How to live with model biases ?

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Golden age of Scatterometry (WMO OSCAR)

Instrument	NRT?	Relevance	Satellite	Orbit	DLR	2022	2023	2024	2025	2026	2027	2028	2029	2030	2031	2032	2033	2034	2035
WindRAD		1 - primary	FY-3E	05:40 desc		X	X	X	X	X	X								
WindRAD		1 - primary	FY-3J	05:00 desc							X	X	X	X	X	X	X	X	X
ASCAT	Yes	2 - very high	Metop-B	09:31 desc	50	X	X	X											
ASCAT	Yes	2 - very high	Metop-C	09:31 desc	85	X	X	X	X	X	X								
SCA (Scatterometer)		2 - very high	Metop-SG-B1	09:30 desc					X	X	X	X	X	X	X	X			
SCA (Scatterometer)		2 - very high	Metop-SG-B2	09:30 desc												X	X	X	X
CSCAT		2 - very high	CFOSAT	07:00 desc		X	X												
HSCAT		2 - very high	HY-2B	06:00 desc	273	X	X												
HSCAT		2 - very high	HY-2D	66 °		X	X	X	X	X									
HSCAT		2 - very high	HY-2E	06:00 desc				X	X	X	X	X							
HSCAT		2 - very high	HY-2C	66 °		X	X	X	X										
HSCAT		2 - very high	HY-2F	66 °					X	X	X	X	X						
OSCAT-3		2 - very high	OceanSat-3 (EOS-06	12:00 desc		X	X	X	X	X	X	X	X	X					

Source: https://space.oscar.wmo.int/gapanalyses?mission=12

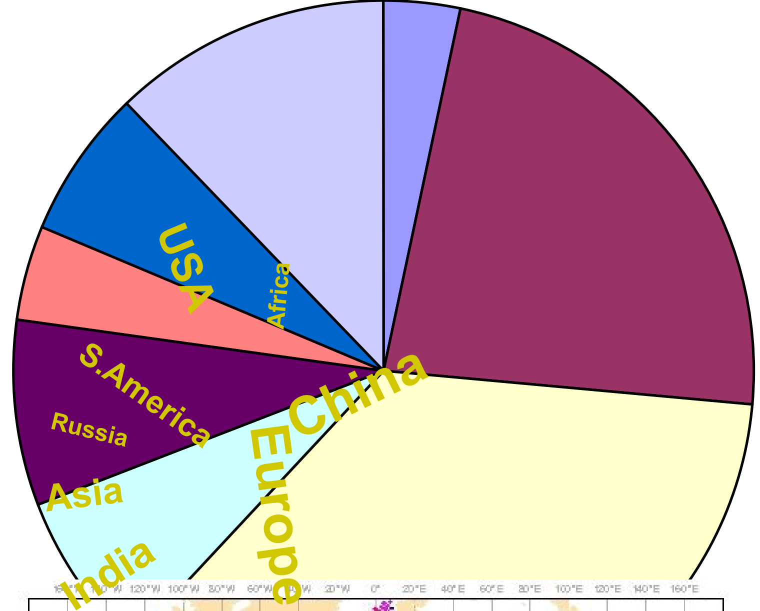
Past C-band missions :

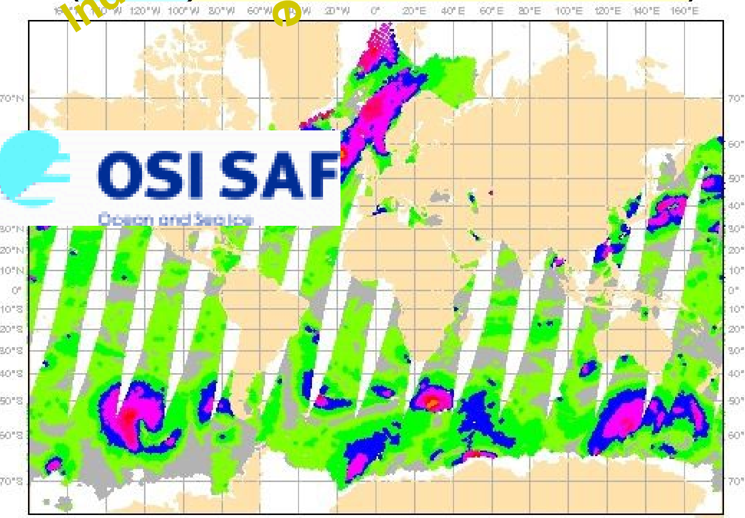
ERS-1,2/ESCAT	10:30 desc.	1992-1996, 1995-2000
MetOp-A/ASCAT	9:30 desc.	2007-2021

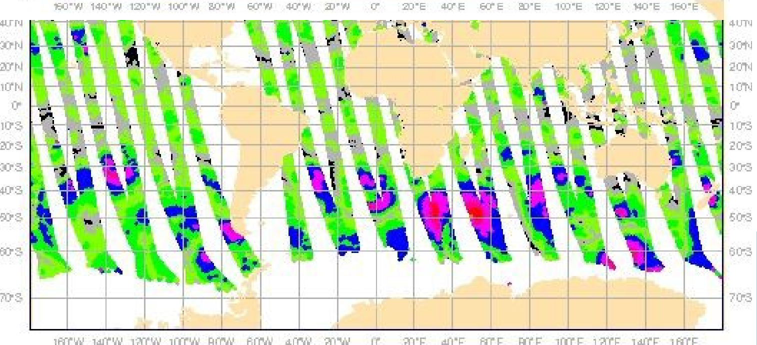
Past Ku-band missions :

SeaWinds/QuikScat	6:00 desc.	1999-2009
RapidScat/ISS	52 *	2014-2016
OceanSat-2/OSCAT-1	0:00 desc.	2009-2014
ScatSat-1/OSCAT-2	8:45 desc.	2016-2021

- Prepare ourselves for many scatterometers ☺
- ~15% forecast error reduction?







Satellite Wind Services

24/7 Wind services (EUMETSAT OSI SAF)

- International constellation of satellites
- High quality winds, QC
- Timeliness 30 min. – 2 hours
- Service messages
- QA, monitoring
- 7 satellites (2 Europe, 5 China)

Software services (NWP SAF)

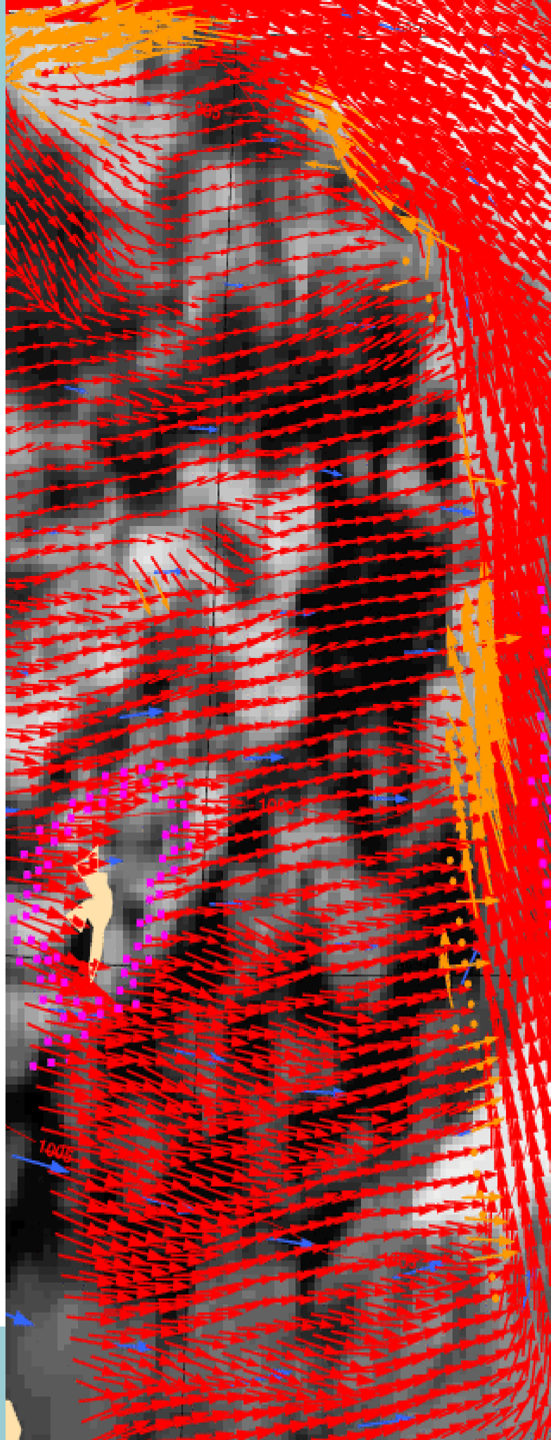
- Portable Wind Processors
- ECMWF model comparison
- Organisations involved:
  KNMI, EUMETSAT, EU, ESA, NASA, NOAA, ISRO, CMA, WMO, CEOS, ..
- Users: NHC, JTWC, ECMWF, NOAA, NASA, NRL, BoM, UK MetO, M.France, DWD, CMA, JMA, CPTEC, NCAR, NL, . . .

More information:

www.knmi.nl/scatterometer

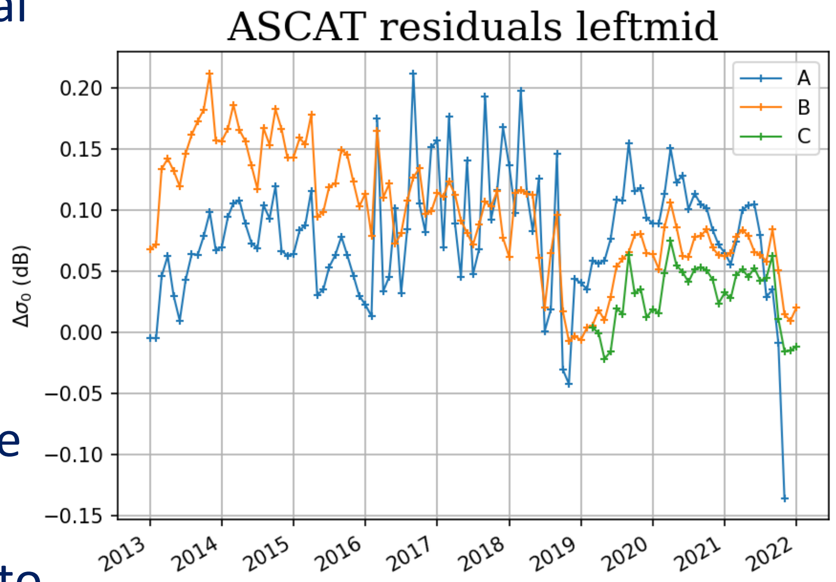
Wind Scatterometer Help Desk

Email: scat@knmi.nl



ASCAT scatterometer calibrations

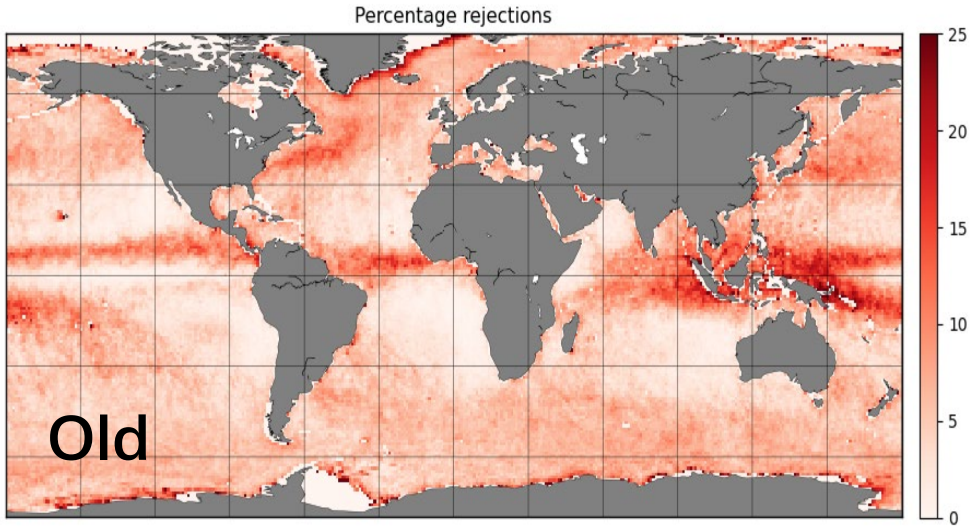
- EUMETSAT OSI SAF contributions to CDRs, e.g., https://scatterometer.knmi.nl/ascat_calibration/
- Supported by Ocean Surface Winds Task Group of the Coordination Group of Meteorological Satellites (CGMS), chaired by Ad Stoffelen
- Scatterometer intercalibration
- Variations due to weather, longer-term differences due to instrument
- 0.1 m/s ≅ 0.1 dB
- Extension to Ku-band and passive microwave sensors (Sisma Samuel)
- EUMETSAT CDOP4 phase from March 2022 to March 2027

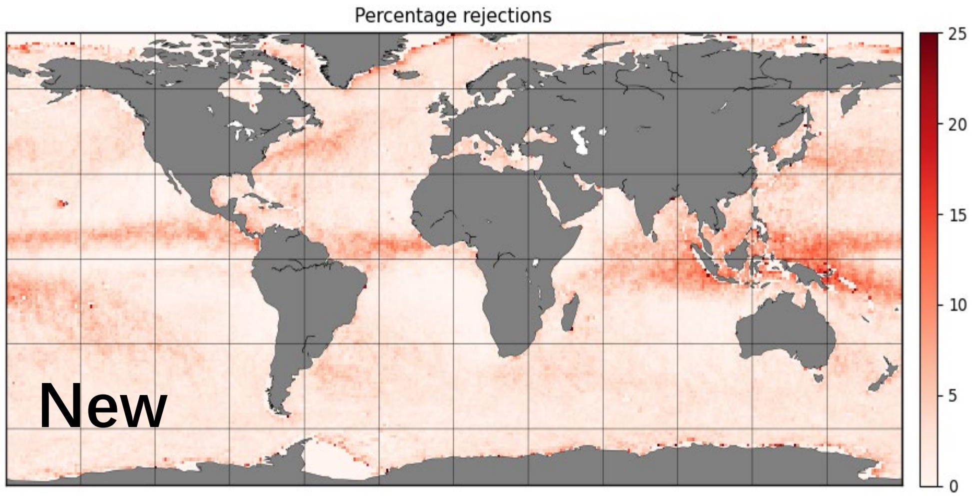


Belmonte et al., 2017

Quality Control and ocean winds

- EUMETSAT OSI SAF continuously improves quality control (QC)
- For Ku-band scatterometers we need to control rain events (=>)
- Develop algorithms to correct for remaining observational sampling biases
- We compare geographical biases between rain-insentitive (ASCAT) and rain-sensitive (Ku-band) scatterometers and collocated ECMWF winds
- This allows correction of the satellite sampling biases using ECMWF
- It allows to estimate the bias due to the systematic removal of about 10% of the Ku-band winds in moist convection
- We work on Ku-band rain correction methods using Bayesian estimation





Zhao et al., 2023

King et al., 2022

Xu and Stoffelen, 2021, 2019

Trindade et al., 2020, 2023

Belmonte and Stoffelen, 2019

The EUMETSAT Network of Satellite Application Facilities

OSI SAF Ocean and Sea Ice

Copernicus Marine Service

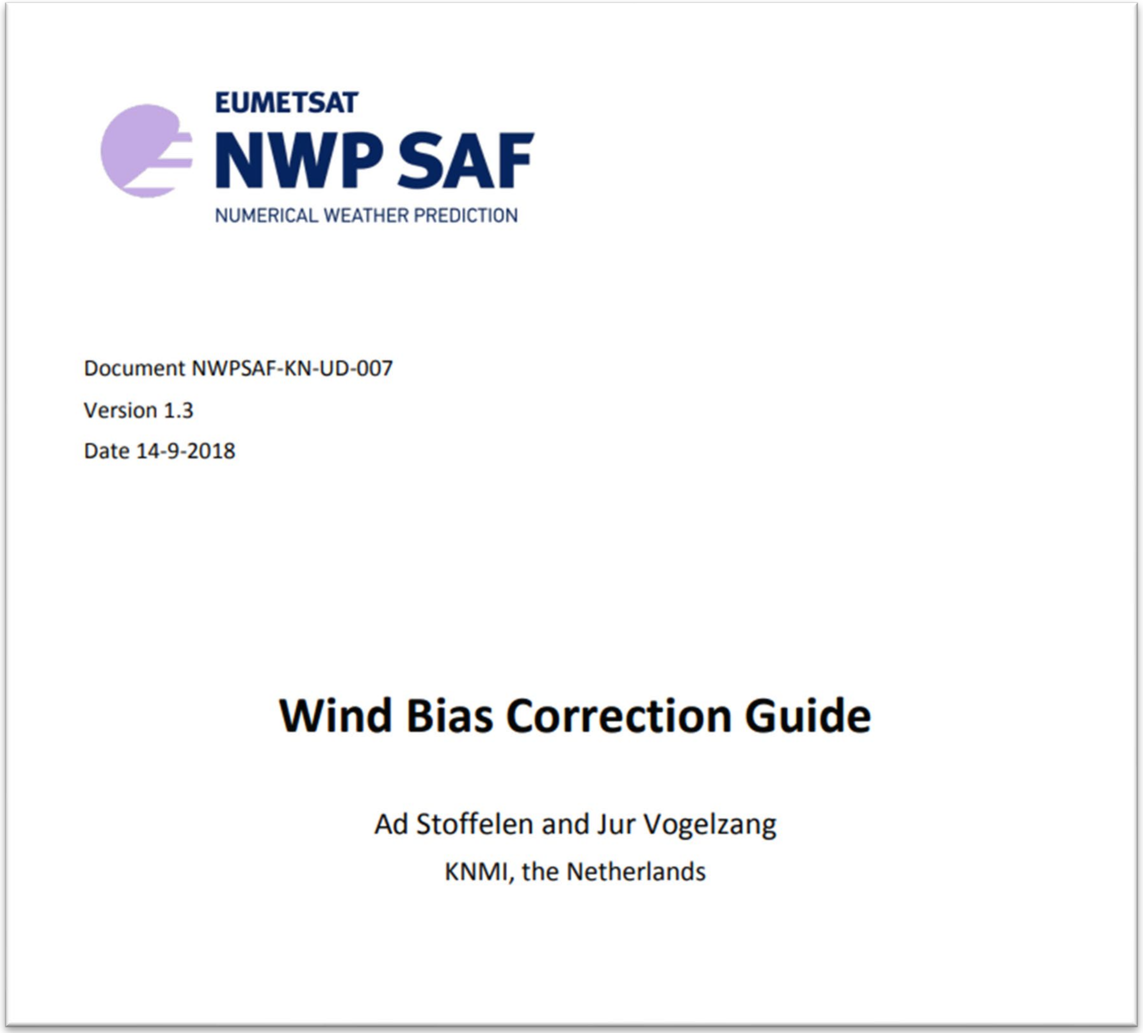
Quintuple collocation analysis

Table 2. Observation error standard deviations and their accuracies.

