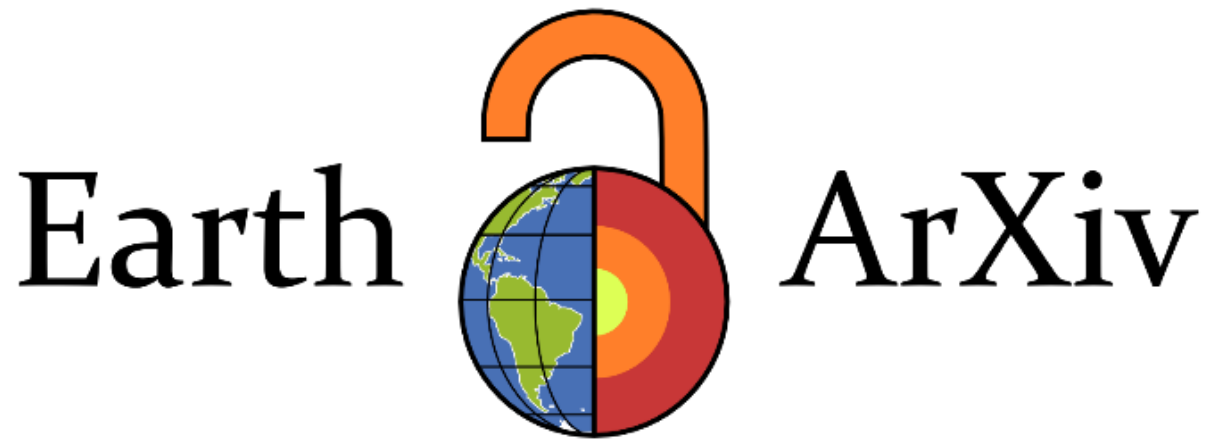




Peer review status:

This is a non-peer-reviewed preprint submitted to EarthArXiv.

**Evaluating the potential of SMART subsea cable pressure sensors to
constrain Subpolar North Atlantic circulation variability through Observing
System Simulation Experiments**

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10 ABSTRACT: Bolstering global ocean observing infrastructure is critical for understanding, quan-
11 tifying, and predicting Earth’s climate variability and change. The SMART (Science Monitor-
12 ing And Reliable Telecommunications) Subsea Cables present an opportunity to acquire high-
13 frequency, seafloor-based observations of ocean variables, encouraging assessment of their value
14 prior to deployment. We conduct Observing System Simulation Experiments to quantify potential
15 for constraining ocean circulation using simulated SMART data from a proposed cable in the Sub-
16 polar North Atlantic. Synthetic daily SMART ocean bottom pressure anomaly observations from a
17 high-resolution global “nature run” are assimilated into a regional ocean model. Model-data misfit
18 is reduced via gradient-based adjustments to atmospheric control variables. Synthetic data value
19 is quantified via the error reduction and improved skill between the regional model and the nature
20 run. Assimilation of synthetic SMART data improves regional estimates of ocean bottom pressure
21 as well as unobserved quantities such as time-mean and time-varying barotropic (depth-integrated)
22 transport and time-mean Arctic freshwater redistribution, demonstrating SMART’s potential to
23 constrain basin-scale ocean circulation. On annual timescales SMART cables complement satel-
24 lite gravimetry data by providing unique constraints on sub-monthly and coastal oceanic mass
25 transport, reducing local ocean bottom pressure uncertainty. Atmospheric pressure, followed by
26 surface winds, is identified as the primary control variable driving daily bottom pressure anomaly
27 correction. The dominance of atmospheric pressure adjustments in inducing ocean mass redis-
28 tribution and associated bottom pressure changes reflects a departure from the inverse barometer
29 response. Our results underscore the value of high-frequency seafloor pressure data for improving
30 estimation and enhancing the spatiotemporal resolution of climate-relevant ocean transports.

31 **Significance Statement**

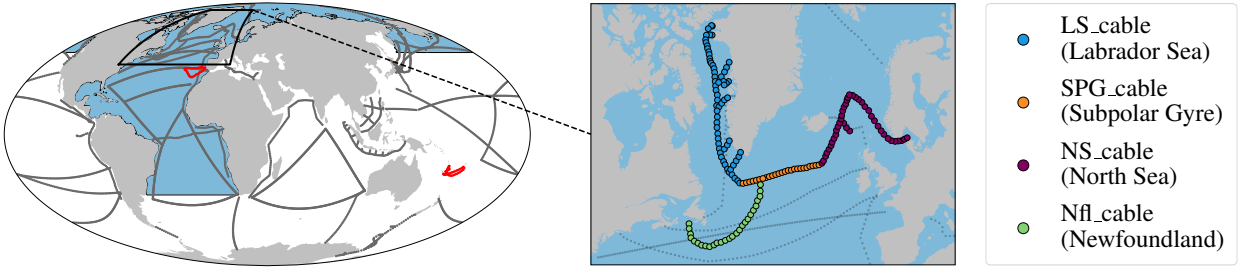
32 The ocean plays a central role in regulating Earth’s climate, but many important processes are
33 poorly measured because existing observing systems do not adequately sample the global ocean.
34 This study explores how commercial seafloor telecommunication cables equipped with scientific
35 sensors (“SMART” cables) could help fill these gaps. Using computer simulations, we show
36 that daily seafloor pressure measurements can reduce uncertainty in ocean mass and freshwater
37 redistribution throughout the Subpolar North Atlantic, a region critical for climate. Our results
38 suggest that sensor-equipped cables provide a complementary constraint to existing satellite-based
39 ocean bottom pressure measurements on the daily to monthly timescales considered. We also find
40 that changes in surface atmospheric pressure and winds strongly influence these signals. These
41 findings encourage further investigation of the potential value of SMART for sustainable long-term
42 climate monitoring and prediction.

43 **1. Introduction**

44 The Science Monitoring And Reliable Telecommunications (SMART) subsea cable initiative
45 represents a new frontier in ocean observation, enabling broadly distributed high-frequency seafloor
46 monitoring through telecommunication infrastructure (Howe et al. 2019). The SMART Cables
47 Network is now part of the Global Ocean Observing System (GOOS), integrating scientific sensors
48 into newly deployed subsea fiber-optic cables. SMART cables will host sensors for ocean bottom
49 temperature, pressure (both Essential Ocean Variables), and seismic motion spaced approximately
50 70 to 150 km apart, with spacing dictated by commercial deployment constraints. These sensor
51 modules are installed as part of the cable system in the factory. This encourages rigorous assessment
52 of SMART’s potential value in advance of cable deployment to best leverage the opportunity for
53 enhancing ocean observing. Here, we conduct observing system simulation experiments (OSSEs)
54 to quantify how in situ ocean bottom pressure (OBP) measurements from SMART cables can
55 improve understanding of ocean circulation and better constrain the time-evolving ocean state.

62 OBP reflects the mass of the overlying water column and atmosphere. It varies in response
63 to circulation change, tides, surface momentum and mass flux (precipitation, evaporation, runoff,
64 and glacial melt). Currently, large-scale OBP variations are primarily observed from space via
65 the Gravity Recovery and Climate Experiment (GRACE) and its follow-on mission GRACE-FO,

66 which infer monthly mean OBP anomalies p_b from changes in Earth's gravity field (Tapley et al.
 67 2004, 2019; Landerer et al. 2020). GRACE-based monthly p_b products have supported extensive
 68 investigation of seasonal to interannual variability in sea level, ocean heat content, and ocean
 69 circulation (see review by Tapley et al. 2019). These products, however, show both non-negligible
 70 discrepancies arising from processing differences (Blazquez et al. 2018) and significant errors
 71 resulting from high-frequency signal aliasing (Quinn and Ponte 2011). GRACE's effective spatial
 72 resolution of roughly 300 km also limits application for coastal and mesoscale oceanography. Our
 73 focus on OBP is motivated by the potential for SMART to complement GRACE by providing
 74 high-frequency in situ p_b estimates, including in regions poorly resolved by GRACE (e.g., coasts,
 straits, marginal seas).



56 FIG. 1. (Left) Representative future global SMART cable network (gray lines) and funded systems in develop-
 57 ment (red lines). The domain of the forecast model (section 2b) used in this study is shaded blue; the discussion
 58 of our results will be focused on (Right) the Subpolar North Atlantic region encompassing the cables used in this
 59 study. The full SPNA cable is divided into 4 segments in our OSSEs; colored circles indicate sensor locations
 60 along each segment with an assumed spacing of approximately 70 km. Corresponding experiment names are
 61 given in the legend.

75
 76 Our work builds on previous investigations of the value of OBP observations within data assimila-
 77 tion (DA) frameworks by Köhl et al. (2012), Saynisch et al. (2015), and Ponte et al. (2026). Köhl
 78 et al. (2012) assessed the impact of assimilating monthly GRACE data into a 1-degree global ocean
 79 state estimate and found that adjustments to the model's basin-scale OBP largely correlate with
 80 changes in the model's barotropic transport. However, this relationship weakens along the coasts,
 81 where steric sea level changes are large (Landerer et al. 2007) and GRACE's coarse resolution be-
 82 comes a limiting factor. Improvements were shown to be largest in the subtropical gyres and polar
 83 latitudes, but were sensitive to the OBP product used, with products differing regionally and close

84 to land. Saynisch et al. (2015) used an ensemble Kalman filter to demonstrate improved model
85 daily OBP when assimilating GRACE data. The improvement was associated with wind-driven
86 adjustments to the barotropic circulation. Improvements were particularly notable at high latitudes,
87 consistent with Köhl et al. (2012). Ponte et al. (2026) expanded on these studies by interrogating
88 the impacts of assimilating an extended OBP record from GRACE and GRACE-FO into a global
89 state estimate, which additionally uses these data to constrain global mean ocean mass. They
90 found improvements to both local and basin-scale OBP variability, factoring in the influence of
91 non-oceanographic geophysical processes captured in GRACE data. These results demonstrate
92 the benefit of GRACE for constraining large-scale mass redistribution while underscoring the
93 limitations imposed by temporal resolution, observational gaps, and processing uncertainties.

94 Here, we seek to quantify the potential benefit of in situ OBP monitoring along SMART cables
95 by conducting OSSEs within the Estimating the Climate and Circulation of the Ocean (ECCO)
96 state estimation framework (Wunsch and Heimbach 2007; Forget et al. 2015; Fukumori et al. 2017).
97 ECCO provides estimates of the time evolving ocean state via nonlinear least-squares optimization
98 in which the model-data misfit is reduced by making iterative gradient-based adjustments to a set of
99 independent, uncertain control variables. We examine both direct impacts of assimilation on local
100 OBP fields and the impacts on remote quantities of interest (QoIs). In contrast with previous studies,
101 we examine how OBP assimilation drives adjustments in these control variables and how these
102 adjustments subsequently impact the ocean state. We focus on proposed SMART observations in
103 the Subpolar North Atlantic (SPNA, Fig. 1 inset), a region that is critically important for the Atlantic
104 Meridional Overturning Circulation (AMOC) and susceptible to major transitions associated with
105 varying Arctic–Atlantic exchanges and freshwater pathways (e.g., Bacon et al. 2022; Weijer et al.
106 2022). Importantly, observational (Lozier et al. 2017) and modeling (Kostov et al. 2021) studies
107 have established that significant variability in SPNA overturning and associated transports of heat
108 and freshwater (Li et al. 2024) occur on intraseasonal timescales, motivating sustained continuous
109 monitoring. The dynamic environment and topographic complexity of the SPNA make it an ideal
110 proving ground for assessing the capacity of regional ocean models to assimilate high-frequency
111 OBP data and improve estimates of key climate indicators such as overturning strength and volume
112 transport through high-latitude gateways.

