



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

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

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*Article begins on next page*

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

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41 **Abstract**

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

64  
65 **1. Introduction**

66         Both paleoecological and contemporary analyses demonstrate that large fluctuations in  
67 fish populations are associated with variations in climate (Baumgartner et al., 1992; Finney et al.,  
68 2002; Lehodey et al., 2006; Finney et al., 2010; Brander, 2010; Holsman et al., 2012; Barange et  
69 al., 2014). Clearly, climate-driven variability has always been part of the fisher and fisheries  
70 manager experience. However, the management response to climate variability has often been  
71 reactionary, and enacting efficient coping strategies has, at times, been difficult (McGoodwin et

72 al., 2007; Chang et al., 2013; Hodgkinson et al., 2014). For instance, unrecognized periods of  
73 climate-driven reduction in productivity contributed to the demise of Pacific sardine (*Sardinops*  
74 *sagax*) fishery in California in the 1950s (Murphy 1966; Lindegren et al., 2013; Essington et al.,  
75 2015), the collapse of the Peruvian anchoveta fishery in the 1970s (Clark, 1977; Sharp, 1987),  
76 and overfishing of cod in the Gulf of Maine (Pershing et al., 2015). Unanticipated temperature-  
77 induced changes in the timing of Gulf of Maine Atlantic lobster (*Homarus americanus*) life-  
78 cycle transitions resulted in an extended 2012 fishing season and record landings, but outstripped  
79 processing capacity and market demand, leading to a collapse in prices and an economic crisis in  
80 the lobster fishery (Mills et al., 2013). Similarly, an unforeseen extreme low water temperature  
81 event resulted in a \$10-million-dollar loss to the Taiwanese mariculture industry in 2008 (Chang  
82 et al., 2013). Failure to prepare for inevitable climate variability on seasonal to decadal scales  
83 can also alter the rebuilding times of stocks that have previously been overfished (Holt and Punt,  
84 2009; Punt 2011; Pershing et al., 2015) and break down international cooperative harvesting  
85 agreements for border straddling stocks and highly migratory species (Miller and Munro, 2004;  
86 Hannesson, 2006; Hannesson, 2012).

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

103           Incorporating environmental forcing into management frameworks for LMRs is  
104 challenging because the emergent effects of climate on marine ecosystems are complex. For  
105 example, atmospheric forcing can drive changes in ecologically significant physical or chemical  
106 variables that directly affect organismal physiology and behavior (e.g. temperature-driven  
107 changes in oxygen demand; Pörtner and Farrell, 2008), species distributions (e.g. Pörtner and  
108 Knust, 2007), phenologies (e.g. Asch et al., 2015), and vital rates such as growth (e.g.  
109 Kristiansen et al., 2011; Audzijonyte et al., 2013; Audzijonyte et al., 2014; Audzijonyte et al.,  
110 2016). Additionally, climate can indirectly impact LMR productivity by affecting key biotic  
111 processes, such as variation in prey fields and energy transfer in response to fluctuations in  
112 alongshore and cross-shelf transport (e.g. Bi et al., 2011; Keister et al., 2011; Combes et al.,  
113 2013; Wilderbuer et al., 2013) or to climate-driven changes in primary productivity and  
114 phytoplankton size-structure (Daufresne et al. 2009). Climate-related variations in the abundance  
115 of predators, competitors, and parasites can also have an indirect effect on LMRs (e.g. Boudreau  
116 et al., 2015), and concurrent responses to fishing, habitat loss, and pollution may further  
117 complicate observed responses (Brander, 2007; Halpern et al., 2008; Andrews et al., 2015; Fuller  
118 et al., 2015; Halpern et al., 2015).

119           While such biophysical complexities challenge efforts to implement climate-informed  
120 fisheries management frameworks, concerted observational and modelling efforts across decades  
121 have led to some improved understanding of climate-ecosystem interactions in many regions  
122 (Lehodey et al., 2006; Alheit et al., 2010; Ainsworth et al., 2011; Hunt et al., 2011; Di Lorenzo et  
123 al. 2013; Bograd et al., 2014). These gains have been mirrored by improved climate predictions  
124 at the temporal and spatial scales relevant to LMRs and their management, e.g. days to decades  
125 (Fig. 5, Hobday and Lough, 2011; Stock et al., 2011). Operational seasonal predictions have now  
126 enabled development of climate services for a range of applications relevant to society (Vaughan  
127 and Dessai, 2014). For example, improvements in model spatial resolution have allowed skillful  
128 prediction of hurricane activity at a sub-basin scale relevant to climate risk management (Vecchi  
129 et al., 2014). Seasonal climate forecasts have also reduced vulnerability of the agricultural sector  
130 to climate variability (Meinke and Stone, 2005; Meza et al., 2008; Hansen et al., 2011;  
131 Zinyengere et al., 2011; Takle et al., 2014, Zebiak et al., 2015 and references therein) and have  
132 informed water resources decision making (Hamlet et al., 2002; Abawi et al., 2007).  
133 Furthermore, seasonal climate forecasts have been incorporated into human health early warning

134 systems for diseases, such as malaria, that are influenced by climatic conditions (Abawi et al.,  
135 2007) and for outbreaks of noxious jellyfish (Gershwin et al., 2014). Enhanced capability has  
136 also made possible skillful seasonal forecasts of LMR-relevant variables at fine spatial and  
137 temporal scales useful to industry (defined here to include fisheries and aquaculture industries)  
138 and management (Stock et al., 2015; Siedlecki et al., 2016). While multi-annual to decadal  
139 predictions are at an initial stage of development and are not yet operational (Meehl et al., 2014),  
140 in specific ocean regions, particularly the North Atlantic, multi-annual forecasts appear skillful  
141 over several years (Yang et al., 2013; Msadek et al., 2014a; Keenlyside et al., 2015), and may  
142 show promise for some LMR applications (Salinger et al. 2016).

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

158

## 159 **2. Predicting environmental change across space and time scales**

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

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

166

### 167 *2.1. Overview of climate prediction systems*

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

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



195

196 *2.1.1. Dynamical coupled global climate models for seasonal to decadal prediction*

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

219 On the other hand, seasonal (months to a year) prediction (Fig. 1, top) skill largely  
220 depends on initializing the model using information specific to the current climate state. Owing  
221 to the chaotic nature of the atmosphere, daily weather has a deterministic predictability limit of  
222 5-10 days (e.g. Lorentz, 1963; Goddard et al., 2001). In seasonal forecasts, the predictability  
223 horizon is extended by forecasting monthly or seasonally-integrated statistics rather than daily  
224 weather, and by exploiting the more slowly evolving elements of the climate system, such as the  
225 ocean. It is assumed that the initial climate state sufficiently determines the future evolution of

226 internal climate variations so that skillful predictions of climate states within the forthcoming  
227 months are possible. Internal climate variability arises from interactions in the components of the  
228 climate system itself and gives rise to phenomena such as El Niño Southern Oscillation (ENSO),  
229 the Pacific Decadal Oscillation (PDO), and the Atlantic Multidecadal Variability (AMV). The  
230 presence of ENSO in June, for example, will impact extra-tropical SST in September via  
231 teleconnections that are now substantially captured by many GCMs, albeit some important biases  
232 remain (Deser et al., 2010).

233 In today's coupled dynamical prediction systems seasonal prediction is thus classified as  
234 an initial value problem rather than a boundary value problem, as the response to changes in  
235 external forcing like GHGs occurs over much longer time scales. Although external forcing  
236 changes are typically small over periods spanned by individual seasonal forecasts, they can be  
237 significant over the multidecadal periods spanned by successive real time forecasts and the  
238 accompanying retrospective forecasts discussed in Section 2.13, and therefore should ideally  
239 remain included in seasonal forecast models (Doblas-Reyes et al. 2006; Liniger et al. 2007).  
240 Decadal predictability (1 to 30 years), in contrast, arises from both predictable internal climate  
241 variations following initialization and external forcing, presenting a hybrid problem (Fig. 1,  
242 middle panel, Meehl et al., 2014).

243 Another difference between GCMs configured for climate projections and seasonal to  
244 decadal predictions systems has been the successful expansion of the climate change GCM  
245 configuration to earth system models (ESMs) that include biogeochemistry (e.g. Bopp et al.  
246 2013). ESMs can simulate biological and chemical properties strongly linked to LMRs (Stock et  
247 al. 2011), and thus they have been broadly applied to assess climate change impacts on LMRs  
248 (e.g. Cheung et al. 2009, Barange et al., 2014). While incorporation of earth system dynamics in  
249 global seasonal to decadal prediction models remains in an early stage of development (Séférian  
250 et al. 2014, Case Study 4.6), it may yield similar benefits at the seasonal to decadal scale. In  
251 section 2.1, discussion of LMR-relevant seasonal to decadal predictions will be focused on the  
252 physical variables produced by the operational seasonal to decadal global forecast systems, but  
253 priority developments to expand biogeochemical prediction capabilities will be discussed in  
254 Section 6.

255

256 *2.1.2. The global climate observing system supporting climate prediction*

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

271

### 272 *2.1.3. Assimilating observations to constrain the initial climate state*

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

285           Assimilating observations produces an initialized climate state that differs from what the  
286 climate model would simulate were it running freely. This is because dynamical climate models  
287 are an imperfect representation of the real world, and as such show systematic bias (Warner,

288 2011). Once a seasonal forecast begins, the dynamical model drifts back to its freely running  
289 state. Drifts can be as large as the signal being predicted, particularly for longer lead-times, and  
290 can degrade forecast skill (Goddard et al., 2001; Magnuson et al., 2012; Smith et al. 2013). It is  
291 therefore important to remove this drift to obtain the signal of interest for input into LMR  
292 models. While diverse approaches for this have been proposed, they primarily involve  
293 subtracting out the mean drift from across a set of retrospective forecasts (hindcasts). For  
294 example, to correct for model drift in a January-initialized SST anomaly forecast for May, the  
295 mean drift for January-initialized May forecasts from the past 30 years is subtracted from the  
296 predicted temperature trend.

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

318 reanalyses with observations at the scales of interest when possible (Stock et al., 2015), and the  
319 paucity of oceanic variables for which we can robustly evaluate prediction skill.

#### 320 *2.1.4. Analysis and dissemination in support of diverse stakeholders*

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

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

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

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

355

## 356 *2.2. Forecast skill*

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

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

379 (RPSS), a commonly used measure of probabilistic prediction, is used to reflect the relative  
380 improvement given by the forecast over climatology (Fig. 3). Seasonal to decadal prediction skill  
381 is also often compared against that of a persistence forecast. A persistence forecast is a forecast  
382 produced by simply projecting forward the current climate anomaly. For example, a January one-  
383 month lead SST forecast would be compared against a persistence forecast derived from  
384 maintaining the December temperature anomaly into January. Statistical prediction, particularly  
385 for decadal forecasts whose skill also depends on changes in radiative forcing not represented in  
386 a persistence forecast, can act as another useful tool to assess prediction skill against (Ho et al.,  
387 2013). While statistical or persistence forecasts provide an important benchmark against which  
388 to assess the added value of dynamical seasonal forecasts, a skillful statistical (e.g. Eden et al.  
389 2015) or persistence forecast can be as relevant to users as a skillful dynamical forecast.

