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Medium-Term Sea Ice Presence Forecasting using Machine Learning

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CISMaRT, November 26th 2020

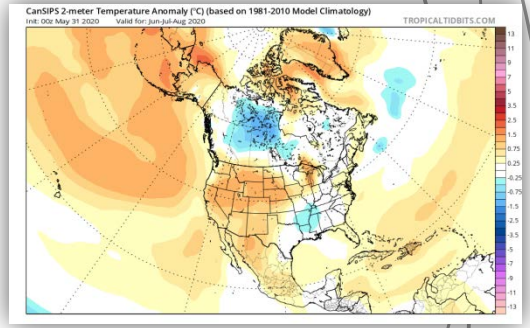
SIFNET – Sea Ice Forecasting using Deep Learning
Existing Products

Existing Products:

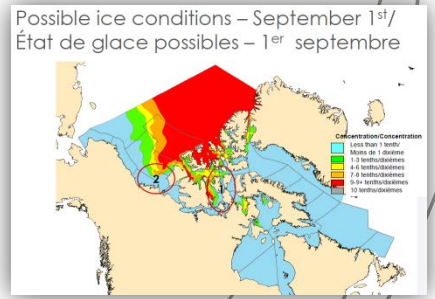
- CIS 30-day ice outlook
- CIS Seasonal Outlook
- ECCC CanSIPS

Current Limitations

- Infrequently Updated
- Text bulletins
- Gridded “below/near/above normal”



Lake Melville.
Current conditions…
4-6 tenths first-year ice with areas of 9-9+ tenths first-year ice. Outlook for June…
June 1-7 - 4-6 tenths ice with patches of 7-8 tenths ice.
June 8-12 - Ice melting completely to open water.
After June 12 - Open water to ice free.
Outlook for July… - Ice free.

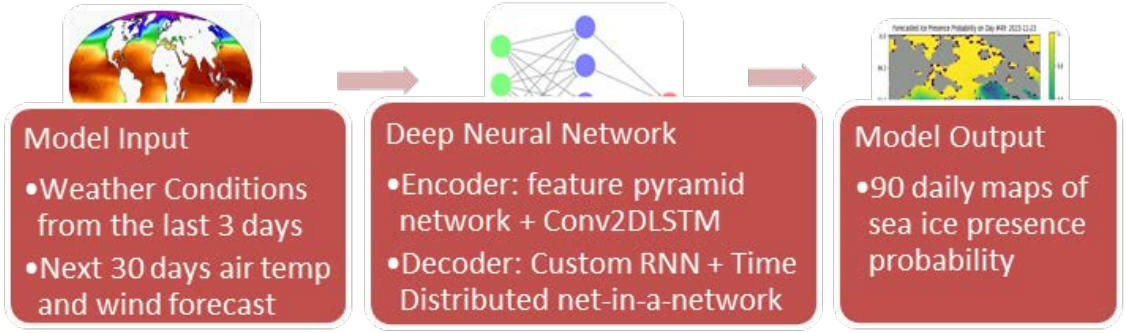


SIFNET – Sea Ice Forecasting using Deep Learning

Objective

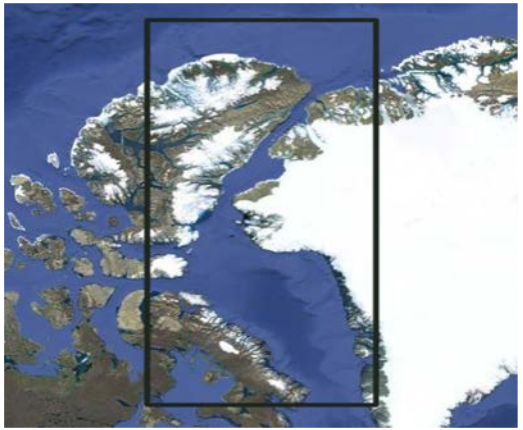
Objective: Forecast sea ice presence 30 to 90 days in advance.

