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Seasonal prediction of ocean biogeochemistry in the Northeast U.S. Large Marine Ecosystem using a regional ocean-biogeochemistry model

Andrew C. Ross[1], Charles A. Stock[1], Vimal Koul[2,3], Liwei Jia[1], Nathaniel C. Johnson[1], and Colleen McHugh[4]

[1]NOAA/OAR/Geophysical Fluid Dynamics Laboratory, 201 Forrestal Road, Princeton, NJ 08540, USA
[2]Princeton University Cooperative Institute for Modeling the Earth System, 201 Forrestal Road, Princeton, NJ 08540, USA
[3]Now at Centre for Atmospheric Sciences, Indian Institute of Technology Delhi
[4]Science Applications International Corporation, Reston, VA 20190, USA

Correspondence: Andrew C. Ross (andrew.c.ross@noaa.gov)

Abstract. We couple an ocean biogeochemical model to a regional ocean model of the Northwest Atlantic and assess the potential skill of bottom dissolved oxygen, aragonite saturation state, and pH forecasts along the Northeast U.S. Continental Shelf using a reanalysis-forced model run as the true biogeochemical state. Across 30 years of retrospective forecasts initialized four times per year, the model has substantial potential skill for all three variables, with skill generally highest in the deep Gulf of Maine and lowest in the shallower Mid-Atlantic Bight and Georges Bank. Forecasts initialized in January and April benefit from the insulation of the bottom from the unpredictable atmosphere by stratification and tend to have greater skill at longer lead times. Using two case studies, we show how predictable variations in ocean temperature, salinity, and currents are associated with predictable variability in bottom biogeochemistry in both the Mid-Atlantic Bight and Gulf of Maine. The forecast model evaluated in this study has been developed as an operational prototype for NOAA's Changing Ecosystems and Fisheries Initiative, with the goal of applying the forecasts to improve the yield and sustainability of living marine resources.

1 Introduction

Skillful forecasts of ocean environmental conditions and associated ecosystem responses on seasonal to interannual time scales have the potential to improve the vitality of coastal economies and fisheries and the management of living marine resources. Tommasi et al. (2017) found that harvest guidelines for Pacific sardine that incorporated predicted sea surface temperatures improved both the stock biomass and yield of the fishery. Norton et al. (2023) demonstrated that seasonal forecasts of ocean conditions can improve forecasts of catch per unit effort in the Oregon and Washington Dungeness Crab fishery and can inform management decisions on fishery opening and closing dates. In the same region, Jin et al. (2024) showed that regularly updated predictions about the presence of *Pseudo-nitzschia* diatoms and neurotoxic domoic acid, based on recent observations, weather forecasts, and information about ENSO and other climate modes, provided positive economic value to fisheries managers, the seafood industry, and recreational fishermen. Wu et al. (2023) found that including predicted chlorophyll-a concentrations in addition to sea surface temperature and height information improved their predicted skipjack tuna distribution. At slightly

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longer time scales, Park et al. (2019) used skillful two-year forecasts of chlorophyll to produce skillful forecasts of fish catches in several Large Marine Ecosystems (LMEs). By exploiting a lagged relation between chlorophyll and catch in the Agulhas Current and Somali Coastal Current LMEs, they were able to extend these two-year chlorophyll forecasts into three-year catch forecasts.

Most demonstrations of skillful ocean environment and ecosystem predictions at seasonal time scales have centered on ocean regions with a strong influence from the El Niño Southern Oscillation (ENSO), the most predictable mode of seasonal climate variability (Tang et al., 2018). Instead, in this study, we focus on seasonal prediction for the Northeast U.S. Large Marine Ecosystem. Though not strongly influenced by ENSO (Drinkwater et al., 2009; Shin and Newman, 2021), this ecosystem has nevertheless exhibited large seasonal to interannual variability across ocean physics, biogeochemistry, and ecology. Most prominently, a "regime-shift" occurred in the late 2000s (Friedland et al., 2020a, b; Smith et al., 2012), which was demarcated by a reduced inflow of cool, fresh Labrador Slope Water (LSW) (Greene et al., 2013; Seidov et al., 2021) and an increased presence of Gulf Stream-influenced Warm Slope Water (WSW) concurrent with more frequent shedding of warm-core eddies from the Gulf Stream (Gangopadhyay et al., 2019, 2020) and more frequent intrusions of high-salinity water (Gawarkiewicz et al., 2022). Remarkable variability has also been observed over shorter space and time scales, including deep mixing in the winter of 2004 that dramatically cooled the deep water in the Gulf of Maine (Taylor and Mountain, 2009) and severe marine heatwaves (Friedland et al., 2024). Recently, cool and fresh waters suggestive of a return of LSW have appeared in the Gulf of Maine (Record et al., 2024), consistent with the forecast for a temporary return of LSW and pause in the rapid warming by Koul et al. (2024).

These physical ocean changes have been associated with numerous biogeochemical and ecosystem changes. Shifts in the water masses entering the region from cooler, newer, and lower alkalinity Labrador Slope and Scotian Shelf Water towards warmer, older, and higher alkalinity WSW have led to lower dissolved oxygen (Claret et al., 2018) but also helped reduce the impact of rising atmospheric CO_2 concentrations on ocean acidification (Salisbury and Jönsson, 2018; Stewart et al., 2025). Intrusions of saline water associated with Gulf Stream warm core rings have been identified as strong predictors of changes in the phenology of larval fish (Weisberg et al., 2024). Early and rapid increases in lobster landings in 2012 and 2016 were successfully predicted based on unusually warm early spring temperatures (Mills et al., 2017; Pershing et al., 2018), although these predictions had unexpected side effects on the local economy (Hobday et al., 2019). Lobster fishers have recently noted unpredictable variability in the timing of lobster sheds and the sizes of lobsters, leading them to express interest in having ocean forecasts to understand and predict these changes (Mason et al., 2024).

Despite this history of large and impactful ocean and ecosystem variability, the Northeast U.S. LME has proven challenging to predict with the coupled global models typically used for seasonal and decadal prediction (e.g., Stock et al., 2015; Hervieux et al., 2017). In addition to the weak seasonal predictability of relevant climate modes in the region, a major driver of lower regional skill is the mismatch between the coarse spatial resolution of most global coupled models and the fine spatial scales over which processes that drive variability in the region occur. Most importantly, the separation of the Gulf Stream from the shelf near Cape Hatteras, which is essential to reproduce in order to predict the downstream ocean, requires a resolution of at least 1/10° to simulate correctly (Chassignet and Marshall, 2008; Chassignet and Xu, 2017, 2021). Coupled global models have

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typically employed much coarser ocean resolutions, generally between 1/4° and 1°, due to the ballooning of computational costs as resolution becomes higher (e.g., Delworth et al., 2020). Resolutions on the order of 1/10° are also necessary to represent regional topographic features, such as the Northeast Channel through which deep water can enter the Gulf of Maine (Saba et al., 2016). Properly representing the shelf/slope exchanges and intrusions of deep water potentially requires even higher spatial resolution (Chen, 2025).

Experiments that downscaled lower-resolution global models with higher-resolution regional ocean models have confirmed that skillful predictions of physical oceanographic variables in the Northeast U.S. LME are possible with improved model resolution. Ross et al. (2024) used a regional ocean model with 1/12° resolution to downscale forecasts from the SPEAR global coupled model (Delworth et al., 2020; Lu et al., 2020), which was run using its medium-resolution configuration with a 1° ocean model and 1/2° atmosphere model. They found that the downscaled model had significantly higher prediction skill for monthly surface and bottom temperature and surface salinity anomalies. Models based on empirical relationships have also confirmed that it is possible to skillfully predict regional ocean variability. Shin and Newman (2021) found that a linear inverse model typically had higher skill than a multimodel ensemble of global coupled models for regional sea surface temperature and height. Chen et al. (2021) developed a statistical model using persistence and advection to skillfully predict seasonal bottom temperature variability along the Northeast U.S. shelf.

As discussed above, physical oceanographic signals are often accompanied by biogeochemical changes that can affect living marine resources, including changes in oxygenation and acidity. In this study, we build on the study of seasonal forecasts of physical oceanographic variables in Ross et al. (2024) by adding a coupled biogeochemistry model and evaluating the potential prediction skill for three primary biogeochemical variables: bottom oxygen, pH, and aragonite saturation state, chosen for relevance to demersal fisheries including American lobster (*Homarus americanus*; Harrington et al., 2020; Keppel et al., 2012), Black sea bass (*Centropristis striata*; Bandara et al., 2024), and Atlantic sea scallop (*Placopecten magellanicus*; Wright-Fairbanks et al., 2025). Potential skill is assessed by evaluating 30 years of retrospective forecasts initialized 4 times per year with 10 ensemble members in every forecast. We also examine two case studies in detail: an intrusion of Gulf Stream water with low dissolved oxygen onto the Mid-Atlantic Bight, and a comparison of advection of water masses into the Gulf of Maine during two consecutive winter and spring periods and associated differences in acidity.

2 Methods

2.1 Numerical model

The high-resolution coupled ocean-sea ice-biogeochemical model used in this study is MOM6-COBALT-NWA12. This model was first described in Ross et al. (2023) and was used to run seasonal predictions without biogeochemistry by Ross et al. (2024). Here we only briefly describe the model; both references provide complete information. The MOM6-COBALT-NWA12 model domain covers a large swath of the Northwest Atlantic Ocean with a nominal 1/12° horizontal resolution (Fig. 1). The model has 75 vertical layers using a z* coordinate (Adcroft and Campin, 2004). Data from the land and atmosphere are used to force the coupled ocean, sea ice, and ocean biogeochemistry components. In Ross et al. (2023) and Ross et al. (2024), this data was

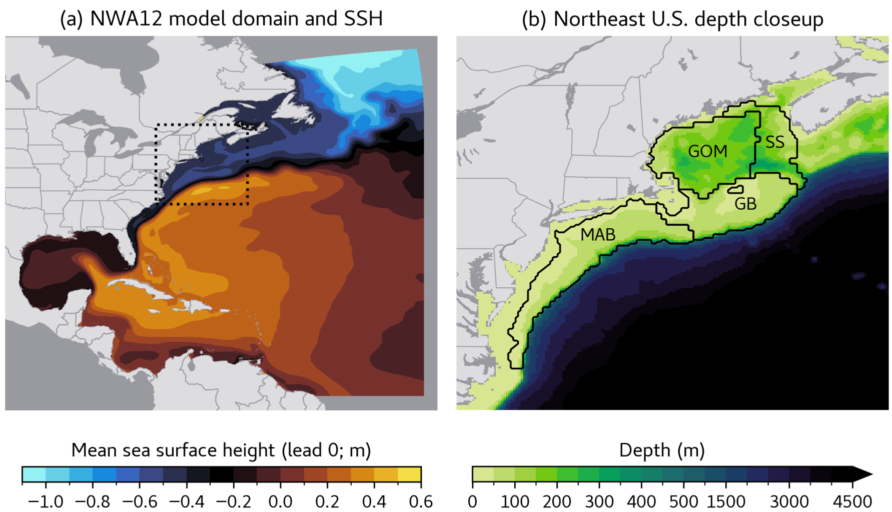

Figure 1. (a) Map of the NWA12 regional model domain, with the average sea surface height from the first month of all retrospective forecasts shaded in color to illustrate the regional sea level and geostrophic currents. Dotted box outlines the region shown in panel b. (b) Close-up of the model domain in the Northeast U.S. LME region. Color shading shows the model depth (note that the shading interval changes after 500 m). Outlines show the four regions over which most results were averaged.

primarily derived from high-resolution reanalysis products, with climatologies of observations or model simulations used for some biogeochemical variables with limited data availability. The data used for the forecast experiments are detailed in the following sections. MOM6-COBALT-NWA12 uses open boundary conditions for the ocean and biogeochemistry along the southern, eastern, and northern borders. These conditions are implemented as described in Ross et al. (2023) and Ross et al. (2024).

