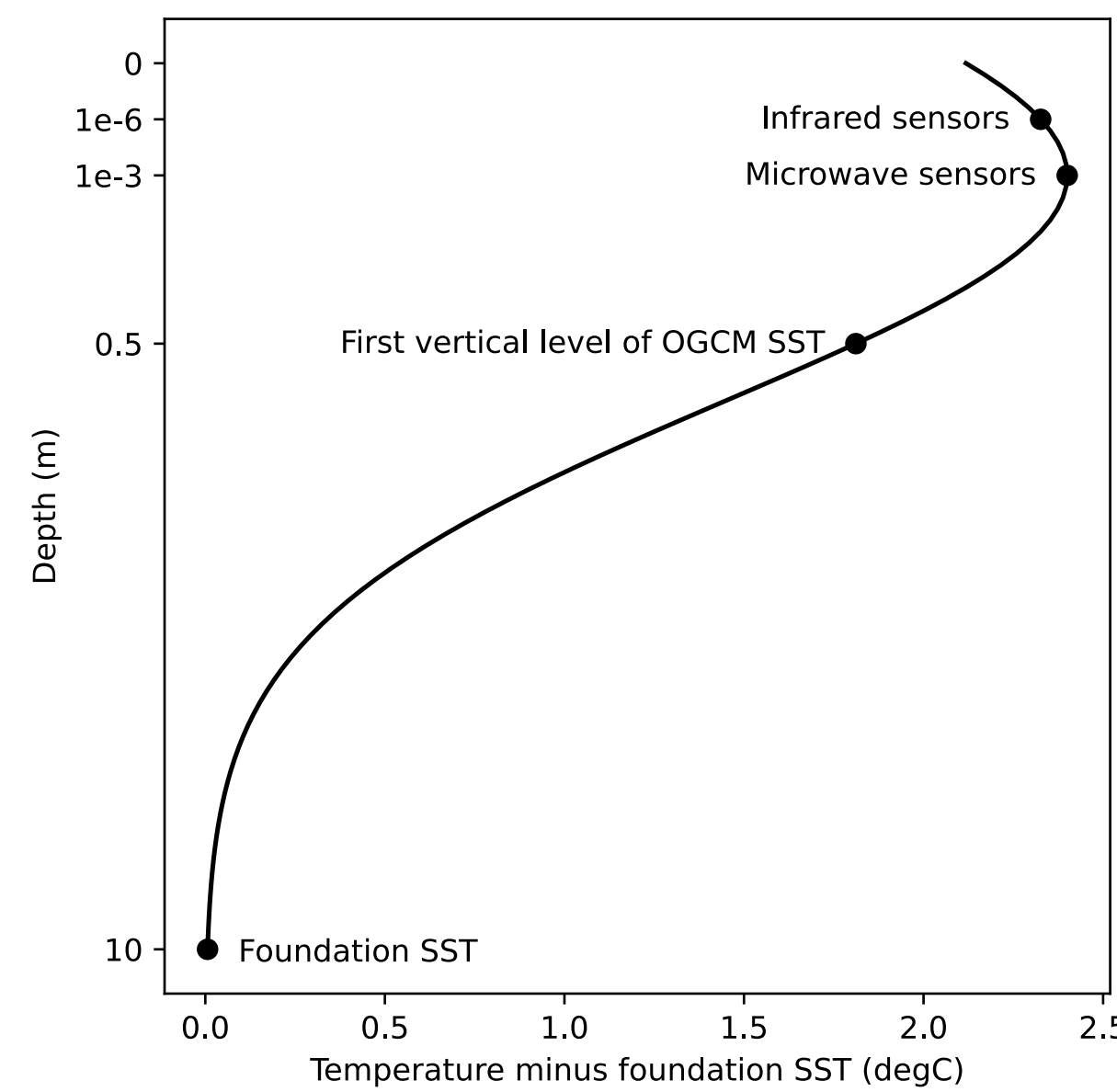


Assimilation of Diurnal Satellite Retrievals of Sea Surface Temperature with Convolutional Neural Network

