

Review

On the use of IPCC-class models to assess the impact of climate on Living Marine Resources

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ABSTRACT

The study of climate impacts on Living Marine Resources (LMRs) has increased rapidly in recent years with the availability of climate model simulations contributed to the assessment reports of the Intergovernmental Panel on Climate Change (IPCC). Collaboration between climate and LMR scientists and shared understanding of critical challenges for such applications are essential for developing robust projections of climate impacts on LMRs. This paper assesses present approaches for generating projections of climate impacts on LMRs using IPCC-class climate models, recommends practices that should be followed for these applications, and identifies priority developments that could improve current projections. Understanding of the climate system and its representation within climate models has progressed to a point where many climate model outputs can now be used effectively to make LMR projections. However, uncertainty in climate model projections (particularly biases and inter-model spread at regional to local scales), coarse climate model resolution, and the uncertainty and potential complexity of the mechanisms underlying the response of LMRs to climate limit the robustness and precision of LMR projections. A variety of techniques including the analysis of multi-model ensembles, bias corrections, and statistical and dynamical downscaling can ameliorate some limitations, though the assumptions underlying these approaches and the sensitivity of results to their application must be assessed for each application. Developments in LMR science that could improve current projections of climate impacts on LMRs include improved understanding of the multi-scale mechanisms that link climate and LMRs and better representations of these mechanisms within more holistic LMR models. These developments require a strong baseline of field and laboratory observations including long time series and measurements over the broad range of spatial and temporal scales over which LMRs and climate interact. Priority developments for

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IPCC-class climate models include improved model accuracy (particularly at regional and local scales), inter-annual to decadal-scale predictions, and the continued development of earth system models capable of simulating the evolution of both the physical climate system and biosphere. Efforts to address these issues should occur in parallel and be informed by the continued application of existing climate and LMR models.

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1. Introduction

Primary production by microscopic phytoplankton within the ocean ecosystem rivals total terrestrial production (Field et al., 1998) and supports a diverse array of organisms within the oceanic food web. These “Living Marine Resources” (LMRs) encompass a broad range of fish, invertebrates, mammals, plants and reptiles that have diverse interacting life histories, habitat needs, and ecologies. Many LMRs are commercially harvested, providing valuable food resources to human populations and a diversity of other economically significant products. Other LMRs greatly enhance local economies through recreation and tourism. All LMRs play a role in establishing and maintaining the structure and function of marine ecosystems, though some LMRs are now threatened by intense harvesting, pollution, and habitat loss (Baillie et al., 2004; NOAA, 2006).

In the past, LMR management has often been based on the assumptions that exploitation is the dominant factor shaping marine populations and that the ecosystem (including physical, chemical, and other biological constituents) is in long-term equilibrium. These assumptions resulted in management strategies that emphasized population management through adjustments in harvest rates. A multitude of studies, in contrast, have identified strong responses of LMRs to climate variability (e.g., Lehodey et al., 2006 and references therein) and evidence for responses to anthropogenic climate change is accumulating (Brander, 2010).¹ Excluding

environmental factors linked to climate in LMR management has led to the misspecification of harvest controls, contributing to the diminished state of many exploited LMRs (Keyl and Wolff, 2008). For LMR management strategies to be effective in a variable and changing climate, they must more directly consider how climate is impacting LMR dynamics.

Reliably predicting the impacts of future climate on LMRs requires both an understanding of the mechanisms through which climate acts and skillful predictions of climate change and variability. Climate model simulations contributed to the assessment reports of the Intergovernmental Panel on Climate Change (IPCC) are a primary means of analyzing climate dynamics and making projections of future climate change. Numerous examples of applications of IPCC-class climate models for assessing the impact of climate change and variability on LMR dynamics have appeared in recent literature (see Section 4), suggesting that IPCC-class climate models have utility for LMR prediction. However, these studies have also revealed critical challenges that often stem from the need to reconcile information from climate models designed to capture large-scale characteristics of the global climate system with the dynamics of individual or multiple LMRs, often at regional spatial scales and time scales of a few decades or less.

This paper is the product of the workshop “Applying IPCC-class Models of Global Warming to Fisheries Prediction” that was held June 15–17, 2009 at Princeton University.² The development of effective and innovative applications of IPCC-class climate models

¹ Detailed definitions of all climate-related terms can be found in the glossary of the IPCC 4th Assessment Report (Baede, 2007) which can be found at <http://www.ipcc.ch/>.

² More information on the workshop, including a list of attendees and presentations, can be found at <http://www.gfdl.gov/fisheries-and-climate-workshop>.

to LMR science and management requires greater shared understanding of the challenges faced by climate and LMR scientists. This paper pursues this broad aim by assessing present approaches for generating projections of climate impacts on LMRs using IPCC-class climate models, recommending practices that should be followed in such applications, and identifying priority developments that could improve current projections. The salient aspects of LMR dynamics and models (Section 2) and climate system dynamics and models (Section 3) are presented first with an emphasis on those aspects that shape applications of climate models to assessing the impact of climate change and variability on LMR dynamics. Specific case studies are then described to further elucidate the strengths and limitations of present approaches (Section 4). The case studies are followed by a discussion of recommended practices (Section 5) and priority developments (Section 6) before concluding remarks are given (Section 7).

2. Dynamics and prediction of Living Marine Resources

While many correlations between LMRs and climate variables have been documented, they often fail over time (Myers, 1998). This limits the utility of such relationships for assessing the impacts of climate change and variability on LMR dynamics. Increased mechanistic understanding of the climate/LMR processes that underlie such correlations is needed for more reliable predictions. The complexity of LMR dynamics and observational limitations pose formidable challenges to achieving this goal. This section provides a synthesis of LMR responses to environmental change and a discussion of the utility of LMR observations and models for assessing the impacts of climate on LMR dynamics.

2.1. The response of Living Marine Resources to environmental change

Environmental conditions affect LMRs in a wide variety of ways. Vital rates such as growth, reproduction, consumption, and respiration are mediated by temperature and other climate-influenced factors such as salinity, oxygen, and alkalinity (Koster et al., 2003; Brander, 2010; Drinkwater et al., 2010a). Biogeographical distributions and migration patterns shift in response to climate-related changes in habitat suitability (Jensen, 1939; Frank et al., 1990; Murawski and Mountain, 1990; Cheung et al., 2009; Nye et al., 2009). Shifts in the timing of seasonal changes can alter life-history dynamics (Edwards and Richardson, 2004; Henson et al., 2009a; Koeller et al., 2009). Climate impacts on LMRs extend to all organisms within the marine food web and can generate notable indirect effects on LMRs through trophic or shared-resource interactions (Stenseth et al., 2002; Richardson and Schoeman, 2004). Lastly, the food web for many LMRs often includes significant commercial, recreational and subsistence harvesting by humans. A growing number of studies suggest that ecosystems become more sensitive to climate impacts when they are heavily exploited (Brander, 1995; Hsieh et al., 2006), and strong connections between LMR dynamics and humans create linkages between LMRs and a broad set of social and economic factors (e.g., Mullan et al., 2009).

The responses of LMRs to the array of interactions described above often are neither gradual nor linear. Many organisms have threshold responses and can be highly sensitive to the short periods of environmental extremes that are far from average conditions (Glynn, 1984). Abrupt shifts in the structure and function of ecosystems among otherwise persistent states, often referred to

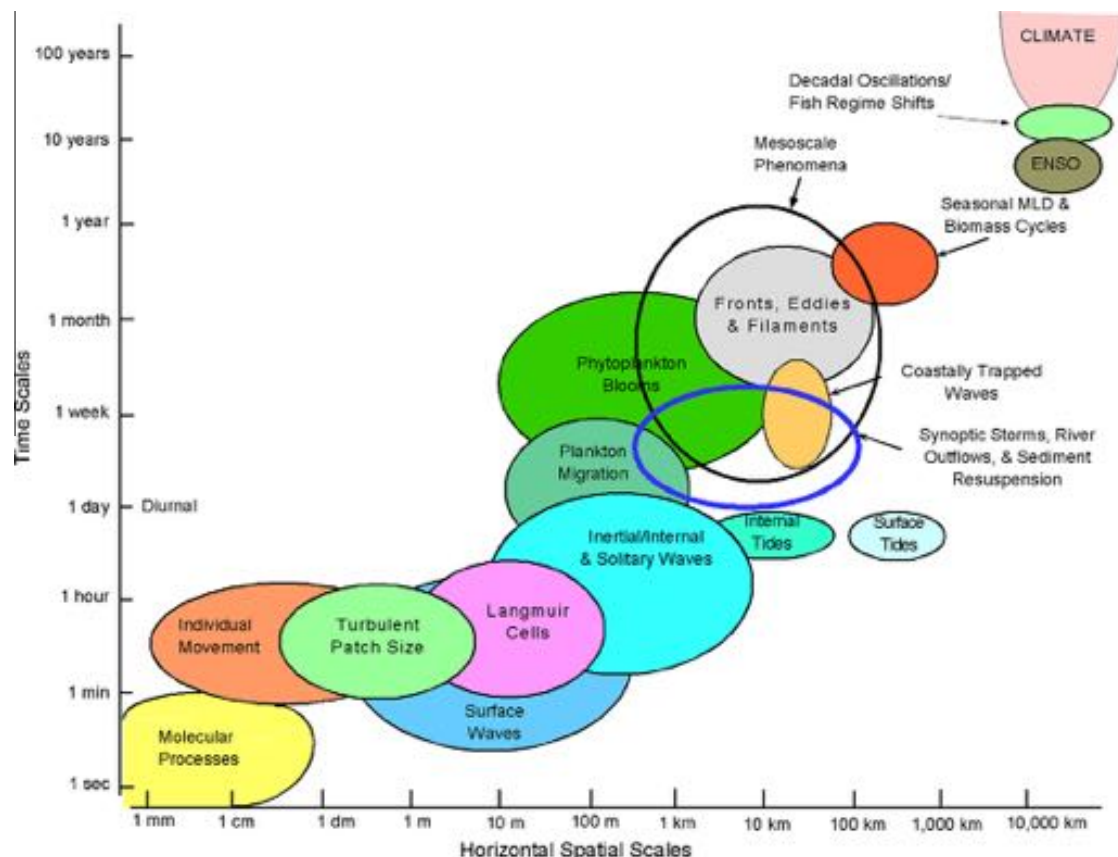


Fig. 1. Time-horizontal spatial scale diagram illustrating the range of scales over which environmental variability and biological processes occur and interact. Source: Dickey (2003)

as regime shifts, have been noted across major ocean basins (Steele, 1998; Hare and Mantua, 2000; deYoung et al., 2008; Overland et al., 2008). Such shifts can have profound impacts on LMRs, the roles they play within ecosystems, and the economies that they support.

Connections between environmental variations and marine populations occur across a large range of interacting spatial, temporal and organizational scales (Haury and McGowan, 1978, Fig. 1; Dickey, 2003). Identifying fundamental scales on which patterns emerge, how these patterns change across scales, and the linkages between processes that unfold on different scales represent key challenges for assessing the impact of climate on LMR dynamics (Levin, 1992). Metagenomic studies have inspired efforts to link suborganismal scales with an understanding of the distribution of organisms. At the next scale, the ability of organisms to encounter their prey (Rothschild and Osborn, 1988; Kiorboe, 2008), successfully fertilize eggs (Levitan and Sewell, 1998) and send and receive chemical signals (Zimmer and Butman, 2000) are affected by hydrodynamic processes that occur at the scale of individual organisms. At intermediate scales, tens to hundreds of kilometers from days to seasons, productivity and community species composition can be influenced by submesoscale and mesoscale ocean features such as fronts, eddies, and the strength of upwelling structures (Bakun, 1996, 2001; Ji et al., 2008; Boersma et al., 2009; e.g., Richardson et al., 2009). At longer time scales and broader spatial scales, inter-annual to decadal fluctuations in the climate system occurring across thousands of kilometers such as El Niño, the North Atlantic Oscillation, and the Pacific Decadal Oscillation may affect broad regional and ocean basin-scale variations of LMR populations (e.g., Mantua et al., 1997; Schwartzlose et al., 1999; Hollowed et al., 2001; Alheit et al., 2005). At the largest scales, variations resulting from global-scale climate changes occurring over centuries come into play. Linkages between evolutionary change and ecological processes provide a unifying framework for understanding processes occurring across all these scales.

Many LMRs have complex life histories that include morphologically distinct stages of often vastly different sizes that occupy different habitats. Survival during early life stages (eggs, larvae, and juveniles) may be sensitive to environmental fluctuations with time scales of days to weeks and spatial scales of meters to kilometers (Rothschild, 1986; Fuimann and Werner, 2002). The survival of adult stages, in contrast, may be more sensitive to environmental signals that are coherent across ocean basins and multiple years. The multi-year nature of LMR life cycles can provide a buffer between environmental variations and population responses and impose a lag between the initial influence of environmental perturbations and its most observable impacts (Ottersen et al., 2006), further complicating efforts to define mechanistic linkages.

While LMR dynamics reflect the integration of environmental information across a broad range of spatial and temporal scales, many studies suggests that some scales are more important. A disproportionately large amount of harvested LMRs are caught in coastal regions (Pauly and Christensen, 1995; FAO, 2007). Nearly half of marine fish landings in 2004 were caught within 185 km (100 nautical miles) of shore in waters less than 200 m in depth which accounted for <7.5% of the ocean area (Nellemann et al., 2008). Changes in many of these LMRs have been linked to global and basin-scale climate variations, but improved mechanistic understanding of this linkage requires resolving the manifestation of global and ocean basin-scale dynamics on shelf-scale processes. Survival during early life stages is often a major source of variability for LMRs (Rothschild, 1986), and many eggs, larvae and juveniles rely upon near-coastal regions (e.g., inlets, estuaries and rivers) and can be particularly sensitive to the timing of seasonal changes (e.g., Hjort, 1914; Cushing, 1990). Lastly, while understanding the century-scale implications of climate change for LMRs

is of great scientific and economic interest, reliable projections on inter-annual to decadal time scales are essential for ensuring the sustainable harvest of LMRs and for enabling dependent industries and communities to adapt to changes in LMR productivity and distribution.

2.2. Living marine resource observations

The detection and diagnosis of climate impacts on LMRs requires observations over the relevant range of spatial and temporal scales. Consistent observations over several decades are often required to differentiate the effects of climate variability from those of climate change (e.g., Henson et al., 2009b, Section 3.1.2). Observations over a wide spectrum of spatial and temporal scales may be required to understand the mechanisms underlying LMR changes (i.e., Section 2.1, Fig. 1). Meeting these observational challenges requires committed maintenance of existing time series, continued development of LMR observing technologies capable of resolving LMR/climate interaction over a broader range of scales, and the preservation and use of unique historical, archeological and paleoecological measurements that may extend LMR/climate records over multiple centuries.

LMR observations for harvested species can be divided into two broad types. Fishery-dependent data collected during commercial and recreational harvests, and fishery-independent data generally collected during scientific research surveys. Note that while these classifications refer specifically to harvested fisheries, most of the dataset properties discussed below can be generalized to other harvested and non-harvested LMRs (e.g., invertebrates, marine mammals).

The duration of fishery-dependent data varies widely by fishery. Traps for bluefin tuna in the Mediterranean Sea, for example, provide fishery catch records stretching back several centuries (Ravier and Fromentin, 2001). Long-standing industrialized commercial fisheries routinely have several decades of commercial catch records. Less established commercial and subsistence fisheries, in contrast, can have far more limited information. Fishery-dependent data generally includes stock-specific catch numbers and biomass and, in many cases, biological and oceanographic information gathered by observers aboard fishing vessels and portside sampling (e.g., Keller et al., 2008). Catch biomass may include both commercially harvested and incidentally captured stocks. Additional information on limited samples of landed animals may include sex ratios, size frequencies, diet, maturity and fecundity. Many countries have also initiated underway vessel monitoring systems and acoustic echo-integration methods to provide continuous information on the spatial distribution of LMRs. While fishery-dependent data provides invaluable information to LMR science and management efforts, the spatial sampling pattern, frequency, and fishing techniques used may change several times within a fishery-dependent time series. Changes can occur due to new technology, government management actions to restrict or increase catches, and market shifts. Thus, careful study of fishery-dependent observations is necessary to prevent false interpretation of technological, management, or market driven changes as true changes in the productivity, distribution and abundance of LMRs.

