Developing a deep learning model for short term and high resolution prediction of WMO sea ice concentration categories

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Summary of forecast production

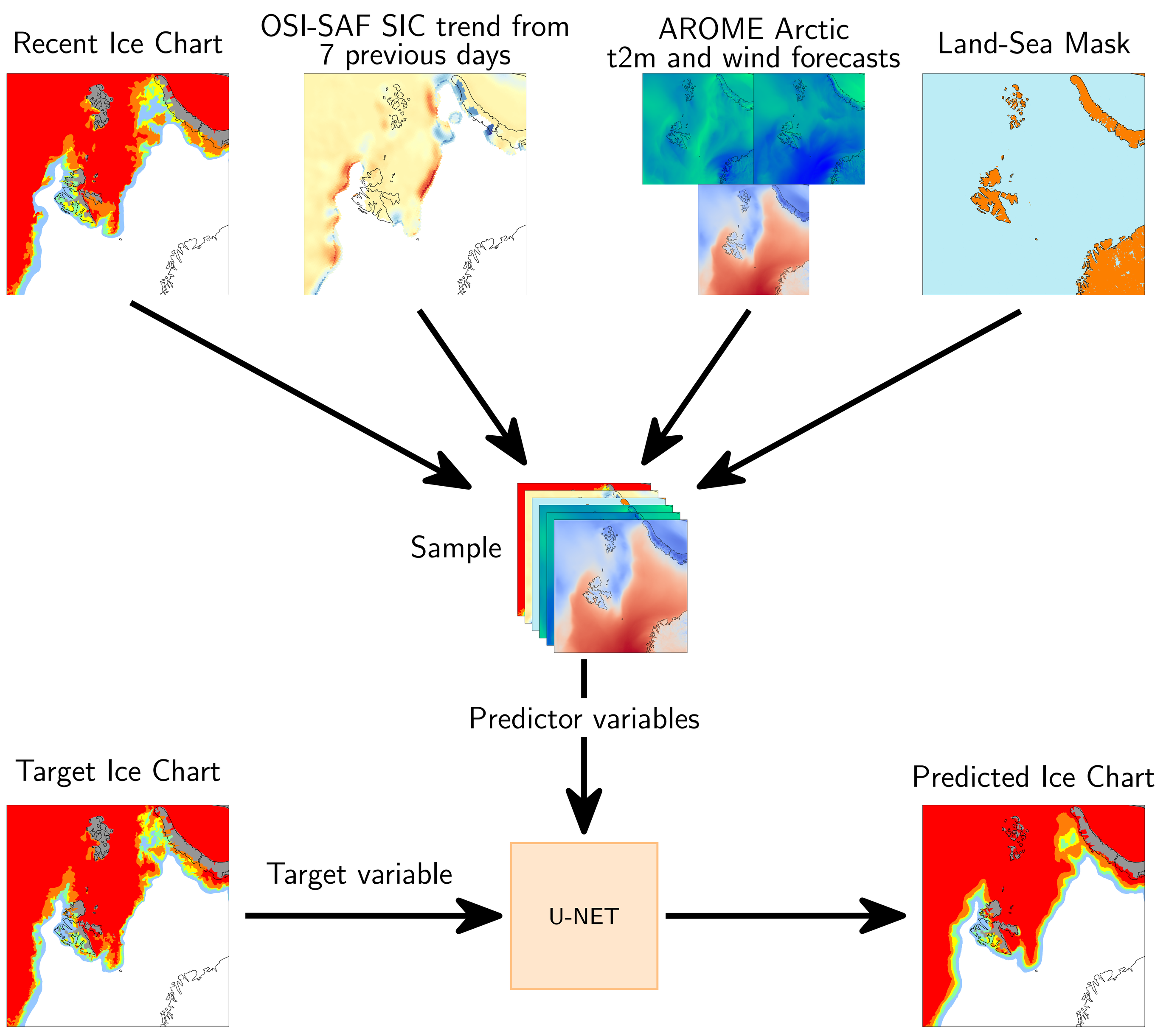

Figure 1: The deep learning forecasting system workflow

Model development

- The deep learning model is based on the U-Net architecture (image to image, pixelwise prediction).
- Each WMO sea ice concentration category is predicted separately.
- The final forecast is the pixelwise sum of the individually predicted sea ice concentration contours.
- 1km resolution (1792 x 1792 grid points) with (1 – 3) day lead time.
- Training period: 2019 – 2020 (288 samples).
- Testing period: 2022 (147 samples).

