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Deep-learning models for Single Image Super Resolution: applications to Mediterranean Sea SST products and SST gradients within the Copernicus Marine Service

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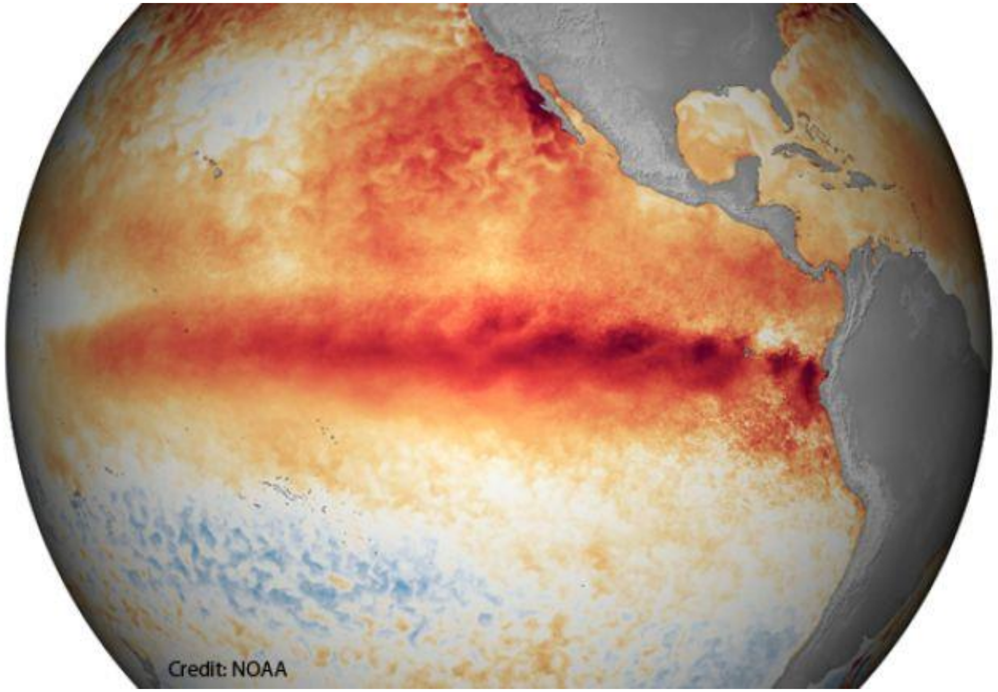
GHRSST
GROUP FOR HIGH RESOLUTION SEA SURFACE TEMPERATURE

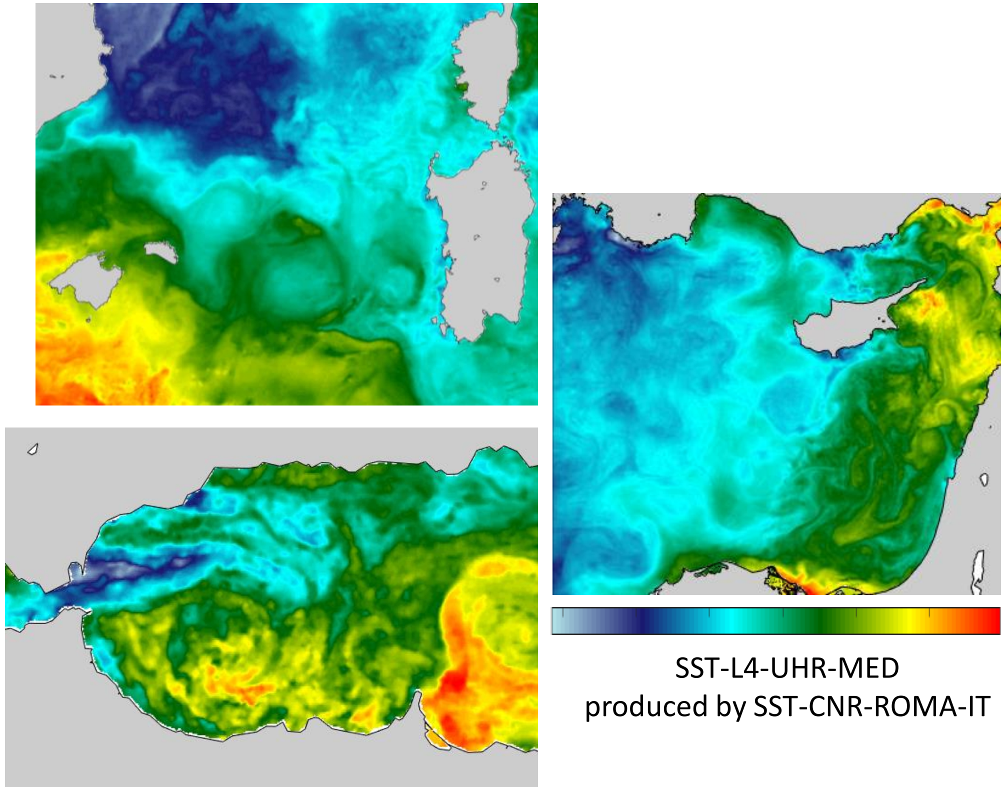
Outline

- Introduction
- Data and methods
  - Convolutional Neural Networks for Super Resolution
  - Datasets
- Results and Discussion
  - SST
  - ∇SST
- Conclusions

Sea Surface Temperature

SST is a key variable to investigate ocean dynamics and climate variability.

