Daily to Decadal Ecological Forecasting Along North American Coastlines

Workshop Report

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Ocean Carbon & Biogeochemistry

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Executive Summary

Coastal areas share unique intersections of large-scale climate variability and local hydrology, wetland, benthic and pelagic ecosystems, and anthropogenic pressures. Forecasting of harmful environmental conditions for planning, adaptation, and mitigation purposes is both complex and urgently needed. Ecological forecasting is the qualitative or quantitative projection of biogeochemical, organismal or ecosystem state variables and their drivers on timescales that can range from "now" to decades from now. Estimating hypoxia in Chesapeake Bay today, predicting acidity conditions in the Northeast Pacific in a few months, or projecting the depth of the Bering Sea nutricline in 2075 are all ecological forecasts relevant to planning, adaptation, and mitigation efforts.

In 2022, the US CLIVAR and Ocean Carbon & Biogeochemistry (OCB) Programs convened a joint workshop to advance the development of US ecological forecasting. The workshop goals were to 1) identify sources of predictability of physical quantities relevant for marine ecosystems along US coastlines; 2) assess the observational needs of forecast systems and limitations due to gaps in understanding; and 3) promote the development of dynamical and statistical models suitable to meet the forecasting requirements. About 80 participants from over 40 US and international institutions joined this hybrid workshop for plenary talks and breakout discussions. Participants represented a diversity of career stages across academic institutions, government agencies, and non-government organizations. By working together, they collectively identified a path forward for a coordinated US ecological forecasting effort as detailed in this report.

Despite identifying potentially important sources of predictability arising from large-scale modes of climate variability, we are still limited in our mechanistic understanding of how these modes of variability modulate processes at the regional scale, especially along the US East Coast. This knowledge gap is exacerbated by the challenges of observing and modeling regional processes that operate over a range of spatial and temporal scales (e.g., tidal forcing, complex geomorphology, biophysical interactions, and open ocean-shelf interactions). There needs to be continued support to extend investigations of climate modes of variability, to clarify their connection with regional processes, and to elucidate the mechanisms responsible for their phase transitions. In particular, an improved understanding of decadal modes of variability will aid in the separation of internal and anthropogenically-forced variations, in evaluating the stationarity of their influence on processes of interest and, where possible, improve predictions on this decision-critical time horizon.

The physical, biogeochemical and ecological datasets that are essential for initializing, forcing, and validating ecological forecasts remain a major limitation of modeling and forecasting efforts. Coastal observing capacity should be enhanced and informed by Observing System Simulation Experiments (OSSEs), which are specifically designed to identify the most impactful data, both at the surface and in the subsurface, to constrain reanalyses and aid forecasting activities. We must also augment, integrate and harmonize the diversity of local and regional observing efforts into compatible coast-wide systems to broadly support ecological forecasting at a national scale. A second key issue stems from the storage and archiving standards used for existing datasets in regional and institutional archives. It is necessary to integrate these existing datasets, including those from the Integrated Ocean Observing System (IOOS) associations, in standard formats as part of a "US coastline dataset," which would directly support ecological modeling and forecasting and reduce the barriers for diverse groups to participate in forecasting efforts.

Coastal reanalyses represent a well-tested strategy with rapid deployment capability for integrating, interpolating, standardizing and contextualizing scarce and valuable historical data. These can bridge the spatial scales between sparse data collection and the large datasets needed for machine learning or artificial intelligence forecasting approaches. However, these efforts also need to be well integrated into a US coastline-wide system that seamlessly connects observing system boundaries. Uncertainties associated with reanalyses should be reported in a transparent manner to assist with uncertainty quantification for forecasting efforts.

Given the broad range of spatial scales of ecological relevance, ecological forecasting along coastlines requires forecasting systems at higher resolution than some currently available operational systems (e.g., the North American Multi-Model Ensemble) to properly (dynamically) downscale coarser climate information to the regional scales of the processes of interest. Forecasting efforts must further leverage data collection and computing advances to address uncertainty. Ensemble modeling approaches, particularly at high resolution, are a critical need. Such ensemble approaches may rely on statistical methods and model emulators. More advanced computing infrastructure is needed to support these efforts.

Finally, there needs to be an increased emphasis on training environmental and ocean scientists in data science, computational modeling and novel machine learning, and artificial intelligence technologies to leverage these advances from other fields for the development of model emulators and parameterizations supporting model development and ecological forecasting around the US coastlines.

1 Motivation and Objectives

Coastal areas at the interface between terrestrial and aquatic habitats share unique intersections of large-scale climate variability and local hydrology, wetland, benthic and pelagic ecosystems, and anthropogenic pressures. Coastal regions are home to 40% of the US population, yet represent only 10% of the US land area (NOAA report). Coastlines host rich and productive marine ecosystems that support industries and services of great economic value—fisheries, aquaculture, tourism, recreation, and shipping—each of which has different forecasting needs. The functioning of coastal marine ecosystems across a broad range of trophic levels is tightly connected with climate variability, which influences physical and biogeochemical coastal environmental conditions including sea level, temperature, salinity, dissolved oxygen, and pH.

Climate change and other anthropogenic activities affect coastal resilience through long-term trends, which are expected to exacerbate extreme conditions, creating serious threats to marine life and to humans living in coastal zones. Understanding the relative influences of anthropogenic and internally driven changes in different regions is key to improving our capacity to predict harmful environmental conditions for planning, adaptation and mitigation purposes. The connection of coastal processes with large-scale climate variability (e.g., El Niño-Southern Oscillation (ENSO), North Atlantic Oscillation (NAO)) can provide an important source of predictability for physical and biogeochemical ecosystem drivers. However, the impacts of large-scale climate variability and trends on coastal regions are mediated by the complexity of local processes specific to each region, involving interactions between land, ocean, hydrology, biogeochemistry, and atmosphere. Some of these processes occur at spatial scales that are not currently resolved by climate models.

Recent syntheses (Jacox et al., 2020) have highlighted many sources of predictability for ecological forecasting at seasonal to interannual scales relevant to specific applications (e.g., fisheries). They revealed a disconnect between open ocean, coastal, and estuarine forecasting communities, particularly in regions with broad shelves. At the estuarine scale, processes like tidal amplitude and mixing, riverine discharge, and nutrient loading are central to successful forecasts. The impacts of these more local processes can be modulated by larger-scale processes, and, conversely, they can influence the broader coastal environment through changes in physical and biogeochemical quantities (e.g., salinity, dissolved oxygen). The ability to properly understand these processes and their interactions is often limited by data availability at the proper spatial and temporal resolutions (Capotondi et al., 2019) of sufficient duration to allow robust inferences. Due to the large spatial heterogeneity of the coastal environment, their characterization requires data at high spatial and temporal resolutions, thus posing significant challenges to ecological forecasting.

The goal of this workshop was to bring together climate scientists, biogeochemists, and global and regional modelers to:

1. **Examine the connections between large-scale physical and biogeochemical processes with coastal processes, and identify sources of predictability at sub-seasonal to decadal timescales that are specific to regions along US coastlines.**
2. **Assess the suitability and needs for observations that robustly characterize the key physical and biogeochemical ecosystem drivers along US coastlines, their interactions across scales, and their responses to climate change in different coastal regions.**

3. **Assess the major gaps in understanding and modeling/observing capabilities that limit our ability to produce reliable ecological forecasts at the scales needed for application and management along US coastlines, and identify potential avenues for accelerating progress.**

Given the inherent interdisciplinary nature of ecological forecasting, this workshop was envisioned as a joint effort between US CLIVAR and the Ocean Carbon & Biogeochemistry (OCB) programs and was co-organized by members and experts of both communities. Previous joint efforts between US CLIVAR and OCB such as the Forecasting ENSO Impacts on Marine Ecosystems of the US West Coast workshop demonstrate the value of bringing together communities that may not otherwise collaborate closely to meet cross-disciplinary challenges.

The workshop was structured in four focused sessions, each with keynote presentations to review current knowledge and potential gaps, followed by shorter contributed presentations that showcased recent relevant research activities (see Agenda, Appendix A). Following the presentations in each session, attendees were assigned to breakout groups with targeted discussion questions (developed in advance by the workshop organizing committee) with the goal of identifying a path forward for coastal ecological forecasting.

- Session 1: Examined sources of predictability in different regions along US coastlines (Figure 1), including the US West coast, the Arctic, and the northern and southern portions of the US East Coast, with the southern portion also including the Gulf of Mexico.
- Session 2: Explored applications of ecological forecasting over a suite of timescales
- Session 3: Reviewed the modeling tools currently available to perform forecasts
- Session 4: Focused on observations and reanalysis products, fundamental for forcing, initializing, and validating prediction models.

This report summarizes plenary and contributed presentations and breakout group discussions and provides a well-rounded set of community recommendations based on these discussions to improve marine ecological forecasting capabilities. Find key workshop documents, including the workshop agenda (Appendix A) and the participant list (Appendix B) at the end of this report.

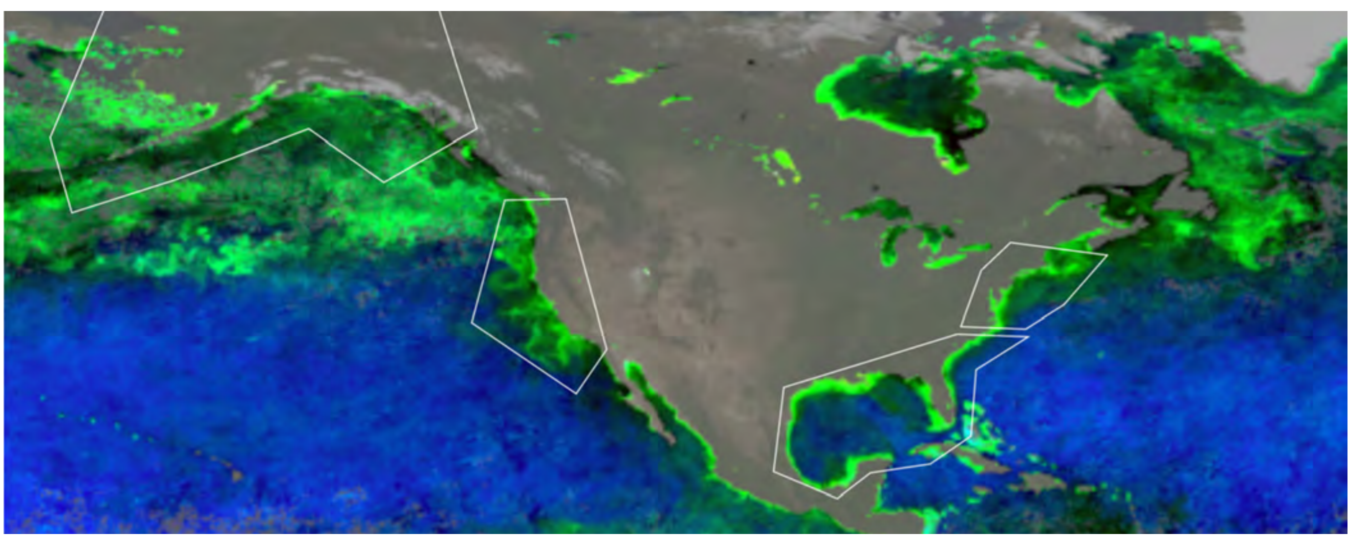

Figure 1: Ocean color image of Chlorophyll-a along the continental US coastlines. White outlines delineate the regions discussed at the workshop—Arctic, US West Coast, Northern US East Coast, Southern US East Coast, and Gulf of Mexico. Source: NASA https://oceancolor.gsfc.nasa.gov/gallery/778

2 Highlights from Plenary Sessions

Session 1: Sources of regional predictability

In the following sections (S1.1 – S1.4), we summarize the keynote presentations. While not necessarily fully comprehensive, these presentations set the stage for discussions on the gaps in our understanding of regional predictability at the coastline. Links to view the talk recordings and download the slide decks presented at the workshop are included in Appendix A.

Key takeaways from Session 1

US WEST COAST	The dominant source of predictability for the US West Coast is the ENSO phenomenon. North Pacific variability at decadal timescale may act as a precursor to Northeast Pacific marine heatwaves. Predicting and validating subsurface fields is a key challenge. Biogeochemical properties sometimes show multi-annual timescale prediction skill.
ARCTIC	New forecasts exhibit skill in forecasting pan-Arctic ice extent in September at different lead times, which is key for navigation as well as fisheries and habitat prediction for endangered marine mammals. Data assimilating models better predict the metabolic index (a measure of oxygen availability) reflecting the value of subsurface oxygen data for prediction skill.
NORTHERN US EAST COAST	Subsurface thermal anomalies may provide prediction skill, but spatially and temporally distributed subsurface data are required. Circulation can provide seasonal predictability for fisheries and plankton ecology in certain regions (e.g. Gulf of Maine, north wall of the Gulf Stream). Strong weather events, and poor model resolution of shelf and coastal dynamics in global models limit predictability in this region.
SOUTHERN US EAST COAST AND GULF OF MEXICO	Although the physical dynamics and biogeochemistry can be simulated in nowcasts, predictability of ocean conditions remains a challenge for this region. Storm events can be large perturbations to the system. The predictability of ocean and biogeochemical properties associated with storms is significant. OSSE experiments may provide a strategy for improving understanding of the shelf-open ocean dynamics and observing needs for enhancing predictability.

S1.1 US West Coast (presenters: Jacox, Amaya, Pozo Buil)

The dominant source of predictability for the US West Coast is the ENSO phenomenon in the tropical Pacific. The evolution of ENSO is associated with the eastward propagation of equatorial Kelvin waves which reach the eastern ocean boundary and then continue poleward along the west coasts of the Americas as coastal Kelvin waves.

During the warm (El Niño) phase of ENSO, the Kelvin waves deepen the thermocline and lead to a reduced nutrient supply from the deeper ocean to the euphotic zone (Capotondi et al., 2019; Jacox et al., 2020). La Niña events are approximately associated with opposite conditions. In addition, sea surface temperature (SST) anomalies in the equatorial Pacific can alter the North Pacific atmospheric circulation through atmospheric teleconnections, which in turn can affect surface conditions and coastal upwelling via changes in surface heat fluxes and surface wind stress along the coast. The ENSO influence leads to enhanced SST prediction skill at seasonal timescales, based on the North American Multi-Model Ensemble (NMME) prediction system (Jacox et al., 2017). The ENSO-related skill is higher in the Northern California Current System (CCS), where the remotely driven wind forcing is more prominent, than in the Southern CCS, which is more affected by the coastally trapped waves of equatorial origin, whose representation in relatively coarse climate models may be inadequate.