Scientific fishery-independent survey programs have been established across much of the globe to address the interpretive limitations of fishery-dependent data and to support fishery management. Most fishery-independent surveys have carefully designed spatial and temporal sampling strategies and use relatively uniform sampling methodologies to provide a consistent census of LMRs within a region. In some cases, surveys include measures of diverse aspects of the exploited stock including relative abundance, weight, distribution, length, age, maturity, and diet. Hydrographic and planktonic (e.g., chlorophyll, primary

production, zooplankton biomass) sampling is also becoming more common based on the early recognition that oceanographic variability can drive variations in fisheries (e.g., Hjort, 1914). In the North Atlantic and North Pacific, many fishery-independent surveys have been operating for multiple decades, and some have been conducted for 50 years or more.

Fishery-independent surveys generally address the interpretive limitations imposed by sampling changes over time that effect many fishery-dependent datasets. The spatial and temporal resolution of fishery-independent surveys, however, remains coarse relative to the space and time scales of many physical and biological processes thought to influence LMRs (Fig. 1). Station spacing for fishery-independent surveys is often tens to hundreds of kilometers and surveys are often annual or restricted to a few times a year at best. This makes effectively sampling multiple species over diverse habitats a challenge.

The coarse resolution of most fishery-independent LMR surveys contrasts with fine-resolution physical measurements provided by advances in satellites, high-frequency radar systems, drifters, moorings, flow-through systems, towed bodies, autonomous underwater vehicles, and ocean observing systems. Closing this sampling gap is important for understanding and constraining the mechanisms that link climate fluctuations and LMR responses. Intensive process-oriented surveys and new LMR observing technologies offer two means of achieving this. Process-oriented surveys supplement census surveys by undertaking more extensive sampling activities for a shorter period of time (often 3–5 years) aimed at resolving key uncertainties in LMR dynamics. New LMR observing technologies can refine the spatial and temporal resolution of observations and have been incorporated into both process-oriented and census surveys. These new technologies include acoustic biomass estimates for LMRs that do not inhabit waters near the benthos. Such estimates have been included in assessment models for a number of LMRs (e.g., Traynor et al., 1990; Overholtz et al., 2006; Hamel and Stewart, 2009) and improved techniques are being developed (Makris et al., 2009). Aerial surveys are enlisted for LMRs that can be detected from the surface (Kenney et al., 1995; Churnside et al., 2003). Towed high-resolution underwater cameras provide additional information on the abundance and movements of both targeted and non-targeted fishery species (Cowen and Guigand, 2008; Rosenkranz et al., 2008). Electronic tags with multiple sensors (temperature, pressure, light) have provided invaluable information on LMR behavior and habitat, particularly for highly migratory fish, mammals, and reptiles (Metcalf and Arnold, 1997; Block et al., 2005).

The information on long time scales of change in populations of fish and other marine taxa from historic, archaeological, or paleoecological studies is increasing rapidly (Emeis et al., 2010; Finney et al., 2010; Poulsen, 2010) and provides a particularly useful perspective on how current understanding of climate–ecosystem dynamics may be limited by our overwhelming reliance on short observational records. The longer records show that bottom-up effects are important and that the strength and even the sign of certain climate–ecosystem relationships may change over time (Finney et al., 2010). For example, the relationship between Pacific sockeye salmon and regional sea surface temperature (SST) has been positive over the past century, but was apparently negative in the mid to late 1800s. This variability does not mean that salmon populations are unaffected by the processes that impact SST, but it does mean that the relationship is more complex than might be assumed from recent records. The complexity of relationships between climate state and fish abundance suggests a variety of modes of climate variability and ecosystem dynamics. Long-term records of marine population fluctuations provide strong evidence that climate affects their production and composition and helps to identify the time and space scales at which these relationships

manifest themselves (Emeis et al., 2010). Comparing the statistics of such long records with historical and control climate model simulations may offer interesting new insight into the factors and modes of climate variability driving observed fluctuations.

2.3. Living marine resource models

A broad range of models are used for LMR assessment and forecasts that could be adapted for climate change applications. The models have different objectives, forms, and governing equations and can be arranged according to their degree of complexity (e.g., Hollowed et al., 2000; Whipple et al., 2000; Plaganyi et al., 2007; Howard et al., 2008). Each model type, ranging from simple to complex, has different trade-offs. Simple models tend to make strong assumptions, relying heavily upon empirical relationships between measured variables and emergent LMR responses that are presumed stationary. Simple models may not accommodate environmental or spatial heterogeneity, may consider the population dynamics of one LMR, or may coarsely aggregate organisms into very broad functional groups. It is generally more feasible to constrain the limited number of parameters in simple models with existing observations (Section 2.2). Simple models often yield more precise solutions and it is generally more feasible to analyze model sensitivity and define the range of forecast uncertainty. This precision, however, arises in part from the rigidity of simple model structures, and model errors or omissions will not be reflected in the range of model outcomes.

Complex models attempt to more comprehensively capture many aspects of LMR dynamics and their associated uncertainty (i.e., Section 2.1). Complex models strive to recreate emergent LMR patterns by combining more direct underlying relationships between organisms, their resources, their predators, and their physical environment. While reliance on more fundamental ecological relationships should make model predictions in a changing climate more robust, model misspecification can occur, and explicit resolution of many additional processes introduces a large number of new parameters that are difficult to constrain with existing observations. This makes the analysis of model sensitivity and uncertainty more difficult and computationally intensive and often results in a broader range of possible outcomes. Alternatively, more flexible and realistic model structures in complex models reduce the potential for model errors arising from oversimplification of the model dynamics.

The rest of this section provides an overview of the models used for LMR assessment and forecasting and, along with the case studies presented in Section 4, discusses their utility (and the implications of the simplicity/complexity trade-offs discussed above) for forecasting LMR responses to climate change. Traditional single-species stock assessment models are discussed first. Single-species stock assessment models focus on the dynamics of a target LMR and form the backbone of many LMR management efforts. Next, a range of other modeling approaches are presented under the broad heading “ecosystem approaches”. This heading reflects a general shift in the model’s emphasis from a single stock of interest to interactions between organisms and between organisms and their environment. It is notable, however, that there is no clear delineation between ecosystem approaches and single-species stock assessment models. Many single-species stock assessment models do incorporate and emphasize environmental and climate interactions (Keyl and Wolff, 2008). The delineation is thus simply a pragmatic means of reviewing fundamental principles and assumptions of widely-used stock assessment models before reviewing the scope of potential climate/LMR modeling approaches.

2.3.1. Traditional single-species stock assessment models

Management of exploited or endangered LMRs can have numerous objectives, but an overarching goal is to maintain healthy

resource populations while allowing economic and societal utilization.³ Human utilization can include the directed take of target species (e.g., fisheries), the by-catch of non-target species associated with target species, or accidental take of endangered species (e.g., ship strike of whales or by-catch of sea turtles in fishing gear). LMR management decisions are usually based on an assessment of the population's past fluctuations and present state (a hindcast), and a forecast of future status. Many single-species assessment models estimate the present state and past fluctuations of three key metrics for a LMR within a management area: how much LMR biomass is present, how much LMR biomass is being removed, and how much LMR biomass is being replenished. Reductions in biomass can occur due to fishing mortality (F), natural mortality (M), and emigration (E). Replenishment can occur due to growth of the existing exploitable stock (G), immigration (I) or the addition of young LMRs to the exploited stock (recruitment, R).

At the core of nearly all single-species stock assessment models is a more complex version of the following basic population dynamics equation that describes changes in biomass (B) due to the processes described above:

$$B_{t+1} = B_t + (R_t + G_t + I_t) - (F_t + M_t + E_t) \quad (1)$$

The time (t) can be measured at a variety of scales, typically in years or seasons. Typical data sources are historical catch records, survey biomass indices, and age and size compositions (Section 2.2). Model parameters are statistically fit to observations.

Single-species stock assessment models are generally used to estimate biological reference points that are used to make management decisions. In fisheries, most biological reference points are based on the concept of maximum sustainable yield (MSY), the largest catch that can be removed from a population over a long period of time (i.e., without depleting the stock). Theoretically, a population is maintained at MSY by balancing removals with population increases due to new individuals entering the population. While maintaining the population at the biomass that provides the MSY harvest would be optimal, it is generally recognized that the MSY estimated by traditional assessment models cannot be maintained perfectly due to LMR variability that is not captured by the models. Precautionary biological reference points are thus recommended (Mace, 2001). In the United States, biological reference points are set such that the target biomass or fishing mortality is less than or equal to the limit biomass or fishing mortality. If the estimated biomass is below the limit, the stock is declared overfished. If the estimated fishing mortality is over its limit reference point, overfishing is occurring. Actions are taken based on these determinations to end overfishing and to allow the overfished stocks to recover. These management actions are informed by model forecasts based upon the model developed from the hindcast. Forecasts are generally made for annual to decadal time scales under a variety of fishing or effort limitation scenarios in order to determine the total allowable catch or effort likely to ensure that biological reference points are satisfied within a specified time.

Many stock assessments rely upon limited observations and relatively simple, highly empirical relationships to constrain the potentially complex processes in Eq. (1). Recruitment (R) is an example of a particularly critical process in most stock assessment models (Myers, 1998; Haltuch and Punt, submitted for publication) that is commonly assumed to be a function of stock biomass (B).

Several mathematical forms are used for this “stock–recruitment relationship” (Hilborn and Walters, 1992; Quinn and Deriso, 1999), one of which is that of Ricker (1954):

$$R_{t+1} = \alpha B_t e^{-\beta B_t + \varepsilon_t} \quad (2)$$

This form assumes an initial increase in R with B proportional to αB_t , followed by a decrease in R as B approaches a habitat's carrying capacity ($\sim e^{-\beta B_t}$). ε_t is a stochastic error around the stock–recruitment relationship which includes the contributions of any other factors that may influence recruitment and can be substantial (Rothschild, 1986). Direct observation of R is rarely possible, so estimates of the stock–recruitment relationship parameters are generally derived by fitting the population dynamics model (Eq. (1)) to the best-fit estimates of recruitment and biomass. Thus, the potentially complex process of recruitment is posed as an empirical relationship with spawning biomass with variance due to other factors.

There are numerous approaches for incorporating climate forcing in single-species stock assessment models. The most common examples include cases where climate variables are used to improve a model's fit by modifying the processes included in Eq. (1) (NMFS, 2001; Keyl and Wolff, 2008). For example, many authors, including case study 4.4 herein, have incorporated environmental variability into recruitment by modifying the Ricker (1954) equation to include an environmental factor (E):

$$R_{t+1} = \alpha B_t e^{-\beta B_t + cE + \varepsilon} \quad (3)$$

E could be any of a number of environmental factors (e.g., SST, salinity, alkalinity) and c is the parameter determining the impact of the environmental data. While environmental information can be readily incorporated into stock assessments in this fashion, it is often difficult for relationships such as Eq. (3) to elucidate the mechanisms driving the relationships between environmental variation and the LMR response. Models that do incorporate environmental data are in some case referred to as Extended Stock Assessment Models (ESAMs).

Long-term projections of traditional stock assessment models with environmental data based on IPCC climate change predictions pose some challenges. Using the stock–recruitment relationship, for example, may be problematic due to the uncertainty in the robustness of emergent relationships between LMR dynamics and environmental factors in a changing climate (e.g., Finney et al., 2010). Furthermore, in most cases the available fisheries data (Section 2.2) are not sufficient to resolve the connections between the population process of interest and environmental factors thought to influence this process, particularly when the effects of environmental change may be confounded by fishing (Haltuch and Punt, submitted for publication). Stocks that show periodic strong recruitment events with little recruitment in between often have only a few strong recruitment events from which to make inferences (Hamel and Stewart, 2009). Issues such as those described above have engendered an active debate regarding the inclusion of environmental correlates in stock assessment models without a more complete mechanistic understanding of the environment–LMR population interactions (Myers, 1998).

2.3.2. Ecosystem approaches

A wide range of alternative approaches for modeling LMR dynamics have been developed and can complement and augment traditional single-species stock assessment models for LMR prediction. Multispecies stock assessment models integrate the dynamics of several interacting resource stocks, but the dynamical relationships between them remain highly empirical. Most of these models attempt to capture the dynamics of several species, simultaneously, usually via a population model (i.e., Eq. (1)), linked via feeding or technical interaction submodels (Hollowed et al.,

³ For more detailed information on stock assessment, an accessible general overview is provided by Cooper (2006) (<http://www.seagrant.unh.edu/stockassessmentguide.pdf>) or Haddon (2001). More detailed treatments are provided by Hilborn and Walters (1992) or Quinn and Deriso (1999). For endangered species, population viability analysis (PVA) is often used. Details of this method can be found in Beissinger and Mccollough (2002).

2000; Whipple et al., 2000; Howard et al., 2008). Most of these models do not explicitly address environmental considerations. The GADGET, BORMICON, and MULTSPEC models (Bogstad et al., 1997; Stefansson and Palsson, 1998; Tjelmeland and Bogstad, 1998; Begley and Howell, 2004) are an exception to this situation. These models can explicitly examine and explore the outcomes among the range of trade-offs resulting from the species interactions and contrast environmental effects with fishing; a useful but rare combination of factors that are considered simultaneously.

Habitat models rely on past habitat observations and physiological information for LMRs to predict changes in stock distribution and range. In the climate change context, habitat models that examine the relationship between climate variables and organism distributions are often referred to as bioclimatic envelope models and have been widely applied to project impacts of climate change on the distribution of plants and animals (e.g., Heikkinen et al., 2006; Cheung et al., 2009). The most basic forms of habitat models assess only habitat suitability and do not take into account food-web interactions, limitation to dispersal ability, or changes in ecosystem productivity. Cheung et al. (2008a) have addressed some of these limitations by integrating bioclimate envelope, population dynamics, and animal dispersal models (see Section 4.1). However, habitat models may still attribute LMR residence in a region to the wrong habitat characteristics. Reliance upon previously observed distributions to define habitats introduces a strong empirical element to habitat models and requires the assumption that the observed distributions are at equilibrium with the environment. Lastly, poorly understood evolutionary adaptations to a changing climate may introduce a source of error to predicted distributions. Incorporating direct physiological constraints for the organism of interest or applying macroecological theory can ameliorate these concerns.

Aggregate biomass models link together groups of LMRs occupying similar positions in the marine food web to capture the basic characteristics of trophic groups, often in the form of mass-balanced energy flows through the marine ecosystem (Polovina, 1984; Heymans and Baird, 2000; Christensen and Pauly, 2004; Dame and Christian, 2006; Plaganyi et al., 2007; Howard et al., 2008). These models can also incorporate fishing and other losses linked to humans. However, the mathematical representation and parameter values used to specify predator–prey interactions are difficult to constrain and can have a large impact on model dynamics (Walters et al., 1997). These difficulties generally lead to less precise solutions though, as was pointed out above, these may more appropriately reflect the range of possible solutions. Greater aggregation of similar species or of age or of size classes within a species can ameliorate difficulties in parameterizing these models, but at the price of losing resolution of inter-species interactions and life cycle dynamics. These models can accommodate some aspects of both spatial dynamics and environmental fluctuations (Pauly et al., 2000; Martell et al., 2005).

Individual-based models (IBMs) simulate LMRs by tracking individuals; the sum of which comprise the population. This approach maximizes the ability to capture the mechanistic underpinnings of emergent observed patterns (Grimm et al., 2005). The IBM approach has been used in forest succession modeling for decades and has seen an explosion of application to fish since the 1990s (Van Winkle et al., 1993; DeAngelis and Mooij, 2005). IBMs are often implemented into highly resolved physical simulations, where behaviors can lead to profound shifts in dispersal and retention (Werner et al., 2001; North et al., 2009). The advantages to the individual-based approach, relative to the more aggregated (biomass, age, stage) approaches, include allowing for more direct simulation of episodic, local, and size-based interactions, direct representation of movement, direct simulation of the effects of

individuals experiencing environmental conditions over time, and including physiological and behavioral plasticity (Huston et al., 1988; Tyler and Rose, 1994). IBMs share the data-intensive parameterization and decreased precision issues that characterize aggregate biomass approaches. They are also computationally intensive, particularly when realistic abundances are desired for food web calculations. However, the use of “super-individuals” (Scheffer et al., 1995; Parry and Evans, 2008) has made such analyses more feasible. Models of lower trophic level organisms (e.g., zooplankton) and early life stages of higher trophic level LMRs (e.g., eggs and larval fish) are available; models that close the life cycle of higher trophic level LMRs so that multiple generational simulations can be performed to assess the long-term effects of climate on LMRs are advancing but remain mostly focused on single-species dynamics (Lett et al., 2009).