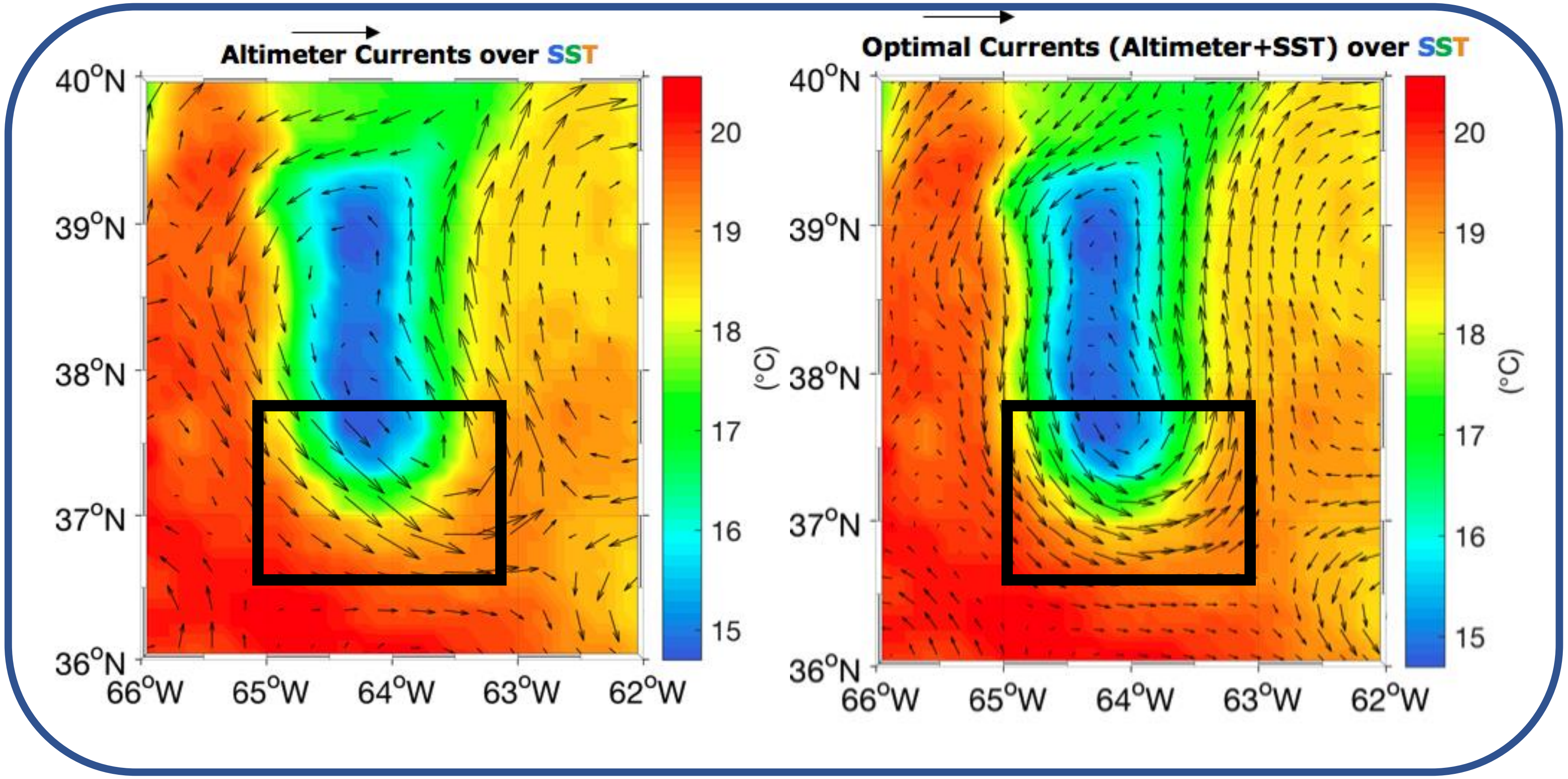




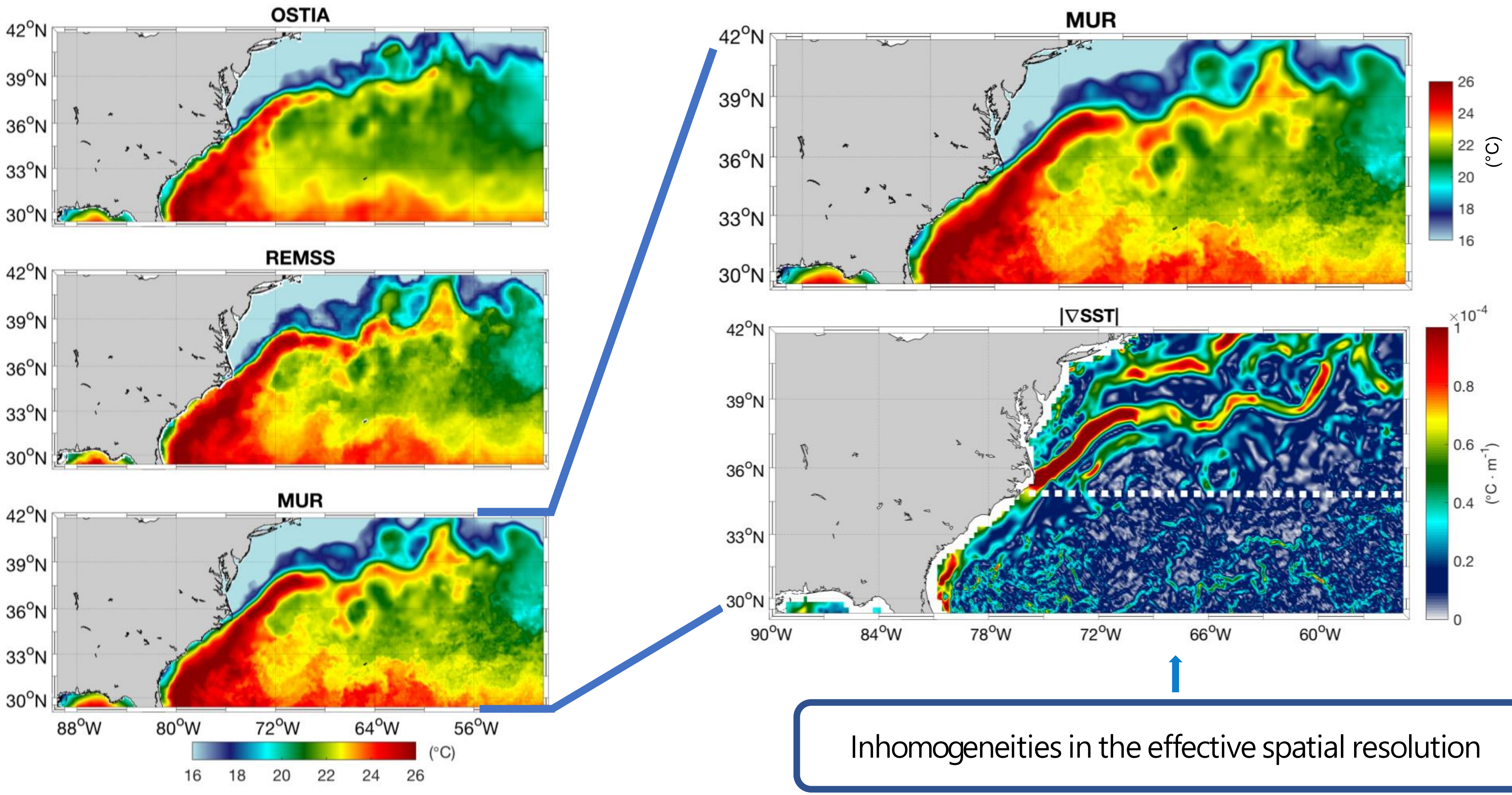
SST-L4-UHR-MED
produced by SST-CNR-ROMA-IT

