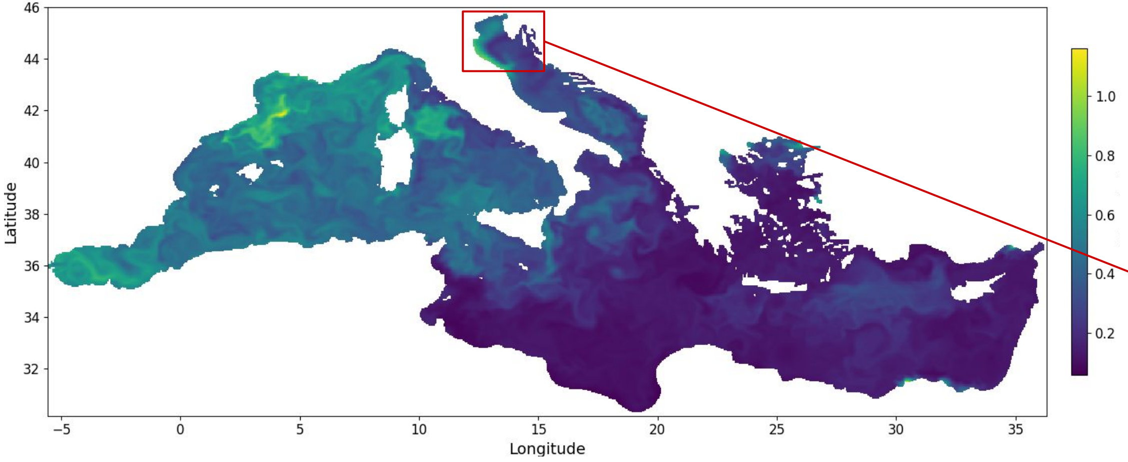
A deep learning approach for coastal downscaling: the northern Adriatic Sea case-study

Federica Adobbati, Lorenzo Bonin, Gianpiero Cossarini, Valeria Di Biagio, Fabio Giordano, Luca Manzoni, Stefano Querin

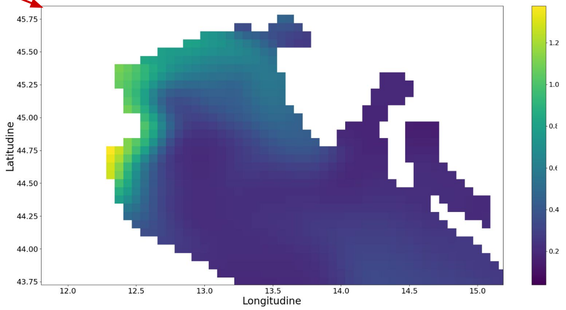
COSS-TT meeting, June 18th, 2025

Problem

Copernicus data are the state of the art at the Mediterranean level, but are not designed to catch **coastal processes** (e.g. river discharge in the ocean). This creates the need for **downscaling** applications, e.g. for forecast and reanalysis tasks in the area

