SICNet - A Spatiotemporal Deep Neural Network for Arctic Sea Ice Forecasting

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ABSTRACT

Arctic amplification has altered the climate patterns both regionally and globally, resulting in more frequent and more intense extreme weather events in the past few decades. The essential part of Arctic amplification is the unprecedented sea ice loss as demonstrated by satellite observations. Accurately forecasting Arctic sea ice from sub-seasonal to seasonal scales has been a major scientific effort with fundamental challenges at play. In addition to physics-based earth system models, researchers have been applying multiple statistical and machine learning models for sea ice forecasting. Looking at the potential of data-driven approaches to study sea ice variations, we propose **SICNet** – a UNet-based based spatiotemporal deep learning model for forecasting Arctic sea ice concentration (SIC) at greater lead times. The model uses an encoder-decoder architecture with skip connections to regenerate spatial maps at future timesteps. Using monthly satellite retrieved sea ice data from NSIDC as well as atmospheric and oceanic variables from ERA5 reanalysis product during 1979-2021, we show that our proposed model provides promising predictive performance for per-pixel SIC forecasting at long lead times. This will substantially improve our ability in predicting future Arctic sea ice changes, which is fundamental for forecasting transportation routes, resource development, coastal erosion, threats to Arctic coastal communities and wildlife.

METHODOLOGY

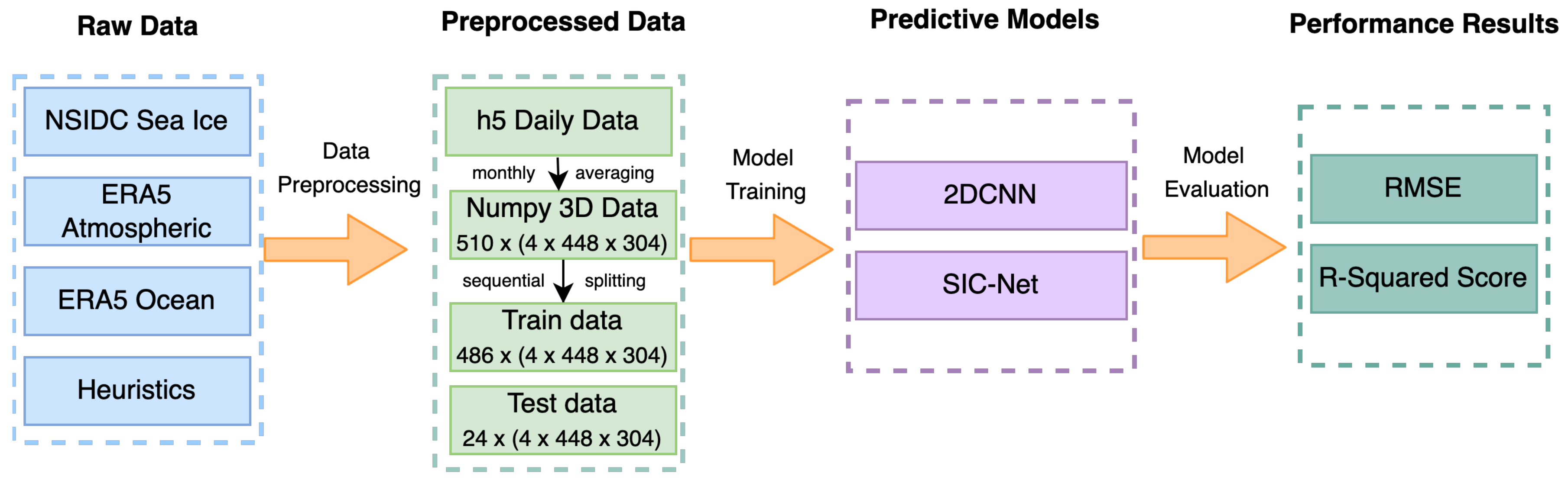

Figure 2: End-to-end pipeline of our predictive framework: starting from raw data to data preprocessing, combining data in 3D numpy for the predictive models, training the models and finally evaluating the trained models.

