Managing living marine resources in a dynamic environment: the role of seasonal to decadal climate forecasts

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Abstract

Recent developments in global dynamical climate prediction systems have allowed for skillful predictions of climate variables relevant to living marine resources (LMRs) at a scale useful to understanding and managing LMRs. Such predictions present opportunities for improved LMR management and industry operations, as well as new research avenues in fisheries science. LMRs respond to climate variability via changes in physiology and behavior. For species and systems where climate-fisheries links are well established, forecasted LMR responses can lead to anticipatory and more effective decisions, benefitting both managers and stakeholders. Here, we provide an overview of climate prediction systems and advances in seasonal to decadal prediction of marine-resource relevant environmental variables. We then describe a range of climate-sensitive LMR decisions that can be taken at lead-times of months to decades, before highlighting a range of pioneering case studies using climate predictions to inform LMR decisions. The success of these case studies suggests that many additional applications are possible. Progress, however, is limited by observational and modeling challenges. Priority developments include strengthening of the mechanistic linkages between climate and marine resource responses, development of LMR models able to explicitly represent such responses, integration of climate driven LMR dynamics in the multi-driver context within which marine resources exist, and improved prediction of ecosystem-relevant variables at the fine regional scales at which most marine resource decisions are made. While there are fundamental limits to predictability, continued advances in these areas have considerable potential to make LMR managers and industry decision more resilient to climate variability and help sustain valuable resources. Concerted dialog between scientists, LMR managers and industry is essential to realizing this potential.

1. Introduction

Paleoecological and contemporary analyses demonstrate that large fluctuations in fish populations are associated with variations in climate (Baumgartner et al., 1992; Finney et al., 2002; Lehodey et al., 2006; Finney et al., 2010; Brander, 2010; Holsman et al., 2012; Barange et al., 2014). Clearly, climate-driven variability has always been part of the fisher and fisheries manager experience. However, the management response to climate variability has often been reactionary, and enacting efficient coping strategies has, at times, been difficult (McGoodwin, 2007; Chang et al., 2013; Hodgkinson et al., 2014). For instance, unrecognized periods of environmentally- or climate-driven reduction in productivity contributed to the demise of Pacific sardine (*Sardinops sagax*) fishery in California in the 1950s (Murphy 1966; Lindegren et al., 2013; Essington et al., 2015), the collapse of the Peruvian anchoveta (*Engraulis ringens*) fishery in the 1970s (Clark, 1977; Sharp, 1987), and overfishing of cod (*Gadus morhua*) in the Gulf of Maine (Pershing et al., 2015, Palmer et al. 2016). Unanticipated temperature-induced changes in the timing of Gulf of Maine Atlantic lobster (*Homarus americanus*) life-cycle transitions resulted in an extended 2012 fishing season and record landings, but outstripped processing capacity and market demand, leading to a collapse in prices and an economic crisis in the lobster fishery (Mills et al., 2013). Similarly, an unforeseen extreme low water temperature event resulted in a $10-million-dollar loss to the Taiwanese mariculture industry in 2008 (Chang et al., 2013). Failure to prepare for inevitable climate variability on seasonal to decadal scales can also alter the rebuilding times of stocks that have previously been overfished (Holt and Punt, 2009; Punt 2011; Pershing et al., 2015) and break down international cooperative harvesting agreements for border straddling stocks and highly migratory species (Miller and Munro, 2004; Hannesson, 2006; Hannesson, 2012).

Negative impacts of climate variability on coastal economies can be exacerbated when fishers, aquaculturists, and fisheries managers make decisions about future harvests, harvest allocations, and operational planning based on previous experience alone, without consideration of potential novel climate states (Hamilton, 2007). For instance, current fisheries abundance forecasts are largely based on historical recruitment (i.e. addition of new individuals to the fishery) estimates, and aquaculture harvests on the basis of historical growth patterns. While this approach makes harvest decisions robust to a range of historical uncertainty, it may be insufficient when an ecosystem shifts to a new productivity state, when a productivity trend moves beyond historical observations, or when the degree of variation in productivity changes (Wayte, 2013; Audzijonyte et al., 2016). Past patterns may not always be a good indication of future patterns, especially under anthropogenic climate change (Milly et al., 2008). Species will experience new conditions across multiple ecologically significant climate variables (Williams et al., 2007; Rodgers et al., 2015), challenging our ability to manage living marine resources (LMRs) under the assumption of stationarity. Adapting our decision frameworks to climate variability at seasonal to decadal scales can serve as an effective step towards improving our long-term planning ability under future climate change (Link et al., 2015).

Incorporating environmental forcing into management frameworks for LMRs is challenging because the emergent effects of climate on marine ecosystems are complex. For example, atmospheric forcing can drive changes in ecologically significant physical or chemical variables that directly affect organismal physiology and behavior (e.g. temperature-driven changes in oxygen demand; Pörtner and Farrell, 2008), species distribution (e.g. Pörtner and Knust, 2007), phenology (e.g. Asch, 2015), and vital rates, such as growth (e.g. Kristiansen et al., 2011; Audzijonyte et al., 2013; Audzijonyte et al., 2014; Audzijonyte et al., 2016). Additionally, climate can indirectly impact LMR productivity by affecting key biotic processes, such as variation in prey fields and energy transfer in response to fluctuations in alongshore and cross-shelf transport (e.g. Bi et al., 2011; Keister et al., 2011; Combes et al., 2013; Wilderbuer et al., 2013) or to climate-driven changes in primary productivity and phytoplankton size-structure (Daufresne et al., 2009). Climate-related variations in the abundance of predators, competitors, and parasites can also have an indirect effect on LMRs (e.g. Boudreau et al., 2015), and concurrent responses to fishing, habitat loss, and pollution may further complicate observed responses (Brander, 2007; Halpern et al., 2008; Andrews et al., 2015; Fuller et al., 2015; Halpern et al., 2015).

While such biophysical complexities challenge efforts to implement climate-informed fisheries management frameworks, concerted observational and modelling efforts across decades have led to some improved understanding of climate-ecosystem interactions in many regions (Lehodey et al., 2006; Alheit et al., 2010; Ainsworth et al., 2011; Hunt et al., 2011; Di Lorenzo et al., 2013; Bograd et al., 2014). These gains have been mirrored by improved climate predictions at the temporal and spatial scales relevant to LMRs and their management, e.g. days to decades (Hobday and Lough, 2011; Stock et al., 2011). Operational seasonal predictions have now enabled development of climate services for a range of applications relevant to society (Vaughan and Dessai, 2014). For example, improvements in model spatial resolution have allowed skillful prediction of hurricane activity at a sub-basin scale relevant to climate risk management (Vecchi et al., 2014). Seasonal climate forecasts have also reduced vulnerability of the agricultural sector to climate variability (Meinke and Stone, 2005; Meza et al., 2008; Hansen et al., 2011; Zinyengere et al., 2011; Takle et al., 2014, Zebiak et al., 2015 and references therein) and have informed water resources decision making (Hamlet et al., 2002; Abawi et al., 2007).

Furthermore, seasonal climate forecasts have been incorporated into human health early warning systems for diseases, such as malaria, that are influenced by climatic conditions (Abawi et al., 2007) and for outbreaks of noxious jellyfish (Gershwin et al., 2014). Enhanced capability has also made possible skillful seasonal forecasts of LMR-relevant variables at fine spatial and temporal scales useful to industry (defined here to include fisheries and aquaculture industries) and management (Stock et al., 2015; Siedlecki et al., 2016). While multi-annual to decadal predictions are at an initial stage of development and are not yet operational (Meehl et al., 2014), in specific ocean regions, particularly the North Atlantic, multi-annual forecasts appear skillful over several years (Yang et al., 2013; Msadek et al., 2014a; Keenlyside et al., 2015), and may show promise for some LMR applications (Salinger et al., 2016).

The objective of this paper is to assess present and potential uses of these advances in climate predictions to facilitate improved management of wild and cultured LMRs. This effort was initiated at the workshop "Applications of Seasonal to Decadal Climate Predictions for Marine Resource Management" held at Princeton University on June 3-5 2015, which brought together 60 scientists spanning climate and marine resource disciplines. This resulting synthesis establishes a common understanding of the prospects and challenges of seasonal to decadal forecasts for LMRs to support further innovative and effective application of climate predictions to management decisions. In Section 2, we describe climate prediction systems and discuss their strengths and limitations. In Section 3, we briefly summarize climate-sensitive decisions made within management of commercially exploited species, protected and endangered species, and for fishing and aquaculture industry applications. Section 4 presents case studies drawn from peer-reviewed literature highlighting the scope of past and present applications. Sections 5 and 6 distill successful components across these existing applications and identify priority developments based on the material in Sections 2-4. Section 7 offers concluding remarks on prospects for expanded use of climate predictions for marine resource management.

2. Predicting environmental change across space and time scales

Advances in global dynamic climate prediction systems raise the prospect of skillful environmental prediction at the time scales relevant to LMR management and industry decisions. In this section, we first describe these prediction systems (Section 2.1), emphasizing characteristics relevant to informing the management decisions which will be described in

Section 3, and then discuss evaluation of forecast skill (Section 2.2). Lastly, we provide a brief overview of existing studies of prediction skill for LMR-relevant climate variables (Section 2.3).

2.1. Overview of climate prediction systems

There exist two types of climate prediction models: dynamical models based on knowledge of the underlying physics of the climate system, and statistical models based on empirical relationships. The focus here is on dynamical seasonal to decadal prediction systems derived from Global Climate Models (GCMs), but it is important to note that statistical climate prediction models have also been used with success at seasonal time scales (Xue et al., 2000; van den Dool, 2007; Muñoz et al., 2010; Newman et al., 2011; Barnston et al., 2012; Ho et al., 2013; Barnston and Tippett, 2014; Chapman et al., 2015). Statistical climate predictions require considerably less computing resources than dynamical prediction systems and are used by climate offices throughout the world, particularly where high-performance computing facilities are not available. However, when developing a statistical forecast, care must be taken to not impart artificial skill through the method used to select predictors (DelSole and Shukla, 2009) or through the forecast sets used for training and skill assessment not being sufficiently independent of each other. Statistical predictions are also limited by the assumption that historically observed statistical relationships between climate variables will be maintained in the future (Mason and Baddour, 2007). By contrast, dynamical seasonal to decadal climate predictions arise more directly from fundamental physical principles expected to hold under novel climate states (Randall et al., 2007). Dynamical models can also forecast quantities that are difficult to observe and thus develop statistical models for (e.g., bottom temperature). We note, however, that many small-scale processes, such as cloud microphysics or submesoscale fronts and eddies, are not resolved by most GCMs and uncertainty connected to the parameterization of such "sub-grid scale" processes within GCMs can impact prediction skill (Warner, 2011).

Dynamical climate predictions on seasonal to decadal time scales rest on the premise that knowledge of the present climate and the dynamic principles governing its evolution may yield useful predictions of future climate states. Four core components are thus required to make such predictions at global scales and translate them for users: 1) global dynamical climate models, 2) global observing systems, 3) a data assimilation system, and 4) analysis and dissemination systems to provide predictions to stakeholders across sectors. We provide a brief overview of each of these components below.

2.1.1. Dynamical coupled global climate models for seasonal to decadal prediction

GCMs are comprised of atmospheric, ocean, sea-ice and land physics and hydrology components, each governed by dynamical laws of motion and thermodynamics solved numerically on a global grid. GCMs used for seasonal to decadal prediction are largely analogous to those used for century-scale climate change projection (e.g. Stock et al. 2011), but the simulation design is different (Fig. 1). In the climate change case (Fig. 1, bottom), the goal is to track the evolution of the climate over multi-decadal time scales as it responds to accumulating greenhouse gases (GHGs) and other anthropogenic forcing. The simulations have three components: a pre-industrial control of several hundred to several thousand years where the model comes to quasi-equilibrium with preindustrial GHGs and aerosol concentrations, a historical segment where GHGs increase in accordance with observed trends, and a projection following one of several future GHGs scenarios (Moss et al., 2010; van Vuuren et al., 2011). Because initial conditions at the start of the preindustrial period are largely "forgotten" except possibly in the abyssal ocean, the only aspects linking historical and future simulations to a specific year are the GHGs, land cover changes, solar forcing, land use changes, and other radiatively active atmospheric constituents (e.g. aerosols). Internal climate variations arising from interactions in the components of the climate system itself such as the El Niño Southern Oscillation (ENSO) are represented in climate simulations, but their timing/chronology does not and is not expected to agree with past observations. The objective is to obtain an accurate representation of the evolving climate statistics over multiple decades, including the statistics of internal climate variation, rather than precise predictions of the climate state at a given time. Indeed, ensembles of historical and future simulations begun from different initial conditions, and containing different realizations of internal climate variations, are often employed in obtaining these statistics (Kay et al., 2015).

On the other hand, seasonal (months to a year) prediction skill (Fig. 1, top) largely depends on initializing the model using information specific to the current climate state. Owing to the chaotic nature of the atmosphere, daily weather has a deterministic predictability limit of 5-10 days (e.g. Lorentz, 1963; Goddard et al., 2001). In seasonal forecasts, the predictability horizon is extended by forecasting monthly or seasonally-integrated statistics rather than daily weather, and by exploiting the more slowly evolving elements of the climate system, such as the ocean. It is assumed that the initial climate state sufficiently determines the future evolution of internal climate variations so that skillful predictions of climate states within the forthcoming months are possible. The presence of ENSO in June, for example, will impact extra-tropical sea-surface temperature (SST) in September via teleconnections that are now substantially captured by many GCMs, albeit some important biases remain (Deser et al., 2010).

In today's coupled dynamical prediction systems, seasonal prediction is thus classified as an initial value problem rather than a boundary value problem. As the response to changes in external forcing like GHGs occurs over much longer time scales, their predictive skill is more dependent on initialization to current climate conditions rather than boundary conditions (i.e. external forcing). Although external forcing changes are typically small over periods spanned by individual seasonal forecasts, they can be significant over the multi-decadal periods spanned by successive real time forecasts and the accompanying retrospective forecasts discussed in Section 2.1.3, and therefore should ideally remain included in seasonal forecast models (Doblas-Reyes et al., 2006; Liniger et al., 2007). Annual to decadal predictability (1 to 30 years), in contrast, arises from both predictable internal climate variations following model initialization and external forcing, presenting a hybrid problem (Fig. 1, middle panel, Meehl et al., 2014).

Another difference between GCMs configured for climate projections and seasonal to decadal predictions systems has been the successful expansion of the climate change GCM configuration to earth system models (ESMs) that include biogeochemistry (e.g. Bopp et al., 2013). ESMs can simulate biological and chemical properties (e.g. oxygen, pH, nutrients, primary and secondary production) strongly linked to LMRs (Stock et al., 2011), and thus they have been broadly applied to assess climate change impacts on LMRs (e.g. Cheung et al., 2009; Barange et al., 2014). While incorporation of earth system dynamics in global seasonal to decadal prediction models remains in an early stage of development (Séférian et al., 2014; Case Study 4.6), it may yield benefits at the seasonal to decadal scale. In Section 2.3, discussion of LMR-relevant seasonal to decadal predictions will be focused on the physical variables produced by the operational seasonal to decadal global forecast systems, but priority developments to expand biogeochemical prediction capabilities will be discussed in Section 6.

2.1.2. The global climate observing system supporting climate prediction

The initialization of seasonal to decadal climate predictions is generated via a range of data assimilation approaches (Section 2.1.3) that draw observational constraints from the global climate observing system. This system collates diverse observations of many climate quantities across the globe including those obtained from satellites, land-based weather stations, radiosondes, weather radars, aircrafts, weather balloons, profiling floats, moored and drifting ocean buoys, and ships (see http://www.wmo.int/pages/prog/gcos/index.php?name=ObservingSystemsandData for a list of the global climate observing system's observational networks and climate variables). Expansion of the global climate observing system across decades has improved prediction skill. For instance, establishment of the Pacific Tropical Atmosphere-Ocean (TAO) moored buoy array in the early 1990s (McPhaden, 1993) was key in enhancing seasonal prediction skill of ENSO and ENSO-related SSTs (Ji and Leetmaa, 1997; Vidard et al., 2007). Similarly, the addition of Argo profiling floats to the global ocean observing network improved seasonal SST forecast skill (Balmaseda et al., 2007).

2.1.3. Assimilating observations to constrain the initial climate state

While the advent of satellites and of observing platforms, such as the TAO array and Argo floats, have considerably increased the number of available observations, much of the Earth system, particularly in the deep ocean (> 2000 m), remains unobserved. Climate prediction systems combine observational and model constraints using a data assimilation system to fully initialize climate predictions. Diverse approaches are used, from nudging methods to four-dimensional variational analyses and ensemble Kalman filters. For instance, the NOAA Geophysical Fluid Dynamics Laboratory (GFDL) coupled data assimilation system produces an estimate of the present climate state by using an ensemble Kalman filter algorithm to combine a probability density function (PDF) of observations, both oceanic and atmospheric, with a prior PDF derived from the dynamically coupled model (Zhang et al., 2007). For more details on data assimilation techniques we refer readers to Daley et al. (1991), Kalnay et al. (2003), Tribbia and Troccoli (2007), Edwards et al. (2015), Zhang et al. (2015), and Stammer et al. (2016).

Assimilating observations produces an initialized climate state that differs from what the climate models would simulate were they running freely. This is because dynamical climate models are an approximation of the real world, and as such can show systematic bias (Warner, 2011). Once a seasonal forecast begins, dynamical models drift back to their freely running state. In some cases, drifts can be as large as the signal being predicted, particularly for longer lead-times, and can degrade forecast skill (Goddard et al., 2001; Magnusson et al., 2013; Smith et al. 2013). It is therefore important to remove this drift to obtain the signal of interest for input into LMR models. While diverse approaches for this have been proposed, they primarily involve subtracting the mean drift from across a set of retrospective forecasts (hindcasts). For example, to correct for model drift in a January-initialized SST anomaly forecast for May, the mean drift for January-initialized May forecasts from the past 30 years is subtracted from the predicted temperature trend.

While a primary goal of data assimilation is forecast initialization, the estimates of atmospheric or ocean state produced via data assimilation are also useful for model verification and calibration, retrospective studies of past ocean variability, and "nowcasts" of present conditions. Such historical time series of past ocean state estimates are referred to as reanalysis datasets. While often taken as "observations" they are obtained using the model and a data assimilation system in the same way as was described for model initialization. Hence, reanalyses are model-dependent and each climate prediction center produces its own version of what the earth system looked like in the past (Table A1). While such reanalyses are generally in agreement for variables that are widely sampled (e.g. SST after the advent of satellites) over scales resolved by the GCMs, there are differences, reflecting model uncertainty, the scarcity of observational data, and the fact that single observations may not be representative of the large-scale climate state. One way to estimate uncertainties among ocean reanalyses is to conduct ocean reanalysis intercomparisons (Balmaseda et al., 2015). Table A1 lists six operational ocean reanalysis products that are available for the period from 1979 to present and that are used in a Real-time Ocean Reanalysis Intercomparison Project (Xue et al., in review). One example of uncertainties of ocean reanalysis products is shown in Fig. 2 for temperature anomalies at a depth of 55 m during April 2015. Some areas, such as the west coast of North America, clearly stand out as being consistent between reanalysis products. This has also been shown in some recent seasonal forecast efforts in the region (Siedlecki et al., 2016), increasing confidence in their treatment as "observations". By contrast, temperature values along the Northeast shelf of North America are more uncertain. This highlights the importance of confirming consistency of reanalyses with observations at the scales of interest when possible (Stock et al., 2015), and the paucity of oceanic variables for which we can robustly evaluate prediction skill.

2.1.4. Analysis and dissemination in support of diverse stakeholders

The goal of analysis and dissemination systems is to take the raw output from the predictions and package it in a way that can be easily accessible and understood by stakeholders. Generally, because of the variety of users and applications of seasonal forecasts, most climate prediction centers focus on ensuring that seasonal climate model output is corrected for model drift (see Section 2.1.3 for more details) and verified. Forecast verification, which entails an assessment of forecast skill, is described in Section 2.2. Any further post-processing, such as downscaling to application-relevant spatial scales, is performed on an ad hoc basis in collaboration with users.

Climate forecasts are inherently uncertain because of the chaotic nature of the climate system, whereby small differences in initial conditions can lead to a diverse range of climate states (Lorenz, 1963; Wittenberg et al., 2014), as well as our imperfect understanding of the climate system. In an attempt to capture some of this uncertainty, a collection of forecasts differing in their initial conditions or model parametrizations, referred to as an ensemble, is produced (see Section 2.2 for more details). For a forecast to be useful for decision making, it needs to represent the likelihood of different outcomes. Probabilistic forecasts constructed from information provided by the ensemble forecast fill this need. Such forecasts are commonly communicated as probabilities that the outcome will be in the lower, middle or upper tercile of the climatological PDF (Fig. 3), although many other possibilities exist. Reliability, the property that forecast probabilities are similar to observed frequencies, is crucial for decision making. However, probabilistic forecasts based on raw forecast output tend to be overconfident, and are thus often recalibrated to improve their reliability (Sansom et al., 2016). Deterministic forecasts describing the average outcome of the forecast ensemble are also sometimes disseminated. While relatively simple to interpret, they are generally less useful than probabilistic forecasts because they contain no measures of uncertainty or the likelihood of alternative outcomes.

