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Centro Euro-Mediterraneo sui Cambiamenti Climatici

Advancing Global Ocean Reanalysis and Forecast Systems

Convolutional Neural Network and the Assimilation of Diurnal Satellite Retrievals of Sea Surface Temperature

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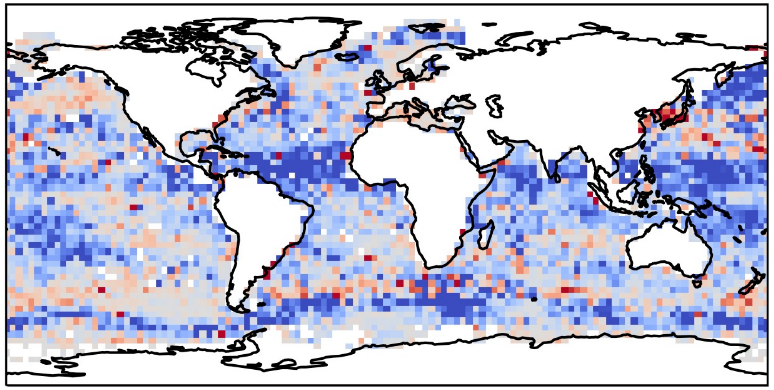
Earth System Modelling and Data Assimilation (ESYDA)
CMCC Foundation



Guest Lectures and Seminars on Climate Science
University of Bologna, 10 November 2025

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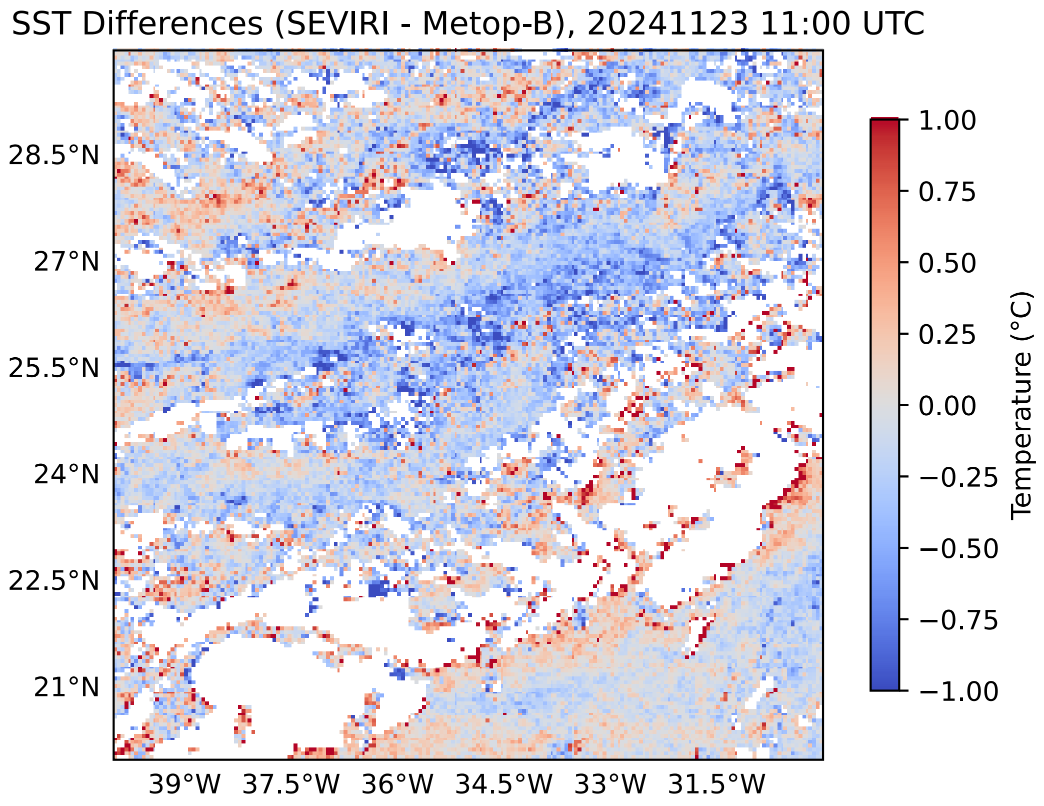
My Career Path, So Far

- BSc in Physics at **University of Bologna**
- MSc in Theoretical Physics at **University of Bologna**
- PhD in Theoretical Physics at **Humboldt University of Berlin**, and **Max Planck Institute for Gravitational Physics**, Potsdam
  - Quantum Gravity and Unified Theory Division
- Postdoc at **CMCC Foundation**, Bologna
  - Earth System Modelling and Data Assimilation Division

Assimilation of Diurnal Satellite Retrievals of SST

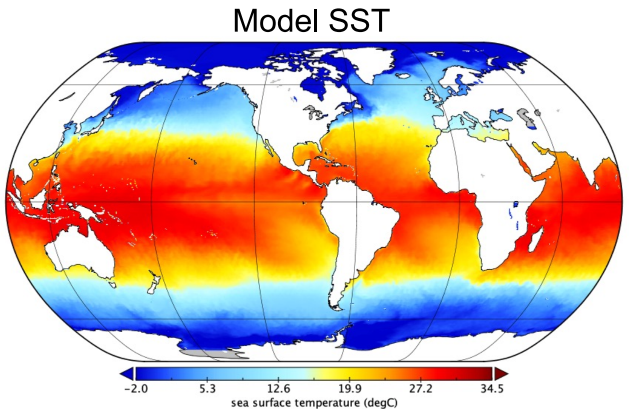
- Assimilation of remote sensing data improves the accuracy of ocean general circulation models [Eyre et al. (2022)]
- Multitude of SST datasets with diverse characteristics [Office et al. (2024)]
- SST retrievals are
  - Affected by dust, water vapours, clouds, instrumental errors
  - Disseminated at different processing levels
  - Based on single or multiple sensors analysis
  - Refer to different depths (e.g. skin, subskin)
  - Tailored for climate or forecast studies
  - …

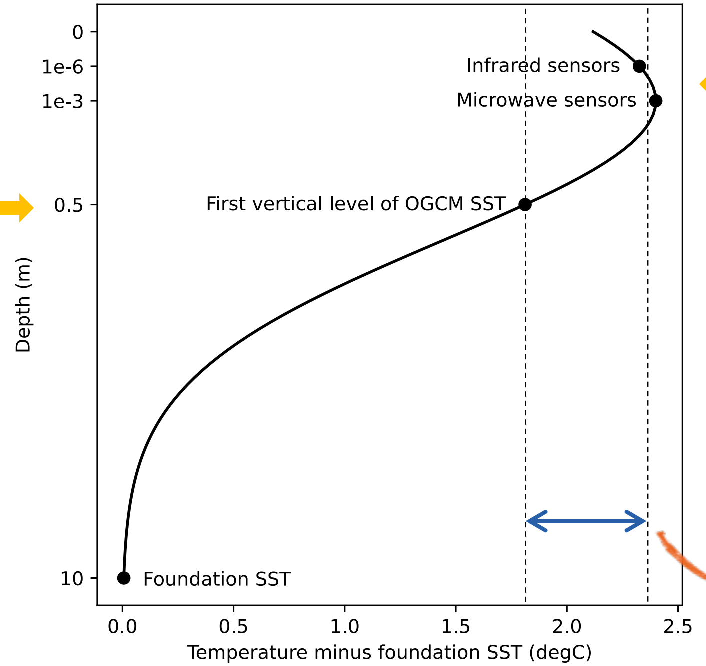


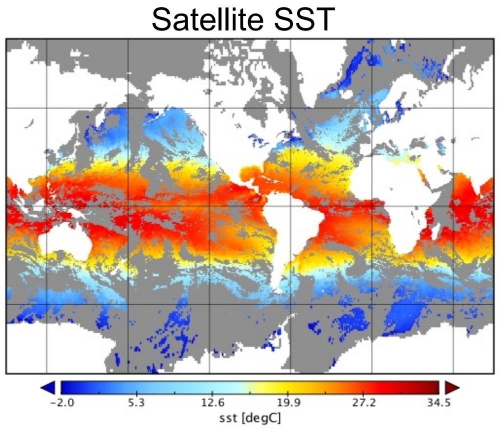
- Map of the difference between the subskin SST datasets from two different sensors onboard different satellites, taken within the same day and hour (23/11/2024 at 11:00 UTC) over an area in the North Atlantic
- The two instruments measure subskin SST, are disseminated at the same resolution and time frequency
- Yet there are significant differences between the two products

Assimilation of Diurnal Satellite Retrievals of SST

- Assimilation of remote sensing data improves the accuracy of ocean general circulation models [Eyre et al. (2022)]
- Multitude of SST datasets with diverse characteristics [Office et al. (2024)]
- Highly correlated with model state variable SST but different at the same time







Direct assimilation can generate **systematic biases**

Careful assimilation:

- Observation operator tailored to the product it assimilates (sub-optimal)
- Our approach: **data-driven construction** of (forward/adjoint) operator

CNN for the Assimilation of Diurnal Satellite Retrievals of SST

Use **machine learning** to construct:

1. Forward operator and assimilate unbiased subskin SST
2. Inverse operator employed as observation operator to assimilate subskin SST

Why deep learning algorithms?

