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Supplement of

Developing a deep learning forecasting system for short-term and high-resolution prediction of sea ice concentration

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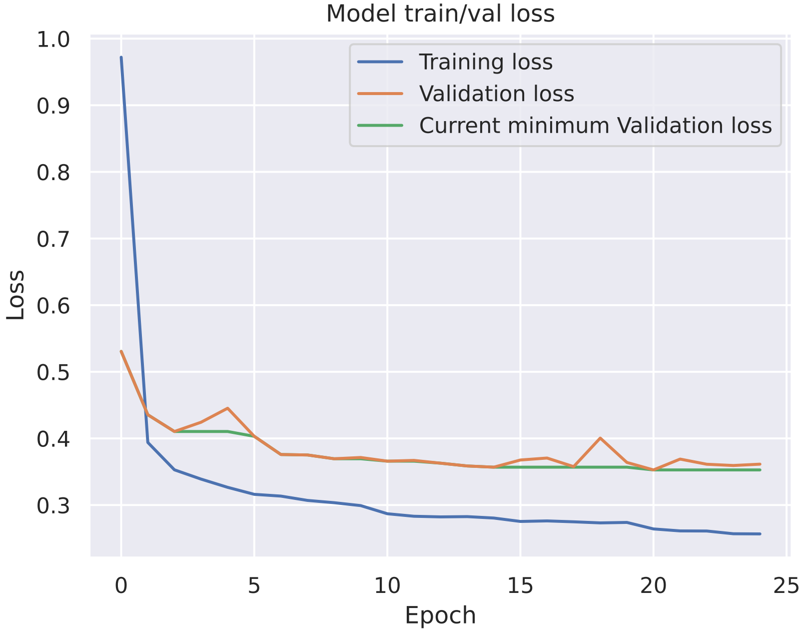

Figure S1. Training and validation loss for a neural network with a 2-day target lead time. The model is initialized with an initial learning rate of 0.001 and a width of 256 channels in the bottleneck.

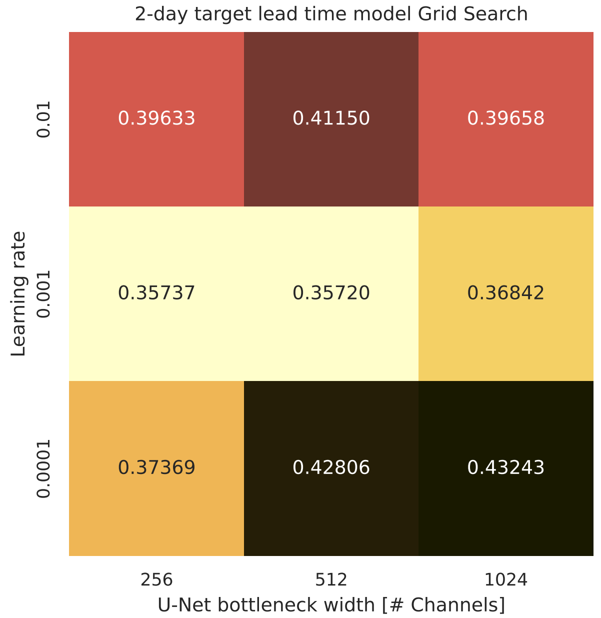

Figure S2. Grid search across varying learning rates and bottleneck widths for a deep learning model targeting 2-day lead time. The scores represent the minimum validational loss achieved before terminating training at 25 epochs.