Not all ENSO events exert a significant influence on the US West Coast (Capotondi, et al., 2019). Impactful events appear to be associated with a North Pacific dynamical mode of variability at decadal timescales that may act as a precursor of Northeast Pacific marine heatwaves (Capotondi et al., 2022), thus indicating a possible modulation of ENSO impacts by North Pacific decadal variations. Also, predictability may vary with the time of year, depending on the variable being considered. SST and Sea Surface Height (SSH) are usually well-predicted, but subsurface variables such as bottom temperature, mixed layer depth and stratification remain difficult to predict. The challenge associated with predicting and validating subsurface fields was a recurrent theme throughout the presentations and discussion. At sub-seasonal timescales, some sources of predictability stem from sub-seasonal Kelvin wave activity forced by wind events in the western equatorial Pacific associated with the Madden Julian Oscillation (MJO; Amaya et al., 2021).

Potential predictability and prediction skill have been demonstrated for multi-annual timescales, especially for biogeochemical quantities such as CO_2 fluxes, net primary productivity (NPP), nitrate (NO_3), pH, and dissolved oxygen (Krumhardt et al., 2020; Lovenduski et al., 2018; Park et al., 2019; Brady et al. 2020). At decadal timescales, sources of predictability may arise from the propagation of subsurface anomalies from the western North Pacific to the US West Coast along isopycnal surfaces (Pozo Buil & Di Lorenzo, 2017), but their influence on US West Coast properties needs to be further investigated. The utility of this predictability is currently being explored through the application of habitat models to small pelagic fisheries such as sardines. Spotlight presentations further note that compositing events into more specific eastern Pacific or central Pacific ENSO events may be needed to mechanistically link observed zooplankton variability with underlying dynamics (Lilly & Ohman, 2021).

S1.2 Arctic (presenters: Bushuk, Chen)

The rapid decline of Arctic Sea ice has provided impetus to improve seasonal sea ice forecasting skill for many applications, including navigation, wildlife management, shipping, ecology, etc. The ability to forecast the sea ice edge months to years in advance is particularly important for fisheries. In the Bering Sea, pollock and cod stocks tend to follow the position of winter sea ice edge (Figure 2; Wyllie-Echeverria & Wooster, 1998).

Sea ice reduces the photosynthetically available radiation (PAR) entering the upper-ocean in spring and summer, shifting the phenology of phytoplankton blooms in seasonal ice zones. The prediction of sea ice thickness can provide predictability for sub-ice summer blooms (Horvat et al., 2017). Because sea ice is a critical habitat for many species (e.g., bowhead whales, seals, walruses, polar bears, etc.), prediction of ice conditions at sub-seasonal, seasonal, and multi-annual timescales can inform decision-making by fisheries and wildlife resource managers. Sources of predictability and sea ice forecasting skill were recently investigated using two different prediction systems developed at GFDL: the FLOR (Forecast Oriented Low Ocean Resolution; Vecchi et al. 2014) and SPEAR-MED (Seamless system for Prediction of Earth System Research; Delworth et al. 2020) models. They are fully coupled systems that are initialized with conditions created through assimilation of a suite of oceanic and atmospheric observations using an ensemble Kalman filter. These systems are used for retrospective ensemble sea ice forecasts initialized at the beginning of each month over the period 1992-2020 (29-year record). Both systems exhibit skill (based on anomaly correlation) in forecasting pan-Arctic sea ice extent in September at different lead times. Skill was found also in detrended data, indicating the models' ability to capture sea ice internal variations (Bushuk et al., 2017; 2022). Regional prediction skill was examined by dividing the Arctic in 14 different regions. This analysis shows potential for skillful predictions of sea ice extent at one to eleven months lead time, which may be controlled by different processes in different regions.

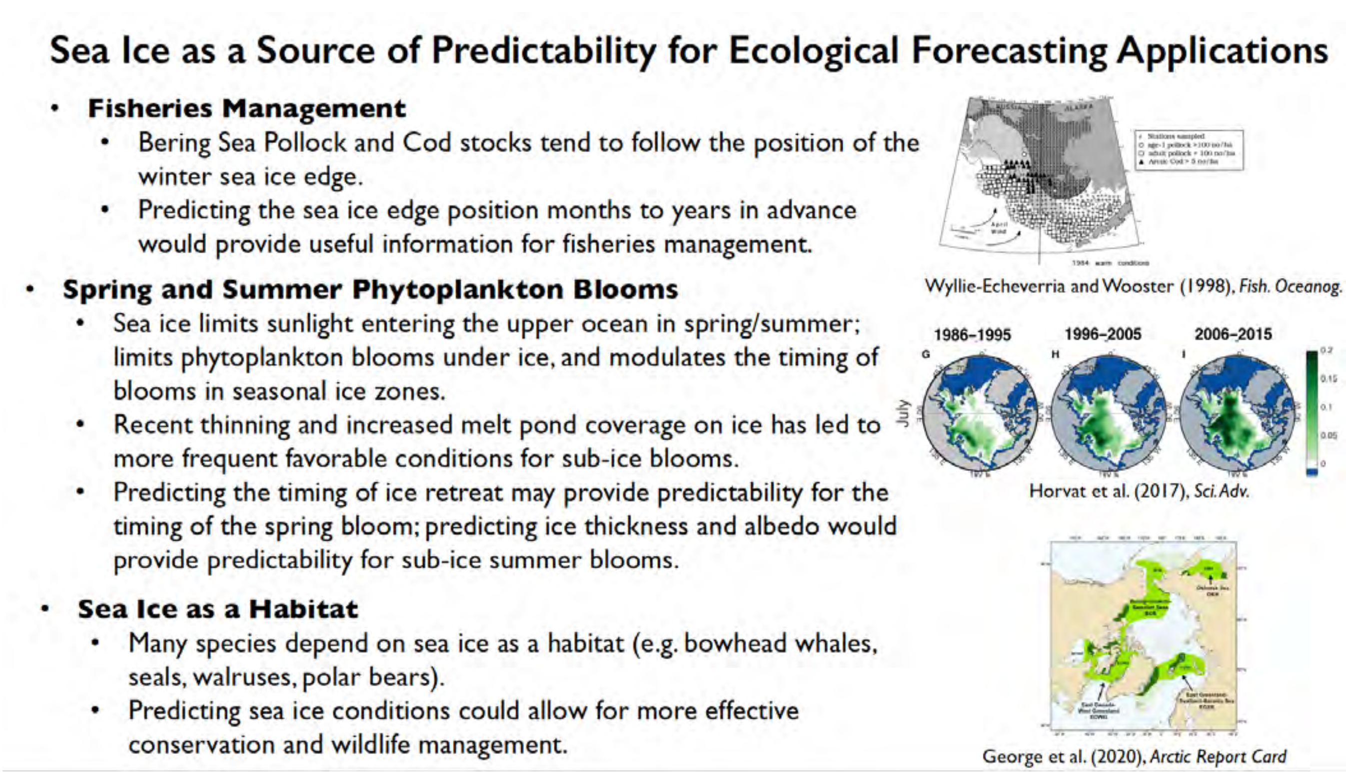

Figure 2: Slide from Buskuk's presentation.

At longer timescales, the CESM Decadal Prediction Large Ensemble illustrates potential for forecasting the metabolic index, a measure of the oxygen availability to animals who acquire oxygen through contact with water. Both temperature and oxygen drive the metabolic index, however their regional importance varies in the Gulf of Alaska and Barents Sea. The more mechanistic forecasting approach that includes data assimilation shows higher skill than a similar hindcast without data assimilation, demonstrating the value of observations in constraining subsurface ocean properties.

S1.3 Northern US East Coast (presenters: Alexander, Santos, Zang)

One basic mechanism for predictability of SST anomalies in the North Atlantic is associated with the subsurface persistence and periodic re-emergence of temperature anomalies (Alexander et al. 1999). Persistence can simply arise from the ocean integration of high-frequency atmospheric forcing, a process that depends upon the upper-ocean mixed layer. The seasonal variation of mixed-layer depth can further modulate ocean memory. For example, winter mixed layer temperature

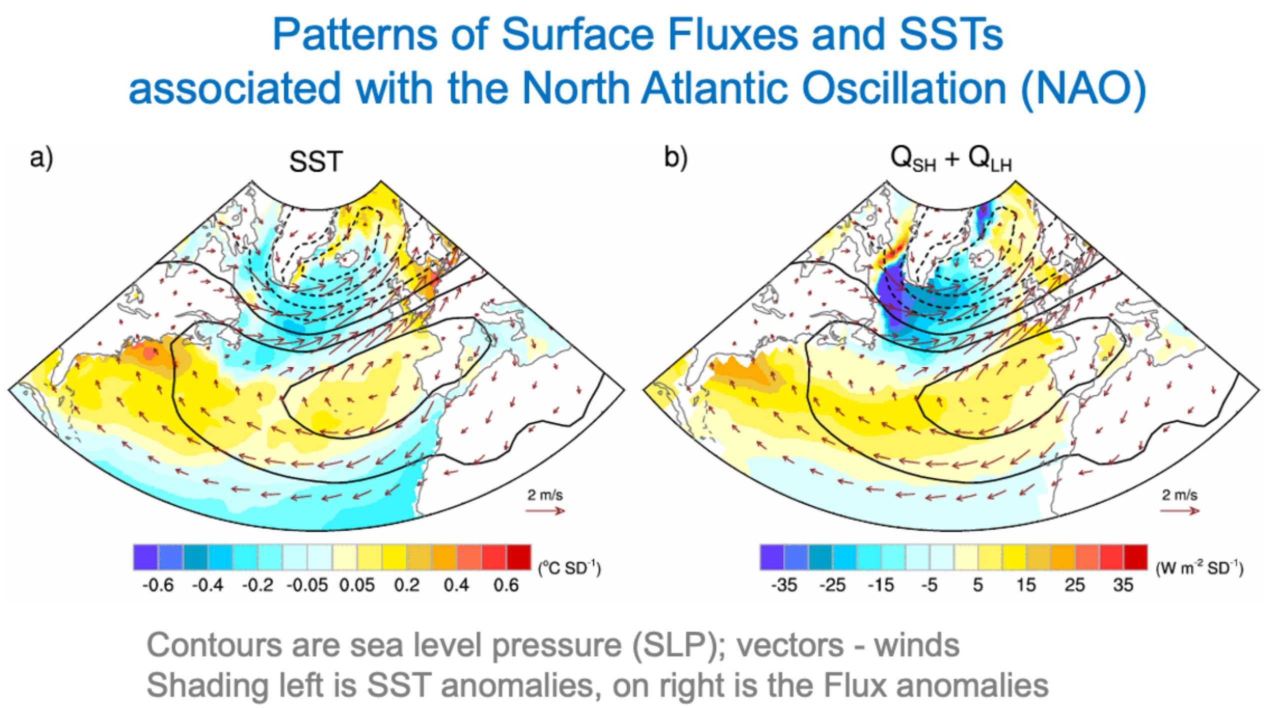

Figure 3: Slide from Alexander's presentation.

anomalies can get trapped below the shallower summer mixed layer and then be re-entrained in the deeper winter mixed layer the following year, providing year-to-year memory. This mechanism can also be "nonlocal" if ocean currents advect the summer subsurface anomalies elsewhere, creating the possibility for their re-emergence at a different location. Thus, subsurface thermal anomalies, or wintertime surface thermal anomalies may improve temperature predictability over a period of time if they are captured by measurements.

Other sources of predictability in this region are associated with large-scale modes of climate variability. The NAO is a sea level pressure (SLP) dipole with one center over the Azores and the other center of opposite sign over Greenland. These SLP anomalies are associated with wind anomalies that can drive anomalous surface fluxes and Ekman transport and circulation changes leading to large SST anomalies along the US East Coast (Figure 3). The leading pattern of SST anomalies in the

North Atlantic associated with the NAO has a tripole structure, with anomalies of one sign in the tropical Atlantic and high-latitudes, and anomalies of the opposite sign along the southern part of the US East Coast (De Coëtlogon & Frankignoul, 2003; Deser et al., 2003; Timlin et al., 2002; Watanabe & Kimoto, 2000).

The NAO is primarily an internal mode of atmospheric variability with limited predictability, but it is also influenced by other factors such as ENSO, stratospheric processes, and North Atlantic Ocean and sea ice conditions. As a result, studies have shown that NAO predictions conducted with Large Ensembles (LEs) do have some skill at one and multi-year timescales, although predicted amplitudes are weaker, and model spread is large. The multi-model ensemble mean prediction shows higher correlation with observations than with their own simulations, a result known as the "signal-to-noise paradox" (Scaife et al., 2014).

Ocean circulation in the western North Atlantic includes the Labrador Current, which follows the coast southward all the way to North Carolina, and the northward flowing Gulf Stream. Both currents exert a strong influence along the US East Coast. Deep circulation is mediated by the complex bathymetry of the area, especially in the Gulf of Maine. Zang et al. (2022) illustrate how knowledge of the deep Scotian Shelf water mass transport associated with variations in Labrador slope and warm shelf water can lead to predictability of the timing and magnitude of the spring phytoplankton bloom in the Gulf of Maine. Wind stress changes in the central North Atlantic can trigger oceanic Rossby waves, which propagate westward and cause changes in the position of the Gulf Stream and its contribution to the water masses along the northwestern Atlantic shelf, either through eddy shedding or subsurface intrusions (Gonçalves Neto et al., 2017). The position of the north wall of the Gulf Stream has been used as the basis for a statistical model to predict silver hake (Davis et al., 2017), and also shows a strong link to SSH variability along the coast (e.g. Ezer et al., 2013; Ezer & Atkinson, 2014).

At decadal timescales, the leading mode of variability is the Atlantic Multidecadal Variability (AMV), also known as the Atlantic Multidecadal Oscillation (AMO). The AMV pattern is characterized by widespread SST anomalies over the entire North Atlantic, which may arise from changes in AMOC, thermal forcing, or aerosol effects. While it is hard to separate the internal and climate change components of the AMOC variability, some skill in predicting AMOC at decadal timescales is found with the GFDL-SPEAR prediction system (Yang et al., 2021) we have developed a decadal coupled reanalysis/initialization system (DCIS. AMV is also closely linked with hurricane frequency in the Atlantic (Goldenberg et al., 2001).

At centennial timescales, projections from three climate models dynamically downscaled to 7-km resolution show warming along the whole US East Coast, with magnitudes that are model-dependent (Alexander et al., 2020). Changes in the circulation lead to local expressions of the warming trend (e.g., reduced warming is found along the path of the Gulf Stream, due to its projected slowdown and reduced northward heat transport).

