Interpretable Spatiotemporal Forecasting of Arctic Sea Ice Concentration at Seasonal Lead Times

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Arctic Sea Ice Forecasting and Climate Change

Arctic Sea Ice Concentration (SIC)

The spatial proportion of the Arctic ocean covered by ice, at a given resolution (e.g., 25km x 25km).

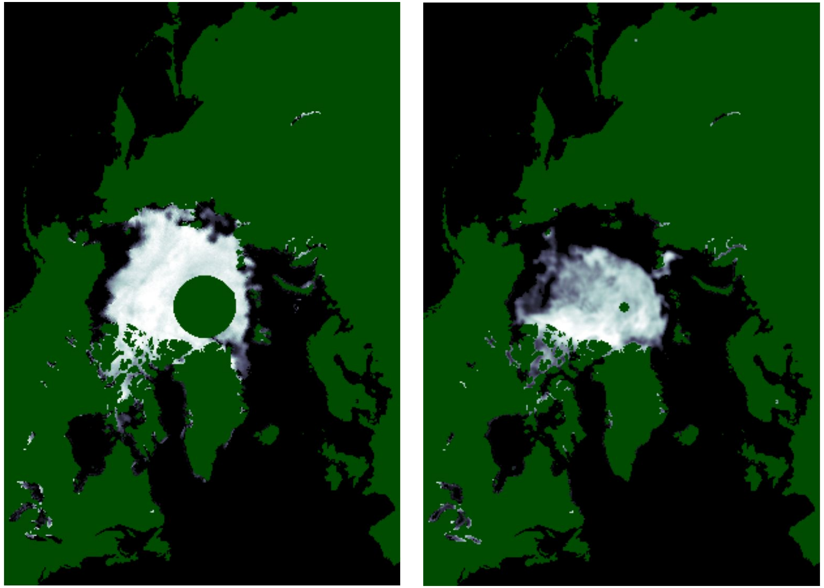
Relevance to Climate Change

Arctic SIC is linked to:

- Regulation of temperature, moisture, and solar radiation.
- Arctic algal blooms, which can poison food supplies.

Forecasting SIC matters:

- September decadal rate of ice decline is 13.16%.
- Better forecasts guide navigation and meteorology in the region and (potentially) beyond.



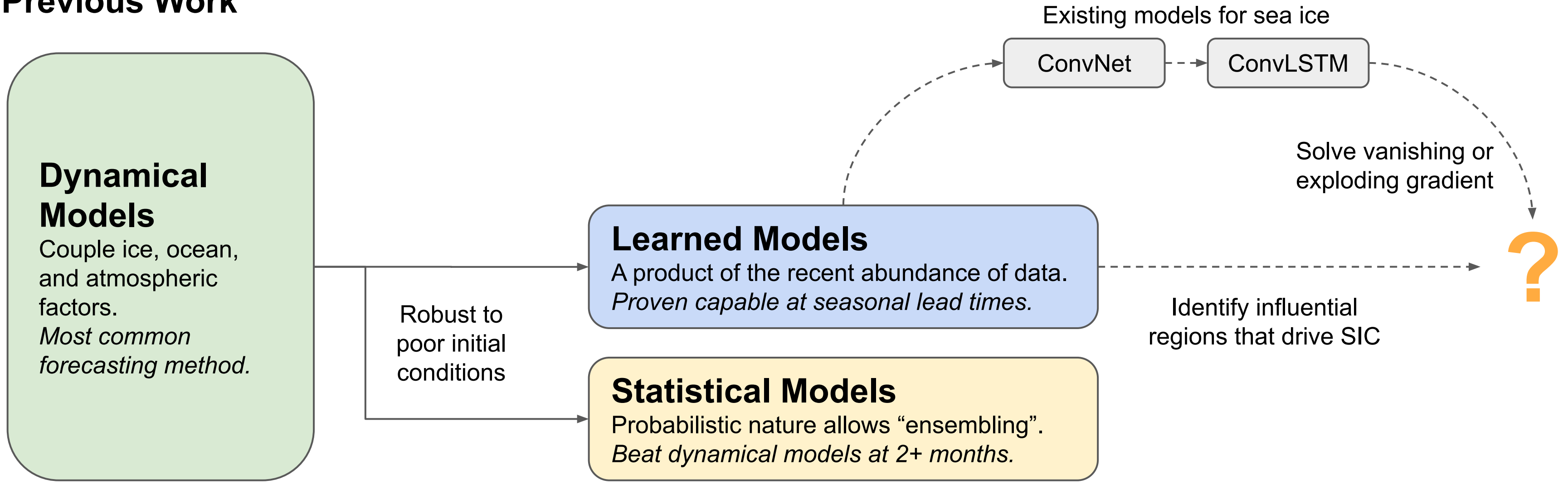
Arctic sea ice concentration[1] on Sep. 1, 1979 (left) and Sep. 1, 2021 (right). Land and unsurveyed areas are shown in green.

