

Article

Validation of satellite-derived sea surface temperature and sea surface salinity gradients: Comparisons with the Saildrone California/Baja and North Atlantic Gulf Stream deployments

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Abstract: Validation of satellite-based retrieval of ocean parameters like Sea Surface Temperature (SST) and Sea Surface Salinity (SSS) is commonly done via statistical comparison with *in situ* measurements. Because *in situ* observations derived from drifting/moored buoys and Argo floats are only representatives of one specific geographical point, they cannot be used to measure spatial gradients of ocean parameters (i.e., two-dimensional vectors). In this study, we exploit the high temporal sampling of the unmanned surface vehicle (USV) Saildrone (i.e., one measurement per minute) and describe a methodology to compare the magnitude of SST and SSS gradients derived from satellite-based products with those captured by Saildrone. Using two Saildrone campaigns conducted in the California/Baja region in 2018 and in the North Atlantic Gulf Stream in 2019, we compare the magnitude of gradients derived from six different GHRSSST Level 4 SST (MUR, OSTIA, CMC, K10, REMSS, and DMI) and two SSS (JPLSMAP, RSS40km) datasets. While results indicate strong consistency between Saildrone and satellite-based observations of SST and SSS, this is not the case for derived gradients with correlations lower than 0.4 for SST and 0.1 for SSS products.

Keywords: Ocean fronts; Sea surface temperature/salinity gradients; Satellite observations, Saildrone

1. Introduction

The paper aims to followup on the work of [1], where the authors compared sea surface temperatures (SSTs) and sea surface salinities (SSSs) from the Saildrone deployment along the California and Baja Coasts with satellite derived products. The primary conclusions of the paper showed good agreement (i.e., correlations higher than 0.95) between Saildrone and satellite-derived SSTs. Those products included the Multi-Scale Ultra-High Resolution (MUR) SST, the Operational Sea Surface Temperature and Sea Ice Analysis (OSTIA) SST, the Canadian Meteorological Center (CMC) SST, the NAVOCEANO K10 SST, the Remote Sensing Systems (RSS) REMS_MW_IR SST and the Danish Meteorological Institute (DMI) SST. Salinity products included the Jet Propulsion Laboratory Captive Active Passive (CAP) SSS and the Remote Sensing Systems (RSS) 40 km and 70 km derived SSS products from the Soil Moisture Active Passive (SMAP) satellite. Salinity comparisons showed significantly lower signal-to-noise ratios, an indication that land contamination and the lower spatial resolution were both contributing to the lower correlations in the SSS comparisons. The Saildrone California/Baja

29 campaign was also used in [2] for the validation of additional parameters that include satellite-derived
30 fluxes and wind vectors. In this study, we extend the previous results, by comparing satellite-based
31 SST and SSS gradients with Saildrone measurements. The importance of also validating gradients
32 with *in situ* measurements has been confirmed for both a data quality and scientific perspective.[3,4]
33 have shown the coupling that exists between the wind stress curl and SST gradients. [3] found
34 that the wind stress divergence was linearly related to the downwind SST gradients in the Eastern
35 Tropical Pacific. Results clearly showed the air-sea coupling associated with the formation of thermal
36 surface fronts. [4] examined the coupling in the Cape Frio coastal upwelling region off Southeastern
37 Brazil. They determined that wind stress curl was more strongly correlated with SST gradients
38 than SST. Thus, SST gradients were critical for the relationship between wind stress curl and the
39 formation of localized upwelling events. A significant conclusion of the work was how wind stress
40 curl could be modified through feedback mechanisms associated with coastal upwelling.[5] also found
41 strong summertime coupling between wind stress and the formation of SST fronts in the California
42 Current associated with coastal upwelling. The summertime coupling is associated with the seasonal
43 intensification of the coastal upwelling system. The coupling was determined to exist for both wind
44 stress divergence and wind stress curl. The results point to the importance of SST gradients in air-sea
45 coupling. As such, precise and accurate measurements of gradients become critical for numerical
46 modeling, inclusive of numerical weather prediction. [6] found that despite statistical consistency,
47 there were differences in SST gradients based on the application of the multi-channel sea surface
48 temperature (MCSST) algorithm or the non-linear (NLSST) sea surface temperature algorithm. They
49 concluded that differences between the SST gradients derived from the two algorithms were most
50 likely due to the use of the first-guess SST field in the NLSST formulation. Unlike the MCSST, the
51 magnitude of SST gradients derived from NLSST showed a clear correlation with SST values. Other
52 studies [7] have also shown that there are warm satellite SST biases in the Eastern Boundary Current
53 regions. In a study comparing Terra MODIS SST and AVHRR SST Pathfinder with *in situ* data, the
54 authors found warm summertime SST biases in four major upwelling regions, with values as high
55 as 3 to 5°C. Such biases are due to over-flagging of valid SST pixels associated with anomalous cold
56 events typical in upwelling regions. More recently, [8] found large biases when comparing several
57 Level 4 SST data sets with buoys measurements during coastal upwelling events. In [9], these biases
58 were also observed in Level 2 MODIS data despite using an improved cloud masking method [10]
59 and can be attributed to the calibration of Level 2 SST retrieval algorithms [11,12] which is based on
60 global *in situ* measurements and thus does not account for atmospheric processes specific to coastal
61 upwelling regions.

