Deep Learning on a Novel Ising Model to Study Arctic Sea Ice Dynamics

By Ellen Wang

Horace Mann School, Bronx NY, USA

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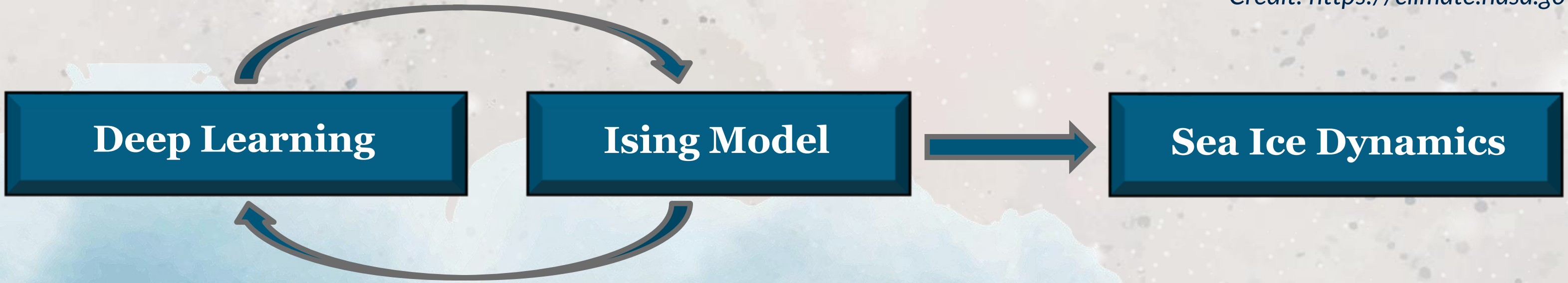
Introduction

- Drastic sea ice loss has been detected in recent years, which is a crucial indicator of global warming; it is critically urgent to better model sea ice dynamics especially after the hottest 2023.
- Many sea ice studies engage deep learning without identifying the fundamental physical mechanisms governing sea ice evolution.
- This study combines the centennial Ising model (IM) in statistical physics with deep learning to study a large area of 1500km x 1500km in the Arctic region, unleashing their strong explanatory and predictive power of capturing sea ice transitions.
- Research framework is illustrated below:



12.3%

September Arctic sea ice shrinkage rate per decade

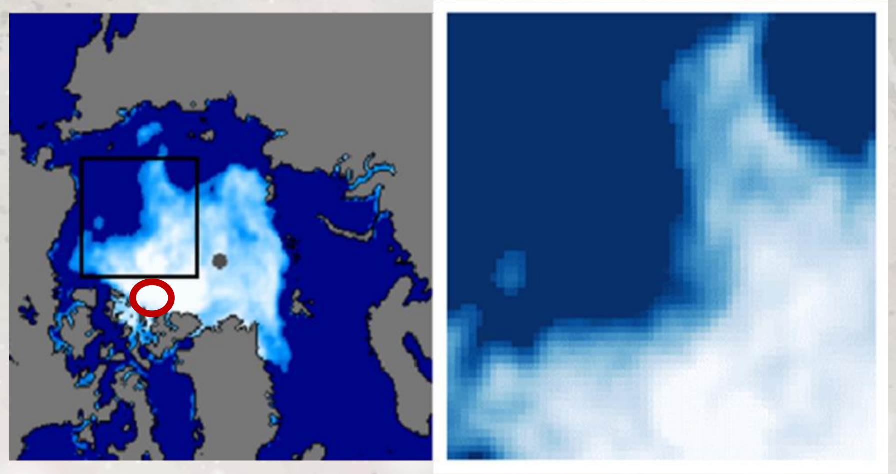
95%

Decline in the oldest and thickest Arctic sea ice over the past 30 years

Credit: https://climate.nasa.gov

Data

- Sea ice data has been diligently collected by the National Snow and Ice Data Center (NSIDC).
- Their publicly accessible data, called "Near-Real-Time DMSP SSMIS Daily Polar Gridded Sea Ice Concentrations" (NRTSI), record daily sea ice concentrations for both the Northern and Southern Hemispheres. These concentrations are generated based on the microwave brightness temperature detected by NASA's satellite sensor.
- Each NRTSI file contains a lattice of 448 rows by 304 columns, covering a large earth surface area with the north pole at the center. Each grid cell represents an area of approximately 25 kilometers by 25 kilometers, with an integer value from 0 to 250 that indicates the fractional ice coverage scaled by 250.



