CFOSAT 2nd International Science team Meeting

CFOSAT and Sentinel-1 intercomparisons for Significant Wave Height measurements

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Visio meeting

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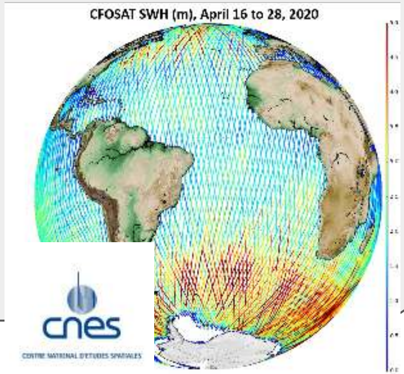
Abstract

This study provides a comparison between CFOSAT and Sentinel-1 wave measurements. Recently, new methods have been developed to analyze Sentinel-1 C-band SAR data acquired over open ocean in the so-called Wave Mode for estimating the significant wave height [Quach et al., 2020] and for classifying the images with respect to the dominant geophysical parameter [Wang et al., 2019]. These two informations are systematically derived from Sentinel-1 A and Sentinel-1 B measurements collocated with CFOSAT. The significant wave height as measured by CFOSAT and Sentinel-1 are then compared. Performances (RMSE, correlation and bias) are presented and analyzed with respect to geographical location, wind regimes and dominant geophysical signatures captured by the SAR. Emphasis on complex situations and/or inconsistent cases are discussed.

Datasets

CFOSAT SWIM Ku-band spectrometer nadir beam Level-2 CWWIC at box 70 x 90 km resolution. Adaptive retracking algorithm.

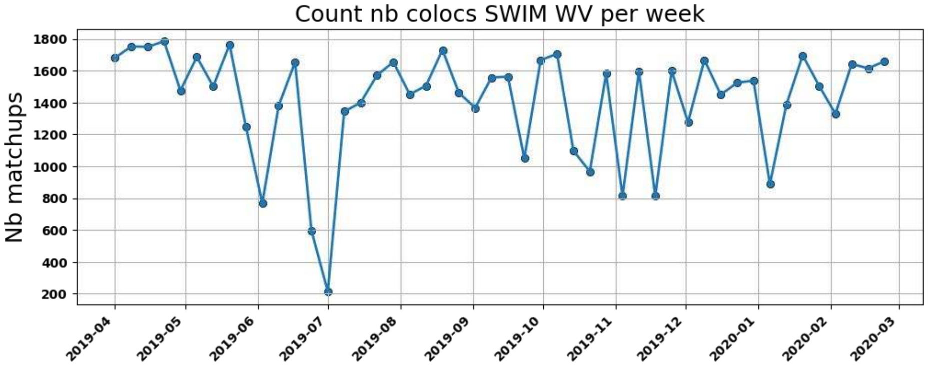


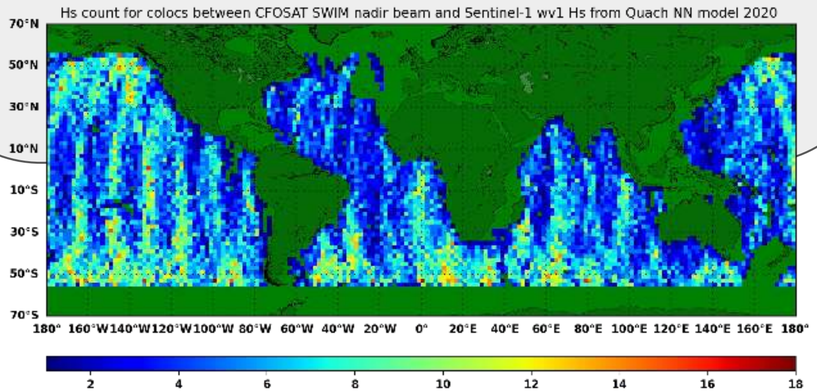
Aviso altimetry courtesy.

CFOSAT and Sentinel-1 units present heliosynchronous orbits that offer very long matchups opportunities. The time criteria used for this study is +/-2 hours and 100 km radius.

Sentinel-1 A & B WV C-band SAR. Leapfrog acquisitions 24° and 37° incidence angle every 200 km (~ 3 seconds) at global scale, Hs dataset build using Quach et al 2020 NN model develop at University of Hawaii and operated at IFREMER in the frame of 2 ESA projects:

- Sentinel-1 MPC (Mission Performance Center)
- CCI Sea state (algorithm selected for official CCI datasets)

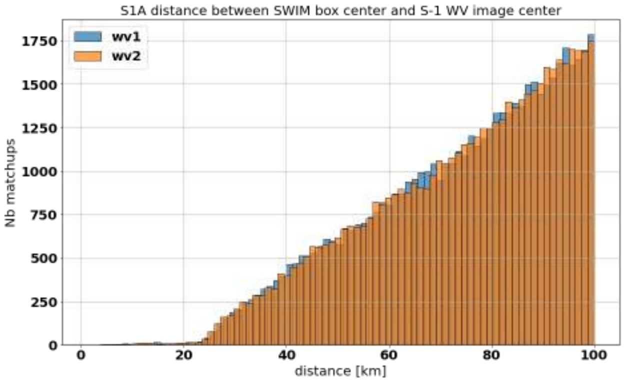


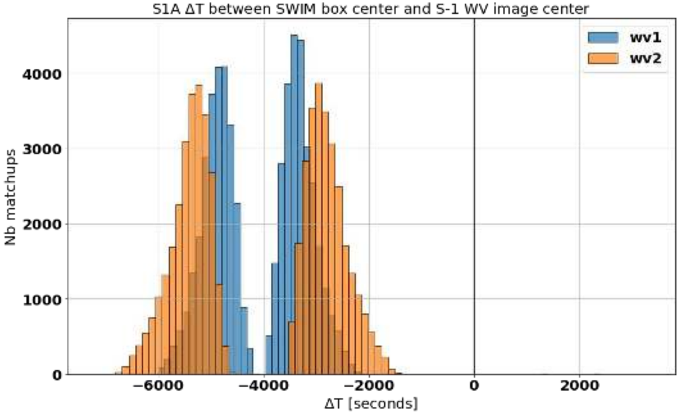


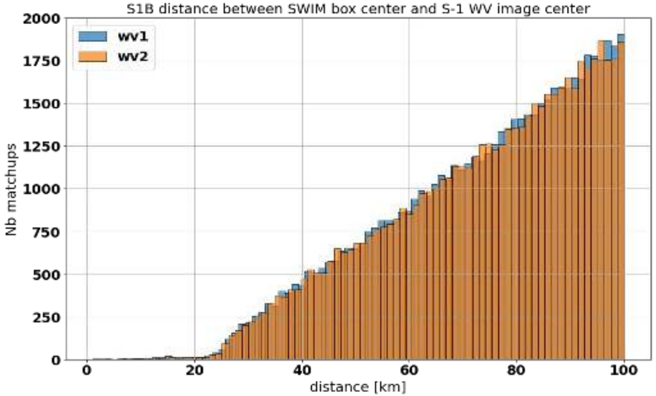
Matchups between SWIM and Sentinel-1 WV

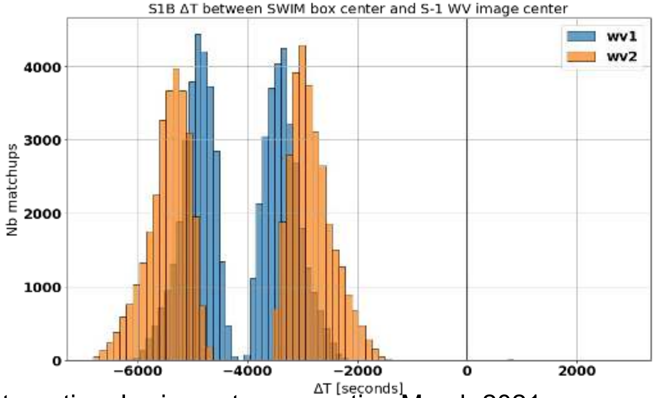
ΔT : +/-2 hours
Δgeographic: 100 km

S1A and S1B are matching CFOSAT 100 km radius with 1 or 2 hours advance .









SAR NN model to get Hs from WV cross spectra: QUACH *et al* 2020

Deep Learning for Predicting Significant Wave Height From Synthetic Aperture Radar

Brandon Quach, Yannik Glaser, Justin Edward Stopa, Alexis Aurélien Mouche, and Peter Sadowski

***Abstract*—The Sentinel-1 satellites equipped with synthetic aperture radars (SARs) provide near-global coverage of the world's oceans every six days. We curate a data set of collocations between SAR and altimeter satellites and investigate the use of deep learning to predict significant wave height from SAR. While previous models for predicting geophysical quantities from SAR rely heavily on feature-engineering, our approach learns directly from low-level image cross-spectra. Training on collocations from 2015 to 2017, we demonstrate on test data from 2018 that deep learning reduces the state-of-the-art root mean squared error by 50%, from 0.6 to 0.3 m when compared to altimeter data. Furthermore, we isolate the contributions of different features to the model performance.**

***Index Terms*—CWAVE, deep learning, machine learning, neural networks, Sentinel-1, significant wave height, synthetic aperture radar (SAR).**

I. Introduction

SYNTHETIC aperture radar (SAR) enables us to measure submesoscale phenomena with unprecedented coverage, resolution, and frequency. By measuring the backscatter from the ocean surface, SAR captures information about ocean swells and sea surface roughness at high spatial resolutions (<10 m) [1], from which many oceanic, atmospheric, and biologic phenomena can be identified [2]. The two Sentinel-1 satellites of the European Space Agency (ESA) take regular SAR measurements of the ocean surface, together covering the entire globe every six days [3], and have already accumulated more than 600 TB of level-1 (L1) wave mode data. However, in order to take full advantage of this technology and the torrent of data being produced, new methods are needed to extract useful information from the high-dimensional measurements.

Sea state information extracted from SAR has been instrumental in understanding swell decay [1], [4], [5], improving swell propagation in numerical models [6], and predicting swell amplitudes and arrivals times by assimilation into numerical models [7]. SAR can also be used to estimate extreme sea states in extra-tropical and tropical cyclones [8]–[10]. A geophysical quantity of particular interest is the *significant wave height*, H_s, defined as the mean of the top third of a wave height distribution, and estimating H_s from SAR has immediate practical uses in alerting ships to dangerously large waves. Traditional "inverse" algorithms for inferring H_s from SAR are slow and perform poorly in windy conditions typical of most storms [11], [12] because of the complex nonlinear mechanism involved in the image synthesis when observing moving scenes. As a result, several recent studies have focused on data-driven statistical models [8]–[10], [13].

Previous data-driven approaches for predicting H_s from SAR used small data sets of buoy observations as targets for training (<5000 examples) [14]–[16], or numerical models of global wave generation such as WAVEWATCH3 [8], [10], [13], [17]. The current state-of-the-art method uses a neural network trained on the latter, and predicts H_s with 0.6-m root mean squared error (RMSE) [10]. However, the WAVEWATCH3 targets are only an *estimate* of H_s and are known to be unreliable in high sea states [18]–[20].

Furthermore, the neural network in [10] relies on a reduced representation of the modulation cross-spectra: a set of 22 engineered features known as CWAVE [13]. Such dimensionality-reduction methods can be very useful, but often come at the cost of discarding relevant information. We hypothesize that the SAR image modulation spectra contains *additional* information about H_s that is lost by the CWAVE dimensionality-reduction step. We propose to *learn* the relevant intermediate data representations using deep learning with artificial neural networks, similar to what has been done in other fields from computer vision [21] to high-energy physics [22]–[24].

In this work, we address both limitations of current data-driven H_s prediction models. First, we curate a data set containing *direct observations* of ocean wave heights by identifying 750,000 collocations of SAR and altimeter satellites. Second, we train a statistical model to extract information directly from low-level SAR image spectra using deep learning. Finally, we analyze the importance of the different inputs to this model, and its performance in different settings.

II. Data and Methods

A. Sensors, Collocations and Preprocessing

Our first contribution is a data set of historical measurements from two types of polar-orbiting satellites: Sentinel-1 SAR satellites and altimeter satellites. Because the satellites are in different orbits, their paths intersect, providing

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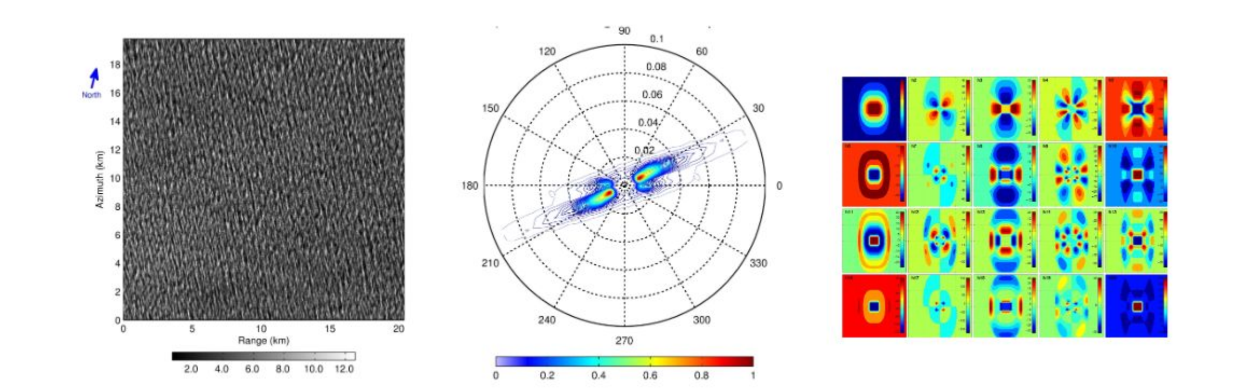
Color versions of one or more of the figures in this article are available online at http://ieeexplore.ieee.org.