Ocean dynamics - ∇SST connection

Improvement of altimeter-derived geostrophic currents



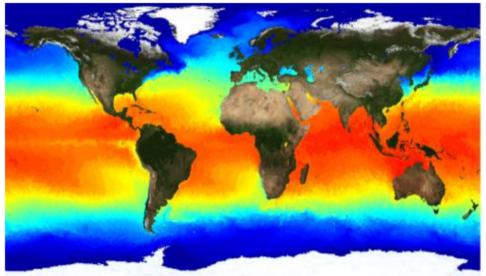
Effective resolution



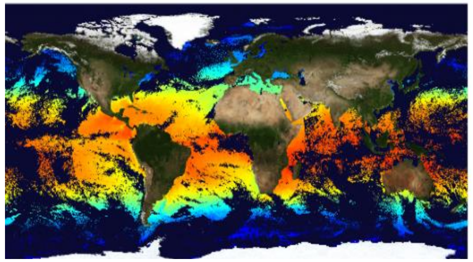
Inhomogeneities in the effective spatial resolution

The SST TAC Catalogue

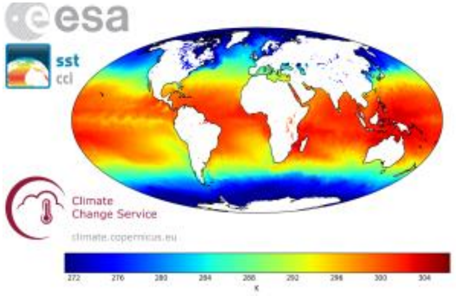
Global (GLO) OSTIA L4 NRT



Odyssea L3S NRT (GLO)

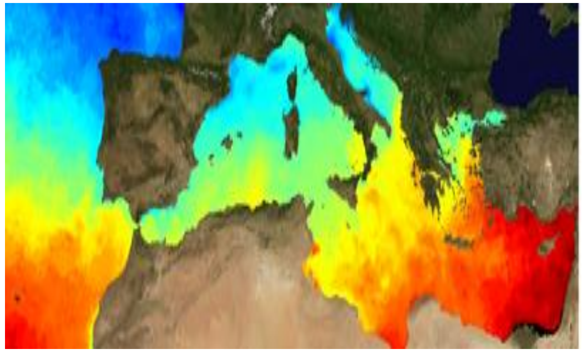


ESACCI/C3S (1981-present) (GLO)

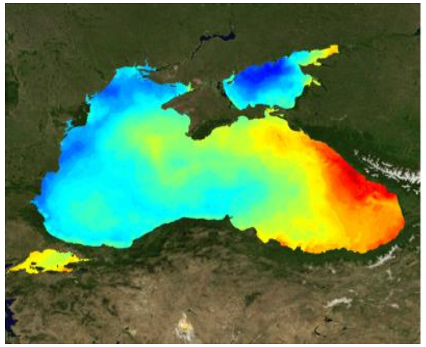


- Within Copernicus Marine Service, the SST TAC is in charge of the **Near-Real-Time (NRT)** and **Multi-Year (MY)**, also known as **Reprocessed (REP**), production of **merged multi-sensor (L3S)**, and **gap-free (L4) SST products** for the **Global Ocean** and the **European regional Seas**
- All the SST TAC products are primarily **based on satellite observations**

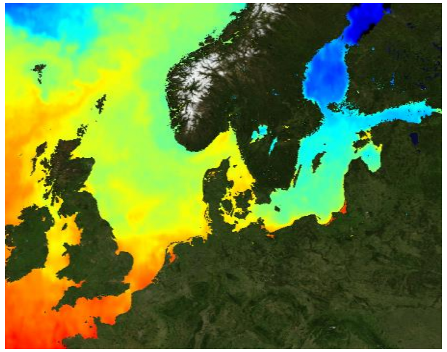
Mediterranean Sea (MED)



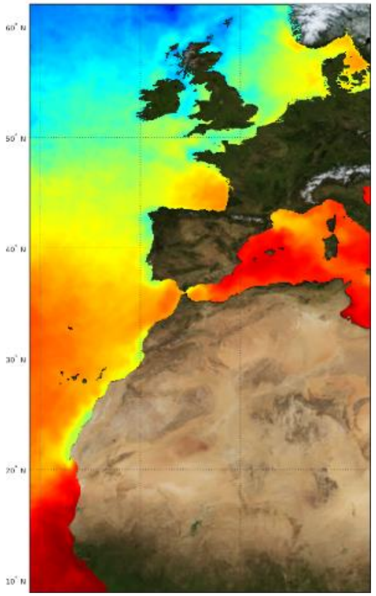
Black Sea (BS)



Baltic Sea (BAL)



ATL (IBI+NWS)



Continuous evolution to improve the quality and provide new products

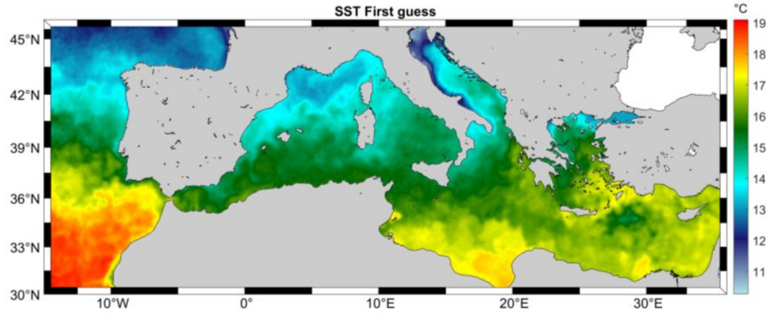
CNR SST processing chain (Med)

Near Real Time

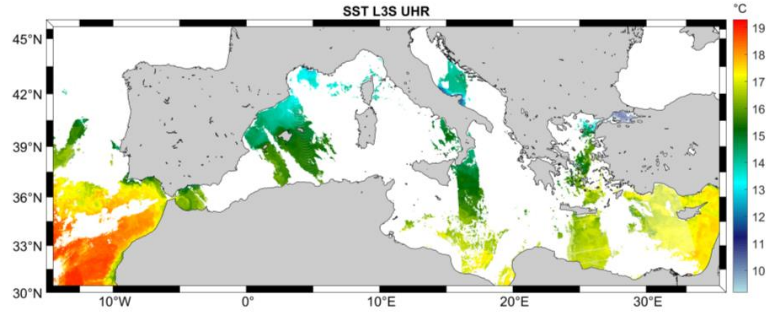
M1		M2		M3		M4		M5	
Get L2P data	→	L2P → L3U	→	L3U → L3S	→	L3S → L4	→	Dissemination	→ L3S (HR & UHR) → L4 (HR & UHR)

