



1 Surface and bottom *in situ*, interpolated hydrographic 2 climatologies of the Northwest Atlantic Ocean for 3 2000-2024

4 Haley Synan^{*1,2,3}, Kimberly J.W. Hyde¹, Colleen B. Mouw², Chris Melrose¹, Linus
5 Stoltz⁴, Sarah Salois¹

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7 ¹National Oceanic and Atmospheric Administration, National Marine Fisheries Service,
8 Northeast Fisheries Science Center, 28 Tarzwell Drive, Narragansett, RI, USA

9 ²Graduate School of Oceanography, University of Rhode Island, Narragansett, RI, USA

10 ³IBSS Corp, 1110 Bonifant St. Suite #315, Silver Spring, MD, USA

11 ⁴Commercial Fisheries Research Foundation, Saunderstown, RI, USA

12 ^{*}Corresponding author: Haley Synan (haley.synan@noaa.gov)

13 Abstract

14 New *in situ*, interpolated hydrographic monthly climatologies were created for the
15 Northeast U.S. Continental Shelf (NES) and surrounding boundary waters for the years 2000 -
16 2024. The climatologies were created at two depth bins: the surface and bottom, where the
17 surface is defined as observations averaged above the mixed layer depth, and the bottom includes
18 all averaged data within 10 meters of the bathymetric bottom. The products described here rely
19 solely on *in situ* measurements rather than satellite imagery, as satellite-derived products can be
20 coarse and only reflect the skin layer of the ocean. Multiple point data sources and data
21 collection methods, including observations collected from traditional vertical oceanographic
22 profiles, flowthrough systems, buoys, gliders, and others, were aggregated to create the *in situ*
23 dataset. Spatiotemporal Barnes objective analysis was performed to create the monthly
24 climatologies for both temperature and salinity at the two depth bins. Root mean squared error
25 (RMSE) and an uncertainty metric were provided with the interpolation. The uncertainty metric
26 highlights regions and seasons that are data-poor and/or highly variable, and where there is lower
27 confidence in the interpolated values. Results were validated using reference climatologies
28 created using Global Ocean Reanalysis and Simulations (GLORYS) modeled data with the same
29 spatiotemporal bounds. The surface temperature and salinity climatologies both yield significant
30 correlations when compared to the reference climatologies (bias<|1.068| °C). Lower correlations
31 in the winter months are observed during validation of bottom temperature climatologies, due to
32 seasonal sampling bias. The products described here provide high-resolution, updated monthly
33 climatologies derived from *in situ* data that may be used for anomaly detection or other modeling
34 efforts. The climatologies can be accessed at doi.org/10.5281/zenodo.20183494 (Synan et al.,



2026a) and the data used to create them can be accessed at doi.org/10.5281/zenodo.22696810
 (Synan et al 2026b).

Introduction

Understanding long-term shifts in dominant water masses and fish habitat in both coastal and pelagic waters is critical for effective management of ocean ecosystems and fisheries. Ocean climatologies provide a useful baseline for analyzing long-term variability and are commonly used in ecosystem modeling, particularly marine heatwave detection and tracking warming trends. Satellite imagery provides data at a consistent temporal resolution that is valuable for creating long-term climatologies, however thermal satellite imagery is only available for the skin surface layer of the ocean. Derived salinity products are available from satellite imagery, but lack the spatial resolution and accuracy required for analysis of local and submesoscale features. Depth-integrated models can provide predictions of hydrographic data near the seafloor. However, direct, *in situ* measurements are more accurate and provide essential validation for satellite- and model-based products.

In situ hydrographic observations are often patchy in both space and time and are collected by multiple entities, leading to multiple data storage locations and repositories. The Northeast U.S. Continental Shelf (NES) is a highly-studied area, with regular surveys covering the shelf and slope regions and moored buoys continuously collecting data, making it uniquely suitable for creating a regional climatology using *in situ* data (Table 1). NOAA NCEI produces two *in situ*, interpolated climatologies for this region: the Extended Reconstructed Sea Surface Temperature Version 6 (ERSST) and the Northwest Atlantic Regional Climatology Version 2 (NWARC2), which produce monthly climatological fields of both temperature and salinity (Boyer et al 2018). The ERSST provides $2^{\circ} \times 2^{\circ}$ spatial resolution with anomalies computed based on the 1991 to 2020 temperature climatology, although data is available starting in 1850 (Huang et al 2025a). The NWARC2 provides vertically resolved decadal monthly climatologies of both salinity and temperature at spatial resolutions of $1^{\circ} \times 1^{\circ}$, $1/4^{\circ} \times 1/4^{\circ}$, and $1/10^{\circ} \times 1/10^{\circ}$ (Seidov et al 2022). The most recent decadal climatology available from NWARC2 is for 2005–2017 (Seidov et al 2022). Both products use interpolation methods to create the climatology, a convolutional neural network (CNN), and Barnes objective analysis, respectively (Huang et al 2025b, Seidov et al 2022).

Parts of the Northwest Atlantic (NWA), particularly the NES, have been experiencing significant warming since the early 2000s (Gonçalves Neto et al 2021, Friedland et al 2020). Additionally, Gangopadhyay et al (2019) noted a regime shift in the number of Warm Core Rings (WCR) produced by the Gulf Stream around 2000. Prior to 2000, there were 18 annual WCR rings detected in the region, while after 2000 there was an annual average of 33 rings per year (Gangopadhyay et al 2019). This regime shift could have been caused by several factors, including reduced gravity between the Slope and Gulf Stream due to warming Slope waters (Gangopadhyay et al 2019). Since this regime shift of WCRs, the Slope Sea and NES have been



undergoing rapid warming (Pershing et al 2015). In particular, the Gulf of Maine, a northern portion of the NES, warmed faster than 99.9% of global oceans between 2004 and 2013 (Pershing et al 2015). To capture the recent warming trends, the climatologies created here reflect the reference years 2000 through 2024.

Due to the region's rapid change, we aim to create an updated, high resolution climatology that reflects the recent warming. Climatologies are traditionally 30 year means; however, the aim of this product is to reflect the averages since the beginning of the warming regime in the early 2000s. Here, we create monthly *in situ* based climatologies for temperature and salinity using spatiotemporal Barnes objective analysis for the years 2000-2024 for the Northeast Continental Shelf and surrounding boundary waters in the Northwest Atlantic at a 1/12° spatial resolution at two depth layers: the surface and bottom. The monthly climatologies described here provide updated high-resolution climatologies with included uncertainties for a twenty-four year baseline that are applicable for many ocean uses including anomaly detection and modeling efforts.

Methods

2.1 Study Area

The Northwest Atlantic (NWA) is a highly dynamic region, defined for this study as the area between 34°N-77°N to 45°N-63°W (Figure 1). The cooler, fresher water on the continental shelf, known as the Northeast US continental shelf (NES), is a productive and economically important region for many U.S. fisheries. The 200 meter isobath is typically used to differentiate the boundary between the continental shelf and continental slope (Chen & He 2015). Here, we refer to the “onshelf” region as the area shoreward of the 200 m isobath, and the “offshelf” region as water seaward of the 200 m isobath (Figure 1). The NES is strongly influenced by several currents, including the Gulf Stream and the Shelfbreak Jet (Churchill & Cornillon 1991; Silver et al 2022). The Gulf Stream transports warm and salty water poleward across the Atlantic, while the Labrador Current transports cold, fresh water southward at mid-depth where it becomes the Shelfbreak Jet as it passes the Tail of the Grand Banks (Gonçalves Neto et al 2021). Warm Core Rings (WCRs) are warm eddies that detach from the Gulf Stream and move westward through the Slope Sea, the region between the continental shelf and the Gulf Stream (Silver et al 2022; Gangopadhyay et al 2019; Bignami & Hopkins 2003). WCRs and other interactions from the Gulf Stream are responsible for much of the northward heat transfer onto the continental shelf (Gangopadhyay et al 2019, Silver et al 2022). Conversely, Cold Core Rings (CCRs) form when the Gulf Stream meanders pinch off south of the Gulf Stream, creating a cyclonic eddy with a core of cooler slope water surrounded by the warm, nutrient-poor water of the Sargasso Sea (Umbert et al 2015).

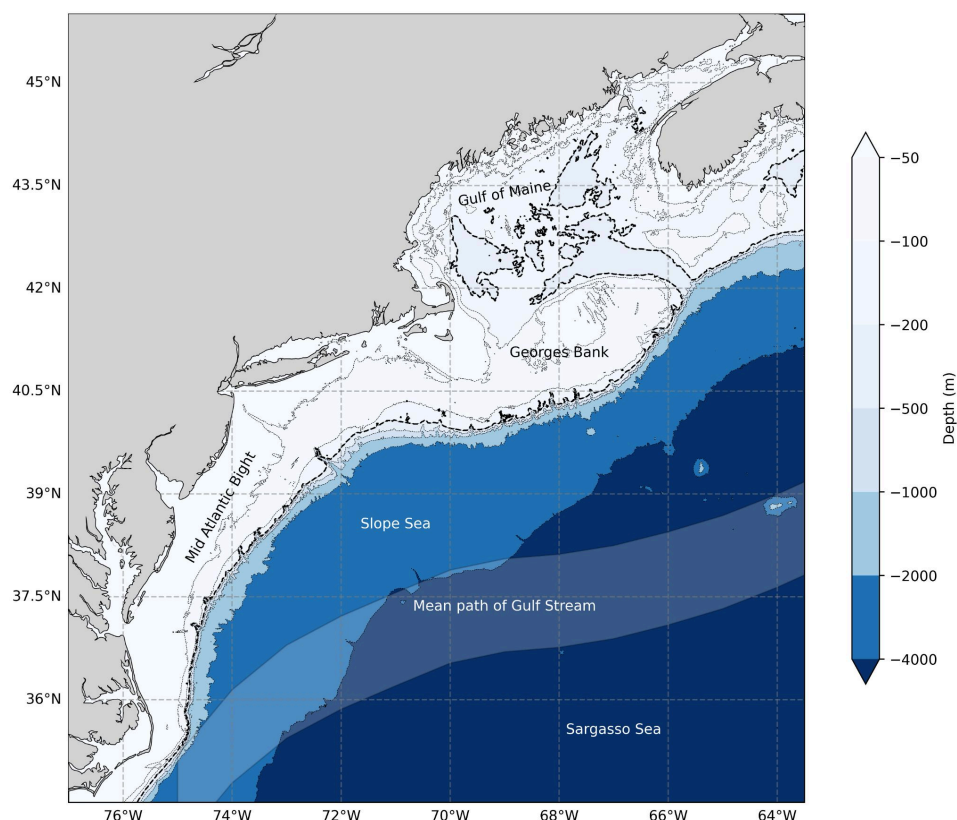


Figure 1. Map of study region depicting bathymetry, as well as main regions and currents. The continental shelf is shown in the lighter blue colors, the region off the continental shelf is much deeper, shown in the darker blue. The 200 m isobath is highlighted along the dotted black line.

