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Supplement of

Improving short-term sea ice concentration forecasts using deep learning

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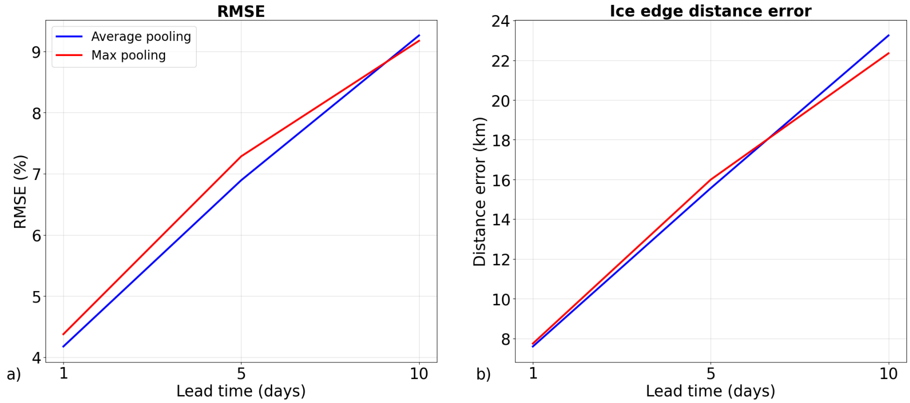

Figure S1. Comparison of the performances of the deep learning models with the Attention Residual U-Net architecture using either average pooling or max pooling in 2021 (validation period) when the forecasts are evaluated using the RMSE (a) and the ice edge distance error (b). AMSR2 sea ice concentration observations are used as reference.

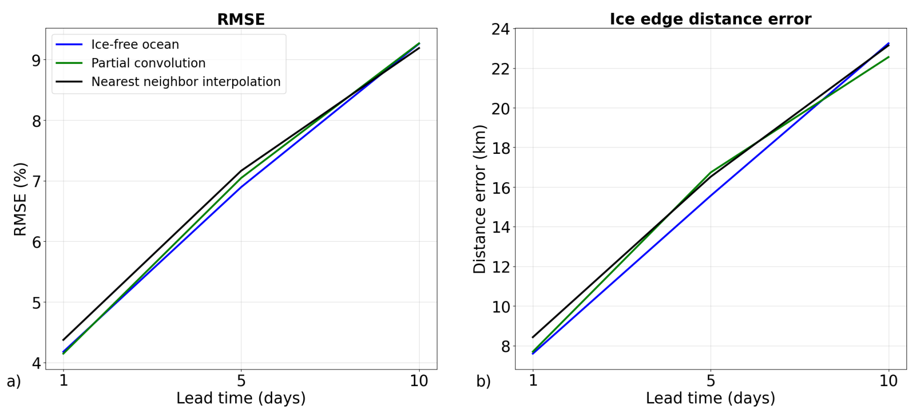

Figure S2. Performances of the deep learning models with the Attention Residual U-Net architecture during 2021 (validation period) with three different approaches for filling land grid points. Blue curves: land grid points are considered as ice-free ocean (the method selected in the paper). Black curves: the land grid points are filled using the value of the nearest ocean grid point. Green curves: partial convolution is used, which is a method where land grid points are masked. AMSR2 sea ice concentration observations are used as reference.