[1]Reported by: Nimbus-760 SMMR, the DMSP -F8/-F11/-F13 SSM/Is, and DMSP-F17 SSMIS.

Problem and Background

Q: Can we forecast Arctic SIC at seasonal lead times, while also providing interpretability into which regions most affect it?

Previous Work



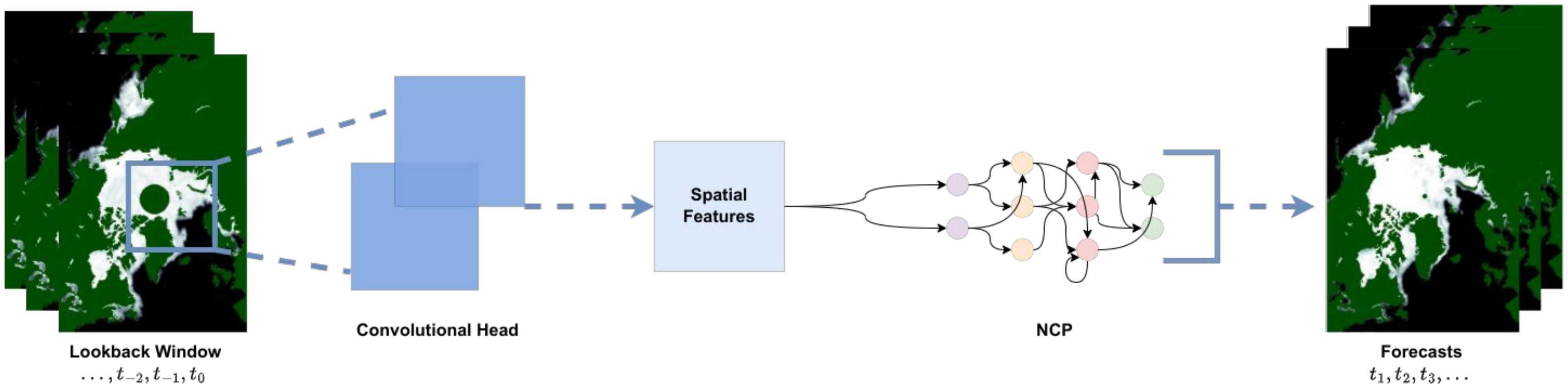
Learning to Predict Sea Ice Concentration

Idea: Use an expressive convolutional-recurrent network to predict SIC far in the future.

- Utilize Convolutional Neural Circuit Policies (ConvNCPs):
  - Deliver interpretability through expressibility.
  - Mixed memory architectures mitigate gradient issues on long sequences.
  - Works with irregular data intervals.

Neural Circuit Policies (NCPs)

- NCPs are a sparse wiring of liquid time constant (LTC) networks, a form of continuous RNN.
  - LTCs combine network depth dimension and RNN time dimension into a shared vector field.
- Internal structures are characterized by neural ODEs.
  - Shown to be highly expressible.