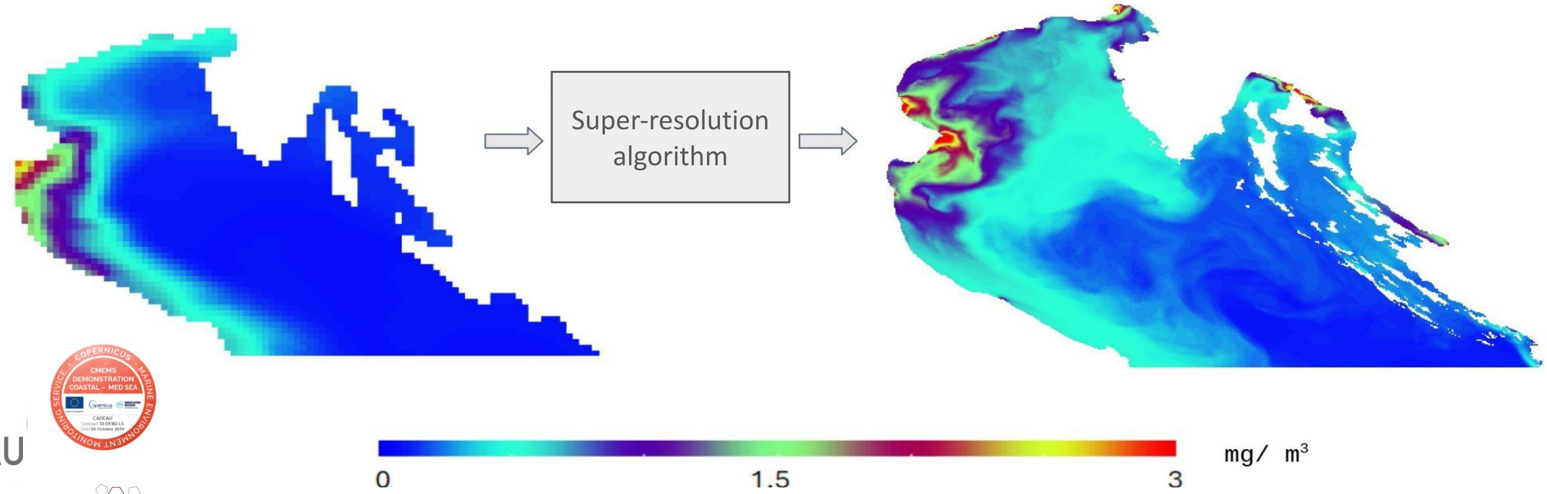


Chlorophyll example



A possible solution: high-resolution nested reanalysis

The CADEAU project provided a **high resolution reanalysis** of the northern Adriatic Sea **physics and biogeochemistry** (2006-2017), produced with a numerical simulation. The system is closely linked with Copernicus Marine data, from which it takes initial and boundary conditions.

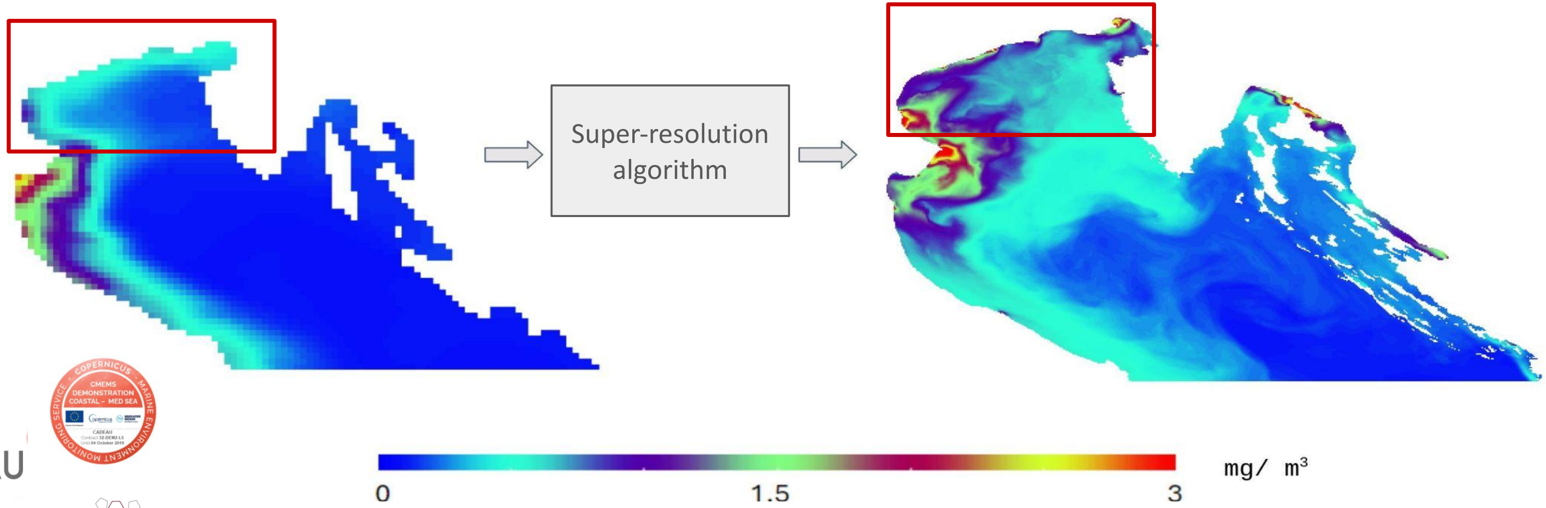


Example of chlorophyll from the reanalysis 2006-2017

Further details about this modeling framework in the next OGS presentations (by Fabio Giordano and Stefano Querin)...

A possible solution: high-resolution nested reanalysis

The CADEAU project provided a **high resolution reanalysis** of the northern Adriatic Sea **physics and biogeochemistry** (2006-2017), produced with a numerical simulation. The system is closely linked with Copernicus Marine data, from which it takes initial and boundary conditions.

