

Managing living marine resources in a dynamic environment: the role of seasonal to 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 a range of climate-sensitive LMR decisions that can be 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 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 Paleoecological and contemporary analyses demonstrate that large fluctuations in fish
67 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,

72 2007; Chang et al., 2013; Hodgkinson et al., 2014). For instance, unrecognized periods of
73 environmentally- or climate-driven reduction in productivity contributed to the demise of Pacific
74 sardine (*Sardinops sagax*) fishery in California in the 1950s (Murphy 1966; Lindegren et al.,
75 2013; Essington et al., 2015), the collapse of the Peruvian anchoveta (*Engraulis ringens*) fishery
76 in the 1970s (Clark, 1977; Sharp, 1987), and overfishing of cod (*Gadus morhua*) in the Gulf of
77 Maine (Pershing et al., 2015, Palmer et al. 2016). Unanticipated temperature-induced changes in
78 the timing of Gulf of Maine Atlantic lobster (*Homarus americanus*) life-cycle transitions resulted
79 in an extended 2012 fishing season and record landings, but outstripped processing capacity and
80 market demand, leading to a collapse in prices and an economic crisis in the lobster fishery
81 (Mills et al., 2013). Similarly, an unforeseen extreme low water temperature event resulted in a
82 \$10-million-dollar loss to the Taiwanese mariculture industry in 2008 (Chang et al., 2013).
83 Failure to prepare for inevitable climate variability on seasonal to decadal scales can also alter
84 the rebuilding times of stocks that have previously been overfished (Holt and Punt, 2009; Punt
85 2011; Pershing et al., 2015) and break down international cooperative harvesting agreements for
86 border straddling stocks and highly migratory species (Miller and Munro, 2004; Hannesson,
87 2006; Hannesson, 2012).

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

103 long-term planning ability under future climate change (Link et al., 2015).

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

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

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

144 The objective of this paper is to assess present and potential uses of these advances in
145 climate predictions to facilitate improved management of wild and cultured LMRs. This effort
146 was initiated at the workshop "Applications of Seasonal to Decadal Climate Predictions for
147 Marine Resource Management" held at Princeton University on June 3-5 2015, which brought
148 together 60 scientists spanning climate and marine resource disciplines. This resulting synthesis
149 establishes a common understanding of the prospects and challenges of seasonal to decadal
150 forecasts for LMRs to support further innovative and effective application of climate predictions
151 to management decisions. In Section 2, we describe climate prediction systems and discuss their
152 strengths and limitations. In Section 3, we briefly summarize climate-sensitive decisions made
153 within management of commercially exploited species, protected and endangered species, and
154 for fishing and aquaculture industry applications. Section 4 presents case studies drawn from
155 peer-reviewed literature highlighting the scope of past and present applications. Sections 5 and 6
156 distill successful components across these existing applications and identify priority
157 developments based on the material in Sections 2-4. Section 7 offers concluding remarks on
158 prospects for expanded use of climate predictions for marine resource management.
159

160 **2. Predicting environmental change across space and time scales**

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

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

167

168 *2.1. Overview of climate prediction systems*

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

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

195 systems to provide predictions to stakeholders across sectors. We provide a brief overview of
196 each of these components below.

197

198 *2.1.1. Dynamical coupled global climate models for seasonal to decadal prediction*

199 GCMs are comprised of atmospheric, ocean, sea-ice and land physics and hydrology
200 components, each governed by dynamical laws of motion and thermodynamics solved
201 numerically on a global grid. GCMs used for seasonal to decadal prediction are largely
202 analogous to those used for century-scale climate change projection (e.g. Stock et al. 2011), but
203 the simulation design is different (Fig. 1). In the climate change case (Fig. 1, bottom), the goal is
204 to track the evolution of the climate over multi-decadal time scales as it responds to
205 accumulating greenhouse gases (GHGs) and other anthropogenic forcing. The simulations have
206 three components: a pre-industrial control of several hundred to several thousand years where the
207 model comes to quasi-equilibrium with preindustrial GHGs and aerosol concentrations, a
208 historical segment where GHGs increase in accordance with observed trends, and a projection
209 following one of several future GHGs scenarios (Moss et al., 2010; van Vuuren et al., 2011).

210 Because initial conditions at the start of the preindustrial period are largely “forgotten” except
211 possibly in the abyssal ocean, the only aspects linking historical and future simulations to a
212 specific year are the GHGs, land cover changes, solar forcing, land use changes, and other
213 radiatively active atmospheric constituents (e.g. aerosols). Internal climate variations arising
214 from interactions in the components of the climate system itself such as the El Niño Southern
215 Oscillation (ENSO) are represented in climate simulations, but their timing/chronology does not
216 and is not expected to agree with past observations. The objective is to obtain an accurate
217 representation of the evolving climate statistics over multiple decades, including the statistics of
218 internal climate variation, rather than precise predictions of the climate state at a given time.
219 Indeed, ensembles of historical and future simulations begun from different initial conditions,
220 and containing different realizations of internal climate variations, are often employed in
221 obtaining these statistics (Kay et al., 2015).

222 On the other hand, seasonal (months to a year) prediction skill (Fig. 1, top) largely
223 depends on initializing the model using information specific to the current climate state. Owing
224 to the chaotic nature of the atmosphere, daily weather has a deterministic predictability limit of
225 5-10 days (e.g. Lorentz, 1963; Goddard et al., 2001). In seasonal forecasts, the predictability

226 horizon is extended by forecasting monthly or seasonally-integrated statistics rather than daily
227 weather, and by exploiting the more slowly evolving elements of the climate system, such as the
228 ocean. It is assumed that the initial climate state sufficiently determines the future evolution of
229 internal climate variations so that skillful predictions of climate states within the forthcoming
230 months are possible. The presence of ENSO in June, for example, will impact extra-tropical sea-
231 surface temperature (SST) in September via teleconnections that are now substantially captured
232 by many GCMs, albeit some important biases 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, their predictive skill is more
236 dependent on initialization to current climate conditions rather than boundary conditions (i.e.
237 external forcing). Although external forcing changes are typically small over periods spanned by
238 individual seasonal forecasts, they can be significant over the multi-decadal periods spanned by
239 successive real time forecasts and the accompanying retrospective forecasts discussed in Section
240 2.1.3, and therefore should ideally remain included in seasonal forecast models (Doblas-Reyes et
241 al., 2006; Liniger et al., 2007). Annual to decadal predictability (1 to 30 years), in contrast, arises
242 from both predictable internal climate variations following model initialization and external
243 forcing, presenting a hybrid problem (Fig. 1, middle panel, Meehl et al., 2014).

244 Another difference between GCMs configured for climate projections and seasonal to
245 decadal predictions systems has been the successful expansion of the climate change GCM
246 configuration to earth system models (ESMs) that include biogeochemistry (e.g. Bopp et al.,
247 2013). ESMs can simulate biological and chemical properties (e.g. oxygen, pH, nutrients,
248 primary and secondary production) strongly linked to LMRs (Stock et al., 2011), and thus they
249 have been broadly applied to assess climate change impacts on LMRs (e.g. Cheung et al., 2009;
250 Barange et al., 2014). While incorporation of earth system dynamics in global seasonal to
251 decadal prediction models remains in an early stage of development (Séférian et al., 2014; Case
252 Study 4.6), it may yield benefits at the seasonal to decadal scale. In Section 2.3, discussion of
253 LMR-relevant seasonal to decadal predictions will be focused on the physical variables produced
254 by the operational seasonal to decadal global forecast systems, but priority developments to
255 expand biogeochemical prediction capabilities will be discussed in Section 6.

256

257 *2.1.2. The global climate observing system supporting climate prediction*

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

272

273 *2.1.3. Assimilating observations to constrain the initial climate state*

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

286 Assimilating observations produces an initialized climate state that differs from what the
287 climate models would simulate were they running freely. This is because dynamical climate

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

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

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

321 *2.1.4. Analysis and dissemination in support of diverse stakeholders*

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

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

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

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

356

357 2.2. Forecast skill

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

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

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

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

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

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

423 Dynamical processes that operate at scales finer than a model's resolution must be
424 parameterized. The spatial resolution of a model grid dictates the breadth of processes that may
425 be simulated, and differences in this resolution can influence model error and thus limit forecast
426 skill. Indeed, an increase in resolution from the 100 to 200-km atmospheric resolution common
427 to many of the current seasonal to decadal prediction systems (Kirtman et al., 2013), to 50-km
428 resulted in better seasonal temperature and precipitation forecast skill, particularly at a regional
429 scale (Jia et al., 2015). Nevertheless, in regions where local and/or unresolved sub-grid scale
430 processes strongly modulate the basin-scale climate signal, even such relatively high resolution
431 (50-km atmosphere and 100-km ocean) predictions have limited skill. For example, global
432 climate models that have an ocean resolution of 100-km to 200-km have a bias in both ocean
433 temperature and salinity in complex coastal environments such as the US Northeast Continental
434 Shelf (Saba et al., 2016). These biases may partially explain the relatively poor predictive skill of
435 seasonal SST anomalies predictions in this region (Stock et al., 2015). When both atmosphere
436 and ocean model resolution are increased (50-km atmosphere, 10-km ocean), such biases are
437 substantially reduced (Fig. 4) because the Gulf Stream coastal separation position as well as
438 regional bathymetry are more accurately resolved. We stress, however, that while enhanced
439 resolution appears critical for some scales and ecosystems, existing models show considerable
440 prediction skill for marine resource relevant variables at other scales and ecosystems (Section
441 2.3). High resolution GCMs (10-km ocean versus 100-km in many prediction systems), are also

442 considerably more computationally expensive to run, currently limiting their use in operational
443 climate prediction systems. Furthermore, biases can remain at this resolution, and can be quite
444 large in specific ocean regions (Delworth et al., 2012; Griffies et al., 2015). This is due, in part,
445 to the challenges of optimizing sub-gridscale parametrizations for higher resolution models
446 (Goddard et al., 2001).

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

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

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

469

470 2.3. *Prediction of living marine resource-relevant physical variables*

471 Variables routinely predicted using current seasonal to decadal forecast systems are
472 LMR-relevant (e.g. SST), and the objectives of seasonal to decadal climate prediction are

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

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

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

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

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

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

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

566 larger scale input from coarser global climate models to produce hydrologic forecasts at scales
567 useful for decision makers (e.g. Mo and Lettenmaier, 2014). As prediction systems increase in
568 atmospheric and land surface resolution, precipitation and temperature prediction skill over
569 mountain regions also increases as topography is better resolved (Jia et al., 2015).

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

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

597 Hodgkinson et al., 2014). Although individual tropical cyclones are very much "weather"
598 phenomena, with no path to predictability beyond a few days, some aggregate statistics of
599 tropical cyclones are strongly influenced by predictable large-scale aspects of climate, such as
600 **ENSO** or other modes of variability (e.g., Gray, 1984). This has led to the development of a
601 number of skillful statistical (Klotzbach and Gray, 2009; Jagger and Elsner, 2010), dynamical
602 (Vitart and Stockdale, 2001; Vitart, 2006; Zhao et al., 2010; Chen and Lin, 2011; Vecchi et al.,
603 2014; Murakami et al., 2015), and hybrid statistical-dynamical (Wang et al., 2009; Vecchi et al.,
604 2011) prediction methodologies, which have targeted primarily basin-wide (e.g., North Atlantic,
605 West Pacific, etc.), seasonally-integrated statistics of tropical cyclone activity. More recently,
606 methodologies that exploit the ability of high-resolution GCMs to represent both regional
607 hurricane activity and its connection to climate variation and change have led to skillful seasonal
608 predictions of tropical cyclone activity at more regional scales (e.g., Vecchi et al., 2014; Zhang et
609 al., 2016, Murakami et al., in review). The coming years are likely to see an expansion in the
610 growth of tools for the seasonal prediction **of** tropical cyclones and many other extreme
611 phenomena, such as tornadoes (Elsner and Widen, 2014 ; Allen et al., 2015), and heat waves (Jia
612 et al., 2016) enabled by the widespread development of high-resolution dynamical prediction
613 models, improved understanding of the connection of weather extremes to large-scale conditions,
614 and the pressing societal need for information about the statistics of high-impact weather events
615 at regional scales.

616

617 **3. Managing living marine resources in a dynamic environment**

618
619 Management of LMRs is an exercise in trade-offs, requiring that managers balance
620 multiple, often competing objectives (e.g. Jennings et al., 2016). For instance, global policies and
621 the legal mandates of many countries require weighting conservation of commercial stocks
622 against their exploitation, protecting bycatch species that are overfished or listed as endangered
623 or threatened, safeguarding of coastal economies and fishing communities, and balancing present
624 benefits to stakeholders against future losses (King et al., 2015). Fisheries managers acting on
625 the best available science are mandated to prevent overfishing while, on a continuing basis,
626 achieving high levels of benefits to society from fisheries and other seafood products. Fishers
627 must balance a parallel tradeoff between the value of current harvest and the maximum value of
628 future harvests. Similarly, aquaculture industry participants have to balance the value of expected

629 returns from capital investment against its opportunity costs.

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

638

639 *3.1. Industry Operations*

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

659 For the fishing industry, key decisions include investments in boats, gear and labor, as

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

668 Such habitat models generally use correlative techniques to define regions of high
669 abundance, or high probability of occurrence, for a species of interest in relation to
670 oceanographic conditions. Species distribution data can be sourced from tagging studies,
671 fisheries-dependent records, fisheries-independent surveys, or other sources. The distribution
672 data is then related to one or multiple environmental variables (e.g. temperature, Hobday et al.,
673 2011) through a variety of statistical methods, including generalized linear models (GLM),
674 generalized additive models (GAM), classification and regression trees (CART), and artificial
675 neural networks (ANN). When making century-scale projections of how fish distributions will
676 change due to shifts in climate and marine habitat distribution, other commonly used models
677 include Maxent (Phillips et al., 2006), Dynamic Bio-climate Envelope Model (DBEM; Cheung
678 et al., 2009), AquaMaps (Kaschner et al., 2006), and the Non-Parametric Probabilistic Ecological
679 Niche (NPEN) model (Beaugrand et al., 2011). These models vary in assumptions and
680 complexity, and can at times give markedly different results when applied to the same dataset
681 (Lawler et al., 2006; Jones et al. 2013; Jones and Cheung 2014, Cheung et al. 2016a). For this
682 reason, it is advisable to use an ensemble of multiple models when it is practicable to do so.
683 Regardless of the statistical model used, all correlative habitat models assume that the
684 relationships observed between species distributions and environmental variables in the training
685 dataset are reliable proxies for actual mechanistic drivers of habitat preference. This assumption
686 can be reasonably robust, for example if statistical associations with temperature closely mirror
687 known physiological constraints, or more questionable, where a correlation is observed but the
688 mechanistic basis is unknown (Peck et al., 2013). This can limit the performance of habitat
689 models when they are extrapolated outside the range of the training dataset: either spatially into
690 other geographic regions, or temporally into past or future time periods (Brun et al. 2016).

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

700

701 *3.2. Monitoring and closures*

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

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

722 such adverse effects, coastal resource managers have to estimate optimal allocation of
723 monitoring resources, as well as appropriate times and locations for beach and shellfish bed
724 closures. If fishers can anticipate HAB-related closures, they can make informed decisions about
725 which stocks to target and develop approaches to compensate for expected lost revenues.