108

109 2.2 Data variables

110 We compiled *in situ* temperature and salinity data from different databases and
 111 repositories within the given geographic bounds (Figure 1). To ensure consistency between data
 112 sources and to comply with recommendations from Thermodynamic Equation of Seawater 2010
 113 (TEOS-10), absolute salinity (SA) and conservative temperature (CT) were calculated and used
 114 in place of practical salinity and potential temperature (McDougall & Baker 2011). Conservative
 115 temperature is proportional to potential enthalpy, a conservative property, and is a more accurate
 116 tracer of heat content than potential temperature (McDougall & Baker 2011). Absolute salinity is
 117 the mass fraction of dissolved material in water and accounts for spatial variation in the
 118 composition of water (McDougall et al 2012).

119 2.3 Data Sources

120 To capture impacts from the warming regime and create a more representative
 121 climatology, data collected between 2000-2024 were used to build the climatology (Pershing et



al 2015, Gangopadhyay et al 2019). Data sources include several publicly accessible databases: the World Ocean Database (WOD), Surface Underway Marine Database (SUMD), Biological and Chemical Oceanography Data Management Office (BCO-DMO), and SeaWiFS Bio-optical Archive and Storage System (SeaBASS) (Boyer et al 2018, Wang et al 2017, Werdell & Bailey 2002, Werdell et al 2003). Additional sources contained data collected from ship-based CTD casts, like NOAA's Northeast Fisheries Science Center (NEFSC) Ecosystem Monitoring surveys (EcoMon), the Commercial Fisheries Research Foundation (CFRF) and Woods Hole Oceanographic Institute's (WHOI) Shelf Research Fleet, and Northeast Area Monitoring and Assessment Program (NEAMAP) (NOAA NEFSC 2024, Gawarkiewicz and Malek Mercer, 2019, Gartland et al 2023). Other ocean observing systems, such as the Pioneer Array, Argo floats, and both the Northeast Regional Association of Coastal Ocean Observing Systems (NERACOOS), and Mid-Atlantic Regional Association of Coastal Ocean Observing System (MARACOOS), and NEFSC Passive Acoustics Branch (PAB) were also included (Knee 2017, Shyka 2017, Wong et al 2020) (Table 1). An aggregated bottom product, Fishing Industry Shared Bottom Oceanography Timeseries (FISHBOT) was incorporated as well. FISHBOT aggregates temperature and salinity data from multiple sources, including both fishery-dependent and fishery-independent sources, into a standardized gridded product (Stoltz et al 2025). Additional information regarding each data source, including location of data and the treatment of data from individual data sources, can be found in the supplementary Jupyter Book (https://hsynan.github.io/READ-EDAB-Synan_hydrographic_climatologies/data_sources.html).

Data source	Instrument	Years covered	Surface num profiles	Bottom num profiles
Argo	CTD	2000-2024	11220	418
CFRF/WHOI	CTD	2014-2024	2135	0
EcoMon	CTD	2000-2024	36325	0
DFO	CTD	2000-2020	221	1662
Maine DMR	CTD	2000-2024	37	3901
NEAMAP	CTD	2007-2023	4685	7948
NERACOOS	Buoy	2001-2024	1135766	0
MARACOOS	Buoy	2021-2024	64130	0
BDO-DMO	varied	2014-2019	289	253
WOD	APB	2019-2024	566	94
WOD	CTD	2000-2024	46978	38525
WOD	Drifting buoy	2011-2011	1	1
WOD	Glider	2010-2024	533556	358308
WOD	Moored buoy	2004-2008	480	0
WOD	CTD/bottle	2001-2021	564	168
WOD	Profiler	2000-2024	10799	217
WOD	Towed CTD	2003-2004	36876	26229
SeaBASS	varied	2000-2019	5714	0
SUMD	varied	2000-2024	125266	0
PAB	Hobo Tidbit	2018-2024	0	189419
FISHBOT	varied	2000-2024	0	184141

Table 1: Hydrographic data sources and data distribution. CTD: Conductivity, Temperature, Depth sensors. APB: Autonomous Pinniped Bathythermograph

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143 2.4 Observation-level data cleaning

144 For instruments expected to measure both temperature and salinity, only observations
145 with coincident temperature and salinity were retained for further processing for quality
146 assurance purposes. Exceptions were made for two data sources, the NEFSC Passive Acoustics
147 Branch and FISHBOT which did not have consistent coincident salinity data. The NEFSC



Passive Acoustics program only measures bottom temperature, however it was included because its high temporal resolution allows us to capture temperature seasonality. Similarly, the FISHBOT product includes data collected from instruments without conductivity sensors, however it was retained due to its broad spatial and temporal coverage of bottom measurements. For all other data sources, observations that were missing either temperature or salinity measurements were removed. For data sources that had flags available, low quality or erroneous data were removed using temperature and salinity flags. Otherwise, erroneous temperature, salinity, and pressure data were identified and removed by defining valid minimum and maximum for temperature and salinity and checking all observations against those ranges. Valid temperatures were required to be above 0 °C and salinity values between 3 and 38 PSU. These ranges were chosen solely to remove erroneous data, rather than for quality control. When applicable, Absolute salinity (SA) and conservative temperature (CT) were calculated using the Python Gibbs Seawater (GSW) implementation of the TEOS-10 (McDougall & Baker 2011).

Data within estuaries (Delaware, Chesapeake, Hudson, Long Island Sound, Narragansett, Casco, Penobscot, Mahone, St. Margaret, Passamaquoddy Bays) and rivers were removed. A 0.15° buffer was applied to the coastlines, and observations inside the buffer were removed. These near-coast waters are subject to intense vertical mixing and high variability and fluctuations in both temperature and salinity. They were removed to ensure the dataset reflects large-scale ocean patterns rather than short-term intense changes near the coast.

2.5 Spatiotemporal binning

Data from multiple sources were split into spatiotemporal surface and bottom bins, herein called “profiles”, collected from differing observation methods, including buoy, flowthrough, and vertical profiles. Buoy data were separated into 1-hour temporal bins to create a quasi-profile. For data collected from a flowthrough system at a fixed intake depth (i.e., TSG), quasi-profiles were created through spatial binning. Data collected using flowthrough systems were put onto an 80x94 grid, and observations within each grid cell were averaged to create hourly spatial bins. Glider data from the World Ocean database were already split into individual profiles when downloaded. Finally, vertical profiles were extracted using the direction of observations (i.e., up or downcast) and a unique profile identifier, like a station ID or coordinates. Only upcasts were retained for further processing.

2.5.1 Surface

Here, we define the surface layer as the top mixed layer of water that interacts with the atmosphere, or the mixed layer. Not all data types (i.e. buoy and flowthrough) have a vertical component; therefore, a modeled product was used to aid in separating the surface signature in the data. GLObal Ocean ReanalYsis and Simulation project (GLORYS12V1) modeled climatological mixed layer depth was acquired from Copernicus Marine Service at a 0.083 degree spatial resolution (datasetID: [cmems_mod_glo_phy_my_0.083deg-climatology_P1M-m](#)). As mixed layer depths are highly variable, a climatological mixed layer depth was used in place of a daily mixed layer depth to standardize the surface bin temporally. Once observations were



grouped into profiles, each profile was matched to a climatological mixed layer depth using a Euclidean distance nearest-neighbor search (Virtanen et al 2020) (Figure 2). Observations above the climatological mixed layer depth were averaged, yielding a single mean surface layer value for each profile (Figure 3). Minimum and maximum temperature and salinity values of the entire profile were retained, as well as the number of observations included in creating the mean surface value and the total number of observations in each profile.

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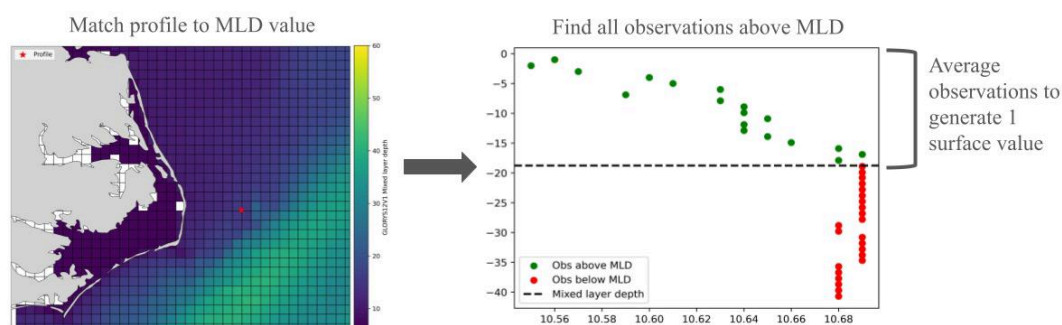


Figure 2: Workflow for matching observations to a mixed layer depth value and averaging values above the mixed layer depth to create one mean surface layer value. The left panel denotes a profile location (red star), as well as the GLORYS12V1 grid cells.

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195 2.5.2 Bottom

For each profile, observations within 10 meters of the bottom were averaged to yield a single mean bottom layer value. Individual profiles were matched to a Shuttle Radar Topography Mission at 15 arc seconds (SRTM 15+) bathymetry value using an Euclidean distance nearest-neighbor search (Tozer et al 2019; Virtanen et al 2020). The SRTM 15+ is a global digital elevation dataset, providing both topography and fixed bathymetry data at approximately a 500 meter spatial resolution (Tozer et al 2019). Bathymetry is created using both satellite altimetry data and *in situ* shipboard soundings (Tozer et al 2019). Values within 10 meters of the bathymetric bottom were retained and averaged to create a single value for the bottom depth bin. Minimum and maximum temperature and salinity values of the entire profile were retained, as well as the number of observations included in creating the mean bottom value and the total number of observations in each profile.

FISHBOT was unique in that its bottom depth criterion differed slightly from the one used in this study, so a sensitivity analysis was done to compare two versions of the product with different depth thresholds. The standard FISHBOT product available at the time of this study provided averaged values of observations from multiple sources within a 20 meter ceiling of the General Bathymetric Chart of the Oceans (GEBCO) bathymetric depth. This version was tested against a modified version of FISHBOT with a 10 meter ceiling to match the current study's threshold. The results, detailed in the supplementary material, revealed minimal differences between the two datasets. Based on these results, we elected to use the standard FISHBOT product, excluding observations where discrepancies between the two datasets exceeded 2°C or 0.5 PSU. As FISHBOT is already averaged and gridded, the matching and averaging steps described above were not necessary.

