

1 **Decadal biogeochemical predictions for the changing bottom marine**
2 **environment of the Gulf of Maine**

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19 **Abstract**

20 The Gulf of Maine and the surrounding Northeast U.S. Continental Shelf are
21 experiencing rapid marine environmental change arising from complex regional
22 dynamics that challenge near-term (1-10 years) predictive capabilities for valuable
23 living marine resources. Here, using a high-resolution regional ocean model, we
24 demonstrate skilful decadal forecasts of ocean bottom habitat characteristics
25 including bottom temperature, dissolved oxygen (O_2), pH and aragonite saturation
26 state (Ω_{ar}). Bottom temperature and pH predictions show substantial skill driven
27 primarily by radiatively forced change and carbon uptake trends, while bottom O_2
28 and Ω_{ar} predictions benefit more from initialization due to stronger internal
29 variability. Retrospective forecasts successfully predicted observed historical
30 changes in water masses and environmental properties, including recent
31 cooling/freshening transitions driven by replacement of Warm Slope Water with
32 Labrador Slope Water. This water mass variability also modulates biogeochemical
33 conditions and ocean acidification buffering capacity, with our recent forecasts
34 indicating that benefits from the expected respite from rapid warming might be
35 tempered by challenges posed by rapid acidification. The demonstrated
36 predictability of coupled physical-biogeochemical processes supports developing
37 integrated prediction systems for climate-informed marine resource management.

38 **Introduction**

39 The global ocean has undergone unprecedented biogeochemical transformation
40 since the onset of the industrial era — absorbing approximately 30% of
41 anthropogenic CO₂ emissions, and over 90% of the excess heat associated with
42 accumulating greenhouse gases (Sabine et al., 2004; Feely et al., 2023,
43 Friedlingstein et al., 2025, Johnson and Lyman, 2020). This oceanic CO₂ and heat
44 uptake has initiated a cascade of interconnected changes that represent some of the
45 most profound shifts in ocean conditions experienced in the past 50 years.
46 Warming has altered ocean stratification and circulation (Levitus et al., 2012;
47 Abram et al., 2016). Acidification has challenged the basic chemistry upon which
48 marine calcifiers depend (Caldeira and Wickett, 2003; Orr et al., 2005). Declining
49 oxygen concentrations have pressed the metabolic limits of marine organisms
50 (Keeling et al., 2010; Breitburg et al., 2018). Ecosystem and fisheries challenges
51 posed by climate change are compounded by those linked to natural climate
52 variability (Lehodey et al., 2006). A capacity to anticipate physical and
53 biogeochemical changes, whether from climate change or natural variability, may
54 help coastal communities and industries mitigate potential negative impacts, and
55 realize new opportunities that may arise (Clark et al., 2001, Tommasi et al., 2017).

56 The Northeast U.S. Continental Shelf (NEUS) — and particularly its highly
57 productive semi-enclosed sea, the Gulf of Maine (GOM) — has been subject to

58 both ocean change trends and pronounced variability. Dynamic warming (Pershing
59 et al., 2015, Saba et al., 2016; Alexander et al., 2018), deoxygenation (Claret et al.,
60 2018) and acidification (Salisbury and Jönsson, 2018, Siedlecki et al. 2021,
61 Stewart et al, 2025) signals have emerged from an interplay of shifting circulation
62 patterns, alterations in the Gulf Stream position, and regional water masses,
63 particularly variations between cold, fresh Labrador Slope Water (LSW) and
64 Warm Slope Water (WSW) associated with greater Gulf Stream influence, that
65 modulate global warming signals through local oceanographic processes (Chen et
66 al., 2020; Gangopadhyay et al., 2019; Brickman et al., 2018; Gonçalves Neto et al.,
67 2021; Friedland and Hare, 2007, Seidov et al., 2021). In the GOM, oceanic
68 variability from interannual to longer time scales is understood to be largely driven
69 by changes in the contributions of these and other source waters which, in turn,
70 modify the temperature, salinity, and nutrient conditions across the entire
71 ecosystem (Mountain, 2012; Townsend et al., 2023). This water mass variability
72 has also generated complex and sometimes counterintuitive local biogeochemical
73 responses to climate change, including an influx of high-alkalinity Gulf Stream
74 waters driving increased buffering to acidification in certain areas despite rising
75 atmospheric CO₂ concentrations (Stewart et al., 2025; Salisbury and Jönsson,
76 2018). Such water mass changes may also influence coastal hypoxia risk by

77 altering stratification patterns that control vertical mixing and oxygen dynamics in
78 coastal bottom waters (Scully et al., 2022).

79 Rapid warming of the GOM has already contributed to the decline of its iconic
80 Atlantic cod fishery and triggered cascading ecosystem changes (Pershing et al.,
81 2015, 2021; Hare et al., 2016). Continued warming, deoxygenation, and
82 acidification pose significant threats to commercially important fisheries,
83 particularly American lobster and shellfish. American lobsters show stage-specific
84 vulnerabilities to acidification and warming that vary significantly between
85 regional populations (Harrington et al. 2019, Niemisto et al. 2025). Early life
86 stages of shellfish consistently show greater sensitivity to acidification than adults,
87 creating recruitment bottlenecks that may drive population declines (Fay et al.
88 2017). Impacts extend beyond commercially harvested species to affect protected
89 species such as Atlantic puffins and northern right whales (Meyer-Gutbrod et al.,
90 2021).

91 Decisions by coastal communities and managers that determine long-term resource
92 and community resilience are made across time horizons and must consider both
93 variability and change. The interannual to decadal time horizon (1-10 years) is
94 particularly notable for its relevance to the setting of annual catch limits, the
95 formulation of stock rebuilding plans, and industry capitalization (Tommasi et al.,
96 2017). Global Earth System Models (ESMs) have demonstrated multiyear

97 predictability for surface temperature, pH, dissolved oxygen, and net primary
98 production, and enhanced subsurface predictability extending to a decade in the
99 North Atlantic where Atlantic Meridional Overturning Circulation (AMOC)
100 variability strongly influences physical drivers (Frölicher et al., 2020, Krumhardt et
101 al., 2020, Park et al., 2019, Msadek et al., 2014). This ocean predictability enables
102 predictability of the distribution of commercially important open-ocean fish
103 species in the North Atlantic over decadal time scales (Payne et al., 2022).

104 Fisheries are concentrated on productive and accessible continental shelves,
105 however, where direct applications of global ESMs are limited by coarse spatial
106 resolution (~100-200 km) that cannot adequately represent the complex
107 bathymetry, coastal dynamics, tidal mixing, and mesoscale circulation features that
108 drive ocean and ecosystem variability on the shelf (Tommasi et al., 2017; Saba et
109 al., 2016, Ross et al., 2023). High-resolution ocean modeling and enhanced
110 observational networks are revealing substantial promise for predicting ocean
111 variability in this highly dynamic region (Gehlen et al., 2015, Ross et al., 2023,
112 2024, Chen et al., 2021, 2024, Koul et al., 2024).

113 In the GOM (Fig. 2a), recent observations show cooler, fresher water entering the
114 deeper regions through the Northeast Channel beginning in late 2023, potentially
115 marking the return of cooling LSW influence after over a decade of warm Gulf
116 Stream dominance (Record et al., 2024). Previous work regional ocean prediction

117 studies demonstrated that this physical transition, and others like it, were
118 predictable (Koul et al., 2024). Such shifts, however, also have significant
119 biogeochemical implications, as LSW offers lower buffering against acidification
120 than Gulf Stream water. If the recent cooling represents a sustained return to LSW
121 dominance, the region could face rapid acidification as the reduced buffering will
122 compound ongoing background acidification trends (Salisbury and Jönsson, 2018;
123 Stewart et al., 2025). Such rapid biogeochemical change could challenge marine
124 ecosystems and shellfish industries adapted to a decade of warm yet less acidic
125 conditions.

126 Here, we build on prior physical ocean prediction studies and present a high-
127 resolution regional physical and biogeochemical prediction system that, when used
128 to downscale global decadal predictions (Delworth et al. 2020), addresses this
129 time-critical challenge by capturing both the physical and biogeochemical
130 dynamics of shifting water masses and persistent change. We furthermore shift the
131 focus of the evaluation to the benthic environment, which is critical for the largest
132 and most lucrative Gulf of Maine fisheries (e.g., lobster, scallops and groundfish,
133 Waller et al., 2023). Through a comprehensive 10-member ensemble approach
134 spanning 60 years of initialized retrospective predictions, accompanied by
135 uninitialized simulations that include only the impacts of external radiative
136 forcings (~6500 years of simulations), we demonstrate skilful decadal (1-10 year)

137 predictions of benthic physical and biogeochemical conditions in the Gulf of
138 Maine. Our experiments allow us to isolate the impacts of radiatively forced ocean
139 warming on prediction skill, and the impacts of predictable water mass variations.
140 Finally, we present probabilistic forecasts for the coming years that may offer
141 fisheries managers actionable insights into the near-term trajectory of the benthic
142 environment in the GOM.

143 **Methods**

144 Several sets of regional ocean simulations were used to study the predictability of
145 physical and biogeochemical changes in the Gulf of Maine. These are summarized
146 here and in Table 1 to provide a broad view of the experiment structure. Further
147 details of each component are then provided in the subsections that follow.

148 First, a large set of 10-member ensemble retrospective decadal (10-yearlong)
149 forecasts, or “hindcasts”, were generated starting each January from 1965 to 2025
150 by downscaling ensemble predictions from the coarse resolution Seamless System
151 for Prediction and EArth System Research (SPEAR) decadal prediction system
152 (Delworth et al., 2020; Yang et al., 2021) to the 1/12° Northwest Atlantic
153 (NWA12) regional ocean model of Ross et al. (2023). These predictions, which
154 comprise nearly 6500 years of simulation, are referred to herein as
155 NWA12_HIND, and the global SPEAR hindcasts used to force them are referred
156 to as SPEAR_HIND.

157 NWA12_HIND hindcasts were initialized with a 10-member ensemble of
158 retrospective NWA12 simulations forced by the same SPEAR ensemble reanalysis
159 used for SPEAR_HIND (Yang et al., 2021). The regional runs were furthermore
160 nudged gently toward the EN4 in waters > 1000m. These simulations, which will
161 also aid in prediction analysis, are referred to as NWA12_EN4_NUDG.