62 Overall, warm SST biases, along with the air-sea coupling and associated relationship to SST gradients,
63 make the case that validation of both SST and SSS, along with their respective gradients, is critical
64 for coastal upwelling regions. In this work, we focus on two oceanic regions usually associated with
65 high spatial-temporal variability, i.e., a coastal upwelling region and a Western Boundary Current
66 region. The Saildrone instrument allows for validation of both SST, SSS, and their gradients using data
67 from two separate campaigns conducted in the California/Baja region and in the North Atlantic Gulf
68 Stream. The paper is organized as follows: section 1 being the introduction, section 2, the methodology
69 and data, section 3 the results and discussion, and section 4 the conclusions.

70 2. Methodology and Data

The validation of satellite SST/SSS gradients using standard *in situ* measurements derived from Argo floats, drifting/moored buoys is a challenging task due to the very different nature of acquired signals. In fact, gradients estimated from satellite observations are bi-dimensional vectors with a given magnitude and orientation, whereas *in situ* data are typically associated to one particular geographical location. The high temporal frequency of Saildrone measurements along its trajectory (1 per minute) allows one to see the acquired data as a one-dimensional signal where values vary as a function of time. Given that the sampling frequency of Saildrone is significantly higher than the temporal scale

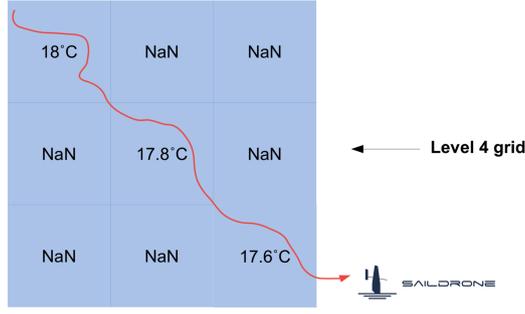


Figure 1. Typical configuration of Saildrone trajectory and collocated Level 4 SST that does not allow to estimate SST gradients using central finite differences.

of ocean submesoscale processes, gradients in the spatial domain can be estimated from successive measurements. One possible approach to compare satellite-based gradients with those obtained from Saildrone is to rely on finite differences. In a lat/lon grid for example, the magnitude of the SST gradient at location (i, j) is typically estimated using a finite central differences scheme as follows:

$$|\nabla \text{SST}(i, j)| = \left(\left[\frac{\text{SST}(i-1, j) - \text{SST}(i+1, j)}{d_{i-1, j}^{i+1, j}} \right]^2 + \left[\frac{\text{SST}(i, j-1) - \text{SST}(i, j+1)}{d_{i, j-1}^{i, j+1}} \right]^2 \right)^{1/2} \quad (1)$$

where $d_{i-1, j}^{i+1, j}$ represents the distance in kilometers between grid points $(i-1, j)$ and $(i+1, j)$. However, this commonly used approach significantly limits the number of grid points where satellite-based gradients can be compared with the Saildrone data. In fact, such method requires the Satellite/Saildrone collocated observations to be available for all 4 locations $(i-1, j)$, $(i+1, j)$, $(i, j-1)$ and $(i, j+1)$ which is seldom the case. Figure 1 shows a typical configuration of Saildrone trajectory where SST gradients from Level 4 collocated data cannot be computed due to missing values in both vertical and horizontal directions. While using a forward or backward finite differences scheme may alleviate this issue, (i.e., when the Saildrone trajectory allows two consecutive collocated values along vertical and horizontal directions) an alternative method is required for the validation of SST gradients. In this paper, we adopt a different collocation strategy from that used for the validation of SST and SSS in [1]. In the following, we denote ds the spatial resolution of the Level 4 satellite SST/SSS field. For each grid point (i, j) , all Saildrone measurements acquired between latitudes $i - ds$ and $i + ds$ and longitudes $j - ds$ and $j + ds$ are averaged. This leads to a collocated dataset of Saildrone and satellite based SST/SSS values in the lat/lon grid. For each location (i, j) , we also compute the average time of all Saildrone measurements, which is then sorted to derive collocated time series of SST (SSS) denoted hereafter Sat_SST (Sat_SSS) and Sail_SST (Sail_SSS) for the satellite and Saildrone observations respectively. The temporal window used for the collocation is the temporal resolution of the Level 4 datasets i.e., one day. The magnitude of SST gradients can then be approximated using forward finite differences of successive measurements, i.e.,

$$\nabla \text{SST} = \frac{|\text{SST}(t+1) - \text{SST}(t, j)|}{d_t^{t+1}} \quad (2)$$

71 where d_t^{t+1} represents the distance between collocated observations obtained at times $t+1$ and t . We
 72 use Equation 2 to calculate the magnitude of SST gradients from Saildrone and various Level 4 SST
 73 products. Grid points with less than 50 Saildrone measurements are discarded as the average of *in*

		Bias	RMSE	Correlation
CMC	SST	-0.074	0.417	0.975
	$ \nabla\text{SST} $	-0.009	0.022	0.315
K10	SST	0.137	0.475	0.969
	$ \nabla\text{SST} $	-0.007	0.022	0.293
REMSS	SST	0.075	0.401	0.977
	$ \nabla\text{SST} $	-0.007	0.023	0.243
OSTIA	SST	0.022	0.365	0.980
	$ \nabla\text{SST} $	-0.008	0.022	0.306
DMI	SST	0.040	0.489	0.966
	$ \nabla\text{SST} $	-0.008	0.023	0.255
MUR	SST	0.285	0.500	0.975
	$ \nabla\text{SST} $	-0.003	0.021	0.395
JPLSMAP	SSS	0.141	0.414	0.429
	$ \nabla\text{SSS} $	0.002	0.005	0.128
RSS v4	SSS	-0.170	0.336	0.464
	$ \nabla\text{SSS} $	0.002	0.004	0.072

