Performance Statistics of a Real-Time Pacific Ocean Weather Sensor Network

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ABSTRACT: A distributed sensor network of over 100 free-drifting, real-time marine weather sensors was deployed in the Pacific Ocean beginning in early 2019. The Spotter buoys used in the network represent a next-generation ocean weather sensor designed to measure surface waves, wind, currents, and sea surface temperature. Large distributed sensor networks like these provide much needed long-dwell sensing capabilities in open-ocean regions. Despite the demand for better weather forecasts and climate data in the oceans, direct in situ measurements of marine surface weather (waves, winds, currents) remain exceedingly sparse in the open oceans. Because of the large expanse of Earth's oceans, distributed paradigms are necessary to create sufficient data density at global scale, similar to advances in sensing on land and in space. Here we discuss initial findings from this long-dwell open-ocean distributed sensor network. Through triple-collocation analysis, we determine errors in collocated satellite-derived observations and model estimates. The correlation analysis shows that the Spotter network provides wave height data with lower errors than both satellites and models. The wave spectrum was also further used to infer wind speed. Buoy drift dynamics are similar to established drogued drifters, particularly when accounting for windage. We find a windage correction factor for the Spotter buoy of approximately 1%, which is in agreement with theoretical estimates. Altogether, we present a completely new open-ocean weather dataset and characterize the data quality against other observations and models to demonstrate the broad value for ocean monitoring and forecasting that can be achieved using large-scale distributed sensor networks in the oceans.

KEYWORDS: Waves, oceanic; Altimetry; Buoy observations; In situ oceanic observations

1. Introduction

Over the past century, a tremendous expansion in sampling of the ocean has facilitated broad progress in our understanding of ocean processes (Davis et al. 2019). Ship-based sampling, underwater gliders, Argo floats, and moored platforms have all contributed to monitoring of chemical, biological, and physical dynamics in the ocean. Despite this progress, Earth's oceans remain heavily undersampled because of the vast scale. In contrast to land and space-based sensing, distributed sensing paradigms are not yet widely deployed in the oceans, and as a result, data density in open-ocean regions remains exceedingly low. Specifically, open-ocean weather data are sparse, and model skill is limited as a result. Marine weather is important for many industries, such as shipping operations and maritime safety, and for coastal inundation on exposed coastlines. Further, waves on the surface of the ocean are critical to describing many environmental processes due to their effect on air–sea interaction (Sullivan and McWilliams 2010; Cavaleri et al. 2012), transport and mixing (Xu and Bowen 1994; McWilliams et al. 2004), shelf exchange (Lentz

et al. 2008), and coastal dynamics (Longuet-Higgins 1970a,b; Battjes 1974; MacMahan et al. 2006). It is clear that accurate monitoring of open-ocean weather conditions has major economic and societal importance, in particular in the presence of a changing climate (Morim et al. 2019). Until recently, ocean sensing was dominated by prohibitively costly hardware, resulting in limited numbers of sensors and little data. Driven by progress in mobile technology, advances in photovoltaic and battery technology, and the increasing availability of alternative satellite communications, large-scale and persistent distributed sensing in the oceans has become increasingly possible.

In this work, we present results from a new distributed sensor network in the Pacific basin consisting of more than 120 sensor nodes. This network was deployed using vessels of opportunity in the period from early 2019 through summer 2020 and is rapidly expanding (both in the Pacific and beyond). All data are freely available to academic research groups worldwide. The network nodes are so-called Spotter buoys, small weather buoys developed by Sofar Ocean that are solar-powered and connected to the internet through satellite. The buoys measure displacement with GPS to calculate the wave spectrum, derive the surface wind stress (and U_{10}), and measure sea surface temperature with hull-mounted temperature sensors. This work describes progress up to mid-2020, and continued developments, particularly to the surface wind inference enabled by the full transmission of the wave spectra, are ongoing.

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FIG. 1. (a) A schematic of Spotter with an attached chain for the free-drifting configuration (not drawn to scale). The housing diameter is 0.38 m, and the 13-link-long attached chain is approximately 0.6 m. (b) A Spotter deployed in San Francisco Bay in 2019.