Finally, an ensemble of simulations of the historical effects of climate change drivers (increasing greenhouse gases, aerosol changes, land use) was generated by downscaling the historical and early projection period of an ensemble of SPEAR climate change simulations. Unlike the predictions in NWA12_HIND and SPEAR_HIND, these climate change runs were not initialized from a data constrained ocean state, but from alternative states from the SPEAR pre-industrial control simulation. The mean of this ensemble is used to estimate the signal associated with climate change, or the “forced” signal, over natural variations. These runs are referred to as “NWA12_HIST” to indicate that they are derived from the historical portion of a climate change simulation. They are also referred to as “uninitialized” runs to indicate that, unlike predictions that aim to anticipate both climate variations and change, they are not initiated from a data-constrained initial state.

The 1/12° regional MOM6-COBALT-NWA12 model

The regional downscaled model developed here inherits most of the configuration and parameters from the MOM6-COBALT-NWA12 v1.0 model developed by Ross et al., 2023 and further refined for applications to decadal predictions by Koul et al., 2024. The model comprises coupled components for ocean physics, biogeochemistry, and sea-ice. Compared to the previously published decadal predictions, we add the COBALT biogeochemical model (Stock et al., 2020, 2025)

and improve the initial physical state estimates by relaxing the downscaled simulation towards the EN4 dataset (Good et al., 2013) at depth greater than 1000m.

The global SPEAR model

We use a 10-member SPEAR-based global simulation (SPEAR_LO; Delworth et al., 2020; Yang et al., 2021) with a low-resolution configuration (1° ocean and sea ice with near-equatorial refinement; and 1° atmosphere and land) to obtain surface forcing and open boundary conditions for the regional model. We use forcing and boundary conditions from the SPEAR_LO global coupled reanalysis to create the NWA12 simulations used to initialize our hindcasts (i.e., NWA12_EN4_NUDG, Table 1), and forcing from SPEAR hindcasts (SPEAR_HIND) to drive NWA12_HIND. For the SPEAR_LO reanalysis, atmospheric winds and temperature were restored toward the 6-hourly Japanese Reanalysis (JRA3Q; Kosaka et al., 2024), and the oceanic SST is restored toward the interpolated monthly-mean observations from the NOAA Extended Reconstructed Sea Surface Temperature version 5 (ERSSTv5) dataset (Huang et al., 2017). The reanalysis ensemble spread originates through alternative deep ocean initializations and is maintained due to the gentle surface-only assimilation approach used by SPEAR_LO (Yang et al., 2021).

Regional Downscaled Simulation (NWA12_EN4_NUDG)

SPEAR_LO reanalysis output was used to force the regional MOM6 model at the ocean surface and at the three open ocean boundaries (see Koul et al 2024) from January 1960 to December 2024. The 10 members of this regional downscaled simulation (NWA12_EN4_NUDG) are derived from the 10 members of the SPEAR_LO: we simply carry forward the member-wise information present in the ocean initial conditions, atmospheric forcing and open ocean boundary conditions. The interior solution of the NWA12_EN4_NUDG simulation was furthermore relaxed with a 90-day timescale towards the full vertical profiles of ocean temperature and salinity from the EN4 gridded dataset in regions where the ocean bottom is deeper than 1000 meters. This moderate relaxation helps keep the model solution closer to the observation-based sub-surface variability, particularly in the late 1990s when the boundary conditions overestimated the propagation of a cool, fresh signal into the domain. Limiting the relaxation to waters deeper than 1000 m helps avoid rapid oceanic re-adjustment in shallower waters upon initialization of retrospective predictions wherein such relaxation towards EN4 is not carried out and is necessary to avoid nudging on the shelf where the 1° EN4 shows low correlation with observed salinity despite maintaining high correlation with observed temperature (Fig. S2, Fig. S3). We also note that the bottom waters of the Gulf of Maine analysed in this study (the deep basins and the Northeast Channel)

221 lie well inshore of the 1000 m isobath and are therefore not directly nudged
222 towards EN4. The relaxation constrains only the off-shelf slope source waters. We
223 do not relax the regional model towards the parent SPEAR model, since SPEAR
224 has coarse ocean resolution and does not assimilate sub-surface ocean data, making
225 it less constrained towards observations than the EN4-gridded dataset.

226 Open boundary data for biogeochemical tracers were obtained exactly as explained
227 in Ross et al., (2023). The time varying boundary data for alkalinity and dissolved
228 inorganic carbon were estimated from SPEAR_LO monthly average temperature
229 and salinity as input to the algorithm from Carter et al., (2021). Climatological
230 river freshwater discharge, nutrient, carbon and alkalinity data were also used as
231 described in Ross et al., (2023) and Koul et al., (2024). This climatological forcing,
232 which includes seasonal variability but not interannual variability, was used
233 because coastwide river observations dating back to the 1960s are not available. In
234 the Gulf of Maine, direct river runoff is estimated to be a minor source of
235 freshwater and nutrients (Smith et al., 2001; Townsend, 1998) and most of the
236 interannual variability is driven by changing sources of inflowing water.

237 **Regional Ocean Hindcasts (NWA12_HIND)**

238 Following Koul et al 2024, we use the regional simulation from the
239 NWA12_EN4_NUDG model to start 10-yearlong retrospective ocean physical-

biogeochemical predictions (NWA12_HIND) every year on January 1st from 1965 to 2025. The last 10-yearlong simulation, which shifts from hindcast to forecast, is from 01-01-2025 to 31-12-2034. The 10-member NWA12_HIND ensemble are started from ocean initial conditions taken from the corresponding 10 members of NWA12_EN4_NUDG, and integrated forward using atmospheric forcing and open ocean boundary conditions from the 10 members of SPEAR_HIND. To ease the transition between the global and regional model of the complex inflow and outflow along the northern boundary, each member of the 10-yearlong predictions is relaxed towards the corresponding SPEAR_LO prediction north of 45°N. The strength of the restoration corresponds to a relaxation time scale of 90 days at the northern boundary and decreases gradually to 0 at 45°N. No bathymetric mask is applied, as the relaxation drops to zero north of the targeted shallower regions. The latitudinal damping rate r (inverse of relaxation time scale) was prescribed as:

$$r(\phi) = (r_{\max} / 2) \times [1 + \cos (\pi (\phi_{\max} - \phi) / (\phi_{\max} - 45))]$$

for ϕ (latitude) from 45°N to $\phi_{\max}$ in the regional model, and zero south of 45°N and

$$r_{\max} = 1/90 \text{ day}^{-1} \text{ at } \phi_{\max}, \text{ where } \phi_{\max} \text{ in the regional model is } \approx 58^{\circ}\text{N}$$

Historical Climate Change Simulations (NWA12_HIST)

The NWA12_HIST is a continuous 75-yearlong simulation started on 01-01-1960 and ending in 31-12-2034. The NWA12_HIST is also a 10-member ensemble

forced with atmospheric forcing and open ocean boundary conditions from the 10 members of SPEAR_HIST. The SPEAR_HIST dataset spans from 1850 to 2100 and incorporates future greenhouse gas concentrations based on the SSP585 emissions scenario (Riahi et al., 2017). It should be noted that differences between SSP585 and other emissions scenarios are negligible over the near future (next 1-10 years) examined in this study. Both NWA12_HIST and NWA12_HIND share the response of the model to the common prescribed natural and anthropogenic radiative forcing but the phase of natural variability in NWA12_HIST is not expected to match the observed phase since the impact of 1960 initial conditions is not retained beyond a few years.

Point observations and observation-based gridded products

Two observation-based gridded data sets were used to assess the quality of model simulations for bottom temperature and salinity: the 1/12° GLORYS12 v1 ocean reanalysis and interim analysis products (Lellouche et al., 2018) and the 1° EN4 gridded dataset (EN.4.2.2, Good et al., 2013) which is used to assess a longer period from 1965-2024 (Fig. S1, Fig. 3 and Fig. 5). For bottom O₂ and bottom Ω_{ar} , we used the Fishing Industry SHared Bottom Oceanographic Timeseries data (https://erddap.ondeckdata.com/erddap/tabledap/fishbot_realtime.html), hereafter called “Fishbot”, and vessel (Jiang et al., 2021) and glider-based (IOOS Glider Data Assembly Center: <https://gliders.ioos.us/erddap/index.html>) datasets

(hereafter called “NOAA OBS”). In addition to these two datasets, we also used the observed bottom temperature and bottom salinity time series (hereafter called “NOAA_SOE”) for the GOM Ecological Production Unit (EPU) from NOAA's State of the Ecosystem reports (NOAA Fisheries, 2025).

Preparation of annual mean anomalies

Area-weighted averages were first computed for the model-simulated ensemble mean and the two gridded observational datasets (GLORYS12 and EN4), excluding grid cells with ocean depths less than 30 meters. Annual anomalies were then derived by subtracting the 1994-2023 mean from the annual mean time series. Figures Fig. S1, Fig. S2 and Fig. S3 show the comparison of annual anomalies from variables across these gridded datasets.

For all Fishbot and NOAA_OBS observations, point data was first linearly interpolated onto a uniform $1/4^\circ \times 1/4^\circ$ grid before area averaging. Monthly anomalies were then computed by subtracting the long-term monthly mean (1994-2023) from each month, provided there were at least three years of data samples. Finally, annual mean anomalies were calculated by averaging monthly anomalies for years with at least four months of data. The uncertainty (error bars in Fig. 2) for that year is $\sigma_{\text{monthly}} / \sqrt{n}$, i.e. the sample standard deviation of that year's monthly anomalies divided by the square root of the number of valid months (n).

Gulf Stream Index and Water mass definitions

The variability of the Gulf Stream's position was assessed using a method established by Pérez-Hernández and Joyce (2014) and subsequently utilized by Ross et al. (2023). First, the Gulf Stream's mean position is defined by the latitude where sea surface height (SSH) variance is highest along meridional lines, spaced 1° apart, from 72°W to 52°W . Then, to quantify the relative position of the Gulf Stream, the Gulf Stream Index (GSI) was calculated as the annual SSH anomaly, relative to the 1994–2023 average, averaged over these mean position points. The proportion of the two water masses, Labrador Slope Water and Warm Slope Water, in the Northeast Channel (Fig. 1) analyzed in this study were computed from water mass definitions as described in Ross et al 2023.