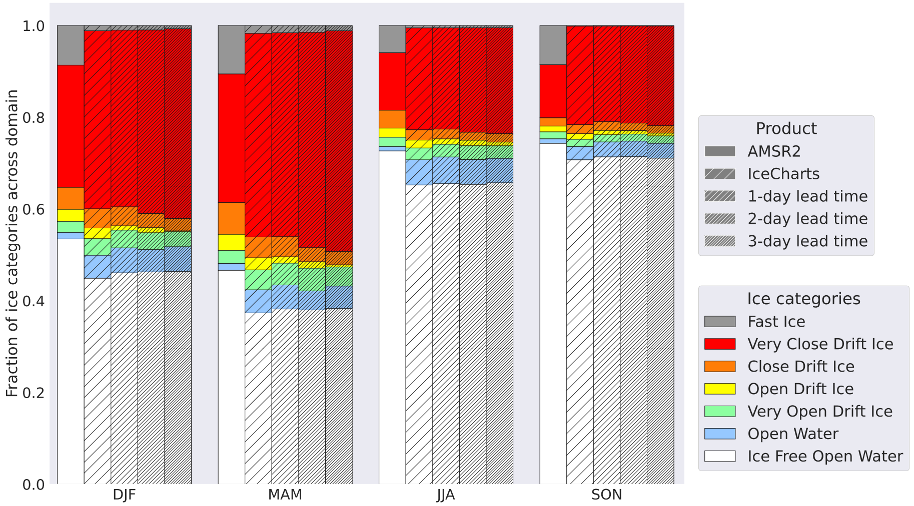

Figure S3. Seasonal distribution of each SIC category for 2022 as fraction of total mean SIC area for AMSR2, ice charts and single output layer deep learning models at 1 –3 day lead time. The single output layer models are fitted with the same input data and hyper parameters as the deep learning models predicting cumulative contours, however instead of predicting cumulative contours the models predict ice charts directly and compute the categorical cross entropy loss function directly.

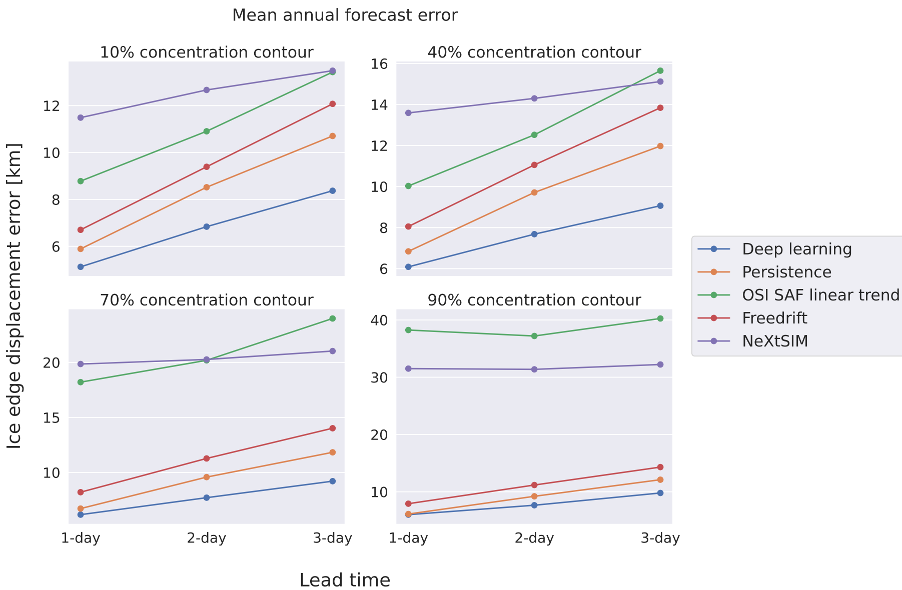

Figure S4. Same as Figure 6 in the manuscript, but using deep learning models trained with additional AROME Arctic data initialized at 12:00 UTC appended to the dataset (data between 12:00 and 18:00 appended). For the 10% concentration contour, the deep learning model with additionally appended AROME Arctic data achieves $(5.127, 6.839, 8.371)$ nIIEE$_{10\%}$ for each lead time (For reference, the deep learning system considered in the manuscript achieved $(5.307, 6.820, 8.112)$ at the same contour). Mean annual ice edge displacement error as function of lead time for different sea ice concentration contours defined by 10, 40, 70 and 90% SIC. Only products with a complete coverage of 2022 has been considered. Ice charts are used as reference product.

