Machine learning is a useful surrogate model to parameterize and understand sea-ice motion in the Arctic.

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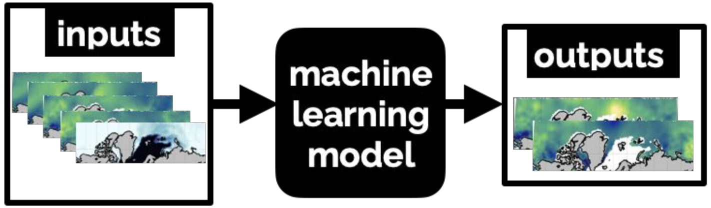
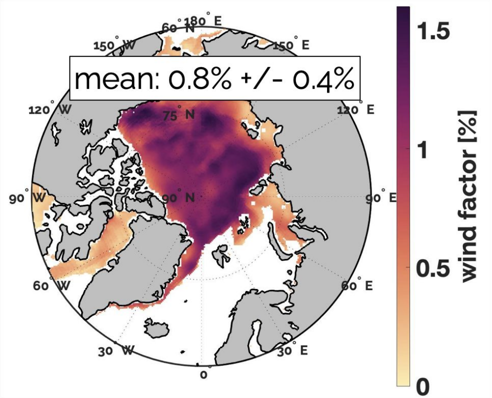
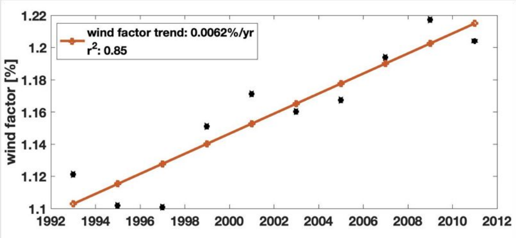
Predictability

Machine learning models are used to make one-day predictions of sea-ice dynamics.



Understanding sea-ice motion





As the ice melts it is becoming more responsive to wind forcing.

wind factor: ratio of sea-ice speed to wind speed

The **wind factor is increasing!**

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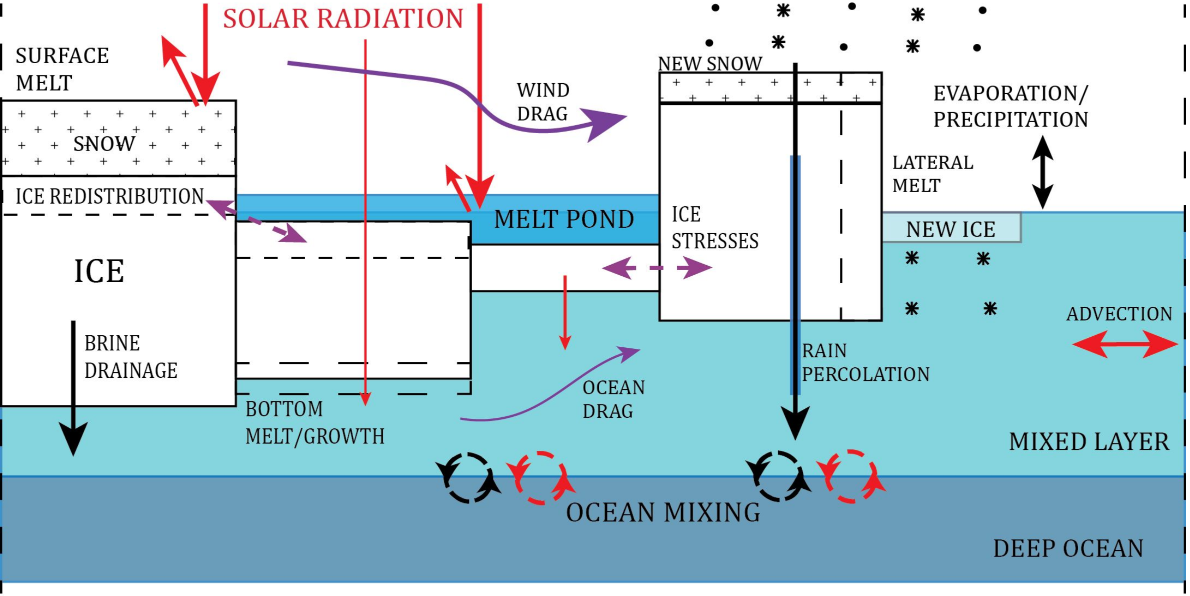
Machine learning models for sea-ice drift have fewer complexities and a lower computational cost than traditional physics-based models.