(a) (b)

(a) *Part of the NRTSI data on Sept 16th, 2022, where the black square marks the focus area for this study and the red oval marks the Canadian Arctic Archipelago area*

(b) *A zoomed-in view of the focus area for this study, a 60x60 square lattice covering approximately 2.25 million square kilometers*

Method: A Novel Ising Model

- The Hamiltonian of an Ising lattice σ in a standard IM is given as $H(\sigma) = -\sum_{<i,j>} J_{ij}\sigma_i\sigma_j - \sum_i B_i\sigma_i$.
- The probability of any configuration follows $P_\beta(\sigma) = \frac{e^{-\beta H(\sigma)}}{Z_\beta}$, where $Z_\beta = \sum_\sigma e^{-\beta H(\sigma)}$, $\beta = (k_B T)^{-1}$.
- The IM in this study allows spin value to be a real number between +1 (100% water) and -1 (100% ice) to better capture real-world ice/water phase transitions. An innovative inertia factor, I, is also introduced to capture the natural resistance to any state change. The probability of a spin flip is:

$$P_{flip} = e^{-\beta\left(\underbrace{H_\nu - H_\mu}_{\text{The system Hamiltonian change before and after the flip}} + I\,\underbrace{|\sigma_i' - \sigma_i|}_{\text{The energy needed to overcome the inertia of the spin change}}\right)}$$

- In practice, we convert the NRTSI data into a 60x60 Ising lattice, choose the simulation period to be consistently half a month apart, and make the following simplifications: I and J are set to be constant each period, β is normalized to 1, and $B_i = B_0 + B_x(x_i - x_0) + B_y(y_i - y_0)$.

Method: Metropolis-Hastings MCMC

Repeat these Markov Chain Monte Carlo simulation steps 50,000 times for each semi-monthly simulation period

1. Select cell i at random from the 2-D lattice of the focus area. Let the spin value of this cell be σ_i.

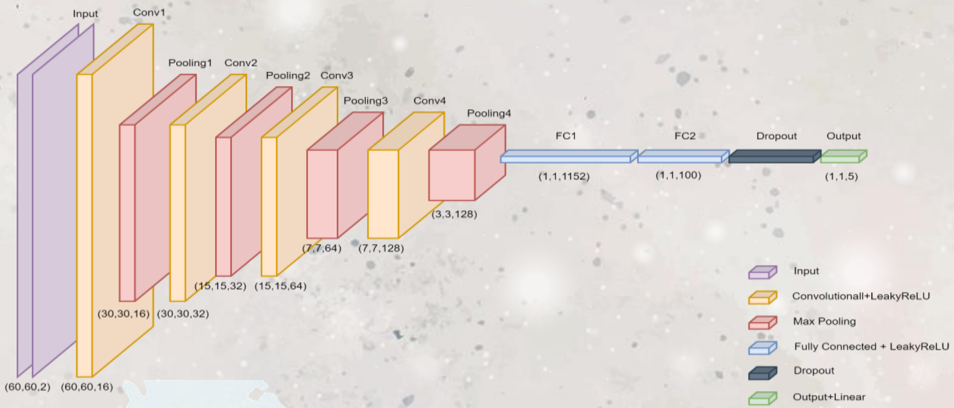
2. Generate another uniform random variable σ'_i between -1 and $+1$.