The ocean model parameters and configuration were mostly the same as in Ross et al. (2023) and Ross et al. (2024), aside from updates to the MOM6 source code and an adjustment to the horizontal viscosity parametrization. The biharmonic Smagorinsky scheme for viscosity was replaced with the harmonic version with a coefficient of 0.05. The ocean biogeochemical model, COBALT version 3, is as described in Stock et al. (2025), except the version used in this study does not include an adjustment to iron uptake that was added after experiments in this study began running. The source code for all of the model components is included in a data repository associated with this paper (https://doi.org/10.5281/zenodo.22210571; Ross et al., 2026a).

2.2 Spin-up and analysis simulation

Three types of model simulation were used in this study: a spin-up simulation, a nudged analysis simulation, and a large suite of retrospective forecast simulations. The spin-up simulation was run first to allow the biogeochemical model state to adjust

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from basic initial conditions. The analysis simulation began with initial conditions from the end of the spin-up simulation and was used to provide initial conditions for the forecast simulations and as a reference for evaluating the forecast accuracy.

In the spin-up simulation, the ocean physics and biogeochemistry were simulated with one year of forcing repeated for 30 years. The atmospheric forcing for this spin-up simulation was obtained from one continuous year, May 1, 1992 through April 30, 1993, from the ERA5 reanalysis (Hersbach et al., 2020). Beginning and ending the repeating year forcing in Northern Hemisphere spring follows the strategy of Stewart et al. (2020) to have the discontinuity in the repeating time series fall during a period of low inter-annual variability. It also facilitates spinning up the model state towards conditions present in January 1993, the beginning of the analysis simulation. To spin up the carbon system towards the 1993 mean state, the Meinshausen et al. (2017) time series of atmospheric CO_2 for the year 1993 was repeated, and alkalinity and dissolved inorganic carbon (DIC) boundary conditions were fixed at values based on 1993 mean temperature and salinity from GLORYS12 using the linear regression version of the Empirical Seawater Property Estimation Routines (ESPER) algorithm (Carter et al., 2021). All other biogeochemical boundary conditions were set to the same climatological values used in Ross et al. (2023). Temperature, salinity, sea level, and velocity boundary conditions were set using a smoothed daily climatology of the GLORYS12 data. This climatology was calculated over years 1993 to 2007, a relatively constant period before a shift towards warmer conditions in the Northwest Atlantic. Using a multiyear average for the physical boundary conditions produced a more stable ocean circulation during the spin-up compared to repeating a single year. River discharge was set to a smoothed daily climatology over 1993–2019 from the GloFAS v3 dataset (Harrigan et al., 2020).

The nudged analysis simulation, which provided the initial conditions for the retrospective forecast simulations, was initialized at the beginning of 1993 from conditions at the end of the 30-year spin-up run. After initializing, the analysis simulation was driven as in Ross et al. (2023), including the use of hourly ERA5 atmospheric forcing, daily GLORYS12 ocean boundary condition data, and daily river runoff from GloFAS. In the analysis simulation, however, the ocean temperature and salinity at all levels throughout the model domain were weakly nudged towards monthly averages from the GLORYS12 reanalysis with a 90-day restoring time scale. This nudging allows information from observations to be integrated into the model simulation without the computational complexity and expense of a full data assimilation system. The same nudging strategy was used to initialize the physics-only downscaled forecast simulations by Ross et al. (2024). The ocean biogeochemistry is not directly affected by the nudging scheme, but it will respond to changes in the hydrography caused by nudging. The analysis simulation was run from the beginning of 1993 through the end of 2024. The first year was subsequently neglected to allow the model time to readjust from the repeating-year spin-up run. Due to data availability and update frequency, beginning in mid-2021, interim reanalysis and analysis data were used from GLORYS, and the GloFAS river discharge version 3 was replaced with version 4 in 2024.

2.3 Retrospective forecast simulations

Instantaneous snapshots of the model state during the analysis simulation, saved at the beginning of every month, were used as initial conditions for the downscaled retrospective forecast experiments. The downscaled forecasts were started at the beginning of January, April, July, and October for every year from 1994 to 2023. Each forecast simulation ran for one year. Ross et al.

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(2024) used the same protocol of initializing year-long forecasts every 3 months; however, they initialized the forecasts in December, March, June, and September. The initialization months were changed for the present study to match the operational production schedule of the model input data going forward.

The downscaled forecasts were forced with atmospheric data from global forecasts produced by GFDL's global SPEAR coupled model (Delworth et al., 2020; Lu et al., 2020), as in Ross et al. (2024). The atmospheric forcing was not corrected for bias or drift; the ocean tendency adjustment scheme in SPEAR helps reduce bias and drift during the course of the SPEAR forecasts. We did, however, replace atmospheric data at SPEAR grid points that were not fully over the SPEAR ocean with an average of the data at the three nearest all-ocean points. This procedure, which was not applied in the physics-only simulations in Ross et al. (2024), improves the accuracy in coastal areas of the downscaled model by more accurately forcing wind-driven mixing. We also improved the wind forcing by switching from daily average winds to 6-hourly instantaneous winds.

Atmospheric CO_2 in the forecast simulations was specified using a combination of historical data from Meinshausen et al. (2017) and the SSP245 scenario from Meinshausen et al. (2020), as in Ross et al. (2023) and the analysis simulation. Open boundary condition alkalinity and DIC were set using the Carter et al. (2021) linear regression ESPER algorithm with temperature and salinity fixed to the 1993–2019 average from the GLORYS dataset and the year varying. In other words, the boundary conditions for the forecasts account for the steady anthropogenic trend in alkalinity and DIC, but not the variability. Boundary conditions for the remaining biogeochemical variables were set to the same climatologies used in the analysis simulation and Ross et al. (2023). Boundary conditions for temperature, salinity, sea level, and velocity were set to a smoothed daily climatology of the GLORYS12 reanalysis, as in Ross et al. (2024). The use of climatologies for the physical and biogeochemical open boundary conditions follows the justification in Ross et al. (2024) that the time scale of advection from the boundaries to the Large Marine Ecosystems along the U.S. coastline is longer than the one-year forecast horizon. River discharge was set to the same climatology used in the spin-up simulation.

Ten ensemble members were run for each forecast initialization. Each ensemble member began from the same initial conditions but used different atmospheric forcing from the corresponding ensemble member of the SPEAR global forecasts. Ross et al. (2024) used the same initialization strategy and found that the ensemble of atmospheric forcing was generally sufficient to force the ocean to diverge from the initial conditions. In total, 1,200 retrospective forecast simulations were run for this study.

2.4 Post-processing

Post-processing of the retrospective forecast model output was performed largely following Ross et al. (2024). From the monthly average model output data, monthly climatologies were calculated separately for each of the four initialization calendar months and each of the 12 monthly lead times. Forecasts from all of the retrospective initializations, between January 1994 and October 2023 inclusive, were used to calculate these lead- and initialization-dependent climatologies. Then, the climatologies were subtracted from the corresponding forecasts to produce time series of anomalies that have been corrected for any lead-dependent drift in the forecasts. In Section 3, we will show the climatologies that were calculated from the forecasts and discuss whether drifts are present in the uncorrected forecasts. In Section 4, we analyze bias-corrected forecasts by adding these anomalies to the matching 1994–2023 climatology from the nudged analysis simulation.

Most results are presented as area-weighted averages over four ecological production units (EPUs) as defined by NOAA Fisheries (NMFS Office of Science and Technology, 2026). From north to south, these are the Scotian Shelf–Eastern Gulf of Maine (SS), Gulf of Maine (GOM), Georges Bank (GB), and Mid-Atlantic Bight (MAB). To avoid including shallow regions where even the bottom ocean is tightly coupled with the atmosphere, model grid cells where the bottom is shallower than 30 m were not included in the averaging.

2.5 Evaluation

The model forecasts were evaluated for accuracy and skill using standard metrics including anomaly correlation coefficient (ACC) and bias (mean difference between forecast and observation/reference). Because of the lack of observational datasets with full space and time coverage of the model domain and forecast time period, we primarily used the output from the nudged analysis simulation as the verification reference. The skill that this comparison measures would traditionally be termed *potential skill* as it is comparing a model prediction against a simulation of the same model (Boer et al., 2019). Here, however, only the biogeochemical component of the model was unchanged between the reference and forecast simulations; the temperature and salinity of the reference were nudged towards the GLORYS reanalysis, and an evaluation of the physical ocean predictions against this reference would essentially measure actual prediction skill. For the biogeochemistry, we refer to the skill that results from this comparison as *reanalysis-referenced potential skill* to indicate that it is potential skill but with the reference biogeochemistry responding to reanalysis conditions. For simplicity, though, we will often refer to this as simply skill.

Before calculating the anomaly correlation coefficient, both the forecasts and the analysis dataset were linearly detrended to remove the contribution of trends in the initialization and verification target to the apparent prediction skill. For the forecasts, the linear trend was calculated separately for each lead time and each of the four initialization months.

To determine the skill of the model forecasts relative to a simple prediction, the correlations between the forecasts and analysis for each region, initialization month, and lead time were compared with the same correlations between a persistence reference forecast and the observations. The persistence forecast assumed that the anomaly in the nudged analysis for the month before the forecast initialization date (e.g., June average anomaly for a July 1 initialization) would remain unchanged during the full length of the forecast. To identify statistically significant forecast skill, the ACCs for the model forecasts were compared with the ACCs of the persistence forecast using the Williams test (Williams, 1959, following Steiger (1980)), which takes into account the use of the same reference in each ACC calculation. The model forecasts were deemed statistically better or worse than the persistence forecast using a two-sided test with $\alpha = 0.05$. To reduce the probability of type 1 error, an effective sample size was used in the test. The effective sample size was calculated following Bretherton et al. (1999) for a first-order autoregressive process fit to the data. To conservatively estimate the effect of autocorrelation on the sample size, the effective sample size was calculated for each of the three correlations used in the Williams test, and the smallest was used as the sample size for the test.

