

1 **Acoustic Doppler Current Profiler Measurements from Saldrones, with**
2 **Applications to Submesoscale Studies**

3 Paban Bhuyan,^a Cesar B. Rocha,^b Leonel Romero,^a and J. Thomas Farrar ^c

4 ^a *University of Connecticut, Avery Point, CT, USA*

5 ^b *University of São Paulo, São Paulo, SP, Brazil*

6 ^c *Woods Hole Oceanographic Institution, Woods Hole, MA, USA*

8 ABSTRACT: Characterizing submesoscale ocean processes requires high-resolution observations
9 in both space $O(1 \text{ km})$ and time $O(1 \text{ hr})$. One way to resolve submesoscale features is to deploy
10 multiple mobile platforms, such as Saildrones (SDs), to achieve high-resolution synchronous
11 measurements, but this requires velocity accuracies of $O(1 \text{ cm/s})$ to resolve submesoscale velocity
12 gradients. In this study, we first assess Saildrone Acoustic Doppler Current Profiler (ADCP)
13 measurements against a high-quality shipboard (R/V *Oceanus*) ADCP data, both collected during
14 the Sub-Mesoscale Ocean Dynamics Experiment (S-MODE). The results show that the standard
15 5-minute average Saildrone ADCP along-track velocity difference variability (3 cm/s) is consistent
16 with shipboard ADCP data, confirming its suitability for submesoscale studies. However, direct
17 ADCP comparisons between a Saildrone and the R/V *Oceanus* give small biases ($\sim 1 \text{ cm/s}$). The
18 biases are unlikely due to the surface waves, whose signal is expected to be significant near the
19 surface; they are more likely be associated with spatial inhomogeneities. We also examined the
20 1 Hz Saildrone ADCP data to determine the best averaging window for high-resolution analyses
21 and found that averaging over 3 minutes ($\sim 250 \text{ m}$ in space) reduces the noise to acceptable levels.
22 We investigate the uncertainty of submesoscale current gradients derived from Saildrone ADCP
23 measurements and find that the velocity gradient at a 2 km scale can be obtained with a $0.1f$
24 uncertainty using four Saildrones. The methodologies we developed to ascertain optimal averaging
25 window are versatile and applicable to other uncrewed surface vehicles (USV) or multiple-ship
26 arrays.

27 SIGNIFICANCE STATEMENT: Submesoscale currents, spanning from a few hundred meters
28 to several kilometers and lasting from hours to weeks, play a key role in transferring energy and
29 redistributing water properties, influencing air-sea interactions and shaping marine ecosystems.
30 However, observing these currents is challenging. Saildrone, an innovative platform, collects
31 oceanic and atmospheric data, including ocean currents, but assessing and refining this data
32 is essential for studying submesoscale processes. In this paper, we assess the ocean current
33 measurements from Saildrone and develop methods to characterize noise in the data. We then use
34 this improved data to estimate the uncertainty in the current measurements and their gradients,
35 helping us determine the reliability of the data for analyzing submesoscale flow characteristics.

36 1. Introduction

37 Submesoscale currents have emerged as an important component of the upper-ocean circulation.
38 These currents (in the vicinity of submesoscale fronts, filaments and vortices) with horizontal length
39 scales of 0.1-10 km and timescales of hours to days are characterized by order-one Rossby and
40 Richardsons numbers (McWilliams 2016), which makes them dynamically distinct from mesoscale
41 currents (Mahadevan and Tandon 2006). Submesoscale flows exhibit large vertical velocities (up
42 to several cm/s). These large velocities are believed to promote substantial exchanges between the
43 mixed layer and the pycnocline, as well as across the air-sea interface, with significant implications
44 for ocean biogeochemical and heat fluxes, respectively— eventually affecting climate (e.g., Lévy
45 et al. 2012; Su et al. 2018).

46 Most of our knowledge about submesoscale processes comes from theory and numerical models,
47 and therefore accurate spatio-temporal velocity observations are required for validation. In this
48 context, contemporary simultaneous autonomous observational tools and ship surveys, particularly
49 those utilizing the Acoustic Doppler Current Profiler (ADCP), stand out as apt choices for making
50 these observations. Shipboard current measurements using ADCPs have been a standard for
51 over forty years (Joyce 1989). ADCPs with a 4-beam Janus configuration measure the Doppler
52 frequency shift of the transmitted acoustic pulse, providing estimates of the currents. More recently,
53 autonomous uncrewed surface vehicles such as Saildrones (Zhang et al. 2019; Gentemann et al.
54 2020) and Wavegliders (Hodges et al. 2023) have been used to measure upper-ocean currents.
55 These platforms will be especially useful for collecting synchronous measurements from multiple

56 platforms in formation to enable the estimation of horizontal velocity gradients. This approach
57 was employed in the Saildrone component of the S-MODE field campaigns, which specifically
58 aimed to collect concurrent velocity measurements at submesoscale resolution using formations
59 of vehicles. In these field campaigns, RDI ADCP-equipped Saildrones, each with 7 m long hull
60 and 5 m tall wing, were deployed in tight formations with approximately 1 km spacing to measure
61 ocean velocities, from which we estimate velocity gradients.

62 Saildrones are much smaller than most ships, so it is possible that their ADCP measurements
63 could be compromised by winds and waves. Their relatively small size means that Saildrones are
64 more strongly affected by steep short waves and susceptible to rolling and pitching, potentially
65 leading to errors in current calculations. High-frequency ADCP observations on Saildrones are
66 thus subject to numerous potential sources of error and bias. These include instrument noise, the
67 effects of high-frequency surface gravity waves, inaccuracies in positioning, signal quality issues,
68 pitch and roll effects, heading bias, fish schooling bias, and wave-induced drift bias. These errors
69 and biases in absolute velocities can stem from either relative velocity measured by the ADCP
70 or the measured platform velocity and orientation. It is therefore crucial to characterize potential
71 biases and errors in Saildrone ADCP data. Submesoscale processes, with velocity signals that
72 are relatively weak compared to large-scale processes, demand high-accuracy, dense observations.
73 Simple propagation of errors suggests we need a root mean square velocity error of about 1 cm/s
74 to resolve a velocity gradient with an accuracy of $O(0.1 f)$ at a 1 km separation in midlatitudes.

75 Previous studies have used a “frozen field” approximation when estimating velocity gradients
76 with a small number of platforms, i.e., treating data taken at different times and locations by a
77 moving platform as if the platform moved infinitely fast and the data were taken synoptically. This
78 interpretation of the data may confuse temporal and spatial variability, which is a form of aliasing.
79 For example sampling from a single platform following a radiator pattern (e.g., Rudnick 1996)
80 leads to space-time aliasing, especially at small scales, which evolve quickly. More recent studies
81 have employed two ships simultaneously (e.g., Shcherbina et al. 2013; Qu et al. 2022) to account for
82 cross-track velocity gradients, but these still rely on the assumption of a frozen field along the ship
83 tracks. It is important to note that when we refer to unaliased (instantaneous) data in our analysis,
84 those data are not truly unaliased, as we perform averaging of the raw data to remove surface wave

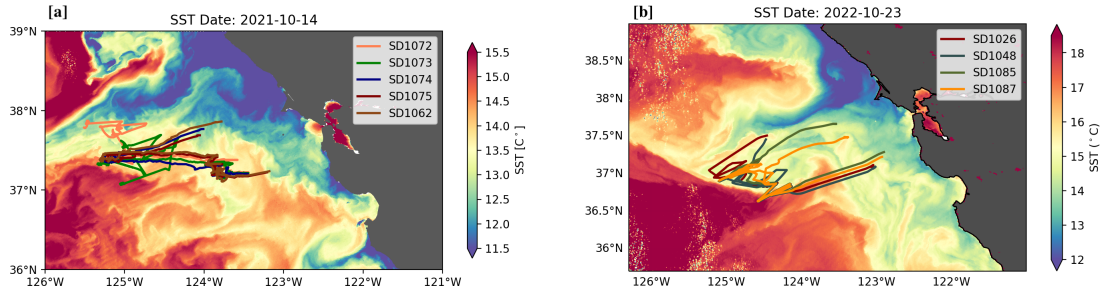
85 and noise signals, which inherently introduces a different form of aliasing. This aliasing results
86 from the smoothing out of high-frequency variability.

87 Our primary objective is to quantify the uncertainties of salidrone ADCP velocities and their
88 gradients computed from two or more platforms. We first quantify biases in the velocity data
89 by comparing them against high-quality ship-based ADCP observations. Then, we examine the
90 noise and unwanted wave signals in velocity data through spectral analysis, velocity difference
91 variability, and structure functions. These analyses are used to consider the temporal and spatial
92 averaging windows that are appropriate to achieve high-resolution and high-quality velocity data
93 for submesoscale studies. Further, the high-quality velocity data are used to estimate horizontal
94 velocity gradients through least-squares plane fits.

95 The paper is organized as follows: Section 2 describes the S-MODE Field campaign, including
96 the environmental conditions of the region, sampling strategies, and instrumentation. Section 3
97 details the methodology adopted, and Section 4 presents the results, which include Saildrone ADCP
98 data validation against ship-based ADCP observations, an analysis of optimal averaging to reduce
99 uncertainties, and a characterization of the uncertainties of the derived velocity gradients. Finally,
100 Section 5 summarizes our findings.