Recent efforts to develop models that fully integrate highly resolved physics, planktonic dynamics, LMR dynamics and human dimensions strive to combine various modeling threads described above (Fulton et al., 2004b; Travers et al., 2007; Lehodey et al., 2008; Senina et al., 2008; Rose et al., 2010; Barange et al., in press). Such models are often referred to as “end-to-end” models and can support a myriad of climate-LMR interactions. They are ambitious attempts to comprehensively represent the scope of LMR dynamics described at the outset of this section. Several concerted efforts to develop end-to-end models are underway. Lehodey et al. (2008) use the marine environment simulated from physical and biogeochemical models to force a simplified three layer-ocean ecosystem with a coarse description of mid-trophic levels but detailed spatial population dynamics of high-trophic level species of interest (e.g., bigeye tuna, see case study in Section 4.2). As in traditional stock assessment models, the model includes a rigorous parameter optimization based on fishing data (Senina et al., 2008) that is a critical step for applying the model to tactical management (e.g., setting specific reference points and quotas). Shin and Cury (2001) used an individual-based approach to simulate a many-species food web (called OSMOSE: Objected-oriented Simulator of Marine eCO-Systems Exploitation) on a 2-D spatial grid of cells and coupled the higher trophic level with a planktonic ecosystem model. The model was used to examine the impact of various aspects of fishing on the food web (e.g., Shin and Cury, 2004; Travers et al., 2007). The IGBEM and BM2 models (Fulton et al., 2004a,b), now called Atlantis, separate each fish species or group into age classes and couple the fish to an elaborate three-dimensional water-quality model. The model has been used for site-specific analyses (e.g., Fulton et al., 2004a) and for exploring general aspects of fishing effects on fish communities (e.g., Fulton et al., 2005). An alternative to representing the community at the species level is size-based models (Baird and Suthers, 2007), whereby the state variables represent a progression of size classes rather than association with any particular species. The QUEST-fish model (Barange et al., in press) uses a combination of climate, planktonic, fishery, and socioeconomic models to study the impact of climate change on global fisheries production and national and regional economies.

While end-to-end models show great promise for revealing the responses of ecosystems to climate change, their parameterization can be daunting and uncertainties can lead to a very wide range of outcomes. Adequately exploring the parameter and structural uncertainty in such models to generate the range of outcomes on climate change time scales also poses a computational challenge. These issues, along with the early developmental stage of most models of this type, caused Rose et al. (2010) to caution against using end-to-end models for management decisions until they are more fully evaluated. Fulton et al. (in press) agree that such models are not yet useful for tactical LMR advice, but argues that these models are quite useful for providing long-term strategic advice (e.g., evaluating the trade-offs and interactions between LMR

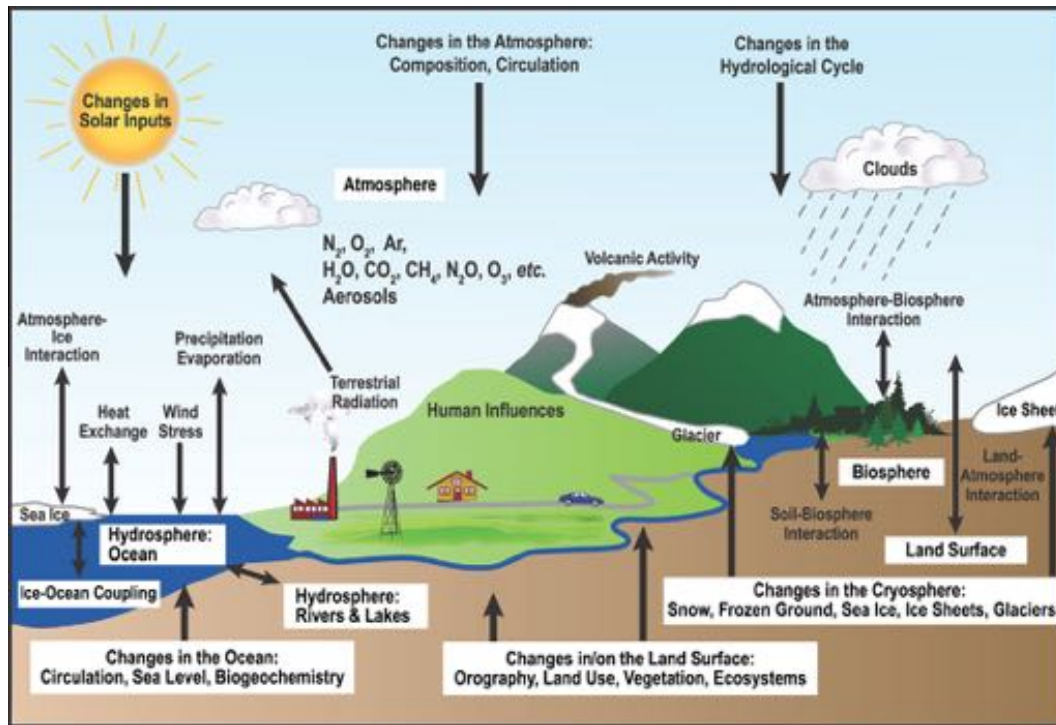


Fig. 2. Schematic view of the components of the climate system, their processes and interactions.. Source: Le Treut et al. (2007), Climate Change 2007: The Physical Science Basis. Working Group I Contribution to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, FAQ 1.2, Fig. 1. Cambridge University Press.

management policies emphasizing marine protected areas, quotas, or vessel buybacks, Fulton et al. (2007)) for LMR management and can accommodate a wide range of climate change effects.

3. IPCC-class climate models

IPCC-class climate models are constructed to understand and predict the dynamics of the earth's climate, which in simplest terms can be thought of as the "average weather". More precisely, climate is a statistical description of relevant quantities (e.g., air and sea surface temperature, precipitation, wind) in terms of mean and variability over a period in time ranging from months to thousands or millions of years (Baede, 2007). To capture these quantities, climate models must represent the components of the climate system that control them (Fig. 2). To predict LMR responses to climate change, this information must then be effectively integrated with tools for LMR prediction (Section 2.3).

This section provides an overview of the architecture of climate models and the century-scale climate change simulations that are central to both the fourth IPCC assessment report (IPCC AR4) and remain critical components of the fifth assessment (IPCC AR5) that is presently underway. Aspects of the models and simulations that strongly affect the manner in which these models can be applied to LMR problems are synthesized. Two relatively new model configurations that may allow for new applications after IPCC AR5 are also described. These are inter-annual to decadal-scale prediction experiments with physical climate models and earth system model simulations.

3.1. Century-scale climate model simulations

The objective of the century-scale climate change simulations conducted for IPCC AR4 and presently underway for IPCC AR5 is to simulate and understand the causes of historical climate

Table 1

IPCC AR4 model resolution. Horizontal resolutions for the ocean are given in degrees of latitude and longitude. Atmospheric resolutions are given by either degrees of latitude and longitude or, for atmospheric models using spherical harmonics, a triangular truncation number (e.g., T 63). This represents the number of spherical harmonics resolved by the model. An approximate formula for the grid resolution for a model with truncation number n is $360/(3n + 1)$. A T 63 atmospheric model thus has a grid resolution of approximately 1.9° . The number following the L gives the number of vertical levels.

Model name	Oceanic resolution	Atmospheric resolution
BCC-CM1	$1.9^\circ \times 1.9^\circ$ L31	T 63 L19
BCCR BCM2.0	$2.4^\circ \times 2.4^\circ$ L24	T 63 L31
CGCM3.1 T 47	$1.85^\circ \times 1.85^\circ$ L29	T 47 L31
CGCM3.1 T 63	$1.4^\circ \times 0.94^\circ$ L29	T 63 L31
CNRM CM3	$2^\circ \times 0.5^\circ$ L31	T 63 L45
CSIRO Mk3.0	$1.875^\circ \times 0.84^\circ$ L31	T 47 L31
GFDL CM2.0	$1^\circ \times 1^\circ$ L50	$2.5^\circ \times 2^\circ$ L24
GFDL CM2.1	$1^\circ \times 1^\circ$ L50	$2.5^\circ \times 2^\circ$ L24
GISS AOM	$4^\circ \times 3^\circ$ L16	$4^\circ \times 3^\circ$ L12
GISS-EH	$2^\circ \times 2^\circ$ L16	$5^\circ \times 4^\circ$ L20
GISS-ER	$5^\circ \times 4^\circ$ L13	$5^\circ \times 4^\circ$ L20
IAP FGOALS	$1^\circ \times 1^\circ$ L33	T 42 L26
INM CM3.0	$2.5^\circ \times 2^\circ$ L33	$5^\circ \times 4^\circ$ L21
IPSL CM4	$2^\circ \times 1^\circ$ L31	$2.5^\circ \times 3.75^\circ$ L19
MIROC HI	$0.28^\circ \times 0.19^\circ$ L47	T 106 L56
MIROC Med	$1.4^\circ \times 0.5^\circ$ L43	T 42 L20
MIUB ECHO-G	$2.8^\circ \times 2.8^\circ$ L20	T 30 L19
MPI ECHAM5	$1.5^\circ \times 1.5^\circ$ L40	T 36 L31
MRI CGCM2.3	$2.5^\circ \times 0.5^\circ$ L23	T 42 L30
NCAR CCSM3	$1.1^\circ \times 1.1^\circ$ L40	T 85 L26
NCAR PCM1	$2/3^\circ \times 1/2^\circ$ L32	T 42 L18
UKMet HadCM3	$1.25^\circ \times 1.25^\circ$ L30	$3.75^\circ \times 2.5^\circ$ L19
UKMet HadGem1	$1^\circ \times 1^\circ$ L40	$1.875^\circ \times 1.25^\circ$ L38

changes (1860 to present day) and to make global projections of climate change over the next century including an assessment of the uncertainty in those projections. Climate model realism has increased steadily over the past decades with increasing computer

power and new understanding of climate system dynamics (Le Treut et al., 2007). A typical climate model used for IPCC AR4 couples dynamical atmosphere, ocean, land, and sea-ice models into what is referred to as an Atmosphere–Ocean General Circulation Model (AOGCM). AOGCMs simulate the dynamics of each of these components and the exchanges of thermal and kinetic energy, water, and potentially gases and aerosols between them. Model dynamics are derived from physical laws (e.g., the laws of motion and thermodynamics) discretized in time and three-dimensional space and solved numerically. The reliance of climate models on fundamental physical principles and their ability to capture prominent observed features of past and present climate give considerable confidence that physical climate models provide credible quantitative estimates of future climate change (Randall et al., 2007). Confidence is generally greater at continental scales and above, however, and varies by climate variable. The biosphere (e.g., Fig. 2, ocean biogeochemistry, land vegetation) was not explicitly resolved in most AR4 models and models of this type are thus often referred to as “physical climate models”. This convention will be maintained herein. The resolution of the physical climate models used for IPCC AR4 varies between models and between components (Table 1). Typical oceanic horizontal resolutions are $\sim 1\text{--}2^\circ$, atmospheric and land horizontal resolutions are $\sim 2\text{--}3^\circ$. The number of vertical levels in the oceanic and atmospheric components may vary from as few as 10 to as many as 50. Atmospheric time resolution is $\sim 10\text{--}20$ min whereas oceanic time resolution is usually an hour or two. Over the course of several months to a year of real time, climate model simulations with these resolutions can be run for the several thousand model years required to conduct the wide range of century-scale experiments analyzed in IPCC AR4. In particular, climate models are run for multi-century integrations in order to characterize internal variability in the natural climate system, forced climate changes due to greenhouse gas accumulation, and any systematic separation (or drift) of the modeled climate away from observations. Results are typically archived at the model’s spatial grid resolution. However, it should be noted that problems associated with data volume place a practical limit on the amount of information archived. Thus, monthly averaged information is archived for most variables, though some are archived at finer intervals⁴.

The effects of oceanic, atmospheric and land processes that occur at spatial and temporal scales finer than the model resolution are represented in climate models by relationships to properties that are resolved. These “sub-grid-scale parameterizations” are often based upon simplified physical models of the unresolved processes or empirical relationships. Oceanic mesoscale eddies, for example, are not captured by typical climate model resolutions. Lateral eddy-driven mixing and stirring in the ocean is thus often represented by a “diffusion-like” equation with the mixing coefficient scaled according to properties of the mean flow (e.g., shear) and the lower limit of the resolved motions (e.g., Smagorinsky, 1963; Gent et al., 1995). Such sub-grid-scale parameterizations vary between models and are a notable source of inter-model differences in climate predictions (see Section 3.1.4).

Century-scale climate model simulations are generally initialized around the year 1860, before the bulk of anthropogenic greenhouse gas emissions. However, since there are very limited ocean observations from before 1960 or so, the simulations must be initialized with model output from long “control” integrations. The radiative forcing (e.g., solar insolation, volcanoes, greenhouse gases, aerosols, land-use and associated albedos) for these control integrations is set to conditions near 1860, and the model is

allowed to reach a quasi-equilibrium with 1860 conditions. This quasi-equilibrium climate defines a baseline from which the impact of changes in radiative forcing can be assessed and analyzed. However, simulations started from such an initial condition will not match the phase of natural inter-annual to multi-decadal-scale climate modes (e.g., NAO, ENSO, PDO) during historical or future periods. At best, the simulations will reproduce the statistical properties of such phenomena if the climate system dynamics responsible for these climate modes are properly represented in the model (Randall et al., 2007).

Climate models require prescription of radiative forcing scenarios. These scenarios can include changes in natural, externally imposed radiative drivers (e.g., the amount of radiation incident upon the earth, volcanic activity) or human-influenced drivers such as greenhouse gases and aerosols. For the historical period, estimates based upon available observations are used to produce a time series for each driver (Forster et al., 2007). Some elements, such as CO_2 , are well constrained. Others, such as the spatial distribution of radiatively active aerosols, are highly uncertain. To make projections, scenarios of future population, technological development, and societal choices are developed, and these are used to estimate future anthropogenic emissions and atmospheric concentrations of radiatively active gases, including all major greenhouse gas species (Nakicenovic et al., 2000). These trajectories form the primary forcing for climate model projections (Meehl et al., 2007). The three primary scenarios used in AR4 are known as SRES scenarios B1, A1B and A2 and essentially correspond to low, moderate, and high future emissions respectively.

Several characteristics of the century-scale climate simulations outlined in the preceding paragraphs must be considered closely when attempting to link climate change to project LMR variations under future climate scenarios: model resolution, the interplay between internal variability and radiatively forced changes, regional model biases, and inter-model spread. The sections that follow discuss each of these issues in detail. Downscaling techniques will also be discussed within the model resolution Section 3.1.1.

3.1.1. Model resolution

The objectives and design of century-scale climate model simulations emphasize global-scale climate dynamics over multiple decades to a few centuries. One of the major challenges in applying IPCC-class climate models to LMR problems is reconciling this emphasis with the space and time scales important to LMRs (Section 2.1, Fig. 1). This issue is particularly prominent in coastal waters, where the majority of LMRs are harvested. In most AR4 climate models, a single grid cell may span the entire shelf width. For example, the left panel of Fig. 3 shows the climatological near-surface horizontal and vertical currents off the Pacific Northwest Coast of the USA from the GFDL CM2.1 coupled climate model (Griffies et al., 2005; Delworth et al., 2006; Gnanadesikan et al., 2006; Stouffer et al., 2006; Wittenberg et al., 2006). Simulations from this model were contributed to IPCC AR4, and it has an oceanic resolution of $1^\circ \times 1^\circ$ and an atmospheric resolution of $2.5^\circ \times 2^\circ$. The right panel of Fig. 3 shows the same quantities for the GFDL CM2.4 coupled climate model (Farneti et al., 2010), which has an oceanic resolution of $0.25^\circ \times 0.25^\circ$ at the equator and an atmospheric resolution of $1^\circ \times 1^\circ$. This resolution translates to ~ 15 km oceanic resolution at this latitude because the CM2.4 model grid preserves the aspect ratio of the grid cells as lines of longitude converge with increasing latitude. Both CM2.1 and CM2.4 are characterized by a southward mean flow and upwelling near the coast, but the finer resolution CM2.4 simulation produces horizontal and vertical velocities that are more consistent with the vigorous, highly divergent observed currents in the region (e.g., Hickey, 1998).

⁴ Model simulations analyzed for IPCC AR4 can be accessed through the Program for Climate Model Diagnostics and Intercomparison (PCMDI) website: <http://www-pcmdi.llnl.gov/>.

