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Harnessing Machine Learning and Deep Learning methods to forecast whitecap fraction and sea-salt aerosol emissions in the ECMWF Integrated Forecast System (IFS-COMPO)

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ESTIMATING WHITECAP FRACTION FOR SEA-SALT AEROSOL EMISSIONS IN IFS-COMPO

Current status of sea-salt aerosol emissions in cycle 49R1 IFS-COMPO:

- The whitecap fraction (WF) is estimated by the **Albert** et al. (2016) parameterization:

$$\boldsymbol{WF = a(SST)[WSP + b(SST)]^2}$$

- Sea-salt aerosol emissions are derived using the **Gong** (2003) assumed size distribution

$$(WSP, SST) \xrightarrow{\text{A16}} WF \xrightarrow{\text{Gong}} Sea\text{-}Salt$$

Our objective : Estimation of whitecap fraction and sea-salt emissions in IFS-COMPO with deep neural networks (DNN) by :

1. Training offline a DNN model to estimate whitecap fraction
2. Integrating this DNN model into IFS-COMPO

INPUT AND TRAINING DATASETS OF THE OFFLINE DNN MODEL

Dataset description

Ground truth : Whitecap fraction (WF) at **10.7** and **37** GHz derived from remote sensing (Anguelova et al 2019)

Time range : 2 years of data with an hourly resolution

Predictors : 8 predictors collected

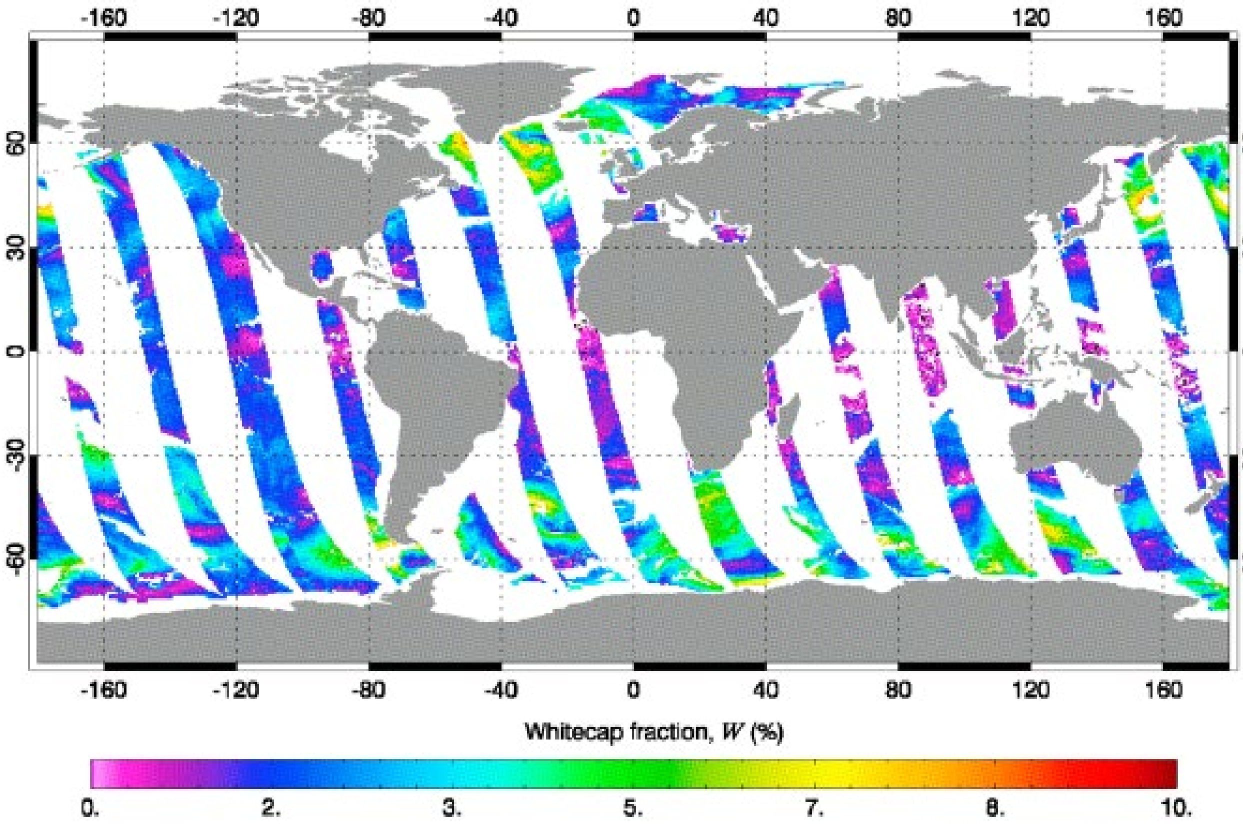
From ERA5 :

- Wind Speed
- Wind Direction
- Sea Surface Temperature
- Mean Wave Period
- Significant Wave Height

From HINDCAST :

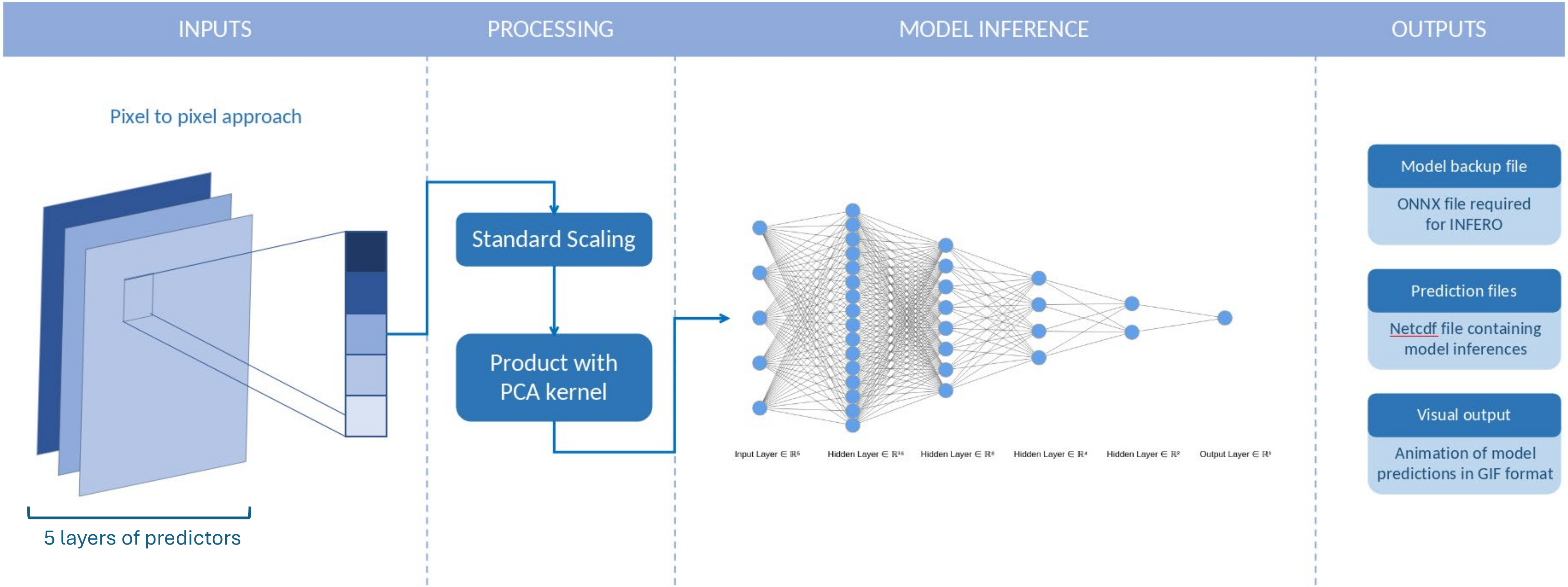
- Total Wave Height
- Significant Wave Height
- Dissipation of turbulent energy from breaking waves

Dimension : around 200 millions pixels



Example of daily map of whitecap fraction from Windsat acquisition [Anguelova et al.]

