Seasonal Sea Ice Presence Forecasting of Hudson Bay using Seq2Seq Learning

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Motivation

- Sea ice presence as an important variable for northern communities and shipping companies
- Significant declining trend in Arctic sea ice extent over the past several decades in response to warming temperatures driven by climate change
- Previously proposed ML approaches not generating a forecast that propagates forward in time in a manner similar to a physics-based forecast model

Seasonal Sea Ice Presence Forecasting

- Sequence-to-sequence learning approach to provide a spatiotemporal forecast of the probability of sea ice at daily time scale
- Probabilistic approach
- Forecast range: 1 to 90 day
- Ice presence: ice concentration > 15%

[1] Sutskever, I., et al. Sequence to sequence learning with neural networks. NIPS 2014.

Data

- Data source: ERA5 - by European Centre for Medium-Range Weather Forecasts (ECMWF)
- Time scale : daily variables from 1979 to 2018
- Spatial scale: 30 km
- Input variables:
  - Sea ice concentration
  - Sea surface temperature
  - 2m air temperature
  - Wind 10 meter U-component
  - Wind 10 meter V-Component
  - Surface sensible heat flux
  - Landmask
  - Freezing degree days/ Melting degree days
- Output variable:
  - Ice presence probability

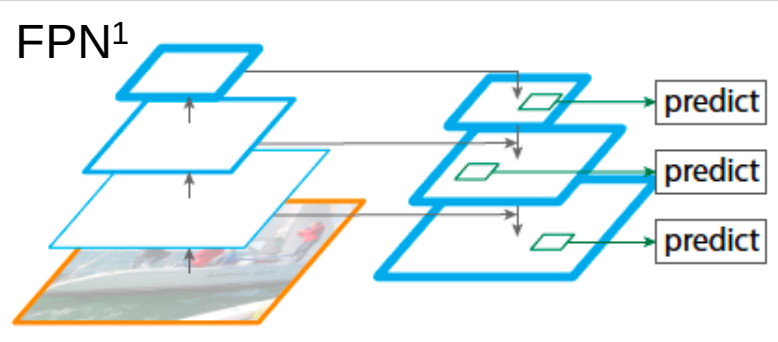
Study Region

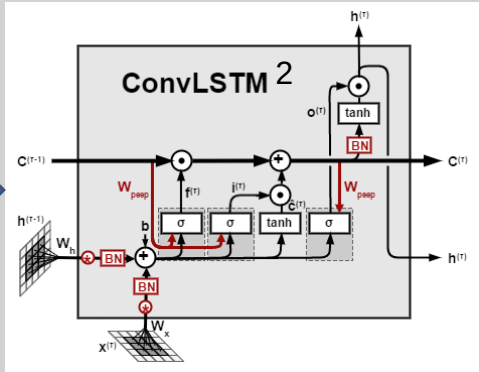
- Hudson Bay, Hudson Strait and Foxe Basin
- Home to several coastal communities
- Year-round shipping to support natural resource extraction in Hudson Strait

Basic Forecast model (Encoder-Decoder)

- Encoder: Generate an encoded state given 3 days historical input

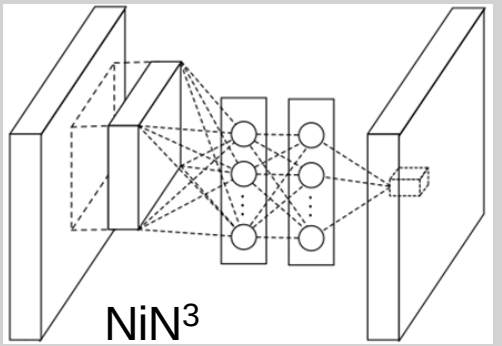
Input (3xHxWx8) → FPN[1] → (3xHxWx24) → ConvLSTM [2] → +last day (HxWx48)





- Decoder: Transform the encoded state into sequence of 90 days

(HxWx48) → **Custom Decoder** → (90xHxWx16) → NiN[3] → (90xHxWx1) → **Final Output**