217



2.6 Data treatment

All valid data from the surface and bottom depth bins were concatenated to create two distinct datasets. The following procedures were applied to both the surface and bottom datasets separately. Data were aggregated from several public sources, introducing duplicate entries if data were hosted across multiple repositories. For the surface dataset, duplicates were identified on a profile-level basis based on geographic coordinates, datetime, temperature, and salinity values. Only the first instance of duplicate data was retained for further processing. The bottom dataset contains a pre-aggregated dataset (FISHBOT), which provides mean gridded values. FISHBOT compiles data from several individual data sources such as EcoMon, WHOI/CFRF Study Fleet, and the OOI Pioneer Array. Instead of identifying duplicative profiles, duplicative datasets that overlapped with the FISHBOT timeseries were removed entirely from the bottom dataset.

To detect outliers, monthly binned observations from all years were binned into 1 degree latitude-longitude grid cells, resulting in a 12 x 14 grid for the study area. Monthly mean and standard deviation were calculated for each grid cell. Following the outlier removal methods outlined in Locarnini et al (2018), temperature and salinity data that were more than three standard deviations from the mean for each grid cell were removed from cells that did not border land. For grid cells that bordered land, data that were more than five standard deviations from the mean were removed to account for the naturally greater variability in coastal regions (Locarnini et al 2018). Upon visual inspection of monthly data, there were some clear salinity outliers in the Gulf Stream and Sargasso Sea regions. Using shapefiles of the mean Gulf Stream path and the Sargasso Sea, observations with salinity less than 30 PSU were manually removed and excluded from the interpolation. Salinities in this region are typically >35 PSU in the Gulf Stream and >36 PSU in the Sargasso Sea (Silver et al 2021; Umbert et al 2015; Bignami & Hopkins 2003). Due to the nature of the interpolation and limited data availability in these regions, these anomalous and potentially erroneous values could falsely appear representative of the grid cells after interpolation and were therefore removed. This outlier detection resulted in the removal of 20,834 and 3,997 profiles from the surface and bottom aggregated point datasets, respectively.

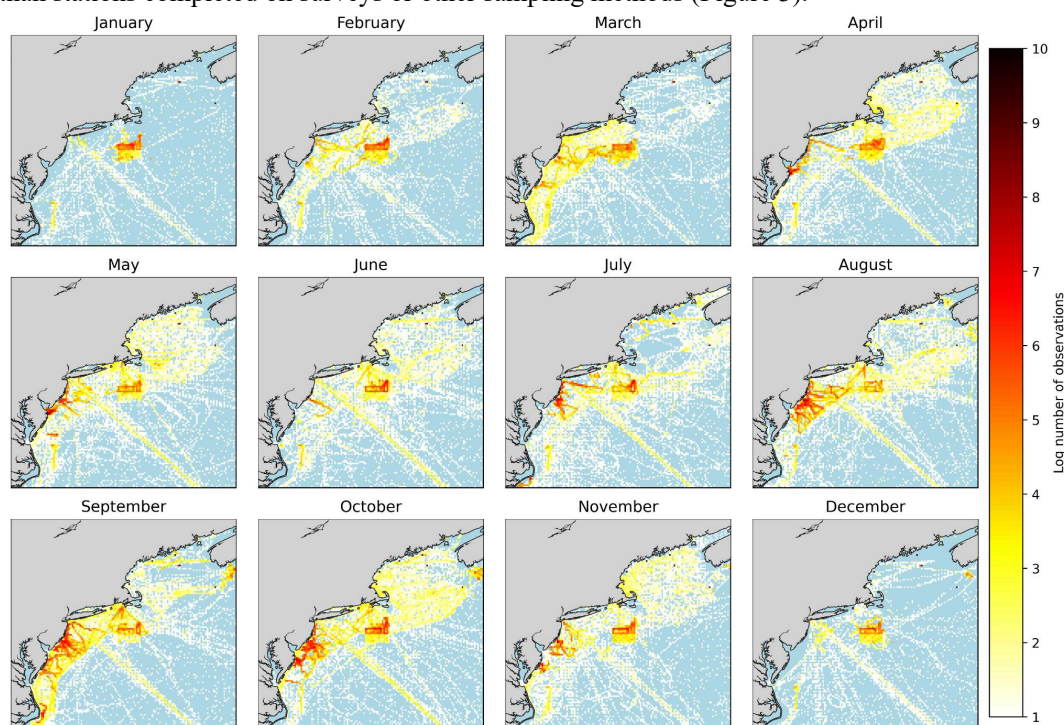
2.7 Spatiotemporal distribution of profiles

2.7.1 Surface

As *in situ* sampling can be coarse in both space and time, data is unevenly distributed spatially and temporally. There is a seasonal bias present in the data, with more data collected in the summer and fall than in winter and early spring. December has the fewest number of profiles during the study period, leaving spatial gaps in the Gulf of Maine and the coastal Mid-Atlantic Bight (Figure 3). Except for December and January, data density is more concentrated in the onshelf region (Figure 3). Although sparser, the offshore region shows a consistent distribution of



254 data (Figure 3). Moored buoys and fixed stations have a significantly higher temporal resolution
 255 than stations completed on surveys or other sampling methods (Figure 3).



256 Figure 3. Density of surface data for each grid cell used in the interpolation. Grid cells with zero observations are shown in light blue. The maximum number of observations for one grid cell is 17131.

257 2.7.2 Bottom

258 During winter months, coverage on the shelf is more comprehensive for the bottom
 259 dataset relative to surface data, driven primarily by the inclusion of fishery-dependent
 260 observations from FISHBOT. The onshelf region is much shallower, typically 50-200 meters,
 261 compared to the offshore region, which can be up to 4000 meters deep, causing much fewer data
 262 to be collected offshore (Figure 1). Due to the large data gaps across almost the entire offshore
 263 region, the bottom climatologies are only available for the onshelf region.

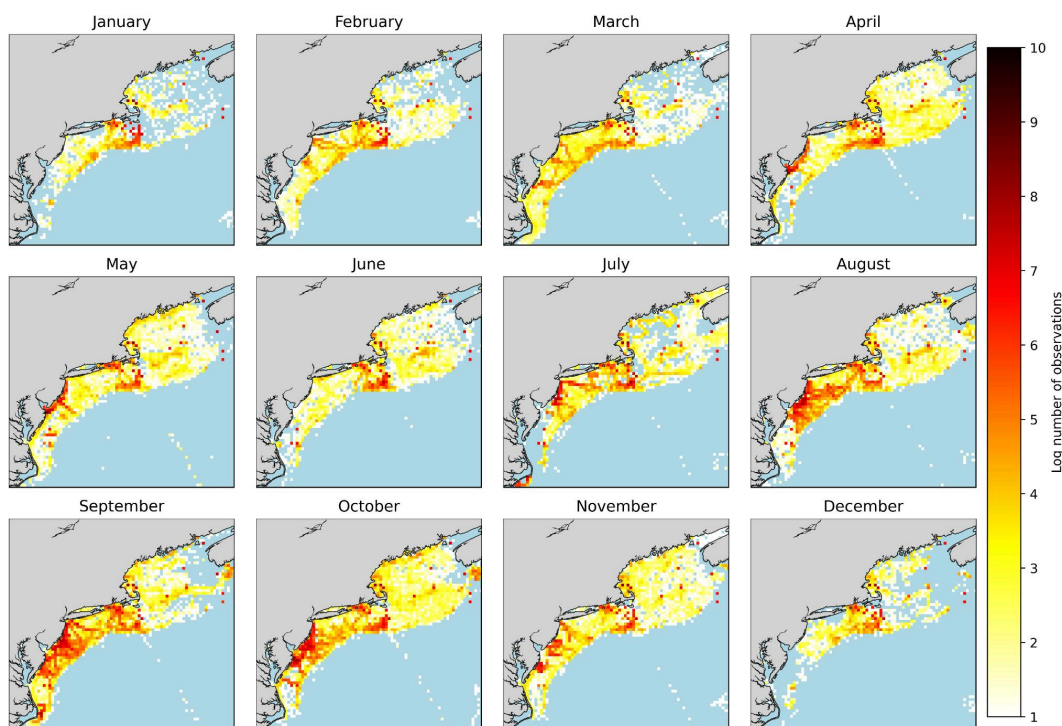


Figure 4. Density of bottom data for each grid cell used in the interpolation. Grid cells with zero observations are shown in light blue. The maximum number of observations for one grid cell is 6832.

2.8 Interpolation

Barnes objective analysis was employed to create the monthly interpolated temperature and salinity climatologies using an equidistant $1/12^\circ$ grid (Bartell 2016). Similar methods have proven successful in creating climatologies, such as the Northwest Atlantic Regional Climatology (NWARCV2) (Seidov et al 2022, Boyer et al 2018). Both 2-dimensional (latitude and longitude) and 3-dimensional (latitude, longitude, month) monthly Barnes objective analysis methods were tested and analyzed (Appendix Figures 5 & 6). The 3-dimensional method, hereafter called the spatiotemporal interpolation, accounts for temporal “closeness” during interpolation. This helps fill in the larger data gaps noted during December and therefore was selected as the final climatological product. During this spatiotemporal Barnes objective analysis, an interpolated value at each grid point is calculated using a three-pass correction. The weighted average of values within a given region of influence (ROI) is used as the “first guess” value for the interpolation, based on a Gaussian weighting function (equation 1).

$$w = \exp\left(-\frac{r^2}{s_s \times \gamma^j} - \frac{\Delta t^2}{s_t \times \gamma^j}\right)$$

(Eq. 1)



In this case, r is the Euclidean distance from observation coordinates to the grid cell coordinate, γ is the convergence parameter (default of 0.2), s is the Gaussian variance (s for spatial, t for temporal), t is the temporal weight, and j is the iteration number (Bartell 2016). The first guess values are a weighted spatiotemporal average of the input data. The temporal variance is only used in determining the first guess value, subsequent passes only use data within the target month. The temporal variance was set to 1, where the weight of the month of interpolation's weights were set to 100%, the weights for the months on either side of the target month were set to 37%. Residuals from the first guess values and all observations in the radius of influence were used to create a weighted average correction. This correction is then applied to the previously interpolated value, and the process repeats for a total of three passes. The second and third passes were 2-dimensional, utilizing data only from the target month. For each successive iteration (pass), the Gaussian function becomes narrower due to a decreasing convergence parameter (γ). This results in a narrowing radius of influence (ROI) with each pass. The ROIs for the interpolation were 0.837° , 0.458° , and 0.251° for pass 1, 2, and 3 respectively. After interpolation, values from land grid cells were removed.