113 The remainder of the paper is arranged as follows. Section 2 describes the OSSE design. OSSE
 114 results are shown in Section 3. This includes a discussion of model-data misfit reduction of p_b
 115 and improvement in unobserved QoIs, namely barotropic velocity and high-latitude freshwater
 116 redistribution. Section 4 discusses the dynamical mechanisms underpinning the OSSE results,
 117 outlining key atmospheric control adjustments and the role of the inverted barometer effect. Section
 118 5 provides a summary of the work and future outlook.

119 2. Methods

120 Below we describe our OSSE design, including the data assimilation methodology and the
 121 configuration of both the nature run (NR) and the forecast model (FM). In an OSSE, a high-
 122 resolution NR is considered to represent the “true” system’s state, e.g., the observed ocean. It
 123 provides a dataset from which synthetic observations are sampled. These synthetic observations
 124 are then assimilated into the FM accounting for their uncertainty. The impact of the observing
 125 system is quantified by comparing diagnostics of the pre- and post-assimilation FM states against
 126 the corresponding NR field (Hoffman and Atlas 2016; Zeng et al. 2020).

127 *a. Data assimilation framework*

128 Our OSSEs are performed in the ECCO framework using configurations of the MIT general
 129 circulation model (MITgcm, Marshall et al. 1997; Adcroft et al. 2004). State estimation amounts
 130 to solving an inverse problem in which the uncertain model input or control variables $\mathbf{u}$, compris-
 131 ing hydrographic initial conditions, surface atmospheric boundary conditions, and ocean mixing
 132 parameters, are adjusted within their uncertainty to minimize the model misfit to all assimilated
 133 observations. Here, we consider only the atmospheric boundary condition subset, $\mathbf{u}_{BC}$, of the
 134 full control vector. Control adjustments are determined by running the adjoint model, obtained
 135 via algorithmic differentiation (Giering and Kaminski 1998), to compute the gradient of the cost
 136 function J to all control variables, where

$$J(\mathbf{u}_{BC}) = \underbrace{\frac{1}{2}(\mathbf{y} - \hat{\mathbf{y}})^T \mathbf{\Gamma}_{\text{obs}}^{-1}(\mathbf{y} - \hat{\mathbf{y}})}_{J_{\text{misfit}}(\mathbf{u}_{BC})} + \underbrace{\frac{1}{2}(\mathbf{u}_{BC} - \mathbf{u}_{BC}^0)^T \mathbf{\Gamma}_{BC}^{-1}(\mathbf{u}_{BC} - \mathbf{u}_{BC}^0)}_{J_{BC}(\mathbf{u}_{BC})}. \quad (1)$$

137 The first term in Eq. 1 computes the uncertainty-weighted misfit between N observational data (or
138 synthetic observations as done here) $\mathbf{y} = [y_1, \dots, y_N]^T \in \mathbb{R}^N$ and model equivalents obtained via the
139 parameter-to-observable map $\hat{\mathbf{y}} = \mathbf{Obs}(\mathbf{x}(\mathbf{u}_{\text{BC}})) = [\mathbf{Obs}_1(\mathbf{x}(\mathbf{u}_{\text{BC}})), \dots, \mathbf{Obs}_N(\mathbf{x}(\mathbf{u}_{\text{BC}}))]^T \in \mathbb{R}^N$ for
140 ocean state $\mathbf{x}(t, \mathbf{u})$. The second term encodes our a priori knowledge about the atmospheric controls
141 $\mathbf{u}_{\text{BC}}$, penalizing deviations from their first-guess $\mathbf{u}_{\text{BC}}^0$ based on their prior error covariance $\mathbf{\Gamma}_{\text{BC}}$.
142 Following general practice, error covariances in Eq. 1 are approximated by their diagonal elements,
143 i.e., their variances (e.g., Wunsch and Heimbach 2007). The gradient obtained by the adjoint model
144 is used to solve $\mathbf{u}_{\text{min}} = \min_{\mathbf{u}_{\text{BC}}} J$ via iterative gradient-based optimization. Following Loose et al.
145 (2020), we assess the relative importance of each atmospheric control in the optimization as follows:

$$\|u_{\text{BC}}\|^2 = \frac{1}{\sigma_J^2} \sum_{i,j} \left(\frac{\partial J}{\partial u_{\text{BC}}(i,j)} \sigma_{u_{\text{BC}}(i,j)} \right)^2 \in [0, 1]. \quad (2)$$

146 In addition to the surface atmospheric variables currently used in the production of ECCO state
147 estimates, we here include atmospheric pressure in $\mathbf{u}_{\text{BC}}$ (Table 1) which has not been done in
148 previous studies. The indices i, j denote horizontal model grid points and the sum is taken over
149 the full model domain. $\sigma_{u_{\text{BC}}(i,j)}$ comprises the entries of the diagonal matrix $\mathbf{\Gamma}_{\text{BC}}$. The sum is
150 normalized by the cost function variance σ_J^2 ; for example, for BC controls,

$$\sigma_J = \sqrt{[\nabla_{\mathbf{u}_{\text{BC}}} J]^T \mathbf{\Gamma}_{\text{BC}} \nabla_{\mathbf{u}_{\text{BC}}} J},$$

so that the sum of contributions $\|u_{\text{BC}}\|^2$ across all controls is equal to 1.

Field	Note
T_{air}	Air temperature
P	Precipitation
R_{sw}	Downward shortwave radiation
R_{lw}	Downward longwave radiation
q_{air}	Specific humidity
u_{w}	Zonal wind
v_{w}	Meridional wind
p_{atm}	Atmospheric pressure

151 TABLE 1. Atmospheric control variables used in this study. Note the addition of p_{atm} compared to the standard
152 set used in ECCO and ASTE.

b. OSSE forecast model (FM)

Our FM is Release 1 of the Arctic Subpolar gyre sTate Estimate (ASTER1, Nguyen et al. 2021). The domain covers the Atlantic as well as the Arctic and neighboring seas, as shown in blue in Fig. 1. ASTER1 is configured on a latitude-longitude-polar cap (LLC) grid with a horizontal resolution of $1/3^\circ$ (~ 22 km in the SPNA), with 50 vertical levels ranging from 10 m at the surface to 450 m at depth. The model uses a nonlinear free surface with rescaled z^* coordinates (Adcroft and Campin 2004) and applies freshwater forcing via a real freshwater flux (i.e., with accompanying change in volume, Campin et al. 2004). ASTER1 spans the period 2002–2017. Lateral open boundary conditions at 32.5°S in the Atlantic and 47.5°N in the Pacific are obtained from the ECCO Version 4 Release 3 (ECCOV4r3, Fukumori et al. 2017) solution. Atmospheric boundary conditions were initialized from the Japanese 55-year Reanalysis (JRA-55; Kobayashi et al. 2015) and adjusted during the gradient-based optimization of ASTER1 (Nguyen et al. 2021). ASTER1 applies a constant atmospheric pressure (p_{atm}) loading of $\sim 10^5$ Pa everywhere. Our FM differs from ASTER1 in applying p_{atm} from JRA-55 and including this variable in the set of control variables (Table 1). This choice is motivated by the strong connection between p_b and p_{atm} on intraseasonal timescales (Stepanov and Hughes 2006; Na et al. 2016). Its inclusion enables a first assessment of the importance of this new control variable for OBP assimilation within ECCO.

A proposed system of SMART cables within the SPNA used in this study spans 73°W to 9°E and connects Baffin Bay to the North Sea with a southwest branch reaching northeastern Canada (Fig. 2). The cables traverse key high-latitude gateways such as the Davis Strait and the Iceland–Faroe Channel, and can potentially provide measurements relevant to monitoring elements of the AMOC. For clarity, we point out that figures and discussion below focus on the SPNA where impacts of assimilation are largest (i.e., a smaller region within the full FM domain, as shown in Fig. 1 with key regions discussed labeled in Fig. 2).

c. OSSE nature run (NR)

Our NR is an existing free-running MITgcm simulation (the “LLC4320”, Gallmeier et al. 2023; Rocha et al. 2016; Wang et al. 2018; Arbic 2022) configured on the LLC grid at $1/48^\circ$ horizontal resolution with 90 vertical levels ranging from 1 to 500 m thickness. Hourly diagnostics are available for 14 months between September 2011 and November 2012. Key differences between

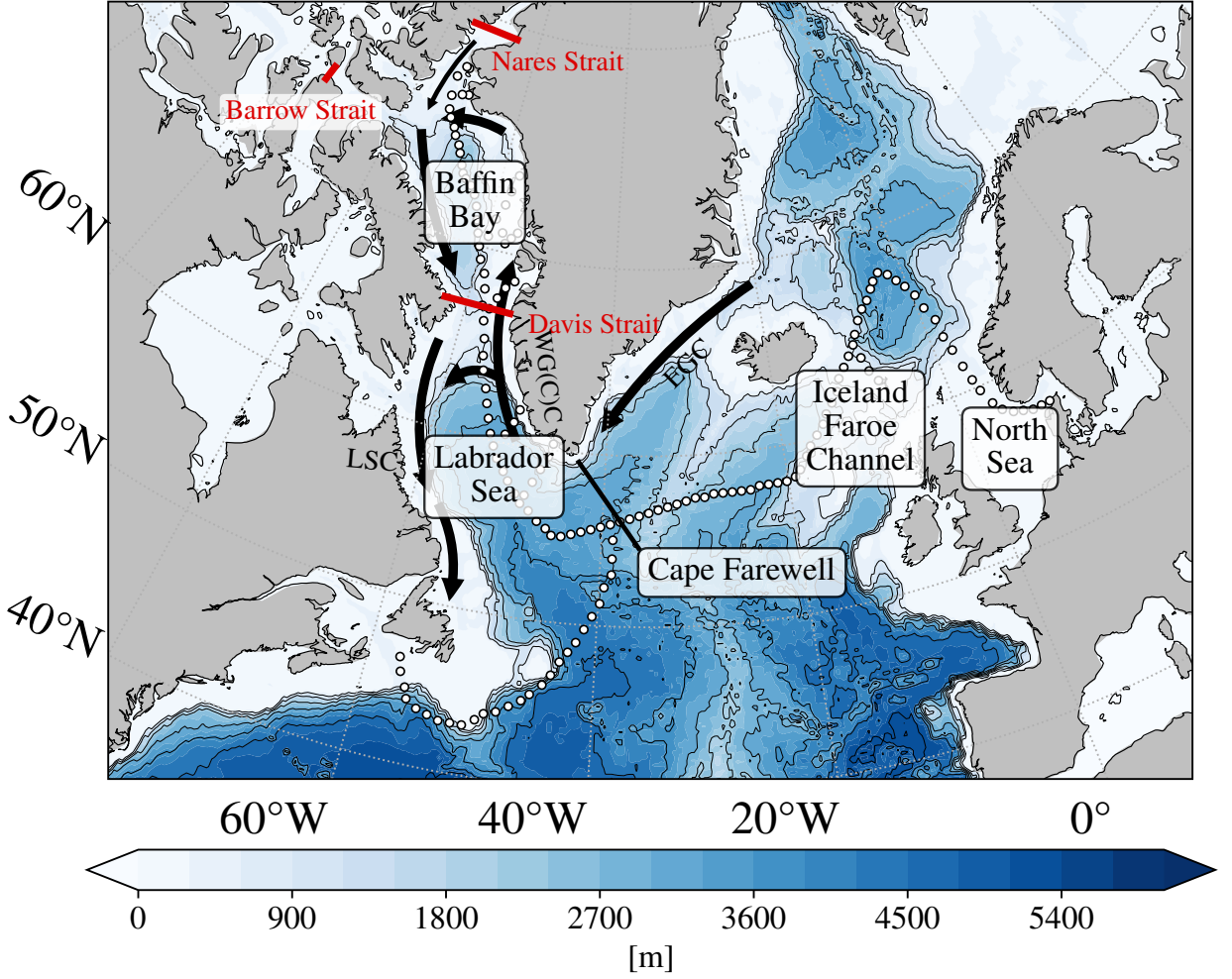


FIG. 2. Bathymetry of the SPNA region (color-filled contours) with labels for regions and straits (red lines) addressed in our discussion. Major currents (black arrows) include the East Greenland Current (EGC), Western Greenland (Coastal) Current (WG(C)C), and Labrador Sea Current (LSC). White dots indicate sensor locations along the SPNA cable system, spaced approximately 70 km apart, and are points at which synthetic observations will be extracted from the nature run.