Digital Object Identifier 10.1109/TGRS.2020.3003839

This algorithm has been published in IEEE TGRS in 2020.

The method aims at investigating the use of DL to start from X-spectra instead of using a predefined decomposition of the x-spectra (so-called CWAVE parameters).

This algorithm has been compared against other algorithms in the framework of CCI and proved to be better for Hs.



Example of Real part of X-spectra and the 20 parameters computed from the spectra for CWAVE

SAR NN model to get Hs from WV cross spectra

Quach 2020 et al methodology described in this paper:

https://authors.library.caltech.edu/104562/1/09143500.pdf

Source datasets for NN model training:

1. Sentinel-1 WV L2 polar cross spectra + radar parameters
2. Altimeter database from IMOS (Young et al). **CFOSAT SWIM measurement are not considered in the training dataset**.

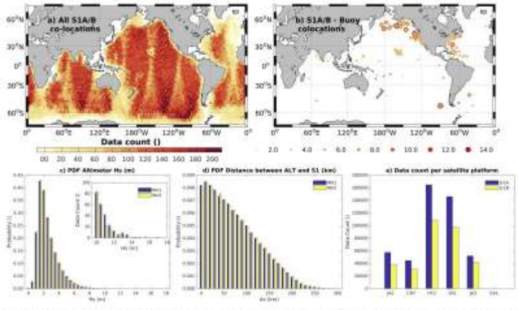


Fig. 1. Collocations between S-1 and satellite altimetry and moored buoys. (a) Total number of S-1/ALT collocations in 2 × 2° bins. (b) Locations of the S-1/buoy collocations, the colors and size of the markers indicating the buoy H_s. (c) Histogram of H_s for S-1/ALT for WV1 and WV2, with the inset showing the tail for extreme sea states. (d) Histogram of distance between the S-1/ALT acquisitions for WV1 and WV2. (e) Bar graph showing number of collocations from each of the altimeter-SAR combinations.

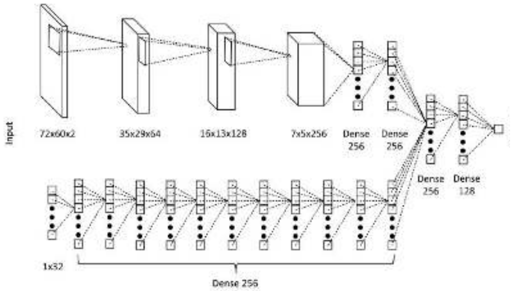


Fig. 3. DNN architecture with two input types. (Top) SAR image spect comprising one real and one imaginary channel. (Bottom) 32 scalar-valu features. The SAR images are processed by multiple 2-D convolution laye before the two branches of the network are combined by three dense layers at the output. We predict H_s in this work, but we expect that the same model architecture could be used to predict other sea state parameters given an adequate training data set.

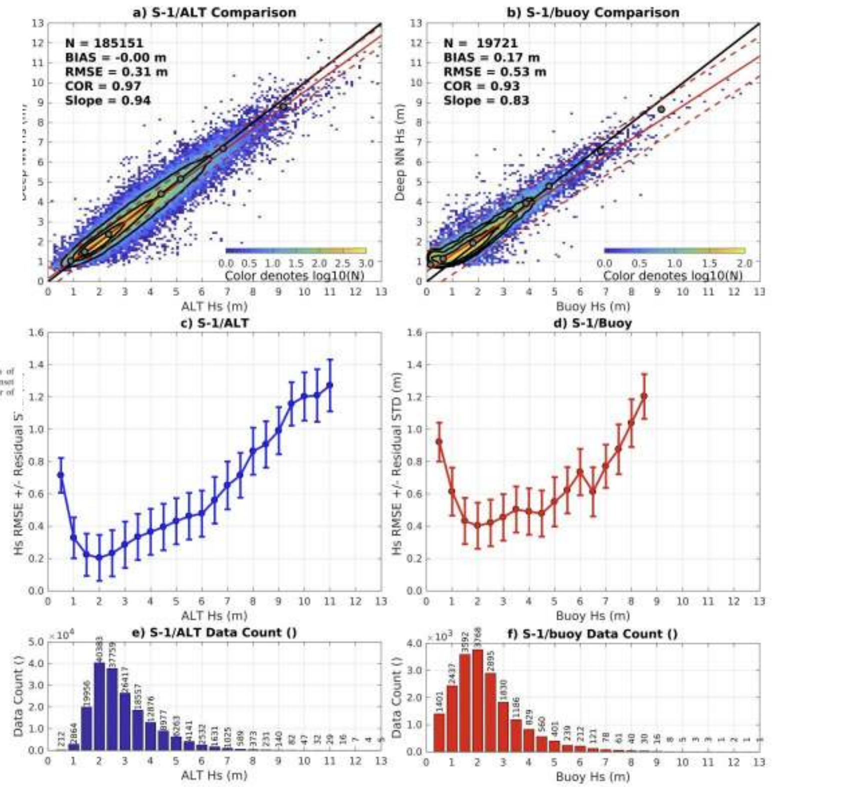
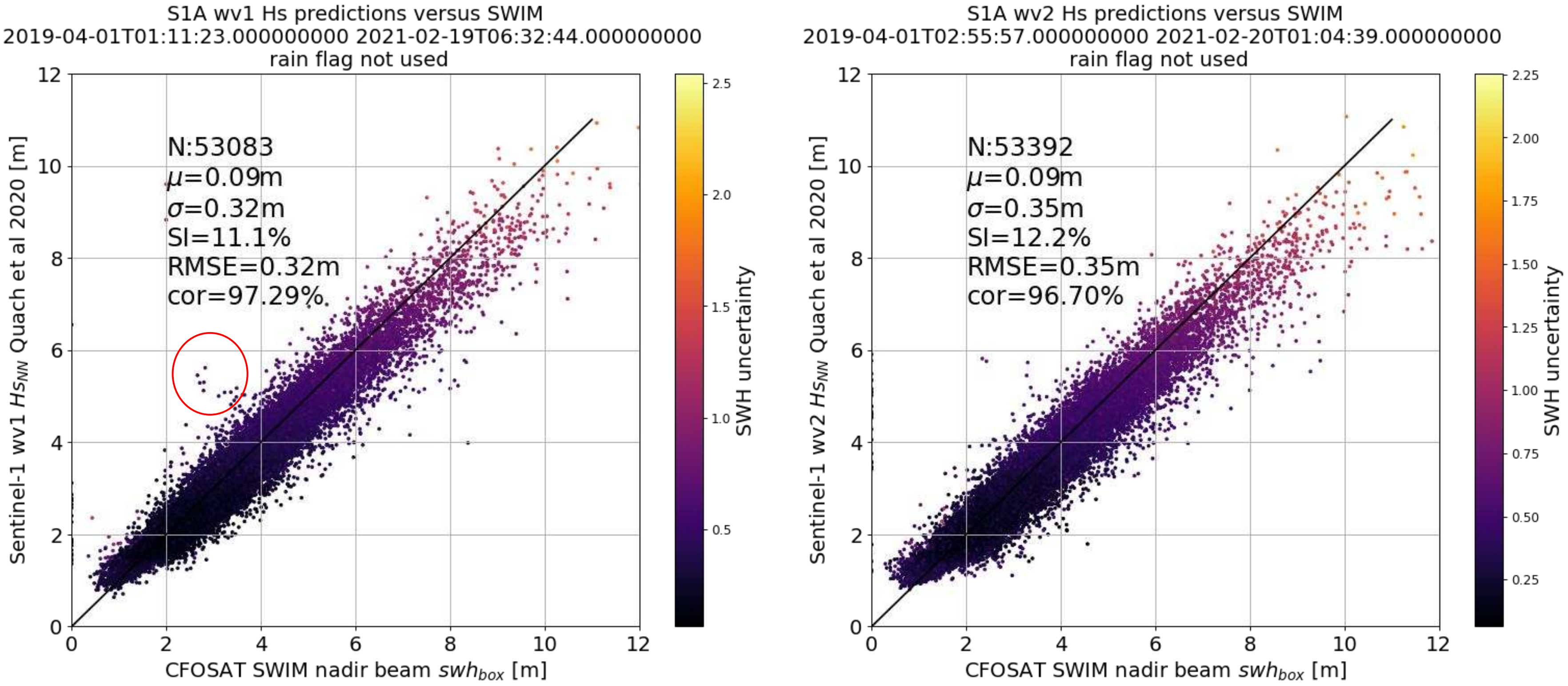
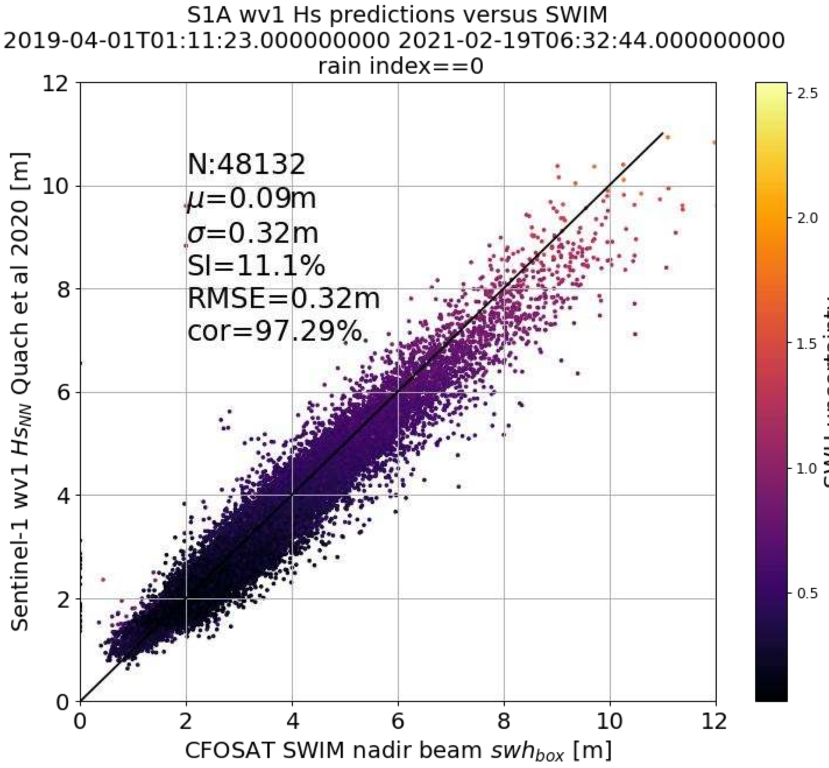


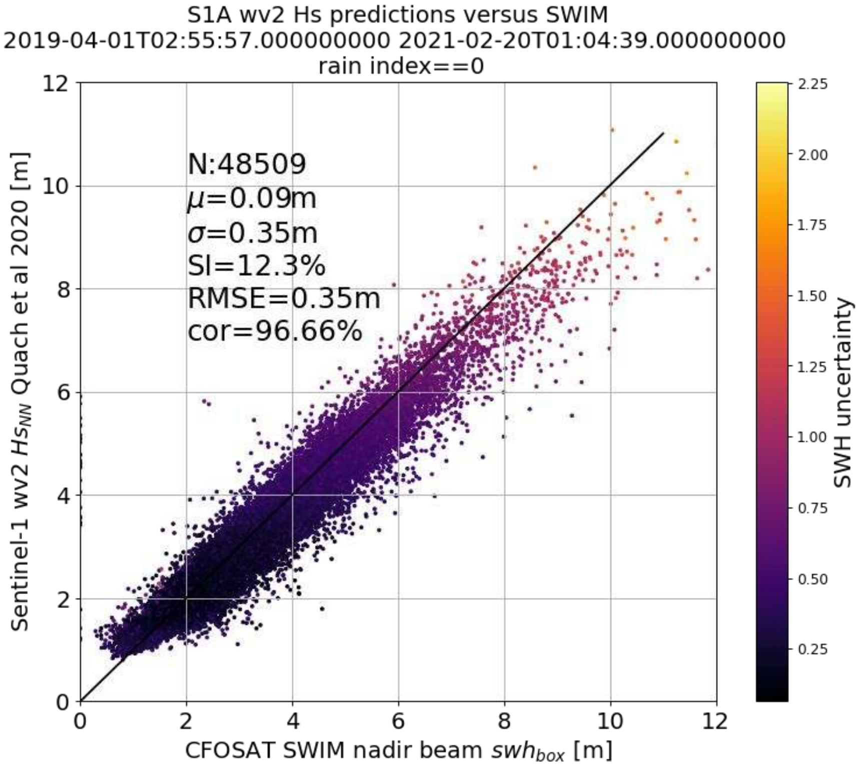
Fig. 7. Comparison of test predictions against (Left) altimeter collocations and (Right) buoy collocations. (a) and (b) Scatter plots of predictions versus measurements. (c) and (d) Plots of prediction RMSE versus measured H_s, with error bars showing the standard deviation. (e) and (f) Histograms of measured H_s where the data count is given in black text. In the top panels, the color denotes data density in 0.1-m bins, solid red lines represent a least square linear regression, and the dashed lines represent 90% of the data. The black contours represent 50%, 75%, and 95% of the data (inner to outer) and the gray dots represent the quantile-quantile points for 1%, 10%, 50%, 90%, 95%, 99%, and 99.9%.