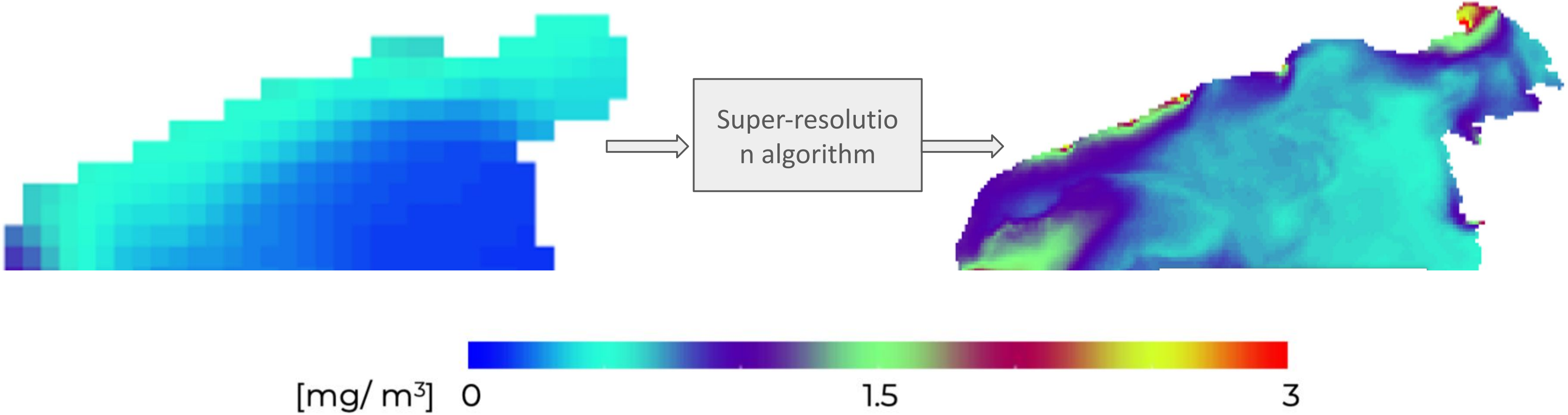


Example of chlorophyll from the reanalysis 2006-2017

Further details about this modeling framework in the next OGS presentations (by Fabio Giordano and Stefano Querin)...

Zoom on the northern coast

In the high resolution map we can observe **coastal features** not present in the Copernicus map. **River discharges** have a strong influence on the variability of the area (ROFI area - region of freshwater influence).

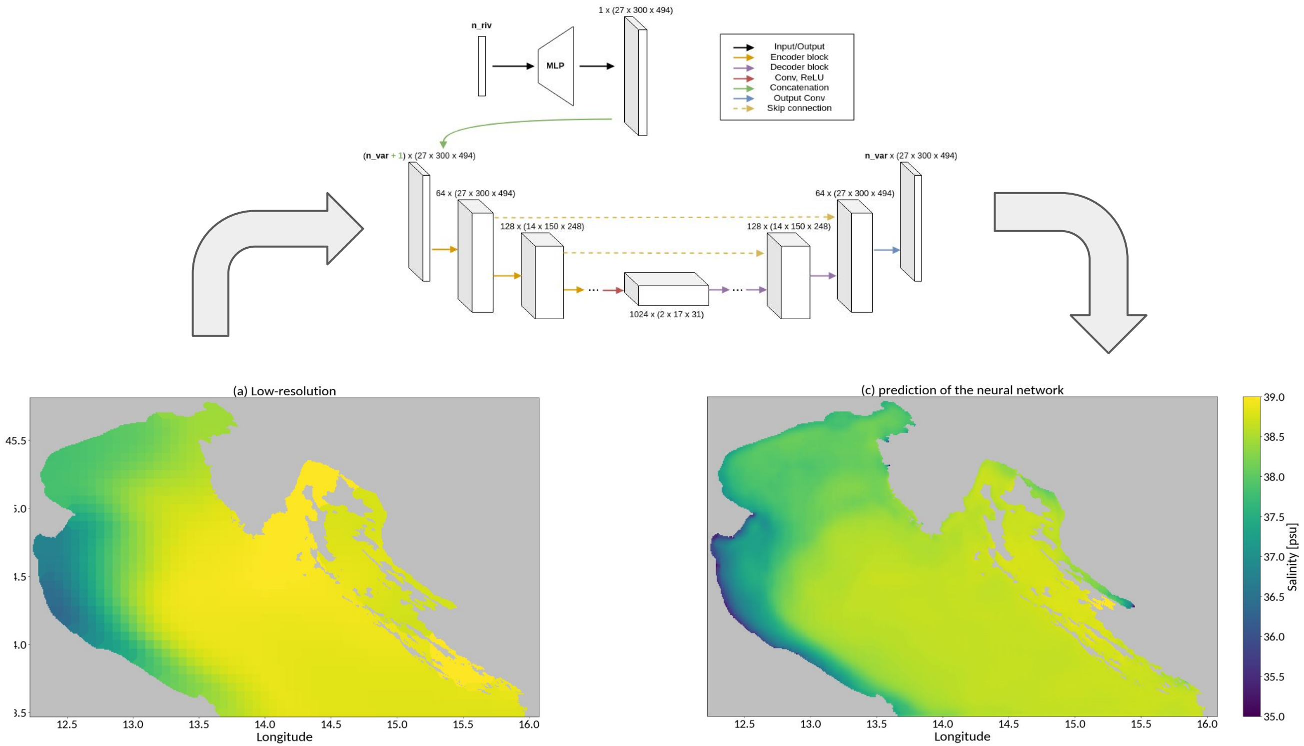


Example of chlorophyll from the reanalysis 2006-2017

Drawback: Numerical simulations have a high computational cost!