the NR and FM are summarized in Table 2. Importantly, the NR is eddy-resolving (resolution ~ 2 km in the SPNA), incorporates additional high-frequency physics such as tidal forcing (Arbic 2022), and produces submesoscale structures that compare well against satellite data (Gallmeier et al. 2023).

	forecast model (ASTER1)	nature run (LLC4320)
Domain	Regional (Atlantic + Arctic + Northern North Pacific)	Global
Horizontal grid spacing at equator	1/3°	1/48°
Vertical levels	50	90
Surface level thickness [meters]	10	1
Deep level thickness [meters]	450	500
Atmospheric forcing	3-hourly JRA-55 bulk formulae (Kobayashi et al. 2015) + optimized control adjustments	6-hourly ERA-Interim analysis 0.14-degree grid bulk formulae
Atmospheric load	Yes	Yes
Runoff	Monthly mean fluxes based on the R-ArcticNET dataset (Lammers et al. 2001; Shiklomanov et al. 2021)	Monthly mean fluxes derived from the GECCO ocean state estimation framework (Stammer et al. 2004)
Tides	No	Yes
Barotropic time-stepping	Adams–Bashforth	Crank–Nicolson
Time step [seconds]	1200	25

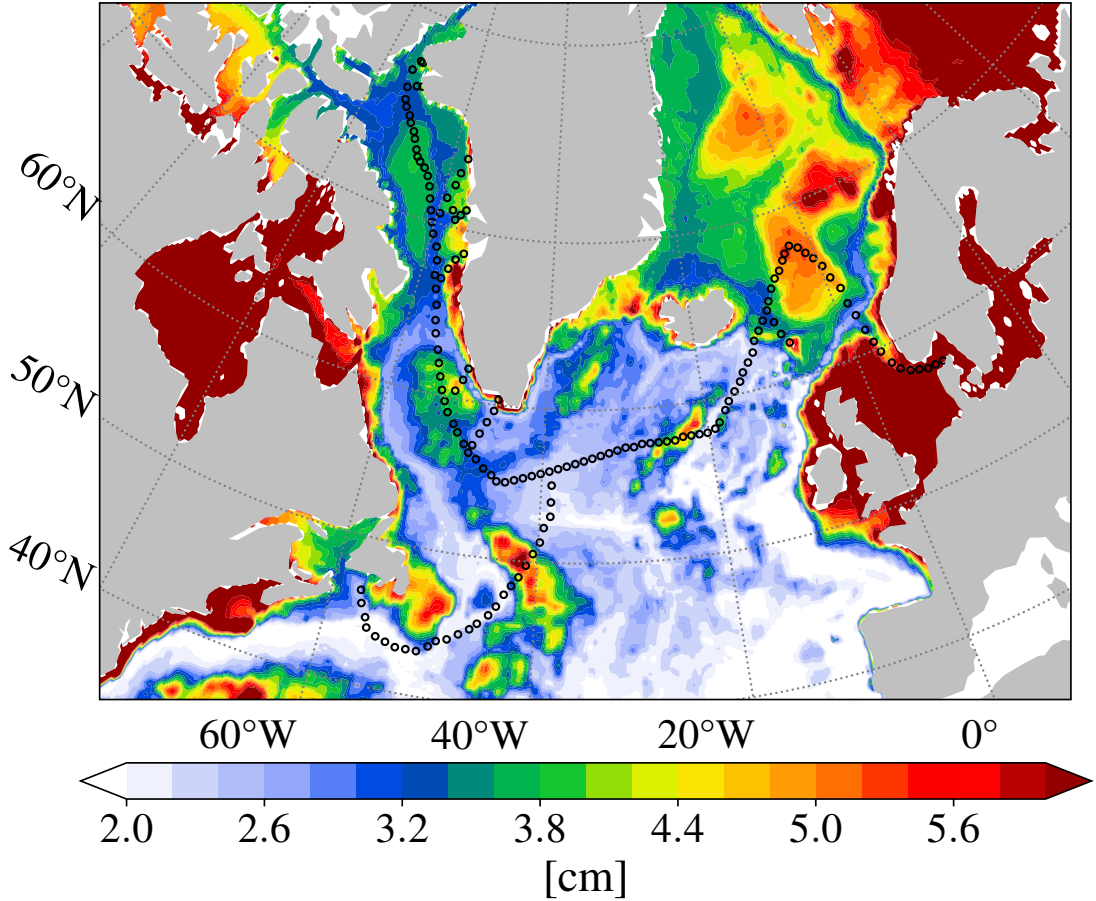
TABLE 2. Summary of forecast model (FM) and nature run (NR) configurations.

d. Synthetic data processing and uncertainty

We process OBP in the NR for assimilation into the FM as follows. First, the mean OBP over the full duration of the NR is computed at each grid cell and subtracted from the NR’s hourly OBP record to eliminate the dynamically unimportant systematic offset arising from differences in local bathymetry between NR and FM. The data were then linearly detrended and detided, removing the sixteen leading tidal constituents, as tides are absent from the FM. Next, monthly means were removed to enable comparison of sub-monthly variability between NR and FM, as the short (14 month) duration of the NR does not allow construction of a monthly climatology. Finally, daily averages were computed from the hourly OBP, which were then averaged spatially to match the FM’s horizontal resolution (see Table 2). The resulting global synthetic OBP anomalies extracted from the NR output as described above are denoted p_b^{syn} , with those at SMART sensor locations denoted p_b^{SMART} . The SMART sensor locations, shown in Figs. 1 & 2, assume a spacing of ~ 70 km (an anticipated repeater spacing, Howe et al. 2019) and are mapped to the nearest neighbor grid point accounting for the irregular LLC grid curvature.

Since the post-processing steps described above remove many of the signals that would normally contribute to a representation error in the FM, we instead impose a time-invariant observational uncertainty based on p_b^{syn} variance as follows. We first compute the temporal standard deviation

209 $\sigma_{p_b}(i, j)$ across spatially bin-averaged daily NR p_b^{syn} , and then convert both fields to an equivalent
 210 water thickness through multiplication by the scalar constant $1/(g\rho_0)$, where ρ_0 is the constant
 211 density 1029 kg m^{-3} and g is the gravitational acceleration 9.81 m s^{-2} . The derived uncertainty field
 212 (Fig. 3) shows high values along the coastal regions due to shallow bathymetry and the heightened
 213 influence of small-scale physical processes affecting p_b . Similarly, the high eddy activity in the
 214 Gulf Stream gives rise to larger transport variability, and in turn higher temporal p_b variability.



215 FIG. 3. Synthetic data uncertainty σ_{p_b} used to weight misfits between synthetic NR and FM-derived p_b in
 216 equivalent cm of water height. Black circles indicate sensor locations along the SPNA cable system.

217 The total observation uncertainty Γ_{obs} is given as the square of the synthetic data uncertainty and
 218 instrument errors:

$$\Gamma_{\text{obs}} = \text{diag}(\sigma_{p_b}^2) + \Gamma_{\text{instr}}, \quad (3)$$

where $\text{diag}(\sigma_{p_b}^2)$ denotes the diagonal matrix whose (n, n) entry is the variance associated with the n -th cable observation. Instrument errors are modeled as independent, zero-mean Gaussian noise with standard deviation 10 Pa (equivalent to 1 mm of water height), consistent with the SMART cable OBP accuracy requirement (JTF Engineering Team 2016). Accordingly, the instrument error covariance is taken to be $\mathbf{\Gamma}_{\text{instr}} = \text{diag}(\sigma_{\text{instr}}^2)$ with $\sigma_{\text{instr}} = 10$ Pa, assuming uncorrelated errors. The synthetic data uncertainty in Fig. 3 exceeds the instrument error in magnitude. We seek to reduce the total cost function (Eq. 1), with the time-dependent p_b misfit contribution defined as

$$J_{\text{misfit}}(\mathbf{s}) = \frac{1}{2} \mathbf{s}^T \mathbf{\Gamma}_{\text{obs}}^{-1} \mathbf{s}, \quad (4)$$

where

$$\mathbf{s} = \mathbf{S} \left[(\mathbf{y} - \overline{\mathbf{y}}) - (\hat{\mathbf{y}} - \overline{\hat{\mathbf{y}}}) \right], \quad (5)$$

and with $\overline{\bullet}$ denoting the time-mean over the length of the assimilation experiment, following Fukumori et al. (2017). $\mathbf{S}$ is an isotropic spatial smoother function implemented as the generalized diffusion correlation operator of Weaver and Courtier (2001), which filters out bottom pressure misfit anomaly signals below 300 km. This smoothing focuses on improving the representation of oceanic and atmospheric processes at these scales, rather than addressing potential noisy grid-scale variations (Forget et al. 2015). In the results ahead, we examine the spatial distribution of model-data differences, i.e., the fields that, when squared and summed in space and time, yield J_{misfit} . To this end, we define the “spatial misfit” at fixed time t to be the field given by $\mathbf{s}(\mathbf{x}(t))/\sigma_{\text{obs}}^{1/2}$ where σ_{obs} are the (diagonal) elements of $\mathbf{\Gamma}_{\text{obs}}$.

e. Iterative optimization

Figure 4 provides a high-level summary of our OSSE methodology. An unconstrained FM run serves as the “reference” experiment, producing diagnostics ϑ of the model state. Next, synthetic observations sampled from the NR are assimilated into the FM model as described above. No other data (e.g., real observations) are assimilated in our OSSEs. The converged “solution” produces model diagnostics $\tilde{\vartheta}$ along with adjustment fields to the control variables $\mathbf{u}$. A skill score $\mathcal{S}$ measures the improvement in the solution experiment diagnostic as its proximity to the coarse-grained NR, θ^{NR} , relative to the reference experiment via the root-mean-square error (RMSE) as

follows,

$$S(i, j) = 1 - \frac{\text{RMSE}_t(\tilde{\vartheta}(i, j, t), \vartheta^{\text{NR}}(i, j, t))}{\text{RMSE}_t(\vartheta(i, j, t), \vartheta^{\text{NR}}(i, j, t))}, \quad (6)$$

where RMSE_t denotes the RMSE computed along the time dimension at each horizontal model grid point (i, j) , as we examine improvement to selected 2D time-varying fields in this study.

