

Article

Arctic Coastal Observing: Assimilating Buoy vs. Fiber Cable Data into Wave Forecast Model

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Abstract

Over the past decade, significant progress has been made in the development of regional wave observational systems. In particular, the Backyard Buoys program deployed multiple wave buoys along the Alaskan Coast to collect real-time wave spectra. In parallel, the expansion of the subsea fiber optic cable network around Alaska has provided a potential new source for high-resolution Significant Wave Height (SWH) observations. In this study, we conduct Observing System Simulation Experiments (OSSEs) to quantify the potential forecasting skill of different observational configurations, including a moored buoy, a single optical cable, and a hypothetical cable network. We use the SWAN wave model configured for the regional domain along the Northern Alaskan Coast and equipped with an extension of the a4Dvar approach, which allows optimization of both the initial conditions and wind forcing. In the OSSEs, it was found that assimilation of the SWH from the network of optical cables provides the most accurate wave forecast of SWH for regular wind conditions, but assimilation of spectral wave observations from the moorings significantly outperforms the skill of a single-cable platform and provides better control of wind forcing and wave direction, especially for stronger winds. In the second part of the study, the same approach was applied to real observations from the Oliktok Point region. Experiments with real observations from the 37 km long optical cable and wave mooring agree well with the main conclusions from the OSSE results.

Keywords: regional wave forecast; SWAN model; wave buoys vs. DAS observations

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1. Introduction

Over the past decade, significant advancements have been made in regional wave observation platforms. Notably, floating free-drifting buoys have become a key source of wave data. These platforms operationally gather and transmit directional spectra; wind; and other data, such as ambient noise, to data centers. Several organizations and universities now provide these free-drifting platforms, including Sofar Ocean Inc., with its Spotter buoys, and the University of Washington, with the SWIFT buoys. Drifting wave buoys are often used as moored stations along coastlines to provide real-time wave observations and forecasts for local communities. For example, the NSF-funded Backyard Buoys program deployed moored Sofar Spotter drifters in roughly 20 locations across Alaska, the Pacific Northwest, and the Pacific Islands (<https://backyardbuoys.org>, accessed

on 20 May 2026). These wave buoys measure wave spectra and key wave parameters (Significant Wave Height, directional spread, period, etc.) alongside various meteorological data, thereby improving the accuracy of regional wave forecasts by assimilating wave and wind data into high-resolution models.

Another novel source of wave observations is sensing from seafloor fiber-optic cables, which are usually used for telecommunications. The seafloor cables have unused optical fibers that can be used to monitor coastal hydrodynamical processes [1,2]. The basic physics of fiber-optic observations relies on changes in the optical properties (e.g., reflection) of the fibers under mechanical deformation (e.g., pressure from gravity waves or tides). The optical changes along the cable can be detected with very high accuracy in space and time. Thus, the single seafloor cable may provide continuous observations of fiber deformation along the cable with a spatial resolution of about 1 m, which can be converted into physically meaningful values (e.g., Significant Wave Height (SWH), Sea Surface Height (SSH), ambient noise level, etc.). Thus, this technique converts optical cables into thousands of along-cable sensors and is known as Distributed Acoustic Sensing (DAS) technology.

In many coastal regions, the telecommunication cable system forms a dense network that can be used for continuous monitoring of coastal processes with high temporal and spatial resolution. For example, in Alaska, the network of seafloor cables connects multiple (~40) coastal villages and currently spans about 1300 km (<https://www.akfiberproject.com/>, accessed on 20 May 2026). Thus, this network provides a basis for monitoring waves and currents along the coast of Alaska.

Recently, Baker and Abbott [3] used observations from a fiber cable that starts at Oliktok Point in the Beaufort Sea and extends northward for 37 km (Figure 1). They captured the rapid transition in ambient noise characteristics from an “ice-free” to an “ice-bound” state. Later, [4] utilized spectral observations from the SWIFT wave buoy [5] collocated with the cable observations and calibrated DAS fiber deformation observations into the SWH observations along the optical cable. The derived cable SWHs were used to estimate wave attenuation during the winter period [4].

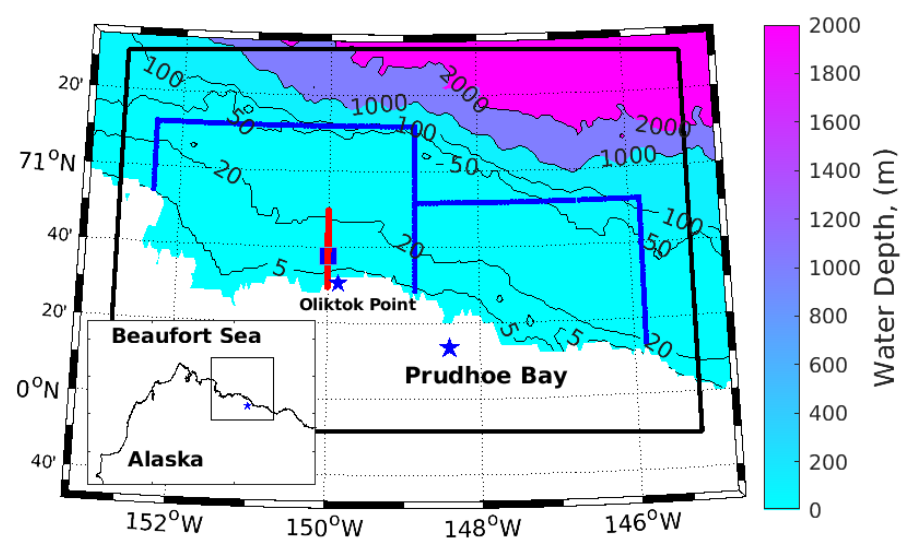


Figure 1. Bottom topography (m) around Prudhoe Bay, Alaska, USA. The black solid line shows the SWAN model domain. The blue solid square shows the location of the SWIFT moored wave drifter deployed during August 2022. The red line designates the optical cable that starts from Oliktok Point. The blue rectangle-shaped solid lines show the hypothetical optical cable network used in the OSSEs. The position of the model domain along the Alaskan coastline is shown in the inset.

Thus, observations from both optical cables and moored wave drifters can be used to monitor nearshore wave conditions. It is also reasonable to assimilate these observations into the regional wave model and provide regional monitoring at larger (~200 km) scales, e.g., [6].

Observations from optical cables are typically converted to SWH observations along the cable, although the frequency spectrum could also be derived. On the opposite, moored wave drifters/buoys provide comprehensive observations of the wave spectrum at the buoys' locations. So, the obvious question emerges: which observations are more efficient for providing more accurate regional monitoring and forecasting? The conventional way to answer this question is to conduct Observing System Simulation Experiments (OSSEs) and, if possible, validate the OSSE results using real observations from both observational platforms [7–10].

In the present study, we use this methodology and conduct multiple OSSEs for the regional data assimilation (DA) system based on the SWAN wave model ([11], <https://swanmodel.sourceforge.io>, accessed on 20 May 2026). The DA algorithm is equipped with the adjoint-free variational DA technique (a4Dvar), which allows for the optimization of the initial state and wind forcing [6].

