



Title: Seasonal forecasts of Northeast Pacific physics and biogeochemistry using MOM6-COBALT-NEP10k

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31 Abstract

32 Seasonal ocean forecasts offer critical insights for marine resource management, particularly in
33 regions like the Northeast Pacific where ecosystem variability can have profound impacts on
34 marine life, fisheries, and coastal communities. Under NOAA's Changing Ecosystems and
35 Fisheries Initiative, we developed a seasonal ocean forecasting system for the Northeast Pacific
36 based on the Modular Ocean Model version 6 (MOM6) ocean model coupled to the Sea Ice
37 Simulator version 2 (SIS2) sea ice model and the Carbon, Ocean Biogeochemistry, and Lower
38 Trophics (COBALT) biogeochemical model. The model domain extends from south of Baja
39 California to the Chukchi Sea with ~10 km horizontal resolution. To evaluate forecast skill, we
40 produced a 32-year set of retrospective forecasts with 10 ensemble members, four initializations
41 per year, and lead times up to 12 months. Forcing for the forecasts was derived from the
42 Geophysical Fluid Dynamics Laboratory's Seamless System for Prediction and Earth System
43 Research (GFDL-SPEAR) global climate forecast system. Forecasts were assessed using ocean
44 reanalyses and *in situ* observations, focusing on three ecologically- and societally-relevant
45 variables: sea surface temperature, bottom temperature, and bottom oxygen concentration.
46 Forecast skill varies by region, variable, and season, but generally remains high (anomaly
47 correlation coefficient; ACC>0.5) for lead times of at least several months across all variables
48 and regions. The downscaled forecasts reduce errors relative to the SPEAR global forecasts and
49 in some cases increase ACC, while also enabling predictions of biogeochemical variables. These
50 new forecasts compare favorably to previous downscaled ocean forecasts off the U.S. west coast,
51 with increased ACC and small forecast errors that may be reduced further by future
52 methodological changes. Routine real-time forecasts, available starting in October 2026, will
53 support proactive decision making by managers, industry, and coastal communities.

54 1. Introduction

56 Along the Northeast Pacific ocean margin, from the Bering Sea to Baja California, ocean
57 ecosystems support diverse and productive marine biological communities and, in turn, human
58 uses including tourism, subsistence and recreational fishing, and lucrative commercial fisheries.
59 Ocean forecasts on seasonal (1-12 month) timescales offer significant potential to improve the
60 management of these resources (Tommasi et al. 2017, Payne et al. 2017, Jacox et al. 2020), and a
61 robust body of research on ecosystem-based management has identified myriad ways in which
62 regional ocean forecasts can improve decision making in the region. Specific examples of
63 existing or proposed forecast products include species distribution predictions (Kaplan et al.
64 2016, Malick et al. 2020), environmentally-informed stock assessments (Tommasi et al. 2017,
65 Kearney et al. 2021, Wildermuth et al. 2026, Feddern et al. 2026), tools to mitigate bycatch and
66 entanglement risk for protected species (Brodie et al. 2023, Jacox et al. 2023), and fishery catch
67 outlooks (Norton et al. 2023). These applications require oceanographic forecasts that faithfully
68 reproduce not only large-scale variability, but also the influences of regionally-important
69 processes including sea ice dynamics, coastal upwelling, and coastal trapped waves.

70



While global seasonal climate forecasts are readily available and are often useful even for regional forecasting applications (e.g., Brodie et al. 2023), available output generally includes a limited number of ocean variables and no biogeochemistry (Minobe et al. 2022). Further, the relatively coarse resolution of these models can be inadequate to resolve key coastal processes or to properly represent nearshore bathymetry and orography (e.g., Drenkard et al. 2021). One approach to addressing these shortcomings is dynamical downscaling, in which a regional ocean model is forced with output from a global forecast system, thereby inheriting predictability from large-scale processes while better resolving their fine-scale manifestation in the region of interest. The viability of such an approach has been demonstrated (e.g., Siedlecki et al. 2016, Kearney et al. 2021, Jacox et al. 2023, Pilcher et al. 2026), though such efforts have been sparse and limited in one or more ways including a lack of routine delivery, small forecast ensembles, omission of ocean biogeochemistry, and relatively small domains that preclude application to wide-ranging, transboundary marine species (Ferriss et al. 2026).

In recognition of the need for regional ocean forecasts and the limitations outlined above, the National Oceanic and Atmospheric Administration (NOAA) launched the Changing Ecosystems and Fisheries Initiative (CEFI) to develop regional ocean models covering U.S. coastlines with a suite of five regional domains – Northwest Atlantic (Ross et al. 2023), Northeast Pacific (Drenkard et al. 2025), Pacific Islands (Negrete García et al. 2026), Great Lakes (Raju et al. 2026), and Arctic (Pagès et al., submitted). Eventually, seasonal forecasts will be routinely produced for all five domains. In the Northwest Atlantic, these forecasts are already operational and have been shown to exhibit forecast skill significantly better than that from global models (Ross et al. 2024). Herein, we describe the new seasonal forecasting system for the Northeast Pacific and evaluate its skill using over 30 years of retrospective forecasts. The model domain is expansive enough to support transboundary applications while maintaining sufficiently fine resolution to capture important coastal processes, and a broad suite of physical and biogeochemical outputs is available. In preparation for routine delivery of real-time forecasts, this skill evaluation serves to establish expectations for their performance.

2. Forecast configuration

The forecast system described below comprises a regional ocean-sea ice-biogeochemistry model forced at the boundaries by output from a global climate forecast system. A nudged historical simulation of the same regional ocean model (Section 2.3) is used to initialize the forecasts, while additional boundary forcing is derived from observation-based datasets for ocean biogeochemistry and river inputs. The full set of retrospective forecasts spans 1993–2024 with four initializations per year (January, April, July, October), lead times up to 12 months, and 10 ensemble members per initialization.

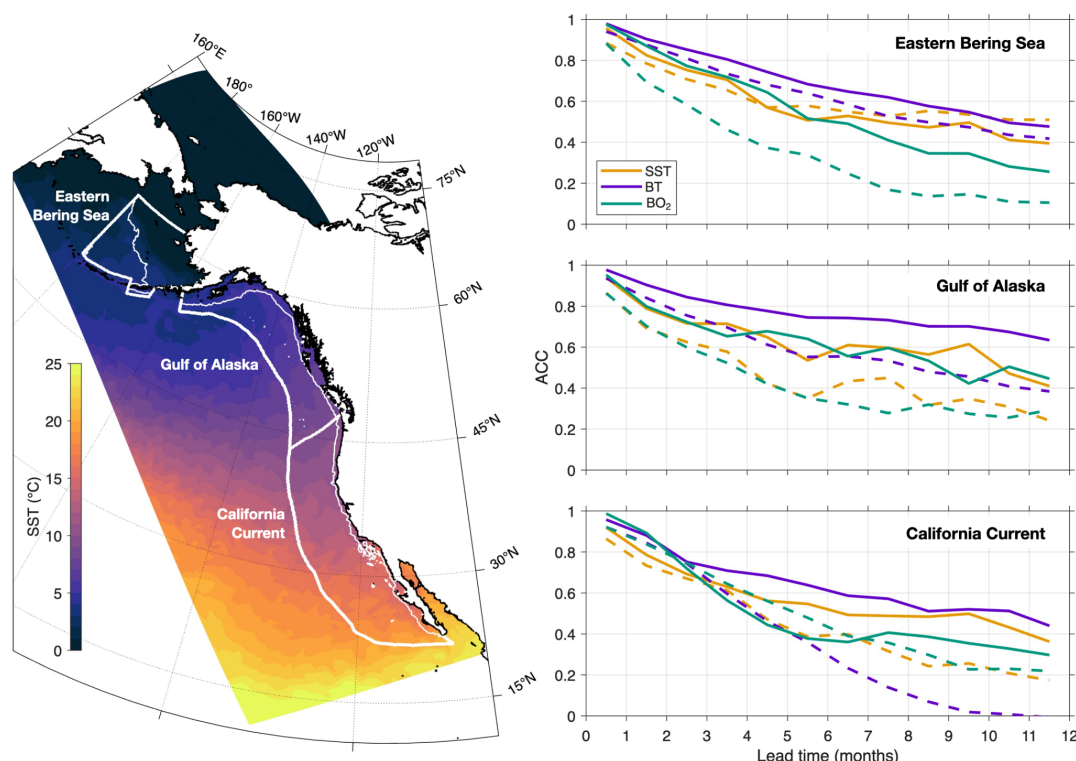


Figure 1: (left) NEP10k model domain, with long-term mean SST shown in color. Thick white lines bound the three large marine ecosystems (LMEs) of primary interest to the study, while thin contours mark the 1000 m isobath used in analyses. (right) Forecast skill (anomaly correlation coefficient; ACC) as a function of lead time for surface temperature (SST), bottom temperature (BT), and bottom oxygen concentration (BO₂). Within each LME, quantities are averaged inshore of the 1000 m isobath. Dashed lines indicate skill of a persistence forecast.

2.1. Regional ocean-biogeochemical model

The forecast system is a fully coupled ocean–sea ice–biogeochemistry modeling system configured for the Northeast Pacific (MOM6-COBALT-NEP10k; hereafter NEP10k). The model configuration is described in detail by Drenkard et al. (2025); here we provide a brief overview.

The physical ocean model is a regional implementation of the Modular Ocean Model version 6 (MOM6; Adcroft et al. 2019). The curvilinear grid measures approximately 3300 x 7800 km (cross-shore x alongshore), spanning from the Pacific Arctic to south of Baja California, and including the Eastern Bering Sea, Gulf of Alaska, California Current, and Gulf of California large marine ecosystems (Fig. 1). The horizontal resolution is ~10 km, and the vertical grid comprises 75 z* levels, with layer thicknesses ranging from 2 m near the surface to 250 m in the deepest portions of the domain. Sea ice is modeled by the Sea Ice Simulator version 2 (SIS2; Adcroft et al., 2019), with five sea-ice thickness categories, four vertical ice layers, and one snow layer. MOM6 is coupled to version 3.0 of the Carbon, Ocean Biogeochemistry, and Lower



130 Trophics (COBALTv3.0; Stock et al., 2025) biogeochemical. COBALTv3.0 employs 40 tracers
131 to represent nutrients, carbon, lithogenic material, four phytoplankton functional groups (pico-,
132 nano-, and microplankton, as well as diazotrophs), three zooplankton functional types, and free-
133 living bacteria (Stock et al. 2014, 2020).

134

135 *2.2. Global climate forecasts (SPEAR)*

136 Atmosphere and ocean boundary forcing for the regional ocean forecasts was provided by output
137 from GFDL-SPEAR (Delworth et al. 2020) configured for seasonal forecasts as described in Lu
138 et al. (2020). SPEAR retrospective forecasts were run with nominal 0.5° and 1.0° horizontal
139 resolution for the atmosphere and ocean, respectively (i.e., the SPEAR_MED configuration).
140 Each SPEAR forecast was run for 12 months. Forecasts included either 15 ensemble members
141 (for forecasts initialized 1991-2020) or 30 (for forecasts initialized 2021-present), though only
142 the first 10 members were used for our regional downscaling. SPEAR output was abstained at
143 daily resolution for atmospheric variables and sea surface height, and monthly resolution for 3D
144 ocean variables.