Overall collocations Hs statistics



The Hs provided by NN model is associated to an uncertainty value. In Quach et al 2020 this uncertainty is the standard deviation of the difference between NN predictions and reference dataset. The 2 figures above are showing that this metric is directly linked with the Hs value but is not performant to detect anomalous observations-predictions.



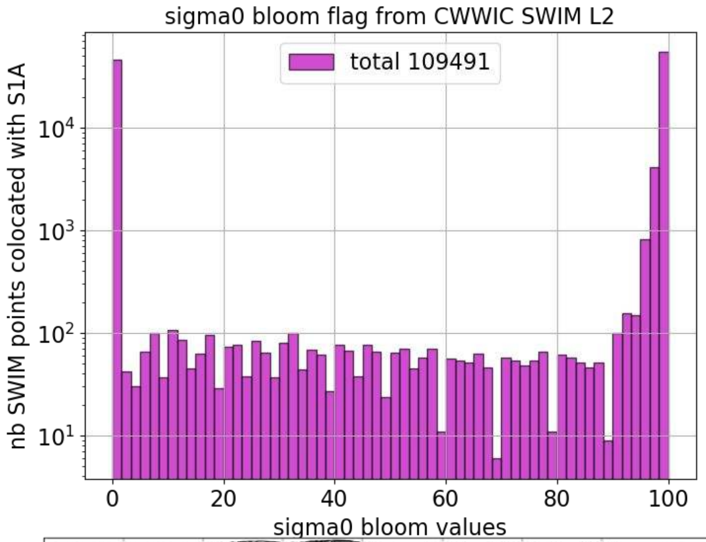


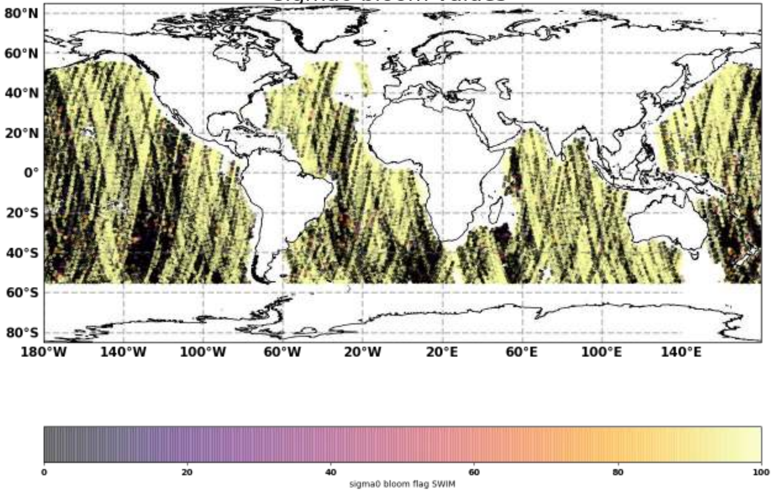
The rain flag provided by CWWIC in the L2 SWIM nadir product allows to remove some outliers. Overall, it doesn't change significatively the performances (even if it reduces by 16% the number of points). This could be a clue that this flag could be improved.

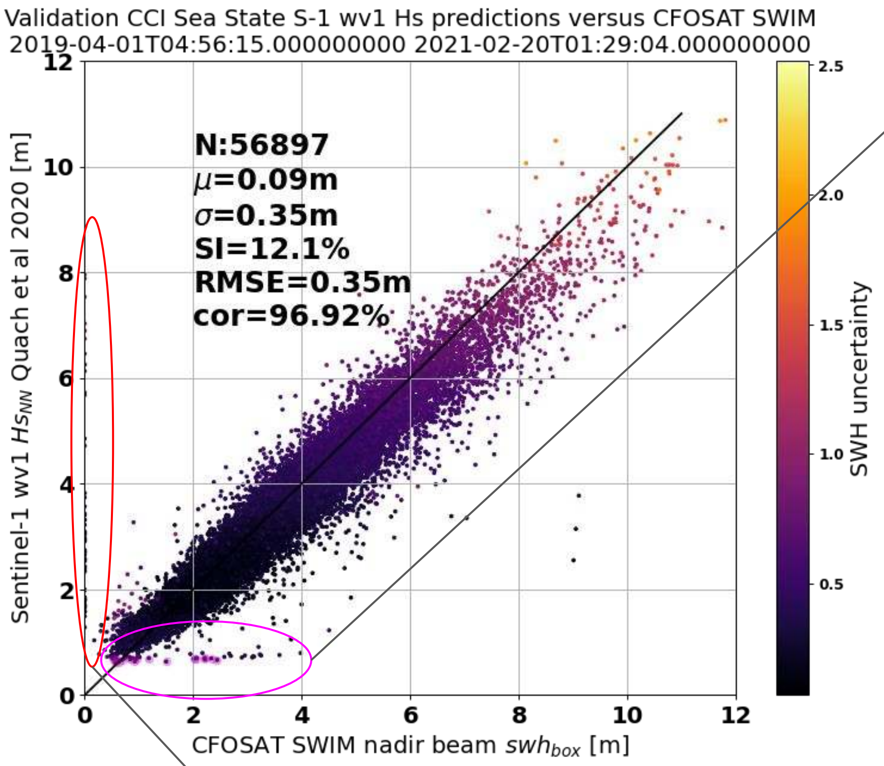
While the sigma0 bloom flag provided is not usable in the latest 5.1.2 version.

SWIM sigma0 bloom flag

SWIM sigma0 bloom flag is designed to filter very low backscatter regions where the Hs retrieval using the altimeter waveforms is not possible or susceptible to be biased. The content of this flag is for now not usable because more than 50% of SWIM boxes are set to 100% bloom. The map is also showing no regional patterns but only full orbits flag with the same value.





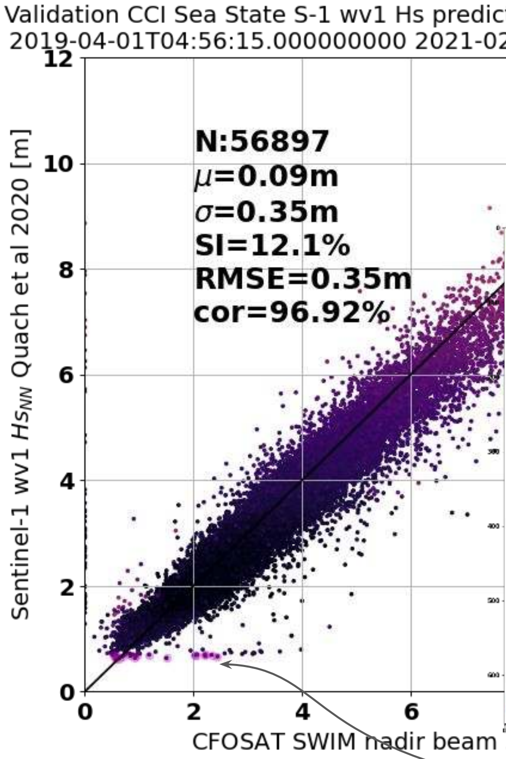


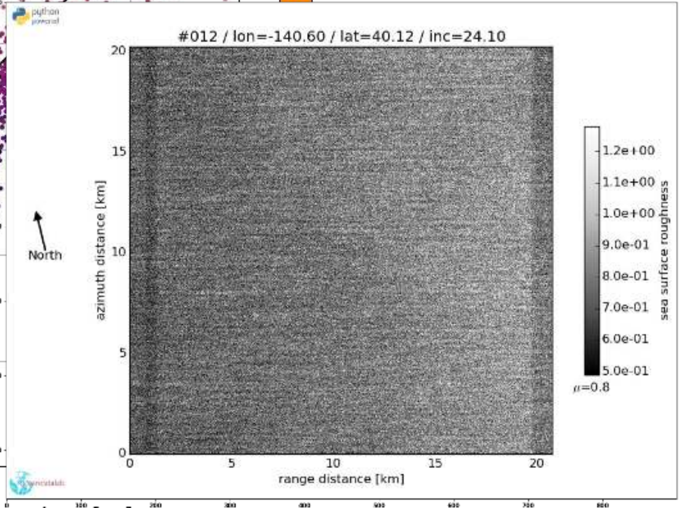
Focus on very low Hs predictions with Quach et al 2020 SAR algorithm.

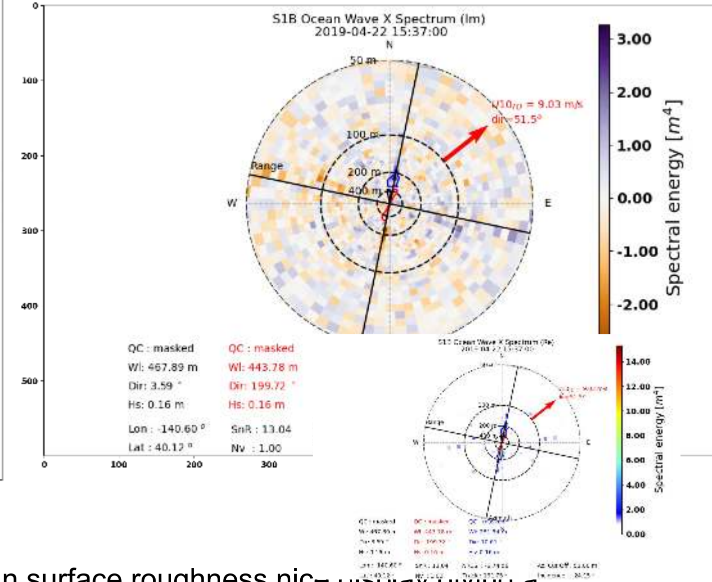
Selection of 17 Sentinel-1 WV images wit Hs < 0.7m

SWIM Hs = 0m are discussed slide 14.

Focus on very low Hs predictions with Quach et al 2020 SAR algorithm.

