Development of multi-parametric Geophysical Modulation Function for scatterometry wind vector retrievals

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Motivation and Objectives

Radar backscattered signal sensitivity and noise properties are different for different microwave bands and incidence angles:

- **nadir:** determined by specular sea surface reflections; sensitive to significant wave height, wind speed
- **near-nadir:** impacted by long wave sea surface modulation; sensitive to the gravitational wave directional spectrum, wind direction (sigma0 goes down with wind speed)
- **moderate angles:** determined mostly by resonant scattering and linked tightly to short capillary wave spectrum, pronounced difference between vertical and horizontal polarizations, sensitive wind vector (sigma0 goes up with wind speed), SST, sea surface currents …

- **C-band:** longer sensing microwave length, backscatter signal contributed by sea surface waves with wavelength ~5 cm. Low sensitivity to precipitations.
- **Ku-band:** smaller sensing microwave length, backscatter signal contributed by sea surface waves with wavelength ~1 cm. High sensitivity to precipitations.

The combined use of collocated multi-angle radar observations potentially allows the improvement of the quality of retrieved geophysical variables, as well, the number of variables involved in the analysis could be extended.

However, every additional variable drastically increases the complexity of the radar backscattering model. The widely used Look–Up Table approach hardly could be extended for high-dimensional models due to exponentially increasing computational costs and memory demands. This problem could be resolved using neural networks as universal approximators to compress final radar backscattering models for the geophysical inversion.

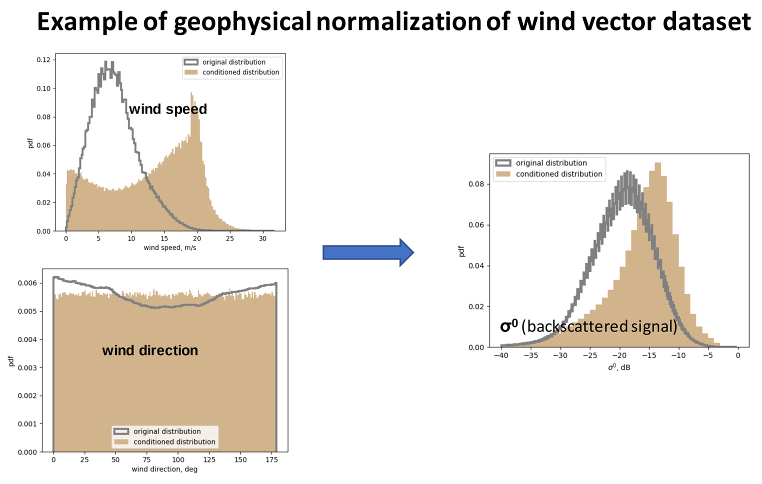
Normalization of input data

Geophysical variables are distributed unevenly. This means that we are most likely will learn values that belong to a narrow range of most probable meteorological situations.

The dataset was conditioned according to the following scheme:

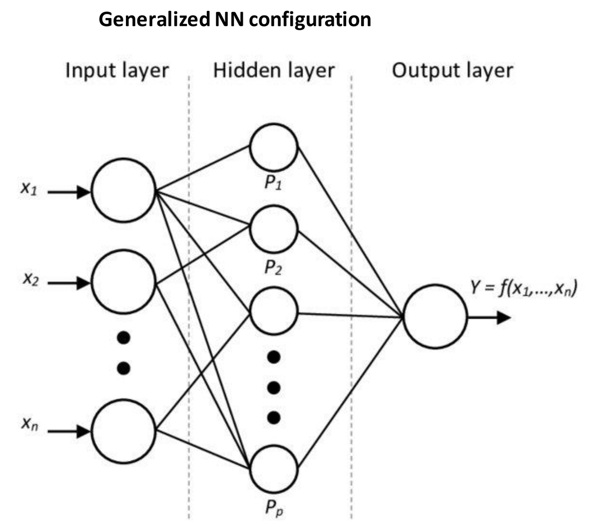
1. The appearance frequency of variable value estimated through the PDF of distribution P(x)
2. The values from original dataset selected randomly with the probability 1/P(x)*μ (μ is the condition variable)
3. This approach reduces the learning dataset by factor 100. Eg. for 30 days observation period we have only ~10M sigma0
4. Then data is ready for the typical normalization to use as learning dataset for neural network