Once the climate predictions are verified, most prediction centers deliver forecasts to users via the internet. For example, seasonal forecasts from NOAA NCEP, GFDL, and numerous other modeling centers can be downloaded from the North American Multi-Model Ensemble

(NMME) (Kirtman et al., 2014) website at http://www.cpc.ncep.noaa.gov/products/NMME/. Hindcasts (i.e. retrospective forecasts) are archived on the same site, and skill assessment maps are also made available. It should be noted that because of the large variety of users and the limited resources devoted to delivery systems, model output presentation and visualization is rarely customized to specific user needs. Thus, there is utility in repackaging standard forecasts specifically for the fisheries and aquaculture sectors as "targeted forecasts" (Hobday et al., 2016; Siedlecki et al., 2016).

2.2. Forecast skill

In addition to providing users with information on forecast uncertainty through well-calibrated probabilistic forecasts as discussed above, skill information is essential for LMR managers or fishing industry personnel to assess confidence in seasonal to decadal forecasts. Hence, model verification, which assesses prediction quality of the forecast through skill assessment, is essential for seasonal to decadal predictions to be practically useful to decision-making. As well as enabling drift correction as described in Section 2.1.3, retrospective forecasts are used by climate prediction centers to establish forecast skill. This involves initializing a suite of predictions across the past several decades and testing whether predictions would have been successful (e.g. given an estimate of climate conditions in January of 1982, how well can the model predict temperature and precipitation anomalies for the rest of 1982). These retrospective forecast suites are also made available to potential users to assess predictability of particular variables of interest.

Numerous prediction skill measures have been developed (Stanski et al., 1989; von Storch and Zwiers, 2001; Jolliffe and Stephenson, 2003; Mason and Stephenson, 2007; van den Dool, 2007; Wilks, 2011). Generally, stakeholders are interested in the correctness of a forecast (Mason and Stephenson, 2007), and thus the anomaly (see Section 3.1.3 for details on how anomalies are calculated) correlation coefficient (ACC) and root mean square error (RMSE) between the model retrospective forecast and observations are among the most commonly used prediction skill measures for deterministic forecasts. For a probabilistic forecast, the Brier Score (BS) is often used to measure of the mean squared probability error of whether an event occurred. The value of the dynamical prediction can also be assessed by comparing the skill of a dynamical forecast output to that of climatology. For instance, the ranked probability skill score

(RPSS), a commonly used measure of probabilistic prediction, is used to reflect the relative improvement given by the forecast over climatology (Fig. 3). Seasonal to decadal prediction skill is also often compared against that of a persistence forecast. A persistence forecast is a forecast produced by simply projecting forward the current climate anomaly. For example, a January one-month lead SST forecast would be compared against a persistence forecast derived from maintaining the December temperature anomaly into January. Statistical predictions, particularly for decadal forecasts whose skill also depends on changes in radiative forcing not represented in a persistence forecast, can also act as useful tools against which to assess dynamical prediction skill (Ho et al., 2013). While statistical or persistence forecasts provide an important benchmark against which to assess the added value of dynamical seasonal forecasts, a skillful statistical (e.g. Eden et al., 2015) or persistence forecast can be as relevant to users as a skillful dynamical forecast.

As discussed in Section 2.4.1, for a forecast to be useful to LMR managers and the fisheries and aquaculture industries, not only does it need to be skillful, but its uncertainty has to be representative of the spectrum of potential outcomes. Climate prediction uncertainty arises from different sources (Payne et al., 2016), with internal variability and model uncertainty being the most important for seasonal to decadal predictions, particularly at regional scales (Hawkins and Sutton, 2009). Internal variability uncertainty stems from emergent chaotic properties of the climate system, and causes predictions differing only a little in initial conditions to evolve to quite different climate states (Lorenz, 1963; Wittenberg et al., 2014). In an attempt to capture some of this internal variability uncertainty, climate prediction centers produce different forecasts characterized by the same global dynamic model started with slightly different initial conditions chosen to reflect equally probable initial states given a set of observational constraints. The collection of such forecasts is referred to as a single-model ensemble.

Forecast uncertainty also arises from our incomplete understanding of the climate system, as reflected in the forecast model being a simplification of the real world. Model error can stem from uncertainties in the parameterizations of physical processes that are either not well understood, act at a scale below the model's spatial or temporal resolution, or are too computationally expensive to be modeled explicitly. Errors in numerical approximations also add to model uncertainty. Multi-model ensembles are a way to characterize forecast uncertainty arising from this model uncertainty. In such ensembles, simulations from entirely different models, often from various prediction centers, are combined to produce a forecast output. The North American Multi-Model Ensemble (NMME) (Section 2.1.4) is an example of such a forecast. Seasonal forecasts from leading US and Canadian prediction systems are combined to produce a multi-model ensemble mean seasonal forecast. Single model forecasts are also provided, but the multi-model mean has been shown to have higher prediction skill than any single model (Becker et al., 2014). The skill increase comes from error cancellation and the non-linearity of model diagnostics (Becker et al., 2014). In addition to a more accurate measure of central tendency, use of a multi-model ensemble often allows for a more complete representation of forecast uncertainty. Ensemble methods thus allow forecasts to be probabilistic, reflecting the range of all potential outcomes (Goddard, 2001). To base decisions on a comprehensive assessment of risk, incorporation of seasonal to decadal predictions into LMR applications should include these estimates of forecast uncertainty.

Dynamical processes that operate at scales finer than a model's resolution must be parameterized. The spatial resolution of a model grid dictates the breadth of processes that may be simulated, and differences in this resolution can influence model error and thus limit forecast skill. Indeed, an increase in resolution from the 100 to 200-km atmospheric resolution common to many of the current seasonal to decadal prediction systems (Kirtman et al., 2013), to 50-km resulted in better seasonal temperature and precipitation forecast skill, particularly at a regional scale (Jia et al., 2015). Nevertheless, in regions where local and/or unresolved sub-grid scale processes strongly modulate the basin-scale climate signal, even such relatively high resolution (50-km atmosphere and 100-km ocean) predictions have limited skill. For example, global climate models that have an ocean resolution of 100-km to 200-km have a bias in both ocean temperature and salinity in complex coastal environments such as the US Northeast Continental Shelf (Saba et al., 2016). These biases may partially explain the relatively poor predictive skill of seasonal SST anomalies predictions in this region (Stock et al., 2015). When both atmosphere and ocean model resolution are increased (50-km atmosphere, 10-km ocean), such biases are substantially reduced (Fig. 4) because the Gulf Stream coastal separation position as well as regional bathymetry are more accurately resolved. We stress, however, that while enhanced resolution appears critical for some scales and ecosystems, existing models show considerable prediction skill for marine resource relevant variables at other scales and ecosystems (Section 2.3). High resolution GCMs (10-km ocean versus 100-km in many prediction systems), are also considerably more computationally expensive to run, currently limiting their use in operational climate prediction systems. Furthermore, biases can remain at this resolution, and can be quite large in specific ocean regions (Delworth et al., 2012; Griffies et al., 2015). This is due, in part, to the challenges of optimizing sub-gridscale parametrizations for higher resolution models (Goddard et al., 2001).

An alternative means of addressing resolution challenges is to embed a regional dynamical downscaling model in a global climate prediction system (e.g. Section 4.5, Section 6). Most of the world's fish catch is produced (Pauly et al., 2008) and most aquaculture operations are located in coastal and shelf seas. Regional models have the added advantage of improved resolution of coastal process (e.g. tidal mixing) that impact predictive skill of LMR-relevant variables at decision-relevant scales. However, these advantages must be weighed against the challenges, such as boundary condition inconsistencies, encountered when nesting models of considerably different structure and resolution (Marchesiello et al., 2001; Brennan et al., 2016).

It is important to note that while some of the current uncertainty in seasonal to decadal predictions can be reduced by, for example, improved model parameterizations, expanded observational networks, or increased model resolution, irreducible uncertainties will remain. Owing to the chaotic nature of the atmosphere, there are inherent seasonal and decadal predictability limits, which need to be clearly communicated to stakeholders (Vaughan and Dessai, 2014; Zebiak et al., 2015). For instance, on the west coast of the US, the seasonal upwelling season ends abruptly with the fall transition. This transition is driven mostly by storms, and consequently may not be predictable on seasonal time scales.

Finally, since reanalysis products are often treated as observations in forecast verification (Section 2.1.3), it is important for users to confirm the fidelity of such data sets to their specific area of interest prior to integration with LMR management frameworks. Where possible, this should be done with additional hydrographic data that may not have been incorporated in the reanalysis. We refer readers to Stock et al. (2015) for an example on how such an analysis can be performed.

2.3. Prediction of living marine resource-relevant physical variables

Variables routinely predicted using current seasonal to decadal forecast systems are LMR-relevant (e.g. SST), and the objectives of seasonal to decadal climate prediction are consistent with the spatiotemporal scale of many of the fisheries management decisions. However, oceanic prediction skill has often only been assessed with a view to its influence on regional weather prediction, rather than being of primary interest in itself (Stockdale et al., 2011). There are, however, a growing number of prediction studies for quantities and spatiotemporal scales relevant to LMR science and management challenges (Fig. 5). Below we discuss several of these, including predictability of SST anomalies, sea ice, and freshwater forcings that influence LMRs, along with recent advances for anticipating extreme events.

SST anomalies are both important drivers and meaningful indicators of ecosystem state (e.g., Lehodey et al., 2006; Brander et al., 2010). Efforts to assess the predictability of SST anomalies have emphasized ocean basin-scale modes of variability often linked to regional climate patterns (e.g., ENSO; Barnston et al., 2012). However, recent work has also revealed considerable SST prediction skill for many coastal ecosystems (Stock et al., 2015). Over short time scales, skill often arises from simple persistence of SST anomalies due to the ocean's substantial thermal inertia (Goddard and Mason, 2002). In many cases, however, skill exceeds that of persistence forecasts and can extend across leads of 6-12 months (Fig. 6). Such seasonal SST predictability may arise from diverse mechanisms, including the seasonal emergence of predictable basin-scale SST signatures following periods dominated by less predictable local variation, transitions between opposing anomalies due to the seasonal migration of ocean fronts, or the predictable re-emergence of sub-surface anomalies following the breakdown of summer stratification (Stock et al., 2015). Further analysis suggests that multi-model based SST predictions can further improve regional SST anomaly prediction skill and more reliably represent prediction uncertainty and the potential for extremes (Hervieux et al., in review). The considerable prediction skill at this LMR-relevant scale has allowed for some pioneering use of SST predictions for marine resource science and management (e.g., see case studies in Section 4), and suggests ample potential for further expansion.

In a few ocean regions, most notably the North Atlantic, SST predictions are skillful for several years (Yang et al., 2013; Msadek et al., 2014a; Keenlyside et al., 2015). This time scale is of particular interest for many LMR applications (Fig. 5). The predictive skill on these time scales emerges from phenomena, primarily in the ocean, that have inherent decadal scales of variability (Salinger et al., 2016). Perhaps the most prominent among these is the Atlantic Meridional Overturning Circulation (AMOC). Decadal-scale variations in AMOC-related ocean heat transport can influence SST over a wide area of the North Atlantic, and are thought to be a critical component of North Atlantic basin-scale SST variation characterized by the Atlantic Multidecadal Oscillation (AMO). For example, the abrupt warming observed in the mid-1990s in the North Atlantic has been retrospectively predicted in several models (Pohlmann et al., 2009; Robson et al., 2012; Yeager et al., 2012; Msadek et al., 2014a), with an increase of the AMOC being responsible for the warming. The Pacific Decadal Oscillation (PDO) also has decadal scales of variability and can be predicted a few years in advance, with significant impacts across a broad area of the North Pacific and adjacent continental regions (Mochizuki et al., 2010; Meehl and Teng, 2012). More idealized predictability studies also suggest the potential for substantial decadal predictive skill in the Southern Ocean (Boer, 2004), associated with deep vertical mixing and substantial decadal scale natural variability (Salinger et al., 2016). Nevertheless, unlike seasonal climate predictions, which are operational, the field of decadal prediction is in a very early stage (Meehl et al., 2014). Performance of decadal predictions needs to be assessed over a wider range of models and systematic model errors have to be reduced further to increase their utility to the marine resource community. Furthermore, the limited number of decadal-scale fluctuations of the 30-40 year period for which retrospective forecasts are possible severely restricts the effective sample size with which to characterize decadal prediction skill. Models may demonstrate an ability to capture several prominent events over this time period, but it is difficult to robustly generalize skill for this limited sample of independent decadal-scale events.

Sea ice is another LMR-relevant variable (Coyle et al., 2011; Hunt et al., 2011, Saba et al., 2013), whose seasonal predictive skill has been assessed at a regional scale. Based on estimates by the National Snow and Ice Data Center, September Arctic sea ice extent has declined at a rate of about 14% per decade since the beginning of satellite records (Stroeve et al., 2014), a trend largely attributed to warming due to accumulating GHGs (e.g. Stroeve et al., 2012). In addition to these long-term changes, large year-to-year variations have been observed in the position of the summer and winter sea ice edge. Operational and quasi-operational initialized predictions show some skill in predicting summer Pan-Arctic sea ice extent when it reaches its minimum in September, with significant correlation 3 to 6 months in advance at best in a few dynamical models (Sigmond et al., 2013; Wang et al., 2013; Chevallier et al., 2013; Msadek et al., 2014b). Sea ice thickness appears to provide the memory for sea ice extent predictability from one summer to the next. Hence more accurate predictions could be expected with improved observations of sea ice thickness and sea ice thickness initialization (Guemas et al., 2016). While predictions of summer sea ice have important implications for shipping and resource extraction, sea ice extent in late winter affects spring phytoplankton bloom timing and ultimately fish production (Hunt et al., 2011). However, while enhanced forecast skill with up to 3 to 4 months of lead-time relative to a persistence forecast has been reported during fall and early winter, forecast skill remains limited in late winter (Sigmond et al., 2013; Msadek et al., 2014b). Processes driving winter sea ice predictability include the representation of atmospheric dynamics like the position of the blocking high (Kwok, 2011), but also oceanic processes like heat convergence that drives SST anomalies in the marginal seas (Bitz et al., 2005). On-going studies based on improved model physics, improved parameterizations, and increased resolution in the atmospheric and oceanic components of the models are expected to improve representation of atmospheric dynamics, oceanic processes, and the mean distribution of sea ice, its seasonal variations, and possibly its predictability. Such improvements may also impact SST prediction skill (Stock et al., 2015).

While oceanic variables are of major importance for production and distribution of wild and aquaculture species, river temperature and flow are additional influences on recruitment and survival of commercially-important anadromous fish species, such as Pacific and Atlantic salmon (Bryant, 2009; Jonsson and Jonsson, 2009) and stocks such as northwest Atlantic river herring that have fallen below historical levels (Tommasi et al., 2015). In addition, these variables affect nearshore ocean dynamics and hence impact aquaculture of estuarine species. Seasonal stream flow predictability is thus of high interest to some industry groups and fisheries management agencies. Land models incorporated in current seasonal to decadal climate prediction systems, however, only provide a coarse representation of topography, river networks, and land cover, and forecasts of hydrological properties are not very skillful if taken directly from global dynamical forecast systems (Mo and Lettenmaier, 2014). Historically, land resolution in models has limited topographic variability, which impacts snowfall, and as a result has downstream influences on surface hydrology (e.g. reduced soil moisture and stream flow) in mountainous regions and surrounding areas dependent on orographic precipitation and spring and summer snowmelt (Kapnick and Delworth, 2013; Kapnick et al., 2014). This bias is pronounced in western North America where mountain hydrology drives water availability (Barnett et al., 2005). As a result, higher resolution hydrological models have been forced by the larger scale input from coarser global climate models to produce hydrologic forecasts at scales useful for decision makers (e.g. Mo and Lettenmaier, 2014). As prediction systems increase in atmospheric and land surface resolution, precipitation and temperature prediction skill over mountain regions also increases as topography is better resolved (Jia et al., 2015).

Aside from issues in resolution, hydrologic predictability is largely a function of initial land surface conditions (primarily soil moisture and snow cover) and seasonal forecasts of rainfall and temperature (Shukla et al., 2013; Yuan et al., 2015). In regions where snow and soil moisture provide a long hydrological memory, such as the western United States or high altitude locations, accurate initial conditions can provide skillful forecasts out to 3 to 6 months, particularly during cold seasons (Koster et al., 2000; Mahanama et al., 2012; Shukla et al., 2013). Similarly, in regions where the flow regime is controlled by groundwater rather than rainfall, persistence of initial flow can provide a skillful seasonal forecast (e.g. Svensson, 2016). However, over most of the globe, persistence skill decreases after a month (Shukla et al., 2013), and improvements in the predictability of streamflow are made by incorporating climate information into hydrological forecasting systems. Climate predictions systems can provide such climate forcing inputs (i.e. precipitation and temperature predictions) (Mo and Lettenmaier, 2014). However, the precipitation prediction skill of current global dynamical forecast systems is often too low to extend hydrological forecast skill beyond 1 month, particularly in dynamically active regions (Mo and Lettenmaier, 2014). Skillful seasonal hydrological predictions out to 3 to 9 months lead-times have been obtained, however, by integrating into hydrological models rainfall predictions derived from a climate index, such as the NAO, from a climate prediction system (e.g. Svensson et al., 2015). Alternatively, skillful seasonal hydrological predictions have been achieved by statistically integrating a climate index directly into a hydrological forecast system (e.g. Piechota and Dracup, 1999; Karamouz and Zahraie, 2004; Wang et al., 2011; Bradley et al., 2015).

Over recent years substantial effort has been placed on seasonal predictions of extreme phenomena, particularly tropical (Camargo et al., 2007; Vecchi and Villarini, 2014) and extratropical (e.g., Yang et al., 2015) cyclones. These extreme events threaten fishers' safety at sea and can dramatically impact the aquaculture and fishing industry through lost production and income with changes in fish survival and growth, reduction in water quality, and destruction of essential fish habitat (e.g. coral reefs, seagrass beds) or infrastructure (Chang et al., 2013;

Hodgkinson et al., 2014). Although individual tropical cyclones are very much "weather" phenomena, with no path to predictability beyond a few days, some aggregate statistics of tropical cyclones are strongly influenced by predictable large-scale aspects of climate, such as ENSO or other modes of variability (e.g., Gray, 1984). This has led to the development of a number of skillful statistical (Klotzbach and Gray, 2009; Jagger and Elsner, 2010), dynamical (Vitart and Stockdale, 2001; Vitart, 2006; Zhao et al., 2010; Chen and Lin, 2011; Vecchi et al., 2014; Murakami et al., 2015), and hybrid statistical-dynamical (Wang et al., 2009; Vecchi et al., 2011) prediction methodologies, which have targeted primarily basin-wide (e.g., North Atlantic, West Pacific, etc.), seasonally-integrated statistics of tropical cyclone activity. More recently, methodologies that exploit the ability of high-resolution GCMs to represent both regional hurricane activity and its connection to climate variation and change have led to skillful seasonal predictions of tropical cyclone activity at more regional scales (e.g., Vecchi et al., 2014; Zhang et al., 2016, Murakami et al., in review). The coming years are likely to see an expansion in the growth of tools for the seasonal prediction of tropical cyclones and many other extreme phenomena, such as tornadoes (Elsner and Widen, 2014 ; Allen et al., 2015), and heat waves (Jia et al., 2016) enabled by the widespread development of high-resolution dynamical prediction models, improved understanding of the connection of weather extremes to large-scale conditions, and the pressing societal need for information about the statistics of high-impact weather events at regional scales.

3. Managing living marine resources in a dynamic environment

Management of LMRs is an exercise in trade-offs, requiring that managers balance multiple, often competing objectives (e.g. Jennings et al., 2016). For instance, global policies and the legal mandates of many countries require weighting conservation of commercial stocks against their exploitation, protecting bycatch species that are overfished or listed as endangered or threatened, safeguarding of coastal economies and fishing communities, and balancing present benefits to stakeholders against future losses (King et al., 2015). Fisheries managers acting on the best available science are mandated to prevent overfishing while, on a continuing basis, achieving high levels of benefits to society from fisheries and other seafood products. Fishers must balance a parallel tradeoff between the value of current harvest and the maximum value of future harvests. Similarly, aquaculture industry participants have to balance the value of expected returns from capital investment against its opportunity costs.

LMR industry or management decisions are made all the more challenging because these objectives must be achieved against the backdrop of a highly dynamic ocean environment. Different decisions are made for different spatial and temporal scales (with regard to both lead-time and the application of the decision), and thus their effectiveness is influenced by climate–driven variability from across the climate system (Fig. 5). In this section, we summarize LMR management and industry decisions made with lead-times from days to decades and the frameworks used to make them, identifying the points where seasonal to decadal climate predictions could inform decisions, and discuss the potential benefits of this information.