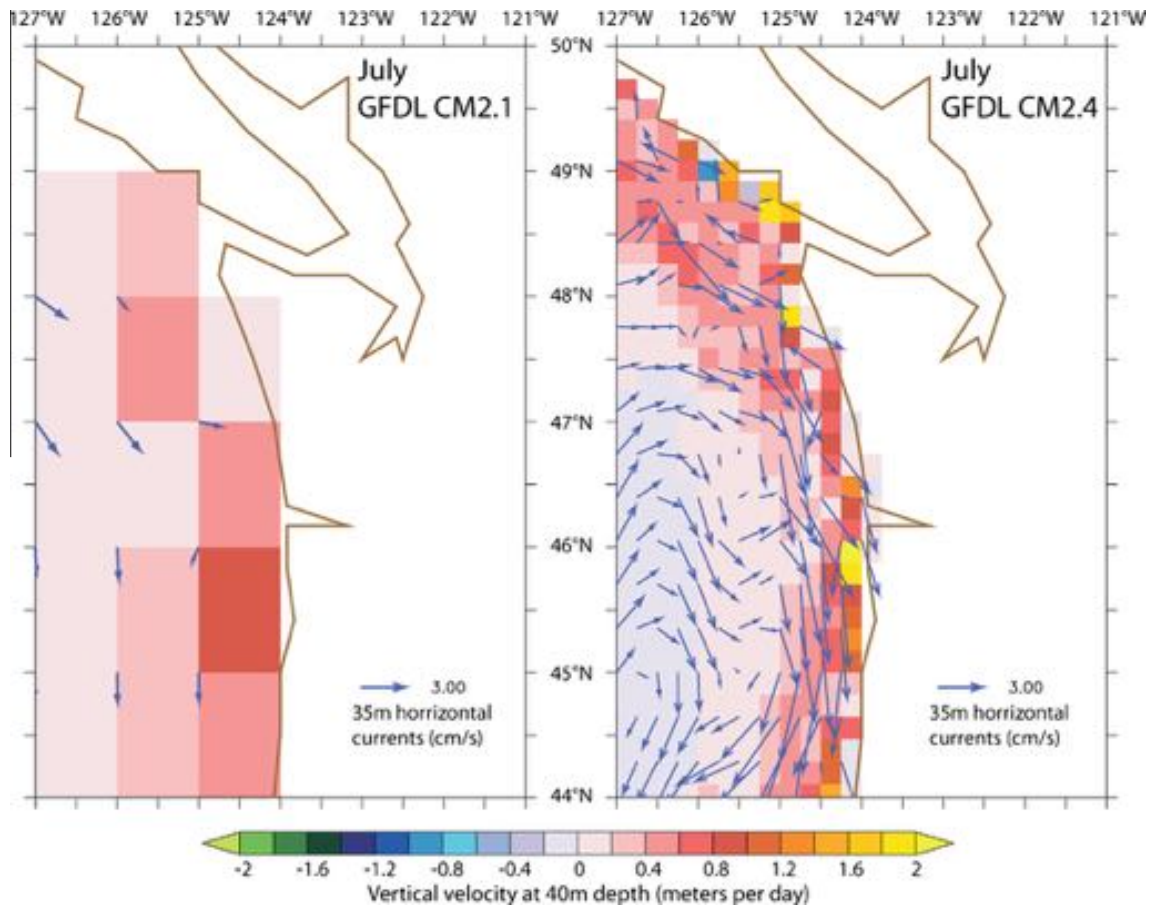


Fig. 3. Illustrative example of the impact of resolution. The left panel shows horizontal current vectors and vertical velocities (color contours) for the Oregon–Washington coast in GFDL CM2.1. This model has a horizontal resolution of 1° at the coast and (~ 68 km horizontal resolution at 47°N). The right panel shows the same quantities for GFDL CM2.4 (~ 17 km horizontal resolution at 47°N). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Refined resolution AOGCMs hold great promise for improving climate models and increasing their applicability to LMR problems. However, the computational costs increase in proportion to the cube when the horizontal grid size halves due to required reduction in the time step that accompanies refined resolution. In addition, developing robust fine-resolution climate simulations requires a careful re-inspection of model physics. Many of the processes previously handled by sub-grid-scale parameterizations (Section 3.1) are now resolved and sub-grid-scale dynamics may need reformulation (e.g., parameterized eddy mixing). Output storage costs are also greatly increased unless adjustments to storage frequency, averaging, or the number of variables saved are made. Some fine-resolution physical climate model results will likely be available for AR5 (joining the MIROC-Hi results from AR4), but the experiments carried out with these models will likely be limited, and the majority of AR5 century-scale simulations will be conducted with resolutions similar to or slightly finer than those in AR4 (i.e., Table 1, resolutions similar to the left panel of Fig. 3).

There are aspects of LMR dynamics that respond to basin-scale patterns directly resolved by climate models. Highly migratory fish such as tuna, for example, react to broad oceanic patterns, and tuna have been modeled using coarse climate model results as environmental inputs (see Section 4.2). However, even in such cases, resolution of the actual oceanic features (i.e., fronts, eddies) to which LMRs respond is often limited. There are, however, “downscaling” techniques by which information about finer spatial and temporal scale dynamics that are not resolved by climate models can be extracted from the coarser, resolved scales. Downscaling techniques fall into the two general categories of “statistical” and

“dynamical” techniques – with hybrid techniques also possible. Statistical downscaling relies on empirical relationships between resolved, larger-scale features and unresolved fine-scale features. An advantage of statistical downscaling is relatively low computational cost. Disadvantages of statistical downscaling include the necessity of assuming stationarity in the statistical relationship, the difficulty in selecting the relevant predictors (multiple statistical predictors can be fit to the training data equally well, but give fundamentally different implications when applied to AOGCMs; e.g., Vecchi et al., 2008), and the potential influence of observational errors on the development of the statistical model.

A wide variety of statistical downscaling models have been used for climate applications over land (Blenckner and Chen, 2003; Salathe, 2005; Christensen et al., 2007) but have been employed much less frequently in the marine environment where there are few long data records needed to establish reliable statistical relationships for climate variables. Nevertheless, statistical downscaling may provide useful information for studying the oceans. For example, Overland et al. (2002) investigated how local air–sea interactions known to be important to the ecosystem of the Bering Sea shelf relate to large-scale modes of climate variability, while Heyen et al. (1996) related sea level anomalies along the Baltic Sea coast to large-scale North Atlantic air pressure anomalies. Another example of statistical downscaling is given in case study 4.4.

A number of methods have been employed in statistical downscaling including linear regression or pattern-based variants such as canonical correlation analyses (CCA, Karl et al., 1990), analogues, where a forecast is matched to past conditions (Hamill et al., 2006), local rescaling of a predicted variable (Widmann et al., 2003)

general additive models (GAMS, Hastie and Tibshirani, 1990) and neural networks (Cavazos, 1997). Hewitson and Crane (1996), Wilby et al. (2004), and Haylock et al. (2006) have evaluated the strengths and weaknesses of various downscaling methods, and Wilby et al. (2004) discuss which ones are appropriate for a given application. One can test the efficacy of the predictors, which can include atmospheric, oceanic and ecological variables, e.g. SST, upwelling, NO_3 , plankton biomass, depending on the LMR variable(s) one wished to predict. The statistical relationships should be tested using a jackknife approach, where some of the data is reserved for validation and not included when developing the model.

Dynamical downscaling uses fine-resolution dynamical models to estimate fine-scale dynamical features. Advantages of dynamical techniques include the physical consistency of the solutions and their reliance upon fundamental physical principles; disadvantages of dynamical techniques include the higher computational cost of running the models, complexity of running fine-resolution models with a coarser resolution (in time and space) physical climate model constraints, and the inability of even very fine-resolution models to represent all of the processes that control some ecosystem-relevant features (i.e. Fig. 1). Lastly, while dynamical downscaling may improve the representation of local climate dynamics, the fine-scale simulations are still strongly influenced by any biases in the global simulations used for the boundary forcing (e.g., Meier et al., 2006).

Common configurations for regional climate model dynamical downscaling include forcing regional coastal simulations with offshore boundary conditions and atmospheric forcing from coarse global climate simulations (Curchitser et al., 2005; Powell et al., 2006; Hermann et al., 2009), forcing fine-resolution regional-scale coupled climate models with boundary conditions from coarse global climate simulations (e.g., Christensen et al., 2007), or forcing a fine-resolution global climate model component with information from coarse coupled model simulation (e.g., Cubasch et al., 1995). The coupling of fine-resolution regional simulations with coarse-resolution global climate models can be “one-way”, with information passed only from the global scale to the regional scale (Hermann et al., 2009), or “two-way”, with information being passed between the regional and global scales. The primary advantage of one-way nesting for regional ecosystem applications is the global simulation does not need to be re-run to carry out the regional simulation. The primary disadvantage is the potential for inconsistencies to develop between the dynamics of the regional

simulation and those imposed by the global-scale simulation. Inconsistencies are not limited to the dynamical scales captured by the refined resolution grid but not captured by the coarse global grid. Larger-scale discrepancies can arise due to the influence of fine-scale motions on broader-scale patterns.

Two-way nesting allows the refined solution to influence the global climate model solution and removes the potential for inconsistencies between the global and regional solutions. Targeted use of two-way nesting with high-resolution models in regions where limited climate model resolution has been linked to model biases (e.g., Section 3.1.3, eastern boundary current upwelling systems, narrow straits and overflows) may provide a means for improving global climate simulations. The primary cost of two-way nesting is that the global simulation must be run in concert with the regional simulation. This can be a significant computational burden for studying climate impacts on regional LMRs. In addition, while two-way nesting methodologies have been developed, nesting in a manner that robustly allows for dynamically consistent, non-diffusive, and conservative transfer of properties between grids of different resolutions is still an area of active research.

3.1.2. Internal variability versus externally forced changes

Changes in climate conditions can arise due to changes in the radiative forcing (referred to as the “forced change”) or due to internal variations in the climate system, and the changes evident at any time and place will be a combination of these two sources. Furthermore the forced change will be due to a combination of natural (e.g., solar, orbital changes, volcanoes) and anthropogenic sources (e.g., greenhouse gases, many classes of aerosols). Multiple, or “ensemble”, simulations are often used to study the relative roles of forced change and internal variability. In particular, they are useful for assessing when changes in a quantity exceed expected variations from climate variability (i.e., to determine when climate change is detectable). These ensembles are generally constructed by using different snapshots from the pre-industrial control run as the initial condition for a climate projection. Members of the ensemble represent a family of equally likely evolutions of the model system under the same forcing. The average, or ensemble mean, is usually a better representation of the observed climate over the past century than any single ensemble member (Reichler and Kim, 2008), but the evolution of the observed climate system should not be expected to exactly follow any individual ensemble member or the ensemble mean.

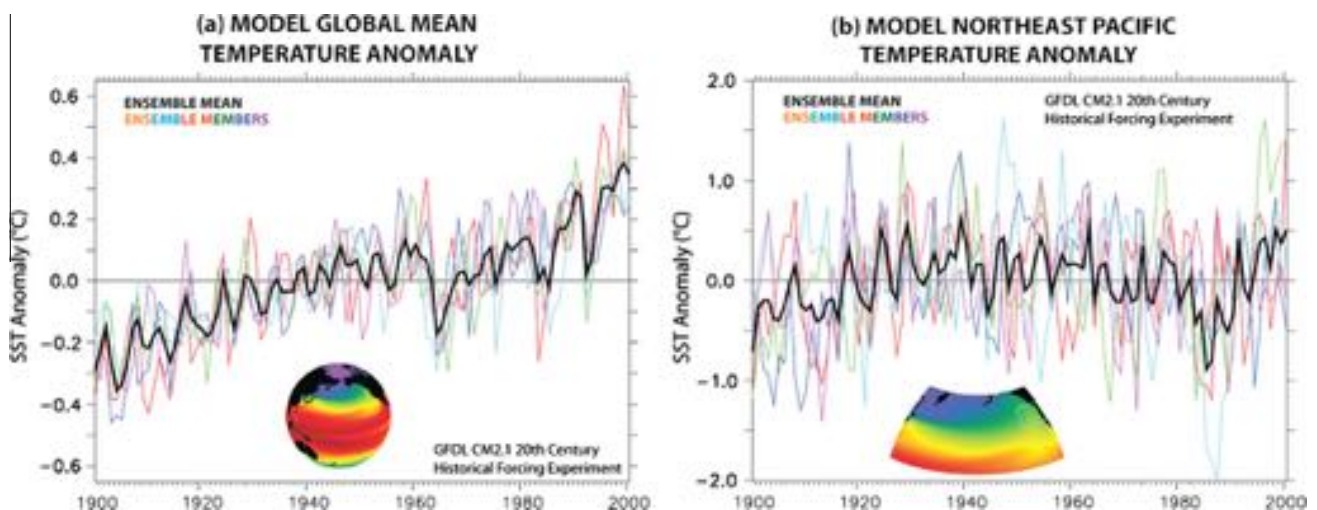


Fig. 4. Detecting the signature of global warming over the historical period of a climate model simulation is generally more difficult at regional scales. The left plot (a) shows a six member ensemble from GFDL’s CM2.1 and the ensemble mean for the global mean temperature. A clear century-scale trend is apparent despite substantial internal variability in the climate system. The right plot (b) shows the same comparison for the Northeast Pacific. Any century-scale trends are obscured by large internal variability.

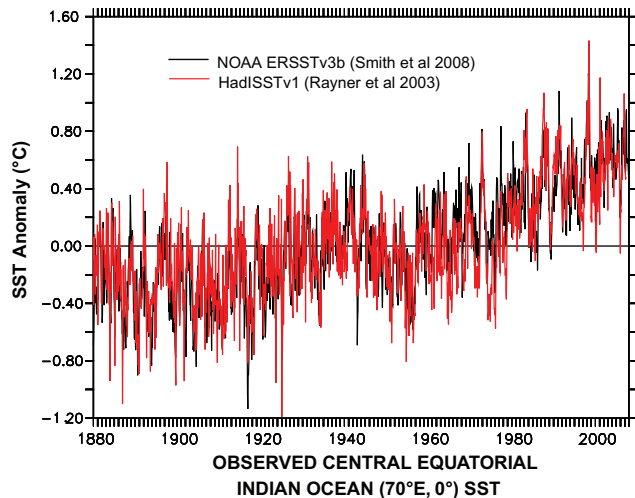


Fig. 5. The relative prominence of decadal variability at regional scales is not universal. This plot shows observed SST variations since 1880 in the central equatorial Indian Ocean from two SST products. Inter-annual to decadal-scale fluctuations are modest and the forced signal is apparent despite the limited extent of the region analyzed. (See above-mentioned references for further information.)

The relative importance of forced climate changes to internal climate variability tends to increase at larger spatial and temporal time scales because quantities that integrate forcing changes over very long space and time scales (e.g., decadal mean global ocean heat content) are tightly coupled to the net radiative imbalance of the planet. Conversely, many variations in regional scale features (e.g., weekly mean discharge of regional rivers) are expected to be driven primarily by internal climate variations (e.g., ENSO,

PDO, random weather events). Fig. 4 illustrates this tendency by comparing global mean SST trends (left panel) with those over the North Pacific from a five-member ensemble using GFDL CM2.1 from 1861 to 2000. In the global case, the ensemble members follow the ensemble mean fairly closely, and a warming trend over the century is apparent. In the North Pacific, the ensemble members vary greatly around the ensemble mean, and no net warming is apparent.

There exist exceptions to the tendency of internal variability to dominate at local scales and forced change to dominate at long (hemispheric, multi-decadal to centennial) scales. Some hemispheric features, like the Walker Circulation, an east–west tropical atmospheric circulation, can be dominated by internal variability that occurs over many decades to a century (Vecchi et al., 2006). The large-scale circulation and temperature structure of the North Atlantic Ocean can exhibit considerable internal variability on time scales of many decades (e.g., Delworth and Mann, 2000). There are also regions like the central equatorial Indian Ocean, in which forced century-scale changes dominate over the internal variability (Fig. 5). Evaluation of the relative roles of the forced signal versus internal variability should be carried on an application-specific basis. However, the strong prevalence of internal variability at regional scales and the fact that century-scale climate models are not designed to match the phase of internal variability (see discussion of model initialization in Section 3.1) means that century-scale climate model simulations generally provide very weak constraints on regional climate changes on time scales of a few decades or less.