OFFLINE DNN MODEL ARCHITECTURE



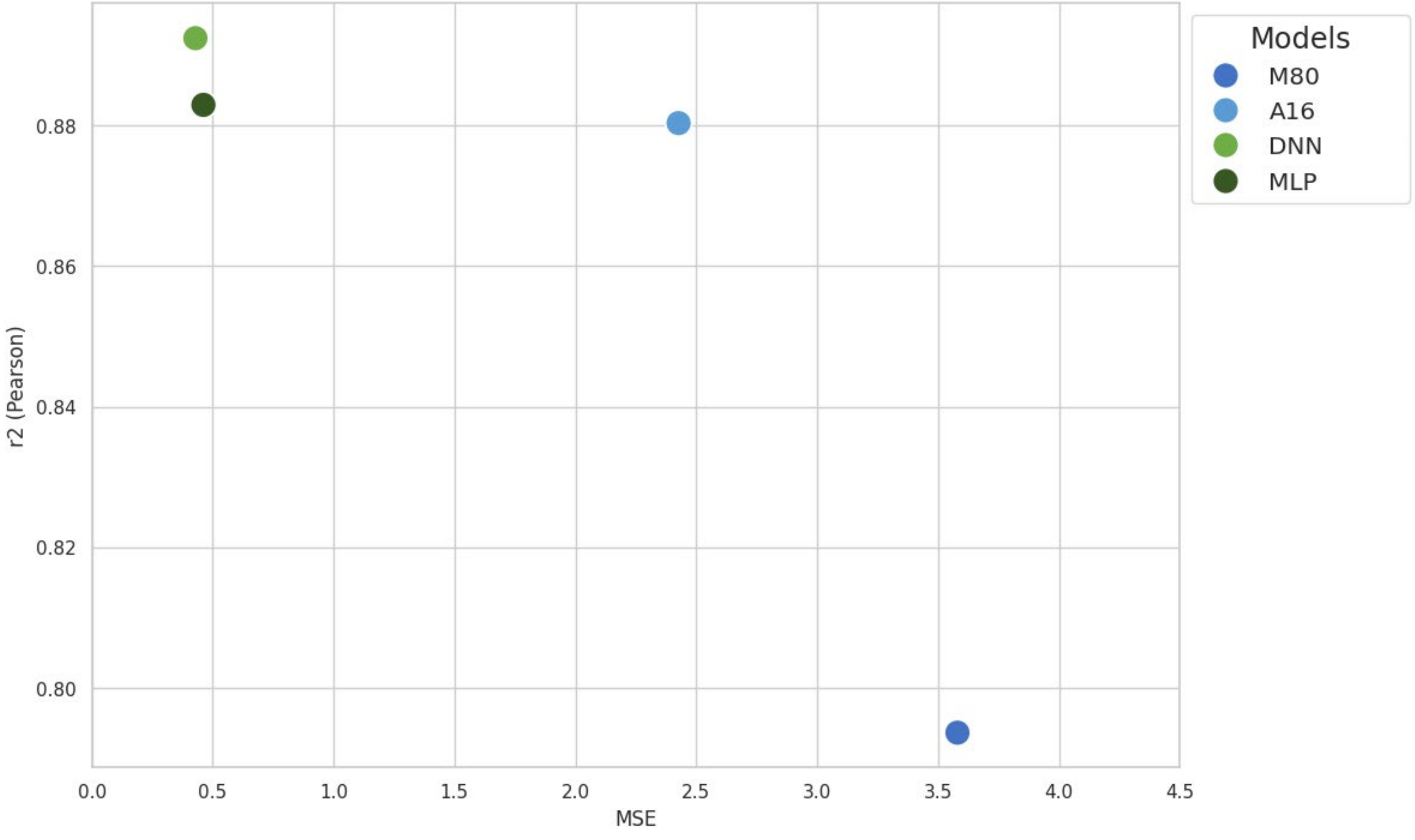
Description of the Deep Neural Network (DNN) model architecture and pre- and post-processing operations

RESULTS OF THE OFFLINE DNN MODEL AND COMPARISON WITH OTHER METHODS

Following results have been obtained by launching a **6 months** simulation

Main comments:

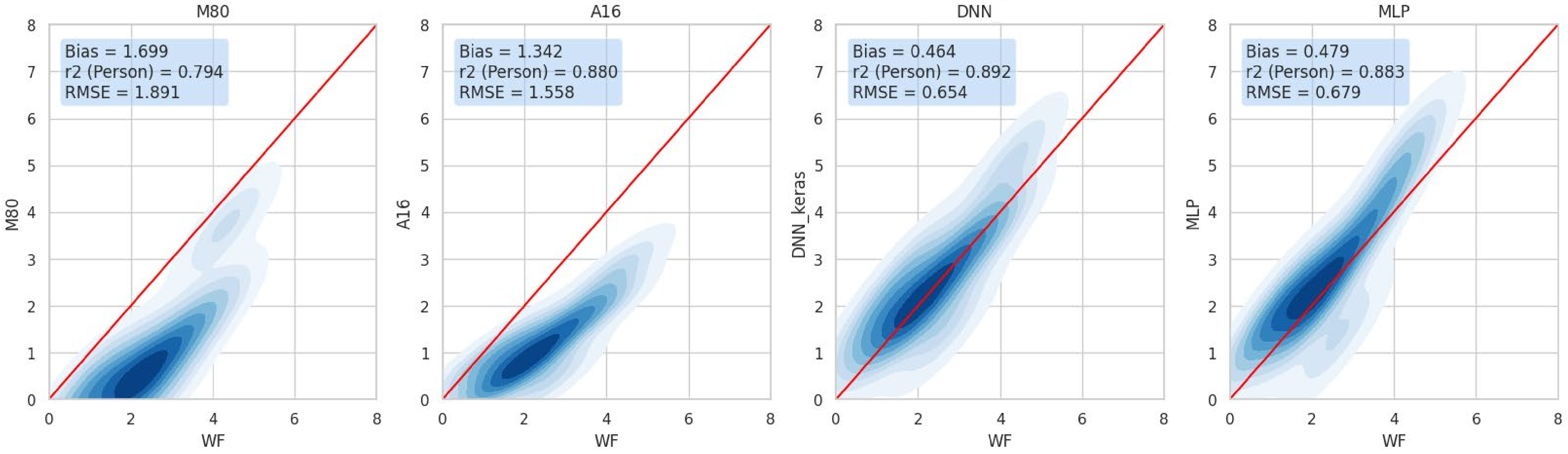
- Arithmetics models (Monahan 80, Albert 16) show a **low bias** as compared to our dataset
- DNN **outperforms** arithmetic models
- DNN manages to score better than a simple neural network architecture (MLP)
- No dependency to SST found



Pearson correlation score versus Mean Squared Error (MSE)

RESULTS OF THE OFFLINE DNN MODEL AND COMPARISON WITH OTHER METHODS

DNN outperforms arithmetic models and a simple neural network architecture (MLP)



