regional Climate Predictions. Bulletin of the American Meteorological Society, 90: 1095-1107.

Hill, S. L., Watters, G. M., Punt, A. E., McAllister, M. K., Quéré, C. L., and Turner, J. 2007. Model uncertainty in the ecosystem approach to fisheries. Fish and Fisheries, 8: 315-336.

Hobday, A. J., Smith, A. D. M., Stobutzki, I. C., Bulman, C., Daley, R., Dambacher, J. M., Deng, R. A., Dowdney, J., Fuller, M., Furlani, D., Griffiths, S. P., Johnson, D., Kenyon, R., Knuckey, I. A., Ling, S. D., Pitcher, R., Sainsbury, K. J., Sporcic, M., Smith, T., Turnbull, C., Walker, T. I., Wayte, S. E., Webb, H., Williams, A., Wise, B. S., and Zhou, S. 2011. Ecological risk assessment for the effects of fishing. Fisheries Research, 108: 372-384.

Hollowed, A. B., Barange, M., Beamish, R. J., Brander, K., Cochrane, K., Drinkwater, K., Foreman, M. G. G., Hare, J. A., Holt, J., Ito, S.-i., Kim, S., King, J. R., Loeng, H., MacKenzie, B. R., Mueter, F. J., Okey, T. A., Peck, M. A., Radchenko, V. I., Rice, J. C., Schirripa, M. J., Yatsu, A., and Yamanaka, Y. 2013. Projected impacts of climate change on marine fish and fisheries. ICES Journal of Marine Science: Journal du Conseil, 70: 1023-1037.

Holt, J., Allen, J. I., Anderson, T. R., Brewin, R., Butenschön, M., Harle, J., Huse, G., Lehodey, P., Lindemann, C., and Memery, L. 2014. Challenges in integrative approaches to modelling the marine ecosystems of the North Atlantic: Physics to fish and coasts to ocean. Progress In Oceanography, 129: 285-313.

Houde, E. D. 2008. Emerging from Hjort's shadow. Journal of Northwest Atlantic Fishery Science, 41: 53-70.

Hunter, L. M., and O'Neill, B. C. 2014. Enhancing engagement between the population, environment, and climate research communities: the shared socio-economic pathway process. Population and environment, 35: 231-242.

IPCC. 2014. Climate Change 2014: Impacts, Adaptation, and Vulnerability: Summery for Policymakers. 44 pp.

Jones, M. C., and Cheung, W. W. 2015. Multi-model ensemble projections of climate change effects on global marine biodiversity. ICES Journal of Marine Science, 72: 741-752.

Jones, M. C., Dye, S. R., Pinnegar, J. K., Warren, R., and Cheung, W. W. L. 2014. Using scenarios to project the changing profitability of fisheries under climate change. Fish and Fisheries: n/a-n/a.

Kearney, K. A., Stock, C., Aydin, K., and Sarmiento, J. L. 2012. Coupling planktonic ecosystem and fisheries food web models for a pelagic ecosystem: Description and validation for the subarctic Pacific. Ecological Modelling, 237: 43-62.

Kerby, T. K., Cheung, W. W., van Oosterhout, C., and Engelhard, G. H. 2013. Wondering about wandering whiting: Distribution of North Sea whiting between the 1920s and 2000s. Fisheries Research, 145: 54-65.

Kirby, R. R., and Beaugrand, G. 2009. Trophic amplification of climate warming. Proceedings of the Royal Society B: Biological Sciences: rspb20091320.

Knutti, R., Furrer, R., Tebaldi, C., Cermak, J., and Meehl, G. A. 2010. Challenges in Combining Projections from Multiple Climate Models. Journal of Climate, 23: 2739-2758.

Knutti, R., and Sedláček, J. 2013. Robustness and uncertainties in the new CMIP5 climate model projections. Nature Climate Change, 3: 369-373.

Koslow, A. J., Goericke, R., and Watson, W. 2013. Fish assemblages in the southern California Current: relationships with climate, 1951–2008. Fisheries Oceanography, 22: 207-219.

Lefort, S., Aumont, O., Bopp, L., Arsouze, T., Gehlen, M., and Maury, O. 2015. Spatial and body-size dependent response of marine pelagic communities to projected global climate change. Global Change Biology, 21: 154-164.

Lehodey, P., Senina, I., Sibert, J., Bopp, L., Calmettes, B., Hampton, J., and Murtugudde, R. 2010. Preliminary forecasts of Pacific bigeye tuna population trends under the A2 IPCC scenario. Progress In Oceanography, 86: 302-315.

