Machine learning-based parameterization of sea ice floe perimeter for CESM

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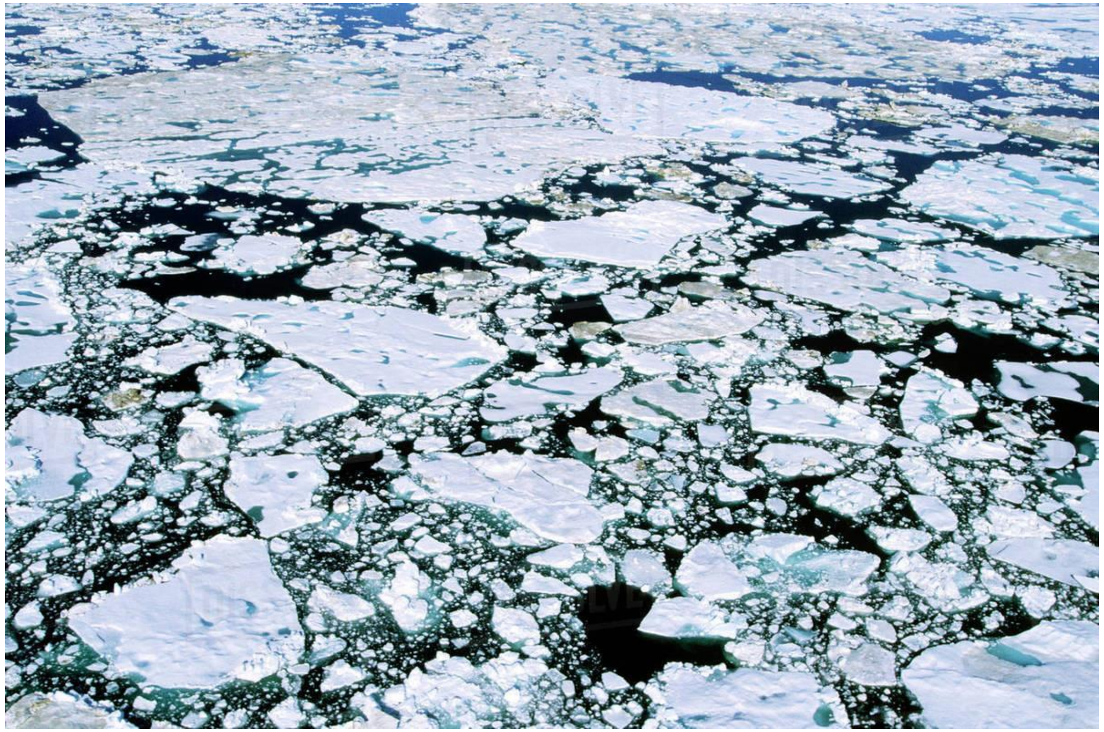
Floe size is not homogeneous!



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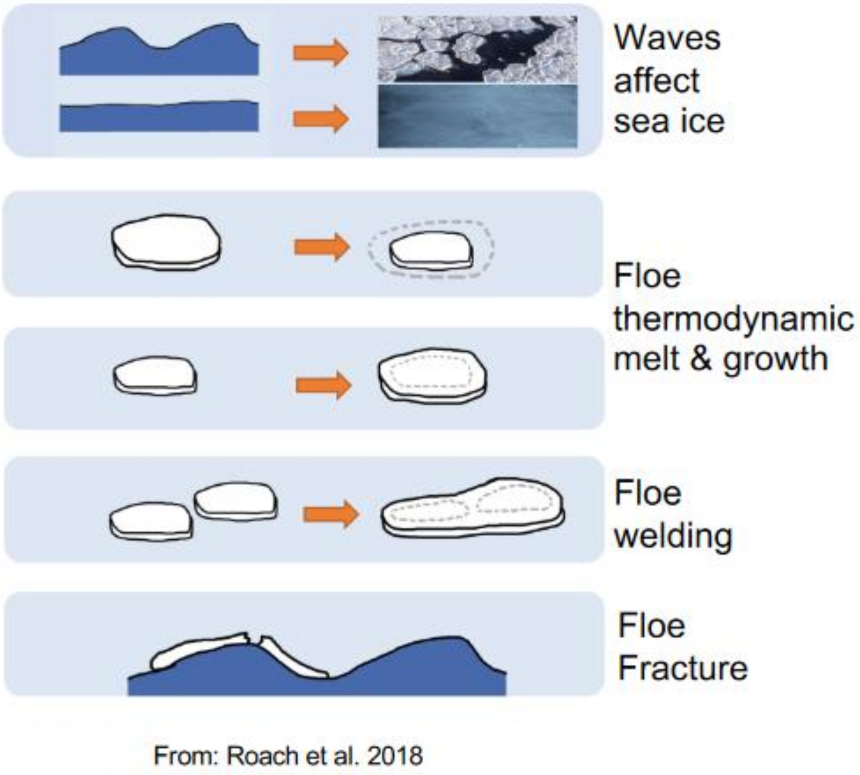
Sea ice floes vary greatly in size, ranging from centimeters to kilometers