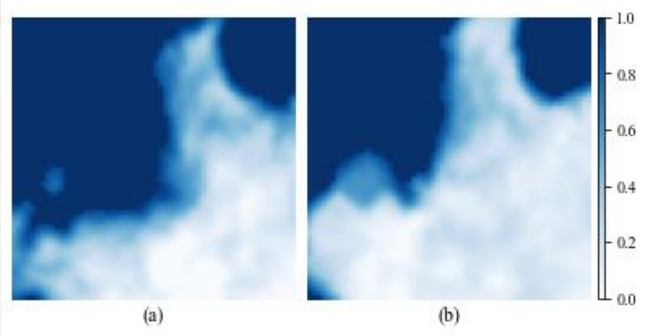
3. Compute the energy change $\Delta Hi = H_\nu - H_\mu$ from σ_i to σ'_i, $I \mid \sigma_i' - \sigma_i \mid$ to overcome the inertia of changing spin value at i, and the total energy change $\Delta E = \Delta Hi + I \mid \sigma_i' - \sigma_i \mid$.

4.
   - ➢ If $\Delta E < 0$, the energy change is favorable since the energy is reduced. The spin value change is therefore accepted to σ'_i ;
   - ➢ If $\Delta E > 0$, the probability of spin flip is determined by the Boltzmann distribution. In this case, another uniform random variable r between 0 and 1 is generated. If r is less than $P = e^{-\beta \Delta E}$, the spin value change σ'_i is accepted; otherwise, the change is rejected and the spin value at i stays at σ_i.

Method: Convolutional Neural Network

- A Convolutional Neural Network (CNN) is built to solve the inverse Ising problem.
- CNN training data: for the initial state of a simulation period, 10,000 samples are generated by the Metropolis MCMC, each associated with a set of randomly-selected Ising parameters.
- The CNN architecture is as follows:





The initial and the final target states of a simulation run from (a) Sept 16th, 2022 to (b) Oct 1st, 2022

- Prediction: for any input of the initial (a) and the final (b) images over a simulation period, the well-trained CNN outputs a vector of 5 Ising parameters (J, B_0, B_x, B_y, I) that match the simulated final state as closely as possible to the final target state (the actual image).

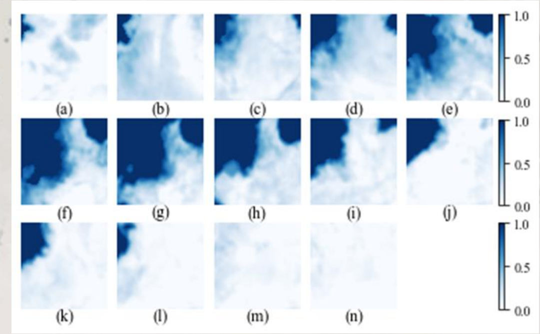
Results: 2022 Ising Parameters

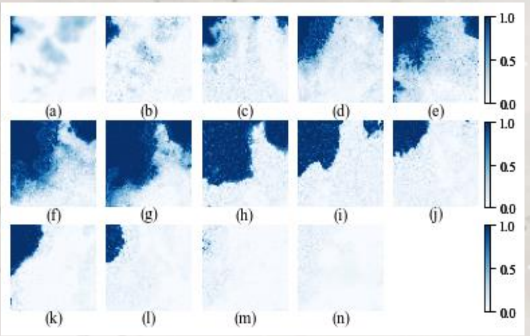
	6/16 to 7/1	7/1 to 7/16	7/16 to 8/1	8/1 to 8/16	8/16 to 9/1	9/1 to 9/16	9/16 to 10/1	10/1 to 10/16	10/16 to 11/1	11/1 to 11/16	11/16 to 12/1	12/1 to 12/16	12/16 to 1/1/2023
J	2.1	2.6	2.9	2.6	2.5	2.5	2.3	2.4	3.5	2.1	2.6	2.3	2.8
B0	2.9	0.5	5.1	7.7	2.8	4.0	-7.1	-12.1	-30.0	-9.4	-18.6	-11.5	-28.0
Bx	3.5	-16.9	-14.9	2.7	-10.6	-7.6	-0.7	-4.1	-28.7	6.8	-1.9	-4.9	-4.3
By	-9.0	6.5	-4.7	3.4	-3.9	1.7	4.7	-6.2	-12.8	-34.5	-12.0	4.3	11.6
I	7.6	10.4	12.1	10.6	9.8	10.2	9.2	9.7	15.4	8.5	11.2	9.3	11.9

