Downscaling Oceanographic Satellite Data with Convolutional Neural Networks

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Motivation

The **ocean circulation** is a central player in regulating Earth's climate and supporting marine life by transporting heat, carbon, oxygen, and nutrients throughout the world's ocean. Yet, our understanding of the processes governing these fluxes is still limited because of the relatively **small spatial scales** involved, which are difficult to observe with current remote sensing techniques. One technique commonly used to enrich the wealth of information contained in satellite data is **downscaling**. It consists in reconstructing a high-resolution (HR) observation from a low-resolution (LR) one's. For 2D fields, this problem is similar to **image super-resolution** in the computer vision community and uses **convolutional neural networks** (CNNs) instead of traditional interpolation techniques to learn the downscaling relationship between LR and HR image. Given the availability of **large datasets** for ocean remote sensing, it appears very tempting to investigate the potential of deep learning models to downscale satellite-derived observations.

Research Objectives

Are deep learning models efficient to downscale ocean remote sensing datasets? This question is non trivial as the spatio-temporal scales involved in oceanographic field might be difficult to reconstruct for CNN. In this work, we will try to rescale both **Sea Surface Temperature** (SST) with a factor of 5 and **Sea Surface Height** (SSH) with a factor of 3, and by comparing different CNN models taken from the super-resolution literature.

Datasets

- The **OSTIA 1/20◦ SST** (satellite data from microwave and infrared sensors combined with in situ data from drifting and moored buoys)
- The **NOAA-OI 1/4◦ SST** (observations from 2 satellites: AVHRR and AMSR-E)
- The **Mercator-GOAFS 1/12◦ SSH** (altimeter data assimilated into the NEMO ocean model
- The **Mercator-GOMASG 1/4◦ SSH** (data from al altimeter missions: Jason-3, Sentinel-3A, HY-2A Saral/AltiKa, Cryosat-2, Jason-2, Jason-1, T/P, ENVISAT GFO and ERS1/2)

References

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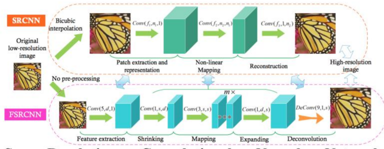
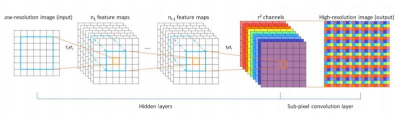
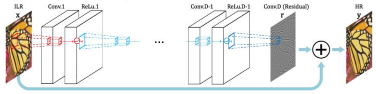
Models Architecture



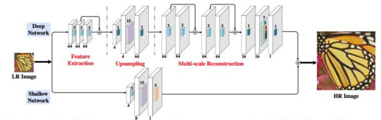
Super-Resolution Convolutional Neural Network (SRCNN) and Fast Super-Resolution Convolutional Neural Networks (FSRCNN) – Dong et al., 2015, 2016



Efficient Sub-Pixel Convolutional Neural Network (ESPCN) -- Shi et al., 2016

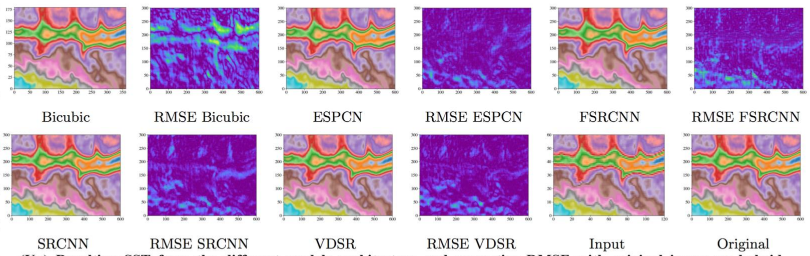


Very Deep Super-Resolution Convolutional Neural Network (VDSR) -- Kim et al., 2016

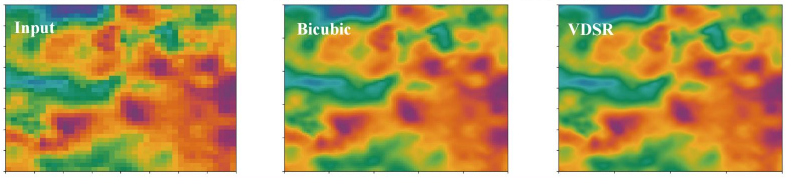


End-to-End Deep and Shallow networks (EEDS) -- Wang et al., 2016

Image Results



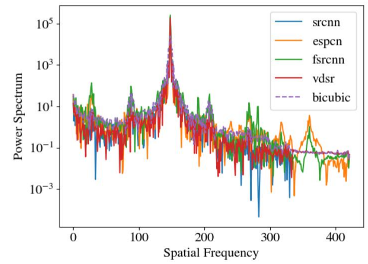
(Up) Resulting SST from the different models architecture and respective RMSE with original image on hybrid distribution from model and satellite in Test dataset. (Down) Results from distribution of satellite data.



Conclusions

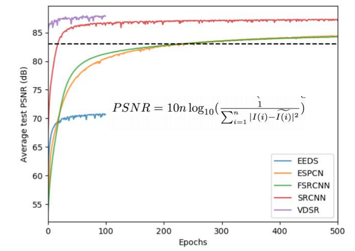
Our experiments clearly points out the relevance of CNNs for the considered dataset with clear improvement over the bicubic interpolation for geophysical fields downscaling. Still, further work are needed to consider other geophysical variables and, more importantly, explore hyper-parameters space of the models used in this study.

Spatial Spectrum



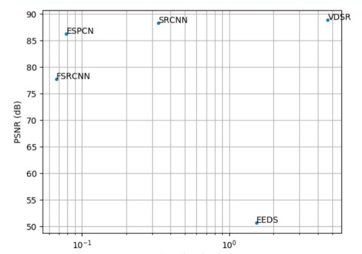
Difference of spatial power spectra between the original image and the reconstructed one for the entire SST field.

PSNR



The horizontal dotted black line denotes the bicubic interpolation score.

Trade-off PSNR vs. Run Time



Run time = time to make a prediction