A deep learning approach for super-resolution

We can train a **neural network** with low and high resolution example pairs, so that it learns to generalize the super resolution process on new low-resolution data

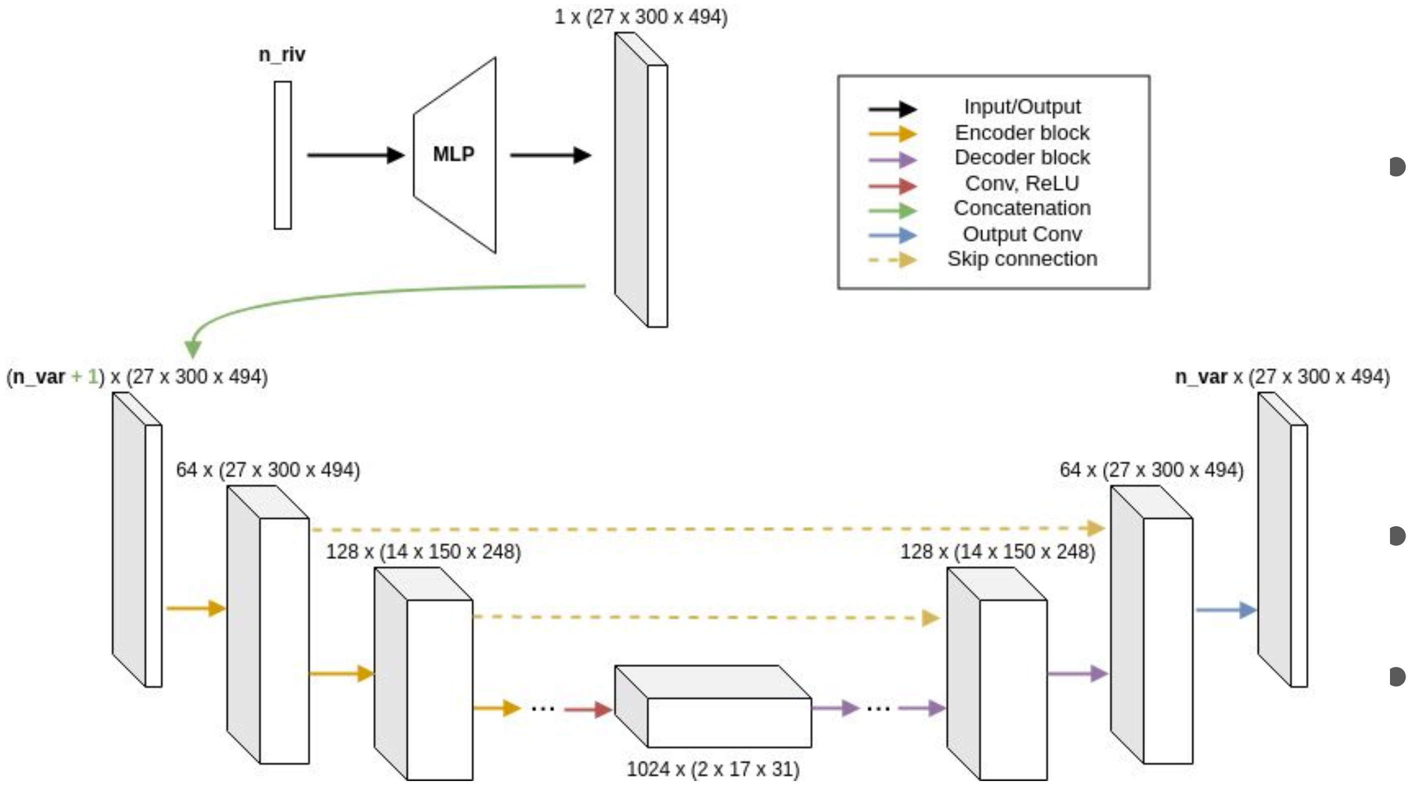


Considered variables:

- chlorophyll
- nitrate
- phosphate
- salinity
- temperature

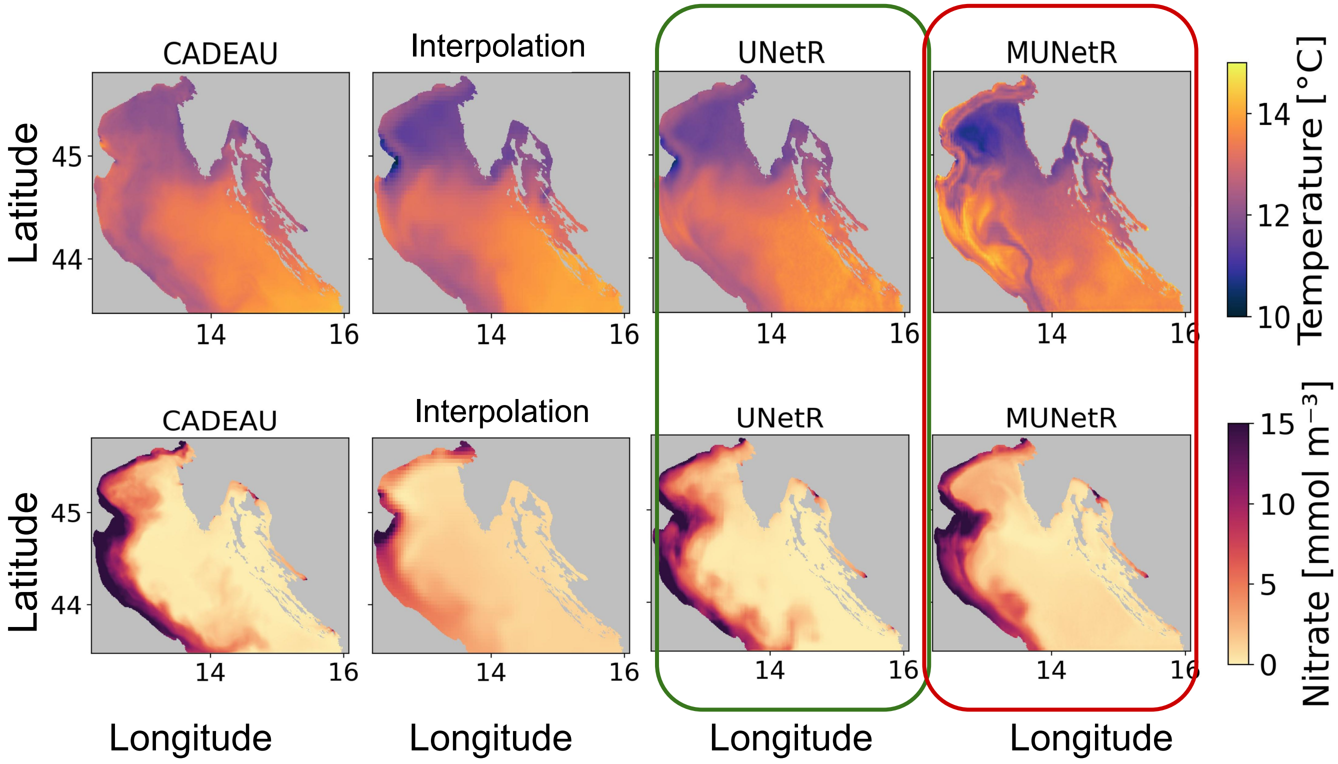
Extensive presentation of this work can be found in: "**A deep learning approach for coastal downscaling: the northern Adriatic Sea case-study**". Federica Adobbati, Lorenzo Bonin, Gianpiero Cossarini, Valeria Di Biagio, Fabio Giordano, Luca Manzoni, Stefano Querin. *Accepted in Ocean Modelling (2025)*

The architecture



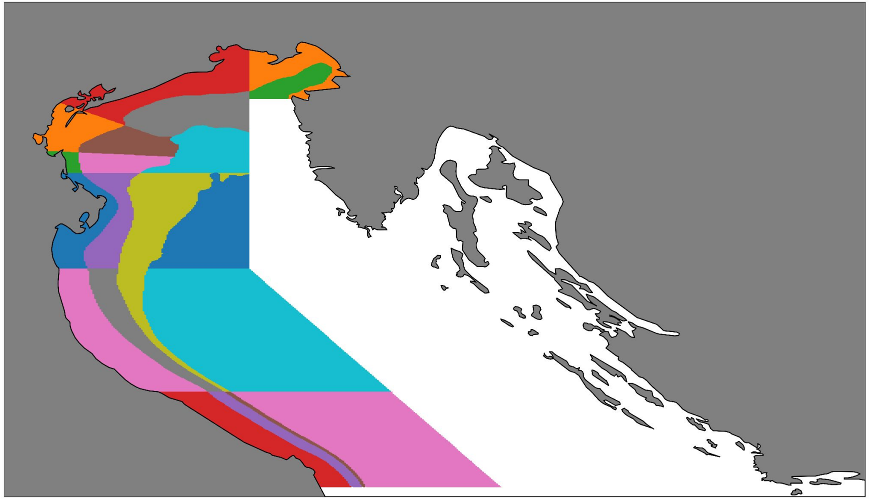
- **Architecture:** MLP connected with a U-net
- **Input:** array of river discharges (MLP) and low resolution Copernicus Marine data (U-net)
- **Output:** high resolution field
- **Training period:** 2006-2017

Different kinds of setups: multi vs single variable approach



The RMSE is smaller in the case of **single variable** training.
In the **multivariate** approach, variables with different spatial patterns have a negative influence on each other

Validation against observations



We divide the area into **sub-basins** based on the **bathymetry** and the **river** presence.

For each of them we compare the **Copernicus** Marine data and the **output of the neural network** with **observations**.

