



Analysis and validation of SeaWinds-derived coastal winds

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Abstract

This document presents a validation analysis of coastal ocean vector winds derived from QuikSCAT using the noise regularization procedure to mitigate land contamination in radar cross sections. The validation is carried out against buoy measurements, retrieved from the ECMWF MARS archive and the homologous wind product provided by NASA/JPL named “QuikSCAT Scatterometer Inter-Calibrated Earth Science Data Record (ESDR) Level 2 Ocean Surface Equivalent Neutral Wind Vectors and Wind Stress Version 1.1”, spanning the entire 2007.

The results of two triple collocation exercises on the same set of collocations are presented in detail.

Both wind products are high-biased at wind regimes lower than $3\text{--}4\text{ ms}^{-1}$ within 20 km from the coastline, while the JPL product also presents high biases at high wind regimes and farther from the coast. In general, JPL wind retrievals are much noisier than OSI-SAF.

It is envisaged that further land contamination mitigation can be achieved by de-biasing wind retrievals.

1 Introduction

Ocean Surface Vector Winds (OSVW) play a crucial role in several geophysical phenomena, both in the open ocean and along the coasts, where a significant portion of the world’s human population resides. Focusing on coastal areas, the dispersion of pollutants, both in the ocean and in the atmosphere, and water upwelling and downwelling are all driven by OSVW. They are of paramount importance also for civil applications such as the design of wind farms and tourism. Additionally, safety at sea becomes a more relevant concern as off-shore infrastructure and sea transports increase. In light of that, accurate monitoring of coastal winds is fundamental.

Scatterometer-derived winds represent the gold standard of remotely sensed OSVW, thanks to their unmatched sampling and accuracy [1]. However, scatterometer normalized radar cross sections (σ_0) may be land-contaminated within 50-60 km from the coastline [2]. This may lead to severe quality control flagging, resulting in a dramatically reduced sampling within 20-30 km from the coastline.

In recent years, several strategies have successfully been implemented to mitigate σ_0 land contamination. The authors of [3] and [4] did that for the European Advanced Scatterometer (ASCAT), which flies onboard the polar orbiting satellites MetOp. The authors of [5] applied a mitigation strategy to the radar cross sections acquired by the SeaWinds scatterometer, which flew onboard the polar orbiting satellite Quick Scatterometer (QuikSCAT) from 1999 to 2009, providing an improved product spanning the entire mission [6]. The authors of [7] successfully applied a different mitigation strategy to SeaWinds.

All these mitigation strategies rely on the accurate computation of the so-called Land Contribution Ratio (f), which represents the specific portion of the radar footprint occupied by the land [2].

The methodology described in [7], so-called “noise regularization”, consists of a Cumulative Distribution Function (CDF) matching technique that projects contaminated σ_0 values in the domain of those non-contaminated. The CDFs of contaminated and non-contaminated σ_0 are first analytically modelled using the estimated specific σ_0 standard deviations (K_p) and the expected σ_0 empirically obtained with the methodology described in [8]. Then, the CDF matching technique is applied. The use of pre-computed look-up-tables (LUT) of K_p as a function of signal polarization and reference σ_0 levels makes the correction procedure very efficient from a computational point of view.

In [7], the authors prove the efficacy of the noise regularization methodology by comparing the wind retrievals against the winds retrieved from the Advanced Synthetic Aperture Radar (ASAR), which flew onboard the Eu-

ropean polar orbiting satellite Envisat. The comparison between the two wind sources is interesting, but SAR-derived winds cannot be considered a gold standard for validation purposes. This is also confirmed by the recent findings from [9]. In this paper, the authors show that ASCAT-derived winds have better accuracy compared to those derived from Sentinel-1, regardless of whether the resolution of SAR is 1 km or 25 km. It is well known that wind direction retrieval from SAR imagery is not yet sufficiently accurate, regardless of the methodology employed. Wind direction errors are then fitted to wind speed. The fact that SAR accuracy does not vary with spatial resolution suggests that errors are retrieved at small scales, as much as the additional signal. One might resolve some wind speed variability, while wind direction variability is projected onto wind speed error.

Moreover, the Convolutional Neural Network (CNN) method developed in [10] for wind direction retrieval from Sentinel-1 imagery yields worse accuracy when applied to ASAR imagery (private communication with Dr. Stefano Zecchetto).

For all these reasons, even if it was planned, the comparison against SAR-derived winds is left for the future, when these issues will be fixed. Hence, an extensive validation of SeaWinds-derived winds obtained with noise regularization is still missing.

In this document, we present such kind of analysis, by comparing wind retrievals against buoy measurements collected by several networks, among which the National Data Buoy Center (NDBC), spanning the entire year 2007. Moreover, winds are collocated with ECMWF Reanalysis 5 (ERA5), and the three sources are intercalibrated using the triple collocation methodology [11].

In addition, the same triple collocation exercise has been carried out using the same buoy measurements and model winds with the QuikSCAT retrievals provided at JPL [5, 6]. Several triple collocation flavors have been considered to exhaustively compare OSI-SAF and JPL winds at different distances from the coast.

This study is a follow-up of previous Visiting Scientist Activities (VSA) carried out in recent years on the same topic. In fact, in [12], the QuikSCAT Spatial Response Function (SRF) was analytically modelled and compared to the pre-computed parameterized SRF LUT provided by Prof. David Long from the Brigham Young University; in [13], the main focus was on the characterization of the QuikSCAT σ_0 noise; in [14], the noise characterization procedure and the algorithm for the computation of f were refined. In addition, a linear regression scheme for σ_0 correction similar to that presented in [4] was implemented. This methodology did not prove to be successful, probably because the noise characteristics of ASCAT are rather different

from those of QuikSCAT, which is much more noisy especially at low-wind regimes and for slices far from the footprint centroid. This empirical correction strategy resulted in an excessive and unrealistic number of negative σ_0 values. Finally, the noise-regularization scheme was developed in [15], which provides much better results both in the σ_0 domain and as regards wind retrievals. In addition, the entire suite for σ_0 correction was optimized, even if some additional work was left for the future.

The report is structured as follows: Section 2 describes the new features and the optimization implemented in the software to produce corrected σ_0 ; Section 3 describes the dataset used for the validation of the retrievals; Section 4 describes the methodology used to compute the LUT of pre-computed empirical CDFs used for the noise regularization procedure. In addition, it describes the collocation and quality control of the wind triplets, the procedure to intercalibrate them and the metrics used for the comparison; Section 5 reports and discusses the results and Section 6 reports the preliminary conclusions and some ideas for future developments.

2 Software optimization

2.1 New features

The most important improvement of the software regards the implementation of the slice σ_0 correction procedure in **C**. Two slightly different **C** projects have been developed: a) one uses analytical CDFs [15] while b) the other uses empirical CDFs. In the first case, analytical CDFs are modelled using a pre-computed LUT of K_p [15]. The flow chart of this implementation is reported in Figure 1. In the second case, pre-computed empirical CDFs are read from an external HDF5 file. The flow chart of this implementation is reported in Figure 2. As can be seen, the structure of the two projects is very similar. In the first stage, input information is read from different files. Input reading steps are drawn at the same level to stress that these operations are independent of each other, and the reading order does not matter. A brief description of the modules follows:

- **d2c L1B** reads the pre-computed distance to the coast of each slice acquisition. This information is stored in an HDF5 file named as `d2c_<orbit ID>.h5`, where `orbit ID` is the unique L1B orbit identifier;
- **LCR** reads the pre-computed f index for each slice. This information is stored in an HDF5 file named as `lcr_<orbit ID>.h5`;
- **WVCIJ** reads some ancillary pre-computed information regarding the slice assignment to the Level 2 (L2) Wind Vector Cell (WVC);
- **K_p LUT (CDF)** reads the pre-computed K_p (empirical CDFs) LUT;
- **Analytical CDF** models the analytical contaminated and non-contaminated CDFs. This module is not present in the second version;
- **σ_0 correction** applies the correction to slice σ_0 values;
- **slice_sigma0 & slice_qual_flag update**, updates the `slice_sigma0` and `slice_qual_flag` arrays, which contain the slice σ_0 and the corresponding quality flag, respectively. These are the only two fields that are updated in the original L1B files. All the other fields are left identical to the original;
- **L1B update** updates the original L1B file with the new modified fields (see previous point);

-
- **Ancillary output** writes some ancillary information that can be used for diagnostic purposes or a-posteriori quality control. At the moment, this information is not yet used;

Input blocks **d2c L1B** and **WVCIJ** are used to reduce redundant operations for the sake of computational efficiency.

2.2 Code performance

The code has been profiled and optimized with the aid of the open source tools **gprof** and **valgrind**. Table 1 shows the performance of the two versions of the code obtained with the Linux tools **time** and **memusage**. They have been evaluated using the laptop with the characteristics summarized in Table 2. “real” stands for total execution time, “user” for user time, “sys” for system time. “heap memory” is the physical memory used by the executable, while “stack” represents the stack memory during usage. The execution time is lower than 2 seconds for both projects, with negligible differences. Their timing is compliant with operational purposes. Concerning the memory usage, the flavor with empirical CDFs uses slightly more memory since it reads the entire CDFs LUT from an external file and stores it in the RAM.

Table 1: Code performance. “real” stands for total execution time, “user” for user time, “sys” for system time. “heap memory” is the physical memory used by the executable, while “stack” represents the stack memory during usage.

	Analytical CDFs	Empirical CDFs
real (s)	1,737	1.618
user (s)	1,013	1.013
sys (s)	0,698	0.604
heap memory (MB)	987	1,232
stack memory (MB)	113	113

2.3 Outlook

At the moment, the orbit with ID 40116 has not been processed due to a bug in the LUT of pre-computed Spatial Response Functions (SRF) provided by Prof. David Long from the Brigham Young University. Therefore, *f* file is missing and the retrieval could not take place. This is due to the presence of some Not-a-Number (NaN) in the LUT. This aspect should be investigated

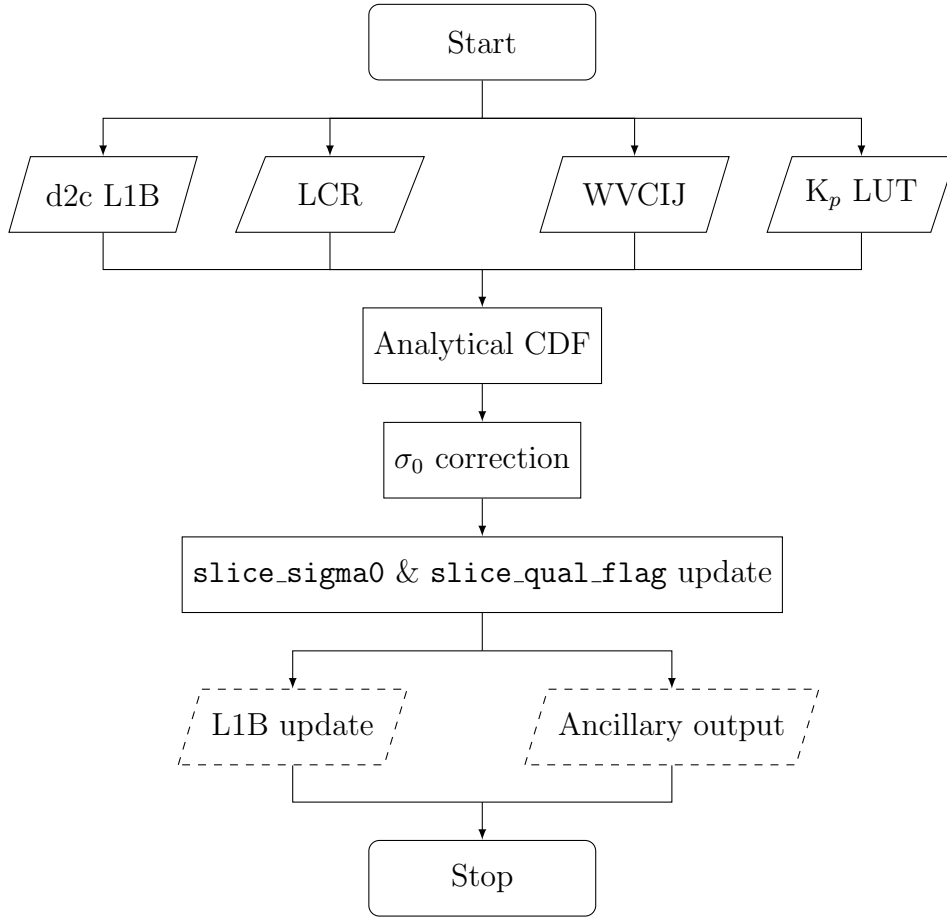


Figure 1: Flow chart of the noise regularization correction procedure with analytical CDFs. Full line (Dashed) trapezium state input (output) operations.

