ON THE USE OF MACHINE LEARNING TO CORRECT NWP MODEL SEA SURFACE WIND FORECASTS WITH SCATTEROMETER DATA INPUT

Evgeniia Makarova, Marcos Portabella, Ad Stoffelen, Ana Trindade, Giuseppe Grieco

BEC Barcelona Expert Center
EXCELENCIA SEVERO OCHOA
Institut de Ciències del Mar
Koninklijk Nederlands Meteorologisch Instituut
Ministerie van Infrastructuur en Milieu
ISMAR ISTITUTO DI SCIENZE MARINE
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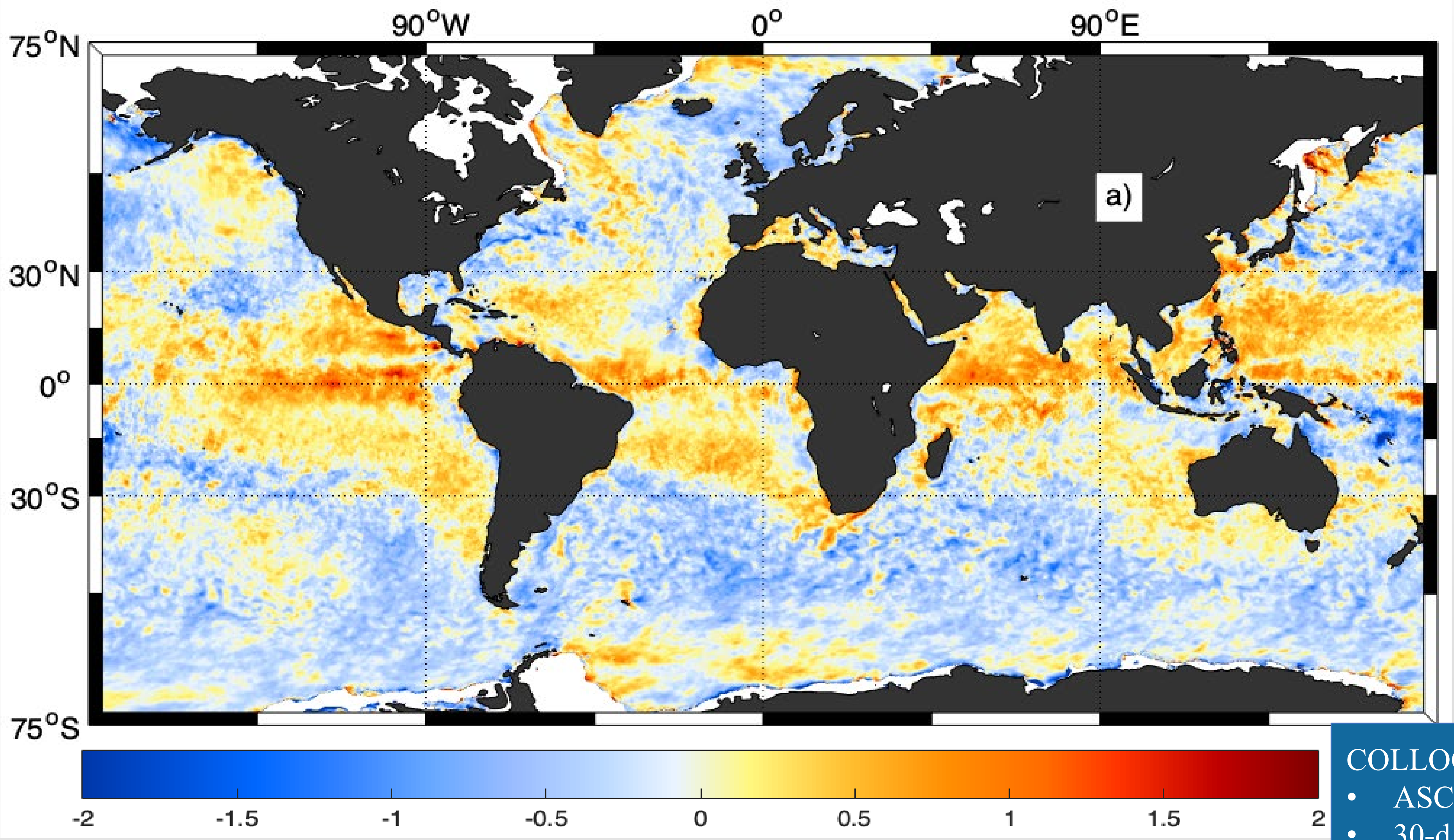
Systematic differences between NWP and scatterometer



COLLOCATIONS
- ASCAT-A/B/C – ERA5 u10S
- 30-d Temporal Window

Zonal component (v10S)

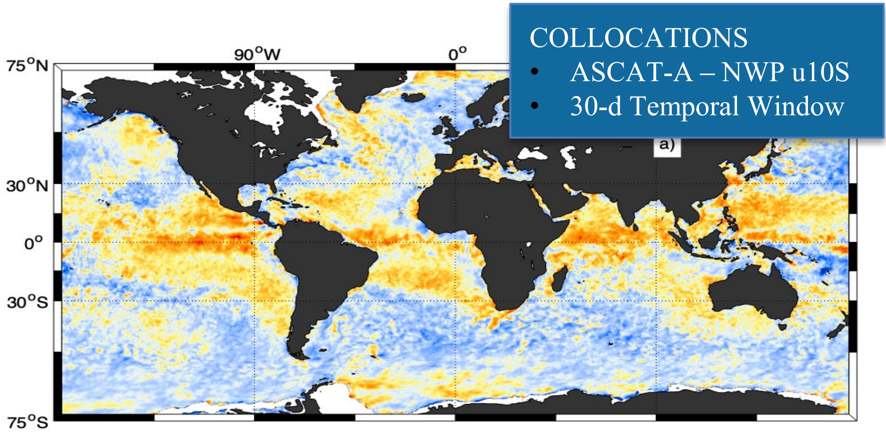
ERA* wind & stress product

Development of ERA*:

1. Scatterometer-based corrections:

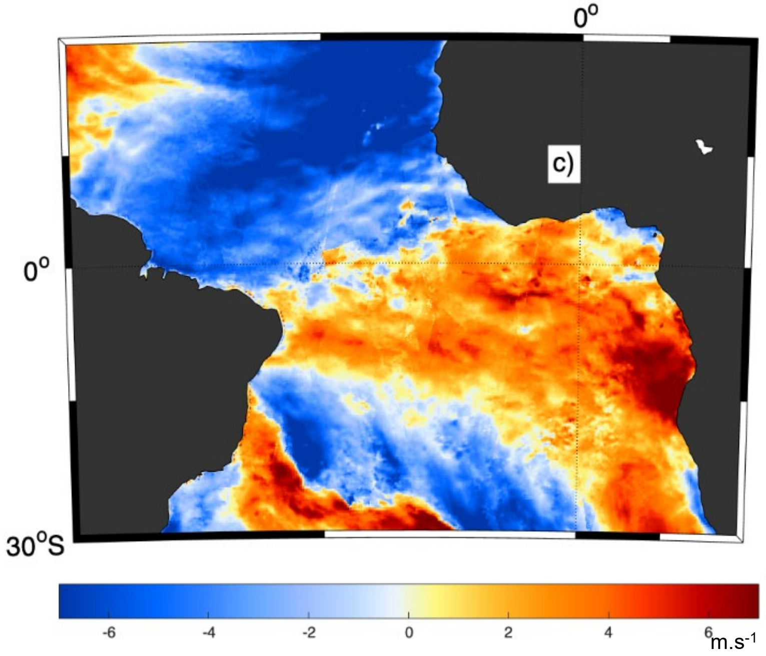
$$SC(i,j,t_f) = \frac{1}{M}\sum_{t=1}^{M}\left(u_{10s}^{SCAT_k}(i,j,t) - u_{10s}^{ERA5}(i,j,t)\right)$$

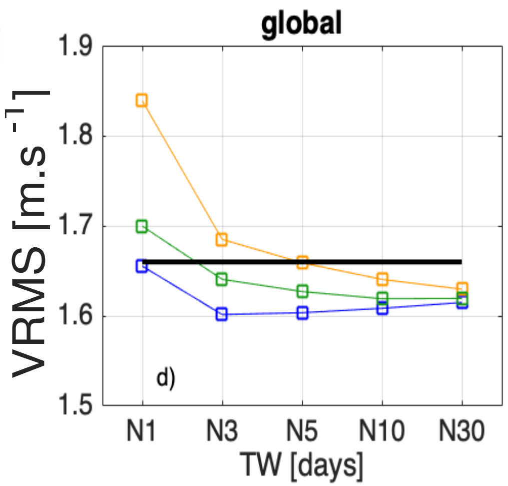
N **length of the temporal window (d);**
k **Scatterometer combinations**
M **is the number of scatt. and ERA collocations**
Applied at every forecast time

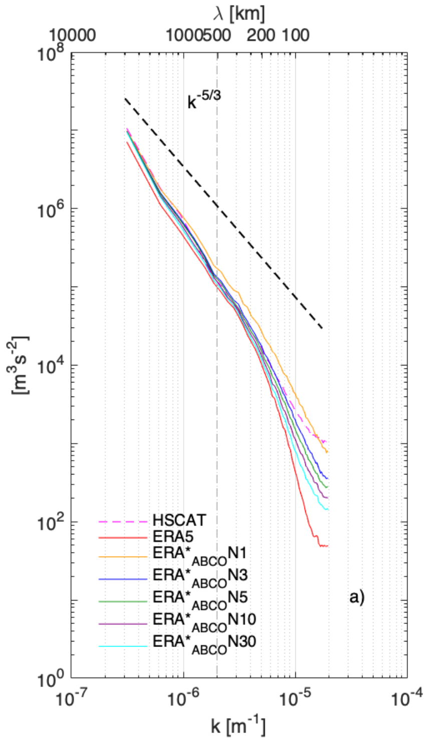


2. ERA5-corrected stress-equivalent winds (ERA5*):

$$u_{10s}^{ERA5^*}(i,j,t_f) = u_{10s}^{ERA5}(i,j,t_f) + SC(i,j,t_f)$$







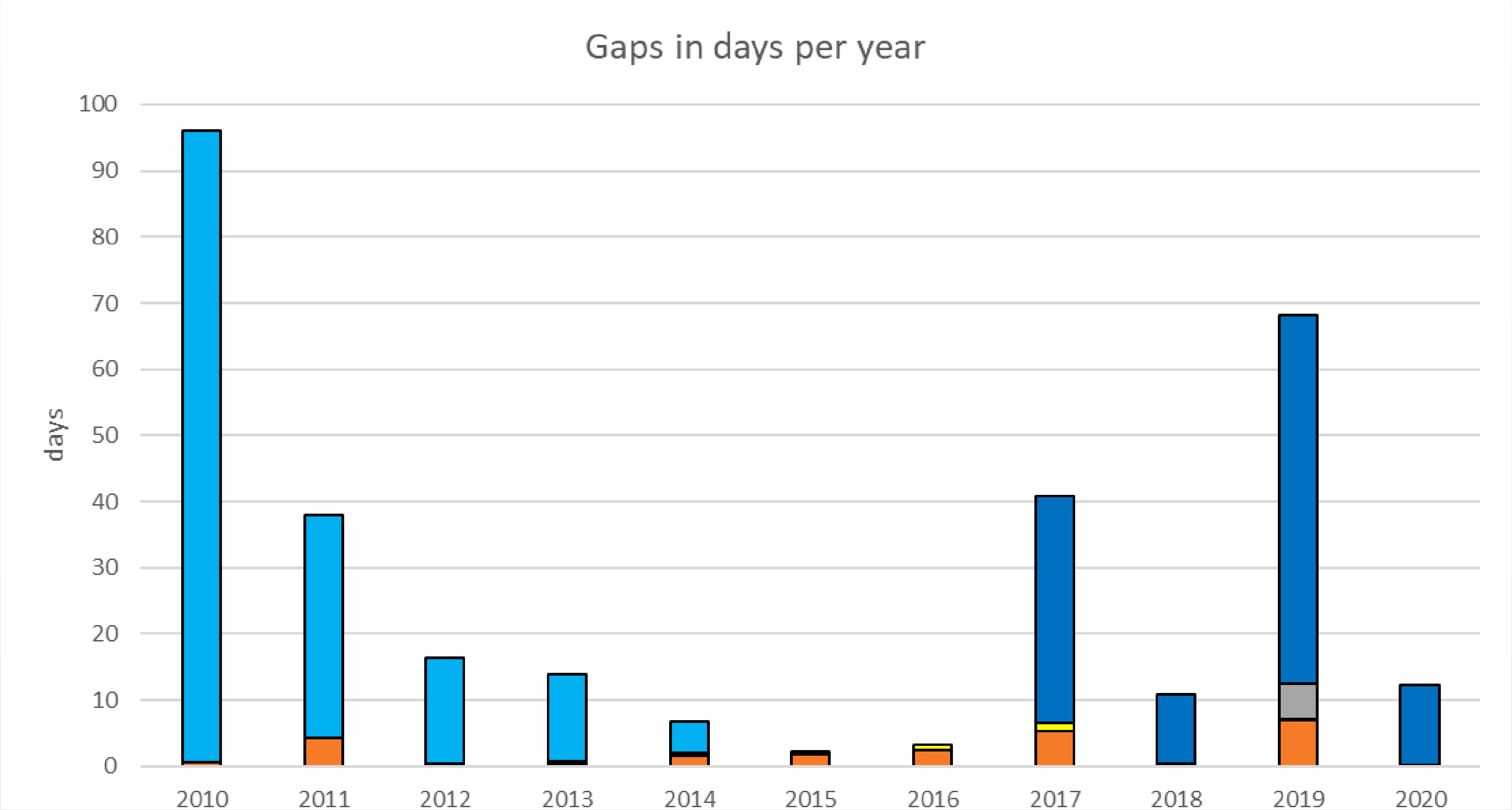
ERA* corrects for large-scale circulation errors and adds small-scale true wind variability, due to oceanic features such as wind changes over SST gradients and ocean currents.

ERA* error variance (w.r.t. HSCAT-B) is 9% lower than that of ERA5

ERA* wind & stress product

- Scatterometer constellation in 2010-2020 (only C-band & Ku-band with global, continuous coverage)
    - 2010-2012: ASCAT-A & OSCAT
    - 2013: ASCAT-A, ASCAT-B & OSCAT
    - 2014-2016: ASCAT-A, ASCAT-B
    - 2017-2018: ASCAT-A, ASCAT-B & OSCAT2
    - 2019-2020: ASCAT-A, ASCAT-B, ASCAT-C & OSCAT2, HSCAT-B
- HSCAT-A and RapidSCAT don’t have full coverage and/or continuous coverage, therefore used for verification purposes only
- The 2019 period is used as testbed for ERA* optimization over the entire period since it contains all the possible combinations of C-band and Ku-band scatterometer sampling
- Validation against buoys is added to independent scatterometer verification

ERA* wind & stress product



Scatterometer constellation → AO AO AO ABO AB AB AB ABO ABO ABCO ABCO

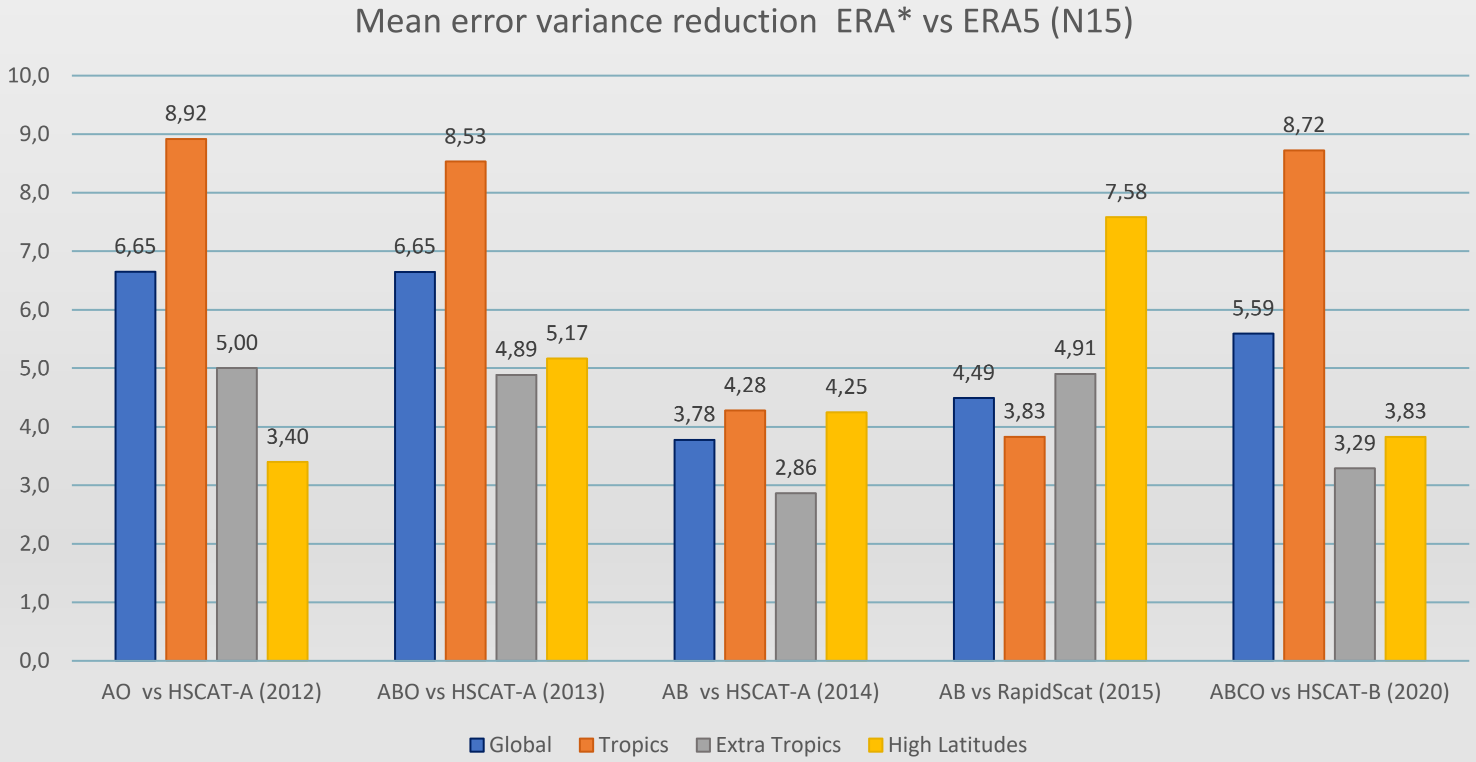
ASCAT-A ASCAT-B ASCAT-C OSCAT1 OSCAT2

Large data gaps in Ku-band systems!

