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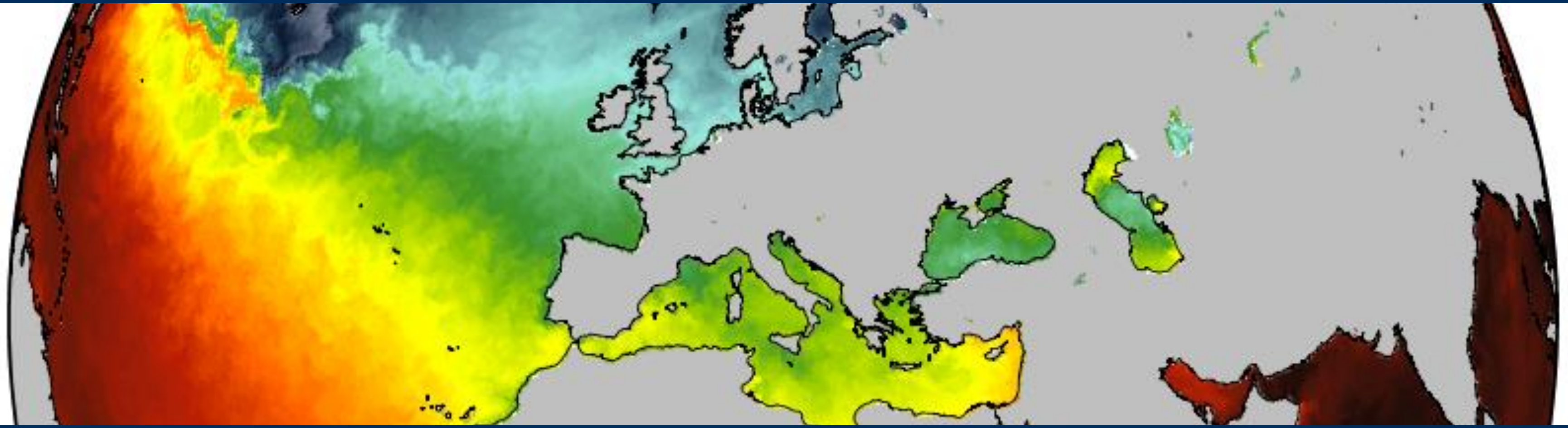

# Improving the effective resolution of satellite-derived SST data via deep learning methods: preliminary results on the application of CNNs and GANs

25 January 2024, GHRSST Talks

GHRSST

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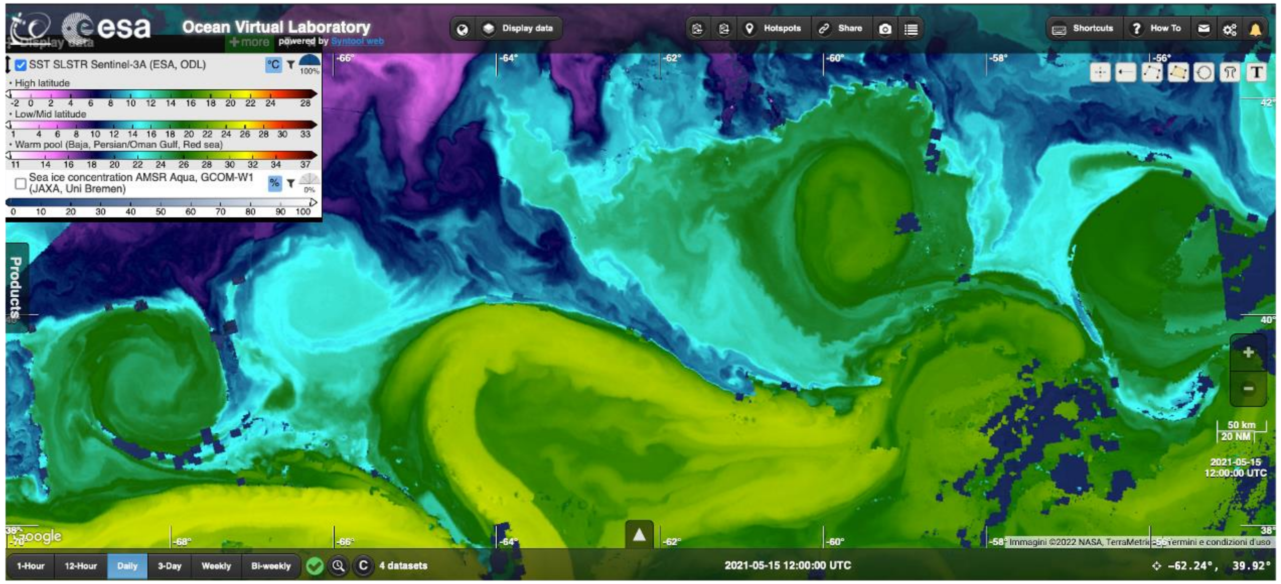
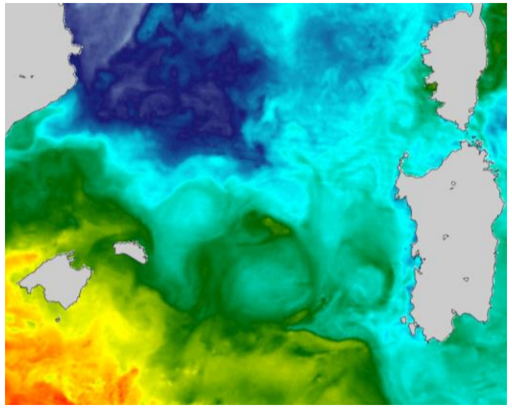
*In collaboration with*
Michele Buzzicotti, Tianyi Li
(University of Rome Tor Vergata)

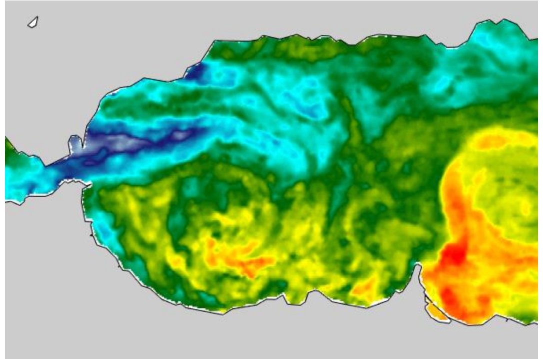
# Sea Surface Temperature

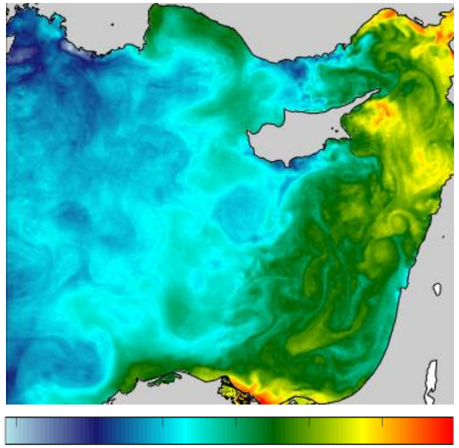
SST is a key variable to investigate ocean dynamics and climate variability