145

146 *2.3. Retrospective forecast configuration*

147 While physics-only regional forecasts may be initialized from global forecast initial conditions or
148 from an ocean reanalysis, the need for biogeochemical initial conditions precludes these
149 approaches in our case. Instead, we initialized regional forecasts from a version of the NEP10k
150 historical simulation building on the configuration introduced by Drenkard et al. (2025) and
151 modified by Dukhovskoy et al. (2026; Section 5.1.1). Notably, in the simulation used for forecast
152 initialization, 3D temperature and salinity were nudged with a 15-day timescale toward the 1/12°
153 Global Ocean Reanalysis and Simulations (GLORYS) reanalysis (Lellouche et al., 2021; see
154 Section 3.1.1). This nudging served to refine the generally skillful representation of seasonal and
155 interannual physical ocean variations in the free-running simulation for forecast applications.
156 This nudged simulation also employed a new sea ice relaxation scheme (Dukhovskoy et al.
157 2026) in the Arctic and Northern Bering Seas to mitigate unrealistic Arctic sea ice cover
158 resulting from closed sea-ice boundaries. Specifically, sea-ice thickness and concentration were
159 relaxed toward the Pan-Arctic Ice-Ocean Modeling and Assimilation System (PIOMAS;
160 Schweiger et al. 2011), with a strong relaxation over the Arctic that decayed to zero over the
161 northern Bering (see Table 3 and Figure 3c in Dukhovskoy et al. 2026 for the relaxation mask).

162

163 Daily atmospheric output from each of 10 SPEAR ensemble members was interpolated to the
164 NEP10k grid to drive the ocean forecasts at the surface. At the lateral ocean boundaries, we used
165 daily sea surface height (SSH) from SPEAR to include predictability associated with coastal
166 trapped waves (e.g., Amaya et al. 2022). For consistency with SSH, we interpolated monthly
167 SPEAR output for other ocean variables to daily resolution using a piecewise third-order
168 polynomial interpolation. Note that Ross et al. (2024) used climatological ocean boundary
169 conditions for U.S. East Coast predictions, as their domain was large enough that ocean



boundary conditions did not impact the coastal region of interest on seasonal timescales. In contrast, the seasonal predictability of the U.S. West Coast is strongly influenced by oceanic forcing (Jacox et al. 2023), so we used time-varying ocean boundary conditions from SPEAR. River discharge over the length of the forecasts was supplied as a smoothed daily climatology based on 1993–2024 output from the GloFAS reanalysis version 4 (Harrigan et al. 2020; Grimaldi et al., 2022) and runoff in the Gulf of Alaska (Beamer et al., 2016; Hill, 2023). Similarly, climatological boundary conditions were applied for most ocean biogeochemical variables as described in Ross et al. (2023). NO₃, O₂, PO₄ and SiO₄ conditions were derived from World Ocean Atlas 2018 (Boyer et al., 2019; García et al., 2019a; García et al., 2019b; observations collected 1955–2017). Above 800m, climatologies are represented as seasonal averages, while below 800m they are prescribed as the annual mean. Additional boundary tracers specific to COBALT were derived from annual means (1993–2014) of a global ocean implementation of COBALT (Stock et al., 2014). The exceptions to using BGC climatologies at the open boundaries were dissolved inorganic carbon (DIC) and total alkalinity, which were estimated from physical boundary conditions based on Empirical Seawater Property Estimation Routines (ESPER; Carter et al. 2021) to ensure long-term trends were captured. ESPER fields were computed using the locally interpolated regression algorithm and estimated using monthly mean, spatially-coarsened potential temperature and salinity from GLORYS. For the forecasts, Arctic ice was relaxed to a climatology of the most recent five years to account for long-term trends in sea ice concentration and thickness. In contrast to the nudged historical simulation, no ice relaxation was applied over the Bering Sea during forecasts; the aim was to avoid any influence of unrealistic Arctic ice without directly modifying Bering Sea ice.

3. Forecast evaluation

While a wide array of physical and biogeochemical variables are available in the forecast model output, we focus this initial evaluation on three that are known to be critical to marine ecosystems, and for which model and *in situ* verification data are available: sea surface temperature (SST), bottom temperature (BT), and bottom oxygen concentration (BO₂). The evaluation covers three Northeast Pacific Large Marine Ecosystems – the Eastern Bering Sea (EBS), Gulf of Alaska (GOA), and California Current System (CCS) – with a particular focus on the continental shelf and upper slope (<1000 m isobath) where high spatial resolution is most beneficial and many of the most productive fisheries are located.

3.1. Verification data

Verification is performed using high-resolution ocean models, observations, and reanalyses. Ocean models offer complete spatiotemporal coverage for domain-wide skill assessment, *in situ* observations provide additional ground truthing when available, and reanalyses combine the strengths of models and observations for gap-free data whose fidelity to the real world is generally better than that of an unconstrained model (e.g., Amaya et al. 2023a).



210 3.1.1. Ocean models and reanalyses

211 The GLORYS reanalysis provides physical fields at $1/12^\circ$ (~8 km) resolution starting in 1993.
 212 GLORYS is based on the Nucleus for European Modelling of the Ocean (NEMO) ocean model
 213 and assimilates along-track satellite altimetry, satellite SST, sea ice concentrations, and *in situ*
 214 temperature and salinity profiles from the Coriolis Ocean database Reanalysis (CORA) dataset
 215 (Szekely et al. 2019). For forecast verification, we use GLORYS surface and bottom
 216 temperatures, which have been demonstrated to agree well with observations from satellites,
 217 Argo floats, underwater gliders, ship-based surveys, shore stations, and moorings (Amaya et al.
 218 2023a,b). For pointwise comparisons, we interpolate 2D GLORYS fields to the NEP10k grid
 219 using bilinear interpolation.

220
 221 Since GLORYS is physics-only, we employ the NEP10k nudged historical simulation (Section
 222 2.3) for verification of BO_2 . While this assessment highlights the potential of the model to
 223 predict biogeochemical variability associated with realistic ocean-atmosphere forcing, it likely
 224 provides an optimistic estimate of forecast skill. Since the historical simulation is used to
 225 initialize the forecasts, the forecast initial state is identical to the verification data at that same
 226 time, when in reality the initialization is imperfect. Thus, we consider this verification an
 227 assessment of potential skill rather than true skill (Boer et al. 2019).

228

229 3.1.2. In situ observations

230 *In situ* measurements were obtained from moorings, ship-based surveys, and shore stations
 231 spanning the three LMEs of interest (Table 1). These data provide an independent check on
 232 forecast skill relative to the ocean models and reanalyses described above. For all comparisons to
 233 *in situ* point measurements, NEP10k forecasts were extracted at the nearest ocean grid cell to
 234 assess model skill. Processing for each data source is detailed below.

235

236 EcoFOCI moorings: BT at four locations over the Eastern Bering Sea shelf was obtained from
 237 moorings operated as part of the Ecosystem & Fisheries Oceanography Coordinated
 238 Investigations (EcoFOCI) program (Stabeno et al., 2023). Monthly averages were computed
 239 from daily data, retaining only months with at least 10 days of data available.

240

241 Gulf of Alaska mooring: BT measurements from the Gulf of Alaska (GAK1) mooring were
 242 obtained from <https://research.cfos.uaf.edu/gak1/data/Mooring/>. For most periods, data were
 243 provided at 15-minute intervals, with some exceptions of 3-hourly or 6-hourly data. In all cases,
 244 high-resolution data were aggregated as monthly averages, retaining only months with at least 10
 245 days worth of data (e.g., 960 samples for 15-minute data).

246

247 Olympic Coast National Marine Sanctuary (OCNMS) moorings: An array of moorings in
 248 Olympic Coast National Marine Sanctuary provides hourly BT and BO_2 measurements
 249 (Cervantes et al. 2026). The moorings are operational seasonally; forecast verification is limited



250 to June-September, the months of most reliable data availability. We focus on the mid-depth
251 moorings (42 m bottom depth at Makah Bay, Cape Alava, Teahwhit Head, and Cape Elizabeth,
252 and 27 m depth at Kalaloch), which offer the greatest coverage for bottom oxygen measurement.
253 After removing data with QC flags 3 (“suspect”) and 4 (“fail”), we computed monthly averages,
254 retaining months with at least 10 days (240 hours) of data. Model forecasts were extracted for
255 each location and month with available mooring data, and then both forecasts and observations
256 were spatially averaged across the mid-depth mooring locations.

257
258 Newport Hydrographic Line: Regular cruises off Newport, OR sample water column temperature
259 and oxygen along a cross-shore transect (Risien et al. 2026). Here, we used the water column
260 data to extract near-bottom temperature and oxygen at four stations for which bottom depth <
261 150 m (NH5, NH10, NH15, NH20; station numbers indicate offshore distance in nautical miles).
262 In cases when more than one cruise was conducted in a month, those data were averaged to
263 create a monthly average; for months with only one cruise we use the single cruise data. At each
264 station, we averaged profile data within 10 m of the deepest point, since taking just the deepest
265 point introduces more data gaps. As for the OCNMS moorings, we matched model forecasts to
266 each location and month with available cruise data, and then averaged spatially across the
267 stations.

268
269 Shore Stations Program: At multiple sites along the California coast, shore-based sampling
270 programs have routinely measured SST for many decades. These datasets are compiled under the
271 Shore Stations Program, which provides daily SST data from participating sites (Carter et al.
272 2022). For each of five stations (Farallons, Pacific Grove, Newport Beach, San Clemente, La
273 Jolla), we computed monthly averages from daily data, retaining months for which at least 10
274 days of data was available. We then averaged Newport Beach and San Clemente and treated
275 them as a single site given their close proximity.

276
277 Channel Islands Kelp Forest Monitoring Program: We obtained ocean temperature
278 measurements from mooring sites along the coasts of San Miguel, Santa Rosa, Santa Cruz,
279 Anacapa, and Santa Barbara Islands, focusing on the 16 sites for which monthly data are
280 available beginning in 1994 (Davis 1997). While these sites are in shallow water (~5-15 m
281 depth), bottom depths for model matchups are much deeper (~50-150 m). While MOM6 does not
282 require bathymetric smoothing common in sigma coordinate ocean models, the 10 km model
283 grid resolution is still too coarse to fully resolve bathymetry adjacent to the islands. Thus, we
284 compare the observations to forecast SST, which is more appropriate than forecast BT given the
285 depth mismatch. As for other datasets, we matched model forecasts to each location and month
286 with available data. We then averaged across all sites in the main group of islands (San Miguel,
287 Santa Rosa, Santa Cruz, Anacapa; 13 stations), and separately averaged across the sites at Santa
288 Barbara Island (3 stations).

289



Name	Region	Type	Variables	Years
EcoFOCI	Eastern Bering Sea	Moorings	BT	1996-2023
GAK1	Gulf of Alaska	Mooring	BT	1998-2025
Olympic Coast National Marine Sanctuary	Washington	Moorings	BT, BO ₂	2000-2025
Newport Hydrographic Line	Oregon	Ship-based survey	BT, BO ₂	1997-2025
Shore Stations Program	California	Shore stations	SST	1993-2025
Channel Islands National Park	California	Benthic loggers	SST	1993-2025

Table 1: Summary of *in situ* observations used for forecast verification. Years listed are the maximum extent of data used; time series for specific stations may be shorter.