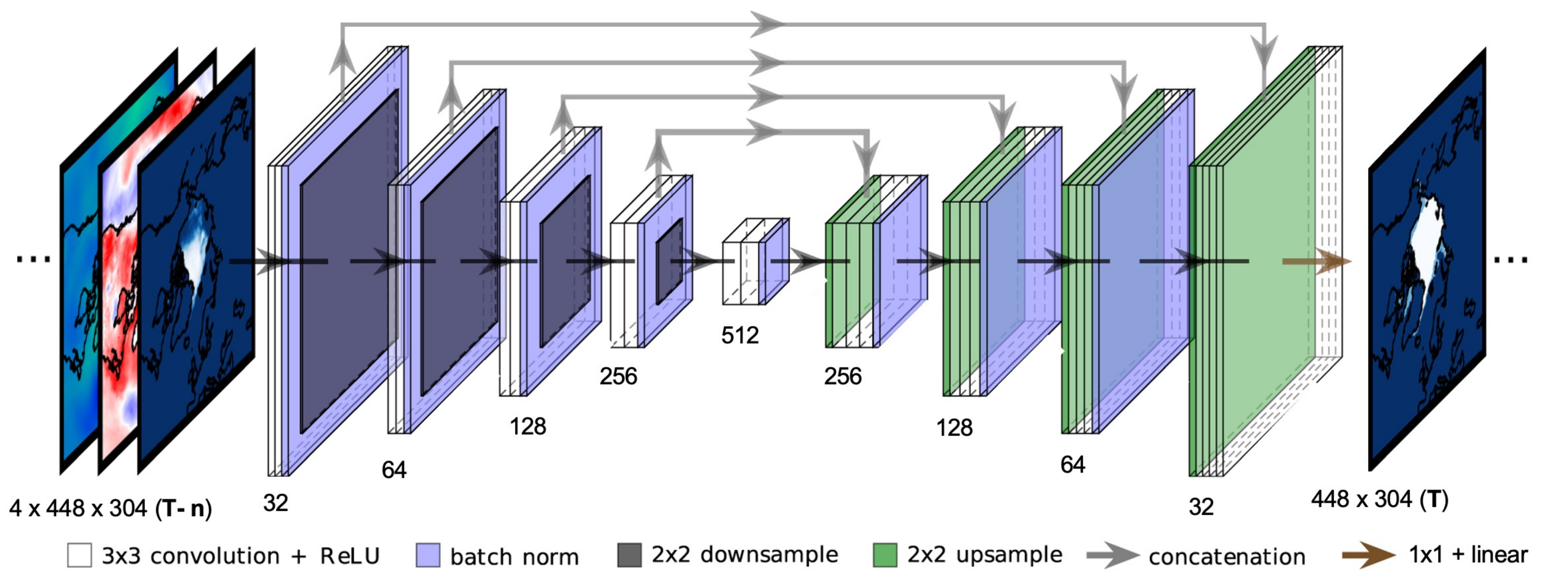

Figure 3: Model Architecture: A Unet-based architecture with 4 upsampling and 4 downsampling blocks. The model takes 3D tensors at timestep $T-N$ and outputs SIC values at timestep T using 1x1 Convolution in the output layer.

PROBLEM STATEMENT

*Given atmospheric and oceanic data along with heuristics of Arctic sea-ice, can spatiotemporal deep learning methods help predict the minimum (melting season) and maximum (freezing season) variations in sea-ice for a lead time of **N** months?*