Simulated (y axis) versus observed (x axis) whitecap fraction (WF) in %

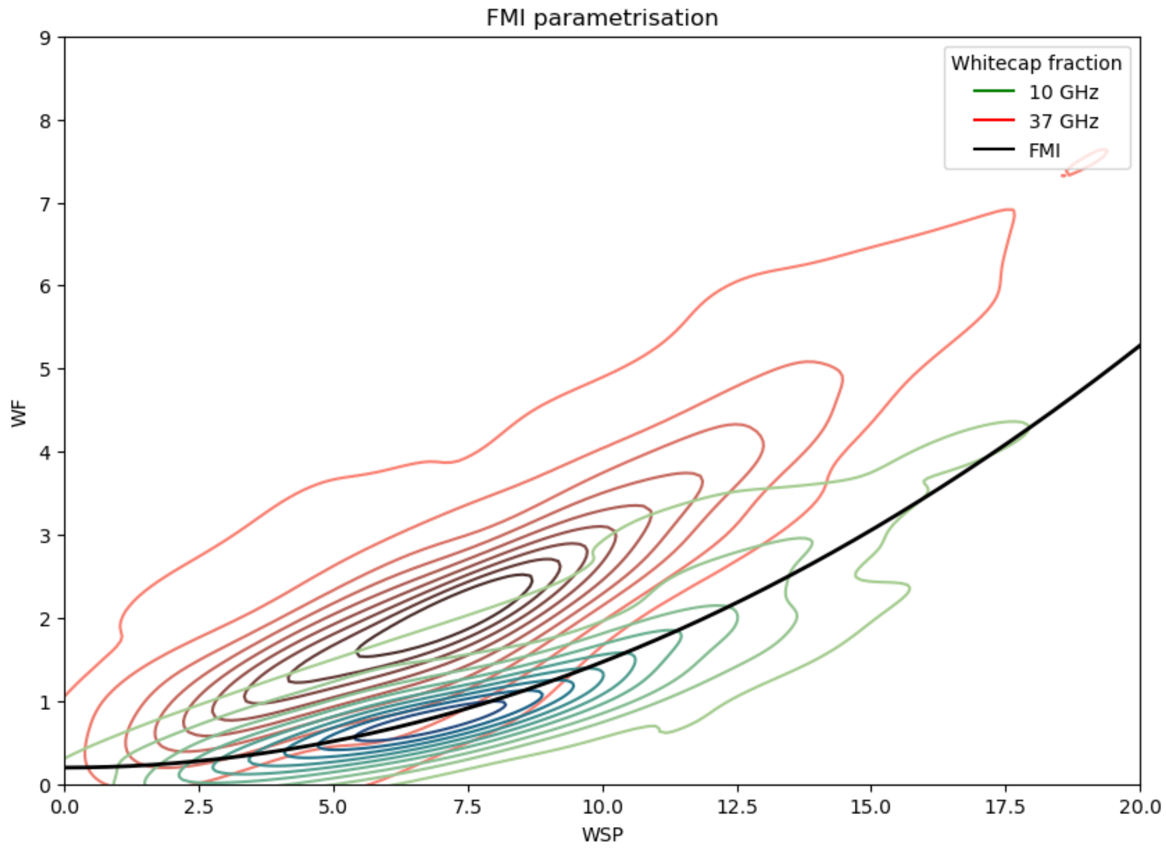
WHITECAP FRACTION AT 10 GHZ

State-of-the-art arithmetic models (Albert 16) are **not adapted** to our dataset ⇒ Use FMI parametrisation

- Our model → **37 GHz**
- FMI model → **10,7 GHz**

⇒ **Duplicate** my work and train my models at this whitecap fraction frequency.

Nevertheless, it is quite long. So, I did not finish yet, but it is on going.



Representation of the whitecap fraction (WF) at both frequencies according to the wind speed (WSP)

INTEGRATION OF THE DNN INTO IFS-COMPO

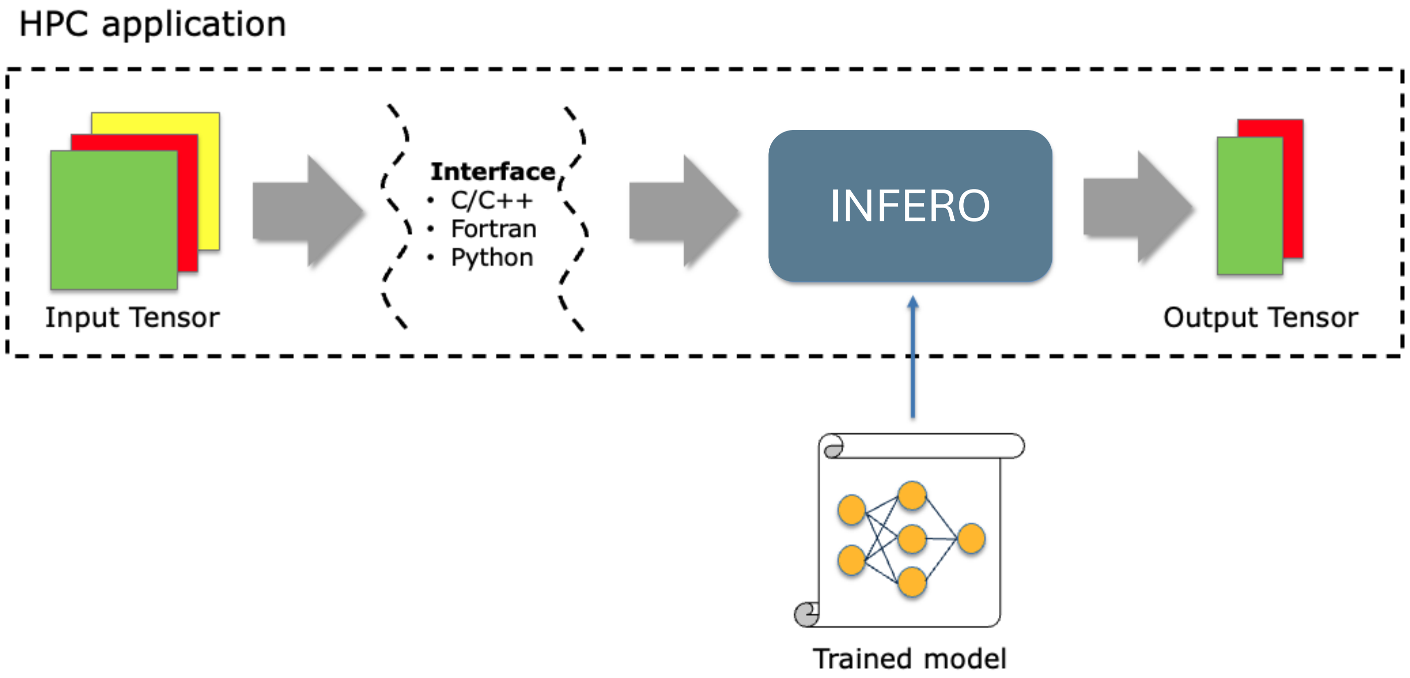
Incorporation of a **reduced version** of the DNN to make an initial estimate of its impact on the skill of simulated AOD over oceanic surfaces

- Reduced model: only 2 predictors (Wind speed / Sea Surface Temperature)

