

Machine Learning Correction of Ocean Forcing Forecasts Using Scatterometer Data

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2026 International Ocean Vector Winds Science Team
(IOVWST) Meeting



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Barcelona Expert Center



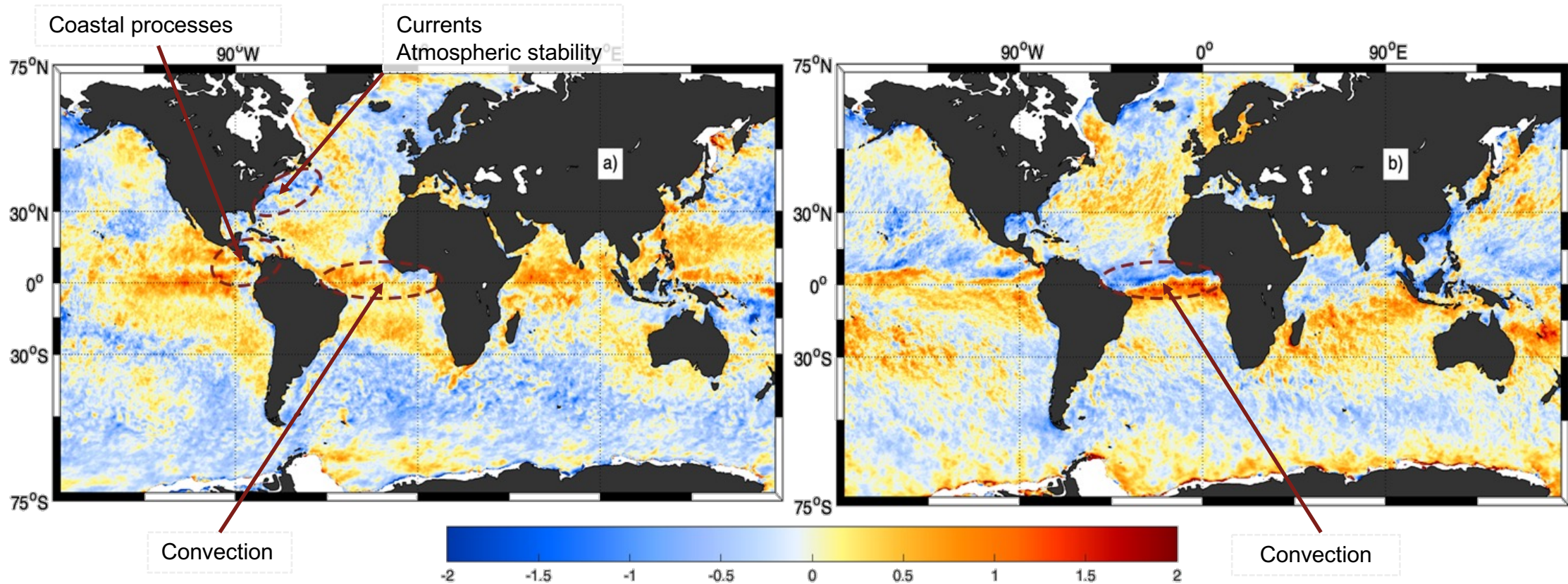
Differences between NWP and scatterometer

Reported persistent **ERA5 U10S** biases:

Excessive mean model westerlies in the middle latitudes

Insufficient mean model poleward flow between 30° and 60°

Wind direction biased clockwise in NH and anticlockwise in SH



Regression ML model to predict NWP stress-equivalent wind (U10S) biases



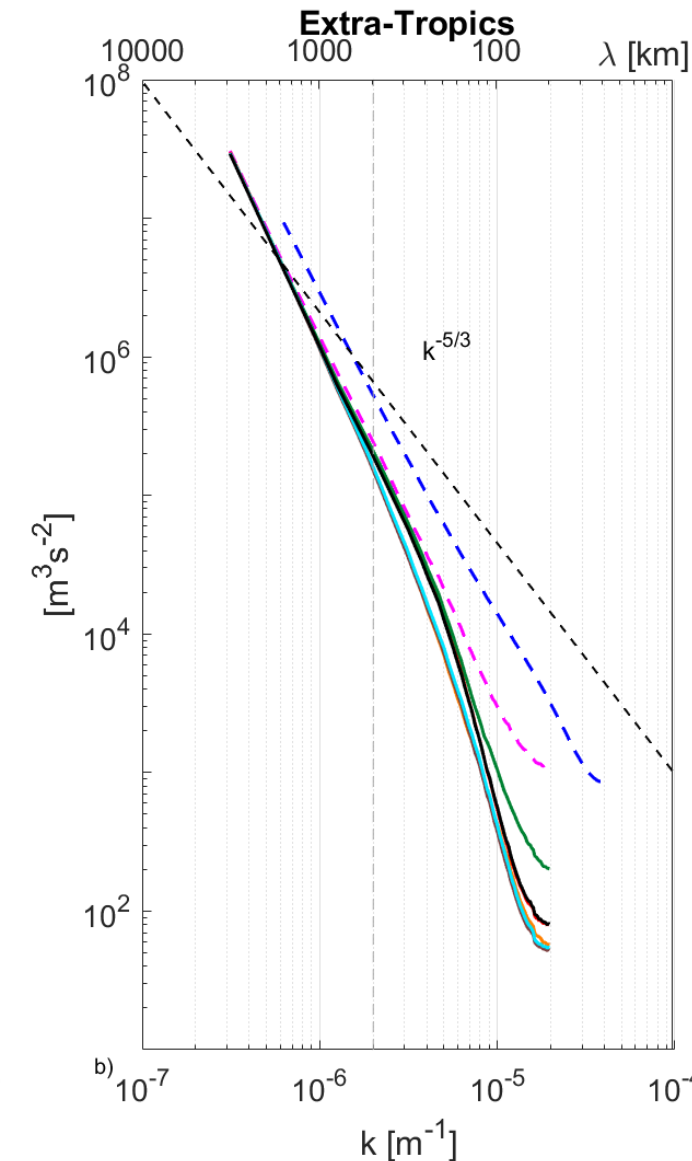
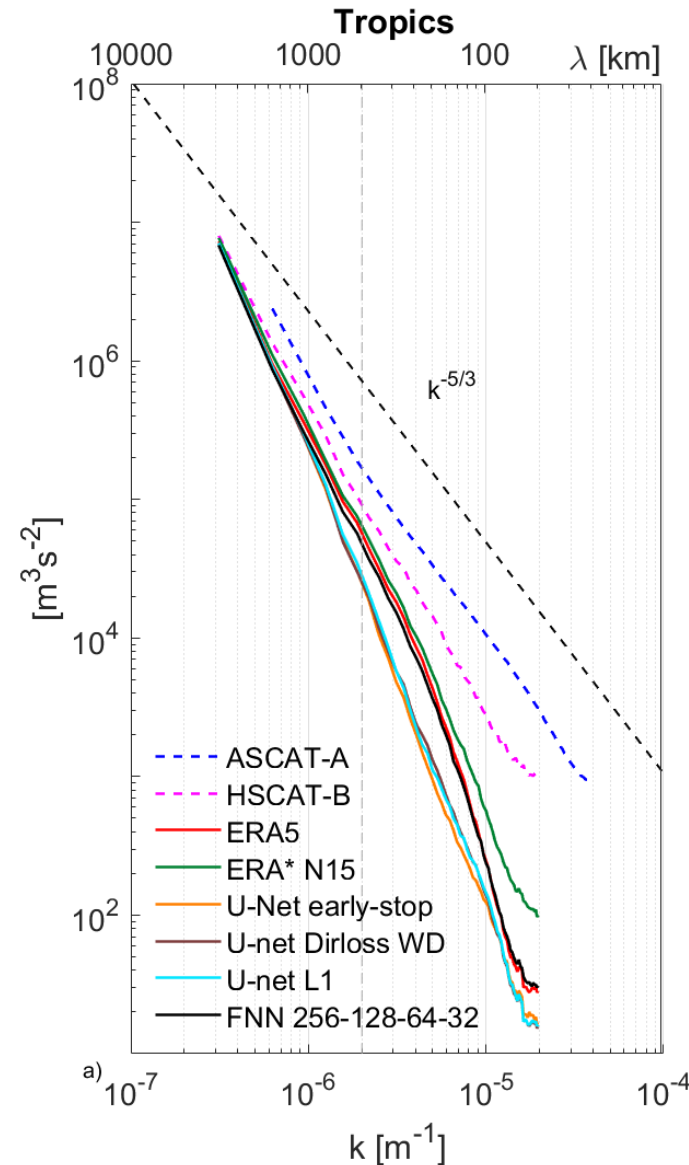
Preliminary work