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

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

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

758

759 *3.3. Provision of Catch Advice*

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

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

781 The effects of ecological (e.g. predator abundance) or physical factors on population
782 dynamics are rarely modeled explicitly: a recent meta-analysis showed that just 24 out of the
783 1200 assessments incorporated such information (Skern-Mauritzen et al., 2015). These

784 unmeasured, non-fishing driving factors are only accounted for by allowing the models to
785 incorporate random variability in key model parameters, particularly recruitment, or by
786 incorporating empirical measured inputs, particularly regarding fish body weight-at-age.
787 However, without including the process causing the fluctuations in the model framework, there
788 is no basis for refining the random forecast into the future.

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

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

815 have proven useful in a timely detection of productivity shifts and improved reference point
816 estimation for semelparous species (Peterman et al., 2000; Peterman et al., 2003; Collie et al.,
817 2012). Temporal variability in reference points can also be introduced via environmental
818 covariates on productivity parameters. When these environmental factors can be skillfully
819 forecasted and the environment-population dynamics relationship is robust, the fish productivity
820 forecast is improved (Maunder and Watters, 2003; Schirripa et al., 2009; Haltuch and Punt,
821 2011; Johnson et al., 2015; Miller et al., 2016).

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

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

843 Addition of climate forecast information into stock assessment models may also reduce
844 uncertainty bounds on stock status projections by narrowing the window of probable outcomes
845 as compared to the use of the entire historical range (Fig. 7a). Furthermore, if a stock

846 productivity parameter is subject to an environmentally-driven shift or directional trend, future
847 values may lie outside of the historical probability space, leading to biased estimates of stock
848 status under the assumption of stationarity (Fig. 7b and 7c). As a result, a climate forecast may
849 serve as an advance warning of shifts in environmental conditions and stock productivity
850 parameters, and may reduce bias in stock status estimates (Fig. 7b and 7c).

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

860

861 *3.4. Spatial Issues and Protected Areas*

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

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

875 Such climate-driven distributional shifts can have important implications for spatial
876 management measures. For example, shifts of juvenile plaice (*Pleuronectes platessa*) towards

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

891 Shifting species distributions can also create important new fishing opportunities, such as
892 the squid fishery in the Gulf of Maine that appeared during a particularly warm year (Mills et al.,
893 2013). Hence, forecasts of species distributions driven by multi-year to decadal climate
894 predictions can help identify which species are likely to spark new fisheries, and then prioritize
895 them for additional research, experimental fishing programs, or short-term closures during the
896 colonization phase. Such forecasts can also warn of distributional shifts outside of the range of
897 current fisheries operations, and may prevent overfishing of the remaining portion of the stock.

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

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

910

911 **4. Case Studies**

912

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

917

918 *4.1 Seasonal forecasts to improve prawn aquaculture farm management*

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

929 Seasonal forecast products for Queensland prawn farms were first developed in 2011-
930 2012 (Spillman et al., 2015) and currently continue to be delivered via a password protected
931 website. Regional temperature and precipitation forecasts are derived from the global dynamical
932 seasonal prediction system POAMA (Predictive Ocean Atmosphere Model for Australia;
933 Spillman and Alves, 2009; Spillman et al. 2011), and then downscaled using local weather
934 station information for participating prawn farms. The forecasts were verified by assessing the
935 probabilistic skill of the model predicting the upper terciles for maximum air temperature and
936 rainfall, and the lower tercile for minimum temperature, as these were the events of greatest
937 concern to prawn farm managers. Forecast accuracy is generally higher for temperature than
938 rainfall, and declines with lead-time (Fig. 8). Forecasts out to lead-times of 2 months, which
939 aligns with several farm operational planning timeframes, such as those for feed management or

940 harvest time (Hobday et al., 2016), are sufficiently skillful to be integrated within prawn farm
941 management decision framework (Spillman et al., 2015).

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

948

949 *4.2 Seasonal forecasts to improve economic efficiency of a large-scale tuna fishery*

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

964 Environmental variables influencing the spatial distribution of SBT in the GAB during
965 summer were explored using location data collected on SBT over many years from electronic
966 tags, and comparing the ocean conditions where fish were found with the conditions available to
967 them throughout the region and time period of interest (Eveson et al., 2015). SST was found to
968 have the greatest influence, with fish preferring temperatures in the range of 19-22°C. Once
969 habitat preferences were established, this information was coupled with POAMA (see Section
970 4.1) to predict locations of preferred SBT habitat in future. Both the habitat preference model

971 and POAMA were evaluated against historical observations, and it was concluded that SST-
972 based habitat forecasts for SBT in the GAB have useful skill for lead-times up to 2 months. A
973 daily-updating website was created to provide industry with forecasts of environmental
974 conditions and SBT distributions for the next fortnight and next 2 calendar months from the date
975 of issue (Fig. 9), along with a suite of other relevant information, including skill of the forecasts
976 (www.cmar.csiro.au/gab-forecasts). Based on feedback from industry stakeholders obtained
977 both formally through a survey and informally through an industry liaison representative, the
978 information provided on the website has proven to be a valuable tool for fishers making
979 decisions such as when and where to position vessels and to conduct fishing operations (Eveson
980 et al., 2015). As the SBT fishery is quota-managed, the forecasting approach will not lead to
981 increased catches (and thus impact sustainability), but will enable fishers to catch their quota
982 more efficiently, thereby increasing profitability.

983

984 *4.3 A statistical seasonal forecast to improve the operational planning of a lobster fishery*

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

997 Motivated by the events in 2012, the possibility of an early warning indicator of lobster
998 fishery timing was explored and it was found that the date when landings in Maine begin to
999 increase is negatively correlated with subsurface temperatures in March and April. Based on this
1000 relationship, a statistical forecast system was developed that takes temperatures at 50 m from a
1001 network of coastal ocean buoys operated by the Northeast Regional Association of Coastal

1002 Ocean Observing Systems (NERACOOS) in spring and estimates the probability of the fishery
1003 shifting into the high-landings period during a particular week in June or July. For the last two
1004 years, the first forecast of the year has been announced to the industry at the Maine Fishermen's
1005 Forum and then updated weekly at www.gmri.org/lobster-forecast and via Twitter (Fig. 10).
1006 Forecasters have now begun to work more closely with harvesters, dealers, and marketers in the
1007 industry to assess how it can be further improved to meet their needs. Other work has identified
1008 value in using sea temperature observations and models to help forecast outbreaks of lobster
1009 epizootic shell disease (Maynard et al., 2016).

1010

1011 *4.4 Seasonal forecasts to improve coral reef management*

1012 Increases in ocean temperature over a coral's tolerance limit are the leading cause of
1013 coral bleaching events (Hoegh-Guldberg et al., 2007). Since 1997, NOAA's Coral Reef Watch
1014 has been using SST satellite data to provide near real-time warnings of coral bleaching (Liu et
1015 al., 2014). While coral reef managers and scientists have been able to use these nowcasts to
1016 execute operational response plans, managers recognized the need for longer lead-time forecasts
1017 to improve management responses to coral bleaching. Following these requests, NOAA Coral
1018 Reef Watch developed the first seasonal coral bleaching outlook, based on a statistical model
1019 from NOAA's Earth System Research Laboratory (Liu et al., 2009). In 2009 the Australian
1020 Bureau of Meteorology developed the first dynamical seasonal forecasts for coral bleaching risk
1021 on the Great Barrier Reef, based on seasonal SST predictions from POAMA (see Section 4.1;
1022 Spillman and Alves, 2009; Spillman, 2011). NOAA Coral Reef Watch, in turn, developed a
1023 dynamical 4 month lead coral bleaching outlook for coral reefs globally using seasonal SST
1024 predictions from the NOAA National Centers for Environmental Prediction (NCEP) global
1025 dynamical climate prediction system, the CFS model (Eakin et al., 2012).

1026 These seasonal coral bleaching forecasts are made publicly available on the internet
1027 (http://www.bom.gov.au/oceanography/oceantemp/GBR_SST.shtml,
1028 http://coralreefwatch.noaa.gov/satellite/bleachingoutlook_cfs/outlook_cfs.php) and they allow
1029 coral reef managers around the world to develop timely and proactive bleaching response plans,
1030 brief stakeholders and allocate monitoring resources in advance of bleaching events. Resource
1031 managers and scientists have been using these bleaching outlooks extensively throughout the
1032 2014-16 global coral bleaching event (Eakin et al., 2014; Eakin et al., 2016).

1033 For example, in August 2010, following severe coral bleaching, the Thailand and
1034 Malaysian governments closed numerous popular dive sites to reduce additional stress to
1035 severely bleached reefs (Thomas and Heron, 2011). In May 2016, Thailand again closed ten
1036 reefs, this time in advance of the bleaching peak (The Guardian 2016,
1037 <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
1038 recently, once Coral Reef Watch alerts were issued in late June 2015 of the high potential for
1039 bleaching in Hawaiian waters (Fig. 11), the Hawaii Department of Land and Natural Resources
1040 (DLNR) immediately began preparations of resources to monitor this event. Having only seen
1041 significant multi-island bleaching in the main islands twice before, in 1996 and 2014 (Jokiel and
1042 Brown, 2004; Bahr et al., 2015), a much more comprehensive effort was needed. Additional
1043 volunteers were trained, who, together with teams from the state, University of Hawaii, NOAA,
1044 and XL Catlin Seaview Survey, were deployed across most of the islands. This group was able to
1045 document and monitor this unprecedented event, while the DLNR was able to alert the public
1046 and work with marine resource users to encourage reduction of activities that could further stress
1047 the corals during the bleaching event. Additionally, DLNR undertook an effort to collect
1048 specimens of the rarest coral species from the main Hawaiian Islands and safeguard them in their
1049 coral nurseries on Oahu and Maui. Many of these species suffered severe bleaching and
1050 mortality, and DLNR staff have been unable to find one of these species alive off Oahu since the
1051 2015 event. Both Bureau of Meteorology and NOAA seasonal forecast tools were also used
1052 extensively by reef management during the most recent bleaching event on the Great Barrier
1053 Reef in the summer of 2015/2016, currently believed to be the worst on record
1054 (<http://www.gbrmpa.gov.au>).
1055

1056

1057 *4.5 Seasonal forecasts of Pacific sardine habitat*

1058 Pacific sardines are notable as one of the few stocks managed with respect to climatic
1059 variability in the US. Just recently, sardine distribution and migration forecasts have been
1060 produced (Kaplan et al., 2016; Fig. 12) for the US Pacific Northwest and Canadian British
1061 Columbia, based on 6 to 9 month predictions of ocean conditions
1062 (<http://www.nanoos.org/products/j-scope/>; Siedlecki et al., 2016). These predictions rely upon
1063 the NOAA NCEP global dynamical climate prediction system Climate Forecast System (Saha et

1064 al., 2006) to force a high resolution (~1.5 km) Regional Ocean Modeling System (Haidvogel et
1065 al., 2008). The efforts are fully described in Siedlecki et al. (2016), including skill assessment
1066 for SST, bottom temperature, and oxygen. Relationships between sardine distribution and J-
1067 SCOPE predictions of ocean physics and chlorophyll were estimated for 2009. The final fitted
1068 relationships between SST and salinity had moderate skill to predict sardine distributions
1069 (presence or absence) in summer 2013 and 2014, with up to 4 to 5 month lead-times. Skill
1070 assessment focused on a “hit rate” metric, area-under-the-curve (AUC), which balances the
1071 desire to correctly predict sardine presence against the risk of false positives. One caveat to the
1072 sardine forecasts is that they predict available sardine habitat (Fig. 12) without accounting for
1073 sardine stock size. Recent declines in sardine abundance (Hill et al., 2015) have likely meant a
1074 contraction of the stock southward (MacCall, 1990), despite availability of suitable habitat in the
1075 US Pacific Northwest and British Columbia.

1076 As with many pelagic species, sardines are seasonally migratory and forecasts of their
1077 distribution by J-SCOPE may be relevant for fisheries management and industry. The sardine
1078 stock is landed by US, Mexican and Canadian fishers and the extent of the northward summer
1079 migration is dependent on both water temperature and population contraction due to low
1080 population abundance. The sardine forecasts by Kaplan et al. (2016) predict the extent of this
1081 northward migration and could be used to plan fishing operations (e.g. whether Canadian fish
1082 processors should expect sardine deliveries) or fisheries surveys. Additionally, quotas apportion
1083 a fixed percent of sardine catch to Canadian vessels, and J-SCOPE provides foresight that that
1084 this portion may be unharvested in a particular cold year. Furthermore, sardine straddle
1085 international boundaries, and short-term seasonal forecasts may help international management
1086 and industry to cope with and prepare for the long-term distribution shifts expected under climate
1087 change (Pinsky and Mantua, 2014). To date, forecasts have primarily been delivered through
1088 collaboration with NANOOS (Northwest Association of Networked Ocean Observing Systems)
1089 via the web (<http://www.nanoos.org/products/j-scope/>). Web products include predictions of
1090 ecological indicators relevant to the regional fishery management council, and will soon be
1091 incorporated in NOAA’s Integrated Ecosystem Assessment (Harvey et al., 2014). Other outreach
1092 efforts are ongoing and aim to produce targeted forecasts (as discussed for Australia above in
1093 Section 4.1) for fishery managers and stakeholders, and to better integrate with fishery
1094 management council needs.

1095

1096 *4.6 Short-term forecasts of Indonesian tuna fisheries to control illegal fishing*

1097 The last decade has seen the generalization of satellite Vessel Monitoring Systems to
1098 monitor licensed fishing vessels, the use of satellite radar images to detect illegal fishing and the
1099 development of Electronic Reporting Systems (ERS) to provide catch statistics in real time.
1100 Integration of these developments in fishery monitoring with an operational forecasting model of
1101 fish spatial dynamics that has the ability to predict the distribution of fish under the influence of
1102 both environmental variability and fishing is assisting Indonesian fishing authorities in
1103 controlling illegal fishing and implementing conservation measures. This operational monitoring
1104 framework (Gehlen et al., 2015) was developed through the INDESO project and integrates a
1105 high resolution regional model system coupling ocean physics to biogeochemistry (NEMO/
1106 PISCES; Gutknecht et al., 2016; Tranchant et al., 2016) to a spatially explicit tuna population
1107 dynamics model (SEAPODYM; Lehodey et al., 2010; 2015). SEAPODYM simulates functional
1108 groups of organisms at the intermediate trophic levels (Lehodey et al., 2010; 2015) and the
1109 dynamics of their predators (e.g. tuna) (Lehodey et al., 2008). The model is complemented by a
1110 quantitative parameter estimation and calibration approach (Senina et al., 2008) which enables
1111 the application of the model to fish stock assessment and testing of management scenarios
1112 (Sibert et al., 2012).