The Pacific Ocean buoy network with collocated wave and wind measurements complements remote sensing from space, coastal networks, and other drifting networks. Specifically, the Spotter network augments in situ data such as from the Argo program, which primarily focuses on the vertical structure of the water column, as well as NOAA's Global Drifter Program, which has approximately 1500 drogued buoys across the world's oceans gathering temperature, pressure, and surface drift velocities (Elipot et al. 2016). The addition of the new distributed network with open-ocean wave-sensing ability can contribute to filling spatial and temporal gaps in coverage and provide complementary measurements for comparative studies, understanding of wave-driven surface processes, and calibration.

In this work, we provide a description of the new distributed ocean network and an analysis of its performance characteristics. Section 2 describes the network and methods of comparison with other observation approaches. Section 3 presents results on the relative performance of Spotter for waves and wind and characterizes its drift dynamics relative to currents. Section 4 discusses the accuracy of measurements and sources of error and section 5 summarizes the utility of the Spotter sensor network and future development toward global ocean observations.

2. Methods

a. The sensor network

As of June 2020, approximately 120 free-drifting Spotter buoys are active in the Pacific Ocean. The network of Spotters was scaled up over approximately four months from April 2019 to July 2019, primarily through collaboration with ships of opportunity. The Spotter buoys were transported in a ready-for-deployment configuration so that they could be dropped into the water from heights of over 30 m, allowing for a streamlined process to seed units across the Pacific with minimal labor from crew. During the initial deployment period, drop locations were chosen to provide maximal spatial coverage while accounting for the time-varying topology of the network. Subsequent Spotter deployments were then focused on network maintenance, filling sparsely sampled regions and regions of rapid divergence of the network.

The Spotter buoy is an approximately spherical surface-following drifter weighing 5.5 kg with a diameter of 38 cm. While the Spotter can be utilized in both a moored and free-drifting configuration (Raghukumar et al. 2019), only the free-drifting units were considered in this analysis. In the free-drifting configuration, a chain (0.6 m long, 1.27-cm-thick steel, with 13 links) and an additional 0.4-kg ballast weight were connected to the base of the Spotter housing to increase stability and fit buoyancy specifications. Specifically, in this configuration the Spotter sits approximately half submerged (Fig. 1). Hull-mounted solar panels provide power to continuously sample indefinitely. However, it is estimated that because of biofouling and degradation the operational lifetime of each Spotter may be between 3 and 5 years. After the initial scale-up period in 2019, more than 12 months of continuous coverage were provided, primarily of the northern Pacific Ocean (Fig. 2).

The buoys are connected to the internet through an Iridium satellite modem allowing near-real-time transmission of data (two new observations transmitted every hour, with negligible latency). The Spotter buoy has the capability to transmit the full wave spectrum; however, in this study, only the bulk parameters were transmitted.

b. Wave measurements

The Spotter buoy obtains wave height estimates with an onboard GPS that measures 3D surface displacements at 2.5 Hz. The complete 3D cross-correlation matrix is computed on board and the designated spectral components and bulk wave parameters are transmitted. During the period from April 2019 to June 2020, most sensors transmitted bulk wave parameters only. Further technical details and validation of wave height measurements can be found in previous work by Raghukumar et al. (2019).

In this analysis, the performance of the Spotter buoy measurement of significant wave height was characterized relative to other methods. In addition to in situ buoys, numerical simulations and satellite observations are used to estimate wave height in the open ocean. However, each method relies upon different assumptions and samples the field over different periods (i.e., long dwell vs short dwell), ultimately measuring different quantities based on varying spatial and temporal resolutions. As a result, determining a ground truth for wave

FIG. 2. Spotter locations (dots) and tracks (lines) (a) from August to October 2019 and (b) from April to June 2020.

height in the ocean, particularly with high spatial and temporal coverage, remains challenging.

Numerical models, such as NOAA's WaveWatch 3 (henceforth NOAA WW3; [WaveWatch III Development Group 2016](#)), provide complete coverage at high spatial and temporal resolution but rely on the accuracy of the initial conditions, particularly the wind forcing. Alternatively, satellite altimeters provide observation-based estimates of wave height from empirically calibrated functions of measured backscatter. However, satellite data are limited to the narrow tracks (on the order of 5 km in width) that the satellite passes over and global coverage takes 5–10 days. Currently, altimeter measurements are often considered the ground truth and assimilated into models (e.g., [Lionello et al. 1992](#); [Voorrips and De Valk 1997](#)) despite noise and reliance upon tuned relationships to backscatter.