Li, Y., Ye, W., Wang, M., and Yan, X. 2009. Climate change and drought: a risk assessment of crop-yield impacts. Climate Research, 39: 31.

Lindegren, M., Checkley, D. M., Rouyer, T., MacCall, A. D., and Stenseth, N. C. 2013. Climate, fishing, and fluctuations of sardine and anchovy in the California Current. Proceedings of the National Academy of Sciences, 110: 13672-13677.

Link, J. S., Ihde, T., Harvey, C., Gaichas, S. K., Field, J., Brodziak, J., Townsend, H., and Peterman, R. 2012. Dealing with uncertainty in ecosystem models: the paradox of use for living marine resource management. Progress In Oceanography, 102: 102-114.

Maunder, M. N., Sibert, J. R., Fonteneau, A., Hampton, J., Kleiber, P., and Harley, S. J. 2006. Interpreting catch per unit effort data to assess the status of individual stocks and communities. ICES Journal of Marine Science: Journal du Conseil, 63: 1373-1385.

McOwen, C. J., Cheung, W. W., Rykaczewski, R. R., Watson, R. A., and Wood, L. J. 2014. Is fisheries production within Large Marine Ecosystems determined by bottom-up or top-down forcing? Fish and Fisheries, DOI: 10.1111/faf.12082.

Meehl, G. A., Boer, G. J., Covey, C., Latif, M., and Stouffer, R. J. 2000. The coupled model intercomparison project (CMIP). Bulletin of the American Meteorological Society, 81: 313-318.

Meinshausen, M., Smith, S. J., Calvin, K., Daniel, J. S., Kainuma, M., Lamarque, J., Matsumoto, K., Montzka, S., Raper, S., and Riahi, K. 2011. The RCP greenhouse gas concentrations and their extensions from 1765 to 2300. Climatic Change, 109: 213-241.

Millennium Ecosystem Assessment 2005. Ecosystems and human well-being, Island Press Washington, DC.

Moser, H. G., Charter, R. L., Watson, W., Ambrose, D., Hill, K., Smith, P., Butler, J., Sandknop, E., and Charter, S. 2001. The CalCOFI ichthyoplankton time series: potential contributions to the management of rocky-shore fishes. CALIFORNIA COOPERATIVE OCEANIC FISHERIES INVESTIGATIONS REPORT: 112-128.

Moss, R. H., Edmonds, J. A., Hibbard, K. A., Manning, M. R., Rose, S. K., van Vuuren, D. P., Carter, T. R., Emori, S., Kainuma, M., Kram, T., Meehl, G. A., Mitchell, J. F. B., Nakicenovic, N., Riahi, K., Smith, S. J., Stouffer, R. J., Thomson, A. M., Weyant, J. P., and Wilbanks, T. J. 2010. The next generation of scenarios for climate change research and assessment. Nature, 463: 747-756.

Myers, R. A., and Worm, B. 2003. Rapid worldwide depletion of predatory fish communities. Nature, 423: 280-283.

Nakicenovic, N., Lempert, R. J., and Janetos, A. C. 2014. A framework for the development of new socio-economic scenarios for climate change research: introductory essay. Climatic Change, 122: 351-361.

O'Connor, M. I., Holding, J. M., Kappel, C. V., Duarte, C. M., Brander, K., Brown, C. J., Bruno, J. F., Buckley, L., Burrows, M. T., Halpern, B. S., Kiessling, W., Moore, P., Pandolfi, J. M., Parmesan, C., Poloczanska, E. S., Schoeman, D. S., Sydeman, W. J., and Richardson, A. J. 2015. Strengthening confidence in climate change impact science. Global Ecology and Biogeography, 24: 64-76.

Ohman, M. D., and Smith, P. 1995. A comparison of zooplankton sampling methods in the CalCOFI time series. CALIFORNIA COOPERATIVE OCEANIC FISHERIES INVESTIGATIONS REPORT: 153-158.

Österblom, H., Merrie, A., Metian, M., Boonstra, W. J., Blenckner, T., Watson, J. R., Rykaczewski, R. R., Ota, Y., Sarmiento, J. L., and Christensen, V. 2013. Modeling Social—Ecological Scenarios in Marine Systems. Bioscience, 63: 735-744.

Overland, J. E., Wang, M., Bond, N. A., Walsh, J. E., Kattsov, V. M., and Chapman, W. L. 2011. Considerations in the Selection of Global Climate Models for Regional Climate Projections: The Arctic as a Case Study*. Journal of Climate, 24: 1583-1597.