101 **2. Field campaign**

102 The data used in this study were collected as part of the Sub-Mesoscale Ocean Dynamics Experi-
103 ment (S-MODE), a NASA-funded project with the main goal of exploring the role of submesoscale
104 vertical transport in the upper ocean. S-MODE brought about a significant advancement in the
105 observational capabilities of submesoscale processes. The experiment employed a range of ob-
106 servational tools, including aircraft-based remote sensing, satellite remote sensing, ship-based
107 measurements, drifter deployments, and a fleet of autonomous vehicles (including Saildrones).
108 The observational phase of S-MODE encompassed three field campaigns, all carried out in the
109 northeast Pacific Ocean within a region influenced by the California Current System approximately
110 100 km off the coast of San Francisco Bay. We deployed arrays of Saildrones in two of the S-MODE
111 field campaigns (Figure 1a and b). The Pilot campaign was conducted in 2021 (October 19 to
112 November 6) and the first Intensive Operations Period (IOP-1) in 2022 (October 3 to November 7).
113 In this study, we analyze data collected during both campaigns.



114 FIG. 1. Map of the study region off central California showing the representative sea surface temperature (colors) measured by
 115 satellite (VIIRS - Visible Infrared Imaging Radiometer Suite) during the Pilot Campaign [a] and IOP-1 [b] campaigns. The solid
 116 lines show the Saildrone tracks during each respective field campaign which are not necessarily coincident in time with the VIIRS
 117 data.

118 *a. Oceanographic conditions*

119 The California Current System (CCS) is an intricate network of large-scale currents and water
 120 masses. It comprises various large-scale currents such as the California Current, California Under
 121 Current (CUC), Davidson Current, and the spring/summer equatorward coastal current. It includes
 122 diverse water masses such as the Pacific Subarctic Water, North Pacific Central Water, and CUC
 123 Southern Water, which are influenced by river outflows (e.g., Marchesiello et al. 2003). The
 124 CCS is among the most studied major eastern boundary upwelling systems worldwide (Kämpf
 125 and Chapman 2016). In the CCS, cold water upwelled particularly near canyons, creates surface
 126 density gradients that sustain mesoscale eddies and filaments, transporting these features hundreds
 127 of kilometers offshore into the oligotrophic region (Kessouri et al. 2020). The sharp horizontal
 128 density gradients release available potential energy, supporting the generation of submesoscale
 129 processes in the surface layer (Capet et al. 2008; McWilliams 2016). The S-MODE research
 130 focuses on these submesoscale features, targeting high-resolution in-situ velocity observations
 131 using ADCPs mounted on several different platforms. Figure 1 illustrates the general SST pattern
 132 near the S-MODE site, which is qualitatively similar during the two field campaigns, where wind
 133 speeds reached up to 15 m/s and significant wave heights reached 9 m during the Pilot and 4.5 m
 134 during IOP-1.

135 *b. Instrumentation*

136 The Sairdrones were each equipped with a downward-looking 300 kHz R. D. Instruments ADCP,
137 sampling at 1 Hz, and an inertial navigation system (VectorNav VN-300), sampling at 20 Hz. The
138 VN300 measures vehicle position, heading, pitch, roll and heave, and these data are used to convert
139 the ADCP relative velocities into absolute velocities in earth reference frame. The ADCP was
140 mounted on the keel, at a depth of 1.9 m below the waterline. The transducers transmit pulses every
141 second, each lasting for a few milliseconds. The Doppler shift in the returned signal is measured
142 for each beam and mapped onto 50 range 2-m vertical bins. The first velocity measurement is at
143 6 m because a 4-m blanking distance is set to avoid acoustic artifacts very close to the acoustic
144 transducers.

145 *c. Sampling strategy*

146 Arrays of Sairdrones was deployed during each campaign, five during the Pilot (SD1062, SD1072,
147 SD1073, SD1074, and SD1075) and four during IOP-1 (SD1026, SD1048, SD1085, and SD1087),
148 with the goal of measuring velocity gradients at kilometer scales across fronts, filaments, and
149 instabilities (Figure 1). In this study, we analyze data from two sampling modes: the inter-platform
150 configuration during the Pilot (Figure 2a) and quadrilateral formation using four Sairdrones during
151 IOP-I (Figure 9). The inter-platform leg comparison involved two Sairdrones and the R/V *Oceanus*
152 sailing parallel tracks separated by less than 2 km for 9 hours, with Sairdrone SD1072 positioned
153 closer to the ship (Figure 2a). During the quadrilateral formation (henceforth quad formation),
154 four Sairdrones moved synchronously across a front, maintaining a spacing of approximately 1 km.
155 Navigating an array of Sairdrones in tight formation can be challenging, particularly in adverse
156 wind and wave conditions and across strong currents. Despite these challenges, we were able to
157 maintain the quad formation without significant distortions for 36 hours from 19 October 2022 to
158 21 October 2022.

159 **3. Methods**

160 *a. Standard Processing*

161 ADCP measurements are subject to several sources of errors that can affect the accuracy of
162 the derived absolute velocity. Here we describe the processing steps involved in obtaining the

163 velocity from the Saildrone ADCP. The process of deriving absolute velocity from relative velocity
164 and vehicle velocity involves several steps, namely (i) the conversion of measured Doppler shift
165 in the returned signal by the scatterers to beam velocity, (ii) beam velocity transformation to
166 instrument coordinates, (iii) transformation of velocities from instrument coordinates to platform
167 coordinates, and (iv) transformation of platform coordinates to Earth coordinates. The final
168 estimated velocity reflects the ocean currents. The ADCP has four transducers aligned in the bow,
169 aft, port, and starboard directions of the Janus configuration, each tilted 20° from the platform's
170 center line, providing one redundant beam. The redundant information improves the confidence
171 in the measurements by providing error-velocity estimates. In the case when one of the beams
172 has bad data, this redundant beam helps measure velocities using the three-beam solution. The
173 screening algorithm marks bad bin data for a particular beam bin if the percent good for that given
174 beam at that depth is 0 (Teledyne 2010).

175 Motion contamination on ADCP velocities occurs due to translation velocity of the ADCP,
176 angular velocity of the ADCP from platform rotation and tilt caused by pitch, roll, and heading
177 variations. Motion correction is performed using the attitude angle, angular velocity, and translation
178 velocity obtained from the VN-300 IMU mounted on the Saildrone. The range-gated ADCP bins are
179 not vertically oriented during pitching and rolling motion, and the bins for each beam are remapped
180 using pitch/roll angle to the nearest 2-m vertical bin without any smoothing or interpolation.

181 The CPU onboard Saildrone performs ping-by-ping corrections for tilt, velocity, angular velocity,
182 speed of sound, bad beam velocity, heading misalignment, etc. This includes using the near-surface
183 hydrographic data from a conductivity-temperature-depth probe to correct for variations in sound
184 speed. All screening, calibration, and processing steps are also performed onboard, including the
185 specific step of deriving velocity in Earth coordinates from the Doppler shift measured for each
186 beam, before the distribution of the data. After the remapping and other corrections are performed
187 onboard the Saildrone CPU, the 1 Hz processed data written to the disk onboard the Saildrone
188 are averaged with a window length of 5 minutes to reduce the impacts of wave motion, GPS
189 vertical-axis errors, and pitching motion. These average data are then transmitted via satellite in
190 near-real-time to Saildrone Inc. headquarters, while 1 Hz raw data are saved to disk onboard and
191 retrieved after the Saildrones are recovered.

192 *b. Heading Misalignment Calibration*

193 The errors in the heading can introduce large uncertainties for current measurements with ADCP
194 (Kosro 1985; Alderson and Cunningham 1999). Therefore heading misalignment calibration
195 between the platform and the ADCP beams is a common check performed on most platforms
196 mounted ADCPs. For this, bottom tracking was activated for the Saildrones in shallow water
197 (<500 m) over the shelf on their way to the sampling region and their return to San Francisco Bay.
198 During bottom tracking mode, transducers emit a long pulse (ping) between a set of normal pulses
199 and measure the Doppler shift in the signal reflected from the ocean floor. This is the bottom (ocean
200 floor) velocity relative to the ADCP (i.e., the opposite of platform velocity measured by IMU/GPS).
201 The number of hours of bottom tracking data, along with the misalignment angles, is detailed in
202 Table 1. The misalignment angle is calculated by evaluating the phase difference between the
203 bottom-tracking vehicle velocity and the vehicle velocity obtained from the GPS/IMU using a
204 cross-correlation method. Additionally, the method for water velocity calculation that uses both
205 the misalignment angle and an adjustment factor for scaling of Doppler current to remove overall
206 system bias (Joyce 1989) yielded similar misalignment angles (as in Table 1) and an amplitude
207 correction under 1%, which was deemed negligible and thus omitted.

208 Heading misalignment correction is important, as any small misalignment (θ) in along-track
209 direction can add a velocity error to the cross-vehicle velocity equal to $\sin \theta$ times the vehicle speed.
210 The calculation of heading misalignment using bottom-tracking data, as shown in Table 1, suggests
211 that the error due to misalignment is relatively small, with misalignment angles ranging from 0.13°
212 to 1.65° . For the maximum Saildrone speed of 1.5 m/s, this heading misalignment translates to
213 an error in the range of 0.3–4 cm/s in the athwartship velocity. However, the misalignment angle
214 correction did not significantly affect the mean velocity (Table 1).