3.2. Skill evaluation

We quantify forecast skill by comparing our 32-year set of retrospective forecasts with the verification datasets described above. We focus on two deterministic skill metrics: anomaly correlation coefficient (ACC) to evaluate the model's ability to predict interannual variability, and root mean square difference (RMSD) to evaluate the combined error introduced by mean biases and variability. Anomalies are calculated relative to the initialization- and lead-dependent climatology. Skill evaluations are performed as a function of forecast initialization month and lead time, using the ensemble mean forecast. ACC skill for the downscaled forecasts is compared to the skill of two reference forecasts: the parent SPEAR forecasts (using the same 10 ensemble members that forced the downscaled model) and a simple persistence forecast, which assumes that the anomaly in observations (i.e., the verification dataset) in the month preceding forecast initialization will persist throughout the length of the forecast. Significance of forecast ACC is determined using Fisher's z transformation with a 95% confidence interval and effective degrees of freedom that are reduced to account for sample autocorrelation (e.g., Stock et al. 2015, Jacox et al. 2023). To test for significant differences between model and persistence forecast ACC, we use Williams' T_2 statistic (Williams 1959, Steiger 1980), which accounts for two time series correlated with the same reference. Model forecast ACC was deemed significantly higher than persistence forecast ACC based on a one-tailed test if $T_2 > 0$ and $p < 0.05$.

4. Results

4.1. Mean spatiotemporal patterns of forecast skill

For all variables (SST, BT, and BO₂) and LMEs (EBS, GOA, CCS) considered here, forecasts exhibit considerable skill over the shelf and upper slope (<1000 m depth). ACC values exceeding 0.5 (indicative of high forecast skill) extend to lead times of 4-12 months depending on variable

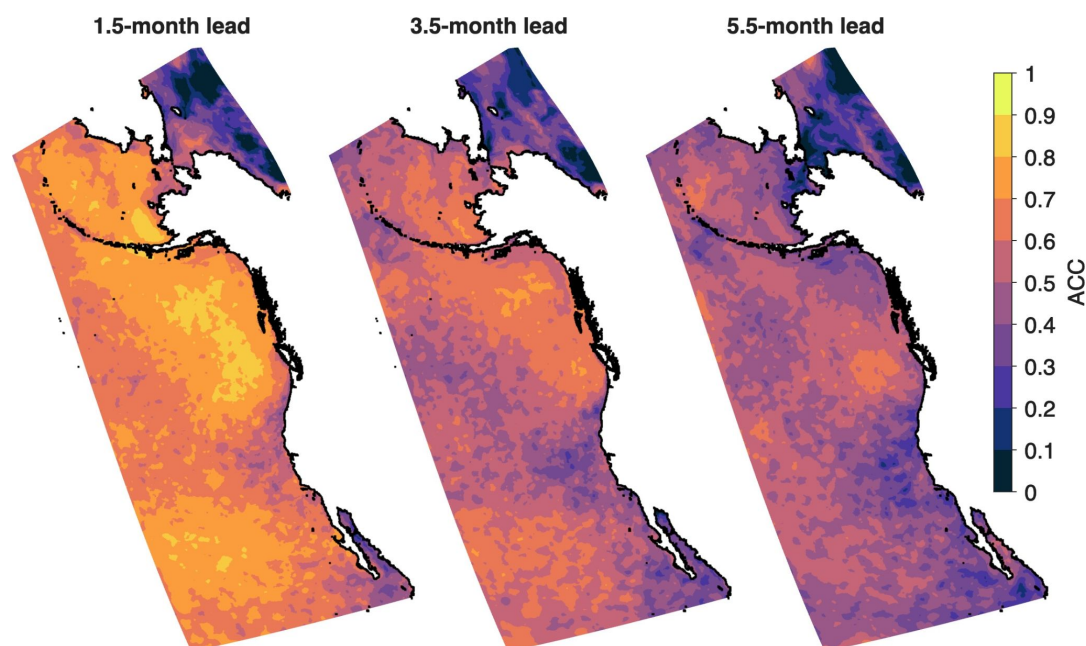


and LME (Fig. 1). In general, BT is the most predictable variable, followed by SST and BO_2 , and the GOA is the most predictable region, followed by the EBS and CCS. Model forecast skill routinely exceeds the skill of a persistence forecast, especially at longer lead times. Notable exceptions to this pattern are visible for SST and BT in the EBS (consistent with the findings of Kearney et al. 2021) and BO_2 in the CCS; in those cases persistence forecasts offer skill that is comparable to or greater than that of dynamical model forecasts.

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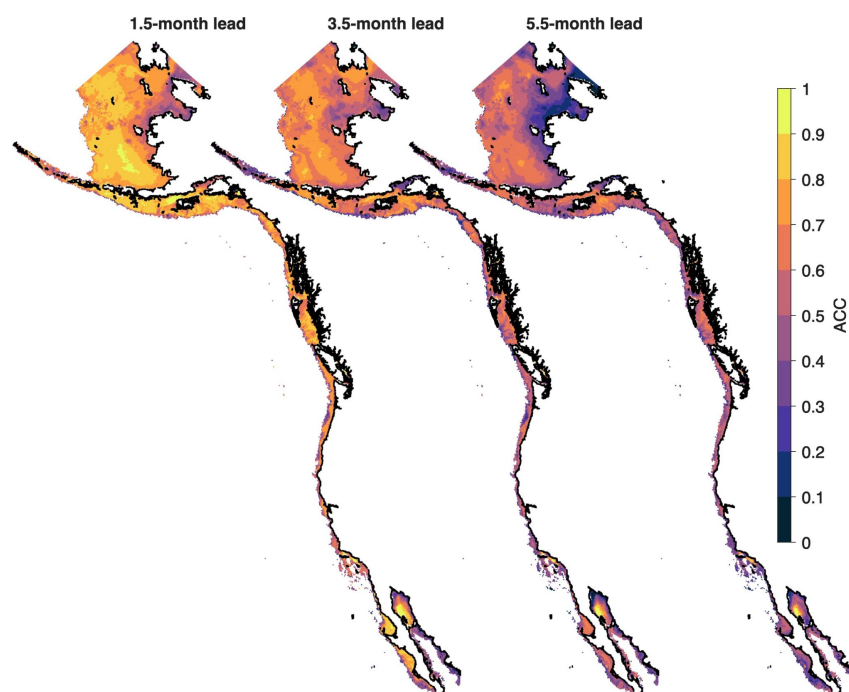
Spatially resolved patterns of ACC reveal considerable heterogeneity in forecast skill, even within LMEs. Significant skill extends to 5.5-month lead for all three variables in most areas of the domain (Figs. 2-4). As lead time increases, ACC spatial patterns remain qualitatively consistent but decline in magnitude. For SST, areas of highest skill include the southeast Bering Sea and much of the GOA (Fig. 2). In contrast, lower SST skill is evident in the northeast Bering Sea (north of the EBS LME) and in the offshore region off central and northern California. The latter region is characterized by particularly high eddy activity (Cordero Quirós et al. 2022), which increases noise and decreases predictability. BT and BO_2 exhibit similar skill patterns to those of SST in the nearshore region. The Santa Barbara Channel off Southern California emerges as an additional area of very high forecast skill (Figs. 3, 4), though this apparent skill is in relatively deep basins and is likely driven by persistence of anomalies present at initialization.

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336

337 Figure 2: ACC maps for SST forecasts at multiple lead times, calculated across all initialization months.

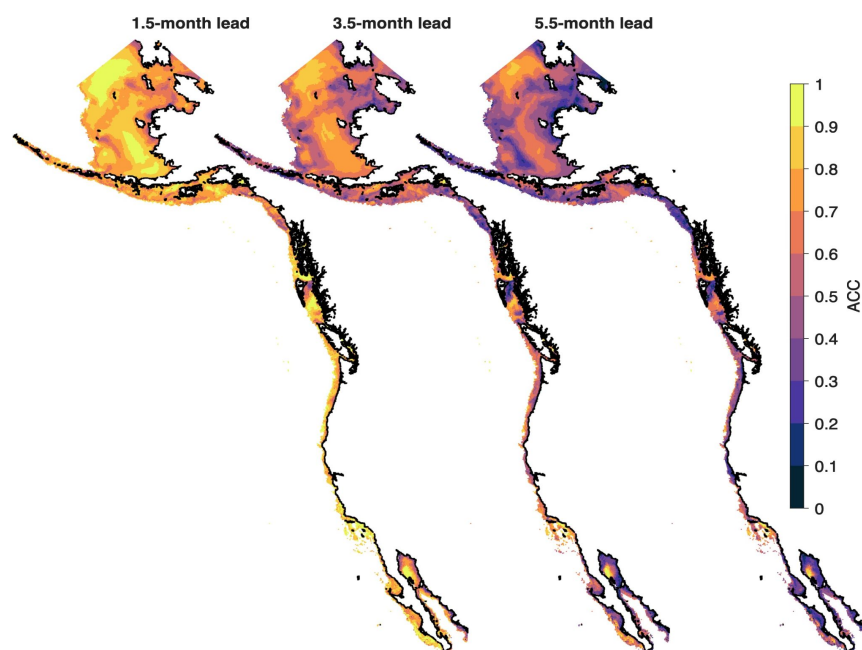


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Figure 3: As in Fig. 2, but for bottom temperature forecasts inshore of the 1000 m isobath.



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342

343

Figure 4: As in Fig. 3, but showing potential skill for bottom oxygen concentration.



4.2. Seasonality and comparisons with global forecasts

Predictability in NE Pacific marine ecosystems is seasonally variable owing to phenological processes including sea ice formation and melt, coastal upwelling, and mixed layer depth variability. Here we quantify forecast skill as a function of initialization month and lead time to investigate its seasonal dependence.

For SST, EBS skill (ACC) is significant for all initializations and leads, with the exception of long-lead forecasts of late winter/spring (i.e., forecasts of February–June initialized in the previous April or July; Fig. 5). In most of these cases, persistence forecasts also offer significant skill. SST ACC in the GOA is significant for nearly all lead times and initializations, and is particularly high for forecasts of February–April, which exhibit significant skill above persistence. In the CCS, ACC is significant across all times except for late summer forecasts initialized in October or January. ACCs are elevated and significantly better than persistence for forecasts of November–January in the CCS and December–April in the GOA, consistent with previous studies (e.g., Jacox et al. 2019) that attributed this skill bump to the predictability of ENSO and its influence on the CCS.

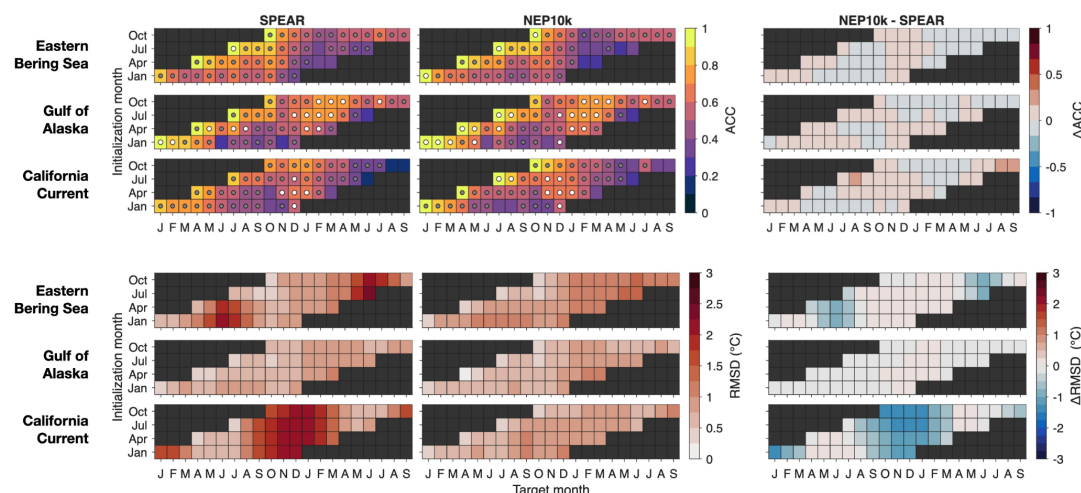


Figure 5: Regional SST forecast skill (top: ACC; bottom: RMSD) as a function of initialization month and target month for each LME (rows). Skill is shown for the SPEAR global model, NEP10k, and the difference between them. Improvements are indicated by higher ACC (red in difference plots) and lower RMSD (blue in difference plots). SST is averaged over the region inshore of the 1000 m isobath. Gray dots indicate initializations/lead times for which model forecast ACC is significantly above zero (95% confidence), and white dots indicate that the model forecast ACC is also significantly higher than persistence forecast ACC.