Preliminary work:

Trained and evaluated only on several months of data.

Architectures:

- XBoost
- **Fully-Connected feed-forward neural networks (FNN)**
- U-Net -> Better RMSE, but drop in spatial variance



Inputs:

ERA5 reanalysis:

- U10S components, wind speed and direction
- Mean sea level pressure
- Air temperature
- Specific humidity
- SST, SST gradients

Currents: Copernicus Global Total, Ekman and Geostrophic currents at the Surface and 15m (GLOBCURRENT)

- Daily mean surface velocity components (u_o , v_o)

Derivatives: ERA5 wind curl, divergence

Targets:

Differences between ASCAT and ERA5

U10S:

OSI SAF ASCAT 12.5 km U10S data

Periods:

OSI SAF project

Train: 2019 – 2022 & 2024

Validation: 2018 Test: 2023

ERAstar AI project (OSI_VSA24_01)

Model

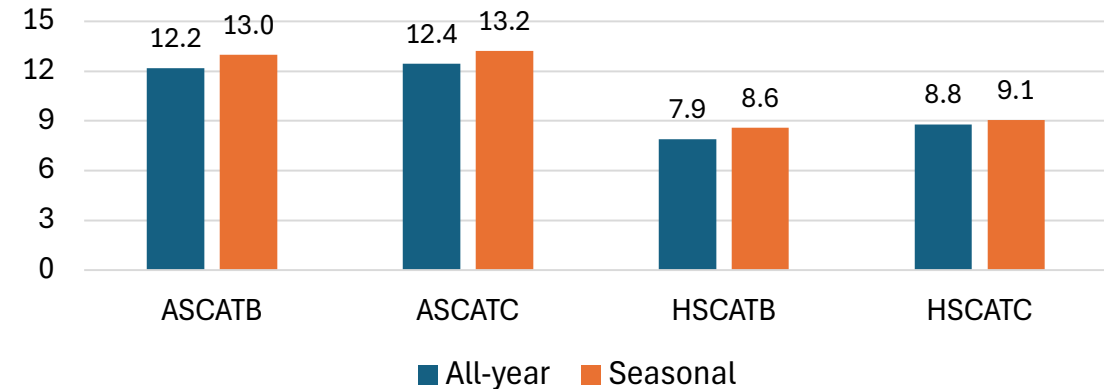
FNN 5 layers (1024-512-256-128-64) with Dropout

- All year model
- Seasonal model (separate NN model per each month)

