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Deep Learning Techniques for High-Resolution Coastal Modeling

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ABSTRACT

In this work, we focused on the development and application of artificial intelligence methods for coastal downscaling, particularly in the context of the northern Adriatic Sea. The motivation stems from the fact that regional-scale oceanographic models, such as those provided by the Copernicus Marine Service, lack the spatial resolution needed to represent fine-scale coastal processes. River discharges, salinity gradients, and nutrient variability are often poorly captured by these models, limiting their usefulness for coastal monitoring and management. To overcome this challenge, our activities concentrated on designing, training, and validating a deep learning model capable of downscaling coarse-resolution outputs into high-resolution fields. The work has been published in Ocean Modelling (2025) [Adobbati et al. 2025].

⇾ DATA PREPARATION

The research relied on two main datasets: the Copernicus Marine Service reanalysis (input, ~4.5 km resolution) and the CADEAU project reanalysis (target, ~750 m resolution), covering the years 2006–2017. Five physical and biogeochemical variables were selected: salinity, temperature, chlorophyll, nitrate, and phosphate. Additionally, discharge data from 19 rivers entering the northern Adriatic were incorporated, using both direct observations and climatological reconstructions. Preprocessing steps included interpolation of input data onto the target grid, standardization, and masking of land points.

⇾ MODEL DEVELOPMENT AND TRAINING

We implemented a three-dimensional UNet-like architecture, with encoder–decoder blocks linked by skip connections. To integrate river discharge information, we developed a Multi-Layer Perceptron (MLP) coupled with the UNet. Training was performed on the EuroHPC Leonardo supercomputer. Dropout layers were included to prevent overfitting and to allow for uncertainty estimation via Monte Carlo dropout. The model was trained for up to 500 epochs with early stopping, using RMSE as the loss function. The method is outlined in Fig. 1.

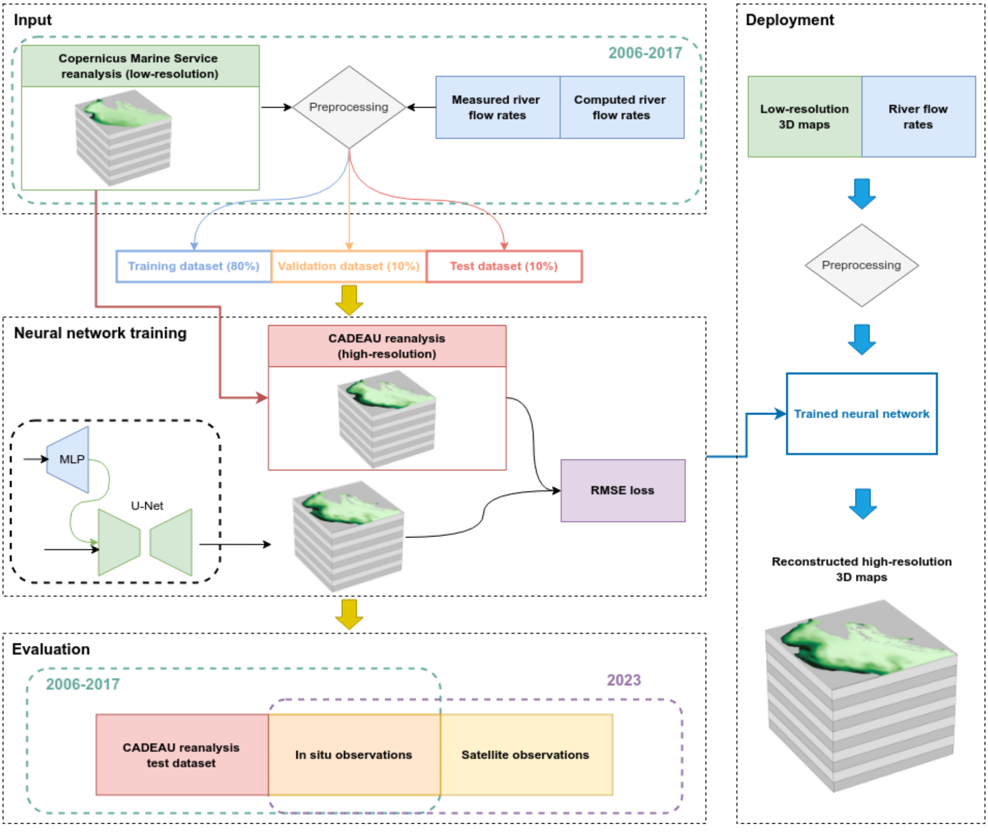

Figure 1
Flowchart of the deep learning method for coastal downscaling of biogeochemical variables.

VALIDATION AND RESULTS

The trained model, UNetR, was validated against independent test datasets, climatological in situ observations, and satellite products (chlorophyll and temperature). Using low-resolution forecasts from the Copernicus Marine Service, UNetR enhanced the resolution of physical and biogeochemical 3D fields without spin-up. Training on individual variables and incorporating local information, such as river flow, improved performance, showing better reproduction of coastal variability and reduced bias in surface chlorophyll, salinity, and phosphate in 2023 data.

The model proved highly efficient, capable of producing high-resolution forecasts in less than one second on a single GPU, compared to nearly one hour with conventional high-resolution models using 95 CPUs. Uncertainty analysis showed larger uncertainties near river mouths and during transitional seasons, consistent with the natural variability of the system.

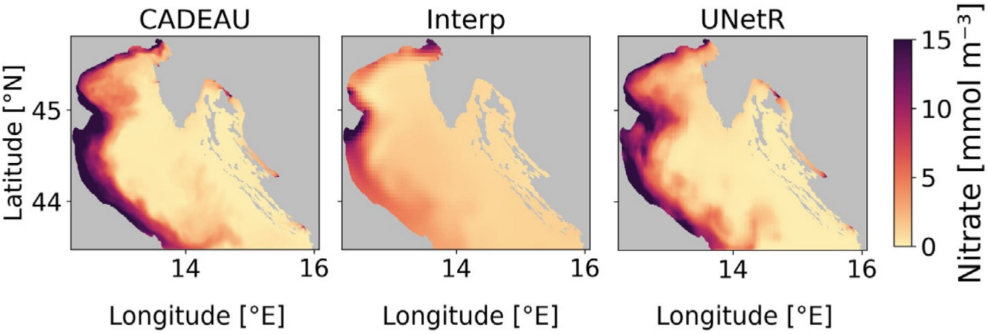

Figure 2
Comparison of the surface fields of a nitrate target map (CADEAU) in the test set with the interpolated low-resolution map and the output of the neural network

DISSEMINATION OF RESULTS

The main outcomes of this work were published in Ocean Modelling (2025). In addition, the codebase, including preprocessing, training, and validation scripts, was made publicly available on GitHub, ensuring reproducibility and accessibility for the scientific community.

ONGOING WORK AND PERSPECTIVES

Building on our previous results, we are now extending the methodology to a global scale. Current efforts focus on directly integrating satellite observations into the training process, exploring spatio-temporal architectures to better capture system dynamics, and evaluating alternative deep learning approaches, such as diffusion models, which enable ensemble predictions.

CONCLUSIONS

The activities carried out demonstrate the feasibility of using deep learning for coastal downscaling. By leveraging UNet architectures and integrating river discharge information, we achieved significant improvements in the representation of physical and biogeochemical variability in the northern Adriatic Sea. The method reduces computational costs dramatically while maintaining scientific robustness. These outcomes provide a strong basis for future research and operational applications.

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