Observing System		σ_u (m/s)	std(σ_u) (m/s)	σ_v (m/s)	std(σ_v) (m/s)
buoys		0.914	0.017	1.063	0.020
ASCAT-A	(C-band)	0.372	0.022	0.505	0.029
ASCAT-B	(C-band)	0.390	0.025	0.444	0.020
ScatSat	(Ku-band)	0.683	0.018	0.594	0.021
ECMWF		0.845	0.017	1.006	0.021

- Scatterometers winds and stresses are unbiased with respect to moored buoys and have the smallest random error among in-situ and NWP winds
- Consolidated several methodologies to solve collocation error equations
- Added better ability to approximate the errors of the errors
- Confirms the excellent accuracy of scatterometer winds
- Stress-equivalent 10-m winds

Jur Vogelzang and Ad Stoffelen, 2022a, 2022b, 2021



EUMETSAT
NWP SAF
NUMERICAL WEATHER PREDICTION

Document NWPSAF-KN-UD-007

Version 1.3

Date 14-9-2018

Wind Bias Correction Guide

Ad Stoffelen and Jur Vogelzang

KNMI, the Netherlands

Model bias correction in NWP data assimilation

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Rianne Giesen, KNMI

Giovanna De Chiara, ECMWF

Sean Healy, ECMWF

Rationale

- ✓ See SCA SAG science plan (drafted 2016)
- ✓ Model biases are rather high compared to innovation, violating Best Linear Unbiased Estimate paradigm in data assimilation
- ✓ A few decades of model improvement have not solved this problem, though we are still trying actively
- ✓ The L4 OPS and ERA5 corrections can be inversely applied to the scatterometer data for the scatterometer winds to be unbiased with respect to the model
- ✓ ECMWF provided a reference run without scatterometers for which NUIST and KNMI computed model biases, averaging over 20 days (like for L4 product)
- ✓ NUIST applied these biases to obtain adjusted BUFR products
- ✓ ECMWF will run an OSE and compare it to reference OSEs with and without scatterometer data assimilation

Model bias correction in NWP data assimilation

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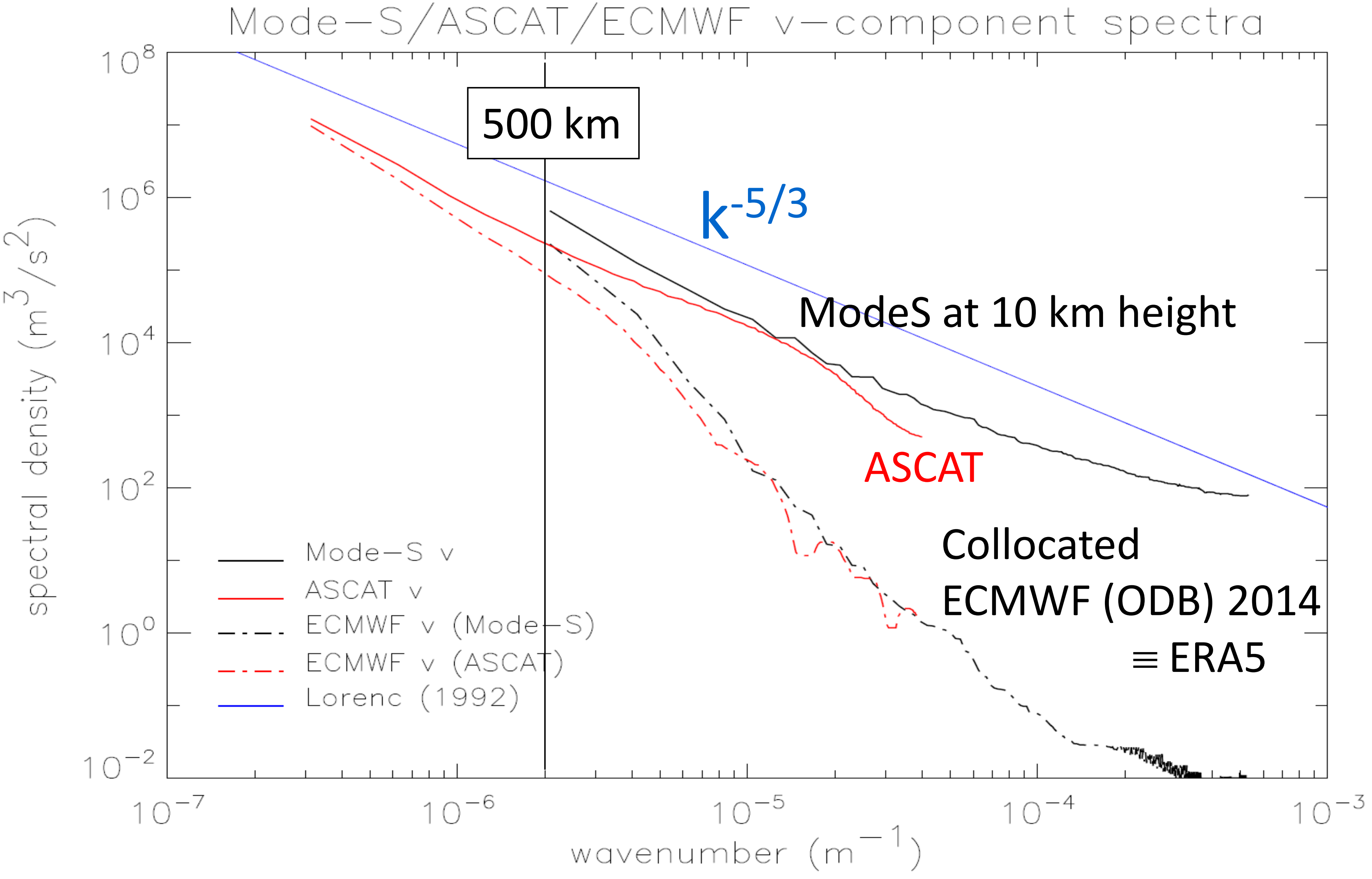
Rianne Giesen, KNMI

Giovanna De Chiara, ECMWF

Sean Healy, ECMWF

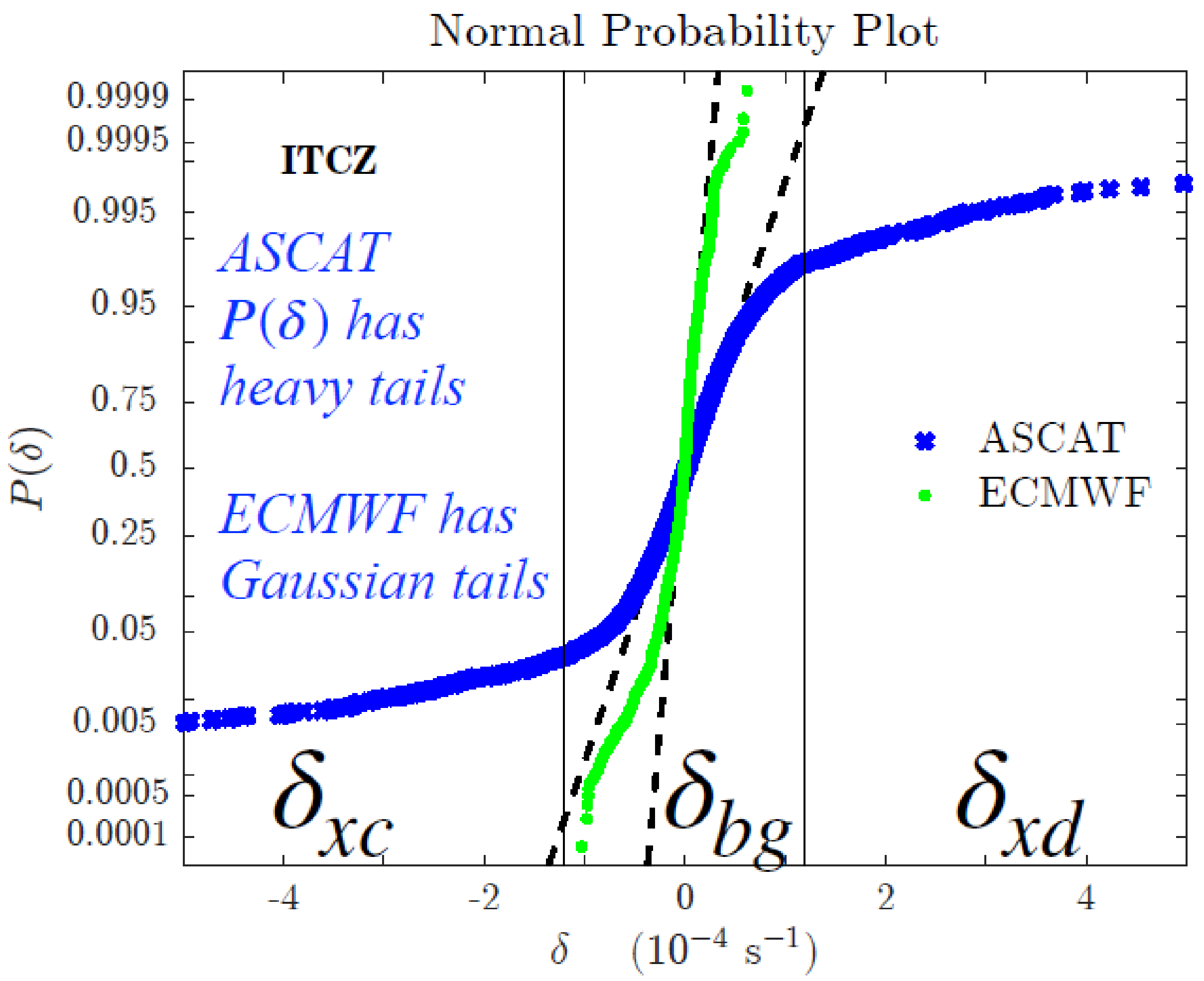
Global NWP gap for small scales

- ✓ Collocation observations and ECMWF (same sample)
- ✓ Below 500-km scales 3D turbulence dictates $k^{-5/3}$ spectrum
- ✓ This is followed by the observations
- ✓ In the upper air and at the ocean surface, ECMWF misses small-scale processes
- ➢ Wind variability is associated with mesoscale dynamics, coupled to sea surface conditions

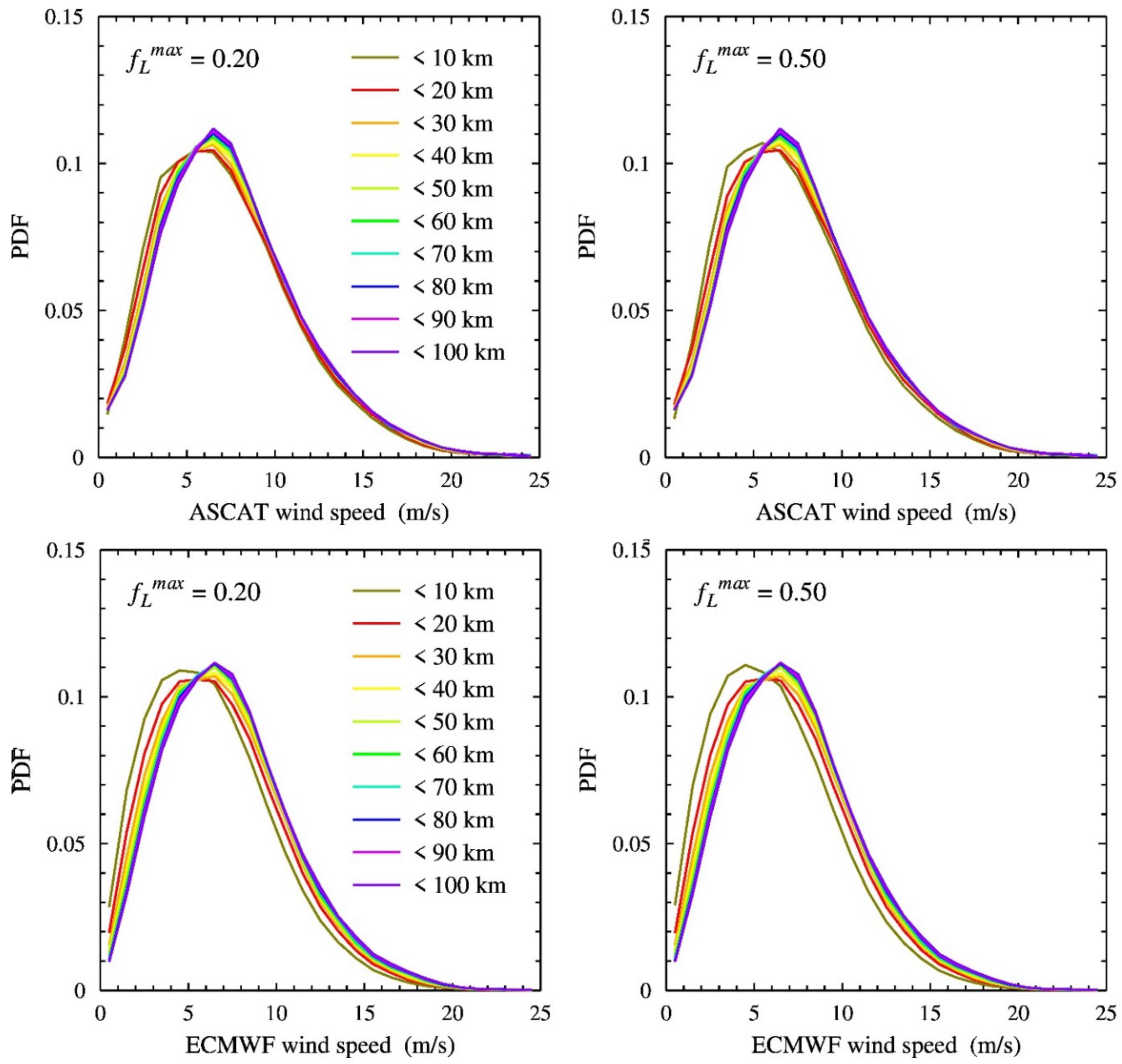


Spatial derivatives of wind and stress fields

- King et al., 2022 (see right) handles divergence PDFs and compares to ECMWF (also part of L3 and L4 files)
- Updrafts and downbursts in moist convection have a large and systematic impact on air-sea interaction, bringing moist air up and dry air down
- King et al. (2022) show scatterometer divergence and convergence (and curl!) are related to moist updrafts and downdrafts resp. by association to rain loops (MSG)
- ➢ These fast (30 min) and mesoscale (few km) processes are not well tracked in collocated global NWP winds (green line)
- ➢ Scatterometers can help to correct climatological biases due to missing processes in models



NWP coastal winds are too low

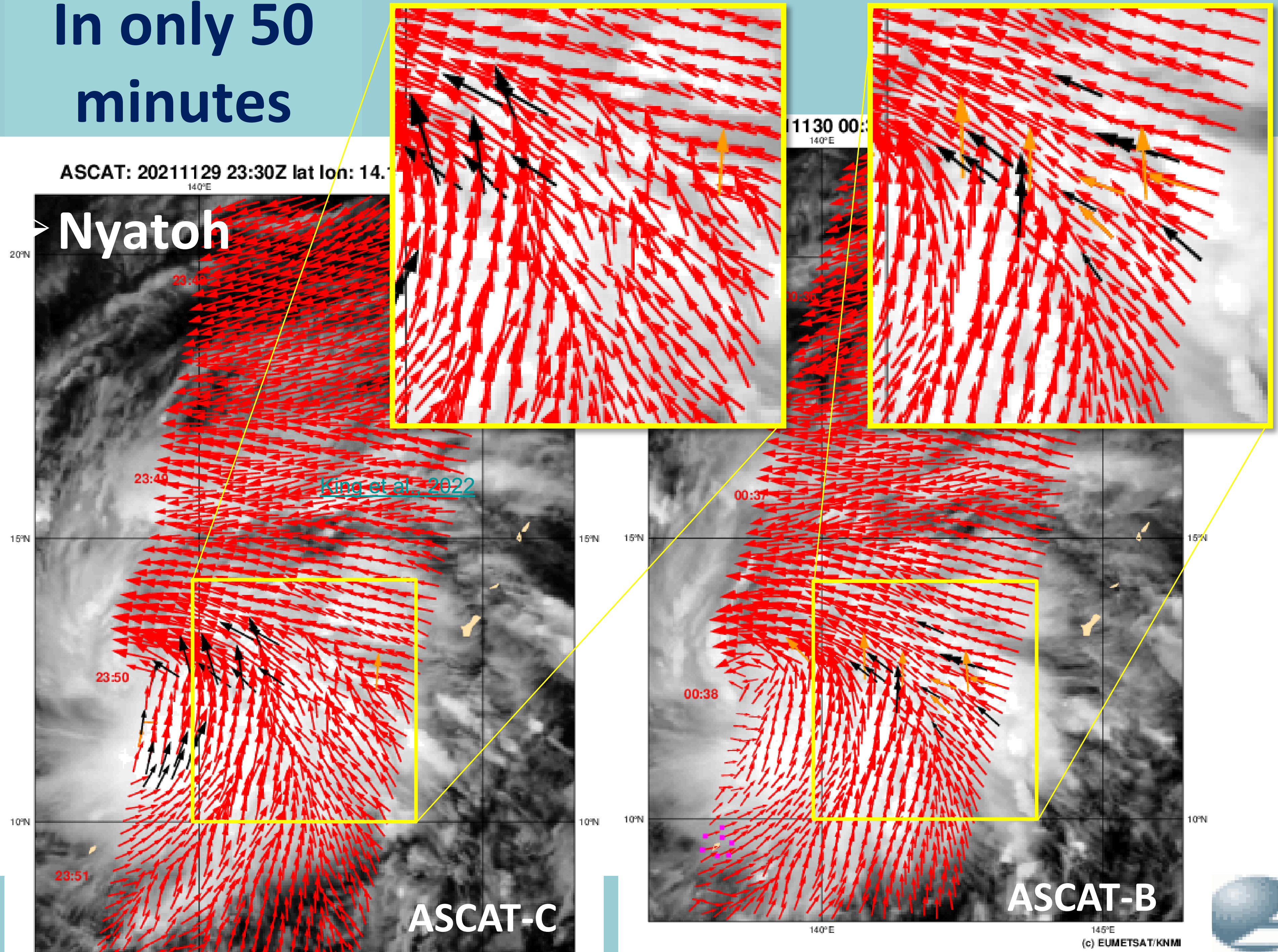


- PDFs of collocated coastal winds
- ECMWF u10s decreases faster towards the coast for < 30 km
- Probably caused by diffusion operator?
- Consistent with downscaling studies with km-scale grids
- While these still reduce the winds before they reach the coast!

➢ This is problematic for coastal model studies

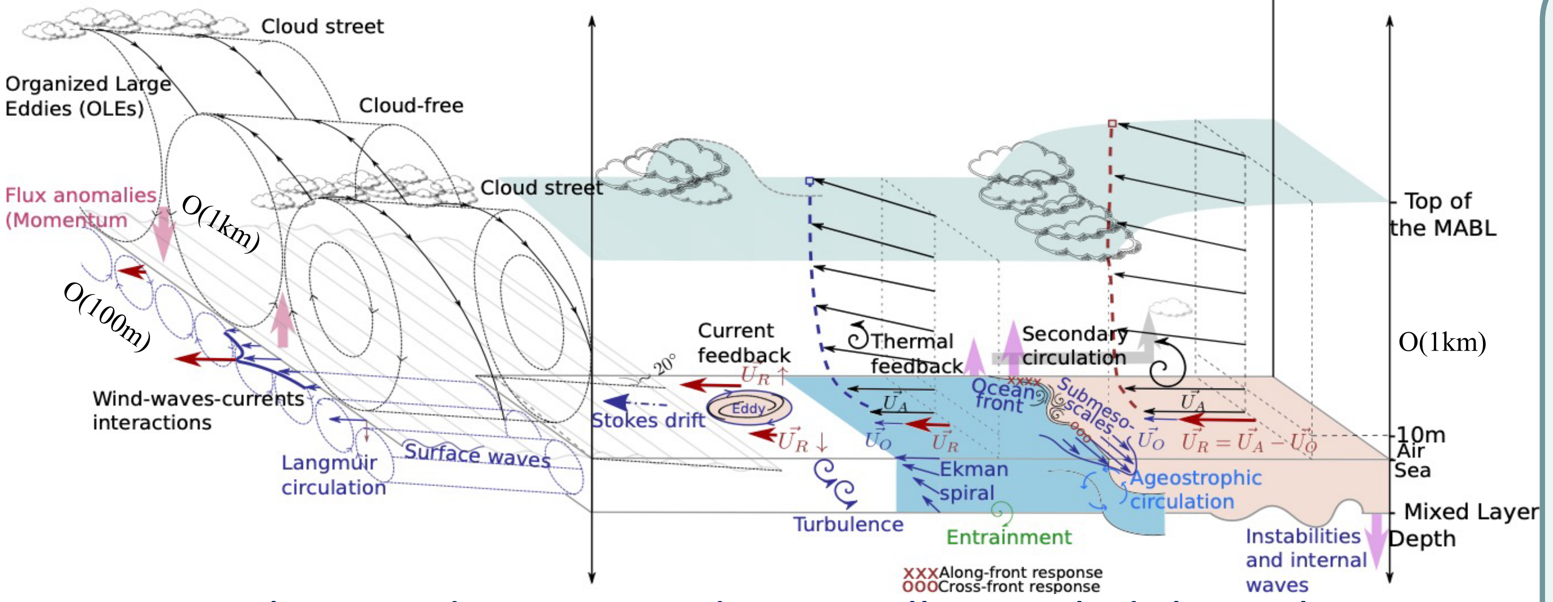
Vogelzang & Stoffelen, 2022

In only 50 minutes



Processes at the air-sea interface

Exchanges of **heat**, **gas**, **momentum** at the air-sea interface depend on the **thermal**, **chemical**, **kinematic** unbalance between ocean and atmosphere that are modulated by many **small-scale processes** that substantially moderate these exchanges.