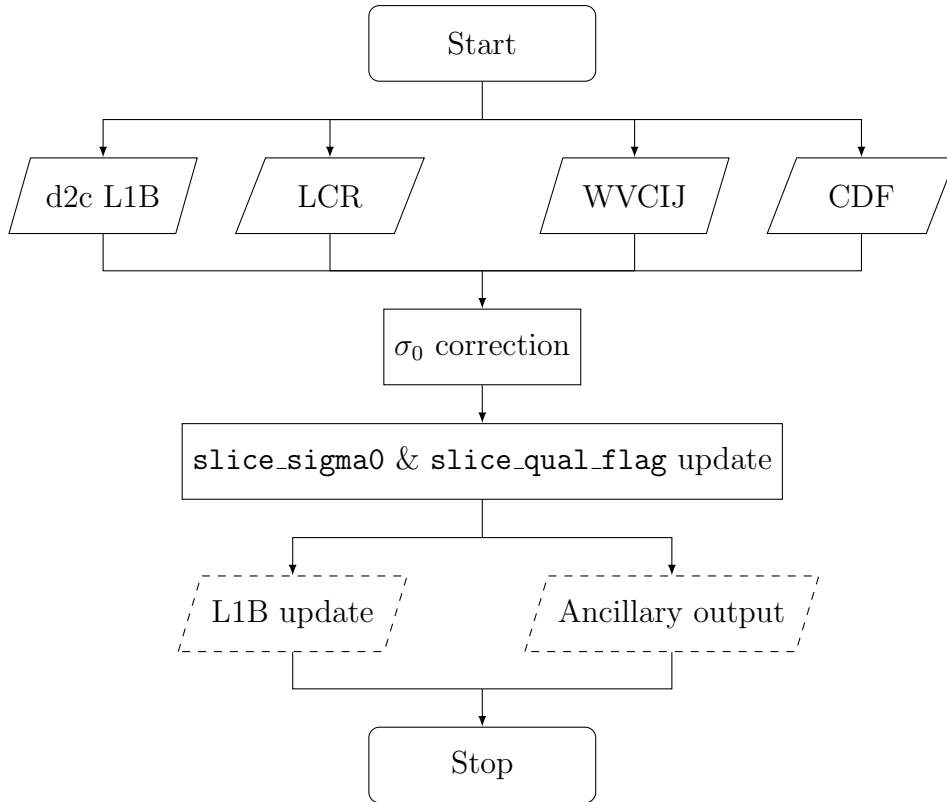


Figure 2: Flow chart of the noise regularization correction procedure with empirical CDFs. Full line (Dashed) trapezium state input (output) operations.

Table 2: Hardware details.

Brand	Dell
Model	Pro 13 Plus PB13250
RAM (GB)	32
Processor	Intel Core Ultra 7 268V
# processors	8
OS	Ubuntu 24.04.2 LTS
OS kind	64-bit
OS kernel	Linux 6.14.0-24-generic

thoroughly and, probably, discussed with Prof. Long.

The coastal winds retrieval procedure from QuikSCAT L1 files consists of several `Python` scripts and `C` executables that are run through a unique `Python` script. The entire procedure lasts between 1 and 2 hours for a single orbit file, depending on the available hardware. The bottleneck of the procedure is represented by the computation of f , which takes approximately 90-95% of the total time. This step has already been optimized, therefore, we cannot expect a further computational time reduction from future code developments/optimization. The good news is that, once this information is available, there is no need to recompute it in case the correction and/or retrieval algorithms are updated.

It is estimated that additional 90 days are necessary to compute f for the entire mission, given that 50 modern CPUs are uninterruptedly fully dedicated to this purpose.

3 Dataset

SeaWinds-derived winds are obtained by inverting the σ_0 provided by the NASA Physical Oceanography Distributed Active Archive Center (PODAAC) catalogue [16]. σ_0 are organized in orbit files that can be downloaded for free upon registration. The reference period is the entire year 2007, accounting for about 5,200 files, from orbit IDs 39,239 to 44,443 included. There is no specific reason to consider this year instead of the others in the QuikSCAT mission.

Wind retrievals are output by the Pencil Bean Wind Processor (PenWP) software package [17], which can be downloaded for free from the EUMETSAT Numerical Weather Prediction Satellite Application Facility (NWP-SAF) website. Before running PenWP, L1B files with corrected σ_0 are pre-processed using the tool `seawinds_l1b_buf_r` provided with the same software suite. In [15], this tool has been modified to produce wind retrievals on a grid with a spacing of 12.5 km. Wind retrievals are provided with some ancillary information, among which are a series of quality control flags/values and the background winds used for the 2 Dimensional Variational Ambiguity Removal scheme (2D-VAR) to remove solution ambiguities. In this study, the background winds come from ERA5 model output and are bilinearly interpolated in time and space at the SeaWinds Wind Vector Cell (WVC) location and time. Finally, winds are provided on a 12.5 km grid, which is optimized towards the coast.

Wind retrievals are collocated with the buoy measurements provided by the ECMWF Meteorological Archival and Retrieval System (MARS) archive. These data are available for free upon registration only for users from ECMWF member countries. Buoy wind measurements are provided with some ancillary information, among which anemometer height, sea temperature, air temperature, air temperature sensor height, relative humidity, wet bulb temperature, dew point temperature, humidity sensor height, surface pressure and salinity. These parameters are used to convert wind measurements to 10-m height, the nominal height of scatterometer wind retrievals. Some of the parameters are not available from measurements and hence come from model output. Both OSI-SAF and JPL wind retrievals have been collocated with buoy measurements using the tool `BuoyCollocate` provided with the PenWP software suite. This tool has been slightly modified to read OSI-SAF and JPL retrieval files. Finally, more importantly, buoy measurements are provided with “black-list” information, i.e., dates/periods for which measurements are not reliable.

Buoy measurements available from the MARS archive come from several networks, among which the most populated is the National Data Buoy Center

(NDBC). The locations of the buoys used in this study are depicted in Figure 3. As shown, most buoys are located along the US coasts, even if some of them are also located in the European seas. Only moored buoys within 60 km from the coastline are considered in this study, for a total of 54, while the number of OSI-SAF (JPL) collocations amounts to 24,059 (23,252), out of which 19,817 (19,065) lie within 40 km from the coastline. The intersection of OSI-SAF and JPL datasets within 60 km (40 km) from the coast amounts to 22,577 (18,703) collocations.

Buoy wind speed (direction) measurements are rounded to 1 ms^{-1} (10°).

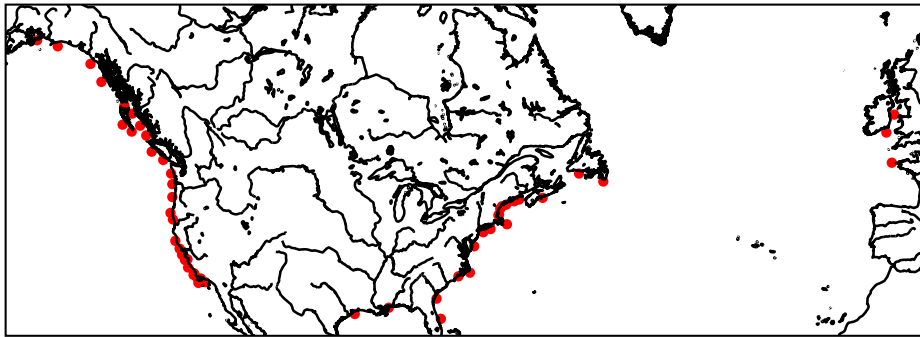


Figure 3: Map of buoy locations.

3.1 Wind quality control (QC)

OSI-SAF winds are quality-controlled (QCed) by excluding retrievals with the flags `knmi_quality_control_fails` and `variational_quality_control_fails` raised.

JPL winds are QCed considering those with the flag value `quality_indicator` ≤ 2 (recommendation by Dr. Bryan Stiles from NASA-JPL). Values higher than 2 correspond to the following flag description:

- likely significant error
- no winds retrieved due to quality control
- no data over liquid water in cell

Finally, black-listed buoy measurements are excluded. This filter is implemented in the tool `get_buoy_data_coastal_from_mars.ksh` that has been used to query the ECMWF MARS archive. This tool is also provided with the PenWP software suite.

Table 3: Left (right) column: 0-based bit position (meaning in the absence of the condition) of the `sigma0_qual_flag` that are required to be 0 [18]

Position	meaning
0	Measurement is usable
3	σ_0 is in acceptable range
4	Scatterometer pulse quality is acceptable
5	σ_0 cell location algorithm converges
6	Frequency shift is within the range of the x factor table
7	Spacecraft temperature is within calibration coefficient range
8	An applicable attitude record was found for this σ_0
9	Interpolated ephemeris data are acceptable for this σ_0

3.2 Slice σ_0 QC

Slice σ_0 values are used in this study to compute the empirical contaminated and non-contaminated σ_0 CDF used in the noise regularization procedure. For this purpose, the following QC is applied:

- `frame_err_status` is required to be 0
- bit-4 (0-based) of `frame_qual_flag` is required to be 0
- the bits of `sigma0_qual_flag` listed in Table 3 are required to be 0

For the sake of completeness, if bit-1 of `sigma0_qual_flag` is raised, it means that the slice σ_0 value is negative, while if bit-2 is raised, it means that the Signal-To-Noise Ratio (SNR) is not acceptable. No constraints are required for these bits. Finally, bits 10-15 are spare and always set to 0. Empirical CDFs are evaluated on January 2007.

4 Methodology

4.1 Empirical CDFs LUT computation

As already said in Section 2, the software developed to apply noise regularization can also work with empirical CDFs. In [15], it was shown that coastal wind retrievals are high-biased at low-wind regimes. Analytical CDFs can only simulate positive slice σ_0 values, while real measurements can also have negative values. To tackle this limitation, CDFs have been evaluated using real QuikSCAT measurements. The aim is to verify if the limitation affecting analytical CDFs plays a role in the residual biases at low-wind regimes. In this section, the methodology used to evaluate these CDFs is described.