1113 Tuna are highly migratory species, and their habitats cover large expanses of the global
1114 ocean. Thus, the simulation of fish stock dynamics at high resolution in the Indonesian region
1115 requires accounting for exchanges (fluxes) with populations outside of the regional domain (i.e.
1116 Pacific and Indian Ocean) under the influence of both environmental variability (e.g. ENSO) and
1117 fishing mortality. Boundary conditions for the regional 1/12° SEAPODYM implementation are
1118 obtained from a 1/4° global operational configuration (Fig.13) driven by temperature and
1119 currents from the operational ocean prediction system Mercator-Ocean PSY3V3 (Lellouche et
1120 al., 2013). Biogeochemical forcings (net primary production (NPP), dissolved oxygen) are either
1121 derived solely from the coupled physical-biogeochemical model NEMO/ PISCES (forecast
1122 mode) or from NEMO/PISCES and satellite ocean color and SST data (to estimate NPP;
1123 Behrenfeld and Falkowski, 1997), along with climatological dissolved oxygen (O_2) (hindcast and
1124 nowcast modes). The regional operational model SEAPODYM also uses a climatological data
1125 set (i.e., monthly average of the last 5 years) of fishing effort prepared from the best available

1126 information to apply an average fishing mortality. The forecasting system runs every week and
1127 delivers one week of hindcast, one week of nowcast, and 10 days of forecast. These outputs are
1128 used by the Indonesian Fishing Authority to improve the collection and verification of fishing
1129 data, to assist illegal fishing surveillance, and to establish conservation measures (e.g.,
1130 identification and protection of spawning grounds and nurseries) required for the sustainable
1131 exploitation of this essential resource (Marion Gehlen, personal communication, June 22, 2016).
1132

1133 *4.7 Seasonal forecasts for dynamic spatial management of the Australian east coast tuna fishery*

1134 Since 2003, a dynamic spatial management approach has been used to limit unwanted
1135 capture of a quota-managed species, SBT, in the Australian eastern tuna and billfish fishery. The
1136 approach combines a habitat model, conditioned with temperature preference data obtained from
1137 pop-up satellite archival tags deployed on SBT and an ocean model to produce near real-time
1138 habitat nowcasts, delivered by email and utilized the same day by fishery managers during the
1139 fishing season (Hobday and Hartmann, 2006; Hobday et al., 2010). Managers use this
1140 information along with other data inputs (such as recent fishing catch rates) to restrict access in
1141 the core (high probability of occurrence) zone to vessels that have both observers and SBT quota.
1142 The habitat model was extended in 2011 to include a seasonal forecasting component using
1143 ocean temperature forecasts from the seasonal prediction system POAMA, with useful forecast
1144 skill out to several months (Hobday et al., 2011). Both nowcast and seasonal forecast habitat
1145 maps produced for managers show probabilistic zones of tuna distribution coded as “OK”
1146 (unlikely to encounter SBT), “Buffer” (likely to encounter SBT) and “Core” (very likely to
1147 encounter SBT) (Fig. 14). Incorporating a seasonal forecasting component has been an
1148 important step in informing and encouraging both managers and fishers to think about decisions
1149 on longer time scales (Hobday et al., 2016). Forecasts are now delivered via a dedicated webpage
1150 (<http://www.cmar.csiro.au/sbt-east-coast/>). The dynamic habitat forecasting approach has
1151 reduced the need for large areas closures while still meeting the management goal, but does
1152 require fishing operators to develop more flexible fishing strategies, including planning vessel
1153 movements, home port selection and quota purchase.

1154

1155 **5. Recommended practices**

1156 Following Hobday et al. (2016) and Siedlecki et al. (2016), there are three main
1157 components to a successful LMR forecast framework: assessment of needs, forecast
1158 development, and forecast delivery. Here, we break down the forecast development and delivery
1159 stages further to provide more details of the forecast implementation process (Fig. 15).
1160 Identification of a clear management need via effective communication between climate
1161 scientists and management or industry stakeholders from the start of the forecast development
1162 process is essential for the utility and widespread adoption of climate prediction tools for LMRs
1163 (Hobday et al., 2016; Harrison and Williams, 2007; Fig. 15). This needs assessment should
1164 include the determination of relevant variables, **spatial domain**, spatial resolution, and timescales.
1165 Once needs have been assessed, it is incumbent upon scientists to provide balanced
1166 communication of both capabilities and limitations to evaluate whether forecasts are likely to be
1167 useful to their partners.

1168 Forecast development is underpinned by an understanding of the mechanisms relating
1169 physical climate variables to the LMR of interest. Once such linkages are found, three forecast
1170 development steps follow: an assessment of the skill of the physical climate variable forecast, an
1171 assessment of the skill of the LMR model forecast, and the uncertainty associated with each. The
1172 prediction skill for the physical climate variables must be assessed at an appropriate timescale
1173 relative to the management decision timeframe and at a spatial resolution able to resolve
1174 environmental driving mechanisms. Skill assessment will make use of retrospective forecasts and
1175 observations. When reanalyses are used in lieu of observations, their accuracy at the scale of
1176 interest should be confirmed against data prior to forecast skill assessment whenever possible
1177 (Section 3). If the skill evaluation indicates that the variables of interest cannot be skillfully
1178 forecasted at an adequate lead-time and/or relevant spatial scale, stakeholder expectations may
1179 be re-evaluated and alternate variables or scales of interest investigated (i.e. it may be necessary
1180 to return to the needs assessment step). Alternatively, downscaling or bias correction techniques
1181 may improve skill at the desired scale in some cases (Section 6). Skill may be assessed using at
1182 least measures of correlation, variability, and bias between forecast and observations, although
1183 further verification analyses are possible (Mason and Stephenson, 2007).

1184 Once a physical climate variable forecast has been developed and determined to be
1185 skillful, the value of using it in an LMR model must be determined. LMR model skill assessment
1186 can employ skill metrics based on “hit rate”, such as AUC or area-under-the-curve (Fielding and

1187 Bell, 1997) and the True Skill Statistics (Allouche et al., 2006), to evaluate whether the LMR
1188 forecasts reproduce biological phenomena (e.g., presence of tuna, occurrence of a coral
1189 bleaching event). While it is well known that climate affects LMRs (Section 1), most of derived
1190 climate-LMR relationships are empirical, with climate variables often acting as proxies of
1191 complex trophic effects, interspecies interactions, and dispersal processes. For climate
1192 information to be included in LMR management frameworks, the environment-fisheries
1193 relationship has to be robust and preferably based on mechanistic, ecologically-sound
1194 hypotheses. A sufficiently long observational data series is required for model calibration and
1195 verification (Haltuch and Punt, 2011), including out-of-sample validation (Francis, 2006; Mason
1196 and Baddour, 2007; Mason and Stephenson, 2007). In addition, if the environment-fisheries
1197 relationship relies on stock assessment model output (e.g. recruitment), it is important that this
1198 relationship be developed within the stock assessment model itself rather than as a post-hoc
1199 analysis to ensure uncertainties associated with the stock assessment model are properly
1200 propagated (Maunder and Watters, 2003; Brooks and Deroba, 2015). Furthermore, to increase
1201 confidence in the robustness of these empirical relationships, meta-analytical techniques can be
1202 employed to ensure that the proposed hypothesis is robust across a species range (Myers, 1998),
1203 taking into account, however, that environmental variables may affect species differently across
1204 their latitudinal range (e.g. Mantua et al., 1997).

1205 As environment-LMR associations may change over time (e.g. with changing baselines
1206 under climate change), these empirical relationships need to be periodically re-evaluated as new
1207 environmental and LMR data are collected. LMR forecast development will therefore be an
1208 iterative process and management has to be dynamic to allow for changing management
1209 decisions as the environment-fisheries relationship evolves with the continuous integration of
1210 new information. Environment-LMR correlations have been observed to be more robust when
1211 tested with new data at the edges of a species range (Myers, 1998). These populations may serve
1212 as initial case studies with which to develop dynamic management frameworks that integrate
1213 climate prediction information. Table A2 includes a list of LMRs for which a sufficient
1214 understanding of how they respond to climate variability has been achieved, and which may
1215 serve as additional case studies. These include those determined by Myers (1998) as robust to re-
1216 evaluation and those that already make use of environmental information in their management as
1217 described by Skern-Mauritzen et al. (2015).

1218 To provide a thorough presentation of risk to decision makers, it will be important to
1219 assess the uncertainty of the climate prediction as well as that of the LMR models. For the
1220 climate prediction, this will involve quantification of processes, variability and model
1221 uncertainty via the use of single and multi-model ensembles (Section 3). Forecasts will be
1222 inherently probabilistic, and ensembles can be used to estimate the probability. On the fisheries
1223 side, there is also uncertainty associated with LMR models' parameterizations (Cheung et al.,
1224 2016a, b). As for climate predictions, ensemble approaches can be employed in LMR models to
1225 account for the high level of uncertainty in the parameterization of biological processes (e.g.
1226 Kearney et al., 2012; Laufkötter et al., 2015; 2016). Uncertainty in the environment-LMR
1227 relationship will also need to be accounted for by, for instance, running multiple simulations of
1228 the LMR model differing in their stochastic error of the LMR-environment relationship (e.g.
1229 Lindegren et al., 2013).

1230 Finally, an effective forecast delivery mechanism is required. The climate prediction
1231 needs to be delivered in a format that can be effectively incorporated into LMR models and
1232 decision frameworks, such as population models used in fish stock assessment. As in all the
1233 stages of LMR forecast development, consistent user engagement is essential to ensure sustained
1234 use of such prediction tools (Harrison and Williams, 2007; Hobday et al., 2016). For instance,
1235 the general difficulty people have in understanding uncertainty and probabilities has limited the
1236 use of climate predictions in the natural resource sector (Nicholls, 1999; Marshall et al., 2011).
1237 Collaboration with social scientists on the most appropriate presentation and delivery options
1238 may enhance adoption of forecast information (Harrison and Williams, 2007). Automated web-
1239 based delivery systems are a common delivery method, although ongoing contact with end users
1240 and acknowledgement of user feedback is important to build engagement and for continued
1241 forecast use (Hobday et al., 2016). Funding for delivery system maintenance, user engagement,
1242 and continued user training should be included in projects to maintain iterative LMR operational
1243 forecast systems.

1244 The value of integrating climate predictions into LMR decision frameworks has to then
1245 be demonstrated to managers or industry. This can be undertaken by employing cost-benefit
1246 analyses (e.g. Asseng et al., 2012) and MSE (Section 2.4, Tommasi et al., accepted). For
1247 example, MSEs can assess the performance of different management strategies (e.g. with and
1248 without climate predictions) in relation to a suite of performance metrics while taking

1249 uncertainty into account. They may also include economic models to better evaluate the specific
1250 economic value of integrating climate forecasts into LMR decisions (e.g. Richardson, 2000).
1251 While MSEs have been developed in the context of fisheries science, such decision support
1252 systems could also be applied to industry or coastal manager's decision frameworks. Results
1253 from these assessments would inform both climate and LMR prediction development by
1254 highlighting further refinements needed to better inform decisions.

1255

1256 **6. Priority developments**

1257 While the potential benefits of seasonal climate forecasts in reducing the climate
1258 vulnerability of the fishery and aquaculture industry and in improving fisheries management are
1259 clear (Section 4), barriers to their widespread adoption also exist. Social, cultural, economic, or
1260 political constraints, such as existing regulations or dissemination difficulties, can limit forecast
1261 use (Nicholls, 1999; Goddard et al., 2001; Harrison and Williams, 2007; Davis et al., 2015).
1262 However, the discussion herein will be limited to priority developments aimed at reducing
1263 technical impediments to climate forecast application. These technical barriers include
1264 incomplete understanding of environment-LMR relationships, limited length and availability of
1265 physical, biogeochemical and biological time series for model development and validation, and
1266 the irreducible predictability limits at seasonal to decadal scales. There is also need for
1267 methodological advancements in LMR models to explicitly consider environmental productivity
1268 indicators and spatial distributions, and apply empirical models in non-stationary systems.
1269 Finally, there is a need for reduction in climate model bias through improvements in model
1270 formulation and initialization, verification of LMR-relevant physical variables at LMR-relevant
1271 spatial scales beyond SST, the development of biogeochemical forecasting capabilities in global
1272 prediction systems, and improvements in climate predictability at LMR-relevant regional scales
1273 through higher resolution global prediction systems or the development of downscaling
1274 frameworks.

1275 On the LMR model side, predictive capacity is constrained by our incomplete
1276 understanding of environment-LMR relationships, especially their response to environmental
1277 fluctuations (e.g. Chavez et al., 2003; Di Lorenzo et al., 2009; Le Mézo et al., 2016). As a case in
1278 point, only 2% of managed fisheries worldwide explicitly integrate past environmental
1279 information into their current tactical decision making and provide an existing framework to

1280 readily incorporate climate forecast information (Skern-Mauritzen et al., 2015). This lies in stark
1281 contrast to ubiquitous climate-marine resource correlations reported in the literature (e.g. Hare et
1282 al., 2010; Mueter et al., 2011; Ottersen et al., 2013). For most populations, the length of
1283 available, co-occurring fishery, biological and environmental time series may be too short to
1284 robustly identify the environment-LMR relationship (Haltuch and Punt, 2011) or to develop a
1285 habitat preference model, highlighting the importance of maintaining and expanding existing
1286 observational data series for environment-LMR model development and verification. Funding
1287 for ocean and LMR observations is limited. Given the importance of having climate observations
1288 over a period long enough to span different environmental regimes, LMR observations that cover
1289 a wide range of population sizes, and large sample sizes to improve estimation of model
1290 parameters, establishment of new monitoring networks must be carefully balanced with the
1291 critical need to maintain current sampling programs (Haltuch and Punt, 2011; Dorner et al.,
1292 2013). Maintenance and expansion of physical climate observing systems, as discussed in
1293 Section 3, are also essential to climate model development to improve climate predictability
1294 through better model initialization (e.g. Servonnat et al., 2014). Including concurrent measures of
1295 basic biogeochemical and lower-trophic-level measurements should be integrated into existing
1296 observing systems, when possible, to facilitate better understanding of physical-biological
1297 interactions in the marine environment and better assessment of model predictive capability.
1298 That said, while spatially-or temporally-constrained (or incomplete) environmental data may be
1299 limited in quantitative utility, such data can help provide qualitative context for decision-making.
1300 For example, time series of conditions can be used to delineate regime-specific parameter
1301 estimates or emergent patterns in indicators can provide justification for precautionary
1302 management actions and intensified monitoring (Zador et al., in press).

1303 Non-stationarity issues are particularly critical for decadal to centennial predictions.
1304 However, for many populations, knowledge of environment-fishery interactions is limited to
1305 basic correlations. These correlative (and often linearly approximated) relationships provide a
1306 useful, existing tool to start integrating climate predictions into LMR models. But if an
1307 ecosystem were to shift into a new, no-analog state and the ecosystem processes that were
1308 empirically described by this correlative relationship were to change, subsequent management
1309 decisions may perform poorly (Dorner et al., 2013). Similar shifts can occur at shorter time-
1310 scales. For example, many species distribution models developed with one decade of data

1311 perform poorly when used to project species distribution during another decade (Brun et al.,
1312 2016). For bias correction of physical climate models, non-linear statistical techniques that are
1313 better at simulating distribution extremes appear to perform better under novel climate conditions
1314 (Gaitan et al., 2014). More sophisticated, model-free statistical approaches also appear promising
1315 in establishing environmental influences on LMRs that can be applied in a management
1316 framework, particularly over short timescales (e.g. Ye et al., 2015). To improve LMR predictive
1317 capacity, it will be necessary to expand the use of such techniques into tactical management
1318 frameworks, and to characterize their benefits relative to more traditional statistical techniques as
1319 well as ecosystem models.