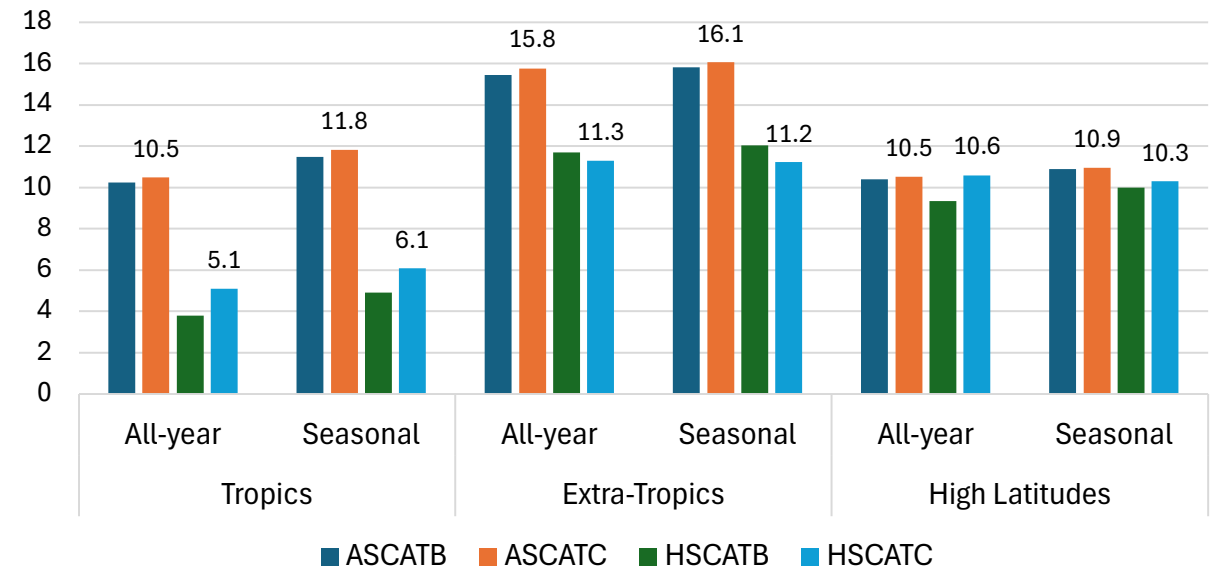
ERA5 Mean VRMS (m/s) – 2023 test period

	Global	Tropics	Extra-Tropics	High Latitudes
ASCAT-B	2.036	1.999	2.026	2.143
ASCAT-C	2.030	1.996	2.020	2.130
HSCAT-B	1.602	1.550	1.593	1.756
HSCAT-C	1.682	1.615	1.687	1.804