In particular:

For the test set period (2006-2017):

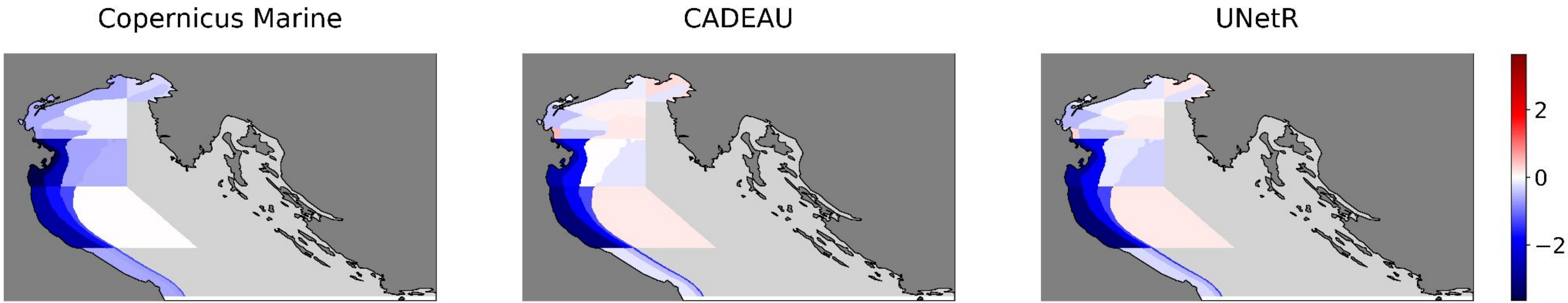
- We compare the 2 models against a climatology built upon **in situ data**

For 2023:

- We compare the 2 models against the climatology built upon **in situ data** (same as above)
- For chlorophyll and temperature, we compare with **satellite data**

Validation in the test set period (2006 - 2017)

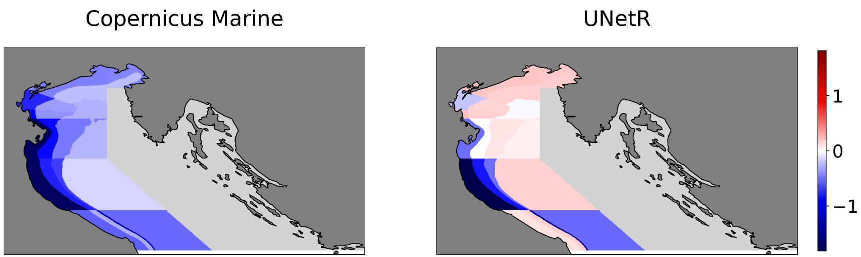
Model vs in situ climatology



Bias for winter chlorophyll in the test set period.

1. The U-net learned to reproduce the CADEAU values.
2. While Copernicus Marine tends to always underestimate the mean value, CADEAU and the output of the U-net slightly overestimate with respect to the in situ data.
3. The best improvements are in the north and central area

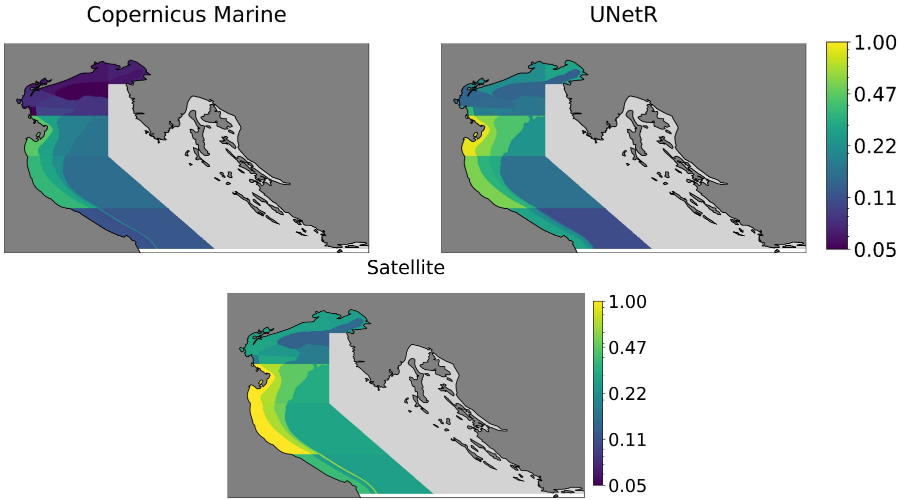
Validation on 2023 data



Bias of Copernicus Marine and of the output of the U-net for winter chlorophyll data with respect to the satellite data

Standard deviation of the values included in each sub-basin for Copernicus Marine data, the output of the U-net and the satellite data for chlorophyll in winter.

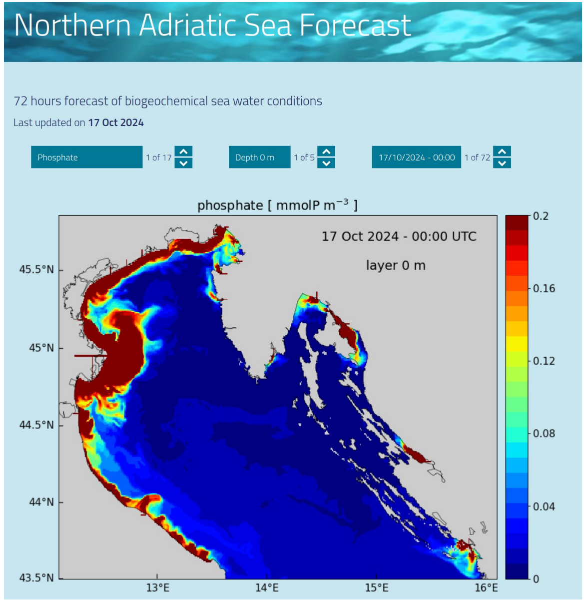
The highest variability is in the satellite data, whereas Copernicus Marine data exhibit the lowest variability