- Probabilistic approach
- Expand forecast range 30 to 90 day horizon.
- Forecast ice presence: Ice concentration greater than 15%.
- Capture both Freeze-up and Break-up dates



SIFNET – Sea Ice Forecasting using Deep Learning
Areas of interest

Hudson Bay



Baffin Bay

Northwest Territories

SIFNET – Sea Ice Forecasting using Deep Learning
Input Data

Unified Data Source: ERA-5

- Produced by the European Centre for Medium-Range Weather Forecasts
- Available from 1975
- 30 Km grid size

Input Variables from ERA-5:

1. Sea ice concentration*
2. Sea surface temperature
3. 2m temperature
4. Surface sensible heat flux
5. Wind 10 meter U-component
6. Wind 10 meter V-Component
7. Freezing degree days / Melting degree days
8. Landmask

* Forecast target

Model Architecture

Encoder-Decoder Architecture

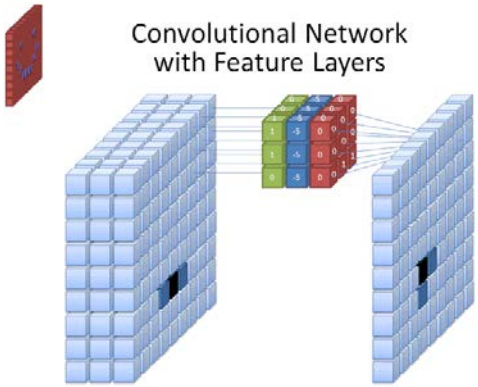
1. Encoder: Generate a state-space representation of all relevant climate information.
2. Decoder: Extrapolate the encoded state into a sequence of states.
3. Interpret state sequence into daily gridded probabilities

Model Architecture - Encoder

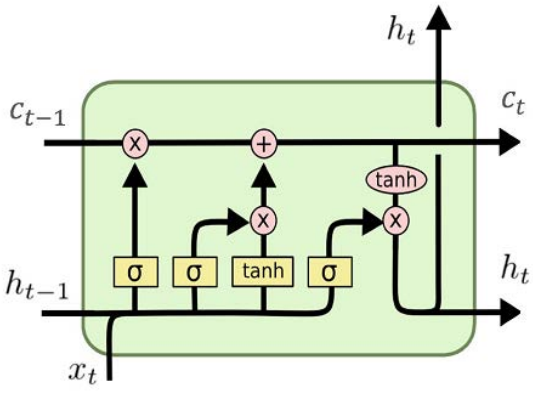
Create a higher-dimensional representation of input data

- Data shape: [input days, height, width, depth]
- Spatial Feature Pyramid
- Convolutional LSTM

- This produces a robust representation of the time series which also preserves spatial locality.



https://commons.wikimedia.org/wiki/File:Convolutional_Neural_Network_NeuralNetworkFeatureLayers.gif



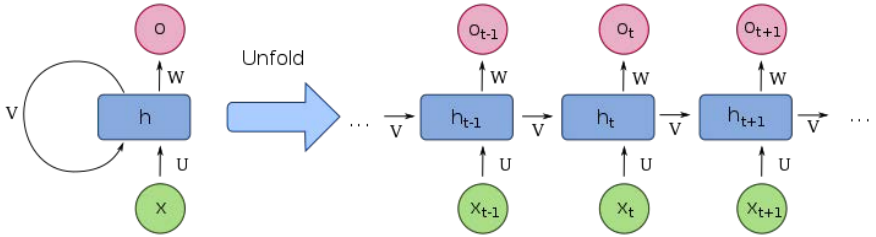
LSTM
(Long-Short Term Memory)

https://commons.wikimedia.org/wiki/File:LSTM.png

Model Architecture - Decoder

Extrapolate across N days

- Data shape: [height, width, depth]
- Custom RNN layer



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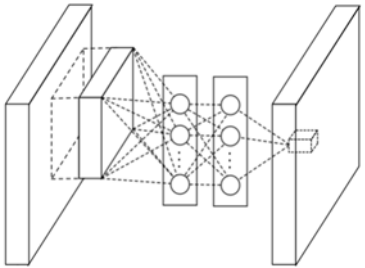
State-space sequence into per-pixel per-timestep probability

- Data shape: [Output days, width, height, depth]
- Network-in-a-Network
- Apply a multilayer perceptron independently to each pixel on each day.