221 *c. Velocity difference variability*

222 The standard deviation of the velocity difference for various averaging time windows t was
223 calculated according to

$$\sigma_{\Delta u}(t) = \langle \sqrt{(\Delta u'_t)^2} \rangle_{n,z}, \quad (1)$$

215 TABLE 1. Analysis of misalignment angle corrections for along- and cross-track velocity component using
 216 bottom track (BT) data for Saildrones. BT data duration, represents the bottom track data used for the analysis.
 217 The misalignment angle is evaluated from the BT data and the GPS/IMU data as discussed in section 3b. $\overline{\Delta u_{along}}$
 218 represents the mean difference between the corrected and uncorrected along-track velocities, $\overline{\Delta u_{cross}}$ represents
 219 the mean difference between the corrected and uncorrected cross-track velocities. NA: Insufficient quality data
 220 for misalignment angle analysis.

Saildrone ID	BT Data Duration (hours)	Misalignment Angle (degrees)	$\overline{\Delta u_{along}}$ (m/s)	$\overline{\Delta u_{cross}}$ (m/s)
SD1062	78	0.08	-0.0000	-0.0001
SD1072	77	0.22	-0.0001	-0.0003
SD1073	109	1.49	-0.0006	-0.0019
SD1074	NA	NA	NA	NA
SD1075	NA	NA	NA	NA
SD1026	72	0.64	0.0003	0.0000
SD1048	72	0.50	0.0002	0.0001
SD1085	48	0.56	-0.0001	-0.0003
SD1087	48	0.14	-0.0000	-0.0001

224 where Δu_t is the velocity difference between data points separated by time t , i.e., $\Delta u_t = u(\tau + t) -$
 225 $u(\tau)$, and $\Delta u'_t = \Delta u_t - \overline{\Delta u_t}$ and $\langle \cdot \rangle_{n,z}$ is the ensemble average over all realizations and depths. Our
 226 rationale for choosing velocity difference variability is that it directly informs us about the expected
 227 variability at different scales. We also use the velocity difference variability as a metric to compare
 228 the current variability at O(1 km) scale of Saildrone and ship-based ADCP measurements.

229 *d. Spectral Analysis (time and space)*

230 For the computation of kinetic energy (KE) spectra in frequency or space domains we selected
 231 36 hours of data from both Pilot and IOP-1 field campaigns. These corresponded to 7 transects
 232 of length about 16 km in the Pilot and 4 transects of length about 30 km in IOP-1. We then
 233 performed linear interpolation to fill any missing data points within each transect and at every
 234 depth, detrended the data, and applied a Hanning tapering window (Romero and Melville 2010;
 235 Rocha et al. 2016). Additionally, we adjusted the estimated spectra to compensate for the variance
 236 loss caused by tapering. Based on a depth decorrelation analysis, we obtained an average vertical
 237 e-folding decorrelation length of 14m corresponding to 7 bins out of 21, which implies nearly
 238 three independent realizations per transects. This resulted in 21 realizations for the Pilot and 12 for

239 IOP-1, leading to 42 and 24 degrees of freedom (DOF), respectively for the depth-average spectrum
 240 in Figure 4 and 5. The depth-average velocity difference variability, and structure-function analysis
 241 described later also shares the same data and DOF (Figure 6, 7).

242 *e. Structure Functions*

243 The analysis of KE spectra and second-order structure functions have been applied to gain
 244 insights into the distribution of energy across different scales (Ferrari and Wunsch 2010; Callies
 245 and Ferrari 2013; Poje et al. 2017), but here we use it to find the optimal averaging window of the
 246 data for submesoscale studies. To calculate the second-order structure function, we utilized the
 247 same transects that were used for the spectral analysis. We interpolated the 1 Hz data to achieve
 248 a 1-meter horizontal resolution at all depths for all transects, ensuring evenly spaced data for the
 249 structure-function calculation. The structure function values were then calculated at increments of
 250 n meters, where n is an array index starting from 1 and increasing to the total number of observations
 251 in the 1-meter resolution transect data. The structure function was computed at each depth for all
 252 transects and then averaged together resulting in a single representative structure function for each
 253 Sairdrone.

254 The structure-function was calculated as

$$S_r = \langle (\overline{\Delta u_r})^2 \rangle_{n,z}, \quad (2)$$

255 where the velocity difference $\Delta u = u(x+r) - u(x)$, $\overline{(\Delta u_r)^2}$ is the mean velocity-difference-square,
 256 which is a function of the scale r (array of n meters), and $\langle \cdot \rangle_{n,z}$ is the ensemble average over
 257 all realizations and depths. The second-order structure function exhibits a scaling behavior of
 258 $S_r \sim r^{\beta-1}$ for an energy spectrum following a power-law of $E(k) \sim k^{-\beta}$ (e.g., Bennett 1984).
 259 Hence, in the case of submesoscale resolving simulations/observations if the KE spectra scales as
 260 k^{-2} , the corresponding structure function would scale as r^1 (Choi et al. 2017; Essink et al. 2019).

261 *f. Velocity gradients*

262 Velocity gradients are enhanced at submesoscales and derived kinematic properties such as ver-
 263 tical vorticity, horizontal divergence, and lateral strain rate play a crucial role in submesoscale
 264 dynamics (e.g., Shcherbina et al. 2013; D’Asaro et al. 2018). Observing submesoscale veloc-

ity gradients in the ocean is challenging as measurements must be collected from at least two ships/platforms (Shcherbina et al. 2013). In this study, we use two or more platforms to calculate submesoscale current gradients by fitting a plane to the available data within a moving window of 2 km by 2 km along the average trajectories of the Sairdrones. By applying a least-squares (LS) plane fit to the velocity data within the search box, the velocity gradients can be obtained as coefficients of the fit, under the assumption of a local linear approximation of velocity around a central point (e.g., Okubo and Ebbesmeyer 1976; Molinari and Kirwan 1975; Shcherbina et al. 2013):

$$\mathbf{U} \approx \bar{u} + u_x(\mathbf{x} - x_0) + u_y(\mathbf{y} - y_0) \quad (3)$$

$$\mathbf{V} \approx \bar{v} + v_x(\mathbf{x} - x_0) + v_y(\mathbf{y} - y_0), \quad (4)$$

where $\mathbf{U} = [u_1, u_2, \dots, u_n]^T$ and $\mathbf{V} = [v_1, v_2, \dots, v_n]^T$ represent observed velocity vectors, and $\mathbf{x} = [x_1, x_2, \dots, x_n]^T$ and $\mathbf{y} = [y_1, y_2, \dots, y_n]^T$ denote the position vectors. On the right, (\bar{u}, \bar{v}) is the average velocities, (x_0, y_0) is the centroid position of the search window, and $u_x, v_x, u_y,$ and v_y are the velocity gradients. The matrix form of equations (3) and (4) is given by

$$\mathbf{U} \approx \mathbf{X}\mathbf{A}_u, \quad (5)$$

$$\mathbf{V} \approx \mathbf{X}\mathbf{A}_v, \quad (6)$$

with $\mathbf{A}_u = [\bar{u}, u_x, u_y]^T$, $\mathbf{A}_v = [\bar{v}, v_x, v_y]^T$, and

$$\mathbf{X} = \begin{bmatrix} 1 & (x_1 - x_0) & (y_1 - y_0) \\ 1 & (x_2 - x_0) & (y_2 - y_0) \\ \vdots & \vdots & \vdots \\ 1 & (x_n - x_0) & (y_n - y_0) \end{bmatrix}. \quad (7)$$

From the velocity gradients estimated through plane fits, we compute vertical vorticity $\zeta = v_x - u_y$, lateral divergence $\delta = u_x + v_y$, and lateral strain rate $\alpha = [(u_x - v_y)^2 + (v_x + u_y)^2]^{1/2}$.

To account for the Sairdrone ADCP data uncertainty, we employ a weighted least-squares (LS) plane fit to determine the velocity gradients. We also estimate the uncertainty of the velocity

282 gradients by propagating the error in the velocities to their gradients. The detailed calculation of
283 the uncertainty in the coefficients is described in Appendix A for the weighted LS fitting. The
284 weighted LS fit takes into account the uncertainties of the currents from each Saildrone, minimizing
285 the uncertainty of the fitted current gradients. Weights are calculated from the standard errors of
286 1 Hz data averaged to 3 or 5 minutes.

287 We also considered the aspect ratio of the formation of the data contained within the box, which
288 is important for the accuracy of the velocity gradient estimates. Here the aspect ratio γ is defined
289 as the ratio of the minor eigenvalue (λ_{min}) to the major eigenvalue (λ_{max}), which is estimated from
290 the position covariance matrix $\gamma = \lambda_{min}/\lambda_{max}$ (Choi et al. 2017). Saildrone formations with an
291 aspect ratio value $\gamma < 0.2$ were discarded (Ohlmann et al. 2017), which occurred when Saildrones
292 were drifting with elongated formations.