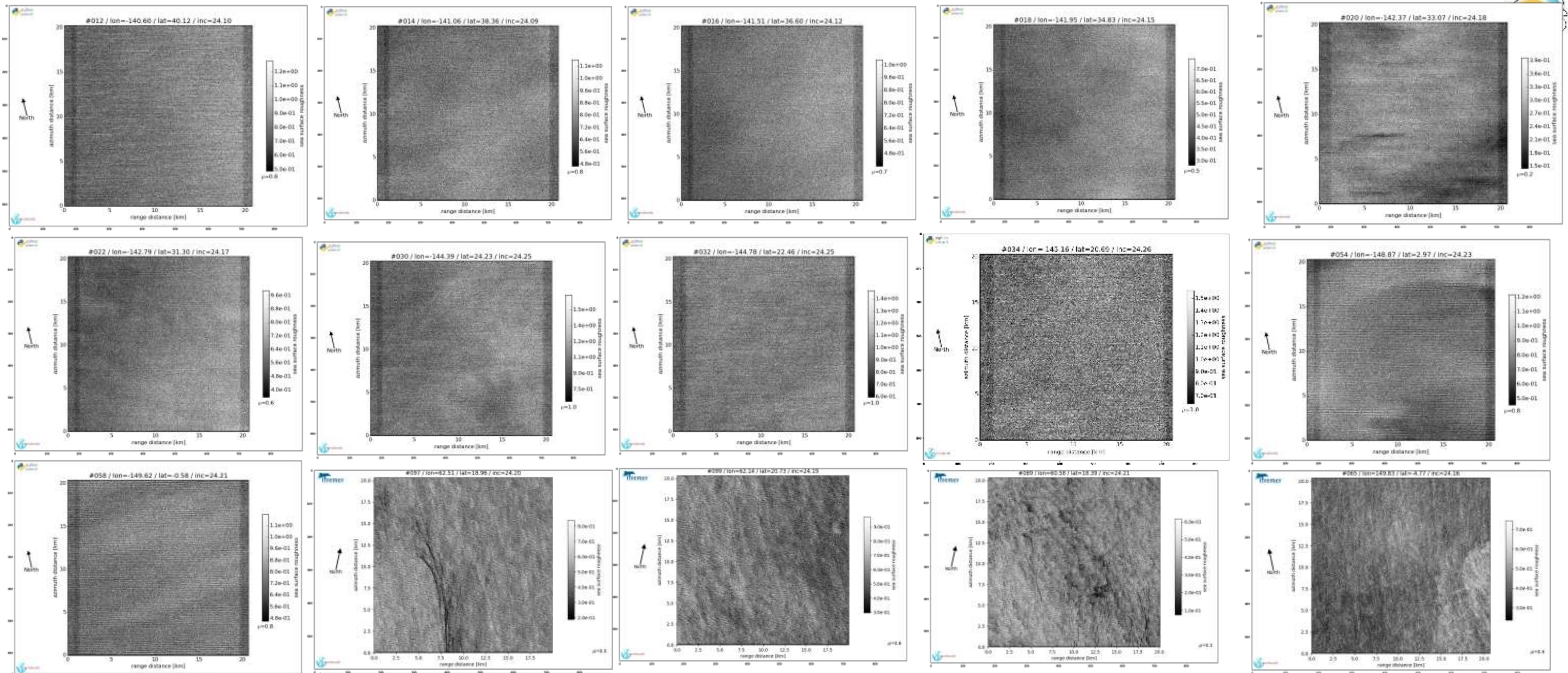


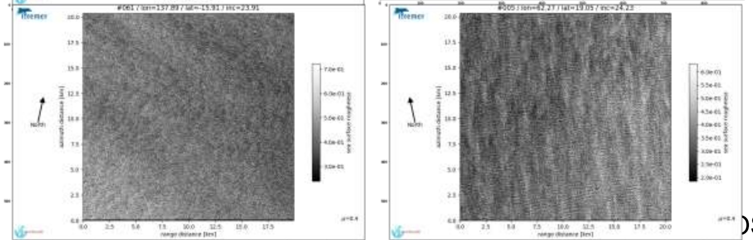




Selection of 17 Sentinel-1 WV images with Hs < 0.7m

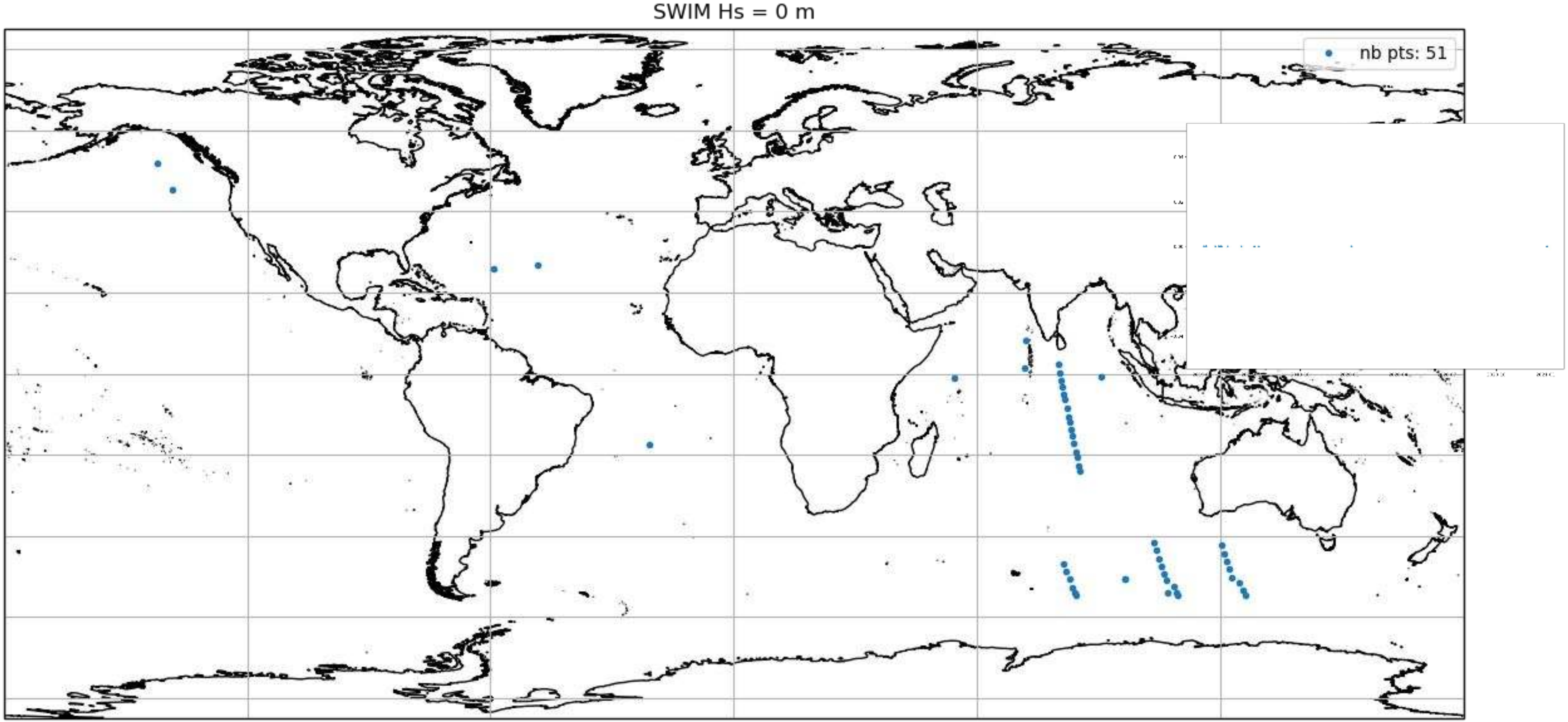
One example of the ocean surface roughness nice display giving a cross spectra with peak of energy along the azimuth axis and ultimately too low Hs.
This image is showing vertical black lines that are artefacts impacting spectral Fourier transform and then Hs retrieval.



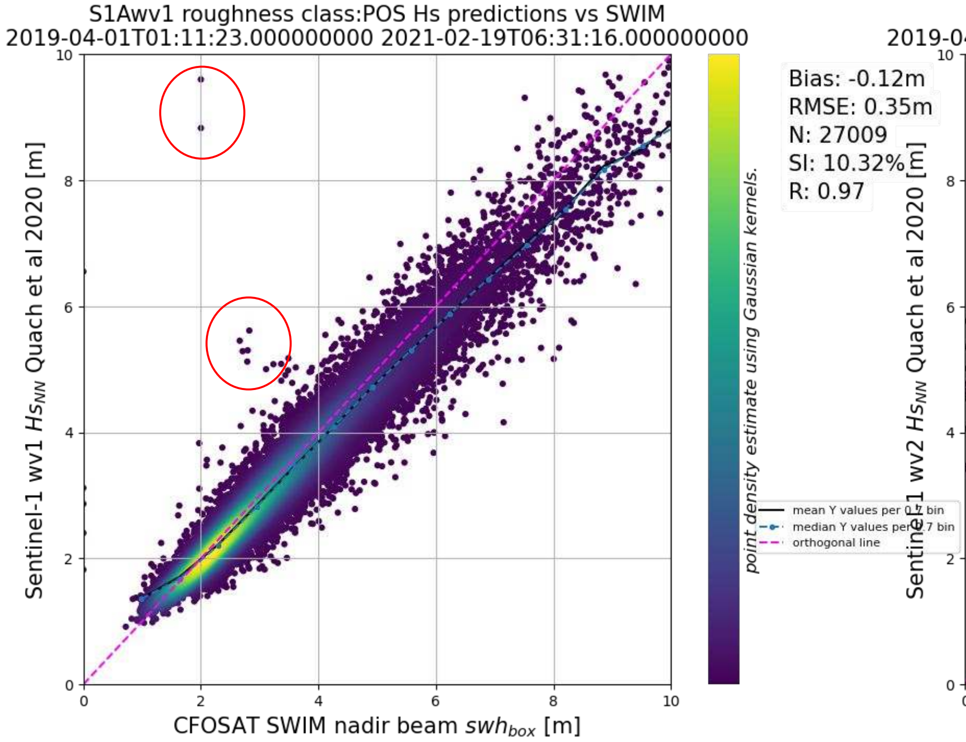


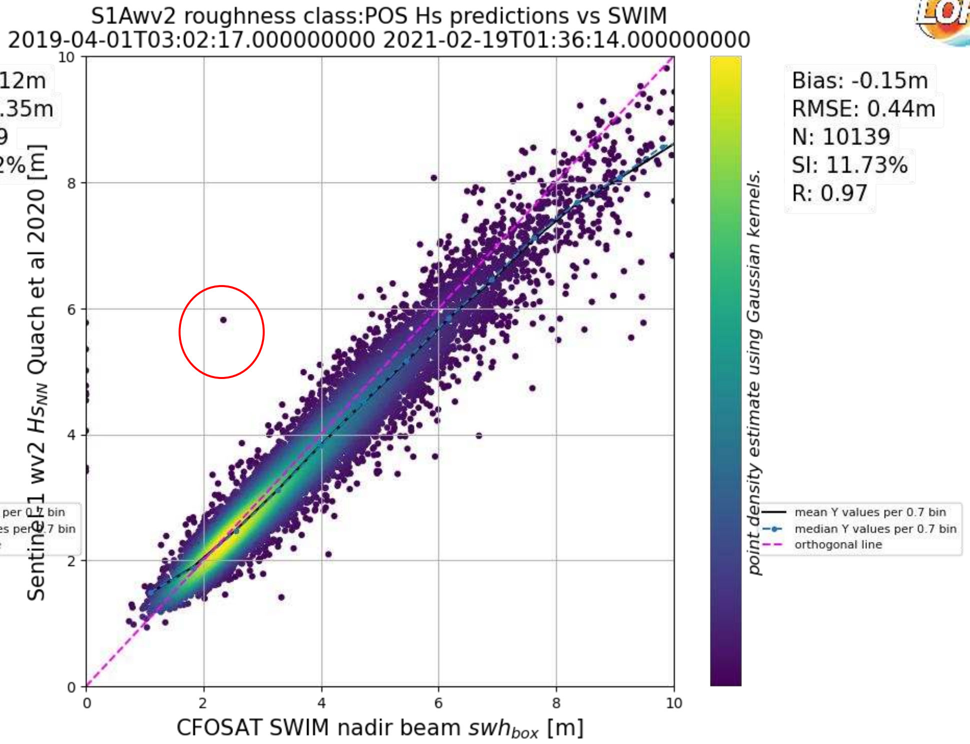
The 17 WV images with Hs<0.7 m are:

- Images with artefact
- Images with low frequency atmospheric or biological contamination

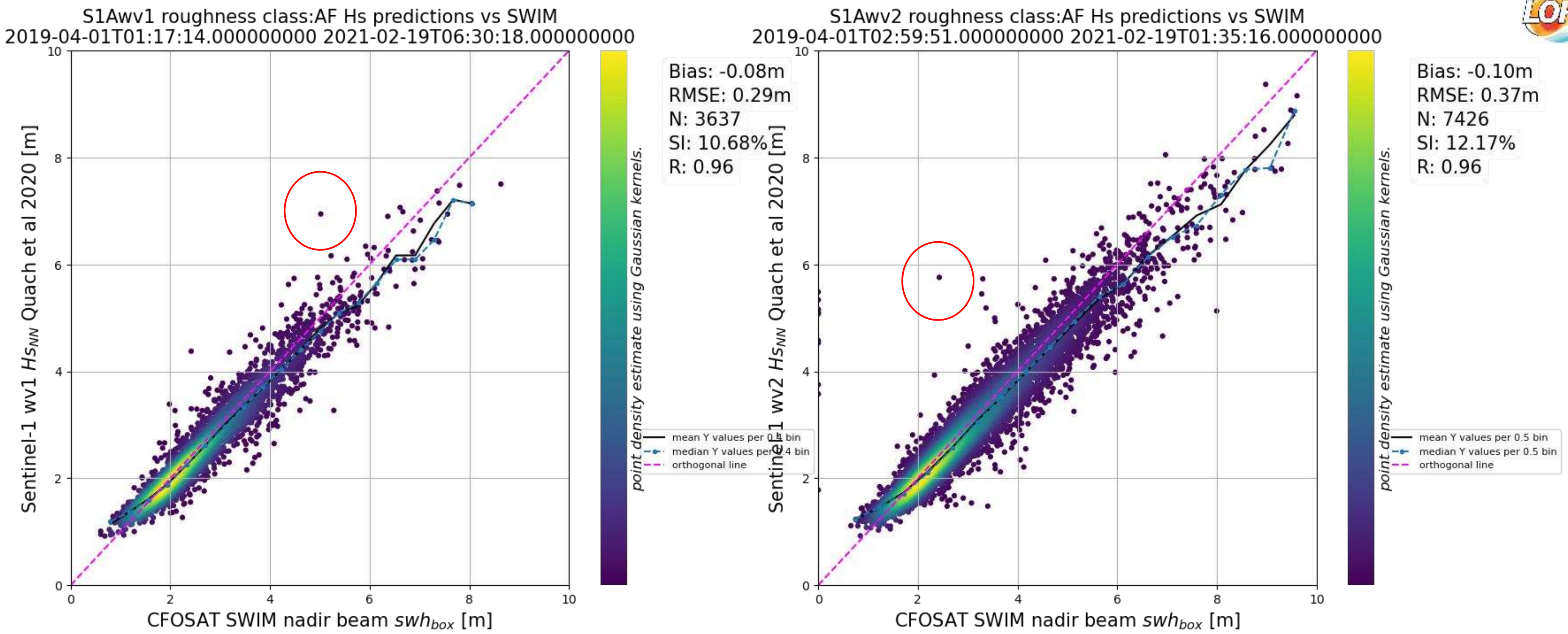


Few SWIM Hs are equal to zero m. They are located along same orbits at the beginning of the mission in 2019, it is very likely corrupted files.