Skill assessment

We used anomaly correlation coefficients (ACC) to quantify the skill in predicting annual mean anomalies of bottom temperature, bottom O_2 , bottom pH and bottom Ω_{ar} . The ACC for area-averaged quantities was calculated for the Gulf of Maine Ecological Production Units (GOM_EPU, NOAA Fisheries, 2024). For bottom temperature, bottom O_2 , bottom pH and bottom Ω_{ar} the NWA12_EN4_NUDG simulation was used as the observational reference, and the skill was calculated over the period 1965-2024. The lead-dependent climatology (1994-2023 mean)

was removed from the initialized hindcasts before calculating the skill metric. This choice of using NWA12_EN4_NUDG as the observational reference was made because continuous spatio-temporal observational records of bottom temperature, O₂, pH and bottom Ω_{ar} , for any of the EPU's or Large Marine Ecosystems (LMEs) were not available. However, to show that the NWA12_EN4_NUDG was a good proxy for in-situ observations for the skill estimation, we carried out a point-by-point comparison of temporally and spatially co-located model output and available observations (Fig. S7), as well as additional evaluation of interannual variations and covariance with better-constrained physical properties (Fig. S1, Fig. 3 and Fig. 5). A simple persistence-based skill, defined as the lagged autocorrelation of observed anomalies, was also compared with the hindcast skill. We assessed the statistical significance of the prediction skill from the initialized NWA12_HIND retrospective predictions. This was done by conducting a two-tailed t-test against a null hypothesis of no correlation, adjusting for the reduced degrees of freedom due to autocorrelation. Additionally, we compared this skill to that of persistence forecasts and the uninitialized (NWA12_HIST) simulation. For this comparison, we employed the Williams (1959) method as described in Steiger (1980) to determine the statistical significance between two dependent correlation coefficients.

Prediction probabilities and their skill

338 Probabilistic tercile predictions are developed by post-processing the model
339 forecasts using extended logistic regression (Wilks, 2009). Extended logistic
340 regression fits the probability of the outcome y exceeding a certain threshold q
341 given some data x , and is formulated as

$$342 \quad P\{y > q \mid x\} = \sigma(f(x) + g(q))$$

343 Where the logistic function $\sigma(z) = 1 / (1 + e^{-z}) = e^z / (1 + e^z)$. Here, f is a simple
344 linear function of the ensemble mean prediction x : $f(x) = \beta_0 + \beta_1 * x$, and the
345 extension function g is also a simple function of the threshold q : $g(q) = \beta_2 * q$.

346 Maximum likelihood estimation, following Minka 2001 and Pregibon 1981, is
347 used to fit the three beta parameters for each of the four forecast variables in Figure
348 7. In this method, the forecast probability is a function of only the ensemble mean,
349 and not the individual ensemble members or the ensemble spread. As is common
350 in seasonal to decadal dynamical model predictions, we find that the raw
351 ensembles tend to be overconfident, with insufficient ensemble spread (Fig. S8).

352 Furthermore, the ensemble spread has low correlation with the actual retrospective
353 forecast error. As a result, extended logistic regression provides a reasonable
354 improvement to the estimates of the forecast uncertainty,

355 For evaluating probabilistic predictions, we use accuracy as the verification metric
356 for each tercile. The accuracy is calculated as:

357 Accuracy = (True Positives + True Negatives) / Total Forecasts

358 This metric is computed independently for each tercile category. In this context, a
359 true positive occurs when the tercile with the highest predicted probability
360 correctly matches the observed tercile. A true negative occurs when the model
361 correctly assigns the highest probability to either of the other two terciles
362 (effectively predicting that observations will not fall within the tercile being
363 evaluated).

364 We also calculated the ranked probability skill score (RPSS) for each variable to
365 assess the accuracy of the predictions across all three categories. Persistence of the
366 previous year's category was used as the reference for the RPSS, so positive skill
367 scores indicate that the model forecasts have some ability to predict transitions
368 away from recent conditions.

369 The RPSS is a skill score based on the Ranked Probability Score (RPS), and the
370 Ranked Probability Score (RPS) for a single forecast is defined as

371
$$RPS = \frac{1}{K-1} \sum_{k=1}^K \left[\sum_{i=1}^k P_i - \sum_{i=1}^k O_i \right]^2$$

372 where K is the number of categories (3 in our case: below, normal, or above), P_i is
373 the cumulative forecast probability for category i , and O_i is the cumulative

374 observed probability (0 or 1) for category i . A perfect forecast, which assigns
375 100% probability to the observed category, will have an RPS = 0. Predicting a
376 100% chance of the opposite outcome (i.e., below when the outcome is above)
377 gives an RPS of 1, while predicting normal when an outcome is above gives an
378 RPS of 0.5. The RPS is notable in that it evaluates the distribution of the forecast
379 probability around the outcome, penalizing outcomes that are further away. This
380 makes RPS a more sensitive metric than accuracy.

381 The ranked probability skill score (RPSS):

382
$$\text{RPSS} = 1 - \text{RPS}(\text{forecast}) / \text{RPS}(\text{persistence})$$

383 where RPS (forecast) is the sum of the ranked probability scores comparing the
384 forecast probabilities with the observed categories, and RPS (persistence) is the
385 sum of the ranked probability scores comparing the observed categories with the
386 categories observed in the previous year (in other words, we assign 100%
387 probability to the category observed in the year before the forecast was initialized,
388 and compare that with the actual category for the next 3 years). By the definition of
389 the skill score, if RPSS = 1, the forecasts had perfect accuracy at probabilistically
390 predicting the observations. If RPSS = 0, the forecasts had the same overall score
391 as the persistence forecasts of the previous year's state; in other words, the
392 forecasts would have had no skill at predicting transitions.

Decomposition of the drivers of bottom O₂, Alkalinity and Aragonite

Saturation State (Ω_{ar})

Bottom O₂ saturation ([O₂] sat), was computed from the simulated bottom potential temperature and salinity following Garcia and Gordon (1992). DIC and alkalinity were not saved at the ocean bottom and were thus obtained by solving the carbonate system (PyCO2SYS; Humphreys et al., 2022) from the model's bottom pH and Ω_{ar} together with bottom temperature and salinity at a representative pressure of 150 dbar. The result is largely insensitive to this pressure choice—recomputing Ω_{ar} from the recovered DIC and alkalinity reproduces the simulated Ω_{ar} to within 0.01. COBALT additionally applies minor nutrient alkalinity corrections (PO₄ and SiO₄) that are omitted here, with negligible effect on the bottom anomalies.

The contributions of bottom DIC, alkalinity, temperature (T) and salinity (S) to the bottom pH and Ω_{ar} anomalies were quantified by perturbing each variable in turn about the 1994–2023 mean state; the contributions sum to the total to within 0.0045 in pH and 0.008 in Ω_{ar} . To attribute their anomalies, we used a one-factor-at-a-time perturbation about a fixed reference state defined as the 1994–2023 climatological mean of each driver, (DIC_o, Alk_o, T_o, S_o). The reference values pH_o and Ω_{aro} were obtained by solving the carbonate system at that state.

412 Four perturbation time series were constructed to estimate the contribution of each
413 driver to interannual pH and Ω_{ar} anomalies by allowing a single driver to take its
414 full annual-mean value while the other three were held fixed at their climatological
415 mean. The approximate contribution of each driver to the pH (or Ω_{ar}) anomaly in
416 year t is then the departure of its perturbed solution from the reference. For
417 example, $\Delta pH_DIC(t) = pH(DIC(t), Alk_o, T_o, S_o) - pH_o$.

418 Because the carbonate system is non-linear, the four single-driver contributions are
419 not guaranteed to add up exactly to the total anomaly; the difference is the residual
420 cross-term arising from simultaneous variation of two or more drivers. In practice
421 this residual is negligible here: the sum of the DIC, alkalinity, T and S
422 contributions reproduces the full bottom pH and Ω_{ar} anomalies to within 0.0045 pH
423 units and 0.008 in Ω_{ar} over the whole record.

Results and Discussion:

Bottom Temperature and Salinity

The regionally downscaled retrospective simulations, NWA12_EN4_NUDG, which were used to initialize retrospective forecasts, have an ensemble mean that matches the complex patterns of bottom warming and cooling in the GOM (Fig. 2a). The period from the 1980s to the mid-1990s shows a gradual warming of about 2 °C followed by cooling of the same magnitude until mid-2000s, and intensified warming from the mid-2000s to around the year 2020. This bottom variability in the regional downscaled simulations is consistent with the observed long term surface temperature variations that the Northwest Atlantic Ocean has experienced over the past century, which have been characterized by distinct multi-decadal oscillations and dramatic shifts in water mass properties that have shaped marine ecosystems from the Labrador Sea to Cape Hatteras (Wallace et al., 2018, Townsend et al., 2006; Mountain, 2012). In the late 1990s, after a long period of persistent presence of Warm Slope Water (WSW), cold and fresh Labrador Slope Water (LSW) replaced WSW along the Scotian Shelf and GOM (Drinkwater et al., 1998, Mountain, 2004; Friedland and Hare, 2007). WSW increased in prevalence again during the period from 2004 to 2020 in conjunction with an unprecedented era of accelerated surface and bottom warming in the Northwest Atlantic, making it one of the fastest-warming ocean regions globally (Pershing et al., 2015,

Friedland et al, 2020, Kavanaugh et al., 2017, duPontavice et al., 2023). Real-time Fishing Industry SHared Bottom Oceanographic Timeseries (Fishbot) data and independent observation-based datasets (Fig. 2a, Fig. S1 and Fig. S2; see also Record et al. 2024) suggest that the rapid warming has paused since the early 2020s, as predicted by earlier simulations with the downscaled regional model (Koul et al., 2024), and markedly cooler water has returned to the region in 2024. Simulated bottom salinity closely tracks bottom temperature variability (Fig 2b, Fig. S3; $r = 0.84$); noticeable differences are only seen at the shorter interannual time scales. The correlation between temperature and sparse bottom salinity observations (NOAA_SOE) is weaker but also positive ($r = 0.58$). However, confounding from seasonal and spatial variability limits the inference of annual average salinity anomalies from the sparsely observed salinity field alone. The independent GLORYS12 bottom temperature and salinity estimates, which use a high-resolution model with data assimilation to impute estimates within the spatial and temporal gaps between observations, are highly correlated with our simulation results over the shorter GLORYS record ($r = 0.86$ and $r = 0.70$, respectively) — and have a similarly strong bottom temperature and bottom salinity covariance (Fig 1b, Fig. S3, $r = 0.84$ versus $r = 0.90$).