Signatures of mesoscale



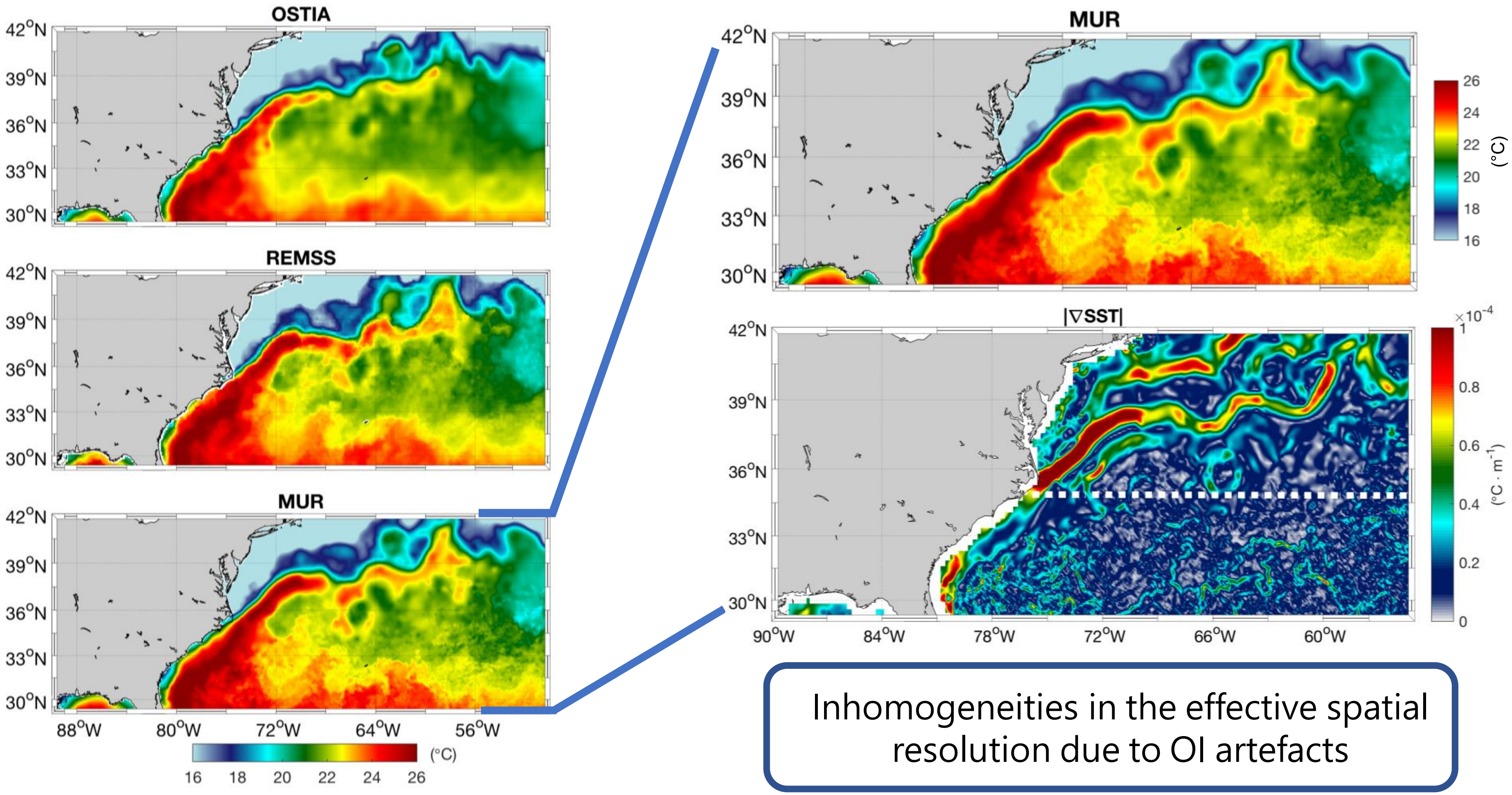




SST-L4-UHR-MED (°C)
0.01° × 0.01°
produced by SST TAC - CNR ISMAR

**Its accurate estimation and regular monitoring from space is crucial**

# Effective resolution



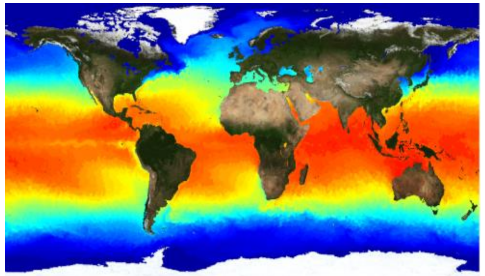

Inhomogeneities in the effective spatial resolution due to OI artefacts

Ciani, D., Rio, M. H., Buongiorno Nardelli, B., Etienne, H., & Santoleri, R. (2020). Improving the altimeter-derived surface currents using sea surface temperature (SST) data: A sensitivity study to SST products. *Remote Sensing*, 12(10), 1601.

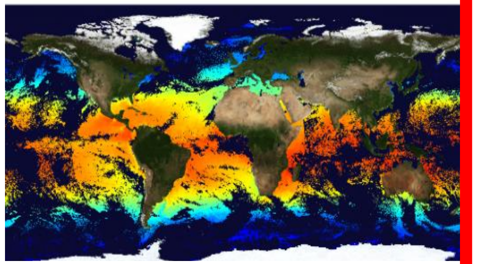
# The SST TAC Catalogue

- 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**

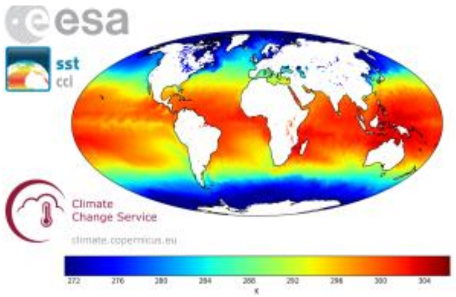
Global (GLO) OSTIA L4 NRT



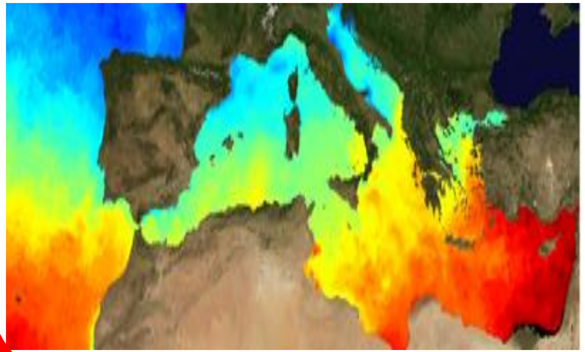
Odyssea L3S NRT (GLO)



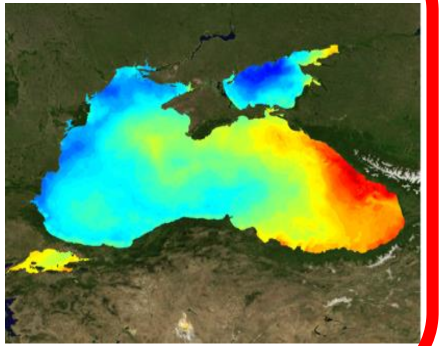
ESACCI/C3S (1981-present) (GLO)



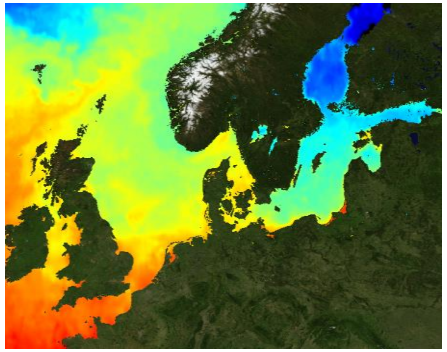

Mediterranean Sea (MED)



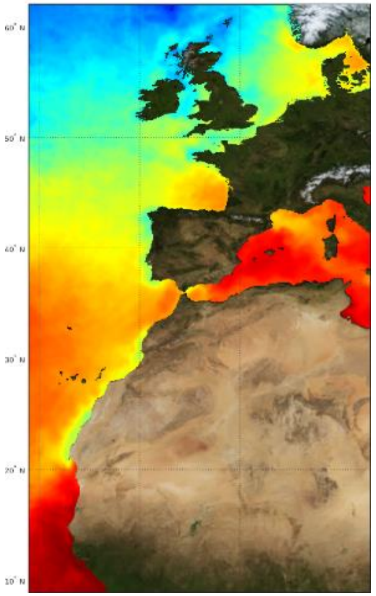
Black Sea (BS)



Baltic Sea (BAL)