CDFs are evaluated on a fixed grid spanning from -3×10^{-3} to 0 with linear spacing equal to 10^{-5} , while positive values are logarithmically spaced from -50 dB to 10 dB with spacing equal to 0.05 dB. Therefore, this grid consists of 1502 points and 1501 intervals over which real measurements are binned. The reference period over which the CDFs are evaluated is arbitrary. The results shown in this report are obtained with empirical CDFs evaluated over the entire January 2007. For each file in the reference period,

- slice σ_0 are QC-accepted as described in Section 3.2;
- acquisitions at latitudes over $\pm 60^\circ$ are discarded;
- land contaminated values are excluded only for the evaluation of non-contaminated σ_0 CDFs;
- data are segregated according to polarization and view;
- a grid of N reference σ_0^U levels is set, spanning the wind speed range from 1 to 50 ms^{-1} . Reference σ_0^U levels are evaluated using the NSCAT4DS GMF, considering the average value of the entire relative wind direction spectrum of values, as described in Equation 4.1, with U the reference wind speed, ψ the relative wind direction and θ the incidence angle. Note that, even if SeaWinds is a pencil beam scatterometer with “fixed” incidence angles for each beam, these can have some residual variation; therefore, the expected value is considered also with respect to (w.r.t.) θ ;
- for each reference σ_0^U level and for every pol-view flavor, egg σ_0 in the range $\sigma_0^U \pm 0.5$ dB are selected;
- slice σ_0 values corresponding to the previous selection are used to evaluate the histogram;

-
- histograms are cumulated file-by-file;
 - the cumulative sum is operated;
 - the cumulative sum is normalized by the total sum to get the final CDF;

The output file of this procedure contains

- CDFs LUT;
- the grid of reference σ_0^U levels for both polarizations;

$$\sigma_0^U = E_\psi[E_\theta[NSCAT4DS(U, \theta, \psi)]] \quad (4.1)$$

CDFs have been evaluated for N equal to 50, corresponding to a grid of 1 ms^{-1} spacing and to 197, corresponding to a grid of 0.25 ms^{-1} spacing.

Figure 4 shows the analytical CDF and the empirical CDFs evaluated on every kind of surface and the sea surface for a noisy case. Instead, Figure 5 shows a low-noise case. As shown in [8], slices far from the egg centroid are very noisy at low wind regimes, while central slices at medium-high wind regimes have a higher signal-to-noise ratio. As expected, when the reference σ_0^U level is very low (Figure 4), analytical and empirical CDFs differ a lot. At the same time, the differences between empirical CDFs are negligible. Note that analytical CDFs are defined for $\sigma_0 \geq 0$, but the green curve starts from values higher than 0. This is due to a visual artifact. Indeed, the bin edges grid contains 0; therefore, the middle-interval grid, of which CDF values are representative, does not.

Also, note that empirical CDFs have non-zero values in the negative part of the σ_0 grid. This is more evident for low reference σ_0^U levels. This means that empirical CDFs can simulate negative slice σ_0 values, while analytical CDFs cannot.

Figure 6 shows the estimated σ_0 shift between the empirical CDF evaluated on every kind of surface and that evaluated on the sea surface, for the same case depicted in Figure 4. When the reference σ_0^U level is low, the σ_0 shift can be considered negligible. This is not the case of higher levels, as depicted in Figure 7. Therefore, both empirical CDFs are used for the second implementation of the noise regularization procedure. The empirical CDF evaluated on every kind of surface is used to model the CDF of contaminated σ_0 , while the other is used for non-contaminated values.

Figure 8 gives an idea of the effectiveness of noise regularization in the σ_0 domain. The dotted black curve represents the CDF of the slice σ_0 values

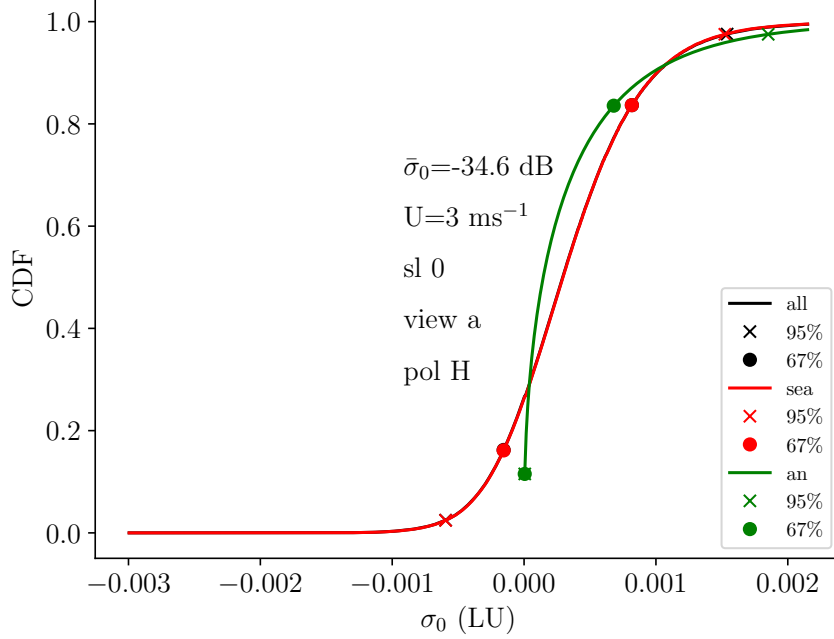


Figure 4: Green curve: analytical CDF modelled according to Equation 3.8 of [15]. Red (black) curve: empirical CDF evaluated with open ocean (all) acquisitions. Full circles (crosses) delimit the 67% (95%) confidence interval. $\bar{\sigma}_0$ is the reference σ_0^U level, U is the corresponding approximate wind speed, “sl”, “a” and “H” stand for “slice index”, “aft” and “horizontal”, respectively. Note that the red curve hides the black one.

before correction for the entire month January 2007. The left panel shows the plots in the σ_0 linear units domain, to evidence negative values, while the right panel x-axis is in logarithmic units (dB). The slice σ_0 values used to evaluate this CDF are those corrected using the empirical CDF depicted with the dashed black curve, and whose reference parameters are reported on the panel. This curve also represents the expected CDF after the correction (solid curve). The two curves differ, showing high biases at high values and low biases at negative values. In other words, the real curve is more inclined than expected. This example refers to very noisy values (slice index equal to 0 and low reference σ_0^U level) [15].

The example in Figure 9 refers to a low-noise case. The plot with the x-axes in linear units is not shown since there are no negative values. In this case, the agreement between the corrected and non-contaminated reference CDF is much better, as expected, even though some residual bias is present

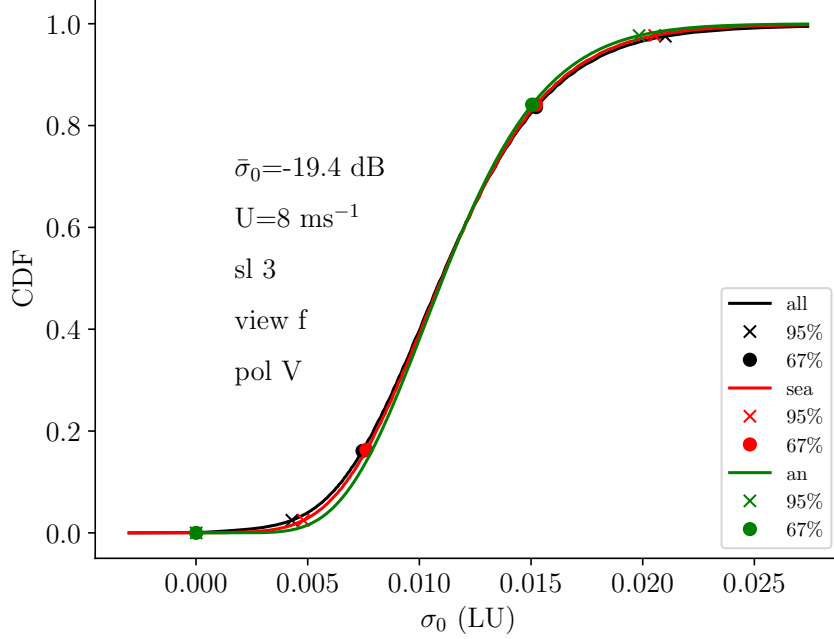


Figure 5: Green curve: analytical CDF modelled according to Equation 3.8 of [15]. Red (black) curve: empirical CDF evaluated with open ocean (all) acquisitions. Full circles (crosses) delimit the 67% (95%) confidence interval. $\bar{\sigma}_0$ is the reference σ_0^U level, U is the corresponding approximate wind speed, “sl”, “a” and “H” stand for “slice index”, “aft” and “horizontal”, respectively.

also in this case. Note that the bias trend is similar to the previous case.

4.2 Triple collocation

Winds from buoys, scatterometer and ERA5 model are collocated by applying the following constraints and methodology:

- The acquisition time difference between scatterometer and buoys is required to be shorter than 30 minutes;
- The closest scatterometer WVC is used, never exceeding 25 km from the buoy location;
- Background winds are bilinearly interpolated in time and space at the WVC location and time

Then, the three sources are inter-calibrated, following the methodology described in [11], considering buoys as the calibration reference system. The

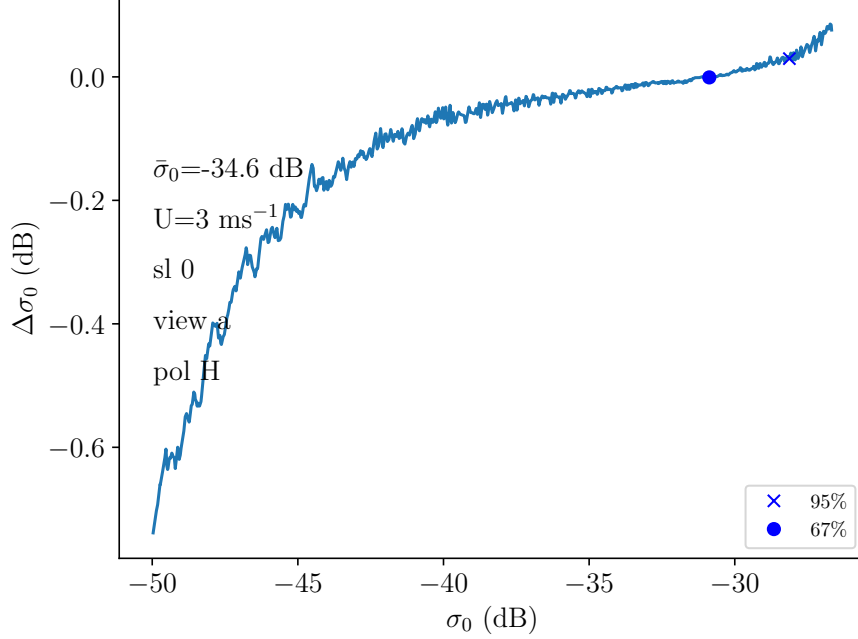


Figure 6: Estimated σ_0 shift in logarithmic units between the empirical CDF evaluated on every kind and sea surface. $\bar{\sigma}_0$ is the reference σ_0^U level, U is the corresponding approximate wind speed, “sl”, “a” and “H” stand for “slice index”, “aft” and “horizontal”, respectively.

representativeness error r^2 is assumed equal to zero. r^2 stands for the wind signal energy resolved by buoys and scatterometer, but not by model winds. Usually, r^2 is not 0 and should be properly evaluated with spectral [19] or spatial variances analysis [20]. Assuming $r^2 = 0$ implies the overestimation of model errors [21]. A more-in-depth analysis will be attempted in the future. The estimate of r^2 in coastal regions is difficult because of the limited sampling geometry. Indeed, you need continuous tracks of at least 1,600 km in length to properly compute spectra or spatial variances.