Global err. var. reduction, %



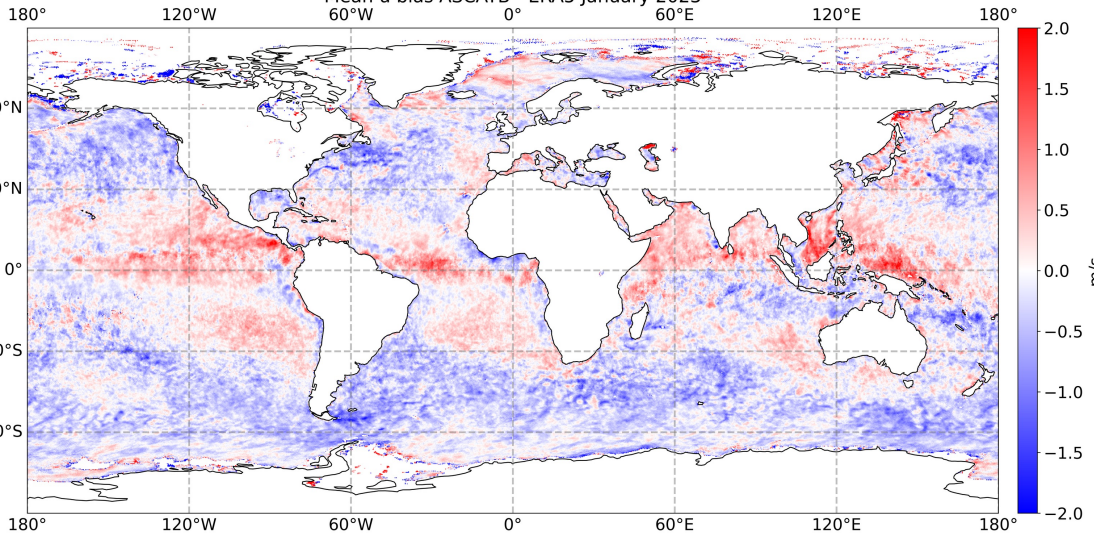
Err. var. reduction, %



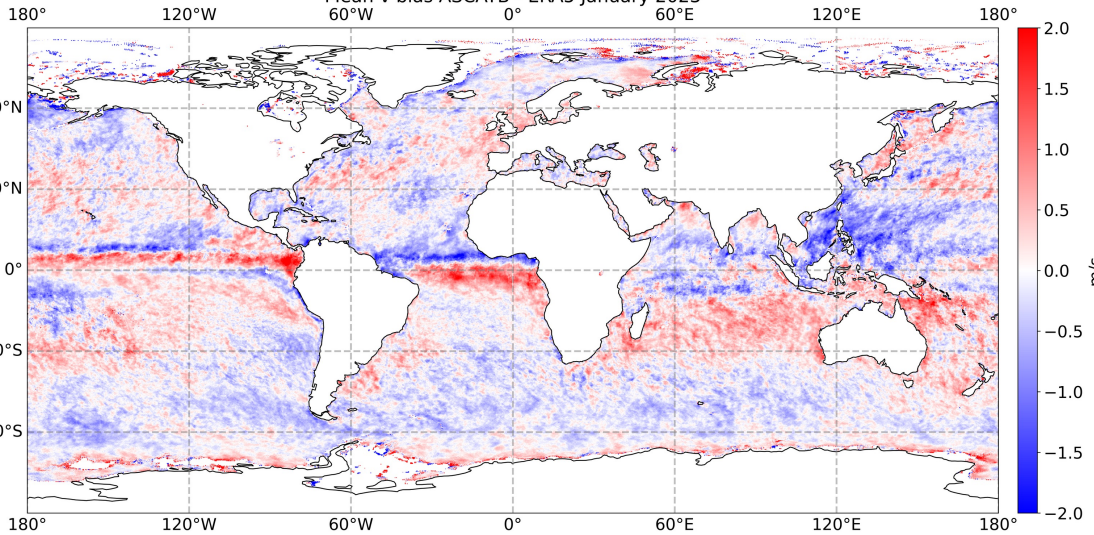
ERA5 biases before correction

ASCAT -B

Mean u bias ASCATB - ERA5 January 2023

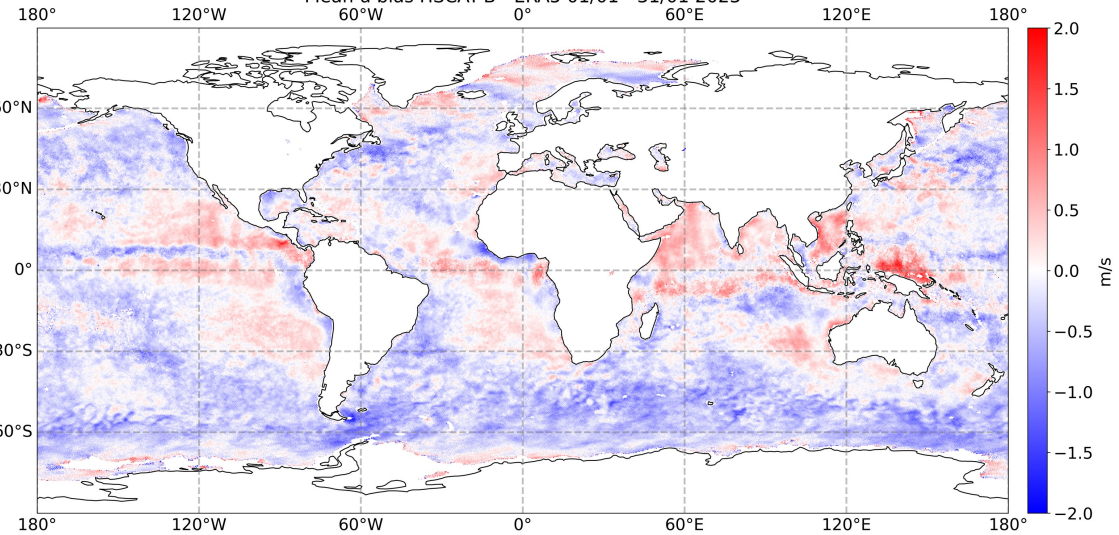


Mean v bias ASCATB - ERA5 January 2023