3.1. Industry Operations

For the aquaculture industry, key decisions include when to release fry, ‘plant’ and harvest fish/shellfish, and when and what remedial actions to take to counter or avoid poor conditions. Extreme events such as floods, storms, and tropical cyclones can dramatically impact the aquaculture industry through reduction in water quality and destruction of infrastructure (Hodgkinson et al., 2014). Anomalously warm or cold conditions can also result in lost production and income via direct mortality effects, changes in growth or disease outbreaks (Chang et al., 2013, Spillman and Hobday, 2014). Hence, nowcasts and daily environmental forecasts are routinely used to improve the operational planning of the aquaculture industry. For example, monitoring networks of coastal water chemistry have been essential to reduce the impact of extremely low pH waters on oyster larval survival, increasing the economic resilience of the Pacific Northwest shellfish industry (Barton et al., 2015). Similarly, estuarine conditions are monitored to time release of hatchery reared salmon fry with optimal environmental conditions for growth and survival (Kline et al., 2008). While information on current environmental conditions is useful, seasonal forecasts of particular environmental variables can further improve the operational planning activities and climate readiness of the aquaculture industry by giving aquaculture farm managers time to develop and implement management strategies that minimize losses to climate, as is outlined in Case Study 4.1 (Spillman and Hobday, 2014; Spillman et al., 2015), or by allowing hatcheries time to adjust their release schedule (Chittenden et al., 2010).

For the fishing industry, key decisions include investments in boats, gear and labor, as well as when, where, and what to fish. Fishers rely on historical knowledge of the influence of environment on fish distribution to optimize such investment and harvest decisions. However, movement of environmental conditions into new ranges and associated changes in fish distribution (Section 1) is now affecting the value of fishers' past knowledge, making it harder to locate fish and make optimal pre-season investments, undermining their business performance (Eveson et al., 2015). As demonstrated in Case Study 4.2, seasonal climate forecasts can be incorporated into fish habitat models to produce fish distribution forecasts and improve the operational planning and efficiency of the fishing industry.

Such habitat models generally use correlative techniques to define regions of high abundance, or high probability of occurrence, for a species of interest in relation to oceanographic conditions. Species distribution data can be sourced from tagging studies, fisheries-dependent records, fisheries-independent surveys, or other sources. The distribution data is then related to one or multiple environmental variables (e.g. temperature, Hobday et al., 2011) through a variety of statistical methods, including generalized linear models (GLM), generalized additive models (GAM), classification and regression trees (CART), and artificial neural networks (ANN). When making century-scale projections of how fish distributions will change due to shifts in climate and marine habitat distribution, other commonly used models include Maxent (Phillips et al., 2006), Dynamic Bio-climate Envelope Model (DBEM; Cheung et al., 2009), AquaMaps (Kaschner et al., 2006), and the Non-Parametric Probabilistic Ecological Niche (NPPEN) model (Beaugrand et al., 2011). These models vary in assumptions and complexity, and can at times give markedly different results when applied to the same dataset (Lawler et al., 2006; Jones et al. 2013; Jones and Cheung 2014, Cheung et al. 2016a). For this reason, it is advisable to use an ensemble of multiple models when it is practicable to do so. Regardless of the statistical model used, all correlative habitat models assume that the relationships observed between species distributions and environmental variables in the training dataset are reliable proxies for actual mechanistic drivers of habitat preference. This assumption can be reasonably robust, for example if statistical associations with temperature closely mirror known physiological constraints, or more questionable, where a correlation is observed but the mechanistic basis is unknown (Peck et al., 2013). This can limit the performance of habitat models when they are extrapolated outside the range of the training dataset: either spatially into other geographic regions, or temporally into past or future time periods (Brun et al. 2016).

Long-term industry decisions, such as long-term resource capitalization and determination of optimal investment strategies for long-term sustainability can also be informed by these same habitat models, driven by multi-annual to decadal rather than seasonal, climate forecasts. Such long-term species distribution forecasts would help the fishing industry determine, and initiate a discussion with managers on optimal licensing strategies in the face of a changing environment, such as more flexible quota-transfer frameworks (McIlgorm et al., 2010). For the aquaculture industry, multi-annual to decadal scale species distribution forecasts would improve capital investment decisions such as where to establish a new site or estimate and sell risk in a market place (Little et al., 2015).

3.2. Monitoring and closures

Public health officials and fisheries managers have to make decisions on when to close a resource to protect the public, the resource itself, or, as for the case of bycatch species, resources caught incidentally to fisheries operations. Decisions also have to be made on how best allocate limited monitoring resources. Advanced estimates of stock distribution via bioclimatic habitat models (Case Study 4.5) or more complex ecosystem models (Case Study 4.6) informed by seasonal climate forecasts can guide planning for observer coverage and for fishery-independent surveys to ensure that stocks are monitored across their distributions. Below we elaborate via three examples on how short-term forecasts of climatic variability can be linked to triggers for fisheries closures (e.g., harmful algal blooms), allow time to prepare response plans (e.g., in response to coral bleaching), and reduce unwanted and incidental captures.

Harmful algal blooms (HABs), pathogens (e.g. *Vibrio* spp.), and dangerous marine species such as jellyfish pose a significant threat to public health and fishery resources. Total economic costs of HABs, including public health, commercial fishery, and tourism impacts, are an average of $49 million per year in the US alone (Anderson et al., 2000). For instance, an unprecedented coastwide HAB in spring 2015 caused widespread closures of commercial and recreational fisheries over the entire U.S. West Coast and led to substantial economic losses to the seafood and tourism industries (McCabe et al., 2016). HAB-related fish-mortality is also recognized as a significant problem in Europe (ICES, 2015), and HAB-related closures of fisheries in eastern Tasmania and the west coast of North America have led to economic hardship and are becoming more frequent (Lewitus et al., 2012; van Putten et al., 2015). To limit such adverse effects, coastal resource managers have to estimate optimal allocation of monitoring resources, as well as appropriate times and locations for beach and shellfish bed closures. If fishers can anticipate HAB-related closures, they can make informed decisions about which stocks to target and develop approaches to compensate for expected lost revenues.

Nowcasts and short-term (e.g. lead-time less than a month) forecasts of pathogens and HAB likelihood or distribution have been successful in helping coastal planners target monitoring, guide beach and shellfish closures, water treatment practices, and minimize impacts on the tourism and fisheries and aquaculture industries (http://coastalscience.noaa.gov/research/habs/forecasting; Stumpf and Culver, 2003; Constantin de Magny, 2009). Such nowcasts and short-term forecasts are generally derived from an empirical habitat model (Section 3.1) incorporating temperature and salinity fields from regional hydrodynamic models driven by weather models (e.g. Constantin de Magny, 2009), though mechanistic HAB models have also been developed (McGillicuddy et al., 2011). Integration of seasonal climate forecasts into such frameworks could extend the lead-times of HABs and pathogen forecasts, allowing coastal planners and impacted industries more time to develop response strategies. Likewise, temperature-based surveillance tools dependent on seasonal SST forecasts have been proposed to help monitor, research, and manage emerging marine disease threats (Maynard et al., 2016).

Reduction of incidental capture of protected or over-exploited species during fishing operations is an important management objective in many jurisdictions; and fisheries managers are tasked with deciding what management actions are warranted to achieve this objective (e.g. Howell et al., 2008; Smith et al., 2007). Spatial management strategies that restrict fisher access in specific zones and at specific times have been successfully used to limit interactions between bycatch species and fishing gears (Hobday et al., 2014; Lewison et al., 2015). However, as fish move to remain in suitable physical and feeding conditions, fish distributions and phenology change with varying ocean dynamics (Platt et al., 2003; Perry et al., 2005; Nye et al., 2009; Pinsky et al., 2013; Asch, 2015), and therefore static time-area closures can be ineffective (Hobday and Hartmann, 2006; Howell et al., 2008; Hobday et al., 2011; Howell et al., 2015). Integration of real-time or forecast ocean conditions into a habitat preference model (Section 3.1) is now being pursued to determine spatial distributions of species of concern and to set dynamic time-area closures (Hobday and Hartmann, 2006; Howell et al., 2008; Hobday et al., 2011;

Howell et al., 2015; Dunn et al., 2016). For instance, nowcasts of the preferred habitat of loggerhead and leatherback turtles are helping to reduce interactions between Hawaii swordfish longline fishing vessels and these endangered species (Howell et al., 2008; Howell et al., 2015). The utility of seasonal forecasts in setting effective dynamic spatial management strategies (Maxwell et al., 2015) to reduce bycatch is exemplified in Case Study 4.7.

3.3. Provision of Catch Advice

Setting annual catch quotas, or adjustments to fishing seasons or effort, is one of the most critical and difficult decisions taken by fisheries managers. In the United States, Annual Catch Limits (ACLs) are mandated to not exceed scientifically determined sustainable catch levels (Methot et al., 2014). Such intensive management of fishing levels occurs in other fishery systems and has been considered key to effective control of exploitation rates (Worm et al., 2009). ACLs are dependent on a control rule that basically defines the fraction of the fish stock that can be safely harvested each year. The control rule is designed to achieve a large fraction of the biologically possible "Maximum Sustainable Yield", based on a forecast of stock abundance over the next one to several years and biological reference points. Reference points, such as the fishing rate that achieves the maximum long-term average yield (F_{msy}), reflect the long-term productivity of a fish stock and are the basis for a management system to maintain annual fishing mortalities at a target level that does not lead to overfishing (Quinn and Deriso, 1999).

Reference points and forecasts of stock status are based upon stock assessment models, which commonly are data-assimilating, age-structured models of a single stock's population dynamics (Methot, 2009; Maunder and Punt, 2013). Typically, these lack spatial structure, while focusing on temporal dynamics on an annual time step over several decades. We refer readers to Quinn and Deriso (1999) for a detailed description of a range of stock assessment models, differing in complexity and data requirements. The parameters of the model, e.g., annual recruitment, natural mortality rates, annual fishing mortality rates, etc., are calibrated by assimilating data on fishery catch, fish abundance from surveys, and the age or length composition of fish in the surveys and catch. Nielsen and Berg (2014) illustrate recent advances.

The effects of ecological (e.g. predator abundance) or physical factors on population dynamics are rarely modeled explicitly: a recent meta-analysis showed that just 24 out of the 1200 assessments incorporated such information (Skern-Mauritzen et al., 2015). These unmeasured, non-fishing driving factors are only accounted for by allowing the models to incorporate random variability in key model parameters, particularly recruitment, or by incorporating empirical measured inputs, particularly regarding fish body weight-at-age. However, without including the process causing the fluctuations in the model framework, there is no basis for refining the random forecast into the future.

Reference points are thus generally computed assuming quasi-equilibrium conditions and stationary stock productivity (Quinn and Deriso, 1999). However, in many fish populations, ecosystem and climate can shift the production curve over time (Mohn and Chouinard, 2007; Munch and Kottas, 2009; Payne et al., 2009; Payne et al., 2012; Peterman and Dorner, 2012; Vert-pre et al., 2013; Bell et al., 2014; Perälä and Kuparinen, 2015), calling this assumption into question. Failure to include variability in any component of productivity, such as recruitment, natural mortality, and growth, into the development of reference points and annual catch advice can lead to unexpected population declines when productivity shifts to unanticipated low levels (Brunel et al., 2010; Brooks, 2013; Morgan et al., 2014). Furthermore, the use of static reference points can contribute to inaccurate estimates of stock recovery time and rebuilding thresholds (Collie and Spencer, 1993; Holt and Punt, 2009; Hammer et al., 2010; Punt, 2011; Pershing et al., 2015).

Nevertheless, robust alternatives to the status quo definitions of reference points have yet to be developed. For stocks that have undergone recognized shifts in productivity over their catch history, dynamic reference points can be constructed using data from the most current regime, as is currently done for Gulf of Alaska walleye pollock (Dorn et al., 2014) or southeast Australian morwong (Wayte, 2013). However, performance of such reference points in achieving management objectives as compared to the status quo has been mixed (Punt et al., 2014a, b). A common shortcoming is that using a shorter time series leads to less biased, but more uncertain, reference points (Haltuch et al., 2009; Dorner et al., 2013; Punt et al., 2014b). Furthermore, even dynamic reference points assume that the recent past will be representative of near future conditions. Because of the noisy nature of productivity parameters, such as recruitment, productivity shifts tend to be recognizable only well after the change has taken place, preventing managers from adjusting harvest strategies in a timely manner, and increasing the risk of overfishing (A'mar et al., 2009; Szuwalski and Punt, 2013). Statistical techniques such as the Kalman filter, which allow for time varying productivity parameters in stock assessment models, have proven useful in a timely detection of productivity shifts and improved reference point estimation for semelparous species (Peterman et al., 2000; Peterman et al., 2003; Collie et al., 2012). Temporal variability in reference points can also be introduced via environmental covariates on productivity parameters. When these environmental factors can be skillfully forecasted and the environment-population dynamics relationship is robust, the fish productivity forecast is improved (Maunder and Watters, 2003; Schirripa et al., 2009; Haltuch and Punt, 2011; Johnson et al., 2015; Miller et al., 2016).

Effectiveness of alternative reference point definitions and climate-robust harvest control rules can be tested through Management Strategy Evaluation (MSE). MSE is a simulation tool for comparing the trade-offs in the performance of alternative management strategies while accounting from uncertainty from different sources, such as climate responses, biological interactions, fishery dynamics, model parametrizations, observations, and management approaches (Cooke, 1999; Butterworth and Punt, 1999; Sainsbury et al., 2000). While the utility of accounting for the environment in achieving management objectives has been demonstrated for some species (Basson, 1999; Agnew et al., 2002; Brunel et al., 2010; Hurtado-Ferro et al., 2010; Pershing et al., 2015; Miller et al., 2016), existing MSEs demonstrate that climate drivers of stock productivity show mixed results with respect to the effectiveness of alternative, potentially climate-robust, management strategies when compared to those currently implemented (A'mar et al., 2009; Punt et al., 2011; Szuwalski and Punt, 2013; Punt et al., 2014). One exception is the Pacific sardine fishery; whose catch targets vary with a reference point dependent on a 3-year moving average of past SST (Hill et al., 2014).

Through the use of seasonal climate forecast information, climate informed reference points as used operationally for the US sardine fishery, would be more reflective of future productivity. This may help managers both adjust annual catch targets in a timely manner and set more realistic rebuilding targets (Tommasi et al., accepted.). Effectiveness of such climate-informed reference points will depend upon achieving climate forecast skill at the seasonal to decadal scale, and on past observations used to identify environmental drivers of productivity being able to adequately characterize future relationships.

Addition of climate forecast information into stock assessment models may also reduce uncertainty bounds on stock status projections by narrowing the window of probable outcomes as compared to the use of the entire historical range (Fig. 7a). Furthermore, if a stock productivity parameter is subject to an environmentally-driven shift or directional trend, future values may lie outside of the historical probability space, leading to biased estimates of stock status under the assumption of stationarity (Fig. 7b and 7c). As a result, a climate forecast may serve as an advance warning of shifts in environmental conditions and stock productivity parameters, and may reduce bias in stock status estimates (Fig. 7b and 7c).

It must be stressed that the theoretical value of climate forecast information detailed in Fig. 7 is dependent on both the strength of the environment-fisheries relationship and climate forecast skill. That is, we assume that the environment-fisheries relationship is robust and stationary, that a relatively high proportion of the unexplained variability can be explained by the environmental data (e.g. Basson, 1999), and the environment can be well predicted. For instance, if the environment-fisheries relationship breaks down, climate-driven harvest control rules will perform poorly (Fig. 2d), highlighting the need for a strong mechanistic understanding of the environment-fisheries link (Dorner et al., 2013), or more conservative management approaches when the fluctuations cannot be predicted with adequate precision.

3.4. Spatial Issues and Protected Areas

In addition to multi-year forecasts of stock status and revisions of reference points (Section 3.3), multi-year to decadal fisheries management decisions encompass long-term spatial planning decisions regarding changes to closed areas, the setting of future closures, preparation for emerging fisheries, and adjustment of quotas for internationally shared fish stocks. Even decisions about which management body has jurisdiction may need adjustment over time.

As for short-term spatial management rules aimed at bycatch reduction (Section 3.2), stock distributions employed in the setting of current long-term closed areas are generally taken as static. Fish assessment models generally lack spatial structure, and thus have no inherent capability to forecast changes in stock distribution as ocean conditions shift the distribution of the stock, nor to calculate the localized impact of a spatially restricted fishery or reserve (McGilliard et al., 2015). However, the spatial distribution of many marine species has been shown to be particularly sensitive to changes in climate over multi-annual to decadal scales (Nye et al., 2009; Pinsky et al., 2013; Poloczanska et al., 2013; Bell et al., 2015; Thorson et al. 2016).

Such climate-driven distributional shifts can have important implications for spatial management measures. For example, shifts of juvenile plaice (*Pleuronectes platessa*) towards deeper waters have made a closed area (the "Plaice Box") set up in the North Sea to prevent recruitment overfishing less effective (van Keeken et al., 2007). One potential solution for stocks that have undergone recognized shifts distribution over their catch history is use of dynamic seasonal-area closures. Climate predictions, particularly of surface and bottom temperatures, could be used to drive species habitat models that help define fishery closure areas (Section 3.1; Link et al., 2011; Makino et al., 2014; Shackell et al., 2014; Rutterford et al., 2015). Furthermore, seasonal to decadal predictions (as well as nowcasts and hindcasts) of environmental conditions may contribute to management even if they are not directly incorporated within stock assessments. For instance, the Northeast US butterfish (*Poronotus triacanthus*) assessment investigated methods to incorporate historical change in thermal habitat to evaluate changing availability to the survey. While habitat-driven time-varying survey catchability was not included in the final assessment, the focused effort to evaluate survey catchability overall altered assessment estimates of scale, permitted more robust estimation of natural mortality, and ultimately increased the catch quota relative to previous results.

Shifting species distributions can also create important new fishing opportunities, such as the squid fishery in the Gulf of Maine that appeared during a particularly warm year (Mills et al., 2013). Hence, forecasts of species distributions driven by multi-year to decadal climate predictions can help identify which species are likely to spark new fisheries, and then prioritize them for additional research, experimental fishing programs, or short-term closures during the colonization phase. Such forecasts can also warn of distributional shifts outside of the range of current fisheries operations, and may prevent overfishing of the remaining portion of the stock.

Advance warning of shifting distributions is particularly important when they impact international agreements, since negotiations can take years. For example, mackerel faced a "double jeopardy" scenario when they partially shifted into Icelandic and Faeroese waters and the additional harvest pressure led to overfishing of the stock (Astthorsson et al., 2012; Hannesson, 2012; Dankel et al., 2015). Pre-agreements between organizations or nations can be drafted to create a clear set of rules for how to adjust quotas and allocations based on indicators of changes in a stock distribution, perhaps including side-payments to compensate for lost fishing opportunities (Miller and Munro, 2004). For instance, forecasts of ocean conditions are used to forecast the proportion of Fraser River salmon migrating around the south end of Vancouver Island, thus dramatically affecting international allocation of the catch opportunity

(Groot and Quinn, 1987). Forecasts may also be critical for building a common understanding of stock trajectories and for motivating the need for pre-agreements.

4. Case Studies

The previous two sections have provided an overview of the range of marine resource decisions that could be improved with climate forecasts and of climate forecast skill for LMR-relevant variables across decision making time scales. In this section, we highlight pioneering applications of the climate predictions discussed in Section 2.

4.1 Seasonal forecasts to improve prawn aquaculture farm management

Pond-based prawn aquaculture in Australia is primarily located on the northeast coast of Queensland (Fig. 8). Growing season length, timing of harvest, and farm production in this region are strongly influenced by environmental conditions, such as air temperature, rainfall, and extreme events, including tropical cyclones. Anomalously cool or warm temperatures can impact production and timing of harvest, thus affecting delivery to market. Rainfall extremes, including tropical cyclones, affect freshwater quality and supply to farms, road access in the case of flooding, and can also cause loss of farm infrastructure. In this situation, predictions of environmental conditions weeks to months in advance can improve risk management and allow implementation of proactive management strategies to reduce unfavorable impacts and maximize positive effects of conditions on farm production.

Seasonal forecast products for Queensland prawn farms were first developed in 2011-2012 (Spillman et al., 2015) and currently continue to be delivered via a password protected website. Regional temperature and precipitation forecasts are derived from the global dynamical seasonal prediction system POAMA (Predictive Ocean Atmosphere Model for Australia; Spillman and Alves, 2009; Spillman et al. 2011), and then downscaled using local weather station information for participating prawn farms. The forecasts were verified by assessing the probabilistic skill of the model predicting the upper terciles for maximum air temperature and rainfall, and the lower tercile for minimum temperature, as these were the events of greatest concern to prawn farm managers. Forecast accuracy is generally higher for temperature than rainfall, and declines with lead-time (Fig. 8). Forecasts out to lead-times of 2 months, which aligns with several farm operational planning timeframes, such as those for feed management or harvest time (Hobday et al., 2016), are sufficiently skillful to be integrated within prawn farm management decision framework (Spillman et al., 2015).

Feedback from prawn farm managers following delivery of the first few forecasts led to refinement of forecast format, visualization and delivery, and resulted in an industry award for the project team. This approach has been applied to other marine aquaculture industries (e.g. salmon; Spillman and Hobday, 2014), with industry recognition that a range of management decisions can be supported by environmental forecasts to improve aquaculture production in the face of climate variability and change.