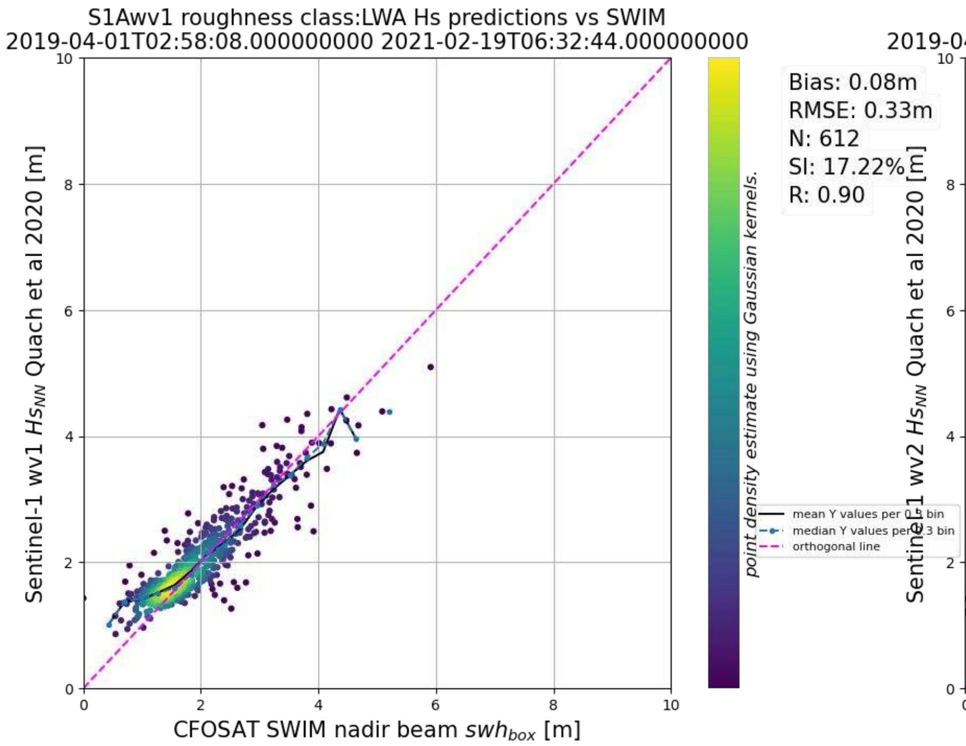


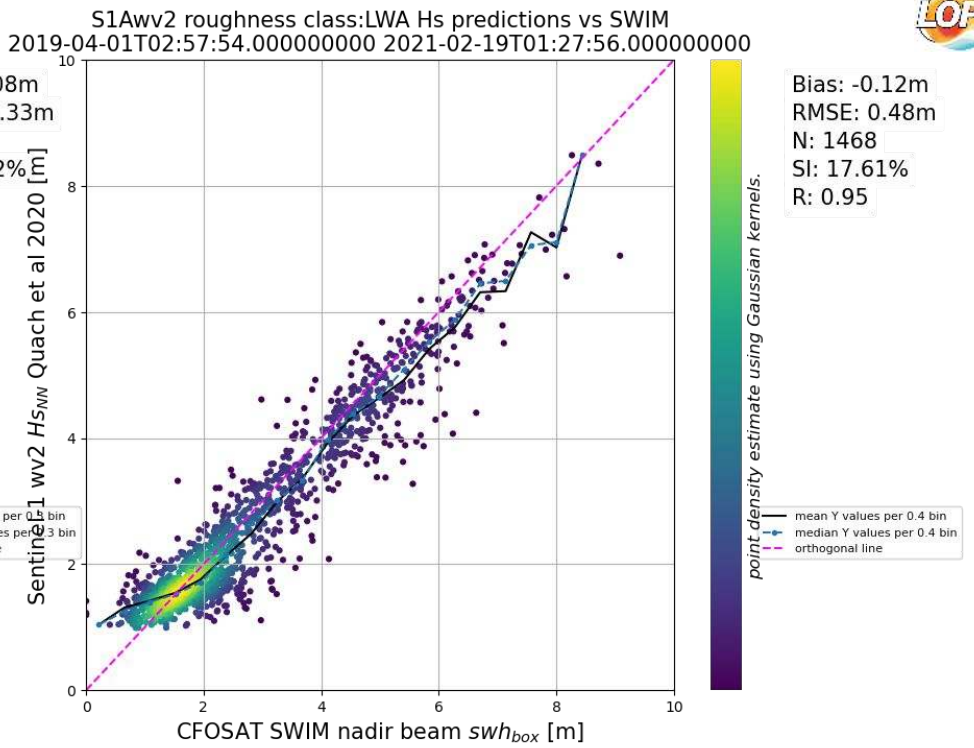


WV classified as "Pure Ocean Swell" by the Deep Learning algorithm developed by Chen et al 2018: https://www.seanoe.org/data/00456/56796/

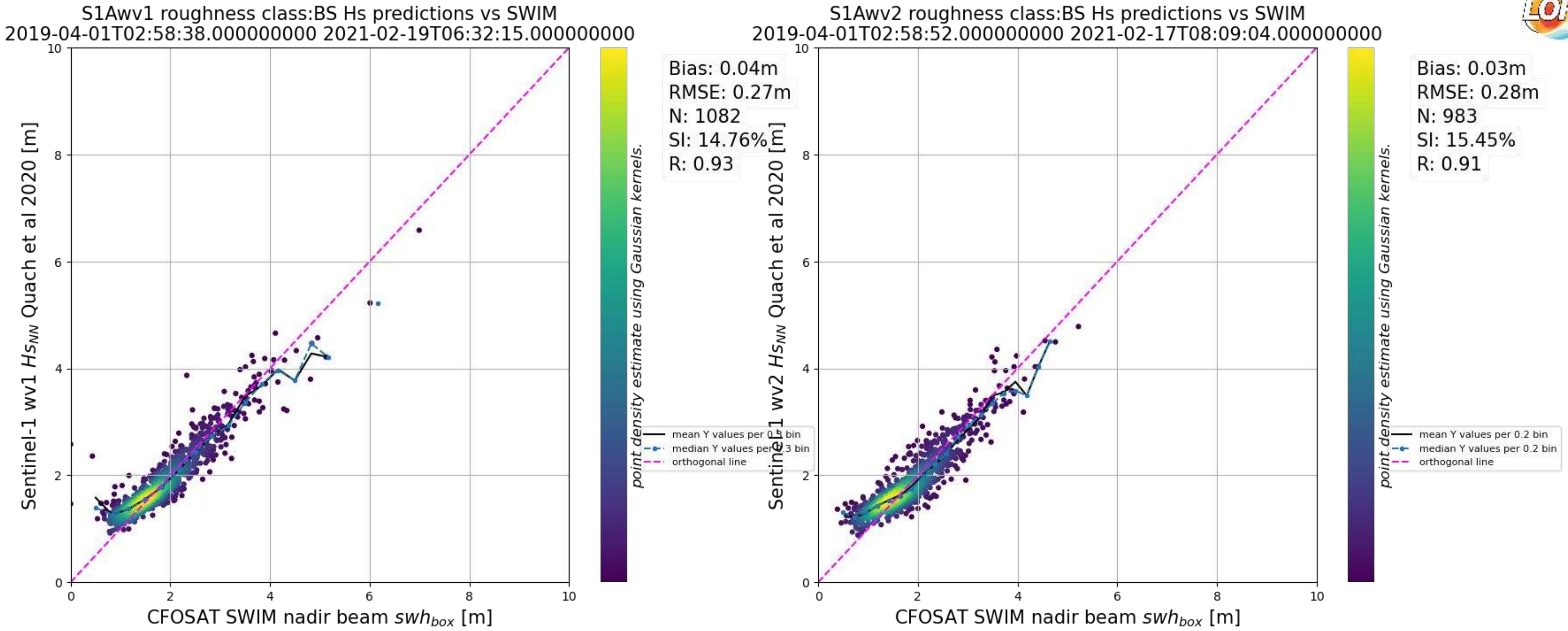


WV classified as “Atmospheric Front“ by the Deep Learning algorithm developed by Chen et al 2018: https://www.seanoe.org/data/00456/56796/

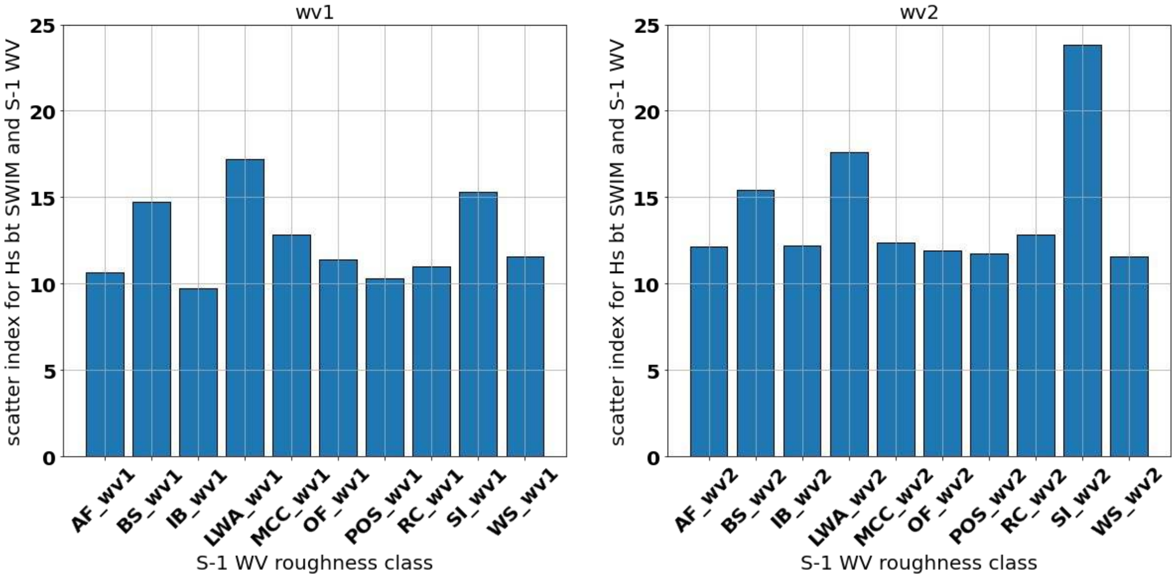




WV classified as "Low wind speed Area" by the Deep Learning algorithm developed by Chen et al 2018: https://www.seanoe.org/data/00456/56796/



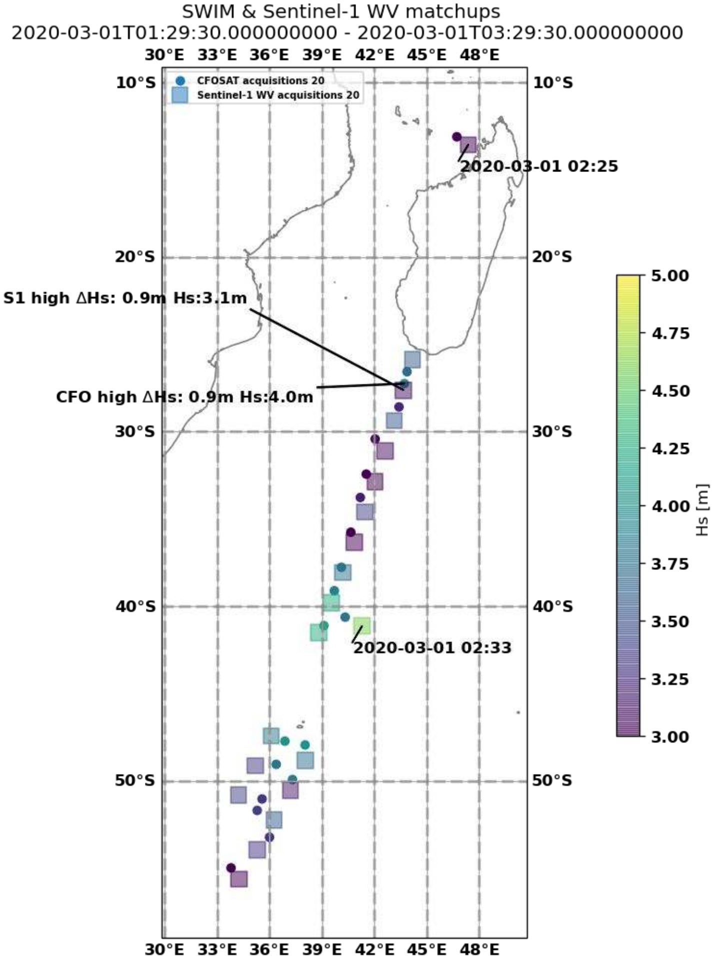
WV classified as “Biological Slicks“ by the Deep Learning algorithm developed by Chen et al 2018: https://www.seanoe.org/data/00456/56796/