From: Roach et al. 2018

+ new ice formation

From CESM Tutorial 2025

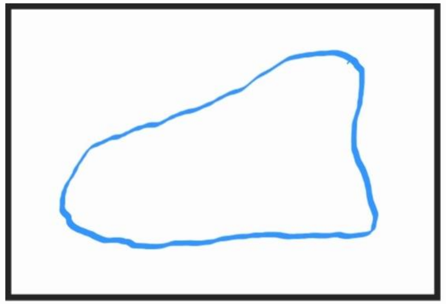
Why do we care about the size of floes?

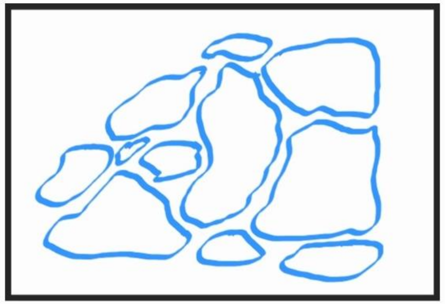
Steele (1992): Parameterization of lateral melting

Change in A due to lateral melting in each ice category n → $\left(\frac{dA}{dt}\right)_{\mathrm{lat},n} = G_r \boxed{P_i} A$

A: Sea ice fraction
G_r: Lateral melting rate
P_i: Total perimeter of floes per unit area

in previous CESM versions: $\mathbf{0.0159\ m^{-1}}$ (constant)





Same A, but higher P_i in lower figure.

The higher P_i, the more fragmented the sea ice is.

The sea ice floe perimeter indicates how much sea ice is exposed to the ocean at the floe edges and therefore the available amount for lateral melting.

Why do we care about the size of floes?

Steele (1992): Parameterization of lateral melting

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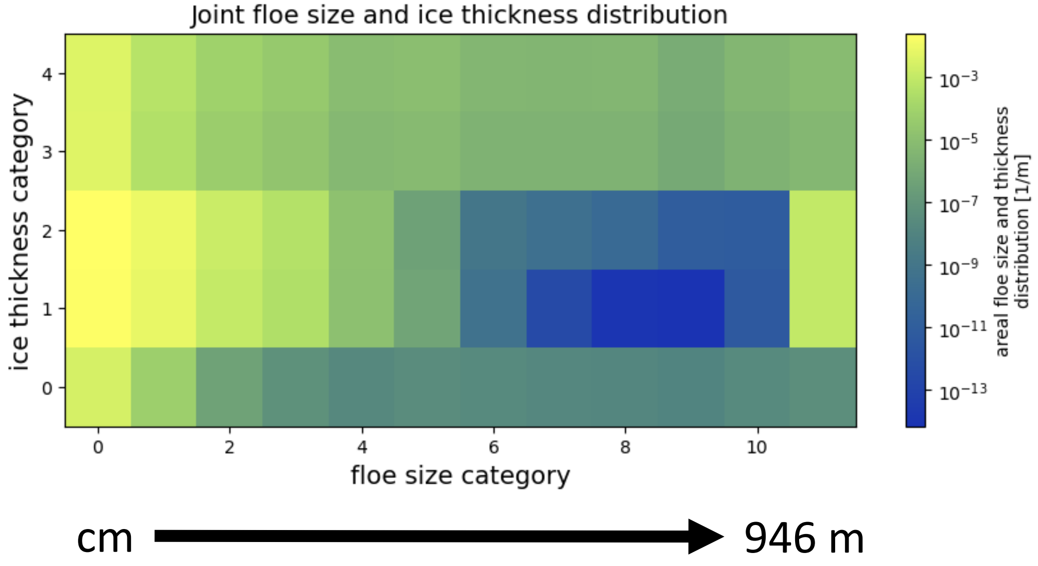
- Roach et al. (2018) introduced the floe size distribution (**FSD**) which will be turned on in CESM3 by default
- **Problem**: it is **computationally expensive**