4.2 Seasonal forecasts to improve economic efficiency of a large-scale tuna fishery

Large numbers of juvenile quota-managed southern bluefin tuna (SBT) (*Thunnus maccoyii*) occur in the Great Australian Bight (GAB) during the austral summer (Dec-Apr), where they are caught in a purse-seine fishery worth ~AUD 60 million annually. In recent fishing seasons, unexpected changes in the distribution of SBT were observed that affected the timing and location of fishing activity and contributed to economic pressure on the fishery. In particular, in the 2011/12 season, SBT moved through the GAB quickly and were distributed further east than in the past two decades. This resulted in less than 15% of purse-seine catches being taken from fishing grounds reliably used over the previous 20 years. The following season (2012/13) also saw unusual SBT distribution patterns that again impacted the fishery. As a result of these observed changes, the Australian Southern Bluefin Tuna Industry Association recognized the need for scientific support to improve operational planning in the purse-seine fishery. Many decisions central to SBT industry members planning their fishing operations need to be made weeks to months in advance, so seasonal forecasts of environmental conditions were regarded as a useful tool.

Environmental variables influencing the spatial distribution of SBT in the GAB during summer were explored using location data collected on SBT over many years from electronic tags, and comparing the ocean conditions where fish were found with the conditions available to them throughout the region and time period of interest (Eveson et al., 2015). SST was found to have the greatest influence, with fish preferring temperatures in the range of 19-22°C. Once habitat preferences were established, this information was coupled with POAMA (see Section 4.1) to predict locations of preferred SBT habitat in future. Both the habitat preference model and POAMA were evaluated against historical observations, and it was concluded that SST-based habitat forecasts for SBT in the GAB have useful skill for lead-times up to 2 months. A daily-updating website was created to provide industry with forecasts of environmental conditions and SBT distributions for the next fortnight and next 2 calendar months from the date of issue (Fig. 9), along with a suite of other relevant information, including skill of the forecasts (www.cmar.csiro.au/gab-forecasts). Based on feedback from industry stakeholders obtained both formally through a survey and informally through an industry liaison representative, the information provided on the website has proven to be a valuable tool for fishers making decisions such as when and where to position vessels and to conduct fishing operations (Eveson et al., 2015). As the SBT fishery is quota-managed, the forecasting approach will not lead to increased catches (and thus impact sustainability), but will enable fishers to catch their quota more efficiently, thereby increasing profitability.

4.3 A statistical seasonal forecast to improve the operational planning of a lobster fishery

The US fishery for American lobster is one of the most valuable in the country. Landings in Maine alone accounted for nearly US$500M in 2015. The fishery is open year-round, but the catch is highly seasonal. In Maine, where the majority of lobsters are landed, landings typically begin increasing rapidly during the first week of July, when lobster migrate inland and begin to molt. During 2012, the Gulf of Maine was at the center of a prolonged “marine heatwave,” which caused temperatures in the spring to lead the normal annual cycle by 3-4 weeks (Mills et al., 2013). The annual lobster migration and molt took place nearly a month early, resulting in very high catches in early June instead of early July. The supply chain was not ready for the influx of newly molted soft-shell lobsters, and the imbalance between supply and demand led to a severe decline in price. Furthermore, record warm air temperatures contributed to increased mortality of lobsters during storage and transport. Thus, even though lobster landings set a record in 2012, it was an economically challenging year for many lobstermen.

Motivated by the events in 2012, the possibility of an early warning indicator of lobster fishery timing was explored and it was found that the date when landings in Maine begin to increase is negatively correlated with subsurface temperatures in March and April. Based on this relationship, a statistical forecast system was developed that takes temperatures at 50 m from a network of coastal ocean buoys operated by the Northeast Regional Association of Coastal

Ocean Observing Systems (NERACOOS) in spring and estimates the probability of the fishery shifting into the high-landings period during a particular week in June or July. For the last two years, the first forecast of the year has been announced to the industry at the Maine Fishermen's Forum and then updated weekly at www.gmri.org/lobster-forecast and via Twitter (Fig. 10). Forecasters have now begun to work more closely with harvesters, dealers, and marketers in the industry to assess how it can be further improved to meet their needs. Other work has identified value in using sea temperature observations and models to help forecast outbreaks of lobster epizootic shell disease (Maynard et al., 2016).

4.4 Seasonal forecasts to improve coral reef management

Increases in ocean temperature over a coral's tolerance limit are the leading cause of coral bleaching events (Hoegh-Guldberg et al., 2007). Since 1997, NOAA's Coral Reef Watch has been using SST satellite data to provide near real-time warnings of coral bleaching (Liu et al., 2014). While coral reef managers and scientists have been able to use these nowcasts to execute operational response plans, managers recognized the need for longer lead-time forecasts to improve management responses to coral bleaching. Following these requests, NOAA Coral Reef Watch developed the first seasonal coral bleaching outlook, based on a statistical model from NOAA's Earth System Research Laboratory (Liu et al., 2009). In 2009 the Australian Bureau of Meteorology developed the first dynamical seasonal forecasts for coral bleaching risk on the Great Barrier Reef, based on seasonal SST predictions from POAMA (see Section 4.1; Spillman and Alves, 2009; Spillman, 2011). NOAA Coral Reef Watch, in turn, developed a dynamical 4 month lead coral bleaching outlook for coral reefs globally using seasonal SST predictions from the NOAA National Centers for Environmental Prediction (NCEP) global dynamical climate prediction system, the CFS model (Eakin et al., 2012).

These seasonal coral bleaching forecasts are made publicly available on the internet (http://www.bom.gov.au/oceanography/oceantemp/GBR_SST.shtml, http://coralreefwatch.noaa.gov/satellite/bleachingoutlook_cfs/outlook_cfs.php) and they allow coral reef managers around the world to develop timely and proactive bleaching response plans, brief stakeholders and allocate monitoring resources in advance of bleaching events. Resource managers and scientists have been using these bleaching outlooks extensively throughout the 2014-16 global coral bleaching event (Eakin et al., 2014; Eakin et al., 2016).

For example, in August 2010, following severe coral bleaching, the Thailand and Malaysian governments closed numerous popular dive sites to reduce additional stress to severely bleached reefs (Thomas and Heron, 2011). In May 2016, Thailand again closed ten reefs, this time in advance of the bleaching peak (The Guardian 2016, https://www.theguardian.com/environment/2016/may/26/thailand-closes-dive-sites-over-coral-bleaching-crisis. Accessed August 15, 2016) and in response to these forecast systems. More recently, once Coral Reef Watch alerts were issued in late June 2015 of the high potential for bleaching in Hawaiian waters (Fig. 11), the Hawaii Department of Land and Natural Resources (DLNR) immediately began preparations of resources to monitor this event. Having only seen significant multi-island bleaching in the main islands twice before, in 1996 and 2014 (Jokiel and Brown, 2004; Bahr et al., 2015), a much more comprehensive effort was needed. Additional volunteers were trained, who, together with teams from the state, University of Hawaii, NOAA, and XL Catlin Seaview Survey, were deployed across most of the islands. This group was able to document and monitor this unprecedented event, while the DLNR was able to alert the public and work with marine resource users to encourage reduction of activities that could further stress the corals during the bleaching event. Additionally, DLNR undertook an effort to collect specimens of the rarest coral species from the main Hawaiian Islands and safeguard them in their coral nurseries on Oahu and Maui. Many of these species suffered severe bleaching and mortality, and DLNR staff have been unable to find one of these species alive off Oahu since the 2015 event. Both Bureau of Meteorology and NOAA seasonal forecast tools were also used extensively by reef management during the most recent bleaching event on the Great Barrier Reef in the summer of 2015/2016, currently believed to be the worst on record (http://www.gbrmpa.gov.au).

4.5 Seasonal forecasts of Pacific sardine habitat

Pacific sardines are notable as one of the few stocks managed with respect to climatic variability in the US. Just recently, sardine distribution and migration forecasts have been produced (Kaplan et al., 2016; Fig. 12) for the US Pacific Northwest and Canadian British Columbia, based on 6 to 9 month predictions of ocean conditions (http://www.nanoos.org/products/j-scope/; Siedlecki et al., 2016). These predictions rely upon the NOAA NCEP global dynamical climate prediction system Climate Forecast System (Saha et al., 2006) to force a high resolution (~1.5 km) Regional Ocean Modeling System (Haidvogel et al., 2008). The efforts are fully described in Siedlecki et al. (2016), including skill assessment for SST, bottom temperature, and oxygen. Relationships between sardine distribution and J-SCOPE predictions of ocean physics and chlorophyll were estimated for 2009. The final fitted relationships between SST and salinity had moderate skill to predict sardine distributions (presence or absence) in summer 2013 and 2014, with up to 4 to 5 month lead-times. Skill assessment focused on a “hit rate” metric, area-under-the-curve (AUC), which balances the desire to correctly predict sardine presence against the risk of false positives. One caveat to the sardine forecasts is that they predict available sardine habitat (Fig. 12) without accounting for sardine stock size. Recent declines in sardine abundance (Hill et al., 2015) have likely meant a contraction of the stock southward (MacCall, 1990), despite availability of suitable habitat in the US Pacific Northwest and British Columbia.

As with many pelagic species, sardines are seasonally migratory and forecasts of their distribution by J-SCOPE may be relevant for fisheries management and industry. The sardine stock is landed by US, Mexican and Canadian fishers and the extent of the northward summer migration is dependent on both water temperature and population contraction due to low population abundance. The sardine forecasts by Kaplan et al. (2016) predict the extent of this northward migration and could be used to plan fishing operations (e.g. whether Canadian fish processors should expect sardine deliveries) or fisheries surveys. Additionally, quotas apportion a fixed percent of sardine catch to Canadian vessels, and J-SCOPE provides foresight that that this portion may be unharvested in a particular cold year. Furthermore, sardine straddle international boundaries, and short-term seasonal forecasts may help international management and industry to cope with and prepare for the long-term distribution shifts expected under climate change (Pinsky and Mantua, 2014). To date, forecasts have primarily been delivered through collaboration with NANOOS (Northwest Association of Networked Ocean Observing Systems) via the web (http://www.nanoos.org/products/j-scope/). Web products include predictions of ecological indicators relevant to the regional fishery management council, and will soon be incorporated in NOAA’s Integrated Ecosystem Assessment (Harvey et al., 2014). Other outreach efforts are ongoing and aim to produce targeted forecasts (as discussed for Australia above in Section 4.1) for fishery managers and stakeholders, and to better integrate with fishery management council needs.

4.6 Short-term forecasts of Indonesian tuna fisheries to control illegal fishing

The last decade has seen the generalization of satellite Vessel Monitoring Systems to monitor licensed fishing vessels, the use of satellite radar images to detect illegal fishing and the development of Electronic Reporting Systems (ERS) to provide catch statistics in real time. Integration of these developments in fishery monitoring with an operational forecasting model of fish spatial dynamics that has the ability to predict the distribution of fish under the influence of both environmental variability and fishing is assisting Indonesian fishing authorities in controlling illegal fishing and implementing conservation measures. This operational monitoring framework (Gehlen et al., 2015) was developed through the INDESO project and integrates a high resolution regional model system coupling ocean physics to biogeochemistry (NEMO/ PISCES; Gutknecht et al., 2016; Tranchant et al., 2016) to a spatially explicit tuna population dynamics model (SEAPODYM; Lehodey et al., 2010; 2015). SEAPODYM simulates functional groups of organisms at the intermediate trophic levels (Lehodey et al., 2010; 2015) and the dynamics of their predators (e.g. tuna) (Lehodey et al., 2008). The model is complemented by a quantitative parameter estimation and calibration approach (Senina et al., 2008) which enables the application of the model to fish stock assessment and testing of management scenarios (Sibert et al., 2012).

Tuna are highly migratory species, and their habitats cover large expanses of the global ocean. Thus, the simulation of fish stock dynamics at high resolution in the Indonesian region requires accounting for exchanges (fluxes) with populations outside of the regional domain (i.e. Pacific and Indian Ocean) under the influence of both environmental variability (e.g. ENSO) and fishing mortality. Boundary conditions for the regional 1/12° SEAPODYM implementation are obtained from a 1/4° global operational configuration (Fig.13) driven by temperature and currents from the operational ocean prediction system Mercator-Ocean PSY3V3 (Lellouche et al., 2013). Biogeochemical forcings (net primary production (NPP), dissolved oxygen) are either derived solely from the coupled physical-biogeochemical model NEMO/ PISCES (forecast mode) or from NEMO/PISCES and satellite ocean color and SST data (to estimate NPP; Behrenfeld and Falkowski, 1997), along with climatological dissolved oxygen (O_2) (hindcast and nowcast modes). The regional operational model SEAPODYM also uses a climatological data set (i.e., monthly average of the last 5 years) of fishing effort prepared from the best available information to apply an average fishing mortality. The forecasting system runs every week and delivers one week of hindcast, one week of nowcast, and 10 days of forecast. These outputs are used by the Indonesian Fishing Authority to improve the collection and verification of fishing data, to assist illegal fishing surveillance, and to establish conservation measures (e.g., identification and protection of spawning grounds and nurseries) required for the sustainable exploitation of this essential resource (Marion Gehlen, personal communication, June 22, 2016).

4.7 Seasonal forecasts for dynamic spatial management of the Australian east coast tuna fishery

Since 2003, a dynamic spatial management approach has been used to limit unwanted capture of a quota-managed species, SBT, in the Australian eastern tuna and billfish fishery. The approach combines a habitat model, conditioned with temperature preference data obtained from pop-up satellite archival tags deployed on SBT and an ocean model to produce near real-time habitat nowcasts, delivered by email and utilized the same day by fishery managers during the fishing season (Hobday and Hartmann, 2006; Hobday et al., 2010). Managers use this information along with other data inputs (such as recent fishing catch rates) to restrict access in the core (high probability of occurrence) zone to vessels that have both observers and SBT quota. The habitat model was extended in 2011 to include a seasonal forecasting component using ocean temperature forecasts from the seasonal prediction system POAMA, with useful forecast skill out to several months (Hobday et al., 2011). Both nowcast and seasonal forecast habitat maps produced for managers show probabilistic zones of tuna distribution coded as “OK” (unlikely to encounter SBT), “Buffer” (likely to encounter SBT) and “Core” (very likely to encounter SBT) (Fig. 14). Incorporating a seasonal forecasting component has been an important step in informing and encouraging both managers and fishers to think about decisions on longer time scales (Hobday et al., 2016). Forecasts are now delivered via a dedicated webpage (http://www.cmar.csiro.au/sbt-east-coast/). The dynamic habitat forecasting approach has reduced the need for large areas closures while still meeting the management goal, but does require fishing operators to develop more flexible fishing strategies, including planning vessel movements, home port selection and quota purchase.

5. Recommended practices

Following Hobday et al. (2016) and Siedlecki et al. (2016), there are three main components to a successful LMR forecast framework: assessment of needs, forecast development, and forecast delivery. Here, we break down the forecast development and delivery stages further to provide more details of the forecast implementation process (Fig. 15). Identification of a clear management need via effective communication between climate scientists and management or industry stakeholders from the start of the forecast development process is essential for the utility and widespread adoption of climate prediction tools for LMRs (Hobday et al., 2016; Harrison and Williams, 2007; Fig. 15). This needs assessment should include the determination of relevant variables, spatial domain, spatial resolution, and timescales. Once needs have been assessed, it is incumbent upon scientists to provide balanced communication of both capabilities and limitations to evaluate whether forecasts are likely to be useful to their partners.

Forecast development is underpinned by an understanding of the mechanisms relating physical climate variables to the LMR of interest. Once such linkages are found, three forecast development steps follow: an assessment of the skill of the physical climate variable forecast, an assessment of the skill of the LMR model forecast, and the uncertainty associated with each. The prediction skill for the physical climate variables must be assessed at an appropriate timescale relative to the management decision timeframe and at a spatial resolution able to resolve environmental driving mechanisms. Skill assessment will make use of retrospective forecasts and observations. When reanalyses are used in lieu of observations, their accuracy at the scale of interest should be confirmed against data prior to forecast skill assessment whenever possible (Section 3). If the skill evaluation indicates that the variables of interest cannot be skillfully forecasted at an adequate lead-time and/or relevant spatial scale, stakeholder expectations may be re-evaluated and alternate variables or scales of interest investigated (i.e. it may be necessary to return to the needs assessment step). Alternatively, downscaling or bias correction techniques may improve skill at the desired scale in some cases (Section 6). Skill may be assessed using at least measures of correlation, variability, and bias between forecast and observations, although further verification analyses are possible (Mason and Stephenson, 2007).

Once a physical climate variable forecast has been developed and determined to be skillful, the value of using it in an LMR model must be determined. LMR model skill assessment can employ skill metrics based on “hit rate”, such as AUC or area-under-the-curve (Fielding and

Bell, 1997) and the True Skill Statistics (Allouche et al., 2006), to evaluate whether the LMR forecasts reproduce biological phenomena (e.g., presence of tuna, occurrence of a coral bleaching event). While it is well known that climate affects LMRs (Section 1), most of derived climate-LMR relationships are empirical, with climate variables often acting as proxies of complex trophic effects, interspecies interactions, and dispersal processes. For climate information to be included in LMR management frameworks, the environment-fisheries relationship has to be robust and preferably based on mechanistic, ecologically-sound hypotheses. A sufficiently long observational data series is required for model calibration and verification (Haltuch and Punt, 2011), including out-of-sample validation (Francis, 2006; Mason and Baddour, 2007; Mason and Stephenson, 2007). In addition, if the environment-fisheries relationship relies on stock assessment model output (e.g. recruitment), it is important that this relationship be developed within the stock assessment model itself rather than as a post-hoc analysis to ensure uncertainties associated with the stock assessment model are properly propagated (Maunder and Watters, 2003; Brooks and Deroba, 2015). Furthermore, to increase confidence in the robustness of these empirical relationships, meta-analytical techniques can be employed to ensure that the proposed hypothesis is robust across a species range (Myers, 1998), taking into account, however, that environmental variables may affect species differently across their latitudinal range (e.g. Mantua et al., 1997).

As environment-LMR associations may change over time (e.g. with changing baselines under climate change), these empirical relationships need to be periodically re-evaluated as new environmental and LMR data are collected. LMR forecast development will therefore be an iterative process and management has to be dynamic to allow for changing management decisions as the environment-fisheries relationship evolves with the continuous integration of new information. Environment-LMR correlations have been observed to be more robust when tested with new data at the edges of a species range (Myers, 1998). These populations may serve as initial case studies with which to develop dynamic management frameworks that integrate climate prediction information. Table A2 includes a list of LMRs for which a sufficient understanding of how they respond to climate variability has been achieved, and which may serve as additional case studies. These include those determined by Myers (1998) as robust to re-evaluation and those that already make use of environmental information in their management as described by Skern-Mauritzen et al. (2015).

To provide a thorough presentation of risk to decision makers, it will be important to assess the uncertainty of the climate prediction as well as that of the LMR models. For the climate prediction, this will involve quantification of processes, variability and model uncertainty via the use of single and multi-model ensembles (Section 3). Forecasts will be inherently probabilistic, and ensembles can be used to estimate the probability. On the fisheries side, there is also uncertainty associated with LMR models' parameterizations (Cheung et al., 2016a, b). As for climate predictions, ensemble approaches can be employed in LMR models to account for the high level of uncertainty in the parameterization of biological processes (e.g. Kearney et al., 2012; Laufkötter et al., 2015; 2016). Uncertainty in the environment-LMR relationship will also need to be accounted for by, for instance, running multiple simulations of the LMR model differing in their stochastic error of the LMR-environment relationship (e.g. Lindegren et al., 2013).

Finally, an effective forecast delivery mechanism is required. The climate prediction needs to be delivered in a format that can be effectively incorporated into LMR models and decision frameworks, such as population models used in fish stock assessment. As in all the stages of LMR forecast development, consistent user engagement is essential to ensure sustained use of such prediction tools (Harrison and Williams, 2007; Hobday et al., 2016). For instance, the general difficulty people have in understanding uncertainty and probabilities has limited the use of climate predictions in the natural resource sector (Nicholls, 1999; Marshall et al., 2011). Collaboration with social scientists on the most appropriate presentation and delivery options may enhance adoption of forecast information (Harrison and Williams, 2007). Automated web-based delivery systems are a common delivery method, although ongoing contact with end users and acknowledgement of user feedback is important to build engagement and for continued forecast use (Hobday et al., 2016). Funding for delivery system maintenance, user engagement, and continued user training should be included in projects to maintain iterative LMR operational forecast systems.

The value of integrating climate predictions into LMR decision frameworks has to then be demonstrated to managers or industry. This can be undertaken by employing cost-benefit analyses (e.g. Asseng et al., 2012) and MSE (Section 2.4, Tommasi et al., accepted). For example, MSEs can assess the performance of different management strategies (e.g. with and without climate predictions) in relation to a suite of performance metrics while taking uncertainty into account. They may also include economic models to better evaluate the specific economic value of integrating climate forecasts into LMR decisions (e.g. Richardson, 2000). While MSEs have been developed in the context of fisheries science, such decision support systems could also be applied to industry or coastal manager's decision frameworks. Results from these assessments would inform both climate and LMR prediction development by highlighting further refinements needed to better inform decisions.