Physical processes now included in state-of-the-art sea ice models such as CICE (Ed Hawkins, 2015).

Hoffman et al. 2023, *submitted*

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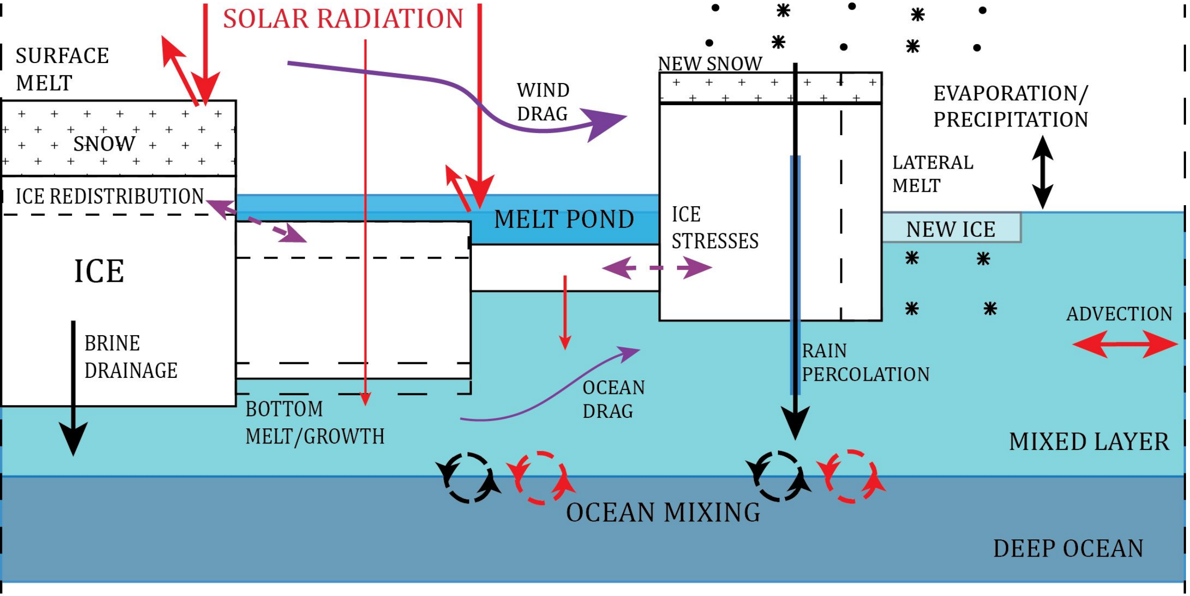

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Machine Learning models can be used to understand sea-ice motion because they are drawing information from the data.

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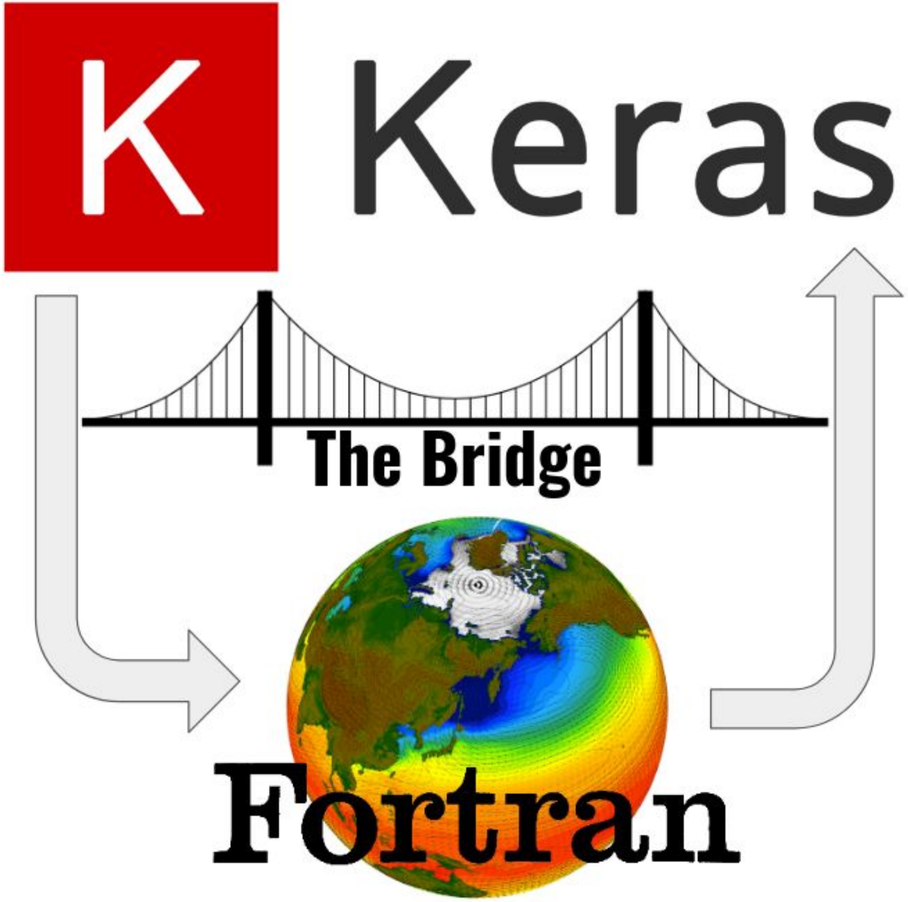