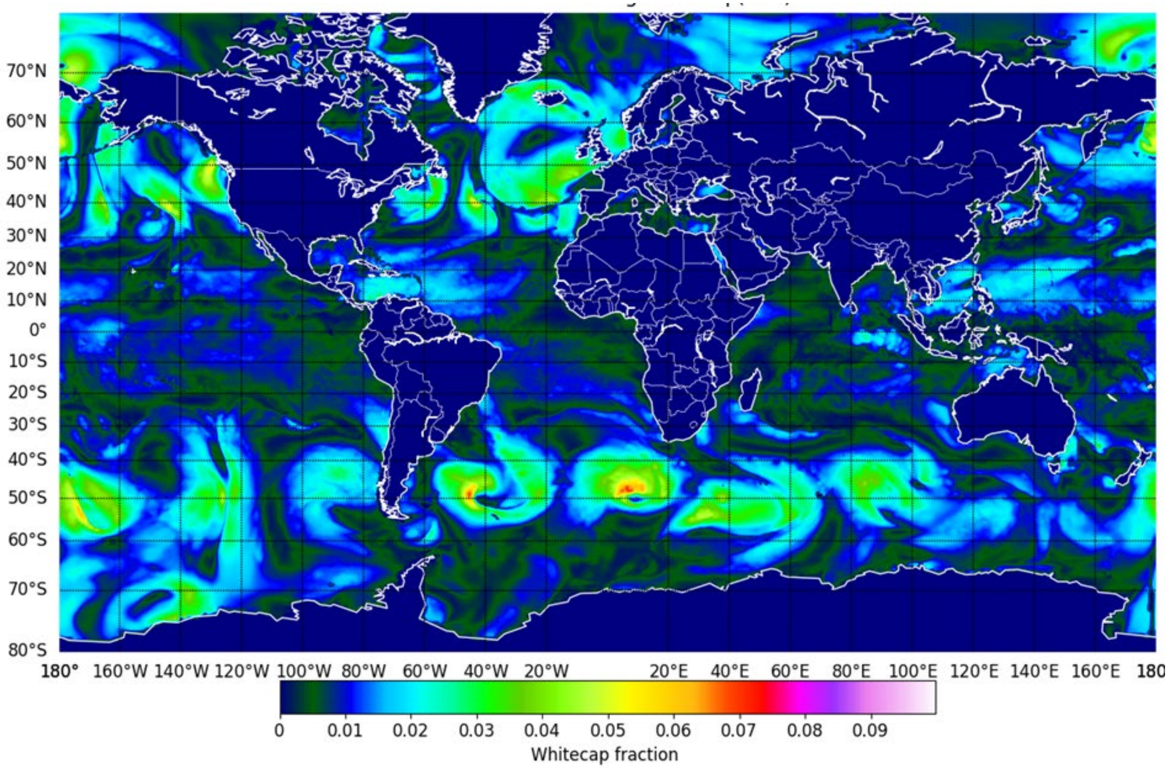
The **INFERO** library has been integrated into IFS-COMPO to interface with Deep Learning models

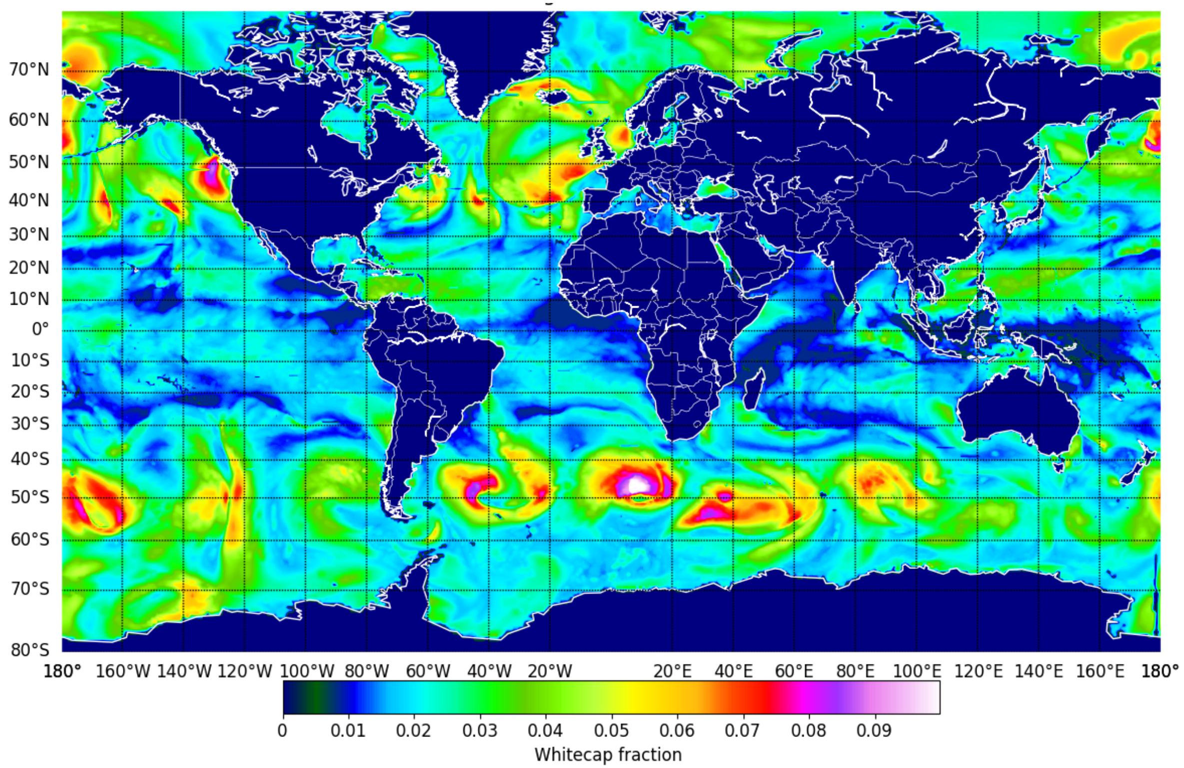
Interest : runs a learning model in ONNX format from a Fortran script