In the 2D skill map, a positive skill score indicates a more accurate solution than the reference experiment. For example, a skill of 0.1 indicates a modest but positive improvement in the solution’s representation of ϑ ’s variability, reflecting a 10% reduction in RMSE relative to the reference state. Equivalently, positive skill can be understood as an increase in explained variance (see Appendix A1).

When assimilating synthetic observation anomalies, the cost function targets the quantity’s *variability* rather than its full state. Because anomalies are defined by removing each run’s own time-mean, the time-mean difference between solution and reference anomalies is identically zero and therefore cannot be used to assess mean-state improvement. To quantify systematic changes, we instead diagnose the time-mean difference in the *full* bottom pressure, P_b . At each grid point (i, j) , we define

$$\delta P_b(i, j) = \overline{\tilde{P}_b(i, j, t)} - P_b(i, j, t), \quad (7)$$

where again $\tilde{\bullet}$ denotes the constrained OBP and $\overline{\bullet}$ denotes the time-mean. We will refer to $\delta P_b(i, j)$ as the “mean adjustment”.

Our set of 14 OSSEs is described in Table 3. In each set, first-guess adjustments for all components in the control vector (Table 1) except p_{atm} are initialized from ASTER1 and interpolated to daily frequency from their original biweekly frequency. Control uncertainties $\sigma_{\mathbf{u}}$ are identical to those used in ASTER1. For p_{atm} , first-guess adjustments are zero and we apply an uncertainty estimated from the spread between the JRA-55, JRA-3Q, and ERA5 reanalyses following Chaudhuri et al. (2014). The amplitude of this uncertainty estimate is consistent with that reported by Ponte and Dorandeu (2003). Given that this is the first application of p_{atm} as a control in the state estimation framework, we impose no penalty on deviations from the first guess, i.e., Γ_{BC}^{-1} for p_{atm} is set to zero in J_{BC} in Eq. 1. The control adjustment frequency is discussed further in Section 4.

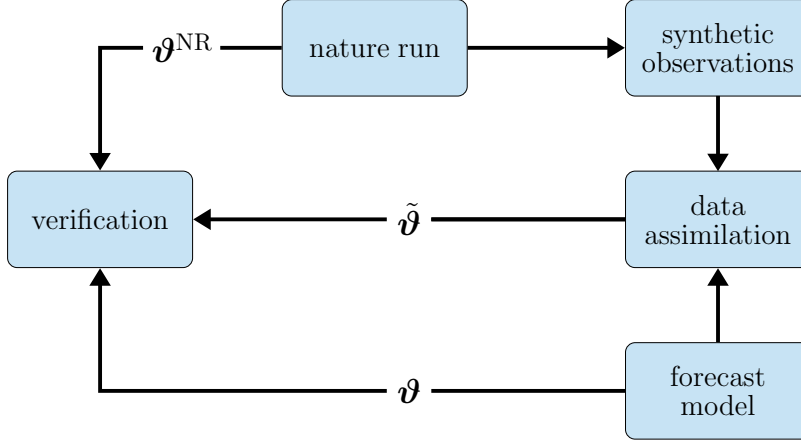


FIG. 4. OSSE flowchart adapted from Hoffman and Atlas (2016). Synthetic observations from the NR are assimilated into the FM. Solution and reference experiment fields $\tilde{\vartheta}$ and ϑ , respectively, are verified against the analogous NR output ϑ^{NR} using a skill score (Eq. 6).

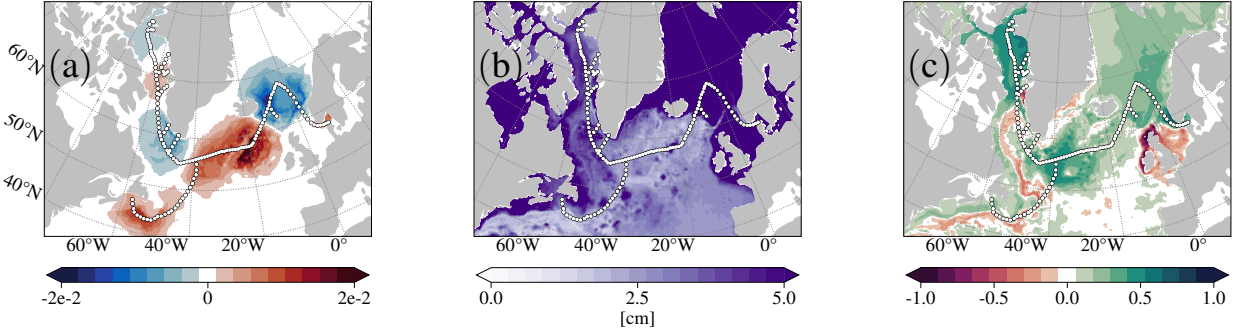
Expt. number & name	Run Time	Aim	Iterations	Notes
1. SPNA_cable	Jan 2012	Assess daily OBP data value from the SPNA cable	20	
2. LS_cable	Jan 2012	Explore spatial origins of daily OBP data value in expt. SPNA_cable.	20	OSSEs assimilating data from the (LS) Labrador Sea, (SPG) Subpolar Gyre, (NS) North Sea, and (Nfl) Newfoundland segments of the full SPNA cable (Fig. 1). Expt. LS_cable also re-run with p_{atm} control excluded.
3. SPG_cable				
4. NS_cable				
5. Nfl_cable				
6. SPNA_cable_annual	Jan–Dec 2012	Explore complementarity of daily OBP data from SPNA cable with monthly global OBP data from GRACE	3	GRACE_annual targets minimization of monthly OBP misfits.
7. GRACE_annual	1–7 Jan 2012	Explore dependence of dominant control on imposed adjustment frequency	20	Misfit computed only during final 2 days. In expt. name, number given in brackets denotes control adjustment frequency in days. For example, expt. SPNA_cable_adjfreq_4 adjusts controls every 4 days.
8–14. SPNA_cable_adjfreq_[1:0.5:4]				

TABLE 3. Summary of OSSE configurations. Horizontal dashed lines group experiments by aim. Experiments 2–5 are referred to in the text as the “partial cable” OSSEs. Unless otherwise stated, all OSSEs are run with the full set of controls listed in Table 1 and target minimization of daily OBP misfits over the full run time.

3. Results

All results below are shown for the final iteration of the optimization for each OSSE (Table 3). We start by describing the results from the full SPNA_cable OSSE, run for the month of January 2012 to test the impacts of assimilating daily p_b^{SMART} data at all sensor locations shown in Fig. 2.

279 *a. Impact on bottom pressure and barotropic velocity*



280 FIG. 5. (a) Normalized p_b spatial misfit on January 1, 2012, (b) RMSE between $\bar{p}_b$ and p_b^{NR} , and (c) p_b skill
281 in the SPNA cable experiment.

282 Figure 5a shows the spatial p_b misfit remaining on January 1, 2012 in the SPNA_cable OSSE at
283 the end of the iterative optimization. Spatial misfits on subsequent days (not shown) are qualitatively
284 comparable, with positive and negative signals extending away from the sensor locations due to the
285 application of the spatial smoother (Eq. 5). The cost has been reduced by 83% and the final RMSE
286 is shown in Fig. 5b. Owing to high p_b variability, the FM and NR show largest differences in p_b
287 in shallow coastal waters and semi-enclosed regions, including the North Sea, Hudson Bay, and
288 Canadian Arctic Archipelago. The skill score (S , Eq. 6) distribution in Fig. 5c indicates significant
289 p_b error reduction both along the cable and throughout the wider SPNA region, extending into the
290 Greenland, Iceland, and Norwegian Seas, with p_b error increases in only a few isolated areas.

291 To explore regional origins of the improved skill (Fig. 5c), we conduct four additional partial
292 cable OSSEs (LS_cable, SPG_cable, NS_cable, and Nfl_cable, Table 3). Each partial cable OSSE
293 assimilates p_b^{SMART} for one of the cable segments shown in Fig. 1. Skill scores for these OSSEs are
294 shown in Fig. 6. Depending on the cable segment assimilated, certain regions, such as the subpolar
295 gyre, Baffin Bay, and northern North Sea, exhibit similarly high p_b skill (Fig. 6a-d) as the full
296 cable experiment (Fig. 5c). We note that spatial misfits in the full cable experiment (SPNA_cable)
297 are not the exact sum of the four partial cable experiment misfits. This is due to interference in
298 the propagation (via oceanic wave/advective mechanisms) of the assimilated information from all
299 observation sources absent when each segment is assimilated in isolation.

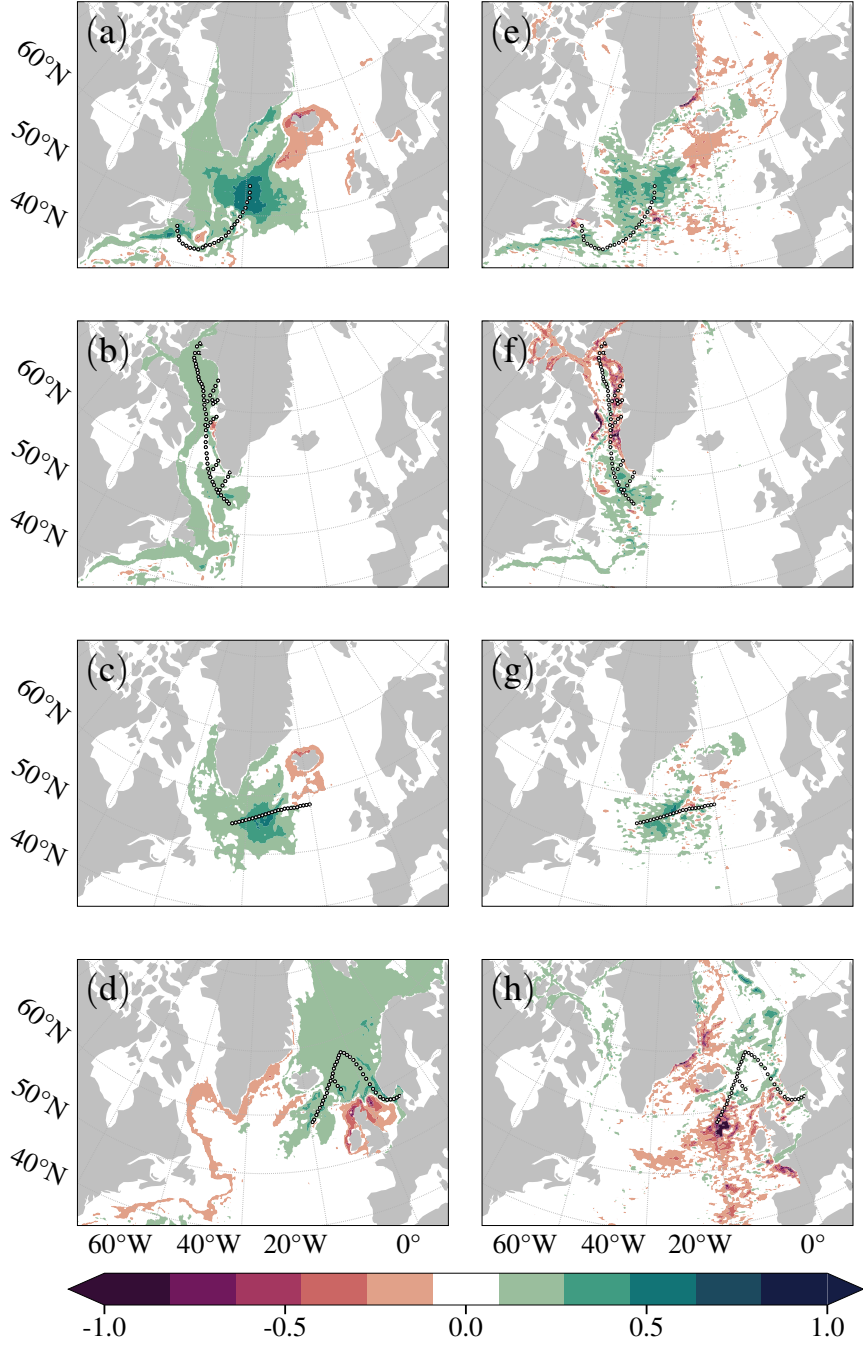


FIG. 6. (a-d) p_b and (e-h) meridional barotropic velocity skill scores for the four January 2012 daily-control partial cable experiments. The zonal barotropic velocity skill scores (not shown) resemble their meridional counterparts.