2.9 Quantifying uncertainty

The nature of the interpolation of irregular point data leads to inherent uncertainty variability across the study area due to seasonal and sampling biases. Areas with many observations but with high variability should have higher uncertainty than areas with lower variability. Areas with few or no observations over the entire time period should have higher uncertainty. The uncertainty metric estimates the point data's standard deviation and inflates the error in poorly sampled areas (Equation 2). This uncertainty metric is provided for each pixel on a standardized 0-1 scale.

$$\text{Uncertainty} = \frac{\sigma}{\sqrt{D_{\max}}} \quad (\text{Eq. 2})$$

Where sigma (σ) is the standard deviation and $D_{\max}$ is the weight of the nearest point data used in the interpolation.

2.10 External validation

The interpolated climatologies were compared with reference climatologies to assess interpolation accuracy. GLORYS12V1 reference climatologies were created using monthly data subset to the same spatial and temporal bounds as the data used in the interpolation (Figure 1). Climatologies were built using sea water potential temperature (thetao) and sea water salinity (so) from the GLORYS12V1 product suite. Bottom climatologies were created using the bottom temperature (bottomT) and sea water salinity values from the deepest depth bin available at each pixel (Appendix Table 1) (Lellouche et al 2021). Potential error in the reference GLORYS12V1 data was not accounted for as it is beyond the scope of this paper. Summary



statistics, including mean bias, root mean squared error (RMSE), mean absolute percentage error (MAPE), Pearson correlation, and normalized root mean squared error (NRMSE), expressed as percentages, were calculated for both on- and offshelf regions for surface climatologies. For bottom climatologies, summary statistics were created only for the onshelf region.

Results

3.1 Surface

3.1.1 Monthly climatologies

Temperature

Interpolated monthly surface climatology fields for temperature show the expected seasonality of colder temperatures in winter (January-March) and maximum temperatures in summer (July-September) (Figure 5). Similarly, the climatologies reflect the expected latitudinal temperature gradients, with the Gulf of Maine typically having the coldest water, while the Sargasso Sea in the southern portion of the study region is the warmest. There is some variability in the Slope Sea region across all months, as this region is very dynamic with a wide range of temperature observations throughout space and time.

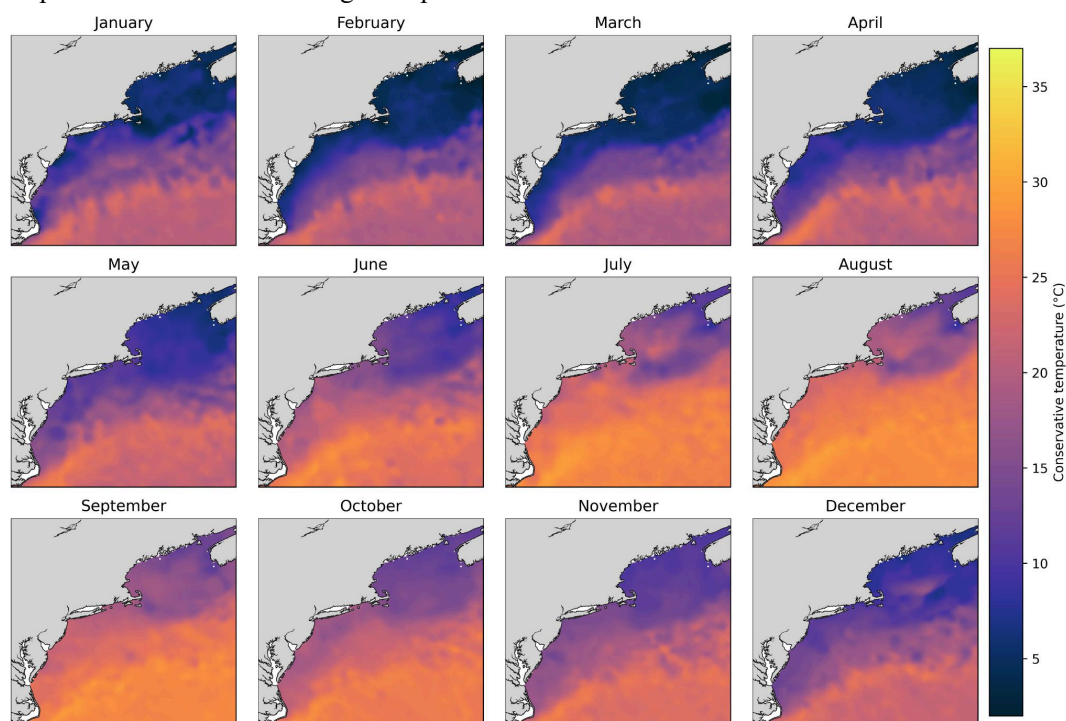


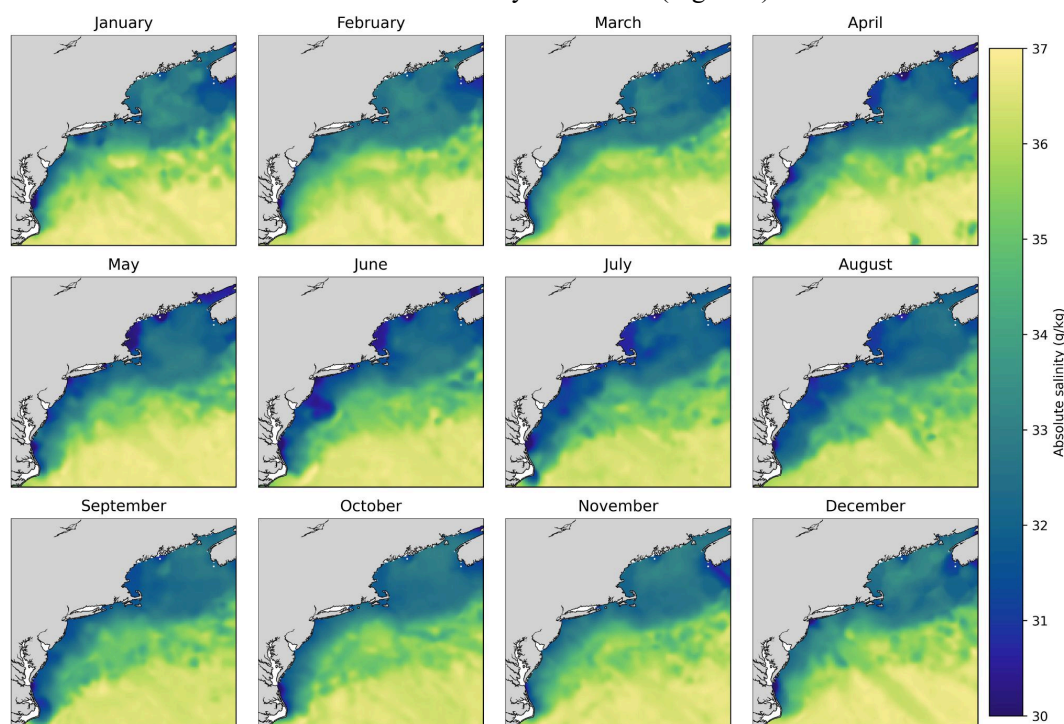
Figure 5. Results from surface monthly temperature interpolation.



332

333 *Salinity*

334 Interpolated monthly surface climatologies for absolute salinity are shown in Figure 6.
 335 Salinity values generally reflect the expected patterns for the region, with little seasonality
 336 evident and offshore waters being more saline than waters on the shelf. Several anomalously low
 337 salinity values appear in the offshore region throughout several months in the climatology, which
 338 are enhanced due to the limited data availability in this area (Figure 6).



339 Figure 6. Results from surface monthly salinity interpolation.

340 3.1.2 Interpolation error

341 Alexander et al. (2015) proposed a target threshold of normalized root mean squared
 342 error NRMSE < 10% for a model to have predictive skill. For temperature, three of the months
 343 do not meet the criteria, with higher values (14.36%) in June (Table 2). The increased NRMSE in
 344 the warmer months is likely due to increased variability in the *in situ* data driven by increased
 345 temperature fluctuations within a shallower mixed layer. The shallower mixed layer limits the
 346 volume of water subject to solar heating and air sea interaction, which can exacerbate
 347 temperature variability (Großelindemann et al 2022). For salinity, all months meet the criteria,
 348 with NRMSE values ranging from 1.15% in February to 4.43% in April (Table 2).

349



Alexander et al. (2015) NRMSE Thresholds

Meets criteria ($\leq 5\%$)
 Meets criteria (5-10%)
 Fails criteria (10-20%)
 Fails criteria ($> 20\%$)

Month	CT RMSE (C)	CT NRMSE (%)	SA RMSE (PSU)	SA NRMSE (%)
January	1.919	7.42	0.368	1.42
February	1.579	5.98	0.305	1.15
March	1.831	6.34	0.449	1.55
April	2.085	7.63	1.211	4.43
May	3.383	12.62	0.978	3.65
June	4.459	14.36	0.738	2.38
July	4.111	15.9	0.529	2.05
August	2.173	8.04	0.341	1.26
September	1.824	6.83	0.466	1.75
October	1.846	7.71	0.338	1.41
November	1.635	6.64	0.352	1.43
December	2.006	8.55	0.401	1.71

Table 2: Root mean squared error from the surface interpolation for both conservative temperature (CT) and absolute salinity (SA), along with normalized root mean squared error color coded by Alexander et al (2015) criteria

350

351 3.1.3 External validation

352 *Temperature*

353 The interpolated monthly climatologies all exhibit statistically significant Pearson
354 correlations and relatively low bias when compared with the model-derived validation dataset
355 (Table 3). Seasonally, the summer months (June, July, August) and December have the highest
356 temperature biases, RMSE values, and MAPE values, likely due to the large data gaps (Table 3).

357 *Salinity*

358 The interpolated monthly salinity climatological fields exhibit low bias relative to the
359 validation climatologies, with similar trends on and off the continental shelf. Pearson correlation
360 values were all statistically significant, but are consistently lower onshelf, ranging from
361 0.535-0.923, compared to the correlations offshelf (>0.941) (Table 3).