This approach is an extension of the a4Dvar technique widely used in various types of numerical models [12–20] of various complexity, including both spectral [6,12] and phase-resolving [19,20] wave models. This paper is organized as follows: In Section 2, we briefly describe the concepts of the wave model, the a4Dvar approach, and the setup of the OSSEs with assimilation of wave observations from various platforms. Section 3 contains the results of the OSSEs. In Section 4, we describe the results of applying the approach to real observations from a moored wave drifter and optical cable. Section 5 summarizes the work and discusses directions for future research.

2. Methodology

Conceptually, the OSSE methodology consists of the following steps: (1) Run a State-of-the-Art model with realistic forcing and initial conditions. This model solution is usually called the “true” or “nature” solution. (2) Extract a set of synthetic observations from the “true” solution by contaminating a subsample of the true fields (e.g., SWH values at specific locations) with prescribed random errors. (3) Run the model with modified forcing and initial conditions. The resulting solution is usually called the First Guess (FG) solution. (4) Assimilate the observations into the model to obtain the optimized model solution, i.e., the wave field and boundary conditions. (5) Compare the optimized solution with the true solution and analyze the efficiency of different sets of observations with respect to the reconstruction accuracy for different periods. Below, we outline these components in more detail.

2.1. Numerical Wave Model

We utilized the SWAN model as the regional wave model [11]. SWAN solves the spectral action balance equation for the wave spectrum $F(\mathbf{x}, \mathbf{k}, t)$, representing the spectral density of wave components with wavenumber $\mathbf{k} = (k_x, k_y)$ at spatial location $\mathbf{x} = (x, y)$:

$$\frac{\partial F}{\partial t} + \nabla \cdot (\mathbf{v}F) = S(F, \mathbf{x}, \mathbf{k}, t), \quad (1)$$

where S denotes the sum of source and sink terms describing wind input, whitecapping dissipation, depth-induced breaking, bottom friction, and nonlinear wave–wave interactions. The operator $\nabla = \{\nabla_{\mathbf{x}}, \nabla_{\mathbf{k}}\}$ represents gradients in spatial and spectral (wavenumber) space, and $\mathbf{v}$ is the four-component velocity vector in physical and spectral space, account-

ing for wave advection and refraction due to ambient currents and depth variations. Wave propagation is constrained by the linear dispersion relation:

$$\sigma^2 = g|k|\tanh|k|h, \quad (2)$$

where σ is the wave angular frequency, g is gravitational acceleration, and $h(x)$ is the local water depth. Given appropriate initial and boundary conditions, as well as ambient currents and wind forcing, Equation (1) is integrated numerically to obtain the evolution of the wave spectrum in space and time. The model domain, shown in Figure 1, was configured with an average spatial resolution of 2 km ($\approx 0.05^\circ$ in longitude and 0.0175° in latitude). The choice of the 2 km spatial resolution is defined by the objective of the Backyard Buoys program, local spatial variability of the wave patterns, and available computational capabilities. The computational grid consists of $m_x = 10,246$ active horizontal grid points. In spectral space, the discretization includes $m_k = 1224$ components, corresponding to 36 directional bins (10° resolution) and 34 logarithmically spaced frequency bins ranging from 0.0418 Hz to 1 Hz, which are the typical choice for SWAN applications. This results in the total of $m_x m_k = 12,541,104$ degrees of freedom for the initial wave spectrum. Gen3 ST6 wave physics package was used for the source terms.

The true solution was obtained in several steps. First, we ran the model over a larger area (180°W – 125.2°W ; 65°N – 80°N) at a coarser spatial resolution ($dx = 0.4^\circ$ and $dy = 0.14^\circ$) for the period from 1 July 2022 to 1 September 2022, with JONSWAP open-boundary conditions ([11], <https://swanmodel.sourceforge.io>, accessed on 20 May 2026). The model was forced by four-hourly wind speed and sea ice concentration from the ERA5 reanalysis [21]. ERA5 reanalysis was chosen as re-analysis with the best spatial ($0.25^\circ \times 0.25^\circ$) and vertical (137 levels) resolutions. As an example, other available re-analyses, namely MERRA-2 and JRA-55 re-analyses, have spatial resolutions of ($0.5^\circ \times 0.62^\circ$) and ($0.56^\circ \times 0.56^\circ$), respectively. Second, from this model solution, we extracted spectral open-boundary conditions for the smaller domain shown in Figure 1. We subsequently ran the model over this domain using the same (upscaled) ERA5 forcing. Finally, we ran SWAN for the three 24 h periods (19 August, 00:00–20 August, 00:00; 21 August, 00:00–22 August, 12:00; and 23 August, 00:00–24 August, 00:00) using interpolated hourly wind forcing. Two periods were selected because, during these periods, both spectral and cable observations were available, allowing verification of the OSSEs' results against realistic data. The third period was chosen to explore the impact of stronger wind forcing.

During these periods, wave generation was insignificant due to relatively weak winds, and SWH did not exceed 2.5 m. To evaluate the efficiency of the observational platforms and the a4Dvar SWAN algorithm for extreme events, we repeated the procedure outlined above with double the wind speed and obtained an additional true solution, where SWH ranged between 1 m and 11 m.

2.2. Wave Observational Platforms

We analyzed the efficiency of two types of observational platforms.

First, observations are taken from a moored wave drifter located approximately 10 km offshore at the depth of 15 m (see Figure 1). Typically, the Wave Sofar Spotter drifters (<https://www.sofaroccean.com/>, accessed on 20 May 2026) provide spectral data across 127 frequency bands from 0.01 to 1.24 Hz, overlapping significantly with the SWAN model's frequency range. Raghunkumar et al. [22] found that, for random waves with SWH around 1 m, spectral errors of the Sofar Spotter ranged between $0.2 \text{ m}^2/\text{Hz}$ and $0.05 \text{ m}^2/\text{Hz}$, decreasing gradually from lower frequencies (0.08 Hz–0.1 Hz) to higher frequencies (>0.2 – 0.3 Hz), being almost negligible below 0.05 Hz. For the a4Dvar procedure,

a similar dependence of spectral errors was adopted. Formally, the spectral errors tend to correlate in the frequency space, and, ideally, we should provide the corresponding error covariance matrices, R , for each type of observation (see [12] for details). However, the error correlations in both spatial and frequency spaces are not well known, so cross-correlations between errors were neglected, resulting in the diagonal approximation of the observational error covariance. Since SWH is derived from the spectrum integral, which effectively averages over the spectral range, relatively small errors of 0.05 m were specified for the SWH observations at the moored wave drifter.

Second, there are the SWH observations from optical cables. It is necessary to clarify that optical cables do not measure SWH directly. Distributed acoustic sensor (DAS) observations measure dynamic strain, or strain rate, of the fiber. This signal is produced by wave-induced pressure variations and also depends on the mechanical coupling between the water column, seabed, cable, and fiber. In the calibration procedure described in [4], the cable signal in the wave-frequency band was used as a proxy of wave energy and was empirically related to the SWH estimated from the co-located SWIFT/moored buoy observations. Therefore, in this study, we assimilate the calibrated cable-derived SWH, but not the raw cable deformation or pressure. The moored drifter observations are also not pressure observations. The buoy measures its motion/displacement, and the wave spectrum and SWH are then estimated from these observations. Since cable-derived SWH is calibrated against buoy-derived SWH, the cable SWH error cannot be expected to be smaller than the buoy SWH error. In addition to the buoy uncertainty, cable SWH also includes uncertainties due to pressure-to-strain conversion, cable-bottom coupling, cable orientation, local bathymetry, spatial and temporal averaging, and calibration residuals. This assumption is also supported in Figure 3 from Smith et al. [4], showing a noticeable difference between co-located SWH observations from the mooring and the optical cable. Because of this, we assumed that SWH observations from optical cables are less accurate and have an error of 0.1 m, while 0.05 m was used for SWH observations at the mooring. This value should be considered an effective observational error used in the a4Dvar procedure.