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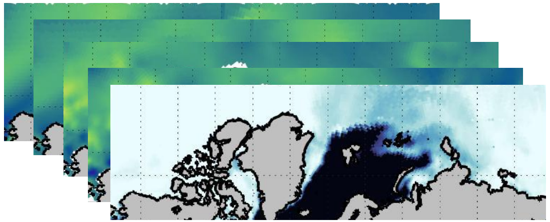
The machine learning models make one-day predictions of sea-ice velocity given input data from satellite & reanalysis sources (1992-2017).

inputs



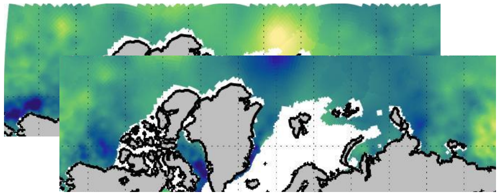
Present-day wind velocity[1]: $u_{a, t = 1}$ & $v_{a, t = 1}$

Previous-day sea-ice velocity[2]: $u_{i, t = 0}$ & $v_{i, t = 0}$

Previous-day sea-ice concentration[3]: $c_{i, t = 0}$

→ **machine learning model** →

outputs



Present-day sea-ice velocity: $u_{i, t = 1}$ & $v_{i, t = 1}$

Model Inputs: [1]JRA55; [2]Polar Pathfinder; [3]Nimbus-7

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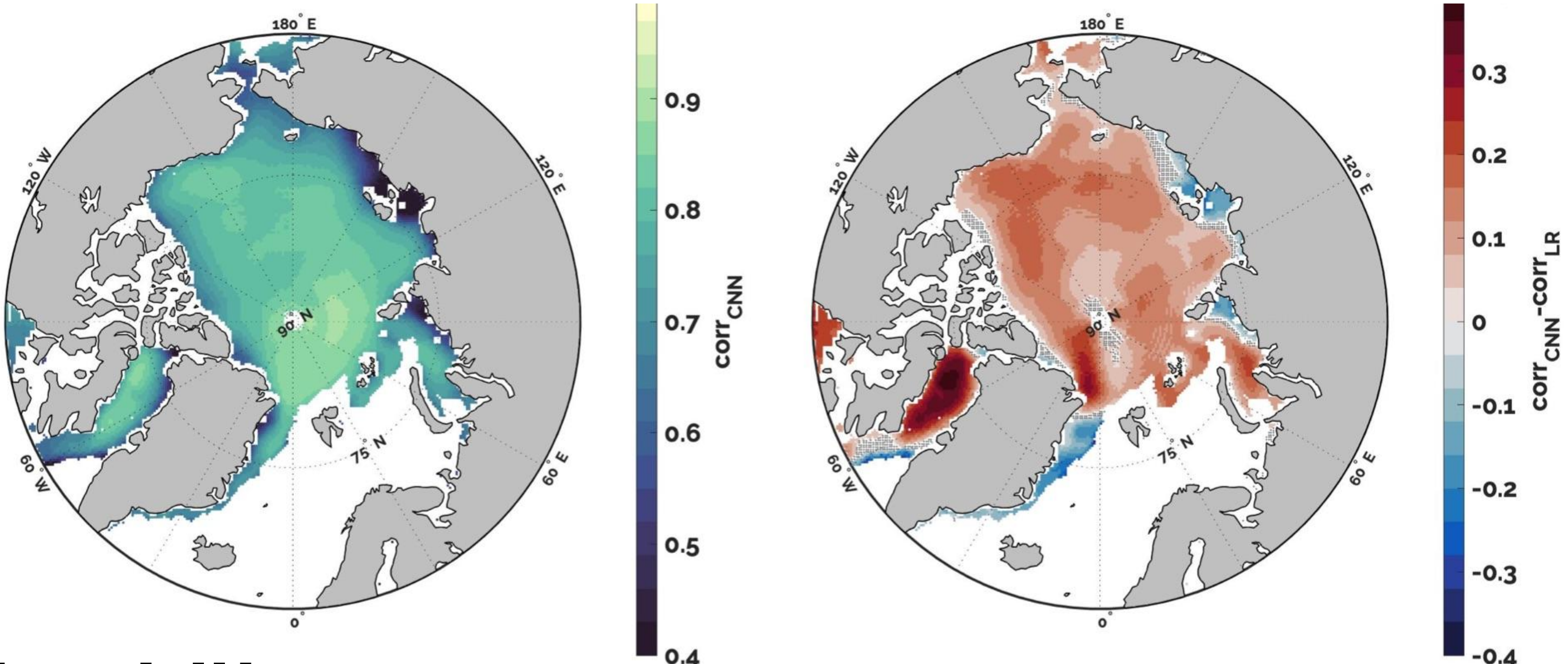
A convolutional neural network (CNN) outperforms linear regression (LR) and persistence (PS) models.