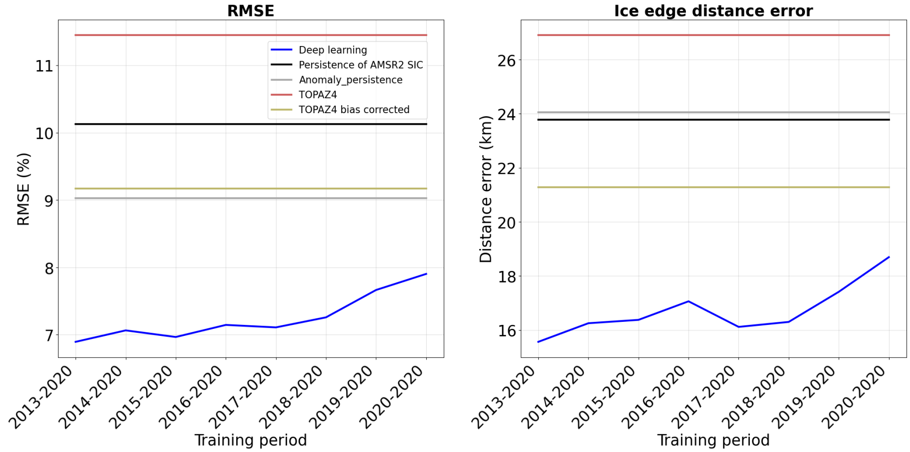

Figure S3. Performances of 5-day forecasts from the deep learning models (with the Attention Residual U-Net architecture) trained over different periods (see x axis) using AMSR2 sea ice concentration observations as reference. This figure shows the performances of the deep learning models in 2021 (validation period). The model trained using the period 2013-2020 has the best performances for the RMSE and the position of the ice edge.

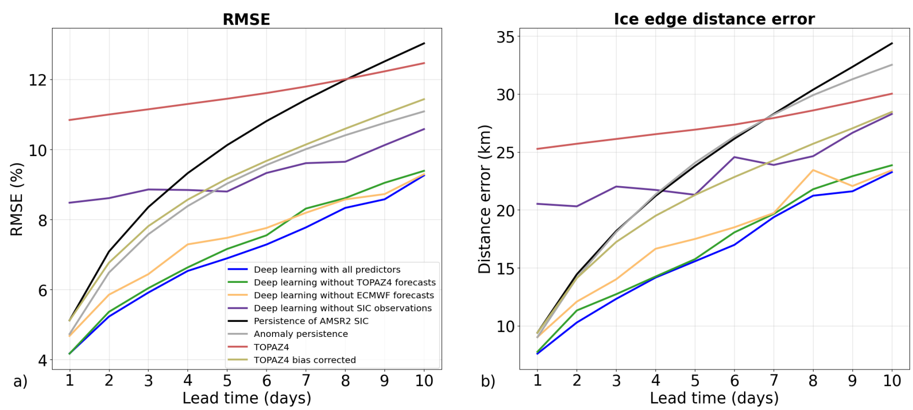

Figure S4. Performances of the deep learning models with the Attention Residual U-Net architecture during 2021 (validation period) using AMSR2 sea ice concentration observations as reference. The deep learning models using all predictors are shown by the blue curves, the models which do not use predictors from TOPAZ4 sea ice forecasts (sea ice concentration forecasts and initial errors) are shown by the green curves, the models which do not use predictors from ECMWF weather forecasts (2-m temperature and wind) are shown by the yellow curves, and the models which do not use predictors from sea ice observations (AMSR2 sea ice concentration, AMSR2 sea ice concentration trend, and TOPAZ4 initial errors) are shown by the purple curves.

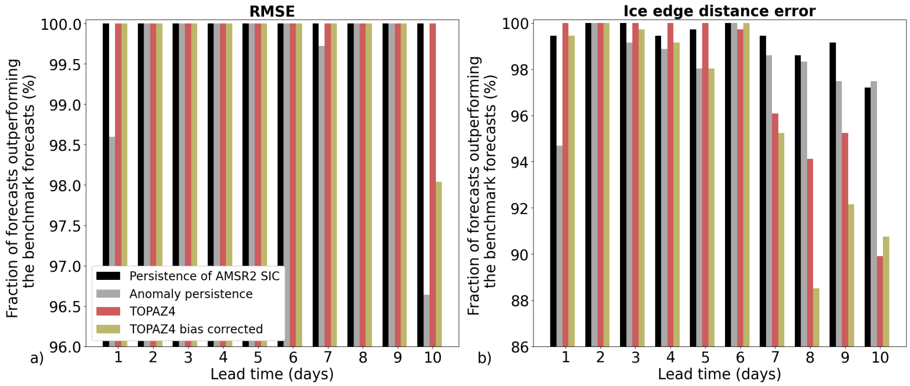

Figure S5. Fraction of days in 2021 (validation period) during which the forecasts from the models with the Attention Residual U-Net architecture outperform the different benchmark forecasts when the forecasts are evaluated with the RMSE (a) and with the ice edge distance error (b). AMSR2 sea ice concentration observations are used as reference.