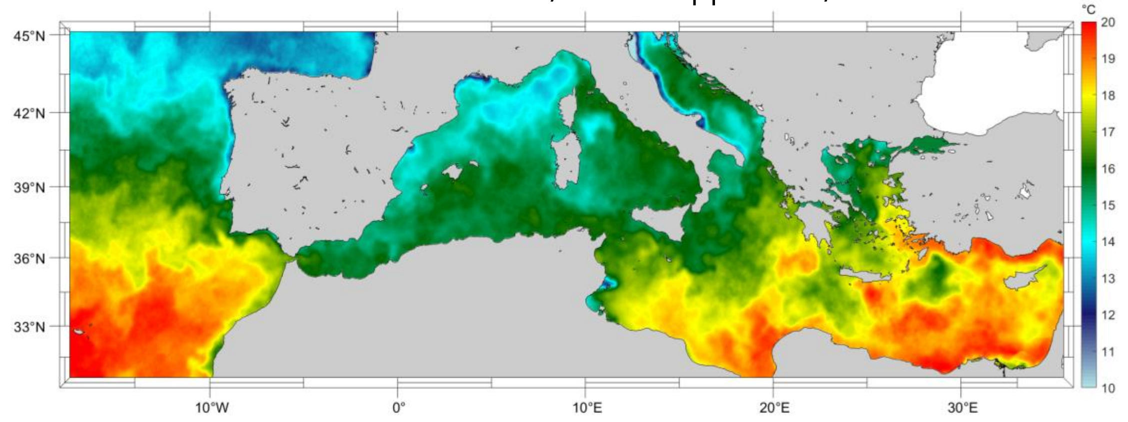
ATL (IBI+NWS)

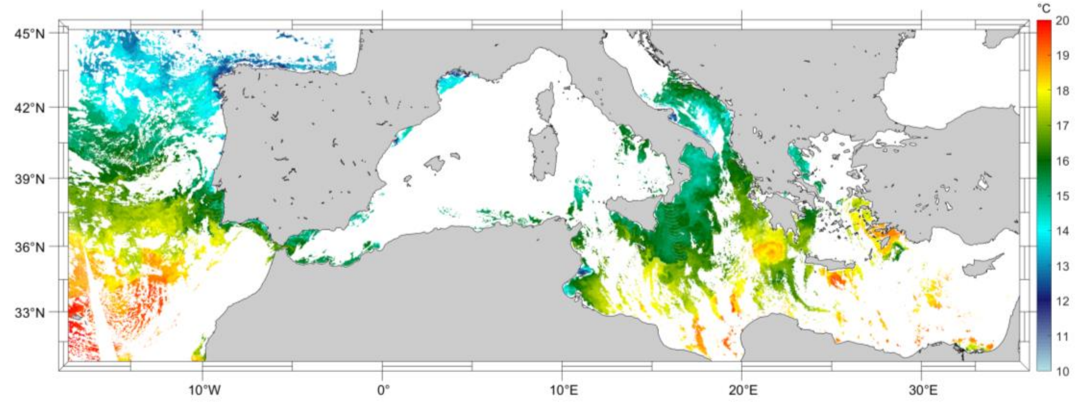


**CNR-ISMAR is responsible for producing and distributing L3 and L4 NRT and REP SST products over the Mediterranean and the Black Seas at 1/16° and 1/100° spatial resolution**

# CNR SST Optimal Interpolation (MED)

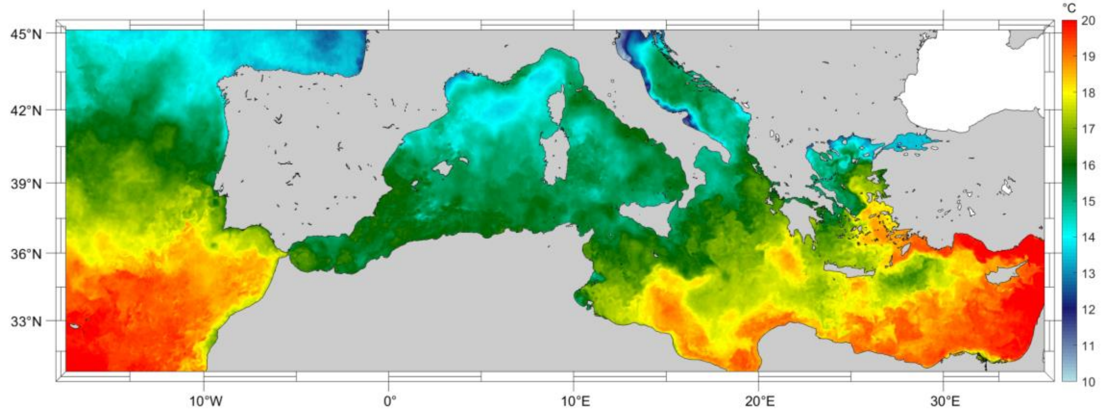
**Background field**
First Guess L4 HR at 1/16° remapped at 1/100°




**L3 at 1/100°**

**Optimal Interpolation**

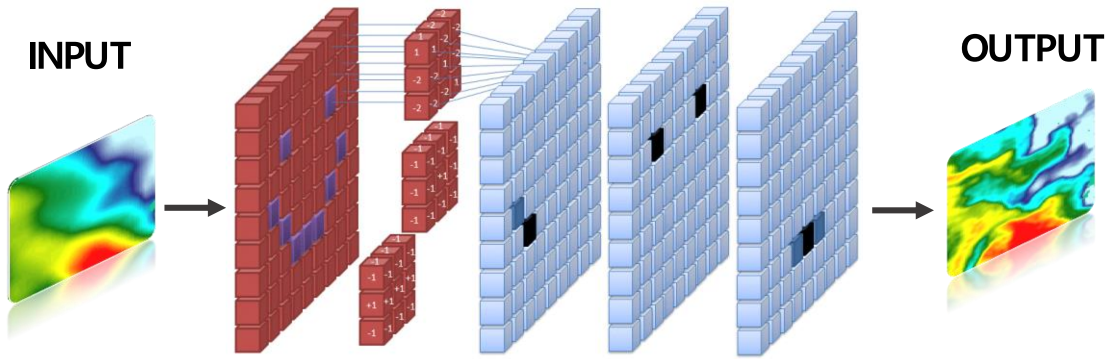



**L4 at 1/100°**

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

## HOW?

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




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

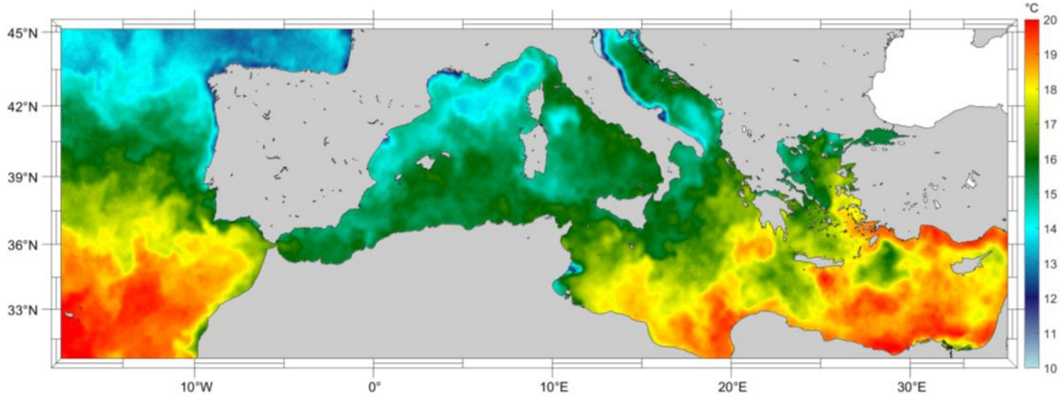
$$g(Y) = f(W_k * Y + B_k)$$

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

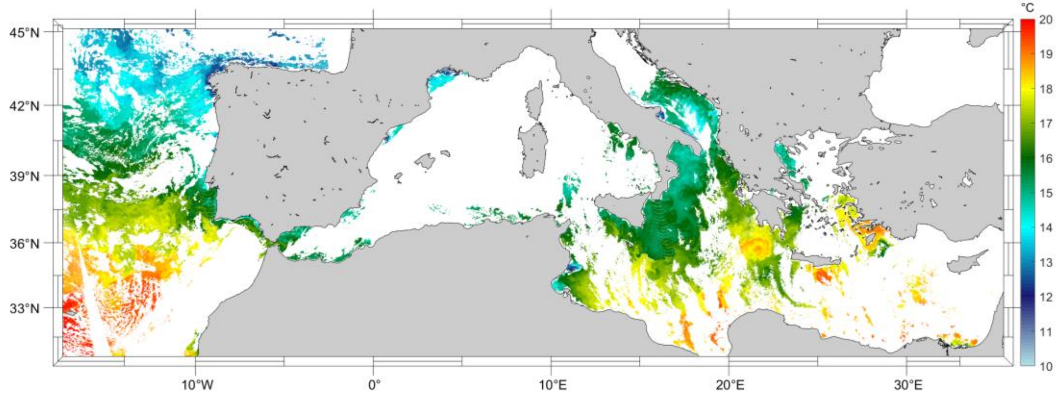
**Learning = optimization process based on minimizing the error between the output and the data from a ground-truth validation set.**