- Satellite (sub)skin SST **non-linearly connected** to the SST at the first model level because:
    1. Retrieval algorithms to transform radiances to (sub)skin SST can differ from product to product [Minnett et al. (2019)]
    2. Surface physical processes resulting in different diurnal warming for (sub)skin SST and first model level SST [Murray et al. (2000), Gentemann et al. (2003)]
- Only re-train the network to assimilate different product

Why convolutional neural network (CNN)?

- Assumption: SST in one position is **highly correlated** to the SST in the surroundings

CNN for the Assimilation of Diurnal Satellite Retrievals of SST

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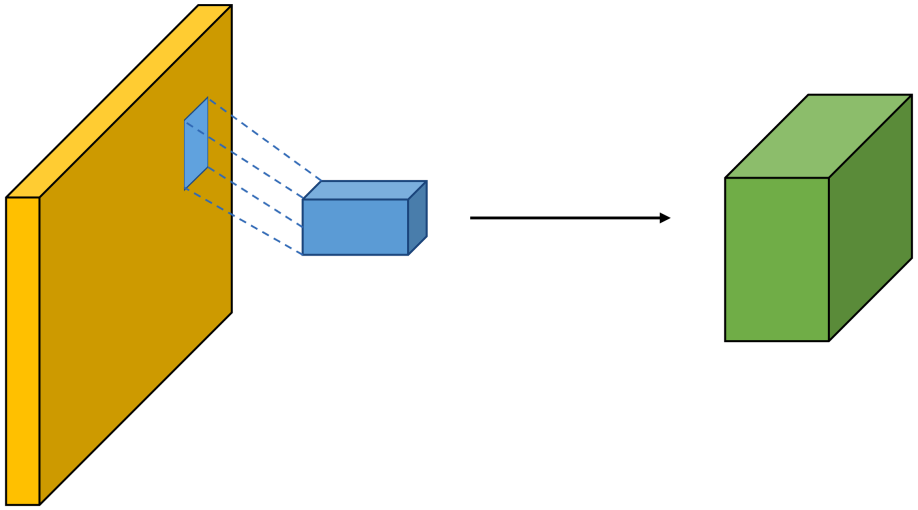
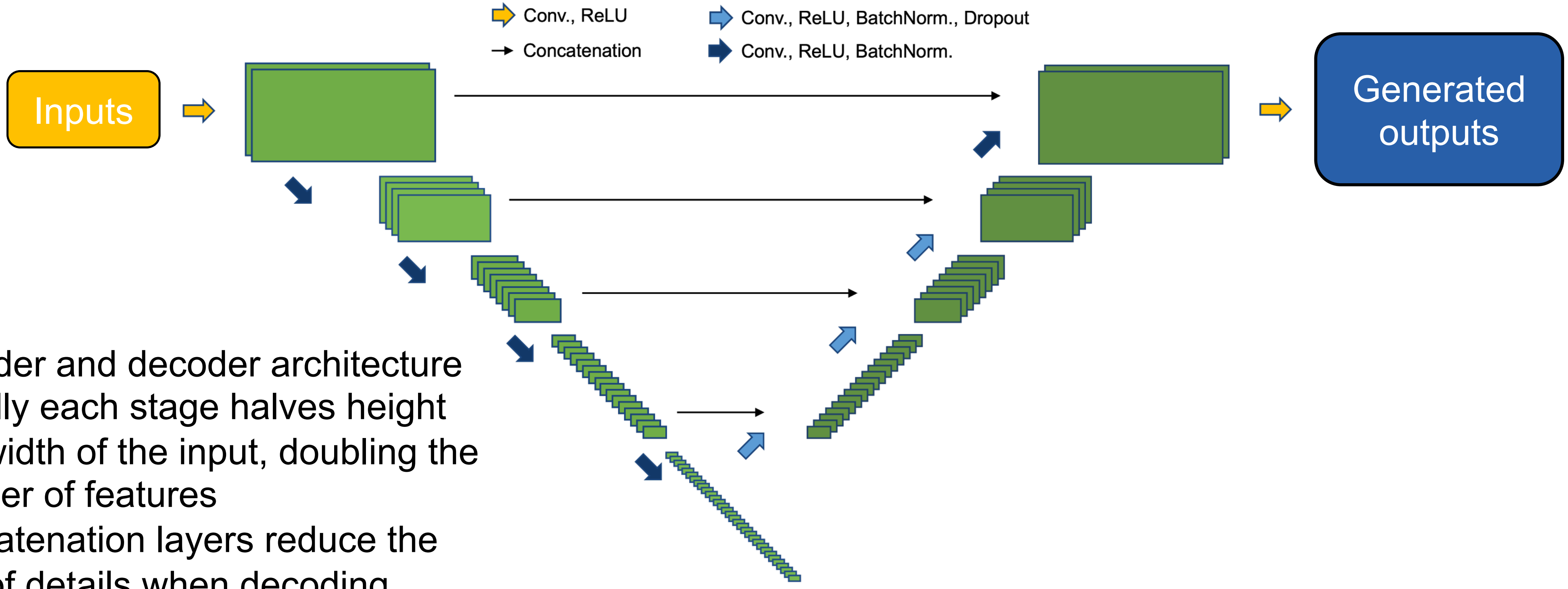


- A convolutional layer consist of:
  1. An input image
  2. A filter
- It convolves (slides) the filter over the image spatially, computing dot products
- It produces feature maps, whose dimensions depend on the dimension of the filter
- In a network, the feature maps are usually inputs for the next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

CNN for the Assimilation of Diurnal Satellite Retrievals of SST

Different approaches considered to construct the forward operator:

- U-Net
- pix2pix
- Random forest
- Persistency
- Multivariate linear regression
- Climatological bias estimation



- Encoder and decoder architecture
- Usually each stage halves height and width of the input, doubling the number of features
- Concatenation layers reduce the loss of details when decoding

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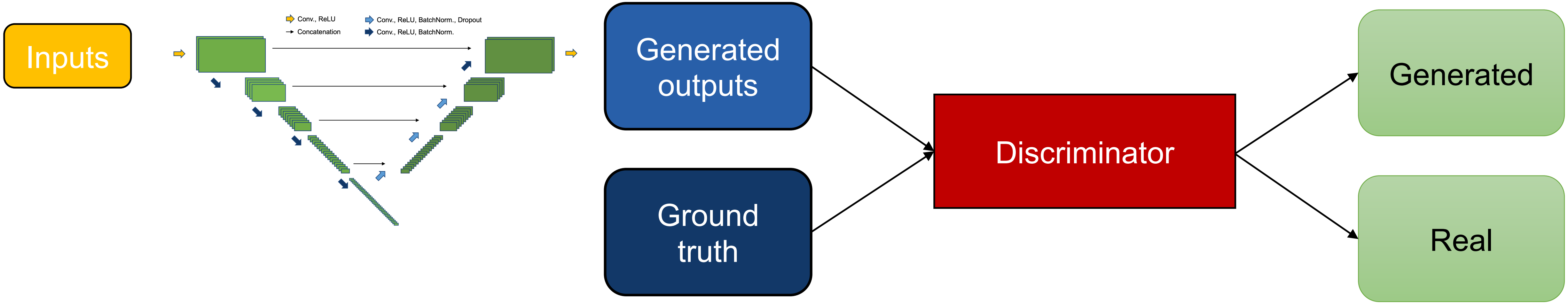

- Generator (U-Net)
- Discriminator (CNN)
- Generator and discriminator trained together
    - Generator rewarded when fooling discriminator
    - Discriminator rewarded when telling real image from generated one
- Training loop needs to balance generator and discriminator losses
- If successful, generator produces realistic images
- After training, only keep generator to produce output

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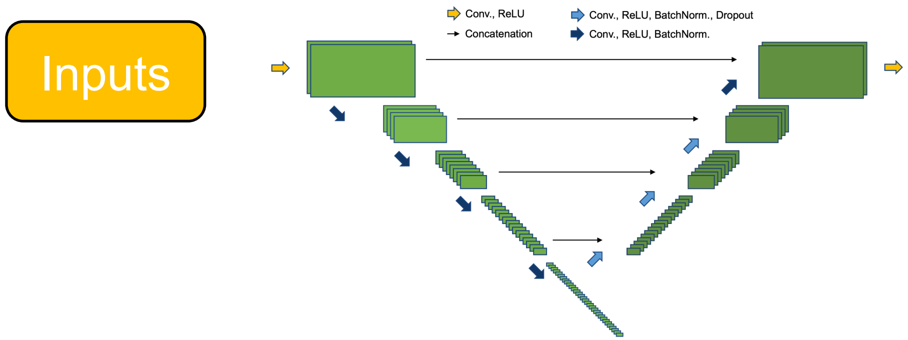