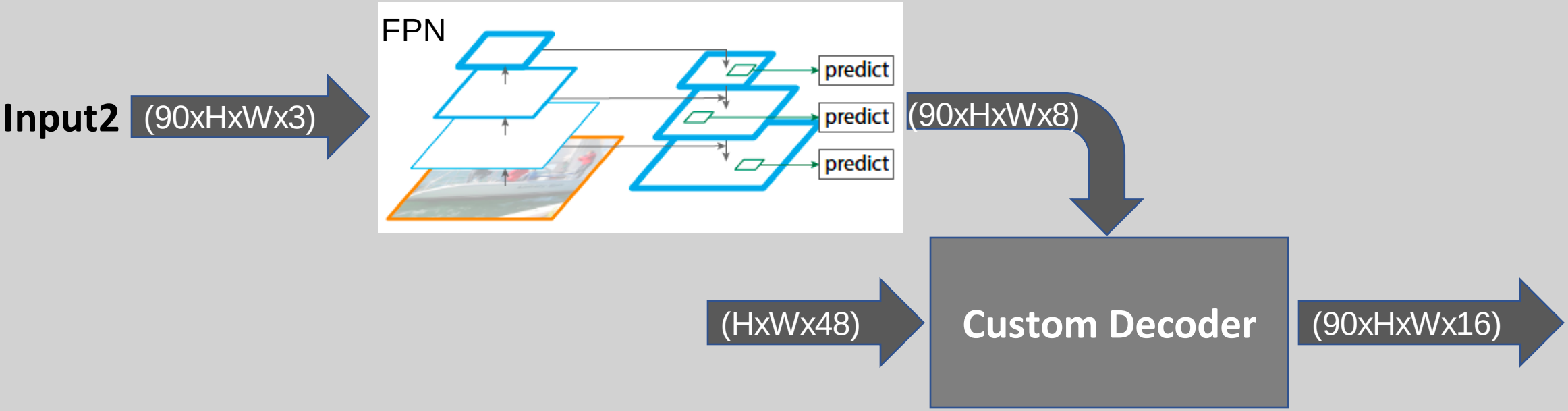
[1] Lin, T. Y., et al. Feature pyramid networks for object detection. *IEEE CVPR 2017.*

[2] Kadupitige, JCS Kadupitiya, et al. "Survey on Deep Learning Models for Time Series Data." 2020.

[3] Lin, M., et al. Network in network.arXivpreprint arXiv:1312.4400, 2013.