Table 1. Statistics of SST/SSS and SST/SSS gradients for the selected Level 4 products for the Baja California campaign

74 *situ* | SST may not be representative of the SST value inside the grid point. Note that experiments
75 conducted with a higher number of Saildrone measurements for each grid point have little impact on
76 results reported in the next section. In this study, 6 GHRSSST compliant Level 4 SST datasets have been
77 used, namely:

- 78 (1) the Canadian Meteorological Office CMC
- 79 (2) the Naval Oceanographic Office NAVO K10
- 80 (3) Remote Sensing Systems REMSS_MW_IR
- 81 (4) the UK Meteorological Office OSTIA
- 82 (5) the Danish Meteorological Institute DMI, and
- 83 (6) the Jet Propulsion Laboratory MUR.

84
85 In addition, two daily SSS datasets produced from 8-day running mean were selected:

- 86 (1) the Jet propulsion Laboratory version 4.0 Soil Moisture Active Passive (SMAP) (JPLSMAP) and
- 87 (2) the Remote Sensing Systems version 4.0, 40 km (RSS40) dataset.

88
89 A detailed description of these SST datasets can be found in [1]. Both SST and SSS datasets
90 were downloaded from the Physical Oceanography Distributed Active Archive Center (PO.DAAC,
91 <https://podaac.jpl.nasa.gov/>) and reprojected into a 0.1° and 0.25° resolution grid respectively, using
92 bilinear interpolation. We used two different Saildrone campaigns for the validation of satellite
93 SST/SSS gradients. The first 60-day campaign, which was used for the validation of SST and SSS
94 in [1], was conducted over the period 11 April 2018 to 11 June 2018 in the California/Baja region
95 (round cruise from San Francisco Bay down to Guadalupe Island). The California/Baja Saildrone
96 campaign data can be download from the PO.DAAC. The second 27-day Saildrone campaign was
97 conducted in the North Atlantic Gulf Stream region from 30 January 2019 to 25 February 2019, and the
98 corresponding data can be downloaded from the European Marine Observation and Data Network
99 (<https://www.emodnet-physics.eu/Portal/>).

100 3. Results

101 The California Current Upwelling System (CCUS) and the North Atlantic Gulf Stream (NAGS)
102 have been selected in this study as they are representative of large spatio-temporal variability associated
103 with both mesoscale and submesoscale fronts. Previous results [6] had already demonstrated how

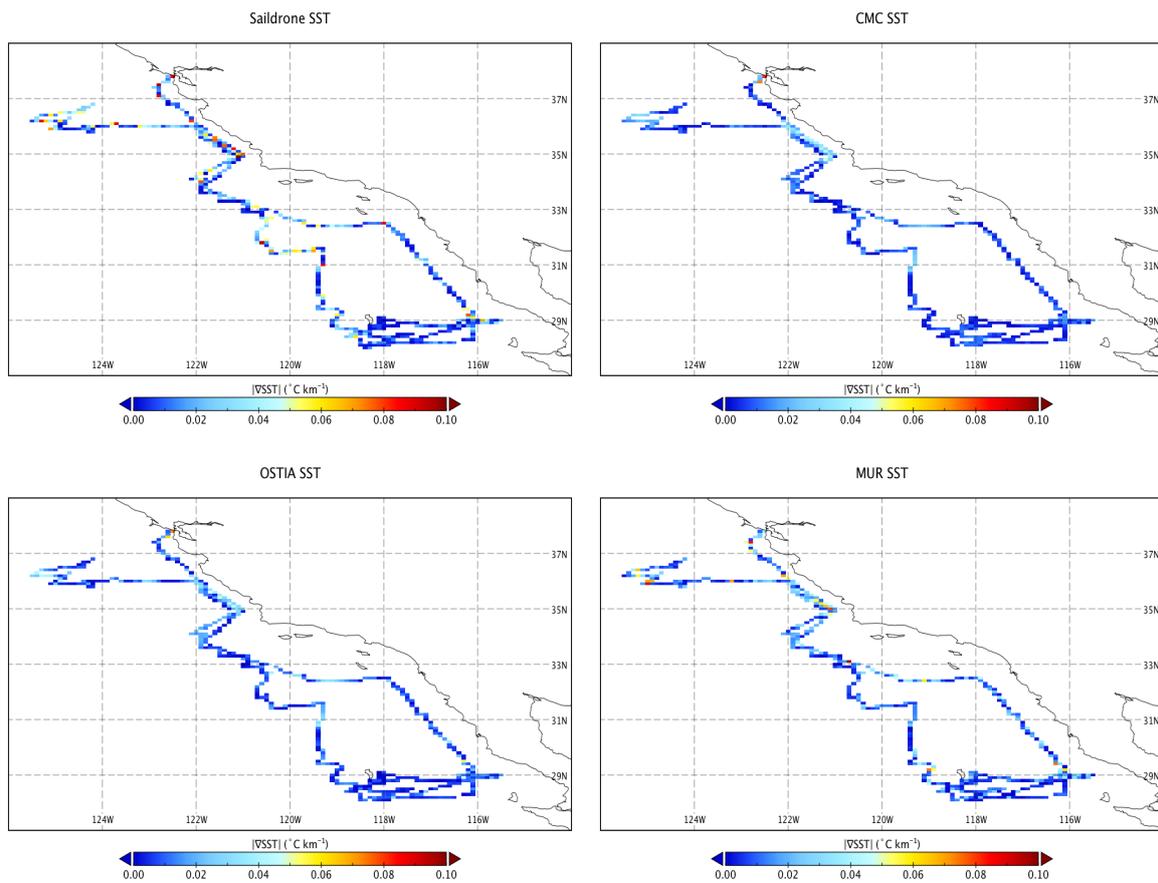


Figure 2. Magnitude of SST gradients derived from Saildrone, CMC, OSTIA and MUR for the Baja California campaign