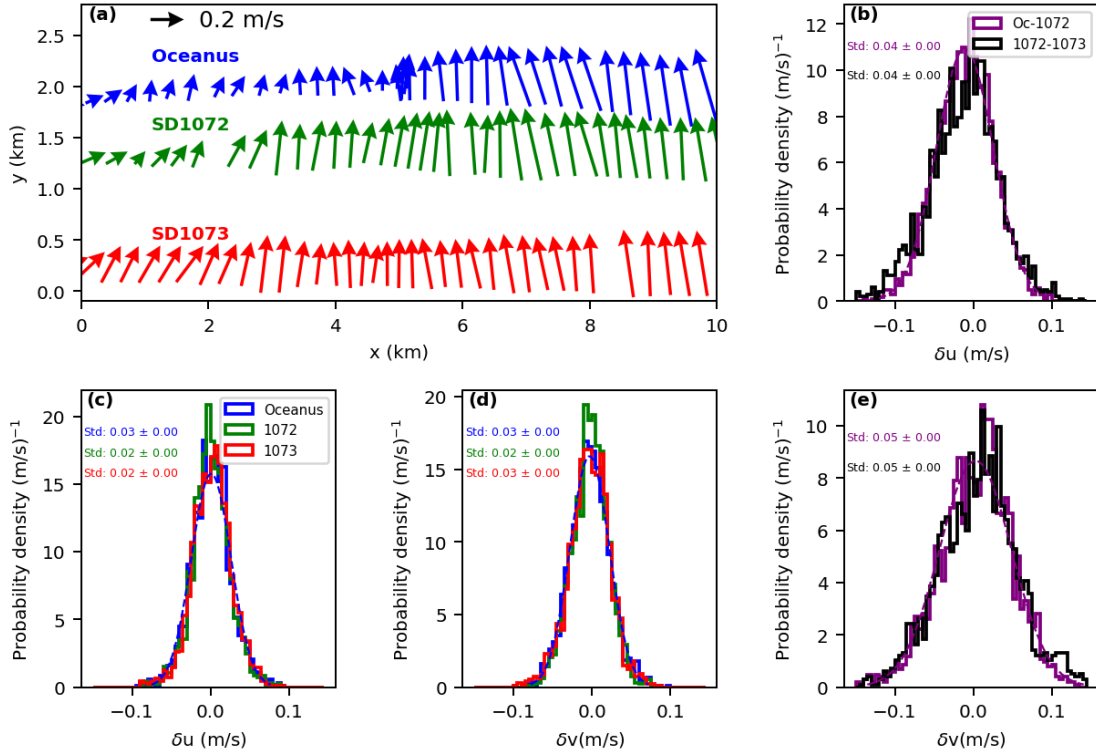
293 4. Results

294 Validating the Saildrone velocity measurements and quantifying its noise are critical steps for
295 using these data for studying submesoscale currents. Once we have a clear grasp of the uncertainty
296 in the velocity measurements, we can better determine the corresponding uncertainty in the velocity
297 gradients and derived kinematic quantities (vertical vorticity, horizontal divergence, and lateral
298 strain rate). This section compares the Saildrone velocity measurements against synchronous
299 ADCP measurements made with a research vessel. This is followed by an analysis of the high-
300 frequency noise to estimate the amount of averaging necessary to attain submesoscale currents
301 with a reasonable noise-to-signal ratio. Finally, the averaged data, with quantified uncertainty, are
302 used to estimate submesoscale velocity gradients and associated uncertainties.

303 *a. Comparison against ship-based observations*

308 During the Pilot field campaign, two Saildrones (SD1072 and SD1073) and the R/V *Oceanus*
309 collected ADCP measurements along parallel tracks for 9 hours. Both Saildrones and the R/V
310 *Oceanus* were equipped with R.D. Instruments Workhorse 300 kHz ADCPs that sampled at 1 Hz,
311 providing a uniform basis for comparison. To minimize the aliasing effect of high-frequency
312 signals, we used 5-minute averaged data when comparing the velocity data of both platforms.
313 Additionally, we limited our analysis to periods when the platforms were located within 2 km from

314 one another. We also restricted the comparison to the top 50 m of the water column, where ADCP
 315 instrument noise is less prominent. Saildrone ADCP data were linearly interpolated in depth to the
 316 *Oceanus*' ADCP depth bins between 10 m (shallowest *Oceanus* ADCP measurement) and 50 m.
 We performed three types of comparison: visual (spatial), direct, and statistical.



304 FIG. 2. Comparison of current vectors and velocity differences for R/V *Oceanus* and two Saildrones. (a): Current vectors from
 305 R/V *Oceanus* (blue), SD1072 (green), and SD1073 (red) at 10 m depth for a track section where platforms were separated by less
 306 than 2 km. PDFs of velocity difference between 10-50 m depths for platform pairs are shown in (b and e), and along each platform
 307 in (c and d). Panels (b,c) and (d,e) display the velocity differences for δu and δv , respectively, with standard deviations indicated.

317
 318 We first compare the velocity vectors at 10 m depth spatially in Figure 2a. The data show visual
 319 agreement between the *Oceanus* and the closest Saildrone, with stronger currents on the right of
 320 the track and substantial variability at kilometer scale. In contrast, the Saildrone (SD1073) located
 321 2 km from the *Oceanus* shows slightly weaker velocity lateral gradients.

322 Scatter plots directly comparing the u and v velocities at depths between 10 and 50 m of the
 323 nearest Saildrone to the R/V *Oceanus* exhibit a pronounced correlation with a slope of 0.93 for
 324 the east-west (u) velocity component and 1.0 for the north-south (v) velocity (Figure 3). The root-
 325 mean-square difference for both the u and v is 0.1 m/s. Additionally, there is a net bias of +1 cm/s

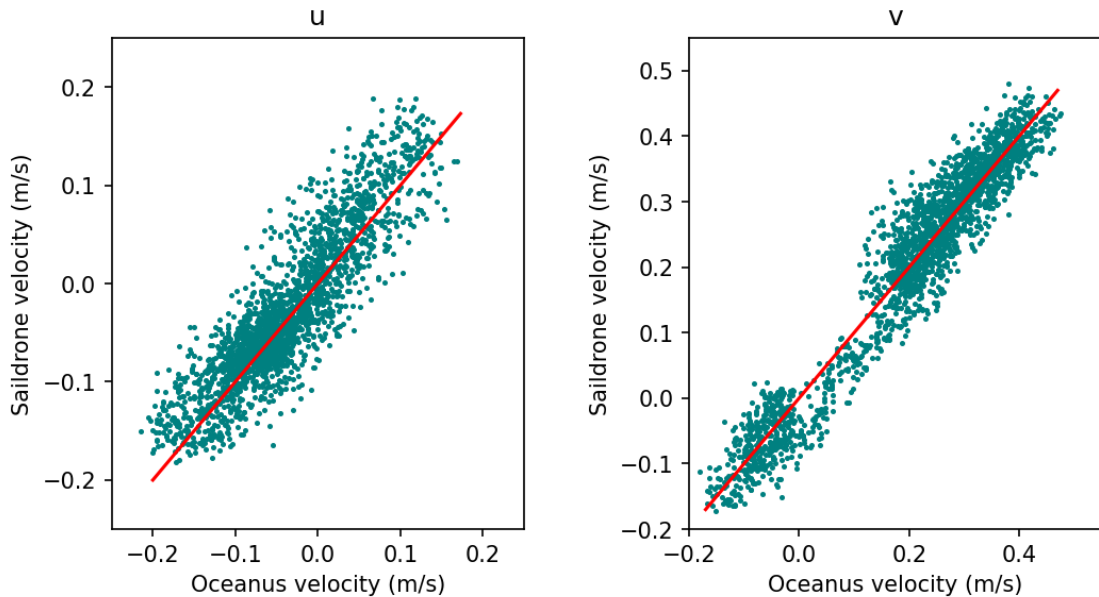


FIG. 3. R/V *Oceanus* and the closest Saildrone (SD1072) scatter plot for u and v velocity components. The red line represents the 1:1 correlation.

326 in the u component and 0.2 cm/s in the v component. This net difference is likely dominated by the
 327 inherent natural variability existing at these separation scales, and is further analyzed as a function
 328 of depth in Section 4c.