To intercompare Spotter measurements without a ground truth, an approach to obtain error estimates using triple collocated measurements was used ([Stoffelen 1998](#); [Janssen et al. 2007](#)). Specifically, we collected all wave height estimates recorded by the Spotter buoys that overlapped with satellite altimeter wave height measurements [*Satellite with Argos and AltiKa* (SARAL) and *Jason-3* satellites; [NASA JPL 2013, 2016](#)], separated at most by 0.5 h and approximately 50 km. The NOAA WW3 model was subsequently queried as a third data source at all collected points. The NOAA WW3 model data at 0.5° spatial resolution and 1-h temporal resolution were interpolated in space and time to match the Spotter location and time in the collection of collocated measurements. The altimeter data contained clear outliers (disagreement with both other sources by greater than 2.5 m) that were removed from the analysis.

TRIPLE COLLOCATION

Following the assumption that measurements of significant wave height H depended on the truth in a linear fashion, we used the triple collocated measurements to gain an estimate of

error from each source. It is assumed that each measurement followed

$$H_{i,\text{meas}} = \beta_i H_{\text{truth}} + e_i, \quad (1)$$

where i corresponds to the measurement method (Spotter, altimeter, or model), $H_{i,\text{meas}}$ is the wave height estimated by that method, H_{truth} is the true wave height at that location and time, β_i corresponds to the linear calibration coefficient for that method, and e_i corresponds to the residual error of the method. The errors, which were assumed to be uncorrelated between sources, were then estimated by first eliminating the calibration coefficients β_i by introducing new variables,

$$H'_{i,\text{meas}} = H_{i,\text{meas}} / \beta_i \quad \text{and} \quad e'_i = e_i / \beta_i. \quad (2)$$

This yielded the calibration coefficient-free equations

$$H'_{i,\text{meas}} = H_{\text{truth}} + e'_i \quad (3)$$

that were then pairwise subtracted to eliminate the ground truth from the equation set. Specifically,

$$\begin{aligned} H'_{\text{Spot, meas}} - H'_{\text{mod, meas}} &= e'_{\text{Spot}} - e'_{\text{mod}} \\ H'_{\text{Spot, meas}} - H'_{\text{alt, meas}} &= e'_{\text{Spot}} - e'_{\text{alt}} \\ H'_{\text{mod, meas}} - H'_{\text{alt, meas}} &= e'_{\text{mod}} - e'_{\text{alt}}. \end{aligned} \quad (4)$$

Relying on the assumption that the error was uncorrelated between sources, each equation was then pairwise multiplied to isolate the individual error following

$$\begin{aligned} \langle e'^2_{\text{Spot}} \rangle &= \langle (H'_{\text{Spot, meas}} - H'_{\text{mod, meas}})(H'_{\text{Spot, meas}} - H'_{\text{alt, meas}}) \rangle \\ \langle e'^2_{\text{mod}} \rangle &= \langle (H'_{\text{mod, meas}} - H'_{\text{Spot, meas}})(H'_{\text{mod, meas}} - H'_{\text{alt, meas}}) \rangle \\ \langle e'^2_{\text{alt}} \rangle &= \langle (H'_{\text{alt, meas}} - H'_{\text{Spot, meas}})(H'_{\text{alt, meas}} - H'_{\text{mod, meas}}) \rangle. \end{aligned} \quad (5)$$

Neutral regression was then used to solve for the calibration coefficients and iteratively solve for the unscaled error from each method. See [Janssen et al. \(2007\)](#) for further details.

With the triple collocated measurements, we were then able to determine the residual error of each method. While this approach was unable to account for potential nonlinear dependence on the truth (e.g., bias at high values), this method, in combination with pairwise comparison among each independent source, provided an estimate of expected errors. To note, this approach relies upon determination of a linear calibration coefficient β for each method that can only be determined relative to values for the other methods. The collocation approach requires initially setting β equal to one for one method and then solving for the other two β values. However, the relative β magnitudes are constant regardless of which method is chosen as the baseline and, importantly, the error estimates are unaffected by initial choice (Janssen et al. 2007).

