Data-driven sea-ice modelling with generative deep learning

To represent the observed temporal and spatial scaling of the sea-ice dynamics, we need to run sea-ice models at the km-scale or with complex physical parameterizations of the subgrid-scale processes at resolutions of around 10 km. However, running such models is numerically very costly, which can prohibit their use in coupled Earth system models. To remedy these shortcomings, we introduce a data-driven sea-ice model based on generative deep learning that predicts together the most important prognostic state variables for sea ice. Trained with more than twenty years of simulation data from a state-of-the-art geophysical model, the data-driven model can extrapolate to previously unseen conditions, like given by forcings from CMIP6 simulations, and thereby exceeding the performance of baseline models. Relying on deterministic data-driven models can lead to a loss of small-scale information, which causes overly smoothed predictions and physical inconsistencies. This is why the ability to perform stochastic forecasts can be instrumental to the success of data-driven sea-ice models. To generate stochastic forecasts with neural networks, we employ denoising diffusion models. We show that the model can predict the uncertainty that remains unexplained by deterministic models. Furthermore, it can recover the information at all scales, which resolves issues with the smoothing effects and leads to higher physical consistency even for long lead times. Therefore, we see a huge potential of generative deep learning for sea-ice modelling, which can pave the way towards the use of highly resolved data-driven models within coupled Earth system models.

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