Previous approach: ERA*

ERA* dataset (2010 – 2020)

- Previous attempt to correct persistent ERA5 U10S biases
- Based on mean scatterometer – NWP differences accumulated over a certain time window



Portabella et al., 2022

Default configuration:
15-day time window

- Best performance in the tropics (reduction up to 8.9% error variance)
- Globally 3.8 – 6.7% error variance reduction, depending on the available constellation

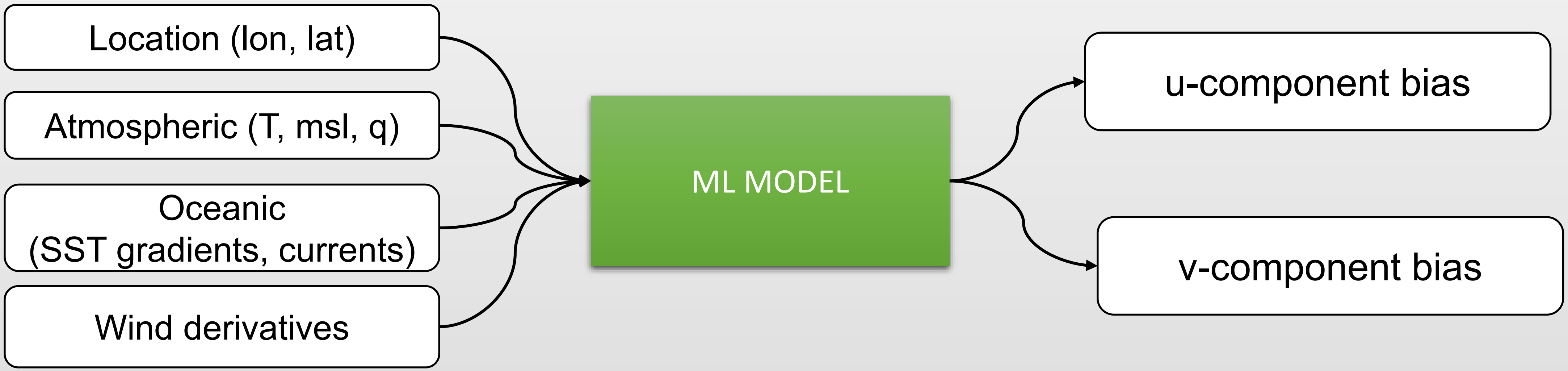
Previous approach: ERA*

Limitations:

- Only corrects local biases persistent over several days
- Very sensitive to scatterometer sampling, especially over shorter time windows
- Doesn’t directly show NWP error dependence on both atmospheric and ocean state conditions
- Has limitations in operational use: computationally expensive and need to shift temporal window (which in turn degrades performance)

Objectives

- Create a preliminary ML model to predict NWP stress-equivalent wind (U10S) biases
- Fit a regression that finds functional relationship between several NWP parameters and U10S biases



- Check the viability of the approach and compare performance of models based on different ML algorithms and libraries
- Train and validate models over a relatively small subset of data

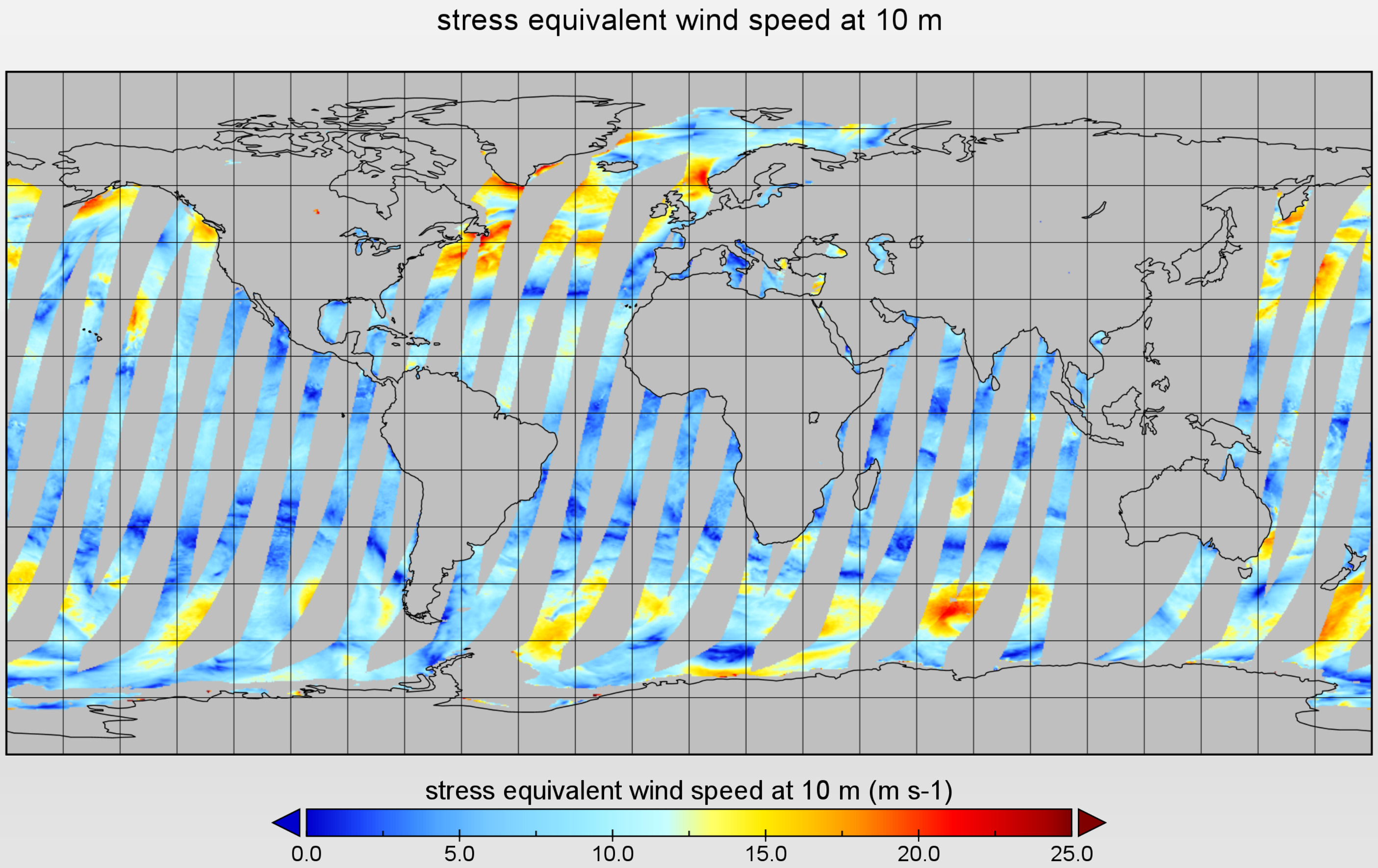
Datasets: Target

Model target: Individual differences between ASCAT-A and ERA5 U10S (components, at each grid point)

$$target = \begin{cases} u_{ascat} - u_{ERA5} \\ v_{ascat} - v_{ERA5} \end{cases}$$

OSI SAF ASCAT-A 12.5 km U10S data

Period used: 02/01/2020 – 01/04/2020
Further split into train/validation and test periods



ASCAT-A descending swaths for February 8th, 2020

Datasets: Inputs

$$U10S = U10N\sqrt{\frac{\rho_{air}}{<\rho_{air}>}} \qquad <\rho_{air}> = 1.225\ \mathrm{kg}/m^3$$

ERA5 reanalysis:

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

Currents: Global Total Surface Current from CMEMS (MULTIOBS_GLO_PHY_REP_015_004)

- Daily mean surface velocities components (uo, vo)

Derivatives: Wind curl, divergence

Additional variables: SST gradients, current speed, cosine between SST and ERA5 U10S

ML Models

<u>1st stage of the project:</u>

- Decision trees

XGBoost

- Feed forward neural networks

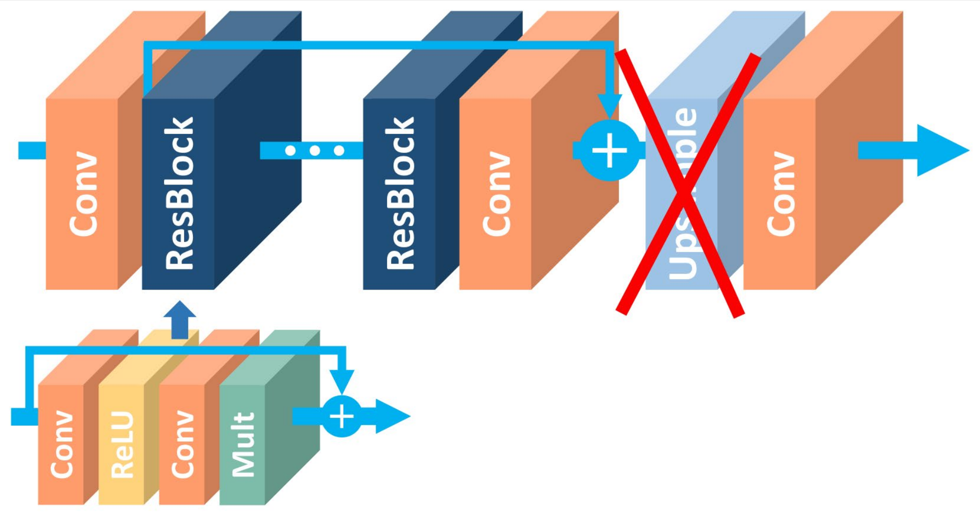
scikit learn MLP Regressor TensorFlow

<u>2nd stage (current development):</u>

- Convolutional neural networks for super-resolution (or semantic segmentation) adapted to regression

Modified EDSR network (arXiv:1707.02921)

└→ no upsample block + dropout2d



- Tests with U-Net and ADSR

Data preparation (XGBoost and FNN)

- Collocation in space and time of 3 datasets
- Calculation of the derivatives
- Normalization for NN models
- Dataset is split into train, validation and test subsets

Train	02/01/2020 - 06/03/2020
Validation	07/03/2020 - 09/03/2020
Test	10/03/2020 - 01/04/2020 (25% of total period)

Random down-sampling of the training dataset to reduce training time:

30 GB -> 2 GB

Methodology: Validation

Metrics:

Vector Root Mean Square Difference (RMSE of wind components)

$$VRMS = \sqrt{\frac{1}{N}\sum_{i}\left(u_i^{scat} - u_i^{model}\right)^2 + \left(v_i^{scat} - v_i^{model}\right)^2}$$

$$relative\ error\ variance\ reduction\ (\%) = \frac{VRMS_{ERA5}^2 - VRMS_{ML}^2}{VRMS_{ERA5}^2} * 100$$

ASCAT-A test dataset:

- 23 days at the end of the period (10/03 - 01/04/2020)
- Complete ASCAT-A swaths, no reduction
- Same ground truth instrument as in training
- Fixed orbit pass times -> only 2 local times are evaluated

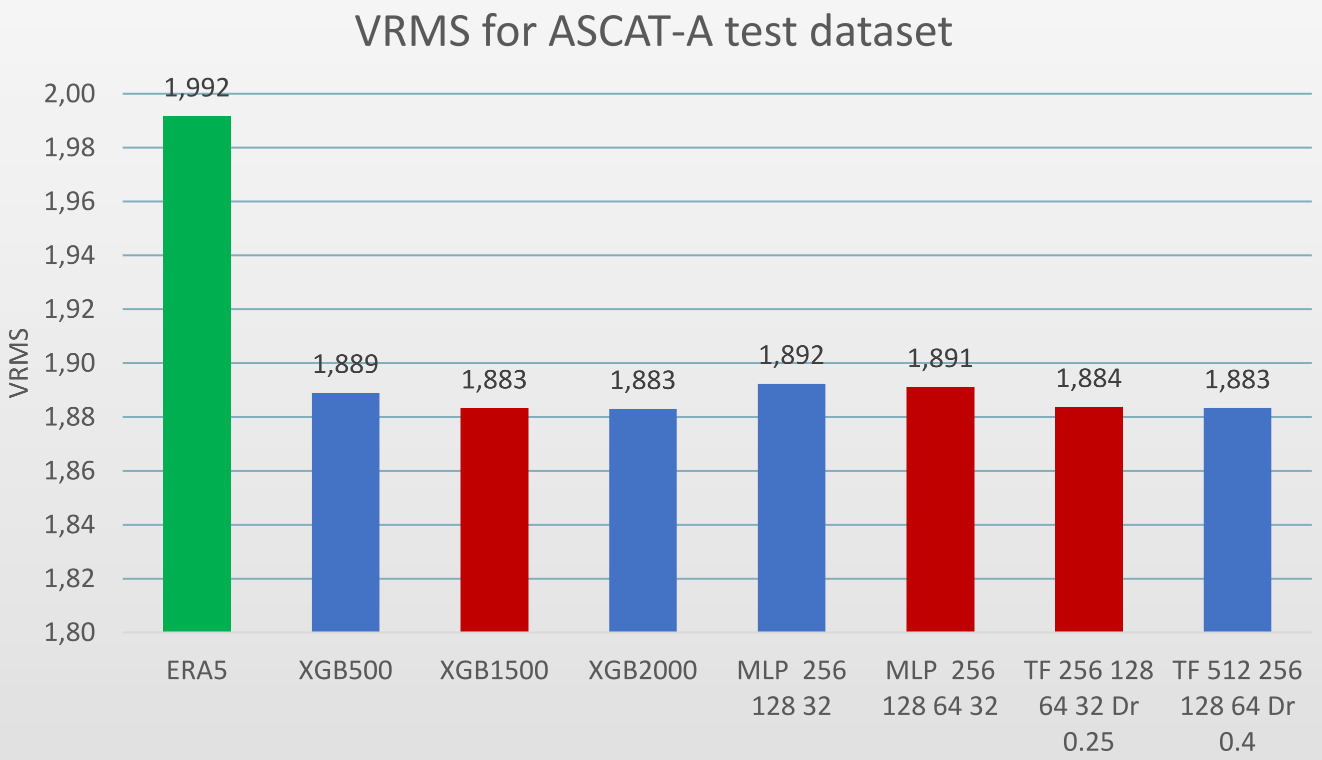
Methodology: Validation against HSCAT-B

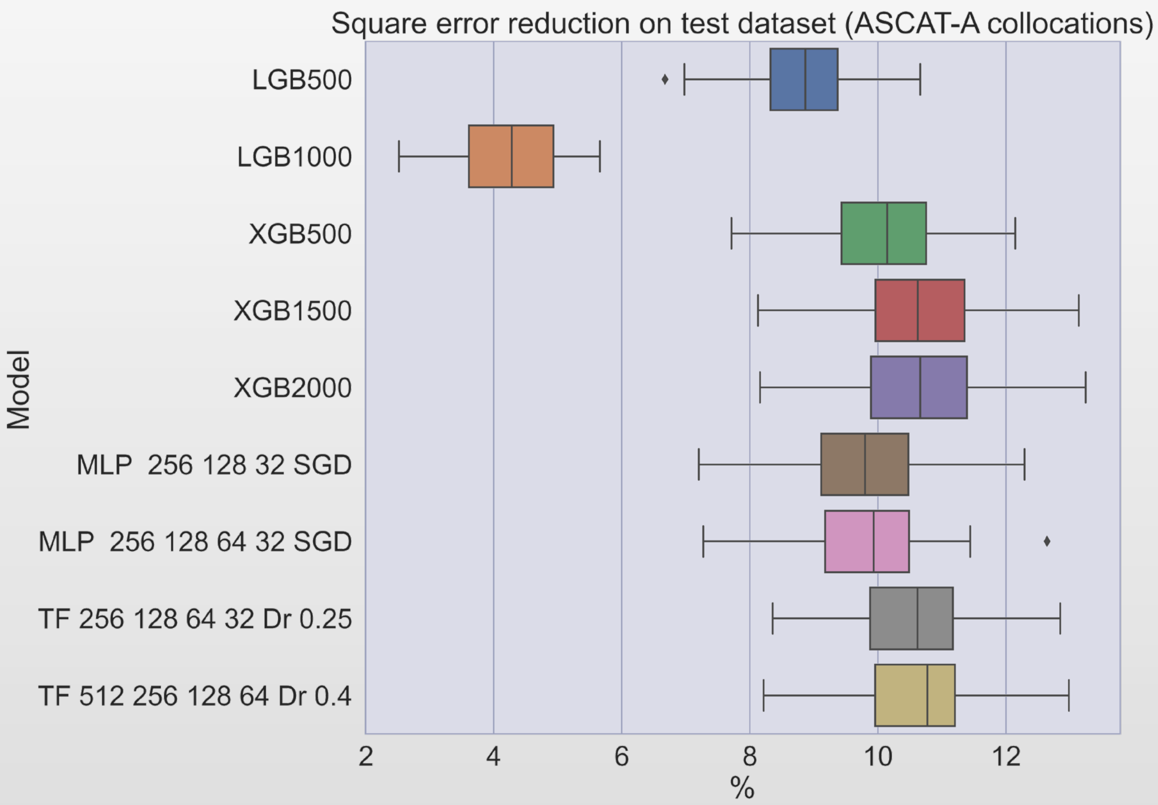
Validation against independent scatterometer HSCAT-B

- Period tested 01/02/2020 - 29/04/2020
- Period includes part of training period and ASCAT-A test period
- One extra month (April) included to study the performance degradation
- Corrections are generated for the entire ERA5 forecasts in the period
- Corrected forecasts are collocated with HSCAT-B
- Local pass time 3.5 hours apart from ASCAT-A