Example of geophysical normalization of wind vector dataset

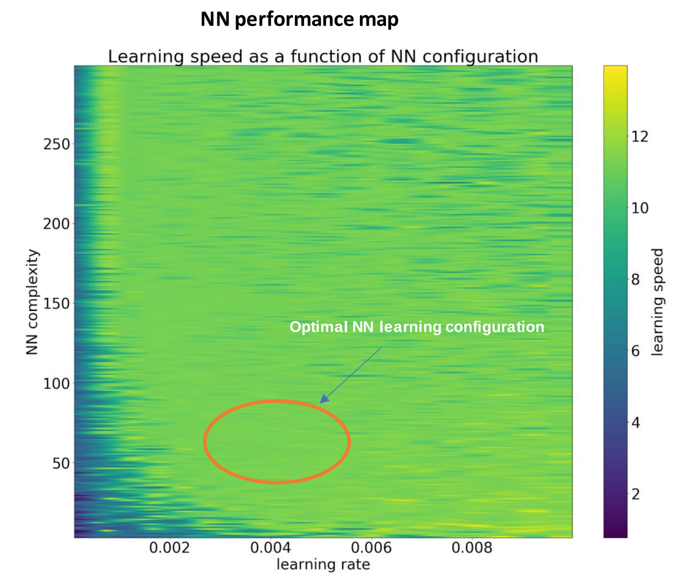


Defining optimal neural network configuration (iterative approach)

Generalized NN configuration

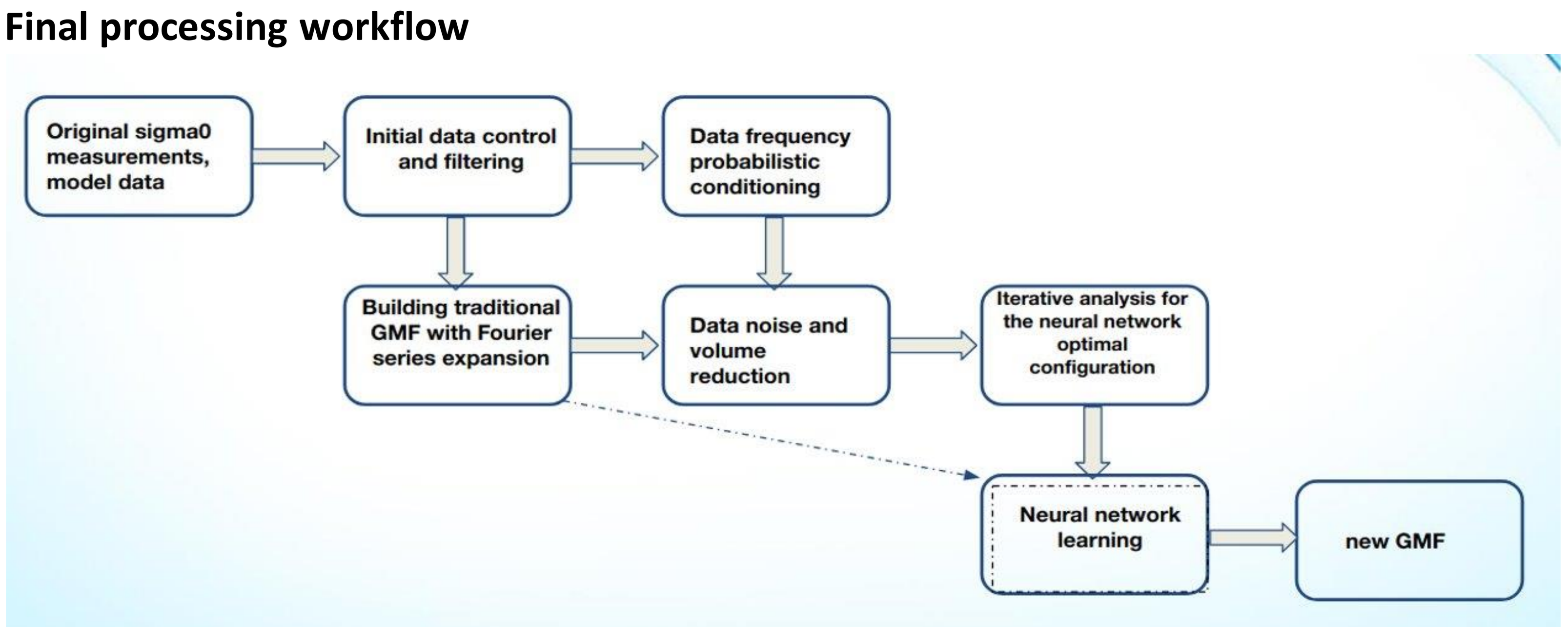


NN performance map



The optimal network configuration and optimal learning parameters could be determined using iterative analysis where the best learning rate is determined by short learning cycles for every combination of NN parameters.