ACC patterns for SST are extremely similar between SPEAR and NEP10k; differences are small and can be of either sign (Fig. 5). As SST in the downscaled forecasts is strongly constrained by the forcing from SPEAR, this result is not too surprising, especially when averaging over relatively large spatial areas. However, for RMSD relative to the GLORYS verification dataset,

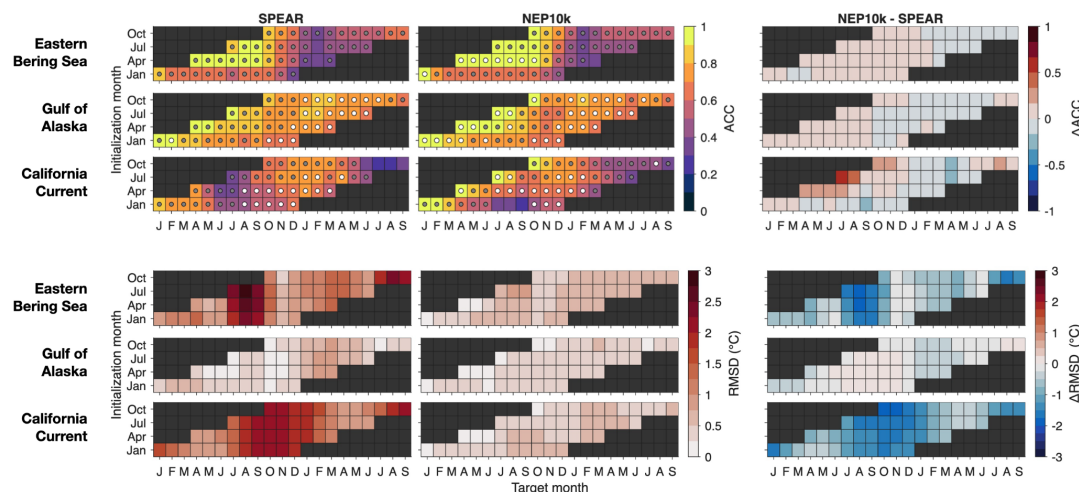


373 differences between SPEAR and NEP10k do emerge. While RMSD for NEP10k is $<1^{\circ}\text{C}$ across
 374 nearly all initializations, lead times, and LMEs, RMSD for SPEAR reaches 2°C or more for
 375 forecasts of May–July in the EBS and for forecasts of September–February in the CCS. These
 376 larger errors are attributable primarily to biases in SPEAR, which are largely alleviated in
 377 NEP10k. The improved mean biases at higher model resolutions are consistent with Amaya et al.
 378 (2026) who showed similar results in the central and southern CCS when comparing high- and
 379 low-resolution forecasts using a different modeling system.

380

381 BT forecast skill is generally higher than that of SST, with higher ACC and lower RMSD (Fig.
 382 6). In the EBS, ACC is significant for all leads and initializations. As for SST, skill is relatively
 383 low in later winter and spring, though the model forecasts exhibit significant skill during these
 384 months while persistence forecasts do not. Skill from spring and summer initializations is very
 385 high, with $\text{ACC} > 0.9$ for lead times up to ~4–6 months. Much of this skill comes from persistence
 386 of BT anomalies that are established during the sea ice season and then isolated from
 387 unpredictable surface mixing due to strong summer stratification after sea ice retreats (Kearney
 388 et al. 2021). Conversely, limited BT skill through winter may be due to an inability to predict
 389 winds in the northern EBS and the associated southward advection of ice (Kearney et al. 2021).
 390 The GOA is the most predictable of the three LMEs for BT, with ACC values that are significant
 391 and quite high (>0.6) across all leads and initializations. Persistence forecasts are also significant
 392 in many cases, though model ACC is significantly better than persistence when predicting late
 393 winter and spring. CCS BT forecasts also have significant ACC for all leads and initializations,
 394 except for July–September forecasts initialized in January. At long lead times (and for any lead
 395 times >3 months from the April initialization), skill is present despite the lack of significant
 396 persistence forecast skill.

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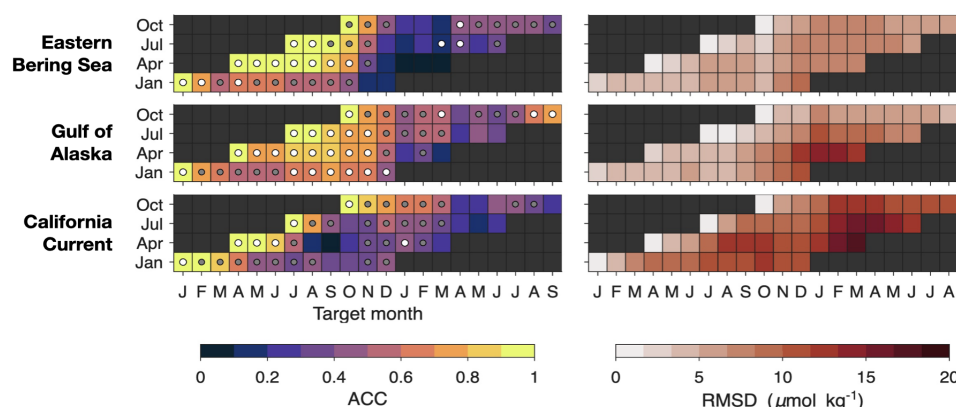
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Figure 6: As in Fig. 5, but for bottom temperature.



401 In the EBS and GOA BT forecasts, ACC differences between SPEAR and NEP10k are small,
402 similar to those for SST (Fig. 6). However, in the CCS, considerable improvements in ACC are
403 visible at short lead times (0-3 months), indicating that the BT initial conditions better match our
404 verification data in NEP10k than in SPEAR, and perhaps that coastal trapped wave signals are
405 better resolved in the higher resolution model (e.g., Liu et al., submitted). RMSD for NEP10k
406 BT is small ($<1^{\circ}\text{C}$) across all initializations and leads, demonstrating that the downscaled model
407 is representing both the mean state and variability quite well. As for SST, these errors are much
408 improved relative to SPEAR, whose BT biases drive large errors in the EBS (especially for July–
409 September) and CCS (especially for August–January).

410



411

412 Figure 7: Potential skill for regional bottom oxygen forecasts (left: ACC; right: RMSD) as a function of initialization
413 month and target month for each LME (rows). Oxygen concentrations are averaged over the region inshore of the
414 1000 m isobath. Dots are as in Fig. 5.

415

416 Regardless of initialization month, BO_2 potential skill in the EBS is quite high until October,
417 consistent with skill patterns for BT (Fig. 7). In November, ACC falls off rapidly and forecast
418 skill is generally not significant for winter (December–March). October-initialized forecasts see
419 a recovery of significant ACC in April after the winter period of low skill. As for BT, the GOA
420 has the overall highest ACC (across all initializations and leads) of the three regions for BO_2 . For
421 forecasts of summer and fall, model skill is often significantly higher than persistence, and for
422 almost all initializations significant skill extends to at least 8.5-month lead time. In the CCS,
423 ACC is high at early lead times (<4 months), and elevated skill is visible for winter months,
424 again consistent with the influence of ENSO. In contrast, the fall is relatively unpredictable, with
425 August–October standing out as having low ACC. When considering regional averages, the CCS
426 has the highest RMSD for BO_2 of the three LMEs; errors are $<10 \mu\text{mol kg}^{-1}$ for lead times under
427 4 months but can exceed $15 \mu\text{mol kg}^{-1}$ for long-lead forecasts of February–April. These errors
428 are also large in relative terms, as the mean BO_2 in the CCS is lower than in Alaskan waters.
429 RMSD patterns for the GOA and EBS are qualitatively similar to those of the CCS, but with
430 lower errors in the GOA and the lowest errors in the EBS ($<10 \mu\text{mol kg}^{-1}$ for all initializations
431 and lead times).



4.3. Verification with *in situ* observations

The preceding sections provided a holistic view of forecast skill using ocean model and reanalysis products. While constrained by observations, those products are not purely observation-based. Here, we augment those analyses with *in situ* data as an independent test of forecast skill, which represents highly local variability. While there are few observational programs that are well suited to this type of forecast verification (consistent sampling at monthly or better resolution over many decades), we have compiled a set of mooring, ship-based, and shore-based datasets to cover our three LMEs and three variables (Fig. 8).

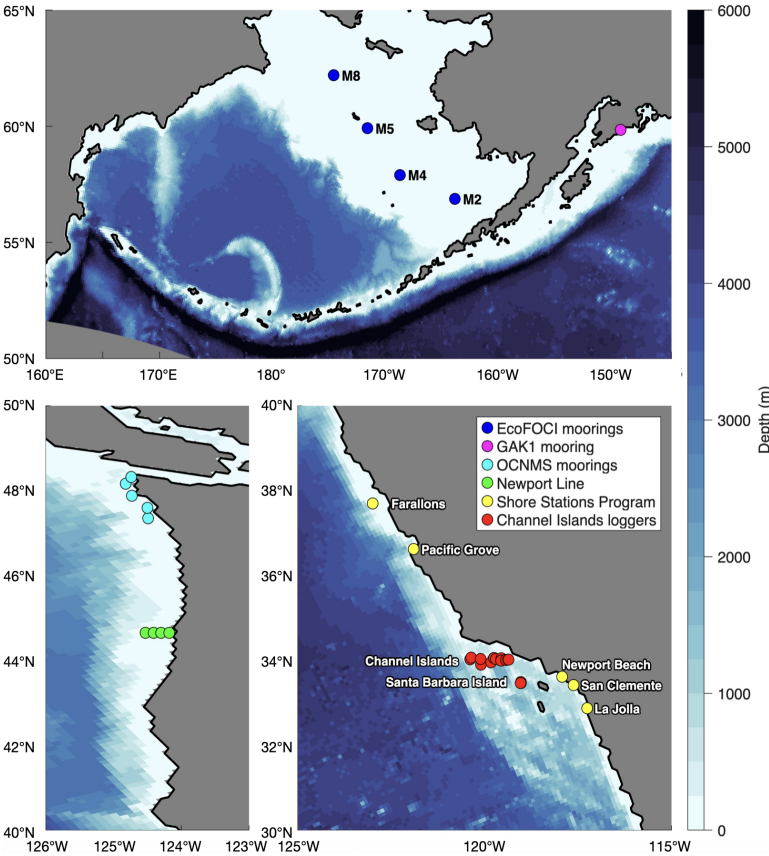


Figure 8: Locations of *in situ* observations used for forecast verification. In Alaskan waters (top), bottom temperatures were obtained from the GAK1 (Gulf of Alaska) and EcoFOCI (Bering Sea) moorings. Off Washington and Oregon (bottom left), bottom temperature and bottom oxygen concentration were obtained from Olympic Coast National Marine Sanctuary moorings and Newport Hydrographic Line cruises. Off California (bottom right), SST measurements were obtained from five monitoring sites in the Shore Stations Program, while near-surface (~5-15 m depth) temperatures were obtained from Channel Islands benthic loggers. Note that Santa Barbara Island is part of the Channel Islands, but is denoted separately as it is assessed separately from the other islands.



