Downscaling Oceanographic Satellite Data with Convolutional Neural Networks

### 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 downsampling 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 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 re-scale both Sea Surface Temperature (SST) with a factor of 5 and Sea Surface Height (SSH) with a factor of 3, and by comparing different 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-OF 1/4° SST (observations from 2 satellites: AVHRR and AMSR-E)
- The Mercator-GEAFS 1/12° SSH (all available data assimilated into the NEMO ocean model)
- The Mercator-GOMASG 1/4° SSH (data from all missions: Jason-3, Sentinel-3A, HY-2A, Metop-A/B, CryoSat-2, Jason-2, Jason-1, TPF ENVISAT, GFO and ERS1/2)

### References

- Li, L., Sun, M., and Wang, L., "Improving the Accuracy of the Moderate Resolution Imaging Spectroradiometer SST Retrieval Using Machine Learning.
- Li, L., Sun, M., and Wang, L., "Improving the Accuracy of the Moderate Resolution Imaging Spectroradiometer SST Retrieval Using Machine Learning.

### Conclusions

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

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**Models Architecture**

- **Very Deep Super-Resolution Convolutional Neural Network (VDSR)** — Kim et al., 2016
- **Feasible Sub-Pixel Convolutional Neural Network (ESPNCN)** — Shi et al., 2016
- **Efficient Sub-Pixel Convolutional Neural Network (ESPCN)** — Shi et al., 2016
- **End-to-End Deep and Shallow networks (EDSS)** — Wang et al., 2016

**Spatial Spectrum**

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

**Trade-off PSNR vs. Run Time**

The horizontal dotted black line denotes the bicubic interpolation score.