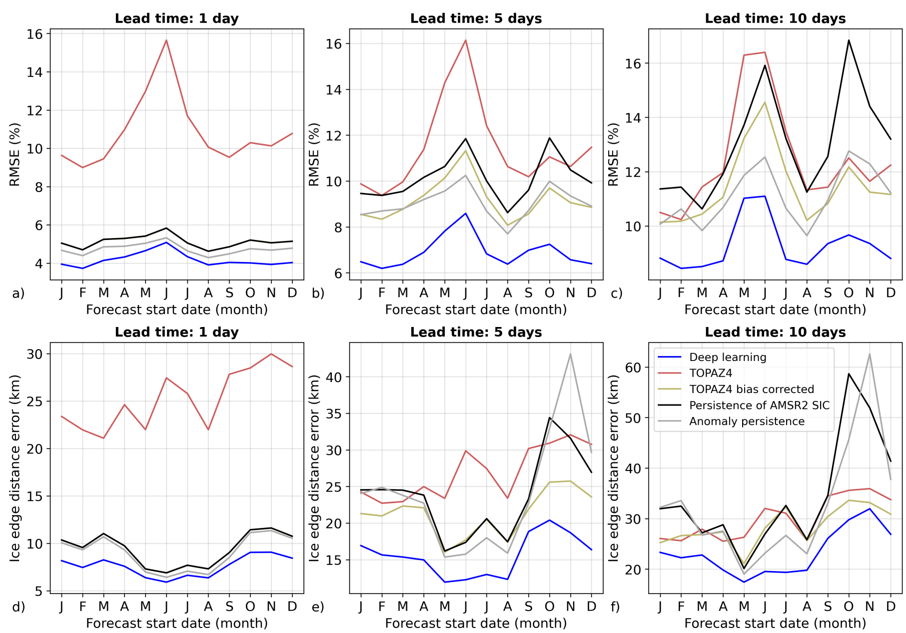

Figure S6. Seasonal variability in the performances of the deep learning models with the Attention Residual U-Net architecture in 2021 (validation period) for different lead times (1, 5, and 10 days) when the forecasts are evaluated using the RMSE (a, b, c) and using the ice edge distance error (d, e, f). AMSR2 sea ice concentration observations are used as reference.

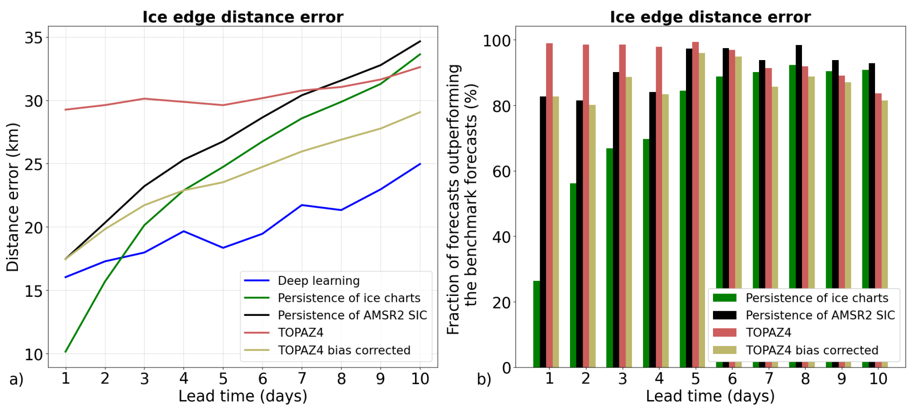

Figure S7. Performances of the deep learning models with the Attention Residual U-Net architecture during 2021 (validation period) using the ice charts as reference. The ice edge position (defined by the 10 % SIC contour) is evaluated. a) Mean ice edge distance errors depending on lead time. b) Fraction of days in 2021 during which the forecasts from the models with the Attention Residual U-Net architecture outperform the different benchmark forecasts when the forecasts are evaluated using the ice edge distance error. It is worth noting that this evaluation is performed over the area covered by the ice charts from the Norwegian Meteorological Institute (European Arctic), and that the number of forecasts evaluated varies depending on lead time because ice charts are not produced during weekends.