Bottom Oxygen, pH and Aragonite Saturation Ratio

463 The water mass variations described above are also accompanied by
464 biogeochemical shifts in both the model and observations (Fig. 2c-e). The annual
465 mean bottom oxygen (O_2) anomalies in the GOM show an inverse relationship
466 with bottom temperature and salinity anomalies. The warming and water mass
467 transitions described above would be expected to influence dissolved oxygen
468 concentrations through differences in O_2 concentration in water masses (Claret et
469 al., 2018), solubility effects, and potential changes in biological oxygen demand.
470 The rise in deep oxygen levels from the mid-1990s, peaking in the latter half of
471 2004 to 2005, corresponds with the cool, fresh, high LSW conditions well
472 documented in the observational record (Mountain, 2012; Feng et al., 2016). LSW
473 is high in oxygen due to high solubility and rapid oxygen uptake during its
474 formation in the Labrador Sea (Koelling et al., 2023). Since 2005 the bottom
475 oxygen levels have largely dropped, aside from episodic increases in 2015, 2019,
476 and 2024. The relationship between internal (natural) variations in bottom
477 temperature and bottom O_2 confirms that the proportion of WSW/LSW in the
478 Northeast Channel acts as an important driver of this co-variability, though
479 meteorologically linked variations in the winter mixed layer also dictate large
480 episodic variations in bottom O_2 (Fig. 5, Fig. S5). The close correspondence
481 between the observed Fishbot data and the modeled bottom O_2 (Fig. 3c) suggests

that our regional downscaled simulation captures the dominant mechanisms
controlling bottom oxygen variability.

The bottom pH and aragonite saturation state (Ω_{ar}) anomalies in the GOM show an
overall declining trend from 1980-2024 consistent with the uptake of steadily
increasing atmospheric CO_2 (i.e., predictable large-scale ocean acidification). The
simulated Ω_{ar} time-series, however, also exhibits more significant inter-annual to
decadal variability than the bottom pH (Fig. 2d, e), which is consistent with
Salisbury and Jonsson (2018). After removing the externally forced ocean
acidification signal, Ω_{ar} variations are positively correlated with temperature (Fig.
3, $r = 0.75$). This is consistent with the carbonate chemistry response to warming
and increased alkalinity in warm and saline WSW waters (Salisbury and Jonsson,
2018). As in Salisbury and Jonsson's surface analysis, the pronounced warming
and shift to WSW from 2010-2020 was associated with increased Ω_{ar} that
counteracted the ocean acidification trend seen in pH. The more recent shift toward
colder and fresher conditions, however, amplifies the acidification trend and causes
a sharp decrease in Ω_{ar} .

Drivers of bottom biogeochemical variability

To isolate the mechanisms underlying this bottom biogeochemical variability, we
decomposed each quantity into its controlling factors (Fig. 4). Bottom O_2 was

501 partitioned into a solubility component, the saturation concentration $[O_2]_{\text{sat}}(T, S)$,
502 and a non-solubility residual, $[O_2] - [O_2]_{\text{sat}}$, which equals the negative of the
503 apparent oxygen utilisation ($-AOU$) and reflects ventilation, respiration and
504 advection (Fig. 4a). The non-solubility residual accounts for approximately 70% of
505 the interannual variance of the bottom- O_2 anomaly ($r = 0.89$ with total O_2),
506 compared with about 21% for the solubility term. The dominant O_2 variations —
507 including the episodic maxima of 2004, 2015 and 2019 — are therefore driven by
508 ventilation of the deep basins through deep winter mixing (Fig. S5) and by the
509 changing oxygen content of the inflowing slope waters, rather than by temperature
510 and salinity-dependent solubility alone. Solubility instead imparts a smaller,
511 smoother decline as the bottom water warms.

512 For the carbonate system, we examined the bottom dissolved inorganic carbon
513 (DIC) and total alkalinity, which mix conservatively and respond in
514 straightforward ways to gas exchange, respiration and $CaCO_3$ cycling. We also
515 examine alkalinity minus DIC ($Alk - DIC$), a proxy that helps separate the
516 mechanisms driving pH and Ω_{ar} (Xue and Cai, 2020; Fig. 4b). In the model the Alk
517 $- DIC$ anomaly is nearly identical to the bottom Ω_{ar} anomaly ($r = 0.996$; Fig. 4b, d)
518 but tracks pH relatively loosely ($r = 0.82$, because pH also responds directly to
519 warming). On interannual timescales $Alk - DIC$ (and hence Ω_{ar}) is set by water-
520 mass alkalinity changes, while its long-term decline ($-2.2 \mu\text{mol kg}^{-1} \text{ decade}^{-1}$),

rising DIC outpacing a smaller alkalinity increase, is the anthropogenic acidification trend.

We attributed the bottom pH and Ω_{ar} anomalies to DIC, alkalinity, temperature and salinity (Fig. 4b–d; see Methods). Bottom DIC rises steadily at about $4 \mu\text{mol kg}^{-1} \text{decade}^{-1}$, which is the likely fingerprint of anthropogenic carbon uptake. Alkalinity varies primarily with water mass, being higher during the high-alkalinity WSW phases and lower during Labrador Slope Water phases (Fig. 4b). The long-term pH decline ($-0.013 \text{ decade}^{-1}$) is led by the rising DIC ($-0.010 \text{ decade}^{-1}$), with warming contributing a further $-0.007 \text{ decade}^{-1}$, increasing alkalinity partially buffering the trend ($+0.005 \text{ decade}^{-1}$), and salinity making up a small remainder ($-0.001 \text{ decade}^{-1}$) (Fig. 4c). The decline is thus quantitatively consistent with anthropogenic DIC uptake, modulated by warming and water-mass alkalinity.

The long-term Ω_{ar} decline ($-0.015 \text{ decade}^{-1}$) is likewise led by rising DIC, whose direct effect ($-0.035 \text{ decade}^{-1}$) is more than halved by two opposing influences: increasing alkalinity ($+0.016 \text{ decade}^{-1}$) and warming ($+0.004 \text{ decade}^{-1}$) (Fig. 4d). Warming thus raises Ω_{ar} even as it lowers pH, which, together with the larger water-mass alkalinity signal, is why the Ω_{ar} decline is weaker and less monotonic than that of pH. On interannual timescales, Ω_{ar} variability is instead governed primarily by alkalinity (about 57% of the detrended variance; $r = 0.91$ with the alkalinity contribution), with only a minor direct thermodynamic effect of

temperature. The interannual DIC anomaly is small and, because the inflowing WSW in the model does not carry elevated DIC (detrended DIC–alkalinity correlation $r = -0.28$), the DIC signal slightly reinforces rather than opposes the alkalinity-driven variability (Fig. 4d). The correlation between Ω_{ar} and temperature (Fig. 2) therefore arises largely because temperature and alkalinity co-vary through the WSW/LSW water-mass variability, rather than from a direct effect of warming on the carbonate equilibria. Bottom salinity, which co-varies strongly with bottom temperature through the WSW/LSW water-mass variations (Fig. 2a, b, Fig S3), is retained as an explicit driver of the pH and Ω_{ar} anomalies in this decomposition (Fig. 4c, d), where its direct contribution is small.

Prediction skill

Decadal prediction skill is derived from both predictable internal variability of the climate system and from predictable natural and anthropogenic external forcing (Meehl et al. 2009). Capturing the latter requires skillful representation of external drivers (e.g., accumulating CO_2) and its impact on the climate, while capturing the former requires skillful initialization of the climate system and the ability to simulate its natural evolution from that state. The analysis in Figs. 2-3 suggested that our retrospective ensemble hindcasts (NWA12_HIND) captured observed variations and covariations across bottom habitat properties, and that the prominence of externally forced and internal variability varies between critical

bottom habitat quantities. Comparison of extensive retrospective forecasts against these patterns show that some aspects of both signals were successfully predicted, but others were not (Fig. 5).

Bottom temperature predictions from NWA12_HIND exhibit significant positive anomaly correlations in most of the 10 lead years (Fig. 5a); and in the first lead year, the prediction skill exceeds the skill from the climate change signal (indicated by the diamonds and squares). Both results are consistent with a predictable bottom-temperature signal from climate change and contributions from predictable bottom-temperature (i.e., water mass) variability in the first few lead years. Closer inspection of the prediction skill after linear de-trending further supports the system's capacity to predict aspects of variability around the climate change trend over all the lead years, except at lead years 4 and 5 when the skill drops (Fig. S9). The prediction skill is robust when verified against GLORYS as the observational reference for the period 1993-2024 (Fig. S4).

Initializations at states far from the uninitialized state, the 1980s warming, the rapid 2005-2015 warming and the recent shift to cooler/fresher conditions from 2020 onward, are all correctly predicted by the retrospective predictions (Fig. 6). The 2025 forecast shows a slow reversal of the recent cooling/freshening during the next decade. These results could be interpreted as the model simply relaxing

580 toward the uninitialized state. However, the overall good correlation skill indicates
581 that the model accurately captures the timing and magnitude of such transitions.

582 The prediction skill for bottom O₂ drops to 0 beyond 2 years and much of the
583 signal for this important habitat factor is linked to predictable internal (natural)
584 variability (Fig. 5b). This is also apparent from the time series (Fig 2c) which
585 shows that bottom O₂ does not have a uniform long-term trend as was the case for
586 bottom temperature. The rapid drop in prediction skill may also be linked to the
587 presence of sharp and likely less predictable meteorologically driven variations in
588 the depth of the winter mixed layer. The winter 2003/04 is a prime example of this
589 phenomenon when large positive winter MLD anomalies in our regional
590 downscaled model drove ventilation of the bottom water and strong positive
591 bottom oxygen anomalies (Fig. 6, Fig. S5). Similar peaks in bottom O₂ coinciding
592 with deep winter mixing and positive MLD anomalies are seen in 2015 and 2019.

