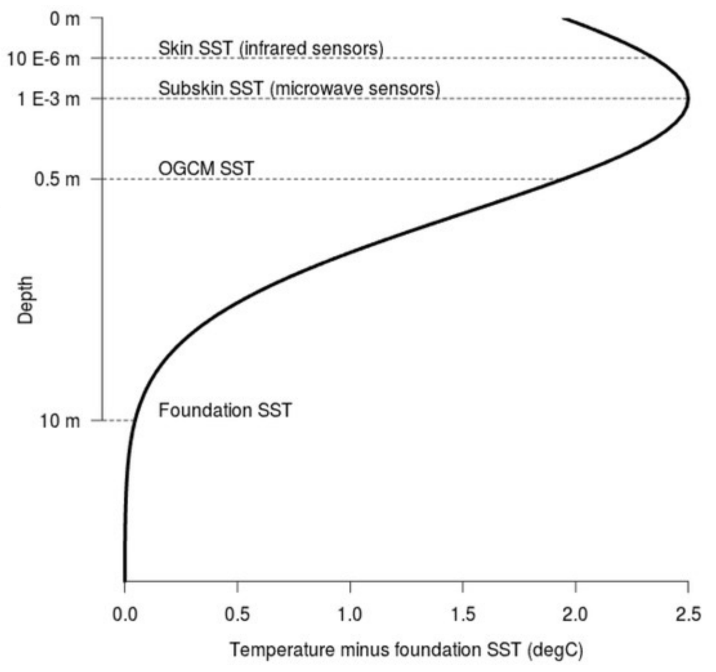
Towards an Observation Operator for Satellite Retrieval of Sea Surface Temperature with Convolutional Neural Network

Matteo Broccoli, Andrea Cipollone, Simona Masina

Fondazione Centro Euro-Mediterraneo sui Cambiamenti Climatici - CMCC, Bologna, Italy

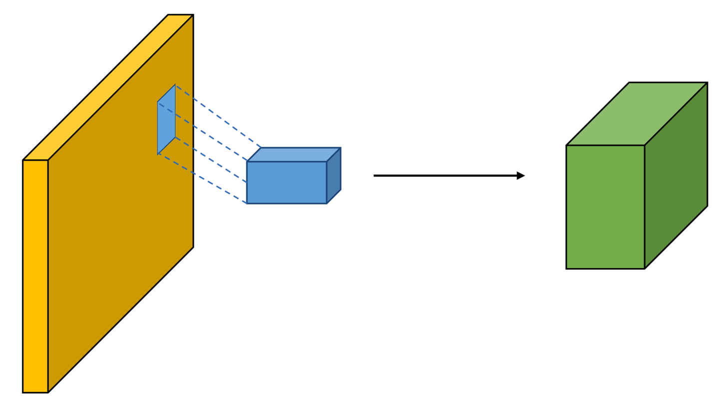
MOTIVATION: ASSIMILATE SEA SURFACE TEMPERATURE FROM SATELLITE RETRIEVALS WITH MACHINE LEARNING