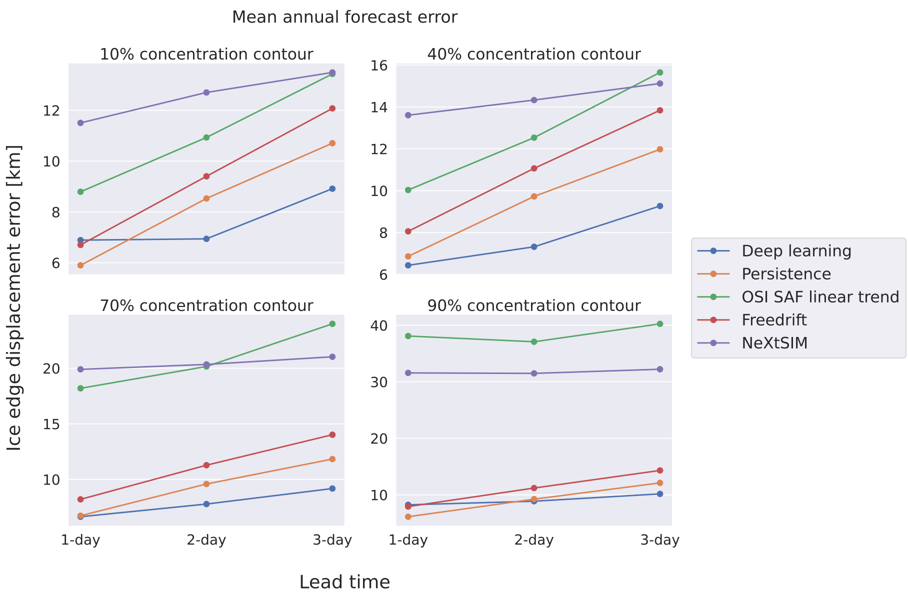

Figure S5. Same as Figure 6 in the manuscript, but using deep learning models trained with AMSR2 passive microwave observations as input (ice chart cumulative contours are still used as target). Mean annual ice edge displacement error as function of lead time for different sea ice concentration contours defined by 10, 40, 70 and 90% SIC. Only products with a complete coverage of 2022 has been considered. Ice charts are used as reference product.

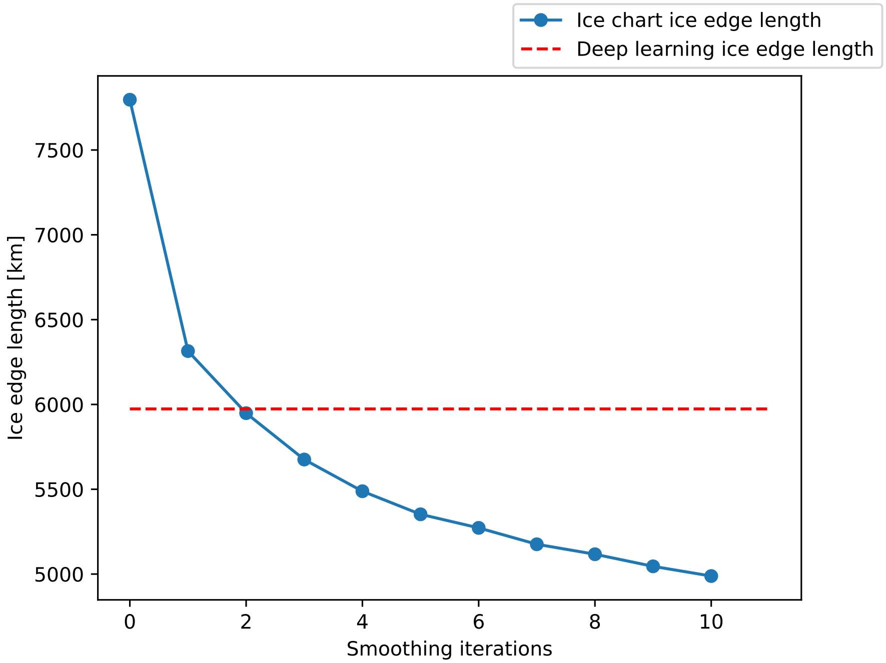

Figure S6. Impact to ice edge length when an ice chart (03-01-2022) is successively smoothed by a (7×7) mean-value filter. A reference deep learning ice chart edge for a 1-day lead time model is shown horizontally as reference. The ice chart ice edge length is shorter than a deep learning ice edge length after the mean value filter is applied twice.