# 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 SST dataset (S3A&S3B) at 1/100° spatial resolution.

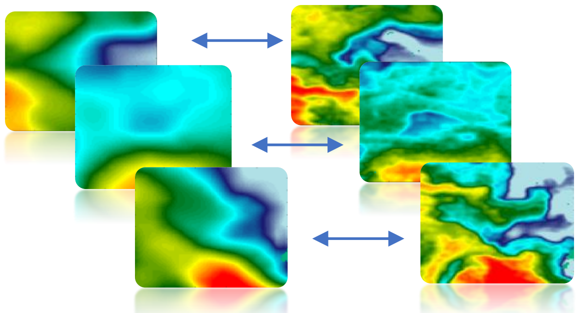



**Mediterranean Sea, year 2020**

- Filtered 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.

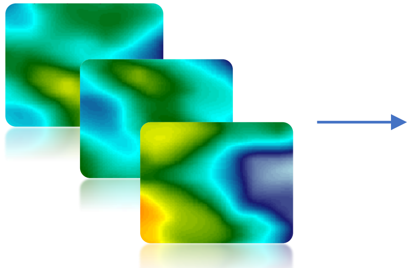
~94 000 pairs of tiles (85%)

TRAINING (& VALIDATION)



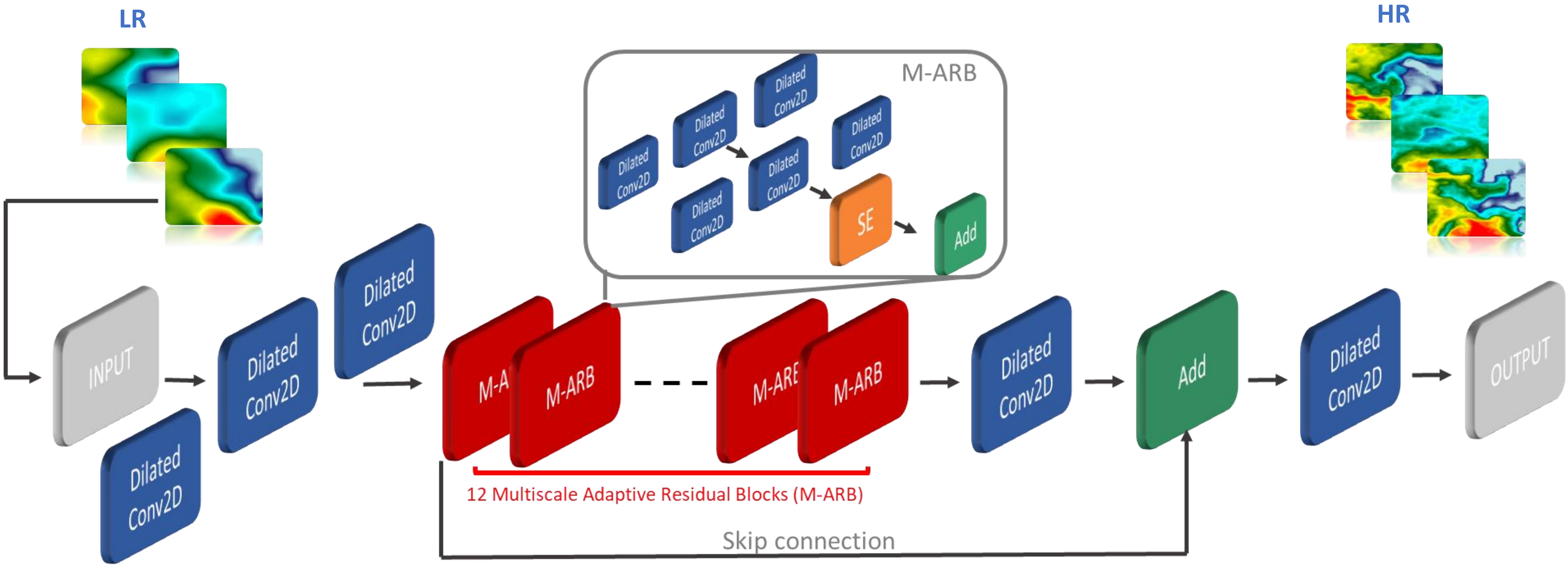
~18 000 Tiles (15%)

TEST



Neural Network Output

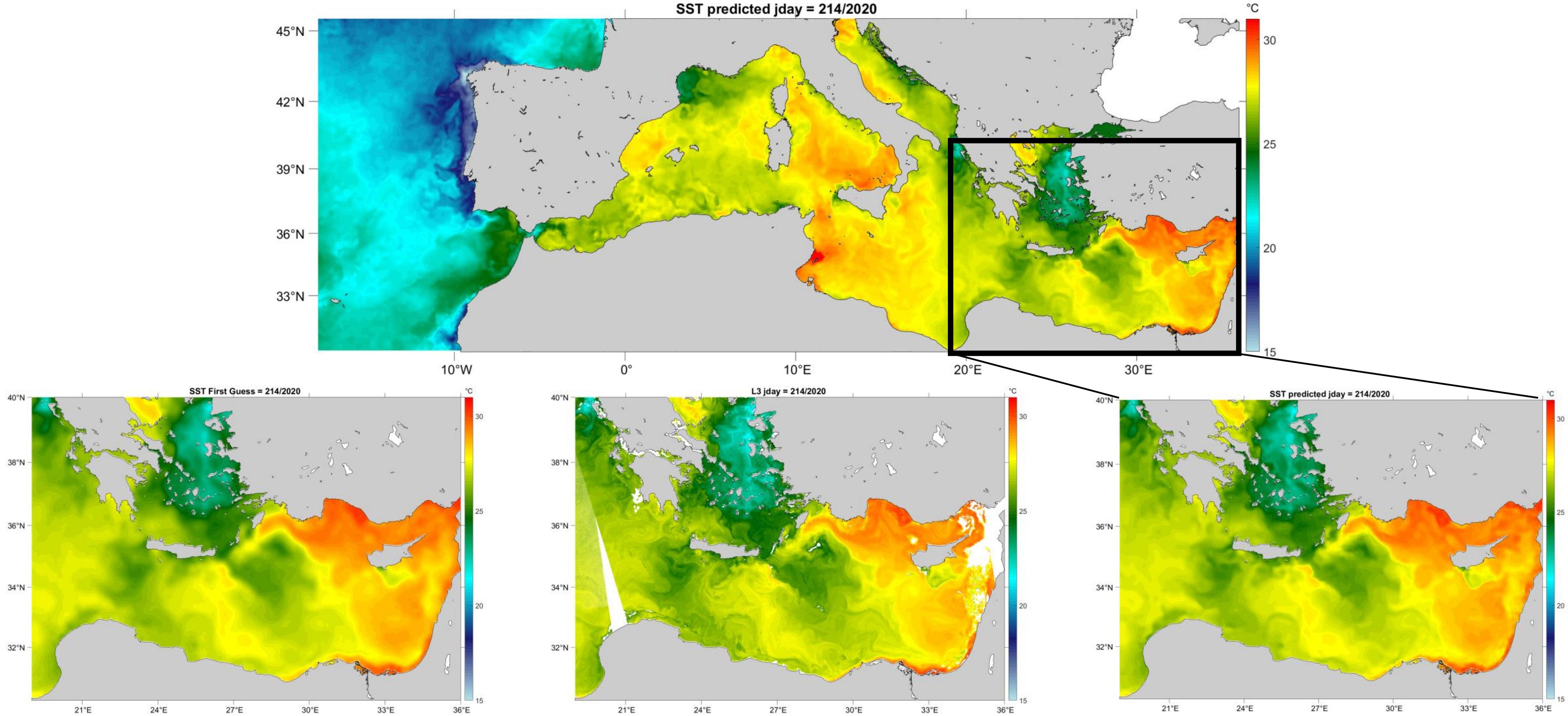
# Dilated Adaptive Deep Residual Network for Super-Resolution




Buongiorno Nardelli, B., Cavaliere, D., Charles, E., & Ciani, D. (2022). Super-resolving ocean dynamics from space with computer vision algorithms. *Remote Sensing*, 14(5), 1159.