- 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

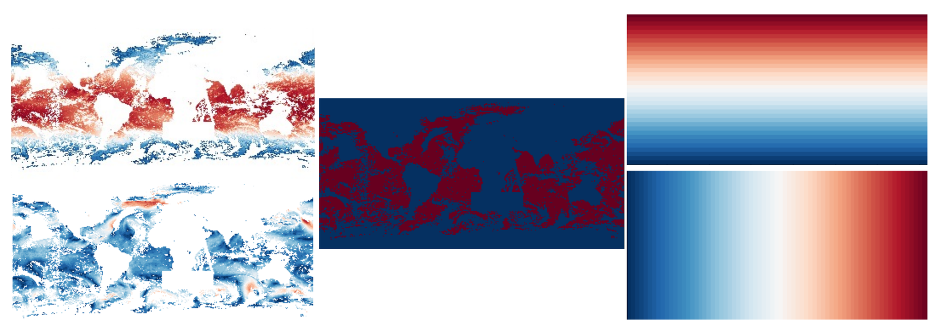


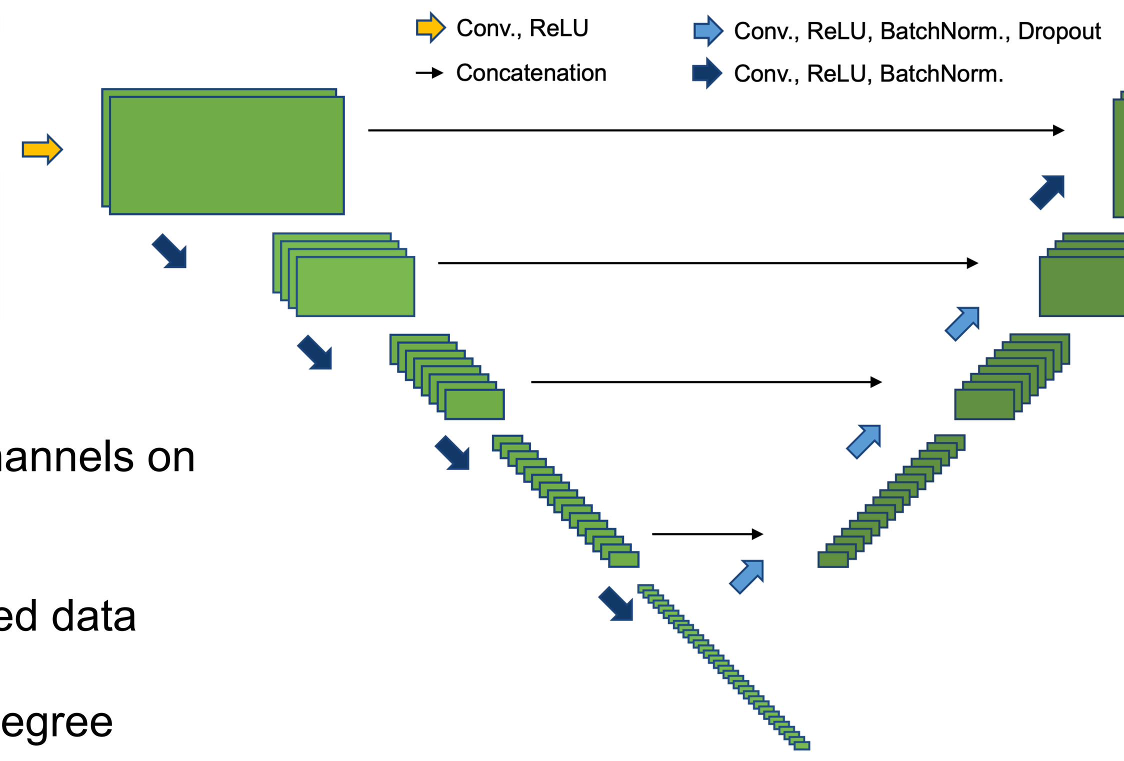
From *Storto and Oddo 2019*

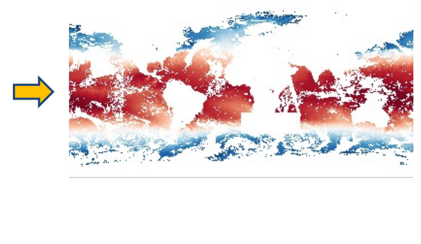
- A convolutional layer consists of:
  1. An input image
  2. A filter
- It convolves (slides) the filter over the image spatially, computing dot products
- It produces feature maps, whose dimensions depend on the dimension of the filter
- In a network, the feature maps are usually inputs for the next 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