c. Wind measurements

Wind speed and direction were inferred from the wave spectrum on board each Spotter using the inherent coupling between waves and the winds driving the wave field. The proxy measurement was implemented based on Thomson et al. (2013). Specifically, assuming that the wind forcing was stationary and homogeneous, the equilibrium range took the form

$$E(f) = E_0 f^{-4}, \quad \text{where} \quad E_0 = \frac{4\beta I u_* g}{(2\pi)^3}, \quad (6)$$

for $f > 1.3f_p$ where f corresponds to frequency, f_p corresponds to the peak frequency, u_* is the friction velocity, and $I = 2.5$ is the Phillips directional constant (Phillips 1985). Assuming a logarithmic wind speed profile, the U_{10} wind speed was related to u_* following

$$U(z) = \frac{u_*}{\kappa} \ln\left(\frac{z}{z_0}\right), \quad (7)$$

where κ is the von Kármán constant, assumed to be 0.4. The roughness length z_0 was obtained from the Charnock relationship (Charnock 1955) following

$$z_0 = \alpha \frac{u_*}{g}, \quad (8)$$

where g is gravity and α is the Charnock constant, chosen as 0.012 (Charnock 1955).

In practice, the onboard Spotter algorithm first found an equilibrium range spanning 20 frequency bins (≈ 0.01 -Hz bin width) within the discrete wave energy spectrum with the minimum variance from an f^{-4} slope. Once the equilibrium range best fitting f^{-4} was found, Eqs. (6) and (7) were combined to solve for U_{10} . The mean wind direction θ (in degrees anticlockwise from east) was then estimated from the Fourier coefficients of the directional distribution (Kuik et al. 1988) following

$$\theta = 270^\circ - \frac{180^\circ}{\pi} \text{atan2}\left(\frac{\bar{b}_1}{\bar{a}_1}\right), \quad (9)$$

where $\bar{a}_1$ and $\bar{b}_1$ are the observed Fourier coefficients averaged over the equilibrium range.

To assess the Spotter wind estimates, triple collocation of measurements followed the same approach as for waves. The satellite altimeters reported inferred winds in conjunction with the wave height; therefore, all the same measurement locations were used. The National Centers for Environmental Prediction Global Data Assimilation System (GDAS) was used as a model data source, providing component-wise wind estimates at hourly temporal resolution and 0.25° spatial resolution.

d. Drift measurements

The drift dynamics of the Spotter buoy were characterized with the buoy locations reported every 30 min. Spotter has a semiexposed spherical design with a chain extending 0.6 m below the surface; therefore, drift velocities are a combination of both surface currents and wind forcing.

Other traditional drifting buoys, such as those from NOAA's Global Drifter Program (GDP), include a drogue that is often several meters long centered tens of meters deep, aimed to reduce the influence of wind drag. Conversely, Spotter buoys possessed only a single chain extending approximately 0.6 m directly below the surface-following buoy housing. Given the variation in buoy designs, we characterized the Spotter drift behavior relative to other drifters as well as estimates of the underlying currents. To calculate the u and v velocity components of the Spotter, we applied a 12-h smoothing window to the latitude and longitude tracks, calculated the great-circle distance traveled between each waypoint reported every 30 min, and divided by the time difference between location reports.

Similar to wind and waves, typical operational estimation of currents is done with models and satellite observations. Ocean Surface Current Analysis Real-Time (OSCAR) currents were obtained for the period from February 2020 to June 2020 [Earth Space Research (ESR); ESR 2009]. These measurements were collocated with Spotter drift estimates within 12 h and 50 km. A third measurement was obtained from HYCOM, collocated with the Spotter measurement time and location. The HYCOM model data at approximately $1/12^\circ$ spatial resolution and 3-h temporal resolution were interpolated in space and time to match the Spotter location and time.

Currents pose additional difficulty because of the three-dimensional variability of the flow, particularly near the surface. Moreover, there are numerous physical drivers of currents with varying spatial and temporal scales whereas individual inferential methods typically only account for a subset of the full physics. For example, the OSCAR program utilizes sea surface height, wind, and temperature from satellites to run a quasi-steady geostrophic model and estimate currents (Bonjean and Lagerloef 2002). However, OSCAR lacks unsteady dynamics from small-scale wind driven flow and the smoothed dynamic topography leads to underestimation of current magnitudes (Bonjean and Lagerloef 2002). Further, due to the reliance on the overpass of a satellite, OSCAR has a temporal resolution of 5 days. Computational circulation models, such as HYCOM, run a global circulation model that relies on several turbulence parameterizations, thus capturing synoptic and mesoscale patterns well but not accurately representing the submesoscale features (Wallcraft et al. 2003). Consequently, attempting to estimate errors utilizing the triple

collocation method is inaccurate as each source was sampling unique aspects of the flow and a linear dependence on the truth was not appropriate. For that reason, we considered both direct comparison of measurements at the same location from different sources and inspection of the overall velocity distributions produced by different sources to provide insight into estimates of the currents from different measurement approaches.