Scope of this study

Goals:

- **Improve** the representation of lateral melting compared to $\mathrm{CESM3}_{\mathrm{noFSD}}$ by capturing the sub-grid scale floe perimeter P_i
- **Reduce** computational costs compared to $\mathrm{CESM3}_{\mathrm{FSD}}$

Emulation of FSD to parameterize the floe perimeter!

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2026-02-05

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Workflow

Multilayer Perceptron Neural Network

ranking of most important input features

balancing model error and complexity

Training data

$CESM3_{FSD}$

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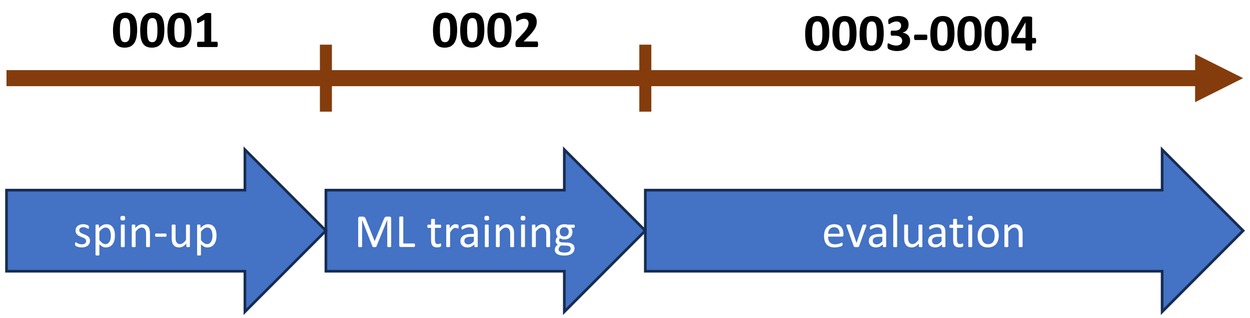
Training data

Model setup

- $\text{CESM3}_{\text{FSD}}$ fully coupled, pre-industrial run
- Spatial resolution: 2/3°
- Temporal resolution: instantaneous, half-hourly
- Simulation length: 4 years



Input features

Variables available in $\text{CESM3}_{\text{noFSD}}$

- Sea ice fraction & volume per unit area (Ice Thickness Distribution), sea ice velocity
- Ocean heat content, sea surface temperature, ocean currents, wave significant height
- Winds at 60m atmosphere, 2m reference specific humidity, 2m reference air temperature, atm/ice stress

Target variable: floe perimeter per unit area P_i [1/m]