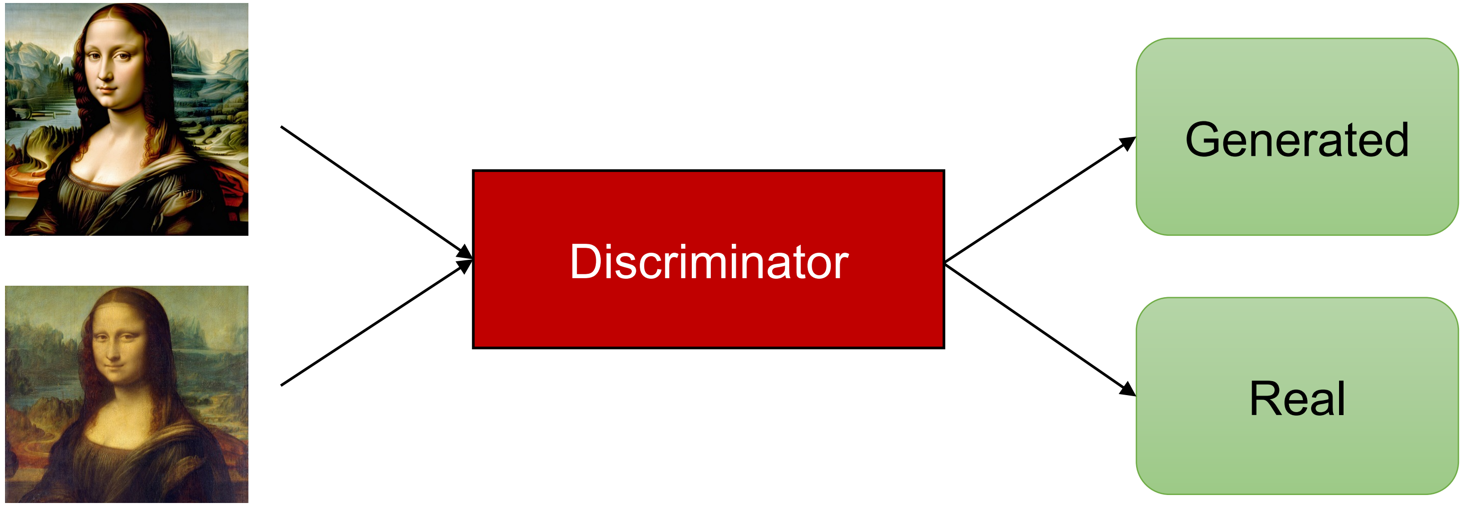

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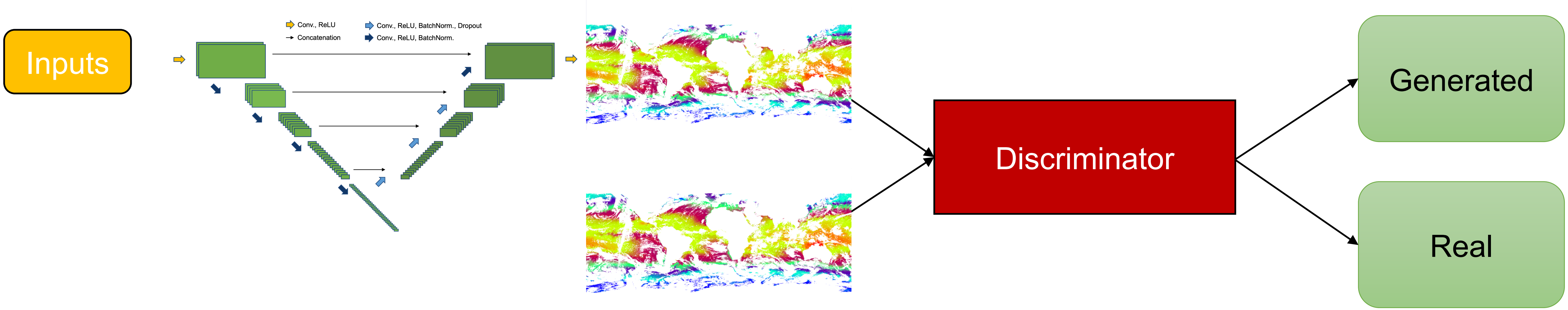

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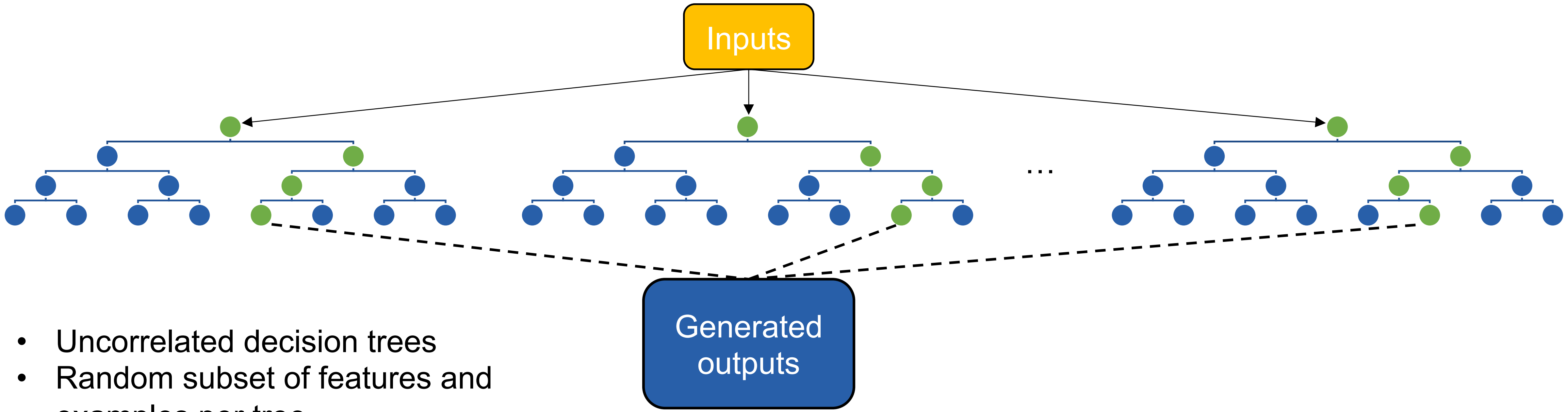

- Uncorrelated decision trees
- Random subset of features and examples per tree
- Easy to train
- No information from surrounding points

CNN for the Assimilation of Diurnal Satellite Retrievals of SST

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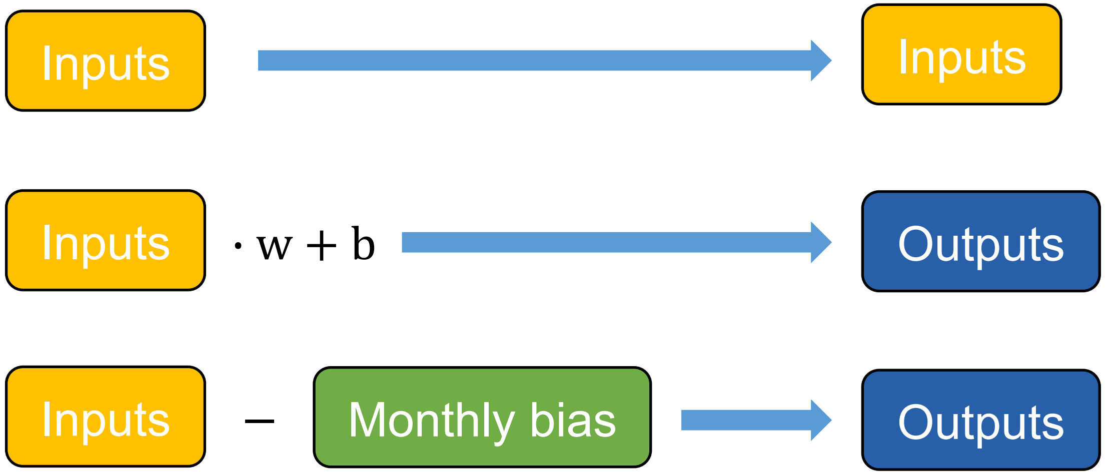

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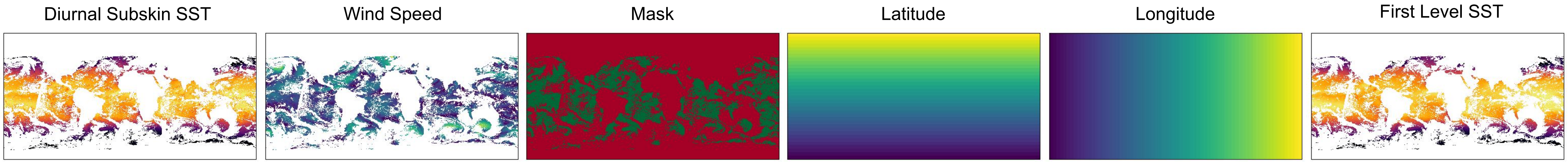


