Applications of deep learning super-resolution methods for coastal ocean modelling

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Abstract

Deep learning algorithms are gaining popularity in oceanography due to their lower computational cost compared to classical numerical methods and to the increasing availability of ocean data. In particular, super-resolution techniques can help recover small-scale features, which are especially important in the analysis of coastal regions. These methods have a wide range of applications, including the generation of high-resolution forecast data, of long-term projections, and the reconstruction of past conditions through the integration of model outputs and observational data. In a recent work, we developed a deep learning method for super-resolution in coastal areas by adapting techniques originally designed for super-resolution of digital images. We applied this method to the northern Adriatic Sea, a sub-basin of the Mediterranean Sea. This allowed us to identify the conditions under which the neural network performs best. We are currently working to integrate the neural network with our existing tools, to combine the advantages of both deep learning and numerical approaches. The aim of this contribution is to present our ongoing work on super-resolution for the northern Adriatic Sea, summarizing the results achieved so far and outlining the current challenges in practical application scenarios.

Keywords

Coastal ocean modelling, super-resolution, deep learning, U-Net, Adriatic Sea

1. Introduction

In the study of coastal areas, high-resolution data for physical and biogeochemical variables is important for understanding the small-scale processes. Deep learning methods for super-resolution can help achieve this goal having two main advantages over classical numerical modelling. The first is the lower computational time required at inference time [1]; once the neural network is trained, it can provide a result significantly faster than numerical models. The second is related to the learning process of the neural networks: in several works, the neural networks are trained on reanalysis datasets (e.g. [2, 3]), which integrate observational data through assimilation techniques to correct and improve model outputs. As a result, reanalysis products are typically of higher quality than pure model forecasts, and can be considered our best representation of reality. When trained on such datasets, neural networks implicitly learn to incorporate observational information, even when applied to forecast data.

In the last decade, several deep learning methods have been proposed for the super-resolution of digital images (e.g. [4]); in the last years, many of these methods have been adapted to increase the resolution also of climate and ocean data [5]. In a recent work [6], we presented a method based on a U-Net-like architecture for the super-resolution of the northern Adriatic Sea, a marginal region of the Mediterranean Sea (see Fig. 1 for a map of the considered area). River discharge strongly influences the

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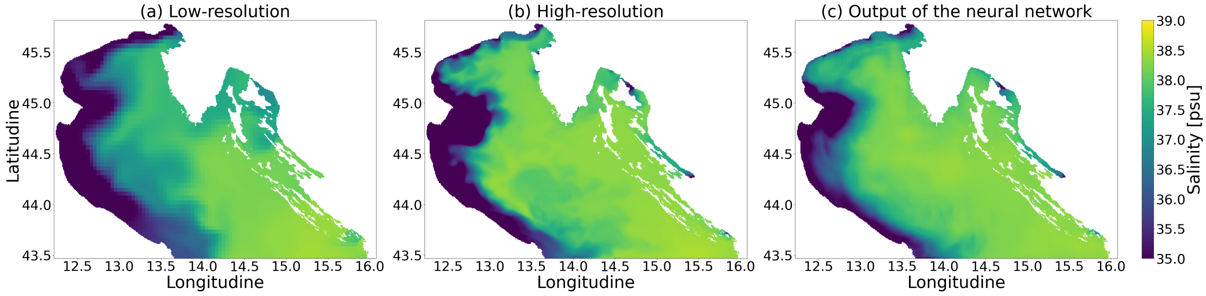

Figure 1: Comparison among Copernicus Marine (a), high-resolution reanalysis (b), and the output of the neural network (c) for a surface salinity map (average data of the period 1-5 April 2011).

coastal variability of this region [7]; however, these effects are poorly represented in low-resolution data. We showed that learning from the high-resolution reanalysis, given as input low-resolution and river discharge data, the neural network is able to reproduce some of the coastal patterns in the high-resolution dataset, also for time periods that were not present in the training set. Hence, we are currently working to apply this method to various forecast tasks, both on the short term and on climatic scenarios. The aim of this contribution is to present the ongoing development of applications based on the super-resolution approach introduced in [6], with a focus on current challenges and planned future improvements.

In what follows, we begin by recalling the architecture and the main features of the tool presented in [6]; we present the application tasks that we are currently tackling and their current state, and we describe the next actions that we plan to take in order to overcome the current issues.