Buongiorno Nardelli et al. (2013)

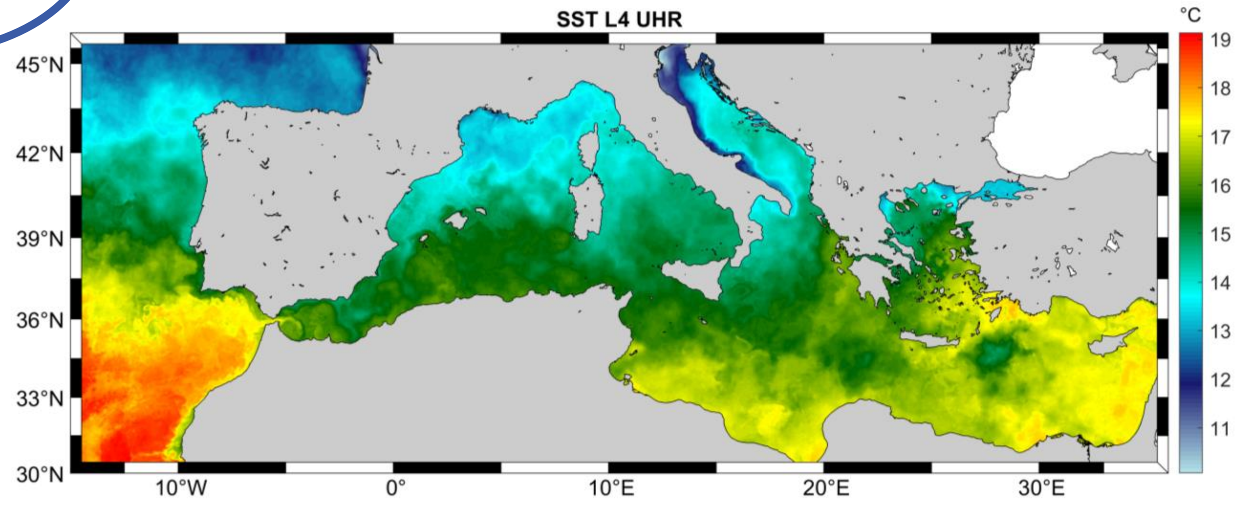
Optimal Interpolation!



L4 HR at 1/16° remapped at 1/100°



1/100°

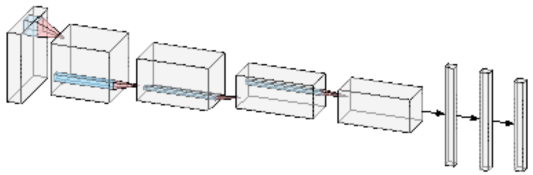


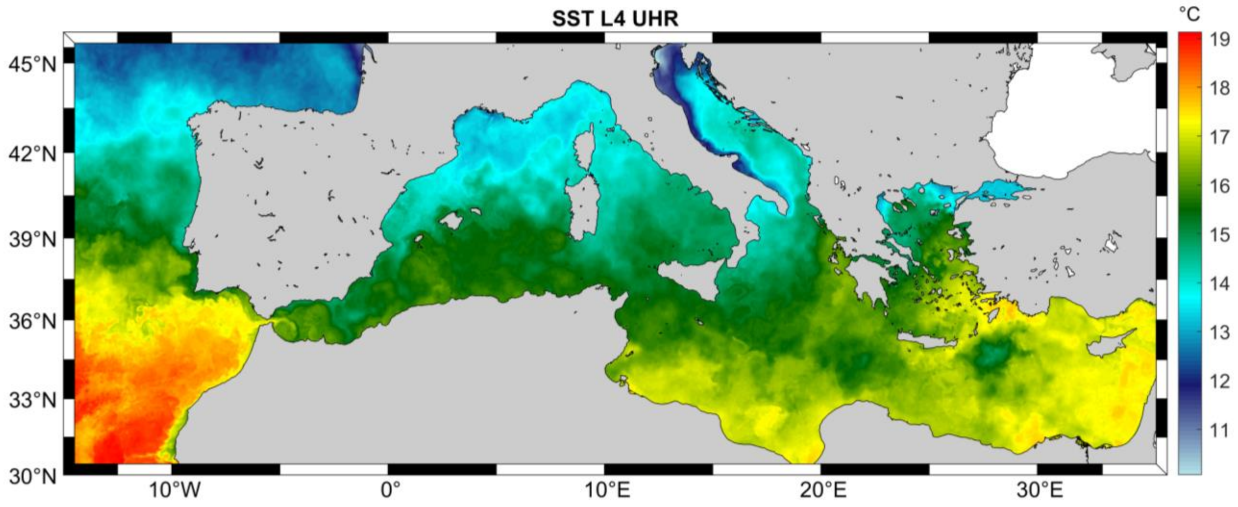
1/100°

AIM

To reconstruct high resolution features when L3 UHR data are missing.

HOW?
Using deep learning methods which makes use of Convolutional Neural Networks to recover high resolution images from low resolution ones (**Super Resolution**).



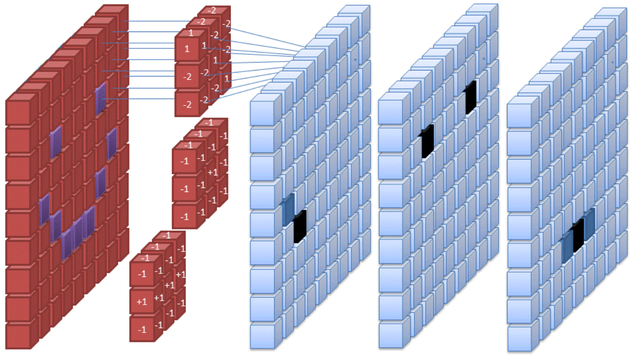


IMPROVING THE <u>EFFECTIVE</u> RESOLUTION

Convolutional Neural Networks (CNNs)

Neural Networks are complex models inspired by the connectivity patterns of neurons in animals' brain, with the ability to manage large-scale datasets while controlling the computational efficiency.

CNNs consist in a series of interconnected layers which use convolutional filters as their main transformation units.