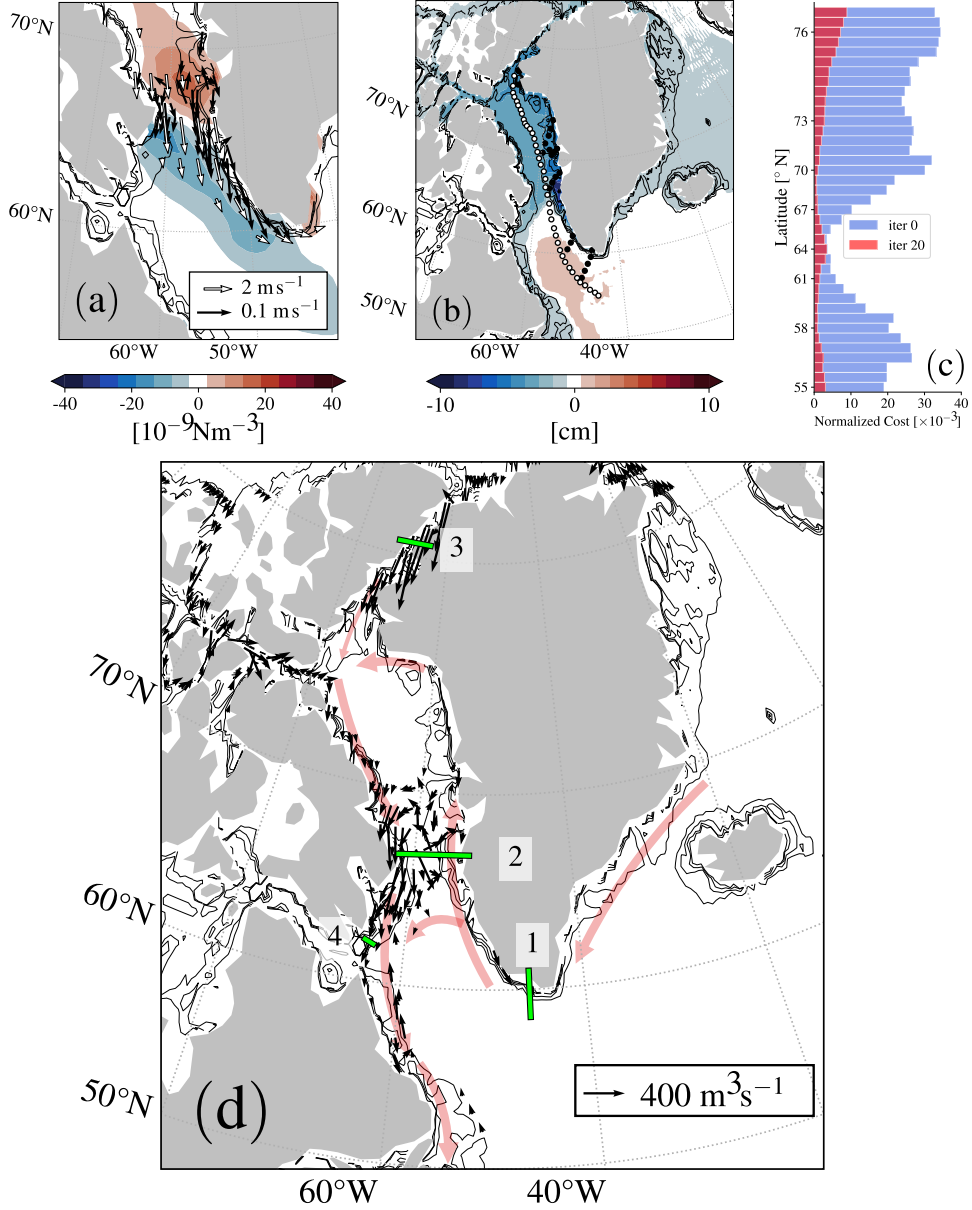
Having demonstrated that OBP assimilation improves OBP representation at both the sensor locations and throughout the wider SPNA, we now inspect impacts on other QoIs in the partial

305 cable OSSEs. We start by examining the response of the barotropic (depth-integrated) velocity,
 306 anticipating improvements due to its linear relation to OBP where geostrophy holds. The skill
 307 score (Eq. 6) for the daily meridional barotropic velocity, V_{bt} , is shown in Fig. 6e-h. Skill scores
 308 for the zonal component, U_{bt} , are not shown but are quantitatively comparable. Skill patterns for
 309 V_{bt} (Fig. 6e-h) and p_b (Fig. 6a-d), show strong similarity due to their dynamical connection (i.e.,
 310 sensitivity to the same atmospheric forcings and subject to the same resulting oceanic adjustments).
 311 In addition to demonstrating the expected relationship between water-column mass and depth-
 312 integrated velocity, the results shown in Fig. 6 highlight the benefit SMART provides toward
 313 indirectly constraining large-scale SPNA circulation upon assimilation.

314 *b. Impact on advective freshwater flux*

315 We now investigate assimilation impacts on high-latitude freshwater redistribution, which is dif-
 316 ficult to constrain via direct observations. These exports are rapidly evolving due to anthropogenic
 317 intensification of the hydrological cycle (Douville et al. 2021), changing sea ice extent (Serreze
 318 and Meier 2019) and river runoff (Weiss-Gibbons et al. 2024), increased Greenland Ice Sheet melt
 319 and calving (King et al. 2020), and shifts in regional export pathways (Zhang et al. 2021; Zhang
 320 and Du 2025), with potentially significant downstream impacts on the AMOC (Haine 2020). We
 321 focus on two primary routes through which Arctic freshwater (FW) reaches the SPNA (Jahn et al.
 322 2010; Haine et al. 2015). The first pathway is through Fram Strait, where FW is transported
 323 southward by the East Greenland Current (EGC, Fig. 2). After rounding Cape Farewell the current
 324 bifurcates: one branch, the West Greenland Current (WGC), continues westward into the Labrador
 325 Sea joining the Labrador Sea Current (LSC), while the other, the West Greenland Coastal Current
 326 (WGCC) turns northward through Davis Strait into Baffin Bay (Pacini and Pickart 2022). The
 327 second pathway delivers Arctic FW through narrow passages in the Canadian Arctic Archipelago
 328 (CAA) including the Nares and Barrow Straits. Along this path, sea ice travels southward along
 329 the western coast of Baffin Bay and exits through Davis Strait, joining the LSC (Münchow and
 330 Melling 2008).

339 To investigate the ability of SMART observations to constrain these transports, we examine
 340 assimilation impacts in the Labrador Sea cable experiment (LS_cable, Table 3). The connection
 341 between the SMART OBP constraints and FW transports is explained in terms of the optimization's



331 FIG. 7. (a) January mean wind (white arrows) and sea surface velocity (black arrows) adjustments, with wind
 332 stress curl adjustment shaded in blue and red. Reference arrows give the wind and velocity magnitude scales.
 333 (b) The January mean P_b adjustment (Eq. 7) in equivalent units of height, with the Labrador Sea cable indicated
 334 by dots. White dots highlight the central vein's sensors, for which a histogram illustrates the p_b misfit reduction
 335 in (c). The January mean advective freshwater flux adjustment in the model's surface layer (upper 10 m) is
 336 shown in (d), chosen to illustrate wind-driven change. SPNA circulation is indicated by red arrows. Green lines
 337 mark gateways where changes in the full-depth freshwater flux are assessed (Table 4). Black contours show f/H
 338 isolines.

implied impacts on the wind-induced circulation, as depicted in Fig. 7. All SMART sensors along the cable’s central vein (filled white in Fig. 7b) exhibit a reduction in p_b misfit at the end of the optimization, as shown in the histogram (Fig. 7c). From the January mean adjustment made to the winds (white arrows, Fig. 7a), we compute a wind stress curl adjustment featuring a dipole centered just south of Davis Strait. A positive curl (red, Fig. 7a) over Baffin Bay and a negative curl (blue, Fig. 7a) over the Labrador Sea induce Ekman transport anomalies (black arrows, Fig. 7a) with cyclonic flow and surface divergence across the Davis Strait. This leads to a local decrease in January mean sea surface height and P_b (Eq. 7), the latter of which is shown in Fig. 7b. The northward WGCC decreases due to the southward surface current adjustment. Ekman transport in response to the wind adjustments (Fig. 7a) deflects these coastal current adjustments west, which shifts water mass away from the coast and into the Labrador Sea, leading to a P_b increase in the Labrador Sea interior (Fig. 7b). The negative coastal OBP anomaly is propagated cyclonically around the Labrador Sea via barotropic waves following f/H contours (e.g., Fukumori et al. 2015; Chen et al. 2023).

The adjustments described above impact the FM representation of advective FW transport, ADV_{fw} . To explore these impacts, we map the change in January mean surface ADV_{fw} (following Eq. 7) in Fig. 7d, where the time-mean surface circulation pathways are illustrated in red. We also quantify assimilation impacts on both time-mean and time-varying FW flux at select locations along the primary pathways of Arctic FW export. These include within the EGC rounding Cape Farewell (gate #1, Fig. 7d), across Davis Strait (gate #2, Fig. 7d), across Nares Strait (gate #3, Fig. 7d), and within the Baffin Island Current north of Hudson Strait (gate #4, Fig. 7d). The cross-gate FW flux is defined as follows:

$$T_{fw}(t) = \int \int_{-H}^{\eta} \hat{\mathbf{u}}(S_{ref} - S)/S_{ref} dz dA, \quad (8)$$

where η is the sea surface height, $\hat{\mathbf{u}}$ is the velocity vector normal to the gate, S is the salinity, $S_{ref} = 34.8$ psu is the reference salinity and the area integral is performed across the full latitude/longitude-depth cross section of each gate (dA). T_{fw} is defined to be positive in the direction of the mean cross-gate transport depicted in Fig. 7d. Impacts on time-varying T_{fw} are assessed by defining a skill score following Eq. 6. Impacts on time-mean T_{fw} are assessed by defining a bias reduction score $1 - |\tilde{b}|/|b|$, where $b = \overline{T_{fw}} - \overline{T_{fw}^{NR}}$ is the T_{fw} bias in the reference experiment and $\tilde{b} = \widetilde{\overline{T_{fw}}} - \widetilde{\overline{T_{fw}^{NR}}}$ is the

bias remaining after assimilation, where the overline denotes a time-average over January. Skill and bias reduction scores are given at all four gates in Table 4 for two runs of the LS_cable OSSE, one with all atmospheric controls active and one with the p_{atm} control inactive. Close comparability of scores between these two configurations confirms that wind adjustments described above dominate the changes in ADV_{fw} described below.