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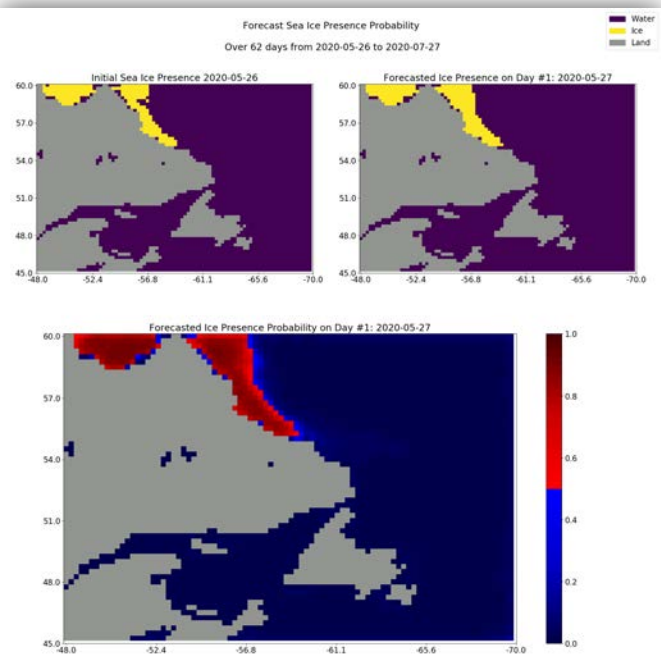
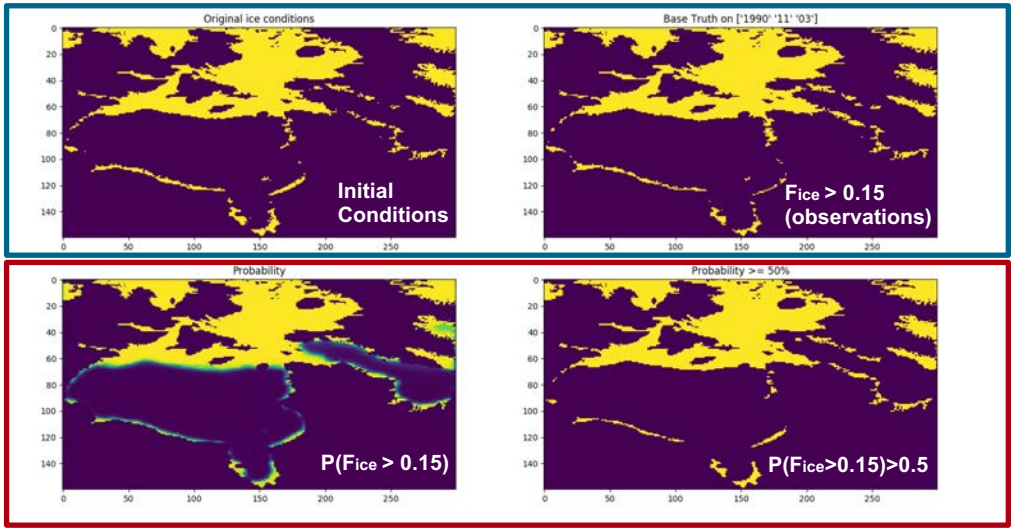
Forecast Products