1) WINDAGE CORRECTION AND FIELD VALIDATION

To account for the wind-induced drift due to the partial exposure of the Spotter and lack of a drogue, a percentage (or wind factor α) of the wind was assumed to affect the Spotter drift velocity components in addition to currents:

$$\mathbf{u}_{\text{Spotter}} = \mathbf{u}_{\text{current}} + \alpha \mathbf{u}_{\text{wind}} \quad (10)$$

The windage-corrected values of Spotter drift, $\mathbf{u}_{\text{Spotter}} - \alpha \mathbf{u}_{\text{wind}}$, could then be used as estimates of the underlying currents. While previous work, such as by Dagestad and Röhrs (2019), has accounted for Stokes drift in Eq. (10), inclusion of Stokes drift estimates did not significantly change results (not shown), and Stokes drift is therefore neglected.

Spotter windage experiments were conducted in the Pacific Ocean off the coast of Santa Barbara, California, in August 2019. In these experiments, three Spotter buoys and one Surface Wave Instrument Float with Tracking (SWIFT v4; Thomson et al. 2019) were simultaneously released from the same location. The set of four instruments drifted approximately 1.8 km over 1.1 h. Over the entire experiment, all Spotter buoys drifted roughly parallel to the SWIFT, maintaining a proximity of less than 200 m. The SWIFT reported 15 min-averaged 10-m wind speed and surface current velocity at 1-m depth calculated from the onboard downward-looking Signature1000 ADP. The SWIFT current velocities were then interpolated to match the Spotter time stamps for comparison.

2) NOAA GLOBAL DRIFTER PROGRAM

To characterize Spotter drift dynamics relative to other Lagrangian drifters, trajectories from NOAA's Global Drifter Program (henceforth GDP drifters; Lumpkin and Centurioni 2019) were collected from March 2020 to June 2020 in the northern Pacific Ocean. GDP drifters were designed to follow the flow, with an approximately 4-m-long drogue, centered 15 m below the surface buoy. Drifter locations were smoothed with a 12-h moving window, and the great-circle distance was calculated between waypoints and divided by the time difference to obtain velocities.

3. Results

a. Waves

A total of 9476 wave measurement triplets were collocated from April 2019 to June 2020 (Fig. 3). All three sources exhibited minimal bias (less than 0.04 m) when compared with each other. Spotter and altimeter measurements exhibited the lowest root-mean-square error (RMSE) of 0.29 m and the

highest Pearson correlation coefficient of 0.97 (Fig. 3). The other pairwise comparisons (Spotter vs WW3; altimeter vs WW3) were similarly in agreement, albeit with slightly higher RMSE. The triple collocation method yielded error estimates of 0.18 m for Spotter, 0.23 m for altimeter, and 0.30 m for NOAA WW3. For the triple collocated wave measurements, the relative β s were found to be 1.000:1.002:1.019 for the altimeter:Spotter:NOAA WW3, indicating nearly a direct linear dependence upon the truth (i.e., a slope of 1).

b. Wind

A total of 9476 wind measurement triplets were collocated from the Spotter, satellite altimeter, and GDAS model. Spotter utilized a preliminary wind inference algorithm, and data were analyzed prior to transmission of full wave spectra and subsequent algorithmic improvements. Wind speed values were reported in 0.5 m s^{-1} bins, resulting in distinct bands in the scatter in Fig. 3. Wind values ranged up to 20 m s^{-1} and bias was largest for the Spotter, notably underestimating high wind speeds that were otherwise approximately in agreement between the altimeter and GDAS. As a result, Spotter versus model and Spotter versus altimeter comparisons had root-mean-square errors of 2.82 and 2.33 m s^{-1} , respectively (Fig. 3). Overall, the altimeter and the model exhibited the strongest agreement, with an RMSE of 1.63 m s^{-1} for all wind speeds. Higher error relative to the measurement magnitude was observed for wind (approximately 15%–19%) than for waves (approximately 6%–8%). The triple collocation error estimation yielded 1.68 m s^{-1} for Spotter, 0.77 m s^{-1} for the altimeter and 1.39 m s^{-1} for the model. The calibration coefficients β scaled as 1.000:0.822:1.046 for the altimeter:Spotter:model.