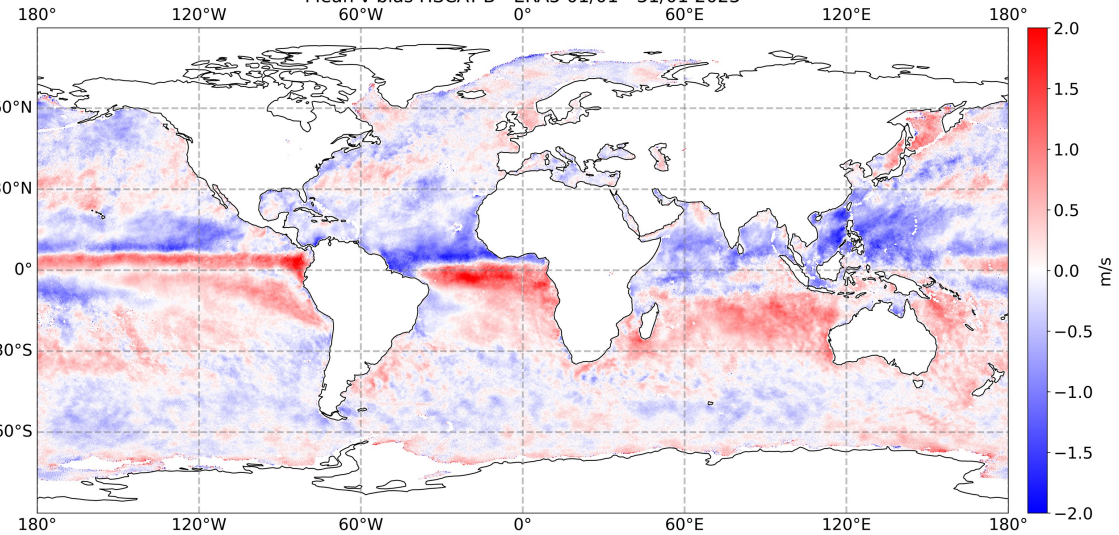


HSCAT -B

Mean u bias HSCAT-B - ERA5 01/01 - 31/01 2023



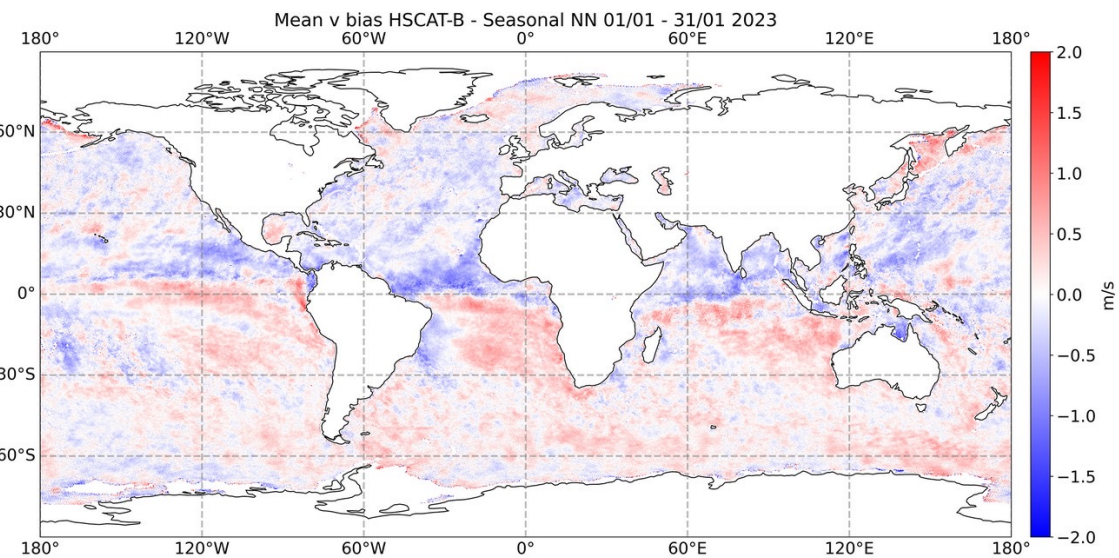
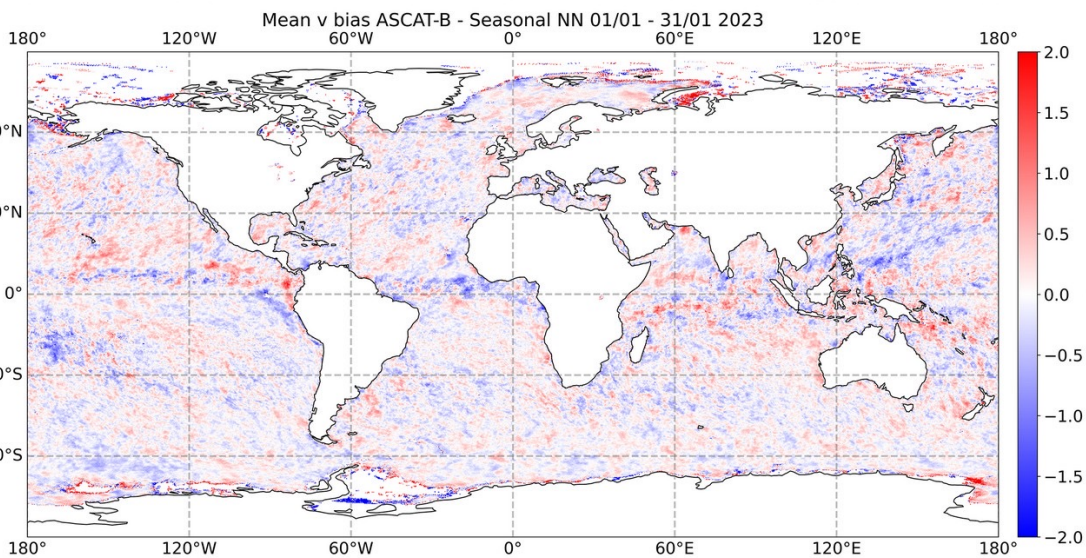
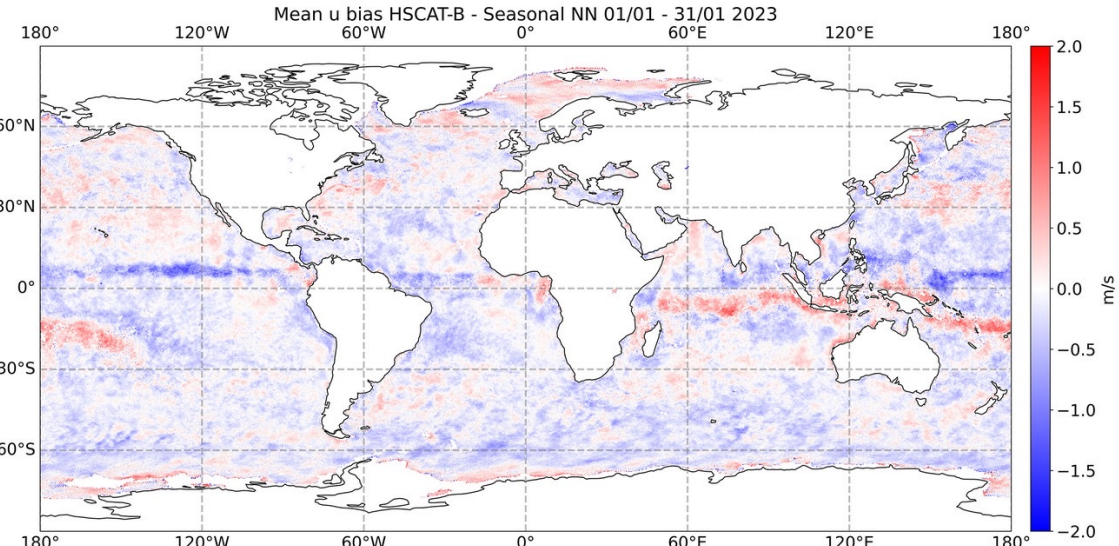
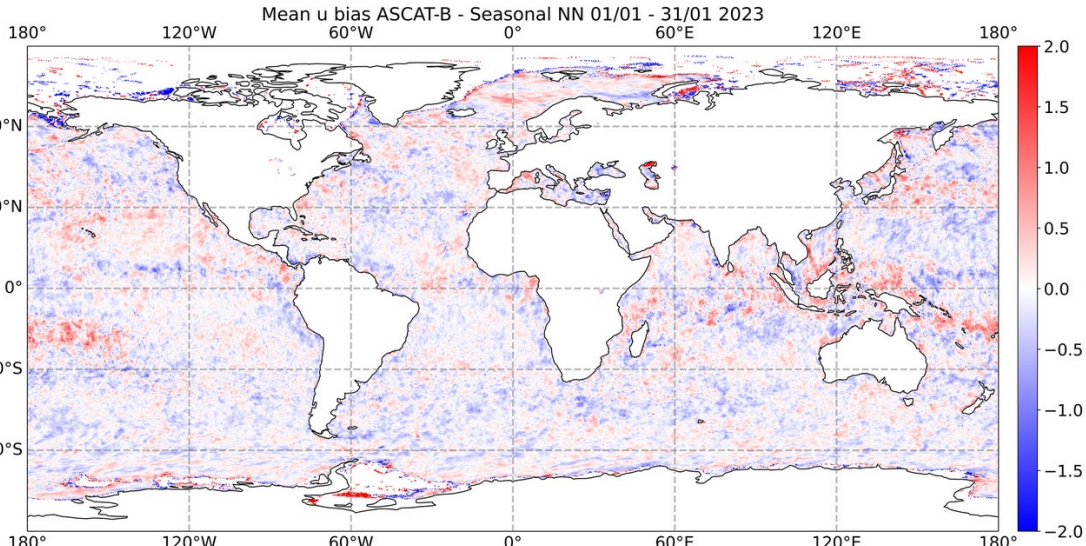
Mean v bias HSCAT-B - ERA5 01/01 - 31/01 2023