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

402 Forecast uncertainty also arises from our incomplete understanding of the climate system,  
403 as reflected in the forecast model being a simplification of the real world. Model error can stem  
404 from uncertainties in the parameterizations of physical processes that are either not well  
405 understood, act at a scale below model resolution, or are too computationally expensive to be  
406 modeled explicitly. Errors in numerical approximations also add to model uncertainty. Multi-  
407 model ensembles are a way to characterize forecast uncertainty arising from this model  
408 uncertainty. In such ensembles, simulations from entirely different models, often from various  
409 prediction centers, are combined to produce a forecast output. The North American Multi-Model

410 Ensemble (NMME) (Section 2.1.4) is an example of such a forecast. Seasonal forecasts from  
411 leading US and Canadian prediction systems are combined to produce a multi-model ensemble  
412 mean seasonal forecast. Single model forecasts are also provided, but the multi-model mean has  
413 been shown to have higher prediction skill than any single model (Becker et al., 2014). The skill  
414 increase comes from error cancellation and the non-linearity of model diagnostics (Becker et al.,  
415 2014). In addition to a more accurate measure of central tendency, use of a multi-model  
416 ensemble often allows for a more complete representation of forecast uncertainty. Ensemble  
417 methods thus allow forecasts to be probabilistic, reflecting the range of all potential outcomes  
418 (Goddard, 2001). To base decisions on a comprehensive assessment of risk, incorporation of  
419 seasonal to decadal predictions into LMR applications should include these estimates of forecast  
420 uncertainty.

421         Dynamical processes that operate at scales finer than a model's resolution must be  
422 parameterized. The spatial resolution of a model grid dictates the breadth of processes that may  
423 be simulated, and differences in this resolution can influence model error and thus limit forecast  
424 skill. Indeed, an increase in resolution from the 100 to 200-km atmospheric resolution common  
425 to many of the current seasonal to decadal prediction systems (Kirtman et al., 2013), to 50-km  
426 resulted in better seasonal temperature and precipitation forecast skill, particularly at a regional  
427 scale (Jia et al., 2015). Nevertheless, in regions where local and/or unresolved sub-grid scale  
428 processes strongly modulate the basin-scale climate signal, even such relatively high resolution  
429 (50-km atmosphere and 100-km ocean) predictions have limited skill. For example, global  
430 climate models that have an ocean resolution of 100-km to 200-km have a bias in both ocean  
431 temperature and salinity in complex coastal environments such as the US Northeast Continental  
432 Shelf (Saba et al., 2016). These biases may partially explain the relatively poor predictive skill of  
433 seasonal SST anomalies predictions in this region (Stock et al., 2015). When both atmosphere  
434 and ocean model resolution are increased (50-km atmosphere, 10-km ocean), such biases are  
435 substantially reduced (Fig. 4) because the Gulf Stream coastal separation position as well as  
436 regional bathymetry are more accurately resolved. We stress, however, that while enhanced  
437 resolution appears critical for some scales and ecosystems, existing models show considerable  
438 prediction skill for marine resource relevant variables at other scales and ecosystems (Section  
439 2.3). High resolution GCMs (10-km ocean versus 100-km in many prediction systems), are also  
440 considerably more computationally expensive to run, currently limiting their use in operational



441 climate prediction systems. Furthermore, biases can remain at this resolution, and can be quite  
442 large in specific ocean regions (Delworth et al., 2012; Griffies et al., 2015). This is due, in part,  
443 to the challenges of optimizing sub-grid scale parametrizations for higher resolution models  
444 (Goddard et al., 2001).

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

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

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

467

### 468 *2.3. Prediction of living marine resource-relevant physical variables*

469 Variables routinely predicted using current seasonal to decadal forecast systems are  
470 LMR-relevant (e.g. SST), and the objectives of seasonal to decadal climate prediction are  
471 consistent with the spatiotemporal scale of many of the fisheries management decisions.

472 However, oceanic prediction skill has often only been assessed with a view to its influence on  
473 regional weather prediction, rather than being of primary interest in itself (Stockdale et al.,  
474 2011). There are, however, a growing number of prediction studies for quantities and  
475 spatiotemporal scales relevant to LMR science and management challenges (Fig. 5). Below we  
476 discuss several of these, including predictability of SST anomalies, sea ice, and freshwater  
477 forcings that influence LMRs, along with recent advances for anticipating extreme events.

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

496 In a few ocean regions, most notably the North Atlantic, SST predictions are skillful for  
497 several years (Yang et al., 2013; Msadek et al., 2014a; Keenlyside et al., 2015). This time scale is  
498 of particular interest for many LMR applications (Fig. 5). The predictive skill on these time  
499 scales emerges from phenomena, primarily in the ocean, that have inherent decadal scales of  
500 variability (Salinger et al., 2016). Perhaps the most prominent among these is the Atlantic  
501 Meridional Overturning Circulation (AMOC). Decadal-scale variations in AMOC-related ocean  
502 heat transport can influence SST over a wide area of the North Atlantic, and are thought to be a

503 critical component of North Atlantic basin-scale SST variation characterized by the Atlantic  
504 Multidecadal Oscillation (AMO). For example, the abrupt warming observed in the mid-1990s in  
505 the North Atlantic has been retrospectively predicted in several models (Pohlmann et al., 2009;  
506 Robson et al., 2012; Yeager et al., 2012; Msadek et al., 2014a), with an increase of the AMOC  
507 being responsible for the warming. The Pacific Decadal Oscillation (PDO) also has decadal  
508 scales of variability and can be predicted a few years in advance, with significant impacts across  
509 a broad area of the North Pacific and adjacent continental regions (Mochizuki et al., 2010; Meehl  
510 and Teng, 2012). More idealized predictability studies also suggest the potential for substantial  
511 decadal predictive skill in the Southern Ocean (Boer, 2004), associated with deep vertical mixing  
512 and substantial decadal scale natural variability (Salinger et al., 2016). Nevertheless, unlike  
513 seasonal climate predictions, which are operational, the field of decadal prediction is in a very  
514 early stage (Meehl et al., 2014). Performance of decadal predictions needs to be assessed over a  
515 wider range of models and systematic model errors have to be reduced further to increase their  
516 utility to the marine resource community. Furthermore, the limited number of decadal-scale  
517 fluctuations of the 30-40 years period for which retrospective forecasts are possible severely  
518 restricts the effective sample size with which to characterize decadal prediction skill. Models  
519 may demonstrate an ability to capture several prominent events over this time period, but it is  
520 difficult to robustly generalize skill for this limited sample of independent decadal-scale events.

521         Sea ice is another LMR-relevant variable (Coyle et al., 2011; Hunt et al., 2011, Saba et  
522 al., 2013), whose seasonal predictive skill has been assessed at a regional scale. Based on  
523 estimates by the National Snow and Ice Data Center, September Arctic sea ice extent has  
524 declined at a rate of about 14% per decade since the beginning of satellite records (Stroeve et al.,  
525 2014), a trend largely attributed to warming due to accumulating GHGs (e.g. Stroeve et al.,  
526 2012). In addition to these long-term changes, large year-to-year variations have been observed  
527 in the position of the summer and winter sea ice edge. Operational and quasi-operational  
528 initialized predictions show some skill in predicting summer Pan Arctic sea ice extent when it  
529 reaches its minimum in September, with significant correlation 3 to 6 months in advance at best  
530 in a few dynamical models (Sigmond et al., 2013; Wang et al., 2013; Chevallier et al., 2013;  
531 Msadek et al., 2014b). Sea ice thickness appears to provide the memory for sea ice extent  
532 predictability from one summer to the next. Hence more accurate predictions could be expected  
533 with improved observations of sea ice thickness and sea ice thickness initialization (Guemas et

534 al., 2016). While predictions of summer sea ice have important implications for shipping and  
535 resource extraction, sea ice extent in late winter affects spring phytoplankton bloom timing and  
536 ultimately fish production (Hunt et al., 2011). However, while enhanced forecast skill up to lead-  
537 times of 3 to 4 months relative to a persistence forecast has been reported during fall and early  
538 winter, forecast skill remains limited in late winter (Sigmond et al., 2013; Msadek et al., 2014b).  
539 Processes driving winter sea ice predictability include the representation of atmospheric  
540 dynamics like the position of the blocking high (Kwok, 2011), but also oceanic processes like  
541 heat convergence that drives SST anomalies in the marginal seas (Bitz et al., 2005). On-going  
542 studies based on improved model physics, improved parameterizations, and increased resolution  
543 in the atmospheric and oceanic components of the models are expected to improve representation  
544 of atmospheric dynamics, oceanic processes, and the mean distribution of sea ice, its seasonal  
545 variations, and possibly its predictability. Such improvements may also impact SST prediction  
546 skill (Stock et al., 2015).

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

565 useful for decision makers (e.g. Mo and Lettenmaier, 2014). As prediction systems increase in  
566 atmospheric and land surface resolution, precipitation and temperature prediction skill over  
567 mountain regions also increases as topography is better resolved (Jia et al., 2015).

568         Aside from issues in resolution, hydrologic predictability is largely a function of initial  
569 land surface conditions (primarily soil moisture and snow cover) and seasonal forecasts of  
570 rainfall and temperature (Shukla et al., 2013; Yuan et al. 2015). In regions where snow and soil  
571 moisture provide a long hydrological memory, such as the western United States or high altitude  
572 locations, accurate initial conditions can provide skillful forecasts out to 3 to 6 months,  
573 particularly during cold seasons (Koster and Suarez, 2000; Mahanama et al., 2012; Shukla et al.,  
574 2013). Similarly, in regions where the flow regime is controlled by groundwater rather than  
575 rainfall, persistence of initial flow can provide a skillful seasonal forecast (e.g. Svensson, 2016).  
576 However, over most of the globe, persistence skill decreases after a month (Shukla et al., 2013),  
577 and improvements in the predictability of streamflow are made by incorporating climate  
578 information into hydrological forecasting systems. Climate predictions systems can provide such  
579 climate forcing inputs (i.e. precipitation and temperature predictions) (Mo and Lettenmaier,  
580 2014). However, the precipitation prediction skill of current global dynamical forecast systems is  
581 often too low to extend hydrological forecast skill beyond 1 month, particularly in dynamically  
582 active regions (Mo and Lettenmaier, 2014). Skillful seasonal hydrological predictions out to 3 to  
583 9 months lead-times have been obtained, however, by integrating into hydrological models  
584 rainfall predictions derived from a climate index, such as the NAO, from a climate prediction  
585 system (e.g. Svensson et al., 2015). Alternatively, skillful seasonal hydrological predictions have  
586 been achieved by statistically integrating a climate index directly into a hydrological forecast  
587 system (e.g. Piechota and Dracup 1999; Karamouz and Zahraie 2004; Wang et al. 2011; Bradley  
588 et al. 2015).