		Bias	RMSE	Correlation
CMC	SST	-0.350	1.310	0.962
	$ \nabla\text{SST} $	-0.012	0.054	0.374
K10	SST	-0.688	1.928	0.917
	$ \nabla\text{SST} $	-0.009	0.062	0.072
REMSS	SST	-0.085	0.962	0.977
	$ \nabla\text{SST} $	-0.016	0.055	0.342
OSTIA	SST	-0.209	1.185	0.968
	$ \nabla\text{SST} $	-0.012	0.053	0.371
DMI	SST	0.002	1.401	0.951
	$ \nabla\text{SST} $	-0.017	0.058	0.210
MUR	SST	-0.051	1.057	0.975
	$ \nabla\text{SST} $	-0.010	0.054	0.321
JPLSMAP	SSS	-0.325	0.437	0.591
	$ \nabla\text{SSS} $	0.001	0.006	0.084
RSS v4	SSS	-0.151	0.457	0.932
	$ \nabla\text{SSS} $	0.001	0.007	0.140

Table 2. Statistics of SST/SSS and SST/SSS gradients for the selected Level 4 products for the North Atlantic Gulf Stream campaign

104 the high correlation between SST values derived from various satellite products does not necessarily
 105 apply when analyzing SST gradient magnitudes. From a similar perspective, the two Saildrone
 106 campaigns are used to compare SST and SSS gradients measured by satellite products with those

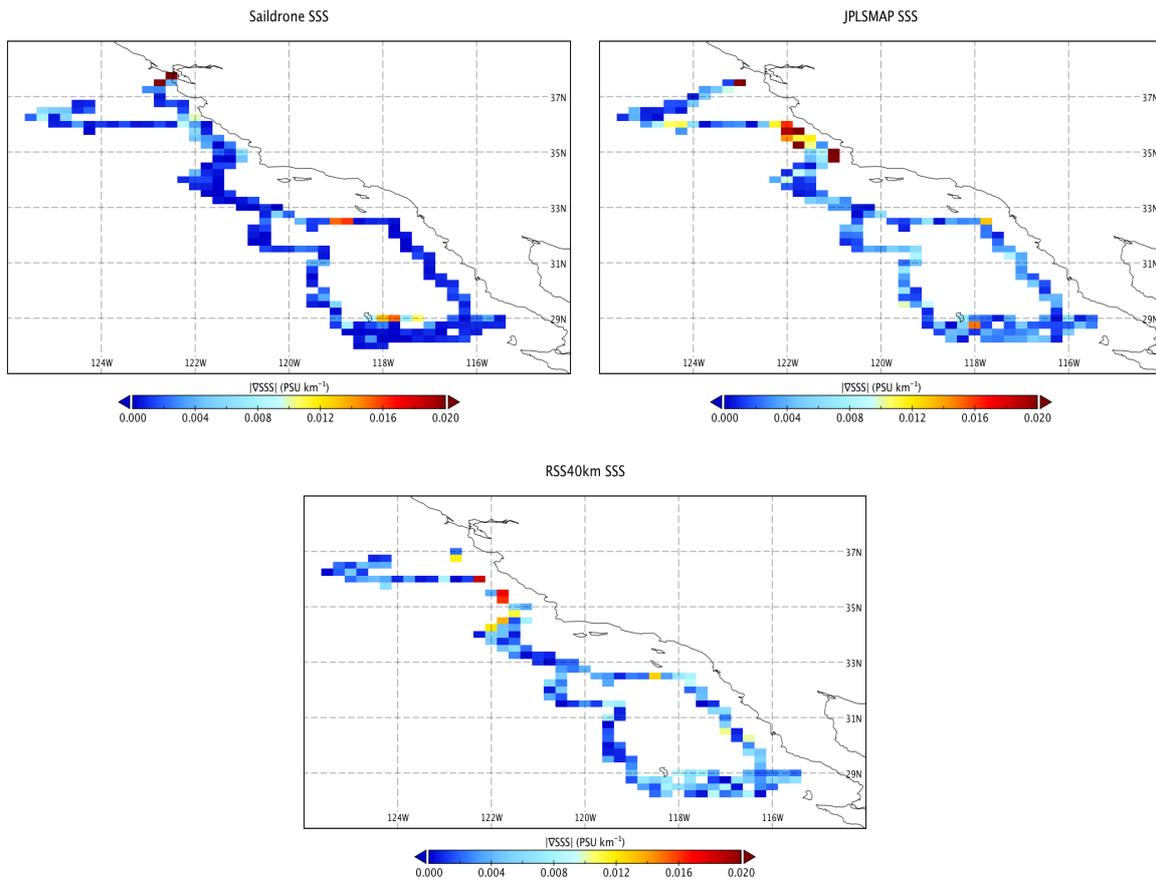


Figure 3. Magnitude of SSS gradients derived from Saildrone, JPLSMAP and RSS40km for the Baja California campaign

107 from Saildrone. Using the methodology described in the previous section, we generated time series of
 108 SST/SSS gradient magnitude for the two Saildrone campaigns. Due to the high temporal variability of
 109 SST/SSS gradients, the time series are not shown here.