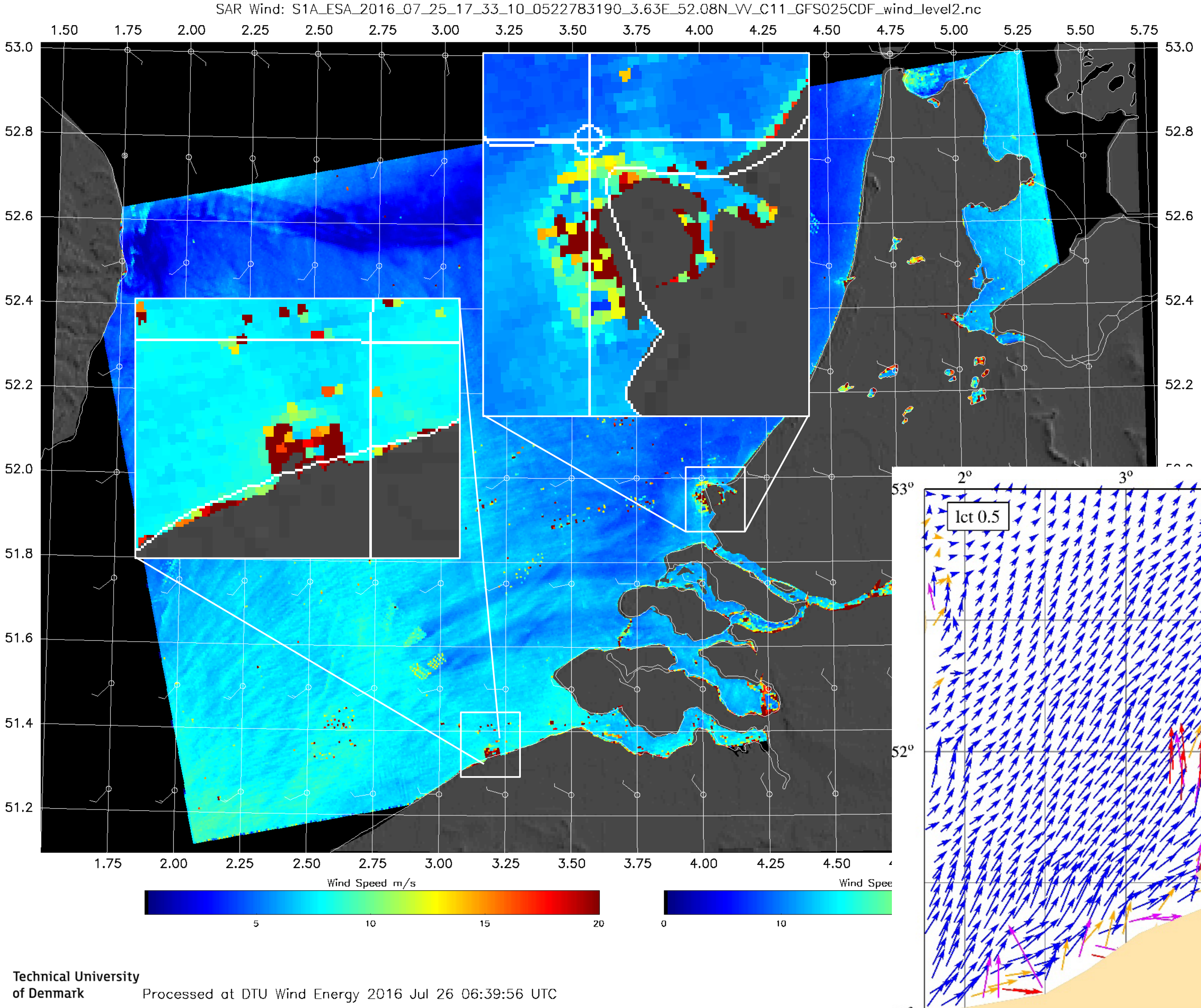
Air-sea fluxes

depend on

- **Surface stress** (impacted by ocean velocity and by air velocity, which is affected by SST)
- **Boundary layer thickness** (which varies by 2 orders of magnitude in different stability conditions)
- **Km-scale** ocean (eddy) dynamical circulations and phenomena

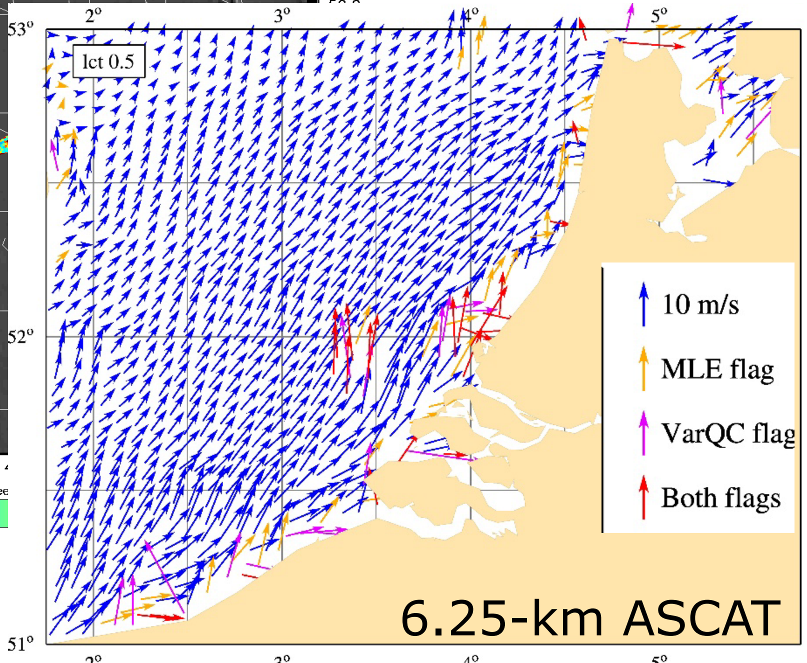
- Atmosphere and ocean are dynamically coupled through parameterizations with errors
- > 70% of earth's surface
- Tropical modes are poorly described (El Nino, MJO, Tropical Instability Waves, ..)
- Will these modes change in a changing climate? With what consequence?

High resolution



Coastal effects:

- Large ships
- Breaking waves?
- RFI
- Lakes?
- Shallow waters
- (Tidal) currents
- . . .

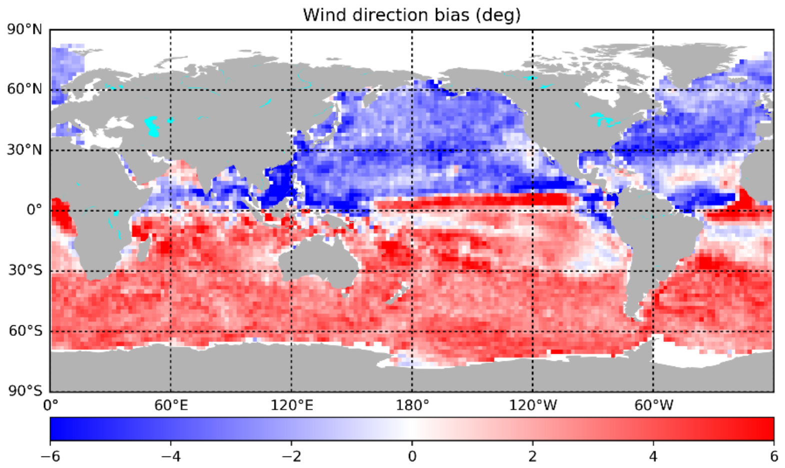


Technical University of Denmark

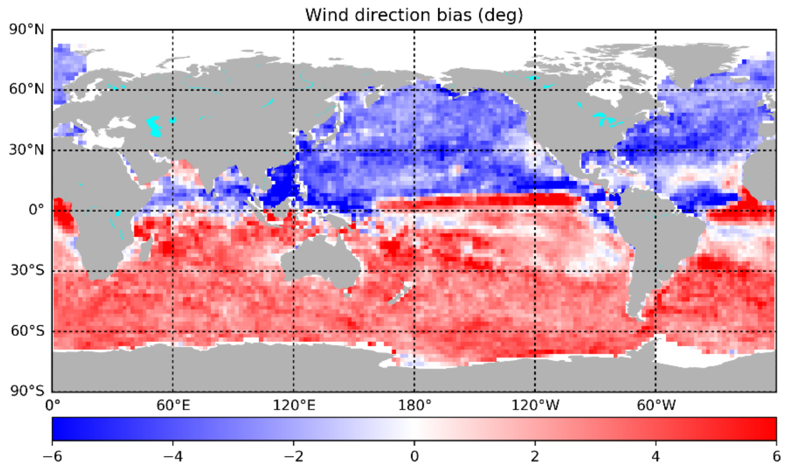
EUMETSAT OSI SAF

Wind **direction** biases of SCA - NWP

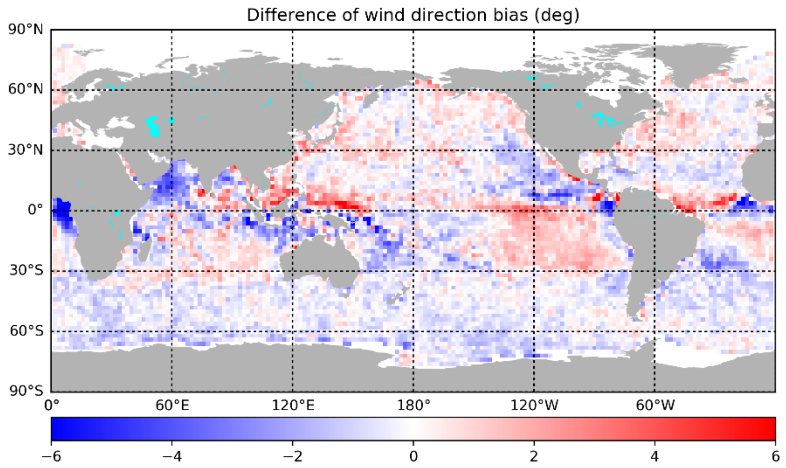
➢ Pattern could be diurnal cycle error



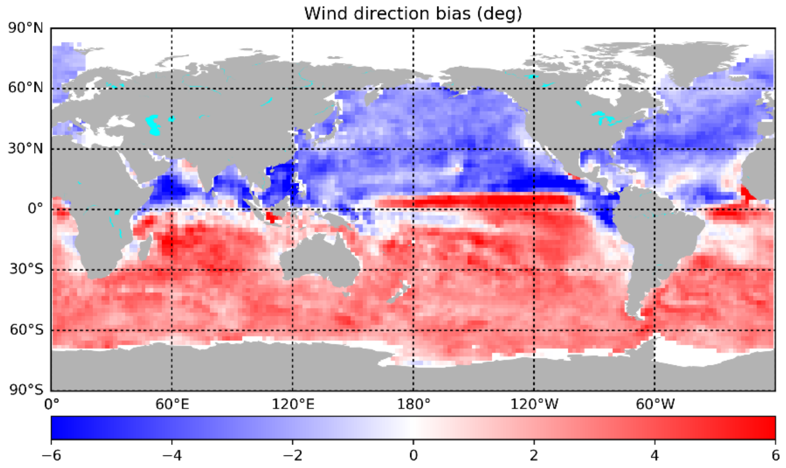
ASCAT-B NRT



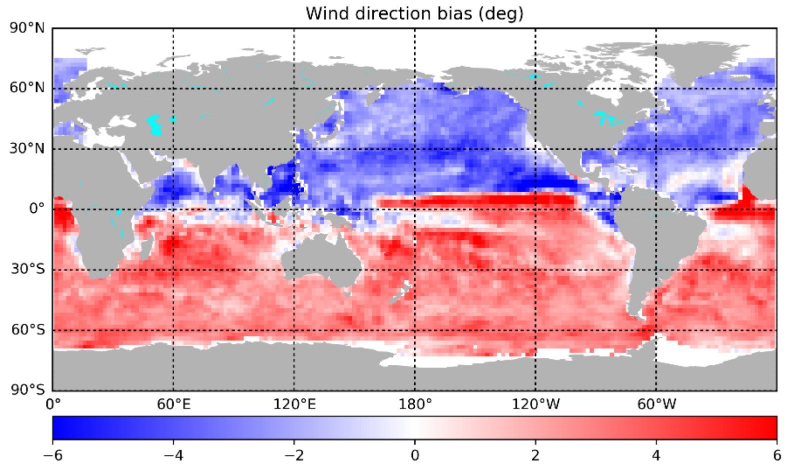
ASCAT-C NRT



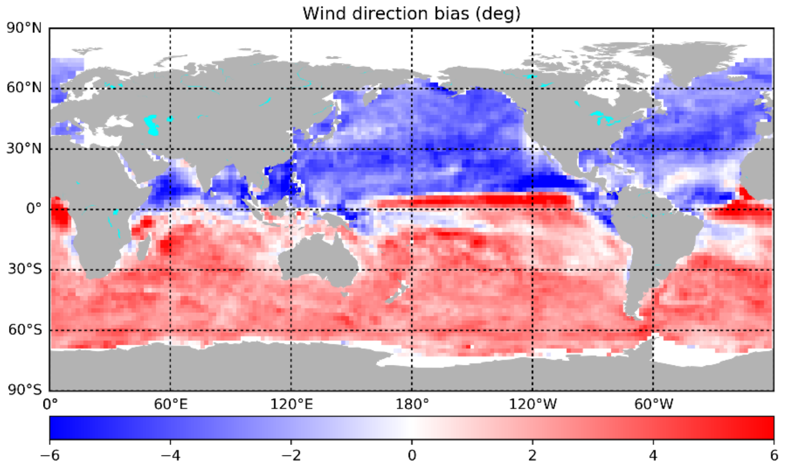
ASCAT-B/NRT – HSCAT-B/Rep02



HSCAT-B Rep02



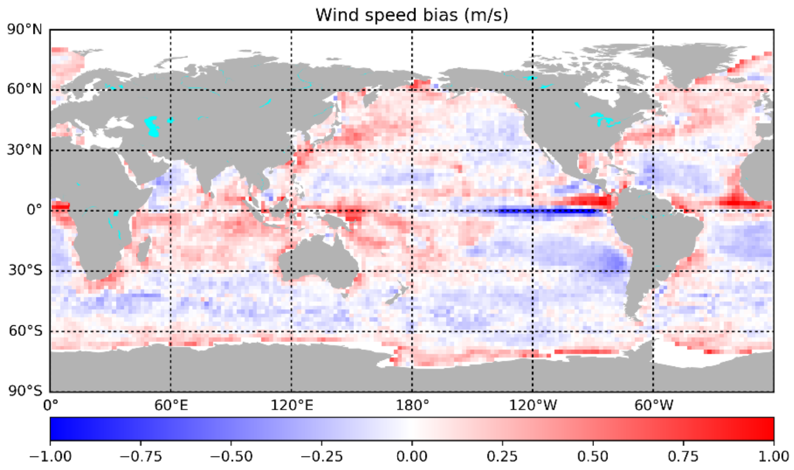
HSCAT-C Rep02



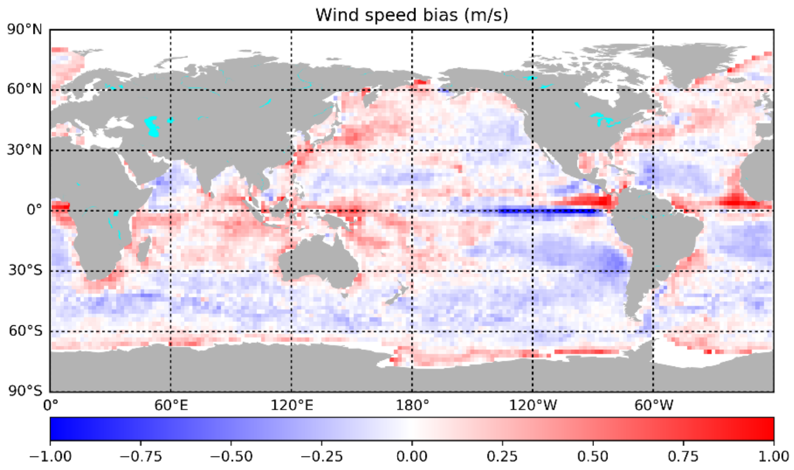
HSCAT-D Rep02

Wind speed biases of SCA - NWP

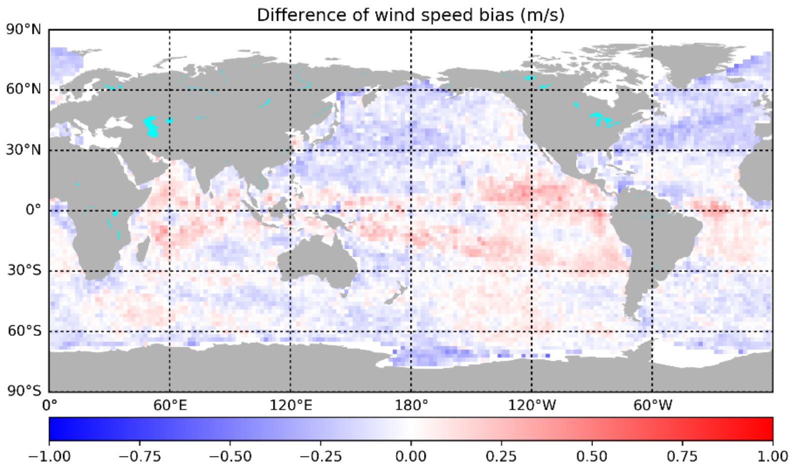
- Pattern could be diurnal cycle error



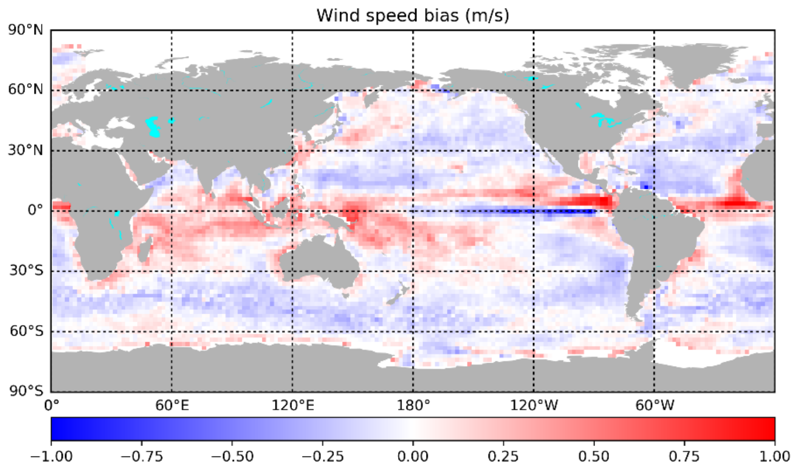
ASCAT-B NRT



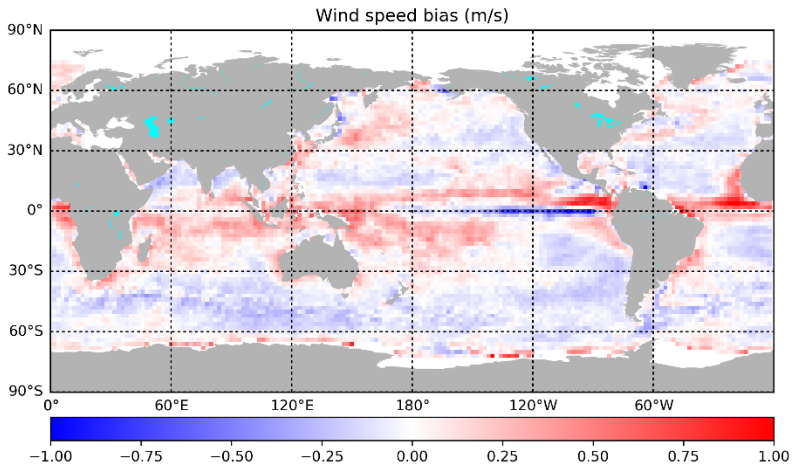
ASCAT-C NRT



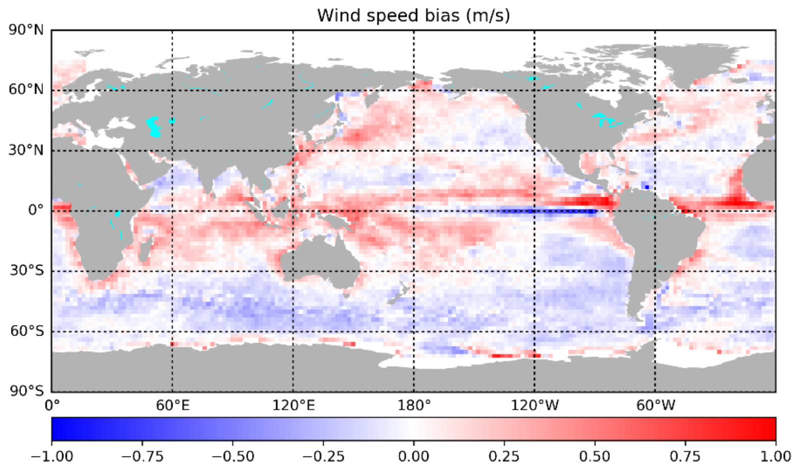
ASCAT-B/NRT – HSCAT-B/Rep02



HSCAT-B Rep02



HSCAT-C Rep02



HSCAT-D Rep02

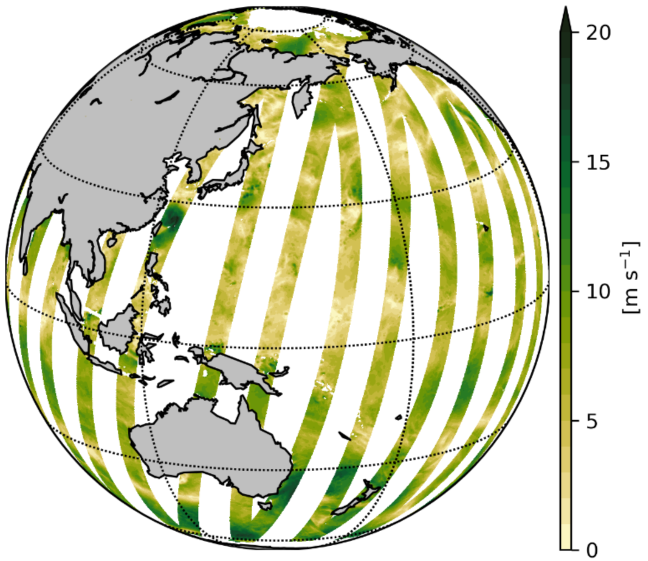
What can we fix?