Several triple collocation exercises have been carried out. They are summarized in Table 4. An acronym is assigned to each triplet experiment to facilitate its identification. Concerning the acronym formation, “B” stands for “buoy”, “O” for “OSI-SAF”, “J” for JPL, “E” for ERA5, “N” for NCEP, “o” for original and “i” for intersection. “Original” means that the entire QC-accepted dataset of collocation triplets is considered, while “Intersection” means that only the common collocations between OSI-SAF and JPL retrievals are considered. Where present, the superscript states the distance

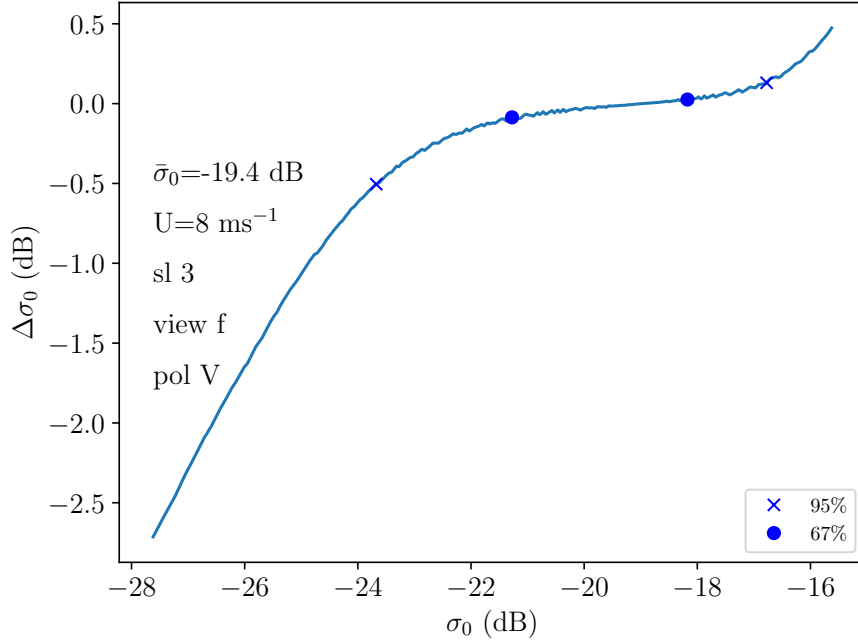


Figure 7: Estimated σ_0 shift in logarithmic units between empirical CDF evaluated on every kind and sea surface. $\bar{\sigma}_0$ is the reference σ_0^U level, U is the corresponding approximate wind speed, “sl”, “a” and “H” stand for “slice index”, “aft” and “horizontal”, respectively.

of the coastal band from the coast, as indicated in the dedicated column.

4.3 Residual land contamination analysis

This section describes the methodology used to check any residual dependency on land contamination. This analysis is limited to OSI-SAF retrievals only, since MLE is not available from JPL retrievals. The correlation between wind speed and MLE is checked at various distances from the coast. There is no reason to expect any correlation between wind speed and MLE. Therefore, the eventual presence of any significant correlation between these two parameters is symptomatic of residual land contamination in the σ_0 and retrievals.

Before computing the correlation coefficient, the eventual dependency of the wind speed distribution on the distance to the coast is filtered out. Indeed, wind speed distribution could be different getting farther from the coast. In particular, it is expected that the closer to the coast we are, the more shifted

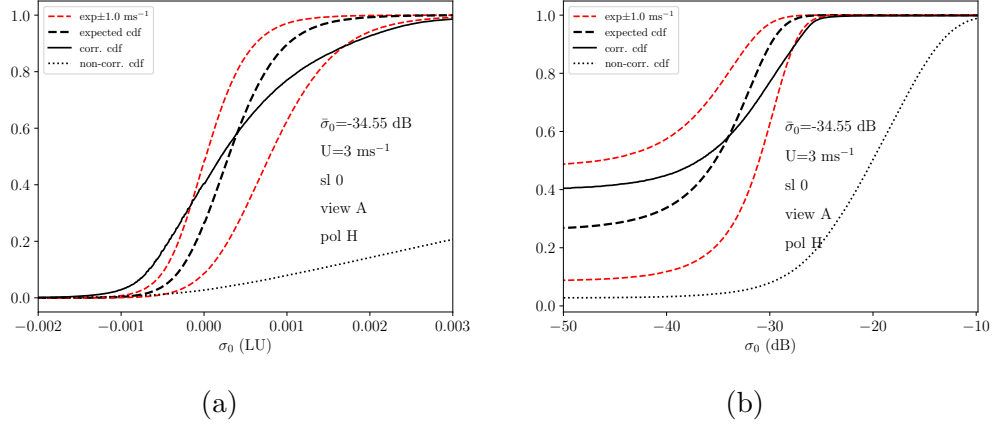


Figure 8: Dotted (solid) black curve: CDF of slice σ_0 values before (after) correction for January 2007. Dashed black curve: empirical non-contaminated CDF. Left (right): σ_0 axes in linear units (logarithmic). $\bar{\sigma}_0$ is the reference σ_0^U level, U is the corresponding approximate wind speed, “sl”, “a” and “H” stand for “slice index”, “aft” and “horizontal”, respectively. Red dashed curves represent the empirical CDF of non-contaminated σ_0 values of adjacent reference σ_0^U levels, corresponding to $\pm 1 \text{ ms}^{-1}$.

towards low wind speed value the distribution is.

The processing consists of the following steps:

- QC-accepted retrievals are binned with the distance to the coast. Four 10-km-width coastal bands are considered: 0-10 km, 10-20 km, 20-30 km and 30-40 km. The four coastal bands are indexed with $d \in \{10, 20, 30, 40\}$;
- The wind speed histograms of each coastal band are evaluated in the range between 0 and 25 ms^{-1} , with bin width equal to 1 ms^{-1} . Let's call $h_{d,U}$ the value of the histogram for the distance d and wind speed bin U ;
- For each wind speed bin, the minimum count value among the four histograms is selected. This new histogram is called h_U ;
- h_U wind speed values are randomly selected for each coastal band and wind speed bin, if $h_{d,U} > h_U$; otherwise all of them are retained.

With this procedure, the number of samples in a given wind speed bin does not depend on the distance to the coast.

The colored curves of Figure 10 show the histograms of wind speed segregated

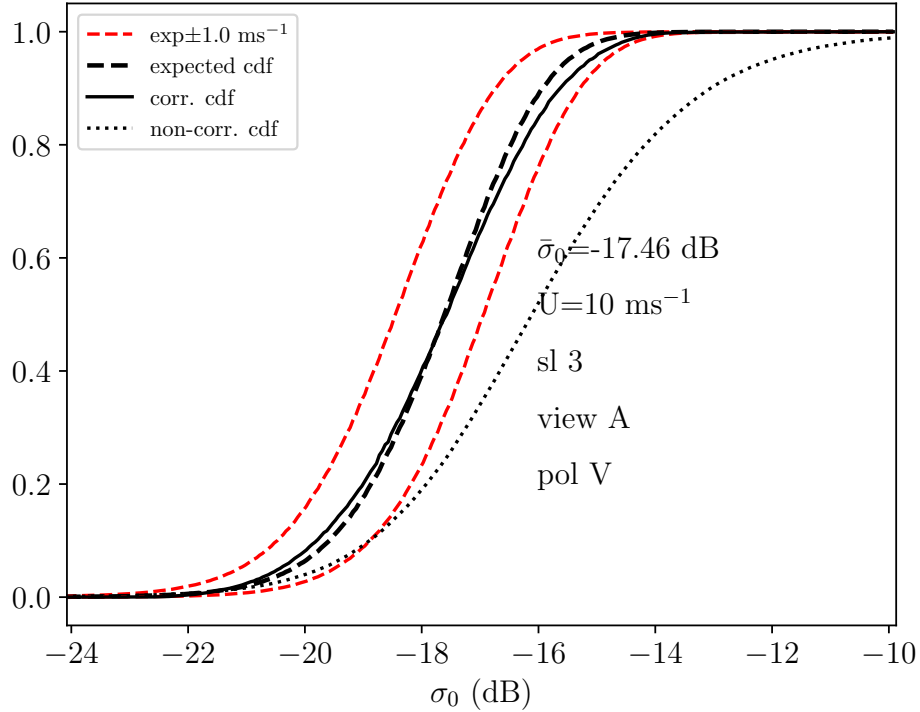


Figure 9: Dotted (solid) black curve: CDF of slice σ_0 values before (after) correction for January 2007. Dashed black curve: empirical non-contaminated CDF. $\bar{\sigma}_0$ is the reference σ_0^U level, U is the corresponding approximate wind speed, “sl”, “a” and “H” stand for “slice index”, “aft” and “horizontal”, respectively. Red dashed curves represent the empirical CDF of non-contaminated σ_0 values of adjacent reference σ_0^U levels, corresponding to $\pm 1 \text{ ms}^{-1}$.

according to the distance to the coast. The dashed black line shows the histogram selected following the aforementioned procedure. Note that the blue curve is much lower than the others. This may be due to the following reasons: a) more severe QC towards the coast; b) fewer buoys close to the coast; c) lack of sufficient usable slice σ_0 s. We anticipate that the second reason plays the main role. This will be shown with more details in Section 5. Also, note that the dashed curve almost completely overlaps to the blue curve, except in the 1st and 22nd bins.

Table 4: List of triple collocation exercises. Concerning the acronym formation, “B” stands for “buoy”, “O” for “OSI-SAF”, “J” for JPL, “E” for ERA5, “N” for NCEP, “o” for original and “i” for intersection. “Original” means that the entire QC-accepted dataset of triplets is considered, while “Intersection” means that only the common collocations between OSI-SAF and JPL retrievals are considered. Where present, the apex states the distance of the coastal band from the coast, as indicated in the dedicated column.

Acronym	Sources	Distance to the coast (km)	Additional info
BOE _o	buoy/OSI-SAF/ERA5	0-60	Original
BJN _o	buoy/JPL/NCEP	0-60	Original
BOE _i	buoy/OSI-SAF/ERA5	0-60	Intersection
BJE _i	buoy/JPL/ERA5	0-60	Intersection
BON _i	buoy/OSI-SAF/NCEP	0-60	Intersection
BJN _i	buoy/JPL/NCEP	0-60	Intersection
BOJ _i	buoy/OSI-SAF/JPL	0-60	Intersection
BOE _i ¹⁰	buoy/OSI-SAF/ERA5	0-10	Intersection
BJE _i ¹⁰	buoy/JPL/ERA5	0-10	Intersection
BOE _i ²⁰	buoy/OSI-SAF/ERA5	10-20	Intersection
BJE _i ²⁰	buoy/JPL/ERA5	10-20	Intersection
BOE _i ³⁰	buoy/OSI-SAF/ERA5	20-30	Intersection
BJE _i ³⁰	buoy/JPL/ERA5	20-30	Intersection
BOE _i ⁴⁰	buoy/OSI-SAF/ERA5	30-40	Intersection
BJE _i ⁴⁰	buoy/JPL/ERA5	30-40	Intersection

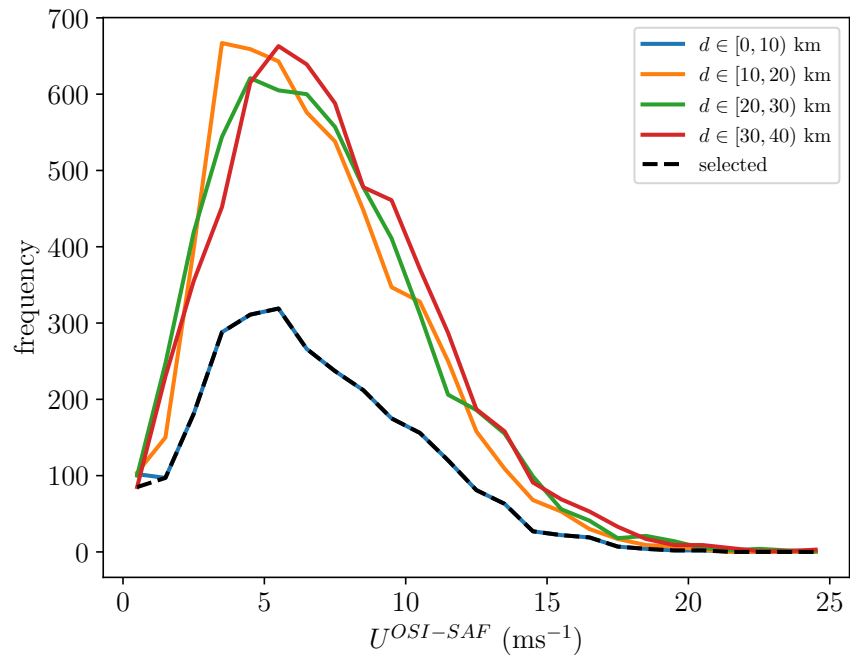


Figure 10: Solid curves: wind speed histograms segregated according to the distance to the coast. Dashed black curve: selected histogram.