589         Over recent years substantial effort has been placed on seasonal predictions of extreme  
590 phenomena, particularly tropical (Camargo et al., 2007; Vecchi and Villarini, 2014) and  
591 extratropical (e.g., Yang et al., 2015) cyclones. These extreme events threaten fishers' safety at  
592 sea and can dramatically impact the aquaculture and fishing industry through lost production and  
593 income with changes in fish survival and growth, reduction in water quality, and destruction of  
594 essential fish habitat (e.g. coral reefs) or infrastructure (Chang et al., 2013; Hodgkinson et al.,  
595 2014). Although individual tropical cyclones are very much "weather" phenomena, with no path

596 to predictability beyond a few days, some aggregate statistics of tropical cyclones are strongly  
597 influenced by predictable large-scale aspects of climate, such as ENSO or other modes of  
598 variability (e.g., Gray, 1984). This has led to the development of a number of skillful statistical  
599 (Klotzbach and Gray, 2009; Jagger and Elsner 2014), dynamical (Vitart and Stockdale, 2001;  
600 Vitart, 2006; Zhao et al., 2010; Chen and Lin, 2011; Vecchi et al., 2014; Murakami et al., 2015),  
601 and hybrid statistical-dynamical (Wang et al., 2009; Vecchi et al., 2011) prediction  
602 methodologies, which have targeted primarily basin-wide (e.g., North Atlantic, West Pacific,  
603 etc.), seasonally-integrated statistics of tropical cyclone activity. More recently, methodologies  
604 that exploit the ability of high-resolution GCMs to represent both regional hurricane activity and  
605 its connection to climate variation and change have led to skillful seasonal predictions of tropical  
606 cyclone activity at more regional scales (e.g., Vecchi et al., 2014; Zhang et al., 2016, Murakami  
607 et al. in review). The coming years are likely to see an explosive growth of tools for the seasonal  
608 prediction of tropical cyclones and many other extreme phenomena, e.g., tornadoes (Elsner et al.  
609 2014 ; Allen et al., 2015), and heat waves (Jia et al., 2016) enabled by the widespread  
610 development of high-resolution dynamical prediction models, improved understanding of the  
611 connection of weather extremes to large-scale conditions, and the pressing societal need for  
612 information about the statistics of high-impact weather events at a regional scale.

613

### 614 **3. Managing living marine resources in a dynamic environment**

615

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

627 LMR industry or management decisions are made all the more challenging because these

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

635

### 636 *3.1. Industry Operations*

637 For the aquaculture industry, key decisions include when to release fry, ‘plant’ and  
638 harvest fish/shellfish, and when and what remedial actions to take to counter or avoid poor  
639 conditions. Extreme events such as floods, storms, and tropical cyclones can dramatically  
640 impact the aquaculture industry through reduction in water quality and destruction of  
641 infrastructure (Hodgkinson et al., 2014). Anomalously warm or cold conditions can also result in  
642 lost production and income via direct mortality effects, changes in growth or disease outbreaks  
643 (Chang et al., 2013, Spillman and Hobday, 2014). Hence, nowcasts and daily environmental  
644 forecasts are routinely used to improve the operational planning of the aquaculture industry. For  
645 example, monitoring networks of coastal water chemistry have been essential to reduce the  
646 impact of extremely low pH waters on oyster larval survival, increasing the economic resilience  
647 of the Pacific Northwest shellfish industry (Barton et al., 2015). Similarly, estuarine conditions  
648 are monitored to time release of hatchery reared salmon fry with optimal environmental  
649 conditions for growth and survival (Kline et al., 2008). While information on current  
650 environmental conditions is useful, seasonal forecasts of particular environmental variables can  
651 further improve the operational planning activities and climate readiness of the aquaculture  
652 industry by giving aquaculture farm managers time to develop and implement management  
653 strategies that minimize losses to climate, as is outlined in Case study 4.1 (Spillman and Hobday,  
654 2014, Spillman et al., 2015), or by allowing hatcheries time to adjust their release schedule  
655 (Chittenden et al., 2010).

656 For the fishing industry, key decisions include investments in boats, gear and labor, as  
657 well as when, where, and what to fish. Fishers rely on historical knowledge of the influence of  
658 environment on fish distribution to optimize such investment and harvest decisions. However,

659 movement of environmental conditions into novel ranges and associated changes in fish  
660 distribution (Section 1) is now reducing the value of fishers' past knowledge, making it harder to  
661 locate fish and make optimal pre-season investments, undermining their business performance  
662 (Eveson et al., 2015). As demonstrated in Case Study 4.2, seasonal climate forecasts can be  
663 incorporated into fish habitat models to produce fish distribution forecasts and improve the  
664 operational planning and efficiency of the fishing industry.

665         Such habitat models generally use correlative techniques to define regions of high  
666 abundance, or high probability of occurrence, for a species of interest in relation to  
667 oceanographic conditions. Species distribution data can be sourced from tagging studies,  
668 fisheries-dependent records, fisheries-independent surveys, or other sources. The distribution  
669 data is then related to one or multiple environmental variables (e.g. temperature, Hobday et al.,  
670 2011) through a variety of statistical methods, including generalized linear models (GLM),  
671 generalized additive models (GAM), classification and regression trees (CART), and artificial  
672 neural networks (ANN). When making century-scale projections of how fish distributions will  
673 change due to shifts in climate and marine habitat distribution, other commonly used models  
674 include Maxent (Phillips et al., 2006), Dynamic Bio-climate Envelope Model (DBEM; Cheung  
675 et al., 2009), AquaMaps (Kaschner et al., 2006), and the Non-Parametric Probabilistic Ecological  
676 Niche (NPPEN) model (Beaugrand et al., 2011). These models vary in assumptions and  
677 complexity, and can give markedly different results when applied to the same dataset (Lawler et  
678 al., 2006). For this reason, it is advisable to use an ensemble of multiple models when it is  
679 practicable to do so. Regardless of the statistical model used, all correlative habitat models  
680 assume that the relationships observed between species distributions and environmental variables  
681 in the training dataset are reliable proxies for actual mechanistic drivers of habitat preference.  
682 This assumption can be reasonably robust, for example if statistical associations with  
683 temperature closely mirror known physiological constraints, or more questionable, where a  
684 correlation is observed but the mechanistic basis is unknown (Peck et al., 2013). This can limit  
685 the performance of habitat models when they are extrapolated outside the range of the training  
686 dataset: either spatially into other geographic regions, or temporally into past or future time  
687 periods.

688         Long-term industry decisions, such as long-term resource capitalization and  
689 determination of optimal investment strategies for long-term sustainability can also be informed



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

697

### 698 3.2. *Monitoring and closures*

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

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

721 closures. If fishers can anticipate HAB-related closures, they can make informed decisions about  
722 which stocks to target and develop approaches to compensate for expected lost revenues.

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

737         Reduction of incidental capture of protected or over-exploited species during fishing  
738 operations is an important management objective in many jurisdictions; and fisheries managers  
739 are tasked with deciding what management actions are warranted to achieve this objective (e.g.  
740 Howell et al., 2008; Smith et al., 2007). Spatial management strategies that restrict fisher access  
741 in specific zones and at specific times have been successfully used to limit interactions between  
742 bycatch species and fishing gears (Hobday et al., 2014; Lewison et al., 2015). However, as fish  
743 move to remain in suitable physical and feeding conditions, fish distributions and phenology  
744 change with varying ocean dynamics (Platt et al., 2003; Perry et al., 2005; Nye et al., 2009;  
745 Pinsky et al., 2013; Asch, 2015), and therefore static time-area closures can be ineffective  
746 (Hobday and Hartmann, 2006; Howell et al., 2008; Hobday et al., 2011; Howell et al., 2015).  
747 Integration of real-time or forecast ocean conditions into a habitat preference model (Section 3.1)  
748 is now being pursued to determine spatial distributions of species of concern and to set dynamic  
749 time-area closures (Hobday and Hartmann, 2006; Howell et al., 2008; Hobday et al., 2011;  
750 Howell et al., 2015; Dunn et al., 2016). For instance, nowcasts of the preferred habitat of  
751 loggerhead and leatherback turtles are helping to reduce interactions between Hawaii swordfish

752 longline fishing vessels and these endangered species (Howell et al., 2008; Howell et al., 2015).  
753 The utility of seasonal forecasts in setting effective dynamic spatial management strategies  
754 (Maxwell et al., 2015) to reduce bycatch is exemplified in Case Study 4.7.

755

### 756 *3.3. Provision of Catch Advice*

757         Setting annual catch quotas, or adjustments to fishing seasons or effort, is one of the most  
758 critical and contentious decisions taken by fisheries managers. In the United States, Annual  
759 Catch Limits (ACLs) are mandated to not exceed scientifically determined sustainable catch  
760 levels (Methot et al., 2014). Such intensive management of fishing levels occurs in other fishery  
761 systems and has been considered key to effective control of exploitation rates (Worm et al.,  
762 2009). ACLs are dependent on a control rule that basically defines the fraction of the fish stock  
763 that can be safely harvested each year. The control rule is designed to achieve a large fraction of  
764 the biologically possible “Maximum Sustainable Yield”, based on a forecast of stock abundance  
765 over the next one to several years and biological reference points. Reference points, such as the  
766 fishing rate that achieves the maximum long-term average yield ( $F_{msy}$ ), reflect the long-term  
767 productivity of a fish stock and are the basis for a management system to maintain annual fishing  
768 mortalities at a target level that does not lead to overfishing (Quinn and Deriso, 1999).

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

778         The effects of ecological (e.g. predator abundance) or physical factors on population  
779 dynamics are rarely modeled explicitly: a recent meta-analysis showed that just 24 out of the  
780 1200 assessments incorporated such information (Skern-Mauritzen et al., 2015). These  
781 unmeasured, non-fishing driving factors are only accounted for by allowing the models to  
782 incorporate random variability in key model parameters, particularly recruitment, or by

783 incorporating empirical measured inputs, particularly regarding fish body weight-at-age.  
784 However, without including the process causing the fluctuations in the model framework, there  
785 is no basis for refining the random forecast into the future.

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

798 Nevertheless, robust alternatives to the status quo reference points definitions have yet to  
799 be developed. For stocks that have undergone recognized shifts in productivity over their catch  
800 history, dynamic reference points can be constructed using data from the most current regime, as  
801 is currently done for Gulf of Alaska walleye pollock (Dorn et al., 2014) or south-east Australian  
802 morwong (Wayte, 2013). However, performance of such reference points in achieving  
803 management objectives as compared to the status quo has been mixed (Punt et al., 2014a, b). A  
804 common shortcoming is that using a shorter time series leads to less biased but more uncertain  
805 reference points (Haltuch et al., 2009; Dorner, 2013; Punt et al., 2014b). Furthermore, even  
806 dynamic reference points assume that the recent past will be representative of near future  
807 conditions. Because of the noisy nature of productivity parameters, such as recruitment,  
808 productivity shifts tend to be recognizable only well after the change has taken place, preventing  
809 managers from adjusting harvest strategies in a timely manner, and increasing the risk of  
810 overfishing (A'mar et al., 2009; Szuwalski and Punt, 2013). Statistical techniques such as the  
811 Kalman filter, which allow for time varying productivity parameters in stock assessment models,  
812 have proven useful in a timely detection of productivity shifts and improved reference point  
813 estimation for semelparous species (Peterman et al., 2000; Peterman et al., 2003; Collie et al.,

814 2012). Temporal variability in reference points can also be introduced via environmental  
815 covariates on productivity parameters. When these environmental factors can be skillfully  
816 forecasted and the environment-population dynamics relationship is robust, the fish productivity  
817 forecast is improved (Maunder and Watters, 2003; Schirripa et al., 2009; Haltuch and Punt,  
818 2011; Johnson et al., 2015; Miller et al., 2016).