Pascoe, S., Herrero, I., and Mardle, S. 2001. Identifying mis-reporting in fisheries output data using DEA. *In* VII European productivity and efficiency workshop, Oviedo, Spain, pp. 25-27.

Pauly, D., Alder, J., Booth, S., Cheung, W. W. L., Christensen, V., Close, C., Sumaila, U. R., Swartz, W., Tavakolie, A., Watson, R., and Zeller, D. 2008. Fisheries in Large Marine Ecosystems: Descriptions and Diagnoses. *In* The UNEP Large Marine Ecosystem Report: a Perspective on Changing Conditions in LMEs of the World's Regional Seas., pp. 23-40. Ed. by S. K. a. H. G. UNEP Regional Seas Reports and Studies No. 182, Nairobi.

Pearce, J. L., and Boyce, M. S. 2006. Modelling distribution and abundance with presence-only data. Journal of Applied Ecology, 43: 405-412.

Peters, D. P., and Herrick, J. E. 2004. Strategies for ecological extrapolation. Oikos, 106: 627-636.

Pinsky, M. L., and Fogarty, M. 2012. Lagged social-ecological responses to climate and range shifts in fisheries. Climatic Change, 115: 883-891.

Pinsky, M. L., Worm, B., Fogarty, M. J., Sarmiento, J. L., and Levin, S. A. 2013. Marine Taxa Track Local Climate Velocities. Science, 341: 1239-1242.

Plagányi, É. E., Bell, J. D., Bustamante, R. H., Dambacher, J. M., Dennis, D. M., Dichmont, C. M., Dutra, L. X., Fulton, E. A., Hobday, A. J., and van Putten, E. I. 2011. Modelling climate-change effects on Australian and Pacific aquatic ecosystems: a review of analytical tools and management implications. Marine and Freshwater Research, 62: 1132-1147.

Planque, B. 2015. Projecting the future state of marine ecosystems,"la grande illusion"? ICES Journal of Marine Science: Journal du Conseil: fsv155.

Polasky, S., Carpenter, S. R., Folke, C., and Keeler, B. 2011. Decision-making under great uncertainty: environmental management in an era of global change. Trends in ecology & evolution, 26: 398-404.

Poloczanska, E. S., Brown, C. J., Sydeman, W. J., Kiessling, W., Schoeman, D. S., Moore, P. J., Brander, K., Bruno, J. F., Buckley, L. B., Burrows, M. T., Duarte, C. M., Halpern, B. S., Holding, J., Kappel, C. V., O'Connor, M. I., Pandolfi, J. M., Parmesan, C., Schwing, F., Thompson, S. A., and Richardson, A. J. 2013. Global imprint of climate change on marine life. Nature Climate Change, 3: 919-925.

Pörtner, H. O., Karl, D., Boyd, P. W., Cheung, W. W. L., Lluch-Cota, S. E., Nojiri, Y., Schmidt, D., and Zavialov, P. 2014. IPCC Fifth Assessment Report Working Group II: Ocean Systems. 138 pp.

Regan, H. M., Colyvan, M., and Burgman, M. A. 2002. A taxonomy and treatment of uncertainty for ecology and conservation biology. Ecological Applications, 12: 618-628.

Robertson, T., Döring, M., Guralnick, R., Bloom, D., Wieczorek, J., Braak, K., Otegui, J., Russell, L., and Desmet, P. 2014. The GBIF integrated publishing toolkit: facilitating the efficient publishing of biodiversity data on the internet. PLoS ONE, 9: e102623.

Rodgers, K. B., Lin, J., and Frölicher, T. L. 2015. Emergence of multiple ocean ecosystem drivers in a large ensemble suite with an earth system model. Biogeosciences, 11: 18189-18227.

Rosenzweig, C., Elliott, J., Deryng, D., Ruane, A. C., Müller, C., Arneth, A., Boote, K. J., Folberth, C., Glotter, M., Khabarov, N., Neumann, K., Piontek, F., Pugh, T. A. M., Schmid, E., Stehfest, E., Yang, H., and Jones, J. W. 2013. Assessing agricultural risks of climate change in the 21st century in a global gridded crop model intercomparison. Proceedings of the National Academy of Sciences, 111(9): 3268-3273.

Saltelli, A., Chan, K., and Scott, E. 2000. Sensitivity analysis Wiley series in probability and statistics. Willey, New York.