Assimilation results in a modest decrease in the EGC rounding Cape Farewell (gate #1, Fig. 7d) and the northward WGCC, reducing FW transport toward the Davis Strait (gate #2). Concurrently, southward FW export from the Arctic through Nares Strait (gate #3) intensifies and travels south along the western Baffin Bay coast. The increased southward FW export continues through Davis Strait to the Baffin Island Current near Hudson Strait (gate #4) and on to the Labrador Shelf. At all gates, the bias reduction score is positive, indicating that assimilation improves the January mean FW transport. The improvement is most significant at Davis Strait, where assimilation results in a reduction of the reference run’s spurious net northward FW transport by approximately 40%. These improvements are, however, accompanied by degradation of the time-varying FW transport, with negative skill found at all gates except Cape Farewell. Simultaneous improvement in time-mean T_{fw} and degradation in time-varying T_{fw} is not precluded within the optimization framework, since neither is directly constrained by the assimilation. Improving time-varying T_{fw} is perhaps more challenging, however, given the inherent difficulty of representing NR variability within a coarse-resolution model, especially in narrow straits and over shallow shelf regions. Weaker representation of the time-varying T_{fw} following assimilation is particularly notable at Davis Strait (skill $\sim -40\%$), consistent with the negative barotropic velocity skill seen here (Fig. 6f).

Gateway	January mean transport and bias (mSv)			Bias reduction (%)		Skill (%)	
	$\bar{T}^{\text{NR}}$	b	$\tilde{b}$	p_{atm} on	p_{atm} off	p_{atm} on	p_{atm} off
1 Cape Farewell	30.19	-49.77	-47.58	4.4	4.4	2.9	2.9
2 Davis Strait	143.76	-56.30	-33.71	40.1	40.2	-40.8	-40.9
3 Nares Strait	69.97	-32.35	-23.50	27.4	27.4	-18.1	-18.2
4 Hudson Strait	83.70	-21.17	-13.83	34.7	34.7	-5.4	-5.5

TABLE 4. Assimilation impacts on the full-depth advective freshwater transport, T_{fw} , normal to the four gateways shown in Fig. 7d. $\bar{T}^{\text{NR}}$ is the January mean NR transport, positive in the direction of the time-mean circulation depicted in Fig. 7d. b and $\tilde{b}$ are the January mean transport biases of the reference and solution experiments, respectively, where $b = \overline{T_{\text{fw}}} - \overline{T_{\text{fw}}^{\text{NR}}}$ and $\tilde{b} = \overline{\tilde{T}_{\text{fw}}} - \overline{T_{\text{fw}}^{\text{NR}}}$. The scores for bias reduction, $1 - |\tilde{b}|/|b|$, and skill (Eq. 6) are reported for runs of the LS_cable OSSE with the p_{atm} control active and inactive.

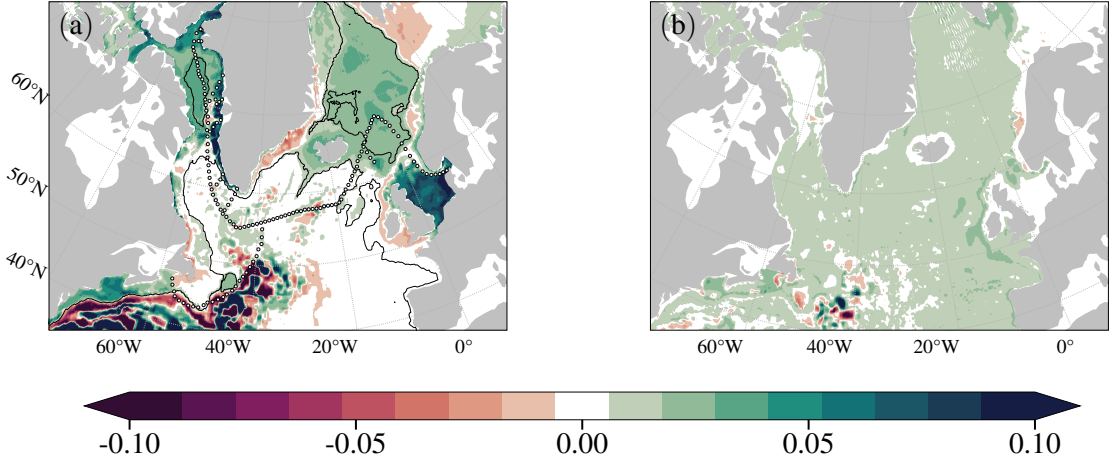
396 *c. Investigating complementarity with existing OBP measurements*

397 We conduct a final pair of OSSEs spanning the year 2012 to demonstrate how SMART’s
398 daily pointwise p_b observations may complement monthly global p_b products from GRACE (or
399 GRACE-FO) due to their distinct temporal and spatial sampling patterns. In the first (experiment
400 SPNA_cable_annual, Table 3) we repeat the full SPNA cable OSSE using daily SMART cable data
401 (as in Section 3a) for the full year 2012 rather than for January alone. In the second (experiment
402 GRACE_annual, Table 3) we assimilate synthetic monthly “GRACE” data, denoted as p_b^{GRACE} ,
403 into the FM, which is sampled from the NR for the full year 2012 as described in Appendix B1.
404 Due to the computational burden of the year-long NR integration, the optimization procedure was
405 stopped after 3 iterations for these final two OSSEs. We anticipate that further optimization would
406 not lead to strong qualitative alteration of our results, however, as in all previous OSSEs run (Table
407 3), skill evolution over successive iterations is characterized by a standing pattern of amplification
408 to first order (see Supplementary Information).

409 For both of these annual OSSEs, skill scores are computed from monthly average fields. As
410 in the January SPNA cable OSSE (SPNA_cable, Section 3a), high skill in SPNA_cable_annual
411 is concentrated where the cable crosses shallow, high-variability regions in which uncertainty-
412 weighted misfits remain large throughout the year. These areas include Baffin Bay, Grand Banks,
413 and the North Sea. Over the full year, we find lower misfits in the subpolar gyre compared to
414 the January experiment (Fig. 5). Consequently, the subpolar gyre skill is lower for experiment
415 SPNA_cable_annual (Fig. 8a). As above, skill in Fig. 8a extends beyond the cable along f/H
416 contours indicative of anomaly propagation by fast barotropic waves. This inference is consistent
417 with the barotropic pathways and timescales identified in numerous adjoint-based sensitivity studies
418 for various ocean metrics in high northern latitudes (e.g., Fukumori et al. 2015, Jones et al. 2018,
419 and Loose et al. 2020).

420 In contrast to the SPNA_cable_annual OSSE, targeted misfit reductions (spatial misfits not shown)
421 are not confined to the Greenland–Iceland–Norwegian Seas in the GRACE_annual OSSE but spread
422 more uniformly through the North Atlantic due to the global coverage of GRACE p_b estimates.
423 As a result, SPNA p_b skill in GRACE_annual (Fig. 8b) is broadly positive, but generally lower in
424 magnitude than in SPNA_cable_annual. Significant negative p_b skill (i.e., worsened representation
425 of NR variability) is seen in the Gulf Stream region in both annual OSSEs. In this highly eddying

426 region, misfit reduction is likely complicated by spatial smoothing and limited control adjustment
 427 frequency in the optimization procedure.



428 FIG. 8. Comparison between 2012 monthly p_b skill attained by assimilating (a) daily synthetic SMART cable
 429 data in experiment SPNA_cable_annual and (b) monthly synthetic GRACE data in experiment GRACE_annual.

430 4. Discussion

431 We have shown that synthetic SMART OBP data may improve representation of both observed
 432 quantities (i.e., collocated OBP) and unobserved quantities (e.g., remote OBP as well as derived
 433 quantities such as freshwater transports in the Subpolar North Atlantic). To understand how this
 434 is achieved, we now examine how the atmospheric control variables are adjusted as part of the
 435 model-data misfit reduction and the way in which they incur circulation improvements in the partial
 436 cable OSSEs (see Fig. 6).

442 Control variable contributions to misfit reduction in the partial cable OSSEs are shown in Fig.
 443 9c, indicating that p_{atm} makes the largest contribution of any single control in each case. Since
 444 we do not penalize p_{atm} deviations from first-guess values, there is a risk that the optimizations
 445 employed excessive p_{atm} adjustments (i.e., exceeding their specified uncertainty $\sigma_{p_{\text{atm}}}$, Fig. 9a)
 446 to achieve misfit reduction. To determine if this was the case, we compute the ratio of the p_{atm}
 447 adjustment and $\sigma_{p_{\text{atm}}}$ amplitudes at each grid cell. Time series of the global maximum of this ratio
 448 are shown for each partial cable OSSE in Fig. 9b, indicating that p_{atm} adjustments remained within
 449 the specified uncertainty, despite the absence of any constraint on their amplitude.

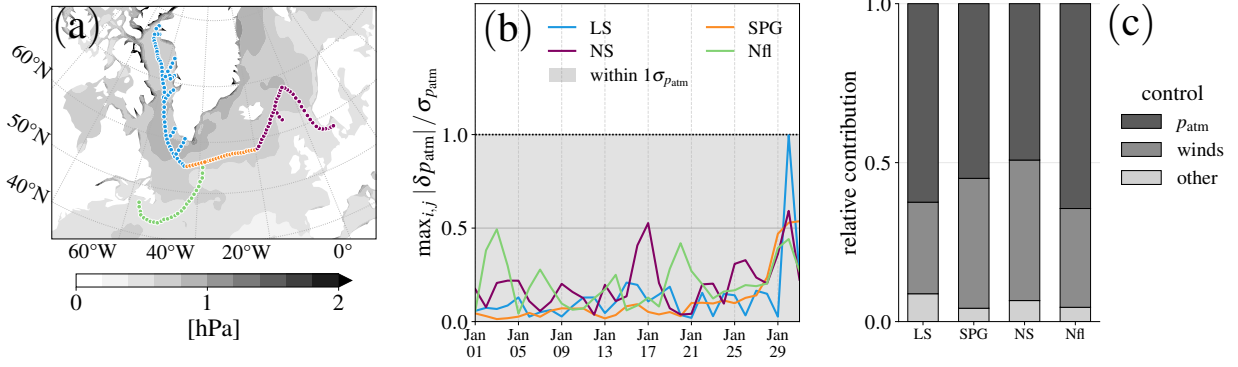


FIG. 9. (a) Applied uncertainty in the atmospheric pressure control $\sigma_{p_{\text{atm}}}$, with the four partial cable segments shown in color. (b) Timeseries showing the global maximum amplitude of p_{atm} adjustments δp_{atm} , where δ denotes an adjustment as in Eq. 7, normalized by the p_{atm} uncertainty (shown in panel (a)) at each grid cell. Values less than 1 indicate all p_{atm} adjustments remained within uncertainty bounds. (c) Relative cost function contributions of p_{atm} , wind, and other controls (Eq. 2), to each partial cable OSSE.