While there are several sources of predictability along the US East coast, several cautionary factors need to be considered: strong weather events can limit predictability; large-scale ocean processes may have limited influence on the shelf; anomaly-correlation used as a measure of forecast skill may obscure other issues (e.g., anomaly amplitude); and skill may arise mainly from the forced (i.e. climate change) signal. Indeed, prediction skill at seasonal timescales in some of the operational prediction systems like NMME is very low along the US East Coast (Shin & Newman, 2021), perhaps due to the coarse model resolution and the models' inability to represent a realistic Gulf Stream.

S1.4 Southern US East Coast and Gulf of Mexico (presenter: He)

A large body of modeling work, based on coupled physical and biogeochemical models of different complexity, exists for the Gulf of Mexico and South Atlantic Bight. An example is provided by the coupled system that uses a high-resolution version of the HYCOM ocean model and the NEMURO biogeochemical (BGC) component. This model was run for 20 years and its output was compared with all observations of zooplankton biomass in the area (Shropshire et al., 2020). Significant progress has been made in the development of BGC and ecological models that show encouraging skill at synoptic to seasonal timescales. But ultimately, the predictability of marine ecosystems and marine resources depends on the predictability of their physical drivers.

The primary physical drivers are storms, especially tropical storms. From 2003 to 2020, there were 321 storms, from tropical depressions to category 5 hurricanes, 80% of which made landfall or moved across the Gulf of Mexico and the Southern US East Coast, with tremendous impacts on regional ocean and ecological processes. A process called "Right-Hand bias" is associated with an asymmetric mixing of temperature, Chl-a, DIC, and air-sea pCO_2 fluxes, as well as re-stratification, providing an interesting example of mesoscale-submesoscale interactions. Sensitivity experiments with an idealized model show important changes in SST, DIC, NO_3, Chlorophyl, and pCO_2 after the storm passage as a function of the storm speed and intensity (McGee & He, 2022). Realistic simulations of the passage of a 2008 hurricane that occurred September 1-15 in the Gulf of Mexico, shows the enhancement of surface DIC and pCO_2 fluxes, highlighting the importance of capturing synoptic variability for ecological predictions (Zong and He, submitted) and the need for accurate prediction of storm trajectories and intensities.

The Loop Current (LC) is an important circulation feature of the Gulf of Mexico. According to a study of the National Academies of Sciences (2018), "the position, strength, and structure of the LC has major implications for hurricane intensity, marine ecosystem state, and the Gulf region's economy." LC modes can be categorized with the self-organizing map methodology applied to sea level: 1) Normal (P1, 42%), 2) Extension (P2, 28%) and 3) Retraction/separation (P3, 30%). The P3 mode occurs more frequently in fall and winter, and less frequently in spring. The interannual modulation of these dynamical patterns are related to interannual variations of the large-scale wind forcing, but forecasting the Loop Current is an active area of research. There is also a correlation between the annual mean frequency of occurrence of the P3 pattern and ENSO indices. However, subseasonal and sub-mesoscale variations in this system are very difficult to predict.

Another important source of predictability at interannual timescales is related to Gulf Stream (GS) eddies and meanders. Lee et al. (1991) showed that eddies shed by the GS can be instrumental in supporting phytoplankton blooms. Large-scale offshore meanders, which can be monitored from space, can alter temperature, nutrient concentrations, and DIC along the entire shelf as the offshore movement of surface water drives upward movement of nutrient-rich deep waters. However, while the dominant sources of predictability reside in the large-scale wind fields associated with the NAO and AMO, it is not clear how exactly the dynamics of the LC and GS are affected by large-scale air-sea interactions, and to what degree the separation of the LC eddies and the development of GS meanders are predictable. Similarly, the interactions between different BGC processes in this region are not well understood. It is also not clear how well these processes are reproduced by models and how they are modulated at decadal timescales. Development of long-term reanalysis products would help improve understanding of key processes, and OSSEs could inform ocean observation strategies.

Session 2: Applications at different timescales

Key takeaways from Session 2

Fisheries Applications	Fisheries management decisions are made on time horizons from days to decades. Short term nowcasts using only observed or nowcast model data can be useful for reducing fisheries bycatch or exposure to pathogens. Seasonal to inter-annual predictions show promise in informing catch advice in ways that reduce overfishing risks and increase catch and many ecosystem drivers, particularly those in the subsurface, have predictability extending over these time horizons. Decadal predictions and multi-decadal projections have the potential to inform strategic decisions on longer timescales, including adaptation to changing stock boundaries and the placement of aquaculture operations.
Seasonal Forecasts of Ocean Health	Using stakeholder-endorsed data sets improves likelihood of the uptake of forecast products. Model ensembles are critical to assessing uncertainty, but often limited in size. Summer predictability is linked to re-emergence of thermal anomalies from the preceding winter, which again highlights the need for subsurface data.
Harmful Algal Blooms	4d-Var data assimilation is useful for HAB forecasting. Machine learning can be used to predict toxicity.
Chesapeake Bay	Stakeholders find the most value in forecasts with short lead times. Multi-model ensembles can be useful in partitioning the sources of uncertainty in future projections.
Marine Heatwaves	Local heatwaves may have their genesis in basin-scale processes (e.g., a North Pacific heatwave co-occurred with a central Pacific ENSO event).

S2.1 Fisheries applications (presenters: Tommasi, Norton)

Forecasting for fisheries applications has potential utility across a range of temporal and spatial scales (Tommasi et al. 2017) but associated observational and modeling needs and decision support potential vary significantly for each scale.

At very short timescales (i.e. near-real-time), forecasts of harmful algal blooms and associated toxins (e.g., *Vibrio parahaemolyticus*) would be impactful for predicting shellfish health and protecting human communities. Forecasts of hypoxia and coral bleaching events are also useful on these timescales, though with less serious implications for human health. These short-range applications involve different forecasting approaches, from mechanistic modeling of hypoxia to empirical statistical models for pathogens such as *Vibrio*. NOAA generates short-term forecasts for bycatch probability using observed remote sensing data coupled with statistical models (Hazen et al., 2018) to yield daily fishing maps that aim to reduce the probability of bycatch (e.g., sharks, seals, turtles, swordfish). Similar nowcasting efforts have been developed for blue whales (Abrahms et al., 2019; Hazen et al., 2017; Fig. 4, loggerhead sea turtles, and sardines (Demer & Zwolinski, 2014; Zwolinski et al., 2011). These nowcasts require only current observations but retain considerable utility in the management of endangered species.

Seasonal applications used for planning purposes can be more challenging, as they require predictability over longer timescales. An early example (Hobday et al., 2010) includes the work of using nowcasts of the Australian operational ocean model, Bluelink, to predict probability of Southern bluefin tuna bycatch on a biweekly basis during the fishing season. Though not strictly a seasonal forecast, this implementation is used for active management through a seasonal period. More recently, analyses of swordfish abundance were made using a decomposition of predictor variables into high-frequency, monthly average, and interannual anomaly data. The monthly data were valuable in predicting the spatial pattern of abundance, but the interannual component

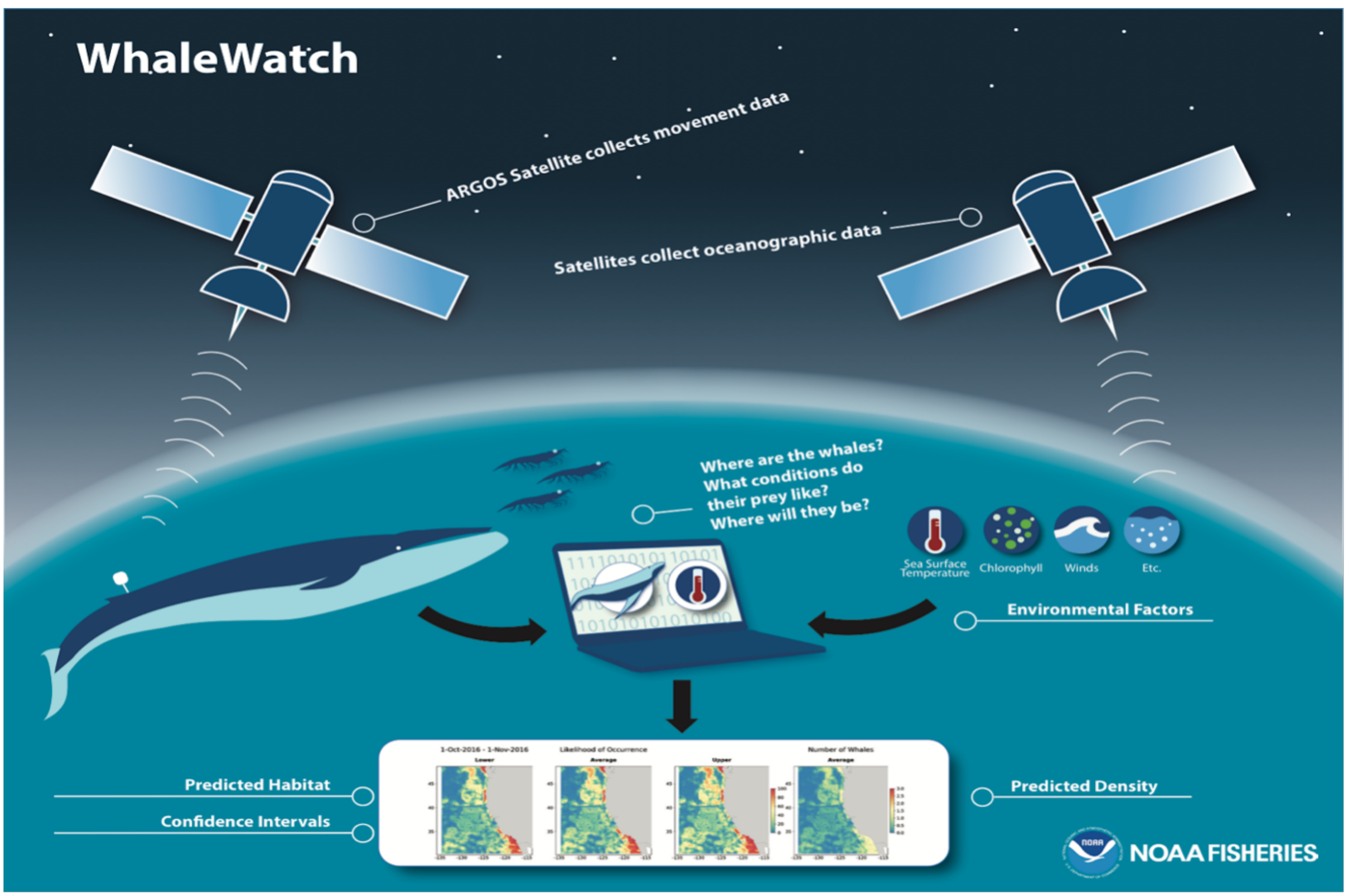

Figure 4: Schematic illustrating the flow of information from remote sensing, whale location data, and the predicted habitat and confidence in the prediction.

yielded the highest skill at predicting catch anomalies, which yields potential predictability at longer timescales for fisheries planning (Brodie et al., 2021). In an exciting example, eight-month lead time subsurface predictions of ocean temperature at 250m were used to predict Pacific Hake in the northern California Current (Malick et al., 2020). This highlights the potential for longer lead time forecasts based on subsurface fields, but challenges remain in validating subsurface fields in ocean models.

Multi-annual timescale forecasts are more challenging to implement. Miesner et al. (2022) used monthly salinity at spawning depth (250-600m) for blue whiting to predict spawning habitat a year in advance, further emphasizing the utility of subsurface data and predictability of subsurface anomalies (as highlighted in Session 1.3), even without significant predictability of climate modes at longer timescales.

Fisheries forecasts often require biomass estimates, which can be more challenging to predict than distribution envelopes. However, inclusion of forecasted SST was shown to improve predicted sardine biomass and yield at <5-month lead time (Tommasi et al., 2017). Future needs include recognizing that mechanistic understanding and an iterative forecast cycle (Dietz et al., 2018), as well as regular model testing are critical for forecast accuracy. Knowledge co-production with end users is critical to ensure that forecasting time scales and products are relevant and useful. Finally, fisheries forecasting would benefit from validation of models for quantities other than SST, which will require long retrospective model simulations that include biogeochemistry.

S2.2 Seasonal forecasts of ocean health (presenter: Siedlecki)

Seasonal forecasts at six- to nine-month lead times are routinely conducted by the J-SCOPE team using outputs from seasonal climate forecasting systems to force a downscaled ROMS model that includes biogeochemistry and carbon variables (Siedlecki et al., 2016). These are coupled with habitat models for species of interest, including sardine, hake, and juvenile and adult crab. Early engagement of stakeholders in critical data collection efforts (e.g., moorings aligned with coastal tribal fishing areas) that are then used to validate the models makes it easier to convince them of the utility of these forecasts. The system also employs a three-member ensemble to evaluate uncertainty, a key innovation needed in this arena. Forecasts are available online to increase transparency and build trust. A retrospective analysis of the model performance is conducted annually, and model biases are openly discussed and shared. Ongoing discussion with stakeholders aids in developing graphical representations of model forecasts in the desired form(s). Forecasting skill is linked to thermal anomaly re-emergence, a consistent theme across sessions.

Crab catch was selected as a forecast target based on the model skill at predicting bottom temperature and oxygen conditions. The model was able to predict the catch per unit effort over a span of years, but the need for more data on fishing behavior still limits the utility of the forecast. Fishing error was treated as static, while the dynamic and lagged ocean variables from the J-SCOPE forecast varied.

S2.3 Harmful Algal Bloom prediction (presenters: Anderson, Evanilla, Horemans)

IOOS efforts have generated a forecast system using a physical model (ROMS) coupled with the NEMURO biogeochemical model that uses a 4D-Var data assimilation system. Chlorophyll-a, temperature, and salinity data are used to make HAB forecasts focused on domoic acid-producing

Pseudo-nitzschia with one- to three-day lead times (lead time of up to two weeks is the target). Weekly monitoring aids in forecast evaluation, but often misses bloom initiation.

Even a high-resolution regional ocean model enlisted in this study failed to capture the nearshore estuarine dynamics required for successful prediction. The coastal model was thus linked with a higher-resolution estuarine model. Tracer advection and a dye study were used to evaluate the coupled model system. Machine learning was used to predict toxicity in crab and shellfish harvest regions, but challenges remain in linking genetic data and blooms initiated offshore into the model.