# SST prediction by dADR-SR-CNN

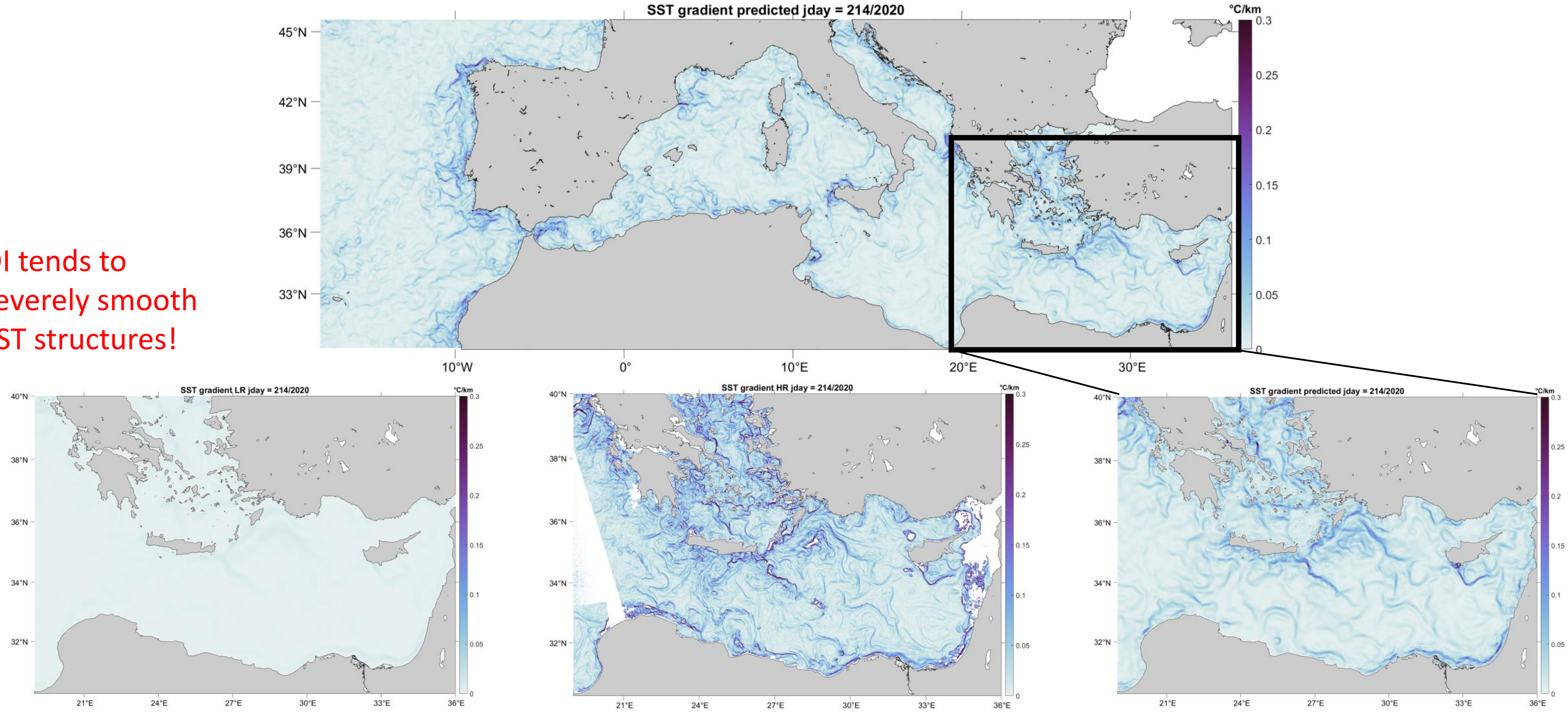
**SST field estimated by the dADR-SR appears much sharper than the first guess map**



# ∇SST approximation by dADR-SR-CNN

**dADR-SR captures high magnitude patterns with a higher accuracy with respect to the LR approximation**

OI tends to severely smooth SST structures!

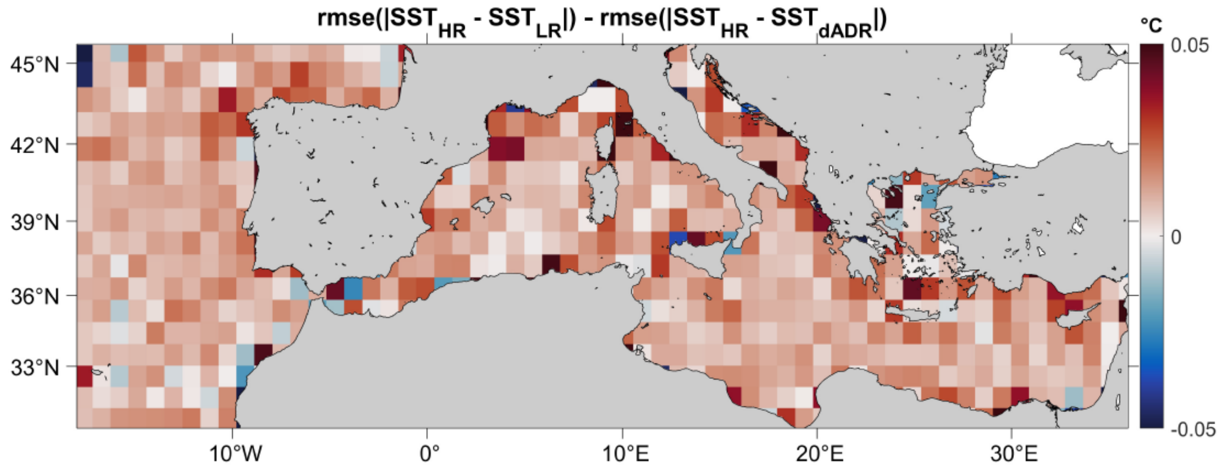


# dADR-SR-CNN performances evaluation

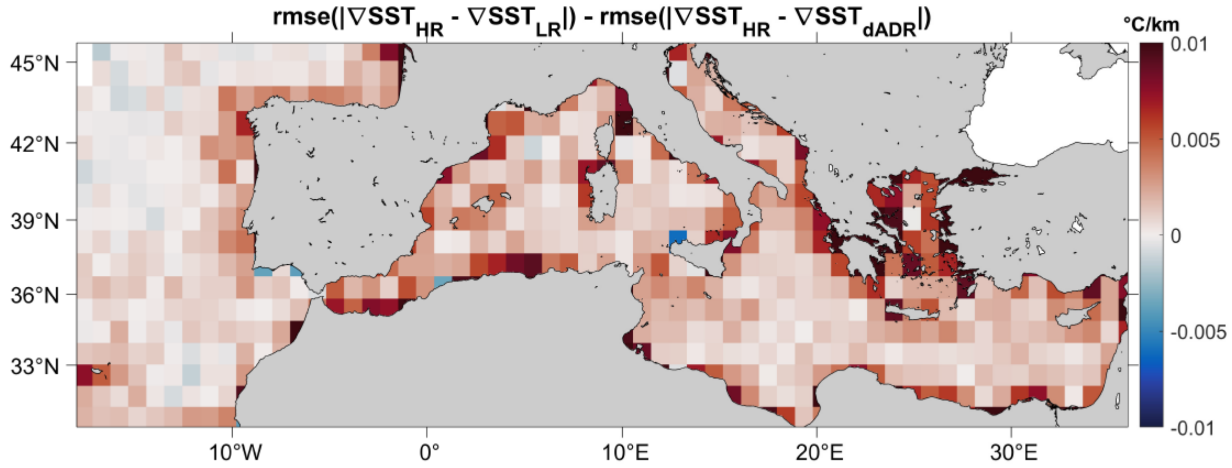
| Model | RMSE (°C) ↓ | PSNR ↑ | SSIM ↑ |
|---|---|---|---|
| **dADR-SR** | **0.31** | **37.9** | **0.54** |
| **Low Resolution** | 0.33 | 37.5 | 0.53 |

red boxes = improvement

***SST***




***∇SST***




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

**Error maps show that the dADR-SR-CNN outperforms the Optimal Interpolation schemes for both SST and SST grads reconstruction**

Fanelli C., Ciani D., Pisano A., Buongiorno Nardelli B. (2024). Single image Super Resolution deep-learning models applied to Sea Surface Temperature (SST) fields in the Mediterranean Sea. *In preparation*.