Observations

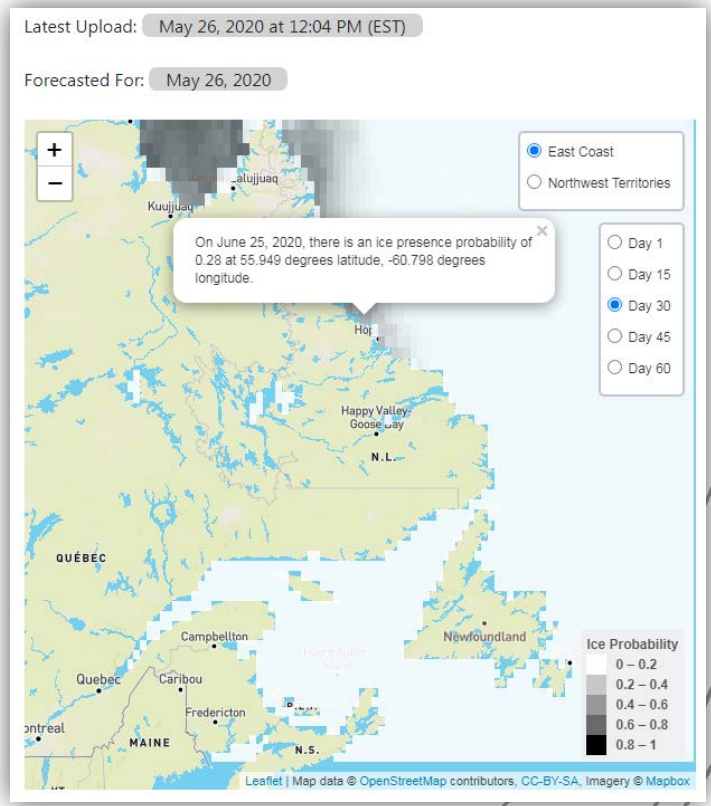


AI Forecasts

System Deployment

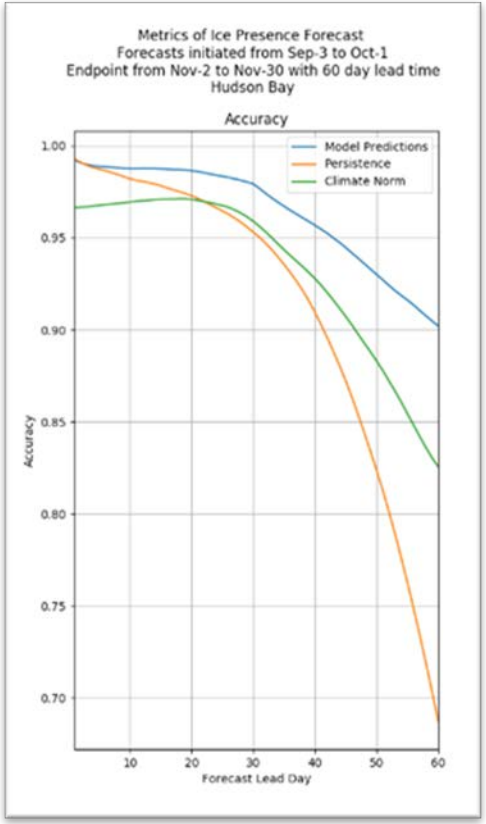
Deployed on Amazon Web Services

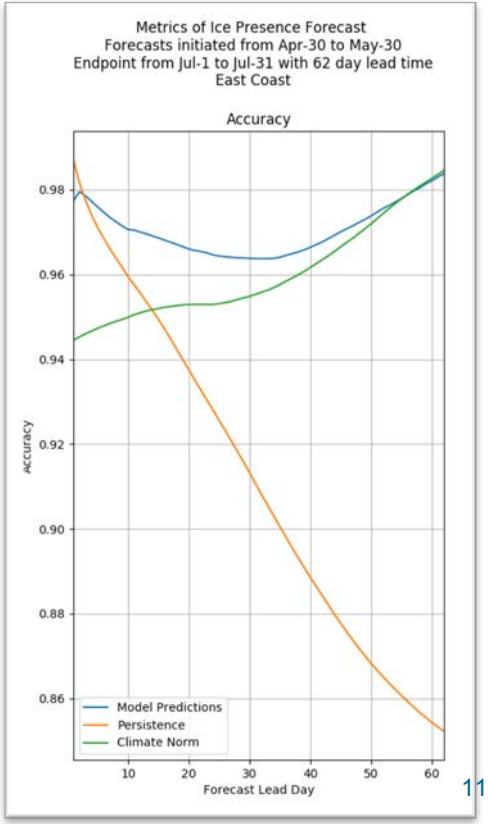
- Daily Inference executed on the AWS cloud
- End-User web-based application



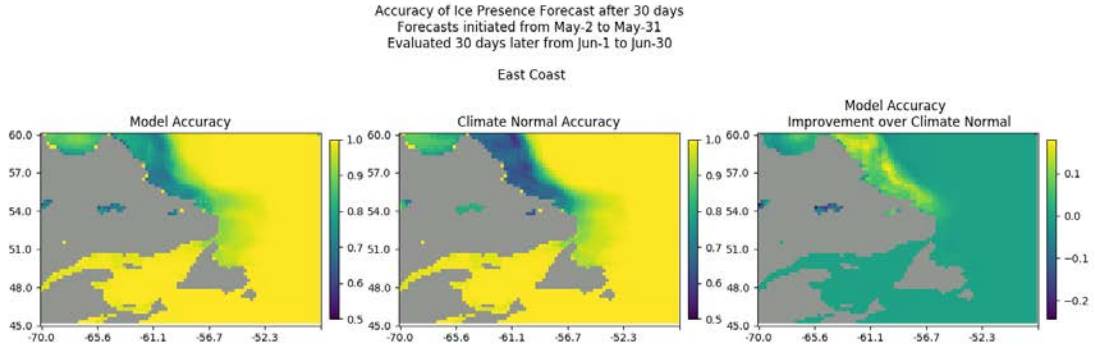