We also analyzed two configurations of the optical cable: a single 37 km long cable, which was used in the studies of Baker and Abbott [3] and Smith et al. [4], and a hypothetical cable network covering the entire domain (Figure 1).

2.3. a4Dvar Approach

The original a4Dvar DA method was developed to avoid the need for tangent linear and adjoint (TLA) models, which are essential for standard 4dVar data assimilation [23].

It was first used to optimize initial conditions in regional general circulation models [13–16], later adapted for the regional WAM wave model [12], and extended for use in strongly nonlinear phase resolving wave models [19,20]. The method works by iteratively minimizing the cost function over low-dimensional subspaces and circumvents the need for TLA model development using a brute-force gradient computation. Essentially, a4Dvar can be seen as a cost function minimizer on the manifold formed by Proper Orthogonal Decomposition (POD) approximations of the eigenfunctions of the Koopman operator, e.g., [24–26], derived from the current model run. An extension of a4Dvar, proposed in [6], enables simultaneous optimization of initial conditions and wind forcing. This extension assumes that, in operational regional wave models, coarse-resolution wind products offer a sufficiently accurate approximation of local wind forcing, especially when there are no strong orographic features along the coast. In such a case, spatiotemporal variability

of the (optimal) wind error correction field, $e_w(x,t)$, can be approximated by the linear transformation of the background wind product, $w(x,t)$, of the following form:

$$e_w(x,t) = \varepsilon R w(x,t) \quad (3)$$

where ε is a scaling parameter, and R is a 2D rotation matrix specified by another parameter (rotation angle, ϕ). Using this representation, we assume that the background wind forcing field varies insignificantly across the wave model domain (100–300 km) during the a4Dvar assimilation window (3–5 h), implying that the error fields behave similarly. Consequently, the unknown wind correction field is parameterized by only two scalars: ϕ and ε .

With this extension, the a4Dvar algorithm gains two additional dimensions, in addition to the fixed number, n , of dynamical mode coefficients optimized at each iteration in the original a4Dvar formulation. Thus, the extended version of the algorithm requires only two additional model runs with perturbed wind parameters, ε and ϕ .

The general form of the cost function used in the data assimilation experiments included regularization (smoothness of the control) and observational (wave spectra and/or SWH) terms. More details can be found in Panteleev et al. [6].

2.4. OSSE Setups

OSSEs were configured in the way described by Panteleev et al. [6]. In particular, the data were generated from the true solutions outlined above; FG solution was obtained by forcing the SWAN model, with winds obtained by contaminating the true winds with the error field that was obtained by setting $\varepsilon = 0.2$ and $\phi = 15^\circ$ in Equation (3) and replacement of the true initial condition with spectral distribution, which was obtained after the integration of the SWAN model for 3 h using the true wind forcing.

We assume that these “smooth” disturbances of the initial conditions and winds simulate a standard initialization procedure (and errors) in a regional wave model. We respectively assimilated three different sets of observations: (1) the wave spectrum and SWH from the hypothetical mooring; (2) SWH from the hypothetical single cable; and (3) SWH from the hypothetical network of cables (Figure 1). Two different sets of the wind forcing were specified: the OSSEs were conducted with regular (ERA5) wind, and the same wind with doubled amplitude.

In order to study the sensitivity of the a4Dvar algorithm with respect to the cable SWH errors, we also conducted three experiments, namely R19Cd, R21Cd, and R23Cd, with regular wind and double (0.2 m) observational errors of the cable SWH. The brief list of parameters characterizing the experiments is shown in Table 1.

Table 1. Space–time means of the true solutions for OSSEs. Abbreviations in the left column are as follows: the first capital letter encodes regular (R) or double (D) wind forcing; the number stands for the starting date of the experiment; and the second capital letter encodes the type of the observational platform, namely mooring (M), single cable (C), or cable network (N).

Experiment, Period	Wind Speed (m/s)	SWH (m)
19–20 August 2022		
R19M	4.5	0.81
D19M	8.9	2.37
R19C	4.5	0.81
R19Cd (double SWH errors)	4.5	0.81
D19C	8.9	2.37
R19N	4.5	0.81
D19N	8.9	2.37

Table 1. Cont.

Experiment, Period	Wind Speed (m/s)	SWH (m)
21–22 August 2022		
R21M	6.4	0.55
D21M	12.7	2.14
R21C	6.4	0.55
R21Cd (double SWH errors)	6.4	0.55
D21C	12.7	2.14
R21N	6.4	0.55
D21N	12.7	2.14
23–24 August 2022		
R23M	10.4	2.17
D23M	20.8	6.68
R23C	10.4	2.17
R23Cd (double SWH errors)	10.4	2.17
D23C	20.8	6.68
R23N	10.4	2.17
D23N	20.8	6.68

In all the experiments, the SWAN model was run for a period of one day, and its solution was saved every hour. The first five hours were considered a DA window, and observations during this period were used for optimizing initial conditions and wind forcing. After the completion of the 5 h optimization procedure, the model was integrated for an additional 19 h to assess the forecast skill.

The SWH (ε_{swh}), mean wave direction (ε_{dir}), and wind (ε_{wind}) error criteria were the RMS difference between the FG and optimized solutions and observations for the 5 h assimilation periods and two forecast periods, spanning 7 h immediately after the end of the assimilation window (5 to 12 h from the initial condition) and the following 12 h (12 to 24 h from the start):