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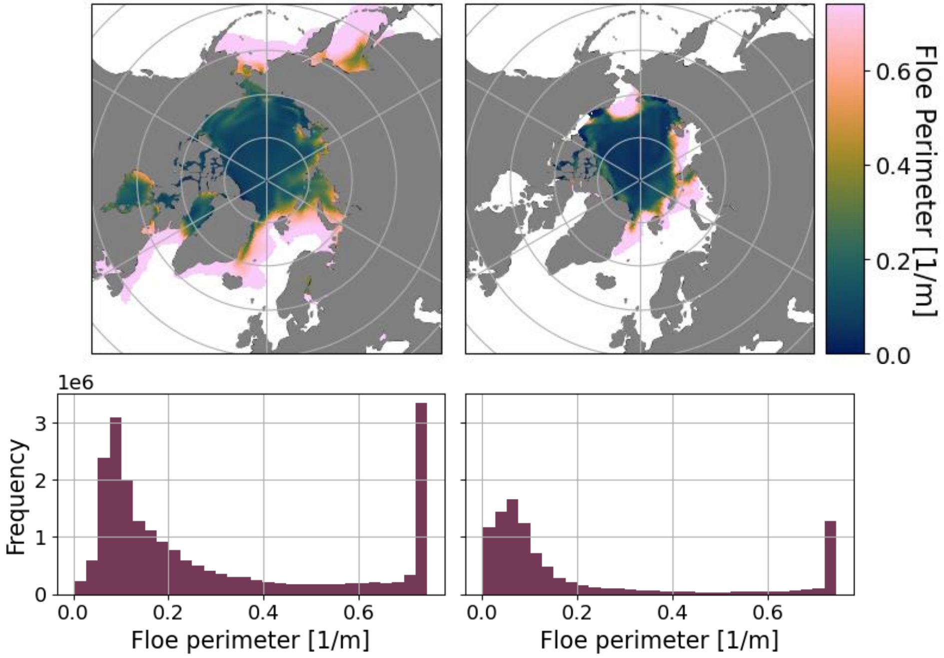
Model output: monthly mean of 0002-03/09

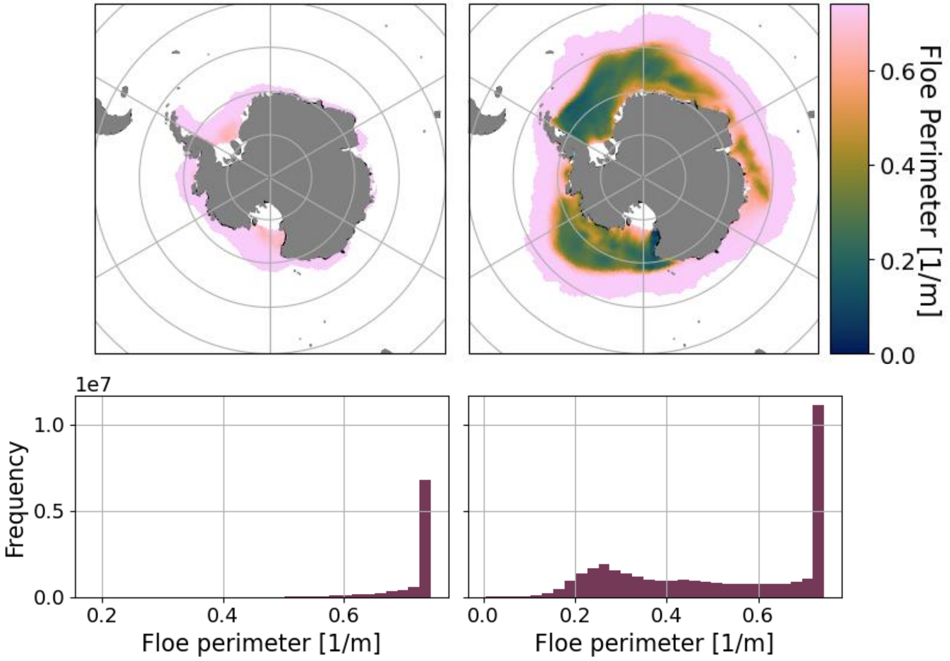
Northern Hemisphere

March September



Southern Hemisphere

March September



- Less fragmented multiyear ice and seasonal ice in NH
- Mostly fragmented, seasonal ice in SH