For U10S

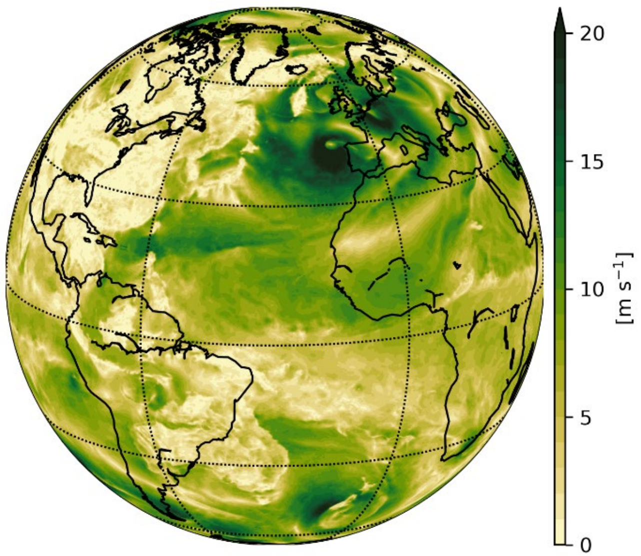
- ✓ Adjust observations to the model biases to make data assimilation more effective, i.e., take profit of the full innovation vector
- ✓ Correct ERA5 and OPS background U10S for the scatterometer biases for every hour (we cannot correct the ERA5 U10S analyses, as these errors are too complicated in their scatterometer dependency)
- ✓ Use ML to learn the biases, such that they can be applied in coupled forecasts (ICM)
- ✓ Link the biases in mean and variance to coupled-model physical parameters (EUMETSAT fellow)
- ✓ Test the impact of the proposed changes on (coupled) ocean and weather forecasts
- ✓ Improve the coupled model based on what we learned

Rationale to bias observations

- ✓ U10 Model biases are locally rather high compared to innovation, violating Best Linear Unbiased Estimate paradigm in data assimilation
- ✓ A few decades of model improvement have not solved this problem, though one is still trying actively (Sandu, 2019); it is a problem for ocean forcing too; this is, the water is forced in the wrong direction
- ✓ ECMWF provided a reference run without scatterometers for which NUIST and KNMI computed model biases, averaging over 20 days (like for the Copernicus L4 product)
- ✓ NUIST applied these biases to obtain adjusted SCAT BUFR products
- ✓ ECMWF will run a SCAT* OSE and compare it to reference OSEs with (SCAT OSE) and without (noSCAT OSE) scatterometer data assimilation
- ✓ EUMETSAT MIDAS project result on scatterometer OSEs with the HARMONIE model also points to a very similar bias problem
- ✓ Geographically unbiased EU Copernicus Marine Service L4 OPS and ERA5 U10S hourly and monthly winds/stress are available



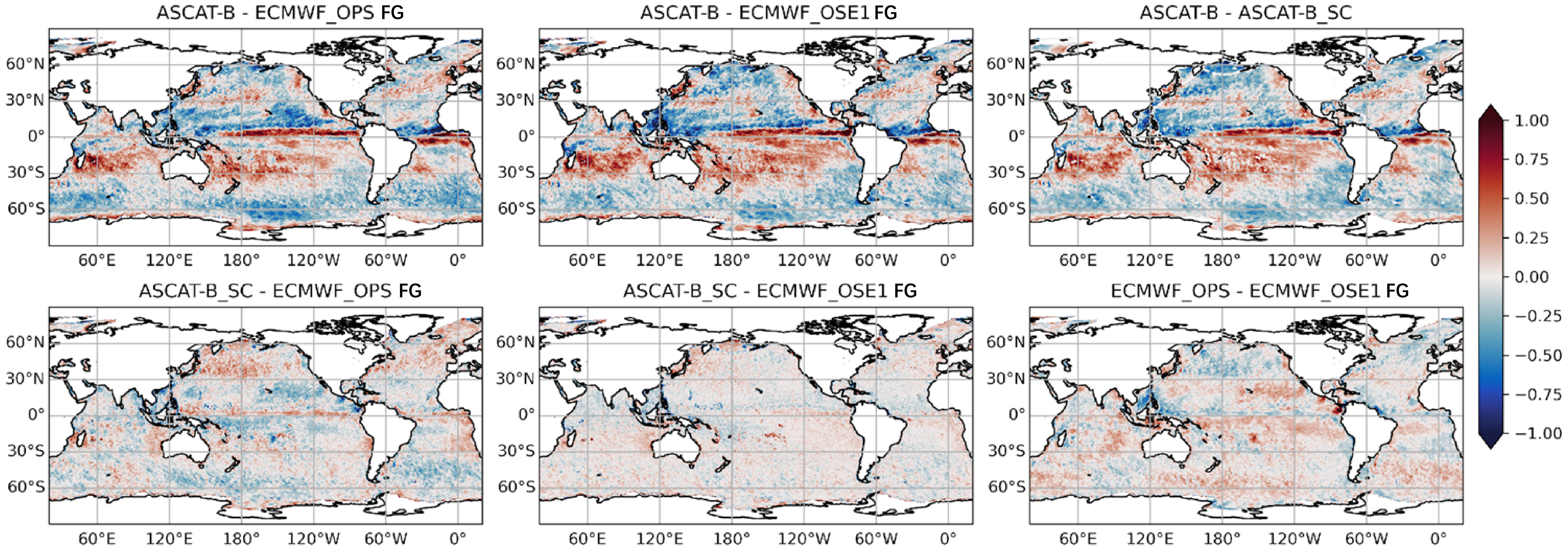
L3 daily Copernicus Marine Service



L4 hourly Copernicus Marine Service

Meridional (v) model bias adjustment

SCATs assimilated | No SCAT assimilated | SCAT and FG differences



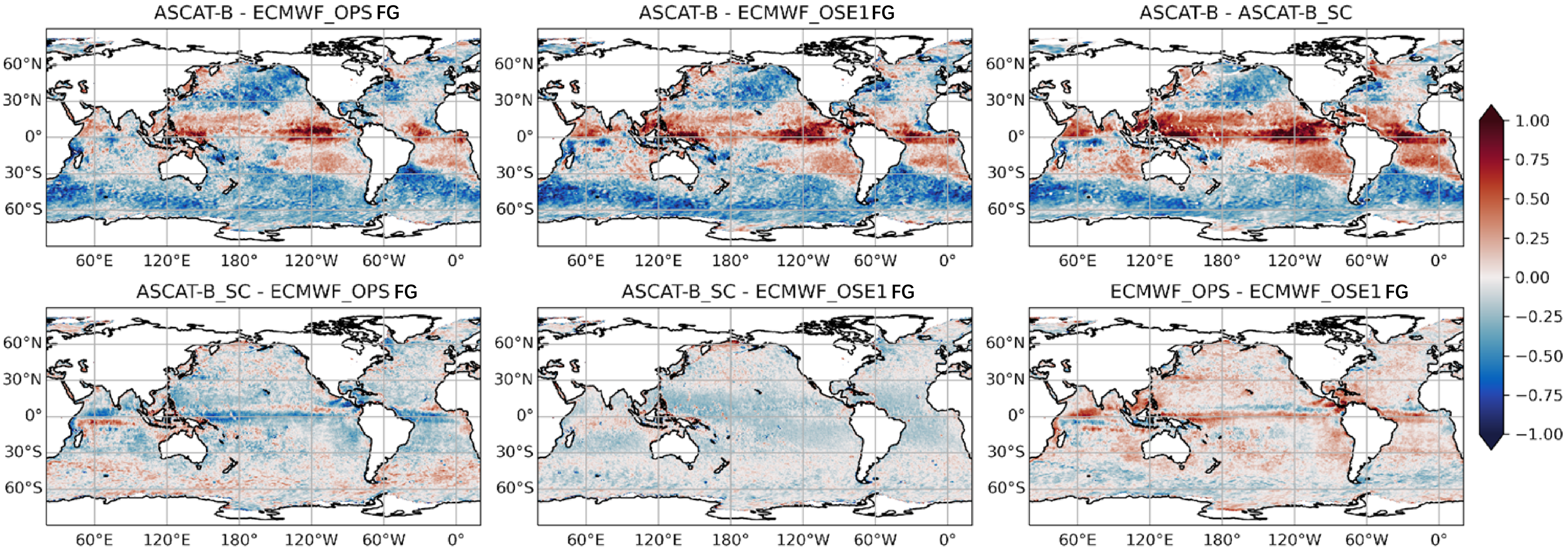
- Top: large v first guess biases, both in runs with (OPS) / without (OSE1) ASCATs and HY2B used
- Bottom: ASCATB_SC is adjusted to OSE1 and not to ECMWF_OPS, while with small biases

- Top: large v first guess biases, both in runs with/without ASCATs and HYB assimilated
- Bottom: ASCATB_SC is well adjusted to OSE1

- Top: large v biases in ASCAT-B_SC as expected
- Bottom: ECMWF_OPS minus OSE1 is complement of ASCAT-B_SC minus OPS (on left)
- OPS FG biases adjust only a little to the scatterometers

Zonal (u) model bias adjustment

SCATs assimilated | No SCAT assimilated | SCAT and FG differences



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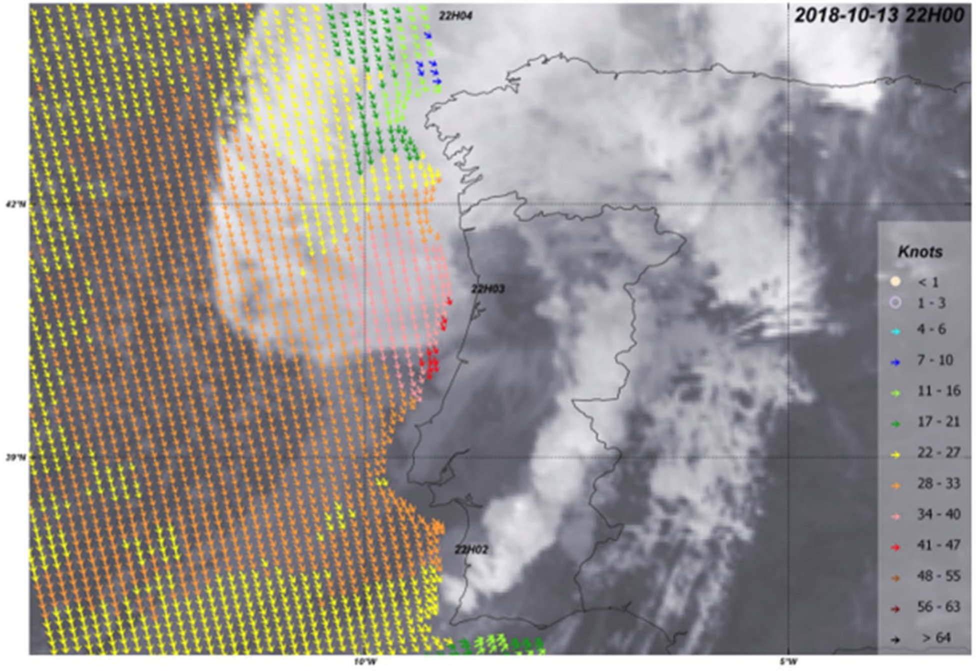


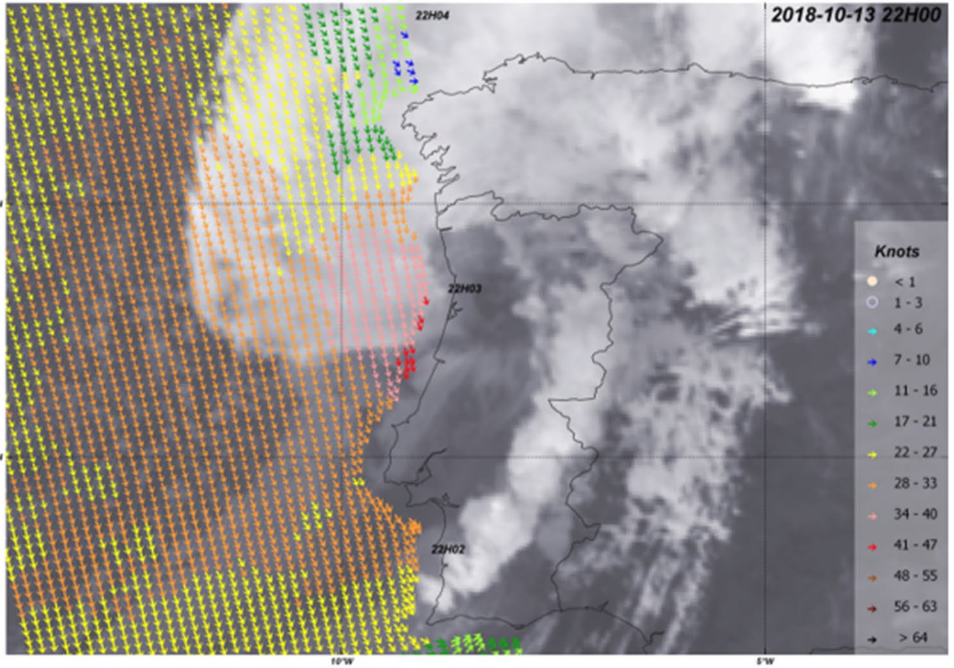
Mesoscale Improved Data Assimilation of Scatterometer winds (MIDAS)

Draft version prepared by:
Isabel Monteiro, Gert-Jan Marseille, Fabíola Silva, Jan Barkmeijer and Ad Stoffelen

MIDAS conclusions

- HARMONIE 3-hour 4D-Var better than the widely used 3D-Var
- ASCAT improves the forecast skill both in 3D- and 4D-Var
- Tested data thinning distances, superobbing and observation error inflation
- Particular effects on the v component
- Error inflation at full density similar to superobbing statistically (as expected in Stoffelen et al., 2020)
- Local model biases are substantial with respect to the innovations and violate the data assimilation BLUE paradigm
- Scatterometer winds are not effectively used to initialise dynamical weather features and model biases need to be accounted for to better exploit scatterometer winds in HARMONIE

This was a EUMETSAT study



Mesoscale Improved Data Assimilation of Scatterometer winds (MIDAS)

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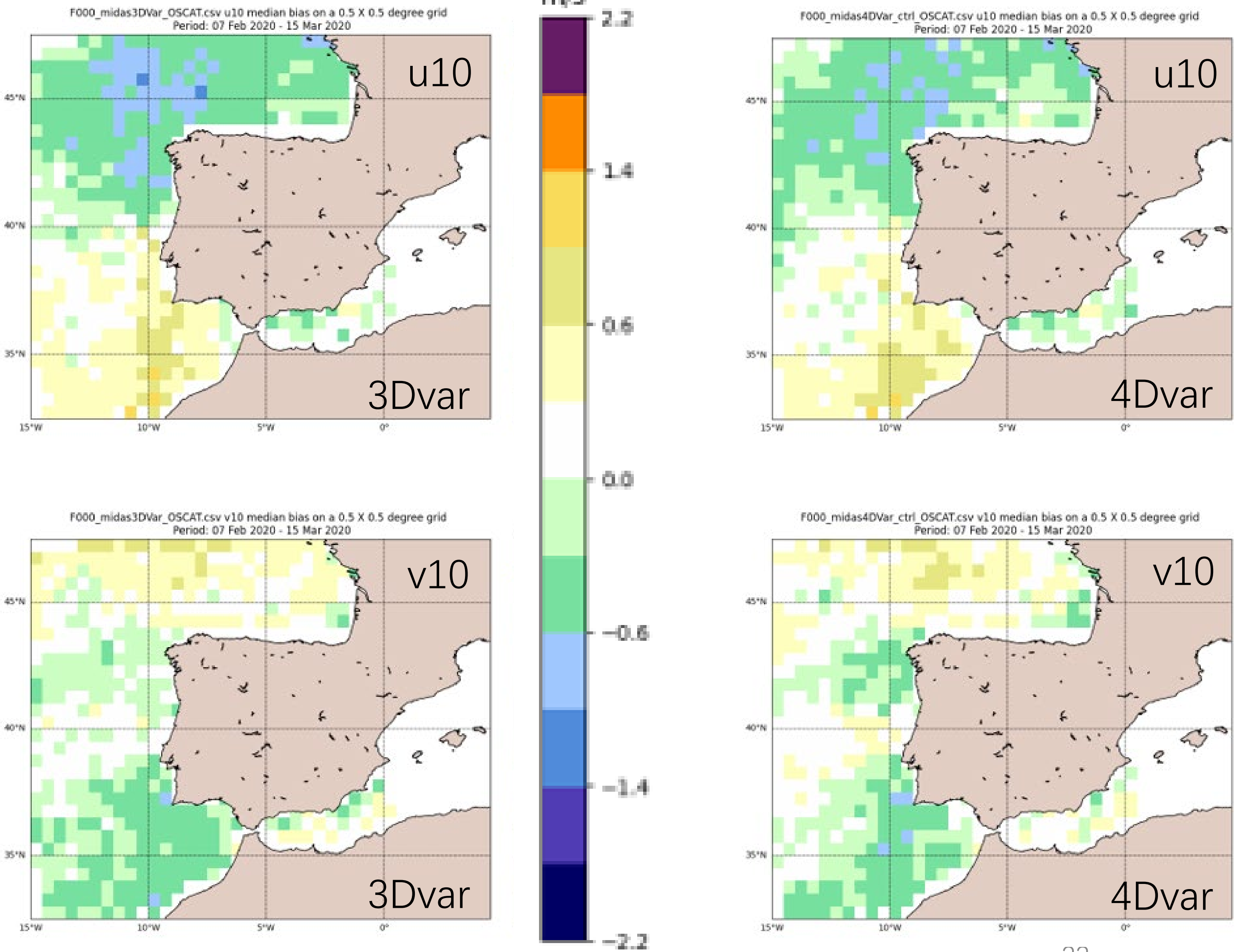
MIDAS conclusions