1320 Dynamic ecosystem models integrate physical variables, lower-trophic-level dynamics,
1321 LMR dynamics, and human impacts, mechanistically, and are critical to enhance our
1322 understanding of LMR responses to climate variability (Travers et al., 2007; Rose et al., 2010;
1323 Le Mézo et al., 2016). Such process-based understanding is necessary to the development of
1324 models able to skillfully predict LMR under novel conditions (Evans, 2012). Furthermore,
1325 because of the inherent complexity, non-linearity, and multi-stressor characteristics of marine
1326 ecosystems, multispecies and ecosystem models can in some cases assess uncertainties and
1327 trade-offs more effectively (Pikitch et al., 2004; Link et al., 2012). Nevertheless, such models are
1328 currently only employed for strategic advice at the decadal and multi-decadal scale, rather than
1329 for short-term tactical decisions (e.g. Smith et al., 2011; Pacific Fishery Management Council
1330 and National Marine Fisheries Service 2014; Fulton et al., 2014; Marine Stewardship Council,
1331 2014). One issue of concern with the use of ecosystem models for tactical decisions is their
1332 inability to integrate all of the data streams, such as catch-at-age data, that are customary in
1333 current tactical fisheries decision frameworks. Another issue is that their complexity comes at the
1334 cost of longer running time, hindering their use within current tactical management process
1335 timelines. Also, they rely on static assumptions and parameterizations, which may not remain
1336 valid under future conditions. Finally, because more processes are modeled and there is
1337 uncertainty in each, the fully characterized uncertainty can be large. This may make decision-
1338 making more difficult but, if this uncertainty accurately reflects the true uncertainty in the
1339 system, it will ultimately result in better decisions. Expanded application of such models for
1340 tactical management decisions will be dependent on improving their parameterizations,
1341 specification of initial conditions, extending quantitative model assessments, and reducing their

1342 uncertainties through additional physiological studies, process studies, and modeling
1343 experiments aimed at understanding the mechanisms driving LMR's responses to climate. LMR
1344 surveys that include more hydrographic, biogeochemical, and lower-trophic-level (plankton)
1345 observations will also be critical to make progress towards expanded use of ecosystem models in
1346 LMR forecasting applications.

1347 Highly resolved spatial and population dynamics models of a specific target species
1348 coupled to a coarser, lower-trophic-level model (Lehodey et al., 2008; Senina et al., 2008;
1349 Section 4.2) or "models of intermediate complexity" – MICE – (Lindgren et al., 2009; Collie et
1350 al., 2014; Plagányi et al., 2014) may be more immediately suited for tactical management
1351 decisions, as their uncertainties are more tractable. MICE use statistical parameter estimation
1352 methods common in current tactical fisheries models to fit multispecies models to data for small
1353 groups of interacting species. Such models are becoming sufficiently advanced, including both
1354 species interactions and impacts of temperature on population dynamics (Holsman et al., in
1355 press.), and can be used in concert with single-species models to provide tactical fisheries advice
1356 from a multi-model suite, similar to operational prediction systems used in weather forecasts
1357 (Ianelli et al., in press.). Combining such models with seasonal and decadal forecasts will help
1358 evaluate risk profiles and trajectories of recovery plans, assess the flexibility of harvest policies
1359 to dynamic conditions, and identify areas of management vulnerability to climate change (e.g.,
1360 are dynamic management policies available in hand to respond to sudden shifts in ecosystem
1361 structure or driving processes?; Holsman et al., in review). While MICE are quite promising for
1362 tactical decision making in the near future, simulation testing to determine whether they can
1363 provide adequate information for tactical management under various information conditions
1364 typical of fisheries management needs to be undertaken. If successful, such applications may
1365 also provide a valuable template for the expansion of holistic whole ecosystem models from
1366 strategic to tactical management decisions.

1367 Expanded use of seasonal to decadal forecasts is also limited by problems of relevance in
1368 terms of critical variables, and spatial and temporal scales (Nicholls, 1999; Hobday et al., 2016).
1369 For some LMR-relevant variables, there are irreducible predictability limits at seasonal to
1370 decadal scales due to the chaotic nature of the atmosphere (Deser et al., 2012). Such variables
1371 will remain unpredictable even with a perfect data assimilation system and model formulation,
1372 and hence management frameworks robust to unpredictable variation will need to be developed.

1373 It will be important for climate scientist to continue assessing predictability limits of LMR-
1374 relevant variables and to communicate such limitations to users, e.g., by providing reliable
1375 probabilistic forecasts accompanied by appropriate measures of historical skill.

1376 For some regions and time scales, however, predictability of LMR-relevant variables is
1377 limited by the systematic errors of GCMs (Goddard et al., 2001). It is critical to find ways to
1378 either reduce this model bias or reduce its negative impacts on forecast skill through novel
1379 techniques (e.g., Batté et al., 2016). Reduction in model bias will involve improvement in both
1380 model physics and parametrizations, as well as data assimilation systems (Goddard et al., 2001;
1381 Meehl et al., 2014; Siedlecki et al., 2016). For instance, as variability in ocean circulation can
1382 depend on both temperature and salinity variations in the ocean's interior, improved observations
1383 of these quantities, as well as improved assimilation systems to make optimal use of these
1384 observations, are critical. As resolution of GCMs increases, representation of the physical
1385 processes responsible for regional climate predictability improves (e.g. Jia et al., 2015), and, in
1386 some cases, this may lead to improved forecast skill of LMR-relevant variables.

1387 Forecasts at the multi-annual to decadal time scales, while of great interest to LMR
1388 management and industry, are not yet operational (Section 3). Continued research to improve our
1389 theoretical understanding and representation of the physical processes and feedbacks responsible
1390 for decadal scale climate variability are required to reduce model bias and improve decadal
1391 forecast skill (Meehl et al., 2014). Furthermore, in order to better assess the performance of
1392 decadal forecasts, predictability studies across more models and with larger ensembles need to be
1393 carried out (Meehl et al., 2014). Demonstration of reliable skill, however, will remain limited by
1394 the small sample size available for verification due to the high time series autocorrelation and
1395 limited quantity of independent samples at decadal time scales (Kumar, 2009; Meehl et al.,
1396 2014). Furthermore, it is important to stress that the decadal predictability of regions, such as the
1397 North Pacific, subject to strong atmospheric forcing, will remain limited (Branstator and Teng,
1398 2010; Meehl et al., 2014).

1399 In addition to improvements in models and initialization, predictability across
1400 spatiotemporal scales of more LMR-relevant physical variables such as bottom temperature, sea
1401 surface height, onset of upwelling, or salinity need to be examined. Biogeochemical prediction
1402 (e.g. chlorophyll biomass, net primary productivity (NPP), export production fluxes, aragonite
1403 saturation in coastal zones, oxygen concentration) is also of major relevance to ecosystem-based

1404 management of marine resources (Levin et al., 2009; Stock et al., 2011). While biogeochemical
1405 prediction is in its early stages and no coupled physical-biogeochemical seasonal to decadal
1406 forecasting systems are yet operational (but see Case Study 4.6 for their use in sub-seasonal
1407 prediction), recent work shows some potential. Predictive skill up to several months has been
1408 shown in the northern CCS for bottom oxygen (Case Study 4.5, Siedlecki et al., 2016), and up to
1409 3 years for NPP in some oceanic domains (Séférian et al., 2014, Chikamoto et al., 2015). In most
1410 cases, the increased predictability in NPP arises from that of nutrients, which directly benefit
1411 from the initialization of the model physical fields (Séférian et al., 2014). These pioneering
1412 results demonstrate that biogeochemical prediction shows promise and highlight the need to both
1413 develop integrated physical-biogeochemical forecast systems, and further quantify
1414 biogeochemical predictive skill over a variety of space and time scales to inform ecosystem-
1415 based management approaches to LMRs. **Application of ESMs in a climate change framework**
1416 **has demonstrated that uncertainty in LMR projections can be large due to uncertainty in the**
1417 **many modelling components, from GCMs to upper-trophic level models, required to assess**
1418 **climate change impacts on LMRs (Cheung et al., 2016b). Computing and personnel resources**
1419 **will hence be required to develop an ensemble approach for biogeochemical prediction able to**
1420 **account for this uncertainty.** An assessment of prediction skill beyond SST to other properties
1421 driving biological responses will also necessitate supporting, collecting, and maintaining
1422 sampling programs and observing systems.

1423 The spatial resolution of global climate models poses another limitation to their skill at
1424 the regional scale relevant to LMR decisions. Downscaling techniques can be used to generate
1425 finer-scale information from large-scale climate predictions. By relating well predicted large-
1426 scale factors to a local process of interest, downscaling, in addition to providing higher spatially
1427 and temporally resolved data, may produce LMR-relevant variables not skillfully generated by
1428 global prediction systems (e.g. Siedlecki et al., 2016). There are two types of downscaling
1429 techniques: statistical and dynamical. The first links the large-scale output from a global
1430 prediction system to local scale variables using statistical-empirical relationships. The second
1431 uses the large-scale output as boundary conditions to regional-scale, physics-based dynamical
1432 models.

1433 Statistical downscaling techniques are computationally inexpensive, so the large
1434 ensembles required to appropriately characterize initial condition and model uncertainty of

1435 seasonal to decadal predictions (Section 2.1.2) can be run relatively fast. The ability to quickly
1436 produce output is an advantage particularly relevant for downscaling of seasonal predictions, as
1437 they have to be produced in a timely manner to be relevant to the decision-making process
1438 (Laugel et al., 2014). However, to construct robust statistical relationships, long observational
1439 records are required (Section 4.1 and 4.3), though are not always available. Second, all statistical
1440 downscaling techniques assume that the large-scale, local climate relationship will remain the
1441 same in the future. While these assumptions may hold for the relatively short timeframe of
1442 seasonal predictions, they may deteriorate over longer-range decadal predictions.

1443 By contrast, dynamical downscaling techniques explicitly model the physical processes
1444 involved and therefore may perform better than statistical methods under changing or
1445 unprecedented conditions (e.g. van Hooijdonk et al., 2015). Dynamical downscaling models,
1446 however, will still inherit any bias of large-scale GCMs, and may even amplify such systematic
1447 errors (Goddard et al., 2001; Hall, 2014). This stresses again the need to reduce bias in global
1448 predictions systems to improve predictability of LMR-relevant variables at a regional scale.
1449 Further research will also be necessary to assess the relative costs and benefits of statistical
1450 versus dynamical techniques for downscaling of LMR-relevant climate predictions. This will
1451 require more resources allocated towards the development of downscaling frameworks for LMR-
1452 relevant climate predictions in regions of interest for LMRs. For instance, coupling to fine
1453 resolution coastal models, like the efforts in the northern CCS and Indonesian region (Case
1454 Studies 4.5 and 4.6), is a promising approach that warrants more studies in other regions.
1455 Furthermore, modeling studies aimed at understanding the extent to which LMR-relevant local
1456 processes are interactive with the large-scale and to what extent they are primarily "driven" by
1457 large-scale processes are required. Such studies would help to identify the type of downscaling
1458 method most appropriate and indicate regions requiring higher-resolution global climate
1459 prediction systems to further enhance predictability and support decision making at fine spatial
1460 scales.

1461 **7. Concluding Remarks**

1462 It is widely recognized that the productivity and distribution of LMR populations change
1463 over time in response to climate and ecosystem variability and long-term trends. Fishers,
1464 aquaculturists, coastal planners, and fisheries managers recognize that many of their operational

1465 planning and management decisions should account for this dynamism. We have shown how
1466 recent improvements in global dynamical climate prediction systems have resulted in skillful
1467 predictions of LMR-relevant variables at many of the spatial and temporal scales at which LMRs
1468 are managed, and how such predictions are already helping industry and managers make
1469 decisions in dynamic environments. By describing climate prediction systems and their
1470 capabilities, as well as the range of decisions currently taken by managers and the fisheries and
1471 aquaculture sector that may benefit from the inclusion of future climate information, new
1472 applications may be developed for wider use. Successful integration of climate information into
1473 LMR decision frameworks will depend on close collaboration and open dialogue between
1474 potential users and climate scientists.

1475 While some progress has been achieved within existing frameworks and resources,
1476 challenges in both climate and fisheries models need to be addressed to further expand utility of
1477 such predictions for LMRs (Section 6). To ensure widespread application of climate forecasts
1478 into LMR decision making and prevent unintended consequences of climate and fisheries
1479 interactions, new methodological approaches that capture complex ecosystem dynamics and the
1480 full range of LMR drivers need to be developed. Such frameworks will inherently be
1481 probabilistic and consist of ensemble methods to account for uncertainties in both climate and
1482 LMR models, improve model accuracy, and help end users understand risk. These frameworks
1483 will also evolve over time as our understanding of environment-LMR links, which remains poor
1484 for many species and regions, is improved through more field observations and experimental
1485 studies. Therefore, management decision systems will need to become more flexible to the
1486 inclusion of new information streams at a variety of both spatial and temporal scales, as well as
1487 to frequent re-evaluation.

1488 As we acknowledged above, seasonal to decadal predictions of climate and LMR
1489 dynamics will sometime fail despite the best efforts, especially given the increasing potential for
1490 no-analog system states and ecological surprises (Williams and Jackson, 2007; Doak et al.,
1491 2008). To cope with this inevitability, we also encourage the development of approaches for
1492 managing unexpected changes once they have happened (Schindler and Hilborn, 2015).

1493 As predictability is the ultimate test of scientific theory, routinely using these climate-
1494 forecast informed frameworks to make predictions of LMR dynamics will also improve
1495 understanding of ecosystem dynamics. In addition, skillful predictions at seasonal to multi-

1496 annual scales will lend confidence to the use of such models to project LMR dynamics over
1497 longer temporal scales, and can be used to build stakeholder confidence in the use of longer term
1498 climate projections. With exploited systems being more sensitive to environmental variability
1499 (Hsieh et al., 2006; Perry et al., 2010), development of such capabilities will be essential to the
1500 **development of climate-ready management systems to effectively manage and culture LMRs in a**
1501 future environment where long term change renders historical experience less valuable.

1502
1503 **Acknowledgements**

1504 The authors would like to thank all the participants of the workshop "Applications of Seasonal to
1505 Decadal Climate Predictions for Marine Resource Management" held at Princeton University on
1506 June 3-5 2015 for the many insightful discussions that inspired this manuscript. A special thanks
1507 to A. Valerio for all the help with the workshop organization and logistics, to the Princeton
1508 University Cooperative Institute of Climate Science for hosting the workshop, and to the NOAA
1509 Fisheries' Office of Science and Technology and NOAA's Office of Oceanic and Atmospheric
1510 Research for funding the workshop. Thank you to Dr. Jon Hare for creating the figure that
1511 inspired Figure 3. Many thanks to Dr. Fernando Gonzalez-Taboada, Dr. Angel Muñoz, and three
1512 anonymous reviewers for the helpful comments and suggestions. CME and Coral Reef Watch
1513 work are supported primarily by the NOAA Coral Reef Conservation Program and the NOAA
1514 National Environmental Satellite, Data, and Information Service's Center for Satellite
1515 Applications and Research. The contents in this manuscript are solely the opinions of the authors
1516 and do not constitute a statement of policy, decision, or position on behalf of NOAA or the U.S.
1517 Government.

1518
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2627

2628 **Figure Captions**

2629 Figure 1. Overview of simulation design for seasonal and decadal predictions and climate
2630 projections. GHG refers to greenhouse gases. Note that the year for shifting from pre-industrial
2631 to historical forcing in climate projections, here set to 1860, can differ between climate models.
2632 “Forcings” in the climate change context refer to specified solar **insolation** and concentrations of
2633 radiatively active **atmospheric constituents**.

2634

2635 Figure 2. Temperature anomalies at 55-m depth from six different ocean reanalysis products for
2636 April 2015 relative to each-product 1981-2010 climatology. The bottom left panel shows the
2637 ensemble mean, and the bottom right the ratio of signal (ensemble mean) to noise (ensemble
2638 spread).