ERA5 biases after correction

ASCAT -B

HSCAT -B



VRMS reduction vs ASCAT

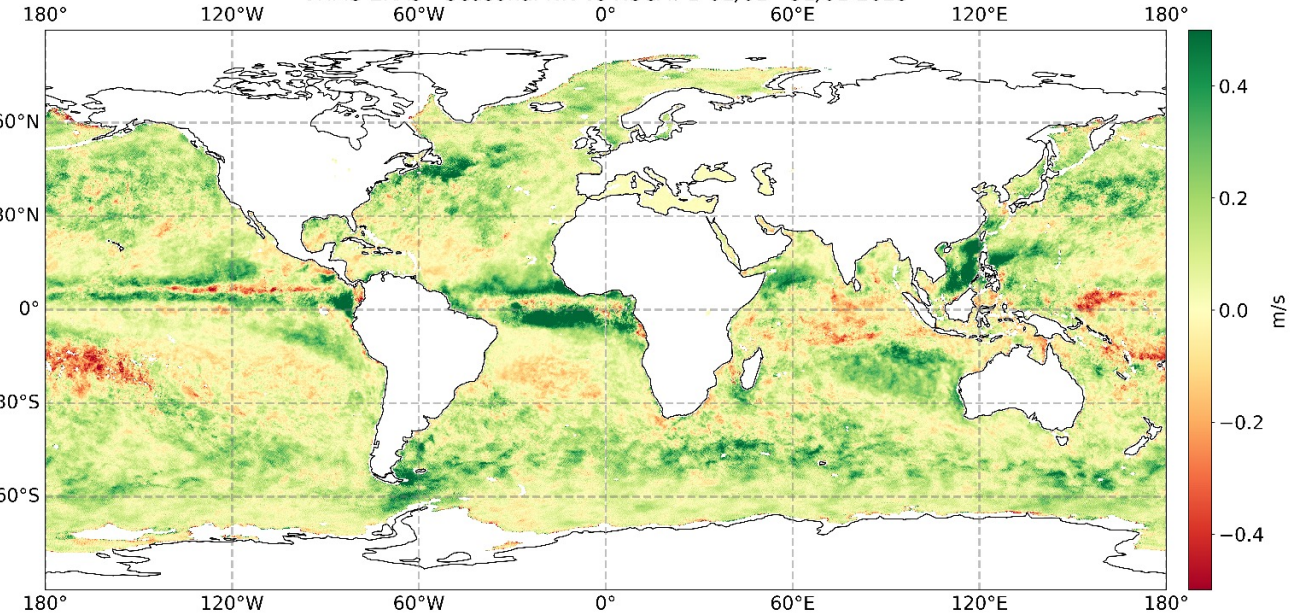
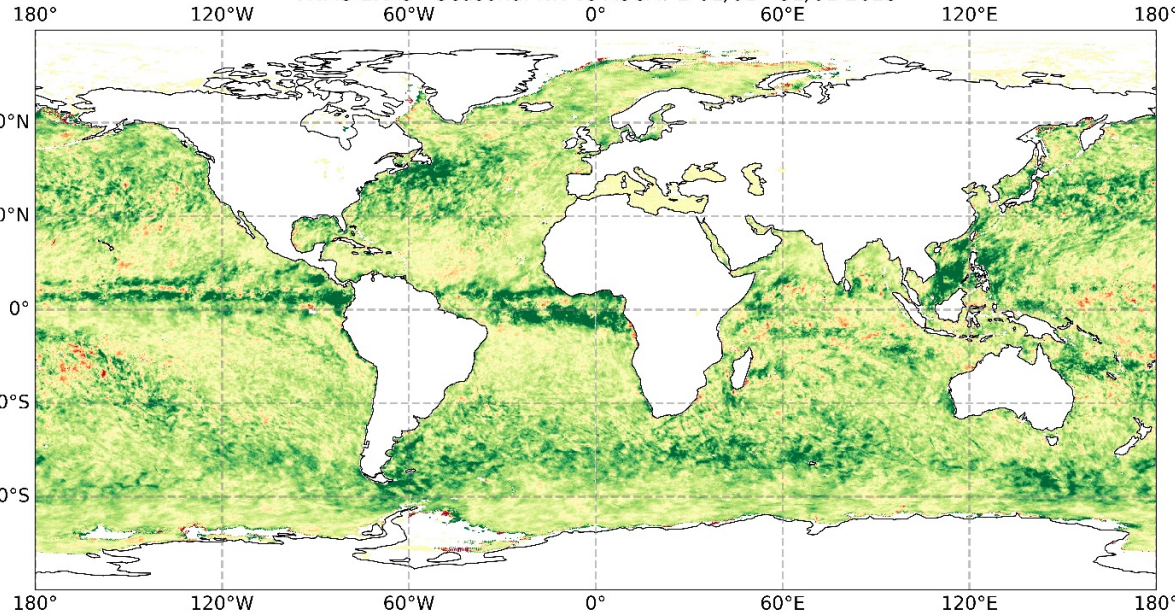
VRMS reduction vs HSCAT

ASCAT -B

HSCAT -B

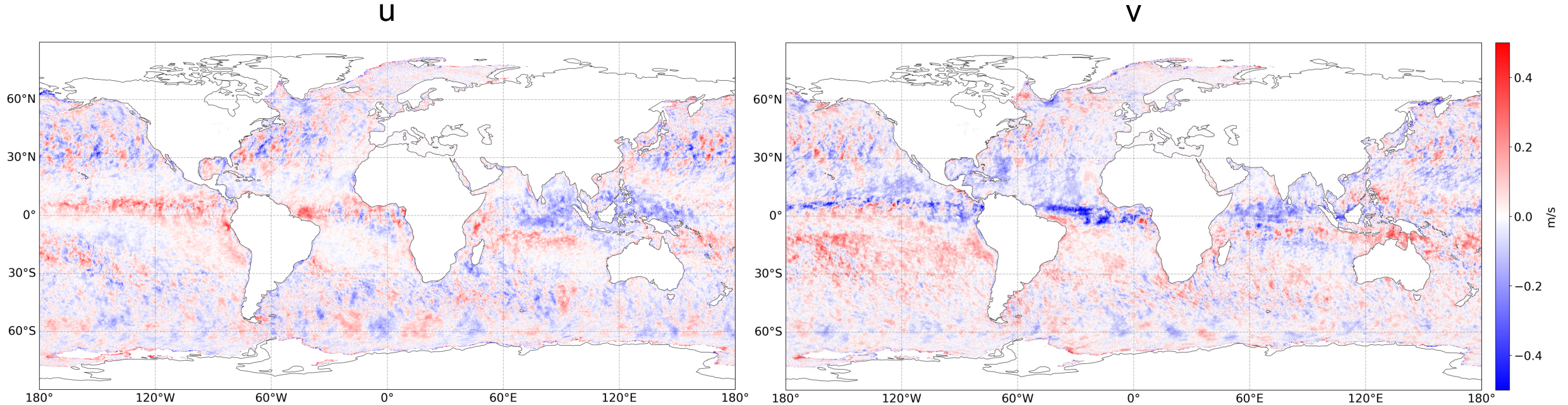
VRMS ERA5 - Seasonal NN vs ASCAT-B 01/01 - 31/01 2023