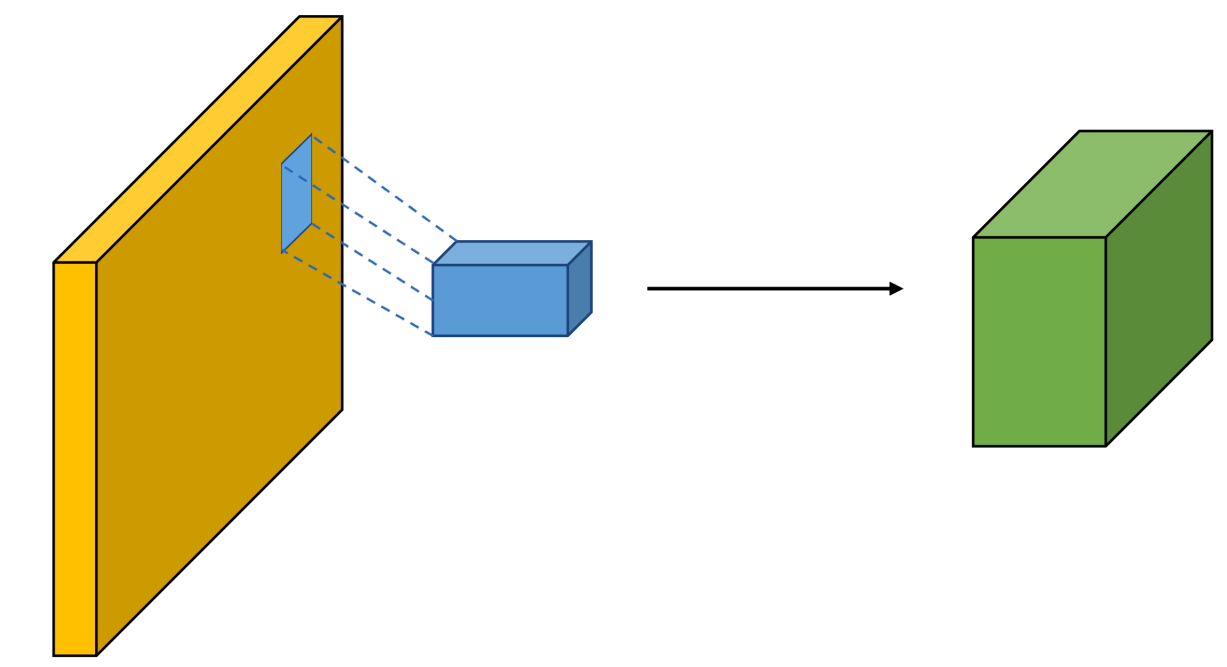
Matteo Broccoli, Andrea Cipollone, Simona Masina
CMCC Foundation - Euro-Mediterranean Center on Climate Change, Italy

MOTIVATION: ASSIMILATE SEA SURFACE TEMPERATURE FROM SATELLITE RETRIEVALS WITH MACHINE LEARNING

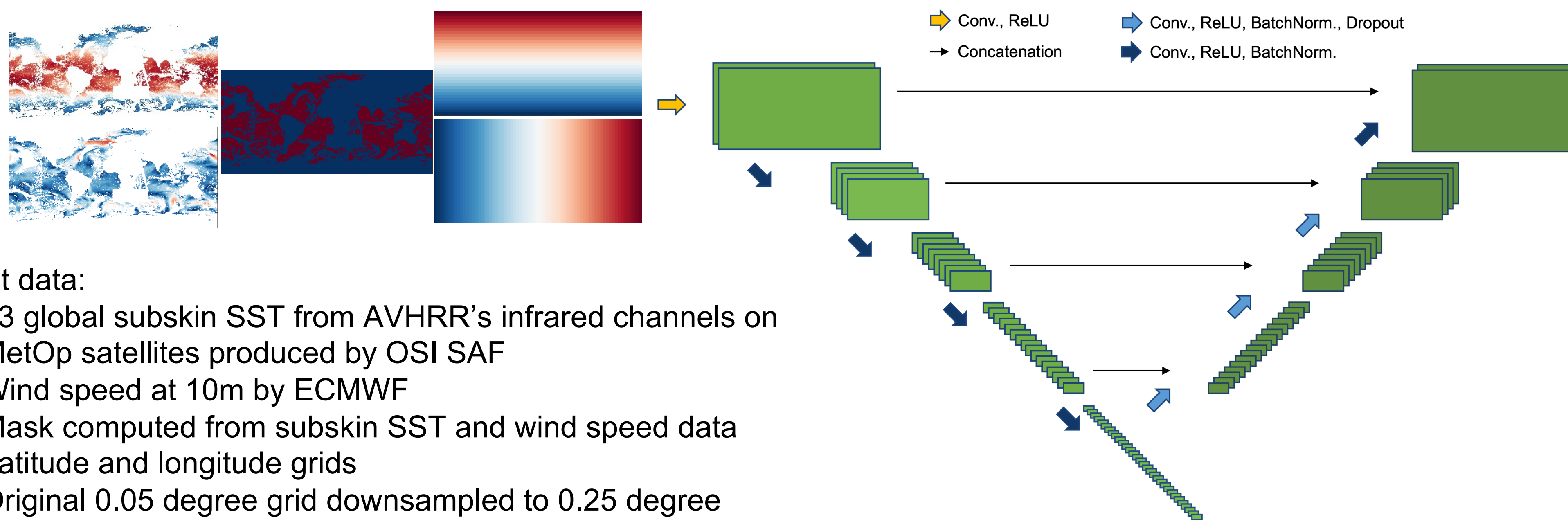
- Global ocean numerical simulations typically work with a vertical subsurface resolution of about 0.5m
- Sea Surface Temperature (SST) can be retrieved from satellites at a reference depth of a few microns or millimeters below the sea surface
- Assimilating such temperatures can lead to bias in the ocean models
- It is thus necessary to project the satellite retrievals to the first model level
- The projection depends on diurnal cycle, winds, latitude, etc.
- The projection is usually performed with complex numerical methods or too simple statistical methods
- We investigate alternative techniques based on machine learning, with Convolutional Neural Networks and Random Forest