110 3.1. California Current Upwelling System (CCUS)

111 Figure 2 shows the magnitude of SST gradients derived from the Saildrone and collocated Level
 112 4 CMC, OSTIA, and MUR along the Baja California deployment. First, we note that the Saildrone
 113 captures a more important number of high SST gradients compared to all Level 4 SST datasets. The
 114 magnitude of SST gradients captured by Saildrone in the CCUS can reach values above $0.1\text{ }^{\circ}\text{C}/\text{km}$,
 115 whereas for CMC, and OSTIA, maximum values are mostly lower than $0.04\text{ }^{\circ}\text{C}/\text{km}$. This can be
 116 explained by the use of optimal interpolation and the underlying spatio-temporal smoothing which
 117 does not preserve small scale features. The Level 4 MUR, which is based on wavelet analysis, is able
 118 to capture higher magnitudes of SST gradients with maximum values of the order of $0.75\text{ }^{\circ}\text{C}/\text{km}$.
 119 As expected, while Saildrone and Satellite SST simultaneously observed several thermal fronts, the
 120 magnitude of gradients is significantly underestimated in Level 4 SST analysis, which only provide a
 121 daily estimate of the SST field as opposed to the synoptic observation from Saildrone. In contrast, the
 122 analysis of SSS gradients illustrated in Figure 3, indicates that higher gradients are found in satellite
 123 products compared to Saildrone. Significant differences of up to $0.02\text{ PSU}/\text{km}$ between the magnitude
 124 of SSS gradients in JPLSMAP/ RSS40km and Saildrone are observed. The maps of Figure 3 indicate
 125 that these discrepancies increase as the Saildrone gets closer to the coast. This can be seen in the
 126 Saildrone track portions located between $34\text{ and }36^{\circ}\text{N}$ and between $29\text{ and }32^{\circ}\text{N}$ and is likely due to

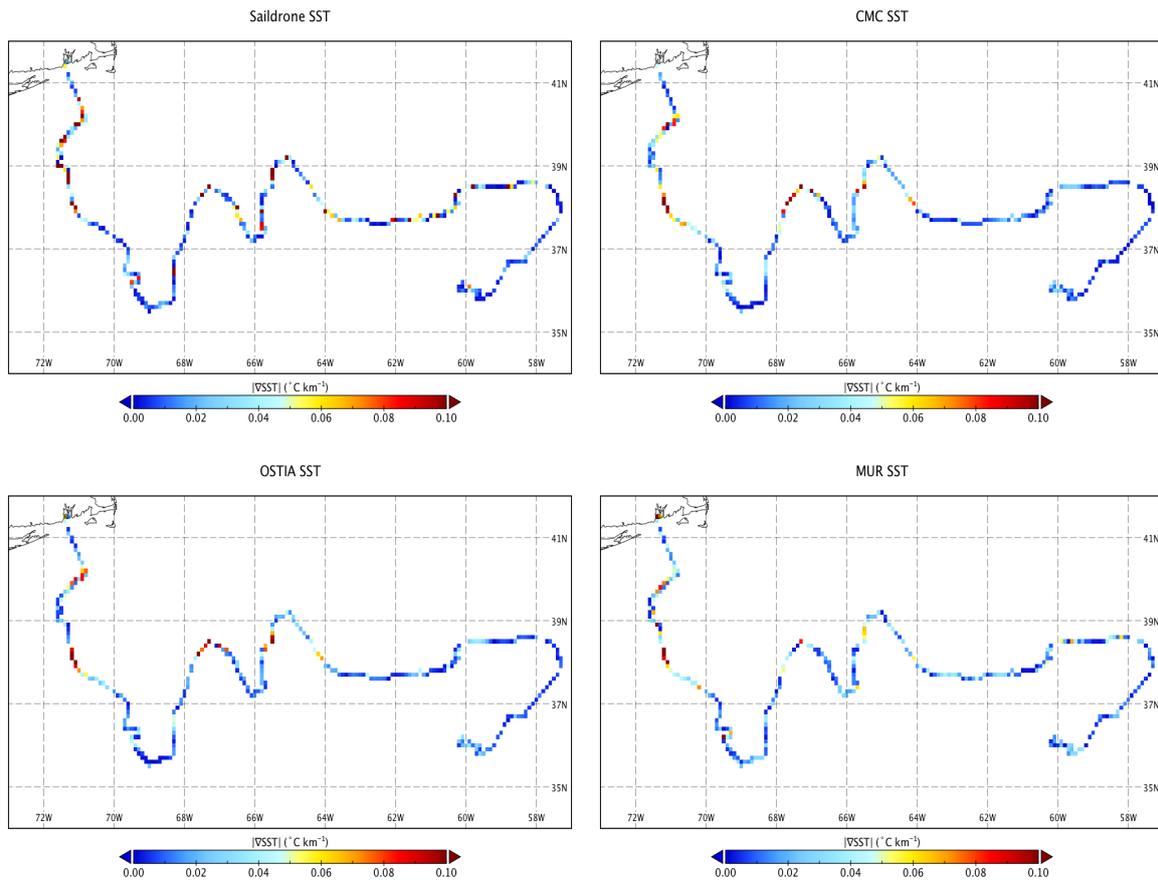


Figure 4. Magnitude of SST gradients derived from Saildrone, CMC, OSTIA and MUR for the North Atlantic Gulf Stream campaign

127 land contamination which affects the accuracy of satellite SSS values and consequently, associated
 128 gradients.