VRMS ERA5 - Seasonal NN vs HSCAT-B 01/01 - 31/01 2023



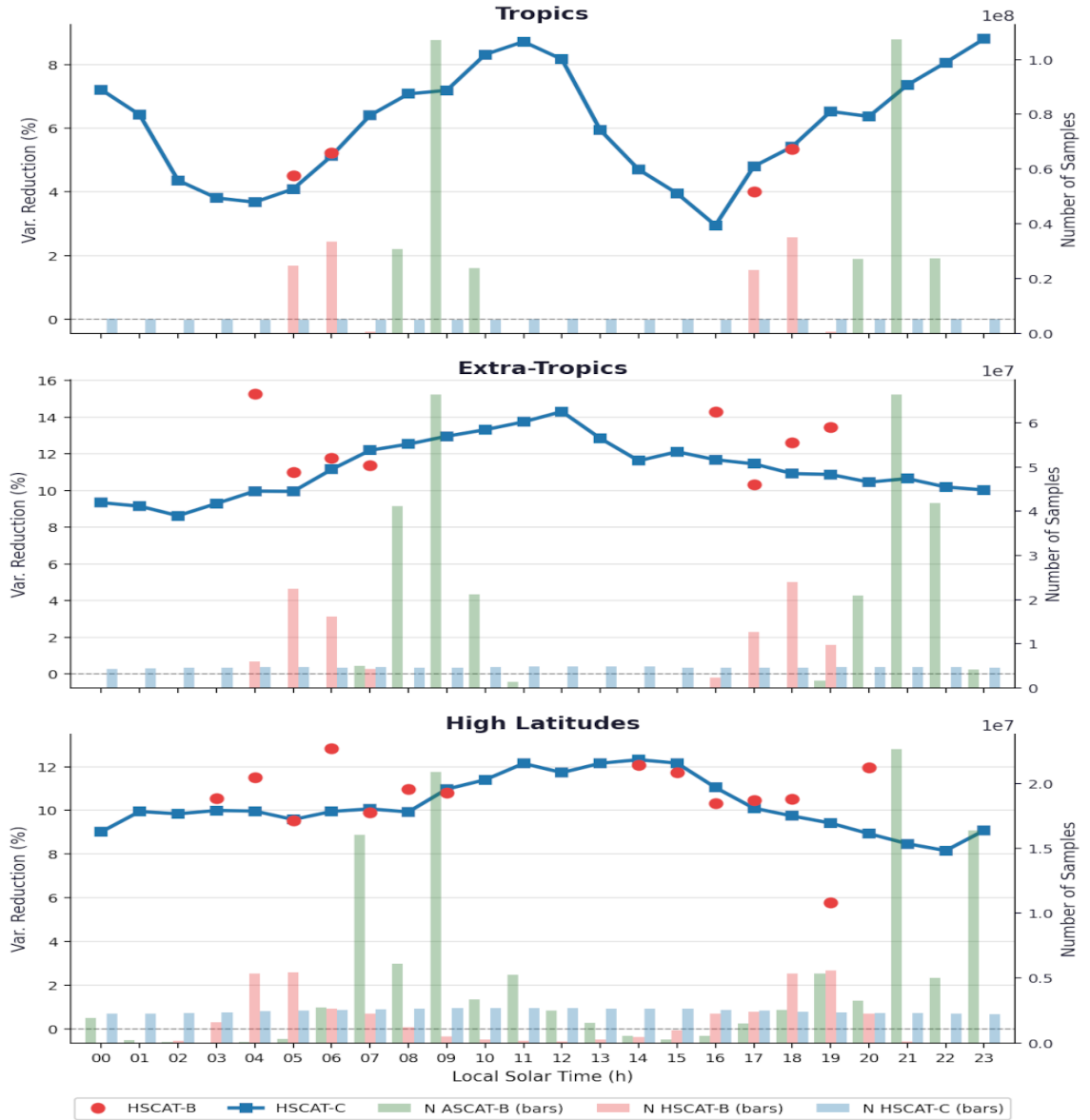
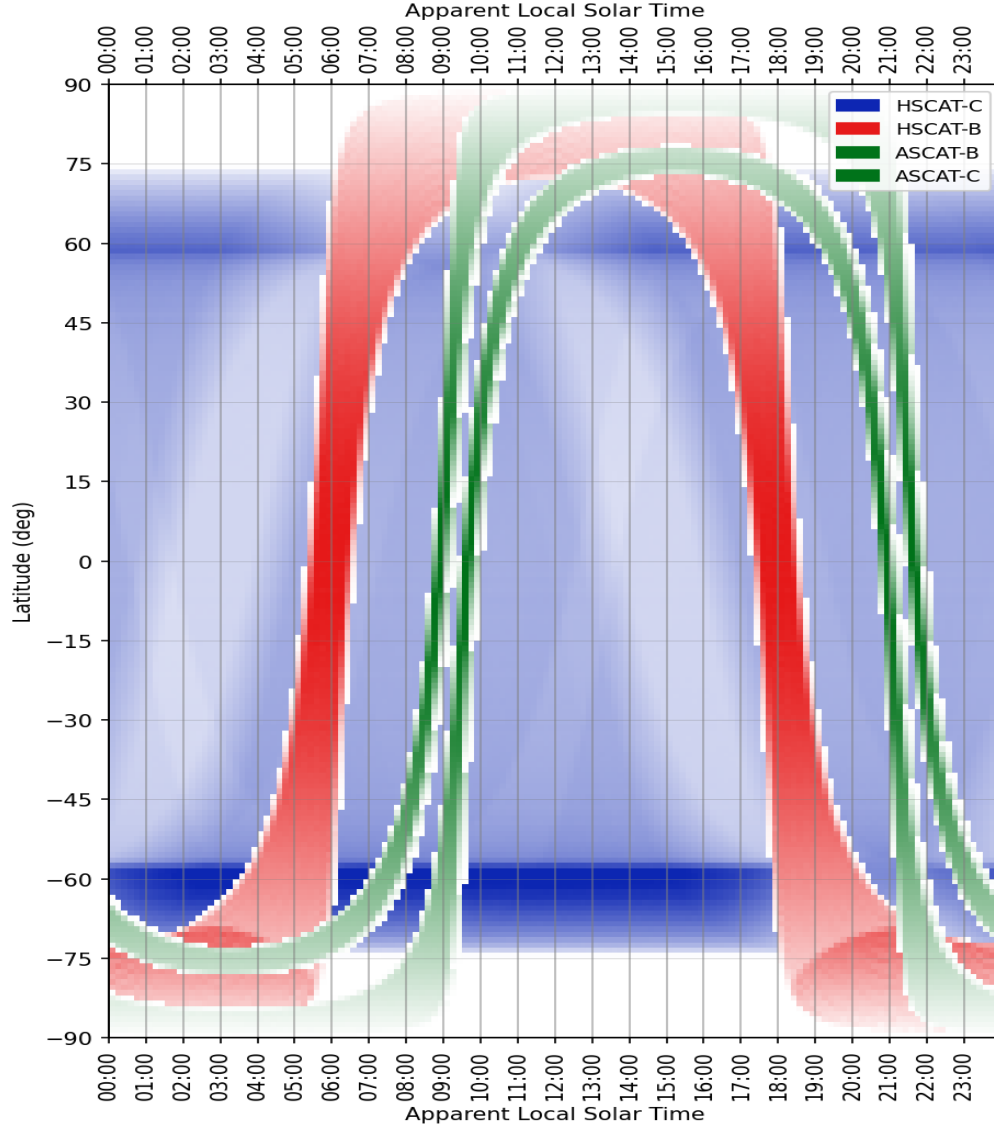
Sampling differences