- A convolutional layer consists of:
 1. An **input image**
 2. A **filter**
- It convolves (slides) the **filter** over the **image** spatially, computing dot products
- It produces **feature maps**, whose dimensions depend on the dimension of the **filter**
- In a network, the **feature maps** are usually inputs for the next layer
- In this work we compare convolutional neural networks against older regression models, i.e. Random Forest



METHOD: CONVOLUTIONAL NEURAL NETWORKS BASED ON U-NET ARCHITECTURE



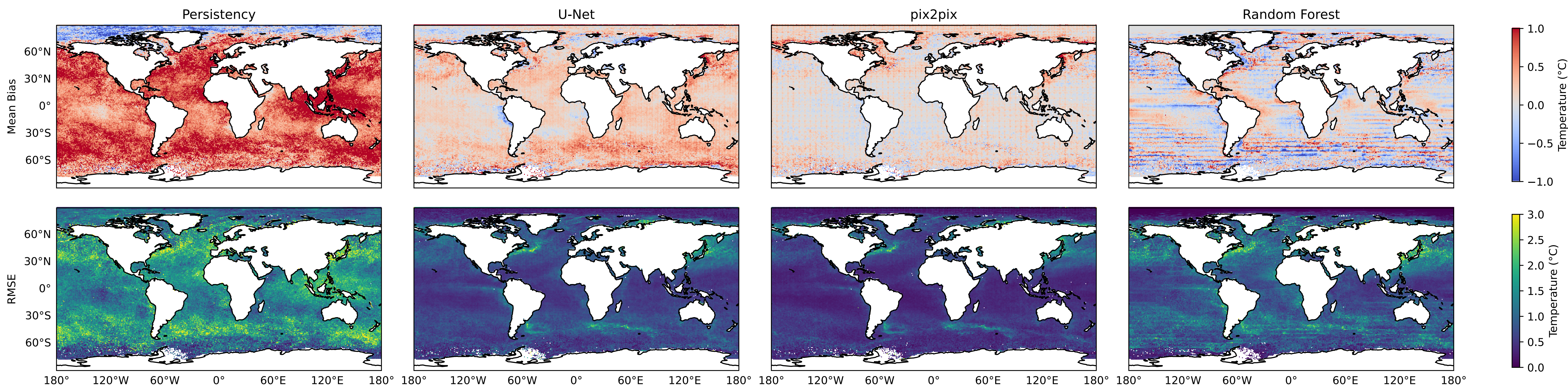
- Input data:
- L3 global subskin SST from AVHRR's infrared channels on MetOp satellites produced by OSI SAF
 - Wind speed at 10m by ECMWF
 - Mask computed from subskin SST and wind speed data
 - Latitude and longitude grids
 - Original 0.05 degree grid downsampled to 0.25 degree

- Ground-truth data:
- L4 first level global SST from ESA SST CCI and C3S by CMEMS
 - Original 0.05 degree grids downsampled to 0.25 degree
 - Fields masked as input data

ARCHITECTURES CONSIDERED:

- U-Net with eight downsampling and upsampling blocks
- pix2pix (cGAN) with U-Net generator and a convolutional PatchGAN classifier as discriminator
- Random Forest with sixty decision trees
- Training on one year of data (2017), divided into 80% for training and 20% for testing

RESULTS: SST BIAS CORRECTION WITH MACHINE LEARNING



Mean bias and its RMSE between the predictions of the different models and the ground truth, i.e. the first level SST; the output of the 'persistency' model is the subskin SST. The predictions are made on the test set with the best model achieved during training in the case of the U-Net and pix2pix. From these metrics, the pix2pix is the model that performs best.