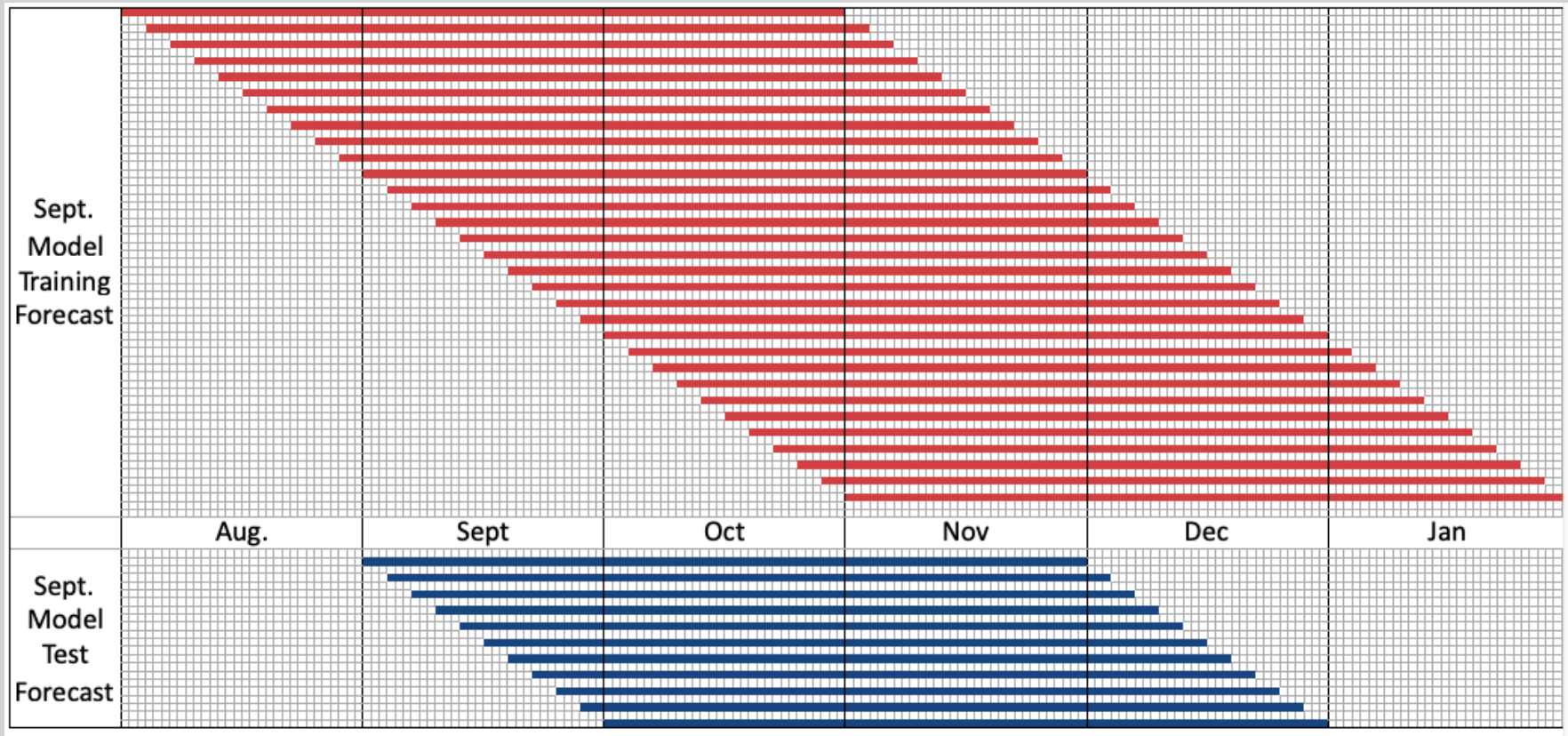
Augmented model architecture

- Climate normal of T2M, U10 and V10 over the forecasting period (90 days) as additional input
- Encode with Feature Pyramid Network and feed into custom RNN

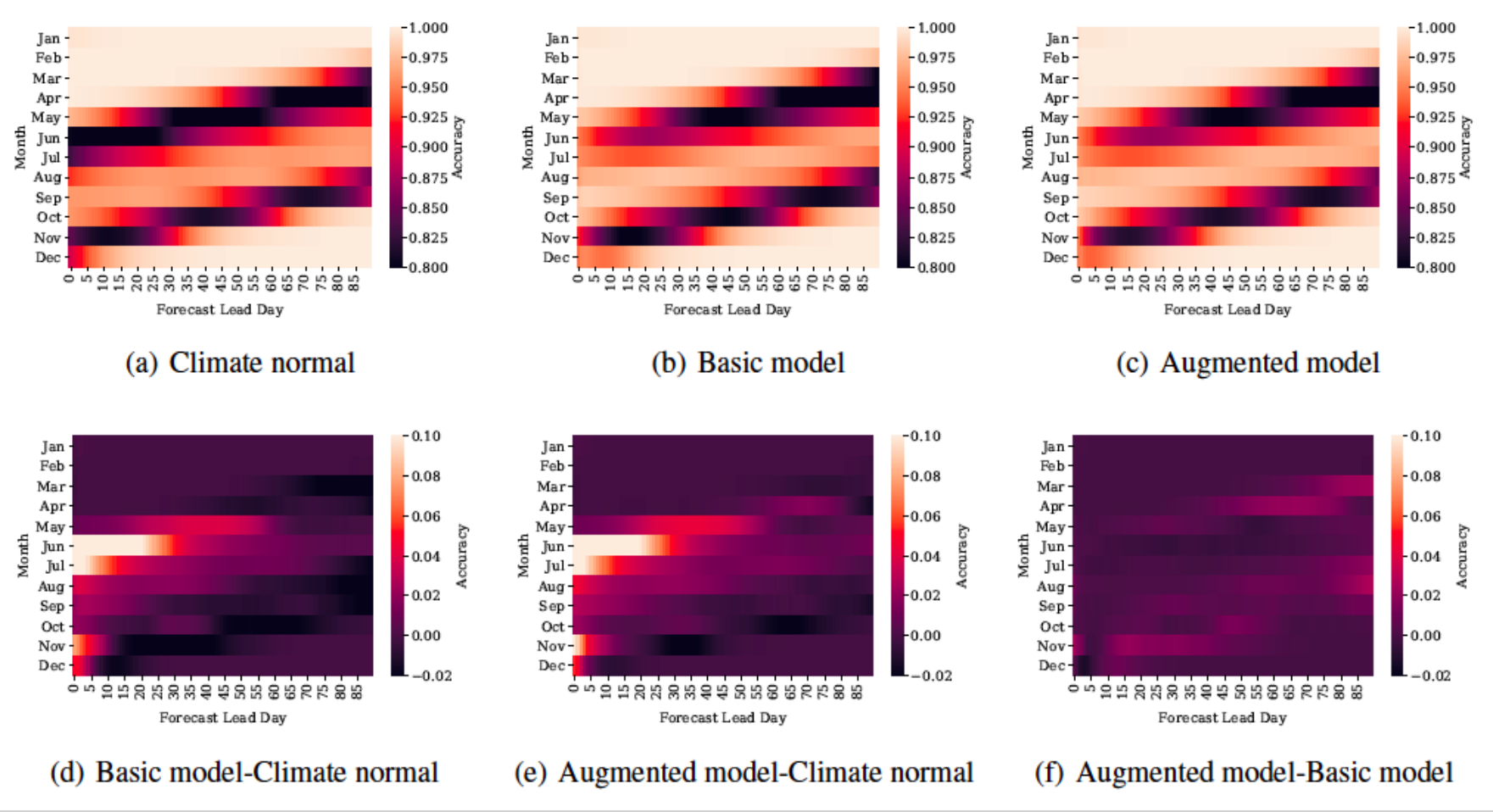


Description of Experiments

- One model per month of year (12 models)
- 10 year initial training, followed by rolling forecast for annual prediction