Results

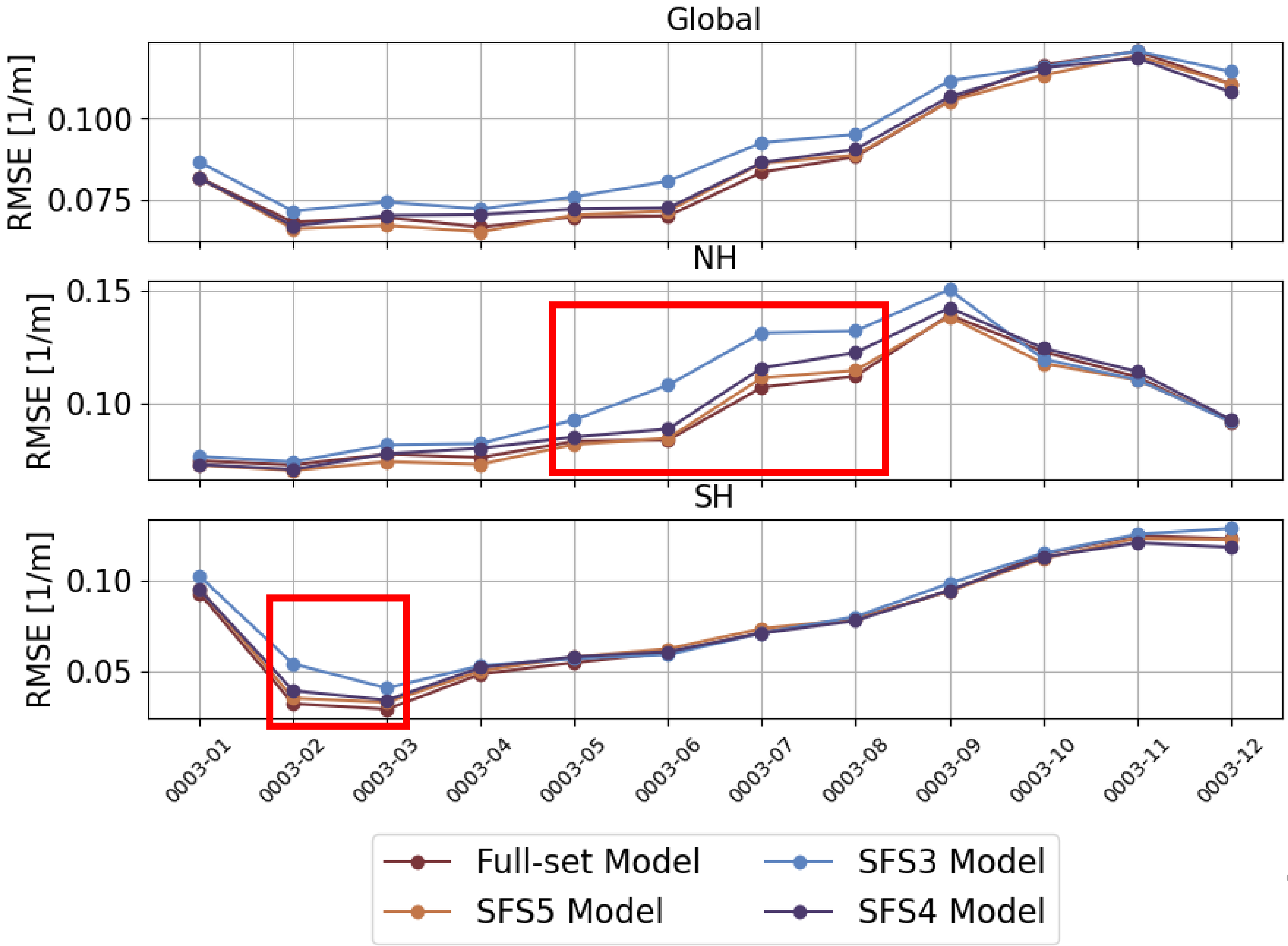
Comparison: full-set model, SFS3-5

SFS Ranking

1. ITD ice fraction
2. Wave significant height
3. ITD ice volume per unit area
4. Ocean heat content
5. SST

ITD: sub-grid scale ice thickness distribution

-> Ocean heat content improves NN prediction during melting season in both hemispheres