2639

2640 Figure 3. Left panel: One-month lead probabilistic forecast of SST for summer (June, July, and
2641 August, JJA) initialized in May 2016 from the North American Multi-Model Ensemble
2642 (NMME). This forecast was produced using all the ensemble members provided by each model
2643 participating in the NMME. It therefore reflects both initial condition and model uncertainty.
2644 Warm colors (yellow-orange) indicate areas with a significant probability of experiencing **upper-**
2645 **tercile temperatures**, with the probability of such terciles ranging from 40-100% depending on
2646 the degree of shading. **Analogous** interpretations exist for the anomalously cool (blue colors) or
2647 near climatological (gray colors) conditions. Right panel: Ranked probability skill score for the
2648 forecast presented in the left panel. The color bar represents the relative improvement of the
2649 probability forecast (left panel) over climatology, with 0 indicating no skill over climatology.
2650 Note the higher predictive skill in the North Atlantic, North Pacific and at the equator.

2651

2652 Figure 4. May-June surface and bottom temperature/salinity biases (model minus observations)
2653 for the US Northeast Continental Shelf. Observations are based on May-June climatologies of
2654 NOAA ship-based in situ measurements from 1977 to 2009. Model output is from each climate
2655 model’s 1990 control simulation (40-year mean). The average global ocean (atmosphere)
2656 resolutions for CM2.1, CM2.5FLOR, CM2.5, and CM2.6 are 100-km (200-km), 100-km (50-
2657 km), 25-km (50-km), and 10-km (50-km), respectively. Note that the operational GFDL seasonal
2658 climate prediction system uses CM2.5FLOR. Refer to Saba et al. 2016 for further details on the
2659 models and experiments.

2660

2661 Figure 5. Temporal and spatial scales of fisheries decisions (circles) and atmospheric weather
2662 phenomena (clouds). Atmospheric weather processes adapted from Troccoli et al. (2007), Fig.
2663 2.1. Note that “resilience and sustainability” and “rebuilding plans and protected areas” decisions
2664 are made across a range of spatial scales. Here they are associated with large spatial scales to
2665 reflect the significant impact of large scale climate processes, such as global climate change, on
2666 their outcome.

2667

2668 Figure 6. Anomaly correlation coefficients (ACCs) as a function of forecast initialization month
2669 (x-axis) and lead-time (y-axis) in the National Atmospheric and Oceanic Administration
2670 (NOAA) Geophysical Fluid Dynamics Laboratory (GFDL) CM2.5 FLOR and NOAA National
2671 Centers for Environmental Prediction CFSv2 global climate prediction systems for the Gulf of

2672 Alaska (GoA) large marine ecosystem (Stock et al. 2015). Note how late winter-early spring SST
2673 anomaly prediction skill exceeds persistence at long lead-times (4-12 months). Grey dots
2674 indicate ACCs significantly above 0 at a 5% level; white upward triangles indicate ACCs
2675 significantly above persistence at a 10% level with $ACC > 0.5$; white downward triangles
2676 indicate ACCs significantly above persistence at a 10% level with $ACC < 0.5$.
2677

2678 Figure 7 Left column: idealized environmental forcing historical time series, and short term
2679 forecast (± 1 standard deviation) based on seasonal climate forecast (blue), forecast based on
2680 assumption that future conditions will be within the historical variability (red), and truth (black);
2681 central columns: probability **density** function of environmental forcing and of environmentally-
2682 dependent productivity parameters; right column: productivity **historical** time series and its one-
2683 year forecast based on a dynamic environmental driver (blue) or on average environmental
2684 conditions (red). Arrows represent the different steps of an environmentally-explicit stock
2685 assessment framework.
2686

2687 Figure 8. Regional probabilistic forecast skill for maximum air temperature (upper tercile),
2688 minimum air temperature (lower tercile), and rainfall (upper tercile) based on tercile probabilities
2689 for each lead-time. The skill score corresponds to the ratio of the number of correct forecasts to
2690 the total number of forecasts for the period of 1981-2010 (Adapted from **Spillman et al., 2015**).
2691

2692 Figure 9. Left: Maps showing the average SST for the GAB as forecast by POAMA on 17 Dec
2693 2015 for the next fortnight and the next two calendar months. The mean SST over the whole area
2694 shown is given in the top left corner of each map. The black line represents the 200-m contour.
2695 Right: Corresponding areas of preferred SBT habitat, where values > 1 indicate more preferred
2696 habitat and values < 1 indicate less preferred habitat.
2697

2698 Figure 10. Example of the GMRI lobster forecast as delivered to the fishing industry via Twitter
2699 on March 24, 2016. The first panel shows the spring temperature from the NERACOOS coastal
2700 ocean buoys in spring 2016 (red line) used to generate the forecast. Temperatures in 2016 have
2701 been higher than the 2000-2014 average. The second panel shows that SST has been
2702 anomalously warm throughout the Maine coastal region for March 2016. The bottom panel is the
2703 actual forecast, predicting a 68% chance that the season will start three weeks earlier than
2704 normal, a 31% chance that it will start two weeks early, and only a 1% chance that it will begin
2705 one week early. The normal high-landings period for Maine lobster is considered to start
2706 between July 3 and 10.
2707

2708 Figure 11. Comparison of (a) Coral Reef Watch 4-Month Bleaching Outlook with (b) 4-month
2709 composite of maximum Bleaching Alert Area from real-time satellite data for the same period,
2710 August-November 2015. The levels refer to potential bleaching intensity, with possible
2711 bleaching starting at a warning thermal stress level, bleaching likely at an Alert Level 1 and
2712 bleaching mortality likely at an Alert Level 2. Note successful prediction of severe bleaching in
2713 Kiribati and Hawaii.
2714

2715 Figure 12. Probability of sardine presence, for July (left) and August (right) of 2015. These two
2716 to three month forecasts are the average of a three-member ensemble, initialized as April 15th,
2717 May 1, and May 15th. Due to relatively warm sea surface temperature, the forecasts predict
2718 habitat suitable for sardine throughout the region. The exception is low salinity water for which
2719

2718 the model would expect sardine to be found at more intermediate rather than warm temperatures.
2719 This leads to low probability of presence in the less saline Columbia River plume. Note that
2720 recent declines in sardine stock size (which is not included in the model) may be resulting in
2721 unoccupied, but suitable, habitat in the northern region.

2722
2723 Figure 13. Example output from the global (top) and regional (bottom) SEAPODYM model
2724 configurations developed through the INDESO project.

2725
2726 Figure 14. Habitat maps indicating zones of SBT distribution (see text for explanation of zones),
2727 obtained using POAMA seasonal forecasts of ocean temperature. The upper left plot shows the
2728 historical daily climatology of the zones (yellow ribbon), the current year's observed zone
2729 locations to date (red ribbon) and the latest monthly forecasts of zone location (red stars). The
2730 arrows along the other panels indicate whether the zones are moving north or south relative to
2731 the POAMA nowcast.

2732
2733 Figure 15. Steps required for successful integration of climate predictions into LMR decision
2734 frameworks. (Adapted from Hobday et al., 2016).

2735 2736 Appendix

2737 Table A1. List of six operational ocean reanalysis products from 1979-present used in the Real-
2738 time Ocean Reanalysis Intercomparison Project. See
2739 http://www.cpc.ncep.noaa.gov/products/GODAS/multiora_body.html for a link to download
2740 some of these reanalysis products. The data assimilation column lists the observation types used
2741 for their estimation (T/S for temperature and salinity; SLA: altimeter-derived sea level
2742 anomalies; SST: sea surface temperature, SIC: sea-ice concentration), as well as assimilation
2743 techniques used for reanalysis: Ensemble Optimal Interpolation (EnOI), Ensemble Kalman Filter
2744 (EnKF), Variational methods (3DVar). The atmospheric surface forcing is usually provided by
2745 atmospheric reanalyses, using either direct daily fluxes, or different bulk formulations. There are
2746 also systems that use fluxes from coupled data assimilation systems (Coupled DA).

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

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

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2751 Table A2. Living marine resources for which there is a linkage between their dynamics and
 2752 environmental variability. These includes those determined by Myers 1998 as robust to re-
 2753 evaluation, marked by an *, and those described by Skern-Mauritzen et al. 2015 as making use of
 2754 environmental information in their management, marked by a †. For all other examples, the
 2755 reference is provided.

2756

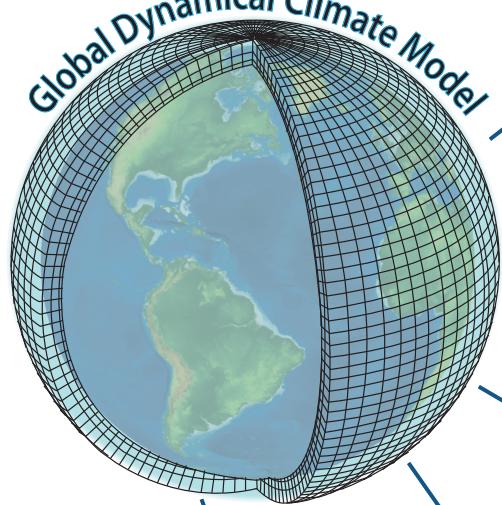
Species	Region	Environmental Driver	Reference
Cod*†	Barents Sea	Temperature	
Cod*	Eastern Baltic	Salinity	
Cod*	Labrador	Salinity	
Cod*	NW Atlantic	<i>Calanus</i> spp. abundance	
Eurasian Perch*	Windemere and Baltic region	Temperature	
Pike Perch*	Netherlands and Baltic region	Temperature	
Herring*	Southern 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	

2757

Global Climate Observing System

e.g. satellites, Argo, meteorological stations



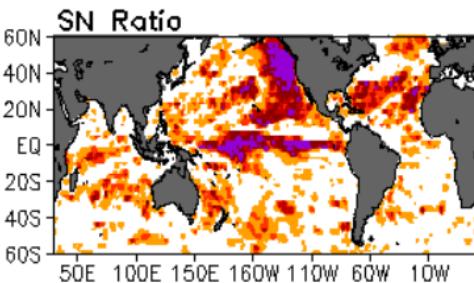
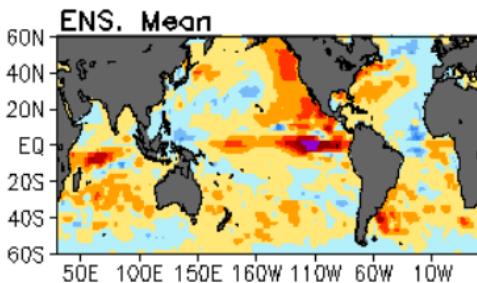
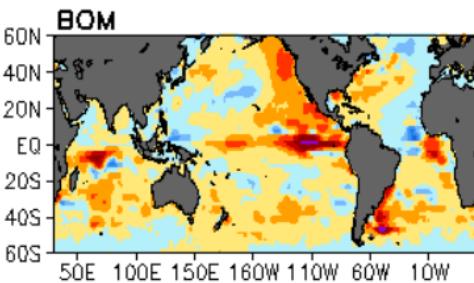
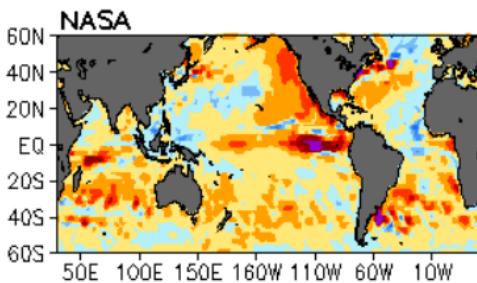
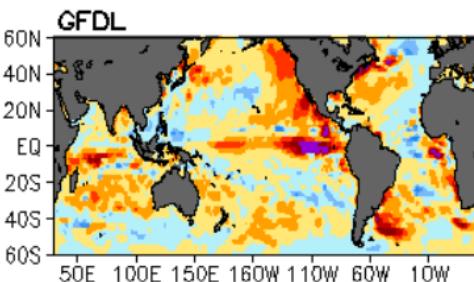
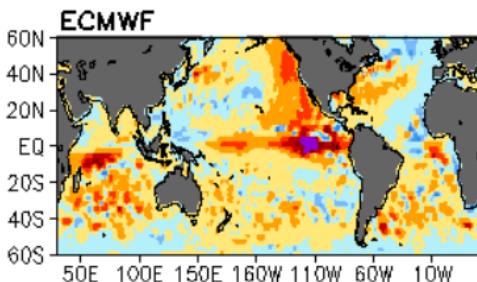
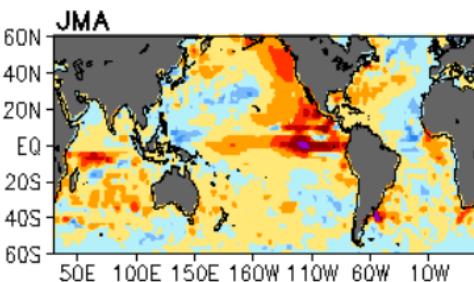
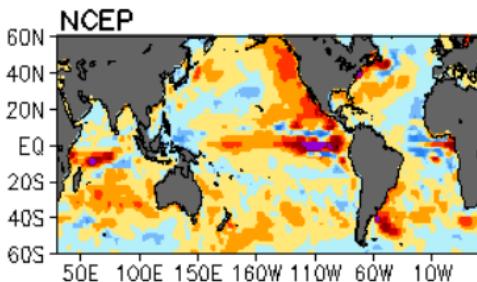
Initial Value Problem

Boundary Value Problem

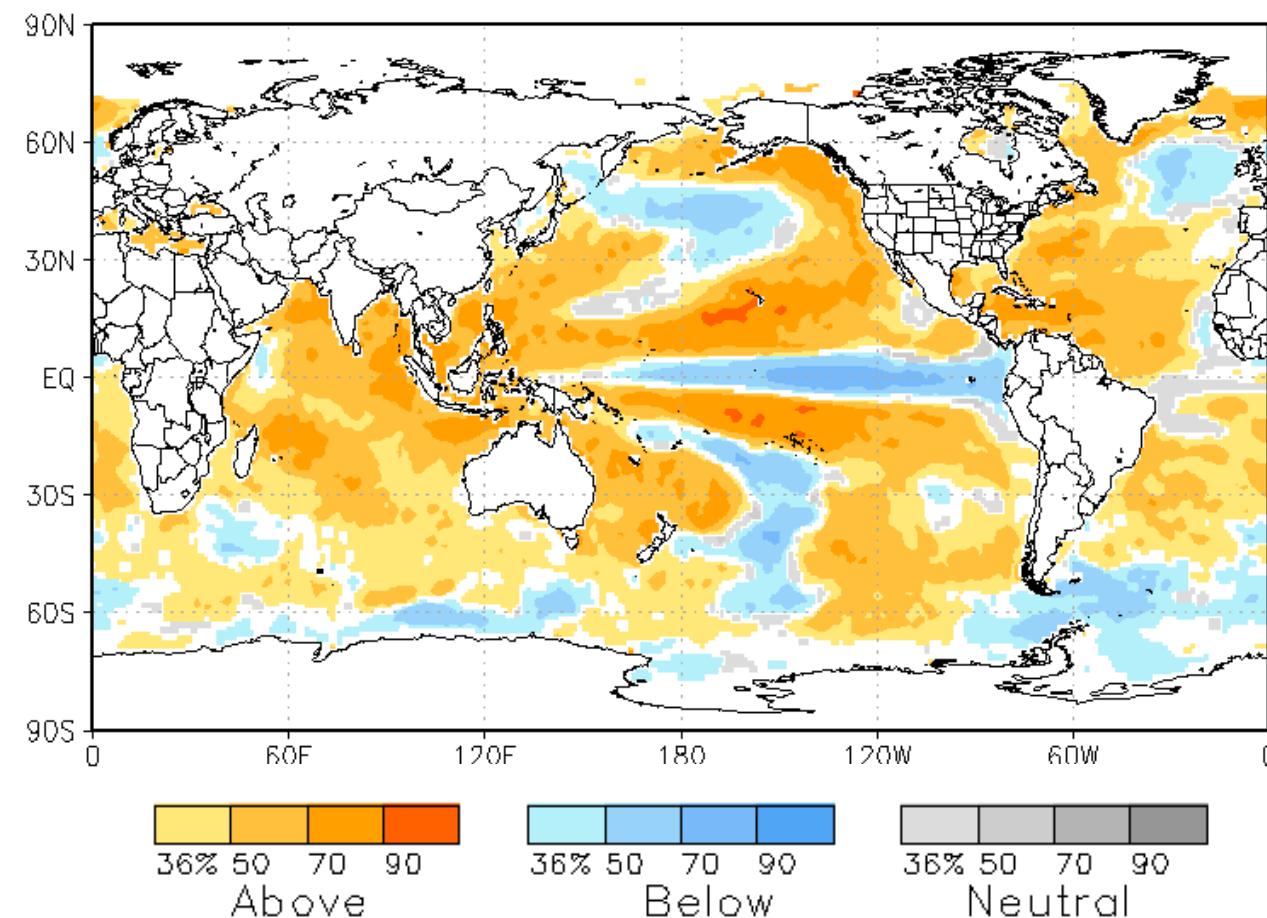
Future Forcings
Forcing Scenarios Present - 2100+