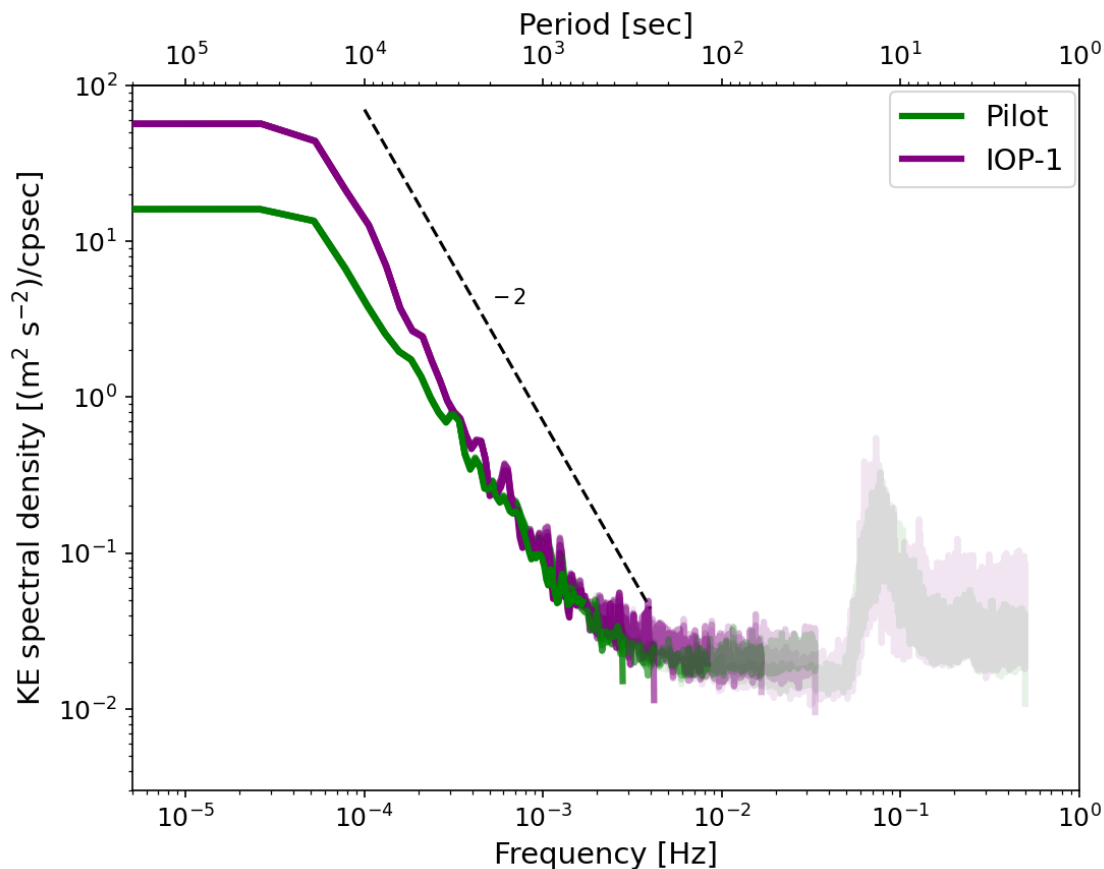
329 The statistical comparison between the Saildrone and ship ADCP measurements was carried
 330 out in two ways. The first analysis involved comparing the probability density functions (PDFs)
 331 of along-track (east-west and north-south) velocity differences. In this analysis we estimated the
 332 root-mean-square (rms) velocity-difference variability ($\sigma_{\delta u}$) for each platform from 9 hours of
 333 Pilot ADCP data when they were cruising in parallel tracks. The results show that all platforms
 334 observed similar velocity-difference variability at this scale (~ 500 m) separation with $\sigma_{\delta u}$ for both
 335 u and v components and all platforms less than 3 cm/s (Figure 2c, 2d). Also, the along-track
 336 velocity differences in the IOP-1 Saildrone ADCP 5-minute data (not shown) also give the same
 337 velocity difference variability of 3 cm/s at 500 m. To assess the significance of the similarity
 338 between the *Oceanus* and Saildrone velocity difference PDFs, each with 2142 observations, we
 339 used the Kolmogorov-Smirnov test (Press 1992; Rudnick 2001), which indicates that the samples
 340 are 99.98% statistically similar.

341 The second PDF analysis involves comparing the PDFs of velocity-difference between platform
342 pairs, which shows standard deviations of δu and δv for all platform pairs being ≤ 4 cm/s (Figure
343 2b, 2e). These results suggest that the two platforms give statistically similar results at the scales
344 analyzed. Additionally, the overall correspondence between the Saildrone and the R/V *Oceanus*
345 ADCP profiles was reasonable, with bias of ~ 1 cm/s. While it is possible that the Saildrone, due to
346 its smaller size, could be more responsive to short, steep waves compared to the ship, we are unable
347 to quantify any wave-related biases. This is because the ship's ADCP measurements start at a depth
348 of 10 m, where wave bias is expected to be minimal (Amador et al. 2017; Hodges et al. 2023). It
349 is important to note that this Saildrone-ship comparison does not provide complete information
350 about the uncertainty of Saildrone ADCP measurements, which we discuss in the next subsection.

351 *b. Temporal and spatial averaging*

352 Measuring currents at a frequency of 1 Hz, the Saildrone ADCP captures substantial high-
353 frequency variability that needs to be minimized before the data can be used in the analysis
354 of submesoscale currents. The frequency spectra shown in Figure 4 exhibit three distinct ranges,
355 which we identify as natural variability with a power-law slope of approximately -2, noise with a flat
356 spectrum, and high-frequency variability due to surface waves. The KE spectra suggest that surface
357 wave signals with periods of 2-15 seconds, which was confirmed by the coherence of pitch and roll
358 with along- and across-platform velocities, respectively. The white noise ranges on average from
359 about 16 to 180 seconds. The cumulative integral of the KE spectrum for the resolved frequencies
360 suggests that the noise band between 16-180 seconds contributes to only a minor fraction of
361 approximately 4% of the total KE, while high-frequency surface wave signals contribute to 76%
362 of the KE. The remaining 20% of KE represents the contribution from submesoscale variability.
363 Thus, the 1 Hz data contain unwanted signals, including noise and surface wave signals, that must
364 be minimized before it can be used for submesoscale analysis.

368 One approach to minimize these unwanted signals is to apply time-averaging to the data. To
369 determine an appropriate averaging window that provides high-resolution and quality data, we
370 applied progressive averaging and tested different methods to find a consistent cutoff. We examined
371 velocity spectra, velocity difference variability, and structure functions to identify the optimal
372 averaging window. The resulting averaged datasets were then tested using the aforementioned



365 FIG. 4. Kinetic energy frequency spectra from two field campaign Saildrone ADCPs. The dashed line provides a reference -2
 366 slope. Spectra of different averaging windows are shown in varying shading to illustrate the position of the Nyquist frequency, with
 367 shading progressing right to the left.

373 methods, allowing us to identify data with minimal unwanted signals and high temporal/spatial
 374 resolution. The KE spectra in Figure 4 demonstrate that with a 3-minute averaging window,
 375 unwanted signals are effectively minimized, leaving only submesoscale variability in the dataset
 376 with a power-law of approximately -2.

377 Figure 6 shows the velocity difference variability as a function of averaging window size.
 378 showing a decreasing trend with increasing averaging window before reaching a minimum at
 379 around 3 minutes. This suggests that a 3-minute average minimizes the variability due to noise and
 380 surface wave signals. This pattern of variability in velocity difference is observed in all four IOP-1
 381 Saildrone datasets (figure not shown), with SD1048 showing higher error compared to the other
 382 three, due to one bad beam in SD1048 ADCP. Despite the higher error at 1 Hz, SD1048 follows the
 383 same decreasing trend and merges with the other Saildrone plots at a 3-minute averaging window.

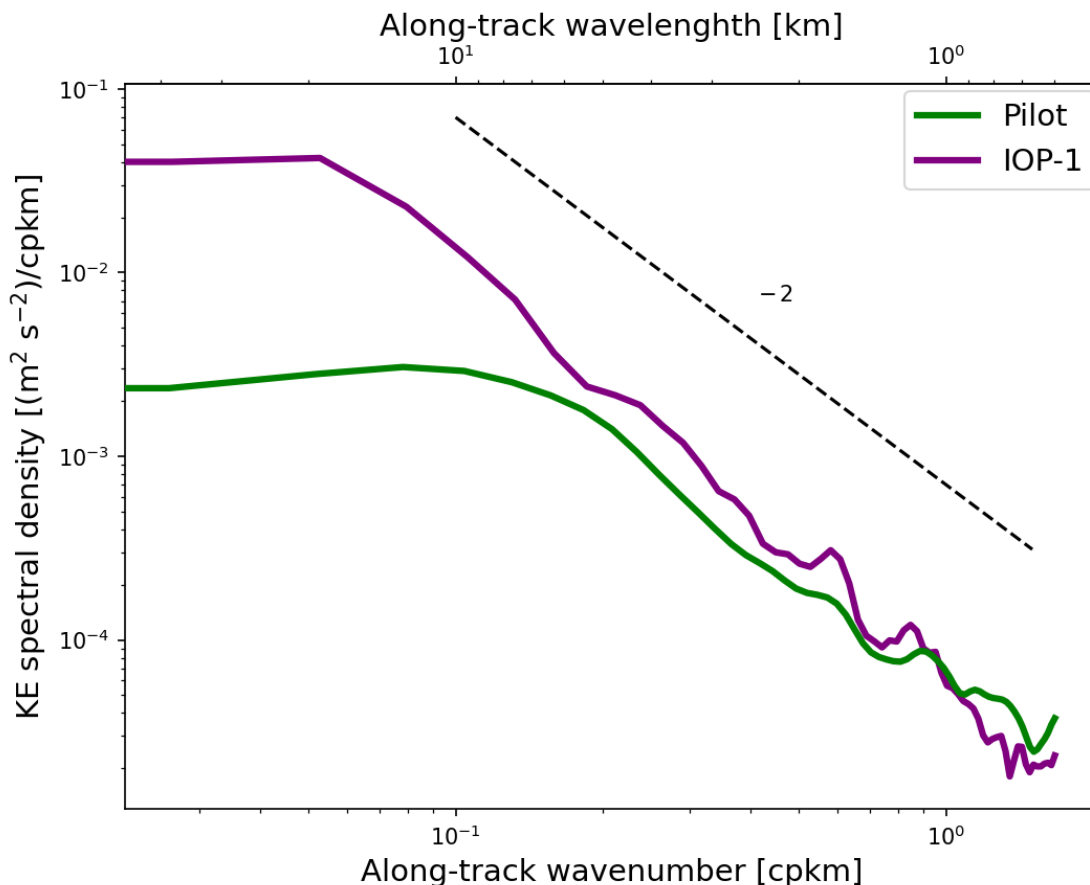


FIG. 5. Kinetic energy wavenumber spectra from two field campaign Sairdrone ADCPs. The dashed line provides a reference -2 slope.