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To build confidence that the reanalysis-referenced potential prediction skill will translate to actual prediction skill, we used datasets of in situ observations to evaluate the accuracy of the analysis simulation. The selection of observation datasets was guided by our intent to develop forecasts that can be used for fisheries management. For bottom aragonite saturation state, we used the same methods as in the latest indicator catalog supporting the NOAA Fisheries State of the Ecosystem Report for New England (Saba and Garzio, 2025). Ship-based near-bottom aragonite saturation samples were extracted from the Coastal Ocean Data Analysis Product in North America (CODAP-NA) dataset (Jiang et al., 2021) and the Ocean Carbon and Acidification Data System (Jiang et al., 2023). For bottom oxygen, we used the Fishing Industry Shared Bottom Oceanographic Timeseries (FIShBOT), a dataset that is a combination of several sources including oxygen sensors attached to lobster traps and other fishing gear (Stoltz et al., 2025). We also used these same datasets to evaluate a few select forecasts in the Discussion (Section 4). To quantify the correspondence between the observations and model, we calculated the bias, correlation coefficient, root mean square error (RMSE), and median absolute error (MedAE; the median of the absolute values of the differences between the model and observations).

3 Results

3.1 Evaluation of nudged analysis simulation

Before assessing the skill of the forecasts, we first evaluate the nudged analysis simulation, which provided the initial conditions for the forecasts and will be used as a reference to assess the forecast skill next. We begin with a qualitative examination of seasonal to interannual variability of temperature in the model and its connection to dissolved oxygen and acidity. In Fig. 2, we show the monthly anomaly time series from the analysis simulation for bottom temperature, dissolved oxygen, pH, and aragonite saturation state ($\Omega_{\mathrm{aragonite}}$), averaged over the full Northeast U.S. Large Marine Ecosystem (but excluding areas where the model bottom is shallower than 30 m). All four variables have prominent variability on seasonal to interannual time scales. In the model, a rapid shift towards cool, oxygenated, and acidic conditions occurred during the late 1990s, associated with increased advection of Labrador Slope Water and a southward shift in the Gulf Stream path (Drinkwater and Gilbert, 2004; Smith et al., 2001). In the early 2000s, the number of warm core rings (WCRs) shed by the Gulf Stream abruptly increased (Gangopadhyay et al., 2019, 2020) and the advection of water from the Scotian Shelf decreased (Feng et al., 2016), which is consistent with the modeled increase in temperature and reduction in dissolved oxygen. Deep mixing occurred during winter 2004 (Taylor and Mountain, 2009), which rapidly lowered bottom temperature and increased dissolved oxygen by ventilating the bottom with cool water. This event also lowered $\Omega_{\mathrm{aragonite}}$ in the model, and this anomaly was maintained by an inflow of cool, low-alkalinity Scotian Shelf Water (SSW) in mid-2004 through 2005 (Feng et al., 2016). The 2012 marine heatwave (Chen et al., 2014; Mills et al., 2013) appears as an abrupt decrease in dissolved oxygen and pH that persisted for most of the year. The series of heatwaves in late 2015 through 2016 (Pershing et al., 2018) is not as clearly associated with biogeochemical changes as the 2012 heatwave. We speculate that this stems from differences in the physical drivers: 2012 occurred as a single event driven by atmospheric forcing (Chen et al., 2014, 2015), whereas 2015–2016 consisted of multiple warm extremes, some driven by atmospheric forcing and some by advection of warm Gulf Stream water (Perez et al., 2021)

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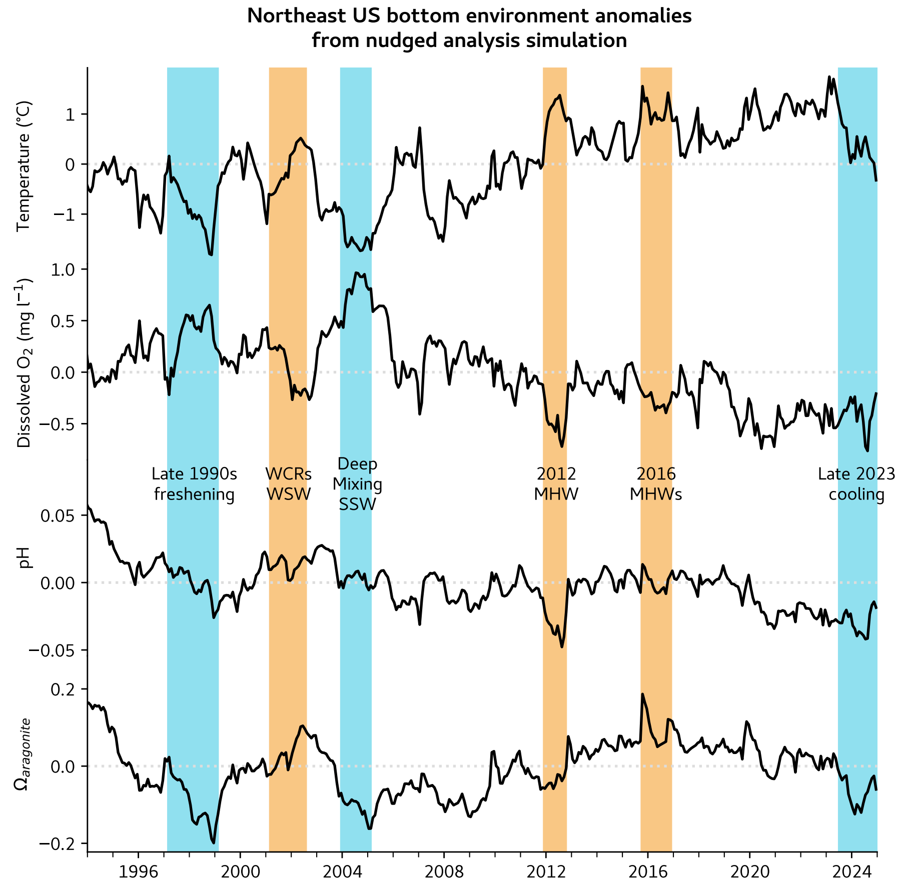

Figure 2. Time series of monthly mean anomalies from the nudged analysis simulation averaged over the complete Northeast U.S. Large Marine Ecosystem. Shaded bands highlight various periods of cool (blue) and warm (orange) conditions discussed in the text.

with different biogeochemical properties. The region steadily warmed throughout most of the 2000s until late 2023 through 2024, when the coolest anomalies in more than a decade were both modeled and observed (Record et al., 2024). At the same time, conditions in the model became more acidic, which is consistent with the replacement of warm, high-alkalinity WSW with cool, low-alkalinity LSW.

Because available in situ observations do not have the coverage over time and space that would be needed to calculate the time series of area-average monthly anomalies shown in Fig. 2, for a quantitative evaluation of the accuracy of the nudged analysis simulation we compare observations with daily average model output from the nearest grid cell. For the two bottom ocean acidification metrics, $\Omega_{\mathrm{aragonite}}$ and pH, the analysis simulation agrees with these point observations fairly well in all four study regions (Figs. 3–4). For both metrics, the bias in the model is negligible, though it is slightly positive in all regions. Model–observation correlations are higher for pH than $\Omega_{\mathrm{aragonite}}$ in all regions except the Mid-Atlantic Bight, a result of pH having a steadier linear trend (Fig. 2) and a more pronounced annual cycle (higher pH earlier in the year declining as the year

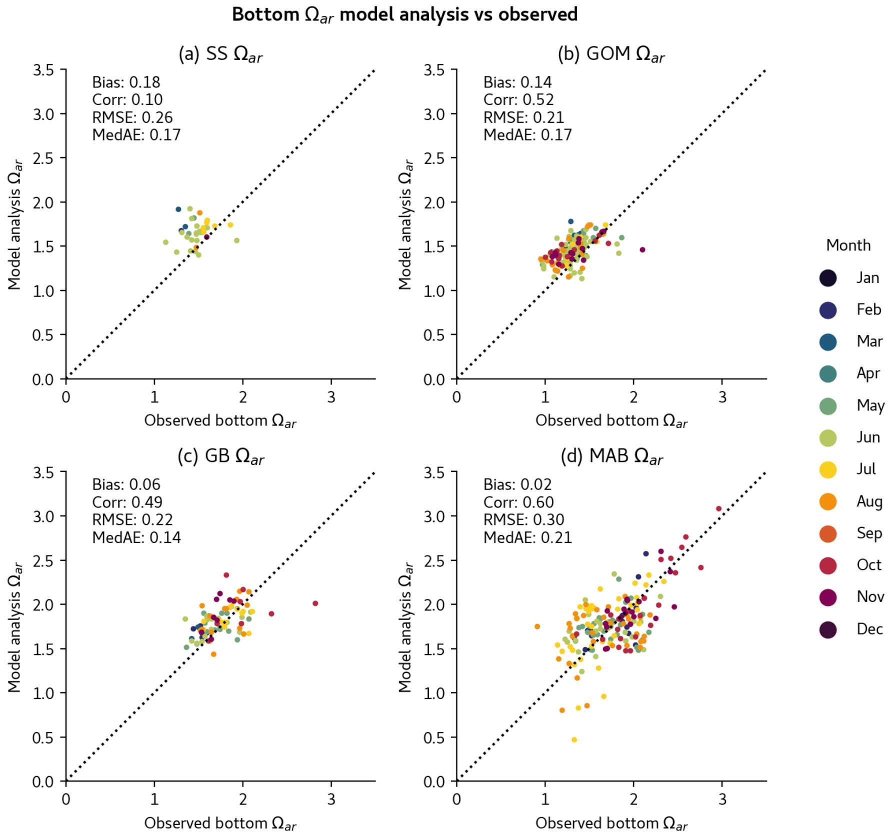

Figure 3. Bottom aragonite saturation state in the nudged analysis simulation (as daily averages) compared with individual in situ observations.

progresses). Lower correlation for pH in the Mid-Atlantic is a result of a few cases where the model simulated extremely low pH values (less than 7.8) that were not observed. These cases were primarily located in shallow water near the outflow of Long Island Sound and Narragansett Bay. The correlation for both metrics is lowest in the Scotian Shelf, which has less variability than the other regions. It is worth keeping in mind that this evaluation compares individual in situ observations with model daily averages, so some discrepancy is expected as a result of instrument errors and sub-daily variability smoothed out in the model. These sources of error would be reduced in monthly averages.