# Generative Adversarial Networks (GANs)

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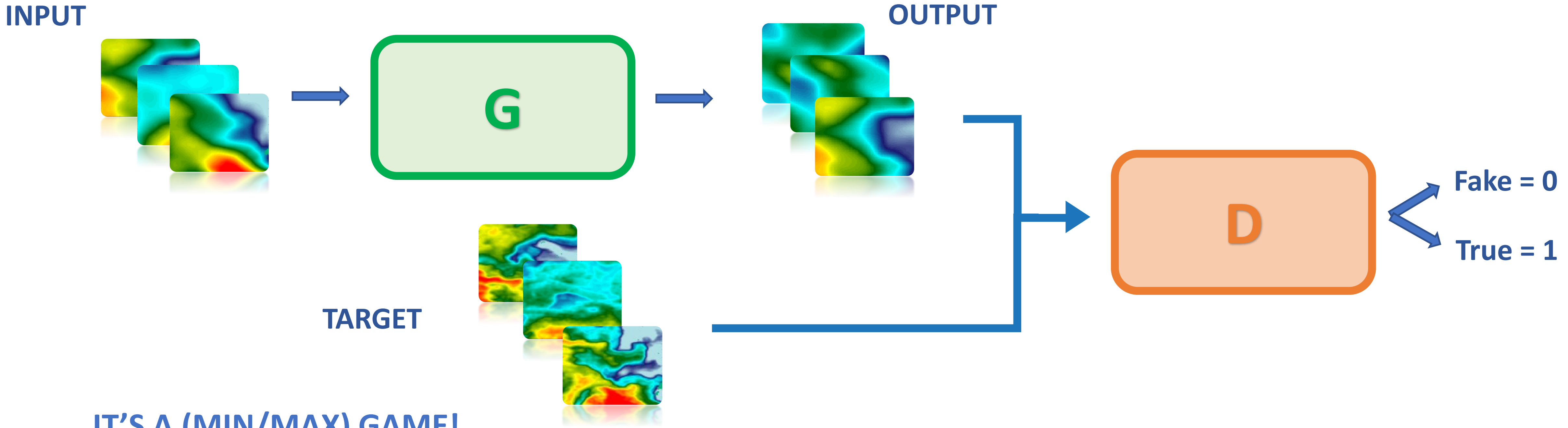
**IDEA**

Competition between the **GENERATIVE** model (producing samples from the input dataset) and a ADVERSARIAL network (the **DISCRIMINATOR**, learning how to distinguish a sample generated by the model from one extracted from the true data distribution)




**IT'S A (MIN/MAX) GAME!**

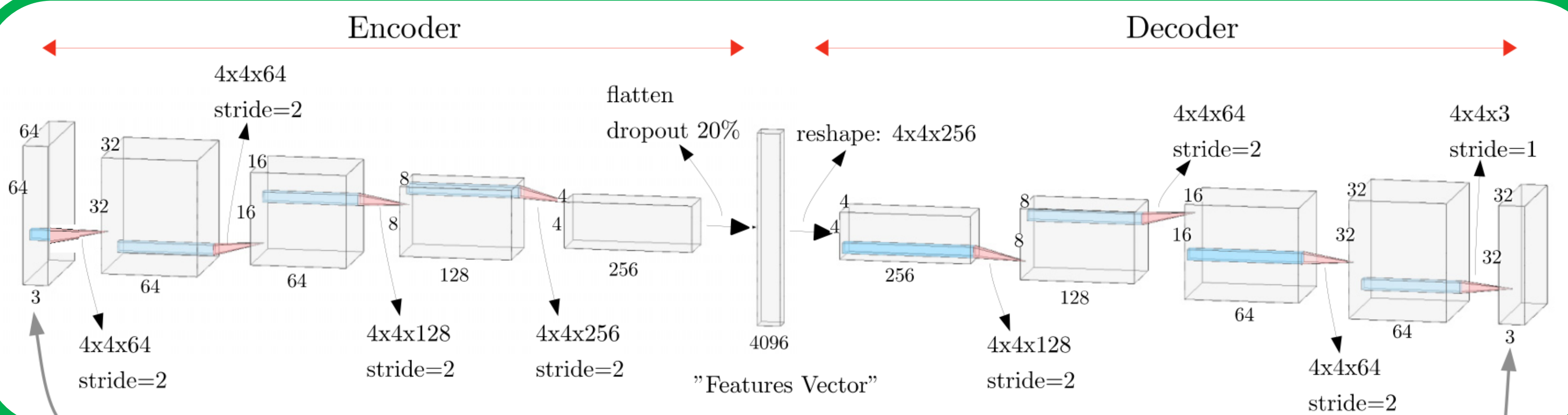
**G** tries to minimize the error between the output and the target

**D** tries to maximize the probability to properly flag synthetic samples

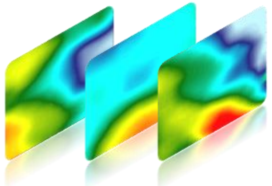
Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., ... & Bengio, Y. (2014). Generative adversarial nets. *Advances in neural information processing systems*, 27.

# GAN reconstruction for SST data

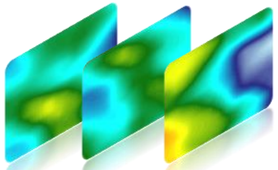
G




INPUT



OUTPUT



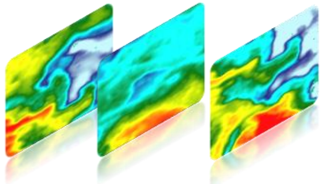
**Loss functions**

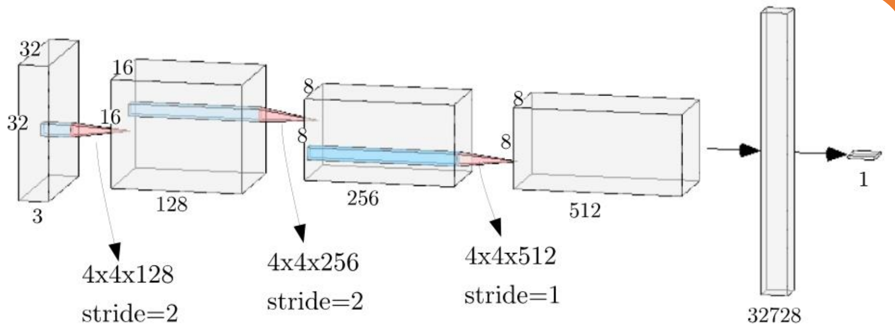
$$\mathcal{L}_G = \|x_{true} - G(x)\|_2$$

$$\mathcal{L}_D = \log(1 - D(G(x)))$$

$$\mathcal{L} = \lambda_G \mathcal{L}_G + \lambda_D \mathcal{L}_D$$

TRUE DATA






D

Buzzicotti, M., Bonaccorso, F., Di Leoni, P. C., & Biferale, L. (2021). Reconstruction of turbulent data with deep generative models for semantic inpainting from TURB-Rot database. *Physical Review Fluids*, *6*(5), 050503.