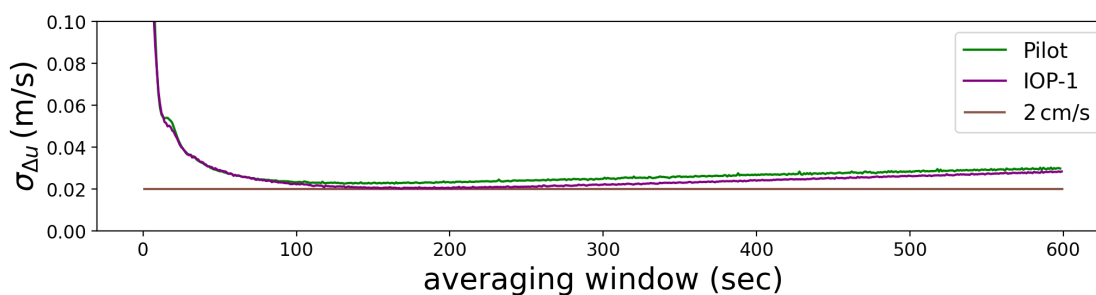


FIG. 6. Velocity difference variability across different averaging windows for both field campaign Sairdrone ADCPs. The grey line represents 2 cm/s base.

384 We used the differential evolution function (Storn and Price 1997) to assess the minima in the
 385 velocity difference variability plots. In Figure 6, it is evident that the minimum values for the two
 386 Sairdrones (SD1072 from the Pilot and SD1085 from IOP-1) are distinct yet closely positioned

387 (150s for the Pilot data and 188s for IOP-1). As a result, on average the 3-minute mark serves as the
 388 cut-off point for obtaining high-resolution, quality data for the Saildrones used in our experiments.

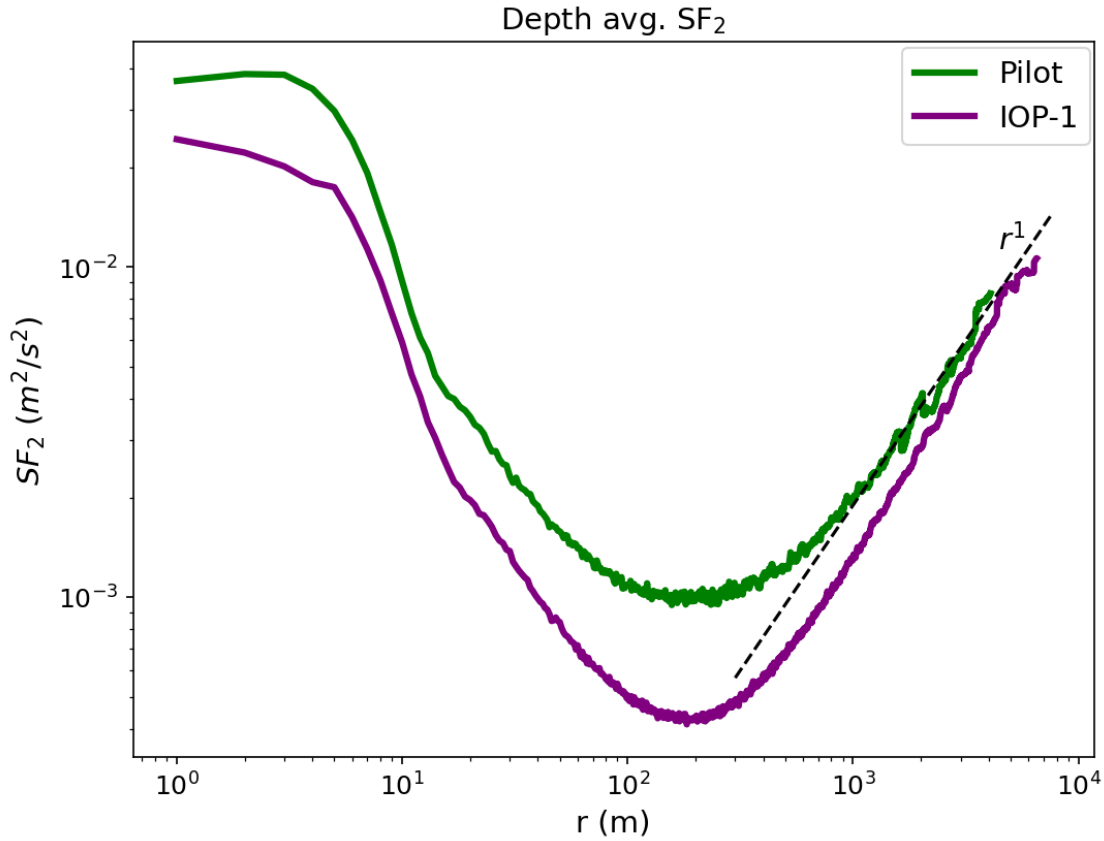


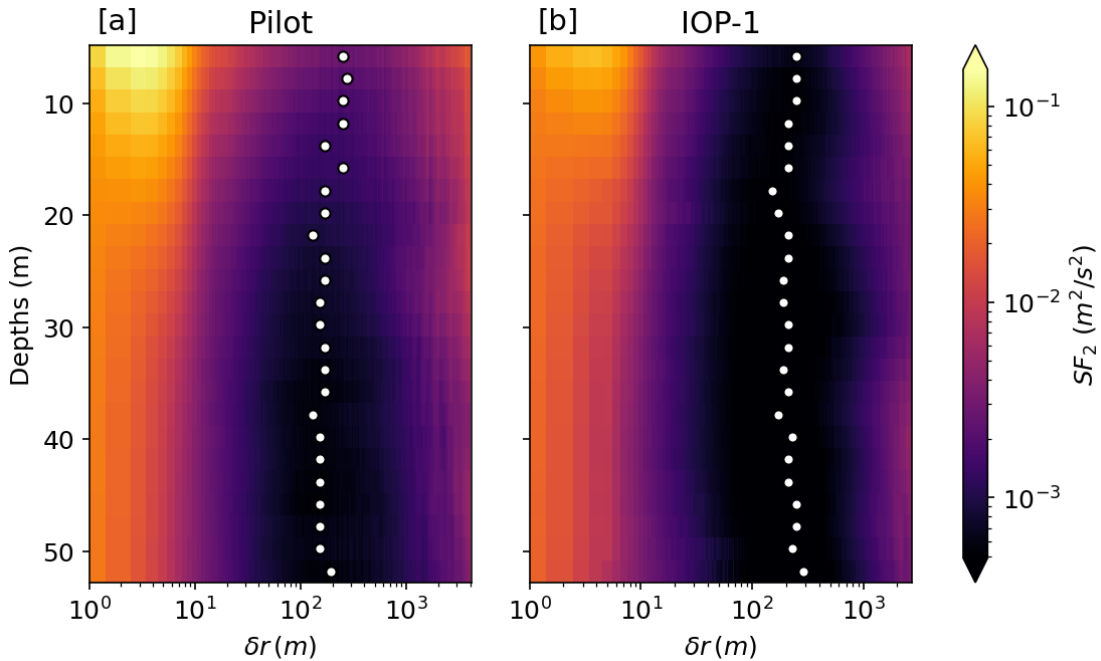
FIG. 7. Depth average structure-function of both field campaign Saildrone ADCPs. Dashed line provides a reference for the +1 slope.

389 The shortest time scale in which noise appears in the spectra and velocity difference variability
 390 analysis aligns with the associated spatial scales observed in the structure function (Figure 7).
 391 A similar result is obtained from the structure function analysis, where unwanted signals (noise
 392 and surface wave signals) decrease with increasing spatial averaging, consistent with the velocity
 393 difference variability analysis. The structure function in Figure 7 indicates a significant reduction
 394 in unwanted signals at a scale of approximately 250 meters, corresponding to the typical distance
 395 covered by a Saildrone in nearly 3 minutes. The observed +1 slope in the structure function
 396 corresponds to submesoscale variability, consistent with the -2 slope in the KE wavenumber
 397 spectra (Figure 5). Again, the differential evolution function (Storn and Price 1997) is applied
 398 to identify the minima in the SF (Figure 7). This function suggests that the minimum spatial

399 averaging required for the Pilot and IOP-1 SAILDRONE data, as depicted in Figure 7, are 227 m and
 400 205 m, respectively. Based on these findings, a 250-meter (3-minute) scale serves as the threshold
 401 for obtaining high-resolution data with high signal-to-noise ratio.