Month	CT Onshelf Metrics				CT Offshelf Metrics				SA Onshelf Metrics				SA Offshelf Metrics			
	Avg Bias	Avg Bias	RMSE	RMSE	MAPE	MAPE	Corr	Corr	Avg Bias	Avg Bias	RMSE	RMSE	MAPE	MAPE	Corr	Corr
January	0.119	-0.217	1.604	1.345	15.77	7.154	0.847	0.958	0.159	0.118	0.456	0.386	1.049	0.768	0.899	0.964
February	0.145	-0.016	0.803	1.496	10.18	11.946	0.945	0.953	0.235	0.105	0.42	0.391	1.016	0.757	0.923	0.964
March	0.159	-0.017	0.696	1.192	10.226	11.432	0.959	0.971	0.266	0.126	0.442	0.478	1.095	0.859	0.916	0.945
April	-0.003	-0.096	0.684	1.371	6.676	7.275	0.966	0.964	0.215	0.094	0.561	0.441	1.28	0.883	0.814	0.954
May	0.087	-0.126	0.888	1.194	6.831	5.356	0.959	0.967	0.218	0.124	0.62	0.376	1.433	0.759	0.785	0.971
June	-0.063	0.104	1.44	1.196	7.806	4.352	0.938	0.957	0.179	0.086	0.698	0.449	1.672	0.796	0.726	0.954
July	-0.27	0.158	1.773	0.938	7.648	2.75	0.917	0.965	0.068	0.084	0.774	0.461	1.686	0.827	0.623	0.948
August	-0.7	0.175	1.701	0.943	6.171	2.335	0.923	0.95	-0.071	0.073	0.864	0.468	1.915	0.918	0.535	0.941
September	-0.753	-0.062	1.19	0.791	4.792	2.33	0.963	0.963	0.013	0.087	0.807	0.458	1.604	0.865	0.574	0.936
October	-0.276	-0.008	0.772	0.8	3.699	2.625	0.968	0.968	0.092	0.013	0.552	0.343	1.215	0.686	0.811	0.963
November	0.546	-0.07	0.941	0.991	5.862	3.477	0.953	0.962	0.083	0.035	0.364	0.34	0.834	0.693	0.905	0.965
December	1.068	-0.132	1.852	1.154	13.684	4.509	0.819	0.961	0.073	0.079	0.464	0.343	1.095	0.735	0.851	0.968

Table 3: Summary statistics for comparison of surface interpolated climatology to validation satellite climatology. Statistics include average bias (avg bias), root mean squared error (RMSE), mean absolute percentage error (MAPE), and Pearson correlation (Corr). Values shown in green represent absolute salinity metrics, while values shown in blue represent conservative temperature metrics.

362

363 3.2 Bottom

364 3.2.1 Monthly Climatologies

365 Temperature

366 Interpolated monthly bottom climatologies for conservative temperature are shown in
367 Figure 8. Seasonal variation is less evident in the bottom temperature climatologies than in the
368 surface climatologies (Figure 5, Figure 7). Temperature varies spatially, with the southern portion
369 of the continental shelf, the Mid-Atlantic Bight, consistently warmer than the northern area of the
370 Gulf of Maine (Figure 7). George's Bank is distinct in the monthly climatologies, exhibiting
371 colder temperatures than surrounding water in the winter and spring, and warmer temperatures



than adjacent water in the summer and fall.

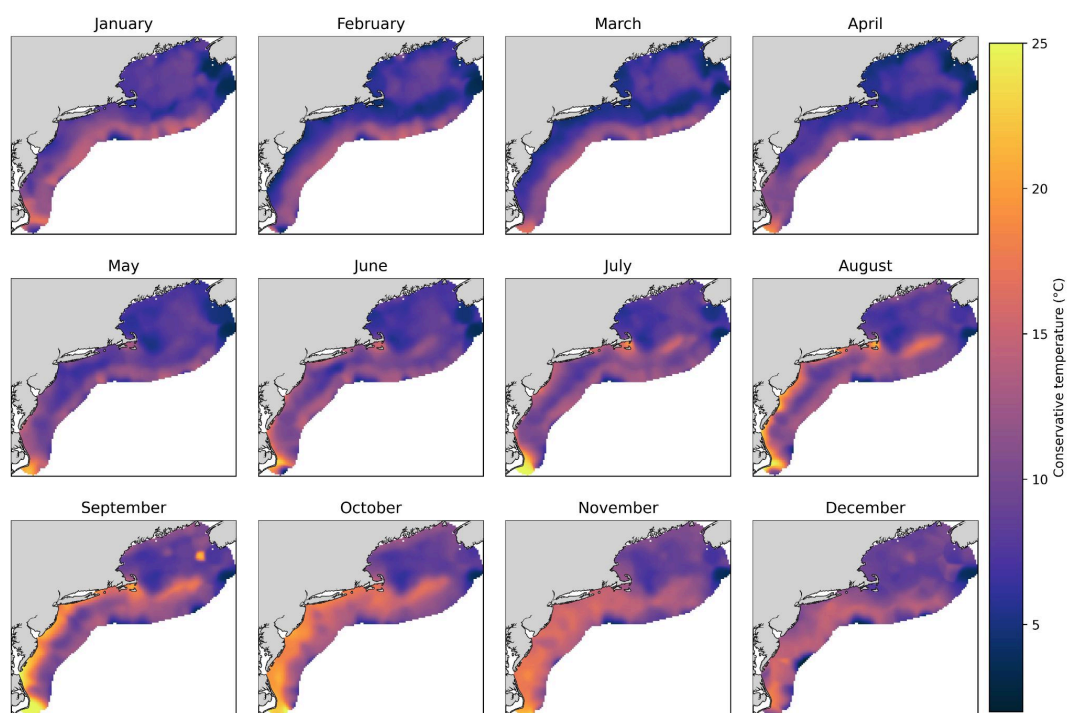


Figure 7. Results from bottom monthly temperature interpolation.

Salinity

The interpolated monthly bottom climatologies for absolute salinity appear consistent across seasons, with George's Bank evident again, presenting as significantly fresher than the surrounding water (Figure 8). In the Mid-Atlantic Bight, there is a salinity gradient, with fresher waters near the coast and more saline waters seaward. There is a distinct lack of data for much of



the Gulf of Maine for December, reflected by the smooth appearance in the interpolated values.

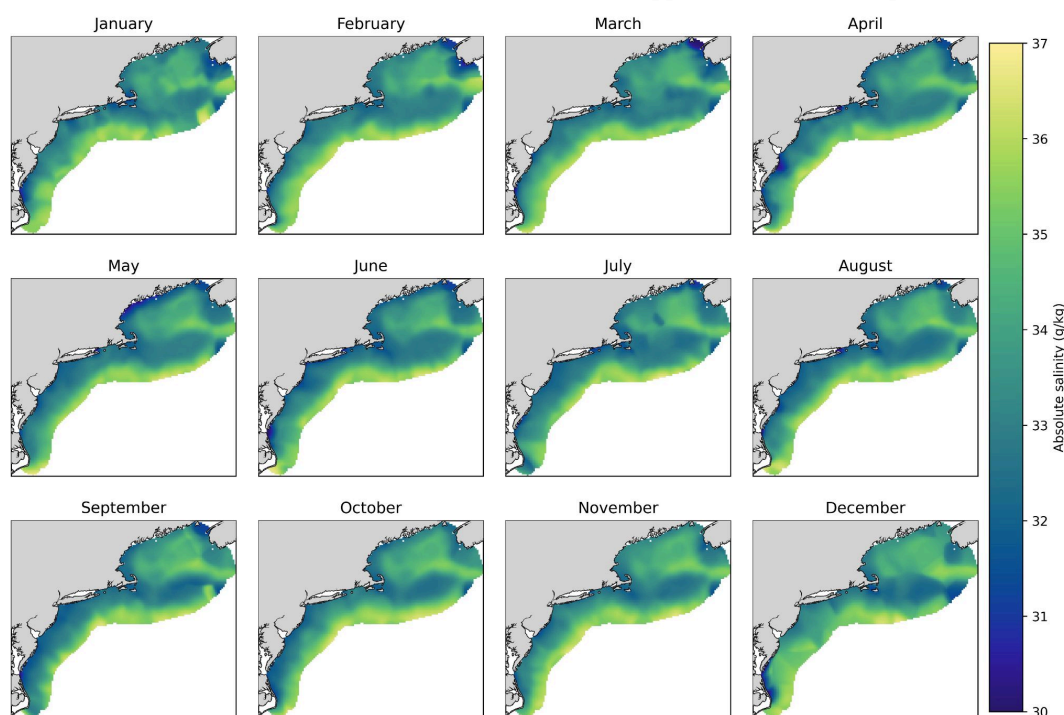


Figure 8. Results from bottom monthly salinity interpolation.

3.2.2 Interpolation error

Temperature NRMSE was above 10% for only three months: August, September, and December (Table 4). The remaining nine months NRMSE values met the criteria, with values less than 8.75%. The increased NRMSE values in August and September likely stem from increased data variability from thermal stratification. The elevated NRMSE found in December is an artifact of limited data availability. All NRMSE values for interpolated monthly absolute salinity met the criteria, ranging from 0.77%-2.74% (Table 4).



Alexander et al. (2015) NRMSE Thresholds
 Meets criteria ($\leq 5\%$)
 Meets criteria (5-10%)
 Fails criteria (10-20%)
 Fails criteria ($> 20\%$)

Month	CT RMSE (C)	CT NRMSE (%)	SA RMSE (PSU)	SA NRMSE (%)
January	2.043	8.58	0.182	0.77
February	1.943	8.29	0.324	1.38
March	1.709	7.56	0.415	1.84
April	1.732	7.09	0.669	2.74
May	2.166	8.75	0.646	2.61
June	2.147	8.41	0.505	1.98
July	2.386	8.68	0.308	1.12
August	4.659	16.42	0.228	0.8
September	5.042	18.36	0.427	1.55
October	2.185	8.54	0.366	1.43
November	1.676	6.8	0.302	1.22
December	2.116	10.06	0.196	0.93

Table 4: Root mean squared error from the bottom interpolation for both conservative temperature (CT) and absolute salinity (SA), along with normalized root mean squared error color coded by Alexander et al (2015) criteria

388

389 3.2.3 External validation

390 *Temperature*

391 When compared to the modeled validation dataset, monthly climatologies of bottom
392 temperature yield relatively low bias but higher MAPE values than the surface temperature
393 comparisons. All Pearson correlation coefficients were statistically significant across all months,
394 although the relationship in January and February were low (0.514) (Table 5). This may indicate
395 that the relationship between the two datasets is real, but the relationship is not strong or may
396 have little practical importance.