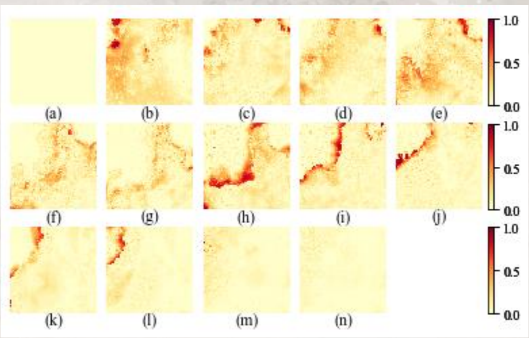
CNN predicted Ising parameters of 2022 sea ice evolution

- The spin interaction coefficient J and the inertia factor I are relatively stable across periods.
- J remains positive across all periods, confirming that the ice/water system displays the feature of ferromagnetism/paramagnetism instead of antiferromagnetism.
- The external force parameters B_0, B_x, and B_y display large variations across different time periods.
  - B_0 is positive from June 1st to Sept 16th and turns negative afterwards, explained intuitively by the seasonal ambient temperature with a lag effect. Other environmental factors that may impact B_0 include albedo or jet streams, which can be further investigated in future research.
  - The values of B_x and B_y are mostly negative due to the geographic distribution of ice coverage.

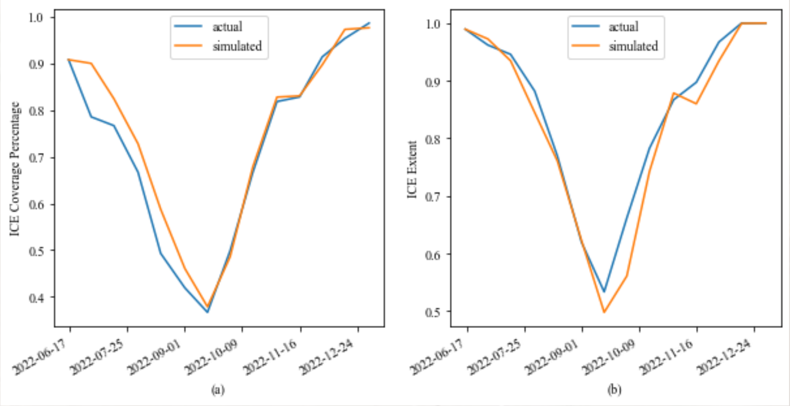
Results: 2022 Similarity







The actual (left) and the simulated (middle) semi-monthly evolution from June 16th, 2022 to Jan 1st, 2023, and the heatmaps (right) illustrating the absolute differences

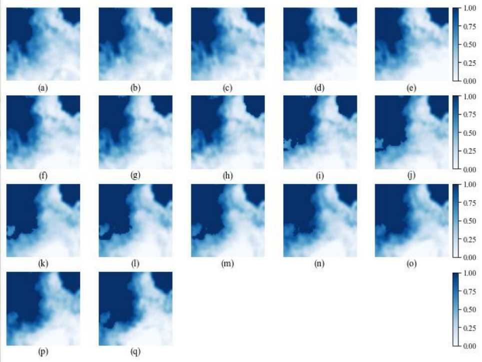
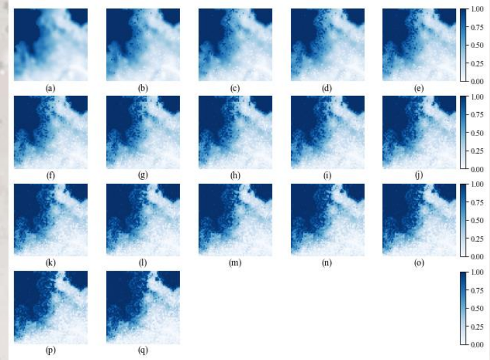
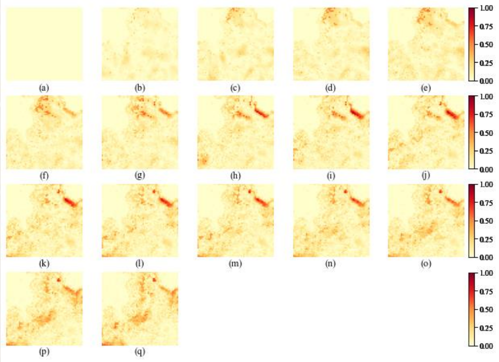