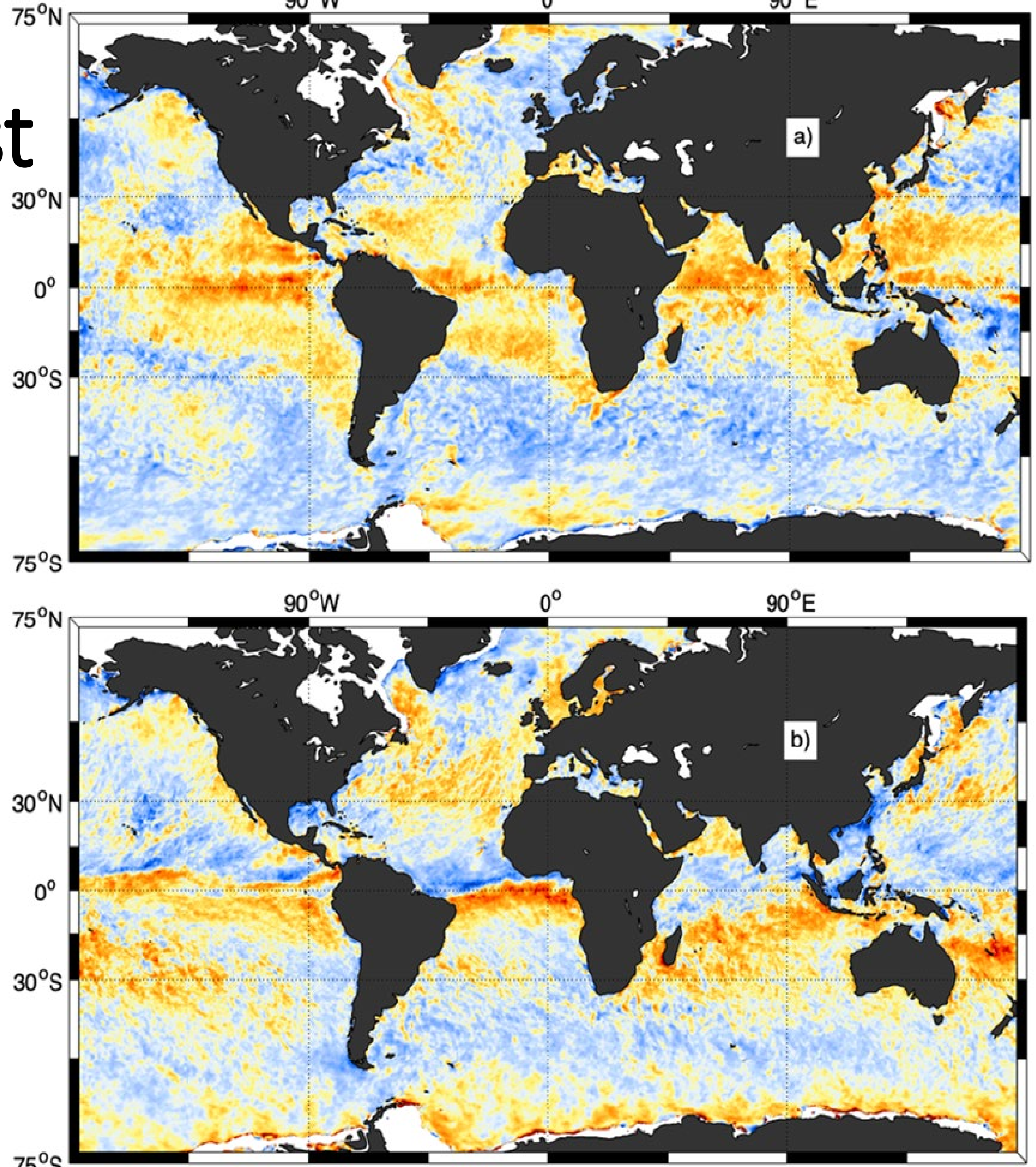
7 Feb – 15 Mar 2020

Median OSCAT – noSCAT FG



Improve the forecast

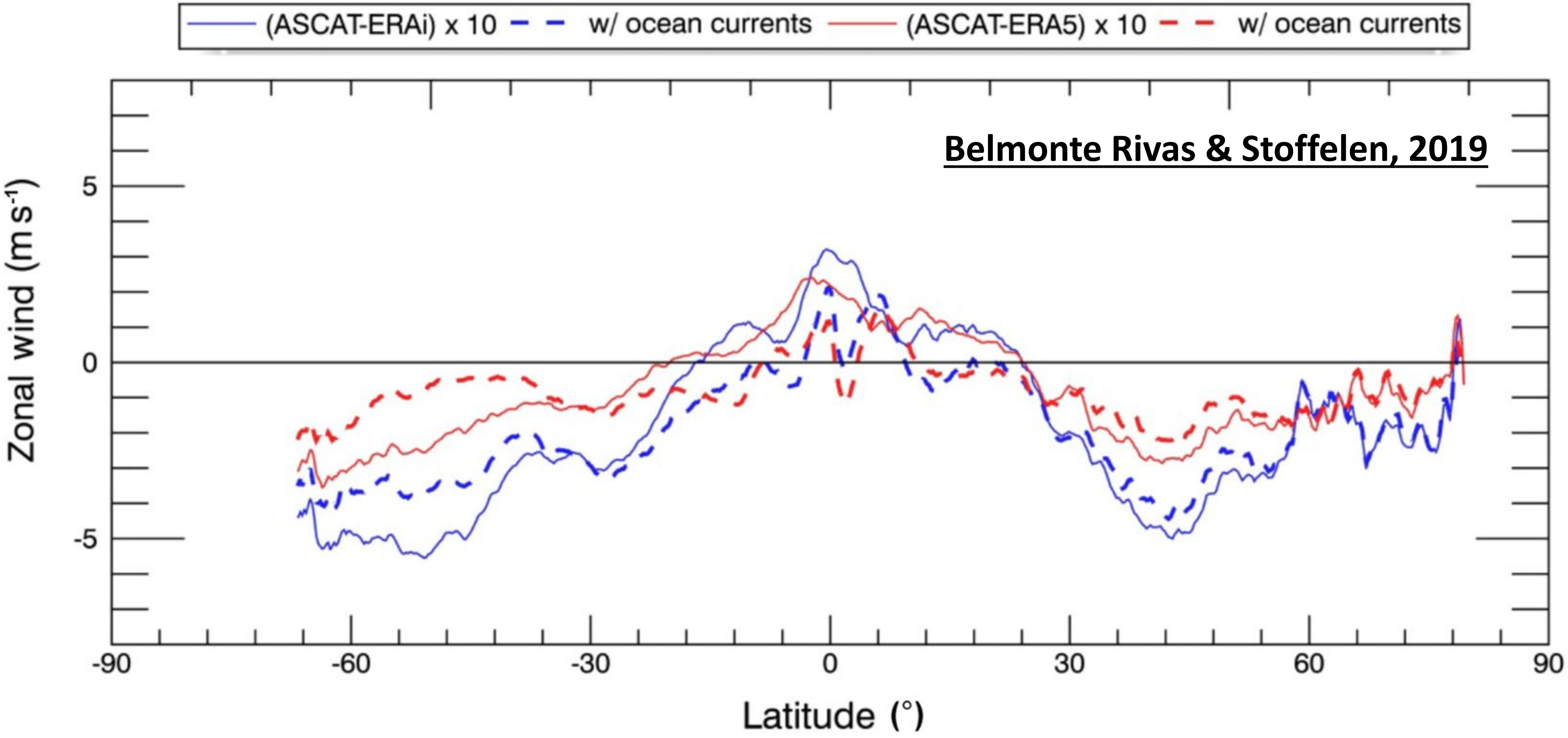
- Model Output Statistics is proven
- MOS is a successful application of ML in meteorology
- ERA*/OPS* biases clearly depend on MABL state, SST, currents, moist convection and dynamical closure
- Does MOS with ML work for ERA*/OPS*?
- If so, we might correct all ECMWF forecasts for weather, seasonal forecasting and climate predictions in coupled models . . .



Conclusions

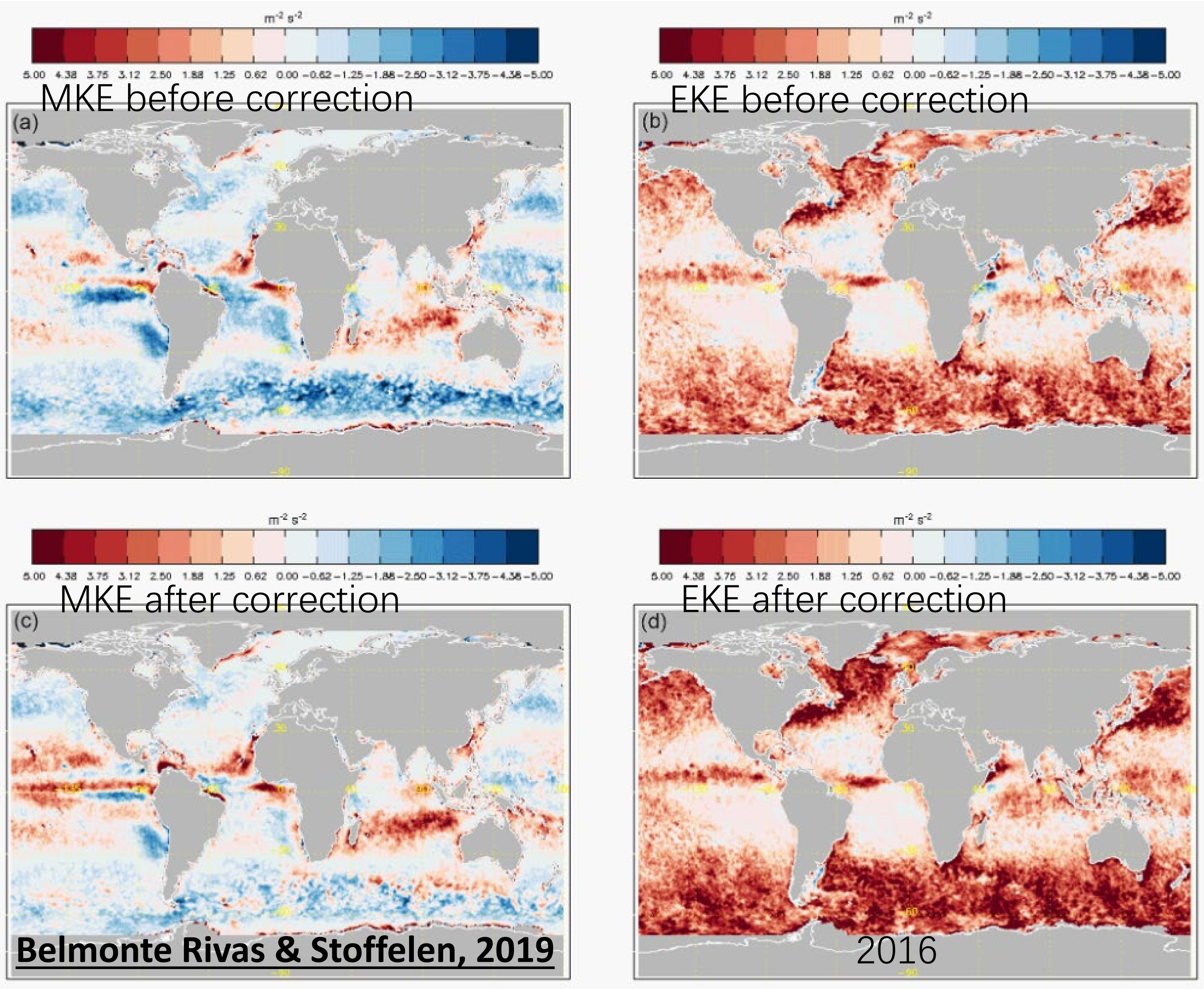
- ML provides many regression options with varying skill, cost and diagnostics
- The last % improvement is the most costly in time/CPU
- It appears straightforward to provide scatterometer corrections that are better than the plain mean from scatterometer sampling
- The ML improvements have skill beyond the training set and period
- Signs of overfitting appear
- Should we develop the best statistical ML ERA* and/or the best physically-based ML ERA* (which can be directly exploited in model development)?
- Further look at spatial maps, spatial derivatives, etc.
- There will be a follow-on OSI SAF study and EUMETSAT fellow . . .

What do we really on ocean currents?



- Copernicus Marine Service ocean currents typically reach 20 cm/s

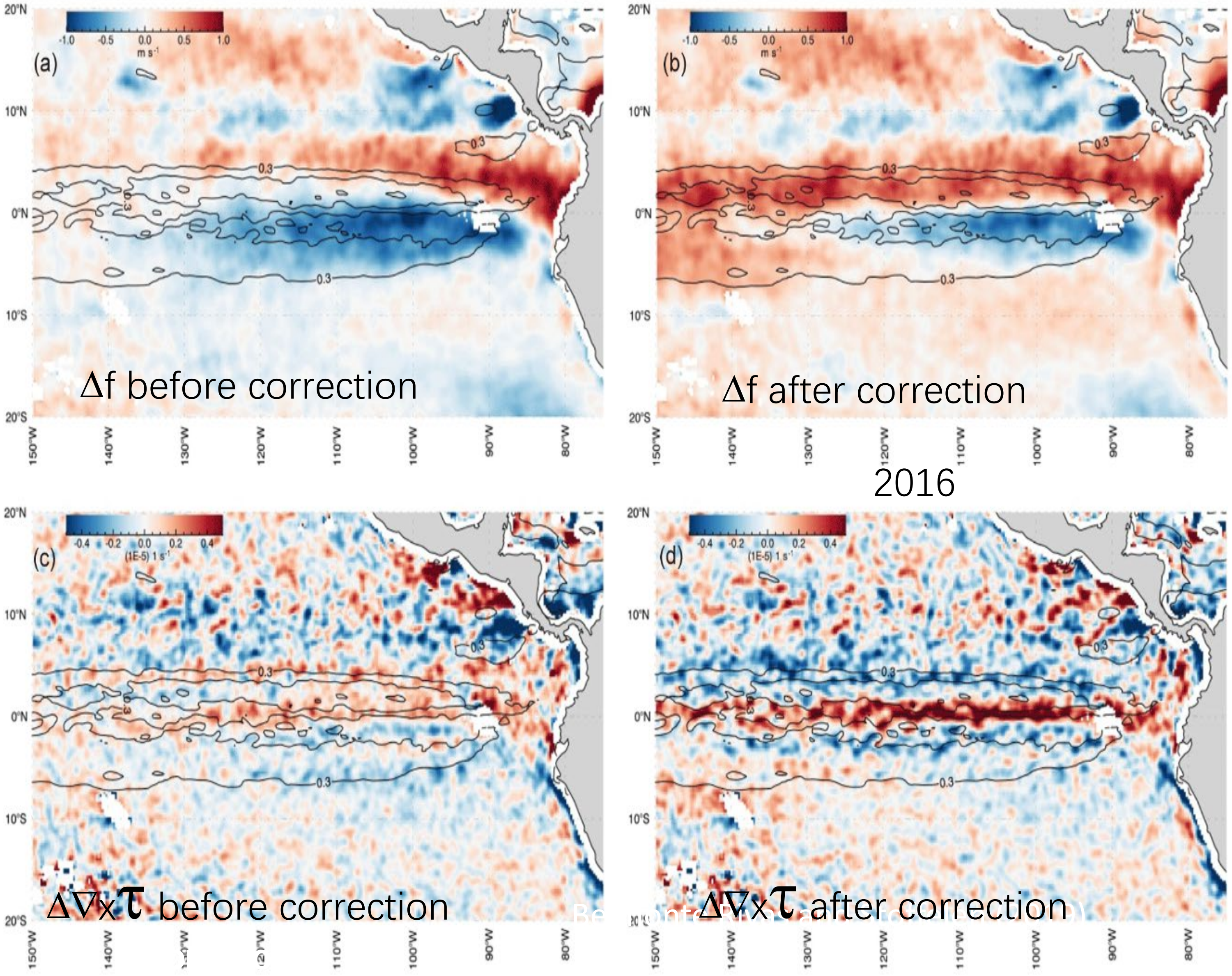
What do we really know?



Belmonte Rivas & Stoffelen, 2019

- These currents generally deteriorate the deterministic differences between scatterometer and ERA5 model
- Variances on m/s level, not cm/s

What do we really know?



- Errors increase after correction, while they appear closer associated with the currents
- Again, variances on m/s level, not cm/s

Belmonte Rivas & Stoffelen, 2019

We really know very little on ocean currents

- No direct current measurement system exist yet
- Geostrophic measurements appear unable to inform small-scale currents
- Much ocean motion is generated by the wind, which changes rather fast, hence collocated measurements of wind and current are very beneficial
- Seeing only large-scale currents will be useful to correct coupled atmosphere-ocean models on a timescale of months to years
- Today's stated requirements appear more based on goals than on thresholds or breakthroughs
- With support from the ocean current community we seek thresholds and breakthroughs for ocean current capability for DopSCA

Conclusions

- Model biases of 10-m stress-equivalent wind (U10s) are substantial with respect to observations; corrected hourly ERA5 and OPS L4 winds are available in the Copernicus Marine Service
- Scatterometers can map out the rather stable spatial biases in mean and variance well
- Biases prevent effective data assimilation (BLUE paradigm)
- Experiment with ECMWF o-b bias correction in progress by adjusting scatterometer BUFR data
- Biases also prevent effective scatterometer data assimilation in HARMONIE (EUMETSAT MIDAS)
- U10s biases in mean and variance affect ocean forcing and hence air-sea coupling and earth system dynamics (ocean is 70% of the earths' surface)
- EUMETSAT awarded a fellow position at KNMI/ICM/ECMWF to address data assimilation, ocean forcing and physical causation of biases
- EUMETSAT OSI SAF visiting scientist Evgenia Makarova at ICM employs Machine Learning based on model parameters to predict the biases (MOS)
- Each scatterometer may contribute a few % in the reduction of the forecast errors and with 7 complementary scatterometers, it may be a worthwhile investment to improve their assimilation by addressing remaining problems, of which model biases is a prominent one
- Furthermore, scatterometers can be well exploited to (much?) improve the coupled model dynamics at the air-sea interface

Further reading . .

Services:

scatterometer.knmi.nl
osi-saf.eumetsat.int
marine.copernicus.eu

ESA Aeolus DISC

Ad Stoffelen

FOLLOW

Active Instruments group leader, Satellite Division, KNMI
Verified email at knmi.nl - Homepage

Wind satellite NWP data assimilation

Google Scholar

TITLE	CITED BY	YEAR
First Results from the WindRAD Scatterometer on Board FY-3E: Data Analysis, Calibration and Wind Retrieval Evaluation Z Li, A Verhoef, A Stoffelen, J Shang, F Dou Remote Sensing 15 (8), 2087		2023
Mesoscale modelling of North Sea wind resources with COSMO-CLM: model evaluation and impact assessment of future wind farm characteristics on cluster-scale wake losses R Borgers, M Dirksen, IL Wijnant, A Stepek, A Stoffelen, N Akhtar, ... Wind Energy Science Discussions 2023, 1-32		2023
A Conceptual Rain Effect Model for Ku-Band Scatterometers K Zhao, A Stoffelen, J Verspeek, A Verhoef, C Zhao IEEE Transactions on Geoscience and Remote Sensing 61, 1-9		2023
Bayesian Algorithm for Rain Detection in Ku-Band Scatterometer Data K Zhao, A Stoffelen, J Verspeek, A Verhoef, C Zhao IEEE Transactions on Geoscience and Remote Sensing 61, 1-16		2023
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Ocean Mesoscale and Frontal-Scale Ocean–Atmosphere Interactions and Influence on Large-Scale Climate: A Review H Seo, LW O'Neill, MA Bourassa, A Czaja, K Drushka, JB Edson, ... Journal of Climate 36 (7), 1981-2013		2023
Satellite remote sensing of surface winds, waves, and currents: where are we now? D Hauser, S Abdalla, F Ardhuin, JR Bidlot, M Bourassa, D Cotton, ... Surveys in Geophysics, 1-90		2023
Ocean remote sensing from meteorological satellites at OSI SAF O Membrive, C Hernandez, H Roquet, S Saux-Picart, S Eastwood, ... EGU23		2023
Tropical Cyclone Wind Direction Retrieval From Dual-Polarized SAR Imagery Using Histogram of Oriented Gradients and Hann Window Function W Ni, A Stoffelen, K Ren IEEE Journal of Selected Topics in Applied Earth Observations and Remote ...	1	2022
On the solution of the multiple collocation problem J Vogelzang, A Stoffelen Authorea Preprints		2022
NWP Ocean Calibration for the CFOSAT wind scatterometer and wind retrieval evaluation	2	2022

Brief Introduction of Datasets

☑ ASCAT-B 25km NRT
☑ ASCAT-C 25km NRT

☑ HSCAT-B 50km NRT (NOC: +0.62(HH), -0.63(VV))
☑ HSCAT-C 50km NRT (NOC: -1.17(HH), -1.32(VV))
☑ HSCAT-D 50km NRT (NOC: -0.34(HH), -0.12(VV))

☑ HSCAT-B 50km Rep01 (new NOC: +0.71(HH), -0.41(VV))
☑ HSCAT-C 50km Rep01 (new NOC: -1.01(HH), -1.11(VV))
☑ HSCAT-D 50km Rep01 (new NOC: -0.26(HH), -0.14(VV))

- NSCAT-4ds GMF
- SST Corr.
- **-mixqc (new rain QC)**

☑ HSCAT-B 50km Rep02 (new NOC: +0.52(HH), -0.56(VV))
☑ HSCAT-C 50km Rep02 (new NOC: -1.19(HH), -1.26(VV))
☑ HSCAT-D 50km Rep02 (new NOC: -0.45(HH), -0.30(VV))

- NSCAT-**4ds.hy2** GMF
- SST Corr.
- **-mixqc**

◆ NWP data are taken from BUFR files, i.e., the same as NRT processing used!