- **Additional** validation metrics for 02/01/2019 – 30/04/2019 vs HSCAT-B

Results: ASCAT-A dataset

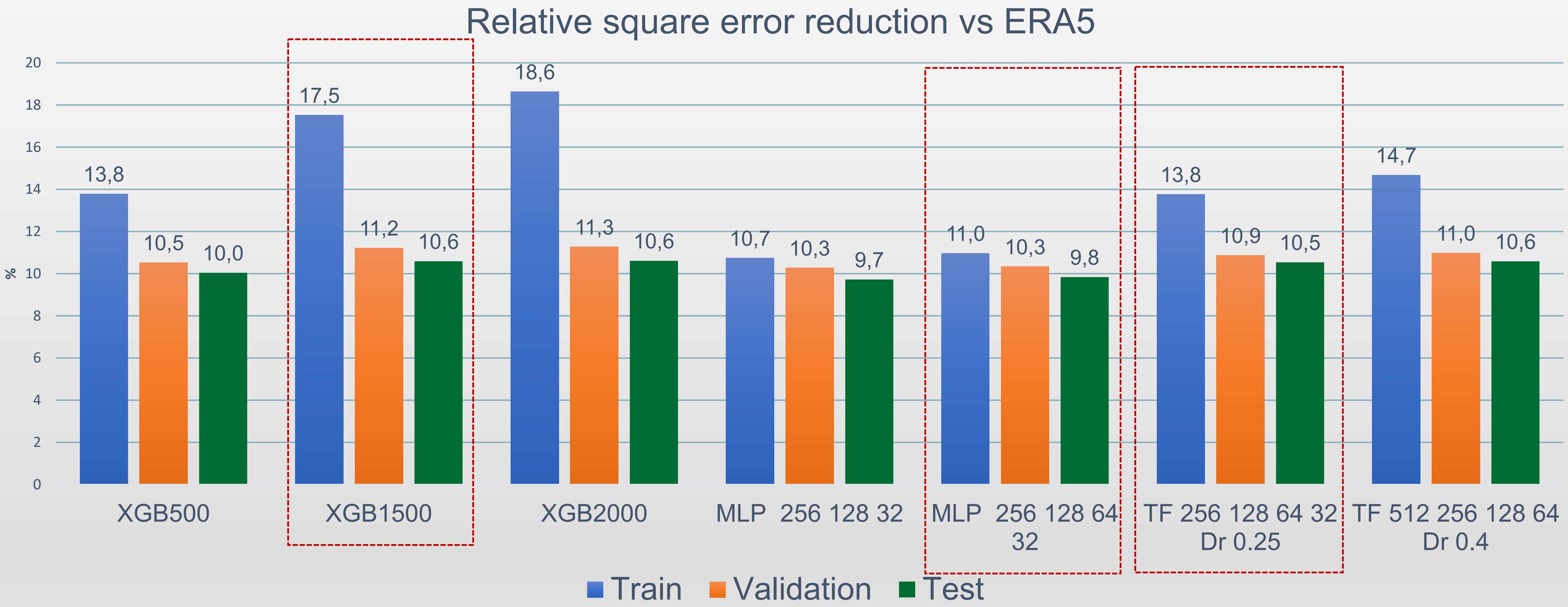




Models in red are selected for second step validation

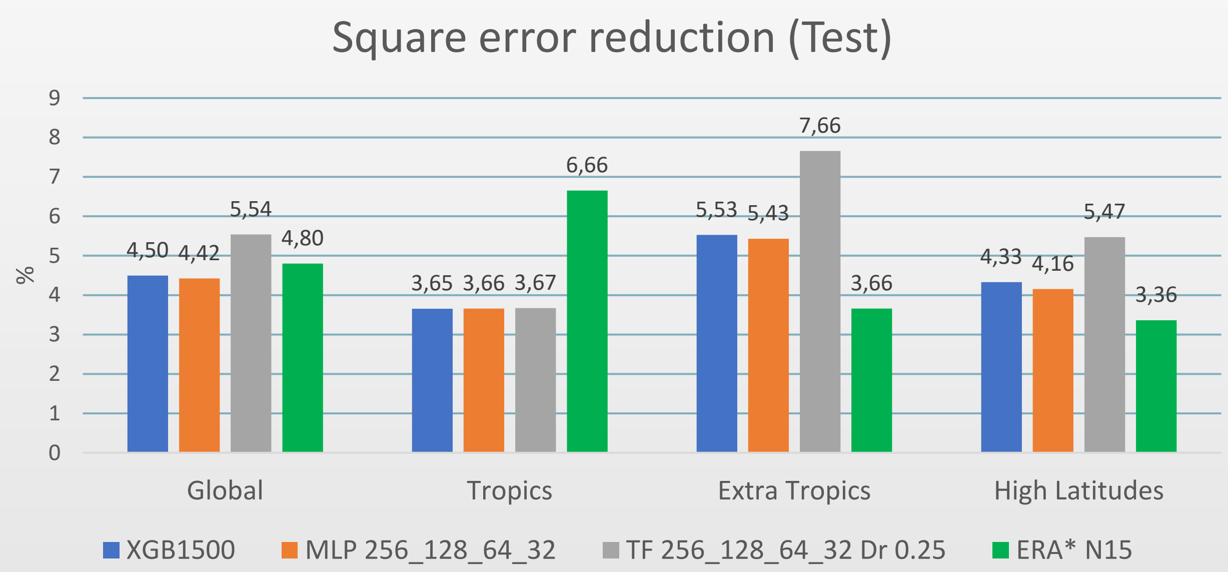
XGBoost shows larger spread in error reduction than Tensorflow NNs

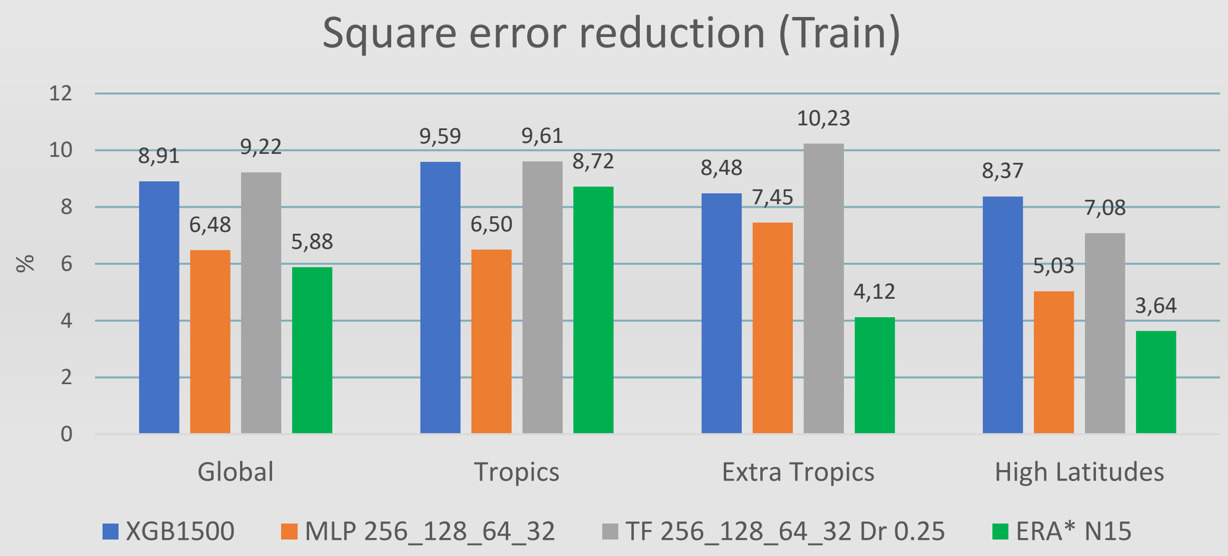
Results: ASCAT-A dataset



XGBoost adjusts much more to the training dataset, possible overfitting

Results: vs HSCAT-B, 2020





Globally:
- VRMS reduced from 1.631 m/s (ERA5) to 1.585 m/s (TF) (5.54% reduction)
- Outperforms ERA*

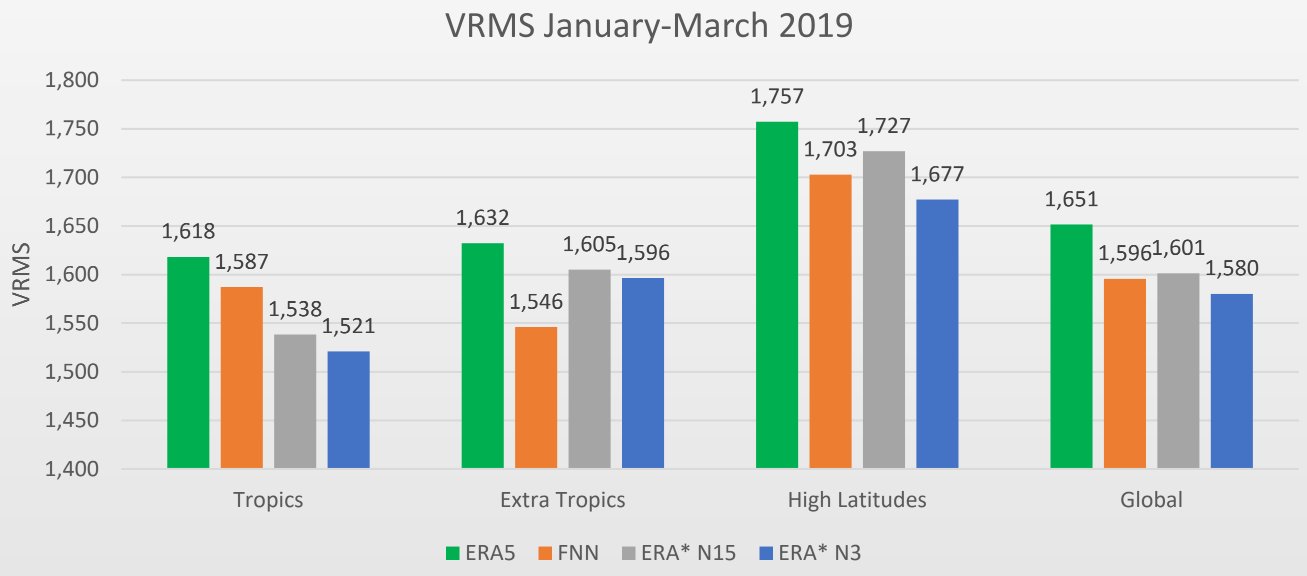
Tropics:
- VRMS 1.55 m/s -> 1.52 m/s
- Lower performance than ERA*

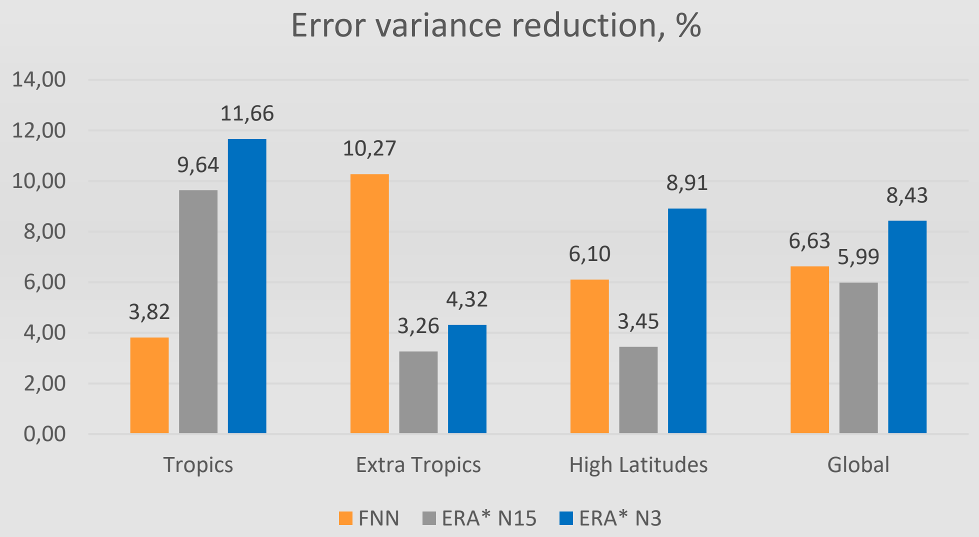
Extra-Tropics:
- Best performing
- VRMS 1.601 m/s -> 1.538 m/s (7.66% reduction, while ERA* shows 3.66%)

High Latitudes:
- VRMS 1.891 m/s -> 1.838 m/s (5.47% reduction)

Period used in training: performance is higher. Can be used for reanalysis datasets.

Results: vs HSCAT-B 2019



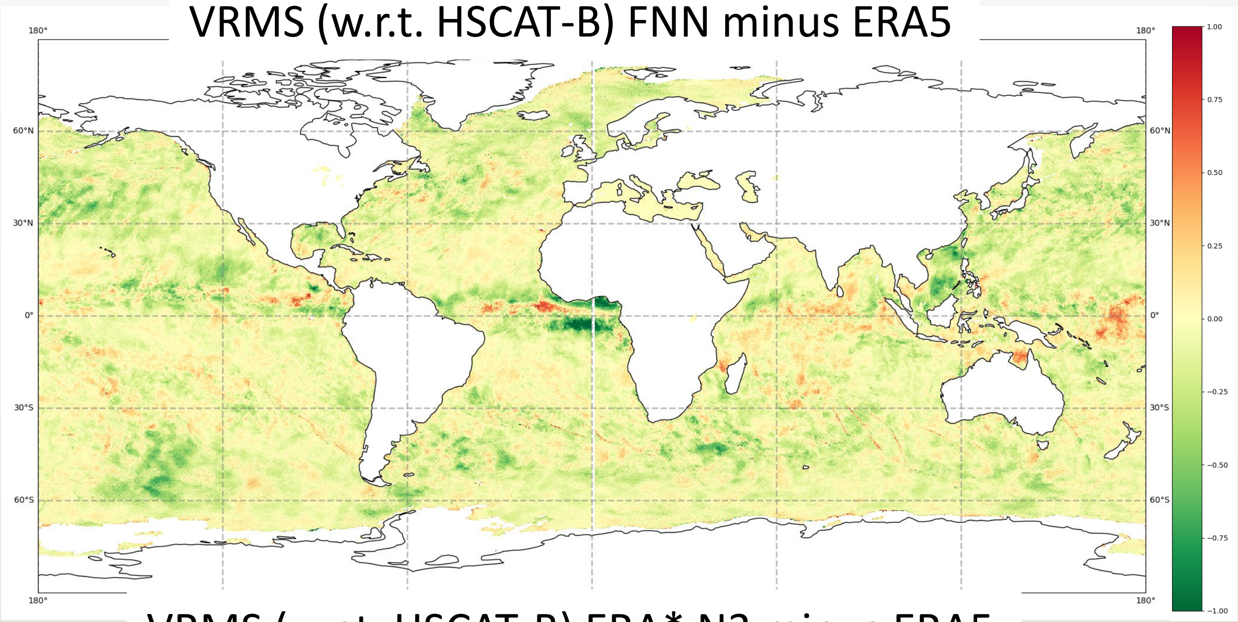


Outputs generated for January – March 2019 by feed-forward neural network or FNN (4 hidden layers)

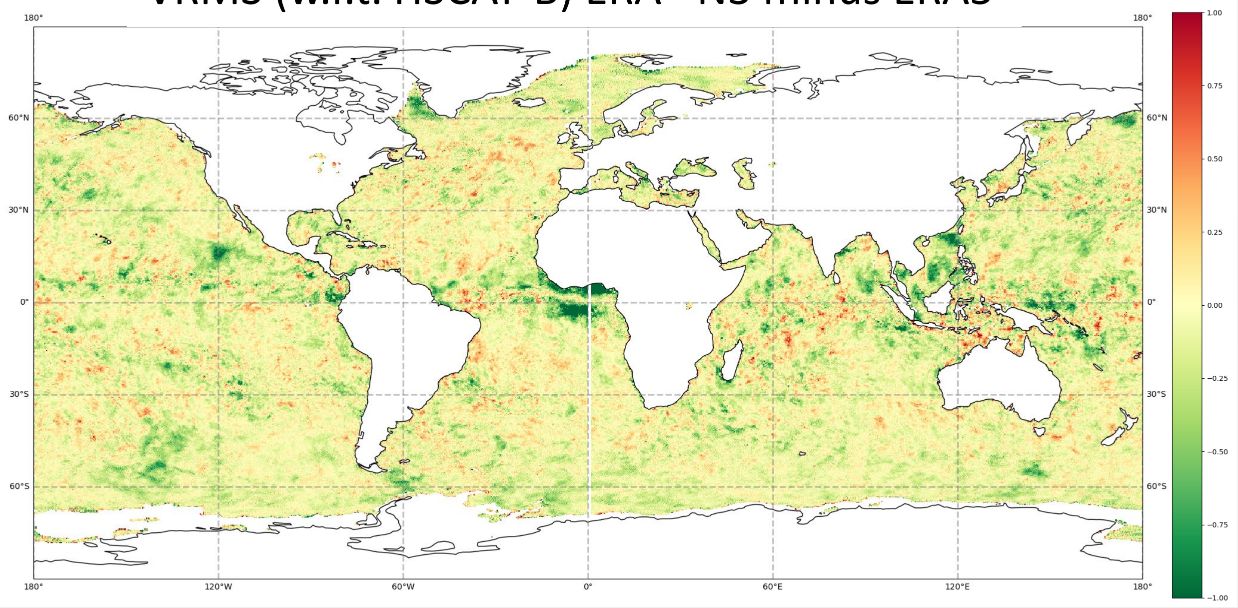
- FNN trained on same months in 2020
- Relatively small improvement in the tropics
- Best results in extra-tropics, error variance reduction up to 10%
- At high latitudes, FNN performs better than ERA* baseline N15 product
- Globally, FNN (**orange**) performance between that of the baseline (**grey**) and the optimized (**blue**) ERA*