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

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

840 Addition of climate forecast information into stock assessment models may also reduce  
841 uncertainty bounds on stock status projections by narrowing the window of probable outcomes  
842 as compared to the use of the entire historical range (Fig. 7a). Furthermore, if a stock  
843 productivity parameter is subject to an environmentally-driven shift or directional trend, future  
844 values may lie outside of the historical probability space, leading to biased estimates of stock

845 status under the assumption of stationarity (Fig. 7b and 7c). As a result, a climate forecast may  
846 serve as an advance warning of shifts in environmental conditions and stock productivity  
847 parameters, and may reduce bias in stock status estimates (Fig. 7b and 7c).

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

857

#### 858 *3.4. Spatial Issues and Protected Areas*

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

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

872         Such climate-driven distributional shifts can have important implications for spatial  
873 management measures. For example, shifts of juvenile plaice (*Pleuronectes platessa*) towards  
874 deeper waters have made a closed area (the “Plaice Box”) set up in the North Sea to prevent  
875 recruitment overfishing less effective (van Keeken et al., 2007). One potential solution for stocks

876 that have undergone recognized shifts distribution over their catch history is use of dynamic  
877 seasonal-area closures. Climate predictions, particularly of surface and bottom temperatures,  
878 could be used to drive species habitat models that help define fishery closure areas (Section 3.1;  
879 Link et al., 2011; Makino et al., 2014; Shackell et al., 2014; Rutterford et al., 2015).  
880 Furthermore, seasonal to decadal predictions (as well as nowcasts and hindcasts) of  
881 environmental conditions may contribute to management even if they are not directly  
882 incorporated within stock assessments. For instance, the Northeast US butterflyfish (*Poronotus*  
883 *triacanthus*) assessment investigated methods to incorporate historical change in thermal habitat  
884 to evaluate changing availability to the survey. While habitat-driven time-varying survey  
885 catchability was not included in the final assessment, the focused effort to evaluate survey  
886 catchability overall altered assessment estimates of scale, permitted more robust estimation of  
887 natural mortality, and ultimately increased the catch quota relative to previous results.

888 Shifting species distributions can also create important new fishing opportunities, such as  
889 the squid fishery in the Gulf of Maine that appeared during a particularly warm year (Mills et al.,  
890 2013). Hence, forecasts of species distributions driven by multi-year to decadal climate  
891 predictions can help identify which species are likely to spark new fisheries, and then prioritize  
892 them for additional research, experimental fishing programs, or short-term closures during the  
893 colonization phase.

894 Advance warning of shifting distributions is particularly important when they impact  
895 international agreements, since negotiations can take years. For example, mackerel faced a  
896 “double jeopardy” scenario when they partially shifted into Icelandic and Faeroese waters and  
897 the additional harvest pressure led to overfishing of the stock (Astthorsson et al., 2012; Cheung  
898 et al., 2012; Hannesson et al., 2013; Dankel et al., 2015). Pre-agreements between organizations  
899 or nations can be drafted to create a clear set of rules for how to adjust quotas and allocations  
900 based on indicators of changes in a stock distribution, perhaps including side-payments to  
901 compensate for lost fishing opportunities (Miller and Munro, 2004). For instance, forecasts of  
902 ocean conditions are used to forecast the proportion of Fraser River salmon migrating around the  
903 south end of Vancouver Island, thus dramatically affecting international allocation of the catch  
904 opportunity (Groot and Quinn, 1987). Forecasts may also be critical for building a common  
905 understanding of stock trajectories and for motivating the need for pre-agreements.

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907 **4. Case Studies**

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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 and 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 frameworks (Spillman et al., 2015).

Feedback from prawn farm managers following delivery of the first few forecasts led to



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

944

#### 945 *4.2 Seasonal forecasts to improve economic efficiency of a large-scale tuna fishery*

946 Large numbers of juvenile quota-managed southern bluefin tuna (SBT) (*Thunnus*  
947 *maccoyii*) occur in the Great Australian Bight (GAB) during the austral summer (Dec-Apr),  
948 where they are caught in a purse-seine fishery worth ~AUD 60 million annually. In recent  
949 fishing seasons, unexpected changes in the distribution of SBT were observed that affected the  
950 timing and location of fishing activity and contributed to economic pressure on the fishery. In  
951 particular, in the 2011/12 season, SBT moved through the GAB quickly and were distributed  
952 further east than in the past two decades. This resulted in less than 15% of purse-seine catches  
953 being taken from fishing grounds reliably used over the previous 20 years. The following season  
954 (2012/13) also saw unusual SBT distribution patterns that again impacted the fishery. As a result  
955 of these observed changes, the Australian Southern Bluefin Tuna Industry Association  
956 recognized the need for scientific support to improve operational planning in the purse-seine  
957 fishery. Many decisions central to SBT industry members planning their fishing operations need  
958 to be made weeks to months in advance, so seasonal forecasts of environmental conditions were  
959 regarded as a useful tool.

960 Environmental variables influencing the spatial distribution of SBT in the GAB during  
961 summer were explored using location data collected on SBT over many years from electronic  
962 tags, and comparing the ocean conditions where fish were found with the conditions available to  
963 them throughout the region and time period of interest (Eveson et al., 2015). SST was found to  
964 have the greatest influence, with fish preferring temperatures in the range of 19-22°C. Once  
965 habitat preferences were established, this information was coupled with POAMA (see Section  
966 4.1) to predict locations of preferred SBT habitat in future. Both the habitat preference model  
967 and POAMA were evaluated against historical observations, and it was concluded that SST-  
968 based habitat forecasts for SBT in the GAB have useful skill for lead-times up to 2 months. A  
969 daily-updating website was created to provide industry with forecasts of environmental

970 conditions and SBT distributions for the next fortnight and next 2 calendar months from the date  
971 of issue (Fig. 9), along with a suite of other relevant information, including skill of the forecasts  
972 ([www.cmar.csiro.au/gab-forecasts](http://www.cmar.csiro.au/gab-forecasts)). Based on feedback from industry stakeholders obtained  
973 both formally through a survey and informally through an industry liaison representative, the  
974 information provided on the website has proven to be a valuable tool for fishers making  
975 decisions such as when and where to position vessels and to conduct fishing operations (Eveson  
976 et al., 2015). As the SBT fishery is quota-managed, the forecasting approach will not lead to  
977 increased catches (and thus impact sustainability), but will enable fishers to catch their quota  
978 more efficiently, thereby increasing profitability.

979

#### 980 *4.3 A statistical seasonal forecast to improve the operational planning of a lobster fishery*

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

993 Motivated by the events in 2012, the possibility of an early warning indicator of lobster  
994 fishery timing was explored and it was found that the date when landings in Maine begin to  
995 increase is negatively correlated with subsurface temperatures in March and April. Based on this  
996 relationship, a statistical forecast system was developed that takes temperatures at 50 m from a  
997 network of coastal ocean buoys operated by the Northeast Regional Association of Coastal  
998 Ocean Observing Systems (NERACOOS) in spring and estimates the probability of the fishery  
999 shifting into the high-landings period during a particular week in June or July. For the last two  
1000 years, the first forecast of the year has been announced to the industry at the Maine Fishermen’s

1001 Forum and then updated weekly at [www.gmri.org/lobster-forecast](http://www.gmri.org/lobster-forecast) and via Twitter (Fig. 10).  
1002 Forecasters have now begun to work more closely with harvesters, dealers, and marketers in the  
1003 industry to assess how it can be further improved to meet their needs. Other work has identified  
1004 value in using sea temperature observations and models to help forecast outbreaks of lobster  
1005 epizootic shell disease (Maynard et al. 2016).

1006

#### 1007 *4.4 Seasonal forecasts to improve coral reef management*

1008         Increases in ocean temperature over a coral's tolerance limit are the leading cause of  
1009 coral bleaching events (Hoegh-Guldberg et al., 2007). Since 1997, NOAA's Coral Reef Watch  
1010 has been using SST satellite data to provide near real-time warnings of coral bleaching (Liu et  
1011 al., 2014). While coral reef managers and scientists have been able to use these nowcasts to  
1012 execute operational response plans, managers recognized the need for longer lead-time forecasts  
1013 to improve management responses to coral bleaching. Following these requests, NOAA Coral  
1014 Reef Watch developed the first seasonal coral bleaching outlook, based on a statistical model  
1015 from NOAA's Earth System Research Laboratory (Liu et al., 2009). In 2009 the Australian  
1016 Bureau of Meteorology developed the first dynamical seasonal forecasts for coral bleaching risk  
1017 on the Great Barrier Reef, based on seasonal SST predictions from POAMA (see Section 4.1;  
1018 Spillman and Alves, 2009; Spillman 2011). NOAA Coral Reef Watch, in turn, developed a  
1019 dynamical 4 month lead coral bleaching outlook for coral reefs globally using seasonal SST  
1020 predictions from the NOAA National Centers for Environmental Prediction (NCEP) global  
1021 dynamical climate prediction system, the CFS model (Eakin et al., 2012).

1022         These seasonal coral bleaching forecasts are made publicly available on the internet  
1023 ([http://www.bom.gov.au/oceanography/oceantemp/GBR\\_SST.shtml](http://www.bom.gov.au/oceanography/oceantemp/GBR_SST.shtml),  
1024 [http://coralreefwatch.noaa.gov/satellite/bleachingoutlook\\_cfs/outlook\\_cfs.php](http://coralreefwatch.noaa.gov/satellite/bleachingoutlook_cfs/outlook_cfs.php)) and they allow  
1025 coral reef managers around the world to develop timely and proactive bleaching response plans,  
1026 brief stakeholders and allocate monitoring resources in advance of bleaching events. Resource  
1027 managers and scientists have been using these bleaching outlooks extensively throughout the  
1028 2014-16 global coral bleaching event (Eakin et al. 2014, Eakin et al. 2016).

1029         For example, in August 2010, following severe coral bleaching, the Thailand and  
1030 Malaysian governments closed numerous popular dive sites to reduce additional stress to  
1031 severely bleached reefs (Thomas and Heron, 2011). In May 2016, Thailand again closed ten

1032 reefs, this time in advance of the bleaching peak (The Guardian 2016,  
1033 [https://www.theguardian.com/environment/2016/may/26/thailand-closes-dive-sites-over-coral-](https://www.theguardian.com/environment/2016/may/26/thailand-closes-dive-sites-over-coral-bleaching-crisis)  
1034 [bleaching-crisis](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  
1035 recently, once Coral Reef Watch alerts were issued in late June 2015 of the high potential for  
1036 bleaching in Hawaiian waters (Fig. 11), the Hawaii Department of Land and Natural Resources  
1037 (DLNR) immediately began preparations of resources to monitor this event. Having only seen  
1038 significant multi-island bleaching in the main islands twice before, in 1996 and 2014 (Jokiel and  
1039 Brown, 2004; Bahr et al., 2015), they realized that a much more comprehensive effort was  
1040 needed. They trained additional volunteers, who, together with a wide array of professional  
1041 teams from the state, University of Hawaii, NOAA, and XL Catlin Seaview Survey, were  
1042 deployed across most of the islands. This group was able to document and monitor this  
1043 unprecedented event, while the DLNR was able to alert the public and work with marine  
1044 resource users to encourage reduction of activities that could further stress the corals during the  
1045 bleaching event. Additionally, DLNR undertook an effort to collect specimens of the rarest coral  
1046 species from the main Hawaiian Islands and safeguard them in their coral nurseries on Oahu and  
1047 Maui. Many of these species suffered severe bleaching and mortality, and DLNR staff have been  
1048 unable to find one of these species alive off Oahu since the 2015 event. Both Bureau of  
1049 Meteorology and NOAA seasonal forecast tools were also used extensively by reef management  
1050 during the most recent bleaching event on the Great Barrier Reef in the summer of 2015/2016,  
1051 currently believed to be the worst on record (<http://www.gbrmpa.gov.au>).