# GAN performances evaluation

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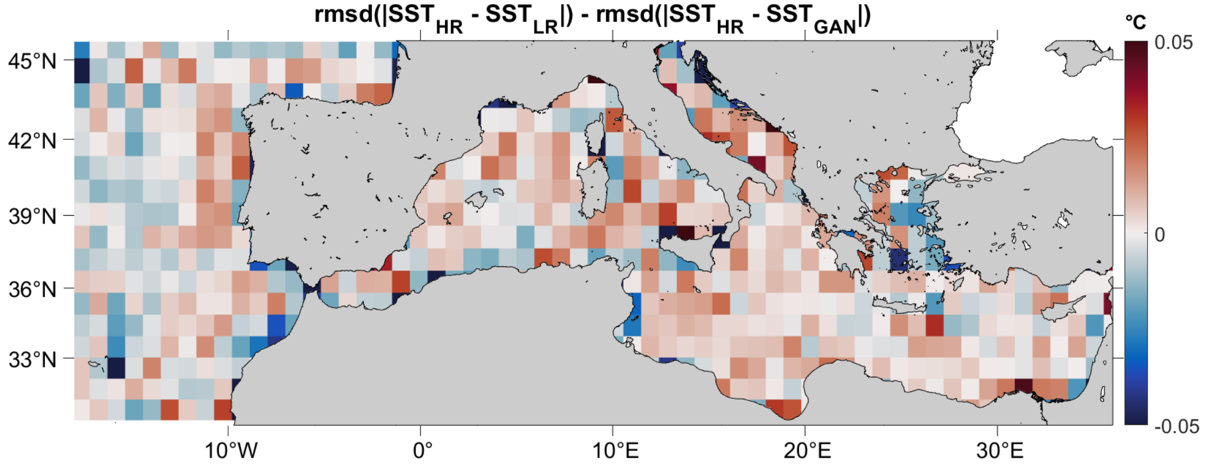
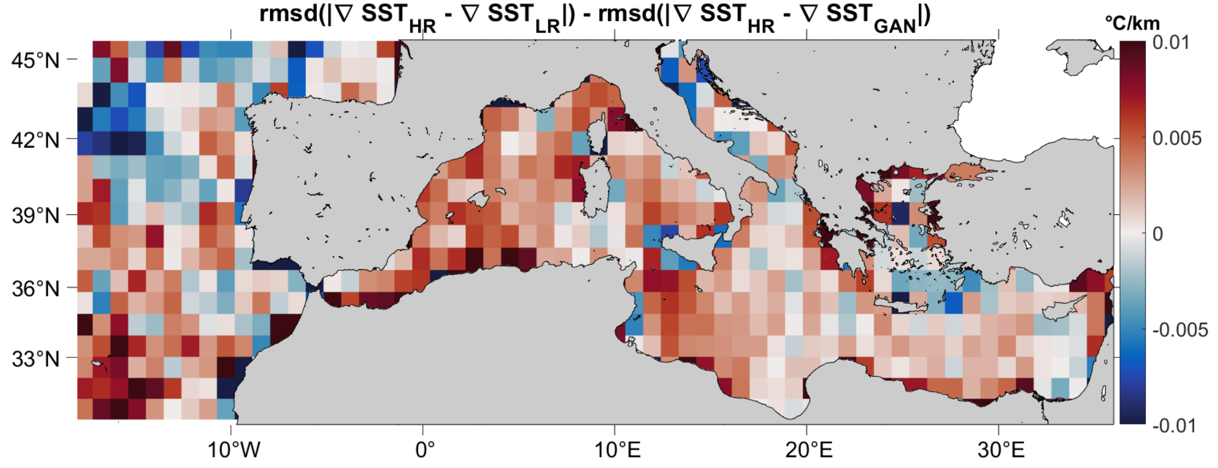
***SST***