c. Drift velocities

1) TRIPLE COLLOCATION

With approximately 100 000 collocated points, large relative scatter was observed for all comparisons between Spotter, HYCOM, and OSCAR (Fig. 4). There was a consistent RMSE of 0.16 to 0.19 m s^{-1} for each pairwise comparison of current components with magnitudes typically less than 1 m s^{-1} . Overall, OSCAR reported notably lower magnitude values, with an average of approximately 0.1 m s^{-1} for OSCAR versus approximately 0.2 m s^{-1} for HYCOM and Spotter. Overall, the correlation coefficients were low, ranging from 0.45 up to 0.62, indicating poor agreement of instantaneous motion. The distributions of velocities from each source indicated substantially better agreement between HYCOM and Spotter than versus OSCAR (Fig. 5).

2) WINDAGE CORRECTION

The HYCOM model estimates and Spotter drift estimates possessed similar distributions, albeit with a slight bias toward higher values for Spotter. Assuming the simple windage correction model of Eq. (10), a linear regression of $\mathbf{u}_{\text{Spotter}} - \mathbf{u}_{\text{HYCOM}}$ yielded wind factors of approximately 0.01. Applying a wind correction factor of 1% to every Spotter velocity altered the overall distribution of Spotter current estimates, reducing the distance between distributions [measured with

FIG. 3. Triple collocation of wave measurements from Spotter, NOAA WaveWatch 3 model, and satellite altimeters from July 2019 to June 2020. (top) Significant wave height and (bottom) wind speed are compared.

a Kullback–Leibler (KL) divergence]. To note, the KL divergence was globally minimized by a factor of 0.0065; however, a value of 0.01 was used to represent a reasonable level of precision to be expected for a windage correction across conditions. Wind experienced by Spotter varied among observations; therefore, pointwise correction of the drift modified the overall distribution shape, reducing the spread and raising the peak to better match the normalized HYCOM distribution (Fig. 6).

A theoretical estimate for the expected windage can also be derived by considering an idealized, half-submerged sphere with zero current and no chain. At steady state, the drag force from the wind on the upper half of the sphere would match the drag force from the water on the lower half of the sphere following

$$F_{\text{air}} = \frac{\rho_{\text{air}}(\mathbf{u}_{0.08} - \mathbf{u}_{\text{Spot}})^2 AC_d}{2} = \frac{\rho_{\text{water}} \mathbf{u}_{\text{Spot}}^2 AC_d}{2} = F_{\text{water}}, \quad (11)$$

where ρ_{air} is the density of air, $\mathbf{u}_{0.08}$ is the wind speed at the geometric center height (0.08 m) of the exposed half sphere, A is the frontal area, and C_d is the drag coefficient. The near-surface-level wind can then be converted to the 10-m wind speed U_{10} , following a log-law wind profile [see Eq. (7)].

Using Eq. (7) evaluated at the two heights to solve for $\mathbf{u}_{0.08}$ yields

$$\mathbf{u}_{0.08} = \frac{\ln\left(\frac{0.08}{z_0}\right)}{\ln\left(\frac{10}{z_0}\right)} \mathbf{u}_{10} = 0.36 \mathbf{u}_{10}, \quad \text{for } z_0 = 0.005. \quad (12)$$

Combining Eqs. (11) and (12) yields a theoretical estimate for windage on a half-submerged sphere of

$$\mathbf{u}_{\text{Spot}} = \left(\frac{\rho_{\text{air}}}{\rho_{\text{water}}}\right)^{1/2} \left[1 + \left(\frac{\rho_{\text{air}}}{\rho_{\text{water}}}\right)^{1/2}\right]^{-1} 0.36 \mathbf{u}_{10} = 0.012 \mathbf{u}_{10} \quad (13)$$

or a wind factor α of 0.012, in agreement with the empirically derived windage factor.

d. Comparison with drogued drifters and underlying currents

The velocity statistics of Spotter and NOAA GDP drifters were compared in the northern Pacific Ocean from March 2020 to June 2020. NOAA GDP drifters exhibited lower median velocities of 0.19 m s^{-1} versus 0.23 m s^{-1} for the Spotter. Introducing a wind factor of 0.01, i.e., subtracting 1% of the collocated wind from each Spotter measurement, notably transformed the Spotter velocity distributions to better align with GDP drifter statistics. Specifically, inclusion of the wind factor shifted the overall magnitudes to lower values, closer to the GDP distribution and reducing the KL divergence (Fig. 7).