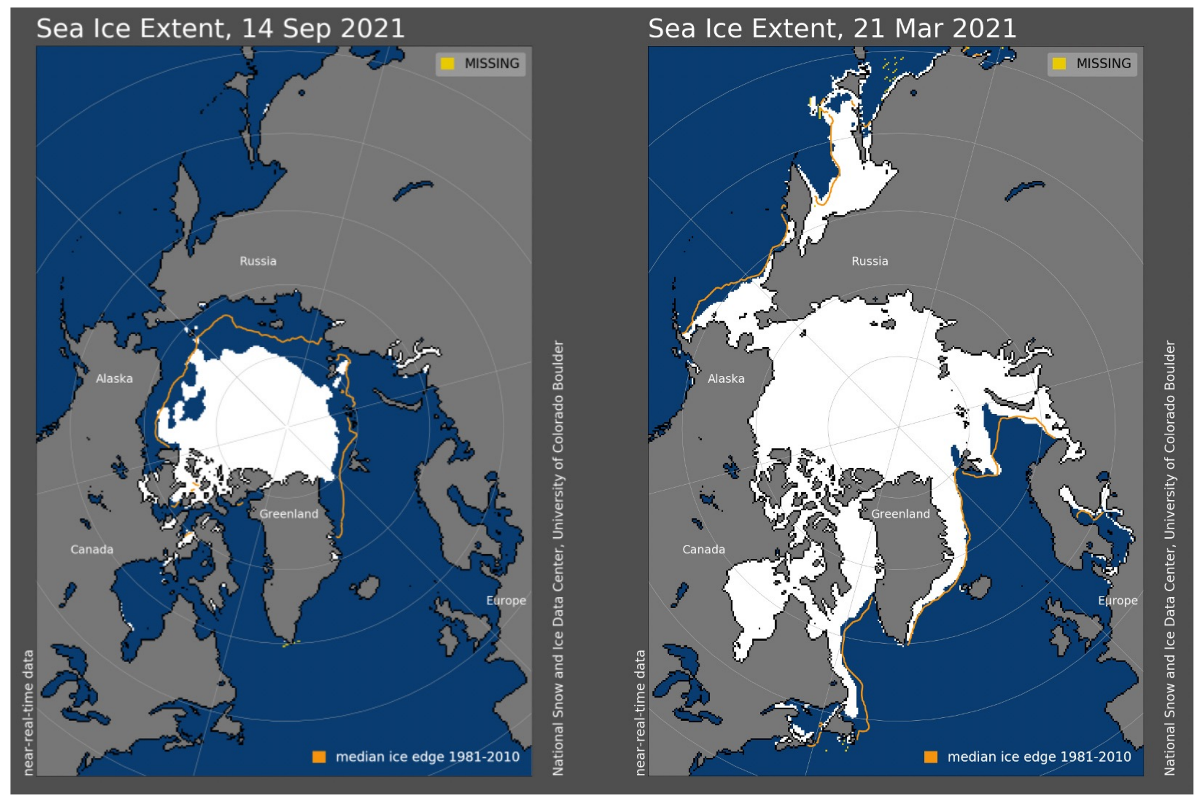

Figure 1: Maximum(right) and minimum (left) Sea Ice observed in 2021. Source: NSIDC

DATASET

This study is performed using 42 years of NSIDC observational and ERA5 reanalysis data from 1979 – 2021 in 25km resolution.

Sr No.	Variable	Source	Unit
1.	Sea Surface Temperature	ERA5	K
2.	Rain Rate	ERA5	mm/day
3.	Snow Rate	ERA5	mm/day
4.	Sea Ice Concentration	NSIDC	%

RESULTS

We compared the performance of our proposed model SICNet against baseline 2DCNN model to predict SIC values at lead times of 1 to 3 months. Both models are evaluated using Root Mean Squared Error (RMSE), given in Table 1, and R2 Score, given in Table 2, respectively. Higher R2 scores and lower RMSE scores indicate better performance.

Table 1: RMSE score for different lead times.

Method	RMSE-lag1	RMSE-lag2	RMSE-lag3
CNN	15.06%	16.24%	16.55%
SIC-Net	9.42%	13.37%	15.25%

Table 2: R2 score for different lead times.

Method	R2 Score-lag1	R2 Score-lag2	R2 Score-lag3
CNN	69.9	64.8	63.3
SIC-Net	88.4	76.0	69.2

As shown in Table 1, SICNet outperforms CNN by 6% to 2% for lead times of 1 to 3 months. As predictive performance decreases for both models with an increase in lead times, we notice that the performance of CNN for lag 1 is equivalent to SIC-Net's performance for lag 3, further strengthening our trust in SICNet.

Illustrated below are spatial maps of SIC over the Arctic region (60N – 90N). We see that SIC-Net is better able to retain North Pole hole, ocean and coastal boundaries information for longer lead times, whereas CNN not only overpredicts SIC but also tends to incorrectly predict SIC over land areas.