The analysis simulation also simulates bottom oxygen fairly well compared with observations across the four different study regions (Fig. 5). Over all months, the correlation between the analysis and observations is highest in Georges Bank, which is on average shallower and more well-mixed than the other regions and more strongly oxygenated by the atmosphere. The correlation is lowest for the Mid-Atlantic Bight, which is also fairly shallow but is influenced by a few large errors where the model simulated hypoxic conditions that did not occur, or failed to simulate hypoxic conditions that did occur. Lower performance in the Mid-Atlantic for both pH and oxygen could be due to the increased importance of river discharge to

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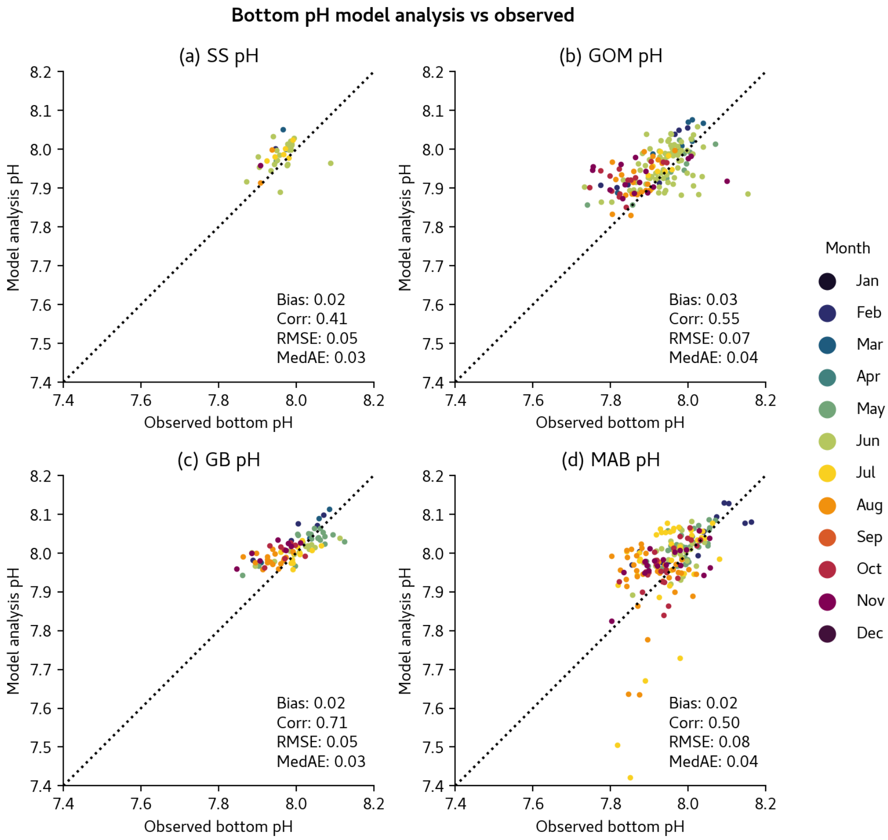

Figure 4. Bottom pH in the nudged analysis simulation (as daily averages) compared with individual in situ observations.

regional ocean dynamics and biogeochemistry and the challenge of simulating it accurately, though alongshelf transport of nutrients into the Mid-Atlantic is still estimated to be much larger than inputs from land (Fennel et al., 2006; Friedrichs et al., 2019). The Scotian Shelf has the smallest bias overall, but this appears to be a result of a low bias in the beginning of the year compensating for a high bias towards the end of the year. The Gulf of Maine has a low bias that is visible in most months.

265 ### 3.2 Evaluation of forecast skill

The climatologies of the seasonal forecasts for bottom oxygen and pH are generally similar to the climatologies of the nudged analysis simulation, which indicates that the forecasts have minimal drift in most cases (Fig. 6). Some drift, however, is evident for bottom oxygen in the Mid-Atlantic Bight: the climatology for each forecast initialization month gradually becomes lower than the analysis climatology. A similar, weaker pattern can be seen in bottom oxygen for Georges Bank, and opposite patterns (forecasts drifting higher than the analysis over time) are found in bottom pH along the Scotian Shelf and Gulf of Maine. The drift in bottom aragonite saturation state is more notable: Across all four regions, regardless of which month the forecast was initialized in, the forecast climatology drifts higher than the nudged analysis simulation over time. Because these tendencies

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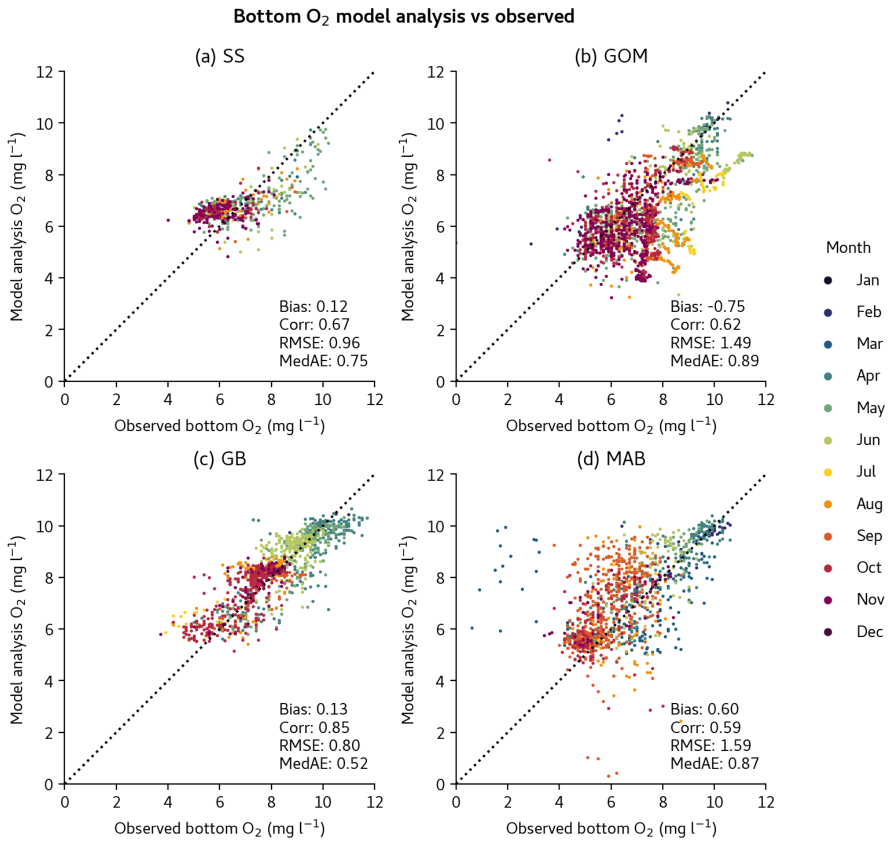

Figure 5. Bottom dissolved oxygen in the nudged analysis simulation (as daily averages) compared with individual in situ observations.

are in the model mean, comparisons based on correlation coefficients (discussed next) will be unaffected, provided that the drift does not nonlinearly affect other qualities of the forecast. Similarly, standard drift correction approaches that subtract the lead-dependent forecast climatology and add back a reference climatology will correct for these drifts.

Forecasts of bottom oxygen have the most pronounced variation in skill across initialization months (Fig. 7a–d). All four EPUs have a similar correlation pattern: forecasts initialized in January maintain high correlations for longer lead times, remaining skillful for almost the full year; and skill gradually declines with each subsequent initialization month until it reaches a minimum for October initializations, which are only skillful for a few months. This pattern is consistent with the hypothesis that an accurate initialization in winter combined with high forecast skill in the first few months creates a baseline of skill that persists through the summer when stratification isolates the bottom waters from the atmosphere. Conversely, predictions initialized in the fall suffer because the effects of weakly predictable atmospheric forcing are mixed down to the bottom during the subsequent winter.

For bottom pH and aragonite saturation, forecast skill varies more by region than by initialization month, though the initialization-dependent pattern is generally still present (Fig. 7e–l). Forecast skill is remarkably high for both variables in

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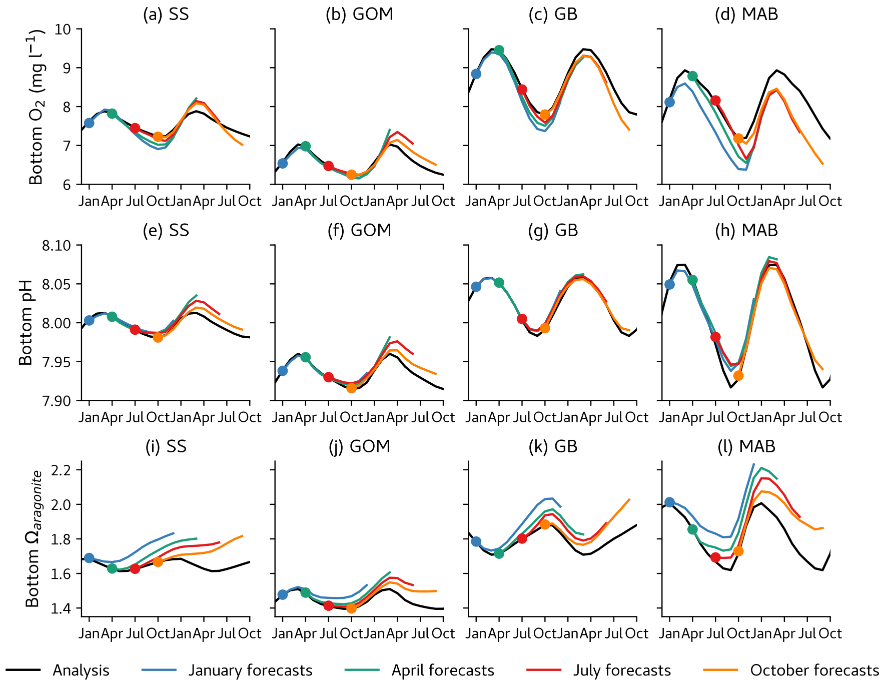

Figure 6. Evaluation of retrospective forecast bias and drift relative to the nudged analysis simulation for bottom oxygen (top row a–d), pH (middle row e–h), and aragonite saturation state (bottom row i–l). Black lines show the monthly climatology of the nudged analysis simulation (note that this line is repeated on the x-axis). Colored lines show the climatology of the retrospective forecasts separately by initialization month.

the Gulf of Maine, and the model forecasts initialized in January have a significantly greater correlation with the analysis than the reference forecast of persistence does for the entire 12-month forecast. Forecasts for the Scotian Shelf EPU are also significantly better than persistence across most lead times, though skill drops off towards the end of the forecast for pH and for October-initialized saturation state forecasts. In Georges Bank, high correlation is maintained across nearly all lead times, though many of these correlations are not significantly better than persistence. Finally, the Mid-Atlantic Bight has the most notable seasonal pattern for both variables: forecasts for conditions in November have abruptly lower skill than forecasts for previous months, regardless of when the forecasts were initialized.