Historical Forcings
e.g. GHG, Aerosols, Ozone, Solar

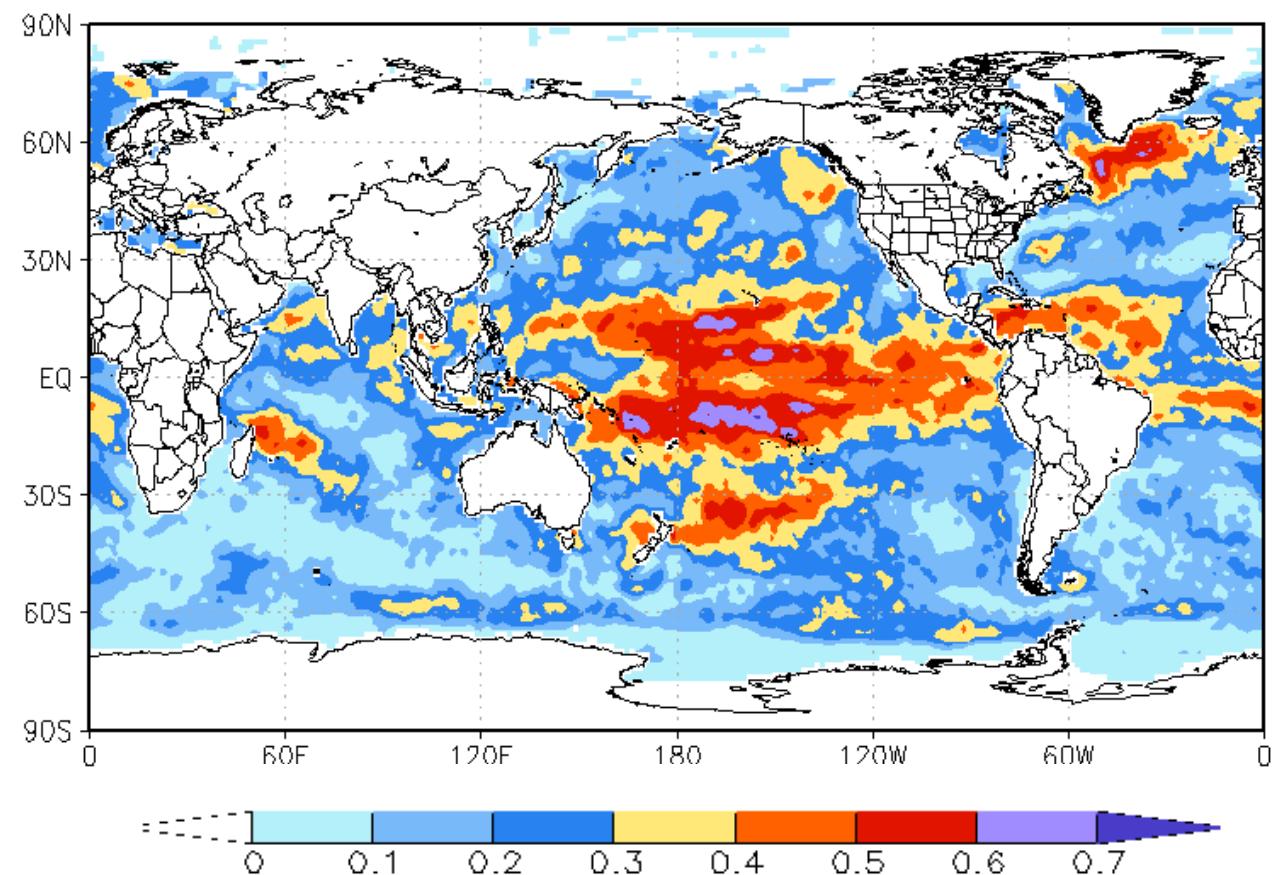
Anomalous Temperature (C) at z=55m: APR 2015

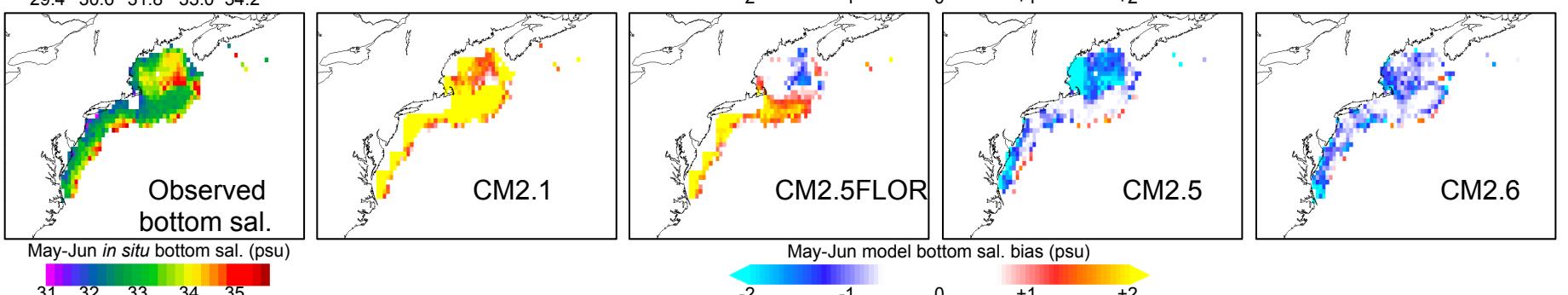
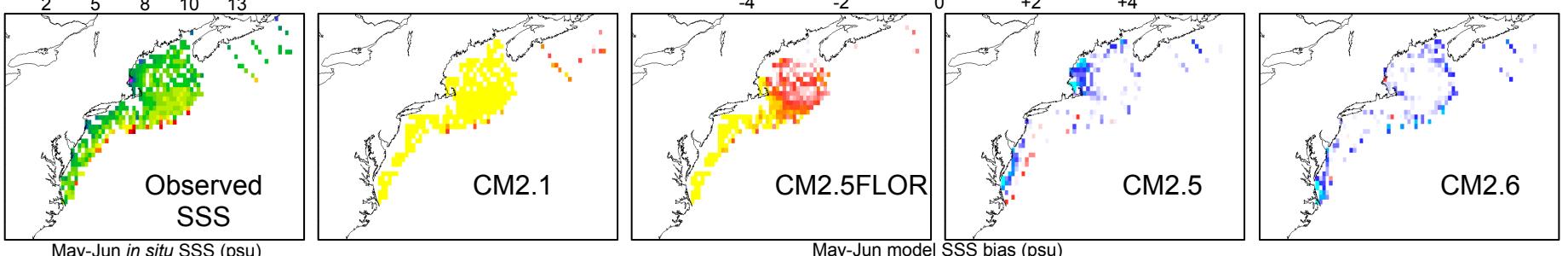
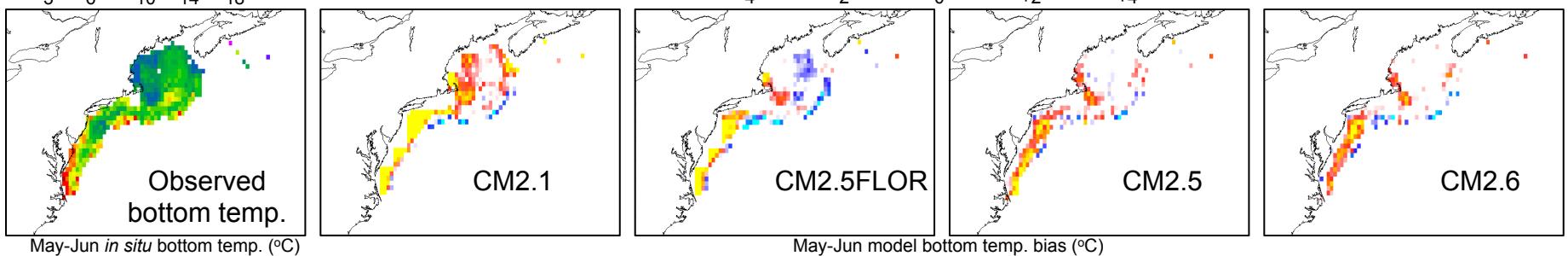
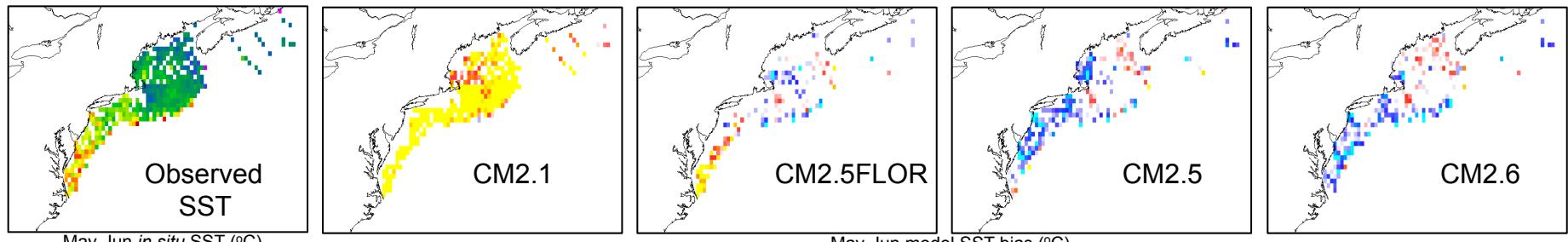


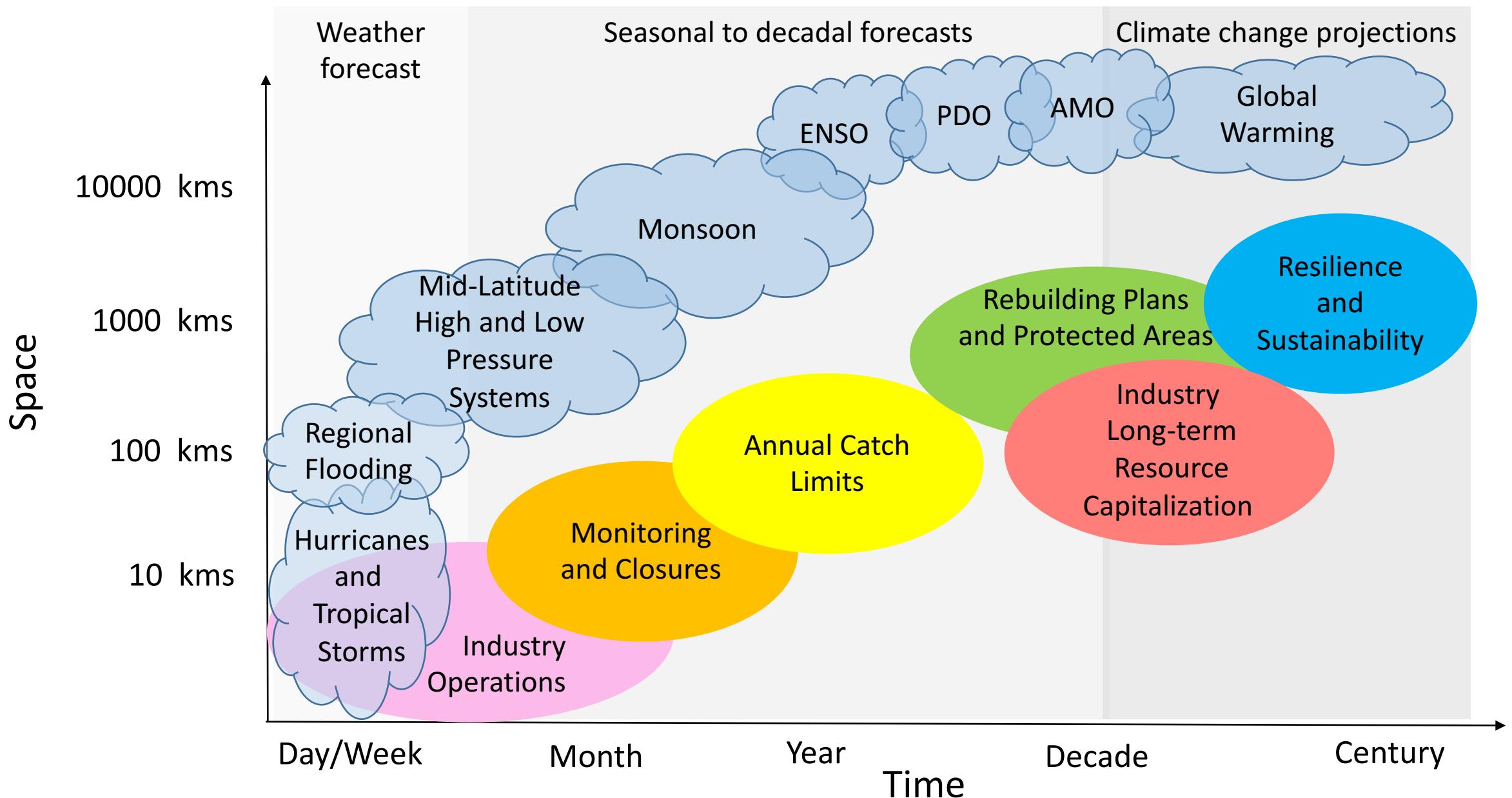
NMME Probabilistic SST Forecast for JJA, lead 1