The output $g(Y)$ of each layer k is a function of a transformation of the previous layer output Y:

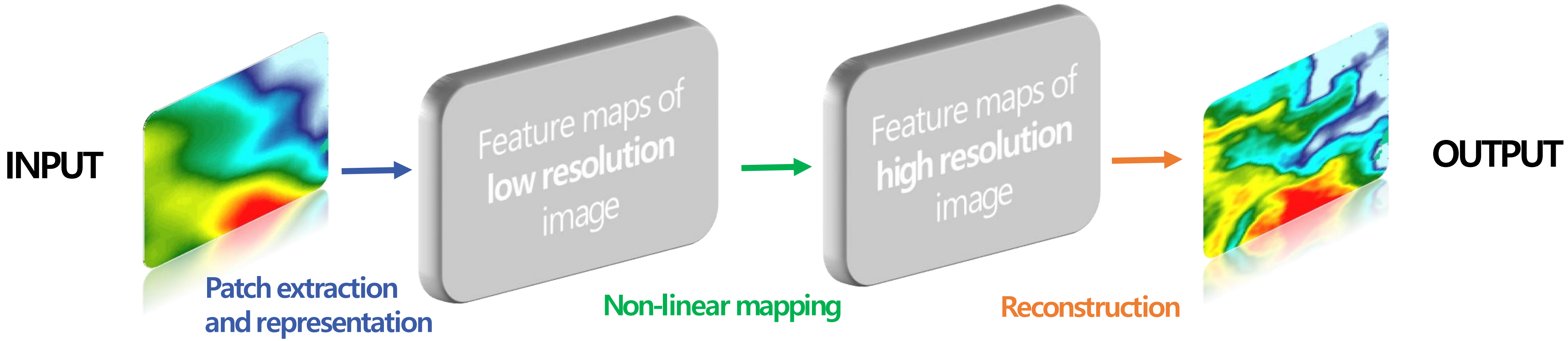
$$g(Y) = f(W_k * Y + B_k)$$

$*$ = convolution operator
f = non-linear activation function
W_k = weights
B_k = biases

Learning = optimization process based on minimizing the error between the output and the data from a ground-truth validation set.

Super Resolution Convolutional Neural Networks

Convolutional Neural Networks that directly learn an end-to-end map between low resolution and high resolution images.



Remote sensing data

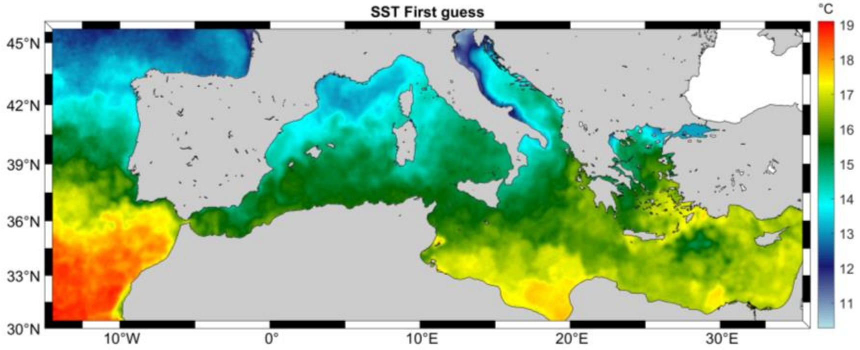
- Availability of large-scale gridded datasets
- Stationary properties of natural images

To be careful

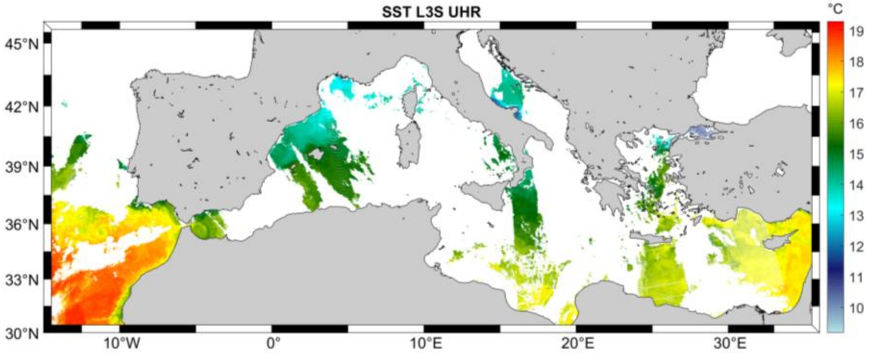
- Depth of the architecture
- Generalization of datasets (overfitting/underfitting)

Training and test datasets

Low resolution: First guess maps (i.e., upsized L4-HR data remapped onto a 1/100° regular grid).



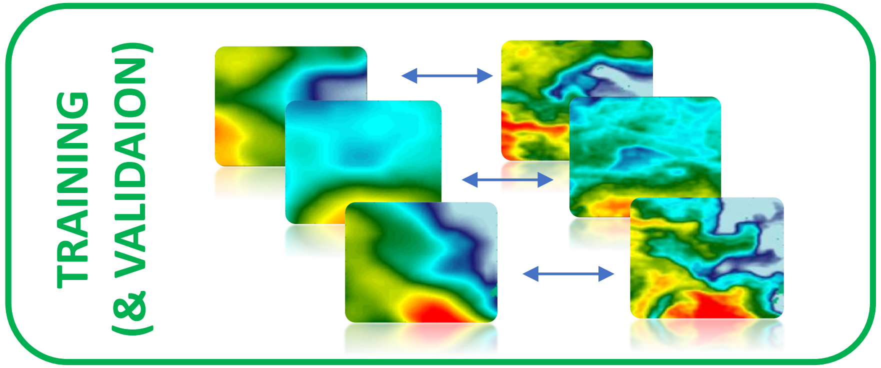
High resolution: A ground-truth L3S-UHR-SST dataset (preprocessed with a low-pass Lanczos filter).



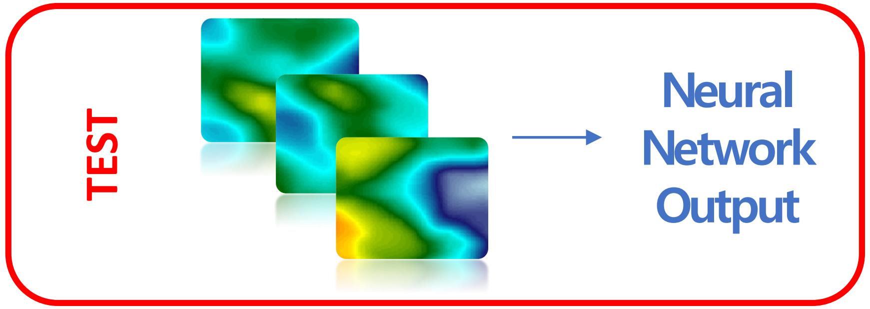
Mediterranean Sea, year 2020

- Overlapping tiles of dimensions 100x100 km (shift = 50 km).
- At least 95% of valid pixels.
- SST values transformed into anomalies (to avoid seasonal variability).
- Min-max normalization between -1 and 1.