Input variables

- Sea ice concentration from the sea ice charts at t_0 produced by the Norwegian Ice Service (1km).
- Linear sea ice trend derived from Ocean and Sea Ice Satellite Apllication Facility passive microwave (SSMIS) using the seven previous days (10km).
- 2 meter temperature and 10 meter winds from a regional NWP system (AROME Arctic) (2.5km). Time steps between forecast bulletin date and target valid date is reduced to a mean-value field that projects temporal information onto a single time step.
- Land sea mask from AROME Arctic (2.5km).

Target variables

- Sea ice charts at time t_0+(1 – 3) days relative to the predictor date.
- The target sea ice concentration is divided into sea ice concentration contours following the WMO sea ice categories

U-Net architecture

- 2,359,047 trainable parameters
- Training is performed on an Nvidia A100 GPU, and takes ~3 hours
- During training, the U-Net uses 52Gb of memory
- After training, a single prediction is made in 6 seconds with a CPU

Introduction

- Sea ice concentration prediction targeting km-scale resolution is challenging.
- Maritime operators in the Arctic are lacking high resolution and high frequency sea ice forecasts for tactical decision making
- Deep learning systems are computationally lightweight, and can create a forecast on a consumer computer in minutes. Training the deep learning system is done on a cluster, once.

Results

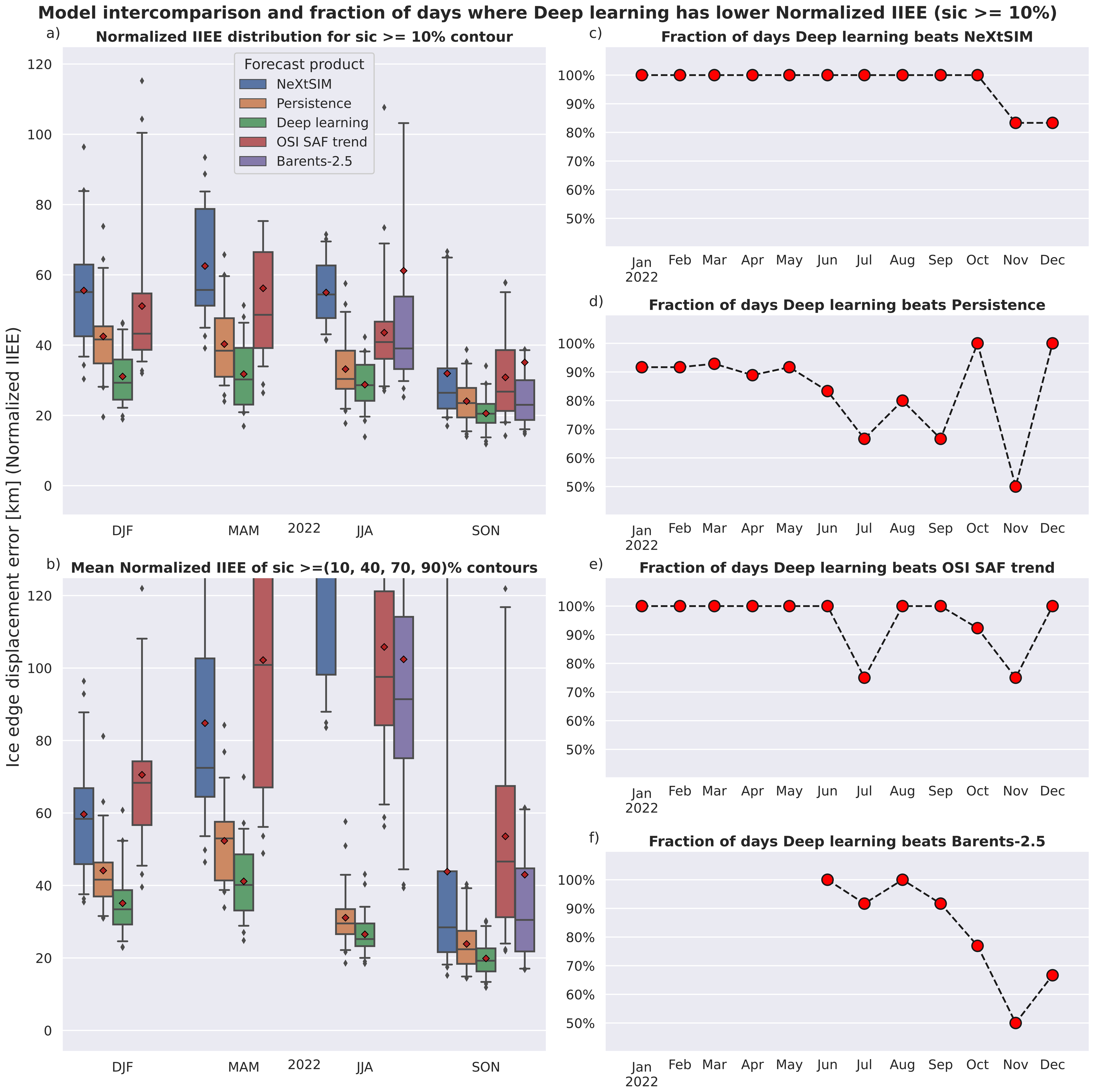