129 3.2. North Atlantic Gulf Stream (NAGS)

130 Figure 4 shows the values of SST gradient magnitudes for Saildrone, CMC, OSTIA, and MUR
 131 along the NAGS deployment. Similarly to what is observed in the CCUS campaign, we note that
 132 gradients in Level 4 SST are also significantly underestimated in the NAGS region. Maximum SST
 133 gradients associated with frontal activity in the GS and measured by Saildrone exceed values of
 134 $0.2^{\circ}\text{C}/\text{km}$. However, for CMC, OSTIA, and MUR, most thermal fronts have magnitudes lower than
 135 $0.1^{\circ}\text{C}/\text{km}$. In this region dominated by intense mesoscale and submesoscale surface fronts, the average
 136 of SST gradient magnitudes for the entire campaign period for MUR, for example, is $0.22^{\circ}\text{C}/\text{km}$,
 137 whereas Saildrone measured an average of $0.35^{\circ}\text{C}/\text{km}$. Analysis of SSS gradients illustrated in Figure
 138 5 also indicates significant discrepancies between Saildrone and satellite observations, including
 139 in areas distant from the coast. As an example, at the end of the campaign, i.e., in the area located
 140 between $35\text{--}38^{\circ}\text{N}$ and $57\text{--}60^{\circ}\text{W}$, RSS40km and JPLSMAP measure many gradients with values higher
 141 than 0.005 PSU/km whereas most values derived from Saildrone are lower than 0.001 PSU/km.
 142 Overall, maps of SST and SSS gradients in the CCUS and the NAGS show that the differences between
 143 Saildrone and satellite data sets are related not only to the magnitude but also to the location of
 144 temperature and salinity fronts.

145

146 To further analyze the consistency between Saildrone and satellite-based observations, biases,

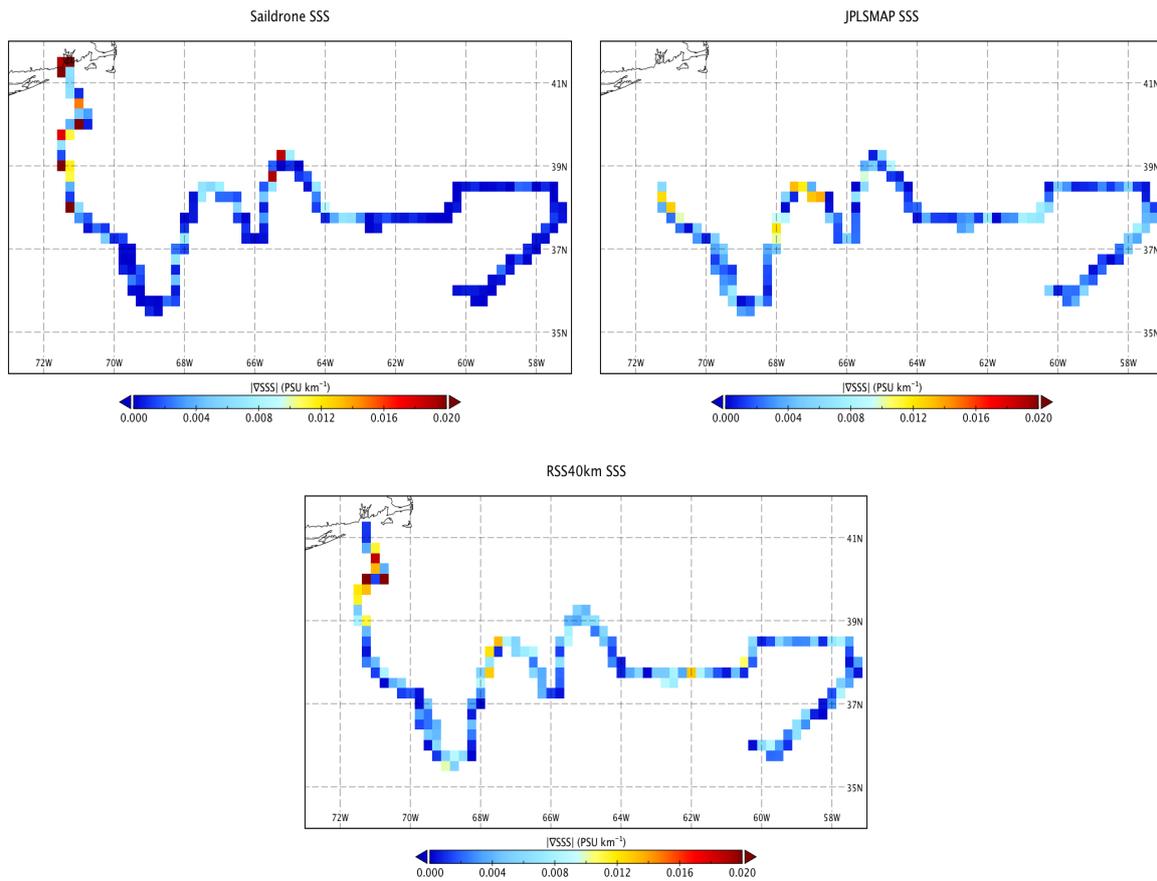


Figure 5. Magnitude of SSS gradients derived from Saildrone, JPLSMAP and RSS40km for the North Atlantic Gulf Stream campaign