The ice coverage percentage (a) and the ice extent (b) from June 16th, 2022 to Jan 1st, 2023

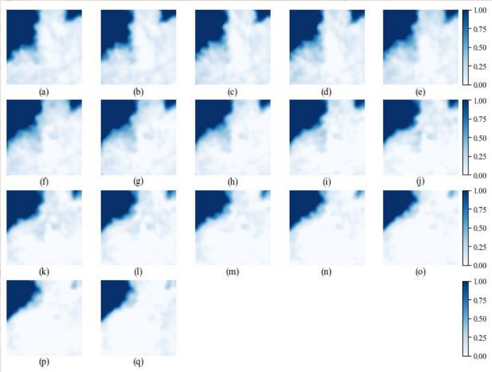
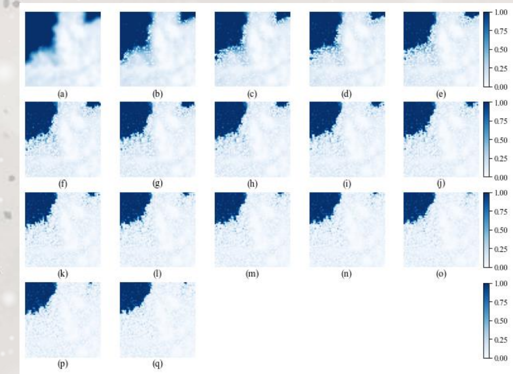
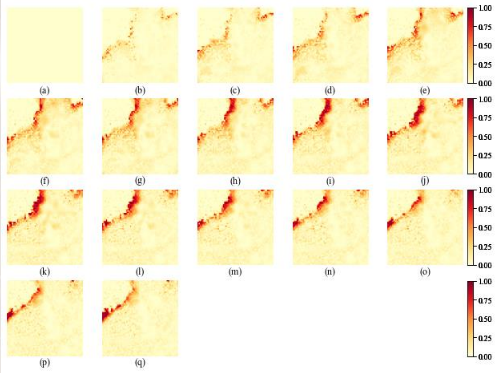
- The simulated sea ice configurations display striking similarity with the actual configurations as illustrated by the heatmaps, where the red patches, indicating discrepancy between simulation and actual, are consistently small and take place at the borders between ice and water.
- The simulated ice coverage percentage and ice extent closely match the observed data.

Results: 2022 Daily Dynamics

The simulated daily evolution exhibits excellent similarity with data, confirming that the IM preserves granular ice/water dynamics.

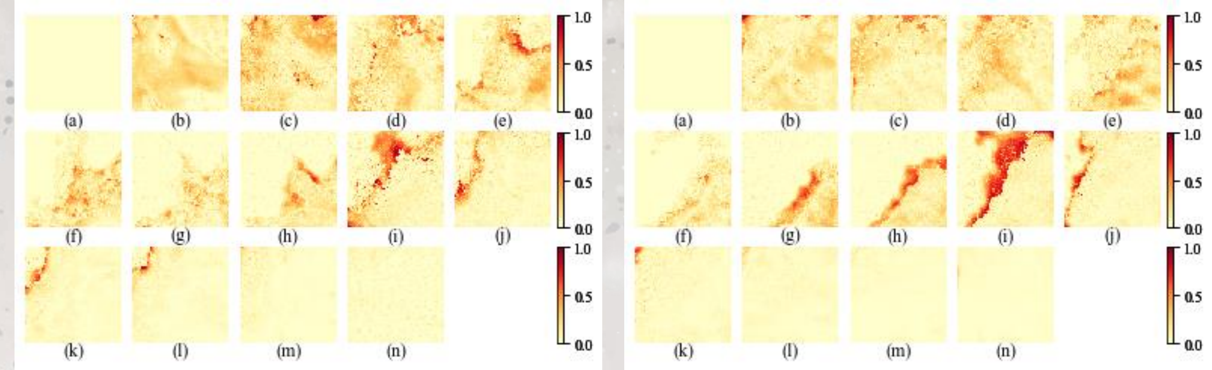




The actual (left) and the simulated (middle) daily evolution during ***a melting cycle*** *from (a) Aug 16th, 2022 to (q) Sept 1st, 2022 and the heatmaps (right) illustrating the absolute differences.*