593 The decadal predictions initialized before and after the 2004 peak (in 2002 and
594 2006 respectively) show that the ensemble mean prediction has difficulties
595 predicting the extent of the rise in bottom O₂, but the subsequent decay of these
596 elevated bottom O₂ levels is well predicted by the model (Fig 6b). These
597 characteristics of the past variability in bottom O₂ are consistent with the high skill
598 of the initialized predictions, which outperform the persistence-based skill and the

skill of uninitialized simulations in the first two lead years (Fig 5b), and the significant drop thereafter.

Both bottom pH and Ω_{ar} exhibit a declining trend (Fig 2e, f), yet they differ in how much the climate change signal influences their prediction skill. Ocean pH is primarily controlled by increasing atmospheric CO₂, while Ω_{ar} is more strongly influenced by ocean water masses with varying alkalinity (LSW versus WSW). As a result, internal variability contributes more to the prediction skill of Ω_{ar} , whereas the climate change signal has a greater impact on the prediction skill of bottom pH (Fig 5 c,d). Beyond lead year 2, the climate change signal predominantly determines the prediction skill of bottom pH, allowing it to remain high and significantly better than persistence for all lead years (except lead year 3) which is not the case for Ω_{ar} where the skill drops rapidly beyond lead year 2. When the linear trend is removed, the skill of internal variability significantly surpasses the persistence and climate change-driven skill in the first two lead years. The notable decrease in the prediction skill of detrended bottom pH, compared to Ω_{ar} , further demonstrates the additional contribution of internal variability to the prediction skill of Ω_{ar} . Individual 10-year forecasts provide further evidence of the capability of the model to track past deviation of bottom pH and Ω_{ar} from the long-term trend (Fig 6 c,d).

Probabilistic predictions

619 The preceding analyses leveraged over 6500 years of retrospective forecasts to
620 assess the capacity of the ensemble mean prediction to anticipate physical and
621 biogeochemical changes on a decadal time horizon. While results suggested
622 significant capability arising from predictable climate variability and change
623 signals, decision-making benefits from actionable information on uncertainties
624 (e.g., Ramos et al. 2013, Roulston et al. 2006). A coastal resource manager or
625 fishing industry representative might ask, “How reliable are forecasts for
626 anomalously warm or cool conditions?” To quantify this in more accessible terms,
627 we calculated the accuracy of probabilistic forecasts derived from the model
628 simulations (Tommasi et al. (2017a), see Methods). We used terciles to define
629 above, normal, and below-normal conditions and focused on predicted conditions
630 averaged over the next 3 years, which corresponds to typical stock assessment
631 timelines in actively managed fisheries (Tommasi et al., 2017b). Extended logistic
632 regression (Wilks et al., 2009) was used to calibrate forecast uncertainty based on
633 the forecast error (see Methods).

634 Our regional downscaled predictions skilfully distinguish between tercile classes.
635 All four variables have positive ranked probability skill scores, and the forecast
636 accuracy for a given tercile exceeds the accuracy of a random forecast (0.56) and
637 the accuracy of consistently negative prediction (0.67) in all but two cases (Fig. 7).
638 The ensemble confidently predicted the observed cooling in the mid-2000s and the

639 subsequent warming phase that extended from 2005 to approximately 2020 (Fig.
640 7).

641 The RPSS for all quantities is > 0 , indicating the model has some capacity to
642 anticipate changes (i.e., probabilistic skill beyond the persistence forecast, see
643 Methods). Oxygen has slightly lower skill (RPSS 0.46, accuracy 0.67-0.81)
644 compared to bottom temperature (RPSS 0.47, accuracy 0.72-0.90), reflecting both
645 the weak predictable climate change signals and the influence of less predictable
646 atmospheric variability. Similarly, predictions for bottom pH, which has a very
647 strong predictable climate change signal, have higher skill (RPSS 0.6, accuracy
648 0.76-0.88) than Ω_{ar} (RPSS 0.51, accuracy 0.62-0.79).

649 The high accuracy of prediction for bottom temperature, O_2 , pH and Ω_{ar} likely
650 reflects both methodological and mechanistic factors. The bottom temperature, O_2 ,
651 pH and Ω_{ar} are validated against the same regional downscaled simulation from
652 which initial conditions were derived (see Methods). While this simulation
653 recreates observed O_2 patterns and covariances with well-constrained physical
654 properties to the extent that they have been observed (Figs. 2-3, Fig. S7), it should
655 be viewed as an upper limit for prediction skill. Additional autonomous
656 biogeochemical observing platforms capable of observing shelf environments may
657 help address this limitation in the future (Henson 2014, Chai et al., 2020).

658 Looking ahead over the next three years (2025-2027), we forecast below-normal
659 bottom temperatures with high confidence (88.3% probability), supported by
660 93.3% retrospective accuracy when issuing similar high confidence forecasts
661 (14/15 hits). We also predict above-normal bottom O₂ levels with high confidence
662 (92.0% probability), with an 85.7% retrospective accuracy at comparable
663 confidence levels (6/7 hits). Additionally, we forecast with very high confidence
664 (>99% probability) both below-normal bottom pH and below-normal Ω_{ar}
665 conditions, both of which are supported by perfect retrospective accuracy when
666 issuing very high confidence forecasts, albeit with limited sample size (9/9 hits and
667 1/1 hit respectively). While these forecasts represent our best estimate, both the
668 confidence levels and the underlying sample sizes should be considered when
669 making decisions based on these predictions, particularly for the forecasts where
670 limited similarly confident historical forecasts constrain our ability to fully validate
671 forecast skill. Nevertheless, the dynamically consistent physical and
672 biogeochemical forecasts provide compelling evidence that the ongoing watermass
673 reorganization will continue to influence bottom water conditions through the
674 2025-2027 period.

675 **Discussion: Towards the Future of Fisheries Management**

676 Future projections indicate the entire GOM will experience suboptimal aragonite
677 saturation for most of the year by 2050 under high emissions scenarios (Siedlecki
678 et al., 2021). The region's demonstrated sensitivity to water mass-driven alkalinity
679 variations makes it particularly vulnerable to rapid acidification once rising CO₂
680 exceeds the buffering ability of the projected increased Gulf Stream water,
681 potentially triggering swift transitions to persistently corrosive conditions that
682 could impact economically vital shellfish industries (Ekstrom et al., 2015).

683 Although the recent transition from a decade of warm water influence to emerging
684 cold water conditions across portions of the Northeast U.S. Continental Shelf,
685 including the deep GOM (Record et al., 2024), may buy time for fisheries to adapt
686 to the projected long-term warming trend, it also may accelerate or alter the
687 projected biogeochemical shifts.

688 We assessed the decadal prediction skill for the Gulf of Maine, a semi-enclosed
689 body of water on the Northeast U.S. Continental Shelf. While the patterns of
690 prediction skill that emerged from the interplay of climate change signals and
691 variability were unique to each quantity and the Gulf of Maine, other coastal
692 regions are subject to similar oceanic and atmospheric forcing (Shearman and
693 Lentz, 2010) and may present opportunities for bottom-habitat prediction. The
694 ubiquity of sea surface temperature prediction skill in coastal systems at seasonal
695 and decadal scales provides grounds for optimism (Stock et al., 2015; Tommasi et

al., 2017b). The methodologies employed herein, while computationally intensive, provide a robust means to diagnose the origins of predictive skill and attach probabilities critical to making forecast information actionable for management applications.

More frequent and extensive observations of the ocean, including deep ocean biogeochemistry, are essential for increasing confidence in the accuracy of the forecasts and providing confirmation of predicted changes (Capotondi et al. 2019). Observations are especially important for verifying interannual to decadal scale ocean predictions, where long time series are necessary to verify that the predictions have more skill than simple forecasts of the forced signal or autocorrelated noise. Here, given the scarcity of past deep alongshelf biogeochemical observations, we utilized a numerical model as the reference for forecast verification. This downscaled simulation was validated using the best available observations (Fig 2, Fig. S1, Fig. S2, Fig. S3, Fig. S6 and Fig. S7). Consequently, the reported skill represents potential skill and may be an overestimation. However, the model successfully simulated observed variability in bottom temperature and salinity and captured the expected covariance between these two variables and the bottom biogeochemistry. Koul et al. (2024) also demonstrated forecast skill for surface temperature when compared against actual observations. Furthermore, the model is likely accurate in predicting much of the

716 forced component of skill, which is driven by steadily increasing greenhouse gas
717 concentrations and resulting impacts on ocean warming and chemistry.

718 Our forecasts of continued cooling alongside below-normal bottom pH, Ω_{ar} and
719 above-normal bottom O₂ levels through 2027 reveal the substantial biogeochemical
720 fingerprint of this water mass transition and potentially offer stakeholders lead time
721 to anticipate ecosystem shifts. Skillful forecasts on these multi-year timescales can
722 meet critical needs of fishers, managers, conservationists, and other stakeholders
723 (Link et al., 2023; Saba et al., 2023). The framework developed here, consisting of
724 a computationally efficient regional model that downscales regularly updated
725 global predictions, is well positioned to meet these needs and is intended to be
726 transitioned towards operational use through NOAA's Changing Ecosystems and
727 Fisheries Initiative. Recognizing that marine resource management is a wicked
728 problem (Jentoft and Chuenpagdee 2009; Rittle and Webber, 1973), however,
729 careful application-specific analyses of the potential costs, benefits, and tradeoffs
730 of using these forecasts for decision-making will be necessary.

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746 **Data Availability**

747 The processed model output and the observations used in this research are publicly
748 available via zenodo (doi: 10.5281/zenodo.16985350)

749 **Code Availability**

750 The regional MOM6 model's source code can be accessed at
751 <https://github.com/NOAA-GFDL/CEFI-regional-MOM6>. MOM6 operates on an
752 open development framework, with Git repositories at [https://github.com/mom-](https://github.com/mom-ocean/MOM6)
753 [ocean/MOM6](https://github.com/mom-ocean/MOM6) and <https://github.com/NOAA-GFDL/MOM6>. Source code for other
754 model components is also available at <https://github.com/NOAA-GFDL>.

755 **Author contributions**

756 V.K., A.C.R., and C.S. conceptualized the research and drafted the initial
757 manuscript. V.K. was responsible for conducting model simulations, performing
758 decadal predictions, post-processing model outputs and observations, and
759 generating the corresponding figures. A.C.R. and C.S. contributed in designing and
760 discussing relevant prediction skill metrics. TD, AW, and LZ developed the
761 SPEAR global prediction model. All authors contributed to the analysis and
762 interpretation of results, as well as the editing of the paper.