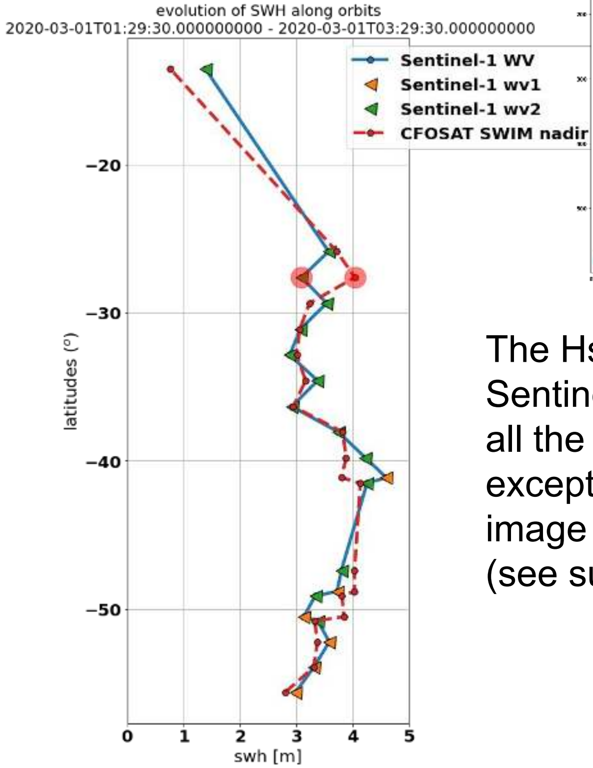


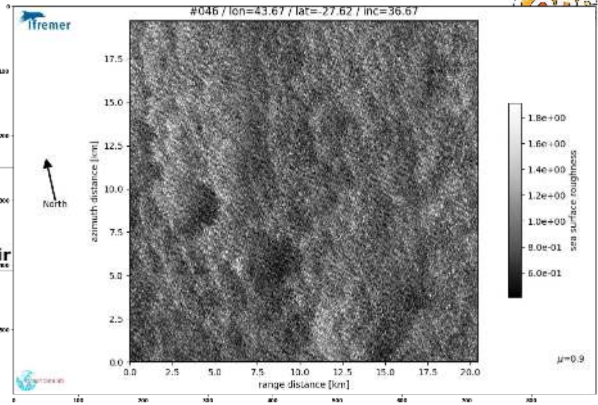
This figure is illustrating the fact that for some SAR images containing non wave geophysical features, the Hs retrieval is not giving the same performances. For instance we can see that the class SI (sea Ice) , or LWA (Low Wind Area) have scatter about ~40% higher than Pure Ocean Swell (POS).

3 case studies to illustrate the performances of both products

Example showing performances of the products along an orbit

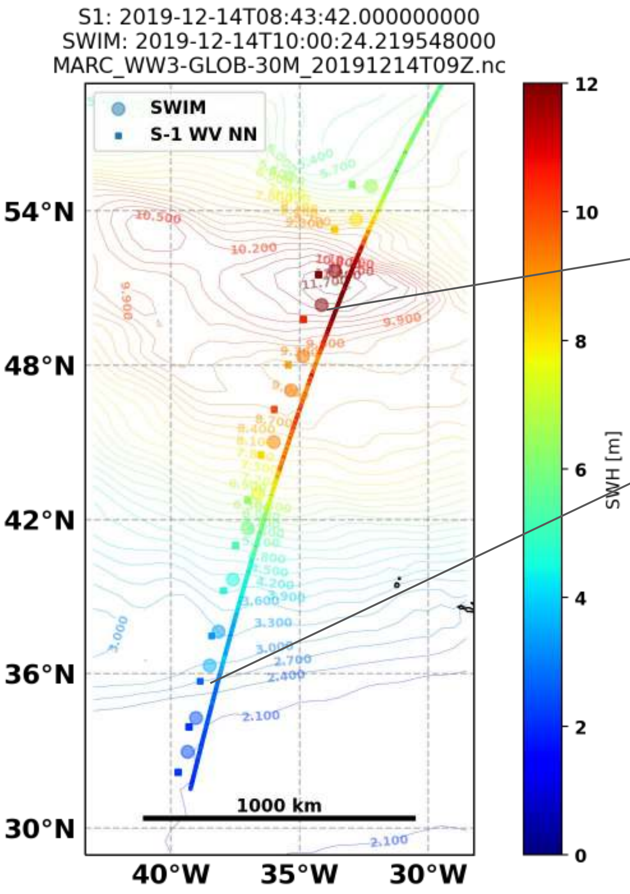


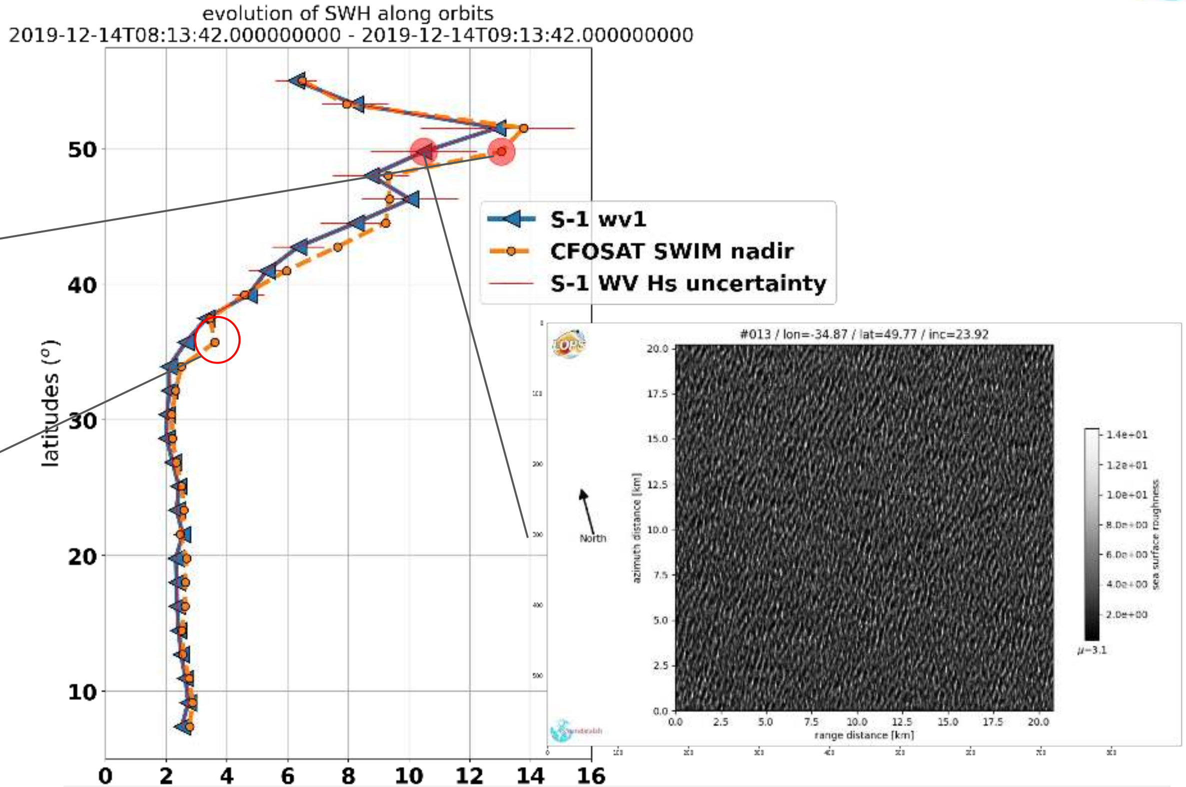




The Hs given by SWIM and Sentinel-1 are in good agreement for all the matchups along this orbit except for cases where the SAR image show the presence of rain cell (see surface roughness above).

Second case study with orbits crossing strong sea state region.

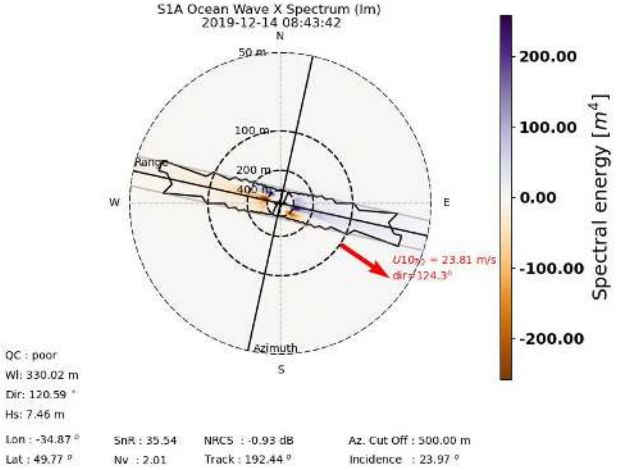


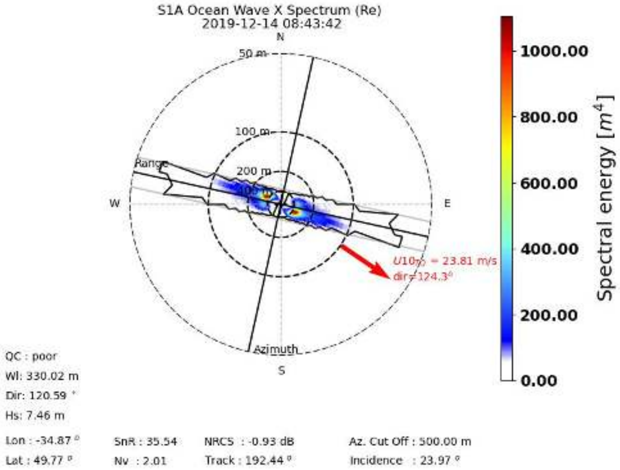


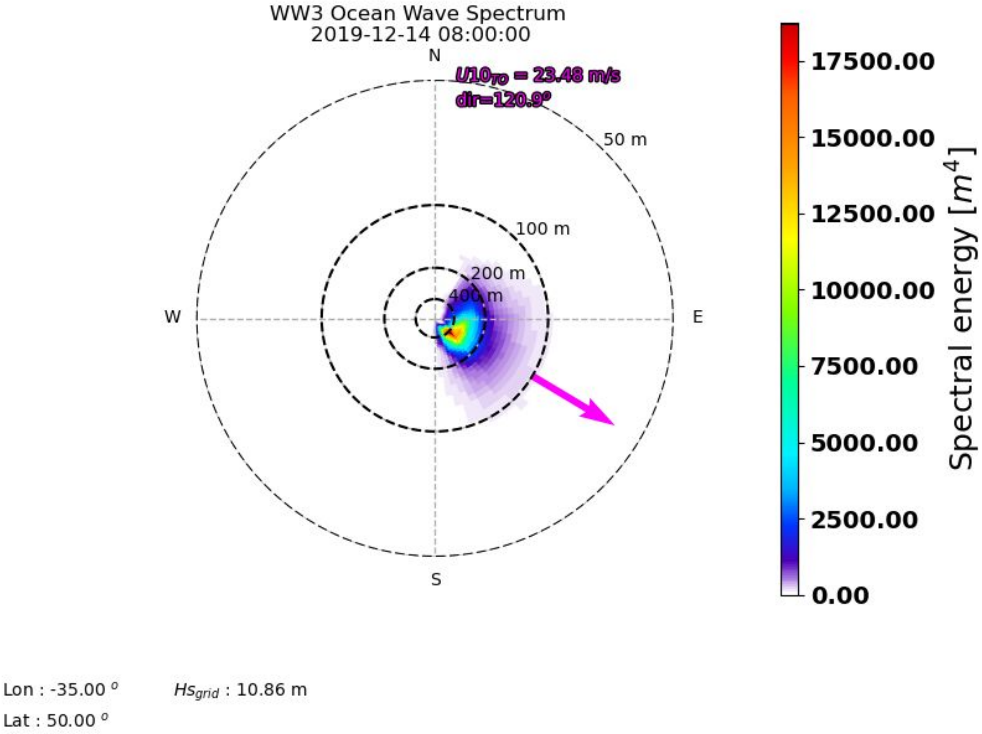
On this case with high Hs we selected the pair SWIM-S1 with the largest difference of Hs. The SAR image is not disturbed by low frequency contamination and the NN model gives a 11 m Hs while SWIM nadir beam is measuring 13 m. This is explained by the sharp sea state change within the 100km separating SWIM and the WV1.