397 *Salinity*

398 All Pearson correlation coefficients show a strong linear relationship between the
399 reference and interpolated climatologies, with significant relationships ranging from
400 0.704-0.905. December shows the weakest relationship with the reference climatology, with the
401 highest MAPE value (1.642%), RMSE (0.78), and lowest Pearson correlation (0.704) (Table 6).
402 Overall, the relationship between the reference and interpolated climatologies is quite strong,
403 with all MAPE values less than 2% and all RMSE values less than 0.78 g/kg (Table 6).



CT Onshelf Metrics SA Onshelf Metrics								
Month	Avg Bias	RMSE	MAPE	Corr	Avg Bias	RMSE	MAPE	Corr
January	0.396	2.42	21.165	0.514	-0.049	0.546	1.145	0.848
February	0.329	2.266	21.926	0.514	0.034	0.555	1.11	0.838
March	0.509	2.051	20.253	0.589	0.029	0.532	1.077	0.85
April	0.342	2.006	19.63	0.601	-0.028	0.485	1.058	0.877
May	0.439	2.025	20.52	0.656	-0.071	0.552	1.199	0.854
June	0.445	2.397	22.166	0.67	-0.167	0.544	1.152	0.874
July	0.325	2.816	23.317	0.617	-0.353	0.745	1.601	0.775
August	0.472	2.79	23.176	0.708	-0.306	0.661	1.459	0.834
September	0.862	2.771	22.84	0.797	-0.284	0.698	1.454	0.802
October	1.106	2.496	21.077	0.84	-0.051	0.496	1.067	0.878
November	1.049	2.434	20.029	0.773	-0.011	0.423	0.915	0.905
December	0.947	2.206	18.676	0.707	-0.006	0.78	1.642	0.704

Table 5: Summary statistics for comparison of surface interpolated climatology to validation satellite climatology. Statistics include average bias (avg bias), root mean squared error (RMSE), mean absolute percentage error (MAPE), and Pearson correlation (Corr). Values shown in green represent absolute salinity metrics, while values shown in blue represent conservative temperature metrics.

3.3 Uncertainty

Examples of the uncertainty metric are provided for each climatology in Figure 9, and all monthly uncertainty maps are available in the supplementary data (Appendix figures 1-4). Salinity is a conservative property and therefore exhibits less fluctuations than surface temperature, causing the salinity uncertainty to be generally lower than the surface temperature uncertainty. Additionally, salinity values exhibit a narrower range of variation than temperature in the Northwest Atlantic. Spatial trends in uncertainty are similar for both temperature and salinity, and a temporal bias exists, evidenced by higher uncertainty in the winter months, particularly December (Figure 9). Climatological predictions for summer have higher confidence as sampling effort is increased and the spread of the data is much more even along the continental shelf (Appendix figures 1 and 3).

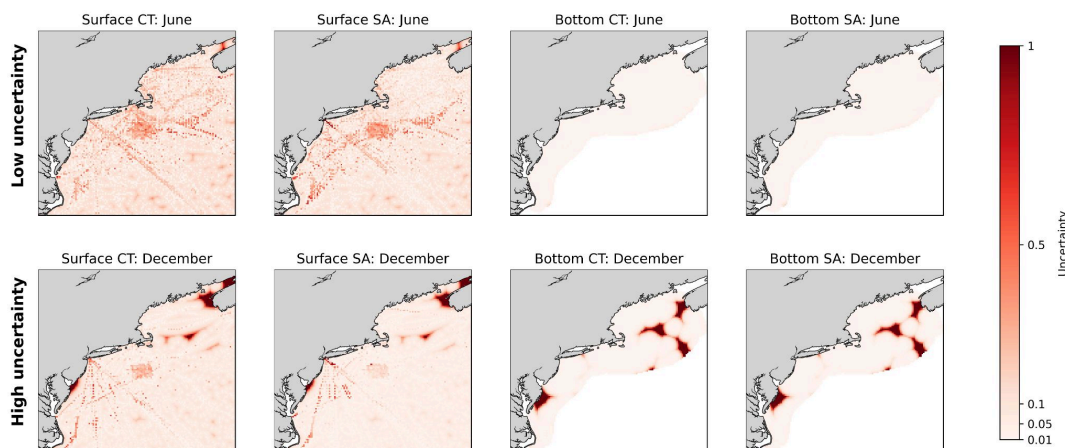


Figure 9. Example uncertainty maps for a month with low uncertainty (June) and a month with high uncertainty (December).



417 *Discussion*

418 We developed monthly climatologies (2000 to 2024) of surface and bottom conservative
419 temperature and absolute salinity using Barnes objective analysis. These interpolated
420 climatologies compare well with reference climatologies, however some months have higher
421 uncertainty due to high variability and/or low sampling frequency. Large spatial gaps and
422 temporal bias introduce limitations on the interpolated climatologies. While these data gaps
423 introduce localized technical limitations, the resulting climatology remains highly robust and has
424 great utility for ecological applications in this region.

425 4.1 External forcings

426 The Northwest Atlantic is a highly variable region, where much of the change in
427 temperature and salinity is driven by the presence and interaction between the Gulf Stream and
428 Labrador Current. Features formed from the Gulf Stream, like warm core rings, cold core rings,
429 and streamers, are major sources of cross-shelf exchange of water masses, adding to the
430 complexity and variability of the region. These dynamics pose a significant challenge for
431 establishing a representative baseline, which is a limitation shared by both data-driven
432 interpolations and complex numerical ocean models. For instance, if a grid cell has a single data
433 point for a given month, which is not representative of the typical temperature in that location,
434 but rather an ephemeral anomaly, the interpolation will not capture the true climatological mean
435 of that grid cell (Locarnini et al 2018).

436 4.2 Spatial limitations

437 An inherent limitation to working with *in situ* observations is the uneven spatial
438 distribution of the data. Many of the consistent data sources (EcoMon, NERACOOS, Pioneer
439 Array, etc.) primarily collect data on the continental shelf, resulting in significantly reduced data
440 availability in the off-shelf regions. *In situ* sampling is expensive and labor intensive and
441 sampling off-shelf is difficult due to the greater distance from the coast. The continental shelf has
442 significantly more data available for the interpolation, but does not automatically result in a
443 lesser uncertainty. The larger sample size can lead to larger variability in the data and a higher
444 uncertainty, particularly in dynamic regions such as the shelfbreak (Figure 9).

445 The sparse spatial sampling in the offshore region leads to the usage of smaller weights
446 during the interpolation for the surface climatologies, which can create a smoothed effect. This
447 effect is nuanced, however. For instance, the Oleander project is a notable exception to the poor
448 spatial sampling of the offshore waters. The MV Oleander has traveled roundtrip, monitoring
449 Gulf Stream variability, from New Jersey to Bermuda once per week since 1992 (Rossby &
450 Gottlieb 1998). Thus, the ship tracks provide consistent spatiotemporal data, which equates to a
451 higher variability in interpolations due to a higher volume of data capturing continuously



452 changing boundaries of the Gulf Stream. Conversely, data collected in the offshore region tends
453 to be more sparse, which results in interpolations with lower variability (Appendix 1). The
454 nuances stem from this tradeoff, where any given grid cell may have higher uncertainty because
455 of the increased data observations introducing higher variance into the mean. In this instance the
456 variance is representative of the actual variability in the region which makes capturing a baseline
457 harder. Conversely, the lack of data offshore can lower the variance, but is not necessarily
458 capturing the true dynamics of the physical environment.

459 4.3 Temporal limitations

460 With the exception of moored buoys that are able to collect data year round, the sampling
461 of many data sources was not consistent throughout the annual seasonal cycle. Many surveys are
462 conducted during targeted sampling windows and during fair weather conditions, leaving large
463 data gaps during the winter months. Lower sampling rates in December and January resulted in
464 high interpolation error, particularly evident in the bottom temperature climatologies (Table 4).
465 The Gulf of Maine has very few bottom observations, resulting in a heavily smoothed
466 climatology and higher uncertainty (Figures 7, 9, respectively). The interpolation would benefit
467 from additional *in situ* measurements, particularly during the winter months.

468 A higher RMSE in the interpolated surface temperature values during the summer months
469 (June, July, August) is likely attributed to the higher variability of temperature in the mixed layer
470 during these months (Table 2). Warming trends are enhanced in the summer, in large part due to
471 marine heatwaves (Pershing et al 2018). This may increase the range of summer temperatures, as
472 more recent years record warmer values than in the 2000s (Großelindemann et al 2022, Friedland
473 & Hare 2007). Furthermore, the mixed layer depth is shallow during the summer, meaning a
474 smaller volume of water is subject to solar heating and air-sea interaction (Großelindemann et al
475 2022). Here, we averaged all values above the mixed layer depth, which may increase
476 temperature variability during the summer months.

477 4.4 Validation of interpolations

478 To assess the precision of the newly created *in situ* climatologies, the temperature
479 climatologies were compared to climatologies derived from modeled temperature and salinity
480 data. A high Pearson correlation and low MAPE indicate a strong, accurate, and predictable
481 relationship between the interpolated hydrographic and reference values, as seen in the
482 relationship between surface salinity and temperature climatologies and their respective
483 reference climatologies (Table 4). However, there are some likely significant outliers in the data
484 poor areas with high uncertainty that inflate the RMSE values for all of the climatologies

485 The lower RMSE values in the salinity comparisons, for both surface and bottom, is
486 likely due to salinity being a conservative property and varies significantly less than temperature
487 in the study region. The summer and fall are also when more Warm Core Rings are produced,
488 which facilitates more northward transfer of high salinity water to the continental shelf (Silver et



al 2021). This leads to potential salinity variability on the continental shelf, which may explain the lower Pearson correlation in the surface comparisons during those months. The weakest relationship for the bottom salinity climatologies, found in December, is still able to predict accurate ranges of salinity values, though it struggles to predict the fine spatial values due to a lack of data.

In making these comparisons, the reference climatologies must be assumed to be the “true” values. However, there are some flaws in this assumption that are not accounted for in the statistics. The interpolated climatologies described above are validated using reanalysis modeled products. While widely used in the scientific community, we did not assess model performance before making the assumption that the data represent “true” values for our region. There is likely some unquantified bias and error in the modeled datasets themselves that are not accounted for in the statistical comparisons. In conjunction with the lower dataset size, this may explain the higher RMSE values in the bottom temperature comparisons than noted in the surface temperature comparisons.

