EGU2020-20177
https://doi.org/10.5194/egusphere-egu2020-20177
EGU General Assembly 2020

Deep neural networks to downscale ocean climate models

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Ocean currents are a major source of impact on climate variability, through the heat transport they induce for instance. Ocean climate models have quite low resolution of about 50 km. Several dynamical processes such as instabilities and filaments which have a scale of 1km have a strong influence on the ocean state. We propose to observe and model these fine scale effects by a combination of satellite high resolution SST observations (1km resolution, daily observations) and mesoscale resolution altimetry observations (10km resolution, weekly observations) with deep neural networks. Whereas the downscaling of climate models has been commonly addressed with assimilation approaches, in the last few years neural networks emerged as powerful multi-scale analysis method. Besides, the large amount of available oceanic data makes attractive the use of deep learning to bridge the gap between scales variability.

This study aims at reconstructing the multi-scale variability of oceanic fields, based on the high resolution NATL60 model of ocean observations at different spatial resolutions: low-resolution sea surface height (SSH) and high resolution SST. As the link between residual neural networks and dynamical systems has recently been established, such a network is trained in a supervised way to reconstruct the high variability of SSH and ocean currents at submesoscale (a few kilometers). To ensure the conservation of physical aspects in the model outputs, physical knowledge is incorporated into the deep learning models training. Different validation methods are investigated and the model outputs are tested with regards to their physical plausibility. The method performance is discussed and compared to other baselines (namely convolutional neural network). The generalization of the proposed method on different ocean variables such as sea surface chlorophyll or sea surface salinity is also examined.