1052

#### 1053 *4.5 Seasonal forecasts of Pacific sardine habitat*

1054 Pacific sardines are notable as one of the few stocks managed with respect to climatic  
1055 variability in the US. Just recently, sardine distribution and migration forecasts have been  
1056 produced (Kaplan et al., 2016; Fig. 12) for the US Pacific Northwest and Canadian British  
1057 Columbia, based on 6 to 9 month predictions of ocean conditions  
1058 (<http://www.nanoos.org/products/j-scope/>; Siedlecki et al., 2016). These predictions rely upon  
1059 the NOAA NCEP global dynamical climate prediction system Climate Forecast System (Saha et  
1060 al., 2006) to force a high resolution (~1.5 km) Regional Ocean Modeling System (Haidvogel et  
1061 al., 2008). The efforts are fully described in Siedlecki et al. (2016), including skill assessment  
1062 for SST, bottom temperature, and oxygen. Relationships between sardine distribution and J-

1063 SCOPE predictions of ocean physics and chlorophyll were estimated for 2009. The final fitted  
1064 relationships between SST and salinity had moderate skill to predict sardine distributions  
1065 (presence or absence) in summer 2013 and 2014, with up to 4 to 5 month lead-times. Skill  
1066 assessment focused on a “hit rate” metric, area-under-the-curve (AUC), which balances the  
1067 desire to correctly predict sardine presence against the risk of false positives. One caveat to the  
1068 sardine forecasts is that they predict available sardine habitat (Fig. 12) without accounting for  
1069 sardine stock size. Recent declines in sardine abundance (Hill et al., 2015) have likely meant a  
1070 contraction of the stock southward (MacCall, 1990), despite availability of suitable habitat in the  
1071 US Pacific Northwest and British Columbia.

1072         As for many pelagic species, sardines are seasonally migratory and forecasts of their  
1073 distribution by J-SCOPE may be relevant for fisheries management and industry. The sardine  
1074 stock is landed by US, Mexican and Canadian fishers and the extent of the northward summer  
1075 migration is highly dependent on water temperature – in fact in cold summers, such as 2013 and  
1076 2014, the stock fails to reach Canadian waters at all. The sardine forecasts by Kaplan et al.  
1077 (2016) predict the extent of this northward migration and could be used to plan fishing  
1078 operations (e.g. whether Canadian fish processors should expect sardine deliveries) or fisheries  
1079 surveys. Additionally, quotas apportion a fixed percent of sardine catch to Canadian vessels, and  
1080 J-SCOPE provides foresight that that this portion may be unharvested in a particular cold year.  
1081 Furthermore, sardine straddle international boundaries, and short-term seasonal forecasts may  
1082 help international management and industry to cope with and prepare for the long-term  
1083 distribution shifts expected under climate change (Pinsky and Mantua, 2014). To date, forecasts  
1084 have primarily been delivered through collaboration with NANOOS (Northwest Association of  
1085 Networked Ocean Observing Systems) via the web (<http://www.nanoos.org/products/j-scope/>).  
1086 Web products include predictions of ecological indicators relevant to the regional fishery  
1087 management council, and will soon be incorporated in NOAA’s Integrated Ecosystem  
1088 Assessment (Harvey et al., 2014). Other outreach efforts are ongoing and aim to produce  
1089 targeted forecasts (as discussed for Australia above in Section 4.1) for fishery managers and  
1090 stakeholders, and to better integrate with fishery management council needs.

1091

1092 *4.6 Short-term forecasts of Indonesian tuna fisheries to control illegal fishing*

1093           The last decade has seen the generalization of satellite Vessel Monitoring Systems to  
1094 monitor licensed fishing vessels, the use of satellite radar images to detect illegal fishing and the  
1095 development of Electronic Reporting Systems (ERS) to provide catch statistics in real time.  
1096 Integration of these developments in fishery monitoring with an operational forecasting model of  
1097 fish spatial dynamics that has the ability to predict the distribution of fish under the influence of  
1098 both environmental variability and fishing is assisting Indonesian fishing authorities in  
1099 controlling illegal fishing and implementing conservation measures. This operational monitoring  
1100 framework (Gehlen et al., 2015) was developed through the INDESO project and integrates a  
1101 high resolution regional model system coupling ocean physics to biogeochemistry (NEMO/  
1102 PISCES; Gutknecht et al., 2015, Tranchant et al., 2015) to a spatially explicit tuna population  
1103 dynamics model (SEAPODYM; Lehodey et al., 2010; 2015). SEAPODYM simulates functional  
1104 groups of organisms at the intermediate trophic levels (Lehodey et al., 2010, 2015) and the  
1105 dynamics of their predators (e.g. tuna) (Lehodey et al., 2008). The model is complemented by a  
1106 quantitative parameter estimation and calibration approach (Senina et al., 2008) which enables  
1107 the application of the model to fish stock assessment and testing of management scenarios  
1108 (Sibert et al., 2012).

1109           Tuna species are highly migratory fish, and their habitats cover large expanses of the  
1110 global ocean. Thus, the simulation of fish stock dynamics at high resolution in the Indonesian  
1111 region requires accounting for exchanges (fluxes) with populations outside of the regional  
1112 domain (i.e. Pacific and Indian Ocean) under the influence of both environmental variability (e.g.  
1113 ENSO) and fishing mortality. Boundary conditions for the regional 1/12° SEAPODYM  
1114 implementation are obtained from a 1/4° global operational configuration (Fig.13) driven by  
1115 temperature and currents from the operational ocean prediction system Mercator-Ocean PSY3V3  
1116 (Lellouche et al., 2013). Biogeochemical forcings (net primary production (NPP), dissolved  
1117 oxygen) are either derived solely from the coupled physical-biogeochemical model NEMO/  
1118 PISCES (forecast mode) or from NEMO/PISCES and satellite ocean color and SST data (to  
1119 estimate NPP; Behrenfeld and Falkowski, 1997), along with climatological dissolved oxygen  
1120 (O<sub>2</sub>) (hindcast and nowcast modes). The regional operational model SEAPODYM also uses a  
1121 climatological data set (i.e., last 5 years monthly average) of fishing effort prepared from the best  
1122 available information to apply an average fishing mortality. The forecasting system runs every  
1123 week and delivers one week of hindcast, one week of nowcast, and 10 days of forecast. These

1124 outputs are used by the Indonesian Fishing Authority to improve the collection and verification  
1125 of fishing data, to assist illegal fishing surveillance, and to establish conservation measures (e.g.,  
1126 identification and protection of spawning grounds and nurseries) required for the sustainable  
1127 exploitation of this essential resource (Marion Gehlen, personal communication, June 22, 2016).

1128

#### 1129 *4.7 Seasonal forecasts for dynamic spatial management of the Australian east coast tuna fishery*

1130 Since 2003, a dynamic spatial management approach has been used to limit unwanted  
1131 capture of a quota-managed species, SBT, in the Australian eastern tuna and billfish fishery. The  
1132 approach combines a habitat model, conditioned with temperature preference data obtained from  
1133 pop-up satellite archival tags deployed on SBT and an ocean model to produce near real-time  
1134 habitat nowcasts, delivered by email and utilized the same day by fishery managers during the  
1135 fishing season (Hobday and Hartmann, 2006; Hobday et al., 2010). Managers use this  
1136 information along with other data inputs (such as recent fishing catch rates) to restrict access in  
1137 the core (high probability of occurrence) zone to vessels that have both observers and SBT quota.  
1138 The habitat model was extended in 2011 to include a seasonal forecasting component using  
1139 ocean temperature forecasts from the seasonal prediction system POAMA, with useful forecast  
1140 skill out to several months (Hobday et al., 2011). Both nowcast and seasonal forecast habitat  
1141 maps produced for managers show probabilistic zones of tuna distribution coded as “OK”  
1142 (unlikely to encounter SBT), “Buffer” (likely to encounter SBT) and “Core” (very likely to  
1143 encounter SBT) (Fig. 14). Incorporating a seasonal forecasting component has been an  
1144 important step in informing and encouraging both managers and fishers to think about decisions  
1145 on longer time scales (Hobday et al., 2016). Forecasts are now delivered via a dedicated webpage  
1146 (<http://www.cmar.csiro.au/sbt-east-coast/>). The dynamic habitat forecasting approach has  
1147 reduced the need for large areas closures while still meeting the management goal, but does  
1148 require fishing operators to develop more flexible fishing strategies, including planning vessel  
1149 movements, home port selection and quota purchase.

1150

### 1151 **5. Recommended practices**

1152 Following Hobday et al. (2016) and Siedlecki et al. (2016), there are three main  
1153 components to a successful LMR forecast framework: assessment of needs, forecast  
1154 development, and forecast delivery. Here, we break down the forecast development and delivery

1155 stages further to provide more details of the forecast implementation process (Fig. 15).  
1156 Identification of a clear management need via effective communication between climate  
1157 scientists and management or industry stakeholders from the start of the forecast development  
1158 process is essential for the utility and widespread adoption of climate prediction tools for LMRs  
1159 (Hobday et al., 2016, Harrison and Williams, 2007; Fig. 15). This needs assessment should  
1160 include the determination of relevant variables, spatial domain, spatial resolution, and timescales.  
1161 Once needs have been assessed, it is incumbent upon scientists to provide balanced  
1162 communication of both capabilities and limitations to evaluate whether forecasts are likely to be  
1163 useful to their partners.

1164 Forecast development is underpinned by an understanding of the mechanism relating a  
1165 physical climate variable to the LMR of interest. Once such a linkage is found, three forecast  
1166 development steps follow: an assessment of the skill of the physical climate variable forecast, an  
1167 assessment of the skill of the LMR model forecast, and the uncertainty associated with each. The  
1168 prediction skill for the physical climate variable must be assessed at an appropriate timescale  
1169 relative to the management decision timeframe and at a spatial resolution able to resolve  
1170 environmental driving mechanisms. Skill assessment will make use of retrospective forecasts and  
1171 observations. When reanalyses are used in lieu of observations, their accuracy at the scale of  
1172 interest should be confirmed against data prior to forecast skill assessment whenever possible  
1173 (Section 3). If the skill evaluation indicates that the variables of interest cannot be skillfully  
1174 forecasted at an adequate lead-time and/or relevant spatial scale, stakeholder expectations may  
1175 be re-evaluated and alternate variables or scales of interest investigated (i.e. it may be necessary  
1176 to return to the needs assessment step). Alternatively, downscaling or bias correction techniques  
1177 may improve skill at the desired scale in some cases (Section 6). Skill may be assessed using at  
1178 least measures of correlation, variability, and bias between forecast and observations, although  
1179 further verification analyses are possible (Mason and Stephenson, 2007).