~112 000 pairs of tiles (85%)

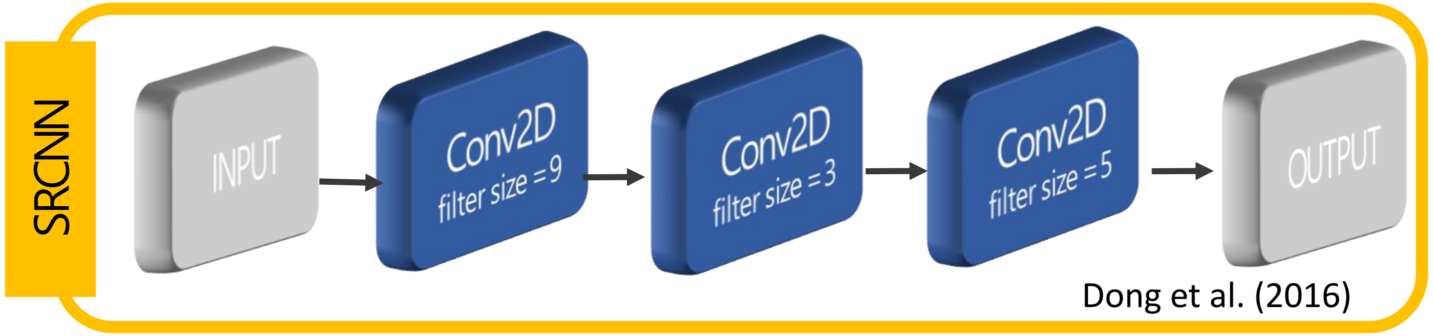


~18 000 Tiles (15%)



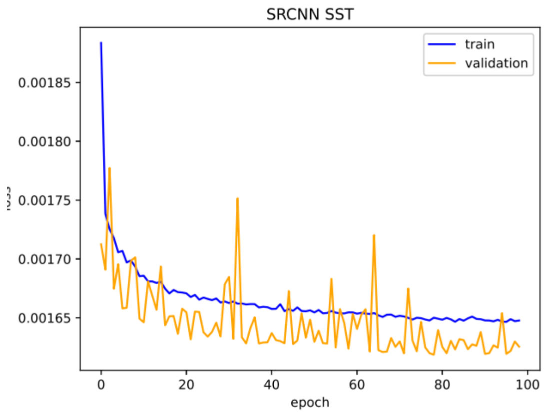
Application of SRCNNs to SST maps

All networks tested are evolutions of the first SRCNN proposed by Dong et al. (2016).



Dong et al. (2016)

- **EDSR**: *Enhanced Deep Residual Network for Super Resolution* (Lim et al., 2017)
- **ADRSR**: *Adaptive Deep Residual Network for Super Resolution* (Liu et al., 2019)
- **dADRSR**: *dilated Adaptive Deep Residual Network for Super Resolution* (Buongiorno Nardelli et al., 2022)

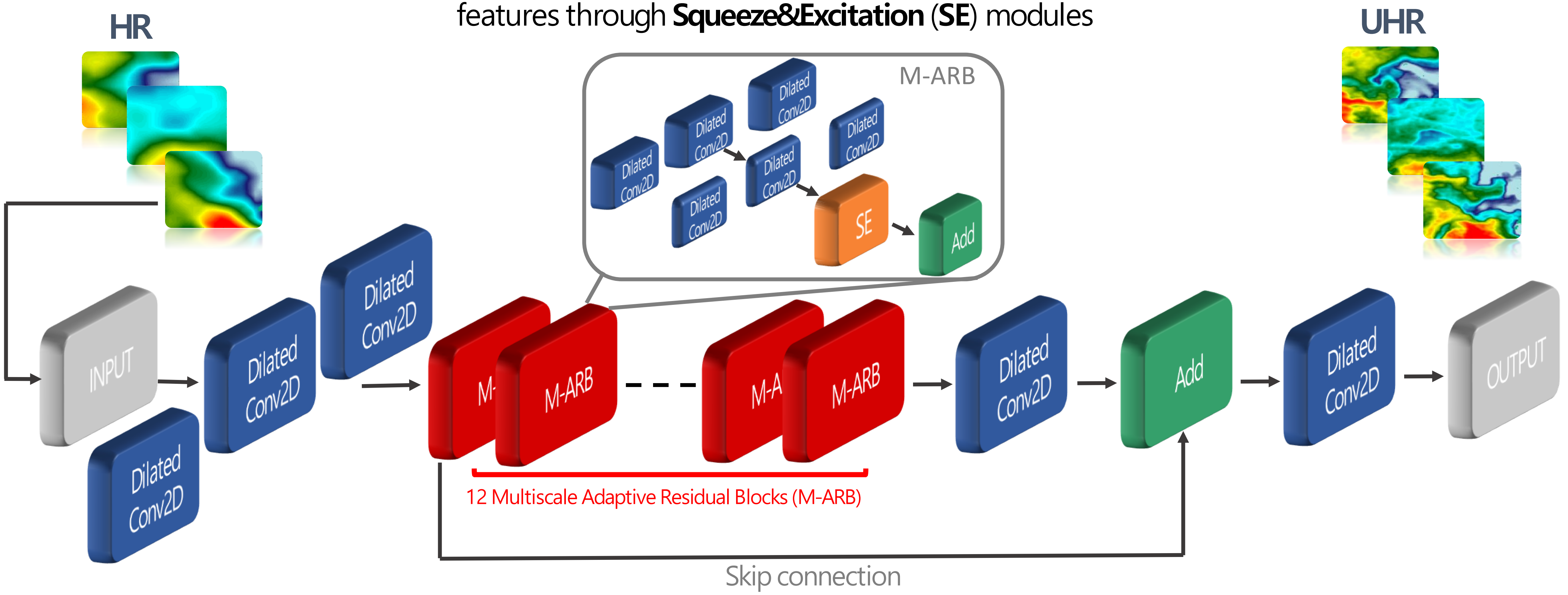


Codes written in **Python** using *Keras* (*TensorFlow*):

- Split Training : Test = 85 : 15
- Activation function → *ReLU*
- Adaptive moment estimator → *Adam optimizer*
- Early stopping condition (with a *patience* value)

Dilated Adaptive Deep Residual Network for Super-Resolution

- **Dilated Conv2D** → Extract information at different scales
- **M-ARB** → Recalibration to better modelling complex interdependencies between features through **Squeeze&Excitation** (**SE**) modules