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765 **Ethics declarations**

766 **Competing interests**

767 At least one of the (co-)authors serves as editor for the special issue to which this
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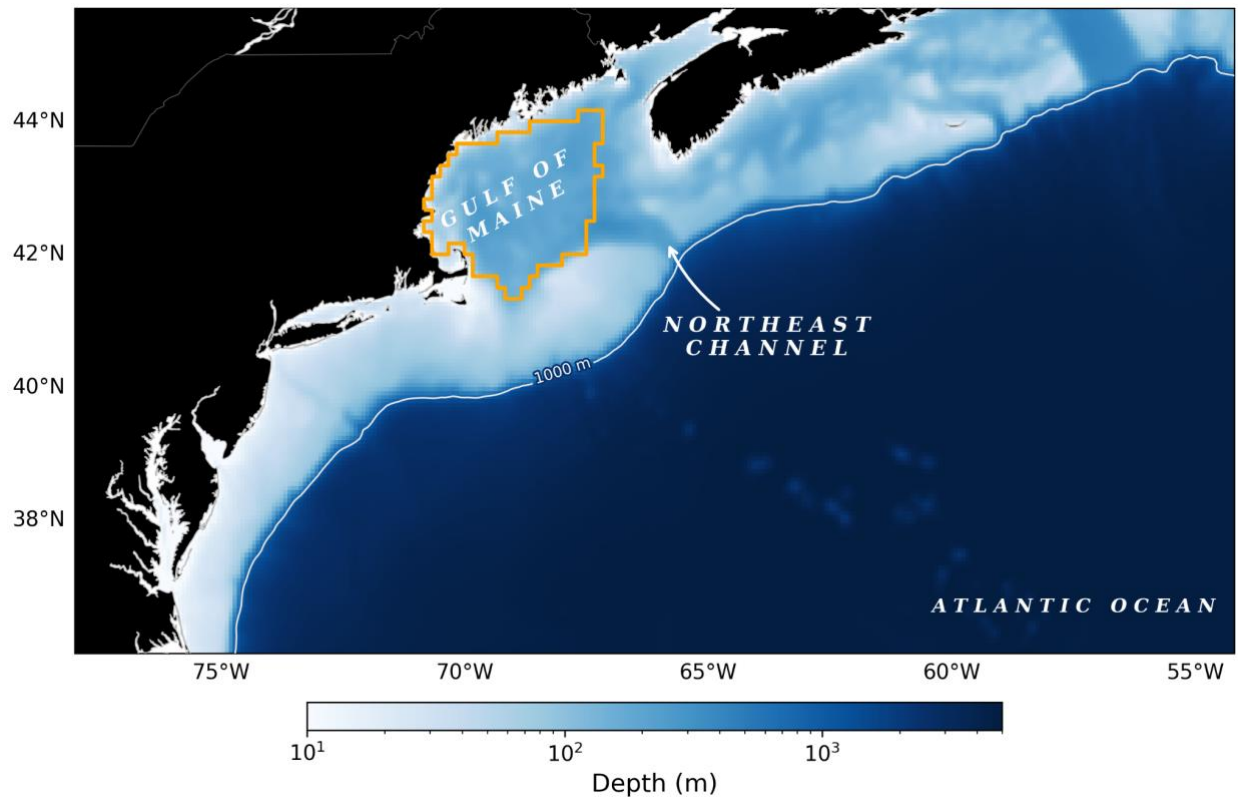
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1164 **Fig 1: The study region and its characteristics.** The locations of the Gulf of Maine Ecological
 1165 Production Unit (GOM_EPU) and the Northeast Channel along the Northeast US continental shelf are
 1166 shown along with the model bathymetry and the 1000-meter isobath (white line).

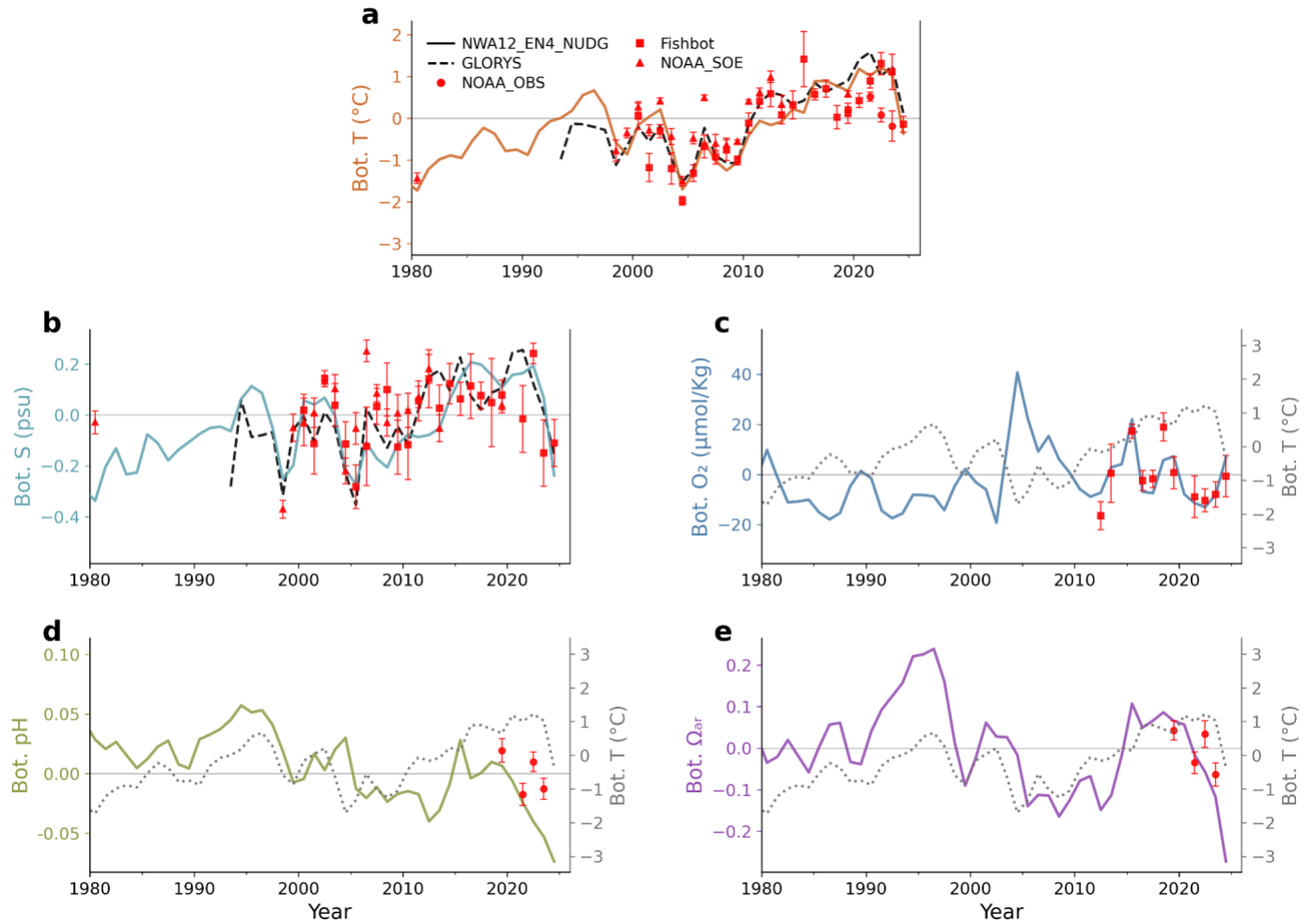


Fig 2: Physical and biogeochemical variability in the GOM. Annual mean anomalies of (a) bottom temperature ($^{\circ}\text{C}$) (b) bottom salinity (psu) (c) bottom oxygen ($\mu\text{mol/kg}$), (d) bottom pH and (e) bottom aragonite saturation state in the GOM from the ensemble mean of the regional downscaled simulations (NWA12_EN4_NUDG, colored solid lines) and observations (markers with error bars). Observations from the NOAA SOE reports (NOAA_SOE, triangles), the Fishbot bottom data (squares) and the aggregated point observations from vessels and gliders (NOAA_OBS, circles) are also shown for available years. The error bars depict the uncertainty of the annual mean (see Methods). The dashed black lines in (a) and (b) are from the GLORYS12 dataset. All anomalies are calculated with respect to the 1994-2023 mean. To highlight physical and biogeochemical co-variability, bottom temperature lines are shown as dotted grey lines in (c)-(e).