Figure 2: (a, b) Box and whisker plot of Normalized IIEE for different forecasting products as well as two benchmarks (Persistence and OSI SAF linear trend). The boxes cover the interquartile range. Whiskers denote the 5^{th} and 95^{th} percentiles. (c,d,e,f) Percentage of days where the Deep learning forecast achieves a lower Normalized IIEE score than the compared to product. (e) OSI SAF trend is a linear trend computed from the past 7 days. (f) Barents-2.5 is an in-development ocean and sea ice model implemented at MET Norway.

Model intercomparison

- The ice edge displacement error (Normalized Integrated Ice Edge Error) for an ice edge defined at the >=10% WMO sea ice concentration contour has on average been improved by **28%** between the four validational products.
- The deep learning model improves **90%** of the forecasted dates between the four validational products, with regards to achieving a lower Normalized IIEE for the >=10% concentration contour.

Comparing persistence with a deep learning prediction

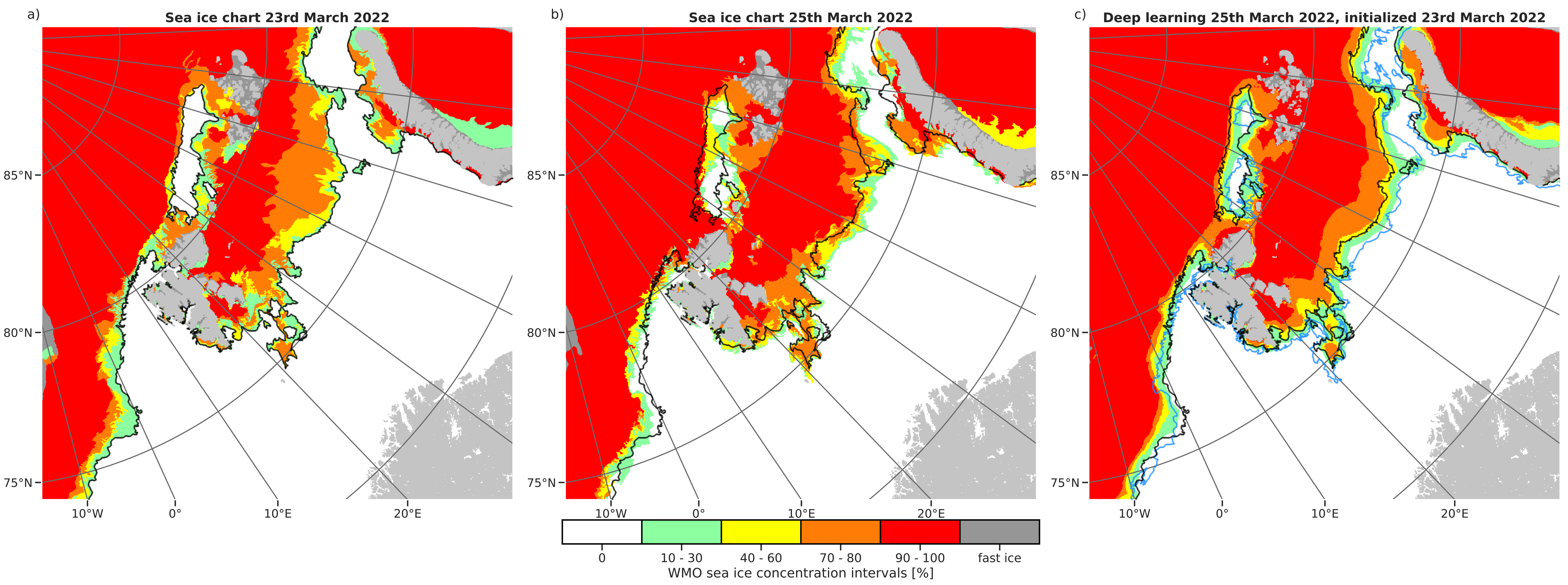

Figure 3: (a) Sea ice chart produced on 23 March 2022. (b) Sea ice chart produced on 25 March 2022. (c) Deep learning prediction for 25 March 2022, with a 2 day lead time. The sea ice chart in (a) was among the input variables for (c). The black line in (a,b,c) is the ice edge for (a) given a >=10% threshold. The blue line in (c) is the ice edge for (b) given a >=10% threshold.

- Persistence sea ice edge displacement error = **65km**.
- Deep learning sea ice edge displacement error = **37km**.
- The displacement error was computed with regards to the >=10% concentration contour.