402 *c. Depth-wise analysis*

406 The structure function computed at all depths (< 50 m) shown in Figure 8 is obtained from the
 407 same data used in the analysis shown in Figure 7. The variability in Figure 8 is larger at small
 408 scales near the surface, in particular during the Pilot than IOP-1, when the significant wave height
 409 (H_s) approached 9 m, compared to IOP-1 with a maximum H_s of 4.5 m. Thus, we observe that the
 410 structure function minima occur at a scale that is 10 m larger for the Pilot compared to IOP-1 within
 411 the top 15 m depth. This indicates the need for a wider averaging window to reduce noise/surface
 412 wave signals near the surface during high wave conditions, as opposed to deeper depths. However,
 413 for consistency, we prefer to apply the same averaging window to the entire water column, for
 414 example, when computing horizontal velocity gradients or vertical velocity at the same spatial
 location but different depths. All three methods described in section 4b, aided by depth-wise

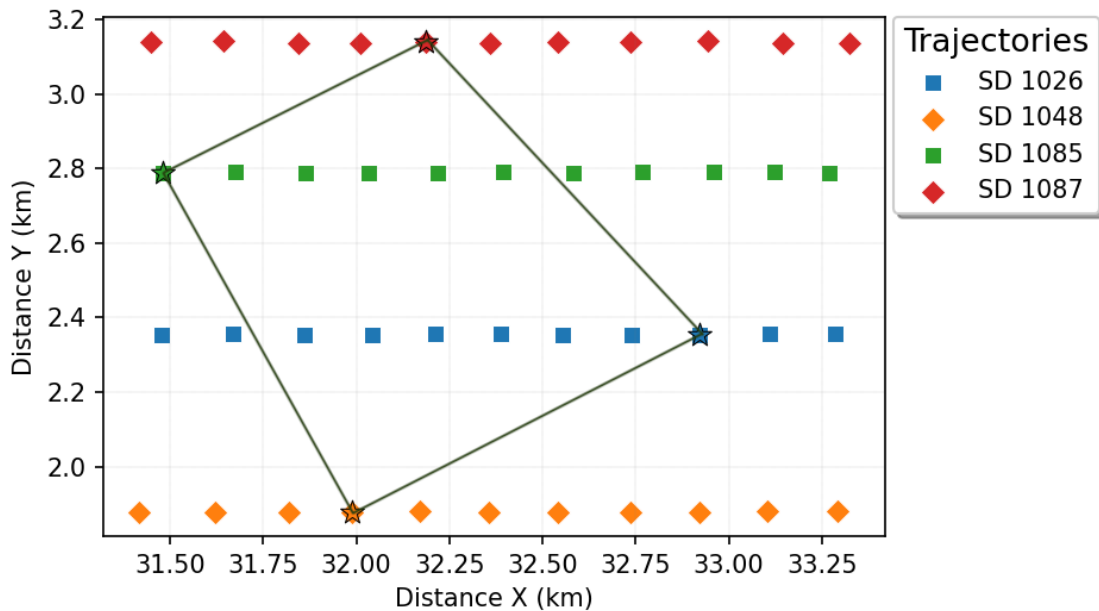


403 FIG. 8. Depth wise structure-function for the Pilot field campaign [a], and IOP-1 [b] SAILDRONE ADCP data. White dots indicate
 404 the minima in the structure function at each depth. This figure highlights the optimal averaging window required at each depth to
 405 achieve minimum noise and high-resolution data.

415 analysis above, are consistent in showing that 3-minute (~ 250 m) averaging provides the highest
416 resolution while minimizing the presence of unwanted signals for submesoscale observations.

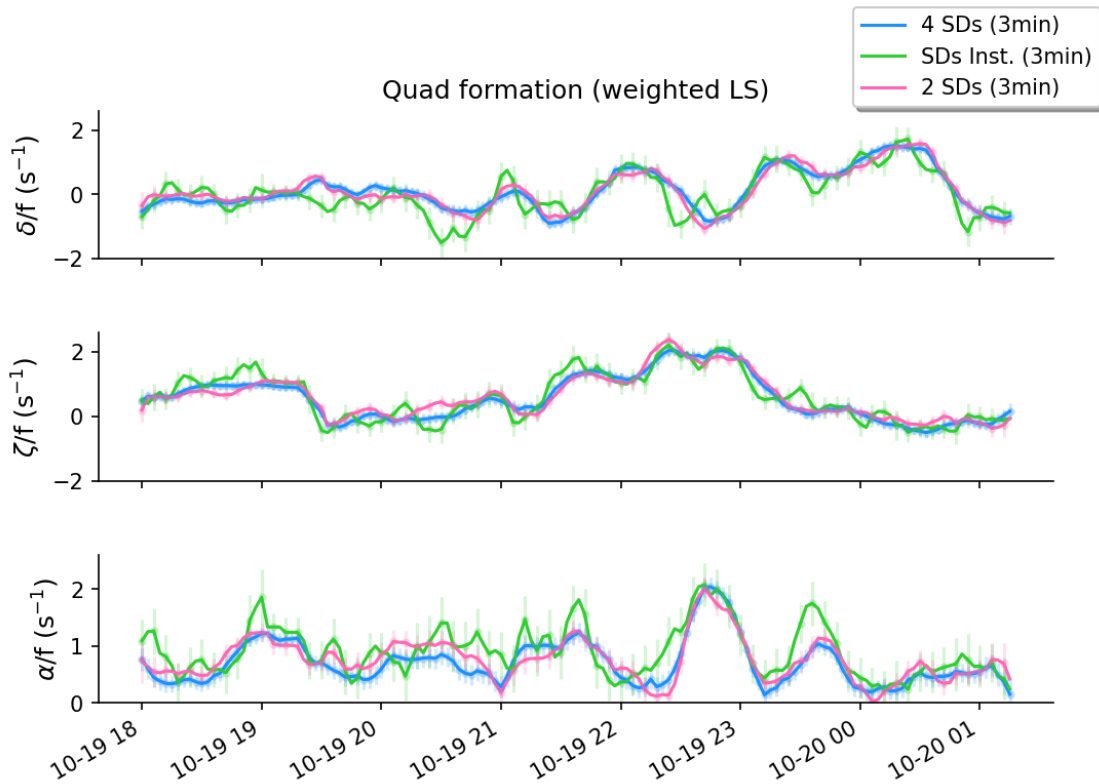
417 *d. Velocity gradient uncertainties*

418 Observing submesoscale processes is challenging because these are small-scale and short-lived,
419 evolving much faster than the mesoscale features that oceanographers have traditionally sampled.
420 Moreover, finding and tracking submesoscale features requires wide and dense sampling, making
421 it a laborious task. The S-MODE experiments using several Saildrones with specific formations
422 provide an excellent dataset for studying the sensitivity of submesoscale velocity gradient quantities,
423 such as vorticity, divergence, and strain rate to the sampling pattern, which can also inform about
424 the errors involved in these measurements. Despite the environmental challenges of sustaining
425 Saildrones in formation, we sampled four times across a strong oceanic front in 36 hours with the
426 4 Saildrones maintaining the desired quad formation (Figure 9).



427 FIG. 9. Example of a single 2 km by 2 km box used in the computation of submesoscale velocity gradients,
428 highlighting the quad formation piloting. The aliased 4 Saildrone velocity gradient calculation, using data from
429 all points within the box, has an RMS average scale of ~ 750 m. The aliased 2 Saildrone calculation, using only
430 data from the outer Saildrones (diamond dots), has an RMS average scale of ~ 850 m. The unaliased calculation,
431 using data from the dots in the quad (marked by stars), has an RMS average scale of ~ 1 km.

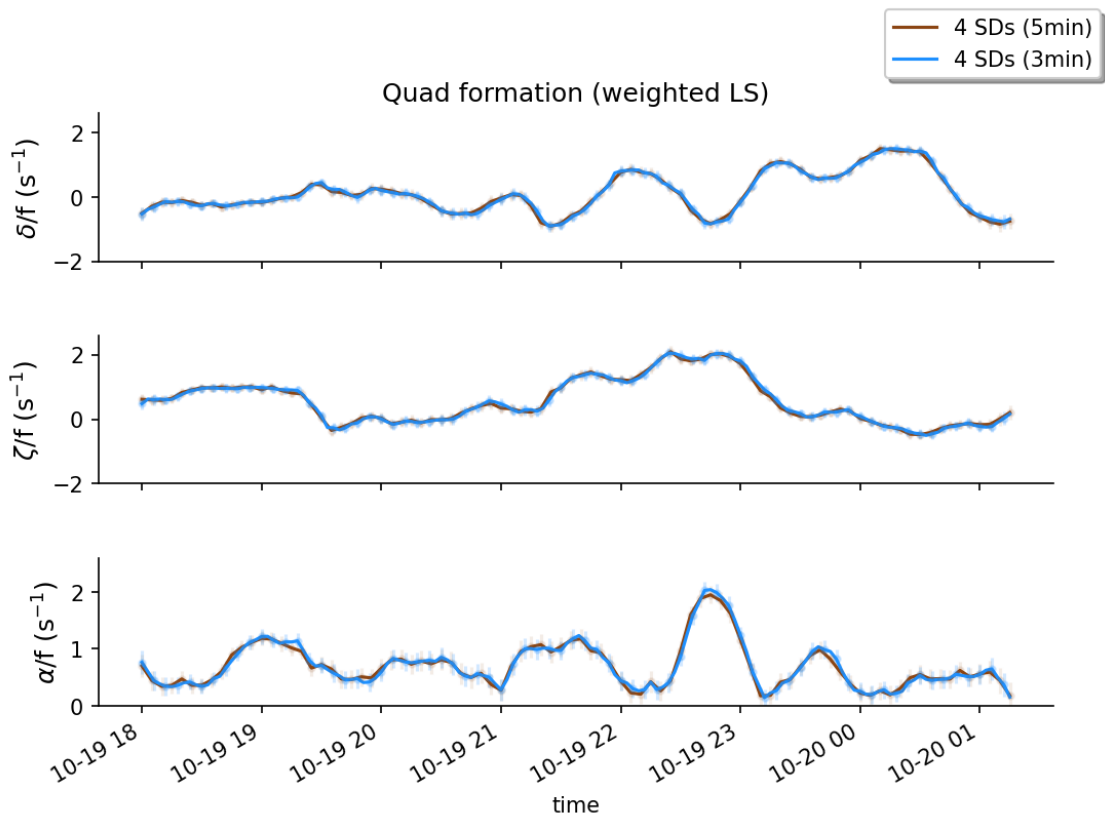
432 For analysis in this subsection, data from only one leg out of the four is used for detailed
 433 comparison. This allows us to show the magnitude and variability of the errors more clearly.
 434 As the maximum across-track spacing of the quad formation reached to nearly 2 km at times, we
 435 search the data in a sliding box of 2 km by 2 km centered on the mean track of 4 Sairdrones.
 436 We intend to examine the impact of using the frozen field approximation, a form of aliasing,
 437 on submesoscale velocity gradients, and the finest resolution of data attainable by Sairdrone for
 438 submesoscale analysis.