5 Results

5.1 Optimal noise-regularization configuration

This section presents a comparative analysis of four different configurations of the correction and retrieval procedures. The aim is to assess the optimal configuration to mitigate high biases in wind retrievals at low-wind regimes, as shown in the following section, and already revealed in [15] against ERA5 background winds. The experiments are named as “EXP01”, “EXP02”, “EXP03” and “EXP04”, and are summarized in Table 5. EXP01 is the control experiment, obtained with analytical CDF in the noise regularization procedure. EXP02 uses empirical CDF with the same number of reference σ_0^U levels (50). EXP03 uses empirical CDF with a finer σ_0^U grid (197 levels) covering the same range. Finally, EXP04 uses the same grid as EXP02, therefore, the corrections are identical; instead, the four σ_0 views are averaged with Gaussian weights, as done in [22], and summarized in Equation 5.1

$$w = \exp \left(- \left[\frac{\Delta}{\sigma_e} \right]^2 \right) \quad (5.1)$$

where Δ is the vertical distance from the regression line and σ_e is the regression error [22].

Table 5: Experiments carried out to set the optimal configuration of the processor. “A” (“E”) stands for “analytical” (“empirical”) and “1” (“G”) for unitary (Gaussian) weight. EXP01 is the control experiment.

Experiment	σ_0 LUT	σ_0 levels	slice weighting
EXP01	A	50	1
EXP02	E	50	1
EXP03	E	197	1
EXP04	E	50	G

The comparison is carried out against buoy measurements from MARS archive for January 2007.

Figure 11a (11b) reports some statistics regarding wind speed (direction) retrievals against buoy measurements, for the four experiments, as a function of the distance from the coast.

Figure 11 does not help to select the most performing configuration. Indeed, both wind speed and direction statistics show minimal, non-meaningful fluctuations; therefore, we can conclude that these configurations are equivalent.

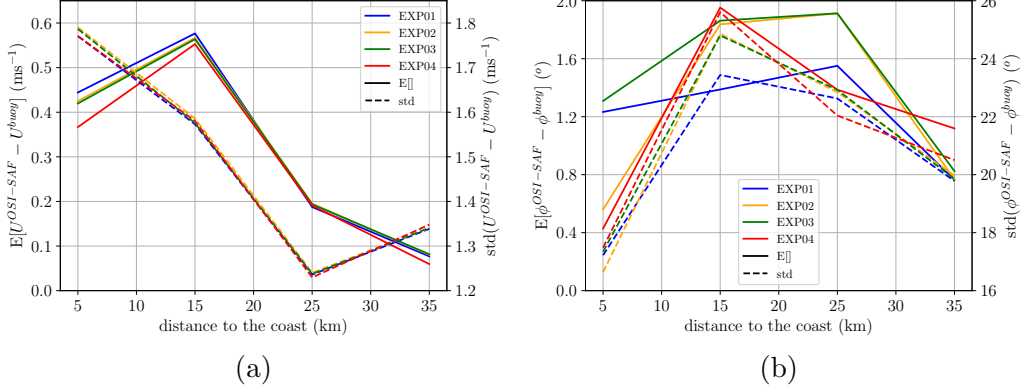


Figure 11: Left plot, solid (dashed) lines: wind speed bias (standard deviation) of the four experiments in the legend as a function of the distance to the coast evaluated on the collocations with MARS buoys of January 2007. Experiments' color code and parameter line style code are reported in the legend. Right plot: same as left, but for wind direction.

The same plots have also been generated for the wind components. They are not reported for the sake of brevity, since they do not add any useful information.

Figure 12 provides information about the sampling characteristics of the four configurations. Figure 12a shows the percentage difference in the number of QCed retrievals w.r.t. EXP01 as a function of the distance to the coast. The reference period is January 2007. Figure 12b shows the percentage difference in the total number of QCed retrievals w.r.t. EXP01. These plots show that even if the total number of QCed retrievals does not have meaningful deviations by changing the processor configuration, the sampling w.r.t. the distance to the coast does, at least as concerns EXP04. Indeed, the application of Gaussian weighting to slice σ_0 impacts the WVC centroid estimation. The effect is that WVC centroids go closer to the coast. In our opinion, this sampling is more realistic, therefore the results presented in Section 5 are obtained with this configuration.

In conclusion, the problem of high biases at low wind regimes is not related to slice weighing in σ_0 averaging and the σ_0 reference grid used for slice σ_0 corrections.

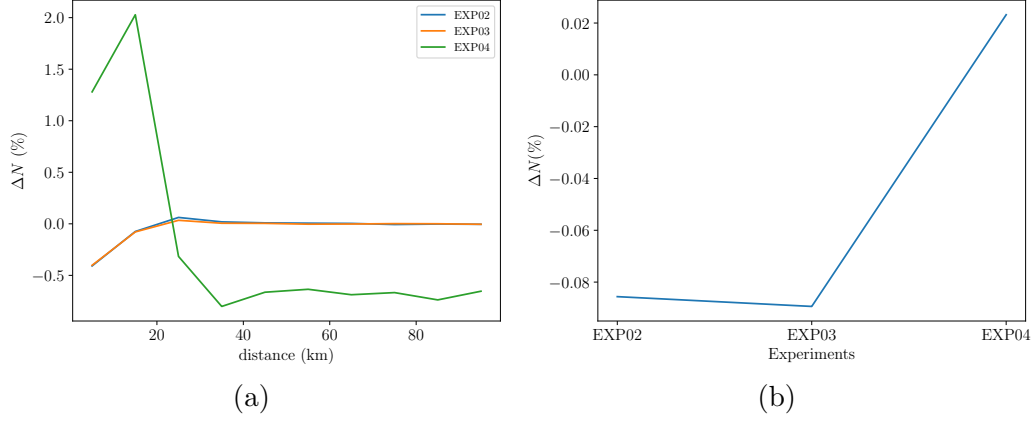


Figure 12: Left: percentage difference in QCed retrievals w.r.t. EXP01 as a function of the distance to the coast. Right: percentage difference in total QCed retrievals w.r.t. EXP01.

5.2 Validation against buoys and JPL Level 2 product

In this section, OSI-SAF wind retrievals, using the EXP04 configuration are validated against buoy measurements and the JPL L2 homologous product [5]. The results from the triple collocation exercises indicated by the acronyms BOE_i and BJE_i are considered here (see Table 4) to pursue a fair comparison on common collocations.

Table 6a (6b) reports the calibration coefficients for each system and wind component, together with the estimated measurement errors for the triplet BOE_i (BJE_i). a (b) stands for slope (offset), while u (v) stands for zonal (meridional) wind component. Finally, ϵ stands for wind component measurement error, measured in ms^{-1} . In this study, errors are referred to the scatterometer scale. Since $r^2 = 0$, model wind errors are overestimated. A finer analysis is left for the future. However, this does not impact the main conclusions of this study.

The figures in both tables suggest that OSI-SAF retrievals are much less noisy than JPL retrievals. Note that buoy and model measurement errors are almost identical for the two exercises, in line with expectations.

This conclusion is also supported by Figures 13, 14, 15 and 16. Figure 13 shows the contour plots of the 2D normalized histograms of OSI-SAF and JPL wind speed retrievals *vs* buoy measurements, segregated according to the distance from the coast. A few aspects are evident from these plots: a) the number of collocations in the first 10 km is much lower than farther from the coast. As anticipated, this is not a matter of QC, but is due to a lack of collocations with coastal buoys very close to the coast. This aspect will

Table 6: 6a (6b) Calibration coefficients and wind component measurement errors for the triplet BOE_{*i*} (BJE_{*i*}). *a* (*b*) stands for slope (offset) and the subscript *u* (*v*) for zonal (meridional) wind component. Finally, ϵ stands for wind component measurement error measured in ms⁻¹. The total number of collocations amounts to 22,577.

	buoy	OSI-SAF	ERA5
a_u	1	1.067	0.935
b_u	0	-0.102	-0.477
a_v	1	1.014	0.951
b_v	0	-0.027	-0.020
ϵ_u	1.71	0.81	1.36
ϵ_v	1.61	0.82	1.31

(a)

	buoy	JPL	ERA5
a_u	1	1.001	0.937
b_u	0	-0.162	-0.475
a_v	1	1.003	0.950
b_v	0	0.046	-0.007
ϵ_u	1.73	1.53	1.34
ϵ_v	1.59	1.25	1.33

(b)

be addressed later in this section; b) The contours scatter reduces with d , as also indicated by SD, ρ and MAE values. This feature is common to both products, even though JPL plots are more scattered than OSI-SAF; c) There is a positive bias at low-wind regimes. This is due to some residual land contamination after correction, as shown in Section 5.3. This trend is again common to both products; d) JPL wind speed retrievals seem high-biased also at high wind regimes, while OSI-SAF retrievals stick quite well to the diagonal; e) contour plots appear clustered around buoy wind speed integer values. This is due to rounding, as already mentioned in Section 3. Note that 10-m buoy measurements have decimal figures, due to the conversion procedure to 10-m neutral winds. However, this does not make the clustering effect disappear.

Figure 14 shows similar plots for wind direction. The plots only contain the collocations with wind speeds ≥ 4 ms⁻¹. This constraint is applied to the average wind speed of buoy measurements and retrievals. The main conclusions are similar to those previously mentioned, as also confirmed by the statistical metrics.

Finally, Figures 15 and 16 show analogous plots for the zonal and meridional wind components, respectively. These plots are also in line with the main conclusions. In particular, both wind components have an “S”-shape towards zero, in agreement with the presence of high biases at low-wind speed regimes. This is more evident within 20 km to the coast, in line with wind speed plots.

Table 7 shows the wind component measurement errors for the triplets BOE_{*i*} and BJE_{*i*}, segregated according to the distance from the coast. Buoy and model wind components measurement errors are not reported to keep

the table concise. Indeed, these figures are quite similar to those reported in Table 6, hence, they do not add any important information. Once more, these figures are in line with the outlined conclusions. Indeed, both ϵ_u and ϵ_v decrease with the distance to the coast, with a minimum in the third band. The reason why they increase at 30-40 km compared to 20-30 km is probably due to random fluctuations.

The figures regarding the other triplets listed in Table 4 are not reported for the sake of brevity, since they do not add any important information to the main conclusions.

Table 7: OSI-SAF and JPL wind components measurement errors in ms^{-1} for the triplets BOE_i and BJE_i segregated according to the distance from the coast. Calibration coefficients and buoy and model measurement errors are not reported because they are quite similar to those reported in Table 6. N is the total number of samples.

Triplet	ϵ_u (ms^{-1})	ϵ_v (ms^{-1})	N
BOE_i^{10}	0.88	0.87	2158
BJE_i^{10}	2.10	1.70	2158
BOE_i^{20}	0.87	0.84	5540
BJE_i^{20}	1.55	1.43	5540
BOE_i^{30}	0.62	0.64	4200
BJE_i^{30}	1.27	1.02	4200
BOE_i^{40}	0.68	0.72	6805
BJE_i^{40}	1.48	1.15	6805

Figure 17 shows the wind speed distribution segregated according to the distance to the coast for each wind source. Some features stand out from these plots: a) buoy wind speed measurements tend to have a bi-modal distribution with the main peak around 5 ms^{-1} , in agreement with the other sources, and the secondary peak around 9 ms^{-1} , at least for winds between 20 and 40 km from the coast. This secondary peak is not present in the other sources, even though ERA5 winds between 30 and 40 km to the coast have a single peak close to 9 ms^{-1} . The reason of this mismatch is not clear at this stage; b) both OSI-SAF and JPL low winds within 20 km from the coast are underrepresented compared to buoy and model winds. This effect is more evident in JPL winds, which is compensated by a higher peak of the distribution at 5 ms^{-1} . This is in line with the high bias at low-wind regimes.