4.5 Potential applications and practical utility

There are inherent tradeoffs in developing climatological baselines based solely on *in situ* data for dynamic oceanographic regions. While a data-driven product may lack data in particular seasons or regions, its use of *in situ* measurements enables it to be more reflective of true ocean conditions compared to surface only satellite measurements or oceanographic models. For instance, *in situ* spatial coverage declines with depth, resulting in data gaps that are most prevalent subsurface, particularly near the seafloor. However, these areas provide crucial habitats for many fisheries species. Here, we aggregate the available *in situ* data to reconcile regional data gaps and create a novel bottom climatology which provides a continuous baseline that can be used for detecting anomalous benthic conditions or used to create fisheries-relevant products.

These climatologies are being used to develop a water mass classification model for the region (Synan et al., in prep). Additionally, these high-resolution climatologies may be used to validate satellite and modeled temperature or salinity data and climatologies for similar reference periods. Both the climatologies and the point data used to create them could be used as data inputs in various oceanographic, environmental, or fisheries modeling efforts. In effort to make this data accessible, all data products are publicly available (doi.org/10.5281/zenodo.20183494 (Synan et al., 2026a), doi.org/10.5281/zenodo.22696810 (Synan et al., 2026b). The climatologies are provided as NetCDFs (Network Common Data Form) with appropriate metadata, while the aggregated point data and relevant summary statistics are available as comma-separated values (CSV) with metadata.



523 5. Conclusions

524 The surface and bottom temperature and salinity monthly climatologies described here
525 represent a recent *in situ* climatology, using 2000 through 2024 as a reference period.
526 Interpolation error and uncertainties are provided, and products are validated using reference
527 climatologies created using modeled data. Additional *in situ* measurements may improve product
528 quality during the winter months, where spatial data gaps are common. In sum, these analyses
529 show that these products are robust and provide useful baselines for quantifying changes in space
530 and time in the Northwest Atlantic.

531 Data availability statement

532 The aggregated hydrographic dataset is available at doi.org/10.5281/zenodo.22696810
533 (Synan et al., 2026b) and the climatologies are available at doi.org/10.5281/zenodo.20183494
534 (Synan et al., 2026a). The individual sources of hydrographic data are listed and described at:
535 https://hsynan.github.io/READ-EDAB-Synan_hydrographic_climatologies/data_sources.html.
536 All data are freely and publicly available, except for NEAMAP data, which is available upon
537 request through the Virginia Institute for Marine Science (VIMS) [Multispecies Research Group](#)
538 [data Request Form](#). The code used to create the climatologies is available at
539 https://github.com/hsynan/READ-EDAB-Synan_hydrographic_climatologies. The code to create
540 the figures shown in this manuscript can be found at:
541 [https://hsynan.github.io/READ-EDAB-Synan_hydrographic_climatologies/manuscript_figures.h](https://hsynan.github.io/READ-EDAB-Synan_hydrographic_climatologies/manuscript_figures.html#)
542 [tml#](#) and the code to create the supplementary figures is available
543 [https://hsynan.github.io/READ-EDAB-Synan_hydrographic_climatologies/supplementary_figur](https://hsynan.github.io/READ-EDAB-Synan_hydrographic_climatologies/supplementary_figures.html)
544 [es.html](#)
545

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553 and verified before implementation.



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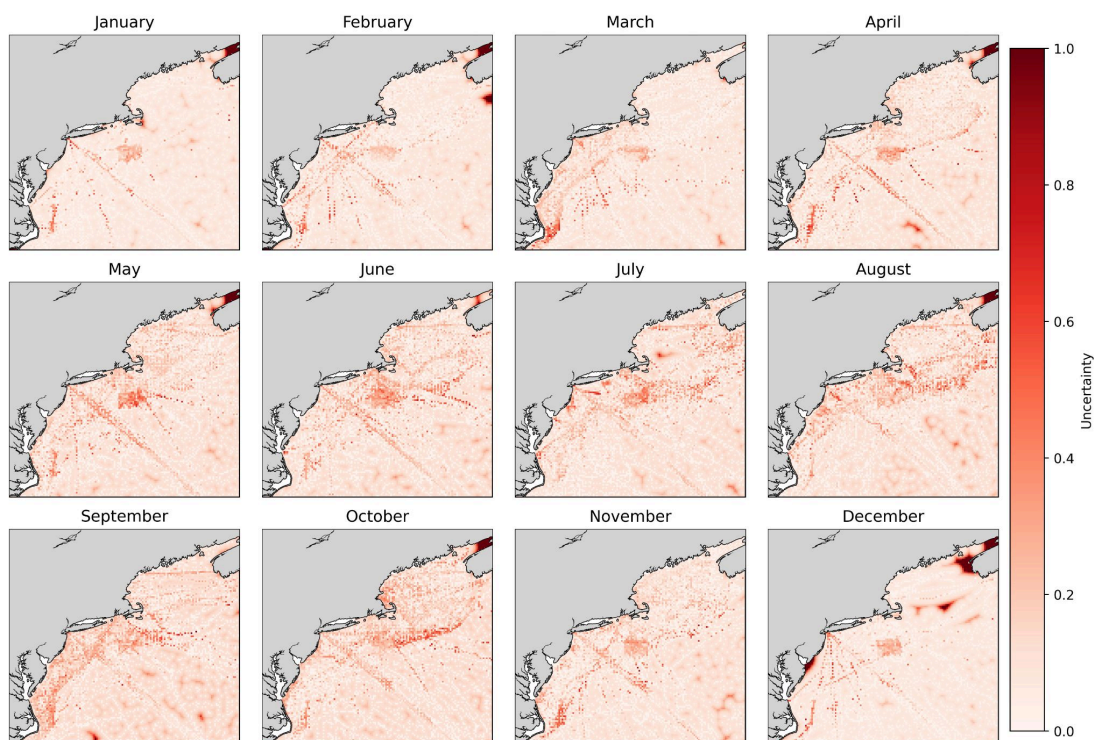


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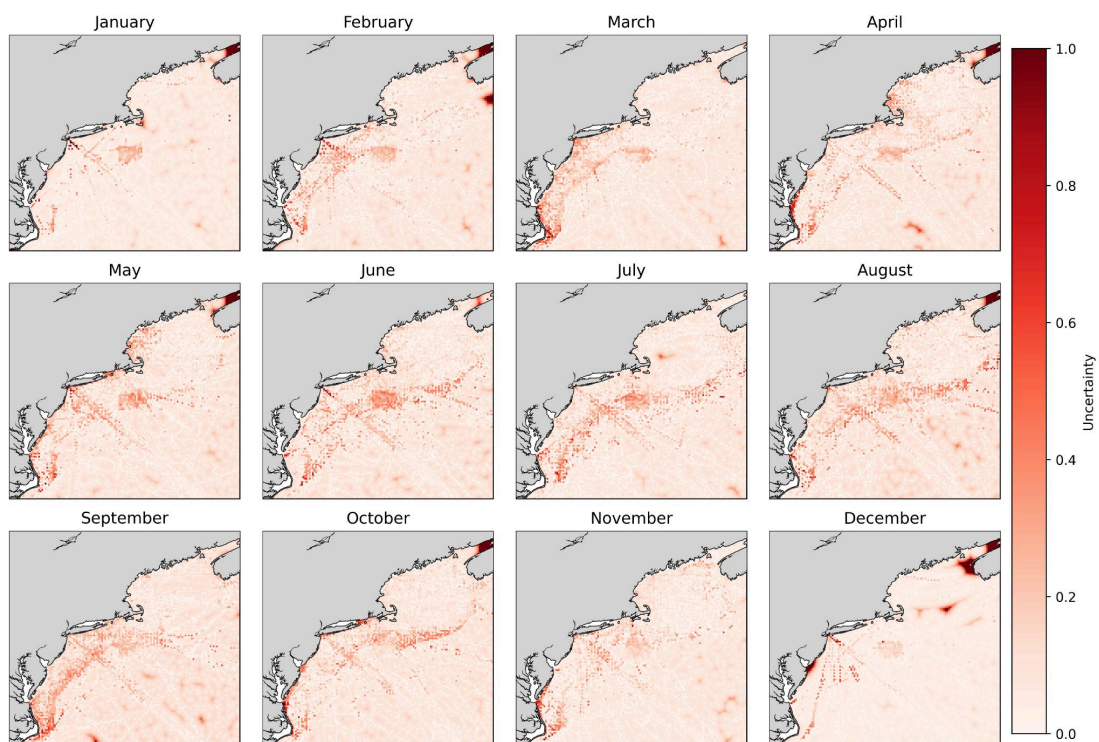


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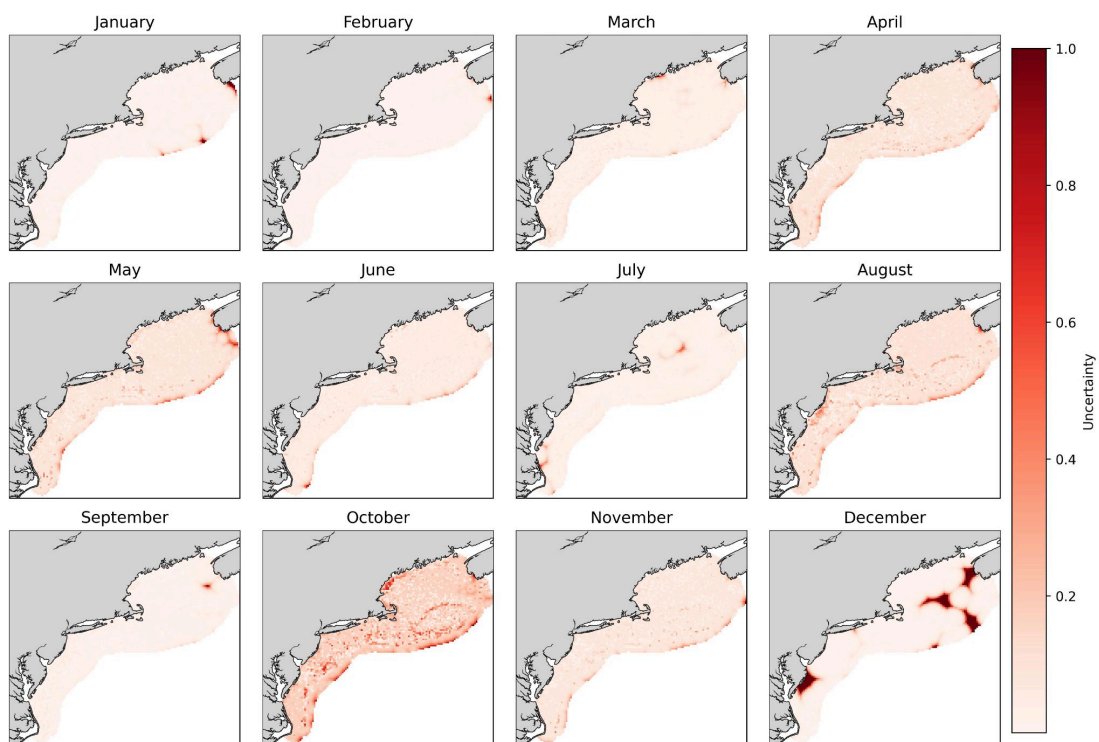
685 Appendix A