Spatial distribution of the errors

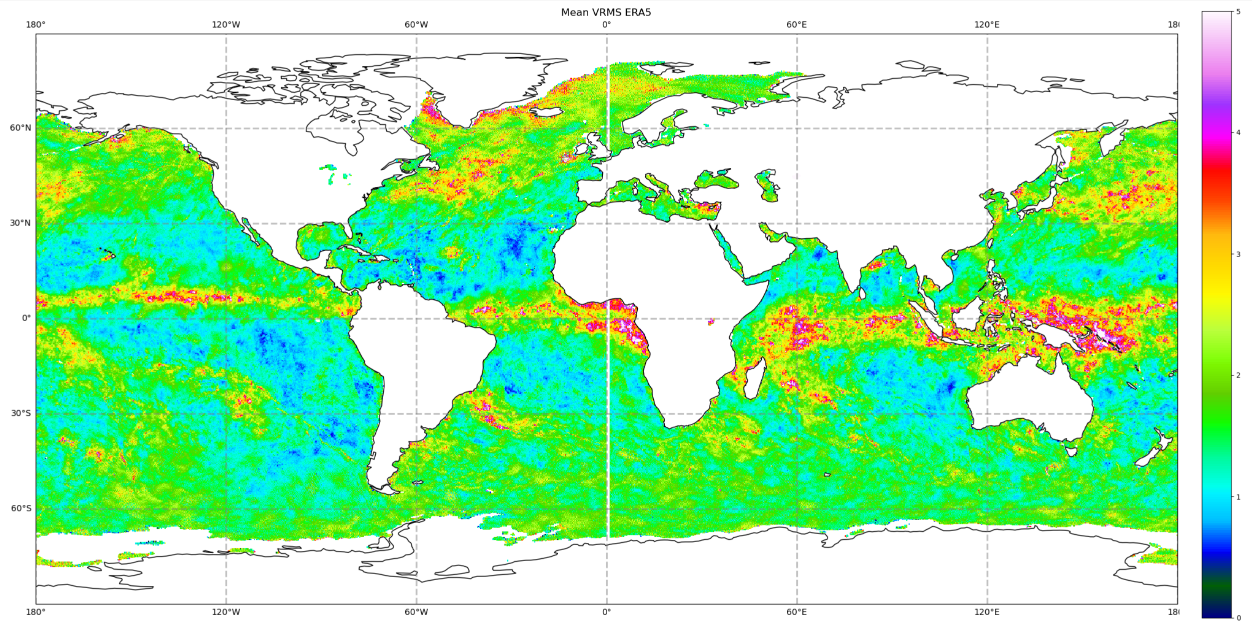
VRMS (w.r.t. HSCAT-B) FNN minus ERA5



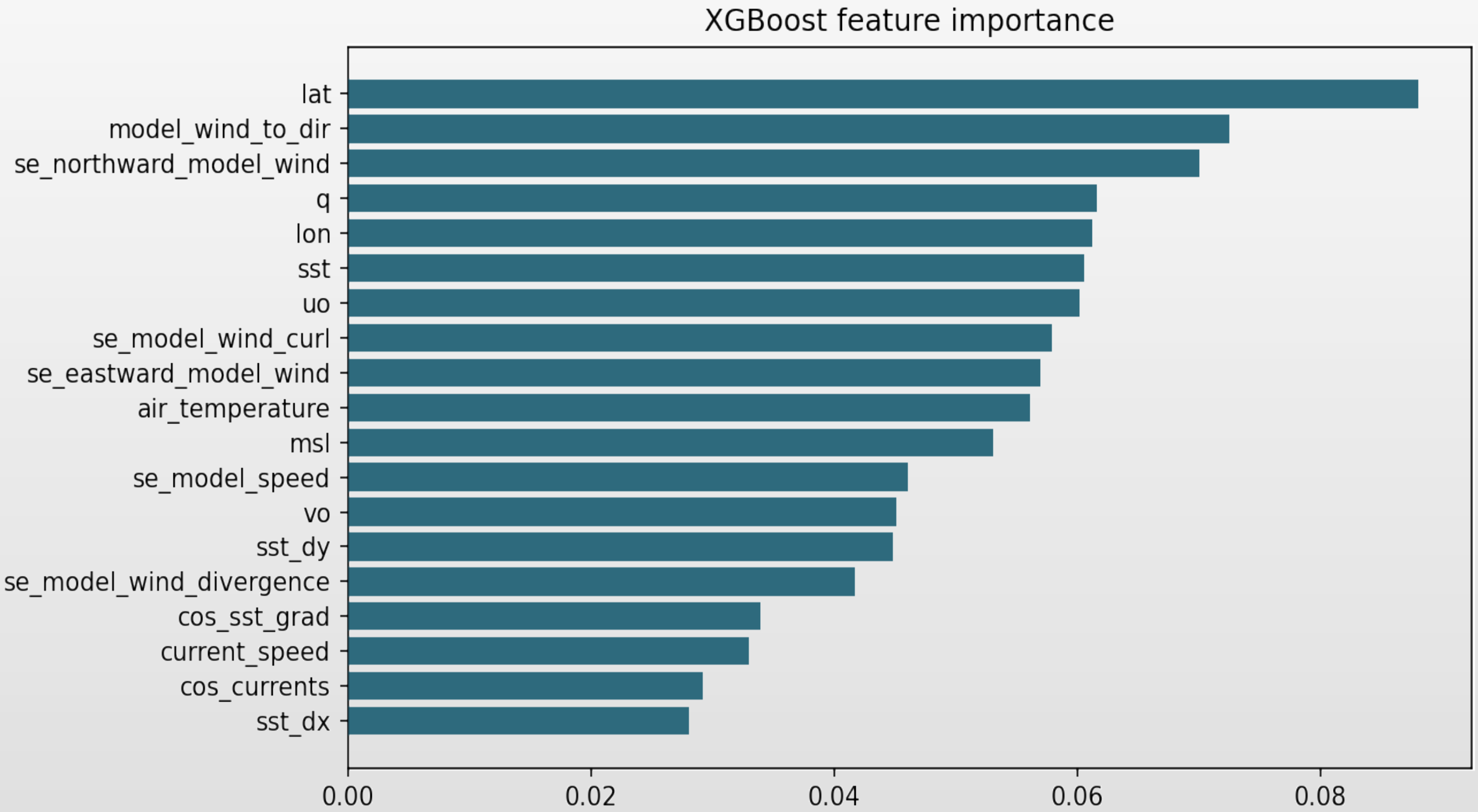
VRMS (w.r.t. HSCAT-B) ERA* N3 minus ERA5



ERA5 VRMS distribution vs HSCAT-B for 02/01 – 10/01/2020



Feature Importance



- Position (lat, lon)
- ERA5 wind (direction & v component)
- Humidity
- SST
- Currents u component
- ERA5 wind curl
- ERA5 wind u component
- Surface air temperature
- Mean sea level pressure

- Some of the input features (air temperature, SST, humidity) are highly correlated, harder to estimate their relevance
- Method used to derive SST gradients wasn't optimal -> noisy gradients with low impact to the model

Datasets: Preliminary analysis

	u_diff	v_diff	lon	lat	se_eastward_model_wind	se_northward_model_wind	se_model_speed	model_wind_to_dir	se_model_wind_divergence	se_model_wind_curl	msl	air_temperature	q	sst	sst_dx	sst_dy	cos_sst_grad	uo	vo	current_speed	cos_currents
u_diff	1	0.01	0	0.04	-0.07	0.05	-0.05	0.06	0.03	0.02	0.03	0.04	0.04	0.07	0	-0.02	0.02	-0.14	0.01	-0.01	0.08
v_diff	0.01	1	-0.01	-0.01	-0.04	0.01	-0.04	0.04	-0.01	-0.07	0	0.02	0.03	0.02	-0	0.02	-0.02	-0.02	-0.07	-0.01	-0
lon	0	-0.01	1	0.11	-0.02	0.03	0.03	0.01	0.01	-0.01	0.08	0.03	-0	0.03	0.01	-0.06	0.05	-0.04	0	-0.07	0.01
lat	0.04	-0.01	0.11	1	-0.17	-0.05	0.13	0.12	-0.02	0.04	0.27	0.13	0.12	0.23	0.04	-0.33	0	-0.16	-0.05	0.07	0.03
se_eastward_model_wind	-0.07	-0.04	-0.02	-0.17	1	0.02	0.29	-0.76	0.01	0	-0.21	-0.4	-0.42	-0.42	0.03	0.08	0.09	0.56	0.07	0.04	-0.06
se_northward_model_wind	0.05	0.01	0.03	-0.05	0.02	1	-0.03	-0.04	0.01	-0	-0	-0	-0.04	-0.01	-0.02	0.03	0.02	-0.04	0.34	-0.05	0.09
se_model_speed	-0.05	-0.04	0.03	0.13	0.29	-0.03	1	-0.21	-0.05	-0.01	-0.25	-0.35	-0.37	-0.35	0.03	-0.04	0.25	0.16	0.03	0.21	-0.02
model_wind_to_dir	0.06	0.04	0.01	0.12	-0.76	-0.04	-0.21	1	-0	-0.01	0.18	0.36	0.37	0.38	-0.02	-0.05	-0.08	-0.44	-0.08	-0.01	0.05
se_model_wind_divergence	0.03	-0.01	0.01	-0.02	0.01	0.01	-0.05	-0	1	0.05	0.18	0.03	-0.02	0.05	0.03	0.02	0.02	-0.01	-0.01	-0.01	0.1
se_model_wind_curl	0.02	-0.07	-0.01	0.04	0	-0	-0.01	-0.01	0.05	1	0.07	0.02	0.01	0.03	0.01	-0	-0.01	-0	0.01	0	0
msl	0.03	0	0.08	0.27	-0.21	-0	-0.25	0.18	0.18	0.07	1	0.59	0.44	0.61	-0.02	-0.04	-0.07	-0.14	-0.03	0.06	0.04
air_temperature	0.04	0.02	0.03	0.13	-0.4	-0	-0.35	0.36	0.03	0.02	0.59	1	0.95	0.98	-0.05	-0	-0.1	-0.28	-0.02	0.17	0.04
q	0.04	0.03	-0	0.12	-0.42	-0.04	-0.37	0.37	-0.02	0.01	0.44	0.95	1	0.93	-0.04	-0.01	-0.1	-0.3	-0.04	0.17	0.03
sst	0.07	0.02	0.03	0.23	-0.42	-0.01	-0.35	0.38	0.05	0.03	0.61	0.98	0.93	1	-0.04	-0.04	-0.11	-0.31	-0.04	0.18	0.07
sst_dx	0	-0	0.01	0.04	0.03	-0.02	0.03	-0.02	0.03	0.01	-0.02	-0.05	-0.04	-0.04	1	-0.04	0.01	0.01	-0.08	0.01	0.05
sst_dy	-0.02	0.02	-0.06	-0.33	0.08	0.03	-0.04	-0.05	0.02	-0	-0.04	-0	-0.01	-0.04	-0.04	1	0.01	0.1	0.03	0.02	-0.05
cos_sst_grad	0.02	-0.02	0.05	0	0.09	0.02	0.25	-0.08	0.02	-0.01	-0.07	-0.1	-0.1	-0.11	0.01	0.01	1	-0.08	-0.04	0.08	0.04
uo	-0.14	-0.02	-0.04	-0.16	0.56	-0.04	0.16	-0.44	-0.01	-0	-0.14	-0.28	-0.3	-0.31	0.01	0.1	-0.08	1	0.03	0.08	-0.1
vo	0.01	-0.07	0	-0.05	0.07	0.34	0.03	-0.08	-0.01	0.01	-0.03	-0.02	-0.04	-0.04	-0.08	0.03	-0.04	0.03	1	-0.01	-0.02
current_speed	-0.01	-0.01	-0.07	0.07	0.04	-0.05	0.21	-0.01	-0.01	0	0.06	0.17	0.17	0.18	0.01	0.02	0.08	0.08	-0.01	1	-0.04
cos_currents	0.08	-0	0.01	0.03	-0.06	0.09	-0.02	0.05	0.1	0	0.04	0.04	0.03	0.07	0.05	-0.05	0.04	-0.1	-0.02	-0.04	1

High correlations between

- Air temperature
- Relative humidity
- Sea surface temperature (SST)
- Mean sea level pressure (msl)

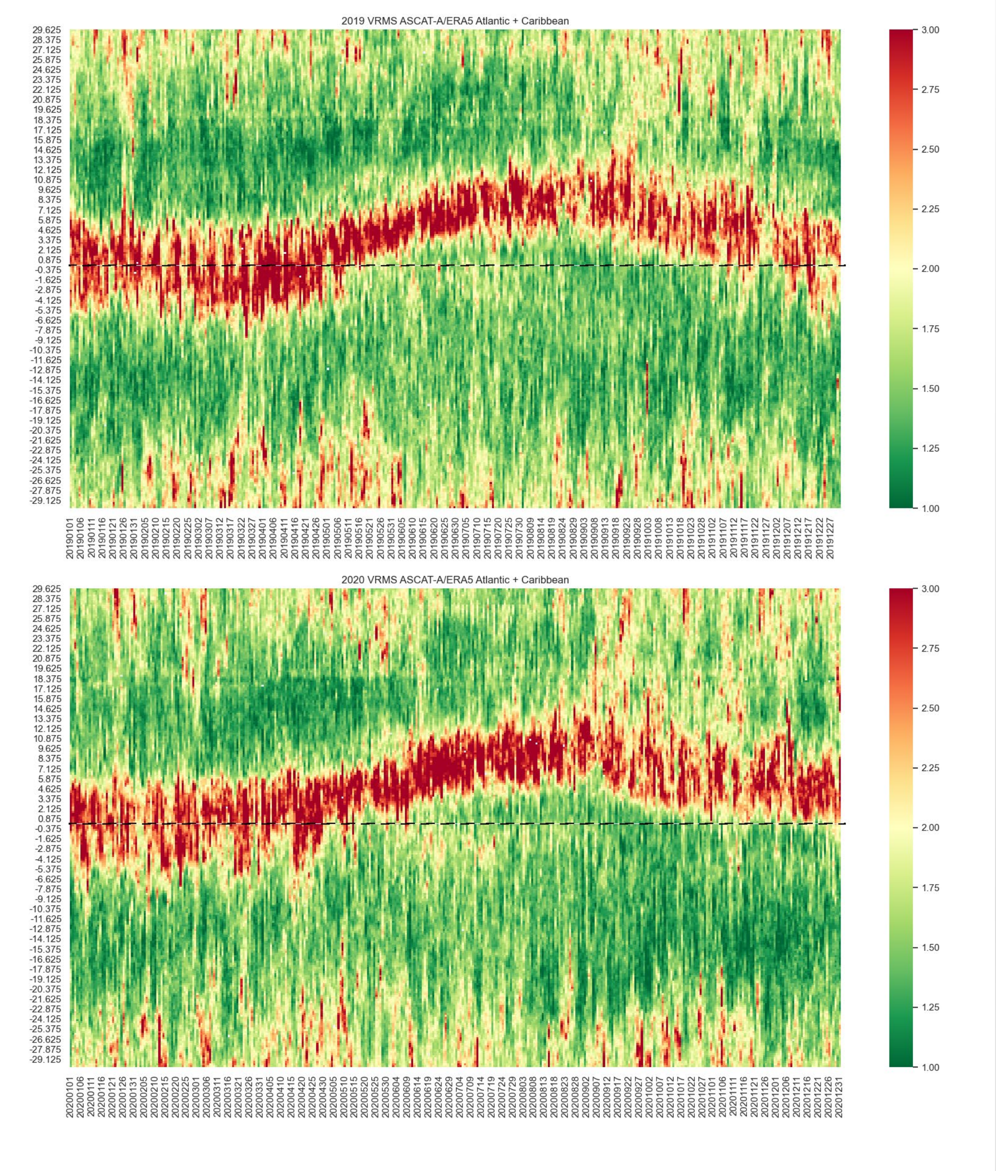
Correlated with latitude:

- SST
- SST meridional gradient
- MSL
- Zonal wind component
- Zonal oceanic velocity
- Temperature
- Humidity

Currents correlated with stress-equivalent wind

Current work

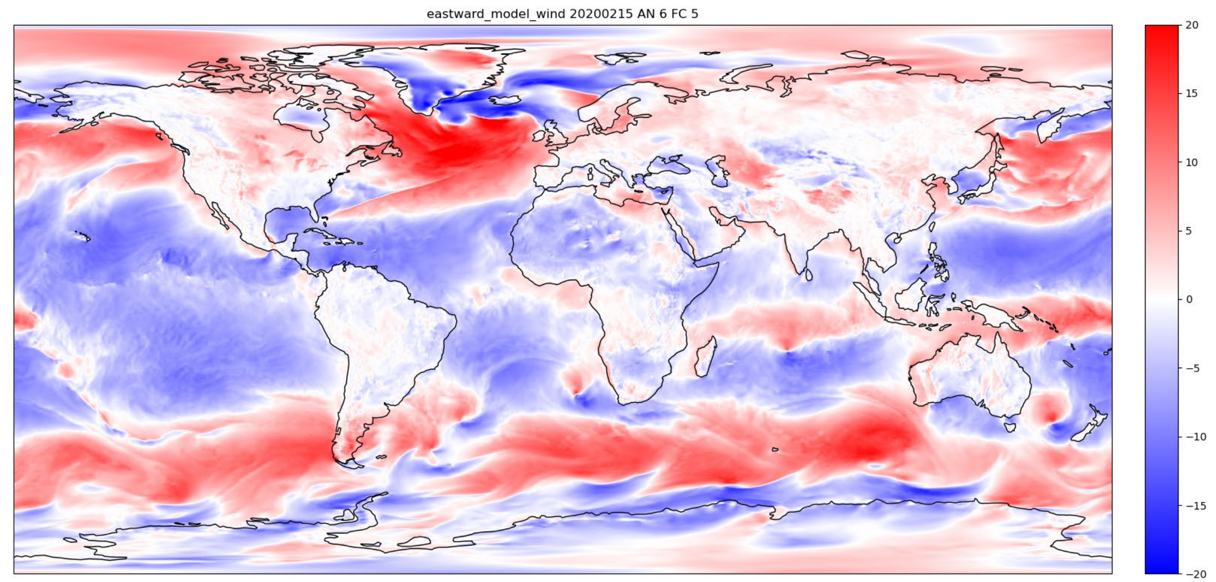
- First tests with CNNs (based on super-resolution networks) do not show significant improvement (work in progress)
- Testing several configurations discarding less important features
- Validation against independent scatterometer HSCAT-B for the same months used in training (2020) but for another year (2019)
- Seasonal analysis of the distribution of the errors to determine the need for dedicated seasonal models



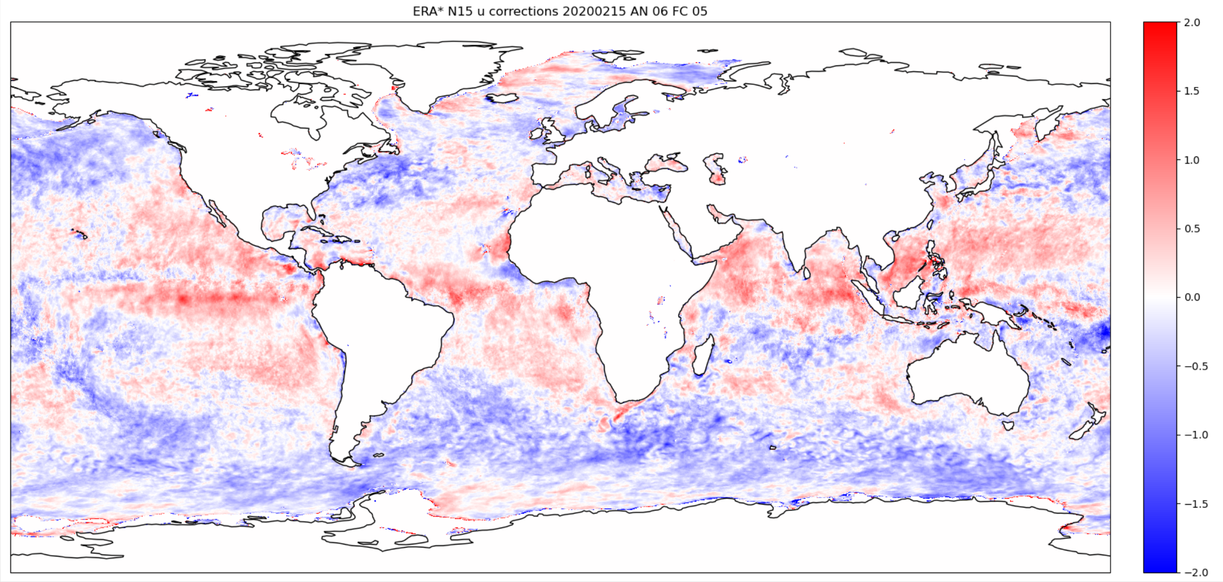
Seasonal variation of ERA5 U10S errors in the tropics for 2019 (top) and 2020 (bottom)