model	correlation
Persistence	0.69 +/- 0.02
Linear Regression	0.77 +/- 0.02
CNN	0.80 +/- 0.01

increasing skill

Hoffman et al. 2023, *submitted*

Models that incorporate non-linear relationships between inputs capture important information (i.e. $corr_{CNN} > corr_{LR}$).



Predictability

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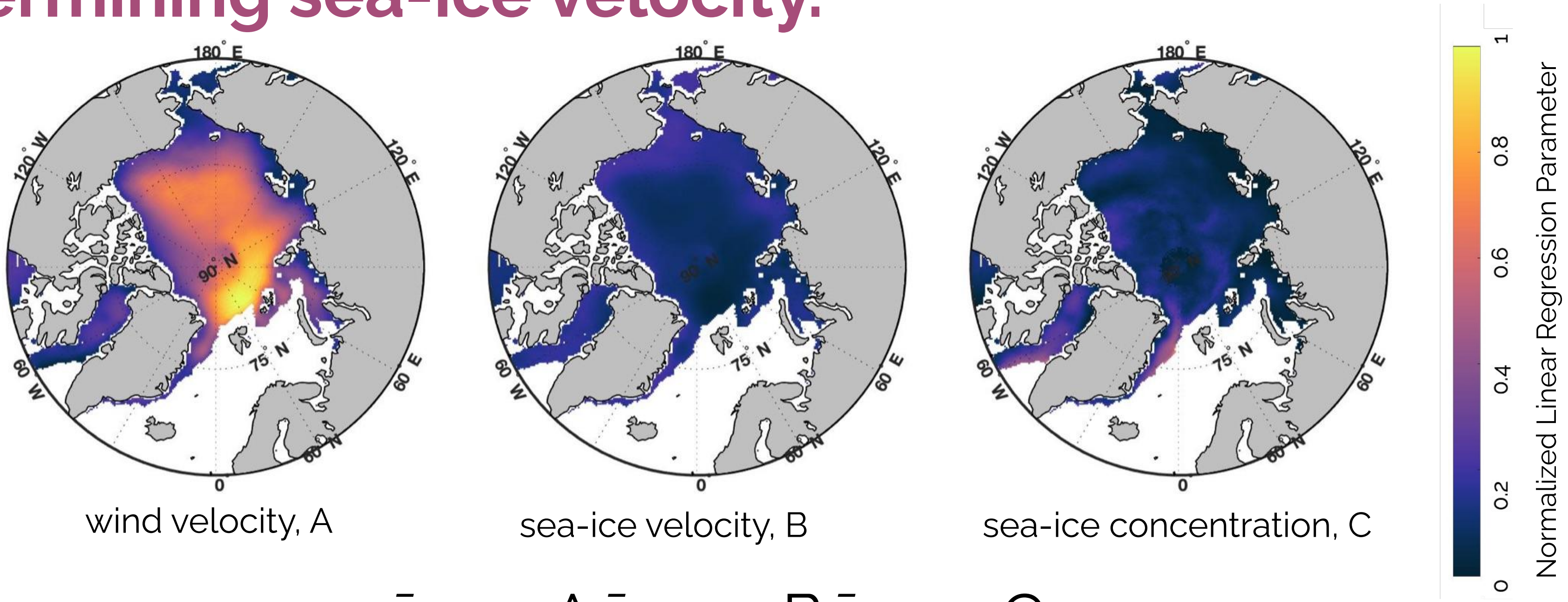
Machine learning methods confirm historical results that wind velocity has the largest relevance in determining sea-ice velocity.