FIG. 4. Triple collocation of current estimates from Spotter, OSCAR, and HYCOM. Data points range from March 2020 to June 2020. (top) Northward and (bottom) eastward components are compared.

The wind factor that produced the minimum KL divergence between the Spotter speed distribution and NOAA GDP drifter speed distribution was found to be 0.011, similarly in agreement with other estimates.

e. Field experiments of spotter windage

With approximately 1.1 h of data corresponding to 135 measurements along the path, the effect of windage on the Spotter buoy drift was estimated by comparison between Spotter drift

and SWIFT current estimates. Equation (10) with $\alpha = 0.01$ provided a reasonable windage correction. That is, subtracting 1% of the wind observed by the SWIFT from the Spotter buoy drift velocities reduced the RMSE of the Spotter–SWIFT comparisons of the u component and magnitude of velocity (Fig. 8). The v -component current and drift velocities were very near zero and negligible northward wind was observed (averaging less than 1 m s^{-1}), thus corrections of this component were not important to the overall accuracy of the

FIG. 5. Normalized distribution of triple collocated (within 12 h and 50 km) current velocity estimates from Spotter, HYCOM, and OSCAR.

FIG. 6. Normalized histograms of collocated velocity components and magnitudes for Spotter buoys and the HYCOM model: (top) original measurements and (bottom) with a correction of 1.0% of the onboard inferred wind speed subtracted from each Spotter velocity measurement.

magnitude. The windage correction improved the agreement between the Spotter u -component distribution and the SWIFT reported values (Fig. 9).

4. Discussion

a. Waves

Triple collocation of significant wave height from Spotter, WW3 model, and altimeters indicated the high fidelity of Spotter measurements across the Pacific basin and reasonable agreement among sources. Discrepancy between measurement methods likely arose from instrument noise and calibrations, as well as the inherent differences in what each instrument was measuring. The altimeter relies upon backscatter measured by a satellite overpass; therefore, data represent mean wave conditions averaged over space and time. As a result, observed wave properties are expected to be smoother than an in situ instrument that only averages conditions in time. Consequently, Spotter-observed true small-scale variability is not represented in other data sources and is therefore attributed to noise in the triple collocation analysis. As a consequence, Spotter errors from the triple collocation analysis are likely an upper bound, and errors for free drifting Spotters are likely to be similar to those observed in moored conditions in

previous studies validating moored Spotter buoys against other in situ wave height sensors (Raghukumar et al. 2019).

b. Wind

Wind triple collocation yielded the lowest error estimate for the altimeter, although the assumption of random noise and linear dependence on the truth for all sources was less reasonable given the large Spotter bias at high windspeeds. The large bias in the Spotter estimate was likely from either not effectively finding the equilibrium region in the recorded discrete wave spectrum or lack of an equilibrium range due to young, energetic seas. Algorithmic improvements to determination of the equilibrium region and flagging when equilibrium assumptions are not met could improve future wind estimates. Further, improvements to the method, as discussed in Voermans et al. (2020), may further increase fidelity. These improvements will be explored in future work when the full wave spectrum, rather than just bulk parameters, is transmitted. Errors were on the order of $1\text{--}3\text{ m s}^{-1}$ from all sources, indicating that (with further algorithmic improvements) compact wave buoys can provide useful proxy wind observations for many use cases when other instrumentation is unavailable.

c. Drift

The triple collocation of satellite, model, and Spotter-derived currents indicated the challenges of capturing both

FIG. 7. Normalized histograms of velocity components and magnitudes for Spotter buoys and AOML drifters. Every data point in the resultant bins is independent (i.e., not collocated with another), and only measurements from March 2020 to June 2020 in the northern Pacific Ocean were included. (top) Shown are the (top) original measurements and (bottom) with a correction of 1.0% of the onboard inferred wind speed subtracted from each Spotter velocity measurement.

the instantaneous small-scale motions along with the overall distribution of velocities for a given measurement technique. Comparison among satellite and model sources indicated that the Spotter buoy does reasonably sample the surface currents.