ERA5 U10S and corrections

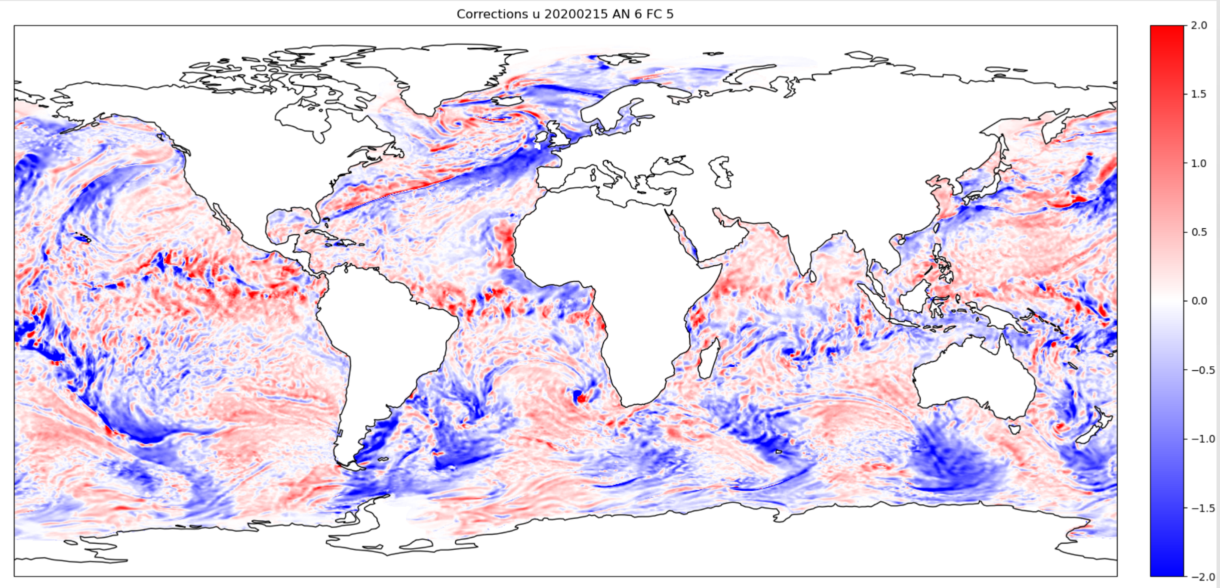
ERA5 u10s



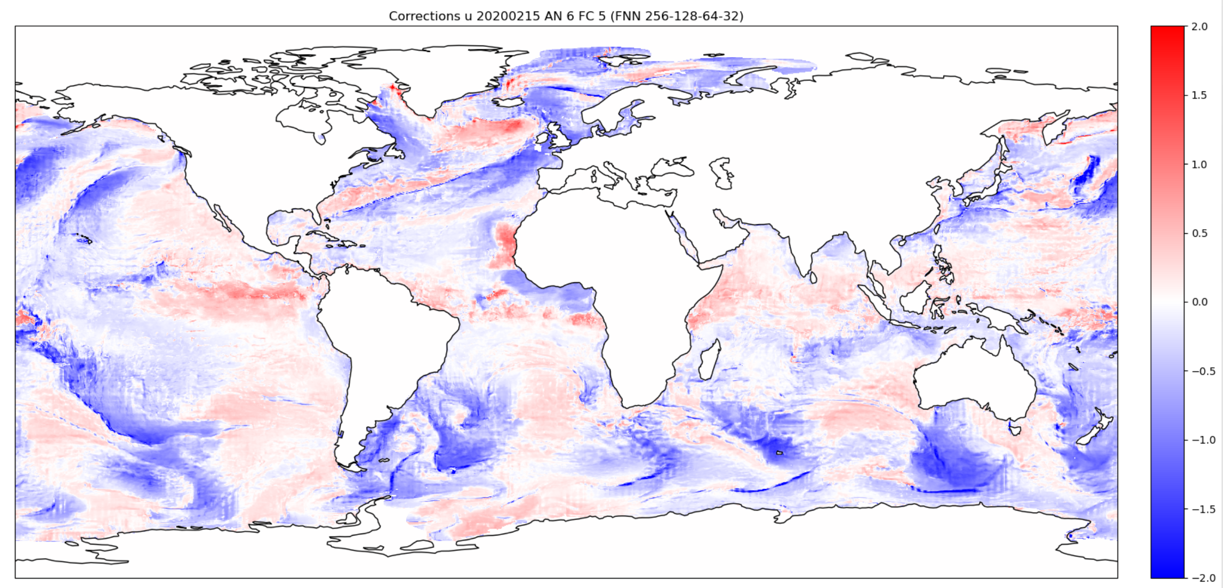
ERA* N15 u10s corrections



EDSR-based model

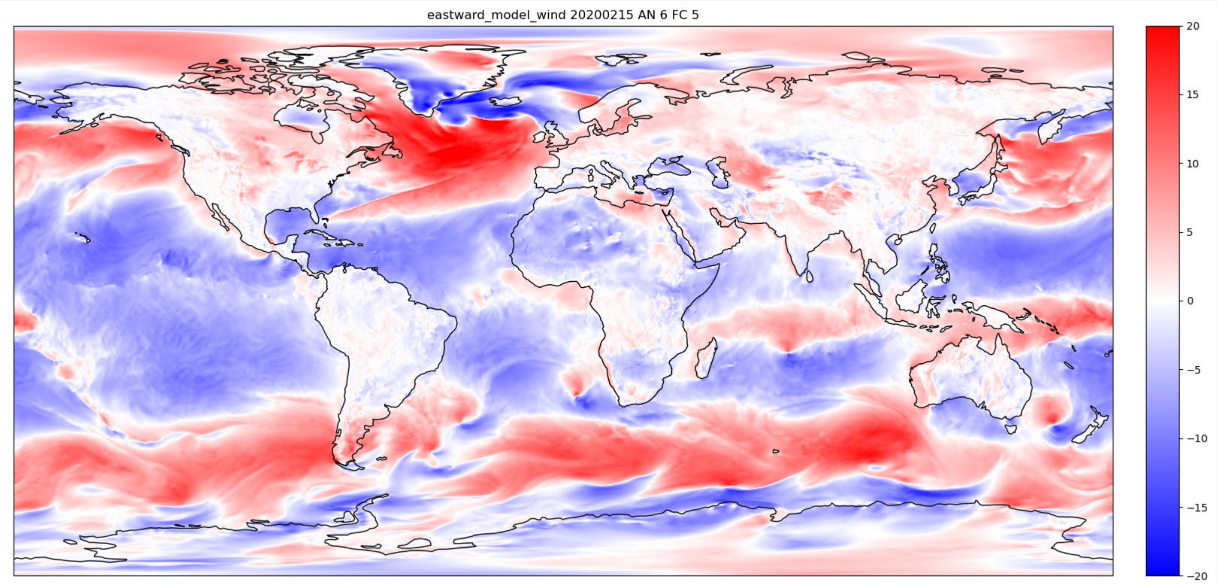


FNN point-per-point

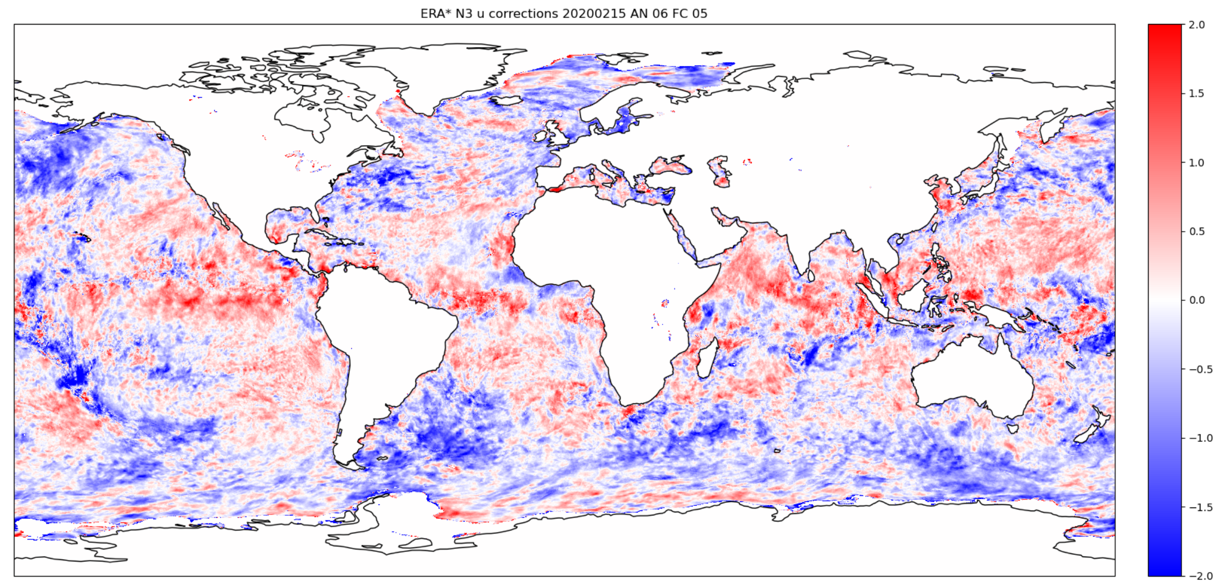


ERA5 U10S and corrections

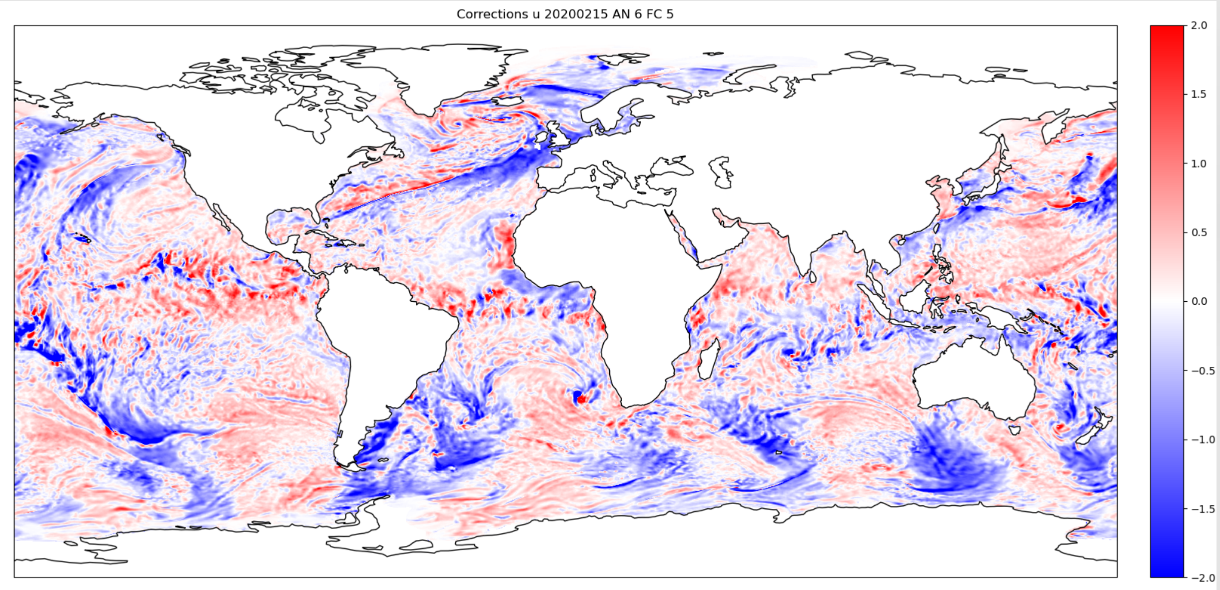
ERA5 u10s



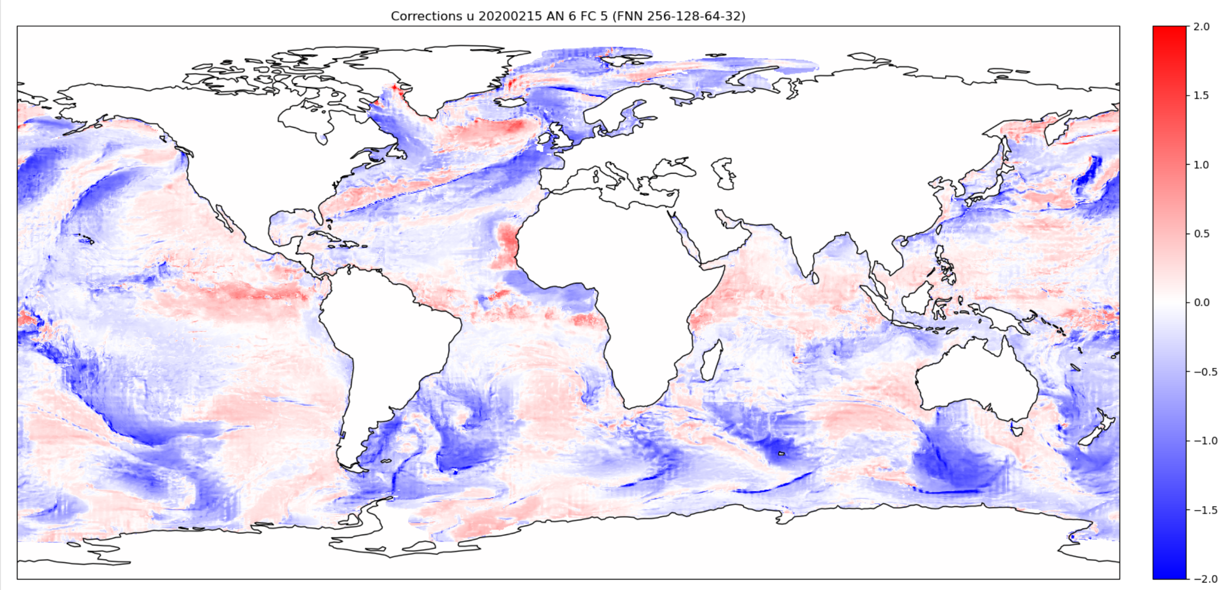
ERA* N3 u10s corrections



EDSR-based model

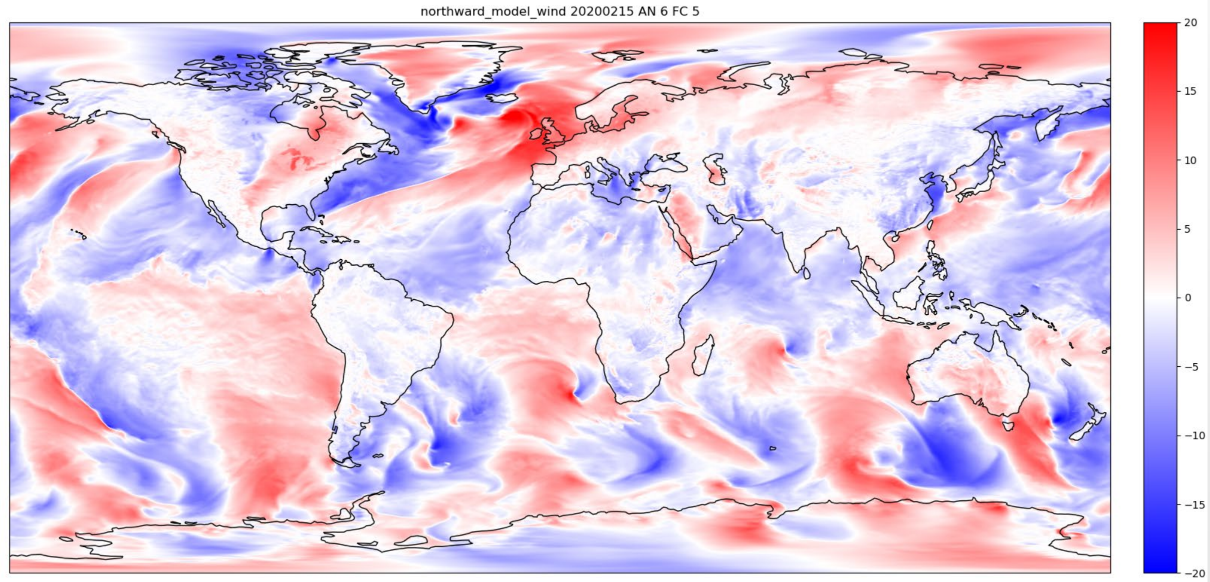


FNN point-per-point

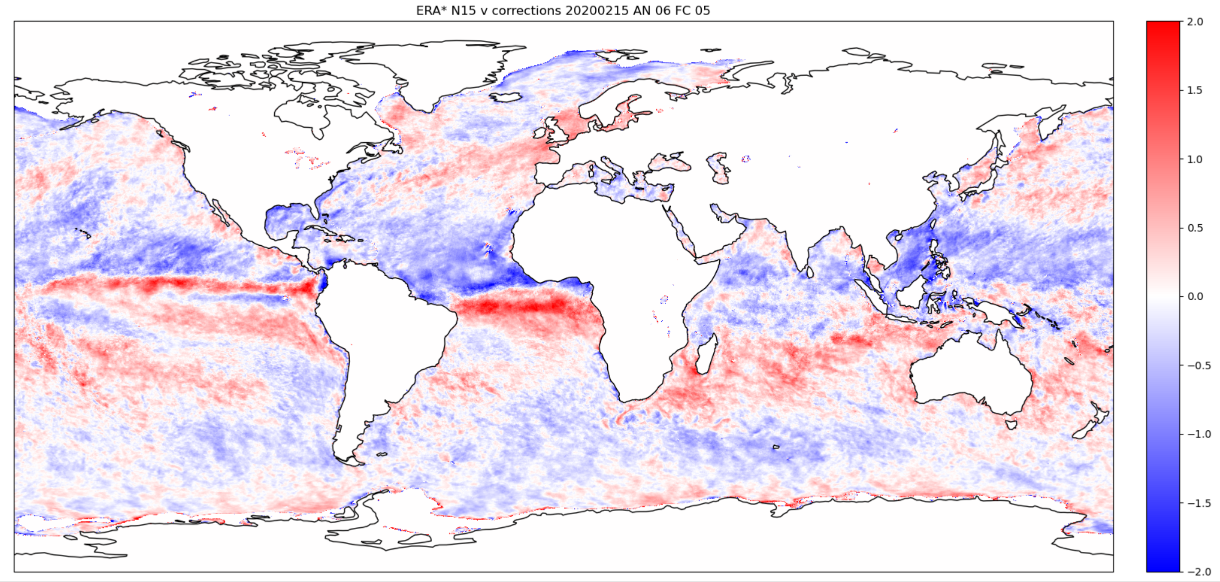


ERA5 U10S and corrections

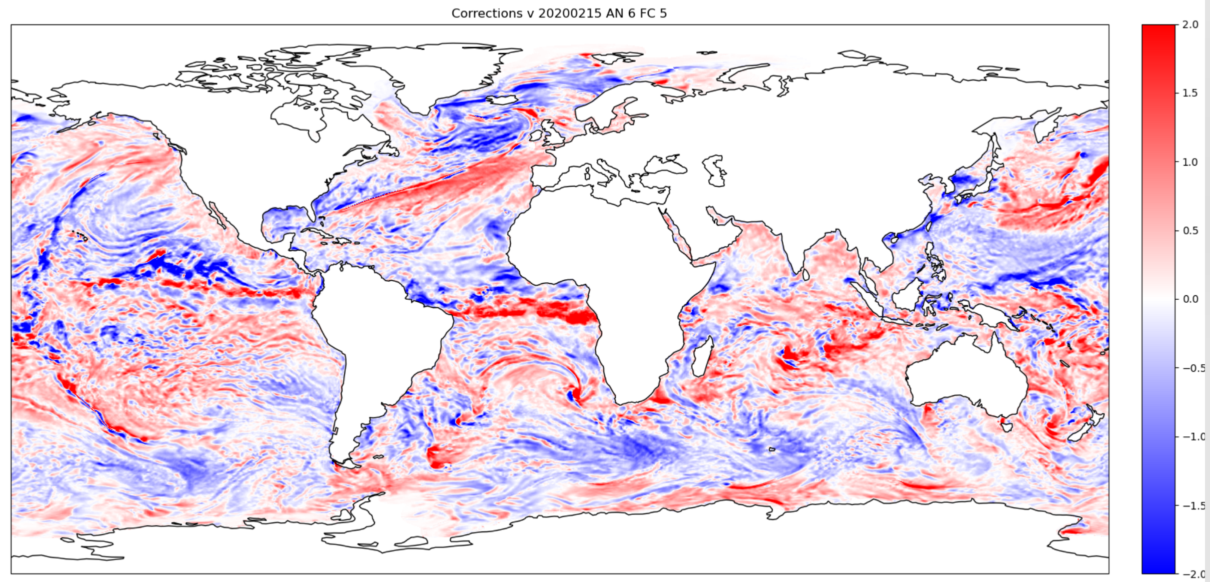
ERA5 v10s



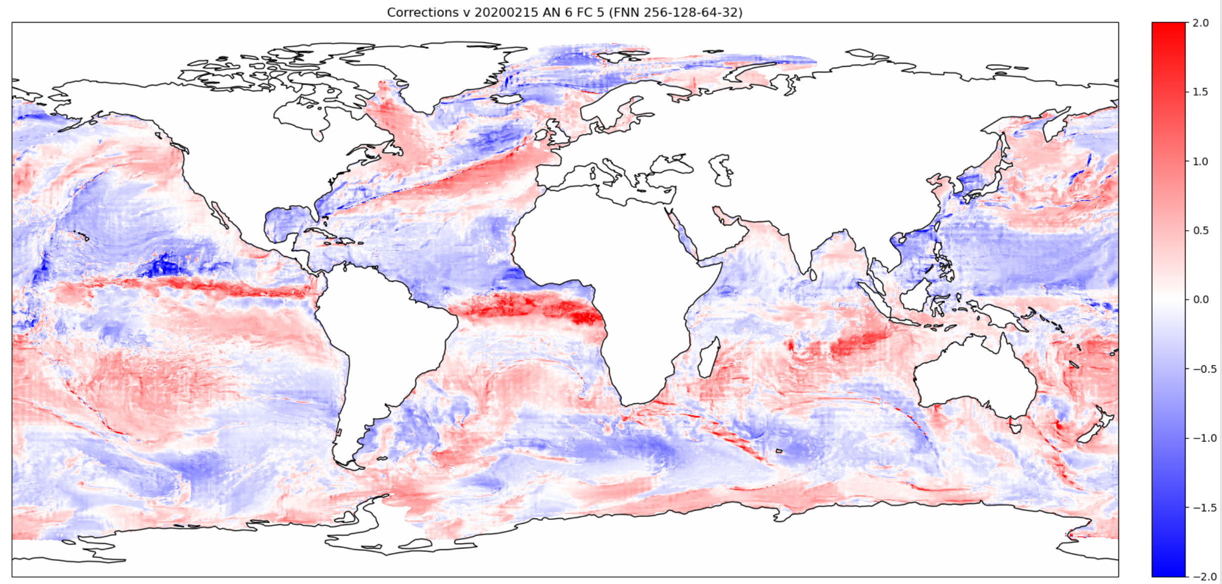
ERA* N15 v10s corrections



EDSR-based model

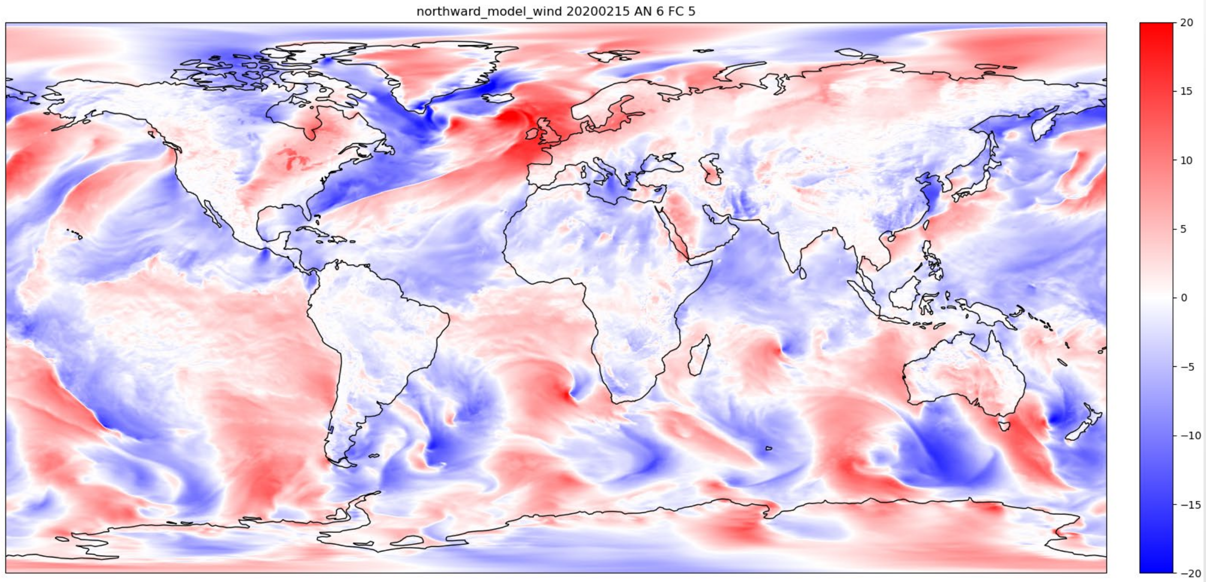


FNN point-per-point

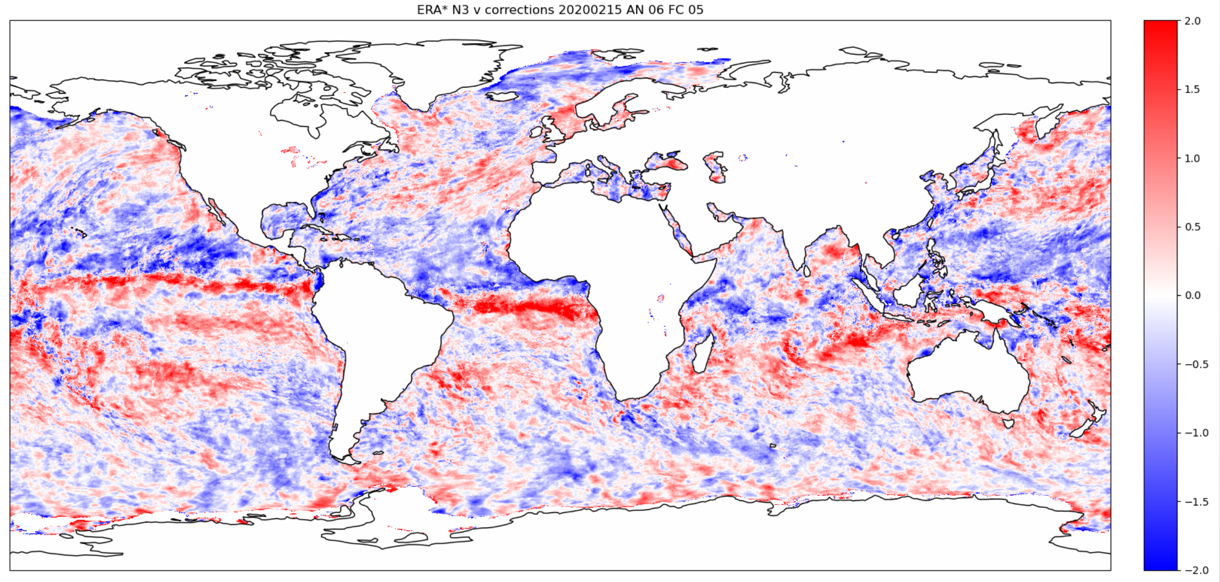


ERA5 U10S and corrections

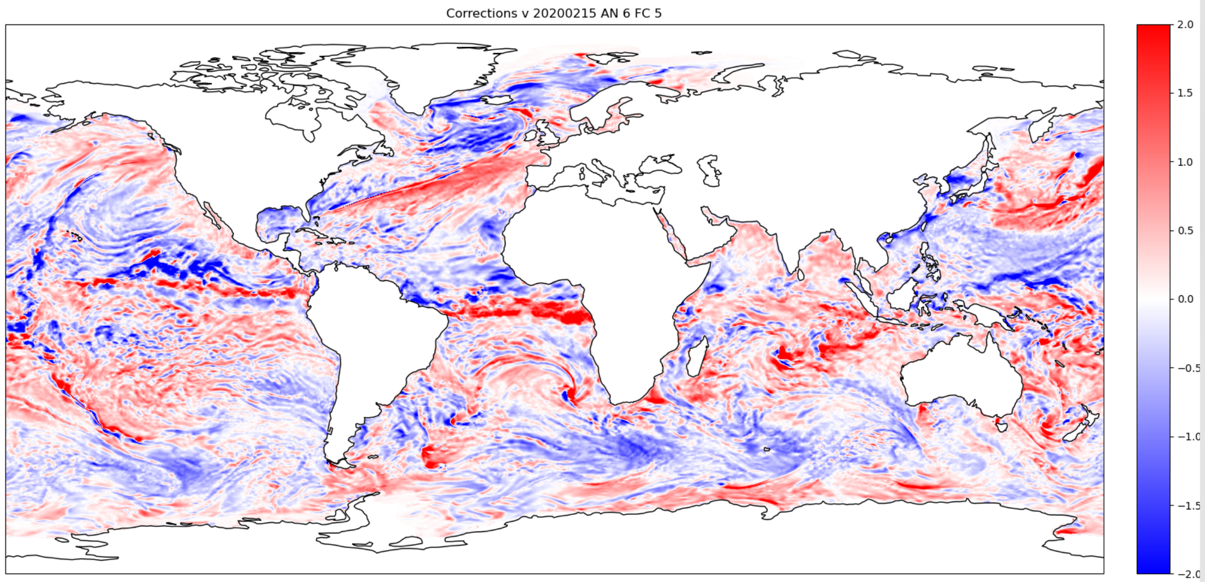
ERA5 v10s



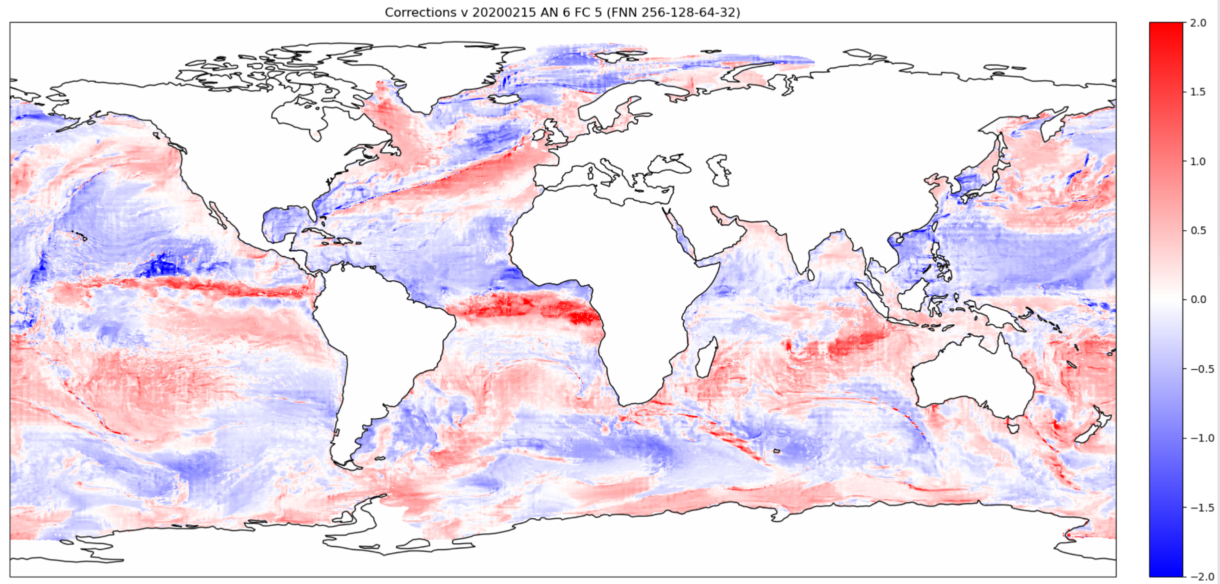
ERA* N3 v10s corrections



EDSR-based model



FNN point-per-point



Conclusions

- Preliminary ML models show that it is possible to predict ERA5 NWP biases using other NWP variables as input