1180 Once a physical climate variable forecast has been developed and determined to be  
1181 skillful, the value of using it in an LMR model must be determined. LMR model skill assessment  
1182 can employ skill metrics based on “hit rate”, such as AUC or area-under-the-curve (Fielding and  
1183 Bell, 1997) and the True Skill Statistics (Allouche et al., 2006), to evaluate whether the LMR  
1184 forecasts reproduce biological phenomena (e.g., presence of tuna, occurrence of a coral  
1185 bleaching event). While it is well known that climate affects LMRs (Section 1), most of derived



1186 climate-LMR relationships are empirical, with climate variables often acting as proxies of  
1187 complex trophic effects, interspecies interactions, and dispersal processes. For climate  
1188 information to be included in LMR management frameworks, the environment-fisheries  
1189 relationship has to be robust and preferably based on mechanistic, ecologically-sound  
1190 hypotheses. A sufficiently long observational data series is required for model calibration and  
1191 verification (Haltuch and Punt, 2011), including out-of-sample validation (Francis, 2006; Mason  
1192 and Baddour, 2007; Mason and Stephenson, 2007). In addition, if the environment-fisheries  
1193 relationship relies on stock assessment model output (e.g. recruitment), it is important that this  
1194 relationship be developed within the stock assessment model itself rather than as a post-hoc  
1195 analysis to ensure uncertainties associated with the stock assessment model are properly  
1196 propagated (Maunder and Watters, 2003; Brooks and Deroba, 2015). Furthermore, to increase  
1197 confidence in the robustness of these empirical relationships, meta-analytical techniques can be  
1198 employed to ensure that the proposed hypothesis is robust across a species range (Myers, 1998),  
1199 taking into account, however, that environmental variables may affect species differently across  
1200 their latitudinal range (e.g. Mantua et al., 1997).

1201         As environment-LMR associations may change over time (e.g. with changing baselines  
1202 under climate change), these empirical relationships need to be periodically re-evaluated as new  
1203 environmental and LMR data are collected. LMR forecast development will therefore be an  
1204 iterative process and management has to be dynamic to allow for changing management  
1205 decisions as the environment-fisheries relationship evolves with the continuous integration of  
1206 new information. Environment-LMR correlations have been observed to be more robust when  
1207 tested with new data at the edges of a species range (Myers, 1998). These populations may serve  
1208 as initial case studies with which to develop dynamic management frameworks that integrate  
1209 climate prediction information. Table A2 includes a list of LMRs for which a sufficient  
1210 understanding of how they respond to climate variability has been achieved, and which may  
1211 serve as additional case studies. These include those determined by Myers (1998) as robust to re-  
1212 evaluation and those that already make use of environmental information in their management as  
1213 described by Skern-Mauritzen et al. (2015).

1214         To provide a thorough presentation of risk to decision makers, it will be important to  
1215 assess the uncertainty of the climate prediction as well as that of the LMR models. For the  
1216 climate prediction, this will involve quantification of processes, variability and model

1217 uncertainty via the use of single and multi-model ensembles (Section 3). Forecasts will be  
1218 inherently probabilistic, and ensembles can be used to estimate the probability. On the fisheries  
1219 side, there is uncertainty associated with LMR models parametrizations (Cheung et al., 2016a,  
1220 b). As for climate predictions, ensemble approaches can be employed in LMR models to account  
1221 for the high level of uncertainty in the parametrization of biological processes (e.g. Kearney et  
1222 al., 2012, Laufkötter et al., 2015, 2016). Uncertainty in the environment-LMR relationship will  
1223 also need to be accounted for by, for instance, running numerous simulations of the LMR model  
1224 differing in their stochastic error of the LMR-environment relationship (e.g. Lindegren et al.,  
1225 2013).

1226         Finally, an effective forecast delivery mechanism is required. The climate prediction  
1227 needs to be delivered in a format that can be effectively incorporated into LMR models and  
1228 decision frameworks, such as population models used in fish stock assessment. As in all the  
1229 stages of LMR forecast development, consistent user engagement is essential to ensure sustained  
1230 use of such prediction tools (Harrison and Williams, 2007; Hobday et al., 2016). For instance,  
1231 the general difficulty people have in understanding uncertainty and probabilities has limited the  
1232 use of climate predictions in the natural resource sector (Nicholls, 1999; Marshall et al., 2011).  
1233 Collaboration with social scientists on the most appropriate presentation and delivery options  
1234 may enhance adoption of forecast information (Harrison and Williams, 2007). Automated web-  
1235 based delivery systems are a common delivery method, although ongoing contact with end users  
1236 and acknowledgement of user feedback is important to build engagement and for continued  
1237 forecast use (Hobday et al., 2016). Funding for delivery system maintenance, user engagement,  
1238 and continued user training should be included in projects to maintain iterative LMR operational  
1239 forecast systems.

1240         The value of integrating climate predictions into LMR decision frameworks has to then  
1241 be demonstrated to managers or industry. This can be undertaken by employing cost-benefit  
1242 analyses (e.g. Asseng et al., 2012) and MSE (Section 2.4, Tommasi et al., in review). For  
1243 example, MSEs can assess the performance of different management strategies (e.g. with and  
1244 without climate predictions) in relation to a suite of performance metrics while taking  
1245 uncertainty into account. They may also include economic models to better evaluate the specific  
1246 economic value of integrating climate forecasts into LMR decisions (e.g. Richardson, 2000).  
1247 While MSEs have been developed in the context of fisheries science, such decision support

1248 systems could also be applied to industry or coastal manager's decision frameworks. Results  
1249 from these assessments would inform both climate and LMR prediction development by  
1250 highlighting further refinements needed to better inform decisions.

1251

## 1252 **6. Priority developments**

1253 While the potential benefits of seasonal climate forecasts in reducing the climate  
1254 vulnerability of the fishery and aquaculture industry and in improving fisheries management are  
1255 clear (Section 4), barriers to their widespread adoption also exist. Social, cultural, economic, or  
1256 political constraints, such as existing regulations or dissemination difficulties, can limit forecast  
1257 use (Nicholls 1999; Goddard et al., 2001; Harrison and Williams, 2007; Davis et al., 2015).  
1258 Here, however, discussion will be limited to priority developments aimed at reducing technical  
1259 impediments to climate forecast application. These technical barriers include incomplete  
1260 understanding of environment-LMR relationships, limited length and availability of physical,  
1261 biogeochemical and biological time series for model development and validation, and the  
1262 irreducible predictability limits at seasonal to decadal scales. There is also need for  
1263 methodological advancements in LMR models to explicitly consider environmental productivity  
1264 indicators and spatial distributions, and apply empirical models in non-stationary systems.  
1265 Finally, there is a need for reduction in climate model bias through improvements in model  
1266 formulation and initialization, for verification of LMR-relevant physical variables at LMR-  
1267 relevant spatial scales beyond SST, for the development of biogeochemical forecasting  
1268 capabilities in global prediction systems, and for improvements in climate predictability at LMR-  
1269 relevant regional scales through higher resolution global prediction systems or the development  
1270 of downscaling frameworks.

1271 On the LMR models side, predictive capacity is constrained by our incomplete  
1272 understanding of environment-LMR relationships, especially their response to environmental  
1273 fluctuations (e.g. Chavez et al., 2003; Di Lorenzo et al., 2009; Le Mézo et al., 2016). As a case in  
1274 point, only 2% of managed fisheries worldwide explicitly integrate past environmental  
1275 information into their current tactical decision making and provide an existing framework to  
1276 readily incorporate climate forecast information (Skern-Mauritzen et al., 2015). This lies in stark  
1277 contrast to ubiquitous climate-marine resource correlations reported in the literature (e.g. Hare et  
1278 al., 2010; Mueter et al., 2011; Ottersen et al., 2013). For most populations, the length of

1279 available, co-occurring fishery, biological and environmental time series may be too short to  
1280 robustly identify the environment-LMR relationship (Haltuch and Punt, 2011) or to develop a  
1281 habitat preference model, highlighting the importance of maintaining and expanding existing  
1282 observational data series for environment-LMR model development and verification. Funding  
1283 for ocean and LMR observations is limited. Given the importance of having climate observations  
1284 over a period long enough to span different environmental regimes, LMR observations that cover  
1285 a wide range of population sizes, and large sample sizes to improve estimation of model  
1286 parameters, establishment of new monitoring networks must be carefully balanced with the  
1287 critical need to maintain current sampling programs (Haltuch and Punt, 2011; Dorner et al.,  
1288 2013). Maintenance and expansion of physical climate observing systems, as discussed in  
1289 Section 3, are also essential to climate model development to improve climate predictability  
1290 through better model initialization (e.g. Servonnat et al., 2014). Including concurrent measures of  
1291 basic biogeochemical and lower-trophic-level measurements should be integrated into existing  
1292 observing systems, when possible, to facilitate better understanding of physical-biological  
1293 interactions in the marine environment and better assessment of model predictive capability.  
1294 That said, while spatially-or temporally-constrained (or incomplete) environmental data may be  
1295 limited in quantitative utility, such data can help provide qualitative context for decision-making.  
1296 For example, time series of conditions can be used to delineate regime-specific parameter  
1297 estimates or emergent patterns in indicators can provide justification for precautionary  
1298 management actions and intensified monitoring (Zador et al., 2016).

1299         Non-stationarity issues are particularly critical for decadal to centennial predictions.  
1300 However, for many populations, knowledge of environment-fishery interactions is limited to  
1301 basic correlations. These correlative (and often linearly approximated) relationships provide a  
1302 useful, existing tool to start integrating climate predictions into LMR models. But if an  
1303 ecosystem were to shift into a new, no-analog state and the ecosystem processes that were  
1304 empirically described by this correlative relationship were to change, subsequent management  
1305 decisions may perform poorly (Dorner et al., 2013). Similar shifts can occur at shorter time-  
1306 scales. For example, many species distribution models developed with one decade of data  
1307 perform poorly when used to project species distribution during another decade (Brun et al.,  
1308 2016). For bias correction of physical climate models, non-linear statistical techniques that are  
1309 better at simulating distribution extremes appear to perform better under novel climate conditions

1310 (Gaitan et al., 2014). More sophisticated, model-free statistical approaches also appear promising  
1311 in establishing environmental influences on LMRs that can be applied in a management  
1312 framework, particularly over short timescales (e.g. Ye et al., 2015). To improve LMR predictive  
1313 capacity, it will be necessary to expand the use of such techniques into tactical management  
1314 frameworks, and to characterize their benefits relative to more traditional statistical techniques as  
1315 well as ecosystem models.

1316         Dynamic ecosystem models integrate physical variables, lower-trophic-level dynamics,  
1317 LMR dynamics, and human impacts, mechanistically, and are critical to enhance our  
1318 understanding of LMR responses to climate variability (Travers et al., 2007; Rose et al., 2010;  
1319 Le Mézo et al., 2016). Such process-based understanding is necessary to the development of  
1320 models able to skillfully predict LMR under novel conditions (Evans, 2012). Furthermore,  
1321 because of the inherent complexity, non-linearity, and multi-stressor characteristics of marine  
1322 ecosystems, multispecies and ecosystem models can in some cases assess uncertainties and  
1323 trade-offs more effectively (Pikitch et al., 2004; Link et al., 2012). Nevertheless, such models are  
1324 currently only employed for strategic advice at the decadal and multi-decadal scale, rather than  
1325 for short-term tactical decisions (e.g. Smith et al., 2011; Pacific Fishery Management Council  
1326 and National Marine Fisheries Service 2014; Fulton et al., 2014; Marine Stewardship Council,  
1327 2014). One issue of concern with the use of ecosystem models for tactical decisions is their  
1328 inability to integrate all of the data streams, such as catch-at-age data, that are customary in  
1329 current tactical fisheries decision frameworks. Another issue is that their complexity comes at the  
1330 cost of longer running time, hindering their use within current tactical management process  
1331 timelines. Also, they rely on static assumptions and parametrizations, which may not remain  
1332 valid under future conditions. Finally, because more processes are modeled and there is  
1333 uncertainty in each, the fully characterized uncertainty can be large. This may make decision-  
1334 making more difficult but, if this uncertainty accurately reflects the true uncertainty in the  
1335 system, it will ultimately result in better decisions. Expanded application of such models for  
1336 tactical management decisions will be dependent on improving their parameterizations,  
1337 specification of initial conditions, extending quantitative model assessments, and reducing their  
1338 uncertainties through additional physiological studies, process studies, and modeling  
1339 experiments aimed at understanding the mechanisms driving LMR's responses to climate. LMR  
1340 surveys that include more hydrographic, biogeochemical, and lower-trophic-level (plankton)

1341 observations will also be critical to make progress towards expanded use of ecosystem models in  
1342 LMR forecasting applications.