Second case study with orbits crossing strong sea state region.

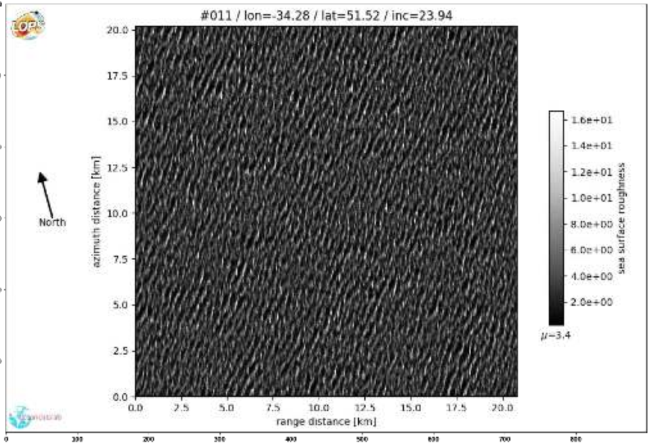
Cross Spectra (real and imaginary part) + WW3 wave height spectra associated to the suspect WV Hs.

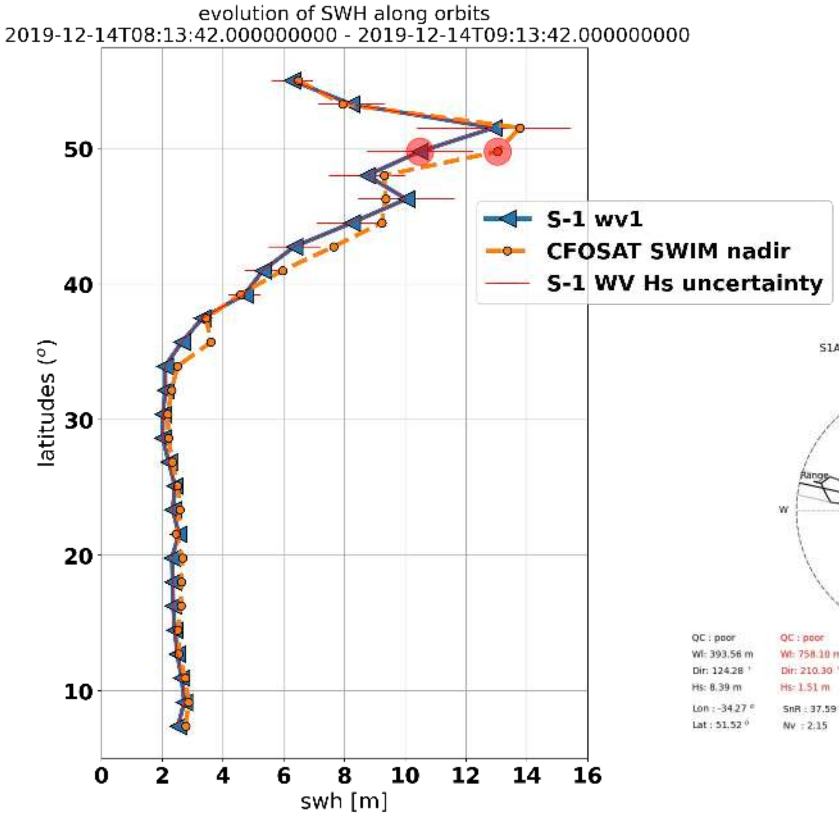


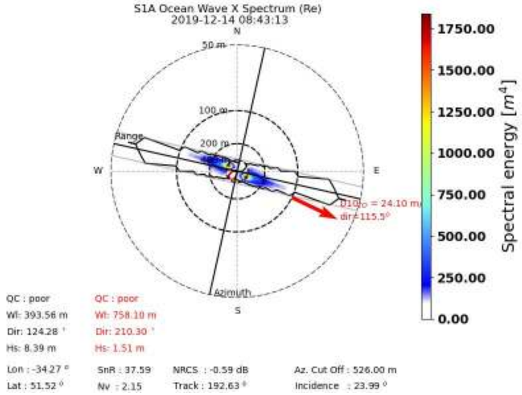




Second case study with orbits crossing strong sea state region.

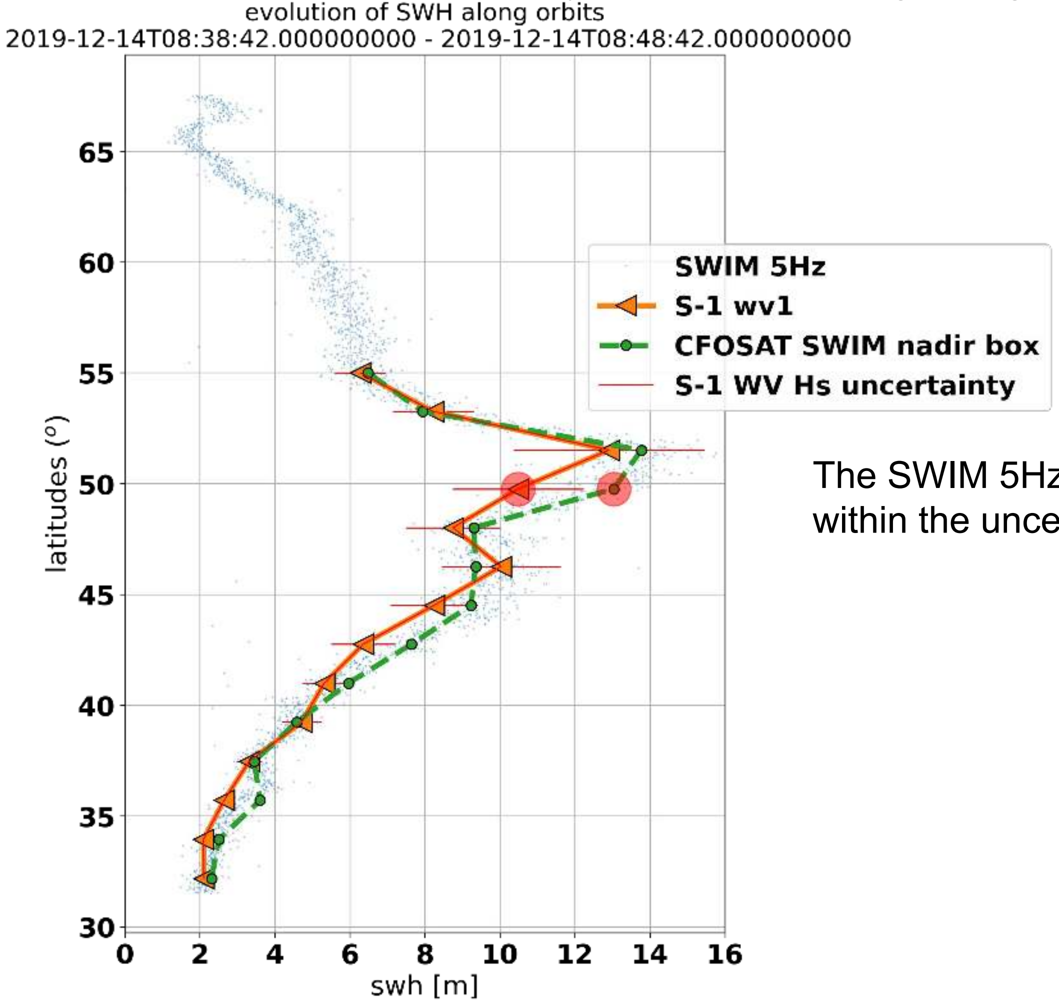






the WV1 just before (#011) 200 km North is in better agreement with SWIM while both products indicate higher Hs. It is simply due to the fact that this matchup has a closer spatial distance and less Hs gradient between the 2 points. This a very encouraging result to see that both products manage to provide Hs with less than 50cm difference within a 13-14m Hs.

Second case study with orbits crossing strong sea state region.



The SWIM 5Hz is a bit noisy but most of the 5Hz points are within the uncertainty given by S-1 NN model.

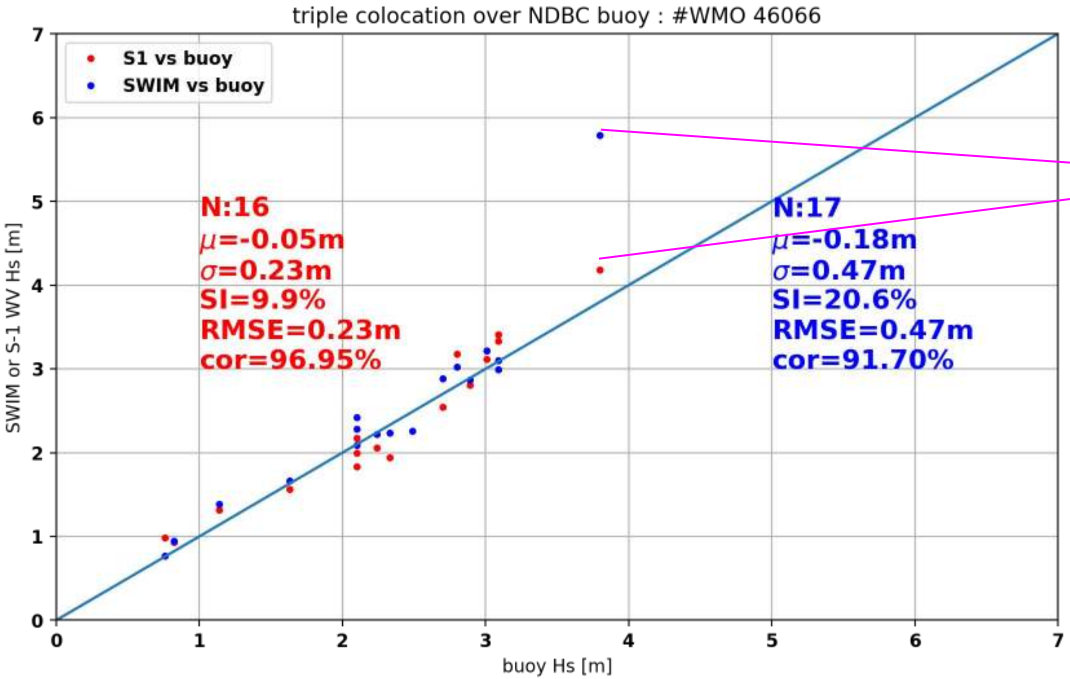
Second case study with orbits crossing strong sea state region.

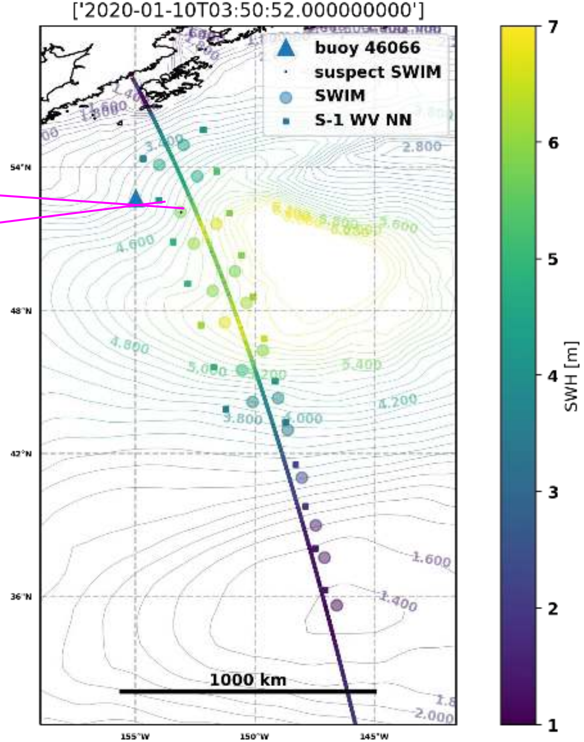
This second case study shows that both products seem to give coherent Hs even in Hs above 12m. It also suggests that colocations between the 2 products should be done with smaller spatial distance. This could be achieve using the intermediate resolution product at 1 Hz for SWIM.