3.1.3. Regional model biases

Climate models can have significant departures from observed patterns in ecosystem-relevant variables (Randall et al., 2007). For, example, Fig. 6 shows global SST biases for a control simulation

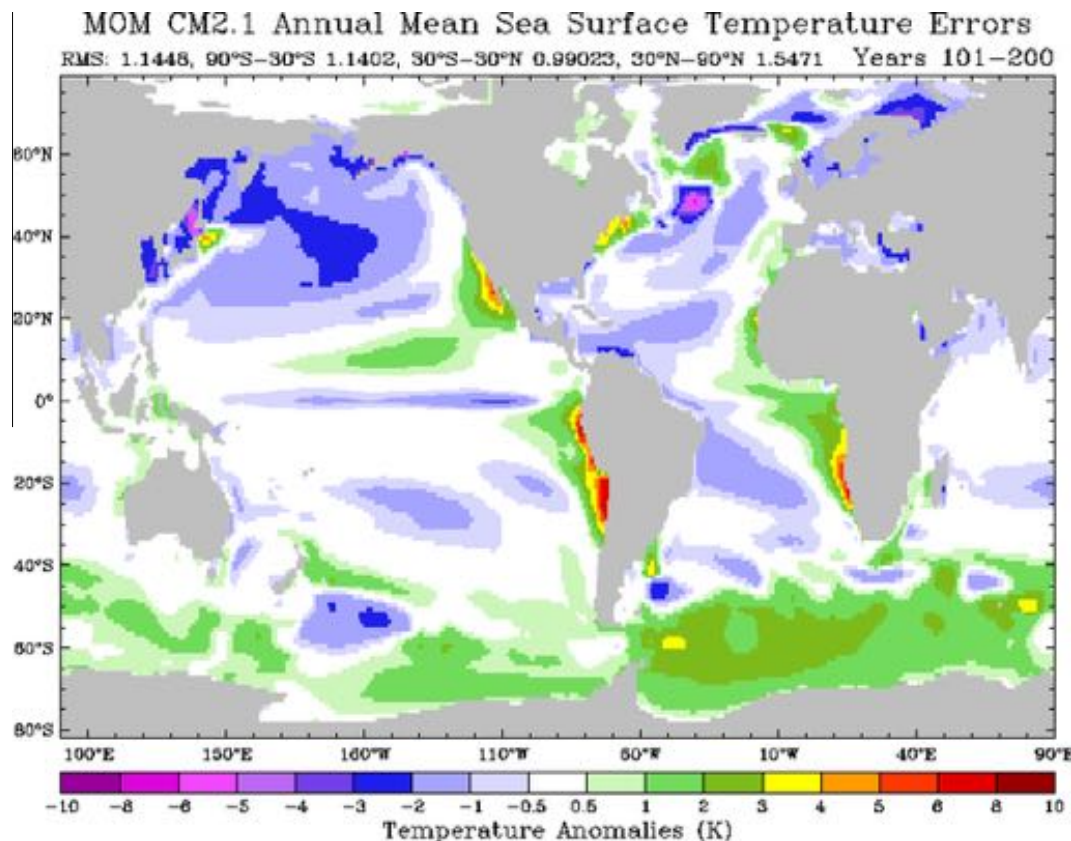


Fig. 6. Annual mean SST difference between the mean SST in CM2.1 under 1990 radiative forcing and observed mean SST between 1982 and 2002.

under 1990 radiative conditions of CM2.1 relative to mean observed SST between 1982 and 2002. The overall root mean square error is 1.14, but biases can be much larger at basin and regional scales. In some cases, such as the eastern boundary current upwelling regions, the warm bias of the model is likely linked to the under-representation of key processes (the formation of tropical low clouds and coastal upwelling) in coarse climate models. Others, such as the Southern Ocean warm bias, are less clearly linked to specific processes and may arise from a suite of interactions and feedbacks within the AOGCM. Lastly, some pronounced model biases, such as the >6 K model cold bias over a limited region of the Northwest Atlantic, are linked to systematic departures in the position of ocean currents. In this case, the Gulf Stream passes too far to the south of this region in this model. Many of the biases highlighted in Fig. 6 and the overall climate model skill with respect to SST are common across most IPCC AR4 climate models, though inter-model variations do exist and are variable-dependent (see Section 3.1.4; Randall et al., 2007).

One methodology that is often applied to adjust projections for systematic model biases is to remove the model climatology from the total model response and compute anomalies. This anomaly is then added to the observed climatology to create a blended dataset. For example, the magnitude of a modeled change in SST in the next century would be added to the observed mean SST, and this would be used to predict LMR responses in lieu of an unadjusted climate projection that exhibited a mean bias.

There are several issues to consider when assessing the viability of such simple adjustments. First, the model bias may reflect an error in the mean climate state or it could simply arise from expected differences in the phase of the inter-annual to multi-decadal internal climate variability between century-scale climate simulations and observation (Section 3.1). Ensemble simulations (Section 3.1.2) could be used to assess if differences between the model and the observations could be explained by climate variability. Long observational time series are often required to detect a bias in the model's mean climate. Second, model biases arise due to potentially complex, non-linear interactions of the climate system. Diagnosing the mechanisms underlying climate model biases is an active area of climate model research and development, and attribution to any single factor is often impossible. One key assumption when applying a simple bias correction to the mean climate state that can be assessed is that the mean climate state and other climate characteristics (e.g., the magnitude of the predicted change or variance in a climate variable) are independent. Calculating the covariance between the model biases and these other climate characteristics provides one means of assessing the independence of the mean climate state (McAfee et al., submitted for publication). Even with this test, simple climate model bias corrections should be applied with caution and the sensitivity of primary results to these corrections should be analyzed and documented.

3.1.4. Inter-model spread in climate projections

While climate models share common structures and underlying principles, they also differ in a myriad of ways, including resolution, grid design, numerical solution techniques, and the form and parameters chosen for sub-grid-scale parameterizations. It remains unclear how to best parameterize many important sub-grid-scale processes (e.g., atmospheric convection, cloud microphysical processes, and ocean mixing). Variations in these sub-grid-scale parameterizations contribute greatly to differences in climate projections and model biases (e.g., Murphy et al., 2007; Kim et al., 2008; Liu et al., 2010).

Some models will reproduce aspects of the climate system better than others. Improving the precision and accuracy of climate projections or improving the ability to detect and attribute climate change signals by restricting or weighting climate model ensembles based on the skill of ensemble members at matching observed

patterns in the present climate state is an active area of research (Hollowed et al., 2009; Pierce et al., 2009; Santer et al., 2009). Such approaches have proven to be effective for short-term weather (Raftery et al., 2005) and seasonal predictions (Krishnamurti et al., 2006). It is not necessarily true, however, that climate models with closer agreement to observed 20th century climatology should be expected to have a more 'believable' response in the 21st century. For example, Jun et al. (2008) found that climate model skill in capturing mean northern hemisphere summer and winter air temperatures between 1970 and 1999 were not generally correlated with a model's ability to simulate the warming trend. At a more regional scale, Pierce et al. (2009) found little relationship between climate projections of winter temperature over the western United States and model performance. This led Pierce et al. (2009) to conclude that there was little relationship between the quality of the model dynamics determining regional patterns in temperature and precipitation and the dynamics determining anthropogenic climate change signal. In contrast, Giorgi and Mearns (2002) argue that individually weighting the models in an ensemble can reduce uncertainty by minimizing the influence of poorly performing models that often represent outliers.

While the limitations imposed by inter-model spread on regional climate predictions support the importance of continued research on model selection and weighting to improve forecast accuracy and precision at regional scales, such techniques still require further development and testing. Any weighting scheme should ideally be justified by both empirical evidence of increased forecast accuracy and precision on climate change time scales and a process-level understanding of the dynamical aspects of the model thought to be deficient in the down-weighted or omitted models. Testing hypothesis about the relationship between observed climatology in a parameter and the validity of the predicted trend can be challenging because, unlike weather prediction, long time series are required. However, a multitude of concerted observational efforts (Bindoff et al., 2007; Lemke et al., 2007; Trenberth et al., 2007) are beginning to make this testing more feasible. In the absence of widely accepted weighting practices, a chosen weighting scheme should be viewed as an important scientific aspect of a study, and results should be analyzed and presented relative to those obtained from a full ensemble. Indeed, there are advantages to larger ensembles that may offset the potential advantages of weighting models or restricting the model ensemble. Analysis at both global (Reichler and Kim, 2008) and regional (Pierce et al., 2009) scales suggests that the average of many models tends to be closer to observed conditions than any single model. It must be recognized, however, that averaging yields smoothed representations (in space and time) of the evolving climate, and for some applications, it may be proper to introduce variability to produce more realistic climate projections.

3.2. Inter-annual to decadal-scale climate model predictions

The focus of the century-scale simulations described in Section 3.1 is an assessment of the climate changes under a relatively large change in radiative forcing. Such simulations project changes in the mean climate and the statistics of climate variability (i.e., frequency of droughts, etc.), but do not predict the detailed time evolution of the real climate system going forward in time. Such simulations do not start from the observed state of the climate system, but rather from some simulated state that resembles the current climate.

Recently efforts have begun to initialize climate models with an estimate of the observed state of the climate system in order to assess whether climate variations on inter-annual to decadal time scales can be predicted (Smith et al., 2007; Keenlyside et al., 2008; Pohlmann et al., 2009). The motivation for such activities

rests in observed decadal-scale climate fluctuations and their associated large-scale climatic impacts. For example, decadal-scale fluctuations in the Atlantic have been linked to a host of physical and ecosystem impacts, ranging from drought in the Sahel region of Africa to ecosystem changes in the Nordic Seas. It has been recognized that there could be great utility in developing a capability to predict such fluctuations, although the degree to which decadal-scale climate prediction is possible is an open scientific question.

Associated with the fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC AR5), a number of modeling centers around the world will conduct a suite of decadal-scale prediction experiments. The various models will be initialized with estimates of the observed climate system and then integrated forward in time to attempt predictions of decadal-scale climate fluctuations. Much of the potential predictability lies in the state of the ocean, and thus ocean temperature and salinity will be key variables for initializing the models. The technique for initializing these simulations will vary among the modeling groups. These techniques include using output from (a) ocean-only assimilation systems, (b) fully coupled ocean–atmosphere assimilation systems, (c) and ocean simulations forced by estimates of past surface flux forcing. In addition, some groups employ an anomaly technique in which observed anomalies (rather than the full fields) are put into the model in an attempt to minimize the impact of model bias on the predictions. All of these techniques start predictions from estimates of the observed state of the climate system while attempting to minimize the inevitable shock to the system that comes from inserting observations into the model. In addition to initialization from the observed state, all of the model simulations should include the effects of time-varying radiative forcing.

Hindcasts will also be conducted in which the models are initialized from past observed states. The hindcasts are then compared to observations for the last several decades in order to evaluate any potential skill in such decadal predictions. However, the changing nature of the climate observing system over that period will complicate interpretation of these results. In particular, since a substantial component of any decadal-scale predictability in the climate system may arise from the ocean, changes in the ocean observing system may be crucial. The advent of ARGO observations over the last decade, which provide a near global set of observations of temperature and salinity over the top 2000 m of the ocean, may be crucial for achieving reliable decadal predictions.

The outcome of these suites of experiments will be an initial assessment of the predictability of the climate system on decadal time scales, as well as an initial set of such predictions. As part of the international protocol for these experiments, the output from these models will be made publicly available. It is hoped that as models and observing systems improve we will be able to increase our ability to predict decadal-scale climate fluctuations, and that such predictions will be of use in assessing any ecosystem impacts.

3.3. Earth system model simulations

One of the primary simplifications of the climate system in the physical climate models described in Section 3.1 is that the dynamics of the land and ocean biosphere and carbon reservoirs are not explicitly modeled. Fluxes between the atmosphere, ocean and land carbon reservoirs significantly impact the accumulation of CO₂ in the atmosphere (Sabine et al., 2004; Denman et al., 2007). Physical climate models must rely upon imposed scenario-based atmospheric CO₂ trajectories that include assumptions concerning the behavior of the land, ocean, and atmospheric carbon reservoirs. Earth System Models (ESMs) address this limitation by adding explicit models of the terrestrial and oceanic biosphere to the ocean, ice, atmospheric, and land hydrology components of the physical climate models and tracking the carbon in each reservoir.

This approach “closes” the carbon cycle: given a set of carbon emissions and an initial carbon inventory, ESMs dynamically resolve the partitioning of carbon between the land, ocean, and atmosphere; model the transformations within each component; and conserve total carbon.

ESMs offer two potentially substantial advantages over physical climate models for predicting the response of LMRs to climate change. First, the explicit ocean biosphere provides estimates of a wide range of ocean chemical and biological properties (e.g., oxygen, alkalinity, primary and secondary production). This allows the direct simulation of important ecological phenomena such as ocean acidification, hypoxia, and anoxia. Also, biological production metrics often have stronger empirical and mechanistic links to LMRs than physical properties (Iverson, 1990; Ware and Thompson, 2005). However, present formulations of marine ecosystem dynamics within ESMs emphasize broad global-scale patterns in carbon and nutrient cycling. They feature detailed resolution of nutrient dynamics, primary production and phytoplankton physiology, but relatively simple representations of marine food web dynamics (Aumont et al., 2003; Moore et al., 2004). Addressing this limitation within ESMs by making food web interactions more explicit and comprehensive would further enhance their utility for LMR applications by allowing the flow of energy to higher trophic level organisms (e.g., fisheries) in the ocean to be diagnosed in more detail. However, it is also notable that marine ecosystem models within ESMs are designed for robust global performance and may thus omit aspects of regional ecosystem dynamics that may be relevant to LMRs. Computational advances should ameliorate this limitation, but ESMs will likely lag behind regional model simulations in terms of the extent to which detailed, region-specific ecology can be captured.

A second potential advantage of ESMs for LMR applications is the ability to better resolve the dynamics governing exchanges of carbon and nutrients between land and the coastal ocean which are strongly impacted by land-use, vegetation types, and precipitation patterns (Green et al., 2004; Seitzinger et al., 2005). Estuaries modulate these exchanges and provide essential habitats for many LMRs, including the early life stages of many species harvested on the continental shelf or in oceanic waters (see Section 2.1). As is the case with present ocean ecosystem models in ESMs, present terrestrial biosphere models emphasize very broad-scale land-use and vegetation patterns that shape global climate – only very large watersheds are resolved, and localized human impacts are omitted. However, as computational obstacles are removed, ESMs provide the necessary framework to comprehensively simulate the impacts of climate change and human activities on estuarine systems and the LMRs they support.

4. Case studies

Sections 2 and 3 have provided broad overviews of the dynamics of LMRs and climate models. In this section, we rely upon this baseline of common understanding to present examples of the coupling of predictive LMR models and climate models to make statements about the impact of climate on LMRs. These case studies illustrate a range of potential approaches, including direct use of climate model output, statistical downscaling, and dynamical downscaling. A range of LMR models are also used, including simple extensions of traditional stock assessment models to relatively sophisticated and highly resolved ecosystem models. Each case study includes a description of the coupling of LMR and climate models and a summary of the main results.

As with the climate projections, it is difficult to directly assess confidence in these LMR projections because they are made over many decades and for a period over which there are no precise past

analogs (Section 3, Randall et al., 2007). Confidence must instead be built upon the degree to which models rely on robust and well-supported ecological and physiological relationships and on the ability of models to match past observed LMR responses to climate. This process is made difficult by both the complexity of ecosystem dynamics and models (Sections 2.1 and 2.3) and the limitations of the observations (Section 2.3). While ensemble methods (Section 3.1.2) provide a means of exploring some aspects of projection uncertainty, there is a general need for more quantitative measures of confidence for both climate and LMR projections (see Section 6). For now, each of the case studies below will conclude with a largely qualitative discussion of projection limitations.

4.1. Projections of global fisheries biodiversity and catch

Cheung et al. (2009, 2010) used IPCC-class physical climate models to examine the questions of how marine climate change may affect global patterns of marine biodiversity and potential fisheries catch. The global pattern of marine biodiversity is determined by the biogeography of marine species which is strongly related to physical conditions of the ocean. Moreover, maximum potential catch of a fish stock is shown to be dependent on the range area of the stock and the primary production therein. Climate change may lead to changes in ocean productivity as well as the range of fish stocks resulting in a shift in the global pattern of potential fisheries catch. Models were thus developed and applied to project future changes in marine biodiversity and fisheries catch in the world ocean (Cheung et al., 2009, 2010).

A dynamic bioclimate envelope model was developed to examine the potential ecological responses of a wide variety of marine animals (over 1000 species of marine fish and invertebrates, Cheung et al., 2008a, 2009). In this model, current species distribution of the studied animals, expressed as relative abundance in a 0.5° latitude \times 0.5° longitude grid of the world ocean, are predicted by an algorithm described by Close et al. (2006) with modifications from Lam et al. (2008). Biological data were obtained from global databases such as FishBase (www.FishBase.org), SeaLifeBase (www.SeaLifeBase.org) and the Sea Around Us database (www.seaaroundus.org). Preferences to environmental conditions, such as temperature, salinity, and habitat types, are inferred from overlaying distribution maps with gridded physical condition data of the ocean as predicted by one of the IPCC-class coupled AOGCMs – NOAA's GFDL CM2.1 (Delworth et al., 2006). Changes in distribution of relative abundance of each studied species were then simulated using a dynamic bioclimate envelope model developed by Cheung et al. (2008a). This model simulated annual changes in distribution of the studied species forced by changes in physical conditions including sea water temperature (surface and bottom), salinity, surface currents and sea-ice extent that were projected from the NOAA's GFDL CM 2.1. Specifically, the movement of the distribution range was determined by the suitability of each $0.5^\circ \times 0.5^\circ$ cell relative to the species' environmental preferences, larval dispersal along ocean currents and migration of adults.