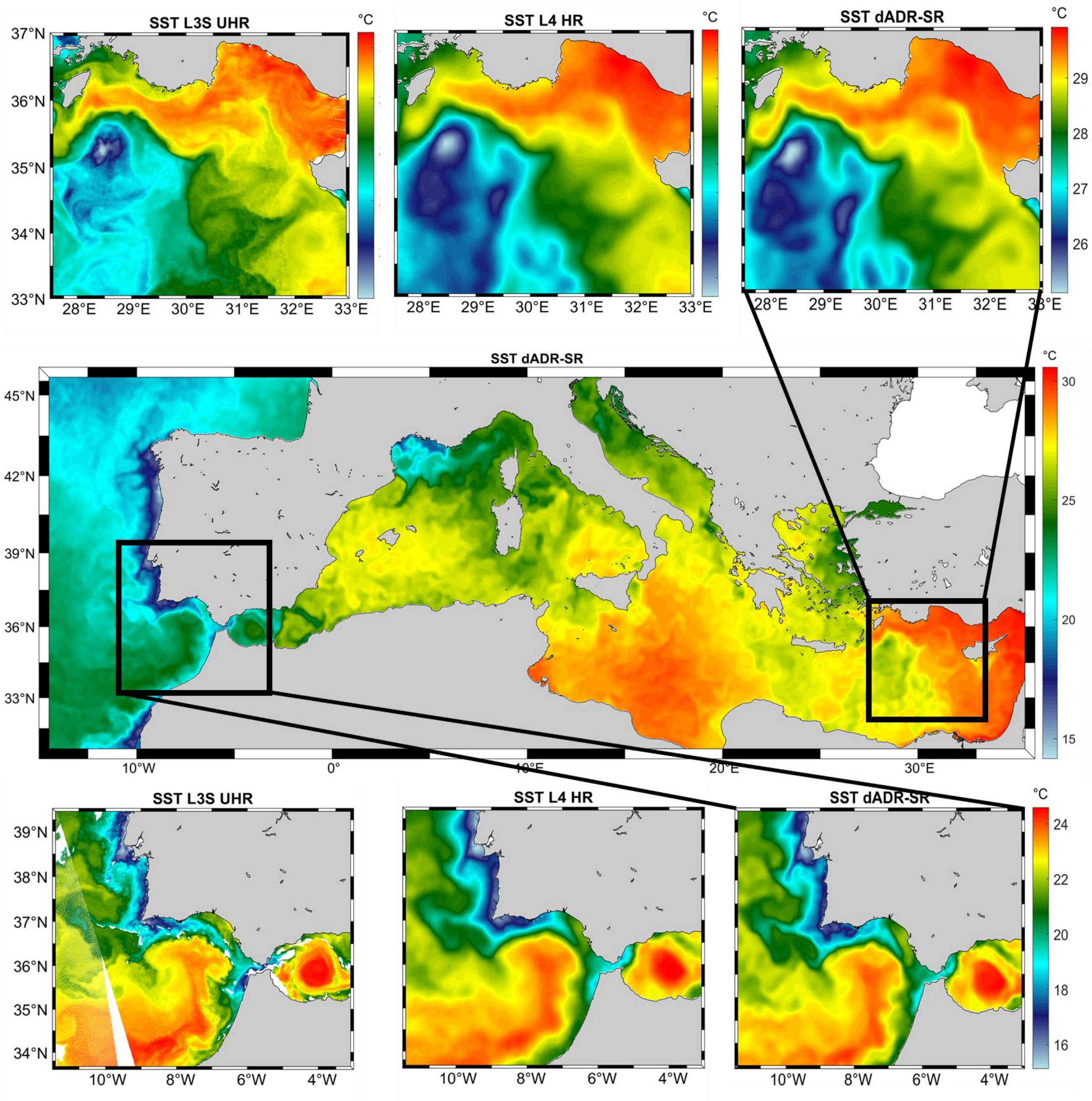
Buongiorno Nardelli et al. (2022)

SST prediction

SST field estimated by the dADR-SR-CNN appears much sharper than the first guess map