Input

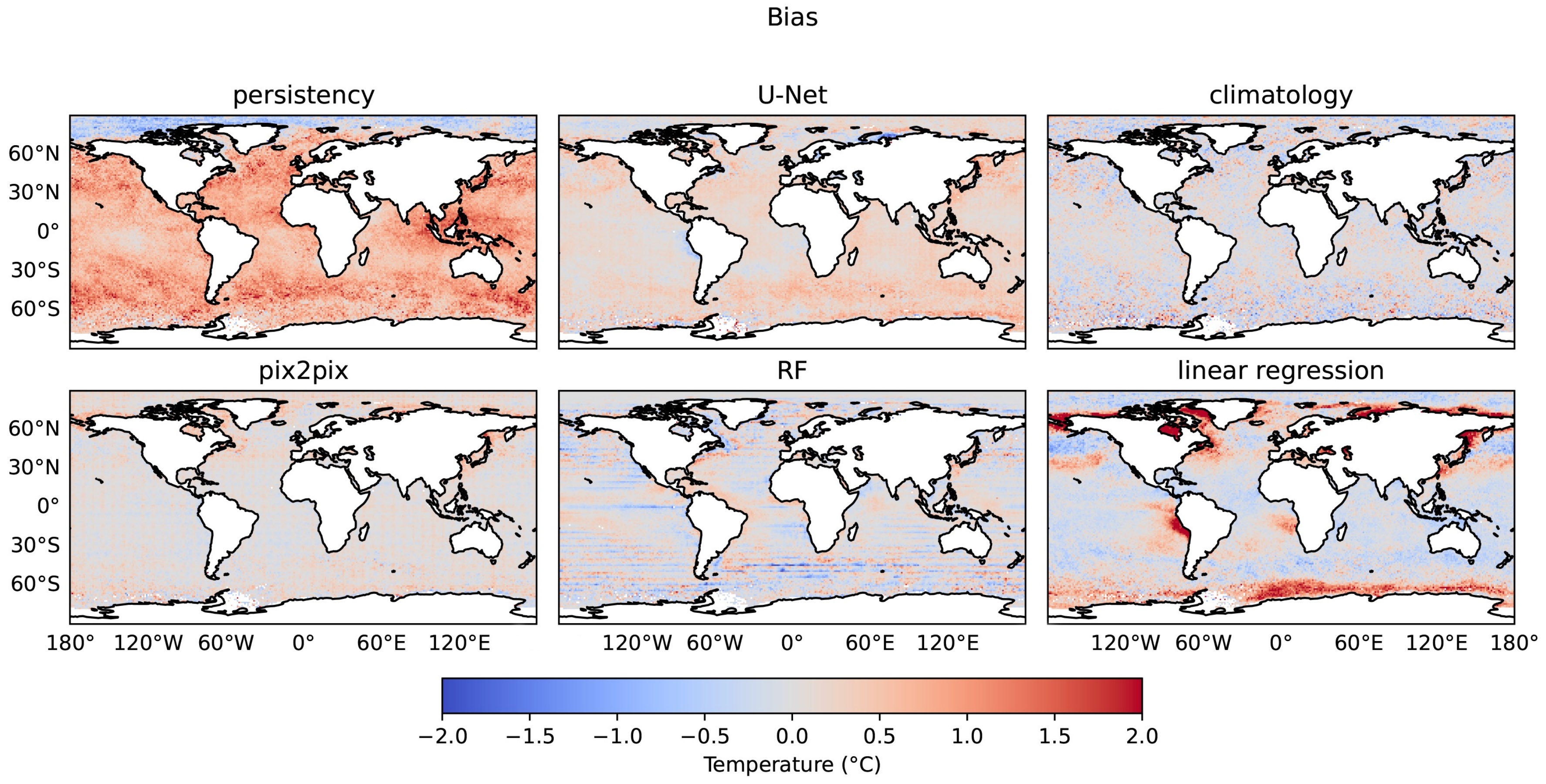
- Diurnal L3 global **subskin SST** from AVHRR’s infrared channels on MetOp satellites produced by OSI SAF
- **Wind speed** at 10m
- **Mask** for land and clouds
- **Latitude** and **longitude** grids

Ground truth

- L4 first level global **SST** from ESA SST CCI and C3S by CMEMS
  - Masked as input data

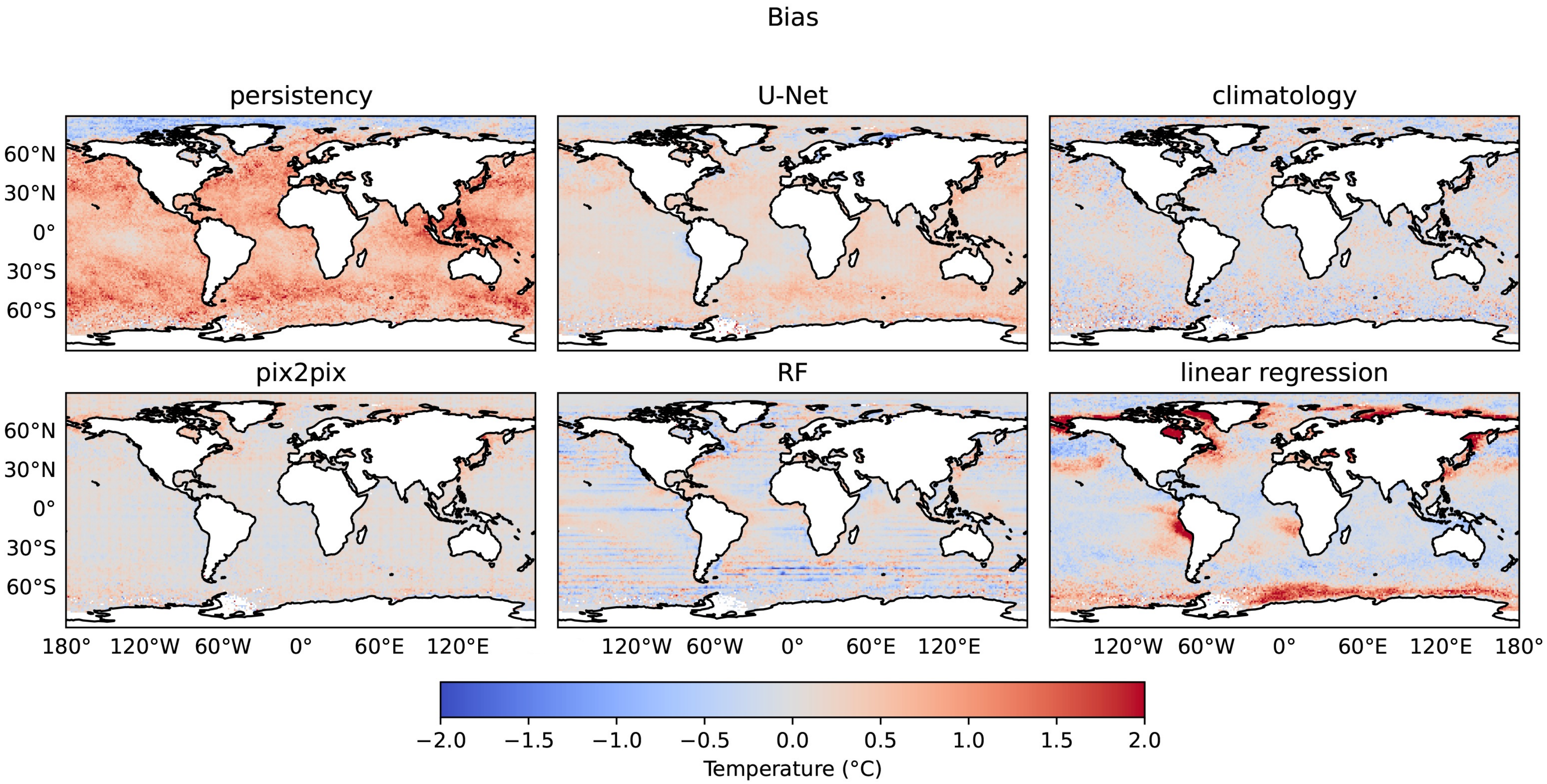
Training on one year of data (2017)
80% training, 20% testing

CNN for the Assimilation of Diurnal Satellite Retrievals of SST



- Bias between the predictions of the different models and the ground-truth on the test set

CNN for the Assimilation of Diurnal Satellite Retrievals of SST



	persistency	U-Net	pix2pix	RF	Climatology	Lin. Regr.
Bias (degC)	0.61	0.20	0.09	-0.01	0.01	0.16