$$\varepsilon_h = \left\langle (SWH - SWH_t)^2 \right\rangle^{0.5} \quad (4)$$

$$\varepsilon_d = \left\langle (Dir - Dir_t)^2 \right\rangle^{0.5} \quad (5)$$

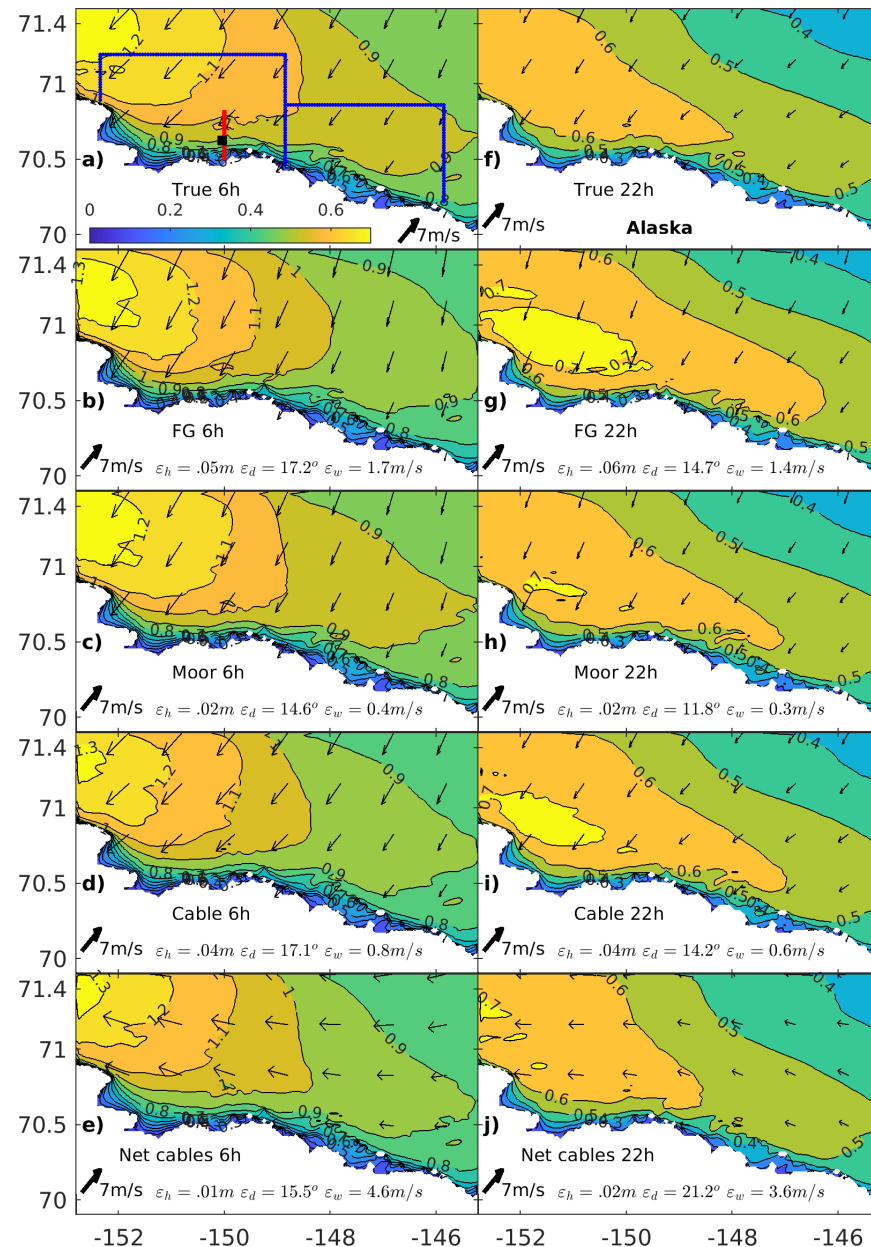
$$\varepsilon_w = \left\langle (uw - uw_t)^2 + (vw - vw_t)^2 \right\rangle^{0.5} \quad (6)$$

Here, angular brackets stand for the space–time average; SWH , Dir , uw , and vw are the SWH, mean wave direction, and wind components from either FG or optimized solutions; and the subscript “ t ” denotes the corresponding values from the true solution. To minimize the impact of open-boundary conditions, the grid points located closer than 20 km from the open boundary were excluded from averaging in Equations (4)–(6). To evaluate the improvements in the SWAN solution, we compute both the absolute errors, (4)–(6), and the values normalized by the errors of the FG solution (i.e., $\varepsilon_h^n = \varepsilon_h^{opt} / \varepsilon_h^{fg}$, $\varepsilon_d^n = \varepsilon_d^{opt} / \varepsilon_d^{fg}$, and $\varepsilon_w^n = \varepsilon_w^{opt} / \varepsilon_w^{fg}$). Thus, smaller values of ε^n correspond to more accurate hindcasts and forecasts.

3. OSSE Results

Figure 2 shows the true and FG solutions after 6 and 22 h of the SWAN model integration and corresponding results of assimilating the spectral and SWH observations from the mooring (OSSE R19M), SWH from the single cable (OSSE R19C), and SWH from

the network cables (OSSE R19N). The FG SWH and wind speed were, respectively, 0.1 m and 1.5 m/s larger than the true SWH and wind. All OSSEs demonstrate the ability to improve SWH forecast. The best SWH forecast skill was achieved in R19N, where SWH errors were reduced three to six times compared to the FG errors, $\epsilon_h^{fg} = 0.05\text{--}0.06$ m.



SWH errors in the R19M experiment were slightly larger, $\epsilon_h^{moor} = 0.02$ m, but assimilation of the wave spectrum significantly reduced the wind errors, which were several times smaller ($\epsilon_w^{moor} = 0.4$ m/s) than in the R19C and R19N experiments: $\epsilon_w^{cable} \sim 0.7$ m/s and $\epsilon_w^{net} \sim 4.6$ m/s, respectively. Accurate optimization of the wind forcing resulted in better reconstruction of the wave direction, as well. It is necessary to note that experiment R19N

demonstrated the worst relative skill in forecasting the wave direction, $(\epsilon_d^{net}/\epsilon_d^{fg}) \sim 1.3\text{--}1.4$, and wind improvement, $(\epsilon_w^{net}/\epsilon_w^{fg}) \sim 2.6$.

In the first period (19–20 August), the wind was very weak (~ 4.5 m/s, Table 1) and thus had only a minor impact on the model solution. As a consequence, SWH optimization was mostly achieved by the adjustment of the initial condition by a large number of SWH observations from multiple cables contributing to the optimization. So, despite inaccurate reconstruction of the wind and wave directions, the R19N experiment was still capable of providing reasonably accurate SWH forecasts.

Assimilation of the wind spectrum from the mooring allowed for the minimization of both wave direction and wind errors in the R19M experiment. This is due to high correlation between wind and waves, so assimilation of the full wave spectrum inherently provides information about wave direction and directly controls the wind forcing. A similar effect was observed by Panteleev et al. [6]. The experiment R19C, assimilating only a single-cable data, demonstrated the largest SWH errors of ~ 0.07 m. This is probably due to the relatively short length of the single cable and its inability to efficiently control the waves over the entire region.

The spatial distributions of the differences between true SWH and optimized SWH in the experiments R19M, R19C, and R19N are shown in Figure 3c,d. In comparison with the corresponding difference between the true and FG SWH (Figure 3a), all experiments demonstrate a significant error reduction. As discussed above, SWH assimilation from the cable network results in the smallest integral errors. Meanwhile, there is a significant difference in the spatial distribution of the errors: assimilating observations from cable network has the strongest impact in the “internal” regions, while assimilation from mooring and single cable (Figure 3b,c) decreases SWH errors over the entire region, preserving similarity with original difference between FG and true SWH (Figure 3a). That is probably the result of more accurate optimization of the wind forcing in the experiments R19M and R19C.

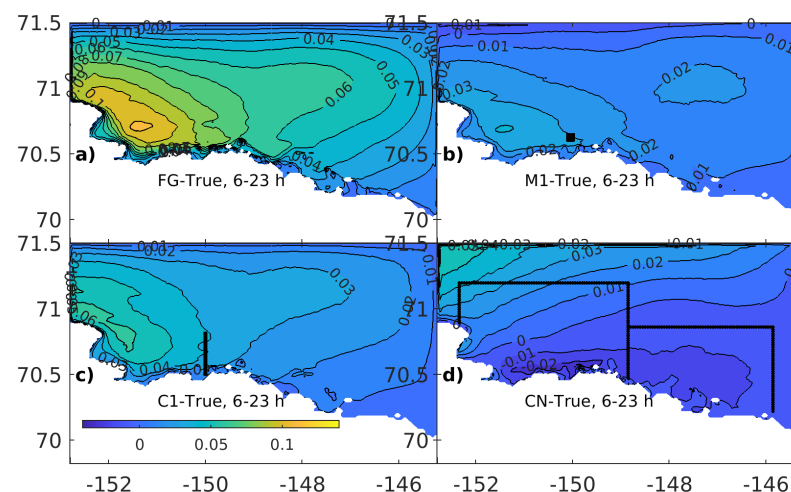


Figure 3. (a) Differences between the FG and true SWH averaged for the forecast period 19 August, 6–23 h. (b–d) The corresponding difference in the OSSEs’ R19M, R19C, and R19N. Locations of the mooring, single cable, and cable network are shown.