3.3 Forecast case studies

The comprehensive evaluation of reanalysis-referenced potential skill for bottom oxygen, pH, and $\Omega_{aragonite}$ revealed substantial skill across the study region. Higher skill was typically found for forecasts initialized early in the year, which we hypothesized is linked to the tendency of anomalies present at initialization, as well as those driven by short-lead predictability, to remain insulated from unpredictable atmospheric forcing throughout the spring, summer, and early autumn. Although the evaluation

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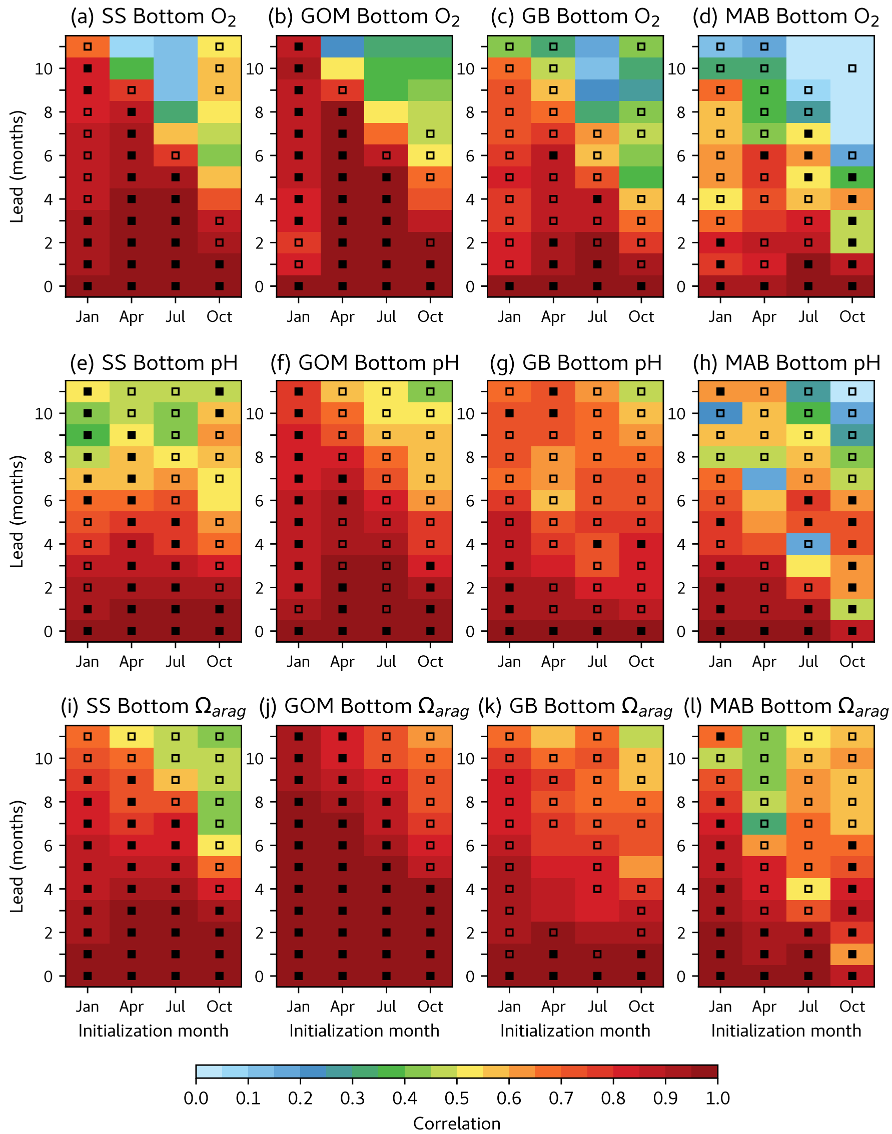

Figure 7. Correlation coefficients for bottom oxygen (top row a–d), pH (middle row e–h), and aragonite saturation state (bottom row i–l). Open square markers indicate where correlation coefficients for the forecasts are greater than the coefficients for persistence. Solid square markers indicate where this difference is statistically significant.

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identified broad forecast skill across regions and seasons, it is not intuitive how these scores translate into useful information about real events. To illustrate the practical relevance and limitations of the forecast skill, we examine two specific events in detail. The first event, an intrusion of slope water onto the Mid-Atlantic Bight, demonstrates the short-term predictability that emerges from the predictable evolution of the Gulf Stream and downstream effects. The second event, contrasting water masses advecting into the Gulf of Maine in spring 2017 and 2018, highlights the importance of oceanic initial conditions despite unpredictable atmospheric variability.

3.3.1 Slope water intrusion onto the Mid-Atlantic Bight in summer 2019

Warm core rings from the Gulf Stream intruded onto the Mid-Atlantic Bight shelf break in 2019, leading to the longest-lasting bottom marine heatwave observed in the Mid-Atlantic Bight (Wu and He, 2024), an offshore flux of oxygen (Zhang et al., 2023), and multiple unusual diatom blooms (Castillo Cieza et al., 2024; Oliver et al., 2021; Selden et al., 2024). To begin studying this event, in Fig. 8 we show the monthly mean sea surface height for July through September of 2019 from the nudged analysis simulation (top row a–c), the downscaled seasonal forecasts initialized at the beginning of July 2019 (middle row d–f), and the downscaled forecasts initialized at the beginning of April 2019 (bottom row g–i). The analysis monthly mean for July contains a northward meander of the Gulf Stream near the central Mid-Atlantic Bight and a ring nearly pinching off to the east around 67 °W. In the August 2019 mean, elevated sea level is evident around 69 °W, a result of the ring finally separating in early August before being quickly reabsorbed into the prominent meander that has moved east to around 70 °W (because these figures show monthly means, features such as rings will be partially smoothed out). In September, the excursion is again farther to the east, and the overall Gulf Stream path is more zonal but farther north than average.

The evolution of the Gulf Stream seen in the analysis simulation, which was nudged towards the GLORYS reanalysis, was predicted exceptionally well by the forecast initialized July 1 (Fig. 8d–f). This forecast correctly simulated the pinched-off ring in August and the zonal Gulf Stream in September. The forecasts initialized in April, by contrast, did relatively poorly (Fig. 8g–i). The ensemble mean of the forecasts initialized in April correctly predicted a northward and highly meandering Gulf Stream in the summer, but the meander was predicted to be too far to the southwest in July and did not show formation of a ring in August. Again, however, these figures show the mean of the 10-member ensemble, and taking the ensemble mean will blur features such as rings and meanders in later lead times and lead to apparently unrealistic ensemble mean predictions.

In both the analysis simulation, observations (Section 2.5), and forecasts (which have been corrected for bias and drift relative to the analysis; Section 2.4), the features indicated by the sea surface height were accompanied by substantial anomalies in bottom salinity (Fig. 9) and temperature (Supporting Information Fig. S1). An intrusion of unusually high salinity water was just beginning to occur in July 2019 and peaked in August along the Northern Mid-Atlantic shelf break. This feature was coincident with the northward excursion of the Gulf Stream and warm core ring. The salinity anomalies were less notable by September. These bottom salinity anomalies were accurately predicted by the forecast ensemble initialized July 1, 2019, and less well predicted by the ensemble initialized in April. The forecast ensemble initialized in July accurately predicted the swath of high salinity anomalies in August and their reduction in September, though the extent in August was overestimated. The

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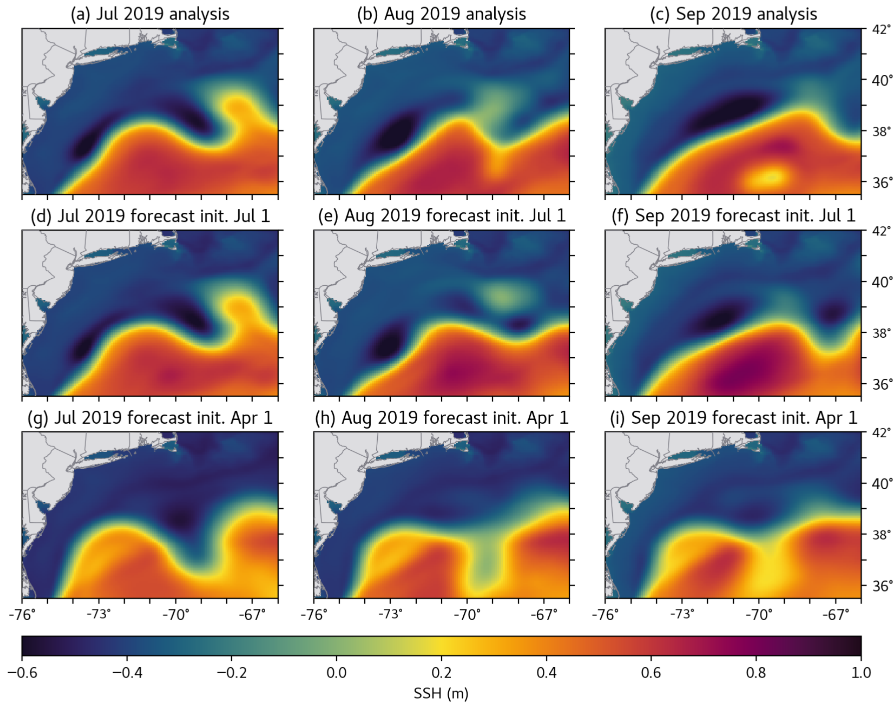

Figure 8. Monthly mean sea surface height for July through September, 2019, from the nudged analysis simulation (top row a–c), and the ensemble mean forecast of the same from the July 1, 2019 initialization (middle row d–f) and the April 1, 2019 initialization (bottom row g–i).

ensemble initialized in April predicted a salinity excursion that was confined to the Southern Mid-Atlantic but extended farther towards the coast, consistent with the prediction of the Gulf Stream in these forecasts.

A biogeochemical signal of low dissolved oxygen was associated with the bottom salinity and temperature anomalies (Fig. 10). In the nudged analysis, the anomalies peaked in August 2019, with a wide region of values more than 2 mg l^{-1} below average along the central and northern Mid-Atlantic Bight and south of Providence, RI. Interestingly, the widest extent and most severe anomalies are in the same region identified as a hotspot for intrusion of deep water by Ullman et al. (2014) and Chen (2024). Available observations indicate that oxygen was even lower than simulated by the analysis along the New Jersey coast and central MAB cold pool, but well simulated in the region with the strongest anomalies. As with previous variables, the bottom oxygen from the forecast ensemble initialized on July 1 closely matched the analysis and observations, though the ensemble mean predicted slightly more extensive low oxygen along the Southern MAB shelf break. The forecast initialized in April, by contrast, predicted an extensive region of low oxygen along the Southern MAB and not in the Northern MAB, consistent with the discrepancies in its prediction of the Gulf Stream and associated temperature and salinity anomalies.