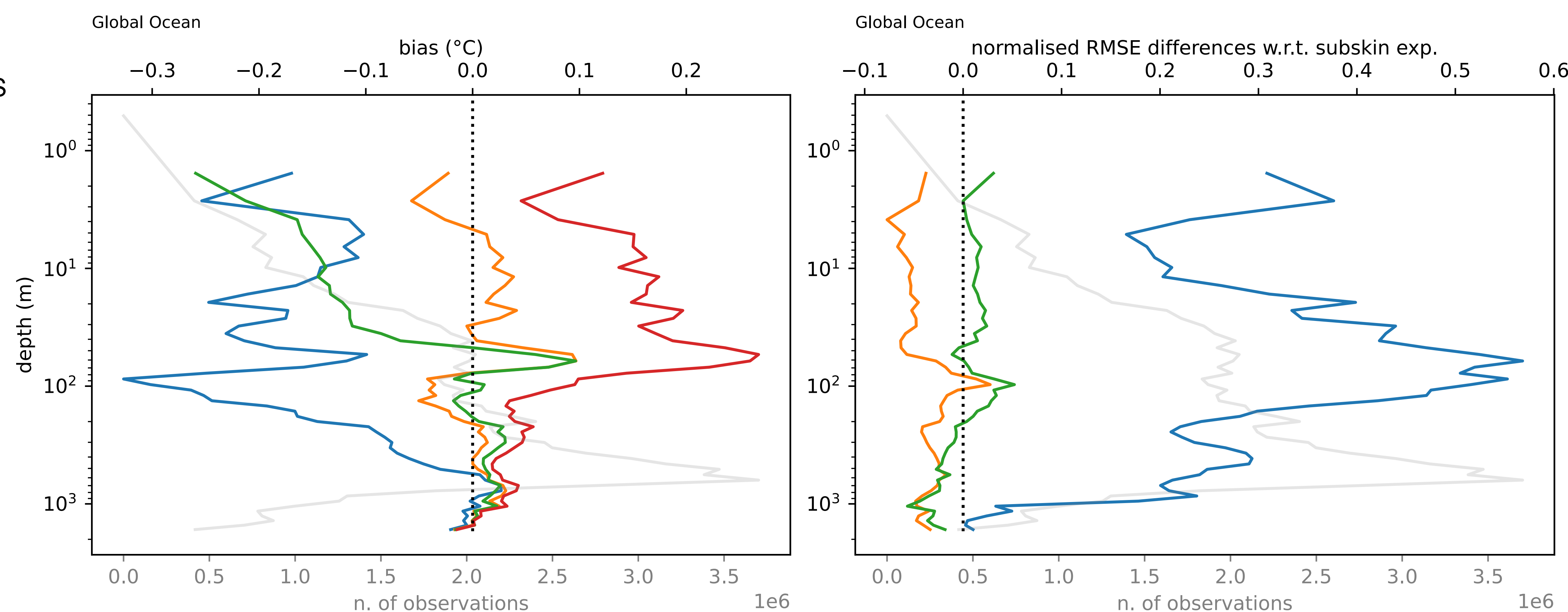
APPLICATION: ONE-YEAR-LONG OCEAN REANALYSIS-LIKE EXPERIMENTS WITH HYBRID ML/DA

Reanalysis-like experiment based on C-GLORS system (OceanVar 3DVAR + NEMO + LIM2) with hybrid ML/DA of:

1. **subskin SST**
 2. **ML-unbiased SST** with pix2pix
 3. **ML-obs.op.** for subskin SST with inverse pix2pix
 4. **Free run** with no assimilation
- Experiments for year 2018

CONCLUSIONS

- Up to 10% improvement in ML-unbiased RMSE w.r.t. subskin assimilation
- ML-obs.op. can be improved by optimizing the network for the inverse projection



Analysis of the misfits against in situ observations for the different assimilation experiments for the global ocean: on the left, vertical profiles of the bias; on the right, the normalized RMSE differences w.r.t. subskin experiment.