Contributions and Path Forward

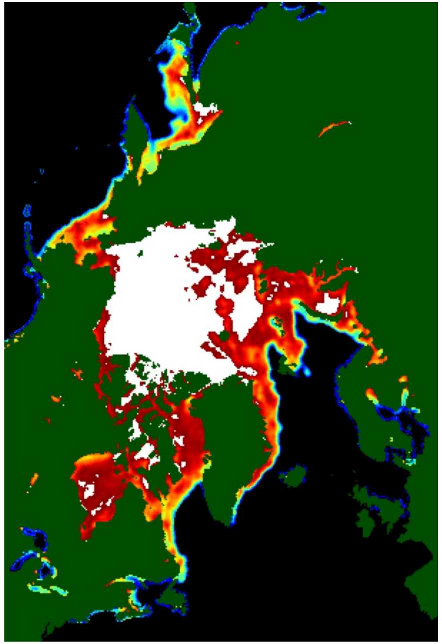
Expectations

Contribute the following compared to existing statistical, dynamical, and learned models:

- Improved performance at long lead times.
- Increased robustness to noisy observations.
- Novel interpretability methods to identify the key drivers of fluctuations in Arctic SIC.

Evaluation and Data Sources

- Utilize the NSIDC SIC dataset[1] of daily satellite observations.
- Supplement training observational data with CMIP6[2] simulations.



Artistic rendering of a saliency map output from the ConvNCP model. Heatmap represents relative attention of the network in spatiotemporal predictions of SIC.

[1]https://nsidc.org/data/nsidc-0051/versions/2. [2]https://pcmdi.llnl.gov/CMIP6/.

Conclusions

Impact

- First spaciotemporal SIC model to offer explainability.
- ConvNCP outputs for Arctic SIC can supplement climate modeling elsewhere, e.g., mid-parallel meteorology.
- Inform policy surrounding the Arctic.

Future Work

- Quantify uncertainty of forecasts by ConvNCP.
- Comparisons against generative models.
  - Retain high resolution at long lead times.
- Extend ConvNCP to related tasks:
  - Sea ice extent.
  - Sea ice thickness.
  - Precipitation.

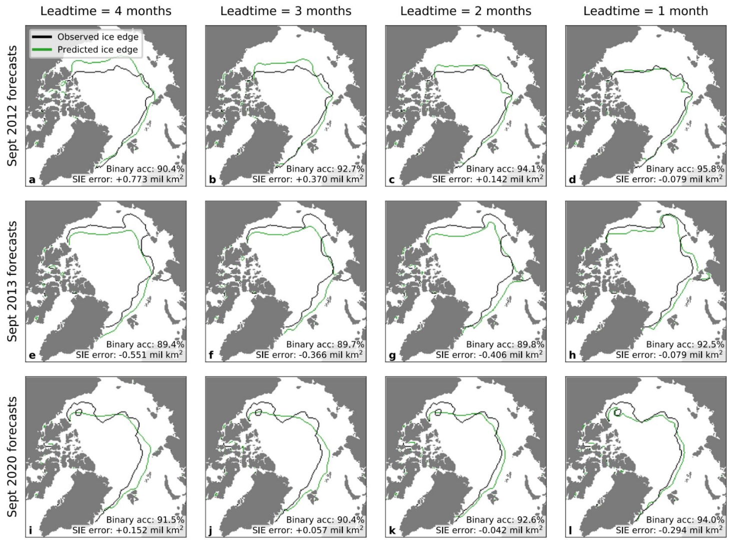


Fig. 2 IceNet's ice edge forecasts for extreme September sea ice events at 4- to 1-month lead times. Forecasts are shown for September 2012 (lowest ice extent on record) (**a**–**d**), September 2013 (anomalously high ice extent) (**e**–**h**), and September 2020 (second-lowest ice extent) (**i**–**l**). The observed ice edge (in black) is defined as the sea ice concentration (SIC) = 15% contour. IceNet's predicted ice edge (in green) is determined from its sea ice probability forecast as the *P*(SIC > 15%) = 0.5 contour. The binary classification accuracy and sea ice extent (SIE) error is shown for each forecast (see 'Evaluation of IceNet's performance' section). 2012 and 2013 are in IceNet's validation dataset and 2020 is in its test dataset.

From Andersson et al., 2021.