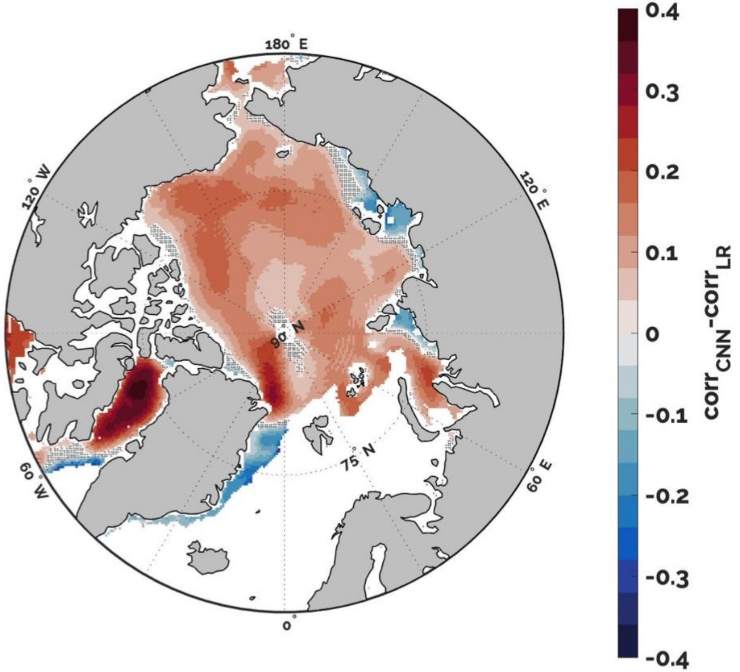


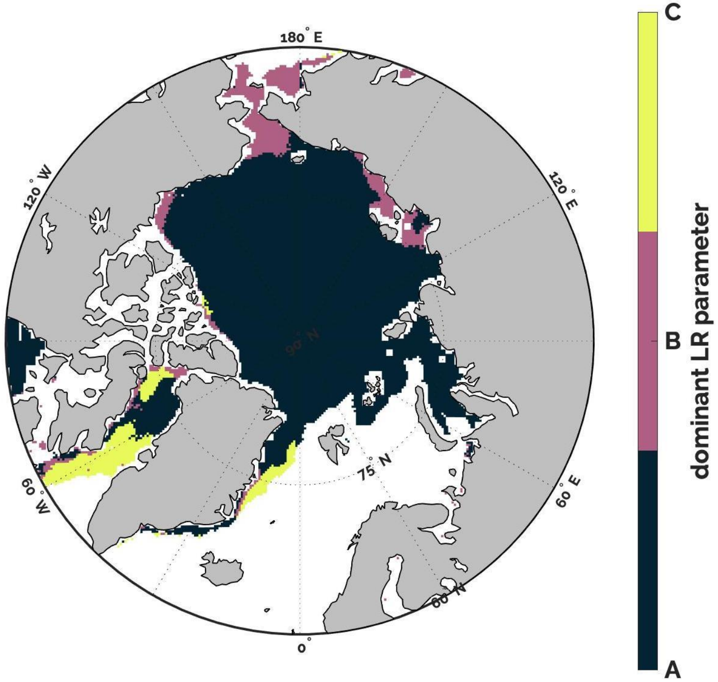
$$\bar{u}_{i,\,t=1} = A\bar{u}_{w,\,t=1} + B\bar{u}_{i,\,t=0} + Cc_{t=0}$$