Based on the outputs from the dynamic bioclimate envelope model, Cheung et al. (2009) projected that biodiversity impact would be highest in the high latitudes, particularly the Polar

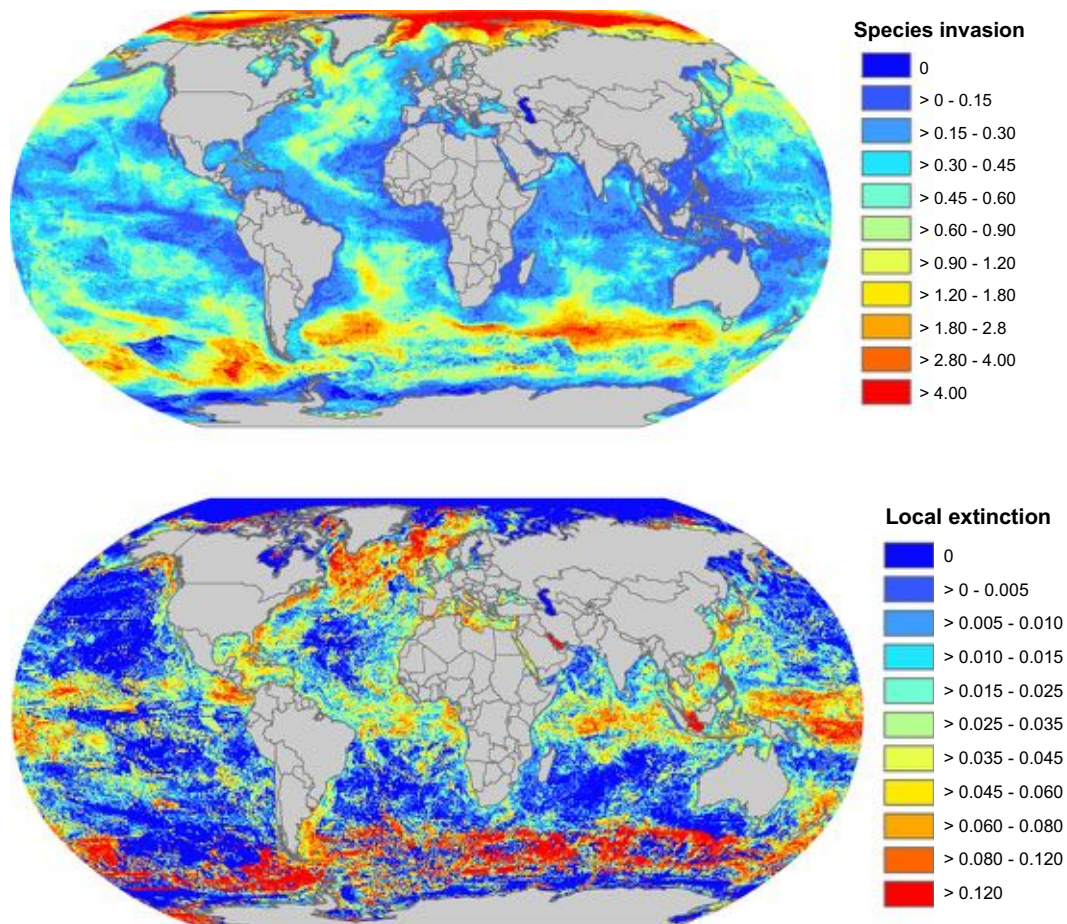


Fig. 7. Predicted global pattern of species invasion (a) and local extinction (b) in 2050 relative to 2000 due to range shifts in marine metazoans SRES A1B scenario. The values are expressed as proportion relative to the initial species richness in each $30' \times 30'$ cell. This is based on an analysis of 1066 species of marine fish and invertebrates (redrawn from Cheung et al. (2009)).

region, the tropics and semi-enclosed seas (Fig. 7). Such impact is expressed in terms of species turnover (i.e., sum of species invasion and local extinction from an area). Specifically, invasion is most intense in the Arctic and the Southern Ocean while local extinction concentrates in the tropics, semi-enclosed seas and the sub-polar regions. Moreover, the distribution ranges of fish and invertebrates are projected to shift generally polewards.

In addition, Cheung et al. (2010) used scenarios of future changes in physical and biological conditions of the ocean to predict how maximum potential catch may re-distribute as a result of shifts in the distribution of exploited species and primary productivity. These predictions are based on empirical relationship between potential catch, habitat area and primary productivity (Cheung et al., 2008b) and predict a decline in potential catch if species' habitat or primary productivity therein decreases, and *vice versa*. Changes in species' distribution range were projected by the dynamic bioclimate envelope model (Cheung et al., 2008b, 2009) while primary productivity was predicted by empirical equations (Sarmiento et al., 2004) with physical data projected by the NOAA's GFDL CM 2.1. In spite of all caveats and a number of scientific uncertainties, a clear pattern emerged, i.e., maritime countries located in low latitudes (e.g., Malaysia, or Indonesia) will lose potential yield (and their fisheries will suffer), while higher-latitude countries (e.g., Iceland and Norway), will gain potential yield and their fisheries might benefit (Cheung et al., 2010).

Outputs from the GCM are critical for the global projections of climate change impacts on marine biodiversity and fisheries; however, there are various uncertainties resulting from limitations imposed by GCM outputs used by the study. The climate model used by Cheung et al., (2009, 2010) is relatively reliable at predicting long-term and large-scale trends and patterns of changes in ocean conditions. However, model skill decreases at smaller spatial and temporal scales (Section 3). The projected biodiversity and fisheries impacts, which are driven by the GCM outputs, inherit such properties. On the other hand, the targeted temporal and spatial scales for the global models of marine biodiversity and fisheries parallel those for the GCM. Thus, scale issues of the GCM outputs do not invalidate the main conclusions from these analyses. A greater impediment to the analyses on marine biodiversity and fisheries is the limited representation of dynamics in coastal and continental shelf regions by the GCM (Section 3.1.1, Fig. 3). These are particularly important for distribution of many exploited marine species and their potential catch. This renders projections of biodiversity at scales finer than the broad latitudinal patterns discussed above and fisheries impacts in coastal region uncertain. Moreover, some of the predicted physical variables that are important to determine habitat suitability for many marine species, such as sea bottom temperature, may be particularly uncertain. Bioclimate models also have limitations (Brander, 2009). For example, the present bioclimate envelope model does not account for species interactions and potential food web changes that may also impact fisheries biodiversity and ranges. Currently, a new version of the dynamic bioclimate envelope model is being developed that account for effects of ocean biogeochemistry such as oxygen level and pH on the eco-physiology and distribution of marine fish. Such a model would require the new generation of Earth System Models (ESMs, Section 3.3) which have explicit biogeochemical components for predicting such variables at a global scale.

4.2. Bigeye tuna in the Pacific Ocean

Bigeye tuna (*Thunnus obesus*) are large (up to 200 kg) highly migratory fish that occupy tropical and temperate oceans and can live for over 10 years. The broad ocean-basin scales of bigeye tuna habitat and migration are consistent with those resolved by climate models. Pacific Ocean bigeye tuna populations support a

large and extremely valuable fishery. Landings over the last 10 years in the tropical Pacific have been valued at between 500 million to 1 billion US dollars (www.seaaroundus.org).

The behavior, life cycle, and survival of bigeye tuna has been related to a range of environmental and ecological factors. Larval and juvenile stages need warm water (>25 °C) to maintain their body-temperatures. However, as they become larger, they must move toward cooler habitats to prevent overheating (Holland et al., 1992; Brill, 1994). Bigeye tuna also avoid regions where dissolved oxygen falls below 1 ml/L. The diet of adult bigeye tuna includes a large spectrum of micronekton ranging in size from several millimeters (e.g., euphausiids and amphipods) to several centimeters (shrimps, squids, and fish, including their own juveniles). Movement during much of the adult stage is dictated by the suitability of a habitat's food resources, temperature and oxygen. Adult tuna must return to warmer waters to spawn, and spawning success depends on temperature, the availability of food for larvae (often microzooplankton), and the abundance of predators of larvae (large zooplankton and micronekton). Mortality varies by life stage and includes both natural losses (predation, starvation, disease, senescence) and fishing mortality.

Mechanistic predictions of the impact of climate change on bigeye tuna requires a model capable of capturing the range of interactions with the ecosystem and the environment outlined above. Lehodey et al. (2010b) combined a climate model (IPSL CM4, Marti et al., 2006), which included an embedded biogeochemical model (PISCES, Bopp et al., 2001), with the latest version of the Spatial Ecosystem and Population Dynamics Model (SEAPODYM, Lehodey et al., 2008; Senina et al., 2008) to provide preliminary forecasts of the response of Pacific bigeye tuna to climate change (in absence of fishing) and to diagnose the underlying dynamics of the response. SEAPODYM is designed as a general framework for integrating biological and ecological knowledge of tuna species and other top-predator species with a comprehensive description of the pelagic ecosystem, including several functional groups of micronekton (Lehodey et al., 2010a). The IPSL CM4 climate model provided physical fields required by both PISCES and SEAPODYM (e.g., temperature, currents), the biogeochemical model provided estimates of oxygen and primary production to SEAPODYM, and SEAPODYM provides estimates of both the adult tuna forage base (i.e., micronekton) and size- and age-structured tuna populations in space and time. The biomass of each cohort within the tuna population is tracked as a spatially distributed density of fish using a system of advection–diffusion–reaction equations. The SEAPODYM calculations are done “off-line”, monthly inputs from the IPSL climate model and the PISCES biogeochemical model are used to drive SEAPODYM, but there are no feedbacks from SEAPODYM to PISCES or the IPSL climate model. This “off-line” approach provides a computational savings by not requiring the global simulations to be re-run to force SEAPODYM, though the lack of feedbacks between SEAPODYM and PISCES can be a source of inconsistencies between the two models.

As far as possible, the mechanisms within SEAPODYM rely on relative rather than absolute parameterization. For example, movements are based on gradients in habitat. The ratio between primary production (the proxy for larval food) and production by mid-trophic level organisms (consumers of larvae) is used to represent the trade-off between availability of prey and exposure to predators in defining favorable spawning habitat. This approach minimizes the impact of magnitude biases in the IPSL CM4/PISCES projection while making the model's representation of spatio-temporal gradients more critical.

Though SEAPODYM contains a relatively small number of parameters (i.e., 15 to describe the entire spatial population dynamics of one species), some have limited constraints (e.g., natural mortality). The model was thus calibrated against fisheries

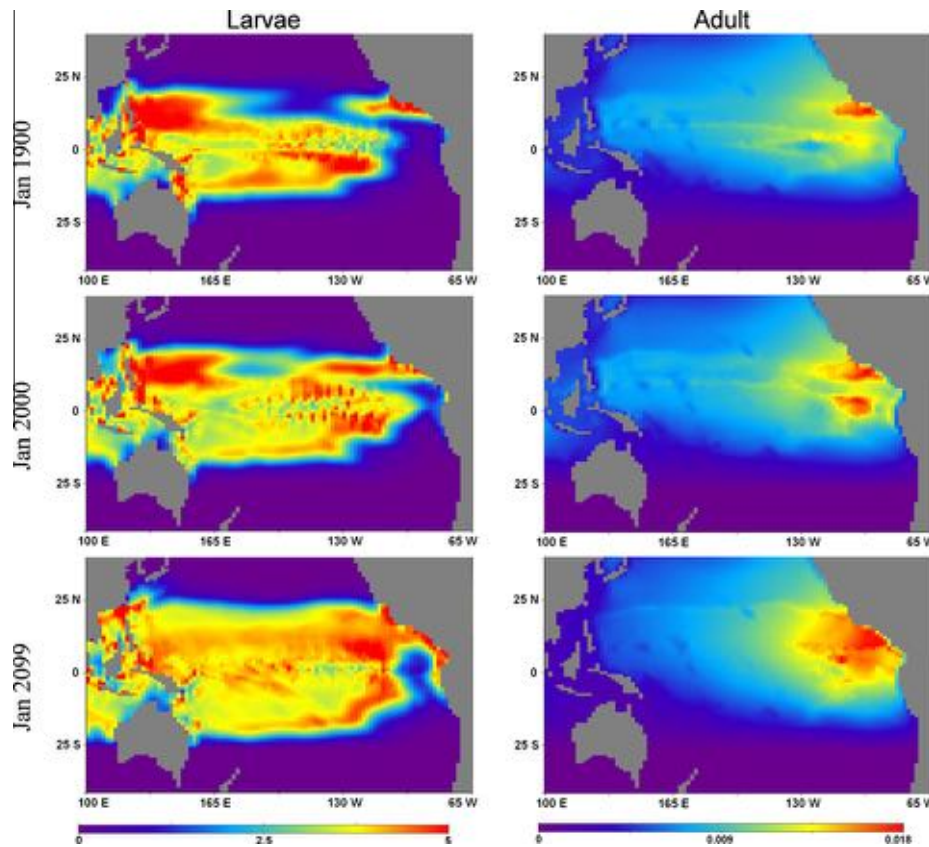


Fig. 8. Density distribution of Pacific bigeye tuna larvae (left, in number per km^{-2}) and adult biomass (right in tons per km^{-2}) predicted with SEAPODYM in January of year 1900, 2000, and 2099 (from top to bottom) from the IPSL-PISCES climate simulation (IPCC SRES-A2 scenario). Reprinted from Lehodey et al. (2010b).

catch data using data assimilation techniques (Senina et al., 2008) for the historical period and with several environmental reanalyses from coupled ocean–biogeochemical models. Lehodey et al. (2010b) then used the IPCC SRES A2 projection of the IPSL climate model to make a preliminary assessment of the bigeye tuna response to climate change in the 21st century. Spawning habitat, which requires high temperatures, was predicted to expand in the eastern tropical Pacific (ETP) and in sub-tropical areas (Fig. 8, left panels). The adult feeding habitat also strongly improves in the ETP (Fig. 8, right panels). This is due to an increase in dissolved oxygen in sub-surface waters that increases the accessibility of micronekton function groups that reside deeper in the water column to feeding bigeye tuna adults. Conversely, in the western tropical Pacific (WTP) the temperature becomes too warm for bigeye spawning, and larval concentrations near the equator decrease (Fig. 8, left panels). This is partly compensated for by an increase in the larval biomass in sub-tropical regions. However, adult mortality also increases in the WTP due to excessively warm surface temperatures, decreasing oxygen concentration in the sub-surface and less food. These conditions drive the movement of surviving fish to the ETP, and the adult biomass in the WTP starts to decline by the end of the century. Fishing in the WTP is likely to exacerbate this decrease if it is continued over the next century.

There were several challenging aspects of the coupling between climate models and highly mechanistic ecosystem models described in this case study. First, the calibration of the SEAPODYM model used for projection was done using fisheries catch data from 1985 to 2000 and compared against results from the IPSL CM4 model during the historical period. As described in Section 3, ENSO timing during the historical period of century-scale climate projections will not match the timing of ENSO events from 1985 to 2000 (see Section 5 for further discussion of calibration using global

ocean-ice simulations forced by atmospheric reanalysis which may ameliorate this issue). Second, while the use of the highly mechanistic SEAPODYM model provided additional insights into the dynamics driving simulated changes in bigeye tuna distributions, it also imposed additional computational demands (e.g., spatially explicit tuna calculations) that restricted the number of climate simulations considered and the exploration of uncertainty. This is a common trade-off when using more complex ecological modeling approaches (Section 2). Lastly, while SEAPODYM includes many food web interactions and constraints due to physiological responses under different feeding habitats and food requirements, notable omissions remain. For example, feedbacks of fish communities on biogeochemical dynamics are not resolved.

4.3. Climate impacts on Alaskan ecosystems and the northern rock sole

The waters off the coast of Alaska support the largest groundfish fishery in the United States as well as large commercial fisheries for salmon, herring, Pacific halibut and Tanner and King crabs. The groundfish fisheries are carefully managed, and none are classified as overfished (Worm et al., 2009). However, notable ecosystem shifts in response to climate variability and change have been observed in Alaskan waters (Grebmeier et al., 2006), and incorporating climate information into resource management is essential for continued effective management. A number of approaches are being pursued, including statistical (A'Mar et al., 2009; Hollowed et al., 2009) and dynamical downscaling (Sigler and Harvey, 2009). This case study will focus on general aspects of the approaches being applied for climate impacts on Alaskan ecosystems and the particular example of northern rock sole on the eastern Bering Sea shelf presented by Hollowed et al. (2009).