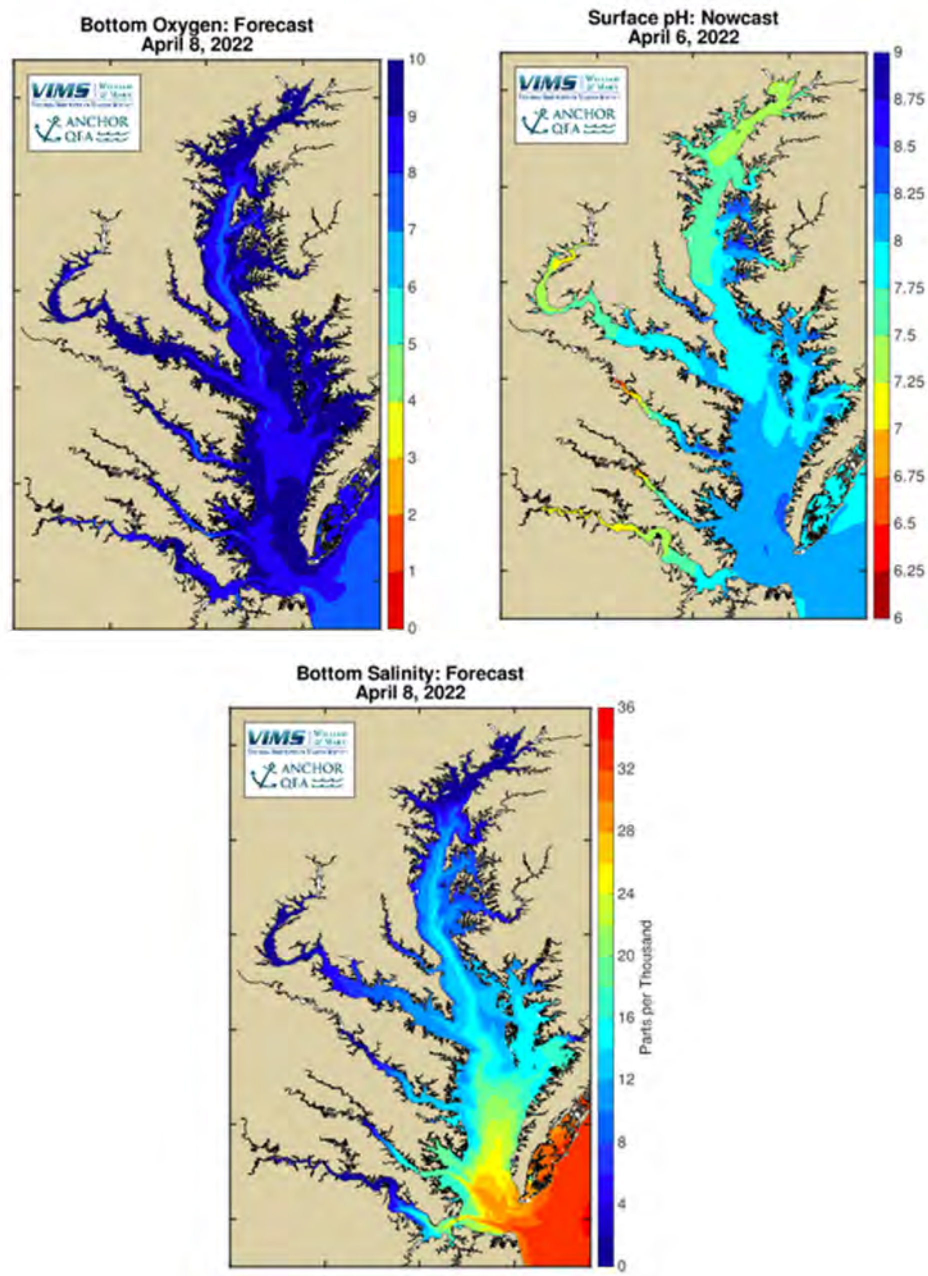

Figure 5: CBEFS forecast system predictions for multiple variables of interest (bottom oxygen, surface pH, bottom salinity) in April 2022.

S2.4 Chesapeake Bay as an integrated system (presenter: Friedrichs)

The Chesapeake Bay system has a diverse array of ecological forecasting products. It is the largest estuary in the continental US, has a long record of data, and supports ~$100 billion in ecosystem services annually. Anthropogenic inputs of fertilizer and increasing carbon dioxide levels have expanded hypoxic zones and decreased pH and carbonate saturation state, respectively. Stakeholders provide the impetus for the timescale of forecasts. Daily-weekly forecasts are relevant to charterboat captains, aquaculture interests, beach management, as well as the general public (Bever et al., 2021). Seasonal forecasts are needed by fisheries managers (e.g., Scavia et al., 2021); mid-century projections (Irby et al., 2018; Hinson et al., 2023, Hinson et al, 2024) are used by states to set nutrient reduction targets and watershed improvement plans.

The Chesapeake Bay Environmental Forecast System (CBEFS; www.vims.edu/cbefs) includes terrestrial, oceanic, and atmospheric inputs and provides forecasts optimized for viewing on mobile platforms. Thirty-five years of data are used to calibrate and evaluate the model product, and nightly forecasts are generated for a two-day period. Forecast products include variables such as the size of the hypoxic region, ocean acidification (ocean carbonate system) metrics, Vibrio presence, temperature, salinity (Figure 5), and HABs (Horemans et al., 2023, Horemans et al., 2024).

Using forcing from different watershed models, the same estuarine model was used to generate mid-century predictions and associated uncertainties needed by managers who set nutrient use and export targets for watershed partners. While 80% of the models agree that ocean hypoxia will increase, the choice of the GCM used to force the model largely determines future hypoxia location and extent (Hinson et al., 2023). The uncertainty is nearly equally partitioned between the global climate model, the watershed model, and the downscaling method, indicating that selection of the model components is a significant source of variability. The model suggests that future hypoxia is substantially less affected by changes in runoff than in air temperature (Irby et al., 2018; Hinson et al., 2023; Hawes 2024).

S2.5 Marine heatwaves (presenters: Capotondi, Xu)

Linear inverse modeling can be used to trace the optimal precursor conditions (SST and SSH) that would give rise to a marine heatwave (Capotondi et al., 2022). The example provided is in the Northeast Pacific, where optimal initial conditions include structures that also lead to the development of a central Pacific El Niño event. The identification of these optimal precursors may provide a tool for predicting both the occurrence and duration of marine heatwaves as basin-scale modes develop.

Session 3: Modeling capabilities and challenges

Key takeaways from Session 3

Global physical & biogeochemical modeling & prediction	Large ensembles show promise for decadal prediction, but careful initialization, bias correction and numerous ensemble members are required. Subsurface oxygen shows predictability associated with ventilation anomalies. Storing and analyzing the large ensemble datasets remains a challenge with current capacity.

Regional modeling using dynamical downscaling	Dynamical downscaling can yield management relevant impacts in coastal regions. Uncertainty is as critical as resolution: downscaling should select models that span a broad range of plausible patterns of change. In light of the importance of ensembles spanning the range of ocean futures, refinement of resolution should be judicious and seek the coarsest possible resolution that resolves the features required for the intended application.
Empirical & mechanistic modeling of marine ecosystems/ fisheries	Where there are mechanistic relationships between model predictors and fisheries, these can lead to skillful predictions. Fish models may help make mechanistic connections between fisheries and environmental drivers.
Statistical/ML approaches to ecological forecasting	Statistical/machine learning approaches have a long history in ecological forecasting. Machine learning can be used when the form of the relationships between predictors and response is unknown. While often viewed as a "black box," statistical and machine learning approaches can help reveal mechanistic relationships between environmental drivers and ecosystem outcomes. Exploiting time series data allows for analysis of changing relationships between BGC model components.

S3.1 Global physical and BGC modeling and prediction (presenter: Long)

Global climate and Earth System modeling (Figure 6) have the potential to make actionable predictions that affect people's lives. Future trajectories for global surface temperature and associated impacts indicate that we are at an inflection point, whereby actions can mitigate future pathways, especially the conservation of natural resources. However, the climate system is highly dynamic, and internal variability should be considered in implementing management actions. For example, 200-m O_2 trends in the North Pacific from the CESM1 Large Ensemble (LE) exhibit large variations across ensemble members due to a forced component (the ensemble mean), which shows a general oxygen decline, and an internal component driven by internal processes, which can generate low-frequency changes that vary significantly across different ensemble members. Some of this variability is predictable, which highlights the benefit of developing initialized "decadal" predictions. These initialized predictions exploit the "memory" of different components of the climate system, which often stems from the ocean. Information contained in the initial conditions can be lost due to model drift or to the impact of the forcing (Branstator & Teng, 2010). Retrospective forecasts of temperature, precipitation and SLP with the Decadal Climate Prediction Project (DCPP) show significant skill in the near-term (two to nine-year time horizon), a large fraction of which is due to the initialization (Smith et al., 2019). Availability of LEs is critical for averaging internal variability and increasing the signal to noise ratio. Efforts are underway to assess the predictability of ocean biogeochemical and ecological quantities.

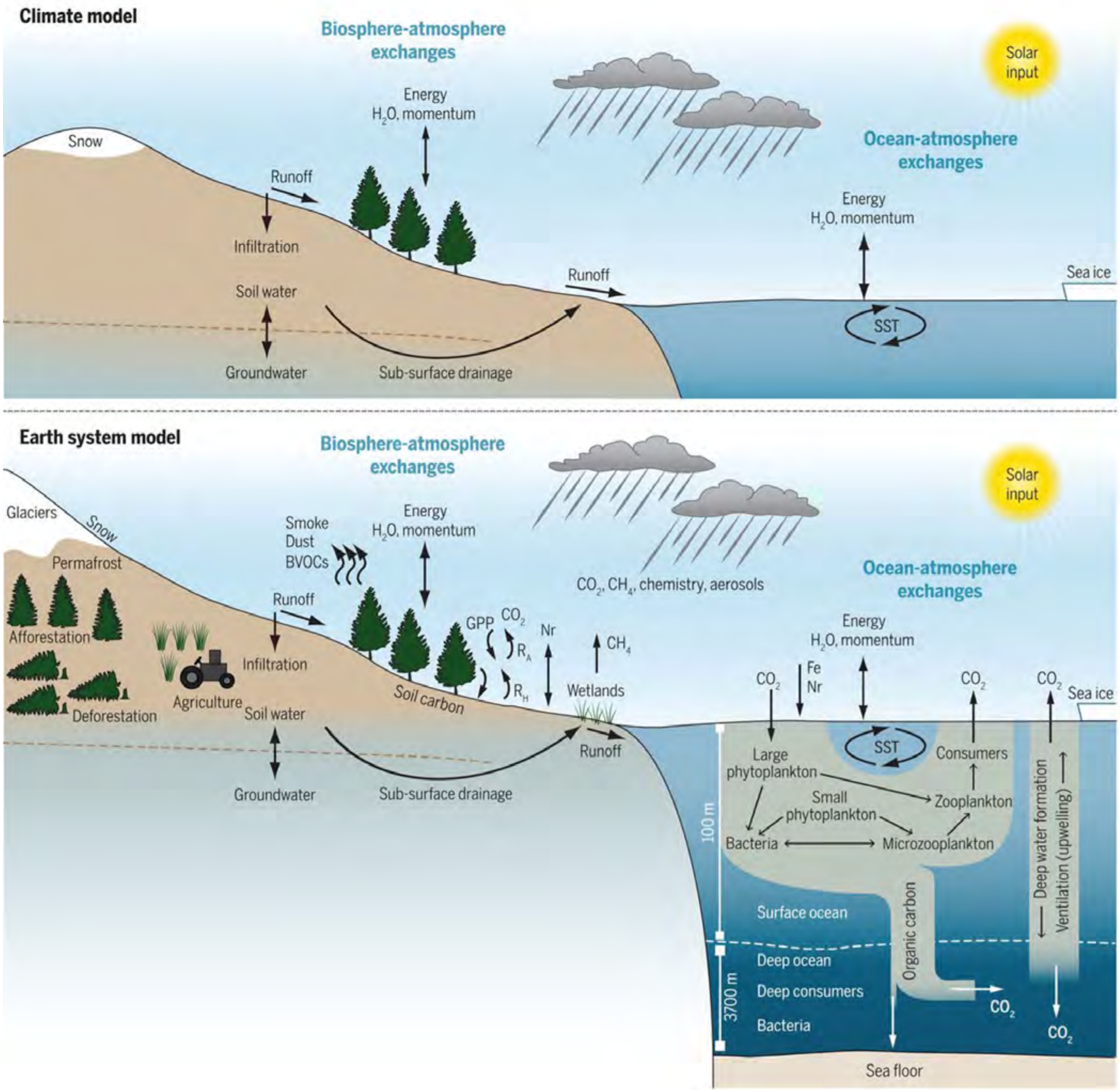

Figure 6: The top panel illustrates that land and ocean are included in climate models, as compared to the lower panel, Earth System Models (ESMs), which incorporate additional processes and complexity. ESMs simulate atmospheric CO2 in response to fossil fuel emissions and terrestrial and marine biogeochemistry. Some ESMs also simulate atmospheric chemistry, aerosols, and CH4. Terrestrial processes (left side of the diagram) include biogeophysical fluxes of energy, water, and momentum; biogeochemical fluxes; the hydrologic cycle; and land-use and land-cover change. The carbon cycle includes component processes of gross primary production (GPP), autotrophic respiration (RA), litterfall, heterotrophic respiration (RH), and wildfire. Carbon accumulates in plant and soil pools. Additional biogeochemical fluxes include dust entrainment, wildfire chemical emissions, biogenic volatile organic compounds (BVOCs), the reactive nitrogen cycle (Nr), and CH4 emissions from wetlands. Ocean processes are shown on the right side of the diagram. Physical processes include sea ice dynamics, ocean mixing and circulation, changes in sea surface temperature (SST), and ocean-atmosphere fluxes. In the ocean the gray shaded area depicts the marine carbon cycle, consisting of the phytoplankton-based food web in the upper ocean, export and remineralization in the deep sea and sediments, and the physiochemical solubility pump controlled by surface-deep ocean exchange (reproduced from Bonan & Doney (2018)).

Results of heat content reforecasts with the CCSM4-DP (decadal prediction) ten-member ensemble at nominal 1° ocean/land/atmosphere resolution show how, after initialization, the model tends to return to its own "attractor," such that a lead time-dependent bias correction needs to be applied to reduce a cold bias (Yeager et al., 2012). Initialization shock, in which the wind forcing used in the model initialization has overly strong easterlies, produced a rebound and the development of spurious El Niño events. In large ensembles, > 30 members are required to improve skill over persistence (Yeager et al., 2018). The NCAR Decadal Prediction Large Ensemble (DPLE) has been used for biological predictions in which its ability to predict nutrient convergence in the surface layer leads to skill in the prediction of Net Primary Production (NPP) at different lead times of 1 to 5 years (Krumhardt et al., 2020). Predictability beyond persistence is also found in California Current System pH (Brady et al., 2020) owing to the model's ability to simulate the Dissolved Inorganic Carbon (DIC) field and its downstream propagation. Anomaly skill score correlations show predictability of dissolved oxygen on the 26.5$\sigma\theta$ isopycnal surface located within the main thermocline in the North Pacific, where potential vorticity anomalies are correlated with oxygen and are driven by ventilation processes. The subsurface expression of these anomalies echoes the thermally driven predictability described in Section 1. An advantage of the mechanistic ESM framework is that they include information about all variables, which can aid in diagnosing the sources of prediction skill. Efforts are underway to incorporate fish models (e.g., FEISTY; Petrik et al., 2019) in the DPLE prediction system to predict total fish biomass.