6. Priority developments

While the potential benefits of seasonal climate forecasts in reducing the climate vulnerability of the fishery and aquaculture industry and in improving fisheries management are clear (Section 4), barriers to their widespread adoption also exist. Social, cultural, economic, or political constraints, such as existing regulations or dissemination difficulties, can limit forecast use (Nicholls, 1999; Goddard et al., 2001; Harrison and Williams, 2007; Davis et al., 2015). However, the discussion herein will be limited to priority developments aimed at reducing technical impediments to climate forecast application. These technical barriers include incomplete understanding of environment-LMR relationships, limited length and availability of physical, biogeochemical and biological time series for model development and validation, and the irreducible predictability limits at seasonal to decadal scales. There is also need for methodological advancements in LMR models to explicitly consider environmental productivity indicators and spatial distributions, and apply empirical models in non-stationary systems. Finally, there is a need for reduction in climate model bias through improvements in model formulation and initialization, verification of LMR-relevant physical variables at LMR-relevant spatial scales beyond SST, the development of biogeochemical forecasting capabilities in global prediction systems, and improvements in climate predictability at LMR-relevant regional scales through higher resolution global prediction systems or the development of downscaling frameworks.

On the LMR model side, predictive capacity is constrained by our incomplete understanding of environment-LMR relationships, especially their response to environmental fluctuations (e.g. Chavez et al., 2003; Di Lorenzo et al., 2009; Le Mézo et al., 2016). As a case in point, only 2% of managed fisheries worldwide explicitly integrate past environmental information into their current tactical decision making and provide an existing framework to readily incorporate climate forecast information (Skern-Mauritzen et al., 2015). This lies in stark contrast to ubiquitous climate-marine resource correlations reported in the literature (e.g. Hare et al., 2010; Mueter et al., 2011; Ottersen et al., 2013). For most populations, the length of available, co-occurring fishery, biological and environmental time series may be too short to robustly identify the environment-LMR relationship (Haltuch and Punt, 2011) or to develop a habitat preference model, highlighting the importance of maintaining and expanding existing observational data series for environment-LMR model development and verification. Funding for ocean and LMR observations is limited. Given the importance of having climate observations over a period long enough to span different environmental regimes, LMR observations that cover a wide range of population sizes, and large sample sizes to improve estimation of model parameters, establishment of new monitoring networks must be carefully balanced with the critical need to maintain current sampling programs (Haltuch and Punt, 2011; Dorner et al., 2013). Maintenance and expansion of physical climate observing systems, as discussed in Section 3, are also essential to climate model development to improve climate predictability through better model initialization (e.g. Servonnat et al., 2014). Including concurrent measures of basic biogeochemical and lower-trophic-level measurements should be integrated into existing observing systems, when possible, to facilitate better understanding of physical-biological interactions in the marine environment and better assessment of model predictive capability. That said, while spatially-or temporally-constrained (or incomplete) environmental data may be limited in quantitative utility, such data can help provide qualitative context for decision-making. For example, time series of conditions can be used to delineate regime-specific parameter estimates or emergent patterns in indicators can provide justification for precautionary management actions and intensified monitoring (Zador et al., in press).

Non-stationarity issues are particularly critical for decadal to centennial predictions. However, for many populations, knowledge of environment-fishery interactions is limited to basic correlations. These correlative (and often linearly approximated) relationships provide a useful, existing tool to start integrating climate predictions into LMR models. But if an ecosystem were to shift into a new, no-analog state and the ecosystem processes that were empirically described by this correlative relationship were to change, subsequent management decisions may perform poorly (Dorner et al., 2013). Similar shifts can occur at shorter time-scales. For example, many species distribution models developed with one decade of data perform poorly when used to project species distribution during another decade (Brun et al., 2016). For bias correction of physical climate models, non-linear statistical techniques that are better at simulating distribution extremes appear to perform better under novel climate conditions (Gaitan et al., 2014). More sophisticated, model-free statistical approaches also appear promising in establishing environmental influences on LMRs that can be applied in a management framework, particularly over short timescales (e.g. Ye et al., 2015). To improve LMR predictive capacity, it will be necessary to expand the use of such techniques into tactical management frameworks, and to characterize their benefits relative to more traditional statistical techniques as well as ecosystem models.

Dynamic ecosystem models integrate physical variables, lower-trophic-level dynamics, LMR dynamics, and human impacts, mechanistically, and are critical to enhance our understanding of LMR responses to climate variability (Travers et al., 2007; Rose et al., 2010; Le Mézo et al., 2016). Such process-based understanding is necessary to the development of models able to skillfully predict LMR under novel conditions (Evans, 2012). Furthermore, because of the inherent complexity, non-linearity, and multi-stressor characteristics of marine ecosystems, multispecies and ecosystem models can in some cases assess uncertainties and trade-offs more effectively (Pikitch et al., 2004; Link et al., 2012). Nevertheless, such models are currently only employed for strategic advice at the decadal and multi-decadal scale, rather than for short-term tactical decisions (e.g. Smith et al., 2011; Pacific Fishery Management Council and National Marine Fisheries Service 2014; Fulton et al., 2014; Marine Stewardship Council, 2014). One issue of concern with the use of ecosystem models for tactical decisions is their inability to integrate all of the data streams, such as catch-at-age data, that are customary in current tactical fisheries decision frameworks. Another issue is that their complexity comes at the cost of longer running time, hindering their use within current tactical management process timelines. Also, they rely on static assumptions and parameterizations, which may not remain valid under future conditions. Finally, because more processes are modeled and there is uncertainty in each, the fully characterized uncertainty can be large. This may make decision-making more difficult but, if this uncertainty accurately reflects the true uncertainty in the system, it will ultimately result in better decisions. Expanded application of such models for tactical management decisions will be dependent on improving their parameterizations, specification of initial conditions, extending quantitative model assessments, and reducing their uncertainties through additional physiological studies, process studies, and modeling experiments aimed at understanding the mechanisms driving LMR's responses to climate. LMR surveys that include more hydrographic, biogeochemical, and lower-trophic-level (plankton) observations will also be critical to make progress towards expanded use of ecosystem models in LMR forecasting applications.

Highly resolved spatial and population dynamics models of a specific target species coupled to a coarser, lower-trophic-level model (Lehodey et al., 2008; Senina et al., 2008; Section 4.2) or "models of intermediate complexity" – MICE – (Lindegren et al., 2009; Collie et al., 2014; Plagányi et al., 2014) may be more immediately suited for tactical management decisions, as their uncertainties are more tractable. MICE use statistical parameter estimation methods common in current tactical fisheries models to fit multispecies models to data for small groups of interacting species. Such models are becoming sufficiently advanced, including both species interactions and impacts of temperature on population dynamics (Holsman et al,. in press.), and can be used in concert with single-species models to provide tactical fisheries advice from a multi-model suite, similar to operational prediction systems used in weather forecasts (Ianelli et al., in press.). Combining such models with seasonal and decadal forecasts will help evaluate risk profiles and trajectories of recovery plans, assess the flexibility of harvest policies to dynamic conditions, and identify areas of management vulnerability to climate change (e.g., are dynamic management policies available in hand to respond to sudden shifts in ecosystem structure or driving processes?; Holsman et al., in review). While MICE are quite promising for tactical decision making in the near future, simulation testing to determine whether they can provide adequate information for tactical management under various information conditions typical of fisheries management needs to be undertaken. If successful, such applications may also provide a valuable template for the expansion of holistic whole ecosystem models from strategic to tactical management decisions.

Expanded use of seasonal to decadal forecasts is also limited by problems of relevance in terms of critical variables, and spatial and temporal scales (Nicholls, 1999; Hobday et al., 2016). For some LMR-relevant variables, there are irreducible predictability limits at seasonal to decadal scales due to the chaotic nature of the atmosphere (Deser et al., 2012). Such variables will remain unpredictable even with a perfect data assimilation system and model formulation, and hence management frameworks robust to unpredictable variation will need to be developed.

It will be important for climate scientist to continue assessing predictability limits of LMR-relevant variables and to communicate such limitations to users, e.g., by providing reliable probabilistic forecasts accompanied by appropriate measures of historical skill.

For some regions and time scales, however, predictability of LMR-relevant variables is limited by the systematic errors of GCMs (Goddard et al., 2001). It is critical to find ways to either reduce this model bias or reduce its negative impacts on forecast skill through novel techniques (e.g., Batté et al., 2016). Reduction in model bias will involve improvement in both model physics and parametrizations, as well as data assimilation systems (Goddard et al., 2001; Meehl et al., 2014; Siedlecki et al., 2016). For instance, as variability in ocean circulation can depend on both temperature and salinity variations in the ocean's interior, improved observations of these quantities, as well as improved assimilation systems to make optimal use of these observations, are critical. As resolution of GCMs increases, representation of the physical processes responsible for regional climate predictability improves (e.g. Jia et al., 2015), and, in some cases, this may lead to improved forecast skill of LMR-relevant variables.

Forecasts at the multi-annual to decadal time scales, while of great interest to LMR management and industry, are not yet operational (Section 3). Continued research to improve our theoretical understanding and representation of the physical processes and feedbacks responsible for decadal scale climate variability are required to reduce model bias and improve decadal forecast skill (Meehl et al., 2014). Furthermore, in order to better assess the performance of decadal forecasts, predictability studies across more models and with larger ensembles need to be carried out (Meehl et al., 2014). Demonstration of reliable skill, however, will remain limited by the small sample size available for verification due to the high time series autocorrelation and limited quantity of independent samples at decadal time scales (Kumar, 2009; Meehl et al., 2014). Furthermore, it is important to stress that the decadal predictability of regions, such as the North Pacific, subject to strong atmospheric forcing, will remain limited (Branstator and Teng, 2010; Meehl et al., 2014).

In addition to improvements in models and initialization, predictability across spatiotemporal scales of more LMR-relevant physical variables such as bottom temperature, sea surface height, onset of upwelling, or salinity need to be examined. Biogeochemical prediction (e.g. chlorophyll biomass, net primary productivity (NPP), export production fluxes, aragonite saturation in coastal zones, oxygen concentration) is also of major relevance to ecosystem-based management of marine resources (Levin et al., 2009; Stock et al., 2011). While biogeochemical prediction is in its early stages and no coupled physical-biogeochemical seasonal to decadal forecasting systems are yet operational (but see Case Study 4.6 for their use in sub-seasonal prediction), recent work shows some potential. Predictive skill up to several months has been shown in the northern CCS for bottom oxygen (Case Study 4.5, Siedlecki et al., 2016), and up to 3 years for NPP in some oceanic domains (Séférian et al., 2014, Chikamoto et al., 2015). In most cases, the increased predictability in NPP arises from that of nutrients, which directly benefit from the initialization of the model physical fields (Séférian et al., 2014). These pioneering results demonstrate that biogeochemical prediction shows promise and highlight the need to both develop integrated physical-biogeochemical forecast systems, and further quantify biogeochemical predictive skill over a variety of space and time scales to inform ecosystem-based management approaches to LMRs. Application of ESMs in a climate change framework has demonstrated that uncertainty in LMR projections can be large due to uncertainty in the many modelling components, from GCMs to upper-trophic level models, required to assess climate change impacts on LMRs (Cheung et al., 2016b). Computing and personnel resources will hence be required to develop an ensemble approach for biogeochemical prediction able to account for this uncertainty. An assessment of prediction skill beyond SST to other properties driving biological responses will also necessitate supporting, collecting, and maintaining sampling programs and observing systems.

The spatial resolution of global climate models poses another limitation to their skill at the regional scale relevant to LMR decisions. Downscaling techniques can be used to generate finer-scale information from large-scale climate predictions. By relating well predicted large-scale factors to a local process of interest, downscaling, in addition to providing higher spatially and temporally resolved data, may produce LMR-relevant variables not skillfully generated by global prediction systems (e.g. Siedlecki et al., 2016). There are two types of downscaling techniques: statistical and dynamical. The first links the large-scale output from a global prediction system to local scale variables using statistical-empirical relationships. The second uses the large-scale output as boundary conditions to regional-scale, physics-based dynamical models.

Statistical downscaling techniques are computationally inexpensive, so the large ensembles required to appropriately characterize initial condition and model uncertainty of seasonal to decadal predictions (Section 2.1.2) can be run relatively fast. The ability to quickly produce output is an advantage particularly relevant for downscaling of seasonal predictions, as they have to be produced in a timely manner to be relevant to the decision-making process (Laugel et al., 2014). However, to construct robust statistical relationships, long observational records are required (Section 4.1 and 4.3), though are not always available. Second, all statistical downscaling techniques assume that the large-scale, local climate relationship will remain the same in the future. While these assumptions may hold for the relatively short timeframe of seasonal predictions, they may deteriorate over longer-range decadal predictions.

By contrast, dynamical downscaling techniques explicitly model the physical processes involved and therefore may perform better than statistical methods under changing or unprecedented conditions (e.g. van Hooidonk et al., 2015). Dynamical downscaling models, however, will still inherit any bias of large-scale GCMs, and may even amplify such systematic errors (Goddard et al., 2001; Hall, 2014). This stresses again the need to reduce bias in global predictions systems to improve predictability of LMR-relevant variables at a regional scale. Further research will also be necessary to assess the relative costs and benefits of statistical versus dynamical techniques for downscaling of LMR-relevant climate predictions. This will require more resources allocated towards the development of downscaling frameworks for LMR-relevant climate predictions in regions of interest for LMRs. For instance, coupling to fine resolution coastal models, like the efforts in the northern CCS and Indonesian region (Case Studies 4.5 and 4.6), is a promising approach that warrants more studies in other regions. Furthermore, modeling studies aimed at understanding the extent to which LMR-relevant local processes are interactive with the large-scale and to what extent they are primarily "driven" by large-scale processes are required. Such studies would help to identify the type of downscaling method most appropriate and indicate regions requiring higher-resolution global climate prediction systems to further enhance predictability and support decision making at fine spatial scales.

7. Concluding Remarks

It is widely recognized that the productivity and distribution of LMR populations change over time in response to climate and ecosystem variability and long-term trends. Fishers, aquaculturists, coastal planners, and fisheries managers recognize that many of their operational planning and management decisions should account for this dynamism. We have shown how recent improvements in global dynamical climate prediction systems have resulted in skillful predictions of LMR-relevant variables at many of the spatial and temporal scales at which LMRs are managed, and how such predictions are already helping industry and managers make decisions in dynamic environments. By describing climate prediction systems and their capabilities, as well as the range of decisions currently taken by managers and the fisheries and aquaculture sector that may benefit from the inclusion of future climate information, new applications may be developed for wider use. Successful integration of climate information into LMR decision frameworks will depend on close collaboration and open dialogue between potential users and climate scientists.

While some progress has been achieved within existing frameworks and resources, challenges in both climate and fisheries models need to be addressed to further expand utility of such predictions for LMRs (Section 6). To ensure widespread application of climate forecasts into LMR decision making and prevent unintended consequences of climate and fisheries interactions, new methodological approaches that capture complex ecosystem dynamics and the full range of LMR drivers need to be developed. Such frameworks will inherently be probabilistic and consist of ensemble methods to account for uncertainties in both climate and LMR models, improve model accuracy, and help end users understand risk. These frameworks will also evolve over time as our understanding of environment-LMR links, which remains poor for many species and regions, is improved through more field observations and experimental studies. Therefore, management decision systems will need to become more flexible to the inclusion of new information streams at a variety of both spatial and temporal scales, as well as to frequent re-evaluation.

As we acknowledged above, seasonal to decadal predictions of climate and LMR dynamics will sometime fail despite the best efforts, especially given the increasing potential for no-analog system states and ecological surprises (Williams and Jackson, 2007; Doak et al., 2008). To cope with this inevitability, we also encourage the development of approaches for managing unexpected changes once they have happened (Schindler and Hilborn, 2015).

As predictability is the ultimate test of scientific theory, routinely using these climate-forecast informed frameworks to make predictions of LMR dynamics will also improve understanding of ecosystem dynamics. In addition, skillful predictions at seasonal to multi-annual scales will lend confidence to the use of such models to project LMR dynamics over longer temporal scales, and can be used to build stakeholder confidence in the use of longer term climate projections. With exploited systems being more sensitive to environmental variability (Hsieh et al., 2006; Perry et al., 2010), development of such capabilities will be essential to the development of climate-ready management systems to effectively manage and culture LMRs in a future environment where long term change renders historical experience less valuable.

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Figure Captions

Figure 1. Overview of simulation design for seasonal and decadal predictions and climate projections. GHG refers to greenhouse gases. Note that the year for shifting from pre-industrial to historical forcing in climate projections, here set to 1860, can differ between climate models. "Forcings" in the climate change context refer to specified solar insolation and concentrations of radiatively active atmospheric constituents.

Figure 2. Temperature anomalies at 55-m depth from six different ocean reanalysis products for April 2015 relative to each-product 1981-2010 climatology. The bottom left panel shows the ensemble mean, and the bottom right the ratio of signal (ensemble mean) to noise (ensemble spread).

Figure 3. Left panel: One-month lead probabilistic forecast of SST for summer (June, July, and August, JJA) initialized in May 2016 from the North American Multi-Model Ensemble (NMME). This forecast was produced using all the ensemble members provided by each model participating in the NMME. It therefore reflects both initial condition and model uncertainty. Warm colors (yellow-orange) indicate areas with a significant probability of experiencing upper-tercile temperatures, with the probability of such terciles ranging from 40-100% depending on the degree of shading. Analogous interpretations exist for the anomalously cool (blue colors) or near climatological (gray colors) conditions. Right panel: Ranked probability skill score for the forecast presented in the left panel. The color bar represents the relative improvement of the probability forecast (left panel) over climatology, with 0 indicating no skill over climatology. Note the higher predictive skill in the North Atlantic, North Pacific and at the equator.

Figure 4. May-June surface and bottom temperature/salinity biases (model minus observations) for the US Northeast Continental Shelf. Observations are based on May-June climatologies of NOAA ship-based in situ measurements from 1977 to 2009. Model output is from each climate model's 1990 control simulation (40-year mean). The average global ocean (atmosphere) resolutions for CM2.1, CM2.5FLOR, CM2.5, and CM2.6 are 100-km (200-km), 100-km (50-km), 25-km (50-km), and 10-km (50-km), respectively. Note that the operational GFDL seasonal climate prediction system uses CM2.5FLOR. Refer to Saba et al. 2016 for further details on the models and experiments.

Figure 5. Temporal and spatial scales of fisheries decisions (circles) and atmospheric weather phenomena (clouds). Atmospheric weather processes adapted from Troccoli et al. (2007), Fig. 2.1. Note that "resilience and sustainability" and "rebuilding plans and protected areas" decisions are made across a range of spatial scales. Here they are associated with large spatial scales to reflect the significant impact of large scale climate processes, such as global climate change, on their outcome.

Figure 6. Anomaly correlation coefficients (ACCs) as a function of forecast initialization month (x-axis) and lead-time (y-axis) in the National Atmospheric and Oceanic Administration (NOAA) Geophysical Fluid Dynamics Laboratory (GFDL) CM2.5 FLOR and NOAA National Centers for Environmental Prediction CFSv2 global climate prediction systems for the Gulf of

Alaska (GoA) large marine ecosystem (Stock et al. 2015). Note how late winter-early spring SST anomaly prediction skill exceeds persistence at long lead-times (4-12 months). Grey dots indicate ACCs significantly above 0 at a 5% level; white upward triangles indicate ACCs significantly above persistence at a 10% level with ACC > 0.5; white downward triangles indicate ACCs significantly above persistence at a 10% level with ACC < 0.5.

Figure 7 Left column: idealized environmental forcing historical time series, and short term forecast (±1 standard deviation) based on seasonal climate forecast (blue), forecast based on assumption that future conditions will be within the historical variability (red), and truth (black); central columns: probability density function of environmental forcing and of environmentally-dependent productivity parameters; right column: productivity historical time series and its one-year forecast based on a dynamic environmental driver (blue) or on average environmental conditions (red). Arrows represent the different steps of an environmentally-explicit stock assessment framework.

Figure 8. Regional probabilistic forecast skill for maximum air temperature (upper tercile), minimum air temperature (lower tercile), and rainfall (upper tercile) based on tercile probabilities for each lead-time. The skill score corresponds to the ratio of the number of correct forecasts to the total number of forecasts for the period of 1981-2010 (Adapted from Spillman et al., 2015).

Figure 9. Left: Maps showing the average SST for the GAB as forecast by POAMA on 17 Dec 2015 for the next fortnight and the next two calendar months. The mean SST over the whole area shown is given in the top left corner of each map. The black line represents the 200-m contour. Right: Corresponding areas of preferred SBT habitat, where values > 1 indicate more preferred habitat and values < 1 indicate less preferred habitat.