Note that the difference between FG and true SWH is about 0.01 m within the narrow (10–15 grid points) stripe along the northern and eastern boundaries (Figure 3) and significantly increases up to 0.04 m and higher in the internal grid points. After optimization, this difference remains almost the same (~ 0.01 m) along these boundaries and only slightly (up to 0.02–0.03 m) increases in the center of the model domain (Figure 3b–d). Thus, the

DA significantly improves the solution in almost the entire domain, with the exception of 10–15 grid points along the open boundaries, where waves are entering the model domain and the impact of the non-optimized (FG) open-boundary conditions is essential.

Table 2 displays the results of OSSEs with a regular wind and shows error reductions with respect to the FG solution for the data assimilation period (0–5 h, first number), and for the short-range (5–12 h) and longer-range (12–24 h) forecasts (second and third numbers). Similar to the results discussed above, assimilation of the SWH, from the cable network, yields the most accurate SWH reconstruction for the entire experiment, with regular (5–10 m/s) winds. It is seen that the SWH forecast DA, with the network cables, outperforms all other experiments for all the periods considered. On the other side, assimilation of the mooring observations yields better wave direction and wind forcing. The SWH assimilation from a single cable provides the worst result but is still comparable to other experiments.

Table 2. Results of the OSSEs with ERA5 wind forcing. Normalized errors are estimated for the first 5 h of the data-driven a4Dvar model run, and the forecast errors were assessed for the short- (5–12 h) and long-range (12–24) forecasts. The best and second-best scores are underlined with single/italicized with double lines, respectively. Second row shows the corresponding normalized errors in the experiments with doubled observational errors of the cable SWH observations.

	0–5 h Assimilation	5–12 h Forecast	12–24 h Forecast
	M/C/N	M/C/N	M/C/N
08/19/22	Wind 4.5 m/s		
ϵ_h^n	<u>0.4</u> /0.8/ <u>0.2</u> (1.12)	<u>0.29</u> /0.71/ <u>0.29</u> (1.17)	<u>0.33</u> /0.66/ <u>0.33</u> (1.01)
ϵ_d^n	<u>0.84</u> /0.99/ <u>0.90</u> (1.39)	<u>0.81</u> /1.03/1.31 (1.49)	<u>0.80</u> /0.97/1.44 (1.45)
ϵ_w^n	<u>0.24</u> /0.47/2.7 (1.13)	<u>0.24</u> /0.41/2.56 (1.16)	<u>0.21</u> / <u>0.43</u> /2.57 (1.11)
08/21/22	Wind 6.3 m/s		
ϵ_h^n	<u>0.23</u> /0.31/ <u>0.15</u> (0.45)	<u>0.21</u> /0.42/ <u>0.21</u> (0.58)	<u>0.29</u> /0.5/ <u>0.21</u> (0.55)
ϵ_d^n	<u>0.47</u> /0.89/1.0 (1.6)	<u>0.32</u> /0.48/1.0 (0.76)	<u>0.35</u> / <u>0.41</u> /1.0 (0.7)
ϵ_w^n	<u>0.43</u> /0.48/ <u>0.43</u> (0.52)	<u>0.41</u> /0.45/ <u>0.41</u> (0.61)	<u>0.46</u> / <u>0.58</u> / <u>0.46</u> (0.71)
08/23/22	Wind 10.4 m/s		
ϵ_h^n	<u>0.13</u> /0.15/ <u>0.09</u> (0.16)	<u>0.12</u> / <u>0.12</u> / <u>0.1</u> (0.13)	<u>0.10</u> / <u>0.10</u> / <u>0.08</u> (0.11)
ϵ_d^n	<u>0.45</u> /0.56/ <u>0.27</u> (0.59)	<u>0.52</u> /0.68/ <u>0.28</u> (0.71)	<u>0.64</u> /0.75/ <u>0.44</u> (0.76)
ϵ_w^n	<u>0.45</u> /0.60/ <u>0.24</u> (0.61)	<u>0.46</u> /0.59/ <u>0.23</u> (0.61)	<u>0.47</u> /0.58/ <u>0.25</u> (0.60)
	Mean over 3 periods		
$\overline{\epsilon_h^n}$	<u>0.19</u> /0.24/ <u>0.1</u>	<u>0.14</u> /0.25/ <u>0.14</u>	<u>0.19</u> /0.27/ <u>0.15</u>
$\overline{\epsilon_d^n}$	<u>0.67</u> /0.86/ <u>0.76</u>	<u>0.59</u> /0.78/0.95	<u>0.61</u> / <u>0.73</u> /1.08
$\overline{\epsilon_w^n}$	<u>0.41</u> / <u>0.51</u> /0.78	<u>0.38</u> / <u>0.5</u> /0.81	<u>0.43</u> / <u>0.56</u> /0.78

Table 3 displays the results of the OSSEs with stronger (10–20 m/s) winds. In this case, experiments with the cable network yield the smallest SWH errors only for the initial period when the DA was performed, while for the short (5–12 h) and longer (12–24 h) forecasts, assimilating mooring observation scores better. We attribute this to better optimization of the wind by observations from moorings. This effect becomes more important for the stronger winds. Note that good spatial coverage of the network cables allows for better optimization of the initial conditions, which dominate the forecast skill at the initial period of (0–5 h). Single-cable OSSEs typically yield larger SWH errors for all periods and for both regular and double winds.

Table 3. Results of the OSSEs with double (10–20 m/s) wind forcing. Notation is the same as in Table 2. The best and second-best scores are underlined with single/italicized with double lines, respectively.