Preliminary research indicates a potentially large impact of higher model resolution on predictability and prediction skill. First, increased resolution enables models to capture small-scale physical features along coastlines such as mesoscale eddies, which can strongly influence biological processes. Second, higher-resolution models can also predict the frequency of hurricanes, which is important for understanding their impacts on coastal communities and ocean BGC and ecology. Finally, although one would expect that a larger level of "system noise" is introduced by the explicit simulation of small-scale ocean features, it appears that, in some cases, these features may contribute to ocean forcing of the atmosphere in ways that lead to enhanced predictability, with smaller ten-member ensembles having equivalent skill to 40-member ensembles at lower resolution; more investigation is needed to more robustly confirm this result.

Large ensemble simulations produce massive amounts of data, even at coarse resolution. Data storage and distribution can be a real challenge. The community must encourage and support efforts to facilitate and democratize data distribution and access (e.g., NCAR Earth System Data Science Initiative, PANGEO, Project PYTHIA, LEAP).

S3.2 Regional modeling using dynamical downscaling (presenters: Drenkard, Hermann, Lim, Pozo Buil, Ross)

Many physical and biological processes occur at scales that are smaller than those resolved by ESMs, so there is a need for downscaled regional models at a higher spatial resolution (Drenkard et al., 2021; Liu et al., 2015). For example, managers often require the regional manifestation of climate change projections from climate models. Relative to statistical downscaling, which is based on observations over the historical period, dynamical downscaling allows the representation of unprecedented ocean states. Regional models can be coupled to the atmosphere, utilize unstructured/stretched grids that target resolution in regions of interest, and can include BGC and ecological models for organisms and processes of economic value. Atmospheric deposition of iron-rich dust is shown to affect chlorophyll-a rebound following El Niño in the equatorial Pacific, which requires coupling of an atmospheric dust model with an ocean biogeochemical model. Such a coupling would be important to include in a regional domain, illustrated in a global model (Lim et al., 2022). There are several practical hurdles to consider, including the computational costs, the boundary conditions and surface forcing (one-way vs. coupled), simulation duration and ensemble size. Bias correction of global scale models is needed prior to applying output to regional models as boundary conditions. A synthesis paper (Drenkard et al., 2021) recently presented a protocol outlining steps to consider when designing a marine resource-focused dynamical downscaling experiment, and to make the most of limited computational resources. There are an increasing number of such efforts that include ensembles of higher-resolution BGC. Currently, many are at the "proof of concept" stage and are not being integrated with tactical and strategic management decisions. For this to happen, the models need to be able to represent the range of possible conditions. It may be possible to combine statistical and dynamical approaches to achieve this goal.

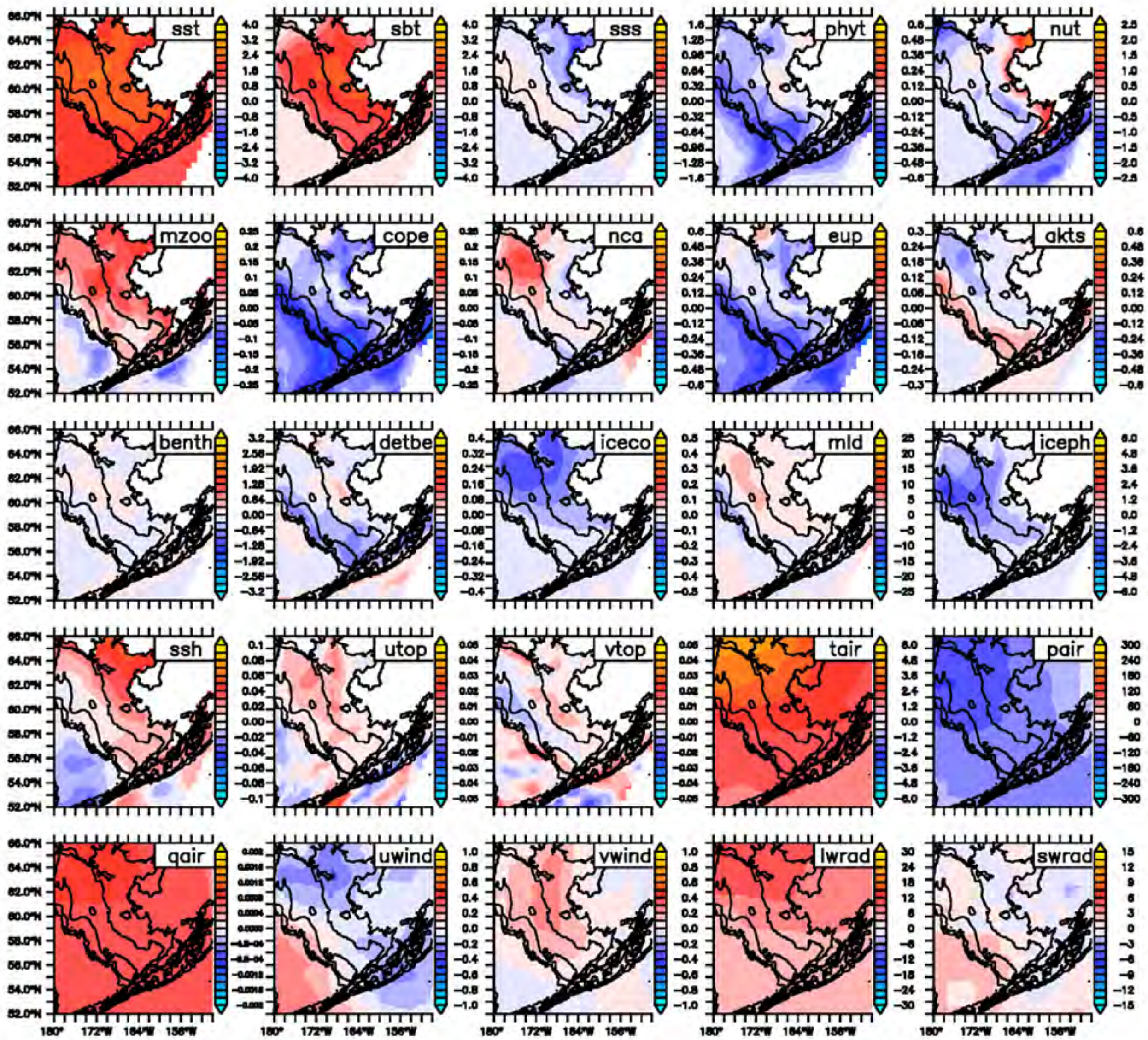

Figure 7. Decadal average change of various quantities in the Bering Sea between 2010–2019 and 2050–2059 from downscaled projections based on GFDL-ESM2M, CESM, and MIROC RCP 8.5 global projections (Hermann et al., 2021).

In future projections, sources of uncertainties can arise from model structure, internal variability, and the future scenario, the latter of which becomes more important while moving forward in time (Hawkins & Sutton, 2009). They also depend on the variable of interest. For example, for SST, the scenario may play the dominant role, but for primary production, model uncertainty is more critical (Frölicher et al., 2016). Drenkard et al. (2021) recommend downscaling to achieve the broadest possible range of model behavior (Muhling et al., 2017). When considering ecosystems, the sources of uncertainties may also vary regionally (Frölicher et al., 2016). Larger ensembles are needed to span the range of uncertainty, but these can be computationally expensive. Possible alternatives are hybrid dynamical statistical approaches. Examples include the prediction of Chesapeake Bay surface temperature and salinity using a statistical method applied to a mechanistic water balance model (Muhling et al., 2018), 35-day probabilistic Chesapeake Bay SST forecasts based on empirical models of atmospheric variables and lagged SST that show skill at two-week lead times (Ross & Stock, 2022), and projections of bottom temperature in the Bering Sea. This latter example first identifies dominant modes of variability through EOF analysis applied to a small ensemble of dynamically downscaled simulations and then uses these patterns to "downscale" future model projections (Fig 7; Hermann et al., 2019).

S3.3 Empirical and mechanistic modeling of marine ecosystems/fishes (presenters: Petrik, Testa, Navarra)

Ocean prediction systems like the NCAR DPLE have produced reforecasts that demonstrate the predictability of different ocean variables. They have shown the existence of predictability for SST, NPP and pH, which are of great importance for marine ecosystems and fisheries. These mechanistic predictions have been used in empirical models. For example, the SST forecasts from the GFDL system were used in a statistical model relating SST to sardine biomass, which provided harvest guidelines for Pacific sardines (Tommasi et al., 2017). This was an application to a specific fish species, but similar approaches can be applied to all fish indices, to fish groups based on functional types, or to an ecosystem as a whole. Park et al. (2019) used the GFDL prediction system to examine the skill for predicting total fish catch in Large Marine Ecosystem (LME) regions, focusing on the relationship between SST and/or chlorophyl-a and fish catch, and found that several regions showed significant skill. But not all LMEs showed skill, suggesting the need to consider other drivers such as secondary production, export production, pH, bottom temperature, DO, and the combined effect of DO and temperature which is defined as the metabolic index (a measure of the oxygen supply vs. the oxygen demand, where the demand is influenced by temperature). The metabolic index can help identify regions in SST/oxygen space that are habitable or inhabitable for a given species, with a threshold that can be compared with observations. This approach has demonstrated predictability for anchovies both in terms of the habitable space and of larval abundance. However, these empirical relationships are often based on what has happened, assuming a stationary system, and must be frequently re-evaluated.

An alternative to empirical relationships is the use of a fish model. An example is FEISTY, a fisheries size and type model (Petrik et al., 2019) that has three different fish sizes, and, when forced by ocean model output, can reproduce empirical relationships determined in nature—e.g., the ratio between zooplankton production and export production is related to the composition of fish catch (van Denderen et al., 2018). Given this skill, a project is underway to combine ESMs with mechanistic fish models to assess the impact of climate on predictability of fisheries. The approach will first examine a broad range of fish predictors, then identify which variables are the dominant ones to characterize fish variability, and then incorporate the fish model in an ESM in a fully-coupled fashion. To assess whether the physics and biogeochemistry of the ESM can explain fish variations, a forced ocean sea ice simulation was used to examine relationships between fish biomass and climate indices. Results indicate large correlations with the Pacific Decadal Oscillation. In particular, the largest correlations at longer leads occur in larger fish with longer generational time spans. Higher frequency variability is associated with smaller, shorter-lived fishes, and lower frequency variability is associated with larger size classes. Zooplankton appear to capture the full dynamics of the system in some LMEs, so that, ultimately, it is critical to assess the predictive skill of zooplankton. However, estimates of historical BGC simulations within ESMs (Séférian et al., 2020) indicate limited skill for chlorophyll and NPP, with a divergence in projected values over the next century (Bopp et al., 2013, Kwiatkowski et al., 2020). There are also limited zooplankton observations globally, especially time series to use in skill assessments. Models show large differences in long-term projections, likely due to differences in BGC parameterizations. More zooplankton observations, especially biological rates, could help constrain models. Similarly, measurements of fisheries-independent fish biomass are very sparse. Although data may be available, they are not shared in easily accessible formats. Linear inverse modeling demonstrates the utility of these types of fisheries indicators (and SST) in forecast skill of up to 5-6 years beyond persistence in the tropical Pacific (Navarra et al., 2022).

Where economic models can be coupled to climate and biogeochemical/organismal models such as for oysters in Chesapeake Bay, the value of improved near-term forecasts can be evaluated in terms of profitability for aquaculture. Coupling human activities to forecasts can yield clear advantages for managers.

S3.4 Statistical/ML approaches to ecological forecasting (presenter: Deyle)

Although Machine Learning (ML) techniques are perceived as new and untested, they have a 30-year track record in ecological forecasting. Also, while often viewed as black-boxes that do not allow physical understanding of the system, ML algorithms can be used in simple ways and provide actionable and predictive mechanistic insights.

Some of the myths about ML depend on the definition and applications. For example, "supervised learning" involves a user's specification of input and output requirements, while "unsupervised" learning does not include any human intervention. Self-organizing maps and pattern classifications are examples of unsupervised learning, while the use of ML for making predictions is an example of supervised learning.

Early efforts (Sugihara, 1994; Sugihara & May, 1990) used a very simple approach (nearest neighbor forecasting and S-map, locally weighted linear regressions) to ask whether the observed ecological time series, which can be viewed as stochastic variations around an equilibrium state, was predictable. The question of predictability is tied to the choice of the model, which is unknown, so in this application they were letting the algorithm choose the "model". According to "Takens Theorem", "observing change over time gives a window into the coupled dynamics even when there are unobserved state variables." That's why these early forecasts were able to use a single time series and make a prediction using it as a multivariate system.

Similar ML approaches were used for prediction of red tides (coastal algal blooms) in Southern California (McGowan et al., 2017). There was uncertainty about the mechanisms and drivers, and questions of whether it was predictable at all, which yields a good test for ML. Good results were obtained especially for in-sample predictions, but also for out-of-sample predictions.

Another ML application is the prediction of hypoxia in Lake Geneva (Deyle et al., 2022). The lake conditions yield questions similar to those from Chesapeake Bay: Will the changes in nutrients through (expensive) management actions continue to work under climate change as physical changes exacerbate hypoxia? Lake Geneva is undergoing large changes in its phosphorous content and related changes in the food web, which in turn change the biological oxygen consumption. A parametric physical model could predict the thermal structure of the lake, but not BGC quantities due to the nonstationary relationship between the plankton and nutrient dynamics. A nonlinear causal measurement method was used on the data to provide information about the coupling, and in particular to provide information about rates and relationships among variables. An empirical dynamical model for the BGC was then developed and fully coupled to the physical model. This system improved long-term forecasts of hypoxia. These examples illustrate the potential of ML techniques for skillful BGC and ecological predictions exploiting all the information contained in the available variables.

Session 4: Reanalysis products and observations

Key takeaways from Session 4

Global physical/ biogeochemical reanalyses	Reanalyses for biogeochemical or ecological forecasting can be challenged by physical perturbations and subsequent biogeochemical instabilities and discontinuities. Assimilation approaches such as those used by ECCO-DARWIN, which modify boundary conditions, initial conditions and mixing parameters rather than directly perturbing the internal solution, may provide smoother and more consistent reanalysis products that can also be used for initialization. Their efficacy, however, depends on the capacity of modulating conditions to address model-data discrepancies.
Regional reanalyses	Biogeochemical predictability can have longer skill than physical predictability. Data availability remains a key constraint in biogeochemical reanalyses.
Data collection & integration across regions: the view from IOOS regional ocean observing systems	Tier 1 products are more standardized across regions. Tier 2 observations are limited by funding gaps.