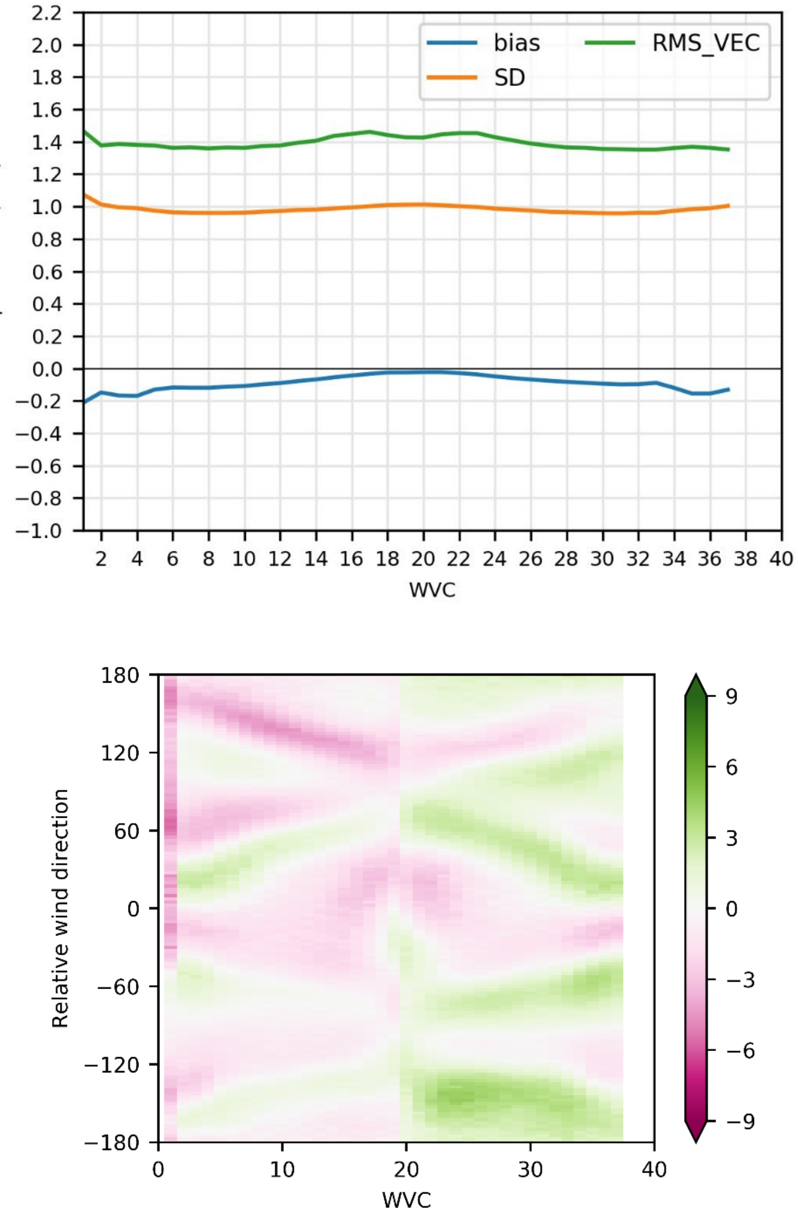
◆ Time period: Dec. 01, 2021 ~ April 30, 2022

◆ SST data are taken from ERA5 at analysis time.

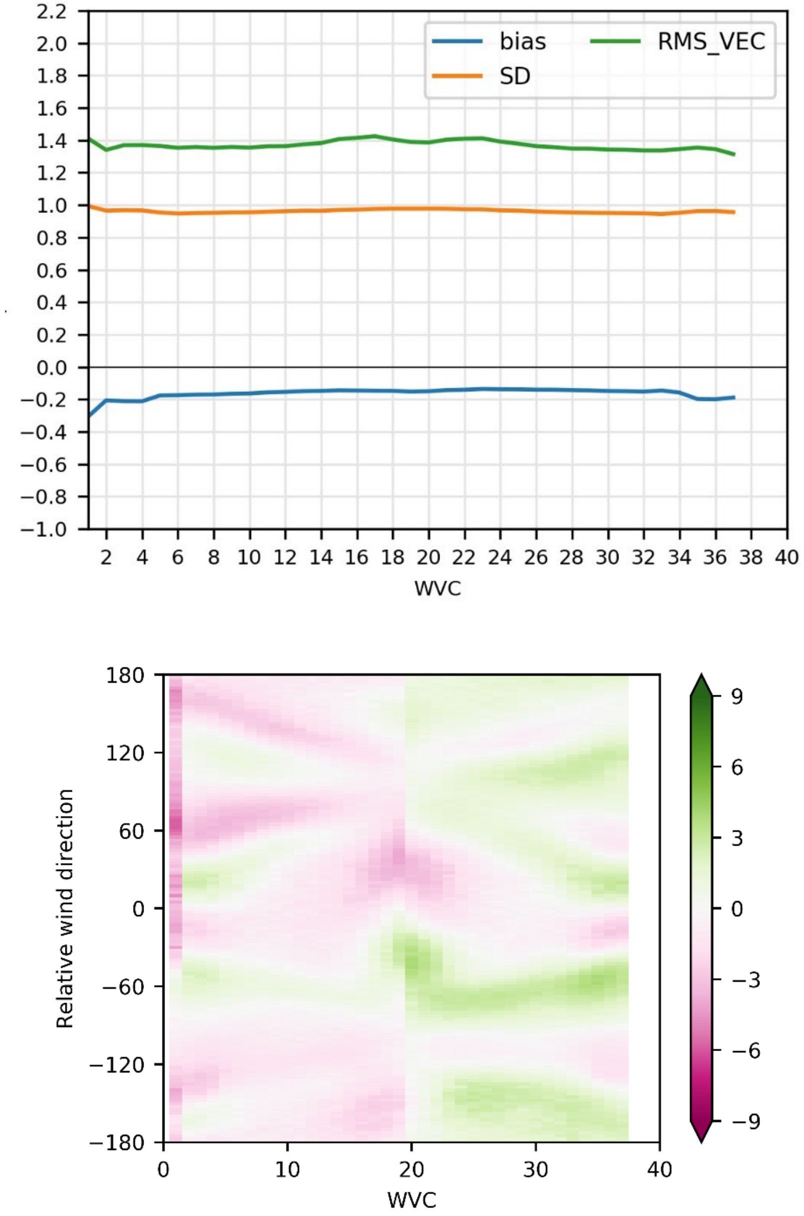
◆ NSCAT-4ds.hy2 GMF was made using CDF matching tech. based on collocated ascatb and hscatc+d winds

◆ New NOC was calculated using NSCAT-4ds.hy2 GMF and NWP winds contained in BUFR files.