- With FNN models 6.6% error variance reduction achieved globally and 10% in the extra-tropics (vs HSCAT-B, January – March 2019).
- Models trained on a larger dataset can be used for operational purposes
- Model corrections for the training period can be used to enhance reanalysis products (as well as applied to the past periods with no scatterometer data assimilation)

Future Work

- Several seasonal models will be trained and compared against a global model that includes date as input feature
- Generate and validate the corrections for several years
- Try newer algorithms including convolutional neural networks (CNNs), generative adversarial networks (GANS) and diffusion models
- Interpretation of the resulting model to assess in which conditions ERA5 is prone to errors

Acknowledgement: This work has been funded by the EUMETSAT OSI SAF through the OSI_VSA22_01 study

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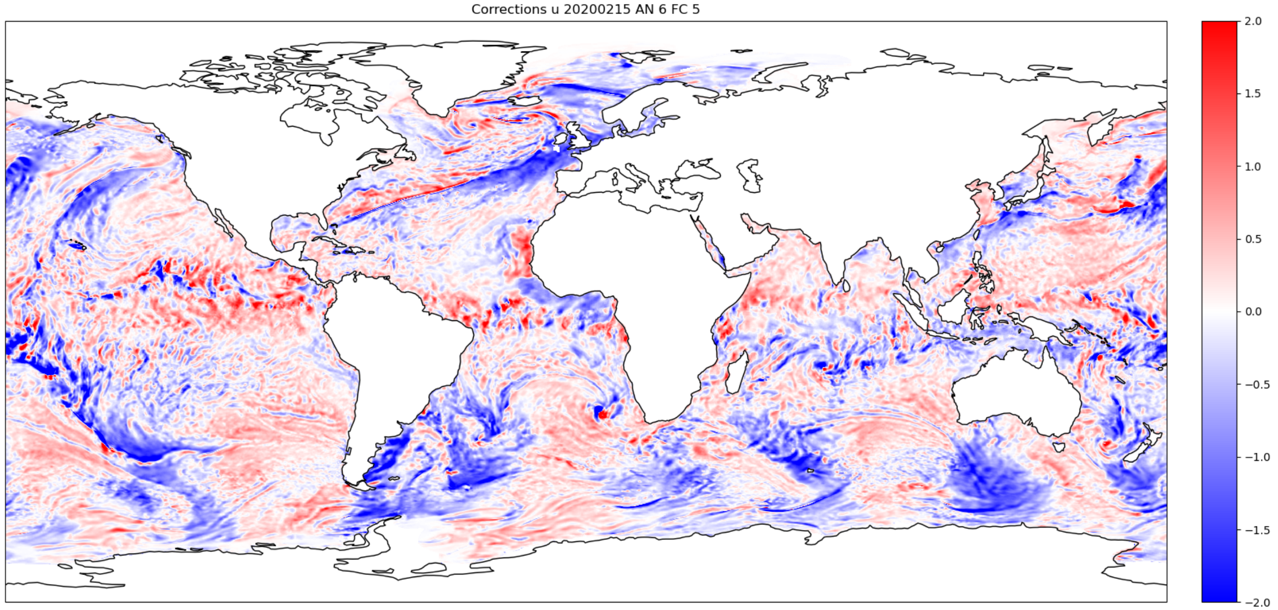
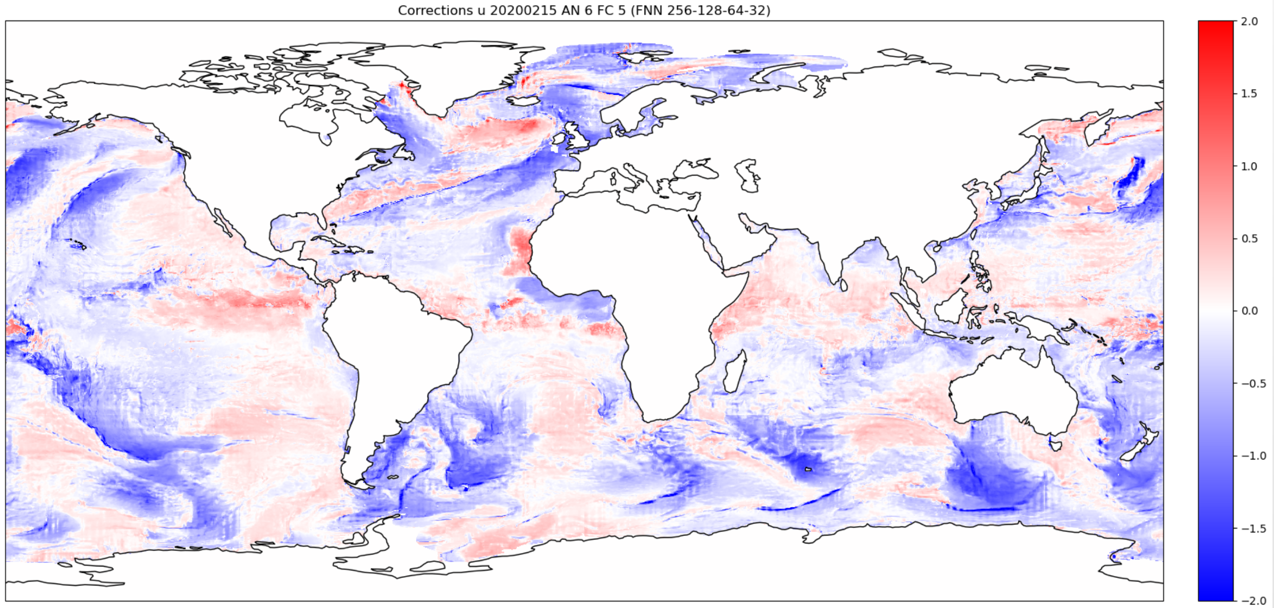
Additional slides