686 Figure A1. Uncertainty estimates for monthly surface climatological temperature predictions



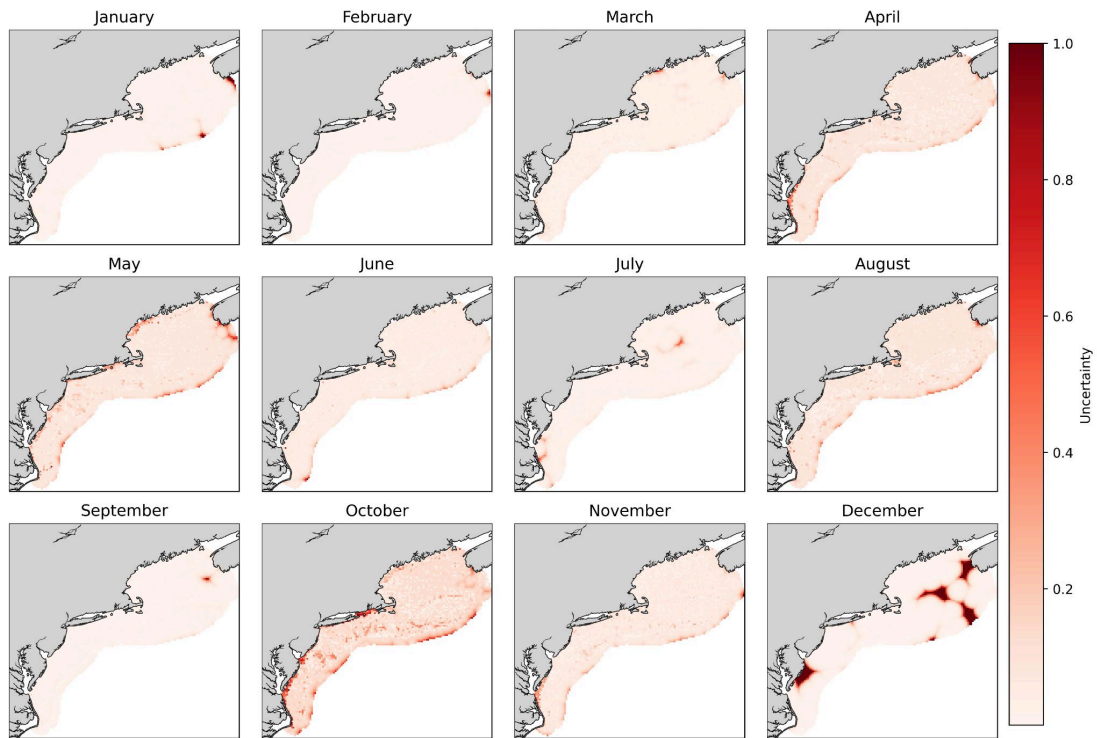
687 Figure A2. Uncertainty estimates for monthly surface climatological salinity predictions



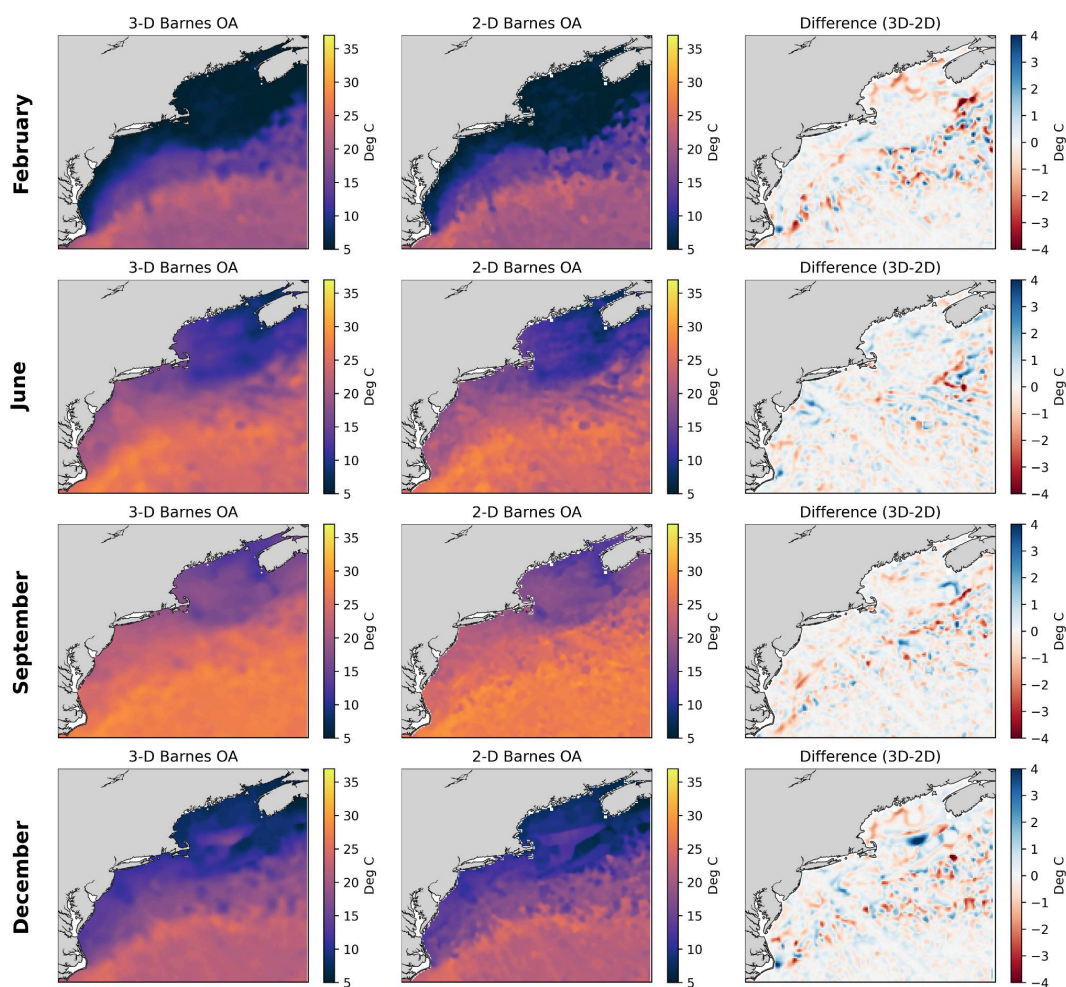
688 Figure A3. Uncertainty estimates for monthly bottom climatological temperature predictions



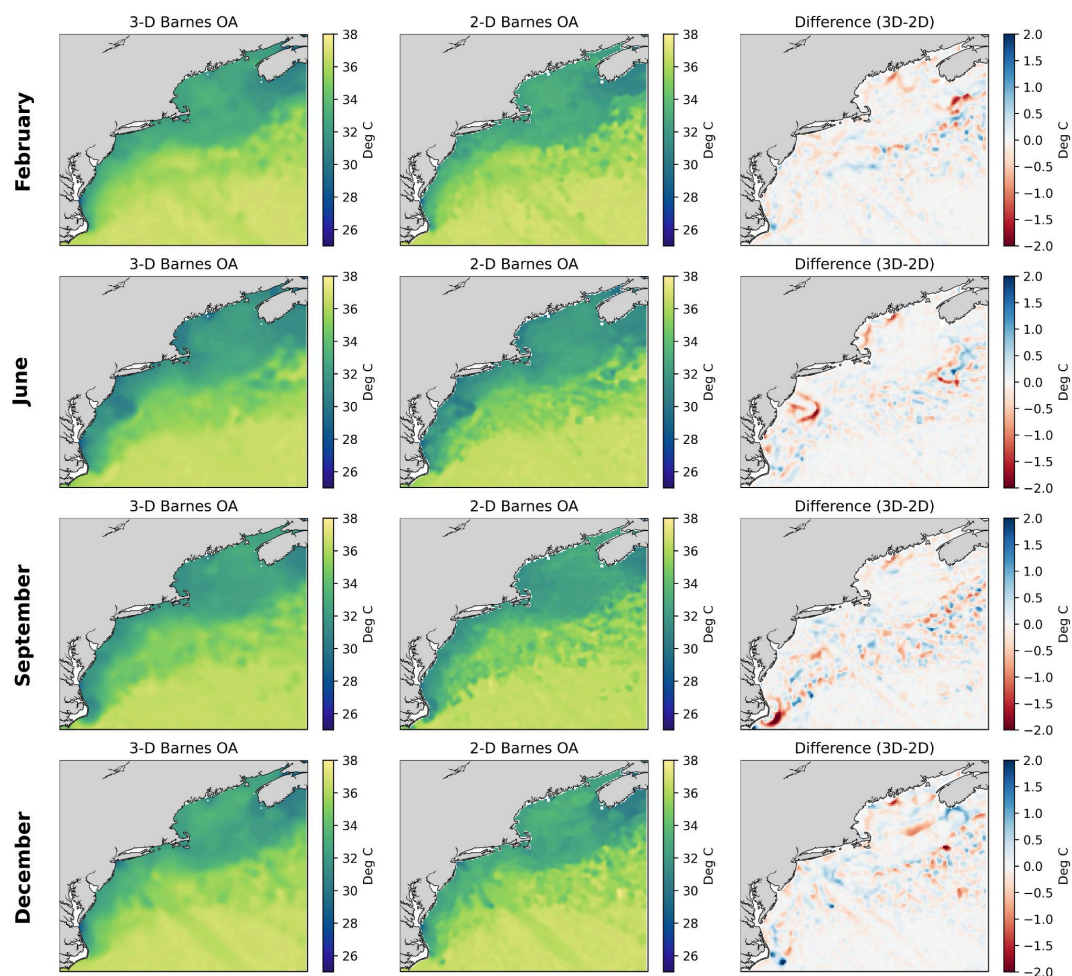
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689 Figure A4. Uncertainty estimates for monthly bottom climatological salinity predictions
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691 Figure A5. Comparisons between 3-D and 2-D Barnes OA interpolations for conservative temperature (CT).



692 Figure A6. Comparisons between 3-D and 2-D Barnes OA interpolations for absolute salinity (SA).