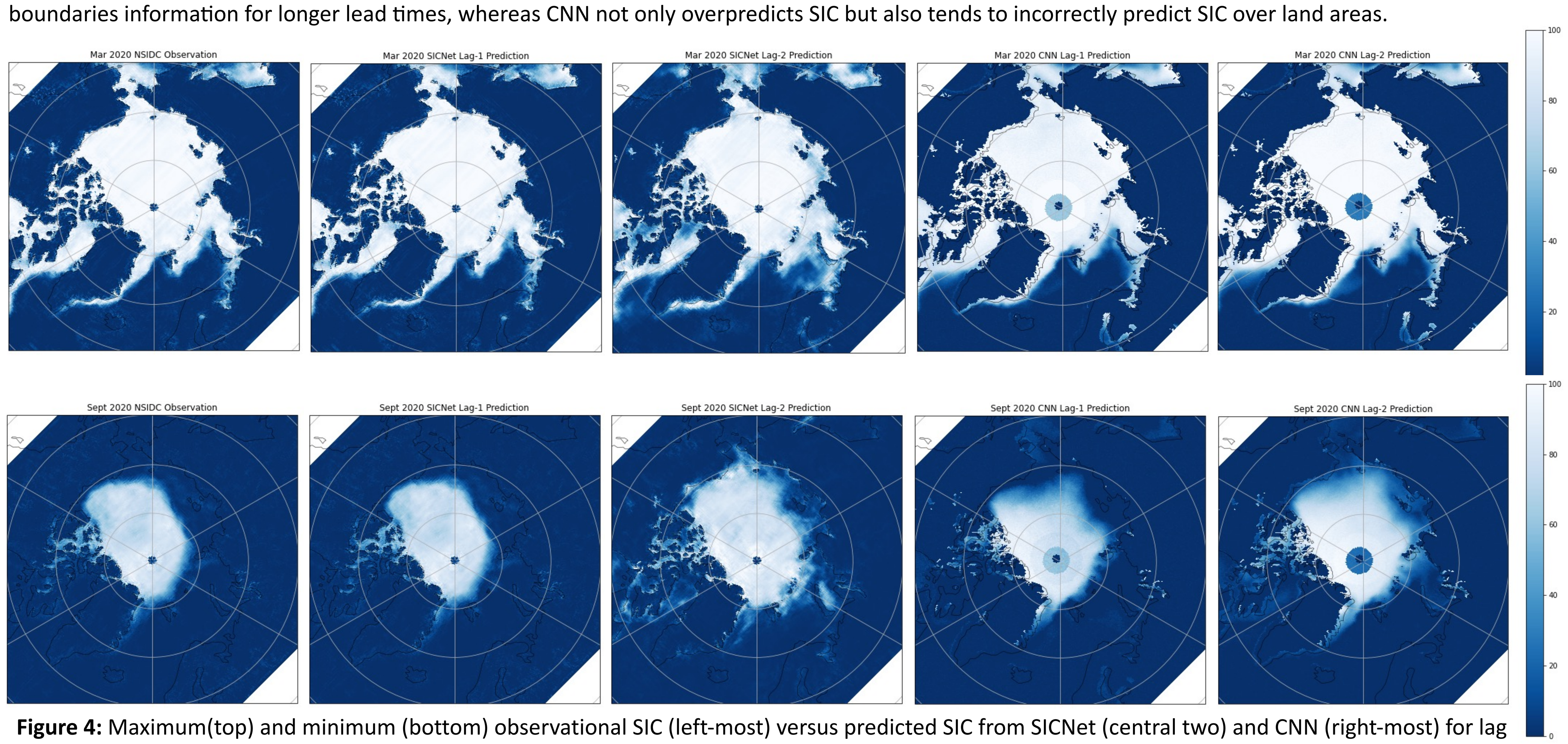

Figure 4: Maximum(top) and minimum (bottom) observational SIC (left-most) versus predicted SIC from SICNet (central two) and CNN (right-most) for lag of 1 and 2 months.

CONCLUSIONS

- We propose SICNet, a Unet-based deep neural network to predict sea ice concentration maps at greater lead times.
- SICNet outperforms CNN by 6% in RMSE and 19% in R2-Score for lead time of 1 month.
- SICNet is better able to retain spatial maps corresponding to land and ocean regions without providing additional land/sea mask.
- In future, we plan to extend this study for a rolling window of 12 months to better capture seasonal patterns at greater lead times.

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[5] The source codes will be available at https://github.com/big-data-lab-umbc/sea-ice-prediction

ACKNOWLEDGMENTS

This work is supported by NSF grants: CAREER: Big Data Climate Causality (OAC-1942714) and HDR Institute: HARP - Harnessing Data and Model Revolution in the Polar Regions (OAC-2118285). We thank Dr. Yiyi Huang (NASA Langley Research Lab) for her assistance in introducing the dataset.