BT data from moorings in the EBS support our findings from the GLORYS-based verification. Skill is generally highest for April and July initializations, with ACC>0.5 for lead times up to at least 6 months (Fig. 9). For all initializations, ACC declines when forecasting the winter months. A latitudinal gradient in skill is also evident, with ACC declining from south (M2) to north (M8), consistent with the spatial patterns identified in Fig. 3. At the GOA (GAK1) mooring, ACC patterns are also qualitatively consistent with those from GLORYS (Fig. 9 cf. Fig. 3), though uniformly lower. As for the EBS, April- and July-initialized forecasts exhibit the highest skill and ACC>0.5 extends to lead times of 5-8 months. For all initializations, forecast skill declines precipitously from December to January, and remains low into spring.

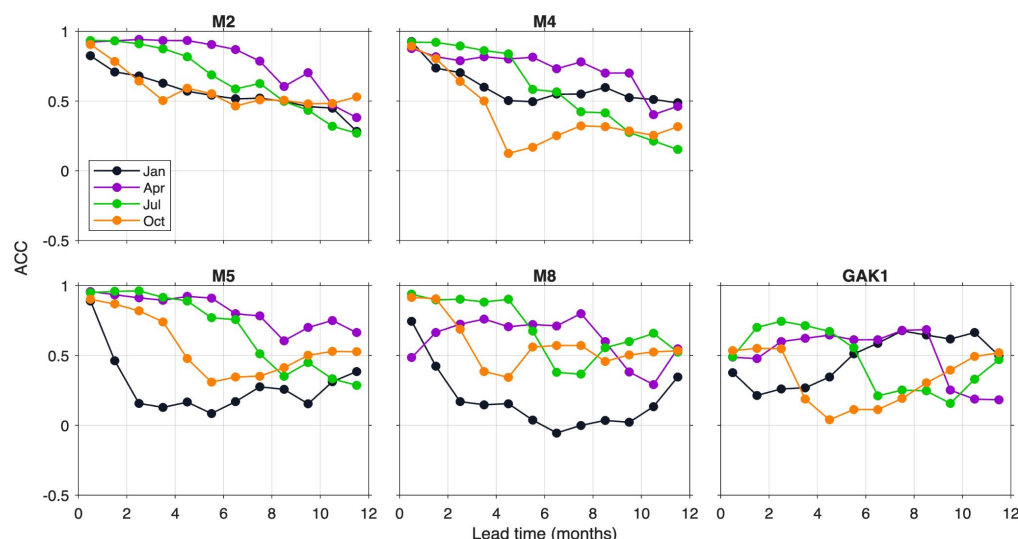


Figure 9: ACC as a function of lead time for bottom temperature forecasts in Alaskan waters, using mooring data for verification (see Fig. 8 for mooring locations). Colors show skill for four initialization months – January, April, July, and October.

Verifications for the Northern CCS, off Washington and Oregon, are based on mooring (OCNMS) and cruise (Newport Line) data for (near) BT and BO_2 . The OCNMS data are limited to June–September, but show that BT in those months can be predicted well (ACC>0.5) for lead times up to ~6 months (Fig. 10). BO_2 ACC is also ~0.5 for lead times up to 4.5 months (i.e., predicting summer from April or July initializations), but ACC from October and January initializations is near zero. Note that August and September are some of the least predictable months for CCS BO_2 (Fig. 7), so the modest skill seen in this *in situ* verification is encouraging. Skill assessments based on Newport Line cruise data are quite noisy, especially for BO_2 , and with ACC generally lower than that found using other verification datasets (Fig. 10). While cruises occur approximately monthly, these data represent snapshots of the ocean state at a given point and will be affected by high-frequency variability not captured in the monthly forecast averages. Thus, while the verification based on the NEP10k nudged historical simulation likely



overestimates the true skill, the verification based on Newport Line cruise data likely underestimates it. Nonetheless, BT ACC of ~0.5 or higher extends for several months from all initializations. Elevated skill for winter month forecasts (December–February) is also evident from all initializations, indicating that ENSO-related predictability discussed previously for SST also applies for BT off the Oregon coast.

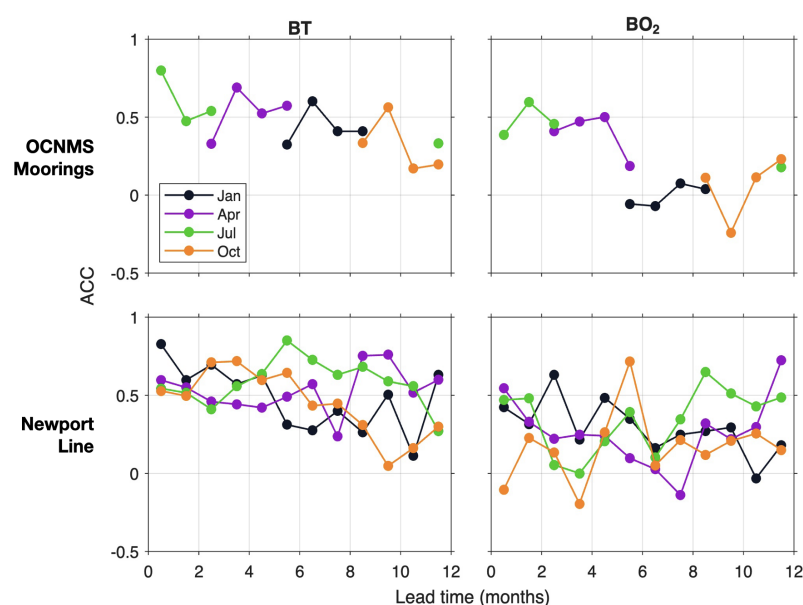


Figure 10: As in Fig. 9, but for (left) bottom temperature and (right) bottom oxygen forecasts verified using (top) OCNMS moorings and (bottom) Newport Line cruise data. Note that OCNMS mooring data is only routinely available for June–September, so forecasts are only verified during those months.

Finally, *in situ* verification of SST forecasts is enabled by shore stations and National Park Service moorings off the California coast. Again, the *in situ* data support the findings of the GLORYS-based verification, with generally suppressed skill for forecasts of late spring through fall (~May–October) and elevated skill for forecasts of winter months (Fig. 11). ACC values are noisy across the shore stations (Farallons, Pacific Grove, Newport Beach/San Clemente, and La Jolla) and across initialization/lead times for a given shore station, despite their relatively close proximity to each other. These patterns reflect the fine-scale variability impacting the observation sites, which may not be captured well even by the downscaled forecasts that have ~10 km resolution and are well suited to predict lower frequency variability. This notion is supported by the relatively high skill and low noise in ACC values for the Channel Islands / Santa Barbara Island (Fig. 11), for which our averaging of multiple mooring sites reduces noise.

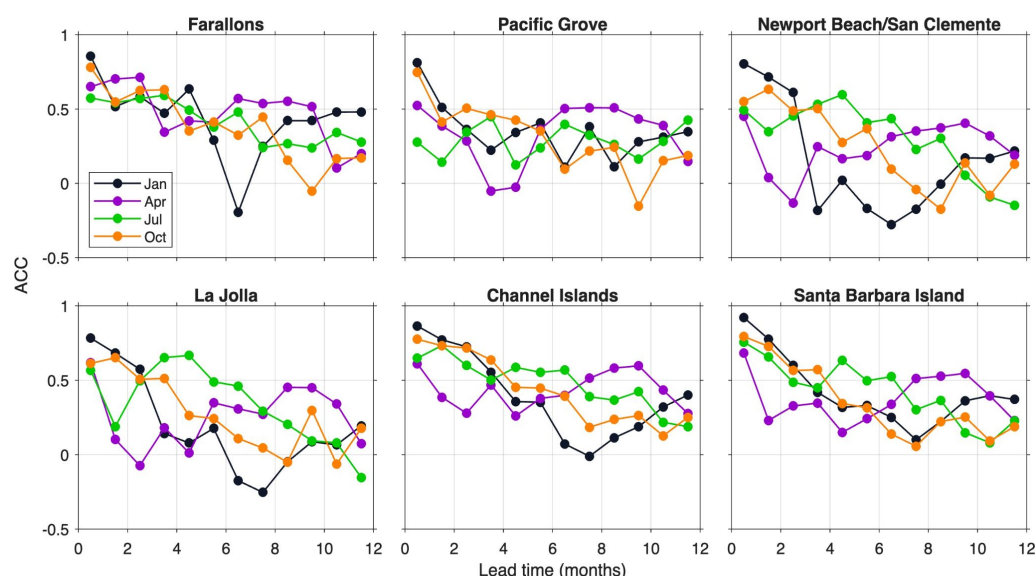


Figure 11: As in Fig. 9, but for SST forecasts verified using shore station and mooring data along the California coast.

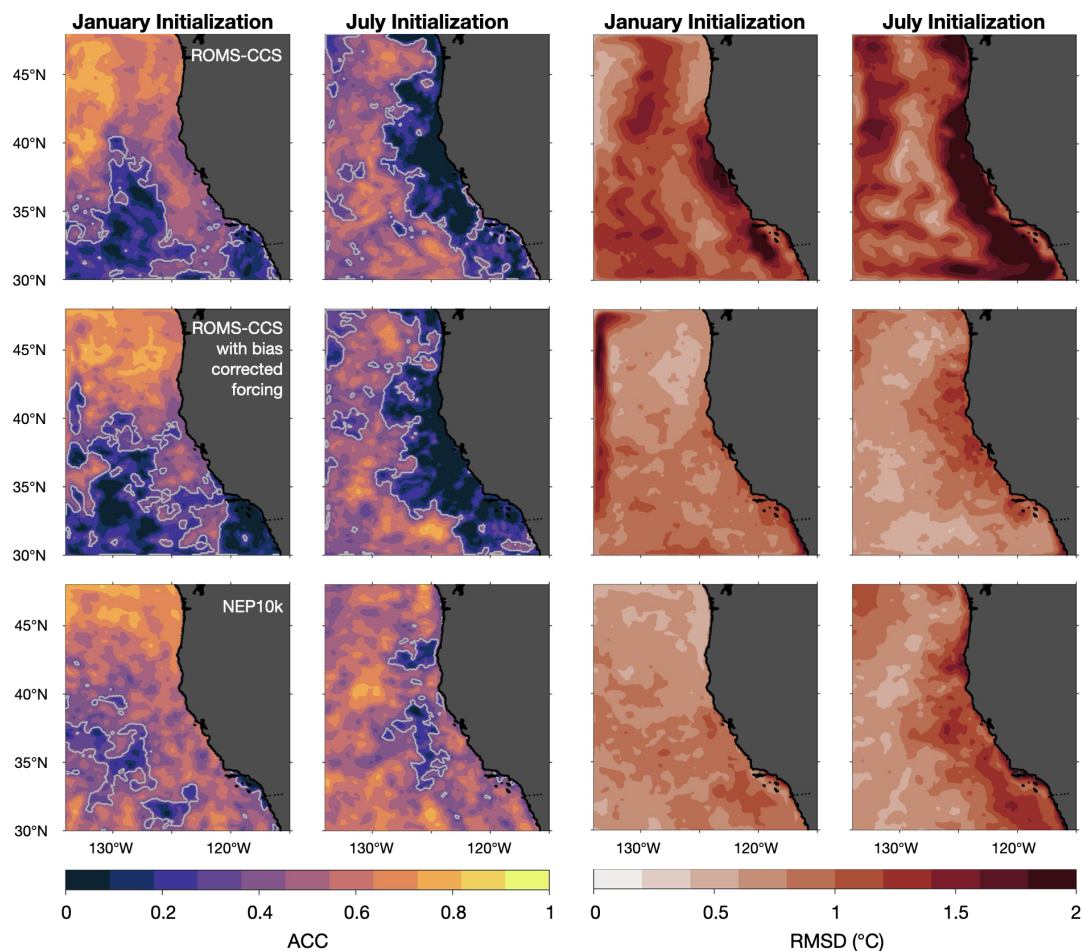
4.4. Comparison with earlier regional forecasts

The forecast system described here builds on a foundation of regional ocean modeling and prediction efforts that includes seasonal forecasts for the EBS (Kearney et al. 2021), Pacific Northwest (Siedlecki et al. 2016), and CCS (Jacox et al. 2023). Those forecasts provide an important benchmark against which our new forecasts can be tested, and here we do so for the CCS case, which used the Regional Ocean Modeling System (ROMS) forced by output from an older version of the Canadian Center for Climate Modelling and Analysis (CCCMA) global coupled forecast system (Merryfield et al. 2013). Of note, those forecasts were produced with two different treatments of the global forcing fields – one in which they were interpolated to the regional grid with no other adjustments (as was done for the NEP10k forecasts herein), and another in which the global fields were bias corrected before driving the regional model (Jacox et al. 2023).