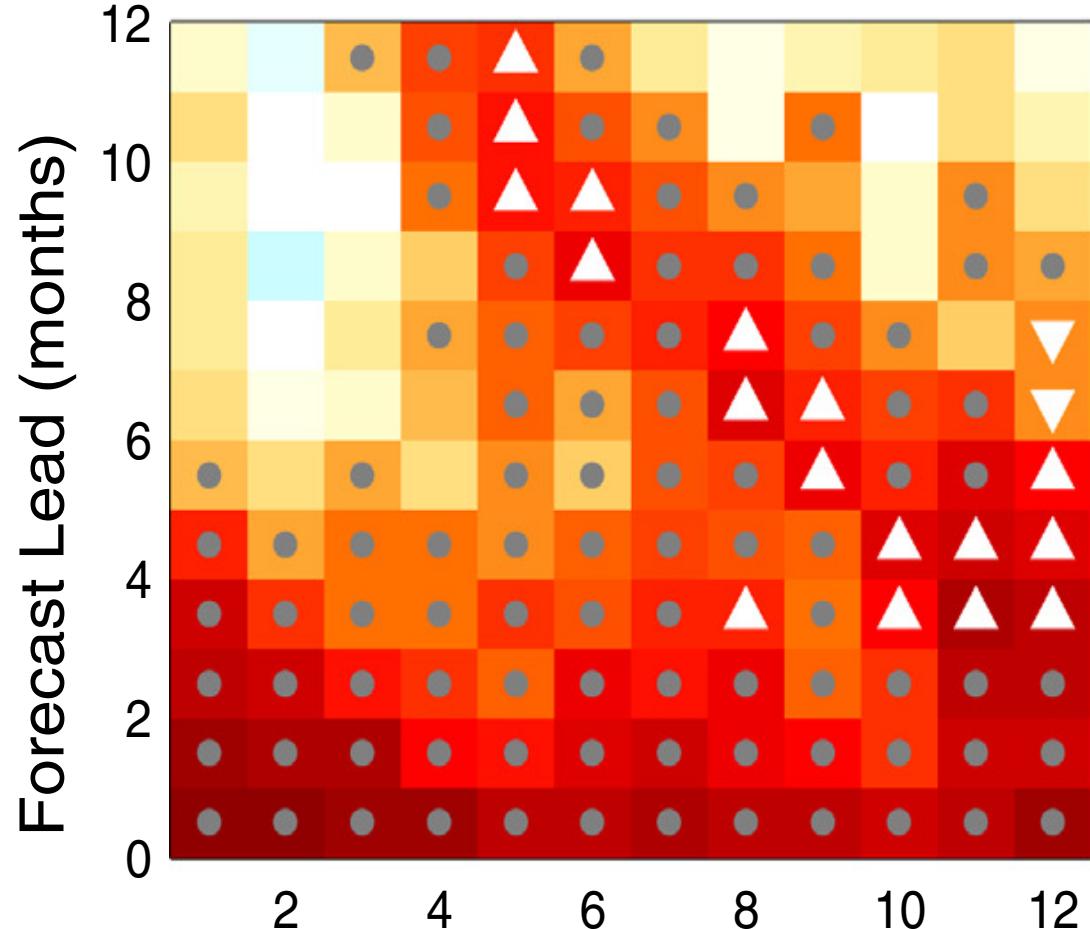
RPSS for the Probabilistic SST Forecast for JJA, lead 1



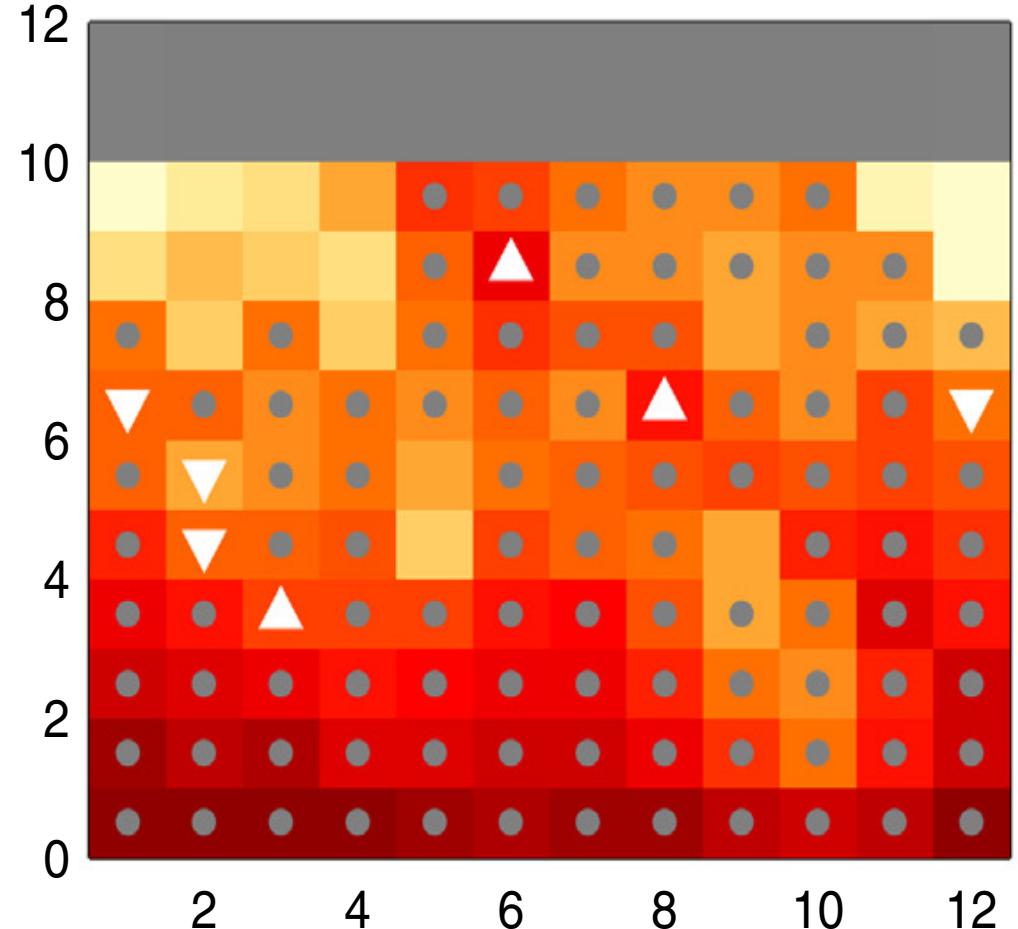




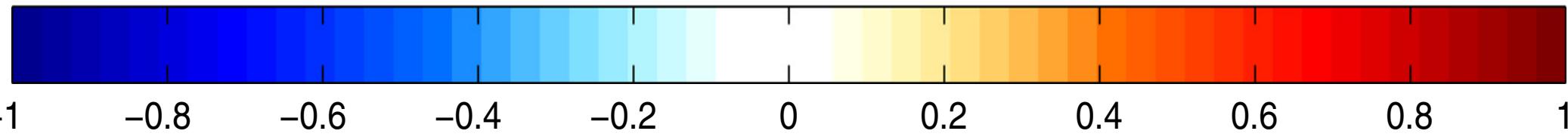
CM2.5 FLOR, GoA

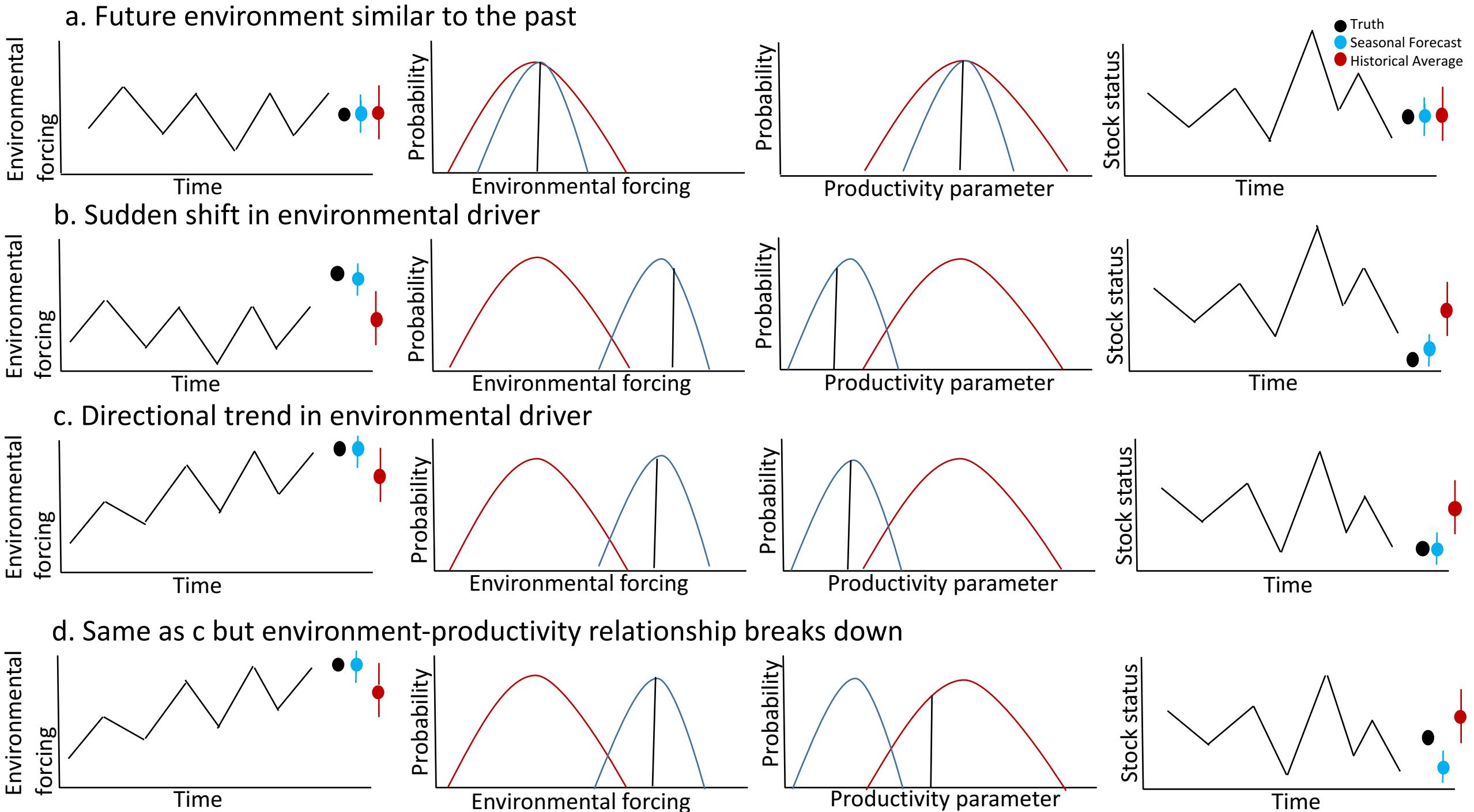


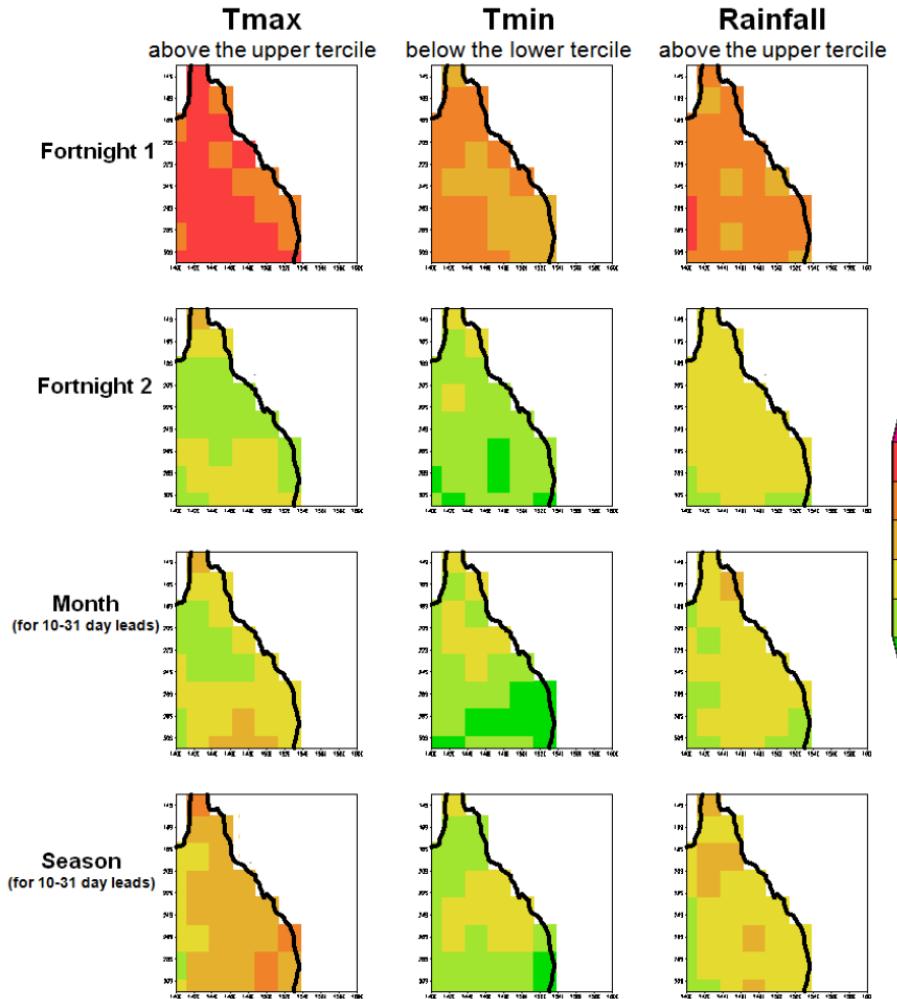
CFSv2, GoA



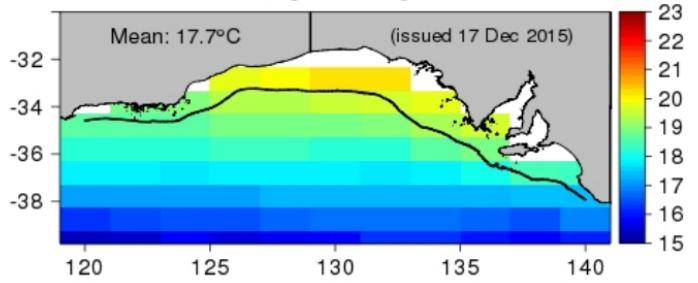
Initializaton Month



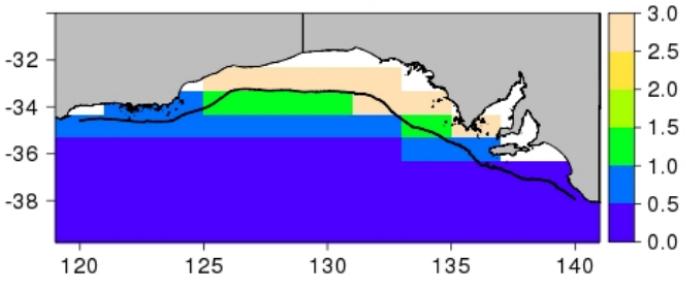




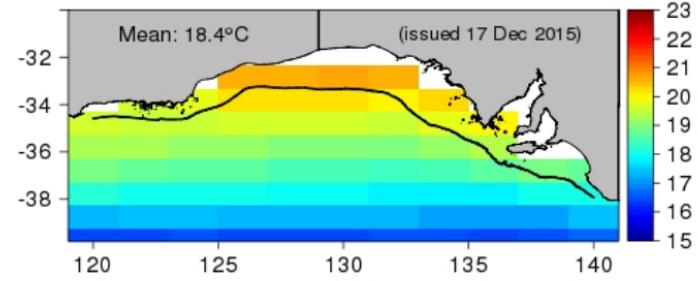
Forecast: fortnight starting 17 Dec 2015