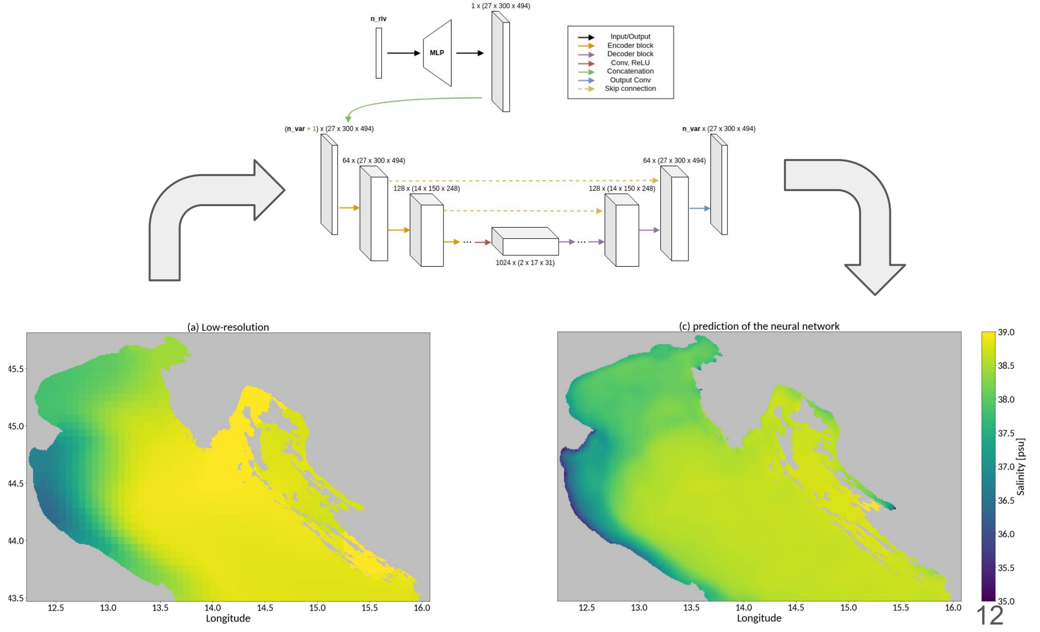


Summary: methods for super-resolution

- Classical interpolation methods
- Nested numerical simulation (e. g. CADEAU/ MEDEAF webpage), used for forecast and for reanalysis
- Deep learning methods (learning from numerical reanalysis), used for forecast

https://medeaf.ogs.it





Comparison between the methods

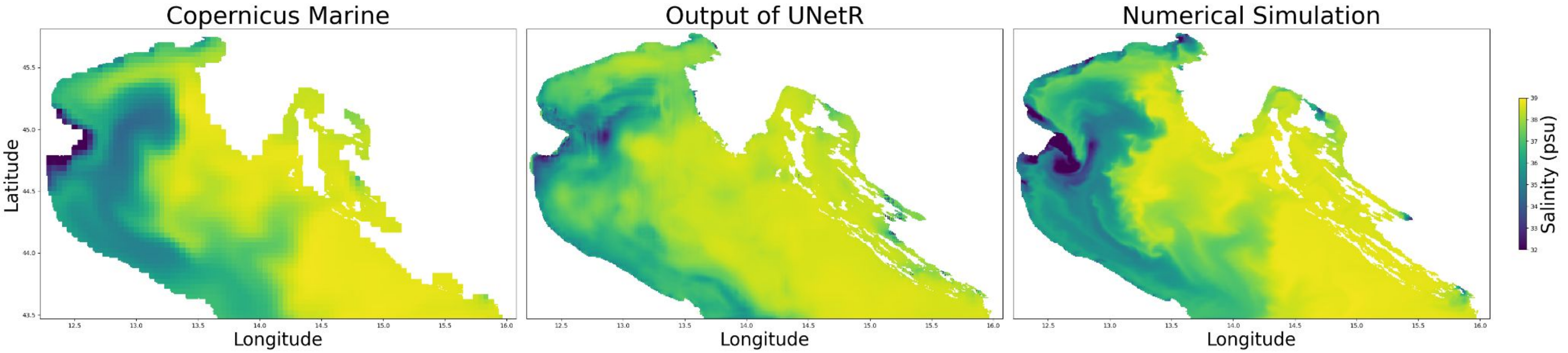
Nested simulations capitalize on our knowledge about hydrodynamic circulation and biogeochemical fluxes, BUT

- They require **time** and **computational resources** at every run
- For the forecast, observational data are ignored

Deep learning methods usually do not explicitly model physics of biogeochemistry, BUT