Representation of the incorporation of our model into IFS



EXAMPLE OF IFS-COMPO SIMULATED WHITECAP FRACTION

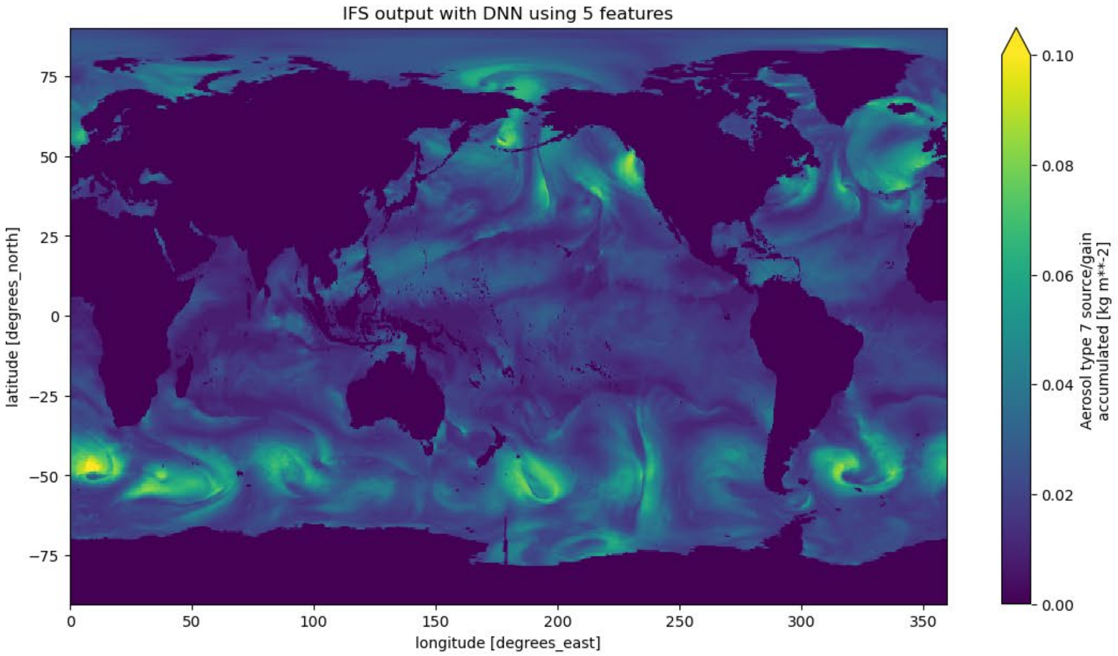


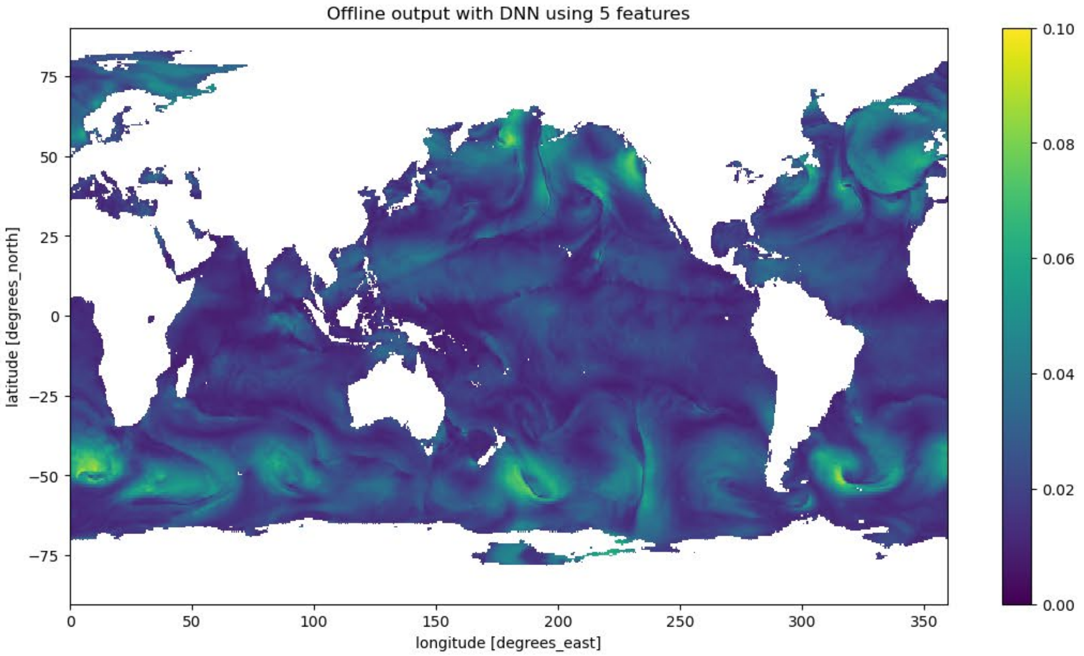


Simulated whitecap fraction by IFS-COMPO on 1/1/2017 0UTC, using the operational A16 scheme (left), and with deep learning model (using 5 predictors) enabled through the INFERO library (right).

IMPLEMENTATION OF DNN WITH 5 FEATURES IN IFS-COMPO

Visual comparison between DNN model in IFS-COMPO (left) and offline DNN model (right) with 5 inputs

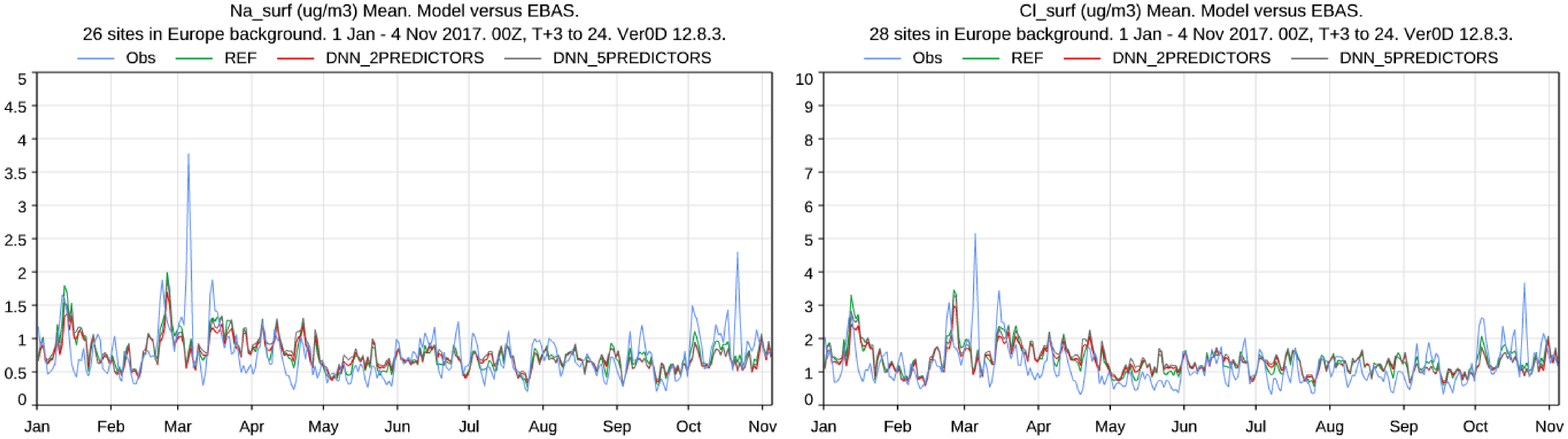




Predictions are pretty **close** but not exactly equal. However, it should be linked to input data differences