Mean monthly differences between NN corrections at ASCAT-B times and those at HSCAT-B times
(January 2023)



Diurnal cycle effects

Sampling distribution - Latitude vs Apparent Local Solar Time
01 Jan 2023 - 31 Mar 2023, 1.0deg lat | 10 min time bins



CERAINE Copernicus Marine service evolution project

- Improve the North-East Atlantic wave and physics model solutions (IBI-MFC short-term forecast services)

Neural network that corrects wind biases in the IBI region

Current architecture:

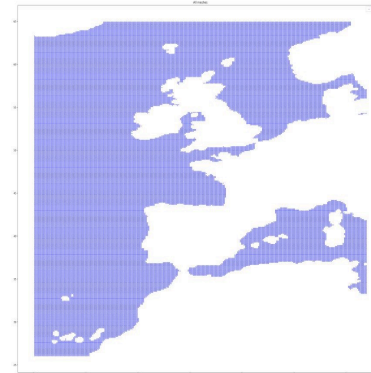
Graph neural networks (GNNs)

Previously: Adversarial neural networks (GANs) for coastal winds trained on SAR

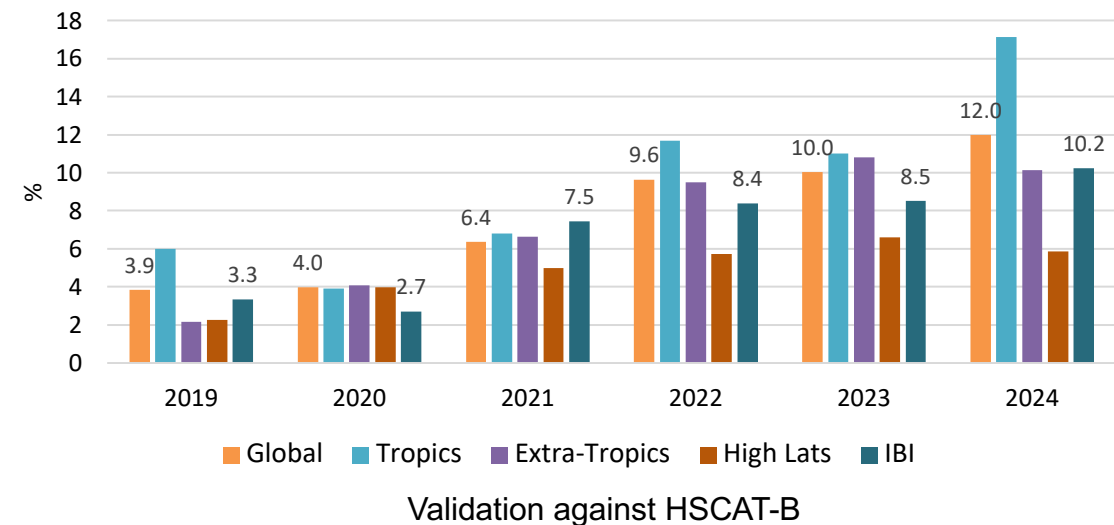
Current GNN configuration requires gap-free training targets.

- Generation of IFS* product (2018 – June 2024)

2018	ASCATA, ASCATB, OSCAT2
2019	ASCATA, ASCATB, ASCATC, OSCAT2
2020	ASCATA, ASCATB, ASCATC, OSCAT2
2021	ASCATA, ASCATB, ASCATC, HSCATC
2022	ASCATB, ASCATC, HSCATC, HSCATD
2023	ASCATB, ASCATC, HSCATC, HSCATD
2024	ASCATB, ASCATC, HSCATC, HSCATD, OSCAT3



IFS* error variance reduction w.r.t IFS



- FNN architecture was chosen over convolutional NNs to preserve the spatial variance
- Global error variance reduction by ~13% (ASCAT) and ~9% (HSCAT), with up to 16% in extra-tropics.
- Seasonal models outperform all-year models, especially in tropical regions with strong seasonal variability.
- Diurnal cycle of the biases is not properly resolved by the current FNN model, notably in the Tropics due to sampling only at 2 local times by ASCATs

- Include scatterometer data from inclined-orbit satellites (HY-2C/HY-2D) to address diurnal cycle
- Explore custom loss functions to improve the consistency in derivatives such as curl and divergence.
- Spectral and multi-scale loss functions to preserve the spatial variance
- Adapt existing Graph Neural Networks (GNNs) architectures to scatterometer data with gaps
- Integration with ECMWF ANEMOI framework
- Related projects:
 - Improved near-surface temperature representation (ESA - COMET)
 - Improved SMOS-derived salinity retrievals (Spanish National Plan - EO4TIP)
 - ML approach in the context of ERA6/7 (Horizon Europe - CHERRI)



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