The Spotter was expected to experience windage, and this was apparent in the bias toward higher speeds relative to the collocated HYCOM estimates. Both data-driven and theory-based arguments estimated windage for spherical buoys

around 1% of the surface wind, in agreement with studies of similar form factor buoys (Dagestad and Röhrs 2019). With wind speed and direction calculated on board, the current velocity accounting for windage could be calculated fully by the Spotter without dependency on external data sources.

The disparity between both Spotter and OSCAR, and between HYCOM and OSCAR (and agreement between Spotter and HYCOM distributions) suggests that Spotter was sampling

FIG. 8. Scatterplot of velocity estimates from Spotter drift vs the SWIFT current meter. Both the unmodified Spotter drift (black) and 1% wind factor (blue) are compared with the current estimates.

FIG. 9. Normalized histograms of velocity components and magnitudes for Spotter buoy drift and SWIFT currents. Measurements were obtained over approximately 1.1 h as the instruments drifted 1.8 km while maintaining a proximity of less than 200 m to the SWIFT current meter. (top) Original (uncorrected for windage) velocity distributions of Spotter drift and collocated SWIFT-measured currents. (bottom) A correction of 1% of the observed wind speed was subtracted from each Spotter velocity measurement and compared with the same SWIFT-measured currents.

the small-scale eddy features that are not captured by a quasi-steady geostrophic model with smoothed dynamic topography (Bonjean and Lagerloef 2002). Further, the large scatter for comparisons between Spotter and HYCOM are likely attributable to inaccuracies in the representation of small-scale motions in HYCOM, which may be misplaced in space, time, or both. However, the velocity magnitude distributions were comparable to what the Spotter sampled (Fig. 5).

Comparison of Spotter buoys with the NOAA GDP drifters indicated similar statistics and provided further characterization of expected Spotter dynamics. However, NOAA GDP drifters are drogued at 15-m depth; therefore, Spotter and GDP drifters are sampling physically different flow fields in addition to sampling at different spatial and temporal locations. Nonetheless, we saw strong agreement between drift statistics of the two drifters with wind corrected Spotter drift velocities slightly larger than GDP drifters as expected for surface (Spotter) versus 15-m depth (GDP).

5. Conclusions

A distributed sensor network consisting of over 100 free-drifting, real-time buoys was deployed in the Pacific Ocean

beginning in early 2019. The sensor network provides estimates of bulk wave parameters, wind, and drift velocity every 30 min and has demonstrated sustained performance for over 12 months with negligible degradation of sampling integrity. Further, the free-drifting sensor network maintained spatial coverage while drifting over the 12-month period (Fig. 2).

Errors in wave height observations were estimated by a triple collocation comparison of Spotter observations with satellite and models, demonstrating reduced errors from the buoy observations. Wind proxy observations at present are less reliable, with higher scatter and likely inaccuracies if equilibrium assumptions are invalid (young seas). Current results indicate that wind inversion from buoys has potential as an additional proxy observation for wind speeds below 10 m s^{-1} if reliable data quality metrics can be formulated. Further, with full spectral data now transmitted from the network, the algorithm itself will be further improved upon. In addition, drift velocity statistics were found to be comparable to those from GDP drifters, HYCOM currents, and currents observed during a field experiment when corrected with a 1% windage factor. The field experiment demonstrated that, with windage correction, drift velocities compared well to

direct flow observations. While such a direct verification could not be conducted in the open ocean, agreement in statistical distributions (once corrected for wind), combined with results from the field experiment suggest that drift velocities describe the surface flow field well.

The effort reported here is ongoing, and the network is planned to expand in scope and capability. As of September 2020, the first 30 units were deployed in the Indian Ocean and South Atlantic Ocean, and expansion of the network to the North Atlantic is under way. Further, measurements from the network have already begun being incorporated into operational wave models, increasing model forecast accuracy, with opportunities for further gains from advanced assimilation techniques (Smit et al. 2021). We hope that this new dataset, freely available for approved research purposes, will contribute to our growing capacity to observe and understand the open ocean.

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Data availability statement. Historical data from Spotter buoys, including those used in this study, are freely available for research use through Sofar Ocean Technologies by contacting the authors or requesting them online (<https://www.sofar-ocean.com/products/sofar-free-marine-data-for-research>).

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