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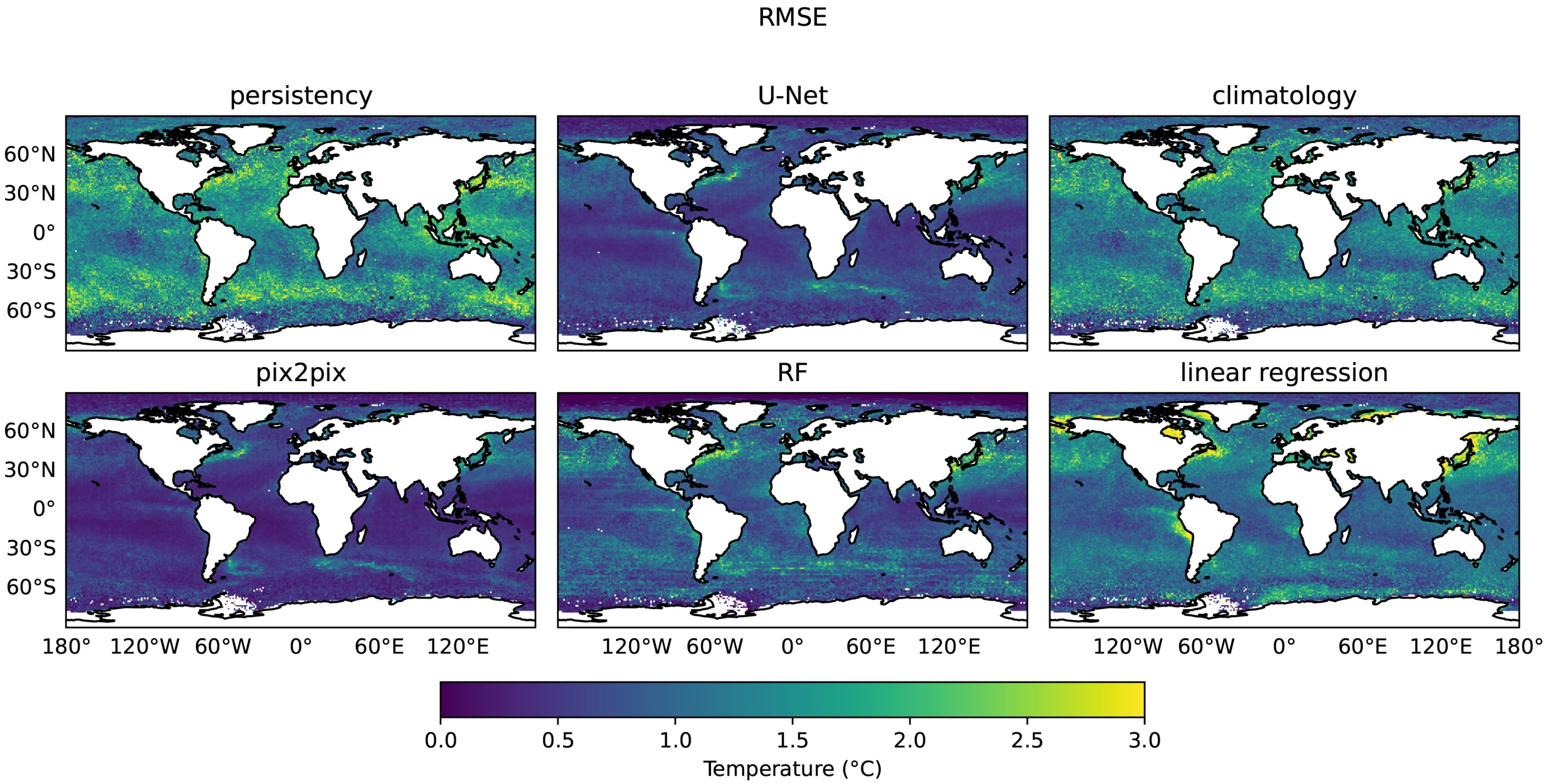
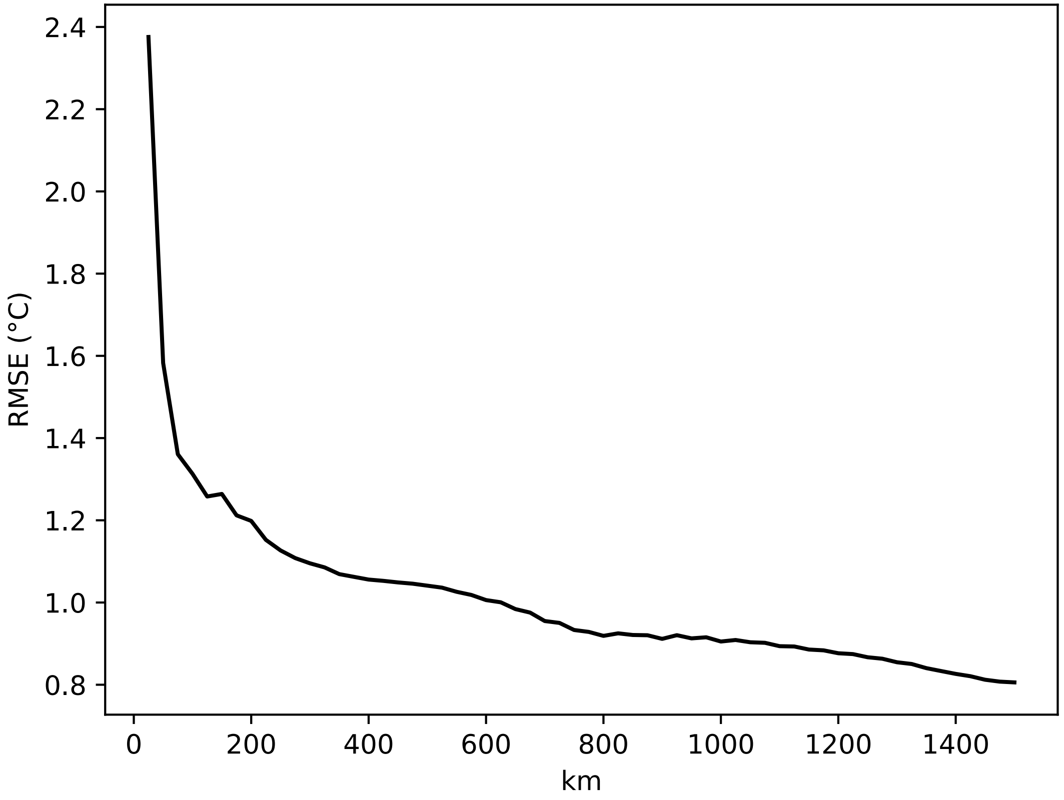


	persistency	U-Net	pix2pix	RF	Climatology	Lin. Regr.
Bias (degC)	0.61	0.20	0.09	-0.01	0.01	0.16
RMSE (degC)	1.45	0.69	0.53	0.86	1.32	1.17

CNN for the Assimilation of Diurnal Satellite Retrievals of SST



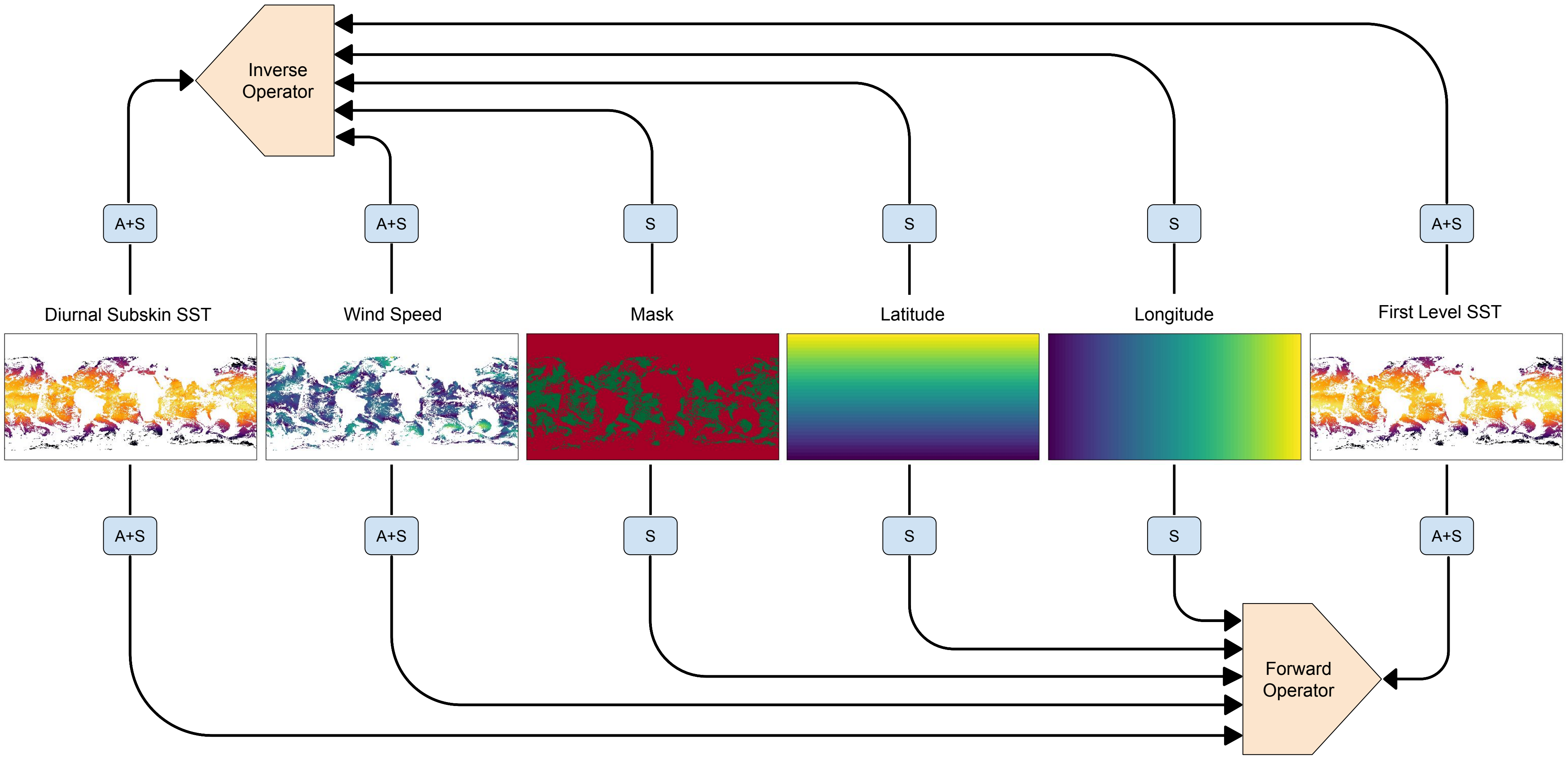
Importance of neighbouring points in CNN

1. Select a point (in the tropical Atlantic)
2. Check the network prediction on that single point against the reference observation
3. Unveil nearest-neighbouring points
4. Check prediction on that single point again
5. Iterate (3) and (4)

In the pix2pix, the **RMSE decreases when including more surrounding points** during prediction