	0–5 h	5–12 h	12–24 h
	FG/M/C/N	FG/M/C/N	FG/M/C/N
08/19/22	Wind 8.9 m/s		
ϵ_h^n	<u>0.48</u> /0.74/ 0.43	0.10 / <u>0.14</u> / <i>0.14</i>	0.09 / <u>0.13</u> / <i>0.13</i>
ϵ_d^n	1.0/ <u>0.87</u> / 0.86	1.10/ 0.85 / <u>1.07</u>	<u>0.97</u> / 0.81 / <u>0.97</u>
ϵ_w^n	0.6 / <u>0.63</u> /0.67	0.59 / <u>0.62</u> /0.68	0.59 / <u>0.63</u> /0.67
08/21/22	Wind 12.7 m/s		
ϵ_h^n	<u>0.19</u> /0.33/ 0.14	0.11 / <u>0.17</u> / <i>0.13</i>	<u>0.14</u> /0.2/ 0.08
ϵ_d^n	0.97 / <u>1.01</u> /1.04	0.12 /0.62/ <u>0.55</u>	0.12 /0.58/ <u>0.30</u>
ϵ_w^n	0.07 /0.49/ <u>0.29</u>	0.07 /0.46/ <u>0.28</u>	0.08 /0.47/ <u>0.29</u>
08/23/22	Wind 20.8		
ϵ_h^n	<u>0.29</u> /0.79/ 0.21	0.15 /0.78/ <u>0.19</u>	0.16 /0.63/ <u>0.17</u>
ϵ_d^n	0.28 /0.86/ <u>0.36</u>	0.22 /0.93/ <u>0.26</u>	0.21 /1.19/ <u>0.32</u>
ϵ_w^n	0.14 /0.77/ <u>0.19</u>	0.19 /0.78/ 0.19	0.20 /0.77/ <u>0.27</u>
	Mean over 3 periods		
$\overline{\epsilon_h^n}$	<u>0.29</u> /0.67/ 0.22	0.12 /0.48/ <u>0.16</u>	0.14 /0.43/ 0.14
$\overline{\epsilon_d^n}$	0.84 /0.93/ <u>0.85</u>	0.52 /0.79/ <u>0.66</u>	0.51 /0.78/ <u>0.59</u>
$\overline{\epsilon_w^n}$	0.19 /0.56/ <u>0.27</u>	0.25 /0.65/ <u>0.33</u>	0.23 /0.64/ <u>0.34</u>

As was discussed in [6], the shape of the wave spectrum is closely related to wind direction, so assimilation of the wave spectra yields better optimization of the wind forcing, thus allowing for a more accurate forecast. A more accurate comparison of the efficiency of the spectral and SWH observations can be accomplished via the adjoint sensitivity analysis, e.g., [7,8], but the unavailability of the adjoint model does not allow us to do that.

Despite the differences in skill, almost all OSSEs demonstrated significant improvement in the FG solution because it was obtained by rotation and amplification of the true wind, i.e., the same method which we use in a4Dvar for optimization of the wind forcing. In view of this, we conducted a set of experiments with real observations from the wave mooring and a single optical cable.

The impact of the inaccuracy of the cable SWH observations was analyzed in experiments R19Cd, R21Cd, and R23Cd, where we assumed the double cable SWH observations errors of 0.2 m. It was found that in OSSE R19Cd, optimization does not improve the FG solution, and all normalized errors are larger than 1 (Table 2). In experiment R21Cd,

all normalized errors are typically about 10–50% larger than in experiment R21C, with standard (0.1 m) errors of the SWH observations, and optimization partly improves the FG solution: almost all normalized errors are smaller than 1. Interestingly, in experiment R23Cd, the errors are only slightly (~5%) larger than the errors in experiment R23C. That can be explained by the gradual increase in the wind in the outlined experiments and stronger impact of the wind on the model solution. It is also necessary to note that, in all experiments, SWH errors were not correlated between each other, and large errors are partly compensated by the relatively large volume of the SWH observations along the cable. That may explain very small deterioration of the optimized solution in experiment R23Cd with relatively strong wind and very high (~2 m) waves. However, in real-world applications, the cable SWH errors may correlate on the larger spatial scale, and that may cause an additional deterioration of the optimized solution.

4. Experiments with Real Observations

In August 2022, wave observations from one moored SWIFT drifter were used for calibration of the optical cable data [4]. This set of the wave observations creates an opportunity to compare two observational platforms in a realistic setting. We conducted two experiments for the periods of 19–20 August and 21–22 August 2022. In the first experiment, we assimilated observations from the wave mooring (wave spectrum and SWH), while in the second, SWH from the optical cable was assimilated. For convenience, we label these experiments M19/M21 and C19/C21, respectively. Satellite SWH observations along several tracks were used for the independent evaluation of the results. We also compare errors with respect to the observations from the mooring and optical cable. Below, we outline the utilized observations and results.

4.1. Observations

4.1.1. Wave Observations from Moored SWIFT Drifter

Surface Wave Instrument Float with Tracking (SWIFT) wave drifter was moored near the Oliktok Point, Alaska, in the second half of August 2022 (Figure 1) [4]. The SWIFT drifter [5] provides SWH observations and spectral observations in 127 frequency bands between 0.01 and 0.49 Hz in the form of frequency dependent Fourier coefficients of the variance density spectrum. The same SWH errors and spectral errors, as in the OSSE experiments, were used in the a4Dvar procedure. Since the model frequency band is wider than the band of the SWIFT observations, the a4Dvar algorithm was respectively adjusted.

4.1.2. SWH from Optical Cable Observations

SWH data from the optical cable stretching northward from Oliktok Point, Alaska, for approximately 37 km (Figure 1) were used. High-resolution SWH data from this cable were averaged for a one-hour period and interpolated onto the SWAN grid. Considering the observed discrepancy between cable SWH and SWH from the collocated moored SWIFT drifter [4], we prescribed a 0.1 m error for the cable observations, which were available for a relatively short period between 14 and 22 August and contained significant gaps. As a result, we were only able to conduct two experiments for the two short periods mentioned above.

4.1.3. Satellite SWH Observations

SWH observations from Saral, Cryosat-2, Sentinel-3A, and Sentinel-3B satellites were used for validation. Park et al. [27] estimated the range of satellite SWH errors to be between 0.2 m for small (less than a meter) waves and around 2 m for large waves in the shallow regions near Korea. Wan et al. [28] analyzed the satellite observations along

the USA coast and ranged satellite SWH errors between 0.2 m and 0.5 m for the satellite observations near the coast. Similar estimates for the English Channel ranged between 0.4 m and 0.6 m [29]. Finally, in the Eastern Chukchi Sea, [30] estimated Envisat satellite errors to be 0.4 m and 0.2 m for the 1 m and 2 m waves, respectively.

Thus, we assume that a 0.2–0.3 m error could be a reasonable SWH error estimate for the satellite errors in the coastal waters of the Beaufort Sea. Satellite SWH observations were not assimilated; they were used for the comparison and validation of the forecast skill only. Seven satellite tracks intersected the modeled domain during 19–20 August and 21–22 August. These data were used for validation with a total number of 113 and 78 SWH observations for the August 19–20 August and 21–22 August periods, respectively. We also compare the FG and optimized SWH with the observations from the mooring and optical cable.

4.2. Results

Figure 4 compares the FG model solution and optimized solutions in M19 and C19 experiments. Assimilation of the observations from both platforms results in the reduction of the mean SWH by 0.1–0.15 m. At the same time, after 6 h, the M19 solution has a clear minimum in the central part of the model domain (Figure 4b), which is not visible in the 6 h C19 distribution. Note that the satellite track intersects the central part of the model domain one hour later (7 h), and the M19 solution demonstrates ~50% better agreement with satellite SWH than C19 (0.25 m vs. 0.36 m). Thus, SWH minimum in the 6 h M19 pattern agrees reasonably well with independent satellite observations, indicating that assimilation of the mooring data may provide a better skill for short (5–12 h) forecasts.