Current work

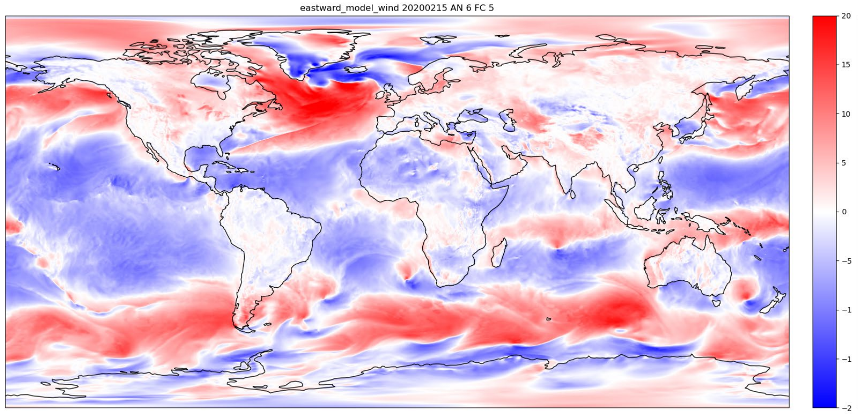
Outputs u-corrections: EDSR-based model



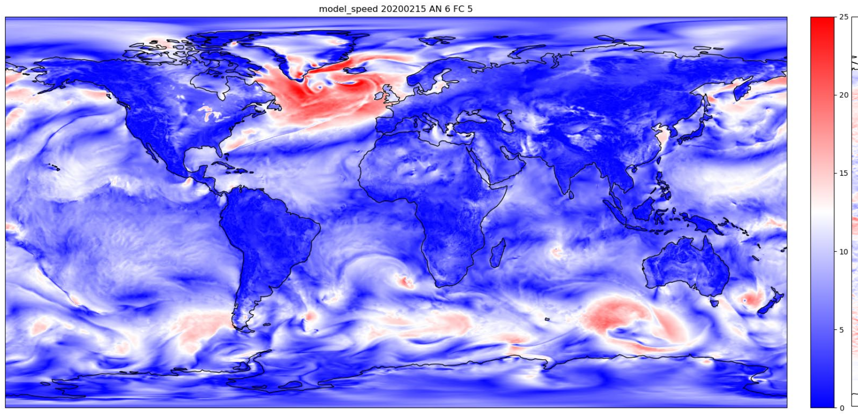
Feed-forward NN point-per-point



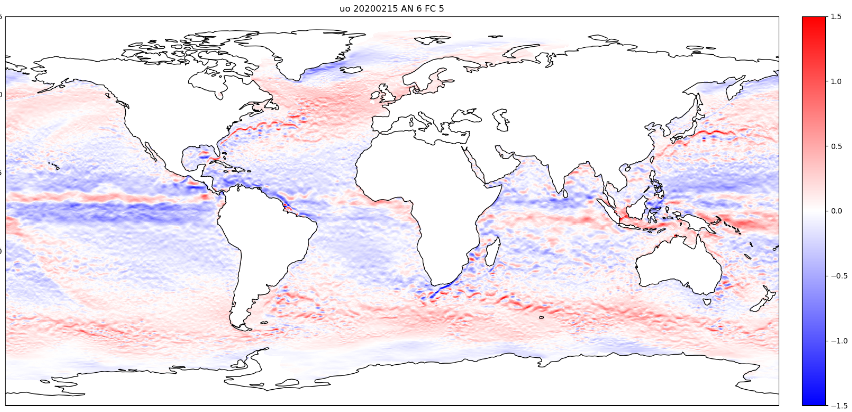
Inputs: ERA5 u10s



ERA5 model speed



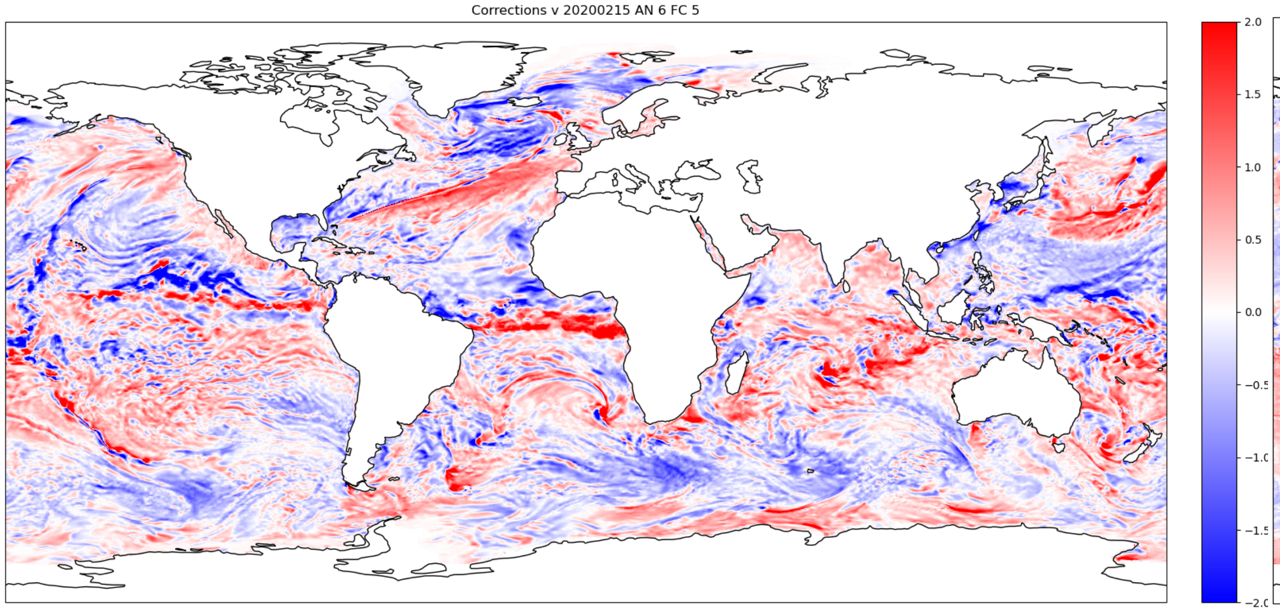
GlobCurrent surface u velocity

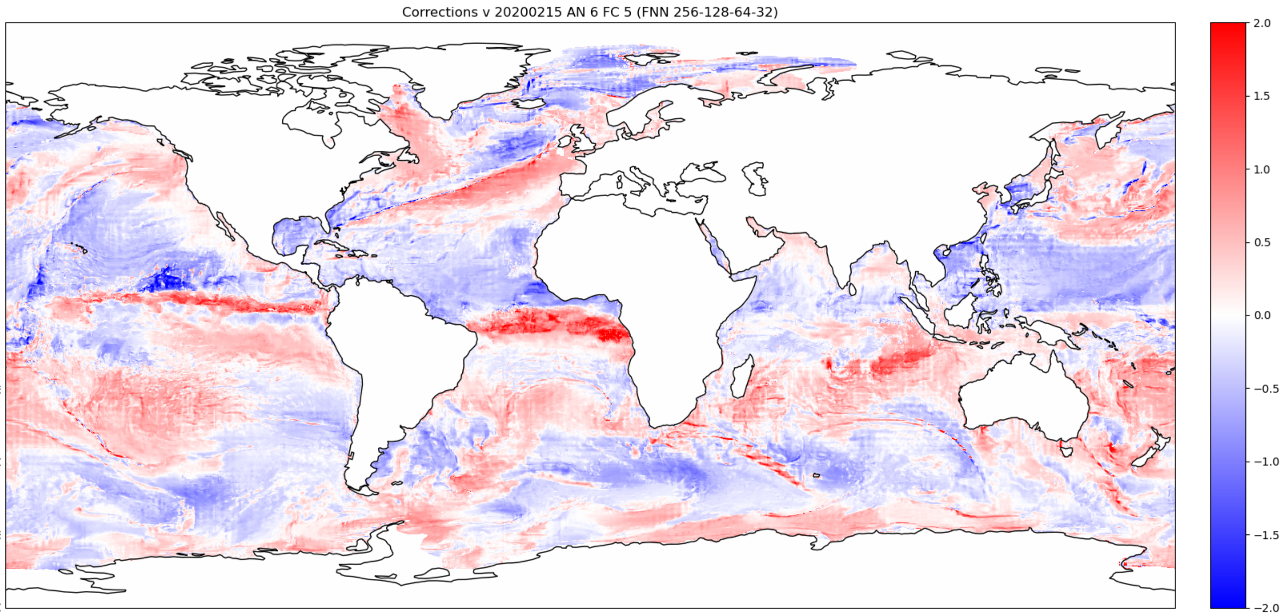


Current work

Outputs v-corrections: EDSR-based model

Feed-forward NN point-per-point

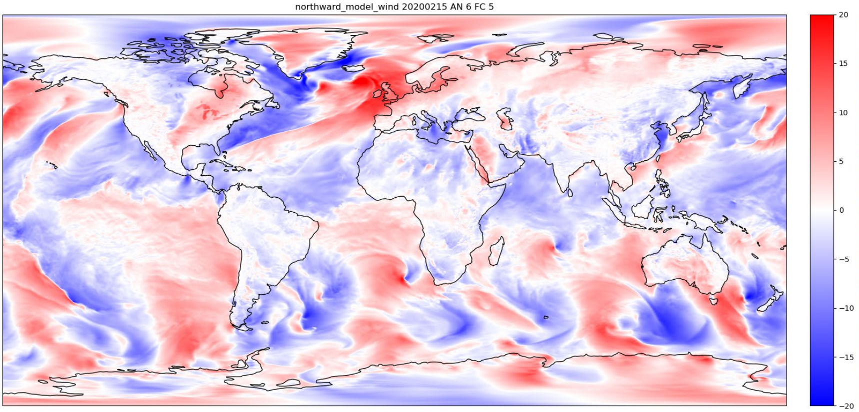


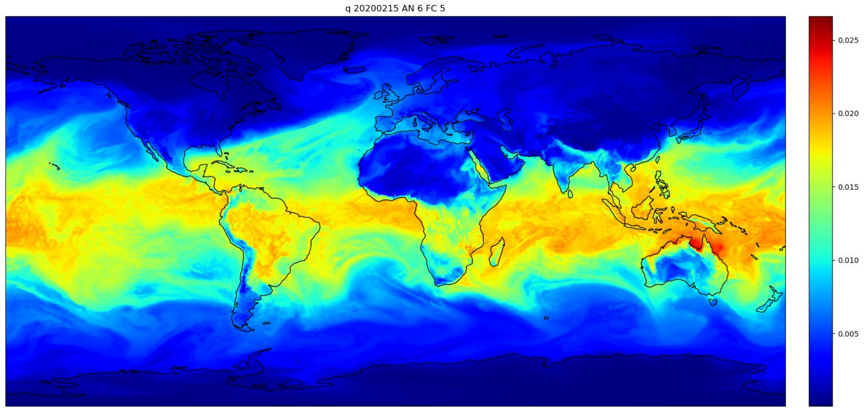


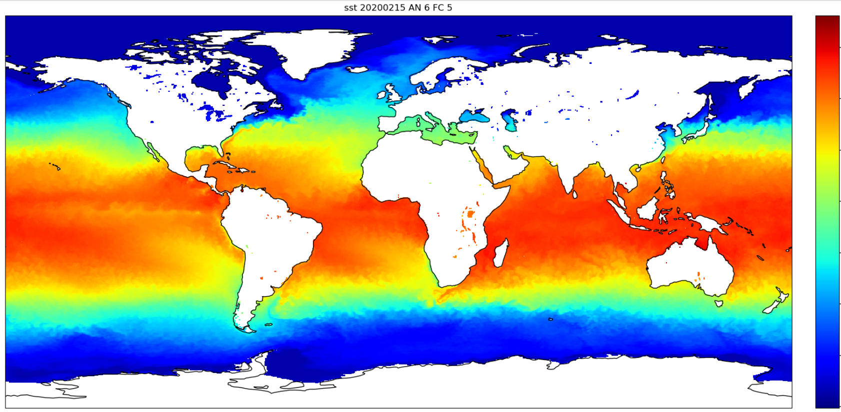
Inputs: ERA5 v10s

ERA5 specific humidity

ERA5 SST







4. Datasets: Preliminary analysis

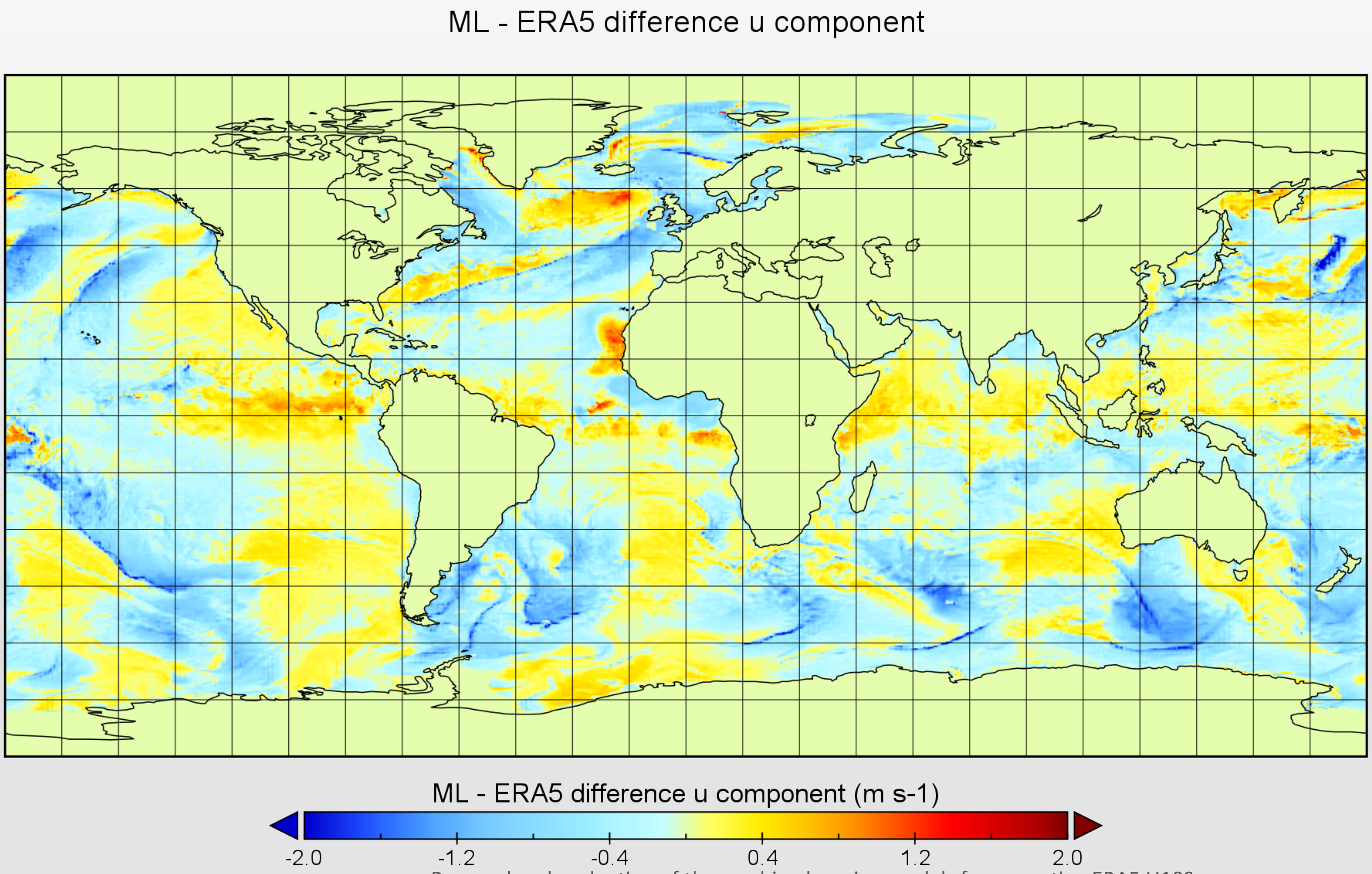
	u_diff	v_diff	lon	lat	se_eastward_model_wind	se_northward_model_wind	se_model_speed	model_wind_to_dir	se_model_wind_divergence	se_model_wind_curl	msl	air_temperature	q	sst	sst_dx	sst_dy	cos_sst_grad	uo	vo	current_speed	cos_currents
u_diff	1	0.01	0	0.04	-0.07	0.05	-0.05	0.06	0.03	0.02	0.03	0.04	0.04	0.07	0	-0.02	0.02	-0.14	0.01	-0.01	0.08
v_diff	0.01	1	-0.01	-0.01	-0.04	0.01	-0.04	0.04	-0.01	-0.07	0	0.02	0.03	0.02	-0	0.02	-0.02	-0.02	-0.07	-0.01	-0
lon	0	-0.01	1	0.11	-0.02	0.03	0.03	0.01	0.01	-0.01	0.08	0.03	-0	0.03	0.01	-0.06	0.05	-0.04	0	-0.07	0.01
lat	0.04	-0.01	0.11	1	-0.17	-0.05	0.13	0.12	-0.02	0.04	0.27	0.13	0.12	0.23	0.04	-0.33	0	-0.16	-0.05	0.07	0.03
se_eastward_model_wind	-0.07	-0.04	-0.02	-0.17	1	0.02	0.29	-0.76	0.01	0	-0.21	-0.4	-0.42	-0.42	0.03	0.08	0.09	0.56	0.07	0.04	-0.06
se_northward_model_wind	0.05	0.01	0.03	-0.05	0.02	1	-0.03	-0.04	0.01	-0	-0	-0	-0.04	-0.01	-0.02	0.03	0.02	-0.04	0.34	-0.05	0.09
se_model_speed	-0.05	-0.04	0.03	0.13	0.29	-0.03	1	-0.21	-0.05	-0.01	-0.25	-0.35	-0.37	-0.35	0.03	-0.04	0.25	0.16	0.03	0.21	-0.02
model_wind_to_dir	0.06	0.04	0.01	0.12	-0.76	-0.04	-0.21	1	-0	-0.01	0.18	0.36	0.37	0.38	-0.02	-0.05	-0.08	-0.44	-0.08	-0.01	0.05
se_model_wind_divergence	0.03	-0.01	0.01	-0.02	0.01	0.01	-0.05	-0	1	0.05	0.18	0.03	-0.02	0.05	0.03	0.02	0.02	-0.01	-0.01	-0.01	0.1
se_model_wind_curl	0.02	-0.07	-0.01	0.04	0	-0	-0.01	-0.01	0.05	1	0.07	0.02	0.01	0.03	0.01	-0	-0.01	-0	0.01	0	0
msl	0.03	0	0.08	0.27	-0.21	-0	-0.25	0.18	0.18	0.07	1	0.59	0.44	0.61	-0.02	-0.04	-0.07	-0.14	-0.03	0.06	0.04
air_temperature	0.04	0.02	0.03	0.13	-0.4	-0	-0.35	0.36	0.03	0.02	0.59	1	0.95	0.98	-0.05	-0	-0.1	-0.28	-0.02	0.17	0.04