Smith, T. M., Reynolds, R. W., Peterson, T. C., and Lawrimore, J. 2008. Improvements to NOAA's historical merged land-ocean surface temperature analysis (1880-2006). Journal of Climate, 21: 2283-2296.

Stock, C., Dunne, J., and John, J. 2014a. Drivers of trophic amplification of ocean productivity trends in a changing climate. Biogeosciences, 11: 7125-7135.

Stock, C. A., Alexander, M. A., Bond, N. A., Brander, K. M., Cheung, W. W. L., Curchitser, E. N., Delworth, T. L., Dunne, J. P., Griffies, S. M., Haltuch, M. A., Hare, J. A., Hollowed, A. B., Lehodey, P., Levin, S. A., Link, J. S., Rose, K. A., Rykaczewski, R. R., Sarmiento, J. L., Stouffer, R. J., Schwing, F. B., Vecchi, G. A., and Werner, F. E. 2011. On the use of IPCC-class models to assess the impact of climate on Living Marine Resources. Progress In Oceanography, 88: 1-27.

Stock, C. A., Dunne, J. P., and John, J. G. 2014b. Global-scale carbon and energy flows through the marine planktonic food web: An analysis with a coupled physical–biological model. Progress In Oceanography, 120: 1-28.

Stocker, T., Qin, D., Plattner, G.-K., Tignor, M., Allen, S. K., Boschung, J., Nauels, A., Xia, Y., Bex, V., and Midgley, P. M. 2014. Climate change 2013: The physical science basis, Cambridge University Press Cambridge, UK, and New York.

Taylor, K. E., Stouffer, R. J., and Meehl, G. A. 2011. An Overview of CMIP5 and the Experiment Design. Bulletin of the American Meteorological Society, 93: 485-498.

Tebaldi, C., and Knutti, R. 2007. The use of the multi-model ensemble in probabilistic climate projections. Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences, 365: 2053-2075.

van Putten, I. E., Kulmala, S., Thébaud, O., Dowling, N., Hamon, K. G., Hutton, T., and Pascoe, S. 2012. Theories and behavioural drivers underlying fleet dynamics models. Fish and Fisheries, 13: 216-235.

Viles, H., and Goudie, A. 2003. Interannual, decadal and multidecadal scale climatic variability and geomorphology. Earth-Science Reviews, 61: 105-131.

Walters, C. 2003. Folly and fantasy in the analysis of spatial catch rate data. Canadian Journal of Fisheries and Aquatic Sciences, 60: 1433-1436.

Warszawski, L., Frieler, K., Huber, V., Piontek, F., Serdeczny, O., and Schewe, J. 2014. The Inter-Sectoral Impact Model Intercomparison Project (ISI–MIP): Project framework. Proceedings of the National Academy of Sciences, 111: 3228-3232.

Watson, J. R., Stock, C. A., and Sarmiento, J. L. 2014. Exploring the role of movement in determining the global distribution of marine biomass using a coupled hydrodynamic–size-based ecosystem model. Progress In Oceanography, doi:10.1016/j.pocean.2014.09.001.

Watson, R., and Pauly, D. 2001. Systematic distortions in world fisheries catch trends. Nature, 414: 534-536.

Webb, T. J., Berghe, E. V., and O'Dor, R. 2010. Biodiversity's big wet secret: the global distribution of marine biological records reveals chronic under-exploration of the deep pelagic ocean. PLoS ONE, 5: e10223.

Weitzman, M. L. 2011. Fat-tailed uncertainty in the economics of catastrophic climate change. Review of Environmental Economics and Policy, 5: 275-292.

Wilby, R. L., and Dessai, S. 2010. Robust adaptation to climate change. Weather, 65: 180-185.

Wittenberg, A. T., Rosati, A., Delworth, T. L., Vecchi, G. A., and Zeng, F. 2014. ENSO modulation: Is it decadally predictable? Journal of Climate, 27: 2667-2681.

Worm, B., Hilborn, R., Baum, J. K., Branch, T. A., Collie, J. S., Costello, C., Fogarty, M. J., Fulton, E. A., Hutchings, J. A., Jennings, S., Jensen, O. P., Lotze, H. K., Mace, P. M., McClanahan, T. R., Minto, C., Palumbi, S. R., Parma, A. M., Ricard, D., Rosenberg, A. A., Watson, R., and Zeller, D. 2009. Rebuilding Global Fisheries. Science, 325: 578-585.

Zeller, D., Booth, S., Craig, P., and Pauly, D. 2006. Reconstruction of coral reef fisheries catches in American Samoa, 1950 – 2002. Coral Reefs, 25: 144-152.