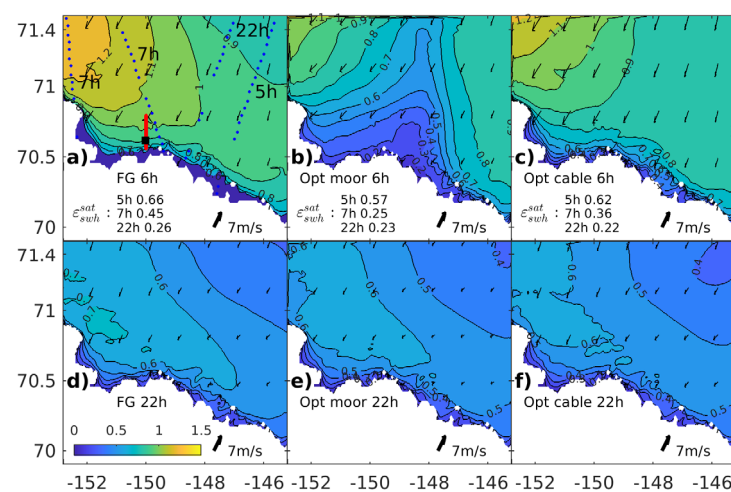


Figure 4. FG (a,d) and optimized SWH distributions from M19 (b,e) and C19(c,f) DA experiments at the end of the data assimilation period (6 h) and forecast period (22 h) respectively. Wind forcing is shown by black arrows. Locations of the SWIFT buoy and optical cable are shown by the black solid square and red line, respectively. Satellite tracks are shown by dotted lines. The numbers 5 h, 7 h, and 22 h denote times of the satellites' passages (relative to the start of model integration), followed by the RMS misfits (ϵ_{swh}^{sat} , m) with the respective model solutions. Subplots, in the bottom row, show SWH after 22 h of model integration.

However, after 22 h, both M19 and C19 SWH turned out to be rather similar, exhibiting nearly the same (~0.22 m and 0.23 m) RMS discrepancy with the SWH from the 22 h satellite track (Figure 4e,d), which is only slightly smaller than the corresponding error of FG solution (0.26 m). This indicates that improvement in the M19 experiment was achieved mostly due to better optimization of the initial conditions, which has a limited impact on the SWAN solution after 12 h, e.g., [6,12]. In this experiment, the weak impact of the

adjusted wind is due to its relatively small magnitude, which is in good agreement with the results of OSSE experiments forced by ERA5 winds and discussed in the previous section.

Along the eastern boundary, both M19 and C19 solutions are rather similar, suggesting a strong impact of the open-boundary forcing, which was not optimized by the a4Dvar algorithm.

Figure 5 shows the results for the experiments M21 and C21 for the second period. In these experiments, optimized SWHs are rather similar to each other (Figure 5b,c,e,f) and differ significantly from the FG (Figure 5a,d). In both experiments, the mean SWH decreased by almost two times, and its maximum moved offshore. Validation against the satellite SWH shows only a minor reduction of the RMS misfits with a 7 h track, which intersects the domain quite close to the western boundary. But for a 14 h track, the RMS decreased nearly two times in both M21 and C21 solutions despite the presence of the intensive boundary layer along the western open boundary caused by the impact of the non-optimized open-boundary conditions (Figure 5e,f).

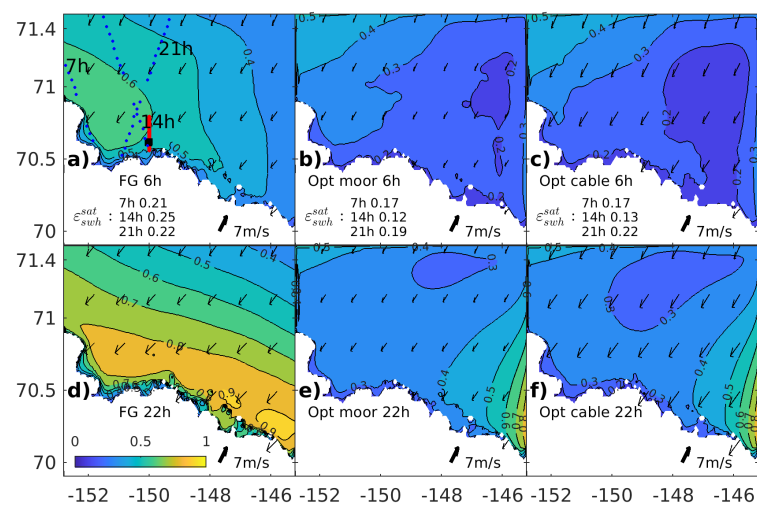


Figure 5. The same as in Figure 4, but for the experiments M21 and C21.

The forecast skills of the M19, M21, C19, and C21 experiments are summarized in Table 4. Table 4 includes FG and optimized errors with respect to the SWH observations from satellites (ϵ_{swh}^{sat}), cable SWH (ϵ_{swh}^{cab}), and SWH from the SWIFT mooring (ϵ_{swh}^{moor}).

Table 4. Mean RMS misfits (m) between the satellite SWH and the FG solution (ϵ_{swh}^{sat}), the optimized solutions assimilating optical cable data (ϵ_{swh}^{cab}) and the mooring data (ϵ_{swh}^{moor}) for all DA experiments. Numbers in brackets show the normalized errors with respect to FG solution (i.e., $\epsilon_{swh}^{opt}/\epsilon_{swh}^{fg}$).

	First Guess	Moor	Cable
08/19/22	Wind 4.5 m/s	M19	C19m
ϵ_{swh}^{sat}	0.51 m	0.38 m, (0.75)	0.44 m (0.86)
ϵ_{swh}^{cab}	0.70 m	0.48 m, (0.69)	0.59 m (0.85)
ϵ_{swh}^{moor}	0.58 m	0.37 m, (0.64)	0.46 m (0.79)
08/21/22	Wind 5.3 m/s	M21	C21
ϵ_{swh}^{sat}	0.22 m	0.14 m (0.63)	0.20 m (0.91)
ϵ_{swh}^{cab}	0.47 m	0.12 m (0.26)	0.10 m (0.21)
ϵ_{swh}^{moor}	0.41 m	0.07 m (0.17)	0.07 m (0.17)

Assimilation of the moored platforms typically reduces the discrepancy with satellite SWH (i.e., ϵ_{swh}^{sat}) 20–40% compared to the FG solution, while the improvement produced by the optical cables ranges between 10% and 15%. The reduction in the discrepancy between the optical cable and mooring SWHs are much greater, ranging between 15% and 83%, suggesting that assimilation of the observations from both observational platforms has a stronger impact on the SWH optimization in the central region. We attribute this to the absence of optimization of the open-boundary conditions. Qualitatively, results of the M19, M21, C19, and C21 experiments agree well with the results of the OSSEs. In particular, all of these experiments indicate that spectral and SWH observations from a single mooring yield better wave forecasts as compared to a single cable.

5. Discussion and Conclusions

In this study, we quantified the efficiencies of SWH observations from an optical fiber cable and observations from a moored drifter, which include accurate observations of the wave spectrum and all the related integral characteristics (e.g., SWH). We utilized the conventional OSSE approach and analyzed the efficiency of three observational platforms: single mooring single optical cable, and an optical cable. The numerical experiments were conducted using a realistic (5–10 m/s) ERA5 wind forcing and doubled “strong” wind forcing. The SWAN model was configured for the coastal domain in the Beaufort Sea with spatial dimensions of 100–200 km. The choice was motivated by the availability of the observations, current continuous studies of the region, and the research interest of the authors.