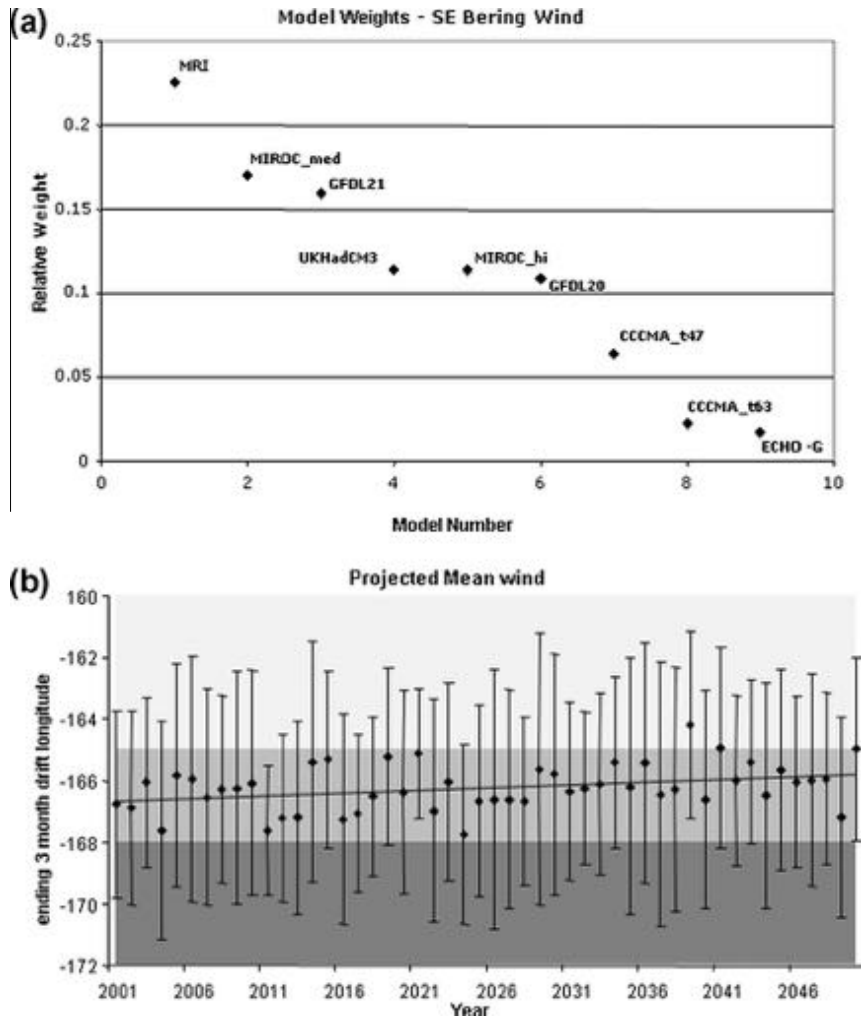


Fig. 9. (A) Weights of various IPCC AR4 models used in forming the ensemble mean using a Bayesian model averaging approach. The criteria used for evaluating models were the accuracy of their hindcasts in terms of reproducing the mean, variance, and trend in the observed wind of the Bering shelf over the last half of the 20th century. (B) Predicted mean and standard deviation of the longitudinal endpoint of projected larval drift from spring winds for 2001–2050. Background shading reflects classification of endpoints according to spring climate condition: on-shelf drift (lightest shading), off-shelf drift (darkest shading), and mid-shelf drift (intermediate shading). Redrawn from Hollowed et al. (2009).

Hollowed et al. (2009) proposed a framework for modeling fish and shellfish responses to future climate change that is being applied in Alaskan waters. There are six steps that are briefly described here. First, mechanisms that explain environmental influences on LMR population dynamics are identified; second, the environmental variables for which projections are needed to model the LMR response are identified; third, the feasibility of using IPCC models to predict these variables is assessed; fourth, IPCC models hindcasts of the variable(s) are compared with observed 20th century conditions to select and weigh IPCC models; fifth, projections of the environmental variables from the weighted ensemble of IPCC models are incorporated into stock projection models; and sixth, the effects of changing environmental conditions on harvest strategy are evaluated.

A notable aspect of the proposed framework is the weighting of IPCC models based on their fidelity with observed conditions for the environmental variables being projected during the historical period of the climate simulations. This is based on the understanding that different models have different strengths and weaknesses, and the assertion that better models for particular parameters and particular regions should receive greater consideration. The procedure suggested by Hollowed et al. (2009) is an adaptation of the method developed by Raftery et al. (2005) for short-term weather

forecasts. The weights can reflect multiple criteria, including the ability to reproduce the mean values, variances, trends and seasonality. However, as discussed in Section 3.1.4, a linkage between climate model fidelity to historical observations at regional scales and the quality of climate change predictions over century-scales has not been established. The weighting scheme suggested by Hollowed et al. (2009) thus continues to be evaluated against observations and approaches using the full ensemble in order to refine the methodology, assess the added value of model weighting, and test the rationale for the weights.

Hollowed et al. (2009) provided an example application of this framework to northern rock sole (*Lepidopsetta polyxystra*) in the eastern Bering Sea. Northern rock sole spawn between February and March, and larvae are carried by ocean currents from April to June. Wilderbuer et al. (2002) found that wind-driven advection of larvae toward highly productive near-shore nursery areas coincided with above-average recruitment. This suggests that the impact of climate change on northern rock sole is linked to climate-driven changes in wind patterns. The ensemble of IPCC models used to predict rock sole was first restricted to 12 IPCC AR4 models that replicate the essential characteristics of the Pacific Decadal Oscillation (Overland and Wang, 2007). These 12 models were then weighted according to their ability to model mean

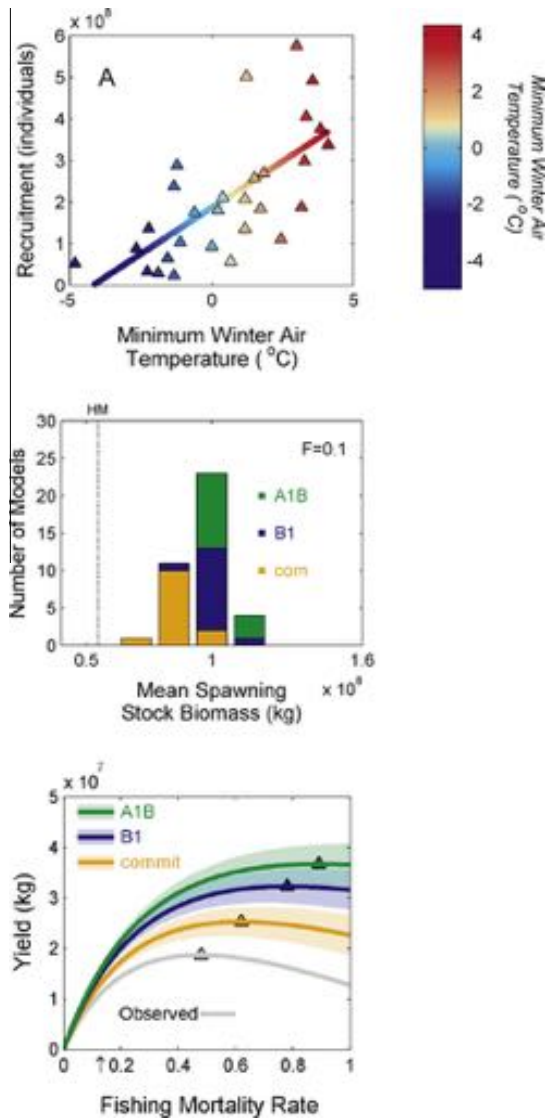


Fig. 10. Predicting climate impacts on the Atlantic croaker. Top panel: the effect of minimum winter air temperature on recruitment. Middle panel: the predicted spawning stock biomass of Atlantic croaker for each of 14 different bias-corrected climate model projections and three different scenarios for a fishing pressure (F) of 0.1 day^{-1} . Lower panel: The predicted yields for each of the three climate scenarios and the present yield as a function of fishing mortality rate. The maximum sustainable yield for each case is marked with a triangle. The shaded regions indicates the range of results across the multi-model ensemble. Redrawn from Hare et al. (2010).

April–June winds on the Bering Sea shelf and the inter-annual variance in seasonal mean winds (Fig. 9A) and these were used to project winds out to 2050. Winds were then converted to an ending longitude for the surface-drifting larvae based on a simple transport model that indicates a slight tendency toward increased shoreward transport (Fig. 9B). The future production of rock sole was then predicted using an empirical recruitment function with environmental terms added. After accounting for recruitment in a given wind regime, the analysis suggested that rock sole would not be substantially affected by climate-driven changes in larval dispersal patterns.

There were several challenging aspects and limitations associated with this method of the coupling between climate models to stock projection models in addition to the aforementioned challenges associated with model weighting. As was the case for the stock–recruitment relationships discussed in Section 2.3.1, a considerable amount of recruitment variability cannot be explained by the emergent relationships between the environment and

northern rock sole recruitment (A'Mar et al., 2009; Hollowed et al., 2009). The analysis was only possible because the variables needed to predict recruitment were reasonably well estimated by IPCC-class climate models. However, proxy variables may be necessary in many cases (e.g., see Section 4.4). The weighting process becomes more complex when multiple predictor variables are needed. Lastly, the approach could not address the potential impacts of and uncertainties in fishing patterns, management, and the socioeconomic factors that govern them.

4.4. Atlantic croaker along the east coast of the United States

Hare et al. (2010) used a statistical downscaling approach to simulate the effect of climate change on the abundance and distribution of Atlantic croaker along the eastern seaboard of the United States. The Atlantic croaker is a relatively small (1–2 kg as an adult), demersal fish inhabiting inshore coastal waters. Atlantic croaker supports an active yet highly variable commercial and recreational fishery in this region, with yearly landings of ~8000 metric tons, worth an estimated US \$9 million (NMFS, 2008).

Variability in Atlantic croaker catch is thought to be primarily due to differences in the survival of estuarine juvenile stages: cold water temperatures lead to lower juvenile survival and ultimately lower recruitment (Hare and Able, 2007). This has been linked to temperatures falling below the physiological thermal tolerance of juvenile croaker (see also Norcross and Austin, 1981; Lankford and Targett, 2001). Estuarine dynamics are generally not resolved or very coarsely resolved in the physical climate models used in IPCC AR4 (Section 3.1.1). However, estuarine water temperatures are closely linked to surface air temperatures in the winter owing to efficient heat exchange in these shallow systems (Roelofs and Bumpus, 1953; Taylor et al., 1957; Hettler, 1992). Winter surface air temperatures are strongly coherent across the eastern United States (Joyce, 2002), thus providing a large-scale indicator of estuarine conditions that is resolved by climate models. Past estimates of Atlantic croaker recruitment were related to minimum winter air temperatures from a historical reanalysis of atmospheric temperature (Fig. 10A). This relationship was then incorporated into the stock–recruitment function (Eq. (3)) of an extended stock assessment model (ESAM, Section 2.3.1). This ESAM was used to project croaker populations forward for three emissions scenarios used in IPCC AR4 (commit, B1 and A1B). These scenarios correspond to atmospheric CO_2 increases to 350, 550, and 720 ppm by the end of the 21st century.

The analysis of Hare et al. (2010) focused on Atlantic croaker stocks in the mid-Atlantic region of the United States. While surface air temperatures are broadly coherent over the eastern US, there is considerable model bias and inter-model spread at this regional scale (Sections 3.1.3 and 3.1.4). Two steps were taken to address these issues. First, climate models were bias corrected by removing the mean surface air temperature bias in retrospective simulations. Second, the simulations from an ensemble of 14 climate models with all three emissions scenarios and retrospective results available were used to test the robustness of findings. A range of fishing mortalities (F) was also included in the simulations. The effect of climate change was assessed by averaging predicted changes between 2010 and 2100 and comparing them with present values which removes the effects of climate variability and isolates the climate change signal which AR4 models simulate deterministically (Section 3.1.1). At current levels of fishing mortality ($F = 0.1 \text{ year}^{-1}$), climate change is predicted to increase the spawning stock biomass of croaker in this region (Fig. 10B). The predicted increase in biomass becomes smaller as F increases, but generally ranges between 60% and 100% of current levels, which translates to a 30–100% increase in the maximum sustainable yield (Fig. 10C). These results suggest a dramatic change in biological reference points used for management as a result of climate change.

Hare et al. (2010) also developed an empirical spatial distribution (habitat) model for croaker that predicts the center and northern extent of range and spawning stock biomass based on winter surface air temperatures and spawning stock biomass. This model was forced with the same 14 model, 3 scenario ensemble described above and the abundance output from the ESAM. A northward shift of 50–100 km in the population was predicted. An issue not addressed in this study is potential changes in Atlantic croaker in the southern part of the range; decreases and northward shifts in the south may be balanced by increased productivity further north.

The Hare et al. (2010) case study provides an example of the use of statistical downscaling, ensemble approaches, and simple bias corrections to adapt IPCC-class climate models for assessing the impact of climate change on Atlantic croaker. The translation of predicted responses to metrics presently used in management (i.e., Fig. 10c) is particularly noteworthy and illustrative of the importance of incorporating climate information into management. The primary limitation of the analysis is that both the ESAM and distribution model rely on empirical relationships between basic, large-scale environmental variables and complex emergent LMR responses. As discussed in Section 2, such empirical relationships can break down. Greater mechanistic resolution of the interactions between croaker and coastal and estuarine processes could enhance the analysis and reveal new patterns of change. This would require enhancements to both the croaker and climate models. However, the mechanistic underpinnings of the key relationships used in this study – that between winter air temperature and estuarine water temperature, and that between estuarine water temperature and juvenile survival, have been examined in both the laboratory and the field (reviewed by Hare and Able, 2007) and suggest that the mechanisms underlying the coupled population–climate model may remain robust.

4.5. Scenarios for North Atlantic cod over the next 20–50 years under climate change

The ICES/GLOBEC Cod and Climate Change program held a workshop in June 2008 to develop projections of possible stock dynamics for cod over the next 20–50 years (Drinkwater et al.,

2010b). Experts in global and regional climate modeling, including decadal prediction, provided climate projections to drive models of biological dynamics, taking into account not only the direct effects on cod but also indirect effects on prey (including zooplankton), predators and competitors. Several types of model (mechanistic coupled physical–biological, statistical multivariate autoregressive, mechanistic stochastic) were applied to reconstruct past time series of observations and to project future changes. The overall conclusion from the workshop was that we are not yet able to produce credible projections of cod stock dynamics for the next 20–50 years due to limitations in global and regional climate models and to inadequate knowledge of biological responses.

An analysis of changes in distribution of North Sea cod over the past century explored the effects of fishing, temperature, winds and other environmental variables. Distribution changes have been large, as shown by fishing surveys and commercial catches, however despite good information on climate and other possible factors, it is not possible to choose among a number of plausible explanations (climate, fishing pressure, meta-population dynamics, biological interactions with prey fields). Our inability to explain such past patterns of change in a well-studied area mandates caution with regard to the credibility of future projections, even if we had reliable regional climate projections, due to biological and environmental complexities.

The Baltic Sea provides another regional example that illustrates the type of insight to be gained from effective linking of climatic and biological models while also revealing the limitations of present models. Climate projections for the Baltic in the 21st century were based on an assessment using dynamic and statistical downscaling (BACC, 2007). A stochastic food web model (Lindgren et al., 2009) was used to quantify the interactions between the three major fish species in the Baltic (cod, sprat and herring) as well as their prey, major environmental drivers and fishing pressure. Salinity plays a greater role than temperature in the biological response of cod in the Baltic and the projected changes in salinity show significant differences, depending upon which global model is used to force the regional scenarios (Meier et al., 2006). A significant decrease in salinity (outside the present day climatic variability) is found only for the runs forced by one AOGCM (ECHAM4) which is also the only AOGCM showing statistically significant change in windfields in this region. The pattern and strength of wind forcing and the magnitude of precipitation are critical for Baltic salinity and are not represented consistently or in detail in AOGCMs. The likelihood that cod will no longer be able to reproduce in the Baltic depends critically on whether and by how much the salinity decreases. The stochastic food web model provides valuable insight into fisheries management strategy that may prevent cod biomass from dropping below the limit reference value as salinity declines (Lindgren et al., 2010, Fig. 11), but the likelihood of such a salinity decline cannot be quantified from current climate models.