2. U-Net for super-resolution of physical and biogeochemical variables

In this section we recall the method presented in [6] for the super-resolution of physical and biogeochemical variables on the northern Adriatic Sea. We considered the Copernicus Marine Mediterranean reanalysis products [8, 9] as low-resolution input data (~ 4.5 km horizontal resolution) and a high-resolution reanalysis dataset produced within the CADEAU project [10] (~ 750 m resolution) as the target. Since the high-resolution dataset spans from 2006 to 2017, we trained the neural network on this time period on 5 variables, namely chlorophyll, nitrate, phosphate, salinity and temperature. Furthermore, we considered the discharge of 19 rivers as auxiliary input. Technically, the neural network receives two inputs: (1) a 3D matrix ($27 \times 494 \times 300$) representing the low-resolution variable interpolated onto the target grid, and (2) a 1D array with 19 elements representing the river discharges corresponding to the same time frame. The output is a high-resolution version of the input variable at that time step.

The architecture of the neural network composes a Multi-Layer Perceptron (MLP) and a U-Net [11] that are trained together. The U-Net has two input channels: the interpolated low-resolution field and a second channel generated by the MLP. The MLP takes the river discharge array as input and outputs a 3D matrix with the same spatial dimensions as the target grid. Both components are trained together by using the Root Mean Square Error (RMSE) as loss function.

The neural network is effectively trained on 80% of the high-resolution dataset, whereas another 10% is used for validation during the training and the last 10% for the testing phase. From the testing we observed that the neural network was able to reproduce the structures of the high-resolution reanalysis giving comparable results. Figure 1 shows an example output of the neural network for a salinity field, alongside the corresponding Copernicus Marine input and the high-resolution reference. In addition we tested the neural network on Copernicus Marine data of 2023, for which the high-resolution reanalysis is not available, and compared the results with climatological values constructed with observational data and with satellite data for chlorophyll and temperature (the only two variables for which satellite data are available). From this analysis, we showed that the neural network preserves the structures of the Copernicus Marine data, generally improving the bias and the variability, especially for chlorophyll data along the northern coast. Since the results were satisfactory, we are now proceeding in the application of the super resolution for the northern Adriatic Sea in various scenarios, that are described in the next section.

3. Applications of super-resolution

This section presents the ongoing applications of the deep learning super-resolution approach presented in the previous section, for studying the northern Adriatic Sea. In particular, we focus on forecasting tasks, aiming both to predict physical and biogeochemical variables on short time periods (i.e., a few days in the future), and to generate high-resolution outputs of climatic scenario simulations.

3.1. Super-resolution for short term forecast

When considering short-term predictions we can follow two main approaches: on the one hand, the Copernicus Marine Service daily produces a 10 days forecast at Mediterranean scale, on which the neural network can be directly applied. This is a straightforward approach, and its performances are studied in detail in [6], where we analysed the outputs of the neural network on forecast data for 2023.

On the other hand, deep learning super-resolution could be integrated with numerical tools for model downscaling, in order to improve their initial conditions. The advantage of the second approach is that classical numerical models preserve the physical ocean dynamics by design, which is in general not guaranteed by the neural network. The main drawback, however, is the high computational cost of numerical simulations, which removes the immediacy in the results offered by the deep learning model. For the northern Adriatic Sea, a numerical tool for coastal downscaling has been developed by coupling two models [12]: MITgcm, a general circulation model commonly used to simulate ocean and atmoshphere dynamics, and the Biogeochemical Flux Model (BFM) used to simulate the biogeochemical processes within marine environments. This system operates by downloading Copernicus Marine data over the northern Adriatic area for the preceding seven days, which are used as initial conditions. The model then evolves forward in time to produce a three-day forecast, simulating a total of 10 days per run.

We are currently working to integrate deep learning and the numerical model by following two steps. Firstly, we modify the initial conditions of the model by applying the trained neural network and by using the resulting variables as initial conditions. This is feasible because the neural network was trained on the same type of data used as input for the numerical model. However, only a subset of the input variables can be enhanced in this way, namely those for which high-resolution reanalysis data were available during training. Moreover, this approach does not reduce the total computational time, since the numerical evolution remains unchanged. Nevertheless, preliminary (non-systematic) experiments show promising improvements, particularly for the salinity field, which is typically underestimated by Copernicus data in the Gulf of Trieste area. These early results suggest that this hybrid approach may be effective in improving current results.

Once this approach has been validated, the next step will be to assess whether the simulation time period can be shortened, by reducing the number of days simulated in the past (i.e. spin-up period) while maintaining predictive accuracy. In particular, we plan to determine how the quality of the prediction changes by reducing the number of days in the past, when we consider improved initial conditions. This could allow us to optimize the trade-off between computational cost and predictive performance.