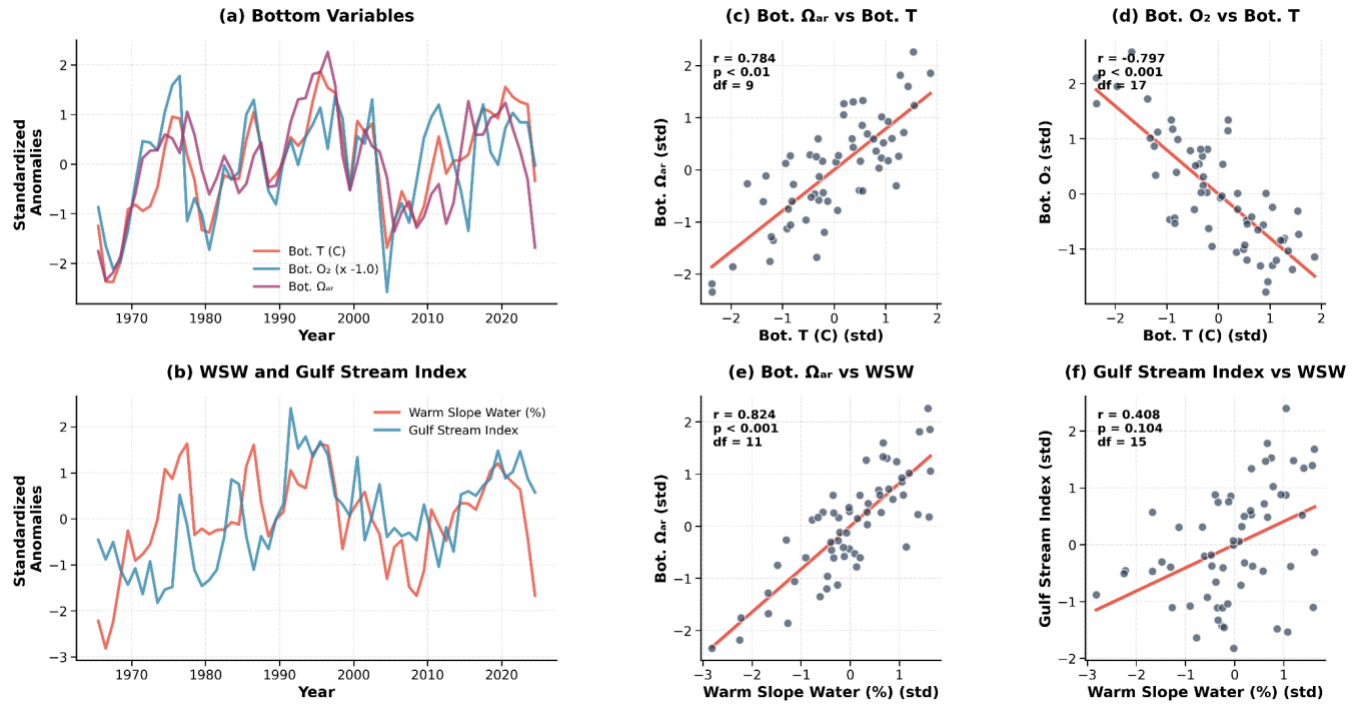


Fig. 3: Drivers of internal co-variability in the GOM. Standardized anomalies (with respect to 1994-2023 period) of the internal (natural) component of the annual mean (a) bottom temperature, bottom O_2 and bottom Ω_{ar} in the GOM (b) percentage of warm slope water (WSW) in the Northeast Channel and the Gulf Stream Index from the regional downscaled simulations. Also shown are scatterplots of internal components of (c) bottom temperature and bottom Ω_{ar} , (d) bottom temperature and bottom O_2 , (e) WSW and bottom Ω_{ar} and (f) WSW and the Gulf Stream Index, along with the linear regression fit (red line). The Pearson correlation coefficient (r), the associated p -value and the degrees of freedom (df) are also provided for each pair of variables. The internal component is the difference between the ensemble mean of the downscaled simulation (NWA12_EN4_NUDG) and the ensemble mean of the uninitialized downscaled simulations (NWA12_HIST). The bottom oxygen in (a) is multiplied by -1.0 to show its covariability with bottom temperature.

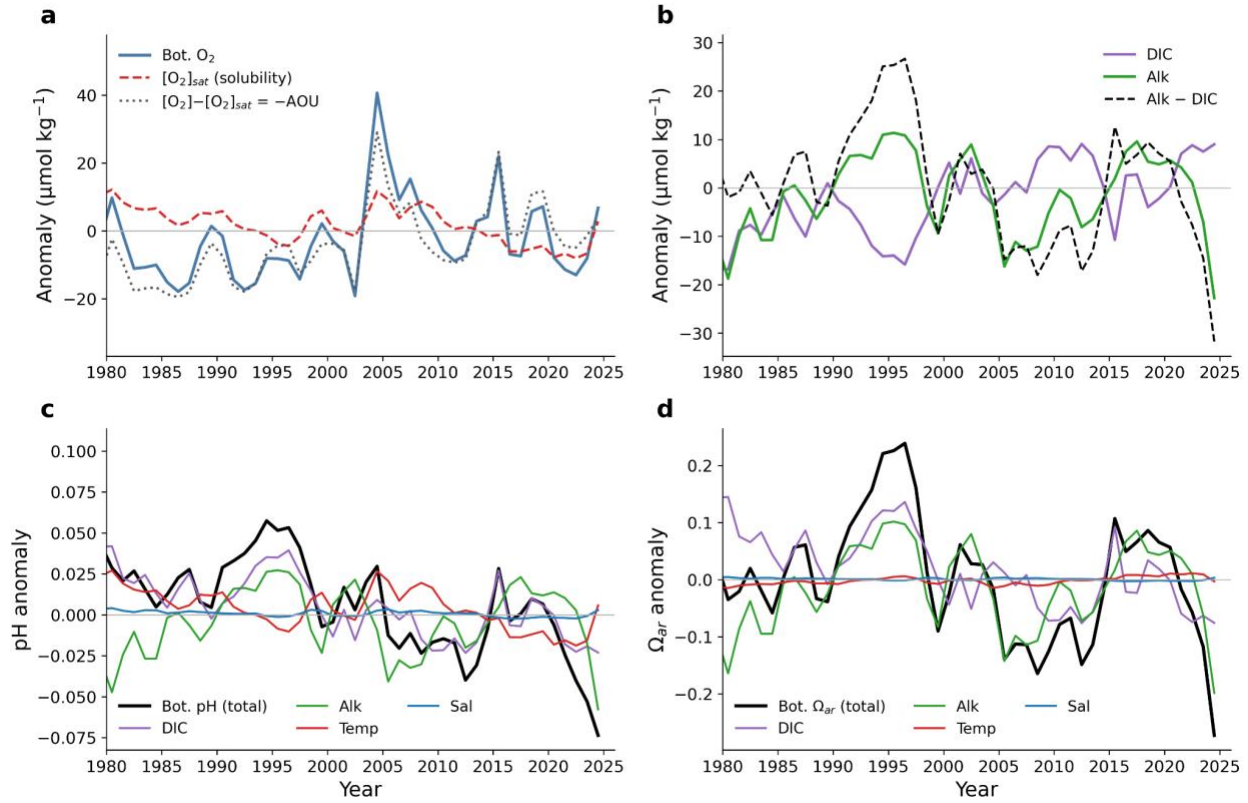


Figure 4: Decomposition of bottom-water biogeochemical variability in the Gulf of Maine. (a) Bottom- O_2 anomaly partitioned into the solubility term $[O_2]_{sat}$ and the non-solubility residual $[O_2] - [O_2]_{sat} (\approx -AOU)$ in the NWA12_EN4_NUDG retrospective simulation (ensemble mean anomalies relative to 1994–2023). (b) Bottom dissolved inorganic carbon (DIC), total alkalinity (Alk) and $Alk - DIC$. (c, d) Attribution of the bottom (c) pH and (d) Ω_{ar} anomalies to DIC, Alk, temperature and salinity, obtained by perturbing each driver about the 1994–2023 mean state; the black line is the total anomaly (see Methods).

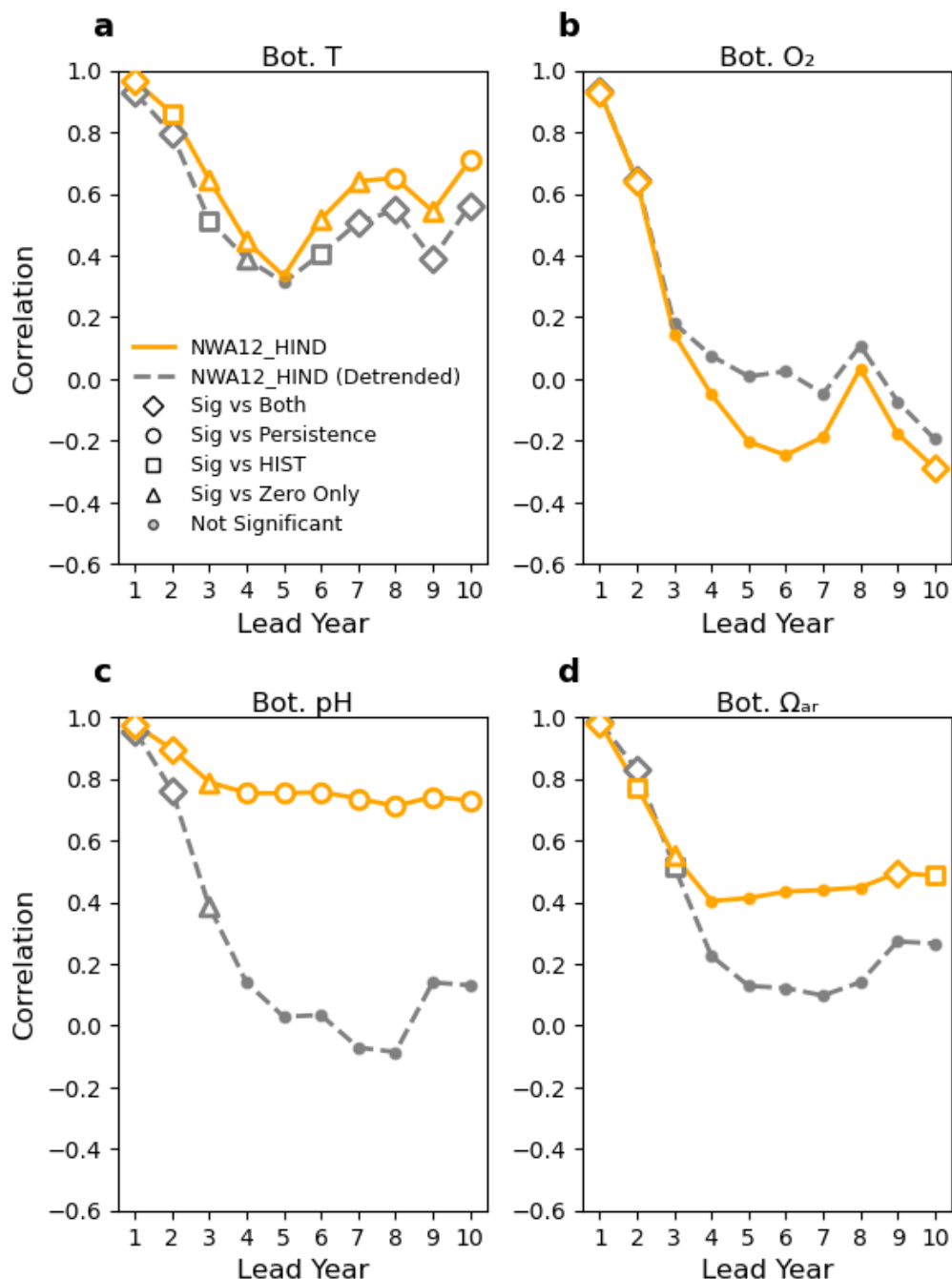


Fig. 5: Decadal prediction skill. Anomaly correlation coefficient of the annual mean anomalies from the initialized regional downscaled model (NWA12_HIND) predictions. The symbols indicate statistically significant differences relative to alternative models of no correlation, persistence, and the uninitialized (historical) simulation (see Methods). The correlation is calculated against the regional downscaled simulation (NWA12_EN4_NUDG)-derived annual mean anomalies (ensemble mean) for (a) bottom temperature (b) bottom O₂ (c) bottom pH and (d) bottom Ω_{ar} over the GOM_EPU. The prediction and persistence skills are calculated for the common 1965-2024 period. The grey dashed lines show skill for the linearly detrended annual mean anomalies.