Although some of the fine-scale ocean features that drove the observed anomalies along the Mid-Atlantic Bight are undoubtedly not resolved by the 1/12° model resolution used here (Chen, 2025), including features like the shelf-water streamer observed

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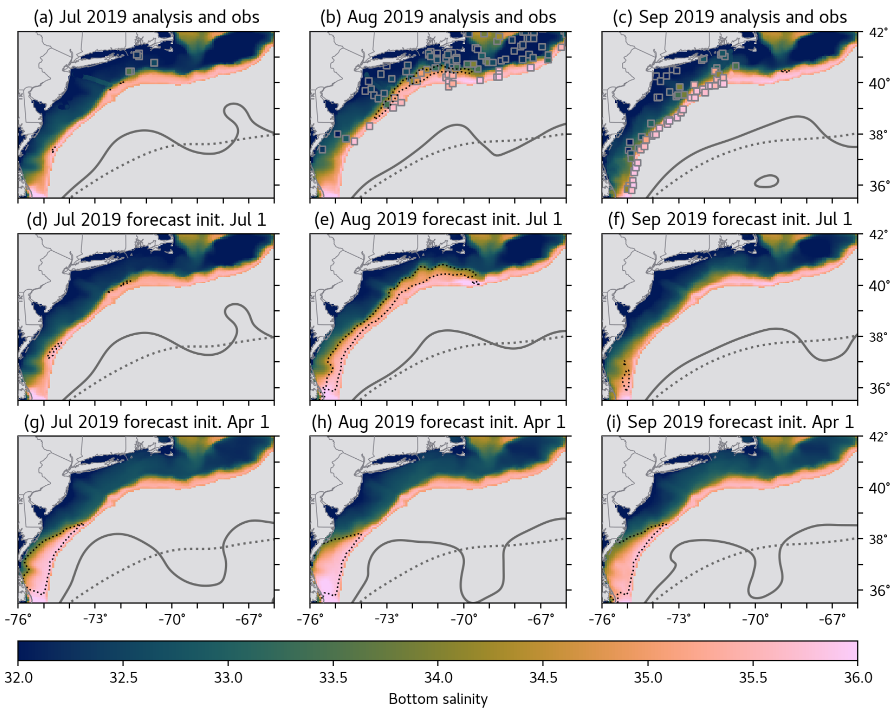

Figure 9. Monthly mean ocean bottom salinity for July through September, 2019, from the nudged analysis simulation (top row a–c), and the ensemble mean forecast of the same from the July 1, 2019 initialization (middle row d–f) and the April 1, 2019 initialization (bottom row g–i). Bottom salinity is shown in color shading where the bottom depth is less than 500 m. Point observations of salinity values are overlaid inside gray squares in the top row, and glider observations are overlaid without an edge color. Thin dotted lines outline regions where the bottom salinity anomaly was more than 1 unit above average. Off the shelf, the solid grey lines show the position of the 25 cm sea surface height contour in the analysis and forecast simulations, and the dotted lines show the long-term mean position of this contour.

in 2019 (Zhang et al., 2023), the success of this prediction as well as a similarly well-predicted temperature and salinity event in 2017 analyzed by Ross et al. (2024) suggests that these intrusions of warm, saline water onto the shelf may be predictable with a few months of lead time. Predictability on this time scale is supported by the time scale for advection along the outer shelf of 2–3 months (Ryan et al., 2024) and the observed lag of several months between along-shelf velocity and the position of the shelfbreak front (Silver et al., 2025).

3.3.2 Variation in Scotian Shelf inflow in the Gulf of Maine in winter/spring 2017 and 2018

The oceanography in the Gulf of Maine was markedly different in the winter and early spring of 2017 compared to the same period in 2018. A large freshwater flux across the southwest Scotian Shelf was observed in December 2016 and January 2017 (Wang et al., 2022; Townsend et al., 2023). Over the next few months, this water entered the eastern Gulf of Maine and spread to the west following the typical cyclonic flow pattern (Wang et al., 2022). By autumn 2017, warm and saline water from a

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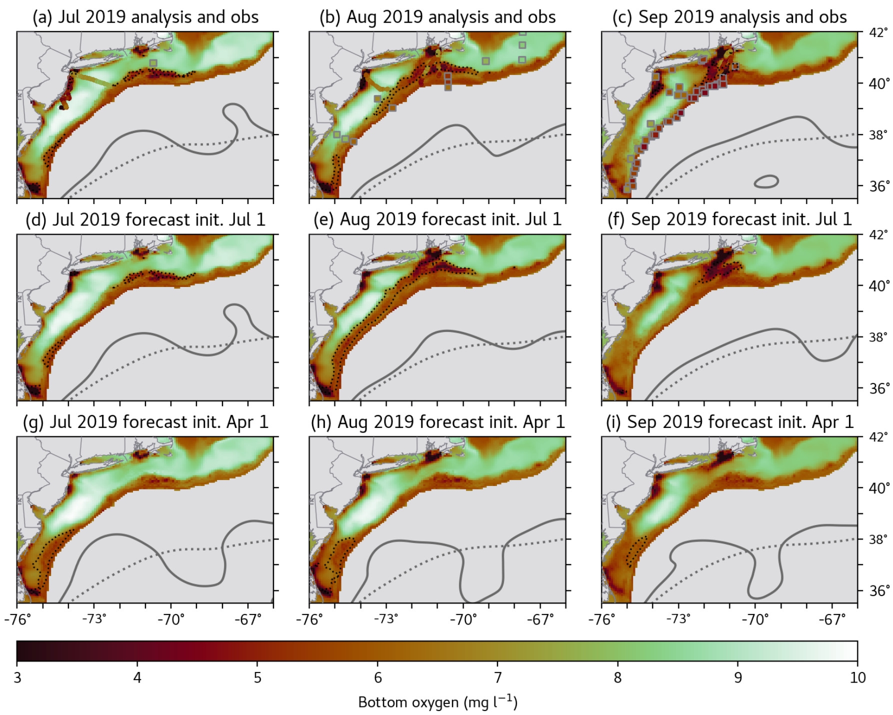

Figure 10. Monthly mean dissolved oxygen at the ocean bottom for July through September, 2019, from the nudged analysis simulation and observations (top row a–c), and the ensemble mean forecast of the same from the July 1, 2019 initialization (middle row d–f) and the April 1, 2019 initialization (bottom row g–i). Bottom oxygen is shown in color shading where the bottom depth is less than 500 m. Point observations are overlaid inside gray squares in the top row, and glider observations are overlaid without an edge color. Thin dotted lines outline regions where the bottom oxygen anomaly was more than 2 mg l^{-1} below average. Off the shelf, the solid grey lines show the position of the 25 cm sea surface height contour in the analysis and forecast simulations, and the dotted lines show the long-term mean position of this contour.

warm core ring was entering the Gulf of Maine through the deep Northeast Channel (Levin et al., 2022; Townsend et al., 2023). At the same time, the southwesterly current along the Scotian Shelf weakened, which significantly reduced the freshwater flux from the shelf into the Gulf leading into the beginning of 2018 (Levin et al., 2022). The inflow of freshwater remained low in 2018, aside from a short-lived inflow in March 2018 associated with winds blowing to the southwest (Wang et al., 2022), which did lower the salinity of the eastern Gulf of Maine (Townsend et al., 2023).

Because the evolution of salinity through late winter and spring was largely pre-conditioned by the beginning of January in both years, we examine whether the forecasts initialized in January 2017 and 2018 were able to predict the different salinity patterns in the region over the following months. We also examine whether differences in ocean acidity were present during these two time periods. Because the salinity differences were associated with differences in the presence of cool, low alkalinity Scotian Shelf Water and warm, high alkalinity Warm Slope Water (Rutherford and Fennel, 2022; McGarry et al., 2021; Gibb et al., 2023; Li et al., 2022), we look for predictable variations in aragonite saturation state. In addition to the

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observational datasets listed in Section 2.5, we also extracted in situ carbonate system observations from the Atlantic Zone Monitoring Program (Gibb et al., 2023) to include information about conditions on the Scotian Shelf. To make the best use of available observations, rather than examining near-bottom data, observations between 40 m and 60 m depth were included in the comparison, and the model data were obtained from a layer centered on 47.5 m in the vertically regridded model output.

The analysis simulation confirms that a sizable layer of fresh water, indicated by the 32 isohaline (solid black line in Fig. 11), was present along the Scotian Shelf at around 50 m depth in January 2017. Lower $\Omega_{\text{aragonite}}$ (though still not undersaturated) was colocated with the low salinity. As the freshwater mass advected southwest and into the Gulf of Maine in the following months, the low $\Omega_{\text{aragonite}}$ was maintained and even strengthened. By May 2017, the low $\Omega_{\text{aragonite}}$ water had nearly circled around the entire Gulf coast. Compared to observations, $\Omega_{\text{aragonite}}$ in the nudged analysis simulation matches the numerous observations collected in April 2017 reasonably well, but the three nearshore observations from February 2017 had lower $\Omega_{\text{aragonite}}$ than the model.

The analysis simulation in January 2018 shows an intrusion of saltier water (marked by the dashed 34.6 isohaline) into the Gulf of Maine, again in agreement with the observations previously discussed. Although some residual water from 2017 with low $\Omega_{\text{aragonite}}$ remained in the western Gulf of Maine, the intrusion of Warm Slope Water and reduced Scotian Shelf inflow resulted in much higher $\Omega_{\text{aragonite}}$ in spring 2018 compared to 2017. The observations collected in April 2018 suggest the model accurately simulated the gradient of $\Omega_{\text{aragonite}}$ along the Scotian Shelf, but overestimated $\Omega_{\text{aragonite}}$ in the western coastal Gulf of Maine.

Ocean currents and freshwater fluxes along the Scotian Shelf towards the Gulf of Maine are influenced by the alongshelf wind stress (Li et al., 2014; Wang et al., 2022), with weaker winds blowing along the shelf towards the northeast associated with stronger currents and freshwater flux towards the southwest. To examine the influence of spring winds on the 2017 inflow of fresh and low-$\Omega_{\text{aragonite}}$ water, we look at predictions of the $\Omega_{\text{aragonite}}$ and salinity anomalies averaged over April and May 2017 from all 10 ensemble members of the forecast initialized at the beginning of January 2017. We ranked the 10 members in order of most accurate alongshelf winds during April 2017 (the beginning of the strongest $\Omega_{\text{aragonite}}$ change in the eastern Gulf of Maine). The alongshelf wind component was defined as oriented along the northeast/southwest axis, positive when the wind had a component towards the northeast (upshelf) and negative when it had a component towards the southwest (downshelf). From the alongshelf wind, we calculated a simple index to approximate the wind stress using $|\boldsymbol{u}|u_{\text{along}}$. The alongshelf wind stress index from the ERA5 reanalysis and the SPEAR forecast ensemble members used to force the regional model were averaged over a box between 42.5–44 degrees north, 296.25–298.25 degrees east (the closest region to the shelf unaffected by the SPEAR land mask). Accuracy was defined as the Earth Mover's distance (or Wasserstein distance; Rubner et al., 2000; Villani, 2009) between the two alongshelf index time series. The Earth Mover's distance measures the difference between two probability distributions; we use it to rank ensembles by how well they match the overall distribution of winds during the month rather than how well they match the reanalysis at each point in time.