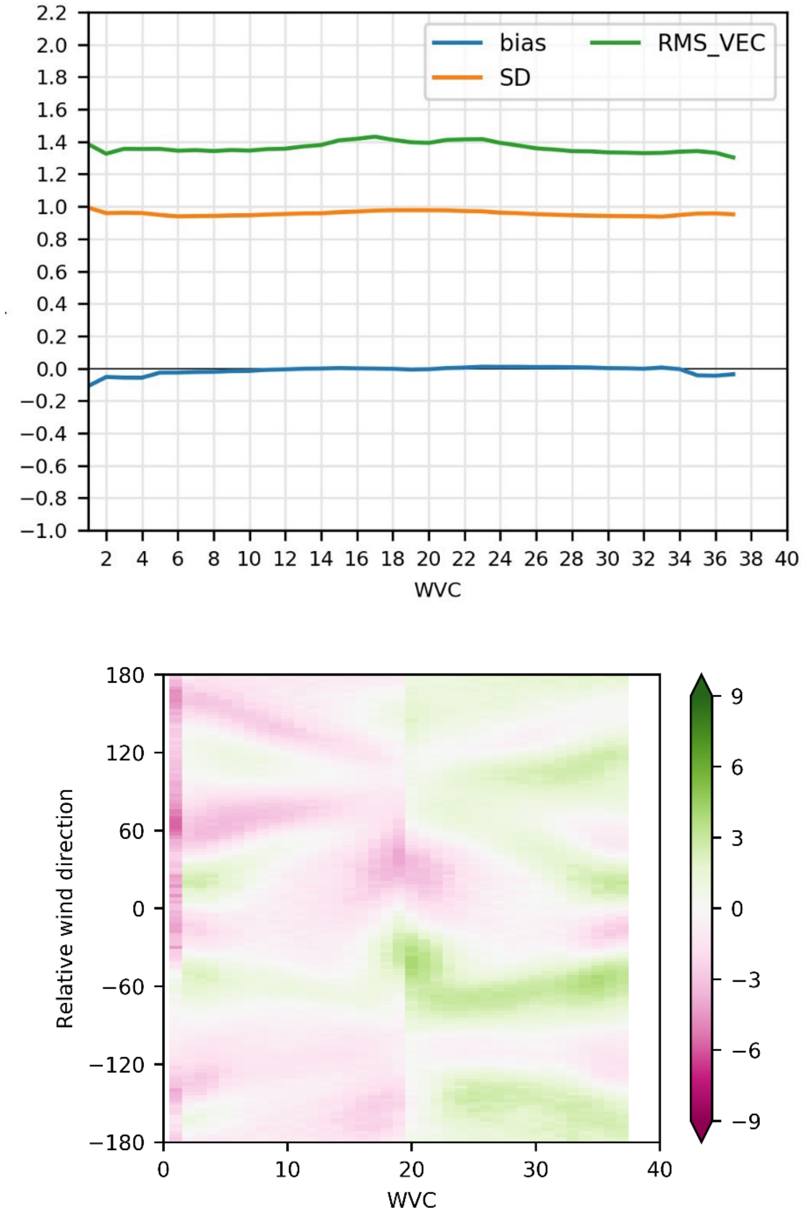
HSCAT-B NRT



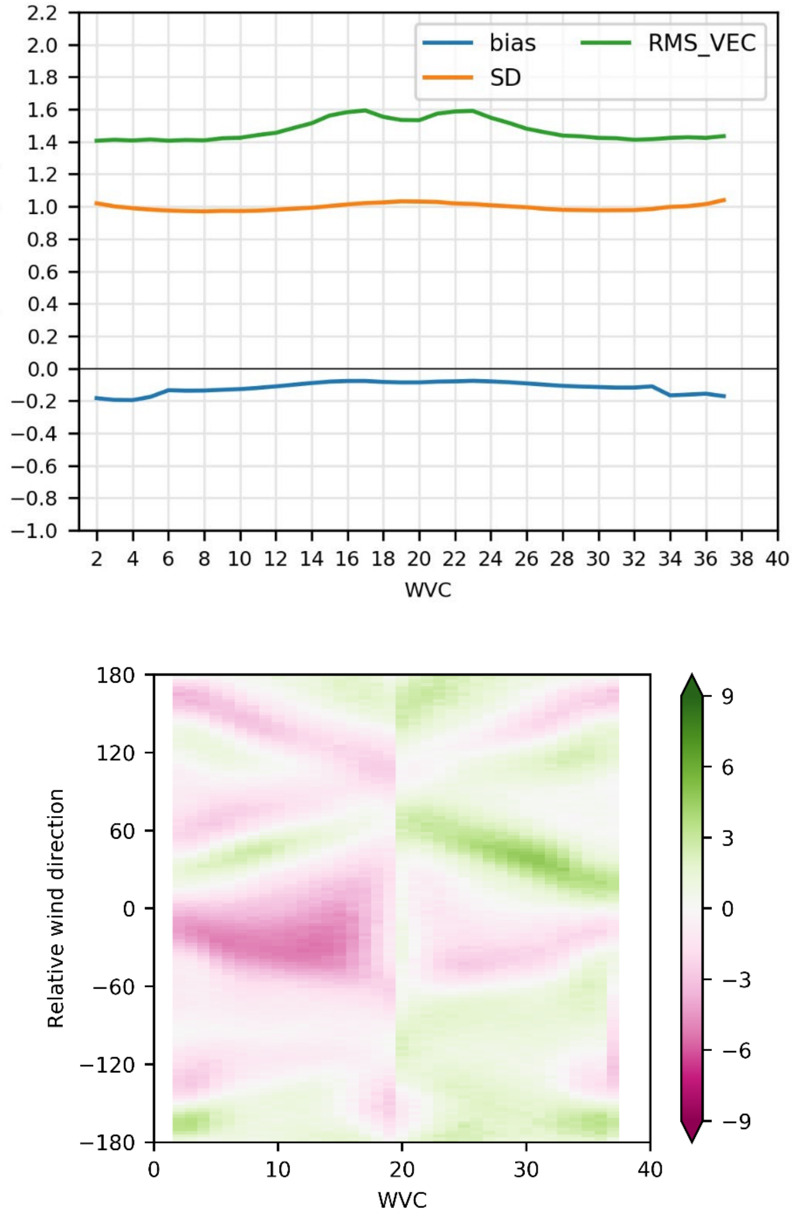
HSCAT-B Rep01



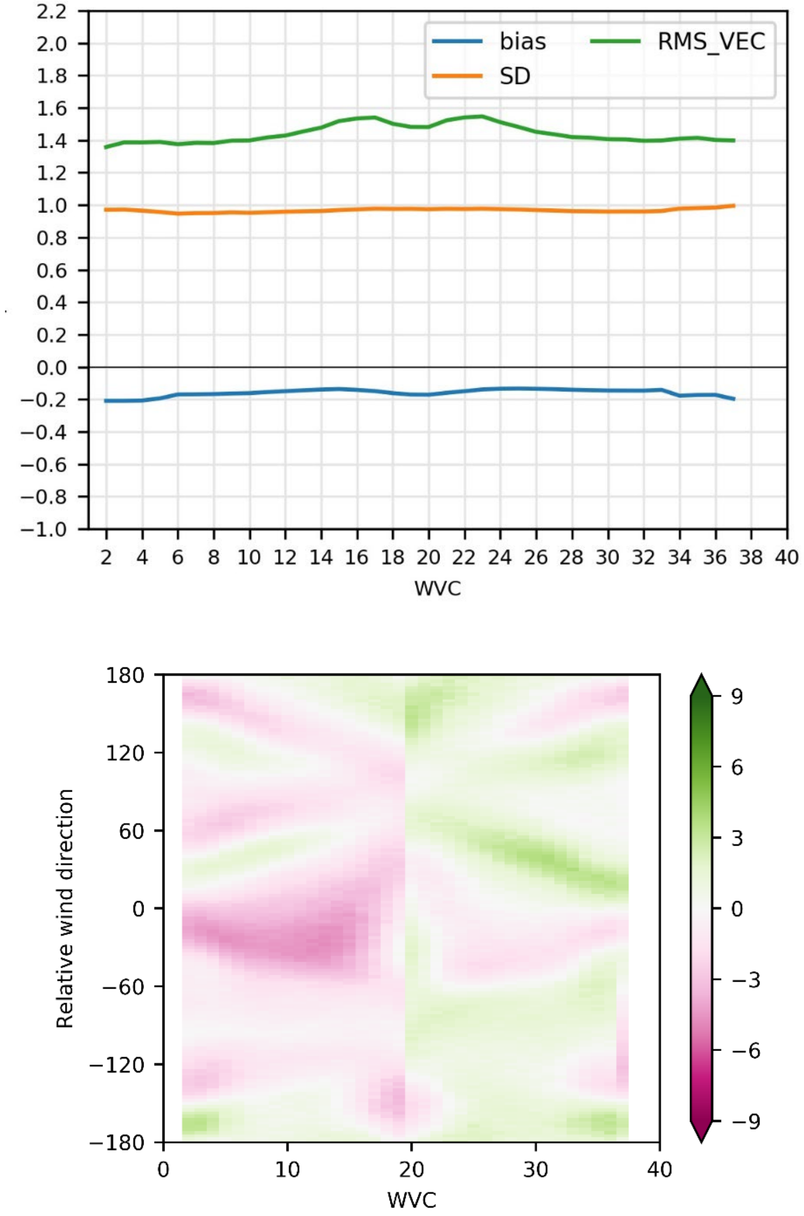
HSCAT-B Rep02



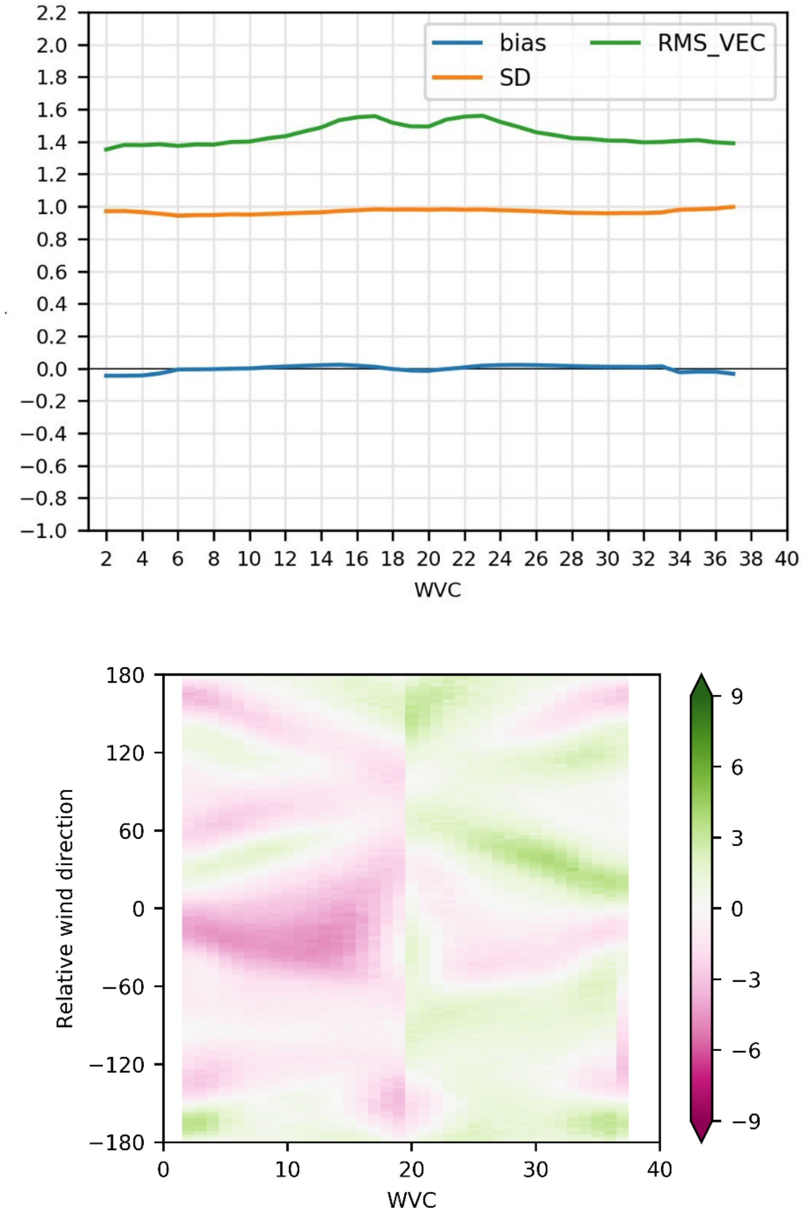
HSCAT-C NRT



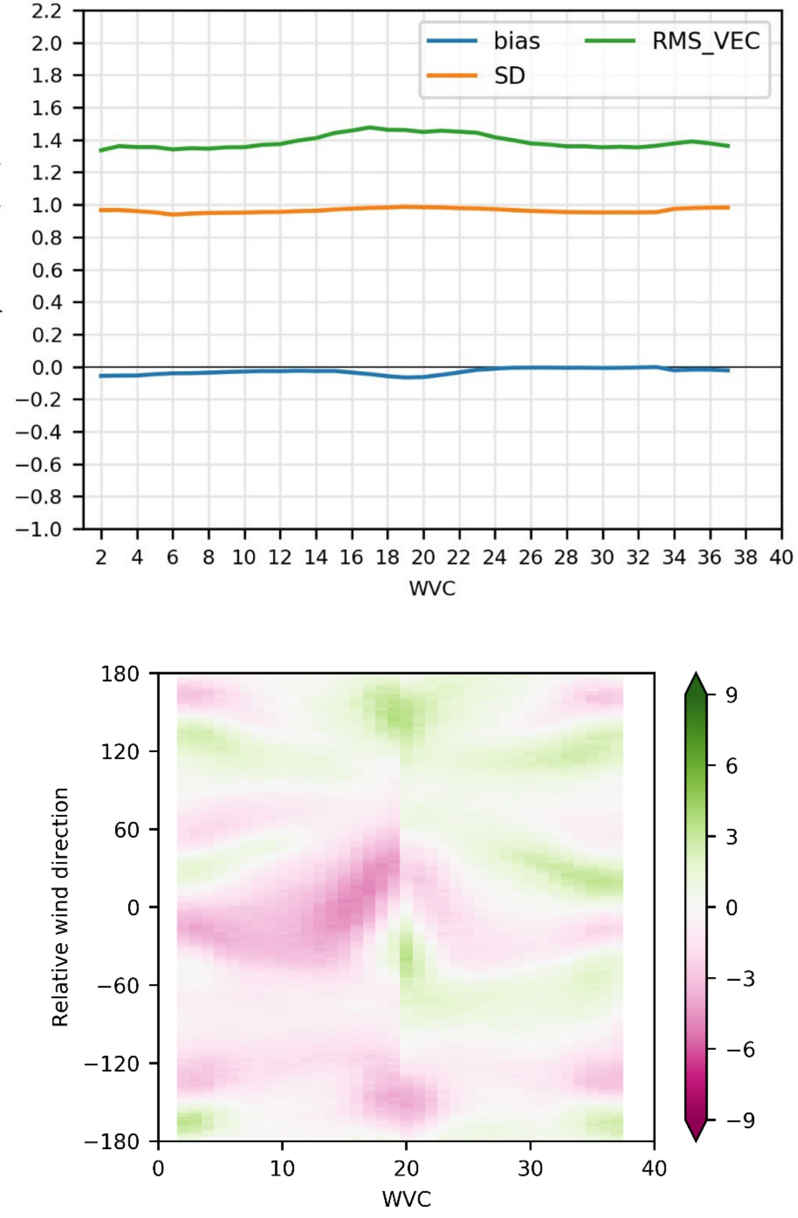
HSCAT-C Rep01



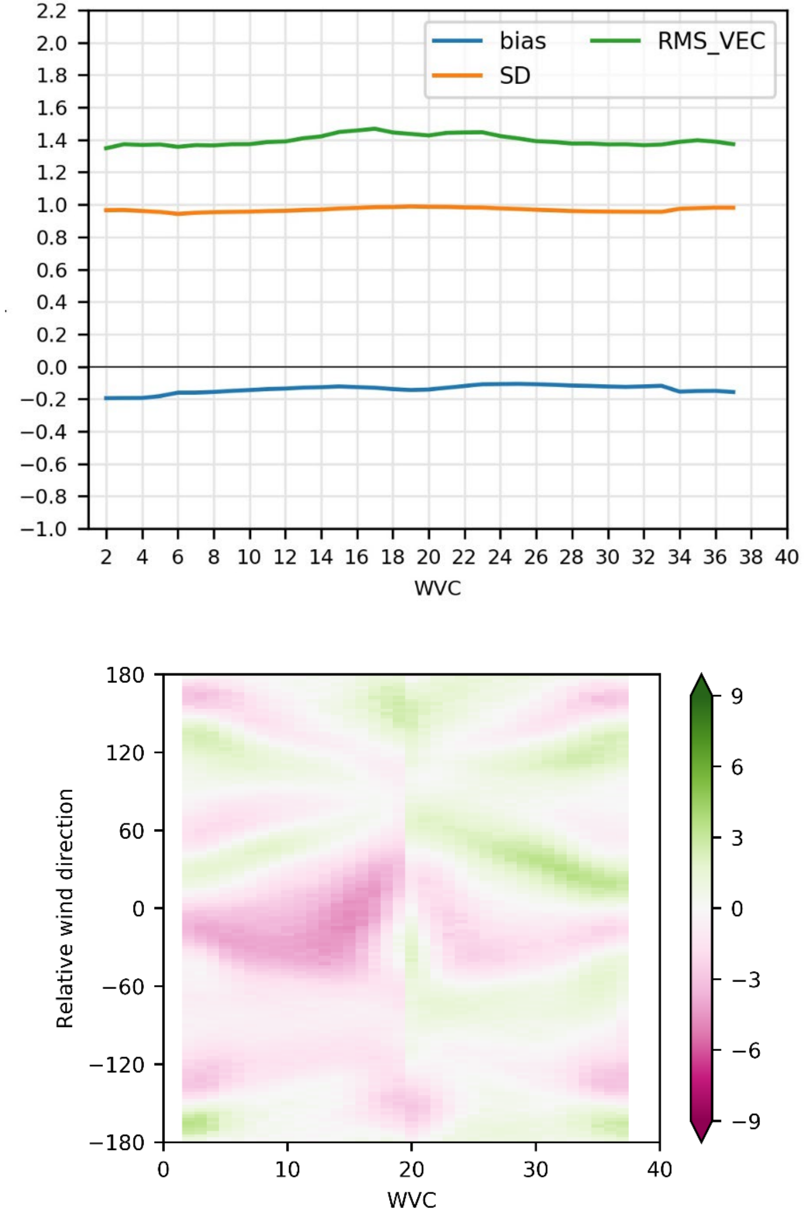
HSCAT-C Rep02



HSCAT-D NRT



HSCAT-D Rep01



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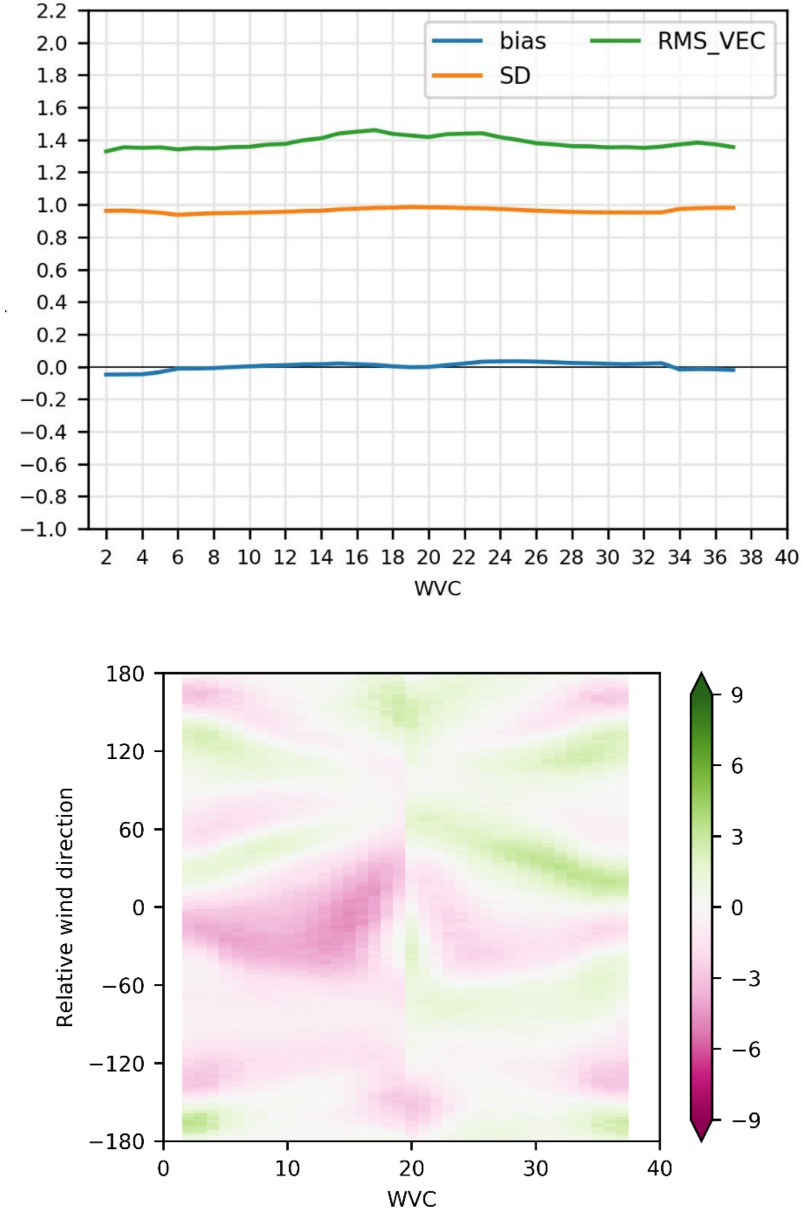
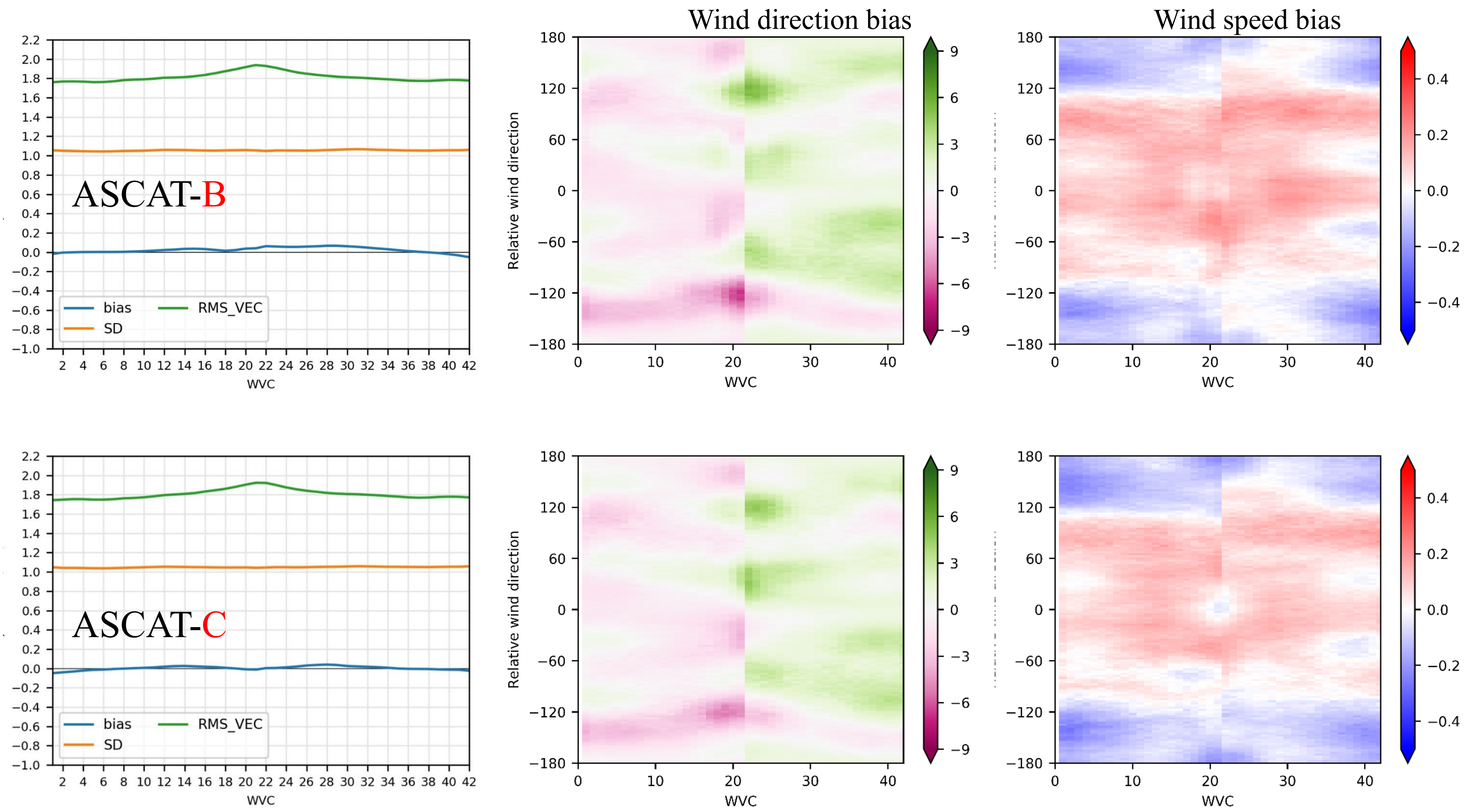


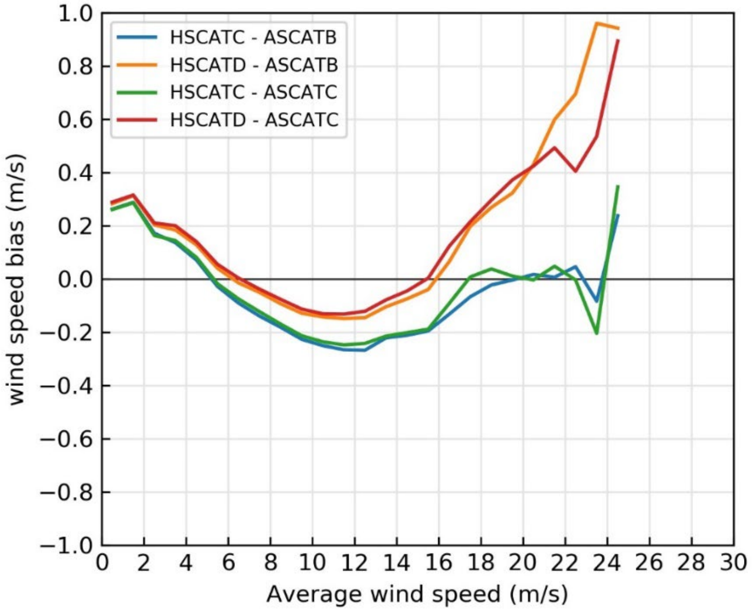

Wind direction bias
Wind speed bias
ASCAT-B
ASCAT-C
bias
SD
RMS_VEC
WVC
Relative wind direction

Collocated
ASCAT and HSCAT winds

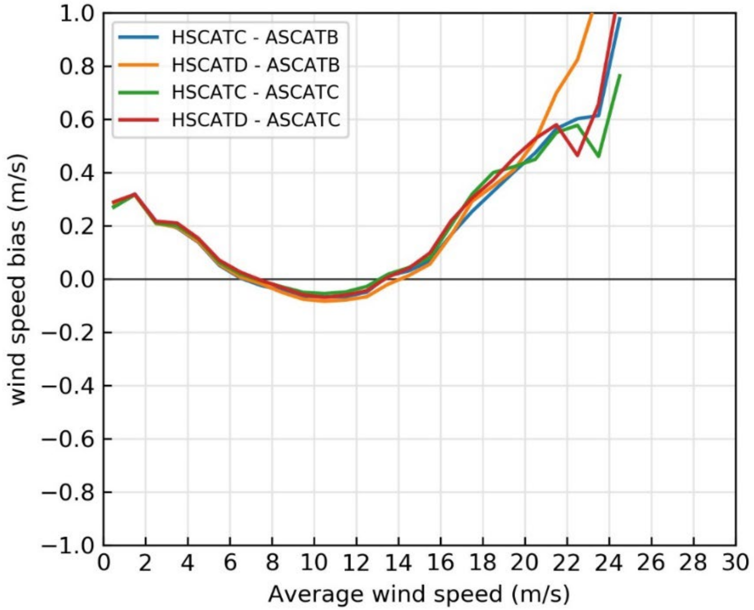
◆ Time diff. ≤ 45min

◆ Spatial distance ≤ 50*0.7071km

HSCAT NRT

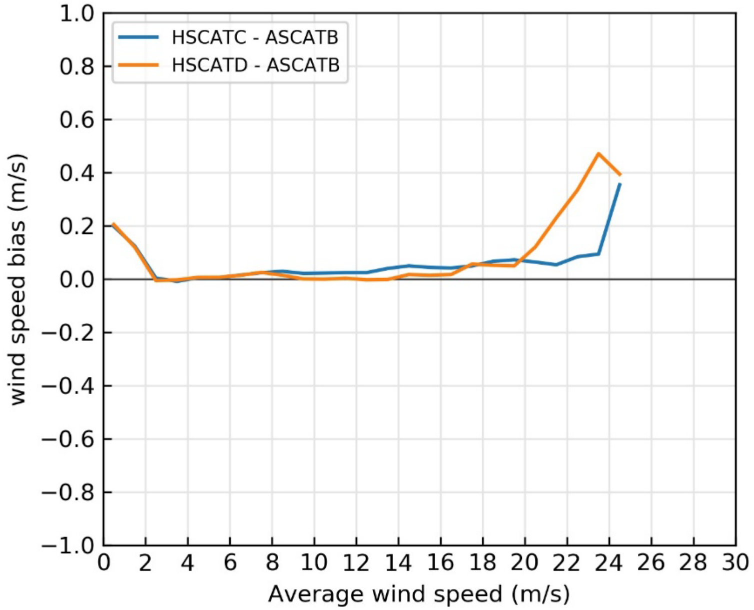


HSCAT Rep01



- NWP Ocean Calibration (NOC)

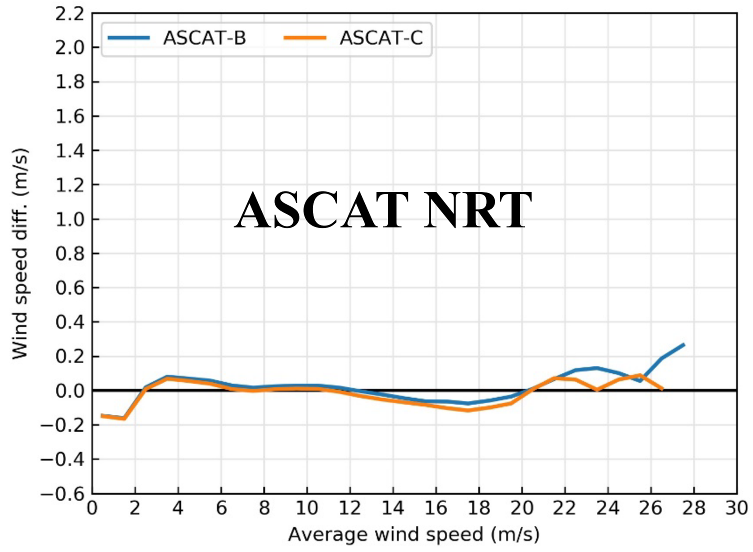
HSCAT Rep02

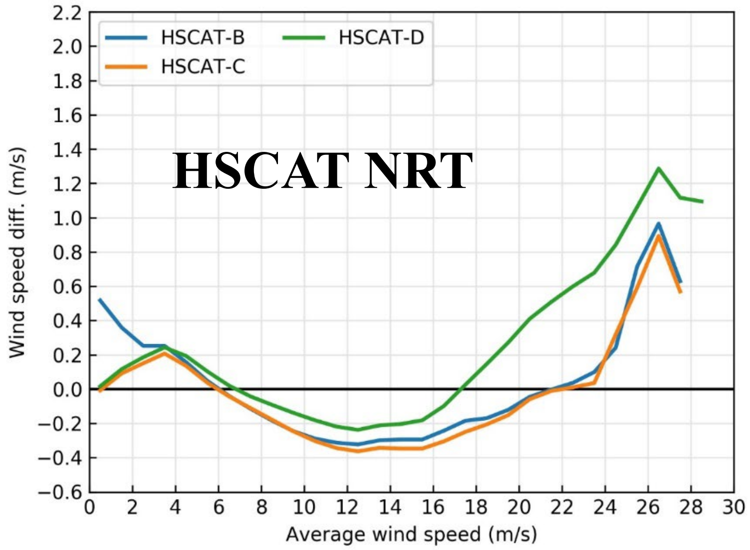


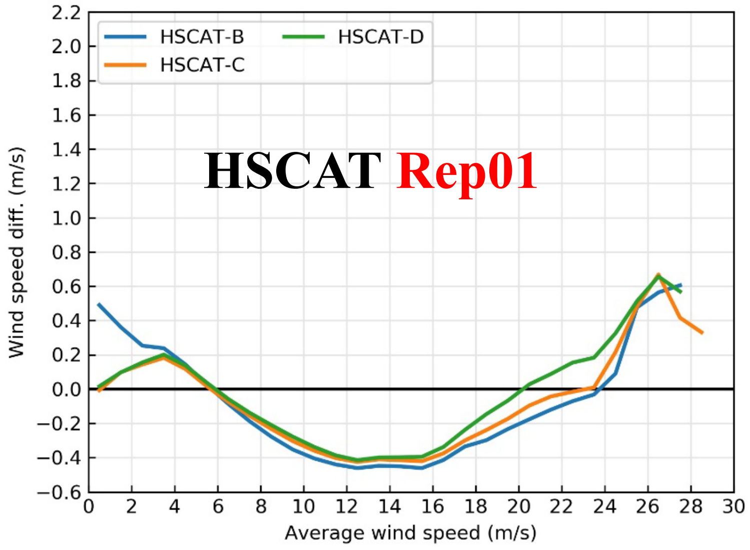
- Improve rain QC
- NOC
- Improve Geophysical Model Functions