Model Validation
Binary Accuracy Over Time

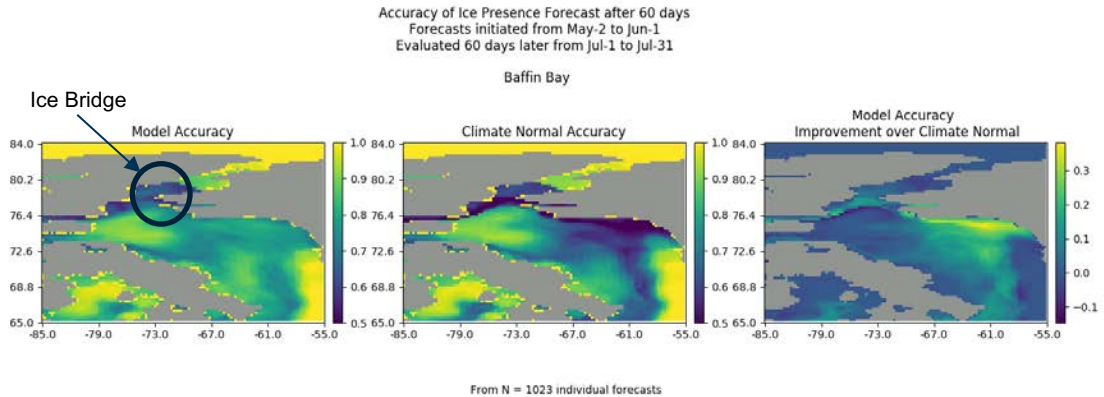
- Measure average binary accuracy of each **lead day** through binary comparison.
- Binary accuracy is calculated for all grid cells for the entire domain, excluding land mask.
- Gives good indicator of model's overall performance