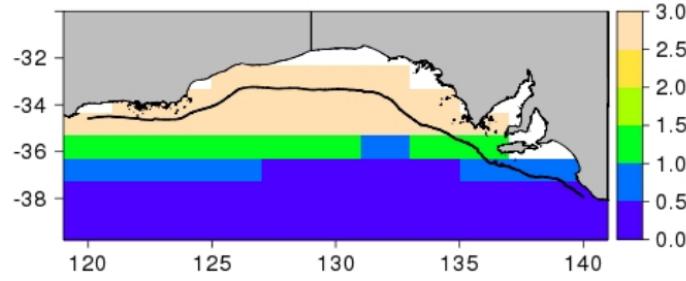
Preferred habitat



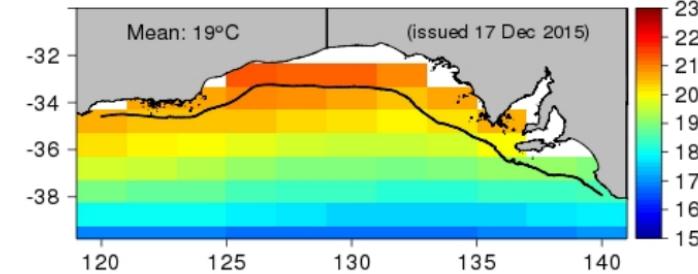
Forecast: January 2016



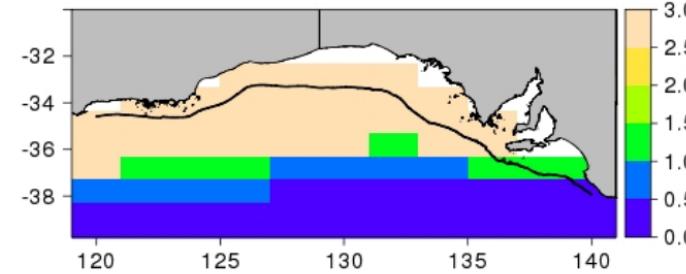
Preferred habitat

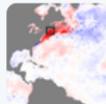


Forecast: February 2016



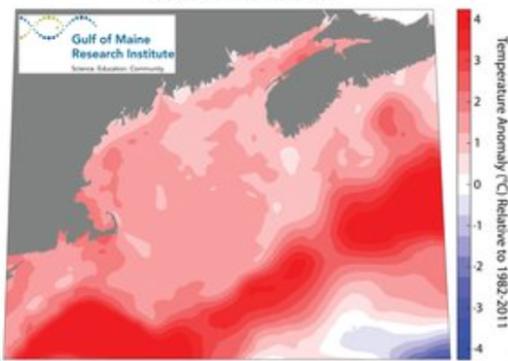
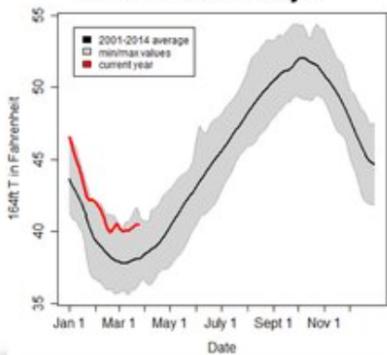
Preferred habitat



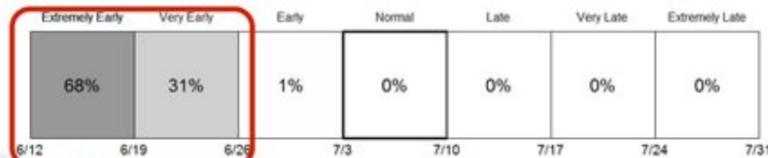


Updated #lobster forecast from @GMRI.
Increasing chance of the season starting 3+ weeks early.

Avg. Temperature at 164 ft (50m) Sea Surface Temperatures, 3/9-3/16/2016
NERACOOS Buoys NASA MURSST



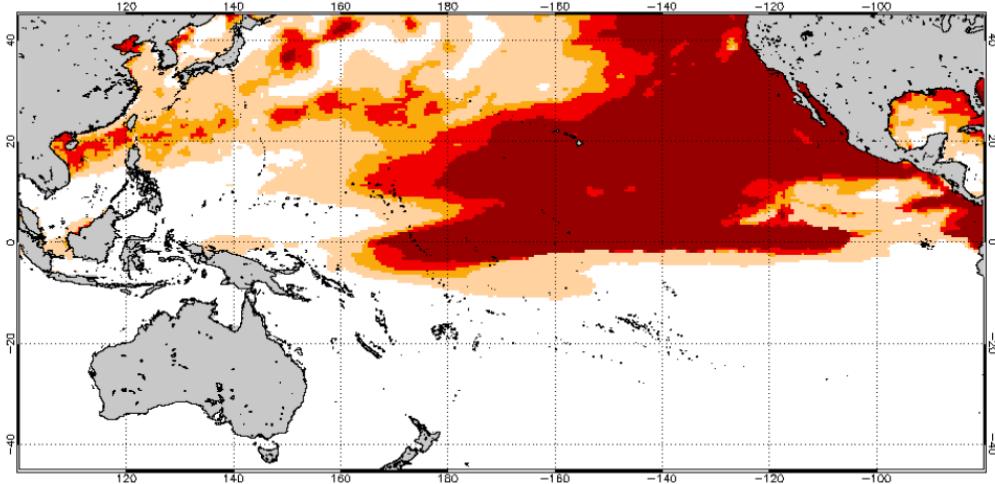
March 24 Forecast for the Start of the Summer Lobster Season



Current forecast: ~3 weeks early

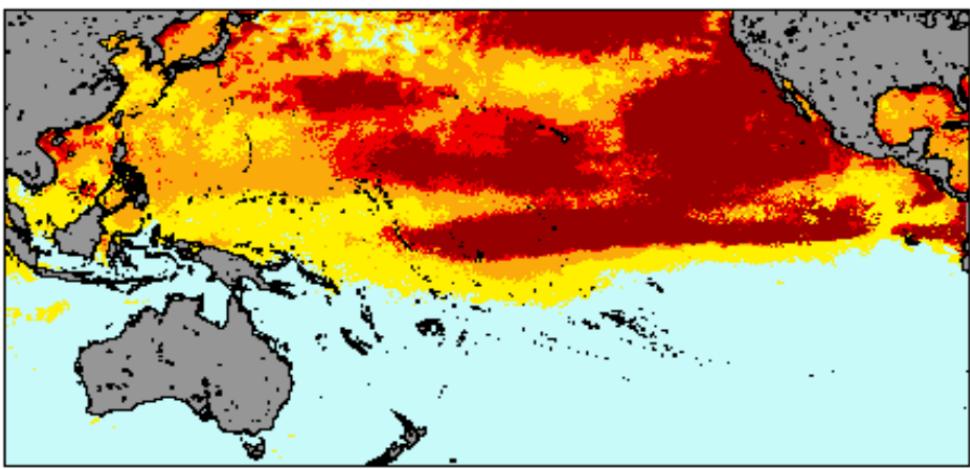


2015 Jun 30 NOAA Coral Reef Watch 60% Probability Coral Bleaching Thermal Stress for Jul–Oct 2015
Experimental, v3.0, CFSv2-based, 28-member Ensemble Forecast



Potential Stress Level: Watch Warning Alert Level 1 Alert Level 2

NOAA CRW 5-km Night-Only BAA Maximum 2015/07/06–2015/10/25



No Data

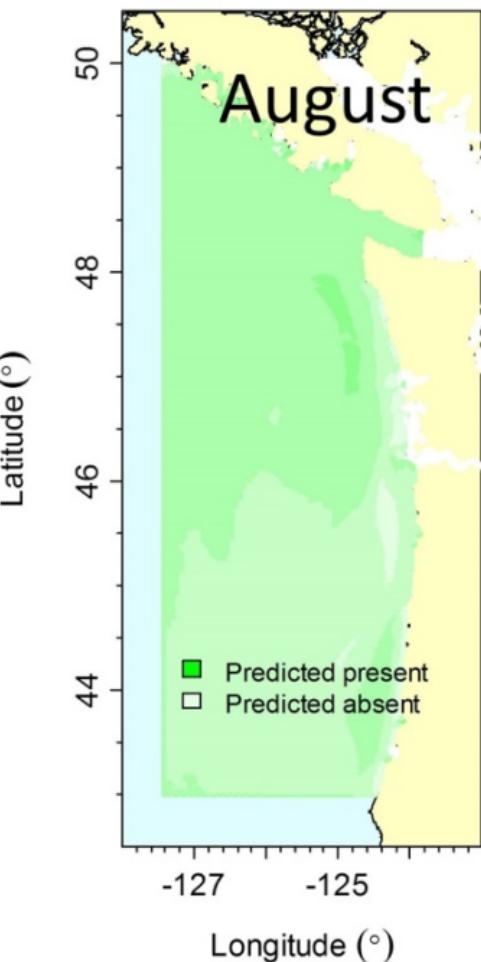
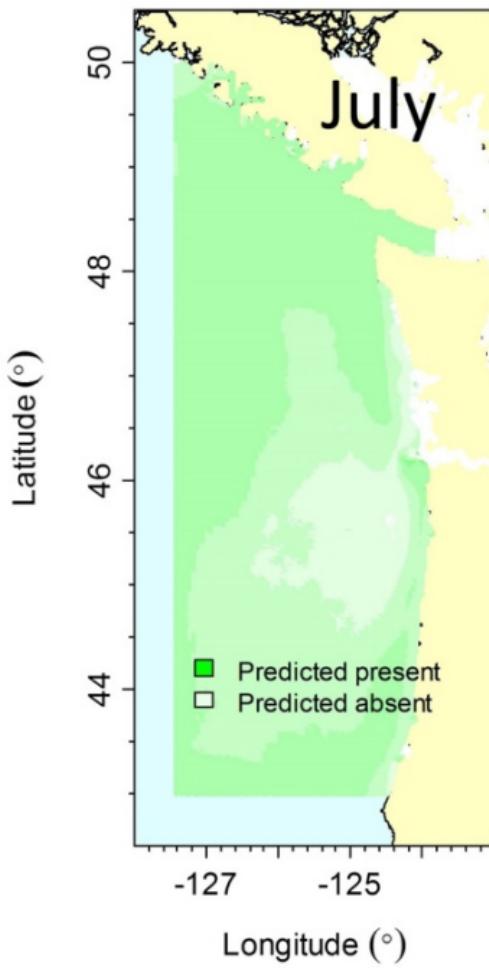
No Stress

Watch

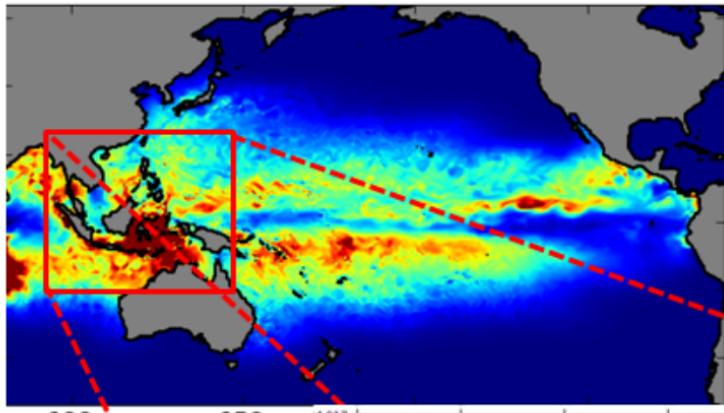
Warning

Alert Level 1

Alert Level 2



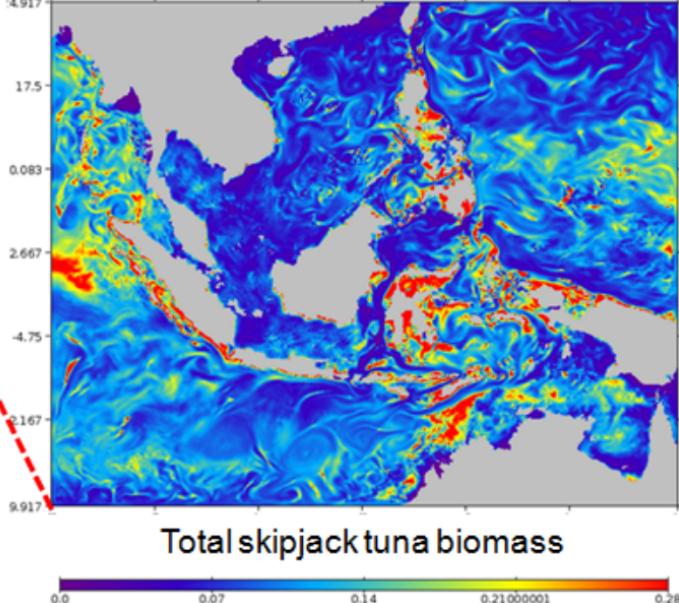
Operational Global Model ($\frac{1}{4}^{\circ} \times \text{week}$) predicting:

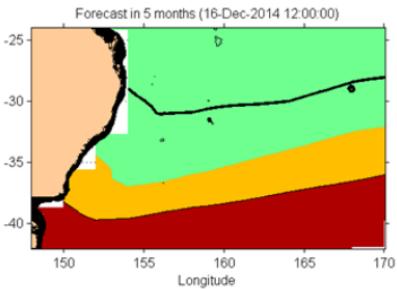
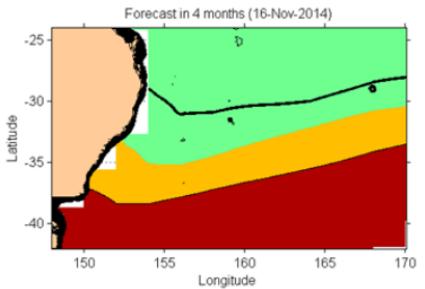
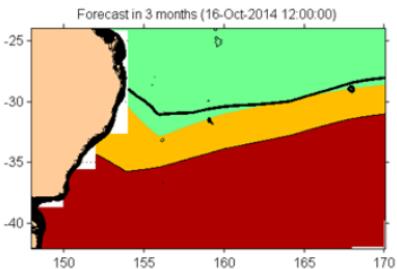
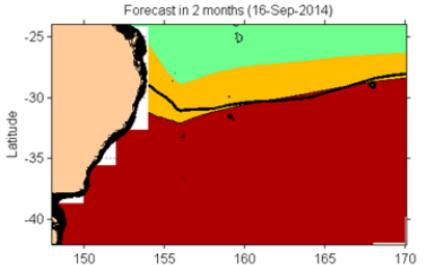
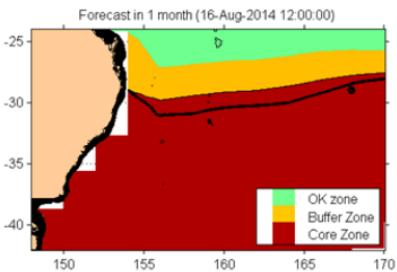
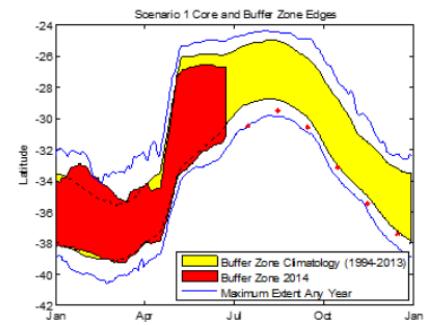


- Zooplankton
- Micronekton
- Skipjack
- Yellowfin
- Bigeye



Regional model
 $(1/12^{\circ} \times \text{day})$
with Open
Boundaries
Conditions provided
from global model





Constant User Engagement