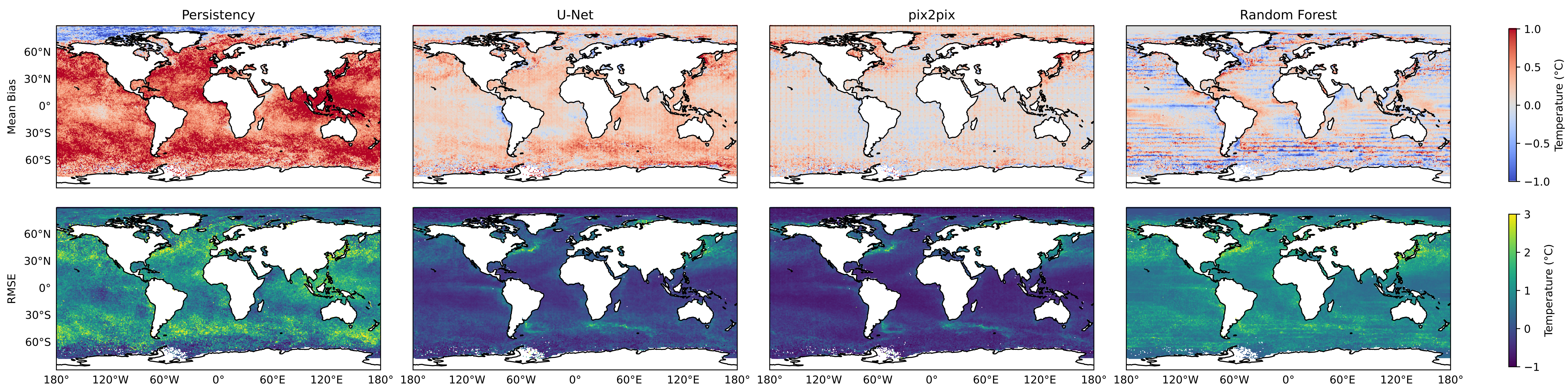
Ground-truth data:

- 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

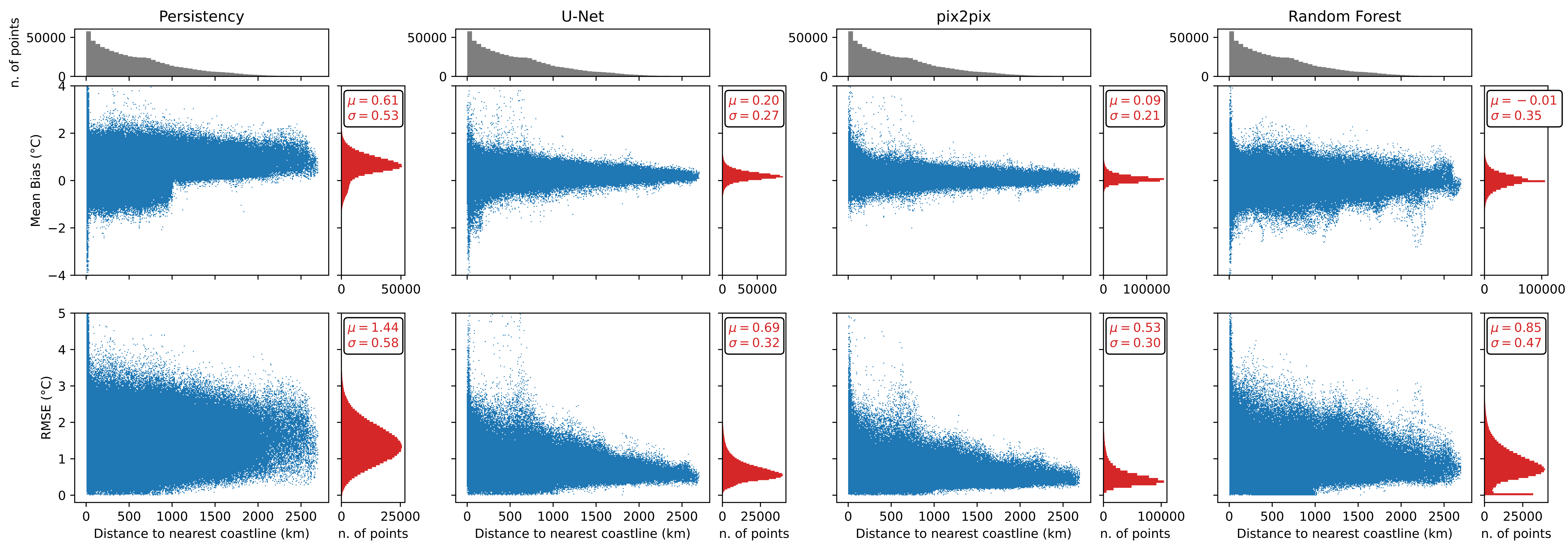
ARCHITECTURES CONSIDERED:

- 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, divided into 80% for training and 20% for testing

PRELIMINARY 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. The data in the maps above are plotted against the distance to the nearest coastline below.



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