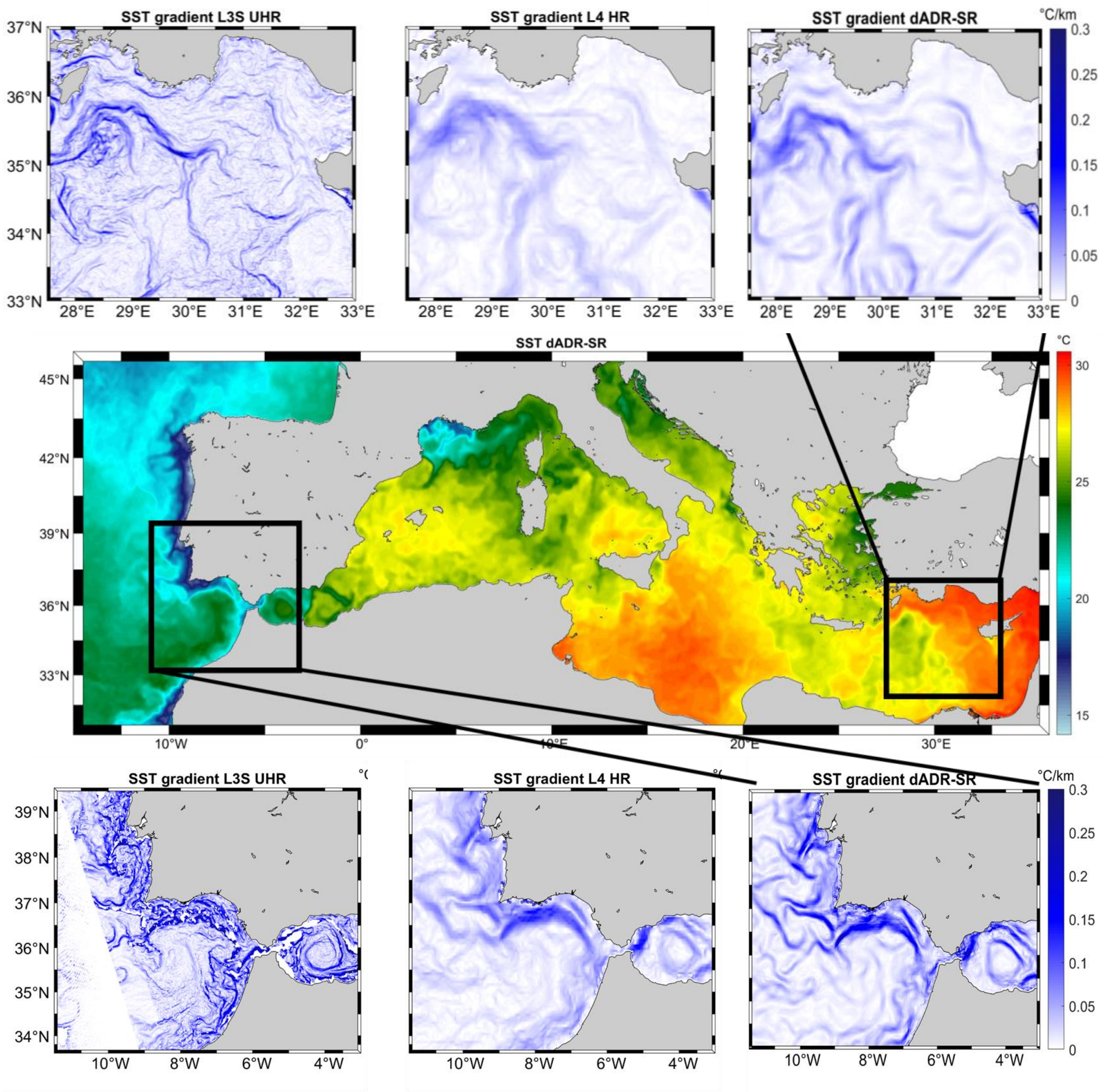
Preliminary results

Model	RMSE (°C)	PSNR (Peak signal-to-noise ratio)	#epochs
SRCNN	**0.34**	36	99
EDSR	0.35	36	40
ADRSR	0.35	36	21
dADRSR	0.37	**36.1**	**9**
Low Resolution	0.4	35.9	-



∇SST approximation

dADR-SR-CNN captures high magnitude patterns with a superior accuracy with respect to the low resolution approximation
(which tends to severely smooth SST structures when ground-truth data are missing).

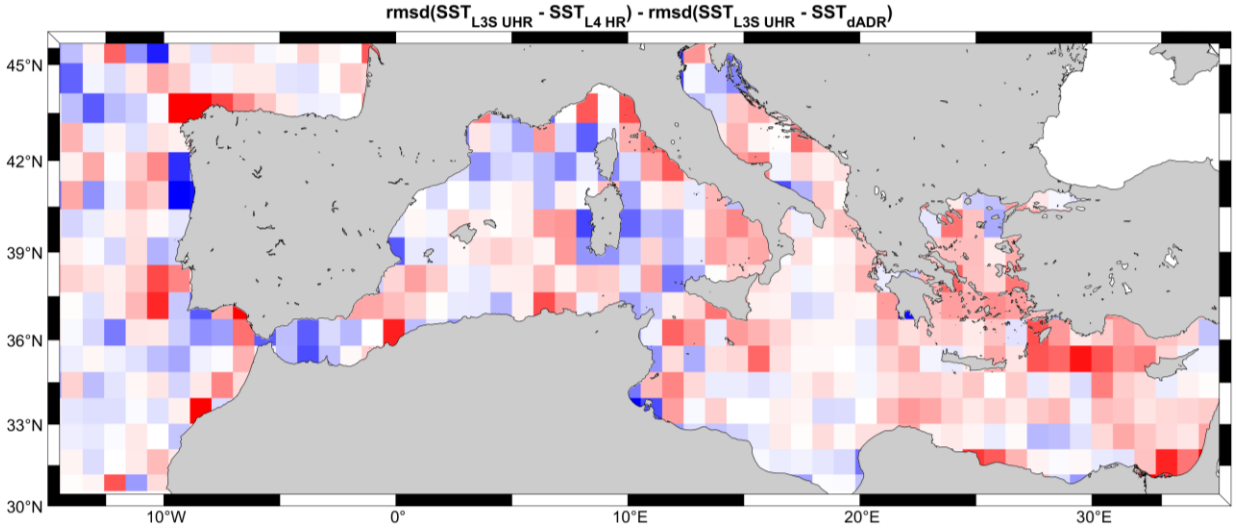


Errors maps

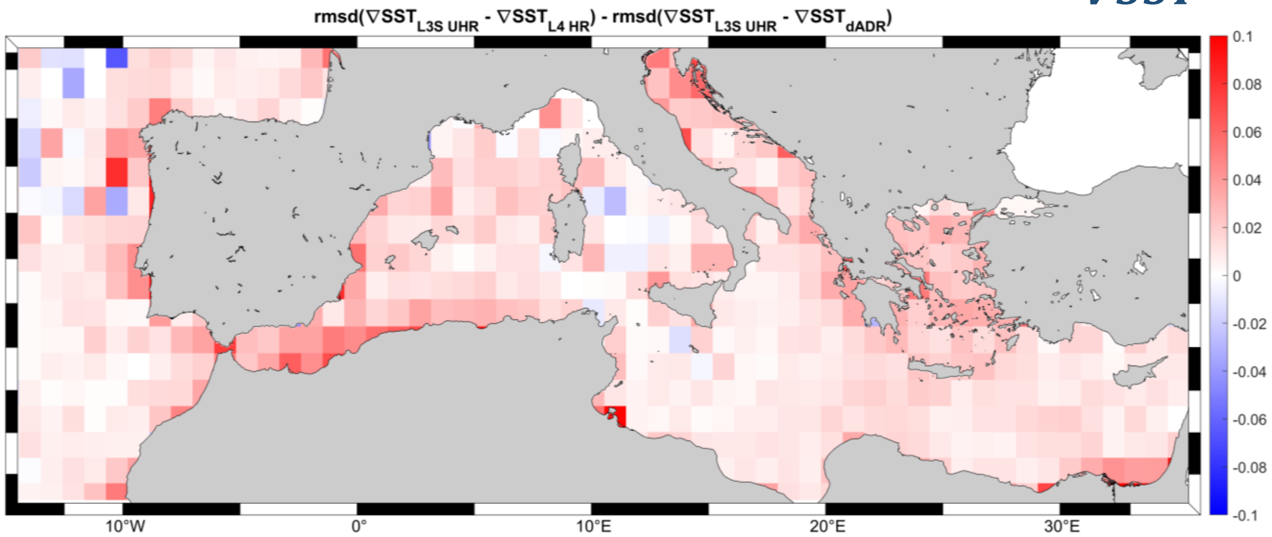
Error maps show an alternative behavior in the case of SST fields but reveal an outstanding performance of the CNN in terms of SST gradients reconstruction.

Optimal interpolated low resolution VS **dADRSR high resolution output**

SST



∇SST



Conclusions

- Wide availability of **large-scale gridded datasets** + **computational efficiency** = **Deep Learning Methods**!

- **Convolutional Neural Networks for Super Resolution** have shown impressive results training with satellite-based observation exploiting **self-similarity** properties.

- The **SST fields** estimated by CNNs appear **much sharper** than the low resolution maps, but the best result is achieved in the estimation of **SST gradients** (especially for high magnitude patterns which are generally smoothed out by interpolation techniques).

Ongoing/future work:

- Increasing datasets time series
- Creating training and test datasets in different ways
- Different choices of CNN parameters

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Thanks for your attention!

Any questions?

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