Figure 18 shows the wind speed distributions segregated with the distance to and direction w.r.t. the coast. This last parameter is defined as the angle between the wind direction and the direction to the coast. Angles lower than

60° identify onshore winds, angles higher than 120° offshore winds and the remaining are classified as parallel.

The distributions of OSI-SAF and JPL wind speeds are in good agreement with each other. The number of samples is not uniformly distributed, even if offshore and onshore winds show similar numbers. Onshore wind speed distributions seem to be wider than offshore, in agreement with buoy wind speed distributions (not shown). In [22], ASCAT wind speed distributions show an opposite trend. At this stage, any meaningful conclusions can be issued. A thorough analysis will be performed in the future, when more collocations will be available.

Blue and orange bars in Figure 19a (19b) show the distribution of buoys' and OSI-SAF (JPL) collocations' distance from the coast, respectively. Note that the blue bars are identical in both plots. These distributions are evaluated on the datasets BOE_o and BJE_o, hence, the total number of samples is slightly different (see Section 3). However, this is irrelevant for the following conclusions. As can be seen, the two histograms are quite similar for both datasets. We can conclude that the lack of collocations in the first 10 km from the coast w.r.t. the other coastal bands considered in this study is mainly due to the lack of buoy measurements at those distances. Indeed, in the case of coastal wind sampling issues, orange bars would be higher than blue bars as we get farther from the coast, with an inverse trend towards the coast.

Figure 20 shows the percentage of QC-accepted OSI-SAF retrievals as a function of the distance to the coast for the month of January 2007. All WVC farther than 90 km are cumulated in the last bin of the plot, which is labeled with ">90". It is apparent that offshore winds show a much better sampling rate compared to WVC closer than 90 km. Moreover, the sampling rate increases by about 10% going from 0 to 90 km from the coast, while it increases by more than 20% when passing from 80-90 km to the open ocean. Probably, the sampling rate in coastal areas is not only affected by land contamination. Indeed, land contamination is expected to dramatically reduce at distances higher than 30 km. We can speculate that coastal wind dynamics is characterized by higher variability compared to the open ocean and that leads to higher MLE, which finally impact QC. This aspect will be addressed in the future.

5.3 Analysis of the land-contamination residuals

Figure 21 shows the 2-dimensional contour plots of the normalized histograms of MLE *vs* OSI-SAF wind speed retrievals segregated according to the distance to the coastline. Note that, thanks to the procedure described in

Section 4.3, the number of samples is equal in all the plots. Moreover, these plots are evaluated on the datasets BOE_o , since there is no need to compare this trend with JPL retrievals on the intersection dataset.

MLE increases with lower wind speeds when getting closer to the coast, when the distance is lower than 20 km. No trend is appreciable for larger distances. This is in agreement with the trend of the correlation coefficient, $|\rho|$. This is the proof of the presence of some residual land contamination in slice σ_0 after the correction. The negative sign of ρ is expected, since land contamination is more evident at low-wind regimes, where the contrast between land and sea σ_0 is stronger.

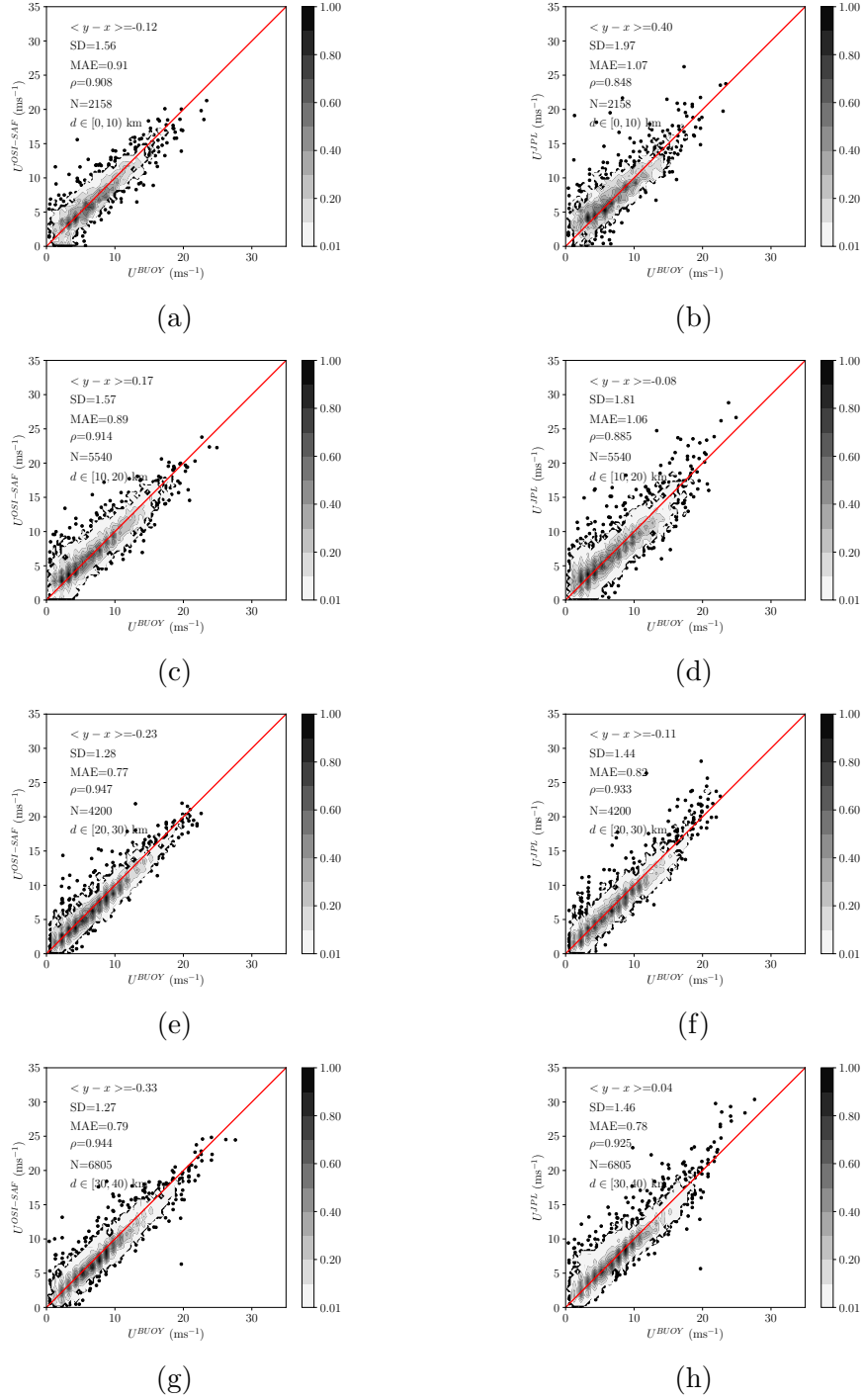


Figure 13: Left (right) column: contour plots of 2D normalized histograms of OSI-SAF (JPL) *vs* buoy wind speed; the rows correspond to different distances to the coast (d). Bias, standard deviation (SD), Median Absolute Error (MAE), correlation coefficient (ρ), number of samples (N) and d are also reported.

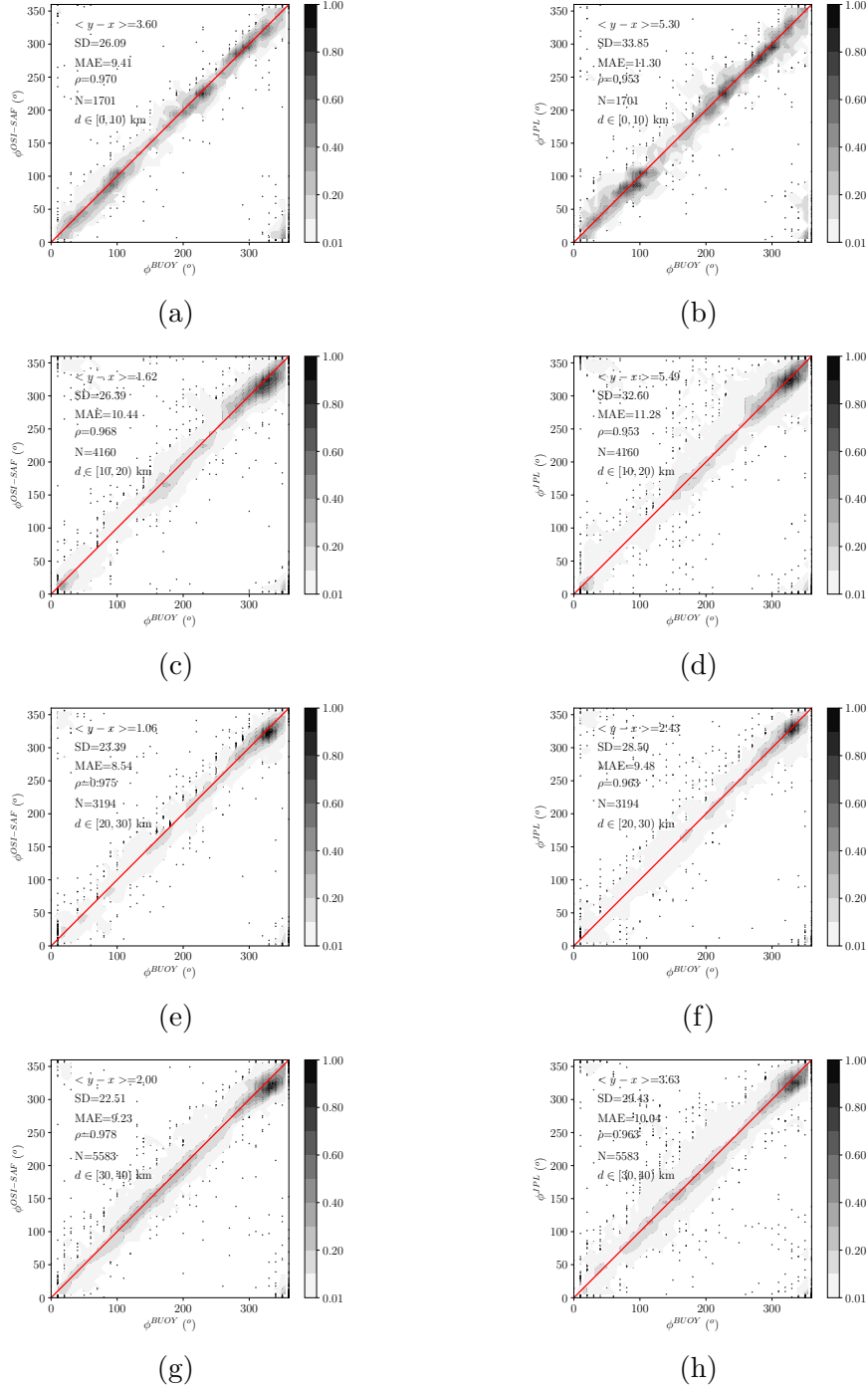


Figure 14: Left (right) column: contour plots of 2D normalized histograms of OSI-SAF (JPL) *vs* buoy wind direction; the rows correspond to different distances to the coast (d). Bias, standard deviation (SD), Median Absolute Error (MAE), correlation coefficient (ρ), number of samples (N) and d are also reported.