Understanding sea-ice motion: LR

Hoffman et al. 2023, *submitted*

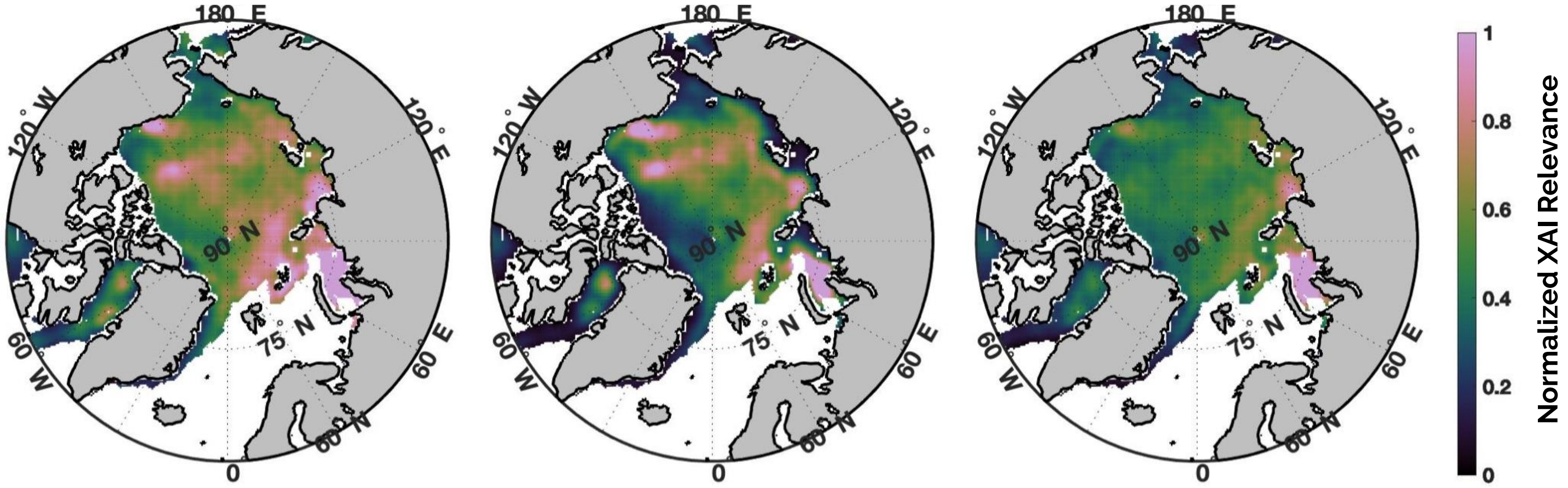
The CNN outperforms the LR primarily in the central Arctic where wind speed (A) is the dominant predictor of ice motion.





Hoffman et al. 2023, *submitted*

Preliminary results from Explainable AI (XAI) show that wind velocity has the largest relevance in determining sea-ice velocity.



wind velocity, A   sea-ice velocity, B   sea-ice concentration, C

Understanding sea-ice motion: XAI

Hoffman et al. 2023, *in prep*

Machine learning is a useful tool to **predict** and **understand** sea-ice motion in the Arctic.

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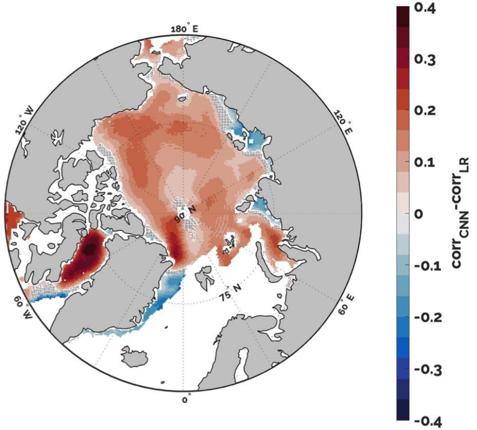
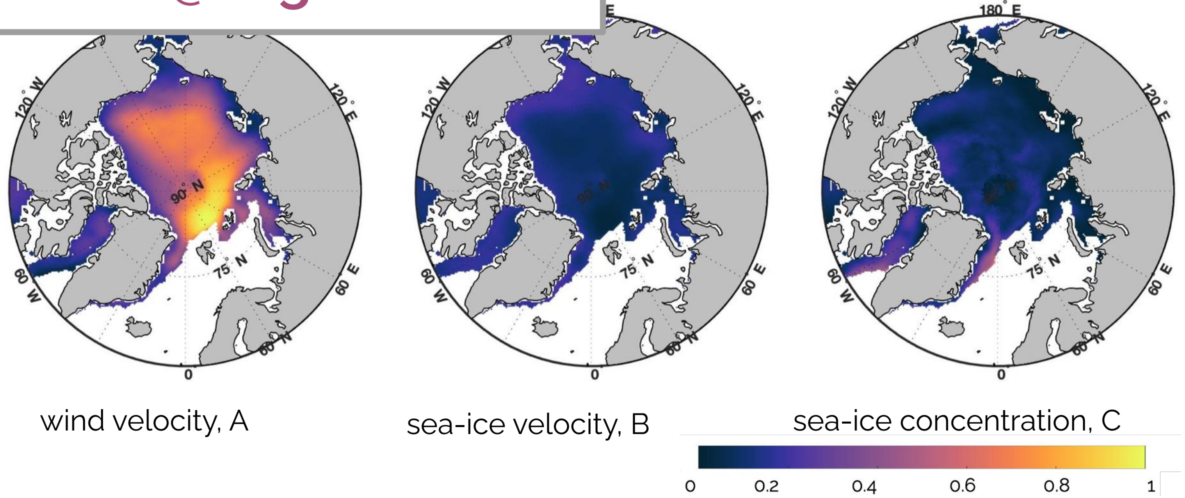