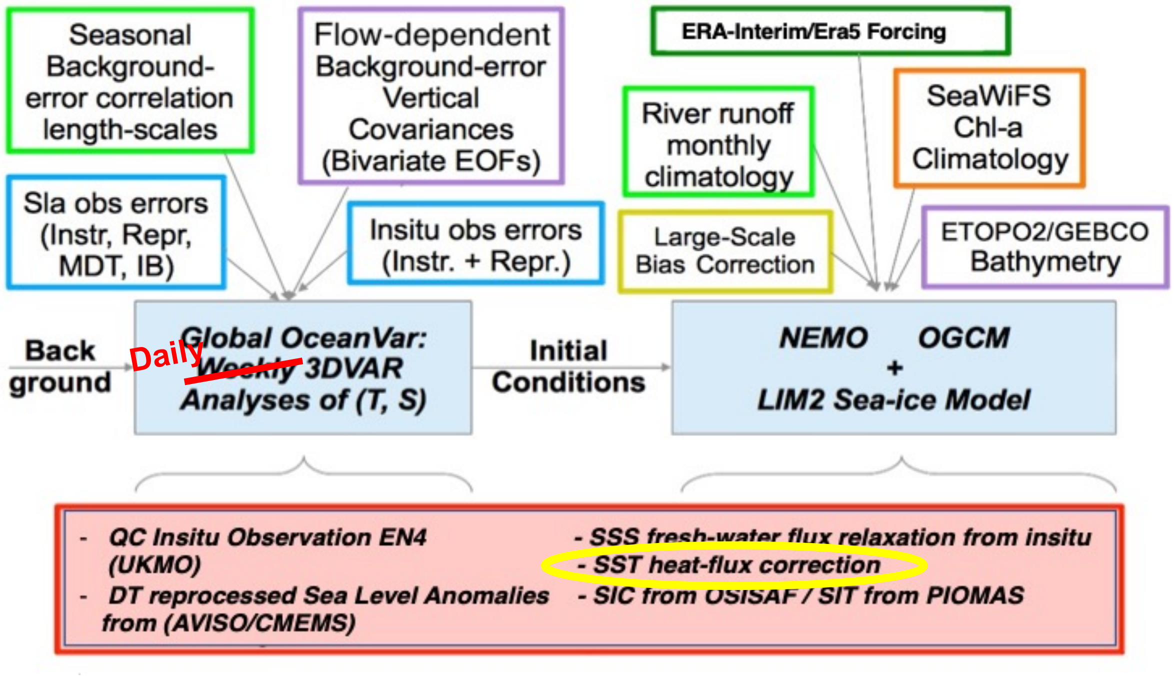
CNN for the Assimilation of Diurnal Satellite Retrievals of SST

Training workflow recap



CNN for the Assimilation of Diurnal Satellite Retrievals of SST

in an Ocean Reanalysis System



ORCA grid at 1/4° (10km to 27km), 75 vertical levels

Adapted from c-glors.cmcc.it [Dobricic and Pinardi (2008), Storto et al. (2010), Storto and Masina (2016)]

The CMCC Global Ocean Physical Reanalysis System (**C-GLORS**) is used at CMCC to simulate the state of the ocean in the last decades by coupling a variational data assimilation system with ocean/sea-ice model

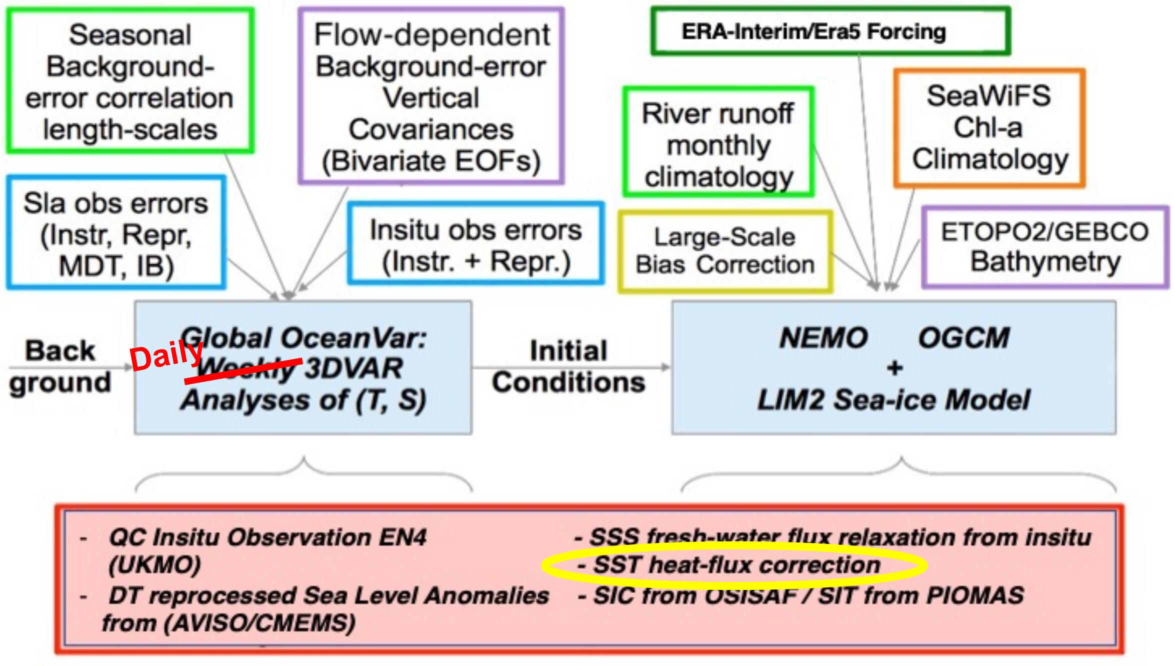
OceanVar: three-dimensional variational (3DVAR) data assimilation scheme that seeks the minimum of the cost function

$$J(\delta\boldsymbol{x}) = \frac{1}{2}\delta\boldsymbol{x}^{\mathrm{T}}\boldsymbol{B}^{-1}\delta\boldsymbol{x} + \frac{1}{2}(H\delta\boldsymbol{x} - \boldsymbol{d})^{\mathrm{T}}\boldsymbol{R}^{-1}(H\delta\boldsymbol{x} - \boldsymbol{d})$$

- $\delta\boldsymbol{x} = \boldsymbol{x} - \boldsymbol{x}_b$, $\boldsymbol{x}_b$ ocean initial and $\boldsymbol{x}$ final state
- $\boldsymbol{B}, \boldsymbol{R}$ background- and observation-error covariance matrices
- $\boldsymbol{d}$ misfits computed with non-linear observation operator
- H tangent-linear version of the observation operator
- Ocean state $\boldsymbol{x} \sim (\mathrm{T},\ \mathrm{S},\ \mathrm{SST},\ \mathrm{SLA})$

CNN for the Assimilation of Diurnal Satellite Retrievals of SST

in an Ocean Reanalysis System



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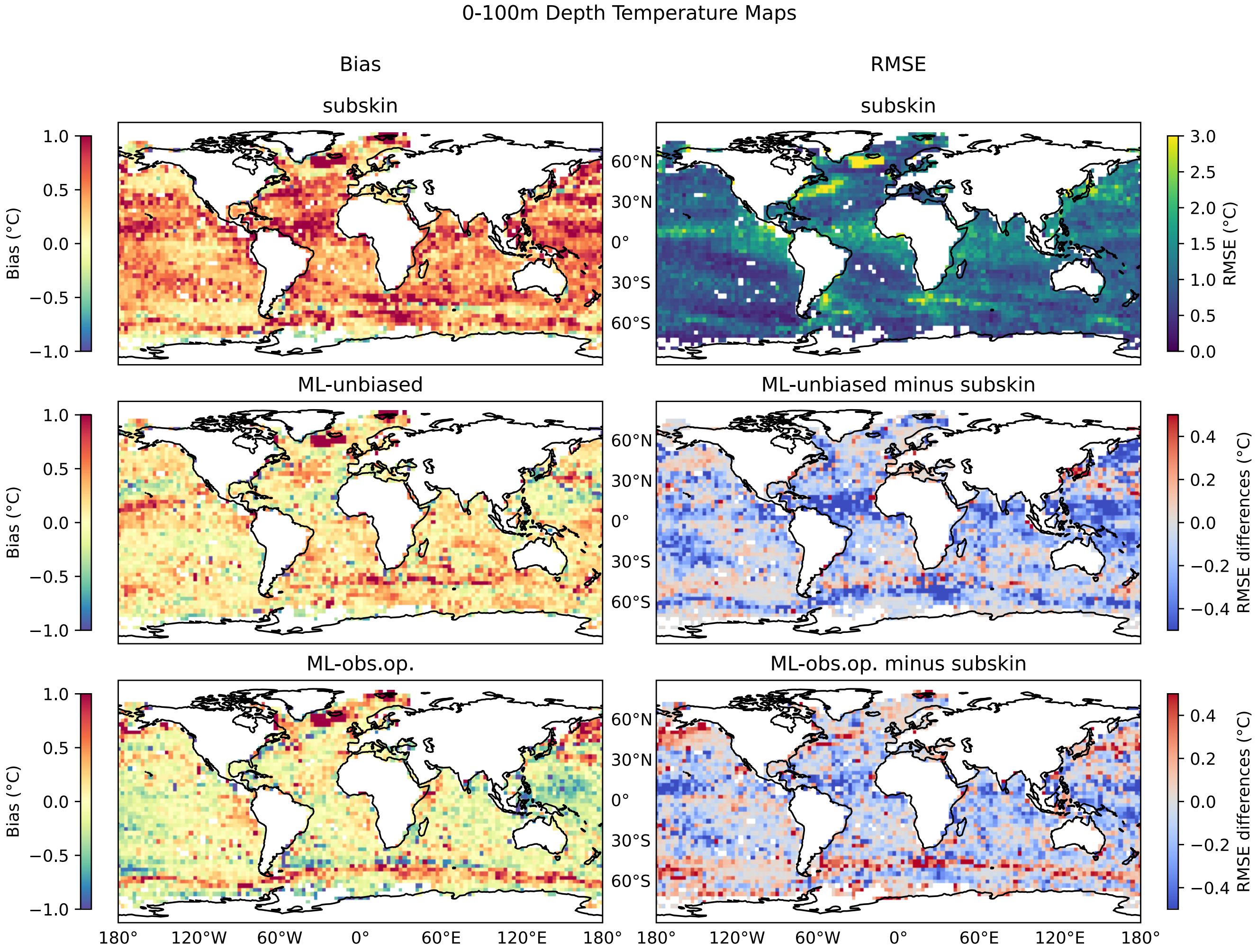
One-year long reanalysis-like experiments with C-GLORS system with hybrid ML/DA of:

1. subskin SST
2. ML-unbiased SST
   - ➢ with forward operator
3. subskin SST with ML obs. op.
   - ➢ with inverse operator
4. Free run with no assimilation

Independent data from ML training (2018)

CNN for the Assimilation of Diurnal Satellite Retrievals of SST

in an Ocean Reanalysis System



Temperature maps of bias and RMSE of different experiments against *in situ* observations

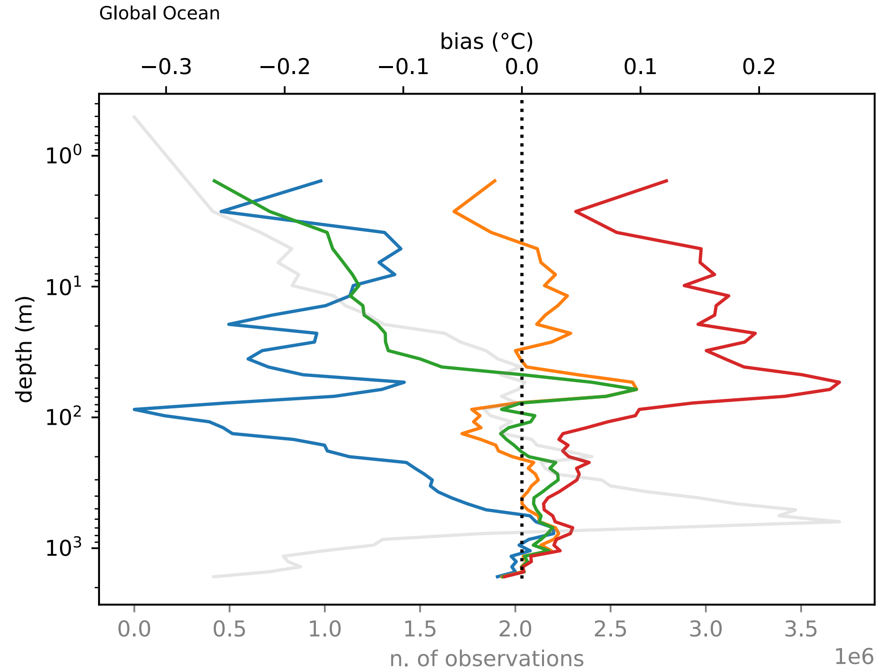
- Warm bias of subskin exp exceeds 1 degC
- Bias reduced in ML approaches
- RMSE improvement in ML-unbiased exp exceeds 0.4 degC
- ML-obs.op. qualitatively similar to ML-unbiased, but less beneficial
- Tropical bands show largest improvements
- Largest errors in extra-tropic regions with strong mesoscale activities (Agulhas, Kuroshio)

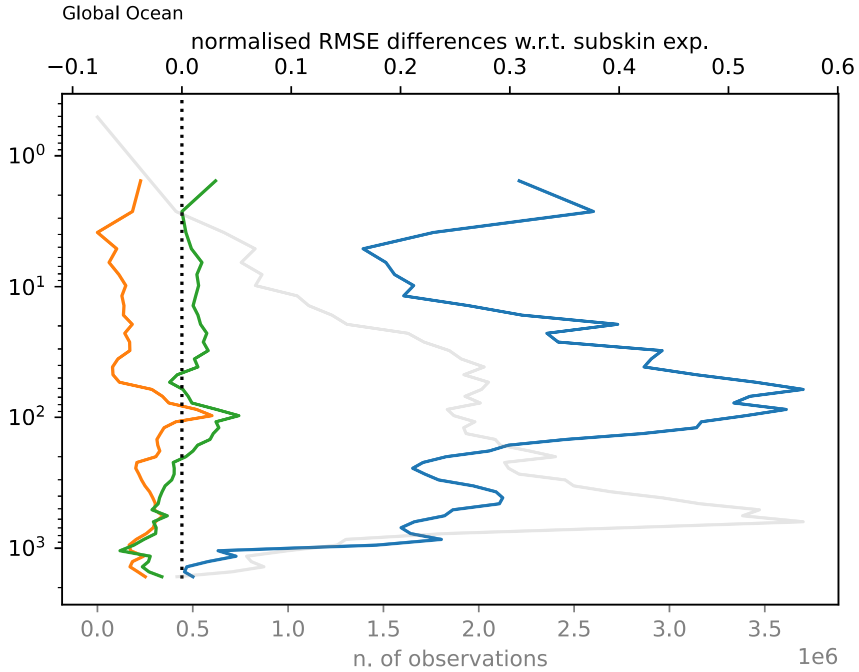
CNN for the Assimilation of Diurnal Satellite Retrievals of SST

in an Ocean Reanalysis System

Temperature vertical profiles of the misfits against *in situ* observations for the experiments with assimilation of:

- Subskin
- ML-unbiased
- ML-obs.op.
- Free run (no assimilation)



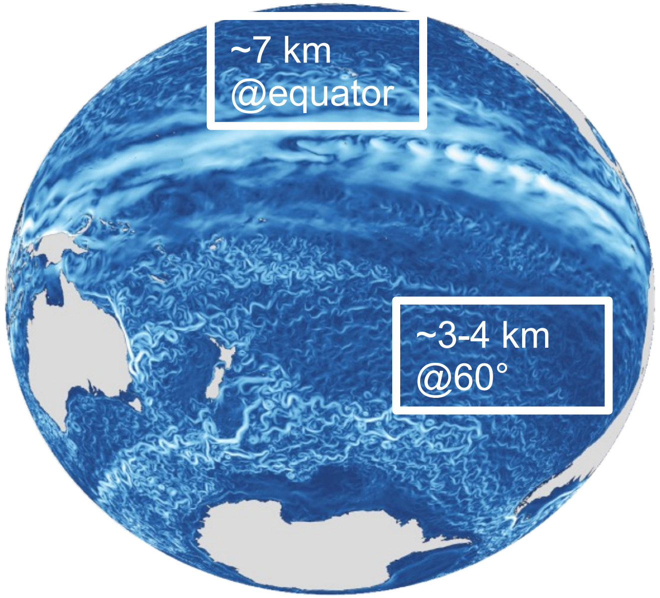


- Subskin exp shows warm bias
- ML-obs.op. reduce the bias only from 100m of depth
- ML-unbiased reduce the bias and also the RMSE

- ML-unbiased improve the RMSE up to 10% w.r.t. subskin
- ML-obs.op. improves only in particular region (e.g. Tropics)

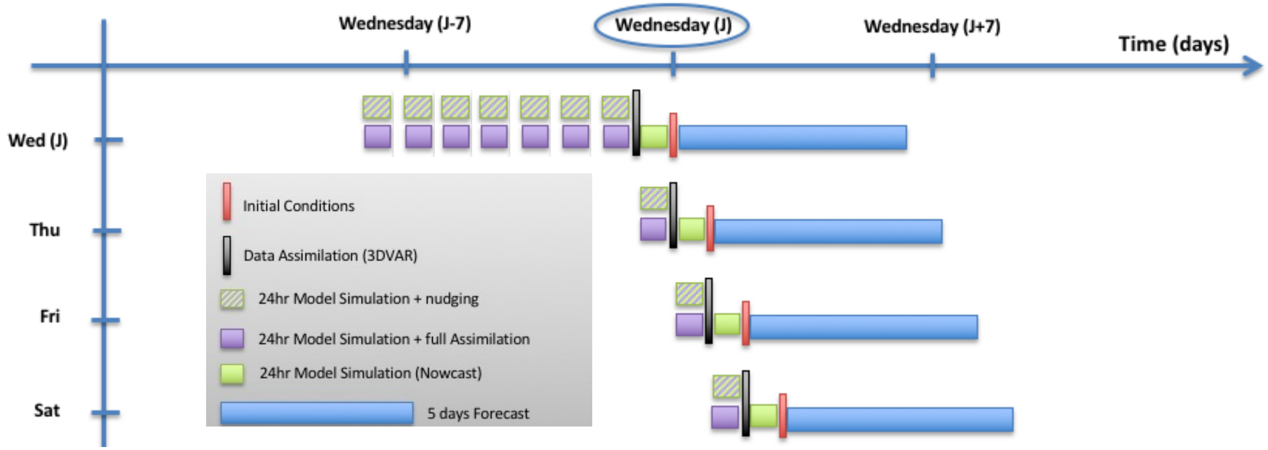
CNN for the Assimilation of Diurnal Satellite Retrievals of SST

in an Ocean Forecast System



https://gofs.cmcc.it/

Website with latest bulletin



Global Ocean Forecast System (**GOFS16**) is an operational ocean analysis and forecast system that runs daily at CMCC