NEP10k forecasts compare favorably to the ROMS-based CCS forecasts, with 3.5-month lead ACC values that are higher than those from ROMS forecasts for both January and July initializations (Fig. 12). ROMS forecasts employed only a 3-member ensemble, compared with the 10-member ensemble employed in NEP10k, and this difference likely contributes to the differences in forecast skill (see Section 5 for more discussion of ensemble size). However, the two forecasts systems also differ in their parent forecast models, regional models, initial conditions, and forcing treatments. Therefore their relative performance cannot be attributed to ensemble size alone. While bias correcting the global forcing for ROMS forecasts had little impact on ACC (also found by Kearney et al. (2021) for the EBS), it did dramatically reduce



527 RMSD (compare the top and middle rows in Fig. 12). Encouragingly, RMSD for the NEP10k
528 forecasts without bias-corrected forcing is comparable to that of the ROMS forecasts with bias
529 correction, and much lower than that of the ROMS forecasts that used the same (no bias
530 correction) approach. These results suggest that the NEP10k forecasts are already performing
531 well relative to past efforts and that additional improvements may be possible by evaluating and
532 refining the global model forcing or applying a bias correction in post-processing.
533



534
535 Figure 12: Comparison of 3.5-month lead SST forecast skill (left: ACC; right: RMSD) between NEP10k and earlier
536 regional forecasts based on the Regional Ocean Modeling System (ROMS-CCS). ROMS forecasts were forced by
537 output from the CanCM4 global forecast system (Jacox et al. 2023) in two ways: (top) with global forcing fields
538 interpolated directly to the ROMS grid, as for the MOM6 forecasts, and (middle) with global fields bias-corrected
539 before running ROMS. Note that the ROMS forecasts used a 3-member ensemble while NEP10k forecasts have 10
540 ensemble members.

541
542



543 5. Discussion

544 Here, we introduced a new regional ocean forecast system for the Northeast Pacific, NEP10k,
545 developed under NOAA's Changing Ecosystems and Fisheries Initiative. We described the
546 forecast system and documented its performance for three key variables – SST, BT, and BO₂ –
547 with verification against ocean models and reanalyses as well as *in situ* observations. All three
548 variables are predictable months in advance in the coastal regions of the EBS, GOA, and CCS.
549 While mechanistic exploration of the sources of predictability is beyond the scope of this paper,
550 the skill patterns we find align with previously documented processes including ENSO
551 teleconnections and sea ice dynamics. The considerable skill of the forecast system provides a
552 foundation from which to pursue physical, biogeochemical, and ecological indices that can
553 support decision making. These dynamically downscaled forecasts can also be complemented by
554 forecasts from alternative techniques including statistical downscaling, linear inverse modeling,
555 and model analogs (e.g., Jacox et al. 2020, Amaya et al. 2026), which can offer comparable skill
556 for some of the ocean properties discussed herein at reduced computational cost.

557
558 Forecast skill was evaluated relative to benchmark forecasts that can be achieved without
559 dynamical downscaling, namely a simple persistence forecast and the global forecast system
560 (SPEAR) used to drive NEP10k. While skill above persistence is greater in some regions than
561 others (e.g., most of the temperature skill in the EBS derives from persistence), the regional
562 model consistently increased ACC relative to persistence and extended the lead times at which
563 forecast skill remains significant. Relative to SPEAR, NEP10k did not alter ACC much when
564 averaging SST over large NEP regions, as has been noted when comparing the influence of
565 resolution in other modeling frameworks (e.g., Amaya et al. 2026). However, other regions have
566 seen benefits in SST ACC from downscaling (e.g., Ross et al. 2024) and we have not performed
567 this comparison on fine spatial scales where downscaling is likely more valuable. For BT in the
568 CCS, we did see improvements in ACC at short lead times in the downscaled model, and RMSD
569 was in some cases dramatically reduced for both SST and BT in the EBS and CCS. In addition to
570 these performance gains for temperature forecasts, NEP10k enables forecasts of biogeochemical
571 variables such as oxygen. Furthermore, the enhanced resolution is more consistent with the
572 scales at which stakeholders seek information, which may help build trust in the forecasts even if
573 broad-scale ACC improvements are marginal.

574
575 Comparison with an earlier implementation of regional ocean forecasts for the CCS (ROMS-
576 CCS) shows that the NEP10k forecasts are performing favorably against existing benchmarks.
577 Part of this improvement is due to the global forcing; the SPEAR forecasts employed here are
578 higher resolution than the CanCM4 forecasts (Merryfield et al. 2013) used in ROMS-CCS, and
579 they also apply an ocean tendency adjustment to reduce forecast bias and drift (Lu et al. 2020).
580 This comparison also highlights two key methodological points. First is the role of bias corrected
581 forcing; while biases in NEP10k are much smaller than biases in a similar configuration of
582 ROMS-CCS, the ROMS forecasts were improved by bias-correcting global forcing before



downscaling. NEP10k may be similarly improved by correcting SPEAR forcing before
downscaling, and in the future we plan to quantify the added value of implementing those
corrections. Second, the ACC difference between NEP10k and ROMS-CCS is at least in part
because of differences in ensemble size (10 members in NEP10k versus 3 in ROMS-CCS). In
terms of deterministic forecast skill, there are diminishing returns for increasing ensemble size
above ~4 members (Fig. 13). However, there are cases in which larger ensembles clearly help.
Taking SST forecasts in the CCS as an example; in a 3-member ensemble, ACC remains above
0.5 until 5.5-month lead time, while in a 10-member ensemble that horizon extends to 9.5
months (Fig. 13). This 10-member ensemble is a significant improvement upon the smaller
ensembles of many past regional downscaling efforts, but is still small relative to the large
ensembles (and multi-model ensembles) available from global forecast systems. These very large
ensembles may be particularly useful for predicting the probability of rare events (e.g., Doi et al.
2019, Jacox et al. 2022) or noisy variables like upwelling (Amaya et al. 2024) for which a larger
ensemble can improve the forecast signal-to-noise ratio.

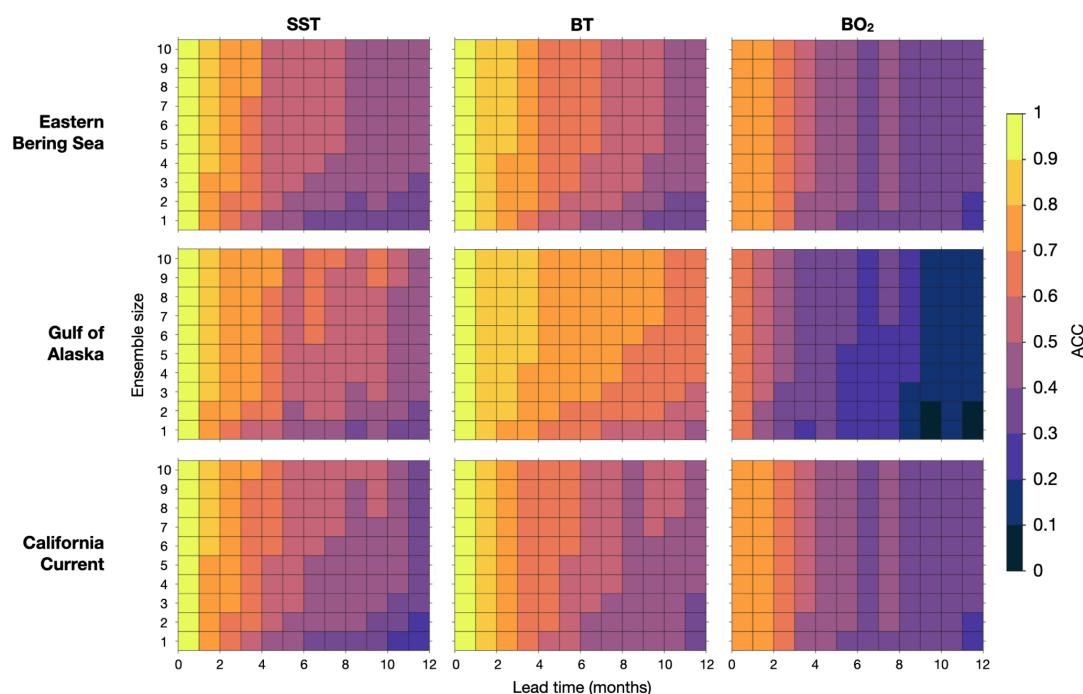


Figure 13: ACC as a function of lead time and ensemble size for each LME (rows) and variable (columns). Variables are averaged inshore of the 1000 m isobath. For each ensemble size N , 1000 forecast ensembles were generated by randomly drawing N members without replacement from the 10-member ensemble. The ACC of each of 1000 forecast ensembles was calculated and the mean of those 1000 ACC values is presented here.

Here, we focused on a small set of key ecologically-relevant variables as a demonstration of the forecast system. Future work will expand on this analysis to include forecast verification for



606 coastal upwelling (Jacox et al. 2018, Amaya et al. 2024), marine heatwaves (Spillman et al.
607 2021, Jacox et al. 2022, Mogen et al. 2024), and compound extremes (Mogen et al. 2026,
608 Freeman et al. 2026). Ultimately, the goal of producing these forecasts is to enable forecasting
609 applications that extend beyond the physical and biogeochemical variables explicitly represented
610 in the model. To that end, many ecological models have been developed for a wide range of
611 Northeast Pacific marine species. Routine delivery of high-resolution regional ocean forecasts
612 will enable provision of ecological forecast products to facilitate agile planning by a variety of
613 users and stakeholders including coastal communities, federal and state fishery managers,
614 industry, and boundary organizations. At the same time, continued work to improve mechanistic
615 understanding, quantify predictability, and evaluate the sensitivity of forecast skill to model
616 configuration will ensure that feedback to model development facilitates iterative improvement
617 of forecast quality.

618

619 **Data availability**

620 Output from the forecasts described herein will be available at psl.noaa.gov/cefi_portal.
621 Observational datasets used for forecast verification are available as described in the methods
622 (Sect. 3.1).

623

624 **Author contributions**

625 DSD and JL led development of the retrospective and real-time forecasts, respectively, with
626 input from MGJ, MAA, EJJ, ACR, and CAS. LJ, NCJ, and CEM performed the global runs used
627 to force the regional model. MGJ performed the analysis with input from DSD, JL, MAA, NMF,
628 DJA, SJB, AAC, NSL, SCM, and MPB. MGJ wrote the manuscript with contributions from all
629 authors.