In the ERA5 reanalysis, the alongshelf winds in April 2017 were roughly equally split in the upshelf and downshelf directions (Fig. 12; note that the cumulative index is nearly equal at the beginning and end of the month). The 3 ensemble members with the most accurate winds during this time followed different trajectories beforehand: member 7 had persistent, strong upshelf

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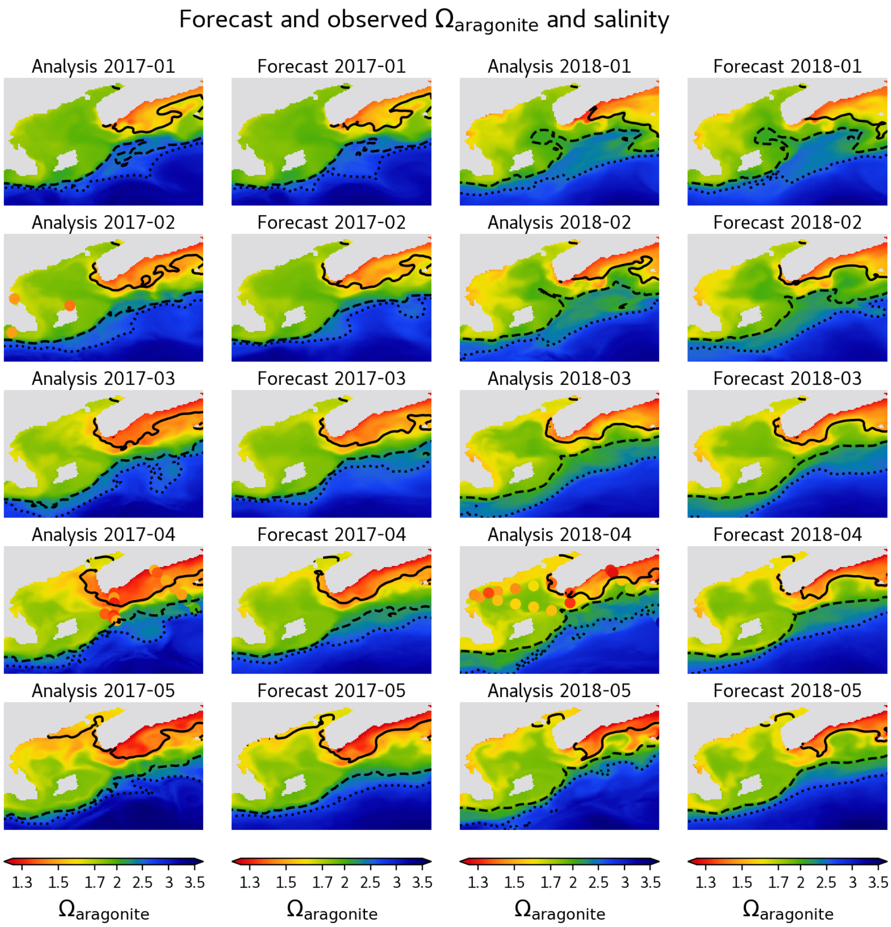

Figure 11. Monthly mean aragonite saturation state and salinity near 50 m depth for January through May of 2017 and 2018, from the nudged analysis simulation and the ensemble mean of forecasts initialized in January. Colored shading denotes the model $\Omega_{\mathrm{aragonite}}$, and points in the analysis panels show observations taken between 40 and 60 m depth. Note that the numerical range is narrower on the left half of the color scale and wider on the right to emphasize details along the shelf while also showing the gradient offshore. Black lines are contours of model salinity at 32 (solid), 34.6 (dashed), and 35.4 (dotted) units.

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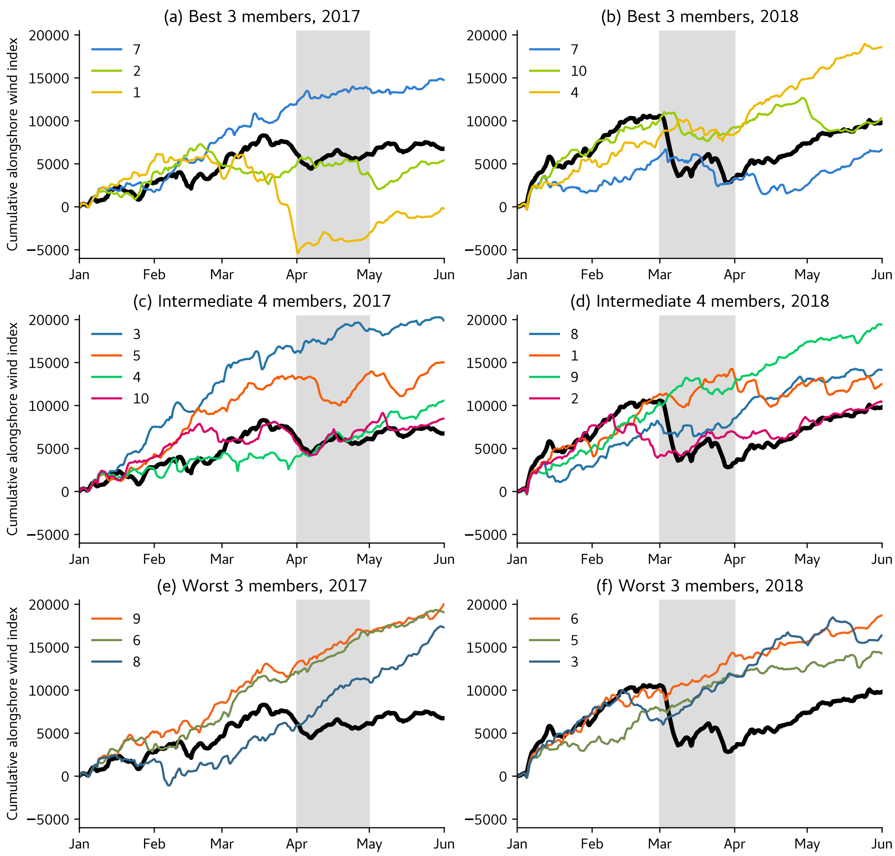

Figure 12. Cumulative alongshelf wind index off the Scotian Shelf from the ERA5 reanalysis (thick black lines) and the ensemble members (colored lines). The ensemble members are plotted in order of the Earth Mover's distance of their alongshelf wind index (not cumulative) relative to ERA5 during the gray shaded periods.

winds, whereas members 1 and 2 had downshelf winds from late February to late March. These differences before April can be seen in the resulting $\Omega_{\mathrm{aragonite}}$ and salinity anomalies predicted over the next two months (Fig. 13, left column): member 7 kept the negative anomalies confined to the Scotian Shelf, consistent with its persistent upshelf winds, while in member 1, which had strong downshelf winds beginning in March, the negative anomalies have spread into the coastal Gulf of Maine.

Of the remaining 7 ensemble members, 2 members with intermediate wind accuracy during April predicted upshelf winds diminishing in March (3, 5) and 2 predicted a fairly accurate cumulative index (4, 10). All 4 of these members predicted negative April-May salinity anomalies along the Scotian Shelf and eastern Gulf of Maine. Finally, the remaining three members with the least accurate April alongshelf winds predicted consistent upshelf winds during most of the time period, including throughout April. The persistence of these winds was sufficient to diminish the negative $\Omega_{\mathrm{aragonite}}$ along the Scotian Shelf and prevent them from reaching the Gulf of Maine.

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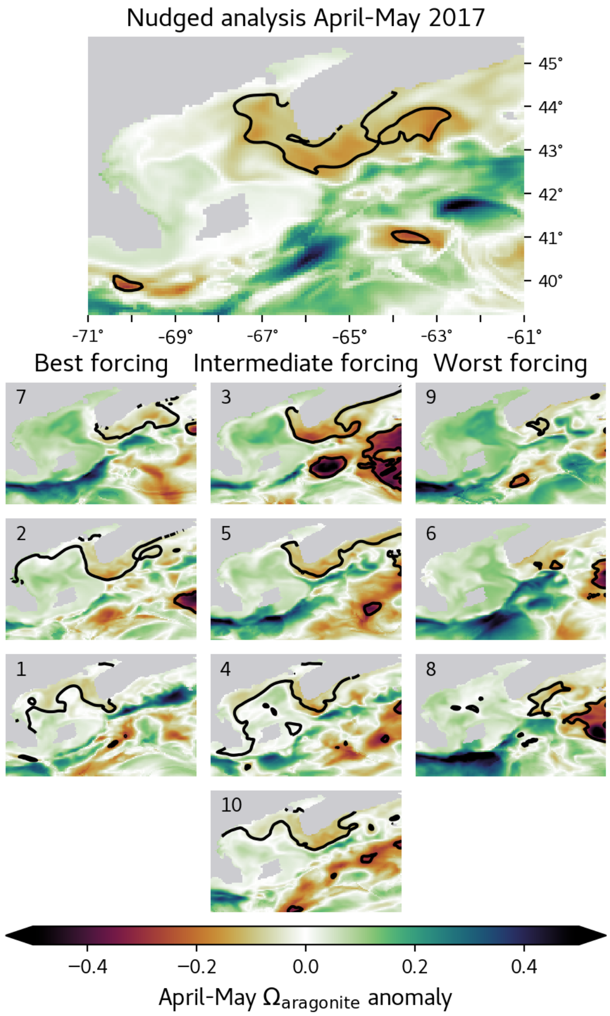

Figure 13. $\Omega_{aragonite}$ anomalies (color shading) averaged over April and May 2017, with contours of -0.25 salinity anomalies plotted as solid lines. The large panel on top shows the analysis simulation. The smaller panels show each ensemble member separately, plotted in order of the member's accuracy at forecasting the distribution of April 2017 alongshelf winds. The number in the top left of each subpanel is the ensemble member number.

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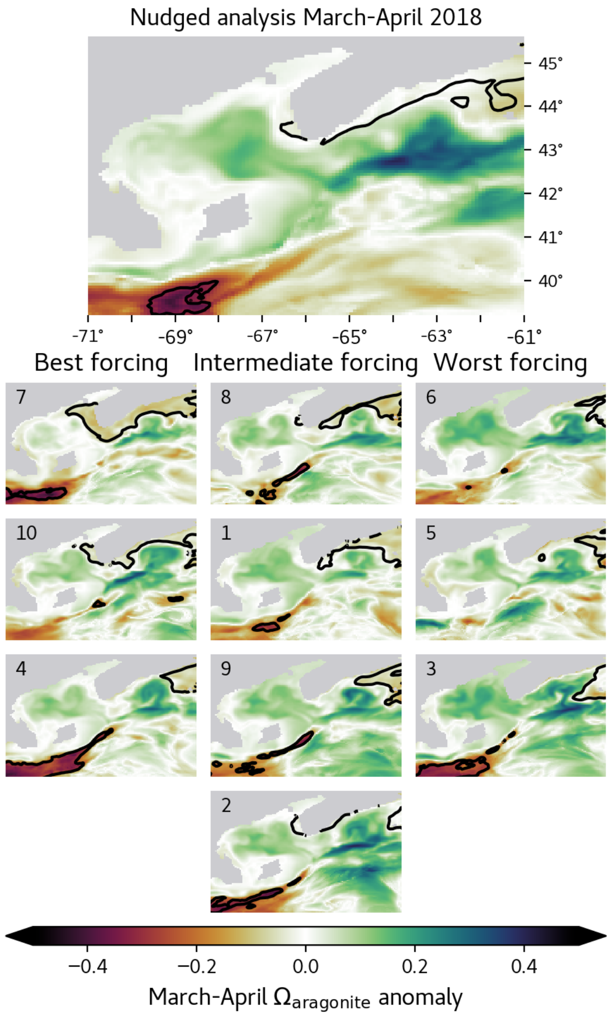

Figure 14. $\Omega_{aragonite}$ anomalies (color shading) averaged over March and April 2018, with contours of -0.25 salinity anomalies plotted as solid lines. The large panel on top shows the analysis simulation. The smaller panels show each ensemble member separately, plotted in order of the member's accuracy at forecasting the distribution of March 2018 alongshelf winds. The number in the top left of each subpanel is the ensemble member number.