Machine learning models that incorporate non-linearities between inputs capture important information.



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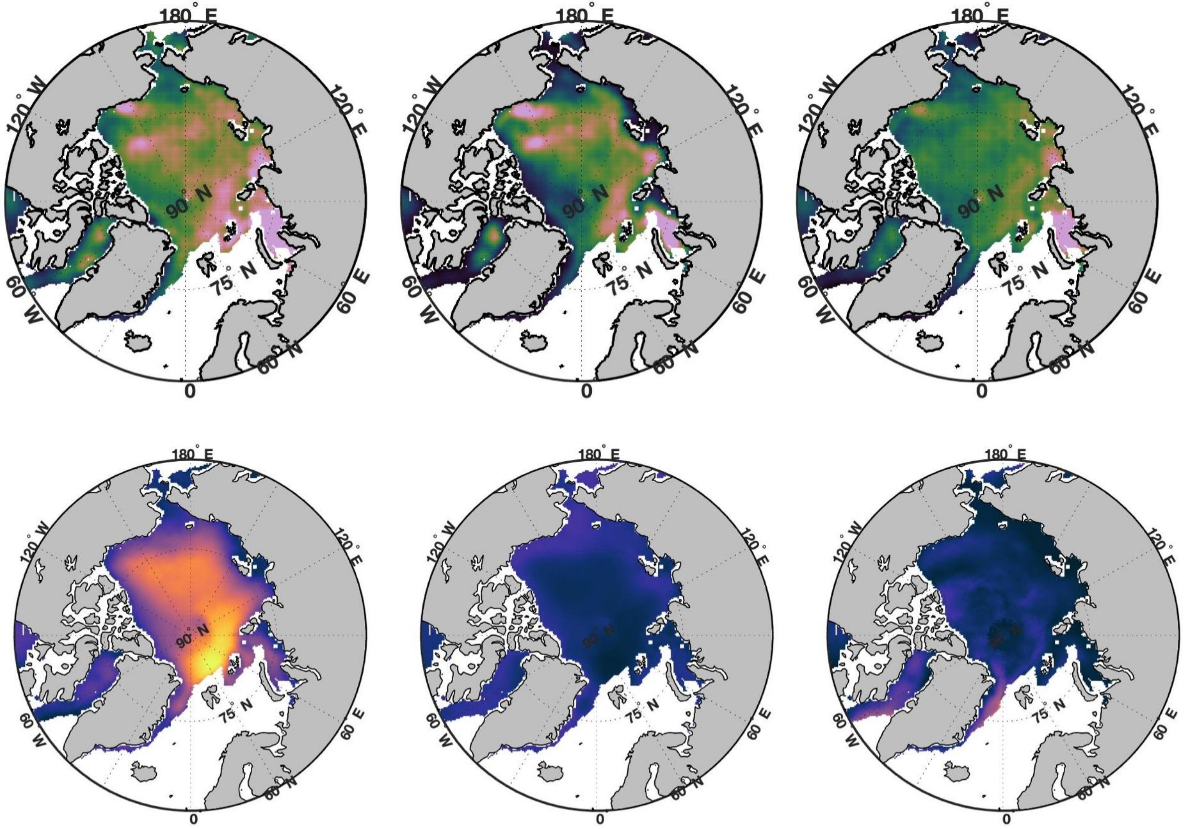
extras