Observing technologies bridging the global and coastal ocean	Stakeholders find the most value in forecasts with short lead times Multi-model ensembles can be useful in partitioning the sources of uncertainty in future projections.
Satellite observing technologies	Hyperspectral satellite data are the future and should enable enhanced discrimination of phytoplankton functional types as well as other optical constituents

S4.1 Global physical/biogeochemical reanalyses (presenter: Menemenlis)

The ECCO-Darwin product, developed at the Jet Propulsion Laboratory (Brix et al., 2015; Carroll et al., 2020; Carroll et al., 2022), can more skillfully reproduce a data-based reconstruction of global-ocean CO2 sink relative to Global Carbon Budget models based on GCMs so it can be used to assess mechanisms.

Traditional reanalysis such as the high-resolution Global Ocean Reanalysis and Simulations (GLORYS) consists of an ocean model that is run forward in time, with observations assimilated ("injected") into the model at given time intervals to keep it close to observations. However, this approach introduces discontinuities in the evolution of the system, and results in lack of property conservation that is particularly important in diagnosing budgets of biogeochemical quantities such as carbon. These factors present challenges for constructing a physical-biogeochemical system since the biogeochemistry needs a smooth time evolution of the physical drivers. State-estimations like ECCO-Darwin do not change the model variables but instead adjust the initial conditions, atmospheric

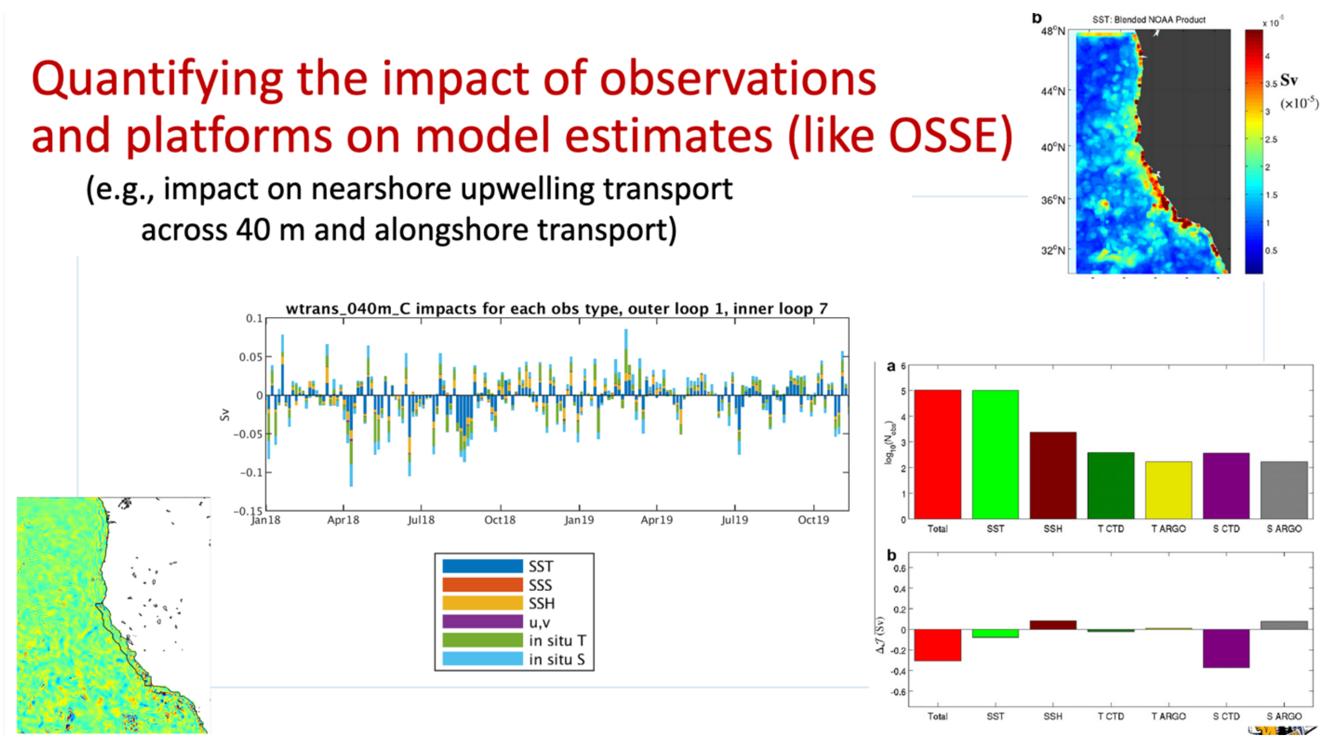

Figure 8. Decadal average change of various quantities in the Bering Sea between 2010–2019 and 2050–2059 from downscaled projections based on GFDL-ESM2M, CESM, and MIROC RCP 8.5 global projections (Hermann et al., 2021).

boundary conditions, and (time-invariant) model mixing parameters to minimize the discrepancy between the model trajectory and the observations (Adjoint method). As a result, the model solution is conservative and has fewer discontinuities. In fact, the motivation for ECCO-Darwin originated from the realization that output of traditional reanalyses produced unrealistic jumps in CO_2 fluxes in tropical regions, while a smoother solution produced results comparable to observations (G. McKinley, personal communication; Park et al. 2018). ECCO-Darwin assimilates satellite and in situ physical and biogeochemical data. The biogeochemistry is done separately from the physics, using the Green's function approach, a coarser approximation than the Adjoint method. The comparison with observations (GLODAPv2) is very good, both at the surface and at depth, due to the accuracy of the physics. One application example has been the use of ECCO-Darwin for the attribution of the spatiotemporal variability of global-ocean DIC in response to physical, biological, and air-sea CO_2 flux drivers. Future studies will focus on assessment of uncertainties, as well as the improved representation of the land-ocean continuum, ocean ecology, carbon chemistry, bottom sediments, and ice-biology-carbon interactions in polar regions. The resolution is currently 1/3°, moving to 1/6° globally, with envisioned regional downscaling. The quality of the solution would be sufficient to initialize a prediction system and could be considered for prediction experiments.

S4.2 Regional reanalyses (presenters: Edwards, Ray, Chen, Amaya)

Regional reanalyses can be important for filling data gaps in the coastal zone. One motivation for the development of some existing reanalysis came from the IOOS regional associations, which use their observations to generate reanalysis products for several coastal applications. Some existing regional reanalyses use the Regional Ocean Modeling System (ROMS) and the 4-Dimensional Variational (4D-Var) data assimilation, including MARACOOS (Northwest Atlantic), PacIOOS (Pacific Islands), University of California Santa Cruz Reanalysis (CCS), and a new very high-resolution reanalysis (WCOS). The latter is run at 4-km horizontal resolution. The assimilation procedure minimizes a cost function, accounting for model and observation error covariances.

The UCSC reanalysis includes both a historical product over the periods 1980-2010 and 1999-2012, which are driven by different forcing fields, and a near-real-time system (2011-present), which is run at a 1/10° horizontal resolution. This system assimilates SST, SSH, surface chlorophyll, temperature and salinity from gliders, and HF radar velocities. The focus is on nowcast and potential short-term predictions. One important application of the state estimation products is that they allow the study of the relationship between past ocean conditions and ecosystem states, enabling statistical relationships between physical and biological variables to be established. An application example is that of dynamic maps of species distribution for fisheries management, as done in ECO-cast (Welch et al., 2019; Brodie et al., 2018). Jacox et al. (2016) used historical relationships to anticipate the chlorophyll signature of the 2015-16 El Niño event. Data assimilation, especially of altimeter data, can greatly improve the simulation of eddy kinetic energy (EKE) in the CCS.

The 4D-Var approach can help identify the observations that are most critical for constraining the system, effectively acting as an (OSSE) to help optimize observations. For any specific variable, one can partition the contribution to the forecast of individual observations (Figure 6). Satellite data appear to provide the dominant contribution, but subsurface observations, like gliders and Argo floats, are also important contributors.

BGC data assimilation is conducted similarly to physical data assimilation using BGC models. Two models are used: Nutrient-Phytoplankton-Zooplankton-Detritus (NPZD; Powell et al., 2006) and and North Pacific Ecosystem. Model for Understanding Regional Oceanography (NEMURO; Kishi et al., 2007). The second includes phytoplankton and zooplankton diversity relevant for some ecosystem applications. Mattern and Edwards (2017) performed a large Monte Carlo optimization to assess the sensitivity of solutions to different parameter choices in the BGC model, and found that only a small subset could produce distinguishable differences in the solutions, given the available observations.

Coupled physical-BGC data assimilation in this example is carried out by augmenting the state vector. This allows full two-way interactions between physics and biology, although the influence of the biology on the physics seems to be small. Comparison of surface chlorophyll from the free-running and assimilated model with observations shows that data assimilation makes a large difference in the evolution of this field (Mattern et al., 2017), and that the biogeochemical fields can show longer skill persistence than the physics. Physical variables are Gaussian-distributed, while BGC variables are skewed (as shown by Campbell, 1995 for chlorophyll). The physical component would benefit from increased subsurface temperature and salinity data. However, the real challenge is posed by BGC data. Increased spatial coverage and availability of other types of observations would be very beneficial.

Regional analyses can be very useful in determining the mechanisms underlying subsurface predictability. Ray et al. (2022) used a reanalysis to demonstrate how winter advection that typically influences subsurface thermal anomalies in the California Current can be disrupted by ENSO through isopycnal heaving and lead to loss of memory of the winter anomalies. Regional reanalysis of ocean bottom temperature in the northeast Atlantic can be predicted seasonally, and nonlocal anomalies improve the skill of these forecasts (Chen et al., 2021). Glider observations that capture subsurface thermal fields similarly seem to improve model simulation of subsurface thermal anomalies (Amaya et al., 2023).

S4.3 Data collection & integration across regions: The view from IOOS regional ocean observing systems (presenter: Kritzer)

US Integrated Ocean Observing System (IOOS) is a federal partnership among 17 different agencies, run by an office within NOAA's National Ocean Service (NOS). The IOOS mission is "To produce, integrate and communicate high quality ocean, coastal, and Great Lakes information that meets the safety, economic and stewardship needs of the nation." IOOS has identified 34 core variables that are measured on several different platforms. For example, the Northeastern Regional Association of Coastal Ocean Observing Systems (NERACOOS) relies heavily on moorings, complemented by buoys, gliders, high frequency radar, satellites, ship-based surveys, smaller coastal stations, and a variety of models. An example from the Central & Northern California Ocean Observing System (CeNCOOS) shows the variables being collected as motivated by the end users. All IOOS activities are directed to the end users, including researchers, managers, fisheries, sanctuaries, tribes, etc. Ecological variables being measured only in a few regions include eDNA, HAB toxins, ocean sound, and plankton images. Variables most relevant to local-regional ecological forecasting are routinely collected by the IOOS regional associations – e.g., Hawaiian Islands and Caribbean are focusing on corals, whereas CeNCOOS and Southern California Coastal Ocean Observing System (SCCOOS) include HAB data sets. Regarding data collection and provision, some regional associations are more sustained and operational than others. However, all regions have submitted proposals to expand their set of variables to include those listed above. This was also the vision of the IOOS founder Ru Morrison.

IOOS data are accessible to everyone, but the mode of access varies across regions. Some biogeochemical/ecological variables require further processing and therefore additional resources (e.g., there are a limited number of ways to measure temperature, but many different possibilities for estimating phytoplankton biomass). A few examples of data assembly centers (DACs) include SanctSound for managing acoustic data, HAB DAC, Marine Biodiversity Observation Network and Animal Telemetry Network for animal tagging and telemetry, and FathomNet for species recognition using AI/ML. Data standards and protocols are established within each DAC. Nevertheless, the regions are engaged in integrating these physical and biogeochemical variables for easier access by external users. The California HAB Bulletin is an example of IOOS priorities for user driven products. Also, NANOOS is part of J-Scope, which provides forecasts of upwelling and bottom conditions useful for local fisheries, especially the crab industry. CeNCOOS is developing a framework for delivering biodiversity and ecosystem observations (Ruhl et al., 2021). At NERACOOS, forecasting of physical variables has been a major focus for some using the Northeast Coastal Ocean Forecast System (NECOFS). On the ecological side, they have devoted resources to long-term observations of the copepod Calanus, a critical prey species for the sand lance (Suca et al., 2021) and whales (Ross et al., 2023).

With the exception of the HAB-DAC and ATN, coordination of observations across regional associations is limited. There are plans to use the cloud to improve cross-region integration. To make progress on BGC and ecological variables (Tier 2), increased funding and mandate to provide information to a national DAC will be required, but the organizations are ready to move forward, as illustrated in a recent white paper on "Detecting the coastal climate signal" (IOOS Association, 2021), which prioritizes ecological forecasting. IOOS has also advocated for enhanced coastal ocean ecological forecasting capabilities in the US contribution to the UN Ocean Decade.

S4.4 Observing technologies bridging the global and coastal ocean (presenter: Wijffels)

We are in a revolutionary era of ocean monitoring. Through the cooperation of > 20 countries, the Argo Program has deployed a globally distributed network of profiling floats, embracing clear design goals and consistent data handling protocols. The Argo mission is to map ocean variability in real time on monthly to decadal time scales – e.g., the evolution of the global average temperature from top to bottom, clearly showing a global warming signal). Similar maps are needed for BGC variables, e.g., pH and oxygen. Even if the focus is on regional changes, it is important to measure globally, via the global backbone, to understand and attribute what happens at the regional scale. The concept of a backbone may also be important for regional observing systems.

New technologies continue to make observing more cost-effective and complete. New designs include Deep Argo floats that can go to 6 km depth, as well as Biogeochemical Argo floats equipped with BGC sensors (nitrate, oxygen, pH, chl-a, suspended particles, and irradiance) that are being deployed throughout the global ocean, including unprecedented measurements in marginal sea ice zones. BGC floats have been funded at a national level. Indeed, the main impediment to more extensive BGC-Argo coverage is the cost of the sensors. The success of Argo is also related to the data flow. Argo data are freely and immediately available through the internet (real-time data flow for forecasting needs, especially hurricanes).