3.2. Application of super resolution to climate projections

Climate projections are very important since they allow to have a glimpse on the state of the sea in the next decades under different emission scenarios. High-resolution climate projections are particularly valuable for identifying specific coastal areas that may be at risk of extreme events. The application

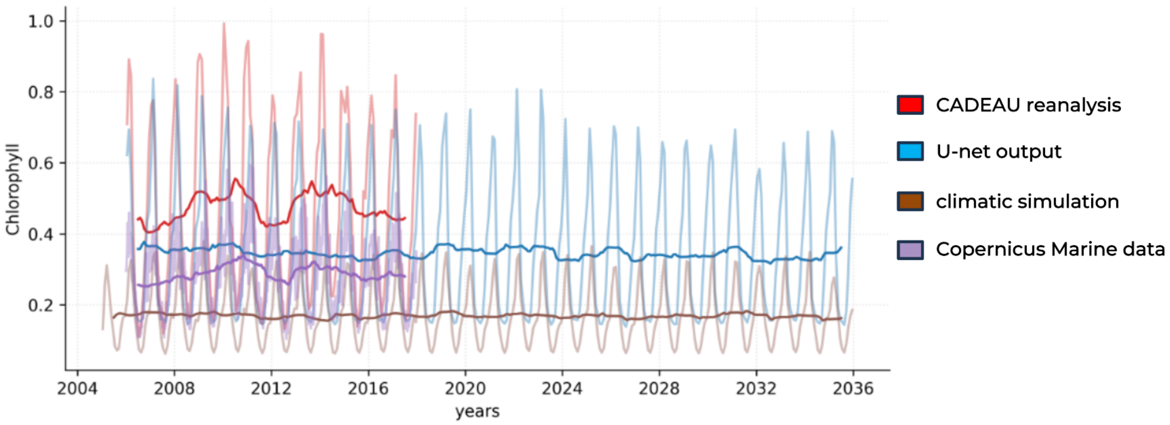

Figure 2: Average values in time for the high-resolution reanalysis, the Copernicus Marine data, the climate projections, and the neural network applied to the climate projections.

of our super-resolution tool to produce climate projections is more challenging, and needs specific strategies. There are two main difficulties.

1. Climate projections data are different from those used in the training (although they were also produced at the Mediterranean scale [13]): they are available at a coarser horizontal resolution (about 6 km instead of 4.5 km), they were obtained by using a different modeling system, and they do not assimilate observations, unlike the Copernicus marine reanalysis.
2. The target data for the training are available only until 2017, whereas we plan to apply the neural network to produce projections until 2099. Specifically, climate projections are available at a monthly scale from 2005 to 2099. This is a problem when predicting variables that change substantially over time, since the neural network may have difficulties in generalizing from its training set.

Despite these limitations, we conducted preliminary experiments using the neural network trained as in [6] directly on the climate projections data to evaluate its performance.

An example of the results of these experiments is shown in Fig. 2, where we compare the mean and standard deviation (solid and shaded lines, respectively) of the monthly data of four datasets for the chlorophyll 3D field: high-resolution reanalysis (red), Copernicus Marine reanalysis (purple), the climate projections under emission scenario RCP8.5 (brown), and the neural network output based on the climate projections input (blue). For clarity, the plots only extend to 2036.

The figure shows that both the mean and the standard deviation tend to decrease with resolution of the data. This likely reflects the absence of the assimilation of the data in the modeling system and the inability of coarse-resolution models to capture the river effect, which significantly drives chlorophyll concentrations and variability. The neural network improves both metrics compared to the original climate projections, although it does not fully reach the values seen in the high-resolution reanalysis. As a next step, we plan to enhance the training of the neural network by including the climate projections data, alongside with the Copernicus Marine data, in order to improve the ability of the neural network to produce prediction on the projections data.

4. Conclusion

Super-resolution methods offer the opportunity to transfer insights and data from well-studied, large-scale ocean regions to smaller, less studied areas with increased spatial resolution. This is the case of the Mediterranean Sea and the northern Adriatic Sea area. Deep learning provides computationally efficient methods for implementing super-resolution, especially in coastal environments where a greater variability among the data is present.

In this contribution, we have outlined ongoing applications of deep learning super-resolution methods in the northern Adriatic Sea, developed in collaboration between the National Institute of Oceanography and Applied Geophysics (OGS) and the University of Trieste. These tools aim to improve our understanding of the region, with potential benefits for local economic activities and coastal monitoring efforts.

Here, we focused mostly on the activities for which we have already obtained (partial) results and have a defined working plan. However, the applications of deep learning methods for super-resolution are broader. Among future directions, we aim to develop super-resolution techniques that incorporate observational data directly into the training process, with the goal of improving the quality of model data describing the past. Additionally, we plan to train the neural network under different boundary conditions (e.g. extreme river discharge conditions) to assess its ability to simulate 'what-if' scenarios.

Finally, we are also interested in testing different architectures of the neural network. For example, we aim to include temporal information explicitly in the deep learning model, and experiment with diffusion models [14], which have shown promising results in image processing tasks.

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Declaration on Generative AI

During the preparation of this work, the authors used GPT-4 in order to: Grammar and spelling check. After using these tools/services, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

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