Figure 10. Example of the GMRI lobster forecast as delivered to the fishing industry via Twitter on March 24, 2016. The first panel shows the spring temperature from the NERACOOS coastal ocean buoys in spring 2016 (red line) used to generate the forecast. Temperatures in 2016 have been higher than the 2000-2014 average. The second panel shows that SST has been anomalously warm throughout the Maine coastal region for March 2016. The bottom panel is the actual forecast, predicting a 68% chance that the season will start three weeks earlier than normal, a 31% chance that it will start two weeks early, and only a 1% chance that it will begin one week early. The normal high-landings period for Maine lobster is considered to start between July 3 and 10.

Figure 11. Comparison of (a) Coral Reef Watch 4-Month Bleaching Outlook with (b) 4-month composite of maximum Bleaching Alert Area from real-time satellite data for the same period, August-November 2015. The levels refer to potential bleaching intensity, with possible bleaching starting at a warning thermal stress level, bleaching likely at an Alert Level 1 and bleaching mortality likely at an Alert Level 2. Note successful prediction of severe bleaching in Kiribati and Hawaii.

Figure 12. Probability of sardine presence, for July (left) and August (right) of 2015. These two to three month forecasts are the average of a three-member ensemble, initialized as April 15th, May 1, and May 15th. Due to relatively warm sea surface temperature, the forecasts predict habitat suitable for sardine throughout the region. The exception is low salinity water for which

the model would expect sardine to be found at more intermediate rather than warm temperatures. This leads to low probability of presence in the less saline Columbia River plume. Note that recent declines in sardine stock size (which is not included in the model) may be resulting in unoccupied, but suitable, habitat in the northern region.

Figure 13. Example output from the global (top) and regional (bottom) SEAPODYM model configurations developed though the INDESO project.

Figure 14. Habitat maps indicating zones of SBT distribution (see text for explanation of zones), obtained using POAMA seasonal forecasts of ocean temperature. The upper left plot shows the historical daily climatology of the zones (yellow ribbon), the current year's observed zone locations to date (red ribbon) and the latest monthly forecasts of zone location (red stars). The arrows along the other panels indicate whether the zones are moving north or south relative to the POAMA nowcast.

Figure 15. Steps required for successful integration of climate predictions into LMR decision frameworks. (Adapted from Hobday et al., 2016).

Appendix

Table A1. List of six operational ocean reanalysis products from 1979-present used in the Real-time Ocean Reanalysis Intercomparison Project. See http://www.cpc.ncep.noaa.gov/products/GODAS/multiora_body.html for a link to download some of these reanalysis products. The data assimilation column lists the observation types used for their estimation (T/S for temperature and salinity; SLA: altimeter-derived sea level anomalies; SST: sea surface temperature, SIC: sea-ice concentration), as well as assimilation techniques used for reanalysis: Ensemble Optimal Interpolation (EnOI), Ensemble Kalman Filter (EnKF), Variational methods (3DVar). The atmospheric surface forcing is usually provided by atmospheric reanalyses, using either direct daily fluxes, or different bulk formulations. There are also systems that use fluxes from coupled data assimilation systems (Coupled DA).

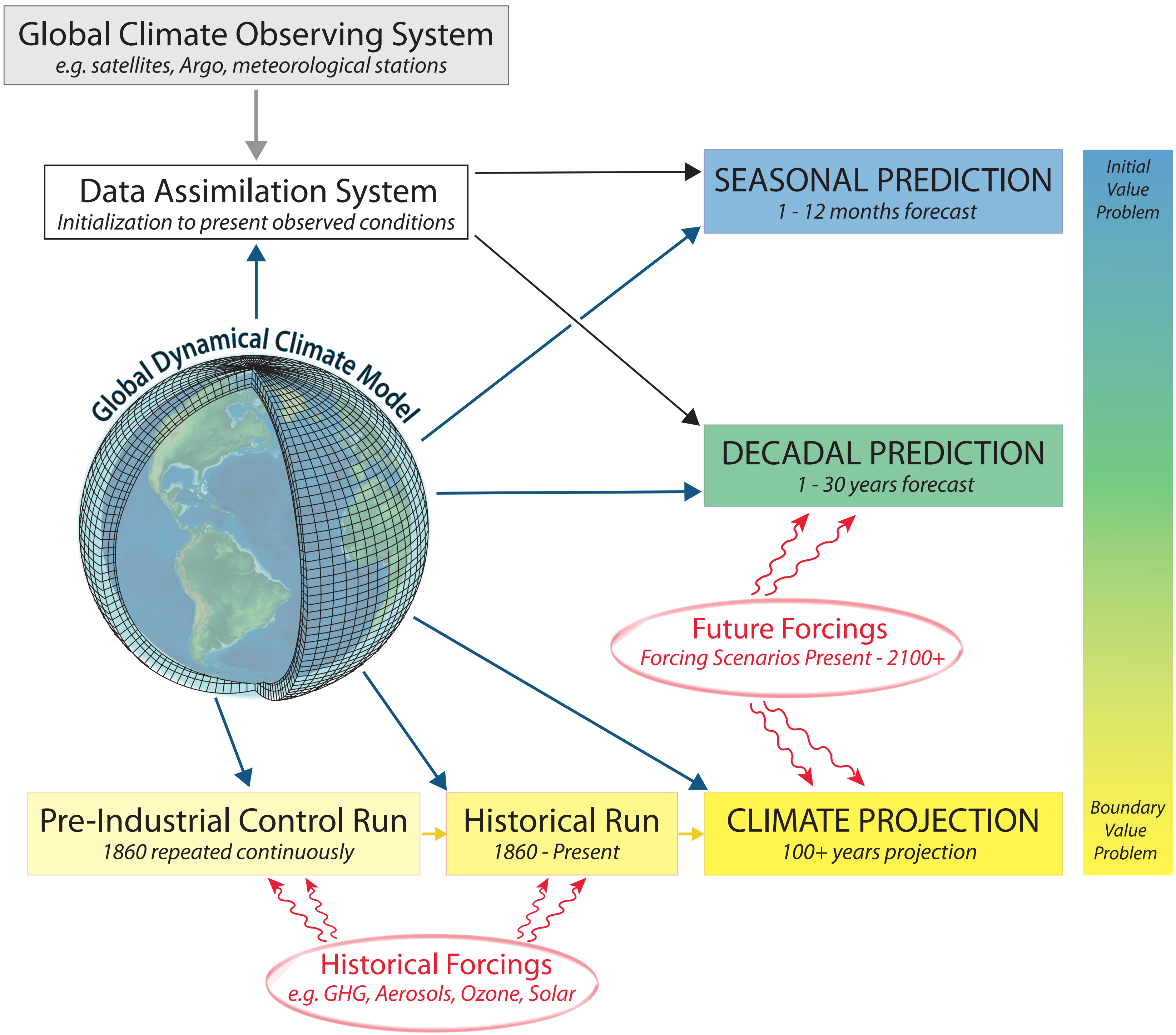
Product	**Forcing**	**Ocean Model**	**Data Assim. Method**	**Ocean Observations**	**Analysis Period**
NCEP GODAS (**NGODAS**)	NCEP-R2	1°x1/3° MOM3	3DVAR	T/SST	1979-present
GFDL (ECDA)	Coupled DA	1°x1/3° MOM4	EnKF	T/S/SST	1979-present
BOM (PEODAS)	ERA40 to 2002; NCEP-R2 thereafter	1°x2° MOM2	EnKF	T/S/SST	1970-present
ECMWF (ORAS4)	ERA40 to 1988; ERAi thereafter	1°x1/3° NEMO3	3DVAR	SLA/T/S/SST/ SIC	1979-present
JMA (MOVE-G2)	JRA55 corr + CORE Bulk	1°x0.5° MRI.CO	3DVAR	SLA/T/S/SST/ SIC	1979-present

		M3			
NASA (MERRA Ocean)	MERRA + Bulk	0.5°x1/4° MOM4	EnOI	SLA/T/S/SST/ SIC	1979-present

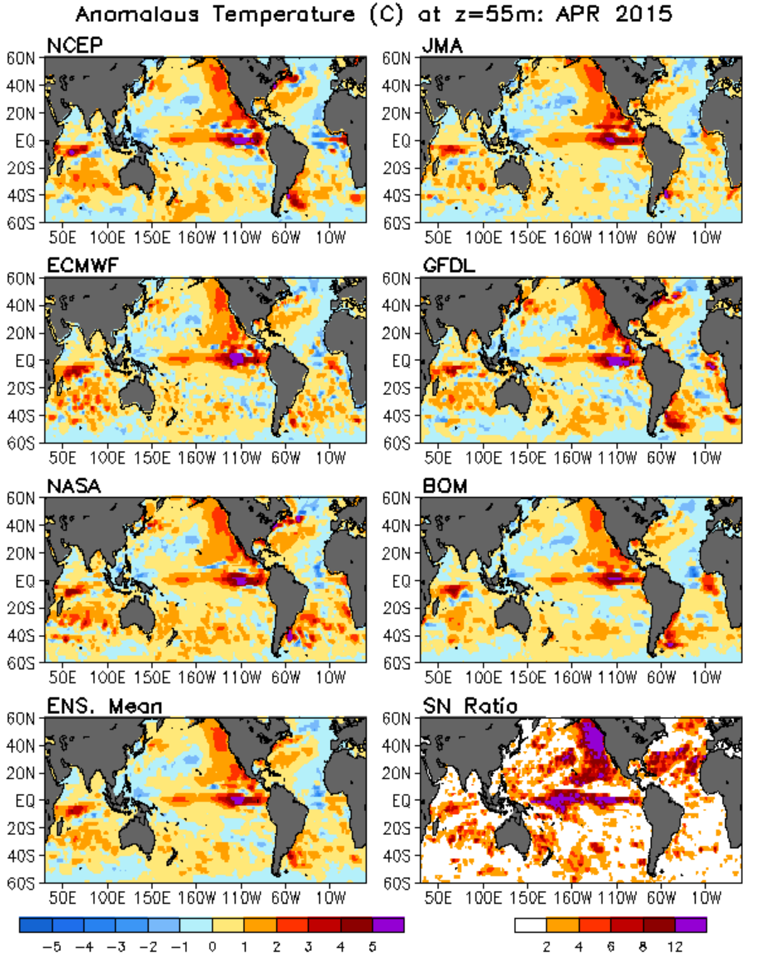
Table A2. Living marine resources for which there is a linkage between their dynamics and environmental variability. These includes those determined by Myers 1998 as robust to re-evaluation, marked by an *, and those described by Skern-Mauritzen et al. 2015 as making use of environmental information in their management, marked by a †. For all other examples, the reference is provided.

Species	**Region**	**Environmental Driver**	**Reference**
Cod*†	Barents Sea	Temperature	
Cod*	Eastern Baltic	Salinity	
Cod*	Labrador	Salinity	
Cod*	NW Atlantic	*Calanus* spp. abundance	
Eurasian Perch*	Windemere and Baltic region	Temperature	
Pike Perch*	Netherlands and Baltic region	Temperature	
Herring*	Southern British Columbia	Temperature	
Herring*	Northern Newfoundland	Temperature	
Sardine*†	California	Temperature	
Sardine†	Mediterranean	Chlorophyll a	
Anchovy†	Mediterranean	Chlorophyll a	
Sea Bass*	South Britain	Temperature	
Smallmouth bass*	Lake Opeongo	Temperature	
Smallmouth bass*	North Lake Huron	Temperature	
White Hake†	Southeastern Atlantic (West Africa)	NAO	
Mutton Snapper†	South Atlantic/Gulf of Mexico	Temperature and salinity	
Yellowtail flounder*	Southern New England	Temperature	
Plaice*	Kattegat	Wind	
Skipjack tuna†	Eastern Pacific	Temperature, ocean currents, primary production	
Swordfish†	Southeastern Pacific	Ocean climate, hydrography, primary production	

Striped Marlin†	Northeastern Pacific	Ocean climate, hydrography, primary production	
Pacific hake	California Current	Ocean currents	Agostini et al. 2006
Sablefish	California Current	Ekman transport, sea level	Schirripa and Colbert 2006
Pink salmon†	North Pacific	Temperature and prey availability	
Coho and Chinook Salmon	Columbia River	PDO and prey availability	Peterson and Schwing 2003, Bi et al. 2011, Peterson and Burke 2013, Burke et al. 2013)
Chinook Salmon	Snake River	Air temperature, river flow, upwelling, PDO	Zabel et al. 2013
Lobster*	Gulf of Maine	Temperature	
Northern shrimp*	Gulf of Maine	Temperature	
Banana prawn*	Gulf of Carpentaria	Salinity	

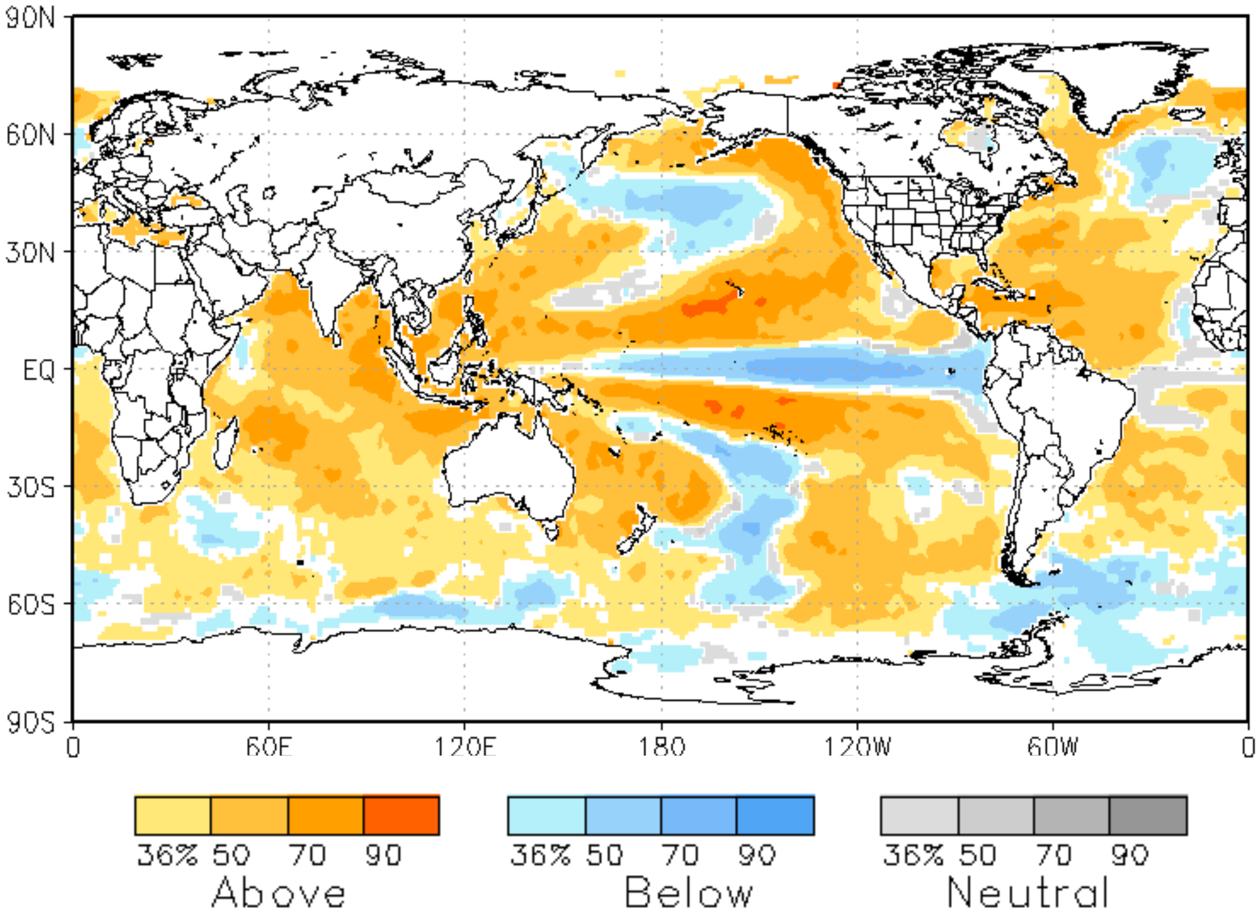


Global Climate Observing System
e.g. satellites, Argo, meteorological stations
Data Assimilation System
Initialization to present observed conditions
Global Dynamical Climate Model
SEASONAL PREDICTION
1 - 12 months forecast
DECADAL PREDICTION
1 - 30 years forecast
Future Forcings
Forcing Scenarios Present - 2100+
CLIMATE PROJECTION
100+ years projection
Pre-Industrial Control Run
1860 repeated continuously
Historical Run
1860 - Present
Historical Forcings
e.g. GHG, Aerosols, Ozone, Solar
Initial
Value
Problem
Boundary
Value
Problem

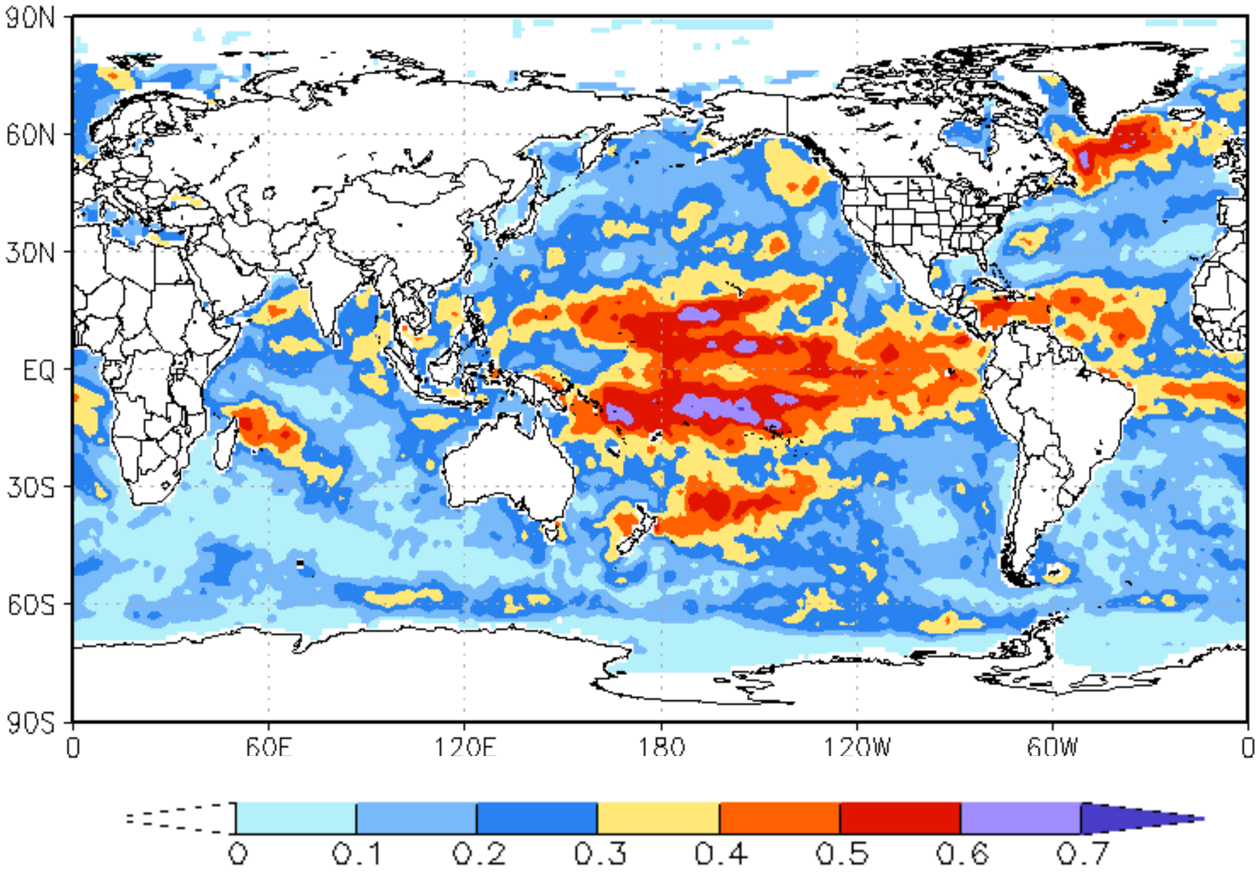


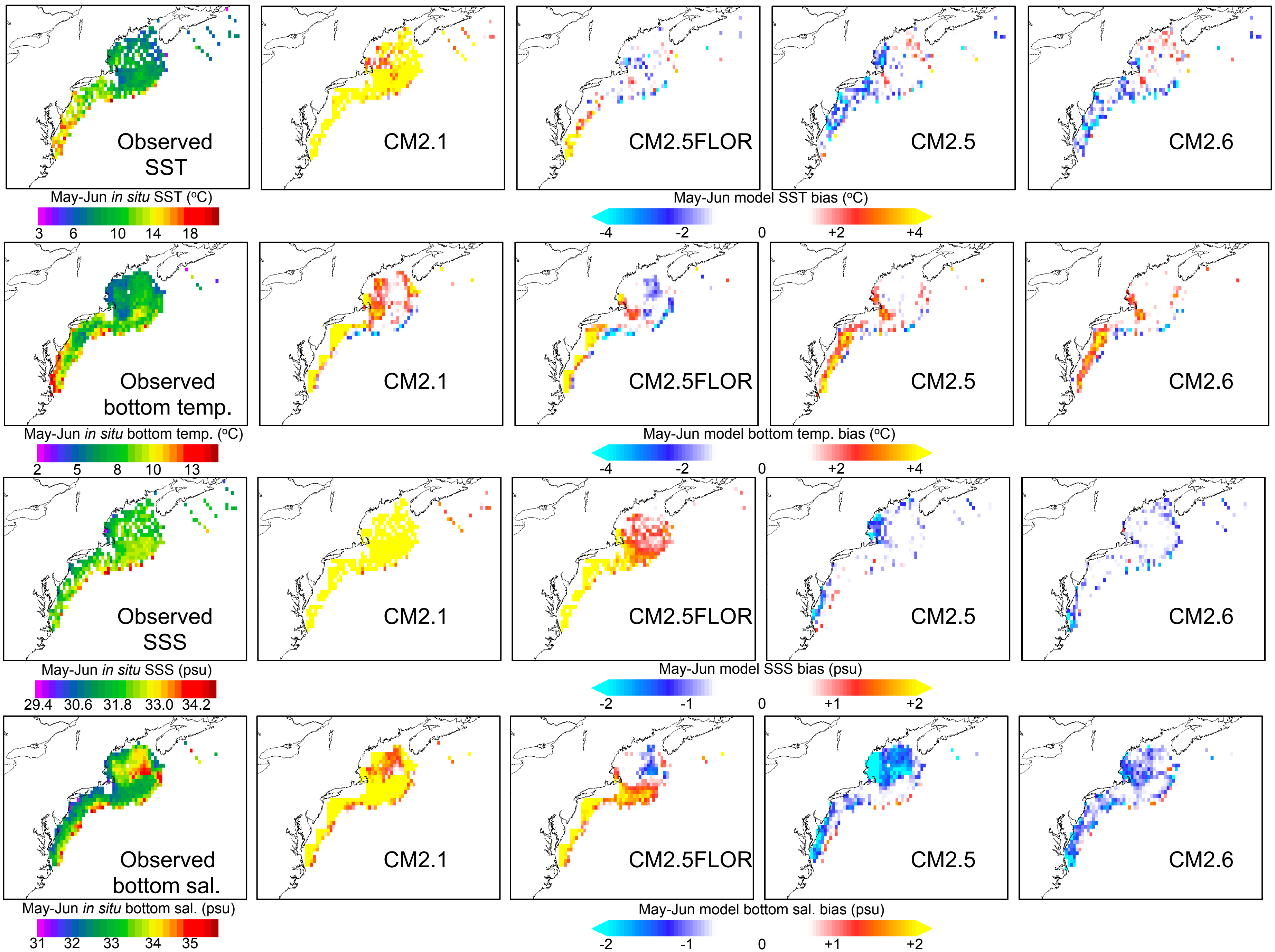
Anomalous Temperature (C) at z=55m: APR 2015
NCEP
JMA
ECMWF
GFDL
NASA
BOM
ENS. Mean
SN Ratio
60N 40N 20N EQ 20S 40S 60S
50E 100E 150E 160W 110W 60W 10W
−5 −4 −3 −2 −1 0 1 2 3 4 5
2 4 6 8 12