On the shelf, routine gliders observations have proven to be very useful (Todd et al., 2019). They can carry the same sensor payload as floats, so there could be a seamless onshore-offshore data flow. Gliders could provide the backbone of a coastal observing system, with reanalyses providing guidance on where sensors are most needed. Adopting common standards and providing data in near-real time, as with Argo, would go a long way towards an operational coastal observing system. However, these requirements come with costs that could reach 30% of the total mission, so proper funding allocations are needed. Bio-optics and bio-acoustics are new promising revolutionary approaches for biological sampling. Their deployment on different platforms should be expedited.

S4.5 Satellite observing technologies (presenter: Craig)

Another great advancement in ocean observing is the constellation of satellites that provide foundational measurements of global ocean color, surface topography, vector winds, precipitation, SST, and sea surface salinity. These remote observing systems must be designed in an integrated way, which depends on the synergies and inter-dependencies of these different networks.

Chlorophyll-a and Inherent Optical Properties (IOPs) are proxies for BGC processes in the ocean. In particular, chl-a is the most commonly used metric of phytoplankton biomass. Chlorophyll-a can be estimated accurately from space in many parts of the ocean using different algorithms, but they come with challenges. The first challenge is to remove the contribution of atmospheric processes to the top of the atmosphere radiance measured by the satellite sensors. The signal of interest, i.e., the "water-leaving radiance," represents only 10% of the total radiance measured by the satellite. The accurate retrieval of ocean color is particularly challenging in coastal areas, where other optically-active water constituents do not covary with chl-a. A different approach based on Empirical Orthogonal Function (EOF) decomposition of the shape of the top of the atmosphere signal provides a more accurate detection of ocean signals (Craig et al., 2012). This was also tested with a coupled ocean-atmosphere model. This approach was recently extended to a Bayesian Neural Network (BNN) model that shows skill in predicting out-of-sample observed water color data. This approach performs much better than other standard approaches, provides robust measures of uncertainty, is resistant to overfitting, and improves as more label data are acquired. A team at NASA is working on using ML methods for predicting phytoplankton community composition from ocean color, which will be revolutionized by the hyperspectral ocean color capabilities of the recently launched NASA Plankton, Aerosol, Cloud, ocean Ecosystem (PACE).

The emergence of geostationary satellite remote sensing capabilities such as the Geosynchronous Littoral Imaging and Monitoring Radiometer (GLIMR) and more cost-effective remote sensing technologies such as CubeSat have the potential to greatly expand coastal data sets in support of ecological forecasting. GLIMR will monitor human- and storm-impacted coastal waters of the southeastern US and Gulf of Mexico with high spatial and temporal resolutions to constrain key physical features (e.g., coastal upwelling, eddies, fronts and filaments) that regulate biological and biogeochemical processes tied to ecosystem health. NASA mandates open data sharing, and PACE has a dedicated Applications team to facilitate training and development, data access, and development of products that benefit science and society.

Session 5: Breakout discussion synthesis

Each plenary session included a small-group breakout session that focused on specific discussion questions (Table 1). Here, common themes are synthesized, and these form the basis for the community recommendations that follow.

Table 1. Breakout discussion questions for each session

SESSION	BREAKOUT DISCUSSION QUESTIONS
Session 1. Sources of regional predictability	Breakout groups, delineated in this session by regional interest (West Coast including islands, East Coast/Gulf of Mexico/Caribbean, Arctic/Bering Sea), were tasked with responding to the following questions as a discussion guide. • What are the major gaps in our ability to predict physics/BGC/ecology in this region at the time scales of interest? Please consider knowledge gaps, as well as data availability and modeling capabilities. • What program would you design to fill these gaps?
Session 2. Applications at different time scales	Breakout groups, delineated in this session by forecasting application (fisheries, HABs, coastal water quality, marine ecosystem health - compound and extreme events) were tasked with responding to the following question as a discussion guide. • What are the major barriers to prediction for management-relevant application? E.g., Inherent lack of predictability? Knowledge of relevant processes? Data? Suitable methodological approaches?
Session 3. Modeling capabilities and challenges	Breakout groups, randomly assigned, were tasked with responding to the following question as a discussion guide. • What are the major challenges in coupling models across scales and disciplines (e.g., open ocean vs. coastal regions, physics/biogeochemistry/fish)? *Please consider computational limitations, data limitations, and gaps in knowledge • How can we leverage machine learning, empirical and mechanistic modeling for physical/ biogeochemical/ecological prediction
Session 4. Reanalysis products and observations	Breakout groups, randomly assigned, were tasked with responding to the following question as a discussion guide. • What do you see as the most promising observational advances (technological /programmatic) that can facilitate progress in physical/biogeochemical/ecological forecasting? • Which variables would be most desirable and what are the prospects for measuring them? • How can we leverage coupled physical/biogeochemical reanalysis products for process understanding and forecast initializations? • What would be the best strategy for promoting data sharing and the creation of integrated archives across regions and disciplines, with consistent data quality and format requirements?

S5.1 Data gaps

In general, surface observations are more readily available than subsurface observations, so prioritization of the latter is recommended. Participants highlighted specific data sets that would be especially valuable for ecological forecasting, including:

- Fisheries-independent data
- Zooplankton and forage fish
- Co-located HAB and environmental data
- Co-located measurements of stocks and rates
- Multi-trophic level integrated datasets
- Benthic flux data

In addition to marine observations, atmospheric, terrestrial, and hydrologic datasets (e.g. winds, ice edge/thickness/volume, riverine inputs) are also integral components of a coastal observing system.

Time series are particularly valuable as they accumulate information over a range of timescales, providing information on shifting baselines and enabling model validation; they can also be interrogated using Machine Learning and/or Artificial Intelligence methods (ML/AI) to establish potential mechanistic drivers and responses. Leveraging existing or developing new time series in ecologically rich settings (e.g., fishery-supporting ecosystems, HAB-impacted regions) would provide a wealth of information to support forecasting.

Spatial biases that oversample the nearshore or undersample regionally can negatively impact development of AI/ML-enabled forecasting (Bardon et al., 2021). Temporal biases such as limited winter sampling also may influence predictability. Increased use of OSSEs can help optimize spatial and temporal scales in coastal ocean observing system design.

Continued development and deployment of novel remote and in situ platforms and sensor technologies will greatly expand the available suite of coastal biogeochemical and biological measurements to support ecological forecasting.

S5.2 Data collection, management, & synthesis

Participants discussed ways to improve data collection, management, provision, and synthesis. Developing a standard core set of ecological forecasting variables and establishing best practices for sample collection, processing, and analysis would make the datasets more broadly usable and interoperable. In addition to collecting new data, investing in data rescue efforts will ensure inclusion and archiving of smaller project/individual investigators' datasets. We can also leverage industry partnerships (commercial fishing, offshore wind, ships of opportunity) and citizen science to augment data streams. Improving coordination across the IOOS regional associations could potentially provide the backbone and organizational infrastructure for an operational observing system for US coastlines.

Forecasts in support of management and decision-making require up to date (as mandated by funding agencies) data sets (including uncertainty estimates) in near-real-time. Making data FAIR (Findable, Accessible, Interoperable, Reusable; Wilkinson et al., 2016) requires up-front investment in data centers and repositories, including data science expertise, tools, and semantic approaches. The development of community-vetted data and metadata reporting standards would facilitate data analysis, synthesis, and ingestion by models.

Ecological forecasting requires equitable data access across a wide range of stakeholders, and diversity, equity, and inclusion should be at the forefront of decision making on data access and interface design. When developing data systems, it is essential to engage prospective data users (i.e. scientists, managers, and other stakeholders) to optimize how data are provided, including available formats, interfaces, and visualization tools.

Having more flexible user-responsive repositories will facilitate data synthesis in support of model development and reanalyses. Employing ML/AI tools (e.g., NCAR climate data guide) and techniques can expedite the data mining process. Building capacity, starting at the student level, in data assimilation and statistical analysis is needed to equip scientists with the data science skills to effectively manage massive data streams.

S5.3 Mechanism-related knowledge gaps

More skillful regional predictions require improved mechanistic understanding of key processes driving regional variability, including:

- Spatiotemporal variability of major regional circulation features (e.g., Gulf Stream, bottom water cold pools)
- Interactions between surface and subsurface (e.g., reemergence of subsurface anomalies) and capacity to predict subsurface processes such as stratification from surface measurements
- Remote influences such as large-scale wind anomalies and oceanic Rossby wave activity
- Interactions between eddies and transient events and their impact on ecological interactions
- Organismal responses to multiple stressors
- Interactions across trophic levels
- Mechanistic drivers of fluxes and exchanges at key interfaces such as land-ocean, sediment-water, and shelf-coastal ocean.

Process studies provide an opportunity to observe all these ecosystem components simultaneously in space and time, which aids in improving mechanistic understanding and detecting regional commonalities and differences.

S5.4 Reanalysis products

Reanalysis products are valuable observation-based tools for supporting forecast model initialization, boundary conditions, and development and assessment of ML/AI forecast systems. Regional reanalyses are urgently needed to support management and decision making in coastal and estuarine systems. To ensure nonlocal upstream-downstream influences and associated impacts are captured, reanalyses should span observing system regions. The community also needs to develop tools and strategies for quantifying uncertainty in data products and state estimations. Intercomparisons of ocean reanalysis products can be very informative. Analysis of data increments could be used to improve model processes.

S5.5 Approaches to prediction

Machine learning (ML) could potentially be used for state estimation, data filling and interpolation. ML algorithms are often used to set boundary conditions in dynamical downscaling for otherwise unavailable gridded products. Development of best practices in ML/AI that include error assessment, development of mechanistic understanding, and characterization of the prediction envelope will improve this nascent field.

More flexible models are needed that can pivot to new forecast targets or assimilate new data streams as needs emerge. Large ensembles should be used more liberally to get more degrees of freedom, assess predictability and skill, and quantify uncertainty (Scaife and Smith 2018). There is potential to use ML methods to replicate dynamical model behavior (i.e. reduced form model) as a means to reduce computational overhead and make ensemble forecasts for uncertainty quantification. Correlative forecasting approaches may function well when persistence is strong but may not function well over a shifting baseline. Community-vetted best practices are needed to assess shifting baselines and empirical forecasts.

Comparison of machine learning, dynamical models and state estimation analysis increments could lead to mutual improvement and address gaps in process understanding. Engaging other communities such as weather forecasting and data scientists to learn from alternative approaches could also accelerate marine ecological forecasting efforts. Funding streams that support model development used in ecological forecasting tend to be locally/regionally focused (e.g., IOOS regional associations). However, it is imperative that overall improvement of process understanding, model development, and predictive capacity transcends the boundaries of regional associations.

S5.6 Communicating with managers and stakeholders

Actionable products require partnering with stakeholders from the outset to develop relevant and user-friendly forecasts (e.g., use of wave forecasts by surfers and co-development of intermediate products such as ecosystem health report cards). Partnerships and development of mutual trust through transparent communication among scientists and other stakeholders requires long-term investment of time and resources. Different stakeholders often work on different timelines, which can pose challenges to collaboration and product development. In addition, scientists often have a difficult time communicating effectively about uncertainty and would benefit from the development of strategies for using low confidence forecasts where sources of variability project weakly onto variables of interest, or where the variability has poor predictability.

3 Summary and Recommendations

The workshop presentations and discussions highlighted increasing interest in and demand for quantitative and qualitative forecasts of physical, biogeochemical and ecological quantities at varying lead times and for a diverse range of applications. Timescales of interest may vary from nowcasts (e.g., to assess the distribution of marine species and avoid bycatch) to decadal timescales for evaluating coastal resilience to sea level rise or management of protected areas. The climate processes that provide predictability vary in their regional projection and intensity. Here, we summarize key areas of progress, gaps, and potential areas for investment.

Key knowledge gaps limit ecological forecasting gains. The exact nature and predictability of climate modes of variability and the processes responsible for their influence at the regional scale need to be further understood. For example, some of the features that are used in predictions, such as the position of the north wall of the Gulf Stream, are not mechanistically understood in relation to climate patterns. Other gaps in knowledge occur at the interface of physical boundaries and communities, such as land/sea, benthic/pelagic, or coastal/open ocean. Adding to these knowledge gaps of the physical environment are those that link biological and ecological processes. Mechanistic understanding of multiple stressors and their ecological impacts as well as energy transfer through trophic levels are needed to move from empirical to mechanistic forecasts of economically and ecologically relevant quantities and processes.

Observations represent the very foundation of forecasting and are needed to initialize and force dynamical ocean models, as well as to assess model forecasts. They are also needed to train and verify statistical/empirical models. There are large discrepancies in observational coverage between the open ocean and coastal areas, with relatively dense sampling provided by Argo floats in offshore regions and, counterintuitively, sparser coverage on the shelf where our interactions with marine ecosystems are strongest. Many observational datasets do exist in regional and institutional archives, especially from the shelf and in nearshore regions. These datasets could greatly enrich the observational resources needed by the broader oceanographic and ecological communities if made available in "integrated" archives and in standard formats. The IOOS associations make measurements in different regions. While available through different portals, the integration of these data in a "US coastlines dataset" would facilitate tremendously the development and verification of reanalysis products, modeling efforts, as well as the training and verification of empirical/statistical models. Ecological forecasting efforts would also benefit from greater consistency in the measurements taken across regions. Hyperspectral and geostationary remote sensing information also provides an opportunity to vastly increase the spatial, temporal, and ecological resolution of the coastal ocean.

Dynamical ocean models coupled with biogeochemical models have been successfully used for dynamical downscaling and prediction applications at the regional scale. The initial conditions for these regional models, as well as the lateral boundary conditions and surface forcing fields are usually obtained from coarser-resolution operational forecasting systems, and the results often reflect the biases of the latter. To make progress, high-resolution coastal reanalyses could be used to interpolate scarce data and initialize forecast models, while the output from empirical models or machine learning approaches could provide the boundary conditions for some specific fields, or for downscaling and bias correcting the output of large-scale operational forecasting systems.

Uncertainty quantification remains a major barrier to the use of observations and forecasts. Given the high levels of system noise, probabilistic forecasts – i.e., forecasts that provide predictive probability distributions of future quantities or events of interest and associated uncertainties – are preferable to deterministic forecasts. Ensemble modeling approaches, particularly at high spatial resolutions, are a critical need, and the computing infrastructure or the development of model emulators needed to support production and analysis of these ensembles should be enhanced. The presentations on observations, ocean reanalysis products, and available methodological approaches have revealed significant further advances that could support the development of forecasting systems along US coastlines in the near future.

Novel forecast methodology, such as Linear Inverse Models and other ML/AI advances, **can provide effective and relatively inexpensive complementary tools to dynamical models**. Trained on observations or reanalysis products, they could be used for downscaling coarser resolution forcing fields and as emulators of the dynamical models and prediction systems themselves, thus allowing for a computationally less expensive approach to probabilistic forecasting. However, ML/AI approaches generally rely on observations and dynamical model/reanalysis results for training. Statistical and ML approaches can also be used in the development of model parameterizations and to incorporate missing processes in the dynamical models.