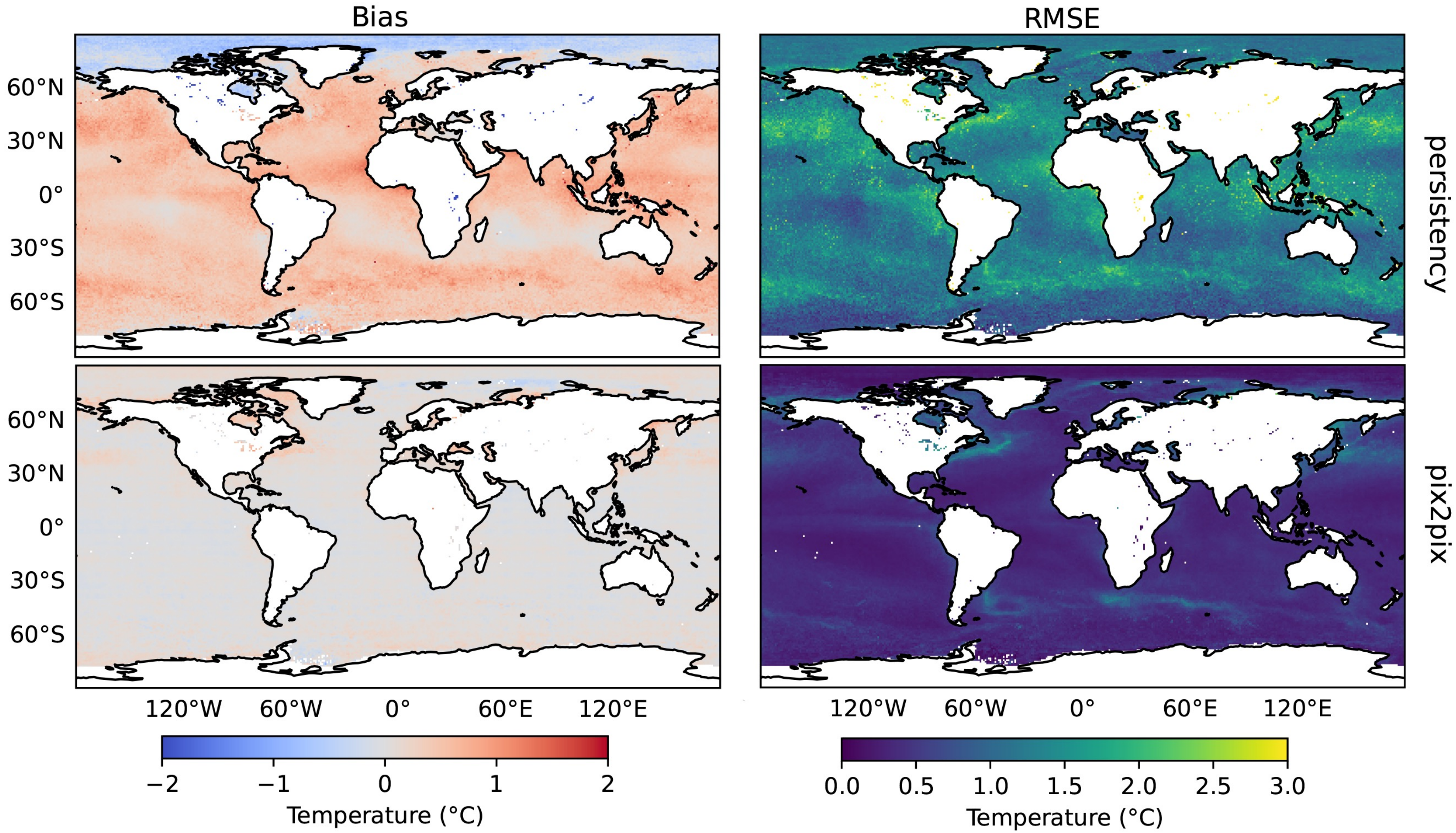
7-day forecasts of the state of the global ocean and sea ice:

- Assimilation system (**OceanVar**)
  - Resolution: ORCA grid at 1/16°, 98 vertical level
  - Assimilation of T/S, SST and SLA
- Forecast model (**NEMOv3.4-LIM2**)
  - Resolution: ORCA grid at 1/16°, 98 vertical level
  - Forecast: T/S, SIC, SIT

No differences w.r.t. surface SST from buoys

CNN for the Assimilation of Diurnal Satellite Retrievals of SST

in an Ocean Forecast System



- 7 years (2017-2023) of training data, 80%-20% train-test split
- Bias and RMSE between MetOp satellite SST and Reynolds SST over the test set
- Re-trained pix2pix bias correction results over the test set

CNN for the Assimilation of Diurnal Satellite Retrievals of SST

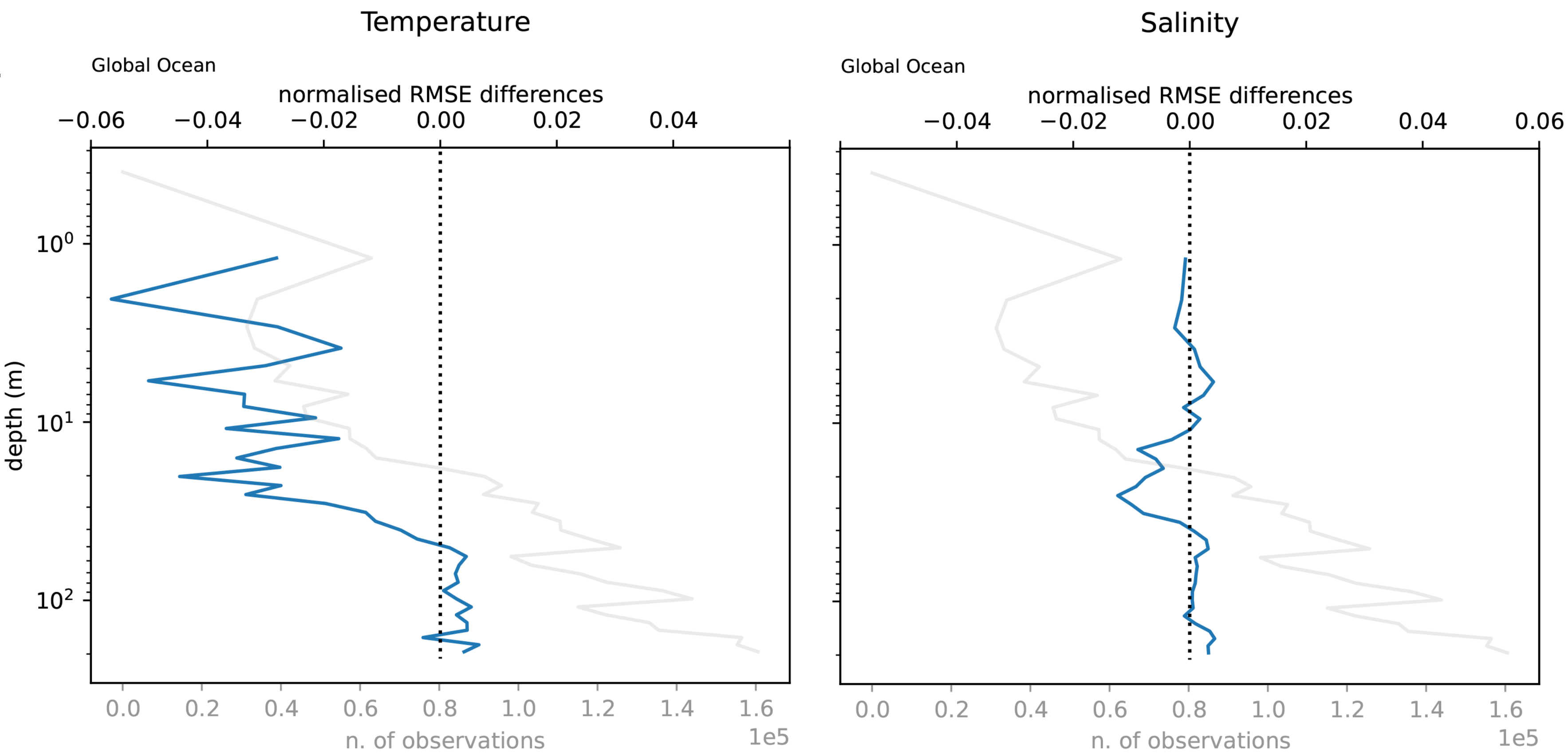
in an Ocean Forecast System

GOFS16 assimilation run for Nov 2024 with ML-unbiased SST

Analysis of the misfits against *in situ* observations for temperature and salinity

- GOFS16_ML minus GOFS16 normalised RMSE differences

- Up to 6% improvement in temperature and 2% in salinity
- No forecast run in GOFS16_ML



Conclusions

- Assimilating diurnal satellite retrievals of subskin SST may introduce biases in reanalysis/forecast system
- Hybrid ML/DA approaches effectively **correct the bias**

Paper available

- ML-based forward operator **easily applicable** to any assimilation system as observation preprocessing
- Only re-train the network to assimilate different product

Network and weights available

- Work in progress: implementation of the ML-unbiasing scheme into **operational products**

THANK YOU!