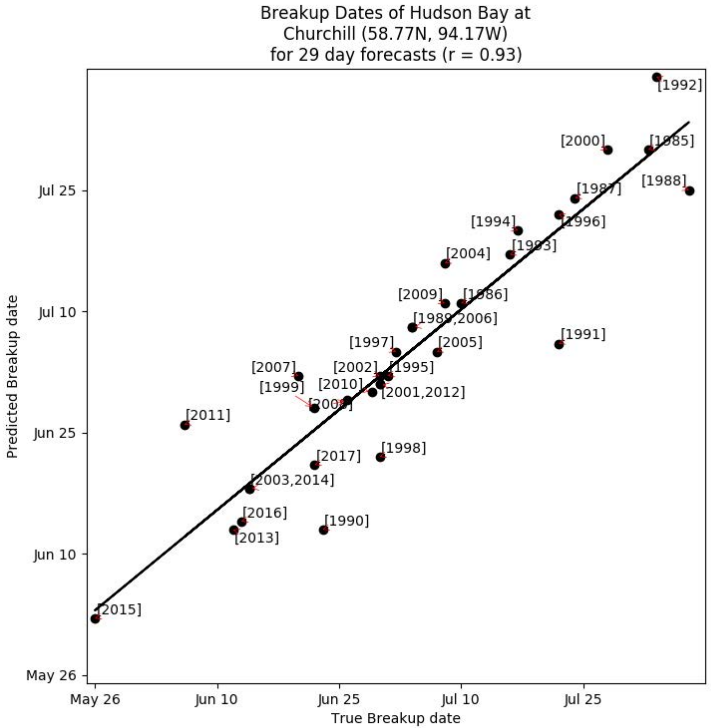


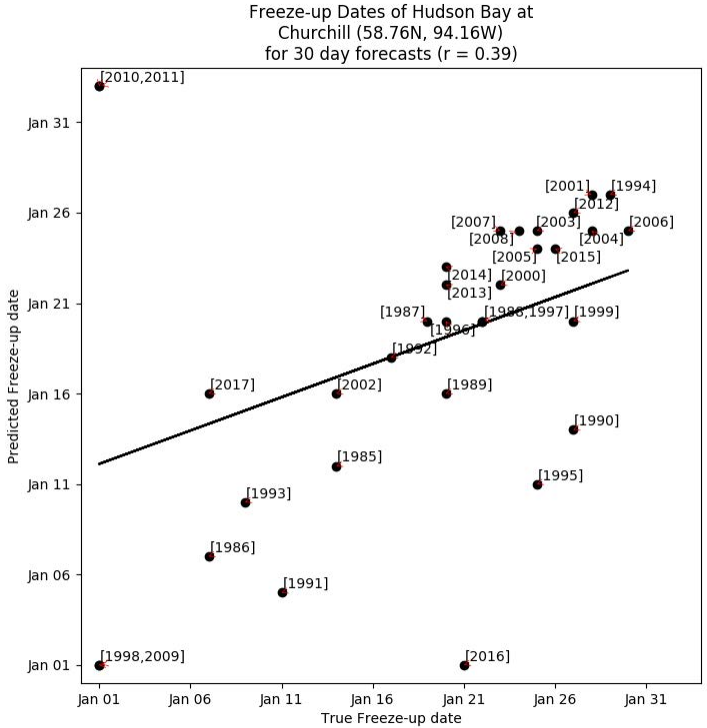
Model Validation
Binary Accuracy Maps



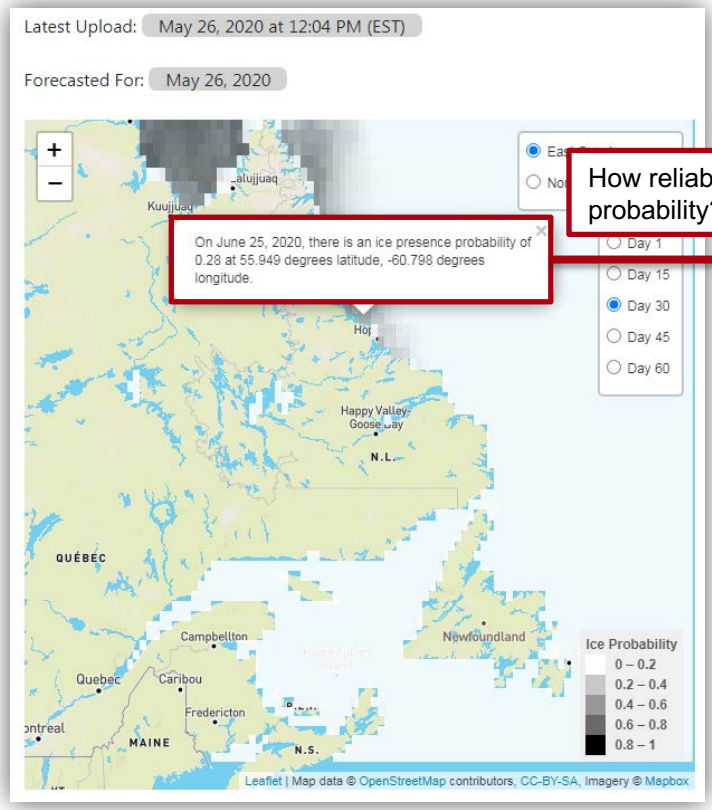


Model Validation
Break-up – Freeze-up Forecast

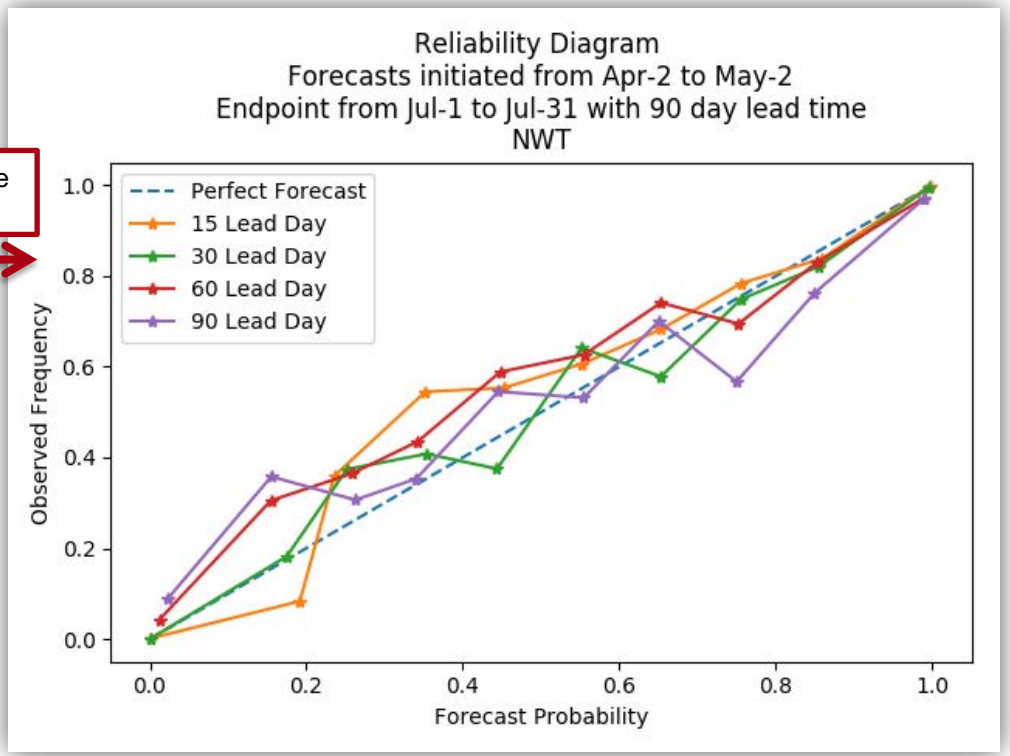




Model Validation
Reliability Diagram



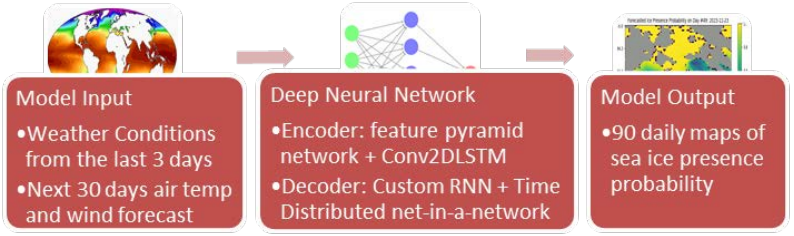
How reliable is the probability?



SIFNET – Sea Ice Forecasting using Deep Learning
Next Steps