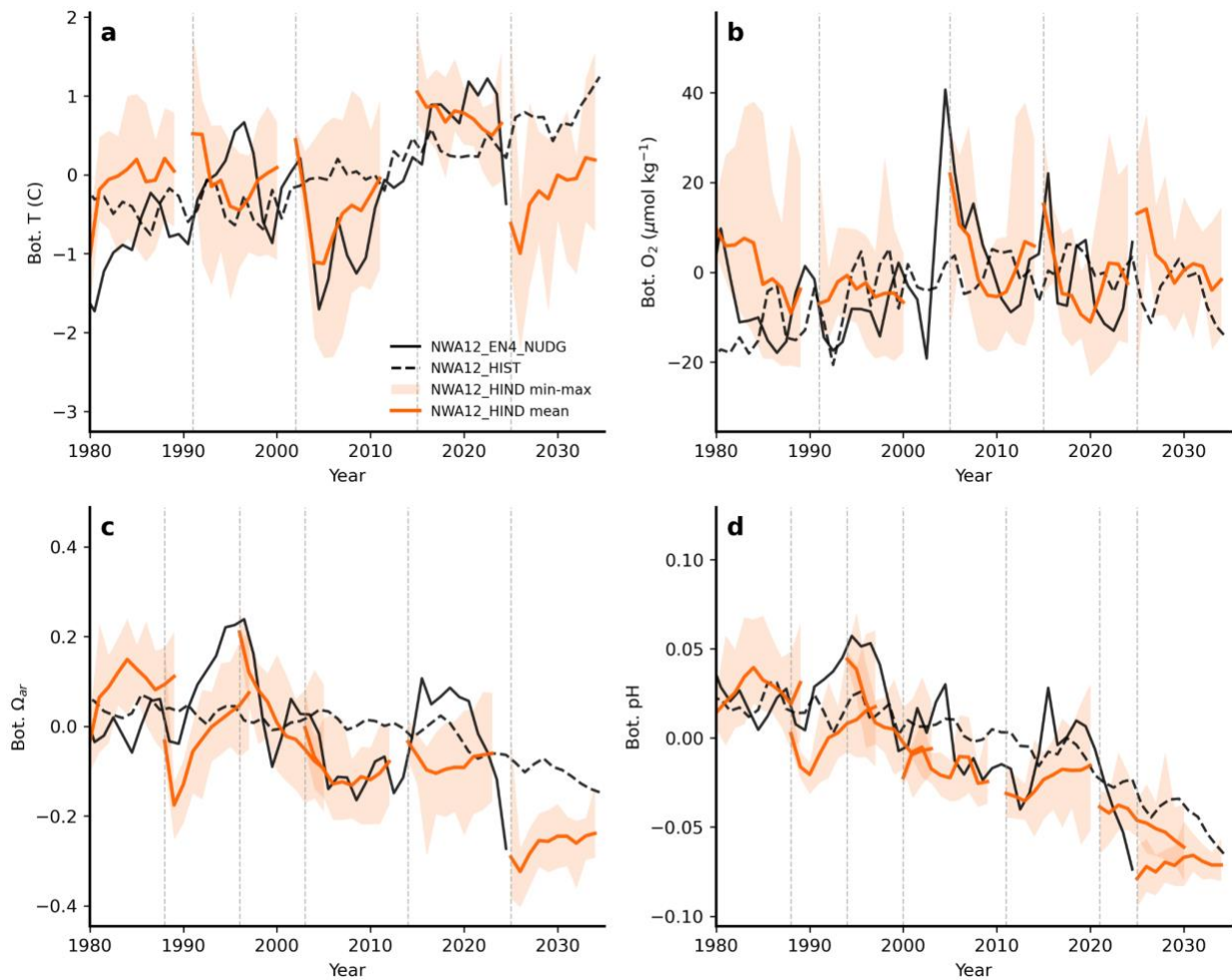


Fig. 6: Physical and biogeochemical predictions in the GOM. Annual mean anomalies of (a) bottom temperature (°C) (b) bottom oxygen ($\mu\text{mol/kg}$), (c) bottom aragonite saturation state and (d) bottom pH in the GOM_EPU. The solid black lines show the anomalies from the ensemble mean of regional downscaled simulations (NWA12_EN4_NUDG, as in Fig. 2), the dashed black lines show the ensemble mean of uninitialized downscaled model simulations (NWA12_HIST) carried under historical anthropogenic forcing and SSP585 emissions scenario. The bold orange lines show the 10-yearlong initialized prediction (NWA12_HIND) and the vertical grey lines depict their year of initialization. The bold orange lines are the ensemble means of the respective 10-member ensemble, and the light shading is the min-max range of the ensemble members. A lead-time-dependent climatology was removed from each ensemble member to create anomalies. All anomalies are calculated with respect to the 1994–2023 mean.

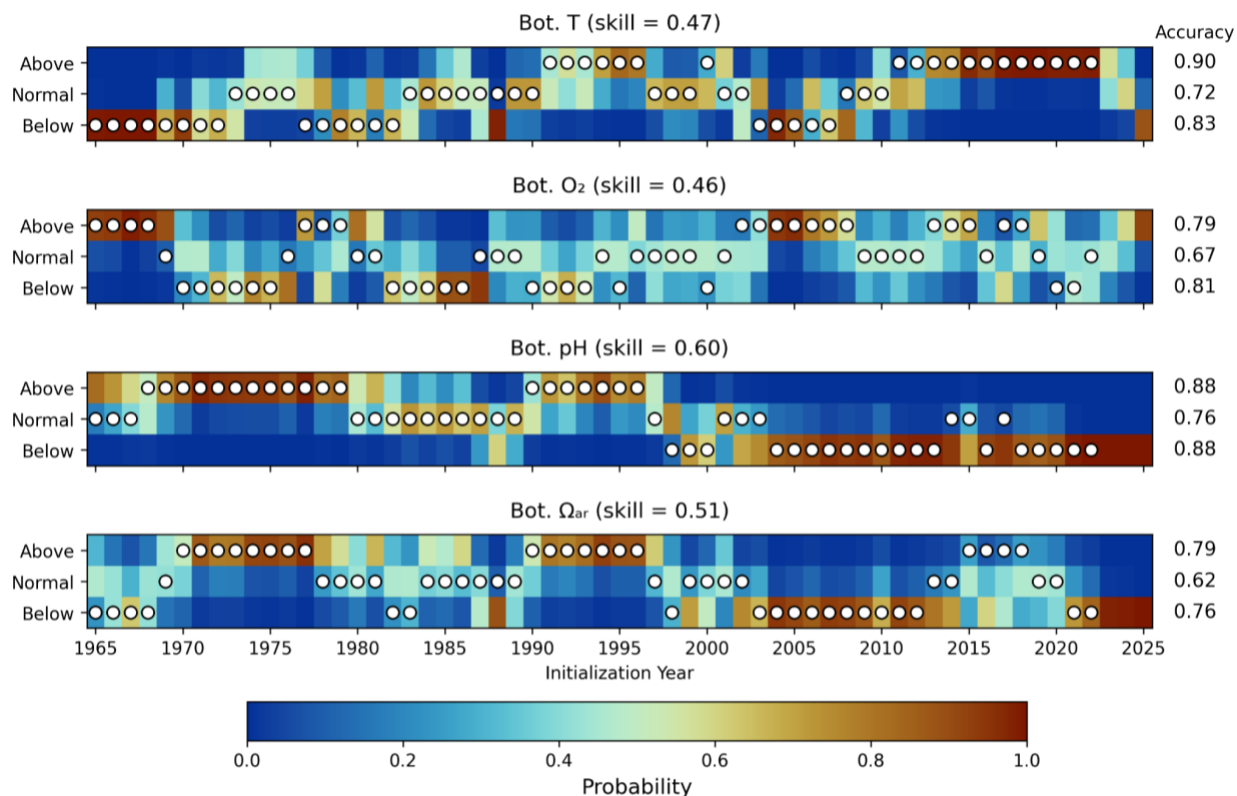


Fig. 7: Probabilistic predictions for the GOM. Probability of the predicted lead 1-3 year mean anomalies (with respect to the 1994-2023 mean) of (a) bottom temperature, (b) bottom O₂ (c) bottom pH and (d) bottom Ω_{ar} from the regional downscaled decadal prediction model (NWA12_HIND). The corresponding classifications of the reference anomalies are shown as white circles from the regional downscaled simulation (NWA12_EN4_NUDG). The tercile boundaries are calculated separately for the predictions and reference/observations. The x-axis shows the initialization year and the 2025 forecast. The forecast accuracy, (True Positives+True Negatives)/Total forecasts, for each tercile is shown on the right. A random forecast that randomly picks one tercile as most likely for each forecast has an accuracy of 0.56 and the accuracy of a consistently negative (counter) prediction is 0.67. The forecast skill compared to persistence is given in the subtitle of each panel.

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	NWA12_EN4_NUDG	NWA12_HIND	NWA12_HIST
Simulation type	Continuously running simulation, 1960-2024	10 year predictions	Continuously running simulation, 1960-2034
Purpose	Proxy for actual ocean state, initial conditions for forecasts	Forecast skill assessment	Isolates predicted effect of greenhouse gas forcing
Number of ensemble members	10	10	10
Atmospheric forcing and open boundary conditions	SPEAR_LO global coupled reanalysis	SPEAR_HIND decadal predictions	SPEAR_HIST uninitialized simulations
Initial conditions	SPEAR_LO global coupled reanalysis followed by spin up	NWA12_EN4_NUDG	NWA12_EN4_NUDG
Nudging	EN4 temperature and salinity, waters > 1000 m	SPEAR_HIND near northern boundary	SPEAR_HIST near northern boundary

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Table 1. Overview of the three types of downscaled experiments presented in this study, focusing on the differences between the experiments.