Based on the workshop discussions and outcomes, **we recommend the following steps** (not in order of importance) **for the development of an integrated ecological forecasting system along US coastlines:**

KNOWLEDGE GAPS

1. Continue and extend investigations of climate modes of variability in both Atlantic and Pacific basins to clarify their connection with regional processes and to elucidate the mechanisms responsible for their phase transitions. In particular, an improved understanding of decadal modes of variability will aid in the separation of internal and anthropogenically forced variations, and in evaluating the stationarity of processes of interest.

2. Interdisciplinary research bridging land/coastlines, shelf/open ocean, land/ice/ocean, pelagic/benthic ecology and biogeochemistry, and biophysical interactions are needed to derive mechanistic understanding of the interactions across these disciplinary but ultimately artificial boundaries.

3. Improved mechanistic understanding of organismal complexity, including responses to multiple stressors, rates of organismal processes (especially losses due to grazing and mortality), and deepened understanding of the complex relationships through which energy flows within marine food webs are needed to better predict the stationarity of the observed correlative inferences that underpin much of the current ecological forecasting.

DATA GAPS

4. Coastal observing capabilities, e.g., a "coastal observational backbone" for ecological forecasting, should be considered and informed by OSSEs that specifically consider forecasting and reanalysis needs. In particular, subsurface data are relatively rare and these observations need to be increased, as they have been linked to enhanced predictability,

including for fisheries relevant quantities. Biogeochemical data needed for initializing and forcing regional models also remain a key limitation for models. Public-private partnerships are one way of increasing the distribution and frequency of these types of measurements (e.g., commercial fishing, offshore wind).

5. Integrating fisheries-independent date (i.e., collected on scientific surveys rather than commercial catches), omics and eDNA data, benthic fluxes, and other new but proven technologies such as imagery (e.g., Flow Cytobot) into a national data distribution network would help bridge the knowledge gaps identified above. These data are often needed in near real time for use in forecasting efforts, and these timescales need to be considered early on in the development of observing networks.

6. Time series data should be expanded and sustained, as they are critical to forecasting efforts due to their resolution of multiple interacting timescales and their potential to assess the stationarity of empirical relationships. Integration of coastal time series into regional reanalyses provides a potentially game changing opportunity to expand their local relevance more broadly.

COASTAL REANALYSIS

7. Physical and biogeochemical US wide coastal reanalysis products that leverage and interpolate scarce observations should be promoted both for developing mechanistic understanding of the knowledge gaps highlighted above as well as to produce downscaled products and emulators of the coastal systems at the needed resolution for specific subregions. These systems could serve as the baseline for OSSE experiments that optimize observing variables, timescales, and spatial distribution. They could also provide synthetic data for re-forecasting efforts that test temporal stability of relationships. Comparison of reanalysis products will provide insight into the emerging field of biological data assimilation.

UNCERTAINTY QUANTIFICATION

8. Characterization of uncertainty in data and reanalysis products as well as ecological forecasts remains a barrier in the field. We need to enhance the development of ensemble method best practices, training programs such as summer schools, and research on the utility and communication of "weak" or low certainty forecasts.

FORECAST METHODOLOGY

9. Model development should be accelerated with focus on the simulation of quantities that are of management interest, which often include higher trophic levels. More flexible ecological models that can more rapidly pivot to novel forecast targets and leverage novel data streams and ML/AI parameterization and optimization should be facilitated. Comparison of machine learning and dynamical models and state estimation analysis increments should be leveraged for mutual improvement. This will aid with gaps and lack of understanding (mechanisms/processes) of sources of predictability from an ecological standpoint. Rapid advances in ML/AI require interdisciplinary training of early career scientists in order to take advantage of gains developed in the private sector that can be applied to model parameterization and development.

INFRASTRUCTURE NEEDS

10. An integrated set of observing infrastructure along US coastlines should be created to include (in consistent formats and quality-controlled standards, e.g., FAIR, APIs that enable reproducible workflows) observations routinely collected by the IOOS regional associations and data collected by different institutions. Current regional delineations are somewhat arbitrary and not linked to the user needs at national scales. Satellite data that is currently available or expected to become available in the near future should also be incorporated in such an archive. While the groups that have collected the data are willing to make them available, additional resources are needed to ensure processing, archiving, and distribution of individual or gridded data with quality/ uncertainty estimates. ML/AI may be of use in data mining. A diversity of stakeholders and knowledge providers such as citizen scientists should be an explicit component of such a system.

ENGAGING STAKEHOLDERS

11. Many stakeholders are hesitant to use available forecasts in their routine activities. Stakeholders should be engaged at the earliest point in the development of coastal forecasting systems and in all phases of development, ideally following a "co-design" approach, to ensure that the tools and products are useful for stakeholders' needs and will be properly and effectively utilized. Trust building should include use of stakeholder data and provision of forecasts that can be rapidly and immediately verified. Additionally, developing products such as ecosystem health report cards in partnership can help clarify mutually important ecological benefits.

The advances outlined in the above recommendations provide a roadmap for the development of a coordinated ecological forecasting system along US coastlines. Implementation of a coherent, integrated coastal database would facilitate high-resolution physical and biogeochemical coastal reanalyses, that could expand the existing regional systems. A dynamical coastal prediction system could then grow out of the reanalysis efforts. This system would utilize the reanalysis fields as initial conditions and be forced by properly downscaled and bias-corrected fields from coarser-resolution forecasting models.

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Appendix A: Workshop Agenda

Slidedecks and recordings for all presentations are available via the workshop website.

Tuesday, April 12, 2022

Time	Agenda	Presenter
07:00	Workshop registration and breakfast	
08:00	Welcome, opening remarks, workshop goals	Antonietta Capotondi (NOAA/PSL) and Victoria Coles (UMCES)
	Session 1: Sources of Regional Predictability Across Timescales	Moderators: Matt Newman and Michelle Gierach
08:10	Timescales and Mechanisms of Marine Ecosystem Predictability Along the US West Coast	Mike Jacox (NOAA/SWFSC and NOAA/PSL)*
08:35	Northern US East Coast	Mike Alexander (NOAA/PSL)
09:00	Arctic and Bering Sea	Mitch Bushuk (UCAR/NOAA GFDL)*
09:25	Gulf of Mexico and Southeast US	Ruoying He (NCSU)
09:50	Break	
10:10	Session 1 spotlight poster talks	
10:40	Q&A and discussion	
11:15	Breakout Session 1: Regions	Breakout Assignments
12:15	Lunch/Break	
	Session 2: Applications/Timescales	Moderators: Andrew Ross and Victoria Coles
13:30	Fisheries applications at different timescales	Desiree Tommasi (UC Santa Cruz and NOAA/SWFSC)
13:55	Predicting hypoxic conditions	Sam Siedlecki (University of Connecticut)
14:20	HAB prediction	Clarissa Anderson (SIO and SCCOOS)
14:45	Chesapeake Bay application	Marjy Friedrichs (VIMS)
15:10	Break	
15:30	Session 2 spotlight poster talks	
15:55	Q&A and discussion	
16:25	Transition to breakout session	
16:30	Breakout Session 2: Applications	
17:30	In-person reception/networking	

Wednesday, April 13, 2022

Time	Agenda	Presenter
08:00	Welcome, day 2 objectives, breakout summaries for sessions 1 and 2	Breakout moderators
	Session 3: Modeling Capabilities/Challenges	Moderators: Mercedes Pozo Buil and Charlie Stock
08:30	Global physical and BGC modeling and predictions	Matt Long (NCAR)
08:55	Regional modeling using dynamical downscaling	Liz Drenkard (NOAA/GFDL)
09:20	Empirical and mechanistic modeling of marine ecosystems/fisheries	Colleen Petrik (SIO)
09:45	Statistical/ML approaches in ecological forecasting	Ethan Deyle (Boston University)
10:10	Break	
10:30	Session 3 spotlight poster talks	
11:05	Q&A and discussion	
11:40	Breakout Session 3: Forecasting Methods	Breakout Assignments
	Breakout Session 1: Regions	Breakout Assignments
12:40	Lunch/Break (Clark 5 Foyer)	
	Session 4: Reanalysis Products and Observations	Moderators: Dillon Amaya and Art Miller
14:00	Global physical/biogeochemical reanalyses	Dimitris Menemenlis (NASA JPL)
14:25	Regional reanalyses	Chris Edwards (UC Santa Cruz)
14:50	Status of data collection and integration across regions	Jake Kritzer (NERACOOS)
15:15	Observing technologies bridging global to the coastal ocean	Susan Wijffels (WHOI)
15:40	Satellite observing technologies	Susanne Craig (NASA GSFC)
16:05	Break	
16:25	Session 4 spotlight poster talks	
16:45	Q&A and discussion	
17:15	Wrap up day 2	

Thursday, April 14, 2022

Time	Agenda	Presenter
08:00	Welcome, day 3 objectives, breakout summaries for breakout session 3	Breakout moderators
	Session 3: Modeling Capabilities/Challenges	Moderators: Mercedes Pozo Buil and Charlie Stock
08:30	Transition to breakout session	
08:35	Breakout Session 4: Observations	
	Empirical and mechanistic modeling of marine ecosystems/fisheries	Colleen Petrik (SIO)
09:35	Transition back to plenary for report out	
09:40	Breakout summaries for session 4	Breakout moderators
	Session 3 spotlight poster talks	
10:10	Break	
	Session 5: Discussion of commonalities in future steps that need broader community support as opposed to more locally focused efforts	
10:30	Discussion	
12:00	Final remarks and next steps	
12:30	Adjourn workshop and box lunch	
13:00	Organizing committee meeting in Clark 507	

Appendix B: Participant List

First name	Last name	Affiliation
Michael	**Alexander**	NOAA/Physical Sciences Laboratory
Simone	**Alin**	NOAA Pacific Marine Environmental Laboratory
Andrew	**Allyn**	Gulf of Maine Research Institute
Dillon	**Amaya**	NOAA Physical Sciences Laboratory
Clarissa	**Anderson**	Scripps Institution of Oceanography/Southern California Coastal Ocean Observing System
Daniel	**Barrie**	NOAA
Christine	**Bassett**	NOAA WPO
Heather	**Benway**	OCB/WHOI
Aaron	**Bever**	Anchor QEA
Rachael	**Blake**	University of Washington
Stephanie	**Brodie**	UC Santa Cruz
Mitch	**Bushuk**	GFDL
Antonietta	**Capotondi**	University of Colorado and NOAA/PSL
Patricia	**Chardon-Maldonado**	Caribbean Coastal Ocean Observing System (CARICOOS)
Zhuomin	**Chen**	Department of Marine Sciences, University of Connecticut
Wei	**Cheng**	University of Washington
Victoria	**Coles**	UMCES
Jack	**Conroy**	NOAA Ocean Exploration
Nathalí	**Cordero Quirós**	NOAA SWFSC/UCSC
Susanne	**Craig**	NASA GSFC/UMBC
Fei	**Da**	Virginia Institute of Marine Science
Ethan	**Deyle**	Boston University
Liz	**Drenkard**	NOAA GFDL
Hubert	**du Pontavice**	Princeton University / NOAA NEFSC

Christopher	**Edwards**	UC Santa Cruz
Johnathan	**Evanilla**	Bigelow Laboratory for Ocean Sciences
Carl	**Friedrichs**	Virginia Institute of Marine Science
Marjorie	**Friedrichs**	Virginia Institute of Marine Science
Jessica	**Garwood**	Princeton University
Michelle	**Gierach**	NASA Jet Propulsion Laboratory
Ruoying	**He**	North Carolina State University
Albert	**Hermann**	UW/CICOES and NOAA/PMEL
Dante	**Horemans**	Virginia Institute of Marine Science
Michael	**Jacox**	NOAA Southwest Fisheries Science Center
Bror	**Jönsson**	Plymouth Marine Laboratory
Hyewon Heather	**Kim**	Woods Hole Oceanographic Institution
Jake	**Kritzer**	NERACOOS
Laura	**Lilly**	Scripps Institution of Oceanography, UC San Diego
Hyunggyu	**Lim**	Princeton University
Chris	**Lindemann**	University of Bergen
Matthew	**Long**	NCAR
Mai	**Maheigan**	OCB/WHOI
Claudia	**Mazur**	Boston University
Dimitris	**Menemenlis**	Jet Propulsion Laboratory, California Institute of Technology
Art	**Miller**	Scripps Institution of Oceanography
Tommy	**Moore**	NWIFC
Julio	**Morell**	CARICOOS
Schuyler	**Nardelli**	NOAA
Gian Giacomo	**Navarra**	Georgia Institute of Technology
Matt	**Newman**	University of Colorado/CIRES and NOAA/PSL
Wenfei	**Ni**	Pacific Northwest National Laboratory
Emily	**Norton**	CICOES/Univ of Washington

Mark	**Ohman**	Scripps Institution of Oceanography
Elise	**Olson**	Princeton University
Nima	**Pahlevan**	SSAI / NASA Goddard
Mike	**Patterson**	US CLIVAR Project Office
Angelica	**Pena**	Institute of Ocean Sciences, Fisheries and Oceans Canada
Colleen	**Petrik**	University of California San Diego
Darren	**Pilcher**	CICOES, University of Washington
Mer	**Pozo Buil**	UCSC/NOAA SWFSC
Josie	**Quintrell**	IOOS Association
Sulagna	**Ray**	SRG at NOAA/EMC
Andrew	**Ross**	Princeton/NOAA GFDL
Camille	**Ross**	Bigelow Laboratory for Ocean Sciences
Joel	**Rowland**	Los Alamos National Laboratory
Sarah	**Salois**	Northeast Fisheries Science Center, NOAA
Miraflor	**Santos**	WHOI
Raphaël	**Savelli**	Jet propulsion Laboratory
Cristina	**Schultz**	Princeton University, NOAA/GFDL
Virginia	**Selz**	NOAA
Samantha	**Siedlecki**	University of Connecticut
Pierre	**St-Laurent**	Virginia Institute of Marine Science (VIMS)
Charles	**Stock**	NOAA Geophysical Fluid Dynamics Laboratory (GFDL)
Desiree	**Tommasi**	University of California Santa Cruz and NOAA SWFSC
Brendan	**Turley**	NOAA-NMFS and UM-RSMAS
Lisa	**Wainger**	University of Maryland Center for Environmental Science
Susan	**Wijffels**	Woods Hole Oceanographic Institution
Tongtong	**Xu**	NOAA Physical Sciences Laboratory
Zhengchen	**Zang**	WHOI
Jennie	**Zhu**	US CLIVAR