147 root mean square differences, and correlation coefficients were computed. Values for both SST/SSS
 148 and derived gradients are reported in Table 1 for the CCUS and Table 2 for the NAGS regions. We
 149 note that for both campaigns, correlation coefficients with Saildrone are higher than 0.96 for all level 4
 150 products. We also note that overall, SST biases in the NAGS are slightly higher than those observed in
 151 the CCUS, where all biases are below 0.15°C in absolute value, with the exception of MUR (bias of the
 152 order of 0.285°). The differences in SST validation statistics between the CCUS and the NAGS can be
 153 attributed to the amount of cloud coverage in these regions as well as the higher magnitude of thermal
 154 fronts in the NAGS, which can lead to over-masking of valid pixel values. Overall, results reported in
 155 Tables 1 and 2 for SST indicate that all Level 4 data sets are statistically consistent with the Saildrone
 156 data. However, this is not the case when analyzing corresponding gradients. Correlation coefficients
 157 computed for the magnitude of SST gradients are lower than 0.4 for both campaigns, indicative of the
 158 discrepancies observed in maps from Figures 2 to 5.
 159 Further, all biases computed for the magnitude of SST gradients for both campaigns are negative.
 160 This is a clear indication that Level 4 SST products tend to underestimate the intensity of thermal
 161 fronts. Similar observations can be made for salinity where correlation coefficients, although lower
 162 than those associated with SST, also significantly decrease when analyzing derived gradients. In the
 163 NAGS region, for example, the correlation between salinity derived from RSS40km and Saildrone is of
 164 the order of 0.93, but only 0.14 for salinity gradients. Although correlations of the gradients between
 165 the satellite-derived SSS products and Saildrone were lower than 0.2, examining the cross-correlation
 166 indicated this could be due to the temporal sampling of the SMAP orbit. Unlike SST, the 8-day files
 167 averages are averages over the full repeat of SMAP. Maxima correlations of approximately 0.2-0.3
 168 were found at lags of several days, indicative that Saildrone could be sampling a front offset from the

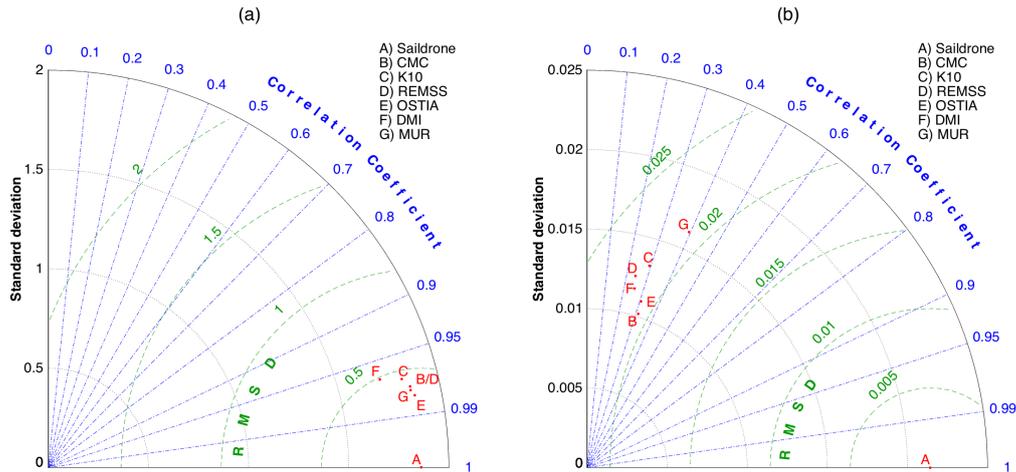


Figure 6. Taylor diagram summarizing the performance of the six GHRSSST Level 4 products for the estimation of SST (a) and SST gradient magnitudes (b) using the Saildrone Baja California campaign

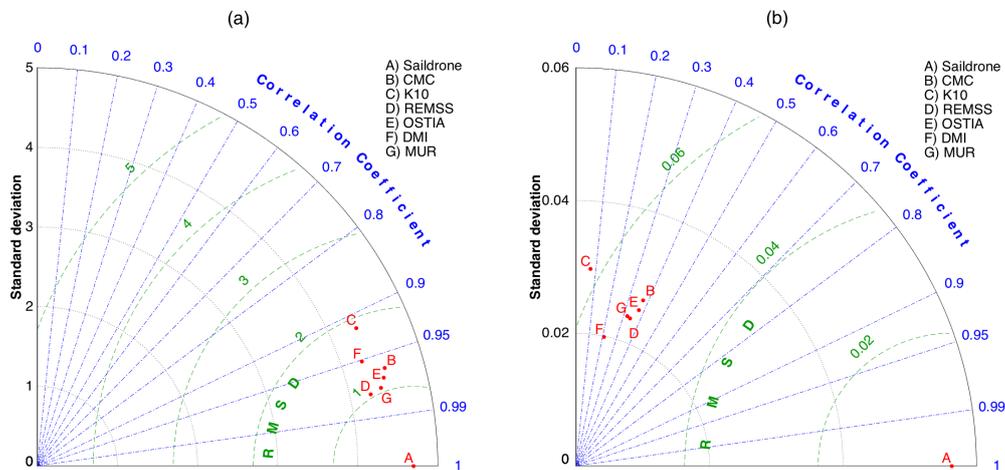


Figure 7. Taylor diagram summarizing the performance of the six GHRSSST Level 4 products for the estimation of SST (a) and SST gradient magnitudes (b) using the North Atlantic Gulf Stream campaign

