Physics-Informed Neural Data Assimilation for High-Resolution Coastal SPM Reconstruction from Model and Satellite data

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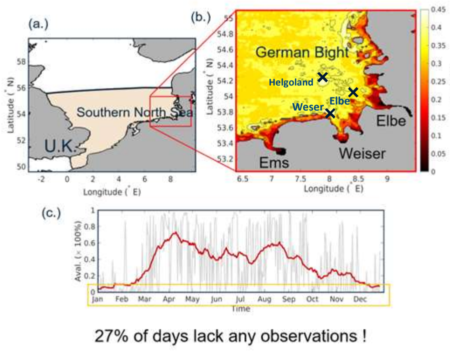
Introduction

Suspended particulate matter (SPM) plays a critical role in estuarine and coastal marine systems. Satellite remote sensing, particularly via platforms such as the Copernicus Marine Environment Monitoring Service (CMEMS), offers synoptic views of ist distribution. However, gaps in data (e.g., Fig 1) limits our understanding of coastal processes. The global SPM reconstructions (Liu and Wang, 2022, 2023) face challenges in coastal applications, because they cannot resolve complex geometry and coastal processes. Moreover, they based on DINEOF omits high-latitude regions due to reduced performance associated with server data missing (e.g. Fig.1c).



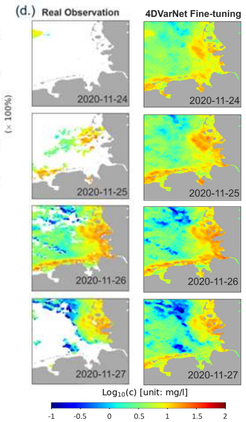
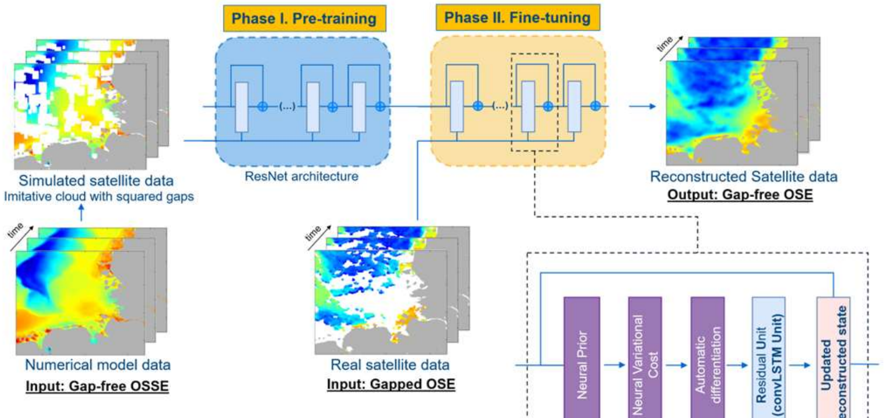


Fig.1: SPM data availability in the German Bight, southern North Sea; (c) The area mean of the availability varies in time with server missing during winter months. (d) left colum shows examples of SPM from satellites.

Method

End-to-end reconstruction of sea surface SPM

4DVarNet: integrates 4-dimensional variational DA principles into an end-to-end trainable deep learning architecture. (https://cia-oceanix.github.io/ocean4dvarnet/). The approach (Fig. 2) employs a novel two-phase transfer learning strategy: (1) pre-training on OSSEs where gap-free model outputs are masked with synthetic cloud patterns, and (2) fine-tuning on OSEs using sparse satellite data. The architecture embeds a trainable dynamical prior and a convolutional LSTM solver to iteratively minimize a cost function that balances data agreement with physical consistency.



OSE: Observing System Experiment
OSSE: Observing System Simulation Experiment

Fig.2: The architecture of 4DVarNet and the workflow sketch of reconstructing gapped SPM data.

Results

I-Examples of reconstructed SPM

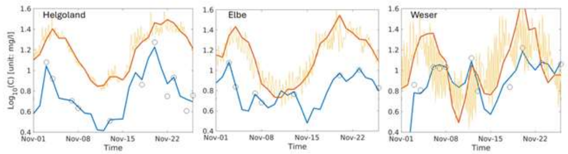
As shown in Fig 1d, we are able to reconstruct SPM field even if large area absent in available data.

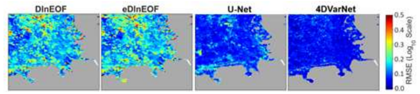
II-Remain physical features of coastal SPM

As shown in Fig 3, the reconstructed SPM aligns well with the satellite obeservations, meanwhile maintains the features due to spring/neap cycles of tides at coast (15 days).

III-Compare with other methods

Fig 4 indicates advances of AI methods (Unet, 4DVarNet) over the DInEOFs, for low data availability parameters. Compare to DInEOF, 4DVarNet improved performance with a 70% reduction in RMSE and 50% increase in SSIM.





Algorithm	RMSE	RE (%)	MAE	SSIM
DInEOF	0.184	37.452	0.129	0.610
eDInEOF	0.192	39.943	0.135	0.611
UNet	0.098	14.754	0.062	0.905
4DVarNet	**0.063** (70%)	**9.315**	**0.038**	**0.916** (50%)

Fig. 3: SPM variation in time at different places (see Fig 1b for locations). SPM curves from numerical model (orange) and 4DVarNet (blue). Dots are observations;

Fig. 4: (upper panels) RMES of reconstruction by different methods; (lower panel) Statistic of RMES, RE (%), MAE, and structure similarity (SSIM) index of different methods.

Contribute to Digital Twin Ocean

- A future operational Digital Twin Ocean (DTO) will require a fully interoperable European marine data space and improved modelling capabilities.
- This work contributes to DTO as an EDTIO-ModelLab service, advances the dimention of CMEMS.
- The work develops novel, seamless coastal forecasting capabilities.

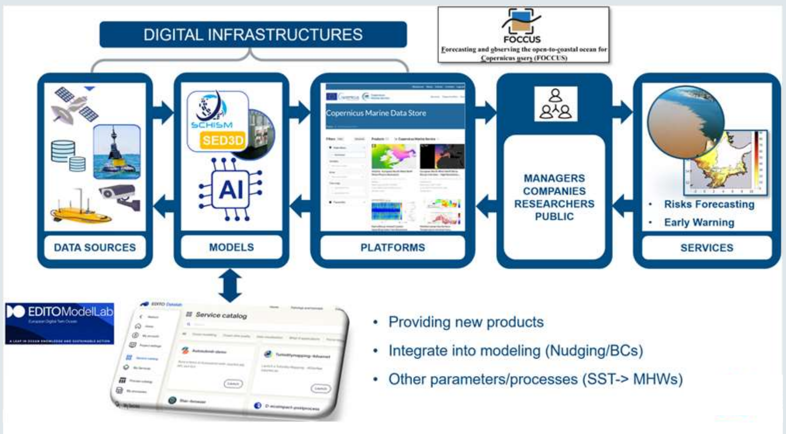


Fig.5: The Digital Twin infrastructure