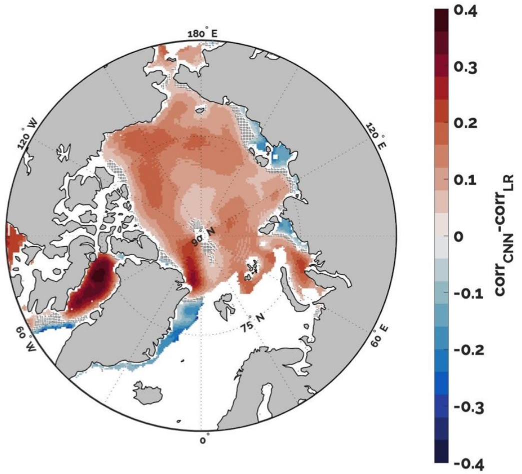
wind velocity, A

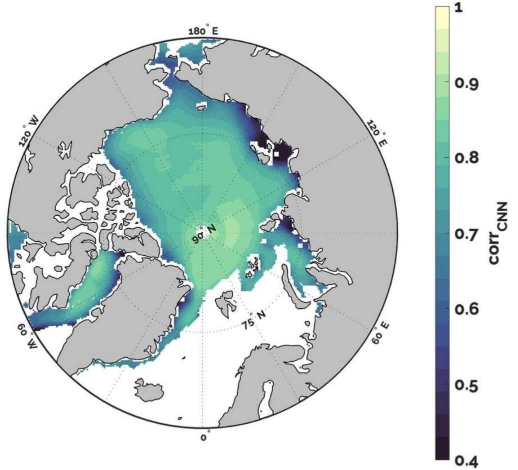
sea-ice velocity, B

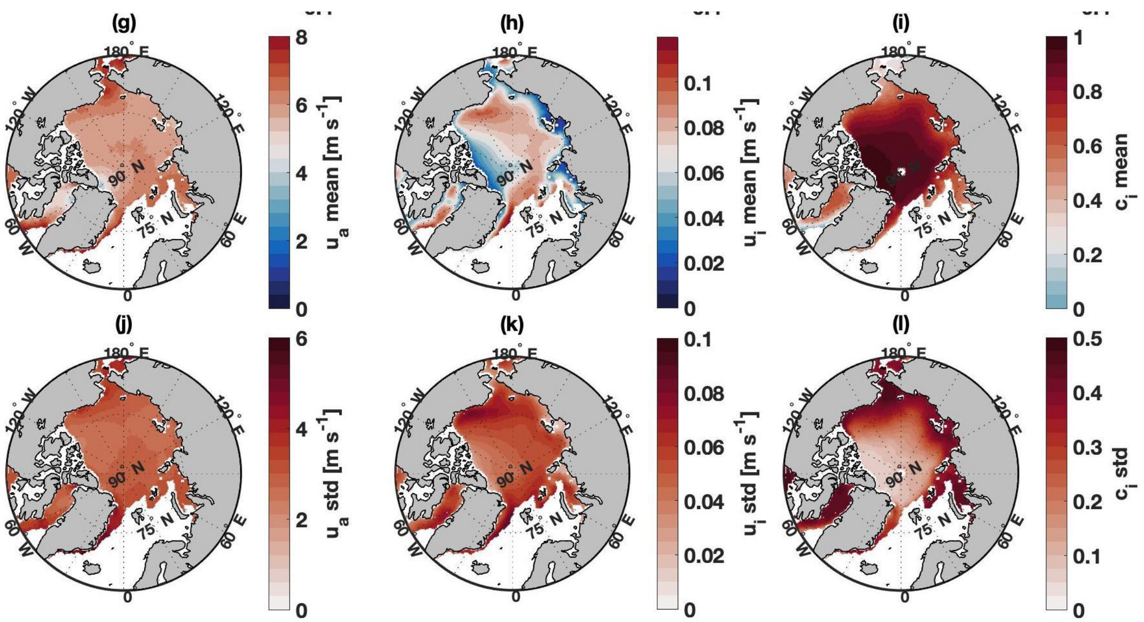
sea-ice concentration, C

Understanding sea-ice motion: XAI vs. LR

Hoffman et al. 2023, *in prep*







Model performance vs. variability of inputs

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