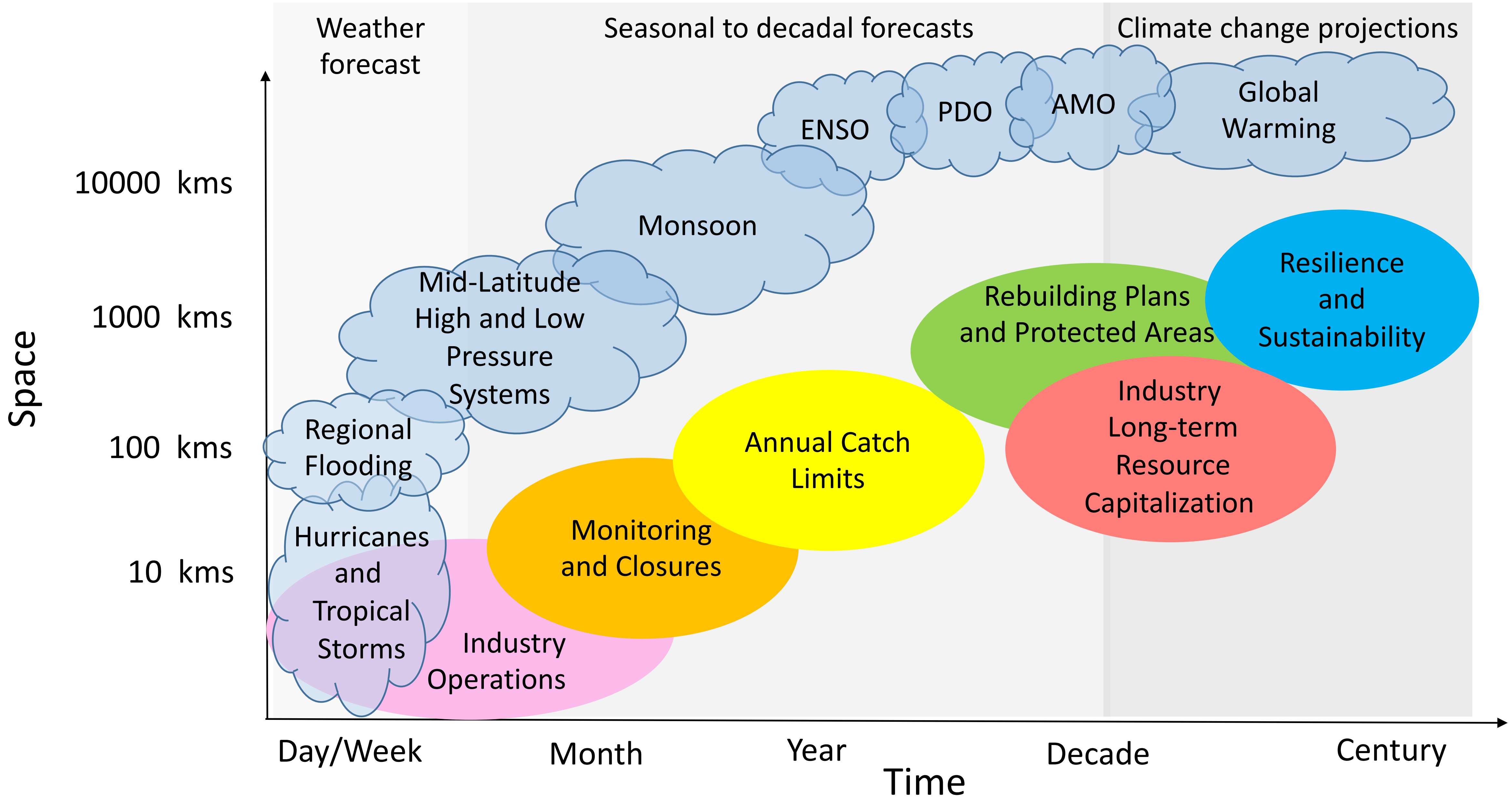
NMME Probabilistic SST Forecast for JJA, lead 1



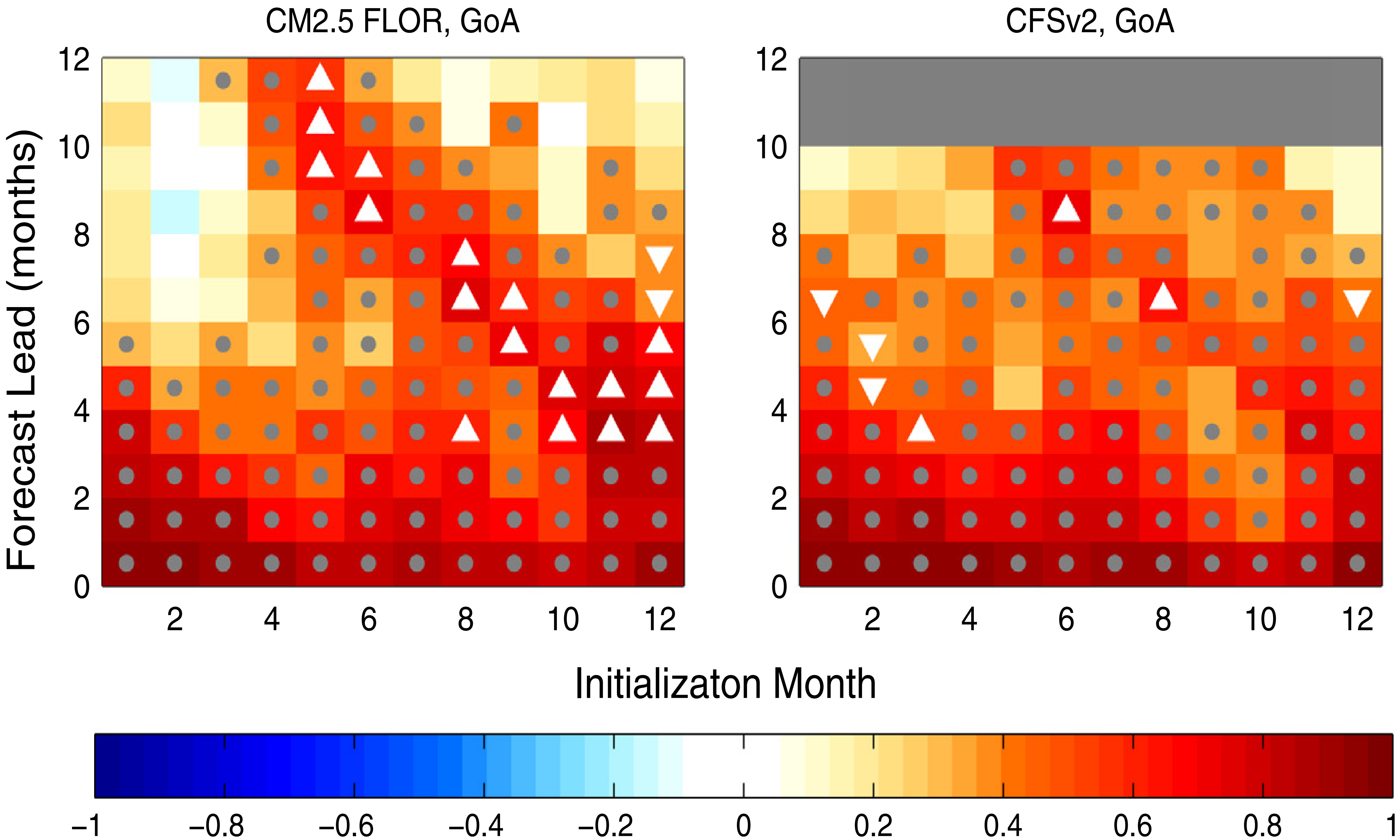
RPSS for the Probabilistic SST Forecast for JJA, lead 1



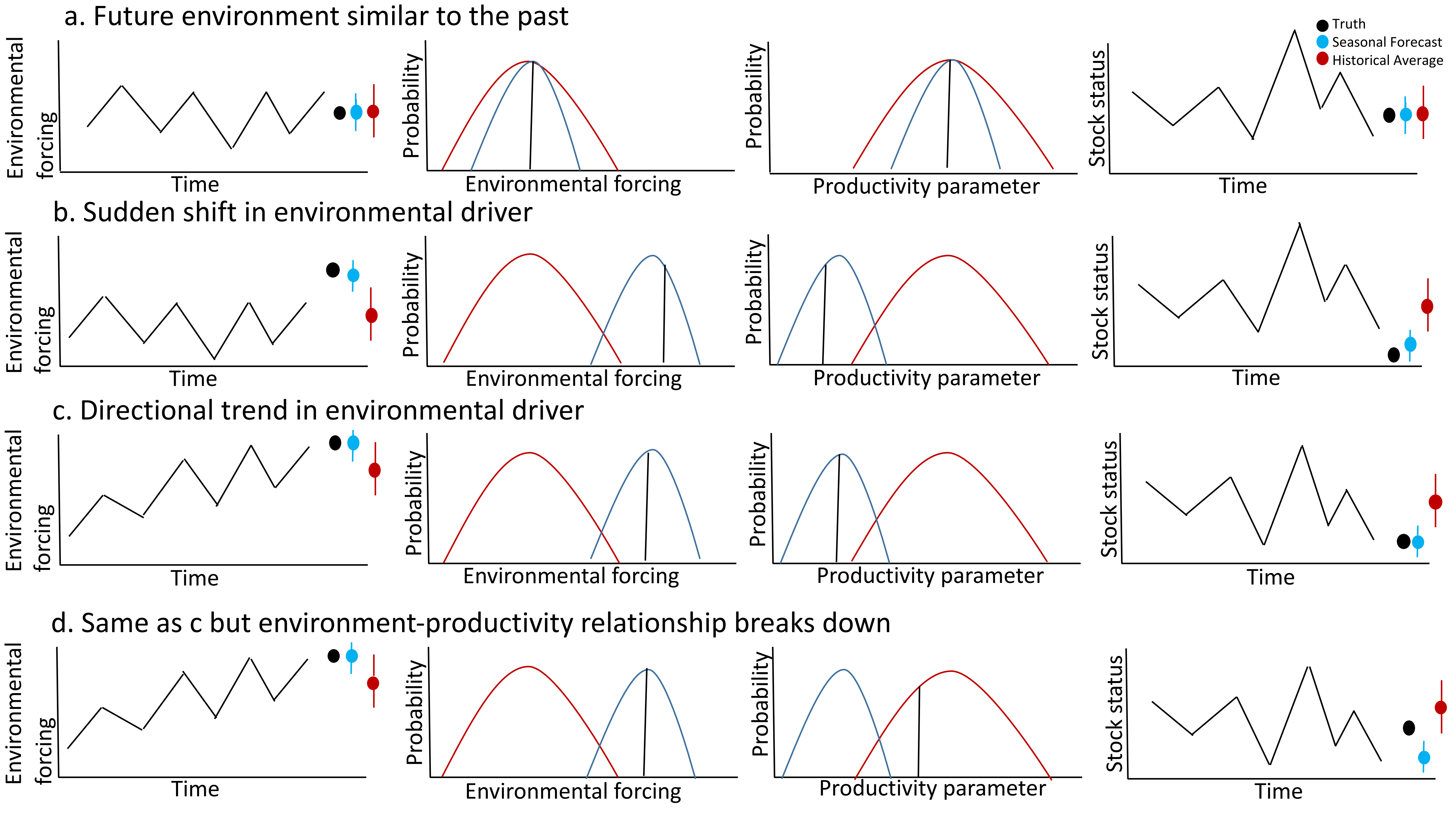

Observed SST
CM2.1
CM2.5FLOR
CM2.5
CM2.6
May-Jun in situ SST (oC)
3 6 10 14 18
May-Jun model SST bias (oC)
-4 -2 0 +2 +4
Observed bottom temp.
CM2.1
CM2.5FLOR
CM2.5
CM2.6
May-Jun in situ bottom temp. (oC)
2 5 8 10 13
May-Jun model bottom temp. bias (oC)
-4 -2 0 +2 +4
Observed SSS
CM2.1
CM2.5FLOR
CM2.5
CM2.6
May-Jun in situ SSS (psu)
29.4 30.6 31.8 33.0 34.2
May-Jun model SSS bias (psu)
-2 -1 0 +1 +2
Observed bottom sal.
CM2.1
CM2.5FLOR
CM2.5
CM2.6
May-Jun in situ bottom sal. (psu)
31 32 33 34 35
May-Jun model bottom sal. bias (psu)
-2 -1 0 +1 +2

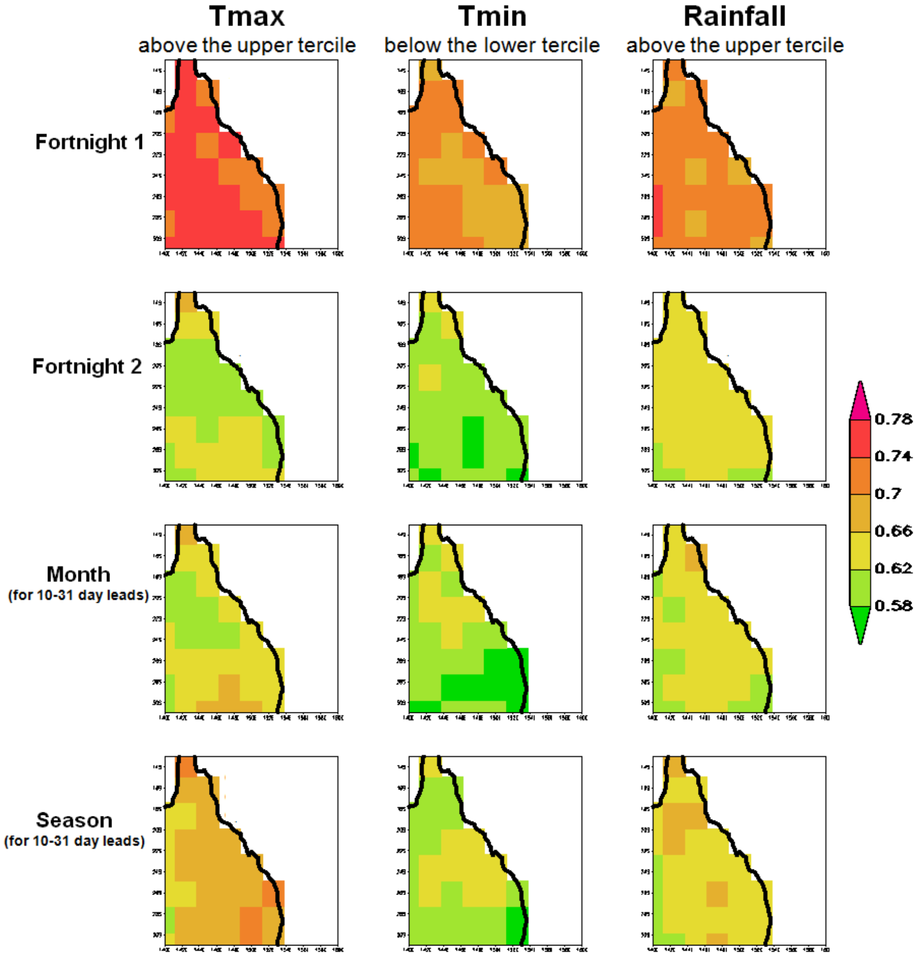


Weather forecast
Seasonal to decadal forecasts
Climate change projections
Space
10000 kms
1000 kms
100 kms
10 kms
ENSO
PDO
AMO
Global Warming
Monsoon
Mid-Latitude High and Low Pressure Systems
Regional Flooding
Hurricanes and Tropical Storms
Industry Operations
Monitoring and Closures
Annual Catch Limits
Rebuilding Plans and Protected Areas
Resilience and Sustainability
Industry Long-term Resource Capitalization
Day/Week
Month
Year
Decade
Century
Time

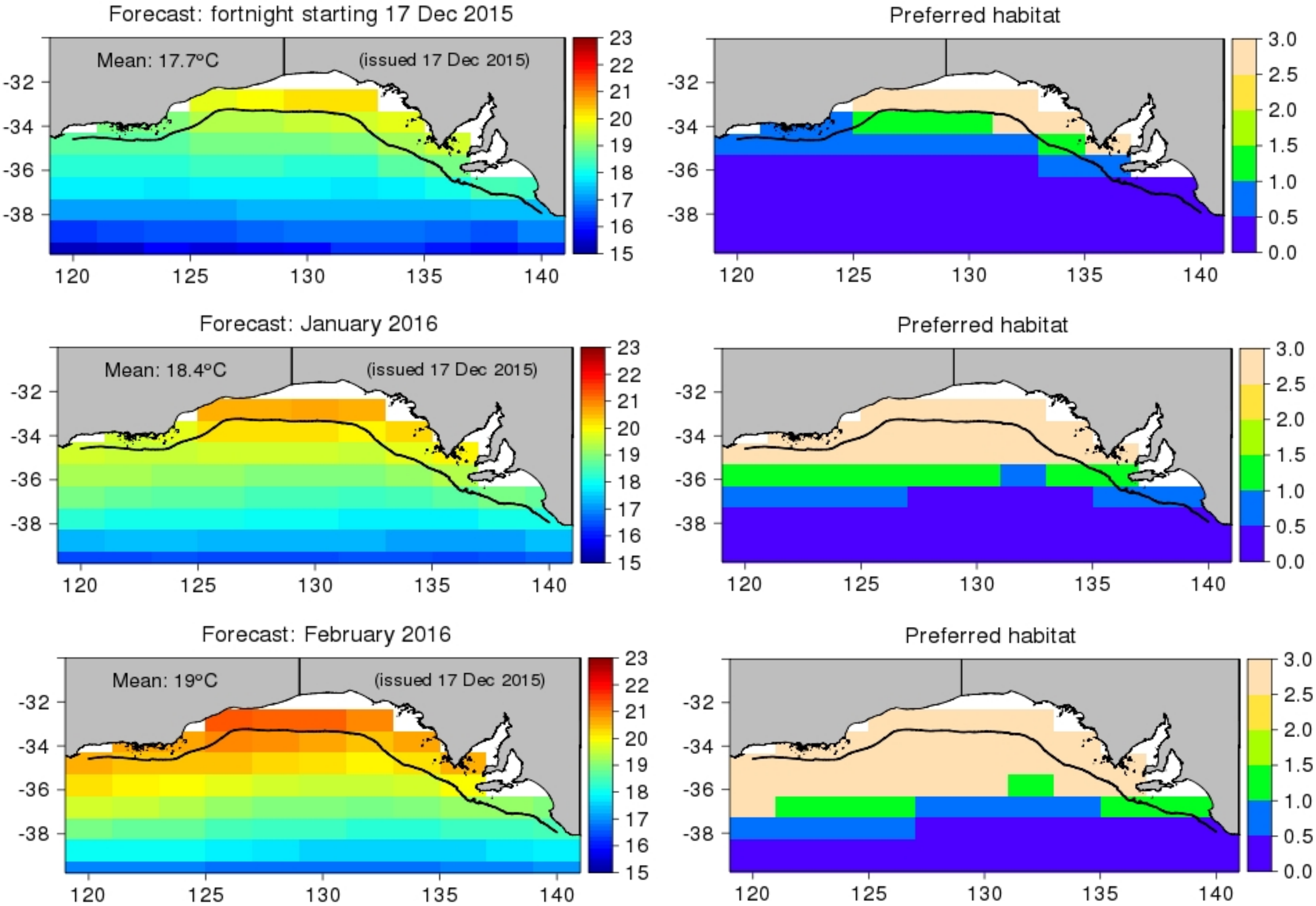


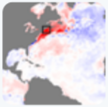
CM2.5 FLOR, GoA
CFSv2, GoA
Forecast Lead (months)
Initializaton Month
0
2
4
6
8
10
12
−1
−0.8
−0.6
−0.4
−0.2
0
0.2
0.4
0.6
0.8
1


a. Future environment similar to the past
b. Sudden shift in environmental driver
c. Directional trend in environmental driver
d. Same as c but environment-productivity relationship breaks down
Environmental forcing
Time
Probability
Environmental forcing
Probability
Productivity parameter
Stock status
Time
Truth
Seasonal Forecast
Historical Average