Final processing workflow



Approach requirements

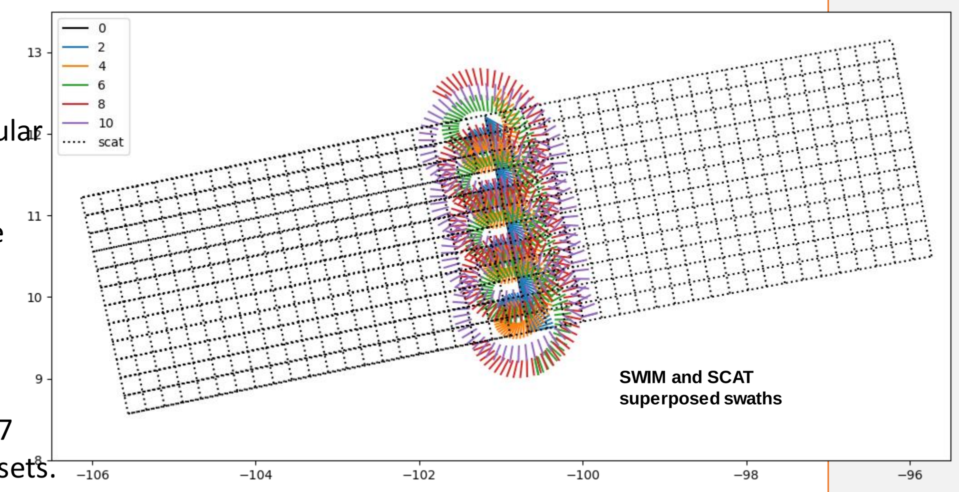
- ML methods requires stable and well calibrated data
- Long observational series required for big number of key variables
- The method is very sensitive to the presence of noise of any kind
- Model-driven approaches for data denoising and interpolation need to be applied (means model-imposed results)

Dataset

IFREMER Wind and Wave Operational Center products
The **Ifremer Wind and Wave Operation Center** (IWWOC) is the downstream French CFOSAT processing center, co-funded by Ifremer and CNES, operated by CERSAT (Ifremer Satellite Data Processing and Dissemination Center) and supported by experts from the Laboratory of Space and Physical Oceanography (LOPS), eOdyn and OceanDataLab

IWWOC is working on two CFOSAT SWIM/SCAT combined L2 products:

- **SWISCA L2S** – collocated SWIM and SCAT data in a common geometrical reference grid (25 km). Together with background model information: wave spectrum, wind, sea surface currents, precipitations, sea ice concentration etc.
- **SCA L2S –** SWIM and SCAT combined wind vector product

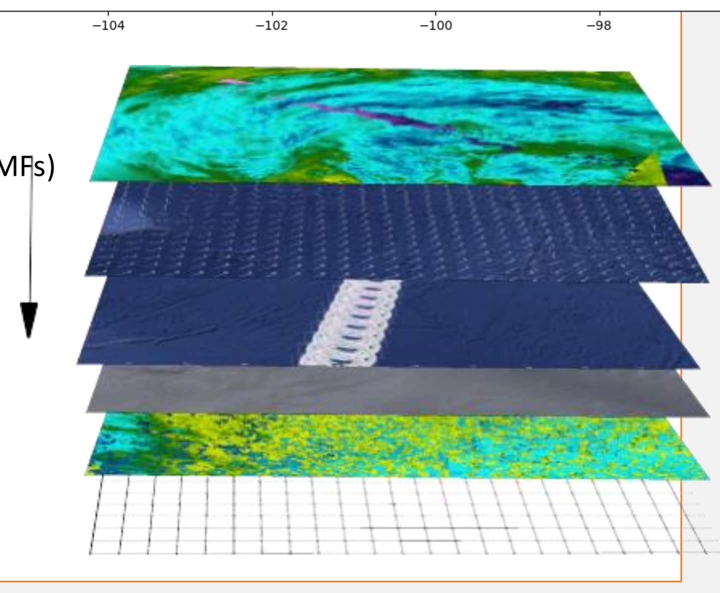


This unique CFOSAT instrumental configuration provides regular collocated radar backscatter measurements to retrieve sea surface state parameters, including significant wave height, directional wave spectrum, and wind vector. For Ku-band the reference GMF is NSCAT-4 model