Iterative Improvements:

- Enhance model architecture
- Improve input variables
- Increase domain to cover the entire Canadian Arctic



New Collaborators:

- 3-Year collaboration with University of Waterloo and NRC AI4Logistics Program
- 5-Year integration with the NRC Canadian Arctic Shipping Risk Assessment System funded under Transport Canada – Northern Trade Corridor Fund initiative (CASRAS-NTCF)

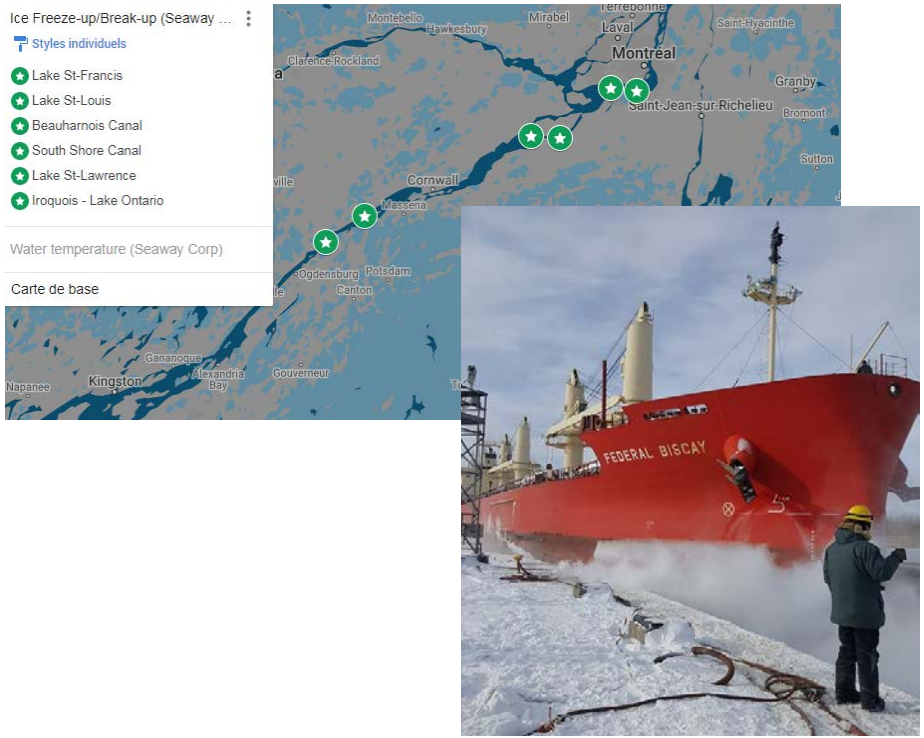
Medium-Range ice presence forecasting on the St Lawrence Seaway using AI methods

Objective:

Developing a forecast model for the seasonal evolution of ice conditions in the St-Lawrence River based on Machine Learning.

Direct Collaborators:

- National Research Council Canada
- McGill University
- Fednav Limited
- ECCC - Environment and Climate Change Canada



THANK YOU

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