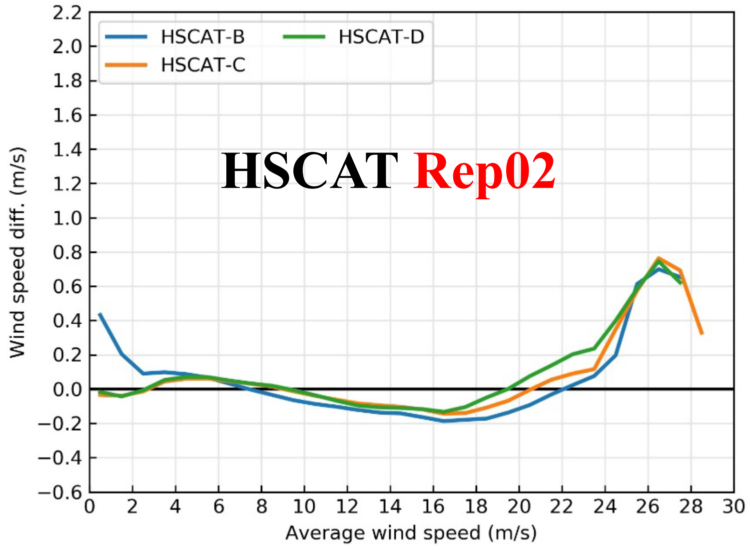
Verifying with ECMWF winds

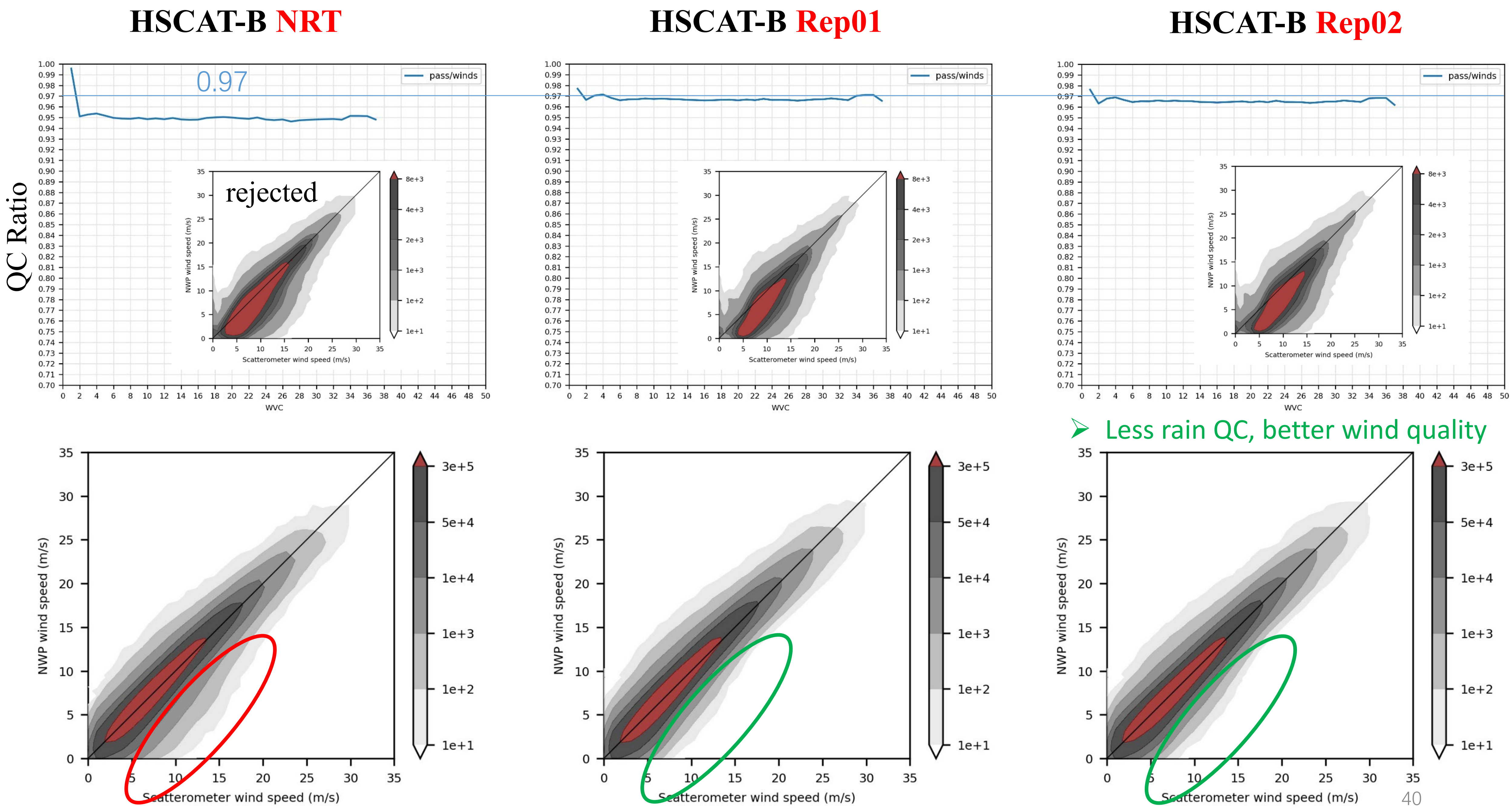
- ☑ It is clear that: HSCAT Rep02 is better.
- ☑ Wind speed dependent wind seed biases are reduced, and the curves of HSCAT become more similar to ASCAT curves.



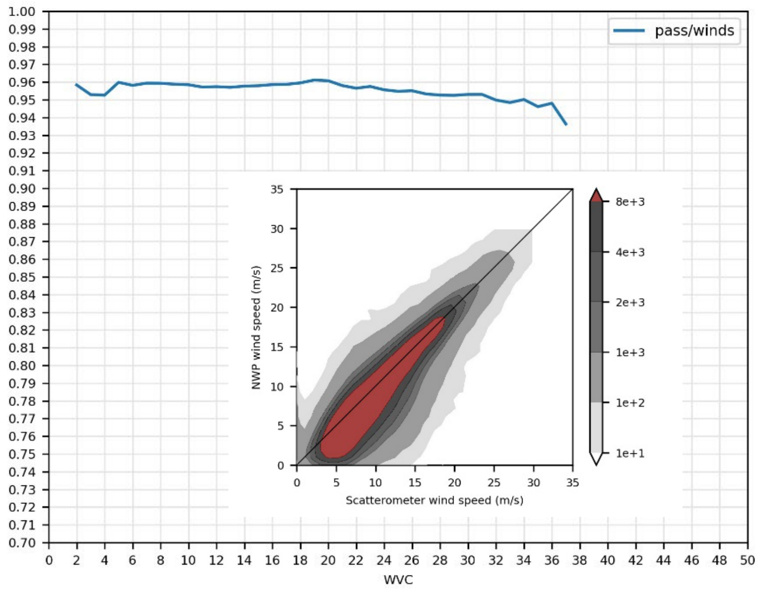


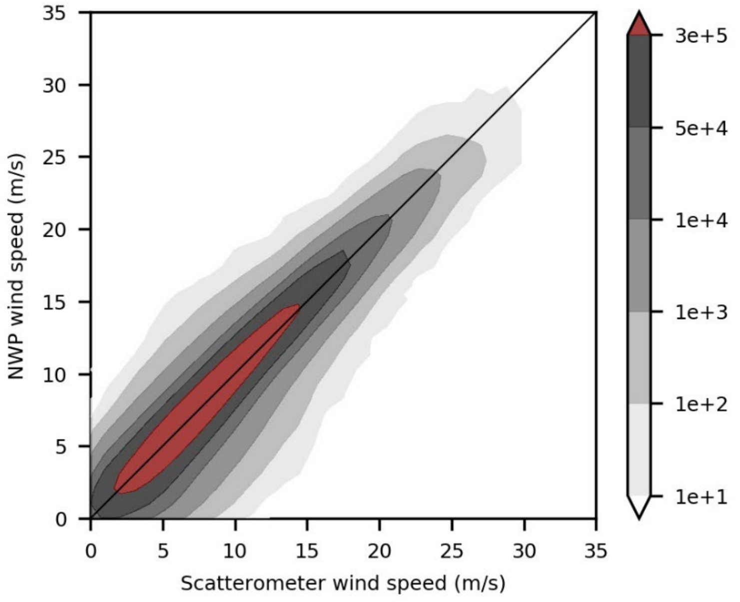




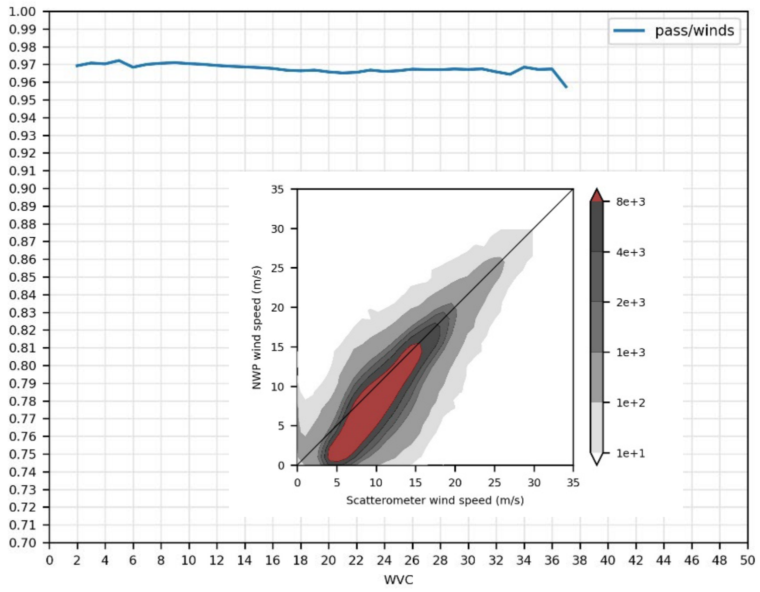

HSCAT-B NRT
HSCAT-B Rep01
HSCAT-B Rep02
QC Ratio
0.97
pass/winds
WVC
rejected
NWP wind speed (m/s)
Scatterometer wind speed (m/s)
Less rain QC, better wind quality

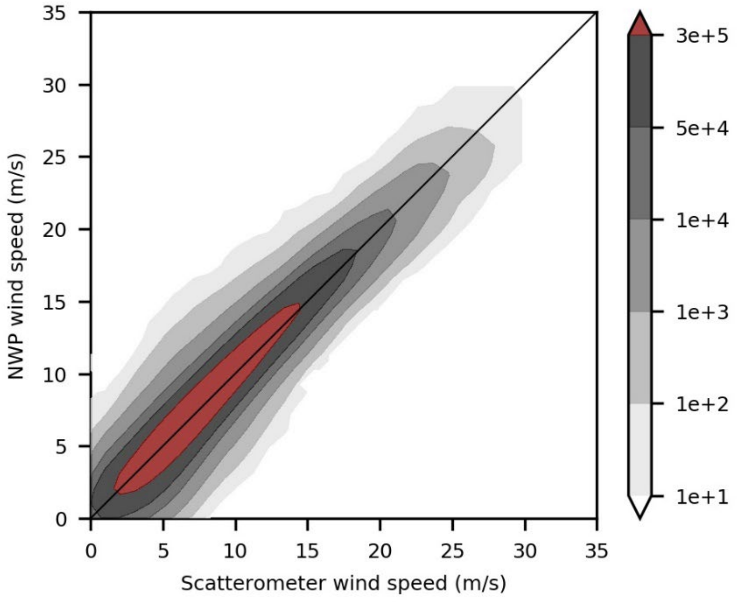
HSCAT-C NRT





HSCAT-C Rep01





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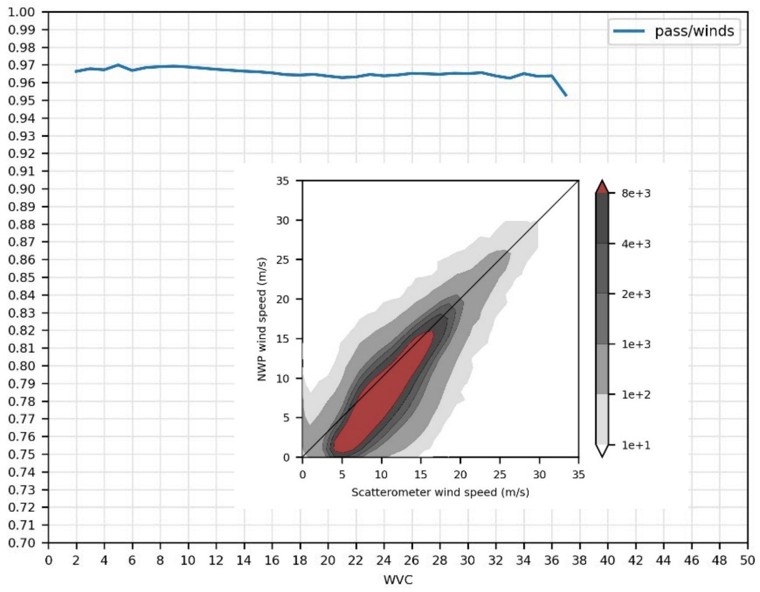
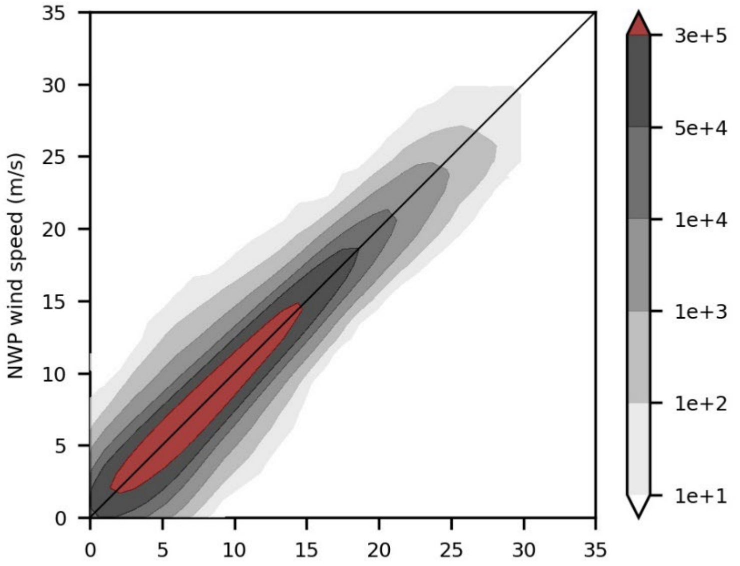
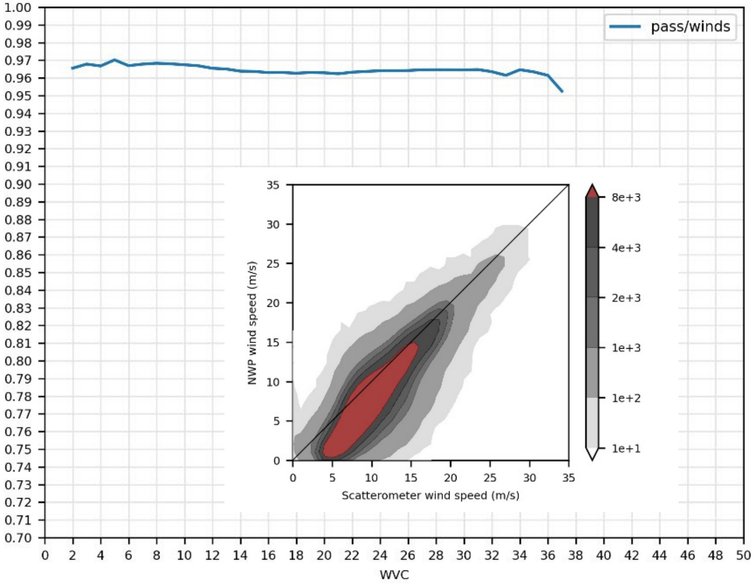
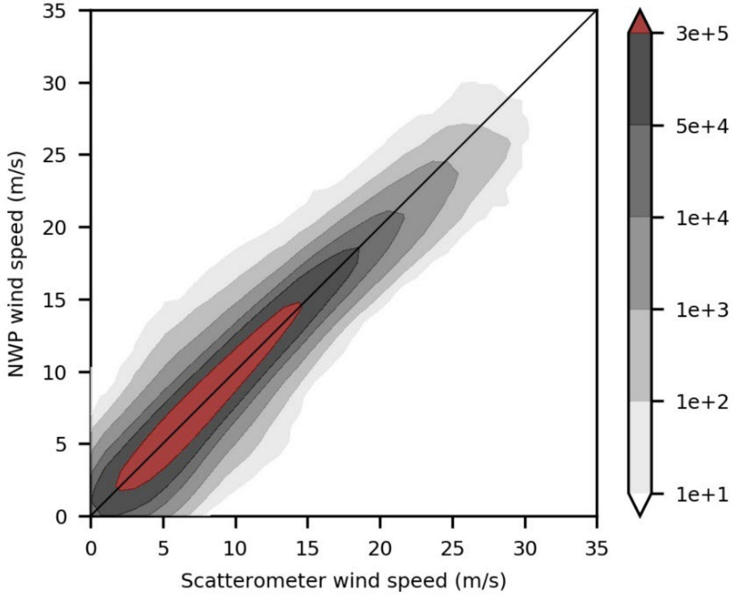


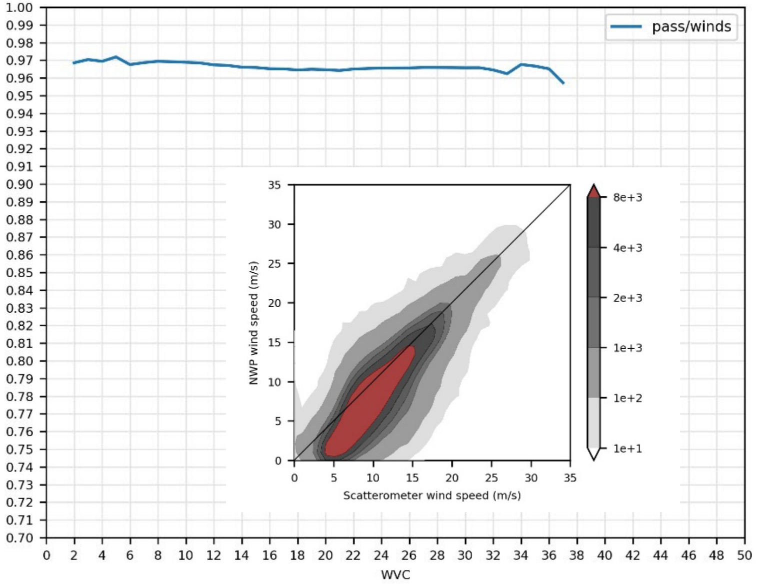


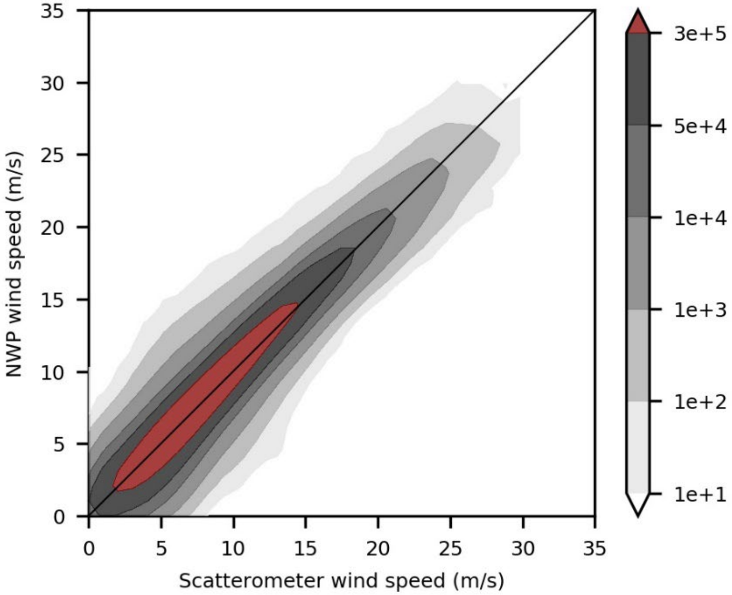
HSCAT-D NRT





HSCAT-D Rep01





HSCAT-D Rep02