1343         Highly resolved spatial and population dynamics models of a specific target species  
1344 coupled to a coarser, lower-trophic-level model (Lehodey et al., 2008; Senina et al., 2008;  
1345 Section 4.2), or “models of intermediate complexity”, (MICE) (Lindegren et al., 2009; Collie et  
1346 al., 2014; Plagányi et al., 2014) may be more immediately suited for tactical management  
1347 decisions, as their uncertainties are more tractable. MICE use statistical parameter estimation  
1348 methods common in current tactical fisheries models to fit multispecies models to data for small  
1349 groups of interacting species. Such models are becoming sufficiently advanced, including both  
1350 species interactions and impacts of temperature on population dynamics (Holsman et al., in  
1351 press.), and can be used in concert with single-species models to provide tactical fisheries advice  
1352 from a multi-model suite, similar to operational prediction systems used in weather forecasts  
1353 (Ianelli et al., in press.). Combining such models with seasonal and decadal forecasts will help  
1354 evaluate risk profiles and trajectories of recovery plans, assess the flexibility of harvest policies  
1355 to dynamic conditions, and identify nodes of management vulnerability to climate change (e.g.,  
1356 are dynamic management policies available in hand to respond to sudden shifts in ecosystem  
1357 structure or driving processes?; Holsman et al., in review). While MICE models are quite  
1358 promising for tactical decision making in the near future, simulation testing to determine whether  
1359 they can provide adequate information for tactical management under various information  
1360 conditions typical of fisheries management needs to be undertaken. If successful, such  
1361 applications may also provide a valuable template for the expansion of holistic whole ecosystem  
1362 models from strategic to tactical management decisions.

1363         Expanded use of seasonal to decadal forecasts is also limited by problems of relevance in  
1364 terms of critical variables, and spatial and temporal scales (Nicholls, 1999; Hobday et al., 2016).  
1365 For some LMR-relevant variables, there are irreducible predictability limits at seasonal to  
1366 decadal scales due to the chaotic nature of the atmosphere (Deser et al., 2012). Such variables  
1367 will remain unpredictable even with a perfect data assimilation system and model formulation,  
1368 and hence management frameworks robust to unpredictable variation will need to be developed.  
1369 It will be important for climate scientist to continue assessing predictability limits of LMR-  
1370 relevant variables and to communicate such limitations to users. Providing reliable probabilistic  
1371 forecasts accompanied by appropriate measures of historical skill is one established mean for

1372 doing so.

1373           For some regions and time scales, however, predictability of LMR-relevant variables is  
1374 limited by the systematic errors of GCMs (Goddard et al., 2001). It is critical to find ways to  
1375 either reduce this model bias or reduce its negative impacts on forecast skill through novel  
1376 techniques (e.g., Batté et al., 2016). Reduction in model bias will involve improvement in both  
1377 model physics and parametrizations, as well as data assimilation systems (Goddard et al., 2001;  
1378 Meehl et al., 2014; Siedlecki et al., 2016). For instance, as variability in ocean circulation can  
1379 depend on both temperature and salinity variations in the ocean's interior, improved observations  
1380 of these quantities, as well as improved assimilation systems to make optimal use of these  
1381 observations, are critical. As resolution of GCMs increases, representation of the physical  
1382 processes responsible for regional climate predictability improves (e.g. Jia et al., 2015), and, in  
1383 some cases, this may lead to improved forecast skill of LMR-relevant variables.

1384           Forecasts at the multi-annual to decadal time scales, while of great interest to LMR  
1385 management and industry, are not yet operational (Section 3). Continued research to improve our  
1386 theoretical understanding and representation of the physical processes and feedbacks responsible  
1387 for decadal scale climate variability are required to reduce model bias and improve decadal  
1388 forecast skill (Meehl et al., 2014). Furthermore, in order to better assess the performance of  
1389 decadal forecasts, predictability studies across more models and with larger ensembles need to be  
1390 carried out (Meehl et al., 2014). Demonstration of reliable skill, however, will remain limited by  
1391 the small sample size available for verification due to the high time series autocorrelation and  
1392 limited quantity of independent samples at decadal time scales (Kumar, 2009; Meehl et al.,  
1393 2014). Furthermore, it is important to stress that the decadal predictability of regions, such as the  
1394 North Pacific, subject to strong atmospheric forcing, will remain limited (Branstator and Teng,  
1395 2010; Meehl et al., 2014).

1396           In addition to improvements in models and initialization, predictability across  
1397 spatiotemporal scales of more LMR-relevant physical variables such as bottom temperature, sea  
1398 surface height, onset of upwelling, or salinity need to be examined. Biogeochemical prediction  
1399 (e.g. chlorophyll biomass, net primary productivity (NPP), export production fluxes, aragonite  
1400 saturation in coastal zones, or oxygen concentration) is also of major relevance to ecosystem-  
1401 based management of marine resources (Levin et al., 2009; Stock et al., 2011; Cheung et al.,  
1402 2012). While biogeochemical prediction is in its early stages and no coupled physical-

1403 biogeochemical seasonal to decadal forecasting systems are yet operational (but see Case Study  
1404 4.6 for their use in sub-seasonal prediction), recent work shows some potential. Predictive skill  
1405 up to several months has been shown in the northern CCS for bottom oxygen (Case Study 4.5,  
1406 Siedlecki et al., 2016), and up to 3 years for NPP in some oceanic domains (Séférian et al., 2014,  
1407 Chikamoto et al., 2015). In most cases, the increased predictability in NPP arises from that of  
1408 nutrients, which directly benefit from the initialization of the model physical fields (Séférian et  
1409 al., 2014). These pioneering results demonstrate that biogeochemical prediction shows promise  
1410 and highlight the need to both develop integrated physical-biogeochemical forecast systems, and  
1411 further quantify biogeochemical predictive skill over a variety of space and time scales to inform  
1412 ecosystem-based management approaches to LMRs. Application of ESMs in a climate change  
1413 framework has demonstrated that uncertainty in LMR projections can be large due to uncertainty  
1414 in the many modelling components, from GCMs to upper-trophic level models, required to  
1415 assess climate change impacts on LMRs (Cheung et al., 2016a). Computing and personnel  
1416 resources will hence be required to develop an ensemble approach for biogeochemical prediction  
1417 able to account for this uncertainty. An assessment of prediction skill beyond SST to other  
1418 properties driving biological responses will also necessitate supporting, collecting, and  
1419 maintaining sampling programs and observing systems.

1420         The spatial resolution of global climate models poses another limitation to their skill at  
1421 the regional spatial scale relevant to LMR decisions. Downscaling techniques can be used to  
1422 generate finer-scale information from large-scale climate predictions. By relating well predicted  
1423 large-scale factors to a local process of interest, downscaling, in addition to providing higher  
1424 spatially and temporally resolved data, may produce LMR-relevant variables not skillfully  
1425 generated by global prediction systems (e.g. Siedlecki et al., 2016). There are two types of  
1426 downscaling techniques: statistical and dynamical. The first links the large-scale output from a  
1427 global prediction system to local scale variables using statistical-empirical relationships. The  
1428 second uses the large-scale output as boundary conditions to regional-scale, physics-based  
1429 dynamical models.

1430         Statistical downscaling techniques are computationally inexpensive, so the large  
1431 ensembles required to appropriately characterize initial condition and model uncertainty of  
1432 seasonal to decadal predictions (Section 2.1.2) can be run relatively fast. The ability to quickly  
1433 produce output is an advantage particularly relevant for downscaling of seasonal predictions, as



1434 they have to be produced in a timely manner to be relevant to the decision making process  
1435 (Laugel et al., 2014). However, to construct robust statistical relationships, long observational  
1436 records are required (Section 4.1 and 4.3), though are not always available. Second, all statistical  
1437 downscaling techniques assume that the large-scale, local climate relationship will remain the  
1438 same in the future. While these assumptions may hold for the relatively short timeframe of  
1439 seasonal predictions, they may deteriorate over longer-range decadal predictions.

1440 By contrast, dynamical downscaling techniques explicitly model the physical processes  
1441 involved and therefore may perform better than statistical methods under changing or  
1442 unprecedented conditions (e.g. van Hooidonk et al., 2015). Dynamical downscaling models,  
1443 however, will still inherit any bias of large-scale GCMs, and may even amplify such systematic  
1444 errors (Goddard et al., 2001; Hall et al., 2014). This stresses again the need to reduce bias in  
1445 global predictions systems to improve predictability of LMR-relevant variables at a regional  
1446 scale. Further research will also be necessary to assess the relative costs and benefits of statistical  
1447 versus dynamical techniques for downscaling of LMR-relevant climate predictions. This will  
1448 require more resources allocated towards the development of downscaling frameworks for LMR-  
1449 relevant climate predictions in regions of interest for LMRs. For instance, coupling to fine  
1450 resolution coastal models, like the efforts in the northern CCS and Indonesian region (Case  
1451 Studies 4.5 and 4.6), is a promising approach that warrants more studies in other regions.  
1452 Furthermore, modeling studies aimed at understanding the extent to which LMR-relevant local  
1453 processes are interactive with the large-scale and to what extent they are primarily "driven" by  
1454 large-scale processes are required. Such studies would help to identify the type of downscaling  
1455 method most appropriate and indicate regions requiring higher-resolution global climate  
1456 prediction systems to further enhance predictability and support decision making at fine spatial  
1457 scales.

## 1458 **7. Concluding Remarks**

1459 It is widely recognized that the productivity and distribution of LMR populations change  
1460 over time in response to climate and ecosystem variability and long-term trends. Fishers,  
1461 aquaculturists, coastal planners, and fisheries managers recognize that many of their operational  
1462 planning and management decisions have to account for this dynamism. We have shown how  
1463 recent improvements in global dynamical climate prediction systems have resulted in skillful

1464 predictions of LMR-relevant variables at many of the spatial and temporal scales at which LMRs  
1465 are managed, and how such predictions are already helping industry and managers make  
1466 decisions in dynamic environments. By describing climate prediction systems and their  
1467 capabilities, as well as the range of decisions currently taken by managers and the fisheries and  
1468 aquaculture sector that may benefit from the inclusion of future climate information, new  
1469 applications may be developed for wider use. Successful integration of climate information into  
1470 LMR decision frameworks will depend on close collaboration and open dialogue between  
1471 potential users and climate scientists.

