Deep learning for monthly Arctic sea ice concentration prediction

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1. Introduction

The Arctic has warmed faster than any other region on Earth, primarily due to Arctic amplification, which increases the impact of anthropogenic global warming [1]. As a result, Arctic sea ice has declined significantly in both extent and thickness over the last four decades, with significant impact on indigenous communities and wildlife in the Arctic. To anticipate these impacts, skillful predictions of sea ice are essential.

Dynamics-based sea ice models typically struggle to represent the complex, coupled interactions between the sea ice, ocean, and atmosphere. However, recent studies have shown deep learning-based statistical methods can make skillful predictions of Arctic sea ice [2, 3]. Building on these studies, we present a work-in-progress, convolutional neural network (CNN) system (IceNet) for predicting pan-Arctic sea ice maps at a lead time of 1 month. **We achieve 95.4% and 95.3% ice/no ice classification accuracy over validation years 2016-18 and test year 2019, respectively, compared with a climatology baseline of 89.5% and 89.0%.**

2. Input/output data and convolutional neural network

Data sources:
- NSIDC OSI-450 & OSI-430b sea ice concentration (SIC) data on a 25 km NH EASE grid
- ECMWF ERA5 monthly-averaged reanalysis data: 2-metre air temperature, sea surface temperature, mean sea level pressure, 10-metre wind velocity & speed, snowfall rate, and precipitation rate

Network outputs:
- Probability of sea ice next month at a particular 25x25 km grid cell (defined as 'ice' for SIC > 15%, 'no ice' for SIC < 15%) - hence this is a binary classification task

Network inputs:
- 11x11 patches from the past 3 months, centred on the output grid cell
- Also input an 11x11 patch at 450 km resolution patch for large-scale phenomena

CNN architecture:
- 3 convolutional layers, one fully-connected layer, sigmoid output

Network training
- Use a binary cross-entropy loss function, weighting class 0 ('no ice') by a factor of two due to class imbalance in the training data
- Train on 1979-2015, validate on 2016-2018, test on 2019

Prediction algorithm
- For a given forecast month, run prediction at every active grid cell for that month (using a monthly 'open ocean' mask) to build up the output map
- If the CNN output ice probability is > 0.5, predict ice
- We use a custom data loader to avoid vast repetition of data for the network inputs

3. Results

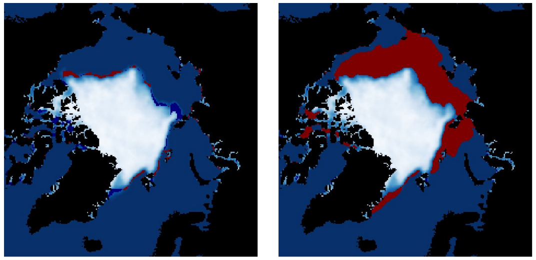

Fig. 2. Left (a): observed September 2019 SIC map with grid cells from IceNet's false positive classification errors coloured red, and IceNet's false negative errors coloured blue. Right (b): observed September SIC map with sea ice anomaly from 1979-2015 climatological mean.

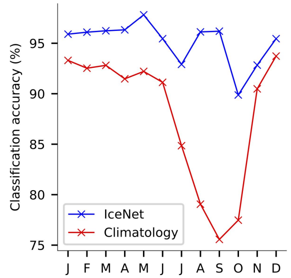

Fig. 3: IceNet's monthly test set classification accuracy versus the 1979-2015 climatology.

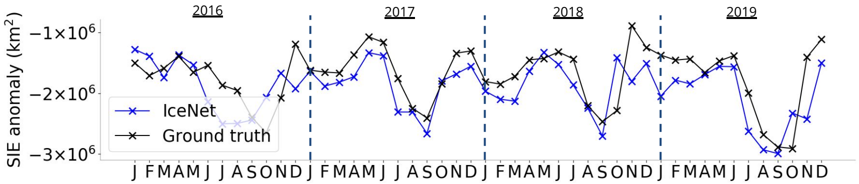

Fig. 4: IceNet's monthly predicted sea ice extent (SIE), plotted as an anomaly from the 1979-2015 climatological sea ice extent.

4. Discussion

Fig. 2a shows an exemplary month from the test set, where IceNet's false positives (predicting ice when there was no ice) are overlaid in red and IceNet's false negatives (predicting no ice when there was ice) are overlaid in blue. This shows the close correspondence between the observed sea ice pack and IceNet's prediction. Fig. 2b further illustrates that IceNet has gone beyond simply learning the climatological mean for the target month.

Fig. 3 breaks down the monthly classification accuracies for 2019. The climatological benchmark suffers from a drop in performance in the summer months due to the significant drop in SIE for summer months, while IceNet's accuracy stays relatively stable.

Fig. 4 demonstrates IceNet's ability to skillfully predict SIE anomaly (R=0.69).

Our pan-Arctic map prediction system performs well on both the validation years 2016-18 and the test year 2019. Future work will investigate network uncertainty quantification, hyperparameter tuning, longer lead times, and variable saliency analysis.

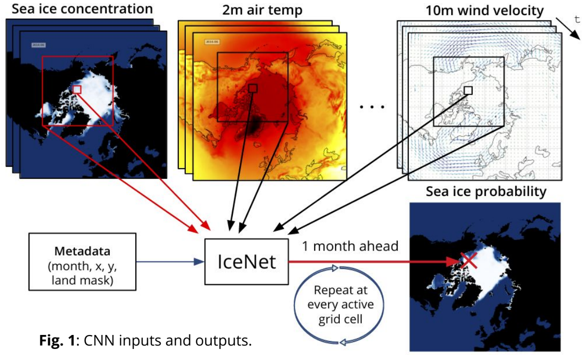

Fig. 1: CNN inputs and outputs.

References

[1] Stroeve, J., Notz, D. (2018). Changing state of Arctic sea ice across all seasons. *Environmental Research Letters*.
[2] Kim, Y. J., et al (2019). Prediction of monthly Arctic sea ice concentration using satellite and reanalysis data based on convolutional neural networks. *The Cryosphere*.
[3] Choi, M., et al (2019). Artificial neural network for the short-term prediction of Arctic sea ice concentration. *Remote Sensing*.

Acknowledgements

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