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Repeating this analysis for 2018, we find that the ERA5 reanalysis had stronger upshelf winds until March 2018 when the winds abruptly reversed (Fig. 12), consistent with the observed winds and decreased freshwater inflow to the Gulf of Maine (Wang et al., 2022; Townsend et al., 2023). The majority of the ensemble members accurately predicted upshelf winds at the beginning of the time period, and the best three members predicted a reversal of the winds in March, although none of the members predicted the reversal would occur so abruptly. After March, the ERA5 reanalysis shows a return of upshelf winds, and most ensemble members follow suit. Regardless of the accuracy at predicting the March winds, essentially all of the ensemble members predicted positive March–April average $\Omega_{\text{aragonite}}$ anomalies in the Gulf of Maine and near-zero anomalies along the Scotian Shelf with positive anomalies offshore. In fact, the one ensemble member (7) with negative $\Omega_{\text{aragonite}}$ and salinity anomalies in the eastern Gulf of Maine averaged over March and April actually had the most accurate March winds, but failed to capture the strong upshelf winds in January and February and the return of these winds in April (Fig. 12).

These results for 2017 and 2018 confirm previous studies finding that alongshelf wind influences the advection of freshwater along the Scotian Shelf and into the Gulf of Maine (Li et al., 2014; Wang et al., 2022) and also indicate a consistent signal of low $\Omega_{\text{aragonite}}$ associated with increased freshwater advection. We were unable to identify any potentially predictable climate pattern associated with the March and April winds in these years. Instead, our hypothesis is that the accurate prediction of $\Omega_{\text{aragonite}}$ and salinity by the ensemble mean forecast derives from the anomalies present along the Scotian Shelf at the forecast initializations in January 2017 and 2018. Although the precise evolution of these anomalies over time was influenced by wind events that are probably unpredictable, having a large enough ensemble to capture a representative distribution of possible winds allows the ensemble to capture the distribution of possible Scotian Shelf Water anomalies and generates a reasonably accurate ensemble mean prediction. Note, for example, that the time series of cumulative alongshore winds from the ERA5 reanalysis in Fig. 12 would be essentially indistinguishable if it was plotted together with all ten ensemble members.

4 Discussion

The evaluation of forecast skill presented in the results showed forecast skill for multiple months of lead time across all of the variables and regions examined. Forecasts initialized in January consistently maintained skill over longer time horizons, and skill dropped off in the autumn as the less predictable surface conditions were mixed downwards. Forecasts for the Gulf of Maine generally had the highest anomaly correlations and skill above persistence, which is consistent with Chen et al. (2021), who found high prediction skill for bottom temperature in the deep Gulf of Maine from predictable advection. Although a bias sometimes developed during the course of the forecast simulations, especially for bottom $\Omega_{\text{aragonite}}$, the high correlation coefficients suggest that the variability is still accurately predicted and a simple mean bias correction could eliminate the bias. In this section, we discuss potential next steps for improving the model.

4.1 Potential improvement to model initialization

The high persistence of the benthic biogeochemical variables in most regions and times of year, as well as the importance of initialization shown in both case studies, are consistent with seasonal forecasting being primarily an initial value problem

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rather than a boundary value problem (Meehl et al., 2021). As a result, using accurate initial conditions in retrospective and operational forecasts is essential for producing skillful forecasts. Ideally, in situ observations would be assimilated into the numerical model to derive accurate initial conditions. These observations should be collected frequently over a wide spatial area due to the importance of fine-scale spatial and temporal variability, especially for coastal ocean biogeochemistry (e.g., De Mey-Frémaux et al., 2019; Song et al., 2016a; Stanev et al., 2016). For retrospective forecasts, these observations would also need to be consistently available throughout the retrospective forecast period to ensure that the estimated forecast skill was not biased by changes in observation frequency and density, and for operational forecasts, the observations would need to be available with a limited time delay. No observational datasets of bottom biogeochemical properties exist that fully meet these requirements. Instead of directly using observations to constrain the forecast initial conditions, we forced the model analysis simulation that was used for forecast initial conditions with reanalysis atmospheric forcing and boundary conditions and further nudged the ocean temperature and salinity towards a reanalysis product. Since these reanalysis products do assimilate observations of ocean and atmospheric physics, they help indirectly constrain the downscaling model with observations. However, future work should consider assimilating ocean physics and biogeochemistry data in the model.

Numerical models like the one in this study, with high resolution, explicit simulation of tides, and coupled ocean biogeochemistry and sea ice components, commonly present a number of challenges to successful assimilation of observations. Directly assimilating biogeochemical data can be difficult due to the number of biogeochemical state variables, the non-Gaussian distribution and complicated covariance of many of them, and the rapid time scales of some biological processes (Edwards et al., 2015). Studies that have successfully developed ocean and biogeochemical assimilation systems have shown that including both physical and biogeochemical observations in the data assimilation system is beneficial, and that including only physical observations often degrades the biogeochemical solution (Ford et al., 2018). For example, in a study of the California Current System, assimilating both physics and chlorophyll data significantly improved the RMSE for both components relative to unassimilated experiments, while assimilating only physics yielded small changes in biogeochemical errors (Song et al., 2016b, a). An additional challenge is that ocean color from satellite remote sensing is the most widely available ocean biogeochemical data to assimilate, and since this data is only a proxy for surface chlorophyll concentration it tends to provide weak constraints on other biogeochemical variables, especially below the surface (Song et al., 2016b, a; Fennel and Testa, 2019). Even though recent studies have made progress towards addressing these challenges, data assimilation still adds significant computational costs that can limit the ability to do extensive retrospective forecasting studies to robustly assess forecast skill.

Rather than developing a data assimilation system, this study used a simple nudging of ocean temperature and salinity towards a data-assimilative reanalysis product to constrain the initial conditions for the forecasts. Although it has been successfully used in other studies (Liu et al., 2023; Ross et al., 2024), the use of the nudging method results in several limitations. First, the forecast ensemble spread will tend to be overconfident, particularly during the first few lead times of the forecast. This overconfidence could be reduced using post-processing methods that add a reliable estimate of uncertainty (e.g., Ross and Stock, 2022). Second, the nudging is only applied to temperature and salinity and does not directly constrain the biogeochemistry. This could be solved by also nudging some or all of the biogeochemical variables, but as with full data assimilation, biogeochemical nudging would be complicated by the limited availability of reliable observations or analysis products, especially those that cover the complete retrospective forecast period, and the potential interactions between nudged and non-nudged variables. Methods that use machine learning approaches to predict unobserved biogeochemical variables from other observed variables can help solve this problem (Amadio et al., 2024; Sauzède et al., 2017). Hybrid data assimilation methods that implement machine learning into traditional data assimilation algorithms, such as Higgs et al. (2026), also have the potential to solve many of the problems with biogeochemical data assimilation.

4.2 Other potential improvements to the model system

Although river discharge estimated by a gridded reanalysis was used to force the downscaled ocean model during the nudged analysis simulation, during the forecast simulations the ocean model received river input following a climatological cycle. The ocean forecasts could potentially be improved by using forecasts of river discharge as forcing. This would be particularly important for some regions of the Northwest Atlantic regional model domain, such as the Louisiana–Texas shelf, where variability in river discharge and nutrient loading is important for predicting coastal hypoxia (Scavia et al., 2003, 2017). In the Northeast U.S. subregion examined in this study, however, river discharge is generally not considered to be a primary driver of ocean or biogeochemical variability. The Gulf of Maine is estimated to receive more than half of its freshwater (Smith et al., 2001) and nearly all of its nitrogen loading (Townsend, 1998) from sources other than direct river discharge to the Gulf. Outflow from the St. Lawrence River is a major external component, but the time scale of advection from the Gulf of St. Lawrence to the Gulf of Maine is long enough that it is not important to predict for seasonal forecasts. The surface freshwater signal of St. Lawrence River discharge is estimated to take between 5.5 and 8 months after the spring discharge peak to reach the entrance to the Gulf of Maine along Southwest Nova Scotia (Ohashi and Sheng, 2013; Rutherford and Fennel, 2018; Shan et al., 2016); however, age tracer methods that represent time average rather than peak discharge conditions estimate that water reaching the entrance to the Gulf of Maine has aged almost a year since leaving the St. Lawrence River estuary (Rutherford and Fennel, 2018). Furthermore, these time scales are for the advection of freshwater at the surface to the entrance of the Gulf of Maine; any impacts on bottom biogeochemistry within the Gulf of Maine would occur with an additional delay. River discharge does contribute to a larger portion of salinity and biogeochemical variability in the Mid-Atlantic Bight, especially in the most nearshore areas (e.g., Wright-Fairbanks and Saba, 2022; Xu et al., 2020), and future studies could consider whether there is any benefit to including predicted river discharge in the forecasts.

5 Conclusions

Using a large suite of downscaled retrospective forecasts from a high resolution regional ocean-biogeochemistry model, we found that the model could skillfully predict changes in oxygen and acidification metrics for bottom water along the Northeast U.S. Large Marine Ecosystem. In most cases, prediction skill was highest for forecasts initialized in winter and spring, when the results of the more predictable evolution of conditions in the first few months then become insulated from the less predictable atmosphere by summer stratification. This long persistence of prediction skill points to the importance of having accurate initial

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510 conditions and suggests coupled biogeochemical assimilation is an important area for future research. However, the forecasts already have a substantial amount of prediction skill that will provide a strong baseline for assessing the utility of forecasts to improve the yield and sustainability of living marine resources.

Code availability. The source code for each component of the MOM6-NWA12-COBALT model has been archived at https://doi.org/10.5281/zenodo.22210571 (Ross et al., 2026a).

515 *Data availability.* All model output that was analyzed in this paper has been archived at https://doi.org/10.5281/zenodo.22211043 (Ross et al., 2026b).

Author contributions. LJ, NCJ, and CM contributed to developing and running the SPEAR global prediction model. VK, CAS, and ACR contributed to the development and initial evaluation of the downscaled prediction model. ACR ran and analyzed the downscaled prediction experiments and prepared the initial draft of the manuscript. All coauthors participated in discussions during various stages of the model
520 development and evaluation and read and approved the final version of the manuscript.

Competing interests. One of the coauthors serves as editor for the special issue to which this paper belongs.

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