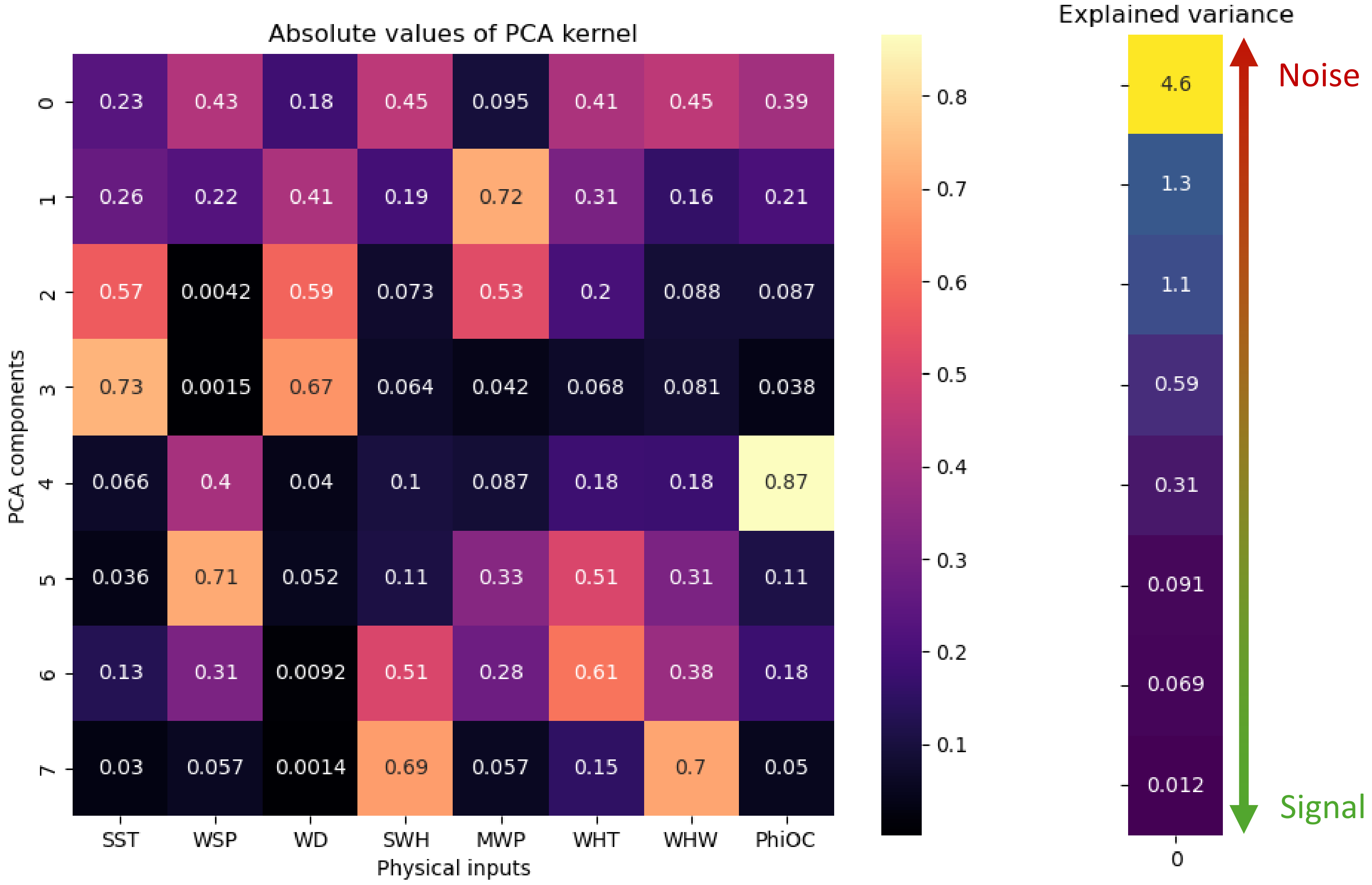
IMPACT ON SKILL SCORES OF SIMULATED SURFACE NA / CL

Skill scores of simulated AOD are very close. Larger impact noted in simulated Na^{+}/Cl^{-} at surface versus EBAS observations:



Simulated and observed daily Na^{+}(left) and Cl^{-} (right) versus EMEP observations

FEATURES SELECTION



Description of principal components according to input features

Motivations :

Better comprehension of features importance and their contribution

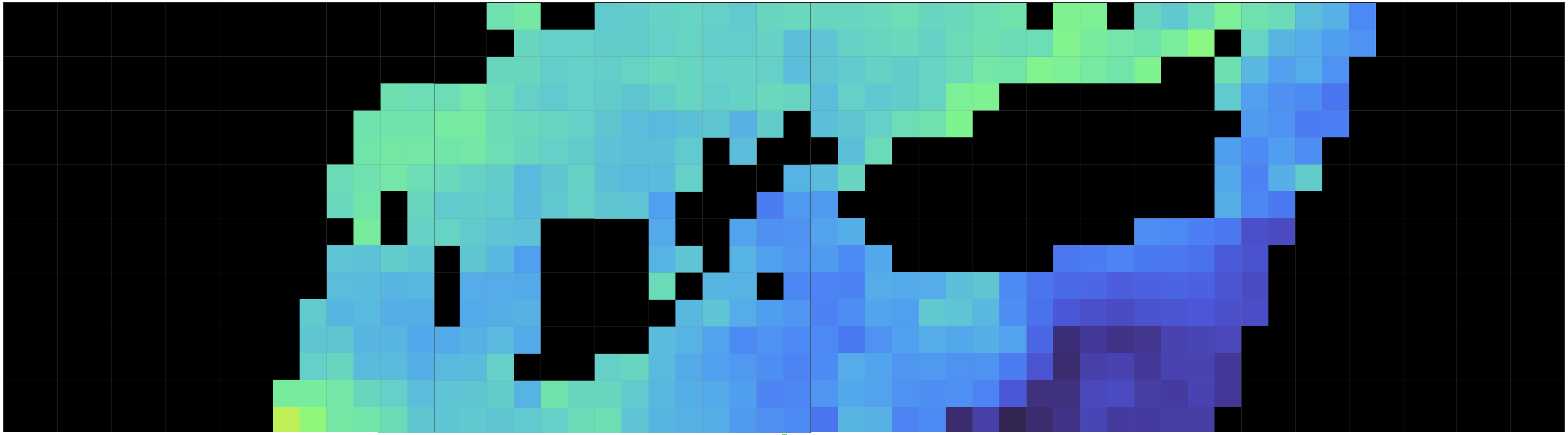
The more input predictors there are, the greater the probability of overfitting

Ideas :

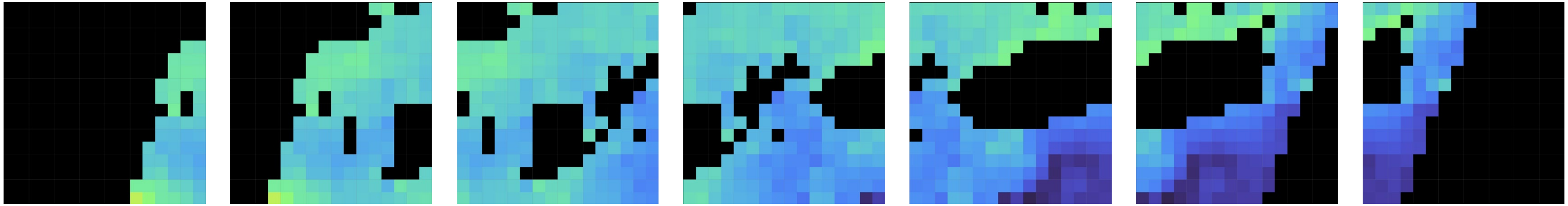
Apply more sophisticated approaches (Qlattice fitting, Lasso CV selection)

GENERATION OF DATASET FOR SPATIAL MODELS

Image showing the Whitecap Fraction in an area extracted from a Windsat orbit

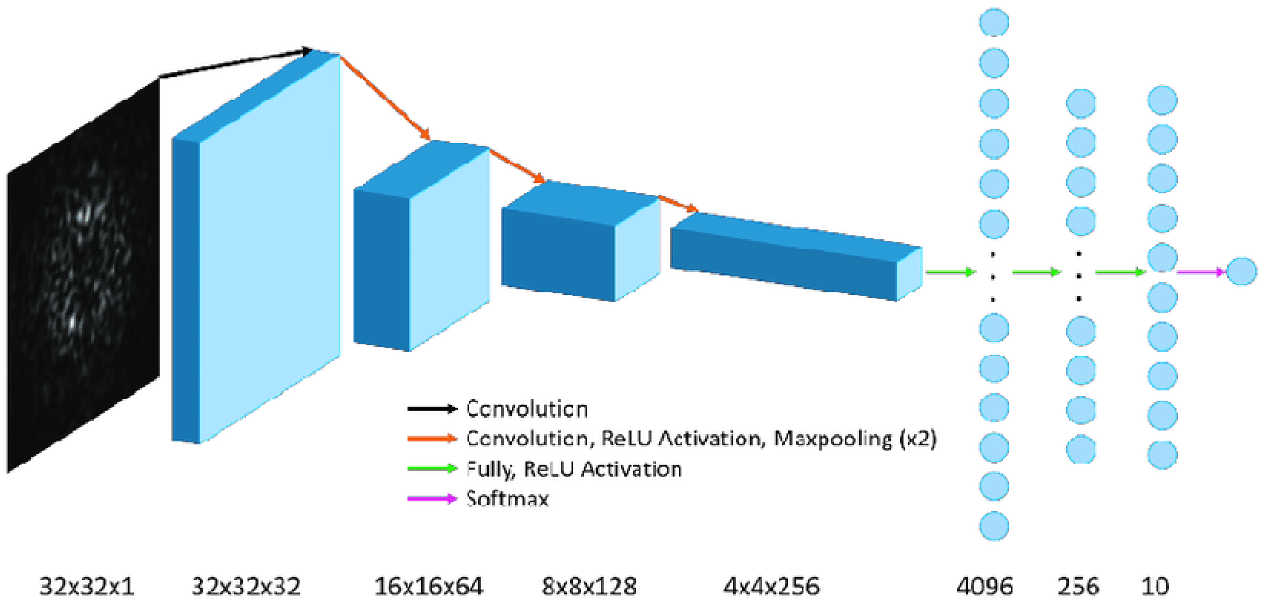


Extraction of 16x16 tiles with 60% overlap



6 millions tiles

IMPLEMENTATION OF MODELS WITH SPATIAL INTERESTS



Example of CNN architecture

Convolutional Neural Network (CNN)