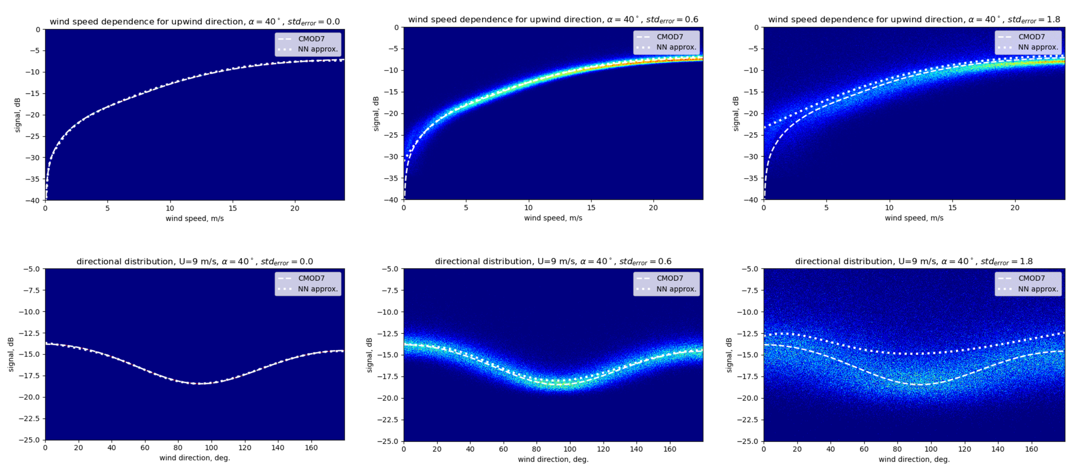
METOP-B Advanced Scatterometer (ASCAT) is a C-band dual swath fan beam radar scatterometer providing a very long observational series of stable σ0. The ASCAT data and CMOD7 GMF were taken as high-quality, well-studied reference datasets.

Additional collocated NWP data:

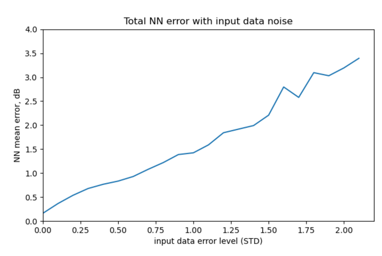
- Common cross-instrumental calibration (NSCAT-4 and CMOD7 GMFs)
- Background wind field based on 1-hour 0.12° ECMWF data
- Sea surface current (CMEMS)
- Sea surface temperature (CMEMS)
- Directional wave spectrum (Wave Watch III)
- Background precipitation (IMERG)
- Sea ice concentration (CERSAT)
- 25x25 km common grid geometry for all data
- Observation period 05/2019 - now



Effect of noise and uncertainties in learning data (simulation analysis)