630

631 **Competing interests**

632 At least one of the co-authors serves as guest editor for the special issue to which this paper
633 belongs.

634

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646 **References**

- 647 Adcroft, A., Anderson, W., Balaji, V., Blanton, C., Bushuk, M., Dufour, C. O., Dunne, J. P.,
648 Griffies, S. M., Hallberg, R., Harrison, M. J., Held, I. M., Jansen, M. F., John, J. G., Krasting, J.
649 P., Langenhorst, A. R., Legg, S., Liang, Z., McHugh, C., Radhakrishnan, A., Reichl, B. G.,
650 Rosati, T., Samuels, B. L., Shao, A., Stouffer, R., Winton, M., Wittenberg, A. T., Xiang, B.,
651 Zadeh, N., Zhang, R. (2019) The GFDL global ocean and sea ice model OM4.0: Model
652 description and simulation features, *J. Adv. Model. Earth Sys.*, 11, 3167–3211.
- 653 Amaya, D.J., Alexander, M.A., Scott, J.D. and Jacox, M.G. (2023a) An evaluation of high-
654 resolution ocean reanalyses in the California current system. *Progress in Oceanography*, 210,
655 102951.
- 656 Amaya, D.J., Jacox, M.G., Alexander, M.A., Scott, J.D., Deser, C., Capotondi, A. and Phillips,
657 A.S. (2023b) Bottom marine heatwaves along the continental shelves of North America. *Nature*
658 *Communications*, 14(1), 1038.
- 659 Amaya, D.J., Jacox, M.G., Alexander, M.A., Bograd, S.J. and Jia, L. (2024) Seasonal upwelling
660 forecasts in the California Current System, *Geophysical Research Letters*, 51(22),
661 e2024GL111083.
- 662 Amaya, D.J., Jacox, M.G. and Alexander, M.A. (2026), Skillful high-resolution seasonal
663 forecasts of the California Current System using model-analogs, *Progress in Oceanography*,
664 103723.
- 665 Beamer, J. P., Hill, D. F., Arendt, A., and Liston, G. E.: High-resolution modeling of coastal
666 freshwater discharge and glacier mass balance in the Gulf of Alaska watershed (2016) *Water*
667 *Resour. Res.*, 52, 3888–3909.
- 668 Boer, G.J., Merryfield, W.J. and Kharin, V.V. (2019) Relationships between potential, attainable,
669 and actual skill in a decadal prediction experiment. *Climate Dynamics*, 52(7), 4813–4831.
- 670 Boyer, T. P., Garcia, H. E., Locarnini, R. A., Zweng, M. M., Mishonov, A. V., Reagan, J. R.,
671 Weathers, K. A., Baranova, O. K., Seidov, D., and Smolyar, I. V.: World Ocean Atlas 2018,
672 <https://www.ncei.noaa.gov/archive/accession/NCEI-WOA18>, 2019.
- 673 Brodie, S., Pozo Buil, M., Welch, H., Bograd, S.J., Hazen, E.L., Santora, J.A., Seary, R.,
674 Schroeder, I.D. and Jacox, M.G. (2023) Ecological forecasts for marine resource management
675 during climate extremes. *Nature Communications*, 14(1), 7701.
- 676 Carter, B. R., Bittig, H. C., Fassbender, A. J., Sharp, J. D., Takeshita, Y., Xu, Y.-Y., Álvarez, M.,
677 Wanninkhof, R., Feely, R. A., and Barbero, L. (2021) New and updated global empirical
678 seawater property estimation routines. *Limnology and Oceanography: Methods*, 19(12), 785-
679 809.



- 680 Carter, M.L., Flick, R.E., Terrill, E., Beckhaus, E.C., Martin, K., Fey, C.L., Walker, P.W.,
681 Largier, J.L., and McGowan, J.A. (2022) Shore Stations Program Data Archive: Current and
682 historical coastal ocean temperature and salinity measurements from California stations. UC San
683 Diego Library Digital Collections. <https://doi.org/10.6075/J0S75GHD>
- 684 Cervantes, B.T., Hough, K.R., Waddell, J., Fewings, M.R., Risien, C.M., and Mickett, J.B.
685 (2026) 26 years of mooring data from Olympic Coast National Marine Sanctuary, Data in Brief,
686 67, 112998, <https://doi.org/10.1016/j.dib.2026.112998>.
- 687 Cordero Quirós, N., Jacox, M. G., Pozo Buil, M., & Bograd, S. J. (2022) Future changes in eddy
688 kinetic energy in the California Current System from dynamically downscaled climate
689 projections. *Geophysical Research Letters*, 49, e2022GL099042.
- 690
- 691 Davis, G.E. (1997) Kelp forest monitoring handbook: Channel Islands National Park. US
692 Department of the Interior, National Park Service, Channel Islands National Park. Ventura, CA,
693 <https://irma.nps.gov/DataStore/Reference/Profile/68421>
- 694
- 695 Delworth, T. L., Cooke, W. F., Adcroft, A., Bushuk, M., Chen, J. -H., Dunne, K. A., Ginoux, P.,
696 Gudgel, R., Hallberg, R. W., Harris, L., Harrison, M. J., Johnson, N., Kapnick, S. B., Lin, S. -J.,
697 Lu, F., Malyshev, S., Milly, P. C., Murakami, H., Naik, V., Pascale, S., Paynter, D., Rosati, A.,
698 Schwarzkopf, M., Shevliakova, E., Underwood, S., Wittenberg, A. T., Xiang, B., Yang, X.,
699 Zeng, F., Zhang, H., Zhang, L., and Zhao, M. (2020) SPEAR: The Next Generation GFDL
700 Modeling System for Seasonal to Multidecadal Prediction and Projection, *J. Adv. Model. Earth*
701 *Sy.*, 12, e2019MS001895.
- 702
- 703 Doi, T., Behera, S.K. and Yamagata, T. (2019) Merits of a 108-member ensemble system in
704 ENSO and IOD predictions, *Journal of Climate*, 32(3), 957-972.
- 705
- 706 Drenkard, E. J., et al. (2021) Next-generation regional ocean projections for living marine
707 resource management in a changing climate, *ICES Journal of Marine Science* 78, 1969-1987.
- 708 Drenkard, E. J., Stock, C. A., Ross, A. C., Teng, Y.-C., Cordero, T., Cheng, W., Adcroft, A.,
709 Curchitser, E., Dussin, R., Hallberg, R., Hauri, C., Hedstrom, K., Hermann, A., Jacox, M. G.,
710 Kearney, K. A., Pagès, R., Pilcher, D. J., Pozo Buil, M., Seelanki, V., and Zadeh, N. (2025) A
711 regional physical–biogeochemical ocean model for marine resource applications in the Northeast
712 Pacific (MOM6-COBALT-NEP10k v1.0), *Geosci. Model Dev.*, 18, 5245–5290,
713 <https://doi.org/10.5194/gmd-18-5245-2025>.
- 714 Dukhovskoy, D. S., Cordero, T., Hedstrom, K., Alexander, M., Jacox, M., Hallberg, R.,
715 Harrison, M., and Liu, J. (2026) Design and Implementation of a Newtonian Relaxation Scheme
716 in the NOAA GFDL Sea Ice Model (SIS2), *Geosci. Model Dev.*, 19, 7169–7196,
717 <https://doi.org/10.5194/gmd-19-7169-2026>



- 718 Feddern, M. L., A. Darby, K. Oken, and N. Tolimieri. (2026) Stage-Specific Indicators of
719 Northern Yellowtail Rockfish (*Sebastes flavidus*) Recruitment in the California Current
720 Ecosystem, *Fisheries Oceanography* 35(4), 630–649.
- 721 Ferriss, B. E., et al. (2026) Leveraging transboundary science to support Northeast Pacific
722 fisheries and protected species management." *ICES Journal of Marine Science* 83, fsag019.
- 723 Freeman, N.M., Hervieux, G., Alexander, M.A., Jacox, M.G., Amaya, D.J., Scott, J.D. and
724 Capotondi, A. (2026) Characterizing compound physical and biogeochemical extremes in the
725 California Current Large Marine Ecosystem, *PLOS Climate*, 5(2), e0000638.
- 726 García, H. E., K. Weathers, C. R. Paver, I. Smolyar, T. P. Boyer, R. A. Locarnini, M. M. Zweng,
727 A. V. Mishonov, O. K. Baranova, D. Seidov, and J. R. Reagan, 2019a. World Ocean Atlas 2018,
728 Volume 3: Dissolved Oxygen, Apparent Oxygen Utilization, and Oxygen Saturation. A.
729 Mishonov Technical Ed.; NOAA Atlas NESDIS 83, 38 pp. <https://doi.org/10.25923/qspr-pn52>.
- 730 García, H. E., K. Weathers, C. R. Paver, I. Smolyar, T. P. Boyer, R. A. Locarnini, M. M. Zweng,
731 A. V. Mishonov, O. K. Baranova, D. Seidov, and J. R. Reagan, 2019b. World Ocean Atlas 2018,
732 Volume 4: Dissolved Inorganic Nutrients (phosphate, nitrate and nitrate+nitrite, silicate). A.
733 Mishonov Technical Ed.; NOAA Atlas NESDIS 84, 35 pp. <https://doi.org/10.25923/ng6j-ey81>.
- 734 Grimaldi, S., Salamon, P., Disperati, J., Zsoter, E., Russo, C., Ramos, A., Carton De Wiart, C.,
735 Barnard, C., Hansford, E., Gomes, G., and Prudhomme, C.: River discharge and related historical
736 data from the Global Flood Awareness System, v4.0 (2022), European Commission, Joint
737 Research Centre (JRC) [data set], <https://doi.org/10.24381/cds.a4fdd6b9>.
- 738 Hill, D.: Coastal freshwater discharge simulations for the Gulf of Alaska, 1931–2021 (2023)
739 Research Workspace [data set], <https://doi.org/10.24431/rw1k7d3>.
- 740 Harrigan, S., Zsoter, E., Alfieri, L., Prudhomme, C., Salamon, P., Wetterhall, F., Barnard, C.,
741 Cloke, H., and Pappenberger, F. (2020) GloFAS-ERA5 operational global river discharge
742 reanalysis 1979–present, *Earth Syst. Sci. Data*, 12, 2043–2060.
- 743 Jacox, M.G., Alexander, M.A., Stock, C.A. and Hervieux, G. (2019) On the skill of seasonal sea
744 surface temperature forecasts in the California Current System and its connection to ENSO
745 variability, *Climate Dynamics*, 53(12), 7519–7533.
- 746 Jacox, M.G., Edwards, C.A., Hazen, E.L. and Bograd, S.J. (2018) Coastal upwelling revisited:
747 Ekman, Bakun, and improved upwelling indices for the US West Coast, *Journal of Geophysical*
748 *Research: Oceans*, 123(10), 7332–7350.
- 749 Jacox, M. G., et al. (2020) Seasonal-to-interannual prediction of North American coastal marine
750 ecosystems: Forecast methods, mechanisms of predictability, and priority developments,
751 *Progress in Oceanography*, 183, 102307.