q	0.04	0.03	-0	0.12	-0.42	-0.04	-0.37	0.37	-0.02	0.01	0.44	0.95	1	0.93	-0.04	-0.01	-0.1	-0.3	-0.04	0.17	0.03
sst	0.07	0.02	0.03	0.23	-0.42	-0.01	-0.35	0.38	0.05	0.03	0.61	0.98	0.93	1	-0.04	-0.04	-0.11	-0.31	-0.04	0.18	0.07
sst_dx	0	-0	0.01	0.04	0.03	-0.02	0.03	-0.02	0.03	0.01	-0.02	-0.05	-0.04	-0.04	1	-0.04	0.01	0.01	-0.08	0.01	0.05
sst_dy	-0.02	0.02	-0.06	-0.33	0.08	0.03	-0.04	-0.05	0.02	-0	-0.04	-0	-0.01	-0.04	-0.04	1	0.01	0.1	0.03	0.02	-0.05
cos_sst_grad	0.02	-0.02	0.05	0	0.09	0.02	0.25	-0.08	0.02	-0.01	-0.07	-0.1	-0.1	-0.11	0.01	0.01	1	-0.08	-0.04	0.08	0.04
uo	-0.14	-0.02	-0.04	-0.16	0.56	-0.04	0.16	-0.44	-0.01	-0	-0.14	-0.28	-0.3	-0.31	0.01	0.1	-0.08	1	0.03	0.08	-0.1
vo	0.01	-0.07	0	-0.05	0.07	0.34	0.03	-0.08	-0.01	0.01	-0.03	-0.02	-0.04	-0.04	-0.08	0.03	-0.04	0.03	1	-0.01	-0.02
current_speed	-0.01	-0.01	-0.07	0.07	0.04	-0.05	0.21	-0.01	-0.01	0	0.06	0.17	0.17	0.18	0.01	0.02	0.08	0.08	-0.01	1	-0.04
cos_currents	0.08	-0	0.01	0.03	-0.06	0.09	-0.02	0.05	0.1	0	0.04	0.04	0.03	0.07	0.05	-0.05	0.04	-0.1	-0.02	-0.04	1

High correlations between
- Air temperature
- Relative humidity
- Sea surface temperature (SST)
- Mean sea level pressure (msl)

Correlated with latitude:
- SST
- SST meridional gradient
- MSL
- Zonal wind component
- Zonal oceanic velocity
- Temperature
- Humidity

Currents correlated with stress-equivalent wind

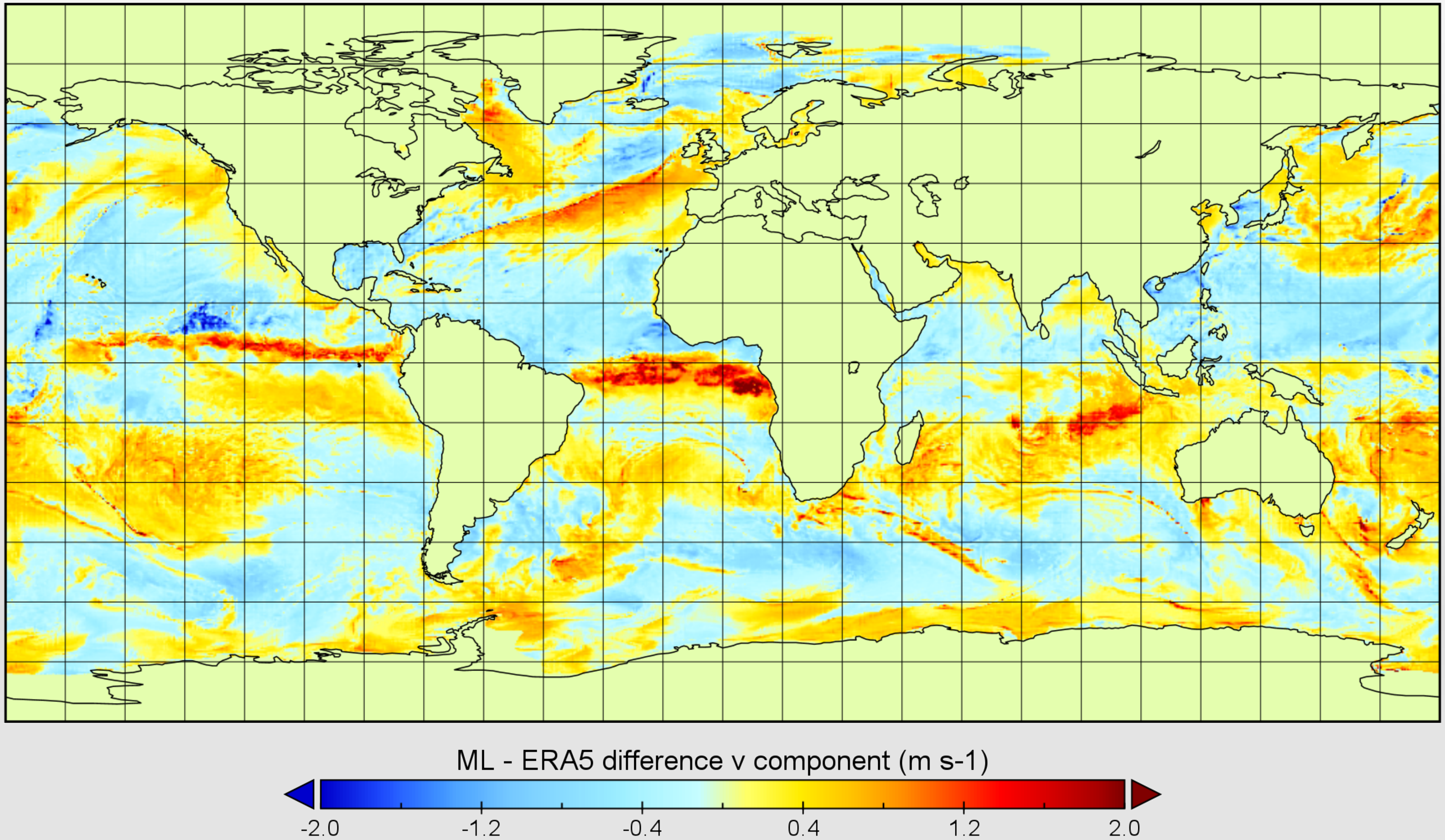
Generated output



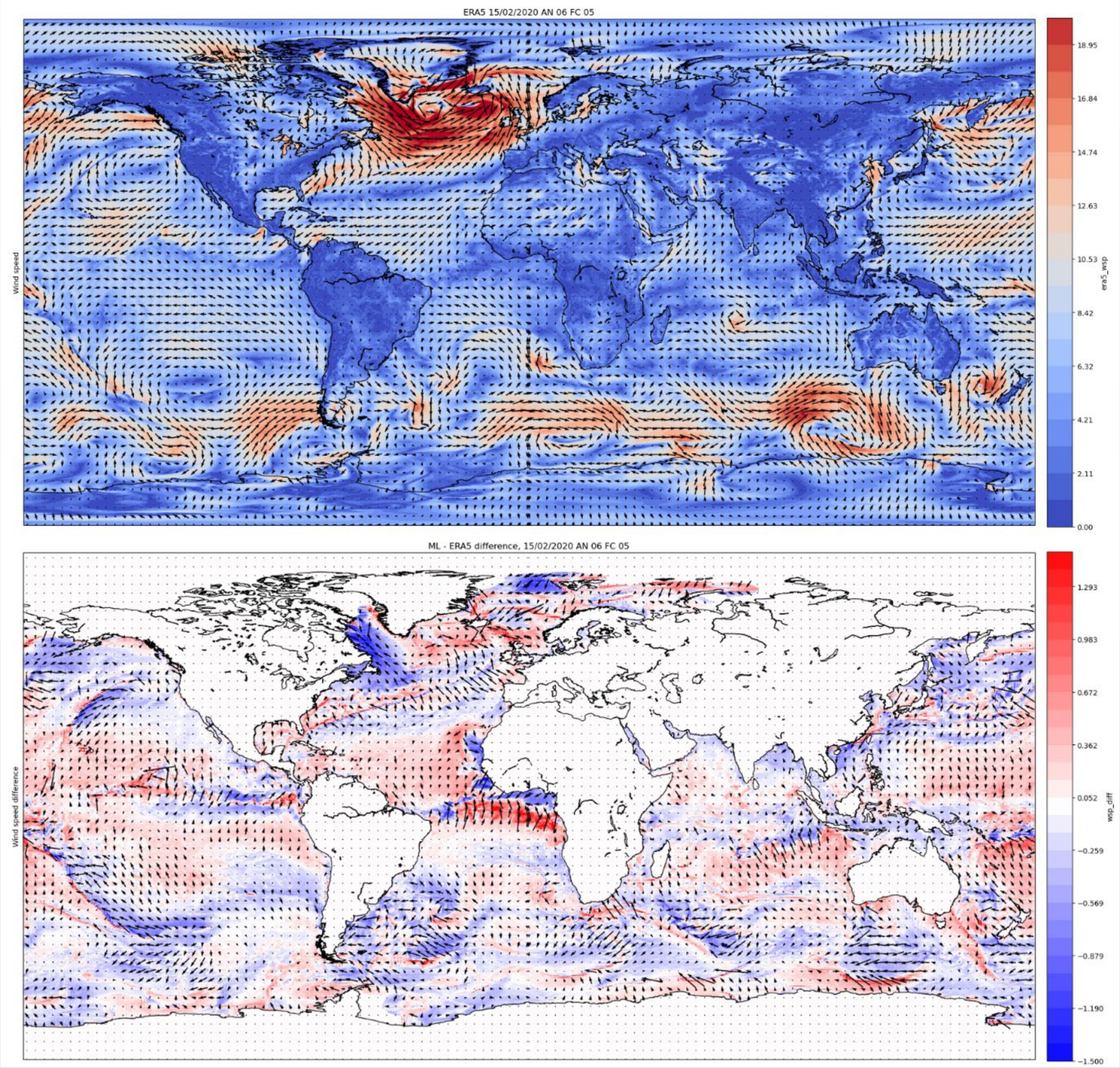
15 February 2020
AN 06 FC 05
11 AM UTC
Tensorflow FNN output
(256 – 128 – 64 – 32)

Generated output

ML - ERA5 difference v component



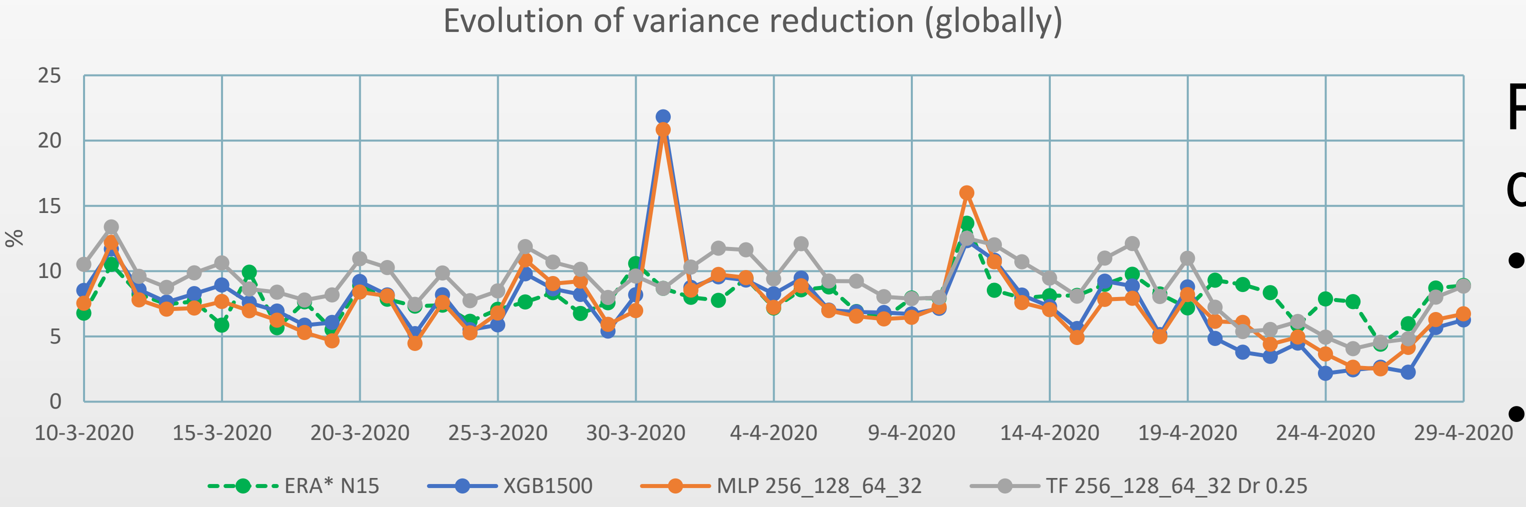
15 February 2020
AN 06 FC 05
11 AM UTC
Tensorflow FNN output
(256 – 128 – 64 – 32)



ERA5 stress-equivalent wind field for 15/02/2020 11:00 UTC, the +5h forecast from the 06:00 analysis (above) and predicted scatterometer differences (below). Background shows wind intensity (above) and predicted difference in wind intensity (below). Arrows show ERA5 wind field (above) and vector difference between corrected field and ERA5 (below).

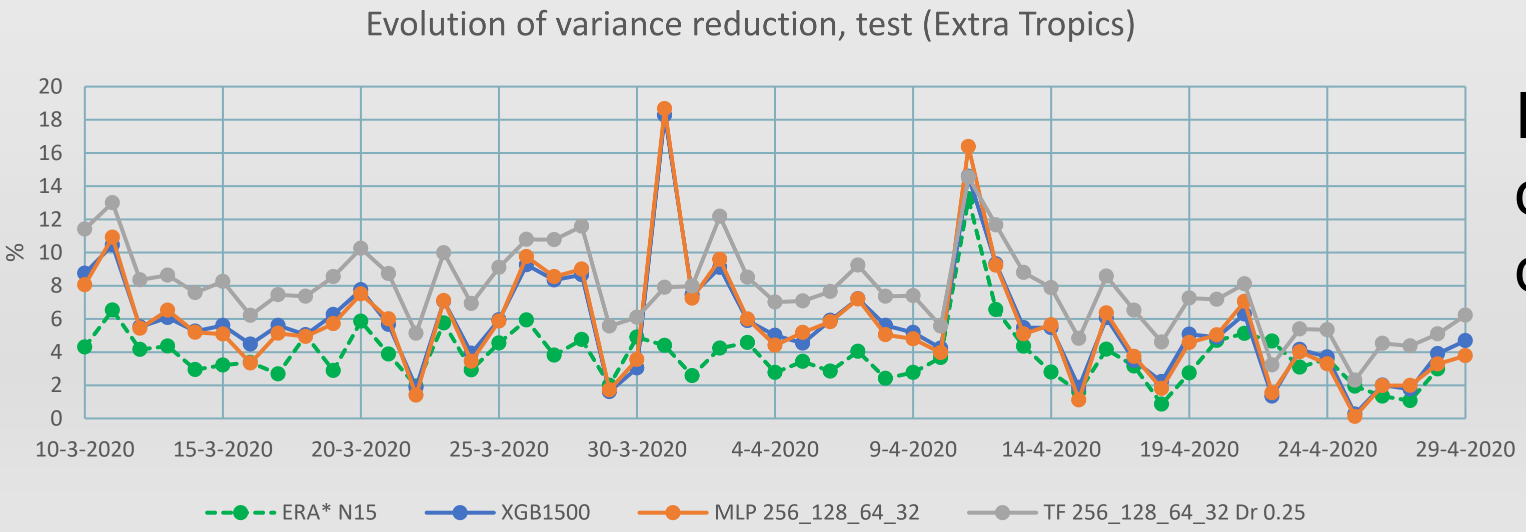
Tensorflow FNN output (256 – 128 – 64 – 32)

Results



Performance degradation ~ 40 days after the training period

- Training only on 65 days of data
- Seasonal variability



In the extra-tropics, TF model outperforms ERA* even after the degradation