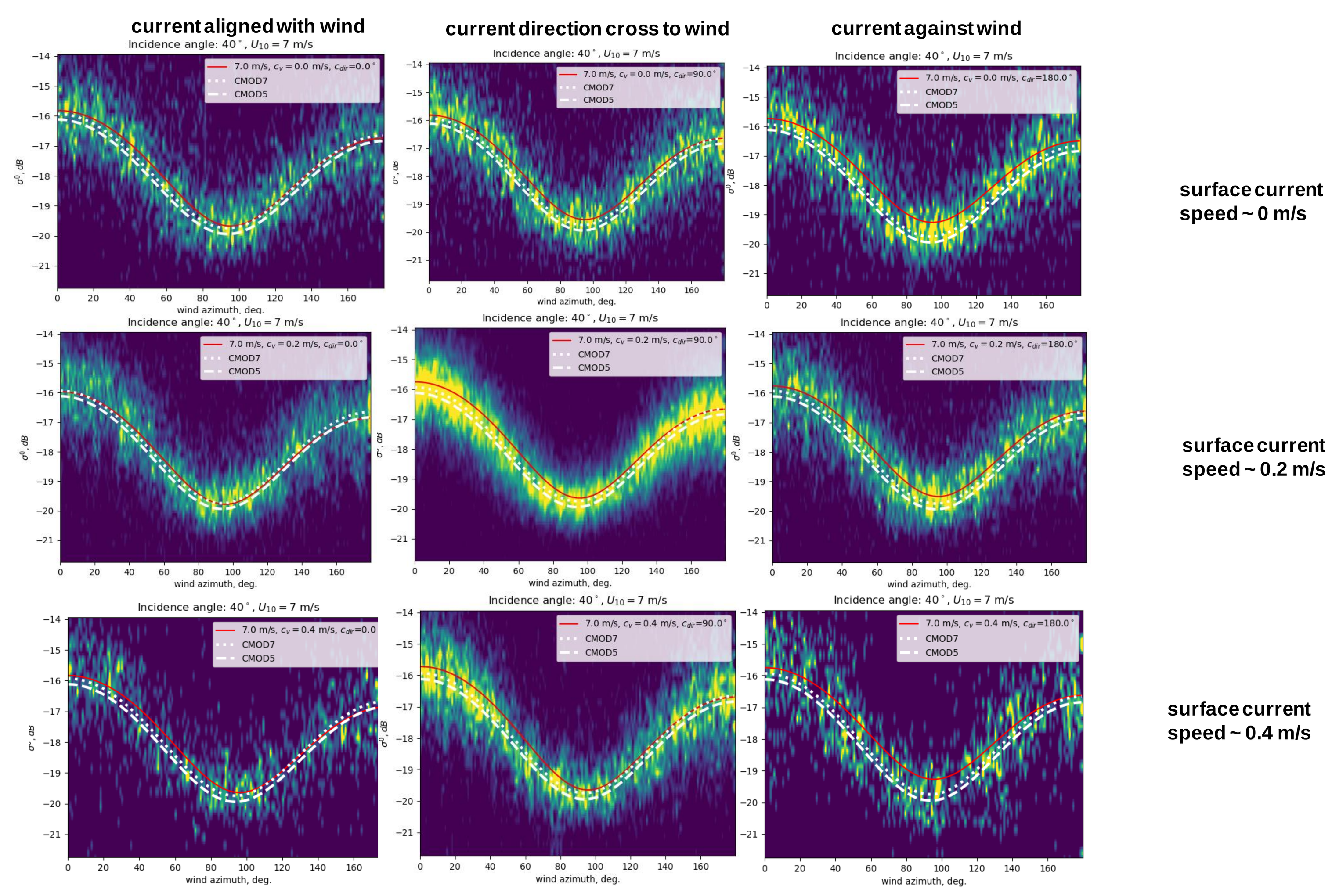
The influence of measurement noise and NWP uncertainties was studied using simulation analysis with CMOD7 model. The NN was learned progressively starting from "clean" simulated data to artificially noised data to emulate realistic measurement noise. Starting from some level of noise the NN could not reproduce the original CMOD7 model.



- The simulation analysis shows that the necessary quality of GMF cannot be achieved even with "infinite" learning dataset at some level of noise, errors or learning data uncertainties
- Noise in the data leads to the degradation of signal in most dynamic parts of derived geophysical function. This effect makes derived GMF less directional and less sensitive to low winds.
- Noise level in training dataset can be reduced or filtered-out by using "traditional" GMF obtained with Fourier series limited expansion
- Neural network attribute to recent sigma0 deviations more weight with respect to averaging techniques. This property allows to adjust very quickly the NN approximation in case of radar signal change. This limits NN learning process for instruments which have unstable signal, but proposes a new opportunity for continuous radar calibration.

Adding additional variables (example with sea surface current vector)

- The proposed approach allows to add any new variable to the backscattering model. For example, sea surface current vector.
- CMEMS sea surface total current vector was collocated with ASCAT data.
- The training dataset was configured to increase the number of rare geophysical situations (i.e. strong currents or strong winds)



Summary

- The existing radar wind vector retrieval algorithms could be significantly extended using collocated multi-instrument data, background NWP and neural network approach.
- Multi-instrument CFSOAT observations provides unique dataset of collocated dual-instruments radar measurements in Ku-band suitable for method validation.
- Mult-angle and multi-band radar observations are very complementary to each other. Potentially this is the way to new high-quality, high-resolution geophysical remote sensing observations.
- Precise calibration/reprocessing work for all data sources need to be done to ensure the quality of geophysical retrieval.
- Straightforward methodology is proposed to build complex multi-parameter GMFs for multi-instrumental geophysical variable retrieval
- ML approach allows to include more additional variables to the model, i.e.: sea surface currents, SST, sea wave spectrum, ascending/descending satellite passes, rain, ice, etc.

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