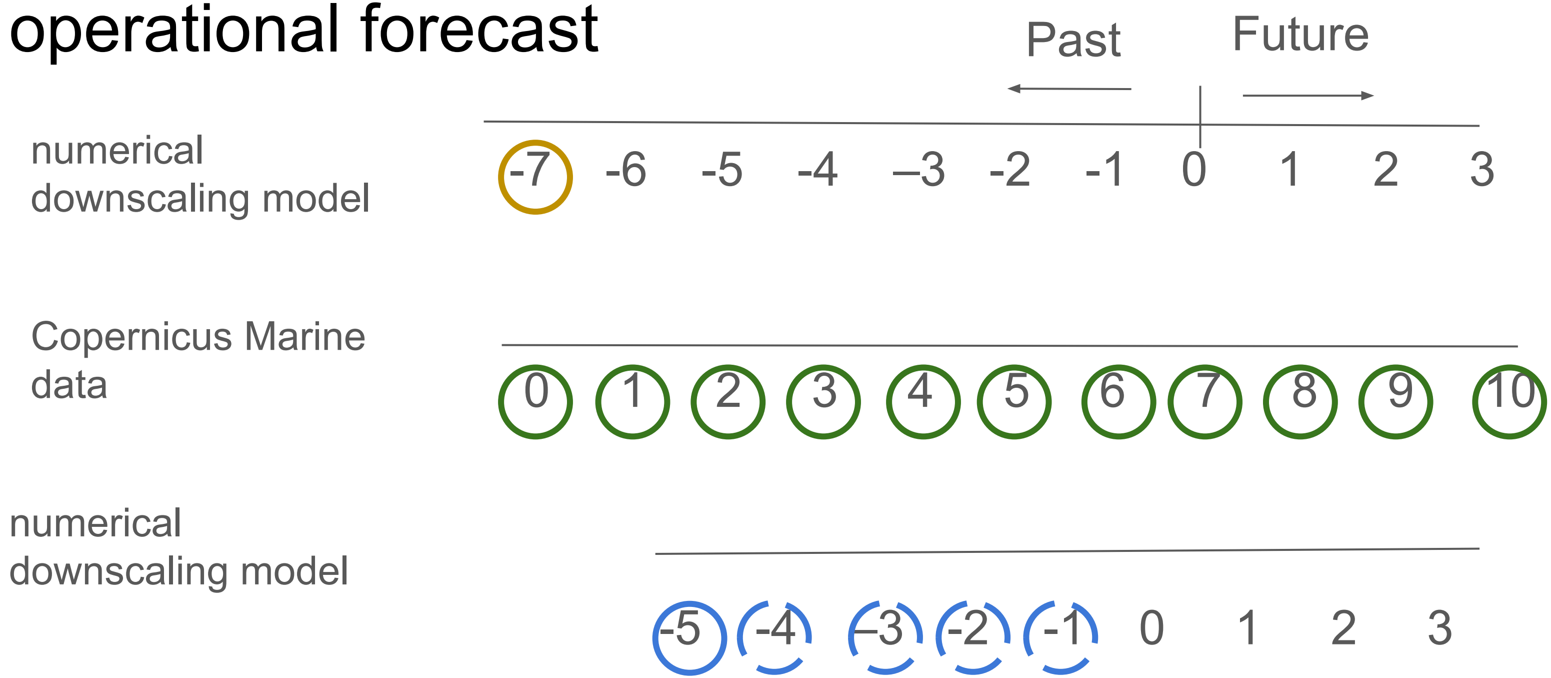
- Once they are trained, they require **less time** and computational resources
- They learned from the reanalysis, where observation have been integrated with data assimilation methods

Comparison between the methods: An example



The structures produced with traditional methods are in general more defined, possibly because the neural network was trained on averages of 5 days

Ongoing work - Application of the neural network for operational forecast



The neural network can be used either to produce directly high resolution forecast or as improved initial condition of the numerical simulation

Conclusion and future perspectives

Developed work:

- We developed a downscaling method based on a **U-net architecture** and applied it to the northern Adriatic Sea area
- Once the neural network is trained, the super-resolution task is performed in < 1s, significantly **faster** than the numerical simulation

Ongoing work:

- The super-resolution tool can be integrated into the numerical simulation in order to improve its quality (better ICs) and reduce the overall computational cost (shorter spinup)

Future perspectives:

- We plan to test new methods based on neural networks (transformers, diffusion models)
- We plan to integrate observations into the training to improve the quality of the reconstruction

Conclusion and future perspectives

Developed work:

- We developed a downscaling method based on a **U-net architecture** and applied it to the northern Adriatic Sea area
- Once the neural network is trained, the super-resolution task is performed in < 1s, significantly **faster** than the numerical simulation

Ongoing work:

- The super-resolution tool can be integrated into the numerical simulation in order to improve its quality (better ICs) and reduce the overall computational cost (shorter spinup)

Future perspectives:

- We plan to test new methods based on neural networks (transformers, diffusion models)
- We plan to integrate observations into the training to improve the quality of the reconstruction

Thank you!!