Next, we seek an understanding of the spatial pattern of p_{atm} adjustment that was inferred to reduce the model-data misfit. Taking experiment SPG_cable as an example, we inspect how the initial p_b spatial misfit pattern (Fig. 10a) is reduced over 20 iterations of optimization to leave a residual spatial misfit pattern (Fig. 10b). The misfit reduction is achieved by an opposite-signed adjustment of p_{atm} (Fig. 10c), which acts to decrease loading over the regions of positive misfit, and vice versa for regions of negative misfit. The p_{atm} adjustments are spatially extended relative to the spatial misfit, due both to smoothing (Section 2d) and oceanic teleconnections propagating the influence of assimilated p_b away from the cable over the OSSE duration. The standard deviation of p_{atm} adjustments normalized by $\sigma_{p_{\text{atm}}}$ (Fig. 9a) is shown in Fig. 10d to be no more than about 20%, reaffirming that the adjustments are reasonable.

The adjustments shown in Fig. 10 reflect deviation from the inverse barometer (IB) effect. Because our OSSEs use daily control adjustments, the IB response is not fully established by barotropic wave adjustment, resulting in larger p_b variations than would occur on longer timescales (Ponte 1992). In Fig. 10 the result of this partial IB response is seen, with (Fig. 10c) daily p_{atm} adjustments being transmitted to the seafloor (Fig. 10b) before changes in atmospheric loading are offset by the local sea level response.

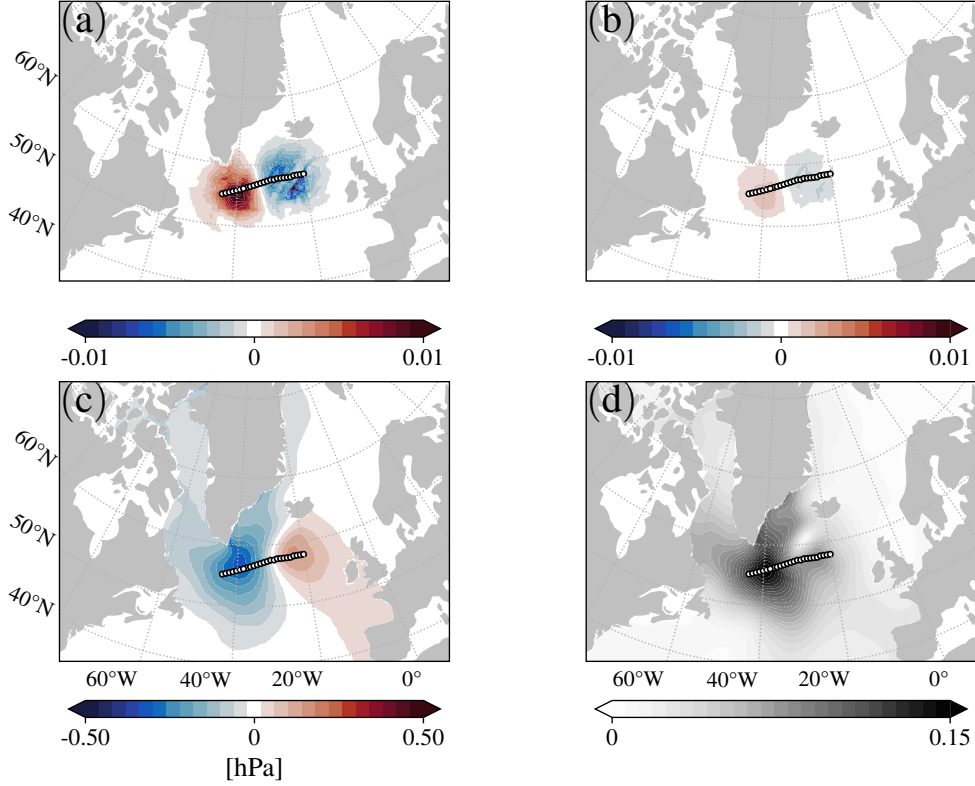


FIG. 10. A smoothed and uncertainty-weighted p_b spatial misfit along the Subpolar Gyre cable taken from one day of the January OSSE after (a) 0 and (b) 20 optimization iterations. An opposite-signed adjustment to p_{atm} (c) is shown for the same day as (a,b). (d) Standard deviation of p_{atm} adjustments taken across all days of the month normalized by the uncertainty field from Fig. 9a.

while all of our OSSEs are driven by adjustments of the atmospheric pressure control, surface wind adjustments play an important secondary role in misfit reduction (Fig. 9c). Specifically, Ekman pumping and suction can drive changes in bottom pressure anomaly when the response is predominately barotropic, as was demonstrated on seasonal timescales in Chen et al. (2023). Despite p_{atm} leading the OBP-driven optimization, we found that it is the wind adjustments that effectively modified our freshwater transport QoIs. This apparent contrast reflects a distinction between the mechanisms that reduce OBP misfit and those that drive dynamically relevant circulation changes; atmospheric pressure adjustments provide an efficient means of fitting OBP through departures from an ideal inverse barometer response, but do not substantially alter freshwater transports (Table 4). Wind adjustments, in contrast, act through Ekman transport and the associated

480 barotropic response, modifying the velocity field on which T_{fw} depends. The close comparability
481 of skill scores obtained with and without the p_{atm} control for p_b (not shown) and T_{fw} (Table 4)
482 confirms this separation.

483 The relative importance of different controls for both misfit reduction and QoI response depends
484 upon many choices made in configuring our OSSEs, including specified control frequency and
485 time lag between control adjustment and misfit/QoI evaluation. To demonstrate this, we perform
486 a final set of seven OSSEs (experiments 8-14 in Table 3) that are identical to SPNA_cable, except
487 that the integration time is reduced to 7 days, daily p_b^{SMART} observations are assimilated on the
488 final two days only, and the control adjustment frequency is varied. As for SPNA_cable, all
489 atmospheric controls from Table 1 are active. The rationale for computing the misfit only at the
490 end of the runs is to investigate the lag between the control adjustment and misfit evaluation, and
491 to expose different timescales underpinning the wind- and pressure-driven adjustments influential
492 in our OSSEs. Figure 11 shows that for control adjustment frequencies exceeding 3 days, the
493 winds overtake atmospheric pressure as the dominant control on OBP variability, consistent with
494 Ponte (1994). On these timescales OBP sensitivities to atmospheric pressure weaken as barotropic
495 adjustments accomplish a complete IB response. On shorter timescales (e.g., the daily timescales
496 considered in our previous OSSEs listed in Table 3) atmospheric pressure variations imprint on
497 OBP, dominating OBP variability and misfit reduction.

502 Both the ASTer1 and ECCO global solutions use biweekly atmospheric control adjustments
503 to reduce misfits to data assimilated over a wide range of frequencies (e.g., including daily and
504 long-term climatologies). In this study, daily control adjustments were critical for best extracting
505 the information from daily data to improve FM skill. Biweekly control adjustments were inves-
506 tigated in a re-run of the SPNA_cable OSSE where we found that cost reductions were achieved
507 but accompanied by degraded skill in many regions (not shown), owing to the definition of skill
508 in terms of improved daily variance and the limited integration period of one month. Since atmo-
509 spheric forcing adjustments cannot strongly influence ocean variations at frequencies exceeding
510 the adjustment frequency, care must be taken in formulating the optimization to fully leverage
511 available observational constraints.

512 Finally, we found that while OBP assimilation improved larger-scale representation of OBP and
513 barotropic velocity, it degraded time-varying transports along primary Arctic freshwater redistri-

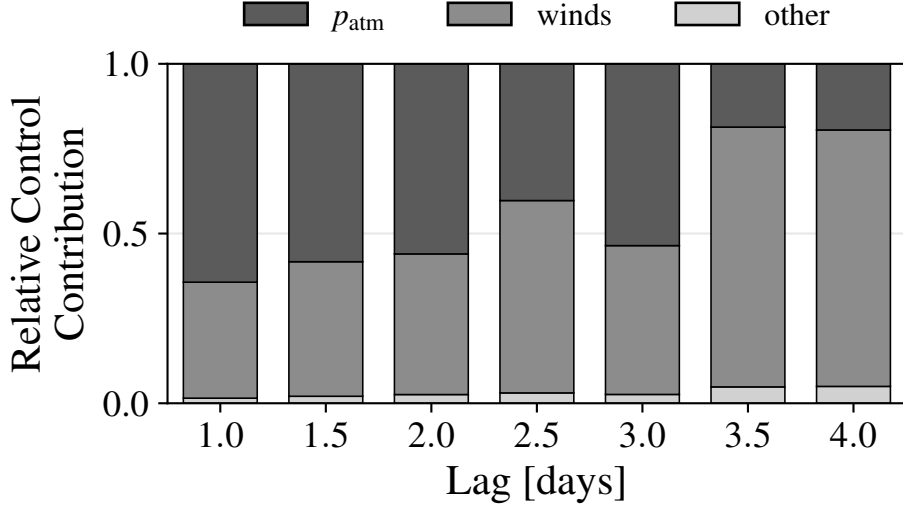


FIG. 11. Relative contributions of atmospheric pressure, winds, and other controls listed in Table 1 to misfit reduction as a function of control adjustment frequency which was varied across the final 7 OSSEs in our ensemble (experiments SPNA_cable_adjfreq_[1:0.5:4] plotted here and described in Table 3). Control contributions are computed via Eq. (2).

bution pathways. These transports depend not only on the barotropic velocity, but also on the baroclinic velocity and salinity distribution, neither of which are directly related to OBP and are therefore not well constrained by OBP assimilation. Importantly, this trade-off is not unique to the experiments presented here but reflects a more general challenge in data assimilation: improving directly constrained variables can come at the expense of unconstrained and/or dynamically unrelated components of the model solution.

5. Conclusions and outlook

In this study, we conducted an ensemble of observing system simulation experiments (OSSEs) in the ECCO state estimation framework to evaluate the potential of the SMART subsea cable observing system to constrain ocean bottom pressure and additional climate-relevant quantities of interest in the Subpolar North Atlantic (SPNA). SMART has emerged over the last decade as a proposed global initiative to leverage commercial subsea telecommunications cables for real-time geophysical observations, including ocean bottom pressure, temperature, and seismic activity. In situ ocean bottom pressure measurements remain sparse yet critically important for understanding

528 ocean mass redistribution and large-scale circulation. The proposed SMART cable route across
529 the SPNA presents a unique opportunity to fill a niche in this climatically sensitive region by
530 providing continuous, high-frequency, vertically integrated mass measurements unavailable from
531 existing networks.

532 The motivation for our OSSEs stems from the desire to quantify how SMART data could enhance
533 ocean state estimation prior to cable deployment. To our knowledge, this work is the first published,
534 detailed OSSE-based investigation into the impact of SMART observations on the ocean observing
535 system. It builds on one previous unpublished study (Tobias Weber, private communication)
536 demonstrating OBP error reduction when assimilating synthetic SMART observations obtained
537 from the Max Planck Institute Ocean Model. In contrast to their ensemble Kalman filter data
538 assimilation approach, we use the dynamically and kinematically consistent adjoint method for
539 assimilation. An added benefit of our approach is that it enables a detailed investigation into
540 the physical mechanisms underlying SMART p_b impacts on both local and remote quantities of
541 interest that are not directly observed.