1472         While some progress has been achieved within existing frameworks and resources,  
1473 challenges in both climate and fisheries models need to be addressed to further expand utility of  
1474 such predictions for LMRs (Section 6). To ensure widespread application of climate forecasts  
1475 into LMR decision making and prevent unintended consequences of climate and fisheries  
1476 interactions, new methodological approaches that capture complex ecosystem dynamics and the  
1477 full range of LMR drivers need to be developed. Such frameworks will inherently be  
1478 probabilistic and consist of ensemble methods to account for uncertainties in both climate and  
1479 LMR models, improve model accuracy, and help end users understand risk. These frameworks  
1480 will also evolve over time as our understanding of environment-LMR links, which remains poor  
1481 for many species and regions, is improved through more field observations and experimental  
1482 studies. Therefore, management decision systems will need to become more flexible to the  
1483 inclusion of new information streams at a variety of both spatial and temporal scales, as well as  
1484 to frequent re-evaluation.

1485         As we acknowledged above, seasonal to decadal predictions of climate and LMR  
1486 dynamics will sometime fail despite the best of intentions, especially given the increasing  
1487 potential for no-analog system states and ecological surprises (Williams and Jackson, 2007;  
1488 Doak et al., 2008). To cope with this inevitability, we also encourage the development of  
1489 approaches for coping with unexpected changes once they have happened (Schindler and  
1490 Hilborn, 2015).

1491         As predictability is the ultimate test of scientific theory, routinely using these climate-  
1492 forecast informed frameworks to make predictions of LMR dynamics will also improve  
1493 understanding of ecosystem dynamics. In addition, skillful predictions at seasonal to multi-  
1494 annual scales will lend confidence to the use of such models to project LMR dynamics over

1495 longer temporal scales, and can be used to build stakeholder confidence in the use of longer term  
1496 climate projections. With exploited systems being more sensitive to environmental variability  
1497 (Hsieh et al., 2006; Perry et al., 2010), development of such capabilities will be essential to the  
1498 development of climate-ready management systems to effectively manage and culture LMRs in a  
1499 future environment where long term change renders historical experience less valuable.

1500

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1516

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2607

## 2608 **Figure Captions**

2609 Figure 1. Overview of simulation design for seasonal and decadal predictions and climate  
2610 projections. GHG refers to greenhouse gases. Note that the year for shifting from pre-industrial  
2611 to historical forcing in climate projections, here set to 1860, can differ between climate models.

2612 “Forcings” in the climate change context refer to specified solar insolation and concentrations of  
2613 radiatively active atmospheric constituents.

2614  
2615 Figure 2. Temperature anomalies at 55-m depth from six different ocean reanalysis products for  
2616 April 2015 relative to each-product 1981-2010 climatology. The bottom left panel shows the  
2617 ensemble mean, and the bottom right the ratio of signal (ensemble mean) to noise (ensemble  
2618 spread).

2619  
2620 Figure 3. Left panel: One-month lead probabilistic forecast of SST for summer (June, July, and  
2621 August, JJA) initialized in May 2016 from the North American Multi-Model Ensemble  
2622 (NMME). This forecast was produced using all the ensemble members provided by each model  
2623 participating in the NMME. It therefore reflects both initial condition and model uncertainty.  
2624 Warm colors (yellow-orange) indicate areas with a significant probability of experiencing upper-  
2625 tercile temperatures, with the probability of such terciles ranging from 40-100% depending on  
2626 the degree of shading. Analogous interpretations exist for the anomalously cool (blue colors) or  
2627 near climatological (gray colors) conditions. Right panel: Ranked probability skill score for the  
2628 forecast presented in the left panel. The color bar represents the relative improvement of the  
2629 probability forecast (left panel) over climatology, with 0 indicating no skill over climatology.  
2630 Note the higher predictive skill in the North Atlantic, North Pacific and at the equator.

2631  
2632 Figure 4. May-June surface and bottom temperature/salinity biases (model minus observations)  
2633 for the US Northeast Continental Shelf. Observations are based on May-June climatologies of  
2634 NOAA ship-based in situ measurements from 1977 to 2009. Model output is from each climate  
2635 model’s 1990 control simulation (40-year mean). The average global ocean (atmosphere)  
2636 resolutions for CM2.1, CM2.5FLOR, CM2.5, and CM2.6 are 100-km (200-km), 100-km (50-  
2637 km), 25-km (50-km), and 10-km (50-km), respectively. Note that the operational GFDL seasonal  
2638 climate prediction system uses CM2.5FLOR. Refer to Saba et al. 2016 for further details on the  
2639 models and experiments.

2640  
2641 Figure 5. Temporal and spatial scales of fisheries decisions (circles) and atmospheric weather  
2642 phenomena (clouds). Atmospheric weather processes adapted from Troccoli et al. (2007), Fig.  
2643 2.1. Note that “resilience and sustainability” and “rebuilding plans and protected areas” decisions  
2644 are made across a range of spatial scales. Here they are associated with large spatial scales to  
2645 reflect the significant impact of large scale climate processes, such as global climate change, on  
2646 their outcome.

2647  
2648 Figure 6. Anomaly correlation coefficients (ACCs) as a function of forecast initialization month  
2649 (x-axis) and lead-time (y-axis) in the National Atmospheric and Oceanic Administration  
2650 (NOAA) Geophysical Fluid Dynamics Laboratory (GFDL) CM2.5 FLOR and NOAA National  
2651 Centers for Environmental Prediction CFSv2 global climate prediction systems for the Gulf of  
2652 Alaska (GoA) large marine ecosystem (Stock et al. 2015). Note how late winter-early spring SST  
2653 anomaly prediction skill exceeds persistence at long lead-times (4-12 months). Grey dots  
2654 indicate ACCs significantly above 0 at a 5% level; white upward triangles indicate ACCs  
2655 significantly above persistence at a 10% level with  $ACC > 0.5$ ; white downward triangles  
2656 indicate ACCs significantly above persistence at a 10% level with  $ACC < 0.5$ .

2657



2658 Figure 7 Left column: idealized environmental forcing historical time series, and short term  
2659 forecast ( $\pm 1$  standard deviation) based on seasonal climate forecast (blue), forecast based on  
2660 assumption that future conditions will be within the historical variability (red), and truth (black);  
2661 central columns: probability density function of environmental forcing and of environmentally-  
2662 dependent productivity parameters; right column: productivity historical time series and its one-  
2663 year forecast based on a dynamic environmental driver (blue) or on average environmental  
2664 conditions (red). Arrows represent the different steps of an environmentally-explicit stock  
2665 assessment framework.

2666  
2667 Figure 8. Regional probabilistic forecast skill for maximum air temperature (upper tercile),  
2668 minimum air temperature (lower tercile), and rainfall (upper tercile) based on tercile probabilities  
2669 for each lead-time. The skill score corresponds to the ratio of the number of correct forecasts to  
2670 the total number of forecasts for the period of 1981-2010 (Adapted from Spillman et al., 2015).

2671  
2672 Figure 9. Left: Maps showing the average SST for the GAB as forecast by POAMA on 17 Dec  
2673 2015 for the next fortnight and the next two calendar months. The mean SST over the whole area  
2674 shown is given in the top left corner of each map. The black line represents the 200-m contour.  
2675 Right: Corresponding areas of preferred SBT habitat, where values  $> 1$  indicate more preferred  
2676 habitat and values  $< 1$  indicate less preferred habitat.

2677  
2678 Figure 10. Example of the GMRI lobster forecast as delivered to the fishing industry via Twitter  
2679 on March 24, 2016. The first panel shows the spring temperature from the NERACOOS coastal  
2680 ocean buoys in spring 2016 (red line) used to generate the forecast. Temperatures in 2016 have  
2681 been higher than the 2000-2014 average. The second panel shows that SST has been  
2682 anomalously warm throughout the Maine coastal region for March 2016. The bottom panel is the  
2683 actual forecast, predicting a 68% chance that the season will start three weeks earlier than  
2684 normal, a 31% chance that it will start two weeks early, and only a 1% chance that it will begin  
2685 one week early. The normal high-landings period for Maine lobster is considered to start  
2686 between July 3 and 10.

2687  
2688 Figure 11. Comparison of (a) Coral Reef Watch 4-Month Bleaching Outlook with (b) 4-month  
2689 composite of maximum Bleaching Alert Area from real-time satellite data for the same period,  
2690 August-November 2015. The levels refer to potential bleaching intensity, with possible  
2691 bleaching starting at a warning thermal stress level, bleaching likely at an Alert Level 1 and  
2692 bleaching mortality likely at an Alert Level 2. Note successful prediction of severe bleaching in  
2693 Kiribati and Hawaii.

2694 Figure 12. Probability of sardine presence, for July (left) and August (right) of 2015. These two  
2695 to three month forecasts are the average of a three-member ensemble, initialized as April 15<sup>th</sup>,  
2696 May 1, and May 15<sup>th</sup>. Due to relatively warm sea surface temperature, the forecasts predict  
2697 habitat suitable for sardine throughout the region. The exception is low salinity water for which  
2698 the model would expect sardine to be found at more intermediate rather than warm temperatures.  
2699 This leads to low probability of presence in the less saline Columbia River plume. Note that  
2700 recent declines in sardine stock size (which is not included in the model) may be resulting in  
2701 unoccupied, but suitable, habitat in the northern region.

2702

2703 Figure 13. Example output from the global (top) and regional (bottom) SEAPODYM model  
 2704 configurations developed through the INDES0 project.

2705  
 2706 Figure 14. Habitat maps indicating zones of SBT distribution (see text for explanation of zones),  
 2707 obtained using POAMA seasonal forecasts of ocean temperature. The upper left plot shows the  
 2708 historical daily climatology of the zones (yellow ribbon), the current year’s observed zone  
 2709 locations to date (red ribbon) and the latest monthly forecasts of zone location (red stars). The  
 2710 arrows along the other panels indicate whether the zones are moving north or south relative to  
 2711 the POAMA nowcast.

2712  
 2713 Figure 15. Steps required for successful integration of climate predictions into LMR decision  
 2714 frameworks. (Adapted from Hobday et al., 2016).

2715  
 2716 **Appendix**

2717 Table A1. List of six operational ocean reanalysis products from 1979-present used in the Real-  
 2718 time Ocean Reanalysis Intercomparison Project. See  
 2719 [http://www.cpc.ncep.noaa.gov/products/GODAS/multiora\\_body.html](http://www.cpc.ncep.noaa.gov/products/GODAS/multiora_body.html) for a link to download  
 2720 some of these reanalysis products. The data assimilation column lists the observation types used  
 2721 for their estimation (T/S for temperature and salinity; SLA: altimeter-derived sea level  
 2722 anomalies; SST: sea surface temperature, SIC: sea-ice concentration), as well as assimilation  
 2723 techniques used for reanalysis: Ensemble Optimal Interpolation (EnOI), Ensemble Kalman Filter  
 2724 (EnKF), Variational methods (3DVar). The atmospheric surface forcing is usually provided by  
 2725 atmospheric reanalyses, using either direct daily fluxes, or different bulk formulations. There are  
 2726 also systems that use fluxes from coupled data assimilation systems (Coupled DA).

2727

<b>Product</b>	<b>Forcing</b>	<b>Ocean Model</b>	<b>Data Assim. Method</b>	<b>Ocean Observations</b>	<b>Analysis Period</b>
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 M3	3DVAR	SLA/T/S/SST/SIC	1979-present
NASA (MERRA Ocean)	MERRA + Bulk	0.5°x1/4° MOM4	EnOI	SLA/T/S/SST/SIC	1979-present

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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	<i>Calanus</i> 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	

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