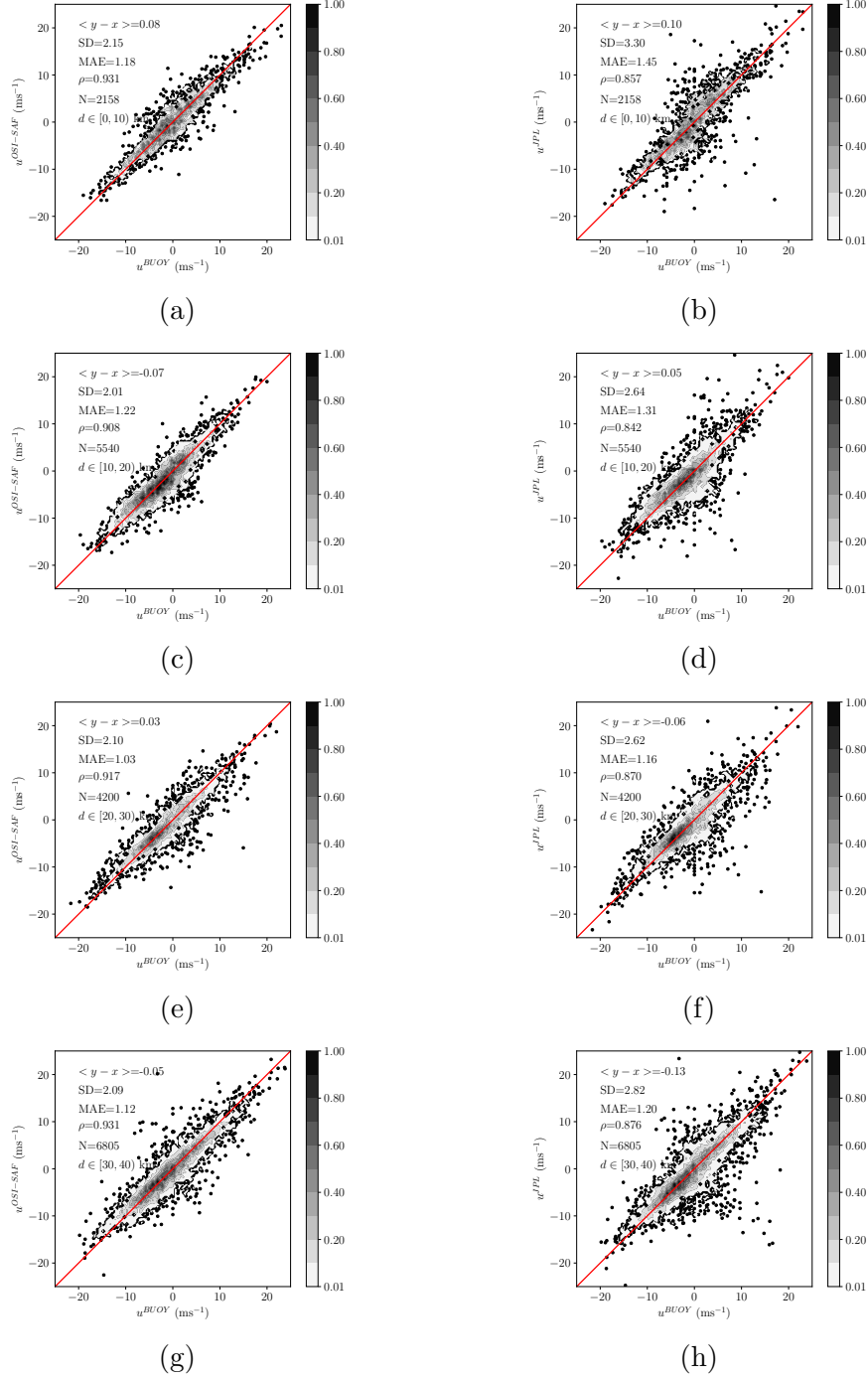


Figure 15: Left (right) column: contour plots of 2D normalized histograms of OSI-SAF (JPL) *vs* buoy zonal wind component; the rows correspond to different distances to the coast (d). Bias, standard deviation (SD), Median Absolute Error (MAE), correlation coefficient (ρ), number of samples (N) and d are also reported.

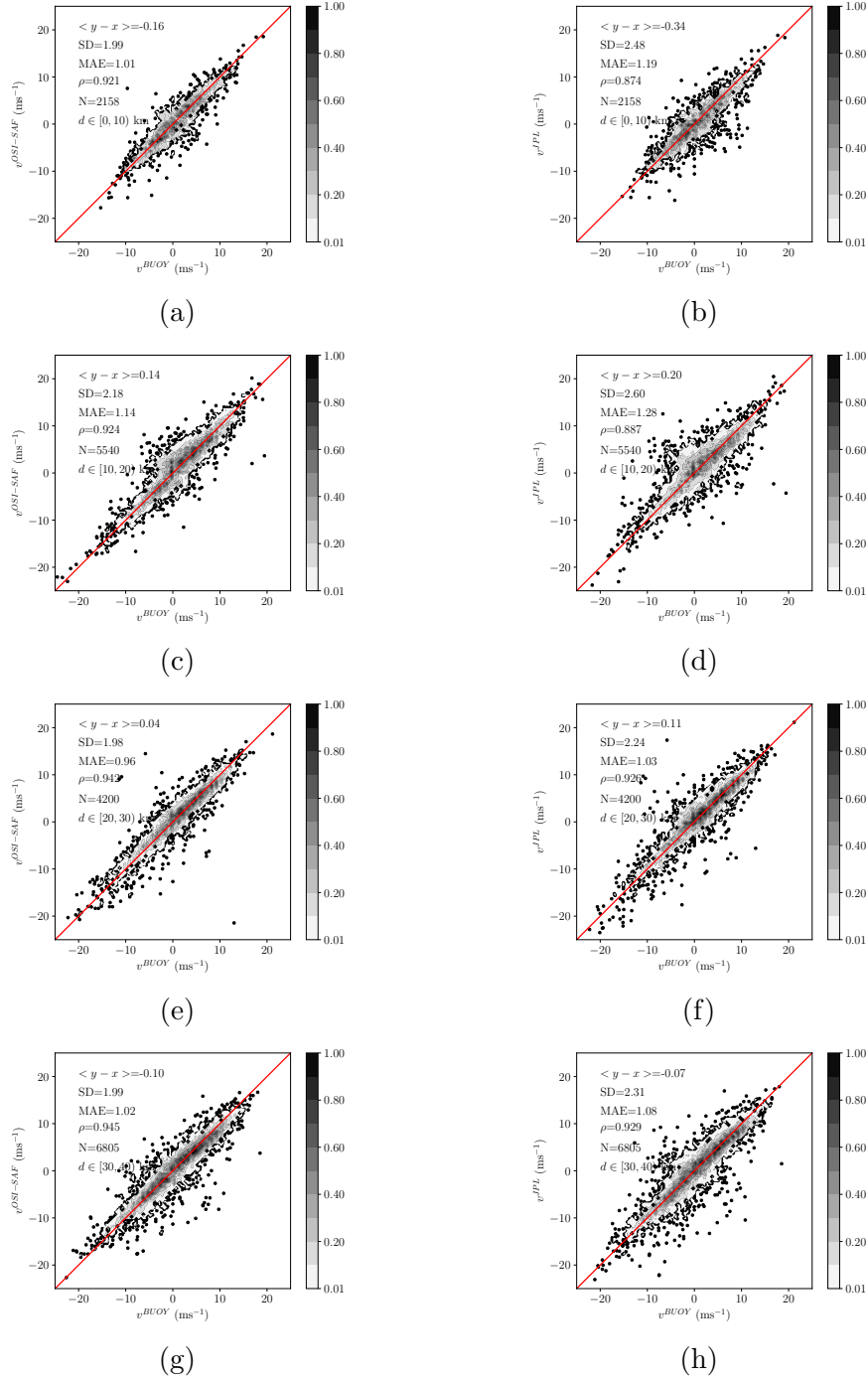


Figure 16: Left (right) column: contour plots of 2D normalized histograms of OSI-SAF (JPL) v vs buoy meridional wind component; the rows correspond to different distances to the coast (d). Bias, standard deviation (SD), Median Absolute Error (MAE), correlation coefficient (ρ), number of samples (N) and d are also reported.

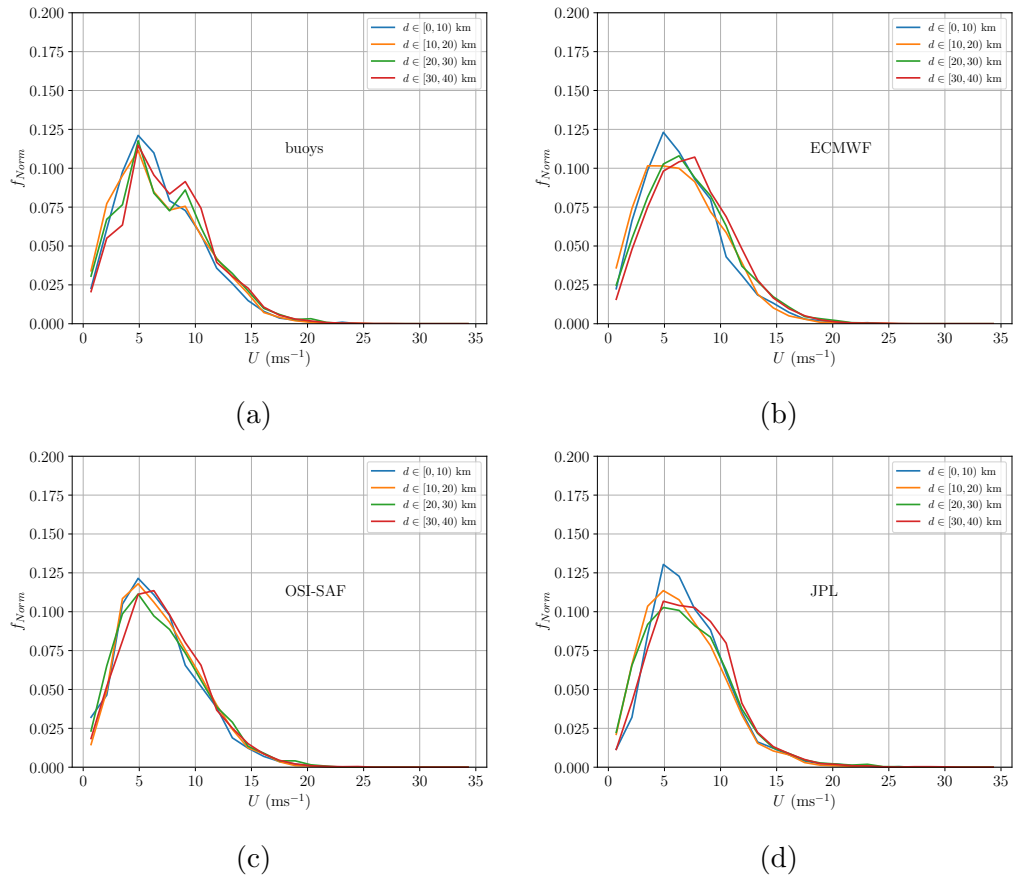


Figure 17: Wind speed distribution segregated according to the distance to the coast.