542 As an expected result, we found that assimilation of (synthetic) p_b observations improves the
543 representation of simulated p_b variability. The improvement is widespread, but strongest local
544 to the cable. Importantly, beyond this direct effect, improvements were also demonstrated in
545 unobserved, state-derived QoIs. We focused on two such QoIs which are closely related to
546 the large-scale circulation. First, SMART's constraint on p_b was found to increase explained
547 variance in barotropic velocities. Second, an improved representation of advective freshwater
548 transports from the Arctic to the North Atlantic subpolar gyre was demonstrated, quantified as
549 a reduction of the January mean transport bias at all four gateways considered, though with
550 an accompanying improvement in transport variability at only one gateway. These examples
551 underscore that SMART's contribution to the global ocean observing system may extend beyond
552 the quantities directly monitored. Additionally, our results demonstrate the value SMART may add
553 to satellite-based OBP monitoring, with SMART providing substantial oceanic mass distribution
554 constraints along shallow waveguides connected to the cable location via oceanic teleconnections,
555 complementing widespread interior constraints provided by GRACE.

556 While our results are encouraging, all OSSEs in our ensemble were limited to run times of
557 one year or less. Since SMART offers a pathway for sustained, long-term OBP monitoring,

future work should interrogate SMART's value for constraining ocean variability on seasonal
 to decadal timescales in extended OSSEs when suitable NR outputs become available. In the
 ECCO framework, this extension could also include longer lead times prior to data acquisition
 to interrogate the potential of future SMART networks to constrain the historic ocean state.
 Importantly, all extended OSSEs should incorporate realistic modeling of time-evolving sensor
 performance, such as the linear-plus-exponential formulation introduced by Hughes et al. (2012),
 to explicitly account for bottom pressure sensor drift. Assessing the complementarity of SMART
 with existing observing networks is another important avenue. Notably, jointly assimilating in
 situ observations from high-latitude boundary currents could avoid the negative impacts p_b^{SMART}
 assimilation was found to have on freshwater transport variability. Assimilating altimetry data
 with p_b^{SMART} would also be beneficial for constraining the sea level response accompanying the
 p_{atm} adjustments. Additionally, by leveraging recent advances in Hessian uncertainty quantification
 (Loose et al. 2020; Loose and Heimbach 2021), this complementarity could be rigorously quantified
 prior to SMART deployment.

Future work could also revisit many choices made in configuring our OSSEs, including the
 specified control frequency. Daily control adjustments were important for maximally extracting
 the constraint from the daily synthetic OBP data assimilated in our OSSEs, but are not currently
 used in production of ECCO state estimates and may also not be appropriate when assimilating
 additional observations at other frequencies. Uncertainties applied to both the assimilated data
 and the control variables could also be revisited in future work. Our choice of synthetic data
 uncertainty incorporated variability that should be recoverable by the FM, which may have served
 to downweight the strength of the assimilated OBP constraint in the state estimation framework. Our
 choice of control uncertainty ignored covariations between control variables allowing, for example,
 atmospheric pressure to be adjusted independently of the winds in our OSSEs. In a geostrophically
 consistent atmosphere the gradient of any p_{atm} adjustment would imply a correlated surface wind
 stress anomaly that itself acts on OBP. Encoding these cross-covariances in Γ_{BC} would likely
 increase the efficacy of the wind controls in our OSSEs (see e.g., Weaver et al. 2005), but remains
 a challenging outstanding issue in ocean state estimation (Forget et al. 2015). Finally, we note
 that our OSSEs were conducted for optimization cycles of 20 iterations or less. while we suggest

587 further iteration would have limited qualitative impact on our results, quantitative impacts could
588 be investigated in future work.

589 The design of the SPNA SMART network is still evolving. While cable routing and sensor
590 types will not be dictated by science requirements, questions remain about optimal sensor spacing
591 (see Appendix C1), placement on continental shelves versus abyssal plains, and the number of
592 observation points needed to maximize impact. OSSEs could help inform these design ques-
593 tions. Our study establishes a methodological foundation for evaluating the unique contribution
594 of SMART cables to the global ocean observing system. Results shown encourage future assess-
595 ment of both the potential constraint SPNA SMART offers on other climate-relevant quantities,
596 including AMOC, and the role SMART could play in an integrated AMOC observing system
597 (Foukal et al. 2026). In addition, SMART offers the potential to install additional sensors, includ-
598 ing thermistors and hydrophones, providing sustained, high-resolution measurements of other key
599 ocean variables. Temperature measurements, for example, would inform bottom boundary layer
600 processes and support closure of regional and global heat budgets. Acoustic measurements would
601 constrain ocean velocities along the cable. Future experiments should investigate the potential
602 value of SMART-based multivariate sensing in addition to potential synergies with the emerging
603 applications of seafloor cables for distributed optical fiber sensing (Naveira Garabato et al. 2026).

604 APPENDIX A

605 A1. Relationship between RMSE and explained variance

606 Explained variance, defined

$$\text{EV}(x, y) = 1 - \frac{\text{Var}(x - y)}{\text{Var}(x)} \quad (\text{A1})$$

607 quantifies the extent to which one variable explains another (Fukumori et al. 2015). That is, EV
608 is closer to 100% the more y accounts for variability in x . Consider one-dimensional zero-mean
609 random variables x, y , and z (e.g., time series of climate anomalies). Without loss of generality,
610 the variance of such a variable is

$$\text{Var}(x) = \mathbb{E}[x^2].$$

611 Next, with root-mean squared error defined $\text{RMSE}(x, y) = \mathbb{E}[(x - y)^2]^{1/2}$, it follows that

$$\text{RMSE}(x, y) = (\text{Var}(x - y))^{1/2}.$$

612 Substituting into Eq. A1, we write the explained variance for mean-zero variables as

$$\text{EV}(x, y) = 1 - \frac{\text{RMSE}(x, y)^2}{\text{Var}(x)}. \quad (\text{A2})$$

613 The denominator $\text{Var}(x)$ is fixed and nonnegative, so clearly a decrease in $\text{RMSE}(x, y)$ increases
614 $\text{EV}(x, y)$. Recalling the definition of skill introduced in Eq. 6, we have

$$S = 1 - \frac{\text{RMSE}(x, y)}{\text{RMSE}(x, z)} = 1 - \frac{(\text{Var}(x - y))^{1/2}}{(\text{Var}(x - z))^{1/2}}.$$

615 Therefore, in the event that the set $\{x, y, z\}$ attains positive skill, $S > 0$ implies

$$\begin{aligned} (\text{Var}(x - y))^{1/2} &< (\text{Var}(x - z))^{1/2} \\ \text{Var}(x) [1 - \text{EV}(x, y)] &< \text{Var}(x) [1 - \text{EV}(x, z)] \\ \text{EV}(x, y) &> \text{EV}(x, z) \end{aligned}$$

616 invoking Eq. A2. In the context of an OSSE involving anomaly fields $\{x, y, z\} = \{\vartheta^{\text{NR}}, \tilde{\vartheta}, \vartheta\}$, this
617 derivation provides an equivalent skill definition: a positive skill means the FM anomaly quantity
618 ϑ explains the analogous NR field ϑ^{NR} to a greater extent, and vice versa, after data assimilation.

619 APPENDIX B

620 B1. GRACE-equivalent synthetic data processing

621 Here we describe additional steps performed to generating synthetic GRACE data, p_b^{GRACE} , from
622 the NR used in the GRACE_annual OSSE. Monthly means were first computed from daily p_b^{syn}
623 data on the $1/3^\circ$ grid before aggregating these data into blocks of side length roughly 300 km
624 (nominally 3°) reflecting the footprint of GRACE’s mass concentration blocks (“mascons”). For
625 this final step, a mascons map was obtained from GRACE data from each month of 2012 and

mapped onto the ECCO $1/3^\circ$ global grid (Zhang et al. 2018). Clusters of grid cells sharing a common value were assigned an index, which was then used to bin-average the monthly mean p_b data. For consistency, we reconstruct the p_b representation error covariance Γ_{obs} by modifying the procedure in Section 2d to compute the standard deviation over monthly-averaged – rather than daily-averaged – NR records.

APPENDIX C

C1. Sensor spacing

Cable sensor placement will be guided by industry standards, and is therefore not the focus of this study. However, a preliminary set of experiments confirm that denser arrays achieve denser p_b skill for month long OSSEs. Fig. C1 shows p_b skill from the January 2012 OSSE after 10 iterations with all controls active repeated for SPNA cables with 70, 140, and 210 km sensor spacing. The sparser cables were generated using a nearest neighbor resampling routine applied to the 70 km cable. Fig. C1 shows p_b skill *differences* between (a) 70–140, (b) 70–210, and (c) 140–210 km experiments. Green regions in all subplots indicate that in general, denser SMART cables improve p_b representation. In North Sea, however, control and resultant p_b adjustments are sensitive to how neighboring sensor misfits blend during smoothing, meaning more p_b observations in this regions can destructively interfere with one another. Future sensor spacing experiments should more closely examine these regions and their sensitivity to the smoothing length scale. Moreover, topographic gradients should inform cable design in favor of the naive downsampling performed here.

Acknowledgments.

This work was supported by the Gordon and Betty Moore Foundation through Grant GBMF10787. The adjoint model was generated using the AD tool Transformation of Algorithms in Fortran (TAF) by Fastopt. AN and HP received additional support from NSF AccelNet program, Award #2114717 and Jet Propulsion Laboratory, California Institute of Technology (JPL/ Caltech) Subcontract (“ECCO- Connections”). We thank three anonymous reviewers for feedback that improved the manuscript.

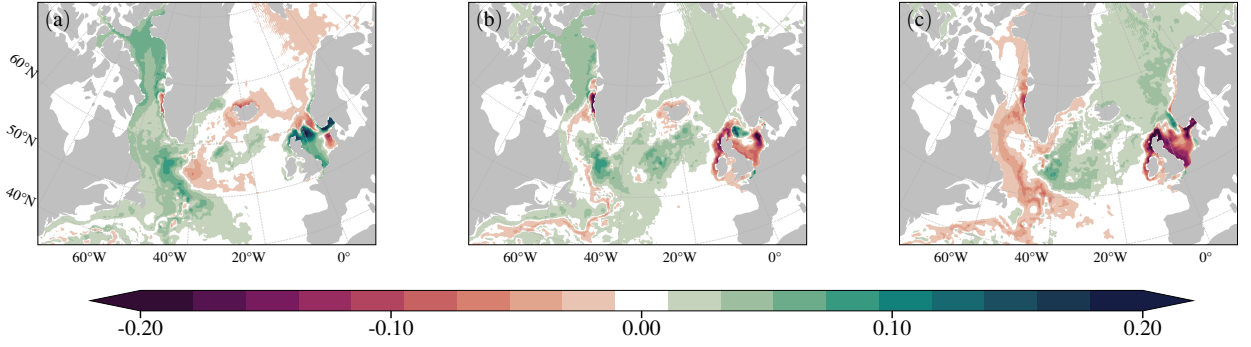


FIG. C1. January 2012 OSSEs are repeated for SPNA cables with sensor spacings of 70, 140, and 210 km and are shown as p_b skill differences between experiments: (a) 70–140, (b) 70–210, and (c) 140–210 km.

Data availability statement.

The nature run data is accessible from ECCO’s public data portal (https://data.nas.nasa.gov/ecco/11c_4320/) and via the Poseidon Project (Haine 2025). The forecast model is a configuration of ASTEr1, available at the Arctic Data Center (<https://arcticdata.io/catalog/portals/ASTE/ASTE>). The JRA-55 forcing dataset can be downloaded at (<https://climatedataguide.ucar.edu/climate-data/jra-55>). Modifications to the forecast model configuration, nature run extraction scripts, and data processing and analysis routines are available on GitHub (<https://github.com/mgoldberg10/smartosse>).

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