As a DA tool, the a4Dvar algorithm was used [6,24]. Optimization of the wind forcing was based on the assumption that global wind reanalysis has a persistent bias on regional (≤ 200 km) scales when the typical time of wind variation exceeds 1–2 days, so that a significant part of the regional wind reanalysis errors could be removed by simple rescaling and rotation, i.e., two-parameter transformation. Formally, a4Dvar does not allow for optimization of the open-boundary condition, but according to <https://swanmodel.sourceforge.io/download/zip/swanuse.pdf> (accessed on 20 May 2026), “SWAN replaces the imposed waves at the boundaries that propagate into the computational area with the computed waves that move out of the computational area at the boundaries”. Thus, the wind adjustment may also cause partial optimization of the open-boundary conditions. We utilized realistic errors for the wave spectrum and SWH observations from moorings. For the optical cable observations, SWH errors were assumed to be 0.1 m, which is twice as large as the errors for the SWH observations from the mooring.

The quality of all OSSEs was quantified by the improvement of the RMS errors of the SWH (ϵ_H), wave direction (ϵ_d), and wind errors (ϵ_w), during the period of data assimilation (0–5 h), and the short-range (5–12 h) and long-range (12–24 h) forecasts. It was found that for regular and relatively calm winds, the network of optical cables provides the best forecast with respect to SWH errors for all analyzed periods. However, assimilation of the wave spectra from a mooring yields better optimization of the wave direction and wind forcing attributed to strong correlation between waves and winds, and relatively small amplitudes of the swell. The assimilation of the observations, from the single optical cable, usually produces SWH errors twice as large as those from the mooring observations.

For stronger (10–20 m/s) winds, observations from the mooring yields more accurate forecasts both for the short- and long-range forecast periods, but the cable network provides superior accuracy during the data assimilation period. We attribute this to the cable network’s better capability of optimizing the initial conditions. Controversially, mooring observations allows better optimization of the wind forcing, which tends to better support the long-range forecasts.

These results are also relevant to ocean surface boundary layer processes under low-wind conditions. In this regime, local wave generation is weak, and the wave field is more controlled by initial conditions, incoming waves at the open boundaries, and coastal bathymetry. Therefore, sparse observations may be insufficient to constrain the surface wave field. Our OSSEs show that cable SWH observations help to constrain spatial distribution of wave energy, while mooring spectra better constrain wave direction and wind forcing. This suggests that the two observing platforms are complementary for low-wind Arctic coastal conditions, where air–sea momentum exchange, Stokes drift, and near-surface mixing are difficult to estimate.

Experiments with real observation from a wave mooring and a single optical cable were validated against the SWH observations from satellite tracks. We found that observations from moorings reduce the FG errors by 20–40%, while the optical cable reduction ranges around 15%, agreeing well with the OSSE results using synthetic observations, and indicate that wave mooring data provide more accurate wave forecasts than the observations from a single optical cable. However, in both cases, the impact of the observations is limited to the central region covered by observational platforms because open-boundary conditions cannot be fully optimized using the a4Dvar approach.

Due to data availability, the experiments with real observations were conducted for relatively weak winds of ~5 m/s. These results agree well with the results of the corresponding OSSEs, so we may expect that the impact of the spectral observations from a single mooring may be even more significant for stronger winds of 15–20 m/s, as it was in the OSSEs with double wind forcings.

We conducted OSSEs for realistic northern and north-easterly winds conditions and doubled wind amplitude. These wind conditions correspond well to the climatological winds observed in the Prudhoe Bay meteorological station, which are predominant easterly during July, August, and September, gradually increasing from about 9 mph to 12–15 mph by the end of September. Thus, our results should be robust for the major part of the ice-free period. Due to approximate east–west symmetry of the coastline, our results are likely to be valid for the westerly winds as well.

The approach utilized can be applied for other regions as well. However, the spatial scale of the domain should not exceed 200–300 km. This limitation is due to simplified representation of the wind control and our assumptions that the background wind forcing field varies insignificantly across the wave model domain (100–300 km) during the period of several days. For larger domains, the wind adjustment algorithm should include additional degrees of freedom, so the wind adjustment method should be modified. One of the options could be weighted wind corrections on the coarse (~200 km) spatial grid, consistent with the decorrelation scale of the wind forcing. Another option is to use a wind ensemble, which is available in the ERA5 reanalysis. Note that, in early summer, ice may still occupy the northern part of the modeled domain. In this case, ice concentration and/or thickness should be taken into account for wave attenuation in the ice-covered subregions. There is also a possibility to use wind and ice ensembles from ERA5 and conduct the joint optimization of the wind–ice forcing.

The inability to optimize the open-boundary conditions remains one of the drawbacks of the a4Dvar approach. To some extent, this can be alleviated by conducting assimilation in a larger region. Note that the increase in the domain may be relatively moderate, because as it was discussed, assimilation significantly improves solution in almost the entire model domain with exception of 10–15 grid points along the boundaries, where waves are entering into the model domain.

In this case, it might also be reasonable to assimilate all available SWH satellite observations, as well. As was shown before, spaceborne observations of surface waves,

being the least numerous, usually have a noticeable effect when assimilated in combination with other types of data. In this respect, it would be especially important to assimilate SWH data from the SWOT mission, whose data volume may be comparable with observations from the optical cables.

Our study is based on multiple OSSEs conducted that address the question, “what is the accuracy of the forecast if we use some particular set of the observations”, but does not specify optimal locations for collecting the observations. Meanwhile, there is a more advanced adjoint sensitivity analysis approach which allows for the optimization of the observational locations with respect to obtaining the best estimates of any Quantity of Interest (QoI, e.g., SWH distribution in some particular region). The approach uses the TL/ADJ model and backpropagates the uncertainties from any QoI, thus defining the observational sites with the highest correlation with specified QoI [7,8]. However, it cannot be realized in the framework of the a4Dvar approach due to the absence of the TL/ADJ model.

In the presented OSSEs, we assumed relatively high (0.1 m) errors of the SWH observations from the optical cables. Single-cable experiments with larger (~0.2 m) SWH errors show a weak impact on the optimized solution for the strong wind conditions, but for the weak winds, the large errors of the cable SWH may be critical. However, these results were obtained under the assumption of non-correlated errors and may change if cable SWH errors are correlated on the larger spatial scale. We also conducted several experiments with SWH errors of 0.05 m, which only slightly improved the skill of the single-cable observational platform. Note also that optical cables may, in principle, provide additional information (e.g., non-directional wave spectrum). This analysis could be an interesting topic for future research.

We do not discuss the cost of different observational systems here. The cost may depend on different factors. For example, expense of the deployment of a moored drifter can be significantly reduced using the local fishing boats of opportunity. From the other side, optical cable observations require deployment of the expensive DAS Interrogator Unit, which usually cannot be left unattended during the winter period.

Results of the present study can contribute to the design of wave monitoring systems that use variational data assimilation into State-of-the-Art wave models [11,31] lacking comprehensive adjoint and tangent linear codes. Today, developing such systems is particularly important for the Arctic seas, which are experiencing a significant increase in SWH variability associated with ongoing ice retreat driven by climate change (e.g., [30,32]).

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Data Availability Statement: All data utilized for this research are from open sources. All inputs to the model experiments are from idealized conditions, as specified in this paper. Model results in this study are securely stored at the Navy DSRC archive server and can be accessed after obtaining an account at the facility. The corresponding author can be contacted for information to access the archived data once an open account has been established.

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