Triple collocations (April 2019-now) over a buoy:
SOUTH KODIAK - 310NM SSW of Kodiak, AK

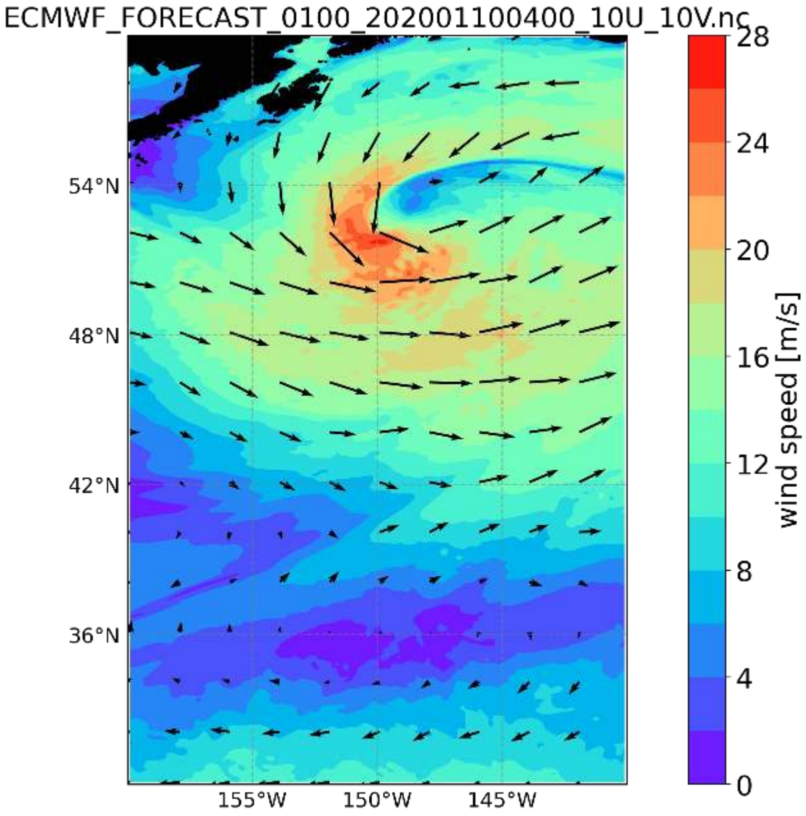
On this example we can see that the SWIM have a point that is +1.8m above S-1 and the +2m wrt the buoy. The collocations is may be too loose on geographic criteria (100 km), while the time and space energy distribution within the 2 products seems coherent.

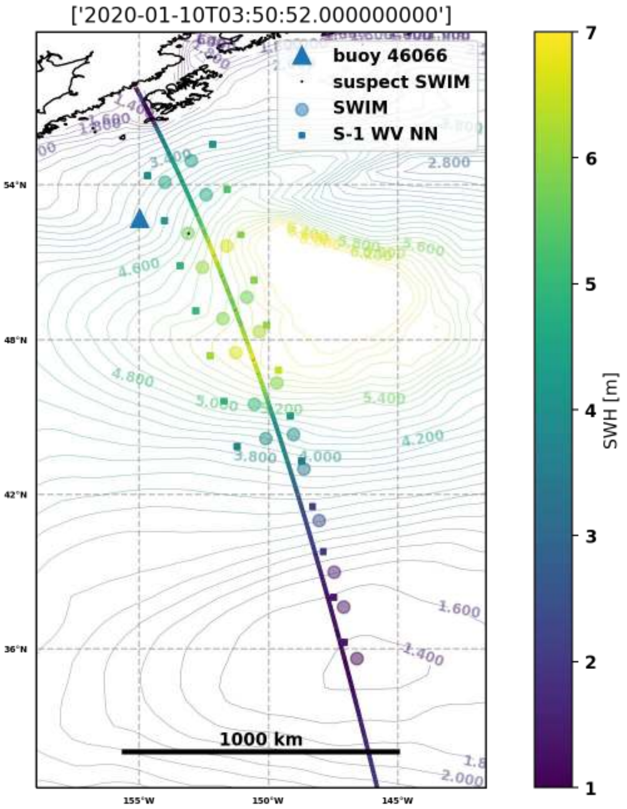
WMO 46066
Owned and maintained by National Data Buoy Center
3-meter discus buoy
SCOOP payload
52.765 N 155.009 W (52°45'53" N 155° 0'32" W)





Triple collocations (April 2019-now) over a buoy:
SOUTH KODIAK - 310NM SSW of Kodiak, AK

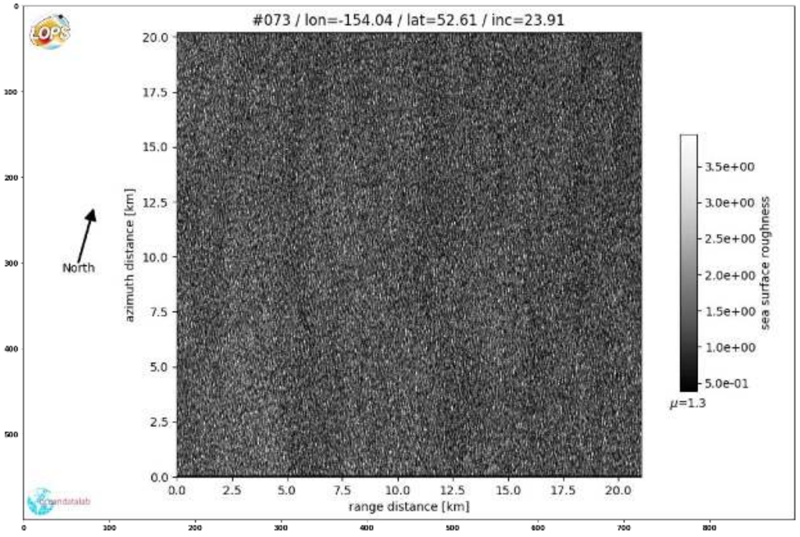


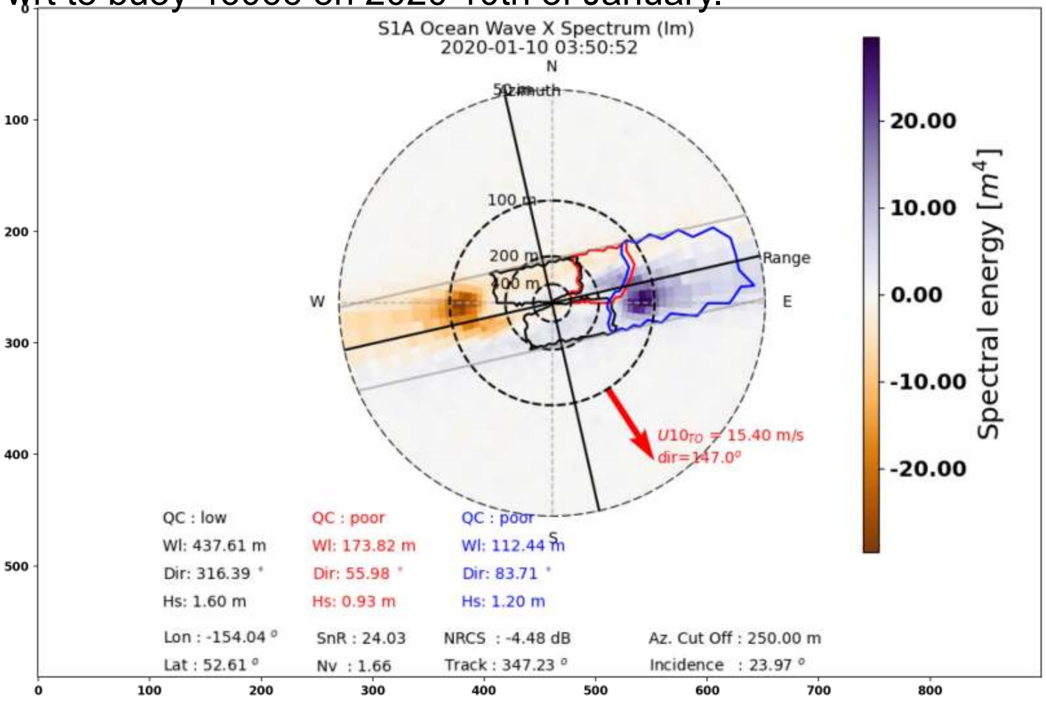


Triple collocations (April 2019-now) over a buoy:

SOUTH KODIAK - 310NM SSW of Kodiak, AK

Illustration of the closest S-1 WV cross spectra wrt to buoy 46066 on 2020 10th of January.



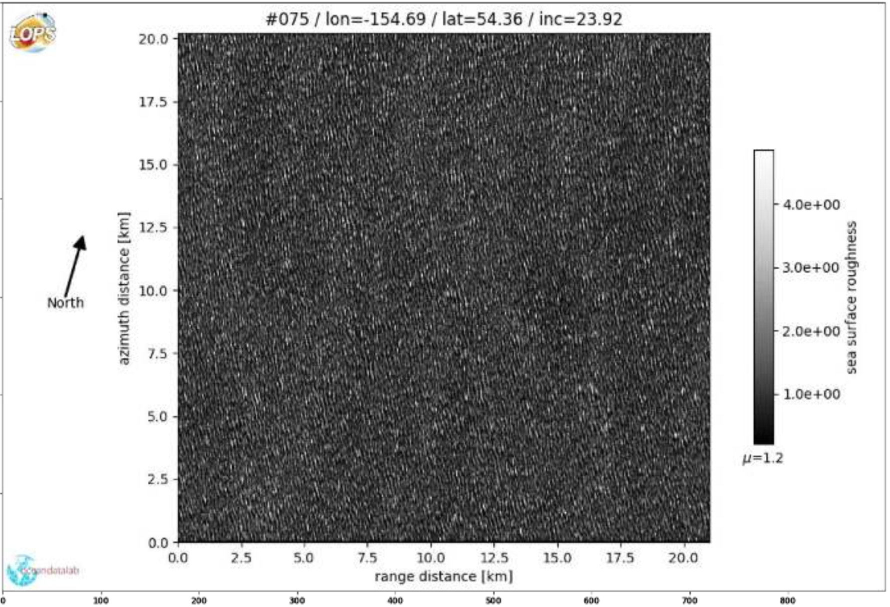


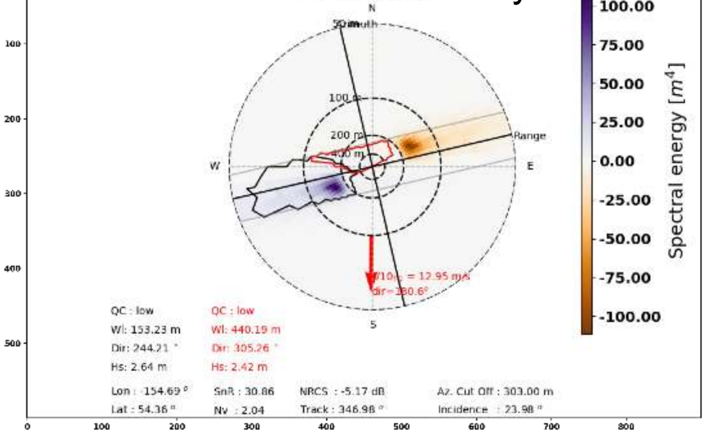
The main swell system dominated by the strong winds blowing to the East gives a quite clean SAR scene.

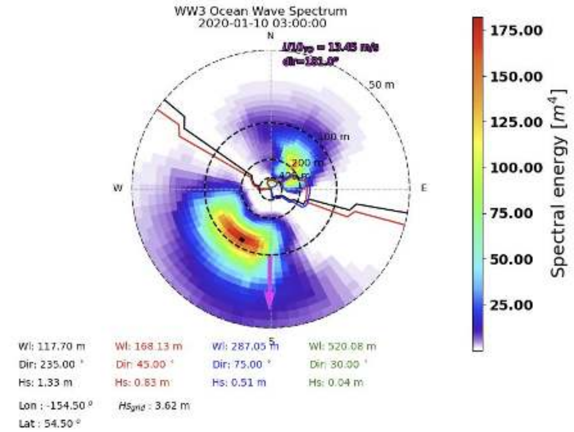
Triple collocations (April 2019-now) over a buoy:

SOUTH KODIAK - 310NM SSW of Kodiak, AK

Illustration of the closest S-1 WV cross spectra wrt to buoy 46066 on 2020 10th of January.







Few kilometers (~200km) to the North the same date, the swell system detected is totally different (storm coming from the North East).

Conclusions

Independent estimates of Hs from CFOSAT (nadir beam) and Sentinel-1 (WV1 an WV2) acquisitions have been collocated and compared.
Overall the agreement between the two sensors is very good no matter Sentinel-1 acquisitions modes:

- WV1 μ=0.09m σ=0.32m
- WV2 μ=0.09m σ=0.35m

Surprisingly, the use of the rain flag as provided in CFOSAT (nadir beam) Level-2 product does not impact the results.
However, the use of the SAR classification show that other geophysical phenomena (e.g. biological slicks) do impact the comparisons. The bloom flag as provided in CFOSAT (nadir beam) Level-2 product seems non-realistic.

Case study are also discussed. They confirm the ability of SAR and CFOSAT to capture the same sea state pattern at ocean basin scale. They also confirm the impact of geophysical phenomena such as rain on the comparisons.

A first attempt of triple colocation has been done on SOUTH KODIAK buoy. Overall it confirms the good consistency between SAR, CFOSAT and buoys:

- SAR-Buoy: μ=-0.05m σ=0.23m
- CFOSAT-Buoy: μ=-0.18m σ=0.47m

Perspectives

Further investigation are necessary to assess the impact of the other geophysical phenomena on CFOSAT and possibly help to refine the bloom flag and the potential/limitations of both missions in case of extremes.

The validation of the directional and wavelength information between the two sensors needs also to be pursued.

Thank you for reading, we are ready to answer your questions.