439 FIG. 10. Comparison of aliased and unaliased normalized-divergence (top), -vorticity, (middle) and -strain
 440 rate (bottom). The unaliased (Instantaneous) values (in green) are computed from 4 SDs instantaneously and
 441 averaged over a 2 km by 2 km box at 6 m depth. The aliased values are computed from all the points in a 2 km
 442 by 2 km box, using all the 4 Sairdrones (dodger blue) or only 2 farthest Sairdrones in the formation (pink). The
 443 vertical lines represent 95% confidence level.

444 We assess the impact of aliasing on the velocity gradient calculations at 2 km scale (Figure 10)
 445 using the 3-minute data. This involves comparing the average unaliased-velocity gradients within

446 the 2 km by 2 km box (Figure 9) to the aliased calculations for the same box using data from 2 and
 447 4 Sairdrones (Figure 10). The chosen track maintained a linearity of 0.6 (Figure 9) allowing for
 448 a direct comparison. The signals from all three approaches shown in Figure 10 are comparable
 449 and generally within error bars, which suggests that aliasing minimally impacts the accuracy of
 450 velocity gradient calculation at this scale. The unaliased results (from 4 Sairdrones) for vorticity and
 451 divergence are comparable to the aliased results obtained using 2 Sairdrones. However, unaliased
 452 estimate of the strain rate is significantly larger at times. This could be attributed to aliasing effect,
 453 differences in a scales, or number of data points.



454 FIG. 11. Comparison of 5-minute vs 3-minute Weighted LS normalized-divergence (top), -vorticity (middle),
 455 and -strain rate (bottom) derived from Sairdrones in quad formation data at a depth of 6 m. The vertical lines
 456 indicates the 95% confidence level.

457 Notice that the uncertainty and variability of the vorticity, divergence, and straining rate are
 458 larger for the unaliased data, which is because the unaliased data has fewer samples and a more
 459 limited spatial distribution. On average, there are 3 unaliased estimates from 4 Sairdrones that are

460 combined together (total of 12 data points) compared to 40 aliased data points from 4 SAILDRONES
461 and 20 from 2 SAILDRONES (Figure 9). This suggests that averaging the unaliased calculations from
462 four SAILDRONES over a 2 km by 2 km box can be deemed reliable.

463 Finally, we compare the standard 5-minute average ADCP for the computation of the current
464 gradients. As expected, we show in Figure 11 that the velocity gradients estimated with the 3-
465 minute data are consistent with those calculated with the 5-minute data, computed within the same
466 2 km by 2 km boxes. Thus, to take advantage of the finer resolution offered by 3-minute data, a
467 tighter formation of the SAILDRONES would be required to obtain higher resolution gradients.

468 5. Summary

469 The prospect of observing the velocity field and its gradients from arrays of uncrewed surface
470 vehicles (USVs) is very attractive, but it is important to characterize the quality of the ADCP data
471 from USVs to understand the extent to which these gradient estimates can be trusted. This study
472 compared synchronous ADCP measurements from SAILDRONES with those from the R/V *Oceanus*
473 collected during the S-MODE field campaigns. The along-track velocity difference variability
474 of SAILDRONE ADCP matches that with 3 cm/s of R/V *Oceanus* data, supporting its suitability for
475 submesoscale studies. We also investigated the choice of averaging interval for velocity data to
476 minimize noise and the unwanted wave signals using three different methods (sections 3c, 3d, 3e)
477 that can also be applied to other surface vehicles. This investigation indicated that a 3-minute
478 (or ~250 m) averaging of the SAILDRONE data provides high-quality, high-resolution information.
479 We recommend employing any of the three methods along with the differential evolution function
480 to determine the optimal averaging window. We then used this 3-minute data to determine the
481 uncertainty in SAILDRONE velocity gradients and derived kinematic properties (vorticity, divergence,
482 and strain rate) through the analysis of synchronous velocity measurements from SAILDRONES in
483 formation.

484 The unaliased (instantaneous) velocity gradients obtained from 4 data points in the quad formation
485 exhibit uncertainties with mean absolute value in the range $0.3f-0.6f$. To incorporate more data
486 from these 4 SAILDRONES into the calculations of these velocity gradients, we used a 2 km by 2 km box
487 approach. Both aliased and average unaliased calculations at this 2 km scale generally agree, except
488 for few instances of strain rate. This suggests that either approach can be adopted, with uncertainties

489 of $0.4f$ for the unaliased computation and $0.12f$ for the aliased computation. Further, testing with
490 a case considering data from only the 2 outer Saldrone in the formation (a subset of the quad)
491 indicates that the obtained aliased values at 2 km scale is comparable to the values obtained from
492 4 Saldrones, with uncertainties in the range of $0.25f$.

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 497 Science Foundation (NSF award 2146729), São Paulo Research Foundation (FAPESP award
 498 2023/10506-0) and Instituto Serrapilheira (SERRAPILHEIRA award 2211-41837).

499 *Data availability statement.* S-MODE Saildrone and R/V *Oceanus* data are freely available at
 500 <https://podaac.jpl.nasa.gov/S-MODE>.

501 APPENDIX

502 **A1. Uncertainty in the coefficients of weighted least-squares plane fit**

503 To estimate the uncertainties in the velocity gradients obtained from the weighted least-squares
 504 plane fit, we begin by scaling equation (5) with a weight matrix $\mathbf{W}^{-1/2}$, where $\mathbf{W} = \langle \mathbf{U}\mathbf{U}^T \rangle$.
 505 Assuming the errors are uncorrelated, \mathbf{W} is given by

$$506 \mathbf{W} = \begin{bmatrix} \epsilon_1^2 & 0 & 0 & \cdots & 0 \\ 0 & \epsilon_2^2 & 0 & \cdots & 0 \\ \vdots & 0 & \ddots & \cdots & \vdots \\ 0 & \vdots & 0 & \epsilon_{n-1}^2 & 0 \\ 0 & 0 & 0 & 0 & \epsilon_n^2 \end{bmatrix}, \quad (A1)$$

506 with ϵ_i the uncertainty (standard error) of i^{th} 3- or 5-minute averaged velocity observation (com-
 507 puted from the 1 Hz data). The weighted form of equation (5) is:

$$508 \mathbf{W}^{-1/2}\mathbf{U} = \mathbf{W}^{-1/2}\mathbf{X}\mathbf{A}_u. \quad (A2)$$

508 And the normal equation of the weighted least-squares case becomes:

$$508 \mathbf{X}^T\mathbf{W}^{-1}\mathbf{X}\mathbf{A}_u = \mathbf{X}^T\mathbf{W}^{-1}\mathbf{U}. \quad (A3)$$

509 Thus the least-squares solution for the model coefficients is:

$$\mathbf{A}_{\mathbf{u}} = (\mathbf{X}^T \mathbf{W}^{-1} \mathbf{X})^{-1} \mathbf{X}^T \mathbf{W}^{-1} \mathbf{U}. \quad (\text{A4})$$

510 The uncertainty in the model coefficients is derived by forming the covariance of $\mathbf{A}_{\mathbf{u}}$:

$$\text{Cov}(\mathbf{A}_{\mathbf{u}}) = \langle \mathbf{A}_{\mathbf{u}} \mathbf{A}_{\mathbf{u}}^T \rangle \quad (\text{A5})$$

$$= (\mathbf{X}^T \mathbf{W}^{-1} \mathbf{X})^{-1} \mathbf{X}^T \mathbf{W}^{-1} \langle \mathbf{U} \mathbf{U}^T \rangle \mathbf{W}^{-1} \mathbf{X} (\mathbf{X}^T \mathbf{W}^{-1} \mathbf{X})^{-1} \quad (\text{A6})$$

$$= (\mathbf{X}^T \mathbf{W}^{-1} \mathbf{X})^{-1}. \quad (\text{A7})$$

511 Assuming a Student's t-distribution, the 95% confidence intervals of $\mathbf{A}_{\mathbf{u}}$ are given by twice the
512 square root of the diagonal terms in $\text{Cov}(\mathbf{A}_{\mathbf{u}})$. Uncertainties in $\mathbf{A}_{\mathbf{v}}$ are calculated analogously. This
513 estimate of the velocity gradient uncertainties neglects the position inaccuracy stemming from
514 the Sairdrone's VN-300 IMU/GPS, which operates at 20 Hz. While this IMU/GPS has a velocity
515 uncertainty of 5 cm/s (VN-300 manual) at 20 Hz, it translates to a velocity error of approximately
516 1 mm/s when data are averaged over a 5-minute span, rendering it negligible.

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