169 center point of the satellite 8-day SSS average. This justifies future research examining correlations
 170 with Level 2 data, but is beyond the scope of this work. We also note that unlike SST, biases for SSS
 171 gradients are always positive, suggesting that the satellite-based estimates of SSS contain more spatial
 172 variability than that observed by Saildrone and likely due to noise in the products. Results for SST
 173 reported in Table 1 for the CCUS campaign are summarized with Taylor diagrams using Saildrone as
 174 a reference. Taylor diagrams simultaneously show the standard deviation, the centered root mean
 175 square difference and the correlation coefficient for each of the six GHRSSST Level 4 SST products.
 176 Figures 6 and 7 illustrate how the performance of Level 4 SST data sets decreases significantly when
 177 analyzing SST gradients instead of SST values. Note that the Taylor diagrams are not used here to
 178 determine which product performs best with respect to *in situ* data but to demonstrate how statistical
 179 validation based solely on the comparison of SST/SSS values does not provide much insight on the
 180 accuracy of derived gradients.

181 4. Conclusions

182 Few studies have attempted to evaluate the ability of satellite-based products to capture the
 183 location and intensity of ocean fronts. In this work, we have described a methodology that exploits
 184 the high sampling frequency of Saildrone in order to validate sea surface temperature and salinity
 185 gradients. Using data from two Saildrone campaigns conducted over regions known for intense frontal

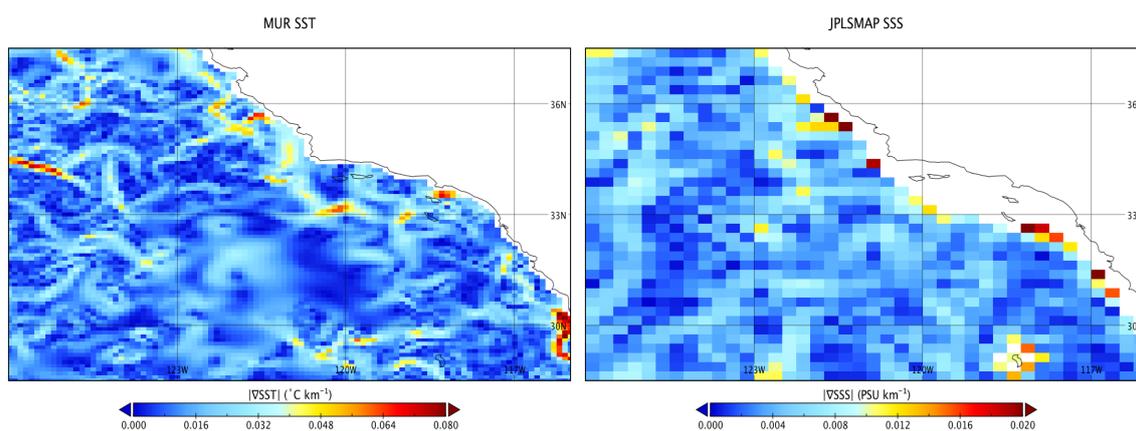


Figure 8. Maps of gradient magnitudes in the CCUS derived from (a) MUR SST and (b) JPLSMAP SSS. The data was acquired on April 24 of 2018

186 activity, we show that Level 4 satellite-based estimates of SST and SSS are overall statistically consistent
 187 with Saildrone measurements but fail to capture both locations and magnitude of surface fronts. In SST,
 188 this is mostly due to the spatio-temporal smoothing and ingestion of low-resolution passive microwave
 189 data required to generate Level 4 gap-free maps of ocean parameters. In SSS, land contamination
 190 introduces noise that increases spatial variability and thus the magnitude of salinity gradients. During
 191 periods of persistent cloud cover, where no satellite-derived infrared pixels are retrieved, the exclusive
 192 availability of the lower resolution passive microwave data leads to smoother SST gradients. As
 193 SMAP is a passive microwave instrument, it will inherently not resolve the submesoscale variability
 194 available under clear sky SST conditions. Animations showing the temporal evolution of SST and SSS
 195 gradient magnitude for all satellite products used in this study for both CCUS and NAGS Saildrone
 196 campaigns are provided as supplemental files. Figure 8 shows a typical example of the gradients
 197 derived from MUR SST and the JPLSMAP SSS products. Clearly visible are the inherent differences in
 198 the resolvability of features associated with the CCUS region.

199 While not shown here, similar experiments were conducted using high-resolution infrared Level 2
 200 data from Terra and Aqua MODIS, with the intent of reducing the temporal size of the collocation
 201 window (one day when analyzing Level 4 products). However, persistent cloud coverage in infrared
 202 observations and the relatively short duration of Saildrone campaigns (1-2 months) results in a
 203 significantly low amount of collocated points to derive reliable statistics. As future Saildrone campaigns
 204 are conducted in the future, the methodology presented here offers a valuable perspective for the
 205 validation of gradients in both Level 2 and Level 4 satellite ocean products. Finally, results reported
 206 here underline the need for improved Level 4 analysis methods, able to provide not only accurate
 207 estimates of surface and salinity but also a reliable representation of ocean surface dynamics.

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 214 publish the results.

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