The Baltic is a particularly difficult enclosed sea to model, but it illustrates some of the problems in coupling from global to regional scales and incorporating the variables (in this case salinity) that play a dominant role in the biological dynamics. AOGCMs do not adequately reproduce the present climate for this region, and although it is possible to choose from among the AOGCMs those which give a better fit, such a selection would be more credible if based on valid structural reasons and more evidence supporting the hypothesis that a better fit to regional dynamics implies a better estimate of climate change trends (Section 3.1.4). The two major modes of variability over the Atlantic Ocean over the last century, the Atlantic Multi-decadal Oscillation (AMO) and the North Atlantic Oscillation (NAO), are represented in AOGCMs but their phasing and variability do not match the observed climate well for purposes of short-term regional forecasting. (Randall

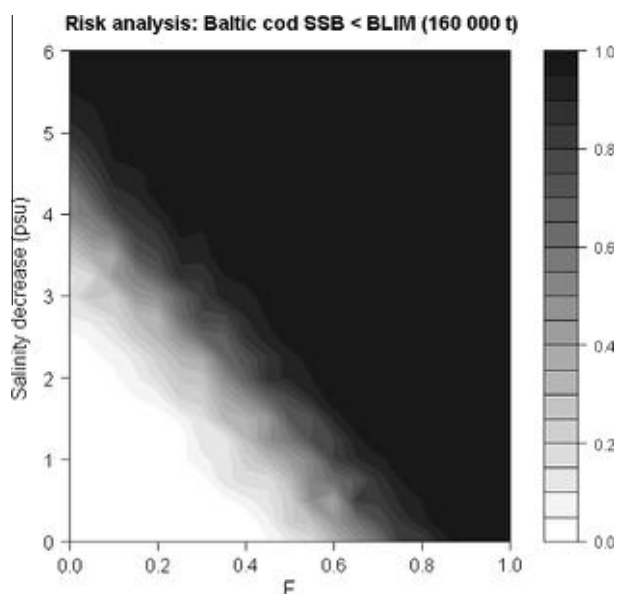


Fig. 11. The probability of Baltic cod spawning stock biomass (SSB) falling below the limiting stock size (Blim). Decrease in salinity is relative to the mean salinity from 1974 to 2004. The risk of falling below Blim increases rapidly and non-linearly as salinities decrease with increasing fishing mortalities (Redrawn from Lindgren et al. (2010)).

et al., 2007). Models that assimilate recent climate data (and include the decadal modes) show useful forecasting skill, at least over periods of a few years (e.g., Smith et al., 2007, Section 3.2), and could provide guidance for fisheries management on likely trends in fish stock dynamics.

4.6. End-to-end model of sardine and anchovy

Landings of sardines show synchronous variations off Japan, California, Peru, and Chile, with populations flourishing for 20 to 30 years and then practically disappearing for similar durations; periods of low sardine abundance have coincided with increases in anchovy populations (Lluch-Belda et al., 1989, 1992; Schwartzlose et al., 1999). The landings data have been related to the low-frequency component of different climate series, including the Pacific Decadal Oscillation (PDO) and El-Niño Southern Oscillation (ENSO) (Chavez et al., 2003) and to the low-frequency signature in global ocean temperature (Tourre et al., 2007). Better understanding of the mechanisms underlying these historical low-frequency fluctuations will provide critical information for evaluating the skill of coupled biophysical models and for forecasting future effects of climate change on these important LMRs.

As part of an ongoing project, an end-to-end model is being developed for sardine and anchovy in the California Current ecosystem. While this effort is in a proof of principle phase, it is included here to illustrate a likely direction that modeling climate effects on LMRs may take over next 10–20 years. The approach is to fuse the ROMS (Regional Oceanographic Modeling System, Shchepetkin and McWilliams, 2005) circulation model, the NEM-URO-NPZ lower trophic level model (Kishi et al., 2007), a full life cycle individual-based model that simulates multiple fish species (Rose et al., 1999), and a bioeconomics model of the fishing fleet. Simulations for 1948–2006 are underway, which include historical variation in climate and several ENSO events. All of the submodels can be solved simultaneously, and downscaled results from AOGCMs can be used as input to the ROMS model, thereby allowing true climate to fishers simulations and permitting, if necessary, explicit representation of feedbacks among all of the submodels. The ultimate goal is to be able to realistically simulate the relative effects of bottom-up (climate-induced), wasp-wait (food web), and top-down effects (predation by apex LMRs; fishing, Cury et al., 2008) on key middle-level forage fish species in the ocean food web.

5. Recommended practices

The previous sections of this paper have illustrated a broad range of issues surrounding and strategies for using IPCC-class climate models to predict the impacts of climate change on LMRs. Each strategy has strengths and weaknesses and the best approach will be problem-specific, but it is possible to provide general guidelines and highlight critical considerations for identifying effective approaches. A first step is to ensure that the LMR prediction objectives are consistent with the capabilities and objectives of IPCC-class climate models. In most cases, this consistency means multi-decadal to century-scale projections of climate change impacts on LMRs due to greenhouse gas accumulation in the atmosphere (Section 3.1). Spatially, changes in many climate variables are more coherent across climate model projections at global to ocean-basin scales and there can be significant differences between climate model projections at local and regional scales (e.g., 500–1500 km). IPCC-class climate models do often capture the statistics of climate variability modes (e.g., ENSO, PDO, NAO) and it is possible to use IPCC-class climate models to study the impact of climate variability on LMRs. However, century-scale simulations

from IPCC-class climate models are not designed to match the phase of climate variability modes and thus cannot be used to predict their evolution for the coming decades. Decadal-scale prediction experiments being conducted as part of the IPCC AR5 may help address this limitation by providing estimates of the state of climate variability modes over the next 1–10 years (see Sections 3.2 and 6).

Information from IPCC-class climate models can be integrated with any of the range of approaches described in Section 2.3, and the processes hypothesized to be critical for the LMRs of interest should dictate the modeling approach. A primary concern with simple LMR models for climate change applications is a common reliance on highly empirical relationships between climate and emergent LMR responses. Such relationships may break down as climate changes (e.g., Section 2). Hypotheses for the mechanisms underlying these relationships should be stated and supported so that some assessment of their robustness under new climate conditions is possible. More complex and mechanistic models can address this issue but require information at the appropriate space and time scales (Sections 2.1 and 2.2) to constrain and validate the model. In addition, exploring a range of possible outcomes in complex models may pose a computational challenge for climate change projections. The trade-offs between simple and complex models supports the value of a “two-pronged” approach similar to that articulated by Hollowed et al. (2009). Progress can be made by incorporating information from IPCC-class climate models into relatively simple to intermediate complexity stock assessment and ecosystem models (e.g., case studies 1–5), while efforts to develop, constrain, and couple comprehensive, “end-to-end” models with climate models continue (e.g., case study 6).

The appropriate number of climate model projections to consider is also contingent upon the objectives of the analysis. Focused diagnosis of the LMR response to a climate projection from a single model is appropriate for studies that emphasize detailed process-level analysis or rely on large-scale climate change features that are robust across models. Multi-model ensembles provide an effective means of defining a range of possible climate impacts and the average of many climate models has been shown to be closer to observed trends in several climate variables than any single model (Section 3.1.4). Refining multi-model projections by weighting or selecting models based on their representation of historical climate conditions is an active area of research, and there are no widely accepted practices for doing so. Recent studies have suggested weak linkages between a climate model’s representation of the mean climate state and the model’s ability to capture the historical climate change trend (Section 3.1.4). Any model weighting or selection scheme should be viewed as an important scientific aspect of a study and should be supported by both empirical evidence of increased skill at matching climate change trends over the historical period and process-level knowledge of the deficiencies in down-weighted models. The sensitivity of key results to the weighting scheme versus the use of a full ensemble should also be assessed. Lastly, care must also be taken to avoid choosing model weights based on random phase differences in climate variability. Any match with changes in the phase of PDO over the last 10 years in a century-scale climate simulation, for example, is purely coincidental (Section 3.1). Evaluating models in ways that reward such a random match may result in an otherwise poor model playing a disproportionate role in an LMR projection.

Adjusting projections using simple bias corrections to a climate model’s mean state for a given variable should be done with caution. Such adjustments assume that the projected climate change is independent of the mean climate state. Calculating the covariance between the projected change and the mean climate state across models provides one means of testing the validity of this assumption (McAfee et al., submitted for publication). Simple bias

corrections must also be calculated relative to long time-series to remove any effects of out-of-phase climate variability, and sensitivity of the primary results to their application should be documented.

The lack of phase agreement of modes of climate variability in century-scale climate simulations to those observed poses a challenge for calibrating LMR models coupled to century-scale climate simulations. Such models should not be calibrated against observations on a year-to-year basis if climate variability is an important mechanism driving year-to-year changes in the LMR of interest. Evaluation metrics that are not compromised by phase differences in climate variability modes, such as the mean and variance of relevant quantities over many years or the mean and variance of quantities during similar phases of the prominent modes of climate variability, should be used instead. If a sufficient time series is not available or if statistical properties are insufficient to evaluate the model, historical ocean-ice simulations forced with atmospheric reanalysis provide an alternative platform for LMR model calibration. The atmospheric forcing used in such simulations reflects observed year-to-year variations in large-scale atmospheric features driven by climate variability (Large and Yeager, 2004; Griffies et al., 2009).

A diverse array of downscaling techniques can be enlisted in cases where the resolution of models is not fine enough to explicitly capture processes critical to the LMR of interest (Section 3.1.1). Crucial steps in establishing the plausibility of statistical downscaling include identifying mechanisms that link the fine-scale features of interest with the coarse scales of climate models, gathering enough data to establish a statistically significant relationship, and assessing if the statistical relationship is likely to remain robust as climate changes. Key considerations for dynamical downscaling include computational cost and whether the coarse-scale forcing from climate models can be effectively coupled with fine-scale domains. One-way dynamical downscaling allows refined simulations to be run independently from global simulations which may offer a distinct advantage for studying the impacts of climate change on regional LMRs. However, this configuration does omit feedbacks from the regional scale dynamics to the ocean-basin and global scales. In all cases, downscaled results are strongly linked to the characteristics of the global, coarse-scale climate model simulation (e.g., Section 4.5). Careful diagnosis of the characteristics of the global-scale simulation in the region of interest is an essential first step for any downscaling activity.

6. Priority developments

While coupling IPCC-class climate models and LMR models can be challenging, substantial progress in predicting and understanding the impacts of climate change on LMRs can be made using present models and observations. There are, however, several areas where improvements to models and observations could greatly improve the capacity to predict climate impacts on LMRs. Efforts to address these issues should be undertaken in parallel with efforts to apply existing tools.

One of the primary limitations of many LMR models for climate change applications is the limited mechanistic understanding of climate-LMR links and the limited representation of these links within models (Section 2). Uncertainties related to the use of highly empirical relationships between climate and LMR responses are difficult to quantify but can be large. Process-oriented field and laboratory observations focused on understanding these mechanisms and constraining their parameterization within LMR models are needed to address this issue. Observational and modeling efforts should be tightly integrated. Process-oriented observations should focus on those processes and parameters that make large

contributions to the uncertainty in projections of the impact of climate on LMRs, and information gained from these efforts should be continually incorporated into model projections to refine projections and reassess dominant uncertainties. Initiating this iterative process requires initial projections to be made despite existing uncertainties.

Understanding the linkages between LMRs and climate change and variability requires co-occurring LMR and physical climate observations over a broad range of spatial and temporal scales. This will require committed maintenance of existing time series and ocean observing systems, coordination of observational efforts between regions, and the initiation of new time series and observing systems in regions without existing measurements. It will also require continued investment in observational technologies capable of resolving finer-scale interactions between LMRs and their environment and closing the scale gap between physical and biological measurements.

Development of comprehensive, robust, and highly mechanistic “end-to-end” LMR models is essential for effectively integrating the combined influence of climate dynamics, ecosystem interactions, and human activities on LMRs (Sections 2.3.2 and 4.6). Critical knowledge gaps in “end-to-end” models need to be identified, and more clearly defined objectives for incorporating information from these models into management decisions are needed. While complex end-to-end models have proven useful for providing strategic long-term advice, incorporating the information from such models into year-to-year reference points and quotas requires the development of rigorous testing and review procedures. This includes augmenting data collection efforts so that the data required to support these models (i.e., constrain interactions, validate dynamics) is available. The review process will require panels with diverse expertise capable of communicating across disciplines.

Key improvements to century-scale physical climate model simulations for LMR applications include better resolution of shelf-scale circulation and basin-shelf exchanges. Increases in computing power over the next decade should enable climate simulations to be regularly run with grid resolutions comparable to present regional ocean simulations (~10 km). Increased resolution, in combination with appropriate changes to sub-grid-scale parameterizations, should help decrease model biases in some coastal regions (e.g., eastern boundary upwelling regions). Model biases and inter-model spread in climate models, however, arise from diverse sources beyond resolution. General efforts to improve understanding of climate system dynamics over a range of scales and improve the representation of these dynamics within climate models are essential to understanding and addressing model biases and inter-model spread.

While improved climate model resolution should facilitate the direct application of IPCC-class climate models for LMR prediction, the large range of spatial and temporal dynamics influencing LMRs (Section 2.1) suggests that downscaling techniques will continue to play an important role in the prediction of climate impacts on LMRs. Finer-resolution global simulations should facilitate dynamical downscaling for continental shelves by providing boundary conditions that better reflect shelf dynamics, bathymetry, and the energetic ocean currents often adjacent to shelves (particularly along the western boundaries of ocean basins). The increases in computing power that enable finer-resolution global simulations should also allow regional simulations to more adequately resolve near-shore regions (e.g., estuaries) critical to the early life stages of many LMRs.

A key limitation of century-scale climate model simulations for LMR applications is that the simulations are not designed to predict the state of climate variability modes over the next decade. Most LMR management plans are formulated over inter-annual

to decadal time scales, and robust decadal-scale climate prediction systems with defined uncertainties are essential for incorporating climate information into LMR management. This is particularly true for ecosystems that exhibit marked climate-driven regime shifts on decadal time scales (Section 2.1). Decadal climate prediction simulations being conducted for IPCC-AR5 will provide further insight into the mechanisms underlying climate variability and a comprehensive evaluation of the extent to which decadal climate prediction can be realized with present climate models and observations.

Continued development of Earth System Models will provide a platform for running simulations that more fully integrate climate dynamics with aspects of ecosystem dynamics and human activities. ESM simulations presently underway for IPCC AR5 will provide projections of numerous ecologically relevant variables (e.g., productivity, oxygen, alkalinity) not included in physical climate model projections. In many cases, these new variables have closer mechanistic links to LMR responses than physical climate variables. Improvements in the representation of marine food web dynamics and the higher trophic levels should further strengthen mechanistic links and provide a strong foundation for end-to-end modeling efforts. It should be recognized, however, that ESMs do include many potentially complex interactions between climate and ecosystems. The scientific understanding and constraints on some of these interactions are low (Denman et al., 2007). Model projections will improve as these interactions become better observed, better understood, and lead to model improvements.

Improved measures of the likelihood and accuracy of LMR projections are essential for devising appropriate management strategies based on projections (Stow et al., 2009; Planque et al., submitted for publication). Ensemble approaches (Section 3.1.2) are essential in this regard, but there are no widely-accepted approaches for refining these estimates based on objective metrics of model skill (Randall et al., 2007). For LMR projections, ensembles should account for parameter uncertainty and, where necessary, consider multiple LMR models capable of explaining past observations and whose model structures are supported on theoretical grounds. The value of detailed diagnosis of individual projections for understanding mechanisms, however, must still be recognized despite the value of ensembles for quantifying uncertainty.

7. Concluding remarks

The importance of understanding the impacts of climate variability and climate change on LMRs has been widely recognized by international and national organizations with mandates to monitor and responsibly manage these valuable resources. IPCC-class climate models will play a central role in studying these impacts and developing forecasts that can be used to formulate appropriate long-term management policies. Understanding of the climate system and its representation within IPCC-class climate models has progressed to a point where many applications of IPCC-class climate models to LMR problems are now possible. Concerted research in the areas outlined in Section 6 over the next decade has great potential to make forecasts of the impacts of climate change on LMRs more robust and mechanistic, decrease the uncertainty in projections, and enable predictions on space and time scales not presently possible.

The success of efforts to predict climate impacts on LMRs is contingent upon close collaboration between climate and LMR scientists, as well as other experts spanning a range of physical, biological, chemical and socioeconomic factors that influence LMRs and the ecosystems in which they reside. Such collaborations must be populated with scientists who are able to communicate across disciplines. The present synthesis is intended to facilitate this pro-

cess, but sustained success will require educational programs with the flexibility and breadth to accommodate the multi-disciplinary nature of climate change impacts problems. Dedicated funding mechanisms will also be necessary to develop the underlying science in relevant research areas, integrate developments, and translate new science to improved management. These are formidable tasks, but rapid progress in recent years gives cause for great optimism.

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