- 752 Jacox, M.G., Alexander, M.A., Amaya, D., Becker, E., Bograd, S.J., Brodie, S., Hazen, E.L.,
753 Pozo Buil, M. and Tommasi, D. (2022) Global seasonal forecasts of marine heatwaves, *Nature*,
754 604(7906), 486-490.
- 755 Jacox, M.G., Buil, M.P., Brodie, S., Alexander, M.A., Amaya, D.J., Bograd, S.J., Edwards, C.A.,
756 Fiechter, J., Hazen, E.L., Hervieux, G. and Tommasi, D. (2023) Downscaled seasonal forecasts
757 for the California Current System: Skill assessment and prospects for living marine resource
758 applications. *PLoS Climate*, 2(10), p.e0000245.
- 759 Kaplan, I.C., Williams, G.D., Bond, N.A., Hermann, A.J. and Siedlecki, S.A. (2016) Cloudy
760 with a chance of sardines: forecasting sardine distributions using regional climate models,
761 *Fisheries Oceanography*, 25(1), 15-27.
- 762 Kearney, K.A., Alexander, M., Aydin, K., Cheng, W., Hermann, A.J., Hervieux, G. and Ortiz, I.
763 (2021) Seasonal predictability of sea ice and bottom temperature across the eastern Bering Sea
764 shelf. *Journal of Geophysical Research: Oceans*, 126(11), e2021JC017545.
- 765 Lellouche, J., Greiner, E., Bourdallé-Badie, R., Garric, G., Melet, A., Drévillon, M., Bricaud, C.,
766 Hamon, M., Le Galloudec, O., Regnier, C., Candela, T., Testut, C., Gasparin, F., Ruggiero, G.,
767 Benkiran, M., Drillet, Y., and Le Traon, P. (2021) The Copernicus Global Oceanic and Sea Ice
768 GLORYS12 Reanalysis, *Front. Earth Sci.*, 9, 698876.
- 769 Lu, F., Harrison, M. J., Rosati, A., Delworth, T. L., Yang, X., Cooke, W. F., et al. (2020).
770 GFDL's SPEAR seasonal prediction system: Initialization and ocean tendency adjustment (OTA)
771 for coupled model predictions. *Journal of Advances in Modeling Earth Systems*, 12,
772 e2020MS002149.
- 773 Malick, M.J., Siedlecki, S.A., Norton, E.L., Kaplan, I.C., Haltuch, M.A., Hunsicker, M.E.,
774 Parker-Stetter, S.L., Marshall, K.N., Berger, A.M., Hermann, A.J. and Bond, N.A. (2020)
775 Environmentally driven seasonal forecasts of Pacific hake distribution, *Frontiers in Marine*
776 *Science*, 7, 578490.
- 777 Merryfield, W. J., Lee, W. S., Boer, et al. (2013). The Canadian seasonal to interannual
778 prediction system. Part I: Models and initialization. *Monthly weather review*, 141(8), 2910-2945.
- 779 Minobe, S., Capotondi, A., Jacox, M.G., Nonaka, M. and Rykaczewski, R.R. (2022) Toward
780 regional marine ecological forecasting using global climate model predictions from subseasonal
781 to decadal timescales: Bottlenecks and recommendations. *Frontiers in Marine Science*, 9,
782 855965.
- 783 Mogen, S.C., Lovenduski, N.S., Yeager, S.G., Capotondi, A., Jacox, M.G., Bograd, S., Di
784 Lorenzo, E., Hazen, E.L., Pozo Buil, M., Kim, W. and Rosenbloom, N. (2024) Multi-month
785 forecasts of marine heatwaves and ocean acidification extremes, *Nature Geoscience*, 17(12),
786 1261-1267.



- 787 Mogen, S.C., Lovenduski, N.S. and Clow, G.L. (2026) Marine phytoplankton extremes and
788 compound extreme events have the potential to be predicted multiple months in advance,
789 *Geophysical Research Letters*, 53(13), e2026GL121872.
- 790 Negrete García, G., Matthews, D., Stock, C. A., Powell, B., Rykaczewski, R. R., Tanaka, K.,
791 Barkley, H., Friedrich, T., Luo, J. Y., Ross, A. C., and Teng, Y.-C. (2026) A new ocean model
792 configuration for management of central North Pacific Marine Resources (MOM6-COBALT-
793 HIC6kv1.0), EGU sphere [preprint], <https://doi.org/10.5194/egusphere-2026-1877>.
- 794 Norton, E.L., Kaplan, I.C., Siedlecki, S., Hermann, A.J., Alin, S.R., Newton, J., Corbett, K.,
795 Ayres, D., Schumacker, E.J., Bond, N.A. and Richerson, K. (2023) Seasonal ocean forecasts to
796 improve predictions of Dungeness crab catch rates, co-developed with state and tribal fishery
797 managers, *ICES Journal of Marine Science*, 80(4), 823-835.
- 798 Pagès, R., Cordero, T. J., Hauri, C., Hedstrom, K., Stock, C. A., Irving, B., Dukhovskoy, D. S.,
799 Drenkard, E. J., Ross, A. C., Cheng, W., Kearney, K., Hermann, A. J., Hauser, D. D. W.,
800 Heeringa, K., Tuuraq, G. R., and Adams, B. A regional physical-biogeochemical model of the
801 Arctic Ocean (MOM6-COBALT-ARC11k v1.0): Supporting marine resource applications and
802 co-production of knowledge with Indigenous Peoples. Submitted.
- 803 Payne, M. R., et al. (2017) Lessons from the first generation of marine ecological forecast
804 products, *Frontiers in Marine Science*, 4, 289.
- 805 Pilcher, D. J., Kearney, K. A., Hermann, A. J., Cheng, W., Cross, J. N., & Monacci, N. M.
806 (2026) Seasonal forecasts of pH and aragonite saturation for the Bering Sea shelf. *Journal of*
807 *Geophysical Research: Oceans*, 131, e2025JC023279.
- 808 Raju, M., Cannon, D. J., Alsip, P., Wang, H., Wang, J., Cordero, T., Hallberg, R. W., Stock, C.
809 A., and Langan, J. A. (2026) Development of a next-generation general ocean circulation model
810 for the Great Lakes, *Geosci. Model Dev.*, 19, 4331–4356, [https://doi.org/10.5194/gmd-19-4331-](https://doi.org/10.5194/gmd-19-4331-2026)
811 2026.
- 812 Risien, C., Fewings, M., Fisher, J., Peterson, J., Morgan, C., and Peterson, W. (2026) Spatially
813 gridded cross-shelf hydrographic sections and monthly climatologies from shipboard survey data
814 collected along the Newport Hydrographic Line, 1997-2025 (Version Version 1.1) [Dataset].
815 Zenodo. <https://doi.org/10.5281/zenodo.20777766>
- 816 Ross, A. C., Stock, C. A., Adcroft, A., Curchitser, E., Hallberg, R., Harrison, M. J., Hedstrom,
817 K., Zadeh, N., Alexander, M., Chen, W., Drenkard, E. J., du Pontavice, H., Dussin, R., Gomez,
818 F., John, J. G., Kang, D., Lavoie, D., Resplandy, L., Roobaert, A., Saba, V., Shin, S.-I.,
819 Siedlecki, S., and Simkins, J. (2023) A high-resolution physical–biogeochemical model for
820 marine resource applications in the northwest Atlantic (MOM6-COBALT-NWA12 v1.0),
821 *Geosci. Model Dev.*, 16, 6943–6985, <https://doi.org/10.5194/gmd-16-6943-2023>.



- 822 Ross, A. C., Stock, C. A., Koul, V., Delworth, T. L., Lu, F., Wittenberg, A., and Alexander, M.
823 A. (2024) Dynamically downscaled seasonal ocean forecasts for North American east coast
824 ecosystems, *Ocean Sci.*, 20, 1631–1656, <https://doi.org/10.5194/os-20-1631-2024>.
- 825 Siedlecki, S.A., Kaplan, I.C., Hermann, A.J., Nguyen, T.T., Bond, N.A., Newton, J.A., Williams,
826 G.D., Peterson, W.T., Alin, S.R. and Feely, R.A. (2016) Experiments with seasonal forecasts of
827 ocean conditions for the northern region of the California Current upwelling system. *Scientific*
828 *Reports*, 6(1), 27203.
- 829 Spillman, C.M., Smith, G.A., Hobday, A.J. and Hartog, J.R. (2021) Onset and decline rates of
830 marine heatwaves: global trends, seasonal forecasts and marine management, *Frontiers in*
831 *Climate*, 3, 801217.
- 832 Stabeno, P. J., Bell, S., Berchok, C., Cokelet, E. D., Cross, J., McCabe, R. M., Mordy, C. W.,
833 Overland, J., Straus, D., Sullivan, M., and Tabisola, H. M. (2023). Long-term biophysical
834 observations and climate impacts in US Arctic marine ecosystems. *Oceanography*, 36(2/3), 78-
835 85.
- 836 Steiger, J. H. (1980) Tests for comparing elements of a correlation matrix. *Psychological*
837 *bulletin*, 87(2), 245.
- 838 Stock, C. A., Dunne, J. P., and John, J. G. (2014) Global-scale carbon and energy flows through
839 the marine planktonic food web: An analysis with a coupled physical–biological model. *Progress*
840 *in Oceanography*, 120, 1–28.
- 841 Stock, C.A., Pegion, K., Vecchi, G.A., Alexander, M.A., Tommasi, D., Bond, N.A., Fratantoni,
842 P.S., Gudgel, R.G., Kristiansen, T., O’Brien, T.D. and Xue, Y. (2015) Seasonal sea surface
843 temperature anomaly prediction for coastal ecosystems. *Progress in Oceanography*, 137, 219-
844 236.
- 845 Stock, C. A., Dunne, J. P., Fan, S., Ginoux, P., John, J., Krasting, J. P., Laufkötter, C., Paulot, F.,
846 and Zadeh, N. (2020) Ocean biogeochemistry in GFDL’s Earth System Model 4.1 and its
847 response to increasing atmospheric CO₂. *J. Adv. Model. Earth Sys.*, 12, e2019MS002043,
848 <https://doi.org/10.1029/2019MS002043>.
- 849 Stock, C.A., Dunne, J.P., Luo, J.Y., Ross, A.C., Van Oostende, N., Zadeh, N., Cordero, T.J., Liu,
850 X. and Teng, Y.C. (2025) Photoacclimation and photoadaptation sensitivity in a global ocean
851 ecosystem model. *Journal of Advances in Modeling Earth Systems*, 17(6), p.e2024MS004701.
- 852 Szekely, T., Gourrion, J., Pouliquen, S. and Reverdin, G. (2019) The CORA 5.2 dataset for
853 global in situ temperature and salinity measurements: data description and validation. *Ocean*
854 *Science*, 15(6), 1601-1614.



- 855 Tommasi, D., et al. (2017) Managing living marine resources in a dynamic environment: the role
856 of seasonal to decadal climate forecasts, *Progress in Oceanography*, 152, 15-49.
- 857 Tommasi, D., Stock, C. A., Pegion, K., Vecchi, G. A., Methot, R. D., Alexander, M. A., &
858 Checkley Jr, D. M. (2017). Improved management of small pelagic fisheries through seasonal
859 climate prediction. *Ecological Applications*, 27(2), 378-388.
- 860 Wildermuth, R.P., Tommasi, D., Kaplan, I.C., Bograd, S.J., Hinchliffe, C., Hunsicker, M.E.,
861 Jacox, M.G., Koenigstein, S., Kuriyama, P., Muhling, B., Pozo Buil, M., and Thompson, A.
862 (2026) Revealing climate impacts on recruitment drivers of small pelagic fish through dynamic
863 factor analysis, *Marine Ecology Progress Series*, 787, meps15152.
- 864 Williams, E. J. (1959) The comparison of regression variables. *Journal of the Royal Statistical*
865 *Society: Series B (Methodological)*, 21(2), 396-399.