IceNet: Pan-Arctic sea ice map prediction using deep learning

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Over recent decades, the Arctic has warmed faster than any region on Earth, resulting in a rapid decline in Arctic sea ice extent, which is often highlighted as a key indicator of anthropogenic climate change. Changes in sea ice disrupt Arctic wildlife and indigenous communities, and likely influence weather patterns as far as the mid-latitudes through remote teleconnections. Furthermore, melting sea ice attenuates the albedo effect by replacing the white, reflective ice with dark, heat-absorbing melt ponds and open sea, increasing the Sun's radiative heat input to the Arctic and amplifying global warming through a positive feedback loop. Thus, the reliable prediction of sea ice under a changing climate is of both regional and global importance. However, Arctic sea ice presents severe modelling challenges due to its complex, coupled interactions with the ocean and atmosphere, leading to high levels of uncertainty in numerical sea ice forecasts.

A promising alternative to existing dynamical and statistical sea ice prediction methods are deep neural networks: a family of powerful statistical algorithms that use multiple nonlinear processing layers to extract increasingly high-level features from raw input data. Advances in such techniques over the last two decades have enabled widespread success in diverse areas where significant volumes of data are available, such as image recognition, genetics, and online recommendation systems. There has been a recent surge of interest in deep learning from the environmental science community, owing to the large and growing quantities of environmental datasets available and deep learning's ability to automatically learn complex relationships between variables. In this study, we train a deep learning sea ice prediction system, which we call IceNet, to predict monthly-averaged pan-Arctic sea ice maps based on input remote sensing observations of the Arctic. In particular, we use inputs of monthly-averaged sea ice concentration maps since 1979 from the National Snow and Ice Data Centre, as well as climatological variables (such as surface pressure and temperature) from reanalysis data (ECMWF ERA5). In addition, we pre-train IceNet using CMIP6 model runs to boost performance on the limited observational record. IceNet comprises an ensemble of independent networks with different random weight initialisations, which improves performance and uncertainty calibration. We benchmark IceNet against simple persistence and linear trend models, as well as a state-of-the-art dynamical sea ice model, ECMWF C3S. Performance is evaluated quantitatively using accuracy metrics and qualitatively by analysing pan-Arctic maps of prediction error and uncertainty.