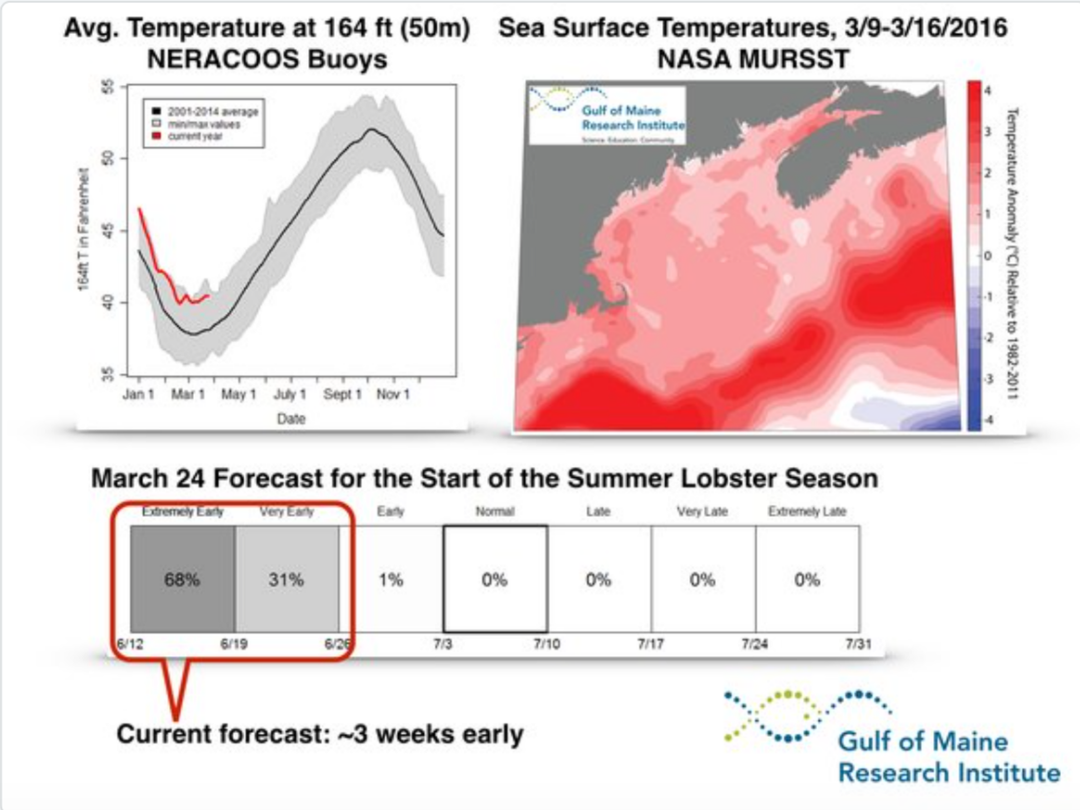
Tmax
above the upper tercile
Tmin
below the lower tercile
Rainfall
above the upper tercile
Fortnight 1
Fortnight 2
Month
(for 10-31 day leads)
Season
(for 10-31 day leads)
0.78
0.74
0.7
0.66
0.62
0.58

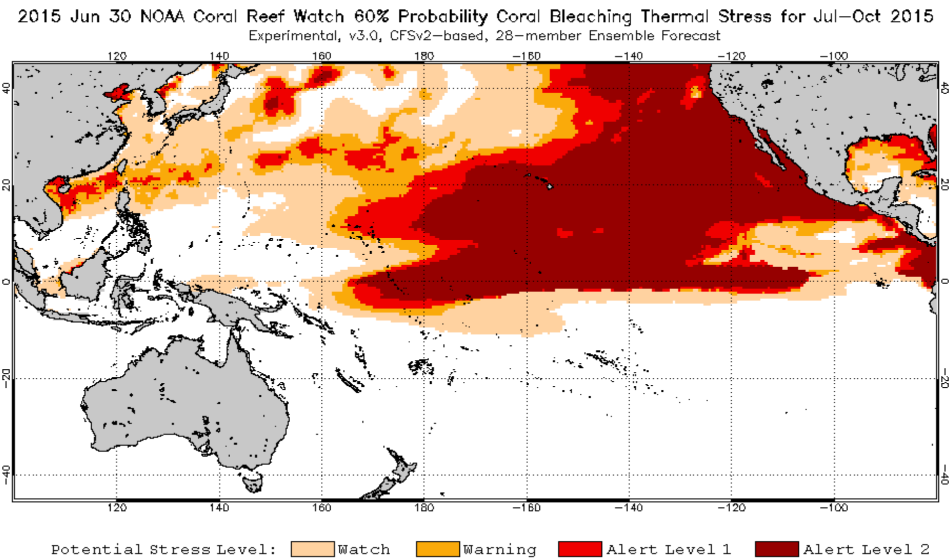

Forecast: fortnight starting 17 Dec 2015
Mean: 17.7°C
(issued 17 Dec 2015)
Preferred habitat
Forecast: January 2016
Mean: 18.4°C
(issued 17 Dec 2015)
Preferred habitat
Forecast: February 2016
Mean: 19°C
(issued 17 Dec 2015)
Preferred habitat
-32
-34
-36
-38
120
125
130
135
140
15
16
17
18
19
20
21
22
23
0.0
0.5
1.0
1.5
2.0
2.5
3.0

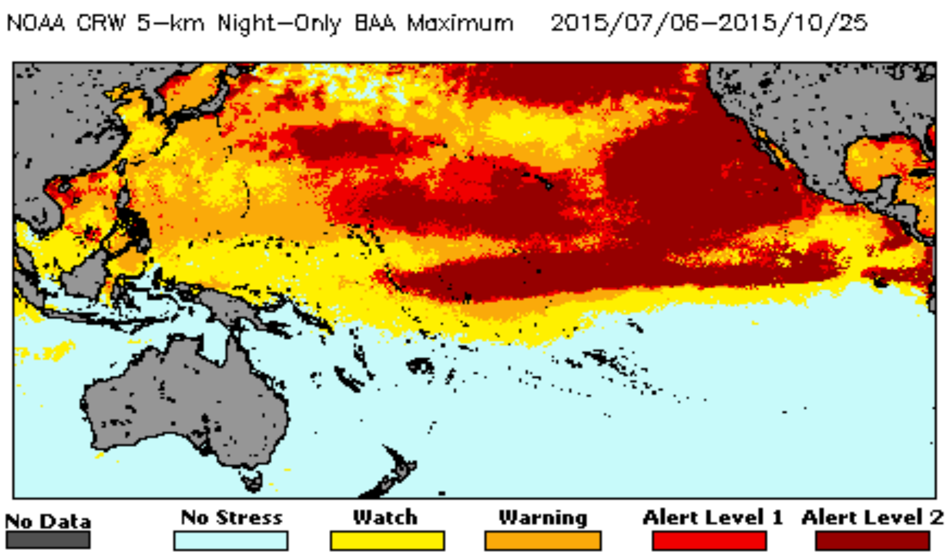


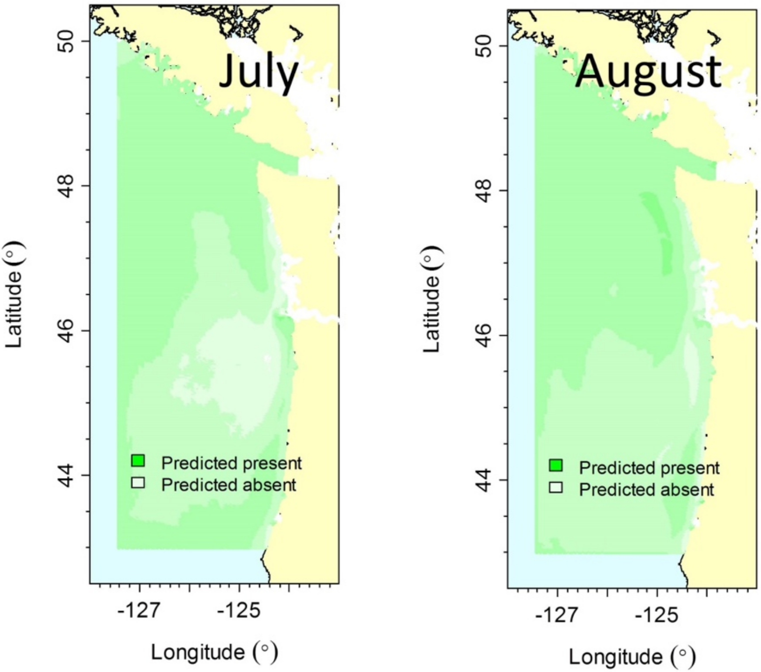
Andrew Pershing @Sci_Officer · Mar 24

Updated #lobster forecast from @GMRI. Increasing chance of the season starting 3+ weeks early.

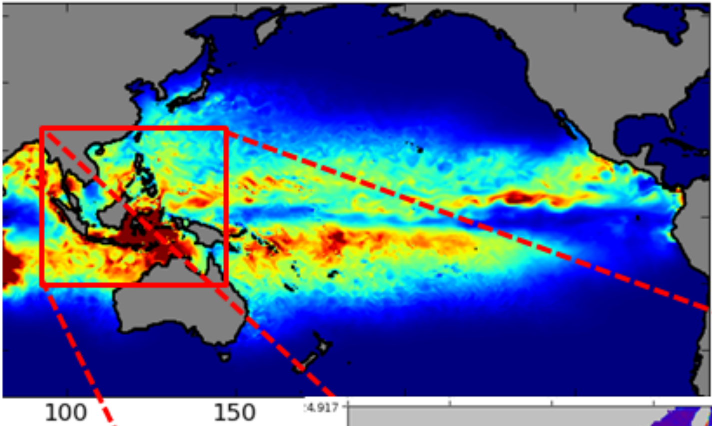



2015 Jun 30 NOAA Coral Reef Watch 60% Probability Coral Bleaching Thermal Stress for Jul–Oct 2015
Experimental, v3.0, CFSv2–based, 28–member Ensemble Forecast
120 140 160 180 –160 –140 –120 –100
40 20 0 –20 –40
Potential Stress Level:
Watch
Warning
Alert Level 1
Alert Level 2

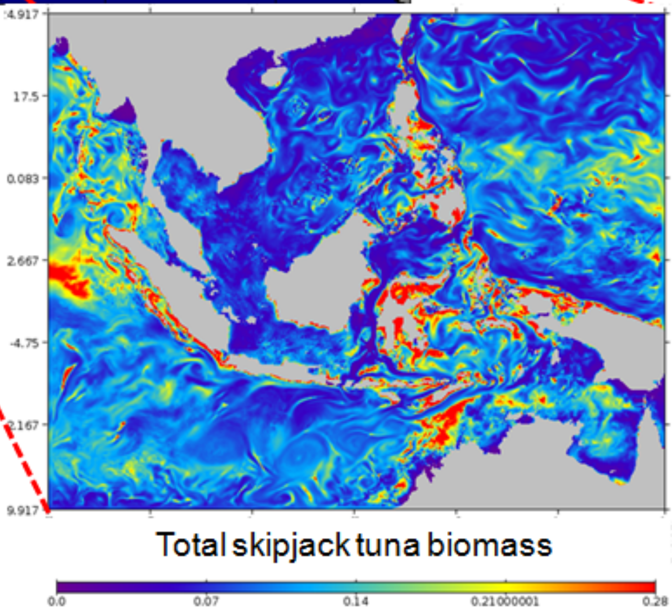

NOAA CRW 5–km Night–Only BAA Maximum 2015/07/06–2015/10/25
No Data
No Stress
Watch
Warning
Alert Level 1
Alert Level 2


July
August
Predicted present
Predicted absent
Predicted present
Predicted absent
Latitude (°)
Latitude (°)
Longitude (°)
Longitude (°)
50
48
46
44
50
48
46
44
-127
-125
-127
-125

Operational Global Model (¼° x week) predicting:

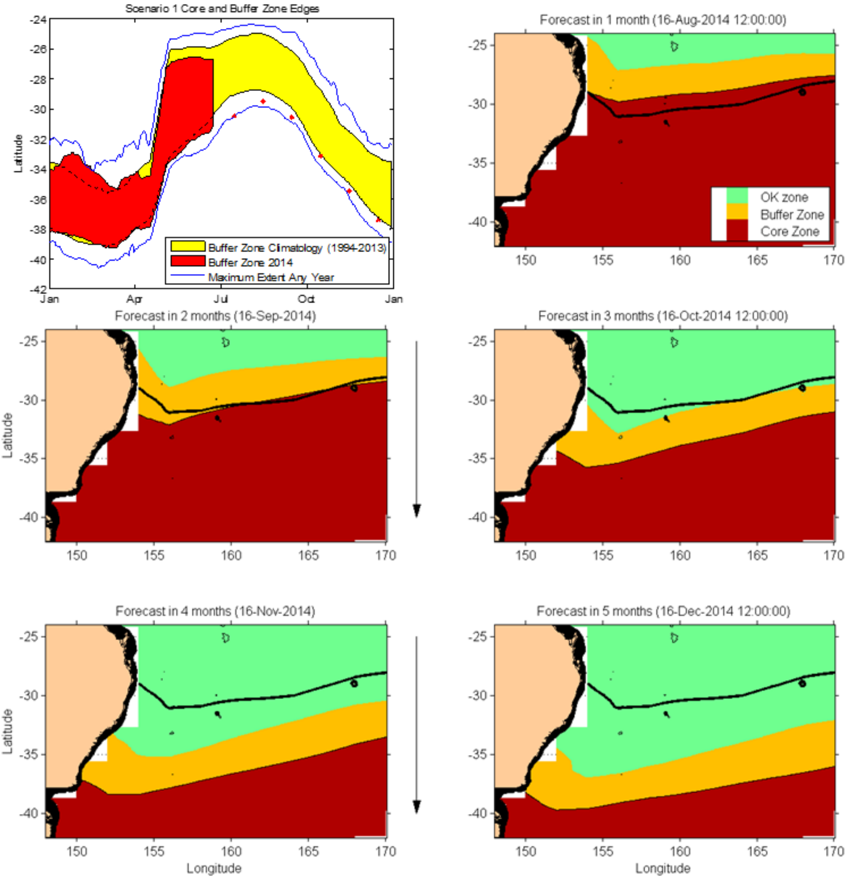


- Zooplankton
- Micronekton
- Skipjack
- Yellowfin
- Bigeye

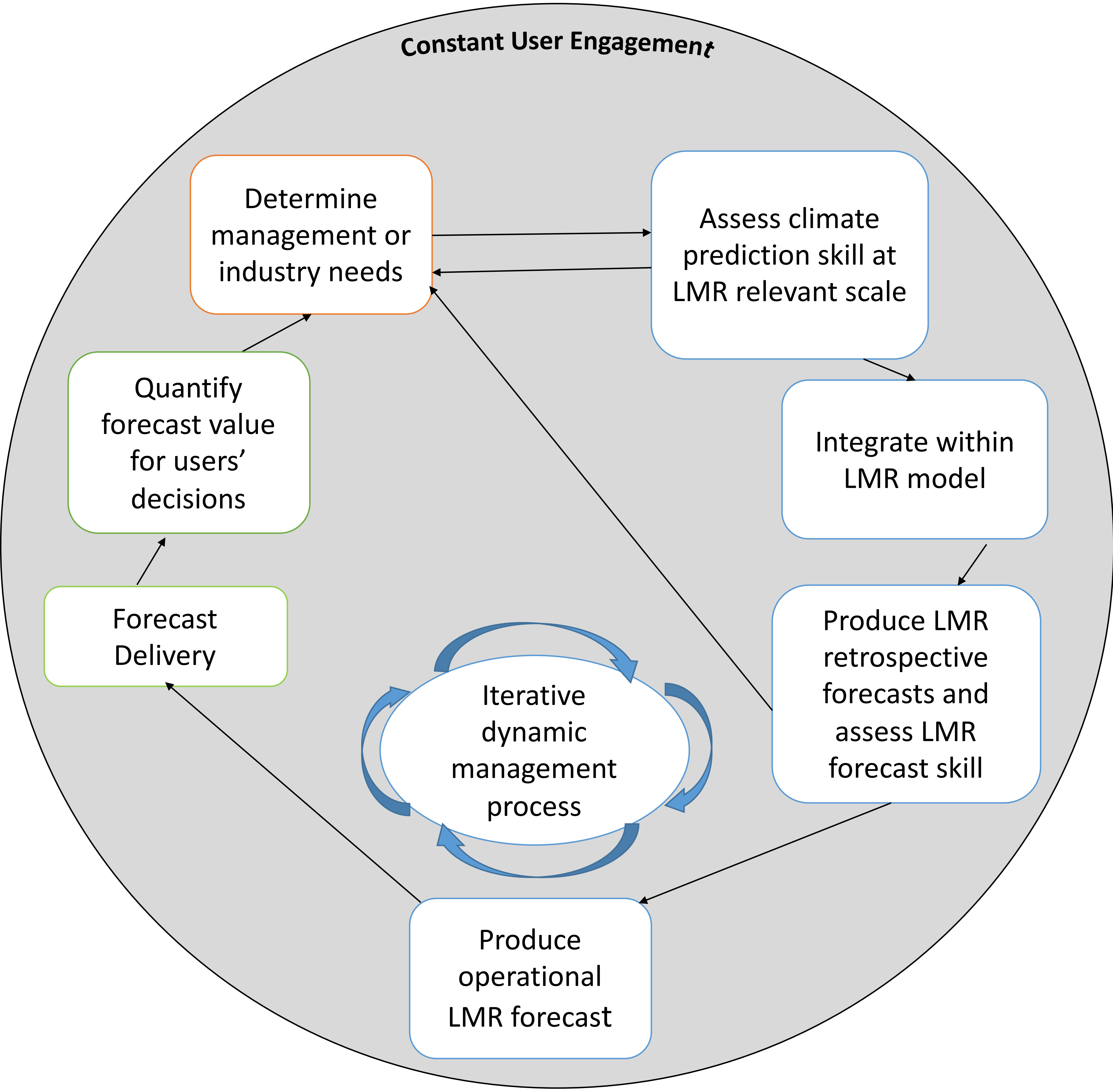


Total skipjack tuna biomass

Regional model (1/12° x day) with Open Boundaries Conditions provided from global model



Scenario 1 Core and Buffer Zone Edges
Latitude
Jan
Apr
Jul
Oct
Jan
Buffer Zone Climatology (1994-2013)
Buffer Zone 2014
Maximum Extent Any Year
Forecast in 1 month (16-Aug-2014 12:00:00)
OK zone
Buffer Zone
Core Zone
Forecast in 2 months (16-Sep-2014)
Forecast in 3 months (16-Oct-2014 12:00:00)
Forecast in 4 months (16-Nov-2014)
Forecast in 5 months (16-Dec-2014 12:00:00)
Longitude
Longitude


Constant User Engagement
Determine management or industry needs
Assess climate prediction skill at LMR relevant scale
Integrate within LMR model
Produce LMR retrospective forecasts and assess LMR forecast skill
Produce operational LMR forecast
Forecast Delivery
Quantify forecast value for users' decisions
Iterative dynamic management process