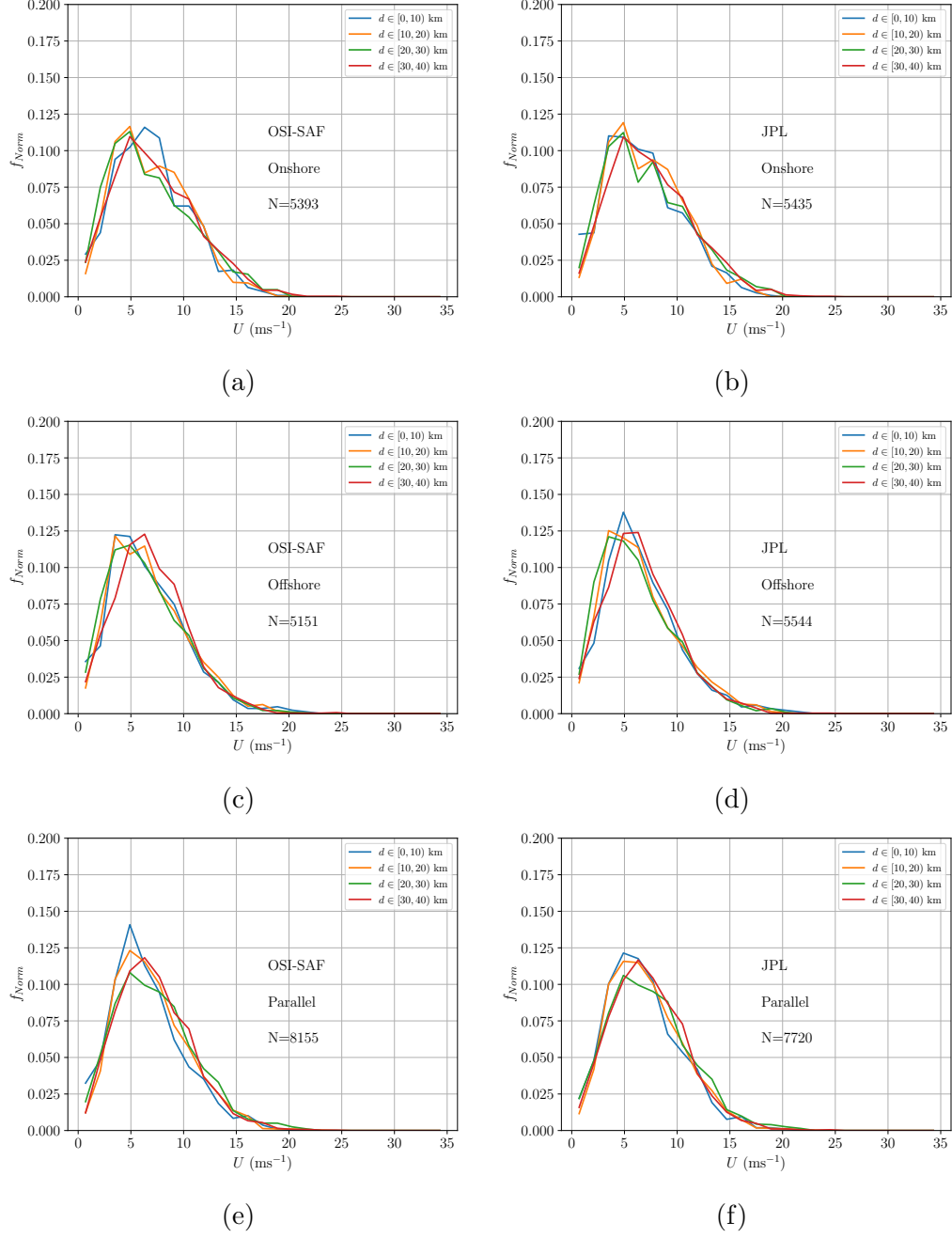


Figure 18: Wind speed distribution segregated according to the distance and direction w.r.t. the coast. The wind source, the class identifying the direction w.r.t. the coast and the number of samples are reported in the panels.

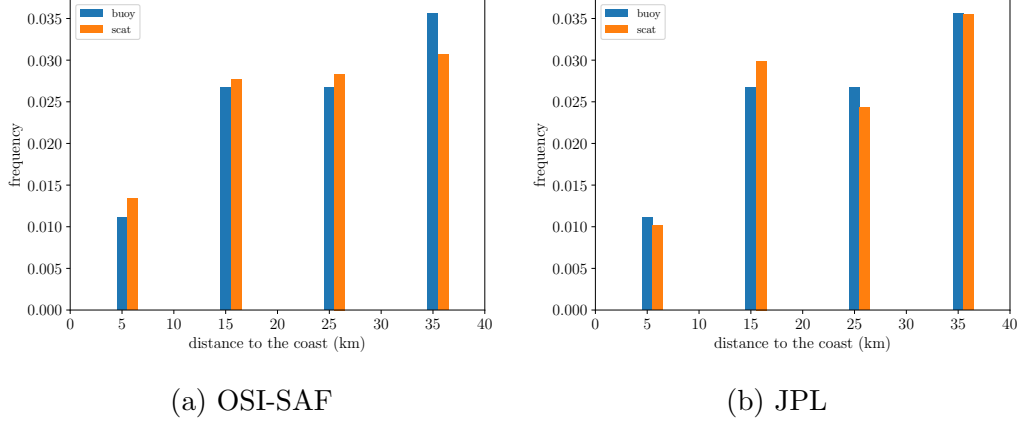


Figure 19: Blue (orange) bars: distribution of buoys' (collocations') distance to the coast for the four 10-km-wide coastal bands up to 40 km. Bars are centered at the middle distance.

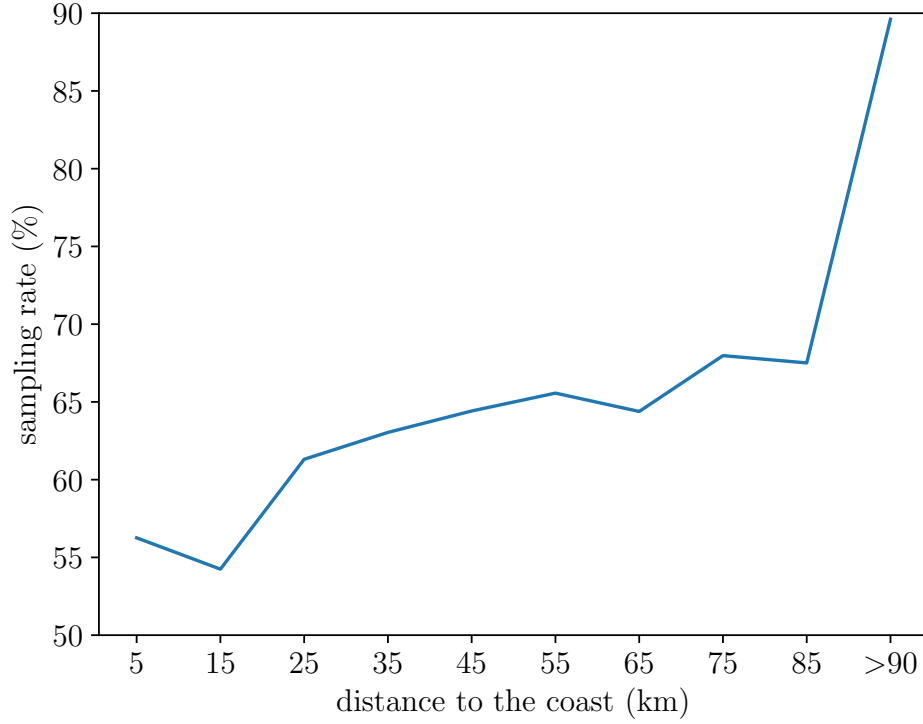


Figure 20: Percentage of QC-accepted OSI-SAF retrievals as a function of the distance to the coast. “>90” means WVC centroids at distances higher than 90 km.

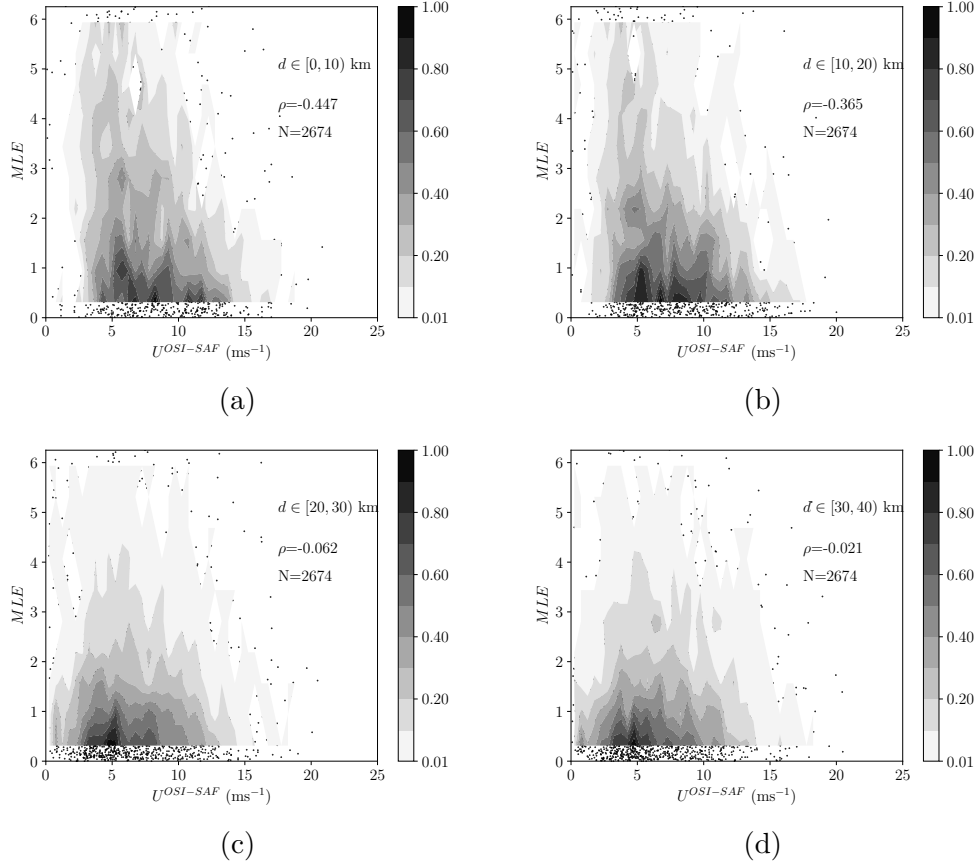


Figure 21: Contour plots of 2-dimensional normalized histograms of MLE *vs* wind speed, segregated according to the distance from the coastline, which is reported on each panel. The correlation coefficient (ρ) and the total number of samples (N) are also reported. Points represent values with normalized frequency lower than 1%.

6 Conclusions and outlook

This study presents a detailed validation of OSI-SAF coastal ocean surface vector winds retrieved from QuikSCAT with noise regularization, spanning the entire year 2007. Scatterometer-derived winds are validated against buoy measurements obtained from the ECMWF MARS archive and the “QuikSCAT Scatterometer Inter-Calibrated Earth Science Data Record (ESDR) Level 2 Ocean Surface Equivalent Neutral Wind Vectors and Wind Stress Version 1.1” produced at NASA/JPL. Both L2 Scatterometer-derived wind products are compared to buoy and ERA5 model winds with two triple collocation exercises on the same set of collocations. The results show that both products are high-biased at low wind speed regimes, specifically those lower than $3\text{--}4\text{ ms}^{-1}$. This is particularly evident within 20 km from the coast. An analysis of the OSI-SAF MLE leads to conclude that coastal radar cross sections are still slightly land-contaminated after noise regularization is applied. JPL winds are much noisier than those from OSI-SAF and also present some high biases at high wind speed regimes.

The triple collocation analysis performed in this study does not reveal any sampling deficiencies close to the coast. At least there are no evident differences in the first 40 km to the coast. However, the sampling rate increases by about 10% going from 0 to 90 km from the coast, while its increment is 20% when passing from 80-90 km to larger distances. This result leads to the conclusion that the sampling rate is not only impacted by land contamination. Indeed, wind variability increases towards the coast, together with the representativeness error and the wind variability resolved by buoys but not by scatterometers. This leads to higher MLE, which finally impacts QC. In conclusion, regardless of the presence of any land contamination, wind retrieval uncertainty is expected to increase towards the coast. In the future, we need to refine our capability to disentangle wind variability from land contamination.

Four different configurations of the OSI-SAF processor have been analyzed to further mitigate land contamination, without success. This leads to the conclusion that the method used to model the CDF used in the noise regularization procedure, analytical or empirical, does not impact the quality of retrieved winds. Moreover, not even the grid spacing of the reference σ_0 levels used to model CDF plays a role in this aspect. Finally, the weights used in the four-look σ_0 averaging before retrieval do not impact the wind accuracy. These results suggest that residual wind biases can be mitigated after retrieval. This study is left for the future.

A more detailed analysis of retrieval accuracies in the outer, sweet and nadir parts of the satellite swath is also left for the future, together with a finer

tuning of MLE threshold values close to the coast.

The climatological dataset spanning the entire QuikSCAT mission will also be produced in the future.

Finally, the noise regularization software has been implemented in C, achieving the optimal computational efficiency. Further steps are needed to improve software readability and management.

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