

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

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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; Poloszanska 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

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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.

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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).

938

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). 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 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,
1024 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>).

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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 (O₂) (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 (Séférián 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 (Séférián 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 (± 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 15th,
2696 May 1, and May 15th. 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.

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

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 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).

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 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 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).

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