red boxes = improvement

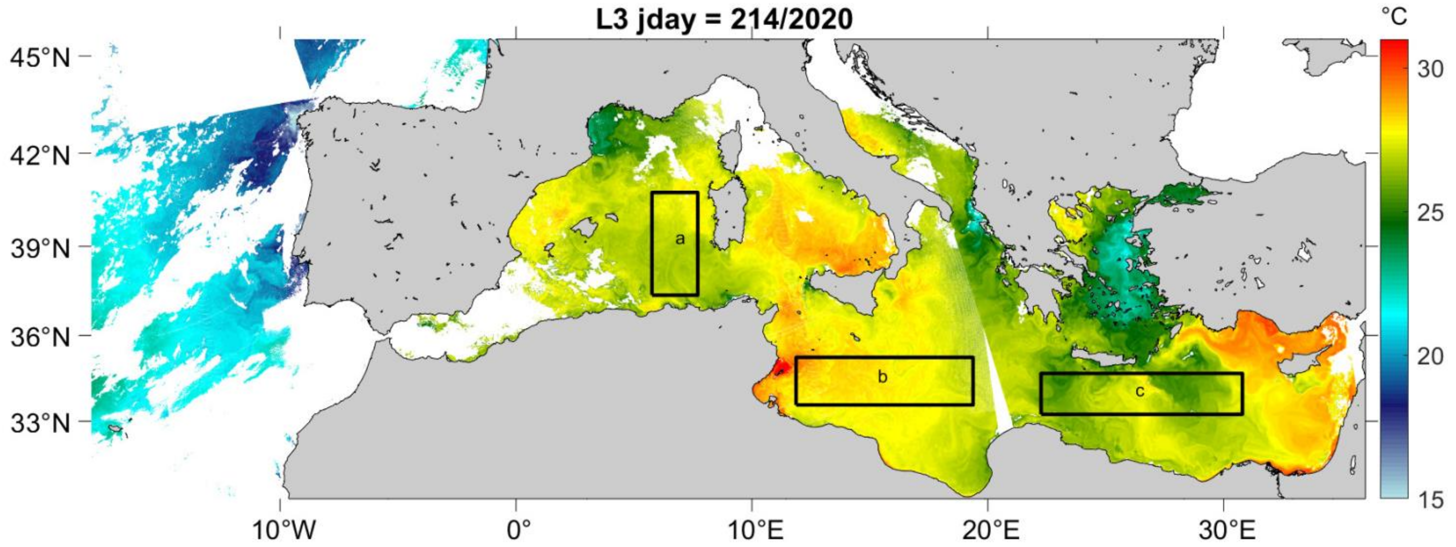
***∇SST***

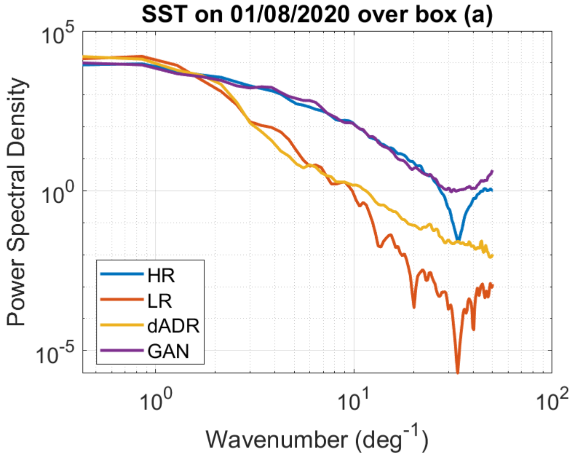


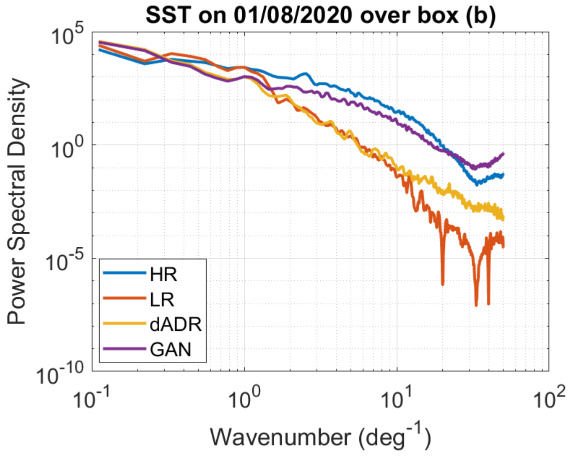



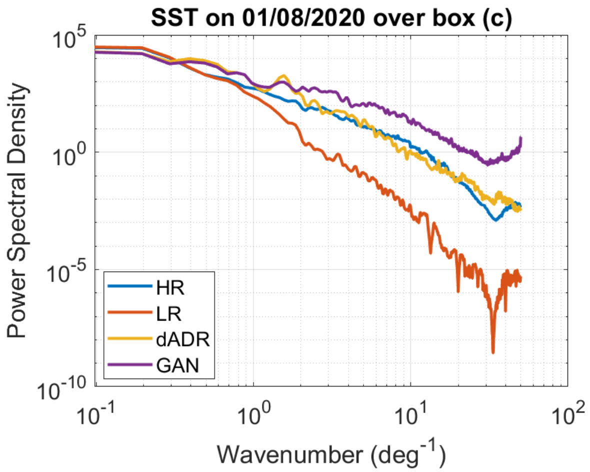

**Optimal interpolated low resolution** VS **GAN high resolution output**

# Power Spectral Density (dADR vs GAN)



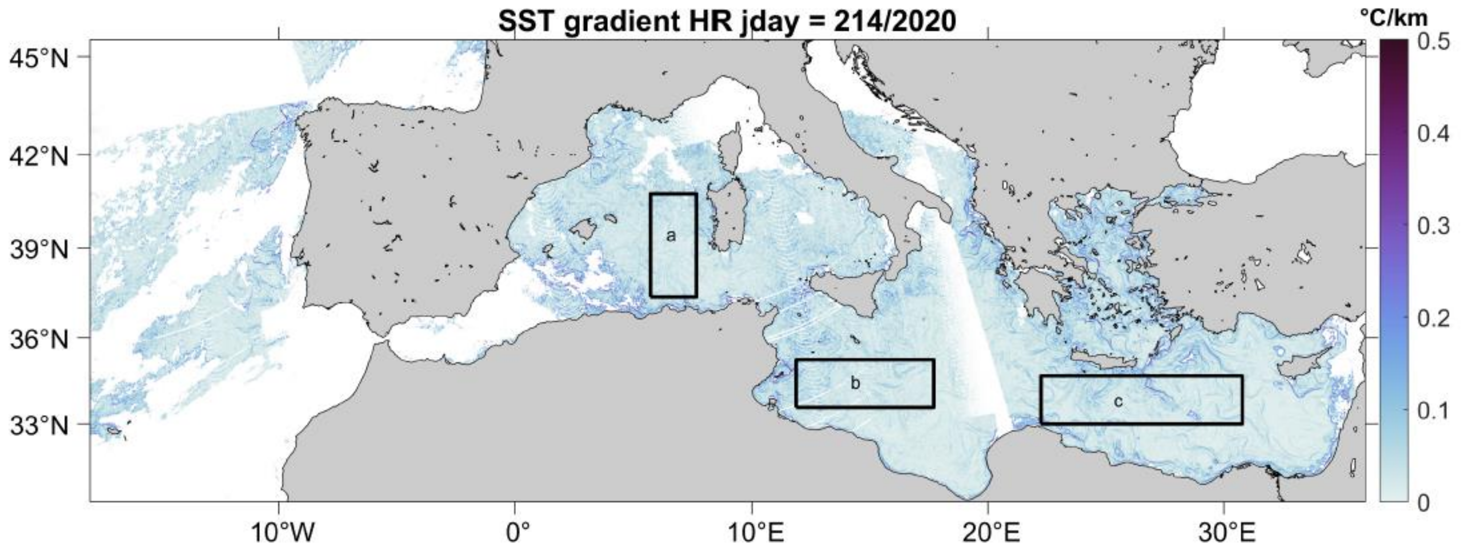



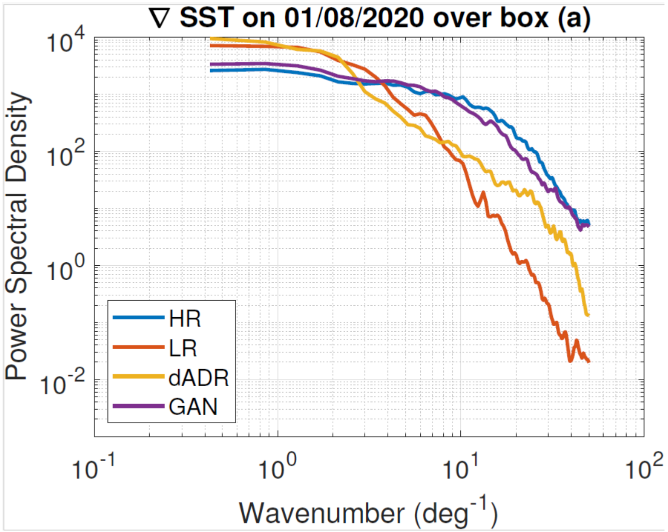



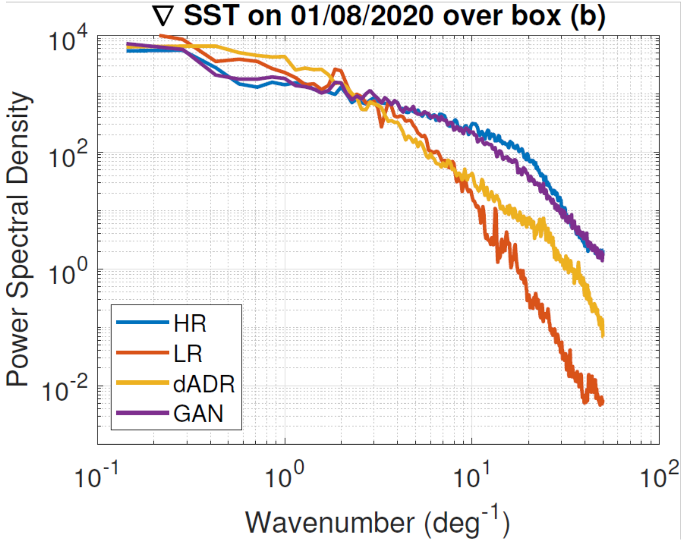



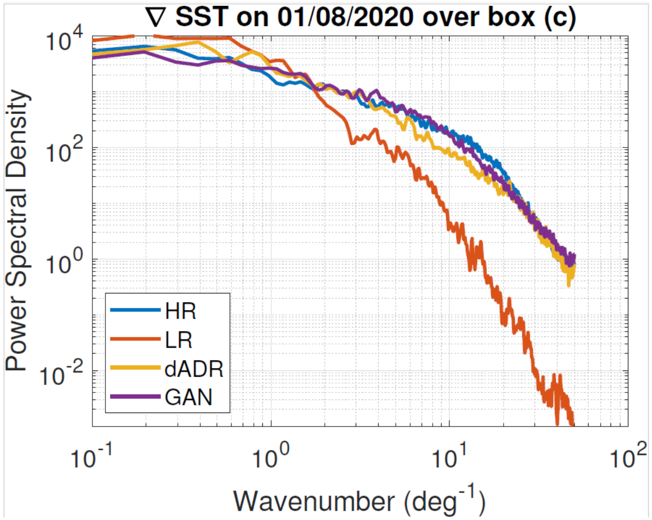
# Power Spectral Density (dADR vs GAN)





# Conclusions

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- dADR improves almost everywhere both reconstructions of SST and SST gradients over the Med Sea
- GAN seems to struggle with SST fields but it captures SST gradients distribution more accurately

## Ongoing/future work :

- Insert the dADR network into the GAN architecture and construct a deeper discriminator able to recognize the mesoscale features
- Extend the temporal series to see the benefits of a larger training dataset
- Fine-tuning of the networks to use them over other regions (i.e., Black Sea)

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# Thanks for your attention!

Any questions?

claudia.fanelli@cnr.it