<u>Description :</u> Encode spatial information (texture, surrounding, …) before using DNN model

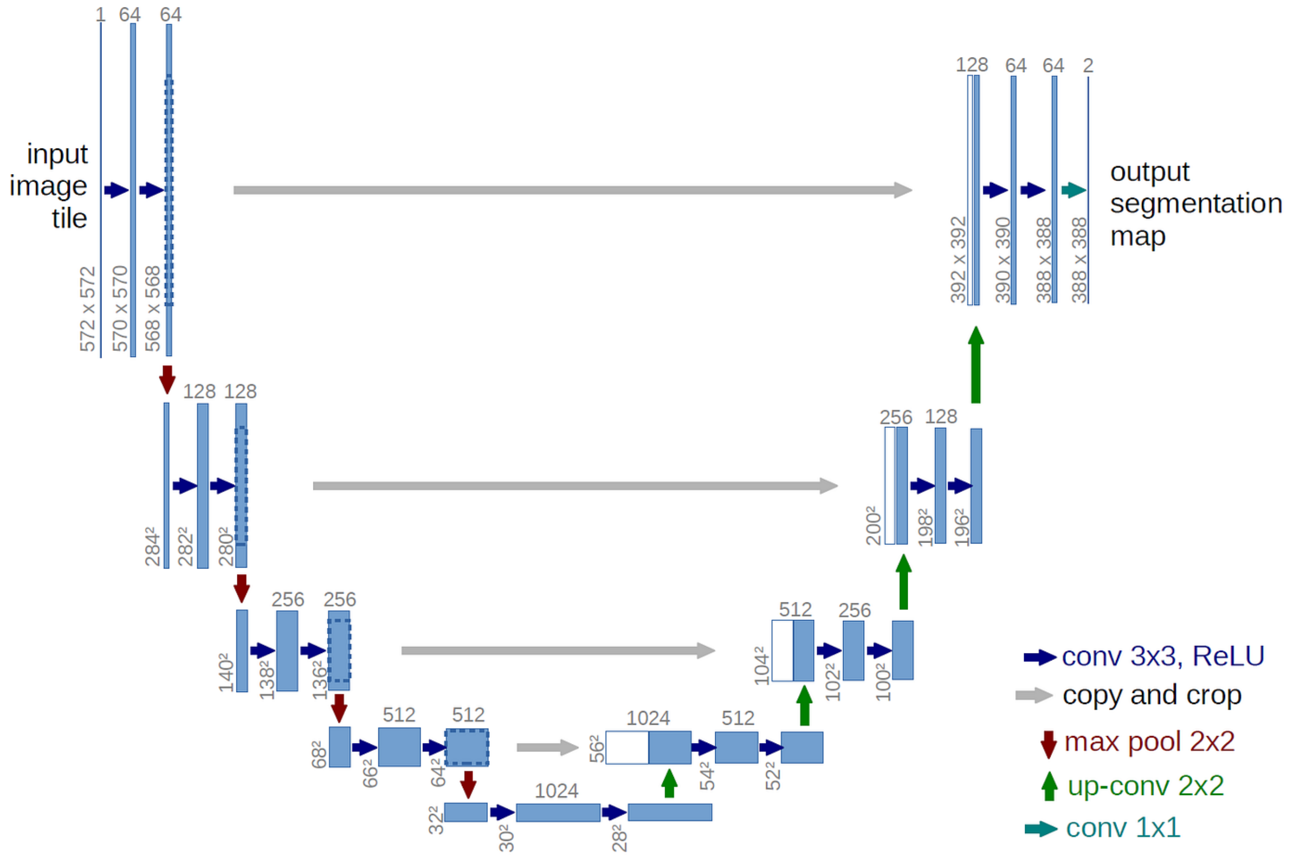
<u>Advantages:</u>

- Spatial interest (Matrix to pixel approach / Texture Extraction)
- Avoid outliers
- Gives meaning to certain entries (WD)

<u>Drawbacks:</u>

- More time consuming
- Difficult to replicate in IFS-COMPO

IMPLEMENTATION OF MODELS WITH SPATIAL INTERESTS



UNet (Encoder-Decoder)

Description : Condenses and processes the inputs in a latent space before bringing it all back to the original resolution

Advantages:

- Spatial interest (Matrix to pixel approach / Texture Extraction)
- Avoid outliers
- Speeds up calculation time

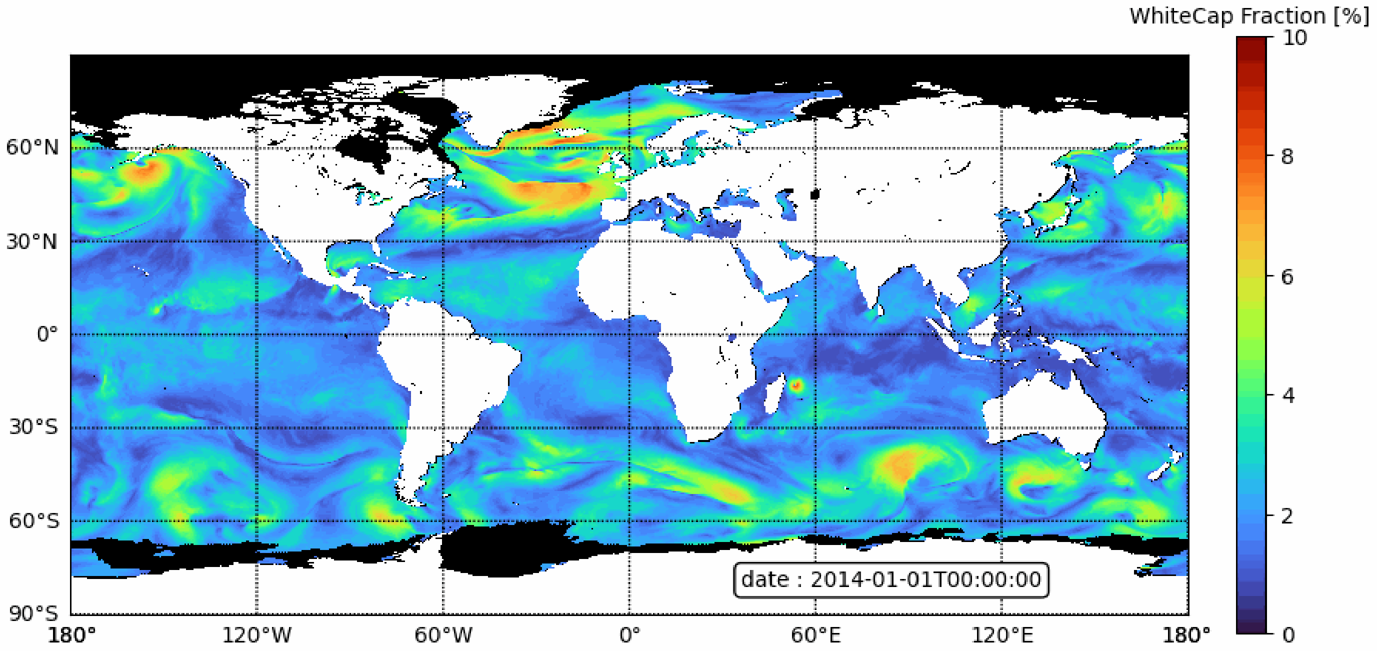
Drawbacks:

- Require more data to be trained
- Difficult to replicate in IFS-COMPO

INCOMING DEVELOPMENTS

Coming next

- Finish the implementation of models with spatial interest (CNN / UNet)
- Improve offline model calibration and test new hyperparameters (loss function, input data representation, etc.)
- Carry out a more specific study for the selection of input features
- Carrying out a full sensitivity study and further analysing the output results at both whitecap fraction frequencies



Animation of Whitecap fraction estimated from our DNN model

CONCLUSION

THANKS FOR LISTENING

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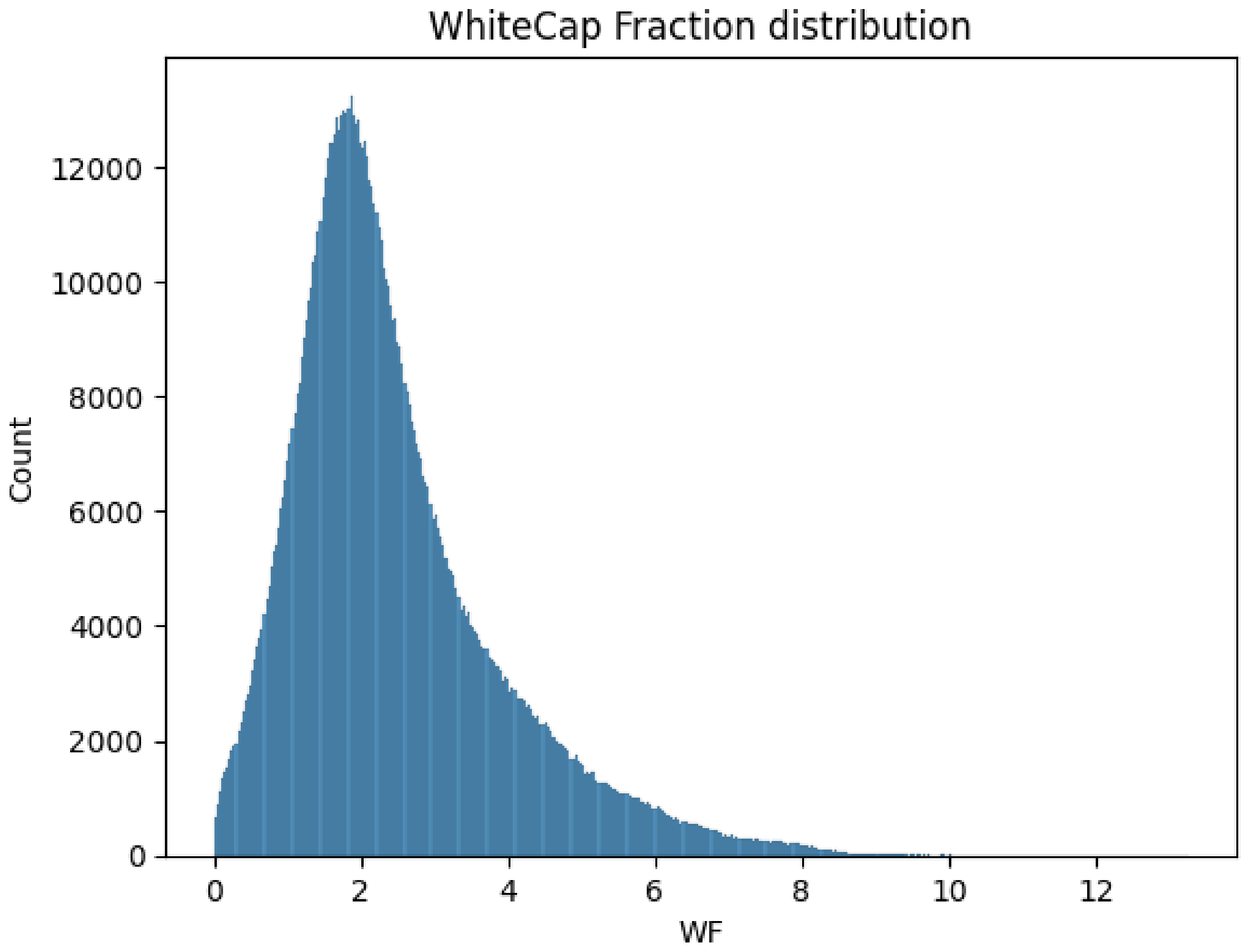
WHY LOSS FUNCTION IS IMPORTANT IN OUR CASE



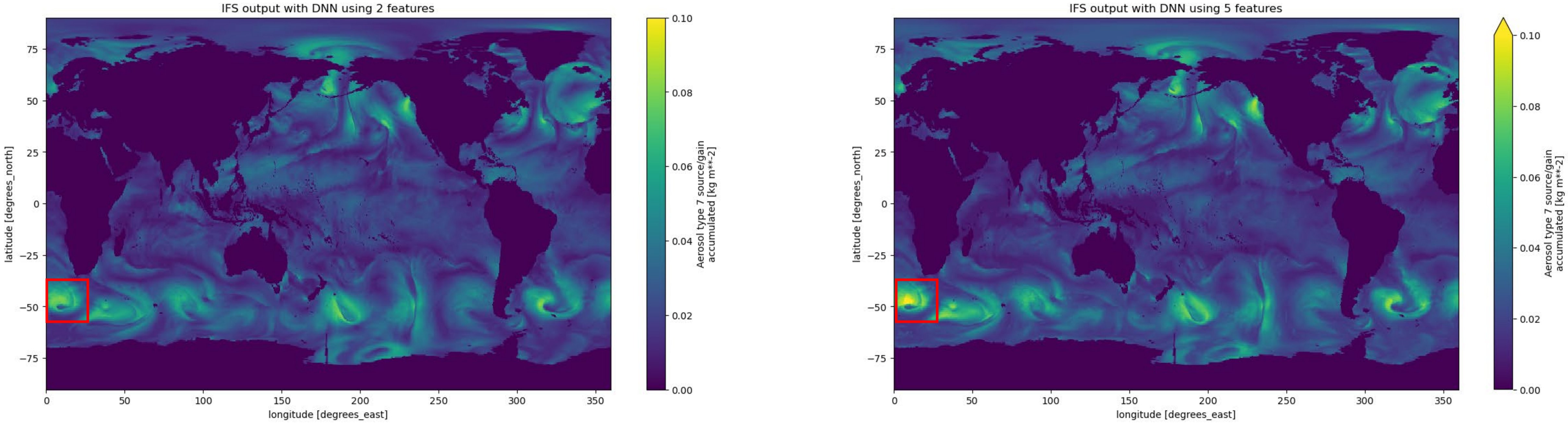
The **loss function** measures how well or poorly a model's predictions **match** the actual outcomes.

By adjusting the model's parameters to reduce the loss, the model learns to make **more accurate predictions**. It's crucial because it **guides** the model's **learning process**.

In our case, an adapted loss function enables us to prevent the model from ignoring minorities.

FROM 2 TO 5 FEATURES

Evaluation of performance for DNN models with different numbers of inputs in IFS-COMPO



Improvement : Better retrieve of high whitecap fraction values without degradation on low values