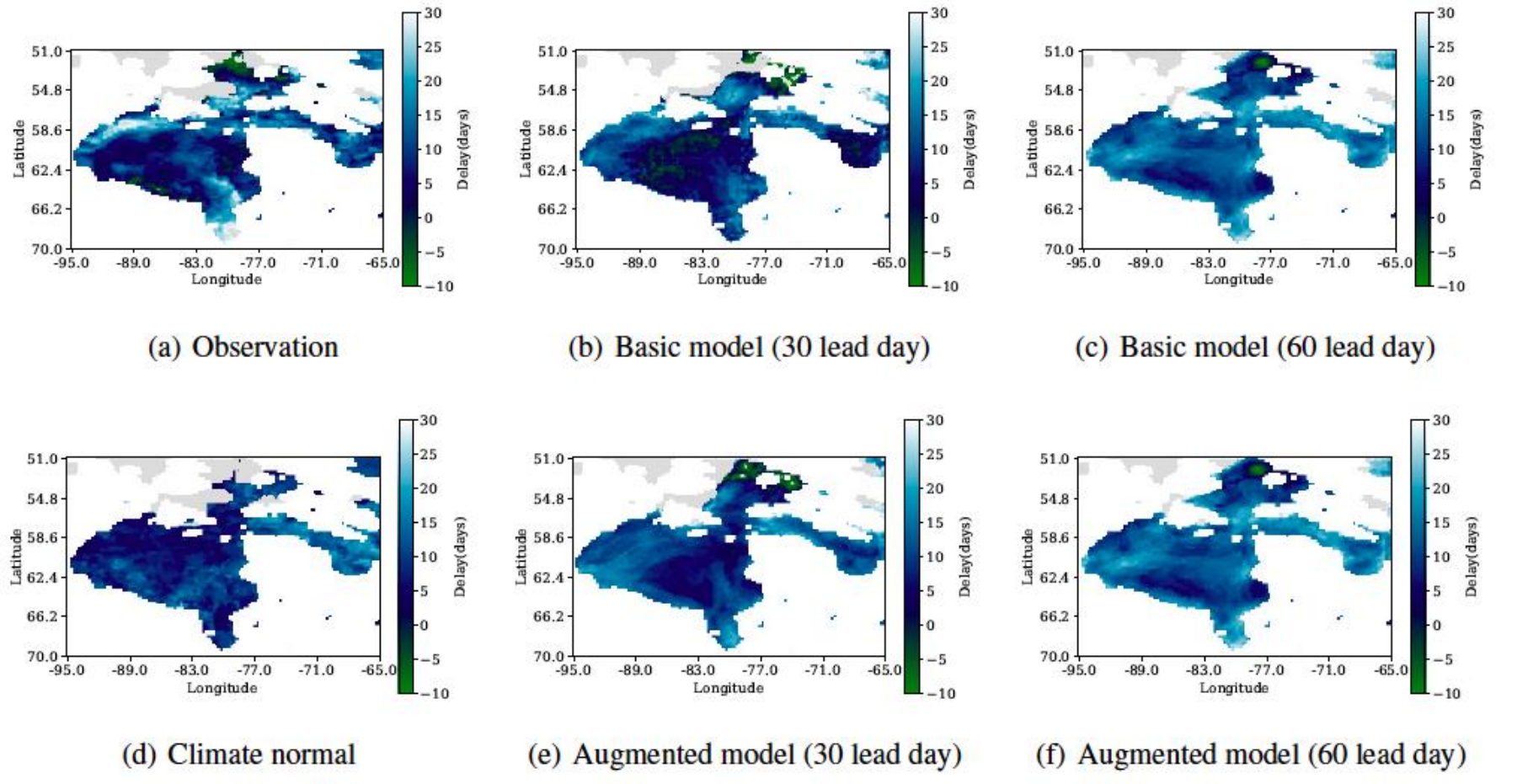


Binary Accuracies



- Climate normal: mean(Ice concentration > 15%)

Assessment of Operational Capability



(a) Observation (b) Basic model (30 lead day) (c) Basic model (60 lead day)

(d) Climate normal (e) Augmented model (30 lead day) (f) Augmented model (60 lead day)

- Difference between the median of the open water season length of two decades (1996-2006 vs 2007-2017) in terms of number of days

Summary

- Proposed models improvement of binary accuracy up to 10% relative to climate normal for breakup and freeze-up season
- Proposed models ability at 30 lead day to capture the trend in increase of open water season at southern and western part of the region in contrast to the climate normal
- The long-term objective is to provide reliable seasonal sea ice presence forecast products within the Canadian Arctic Shipping Risk Assessment System (CASRAS) developed by the National Research Council Canada (NRC).

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