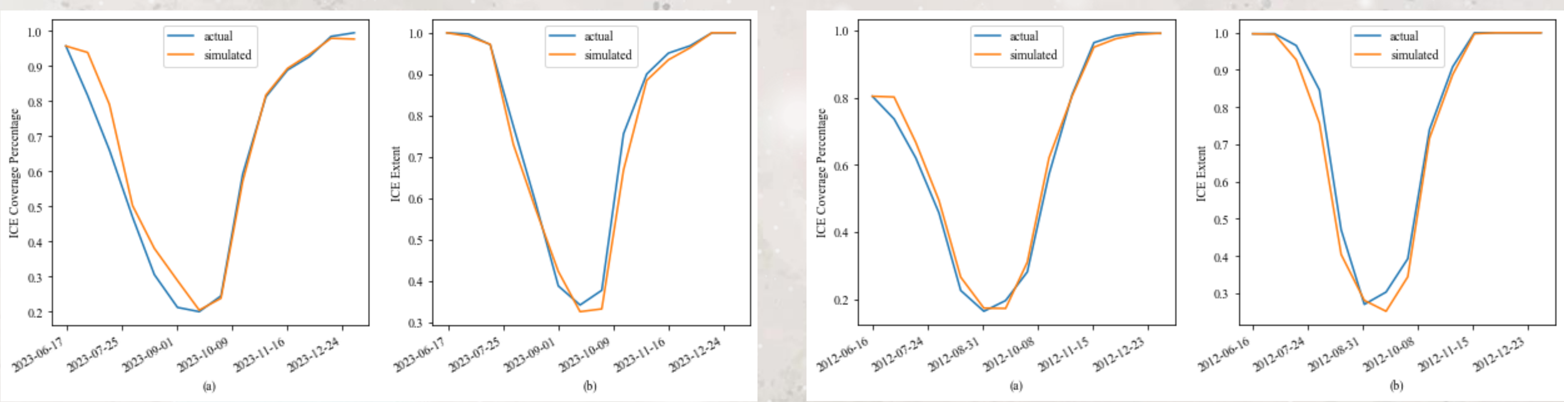
The actual (left) and the simulated (middle) daily evolution during ***a freezing cycle*** *from (a) Oct 16th, 2022 to (q) Nov 1st, 2022 and the heatmaps (right) illustrating the absolute differences*

Results: 2023 vs. 2012



Heatmaps for 2023 (top) and 2012 (bottom) from June 16th to Jan 1st next year

- Heatmaps for 2023 and 2012 (with the historical low of Sept ice extent) confirm the excellent match between the simulated and the actual images in both years.
- Our simulation results verify that 2023 recorded the second lowest Sept ice extent for the focus area.



Comparison between the actual and the simulated ice coverage percentage and ice extent in 2023 vs. 2012

Conclusions / Discussions

What can we conclude?

- When trained with a CNN, the continuous spin Ising model with the novel inertia factor proves to have extraordinary power to replicate and explain sea ice dynamics.
- The CNN-predicted Ising parameters reveal the substantial impact of the external forces on sea ice dynamics.
- This study presents ample possibilities to further enhance the physical modeling to study Arctic sea ice evolution and validates the vast potential of coupling classical physics with modern deep learning technology in environmental studies and other interdisciplinary research.

Questions to ask next?

- Will we see a "Blue Ocean Event" (BOE), i.e., an ice-free Arctic Ocean?
  - Some research predicts a BOE in the 2030s.
  - Will we continue to see even higher temperatures and lower ice extent?
- Will deeper and larger neural networks be capable of learning more enriched Ising parameters?
- Can we explore a Quantum Ising Model (QIM), a.k.a. a Transverse Field Ising Model, to better understand sea ice dynamics by harnessing the exponentially growing power of quantum computing?

References/Acknowledgements

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