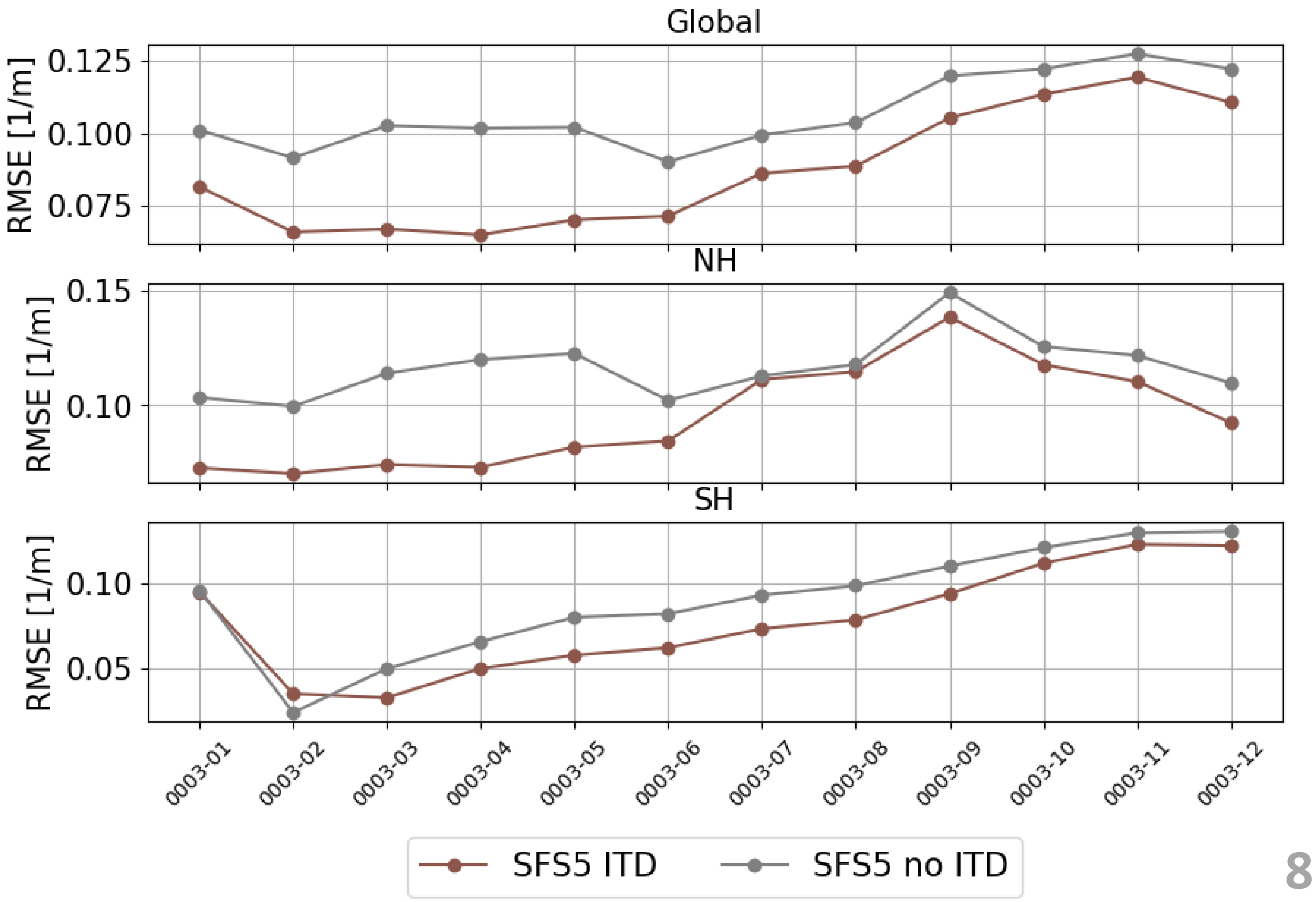
Comparison: SFS5 ITD vs. no ITD

Ranking

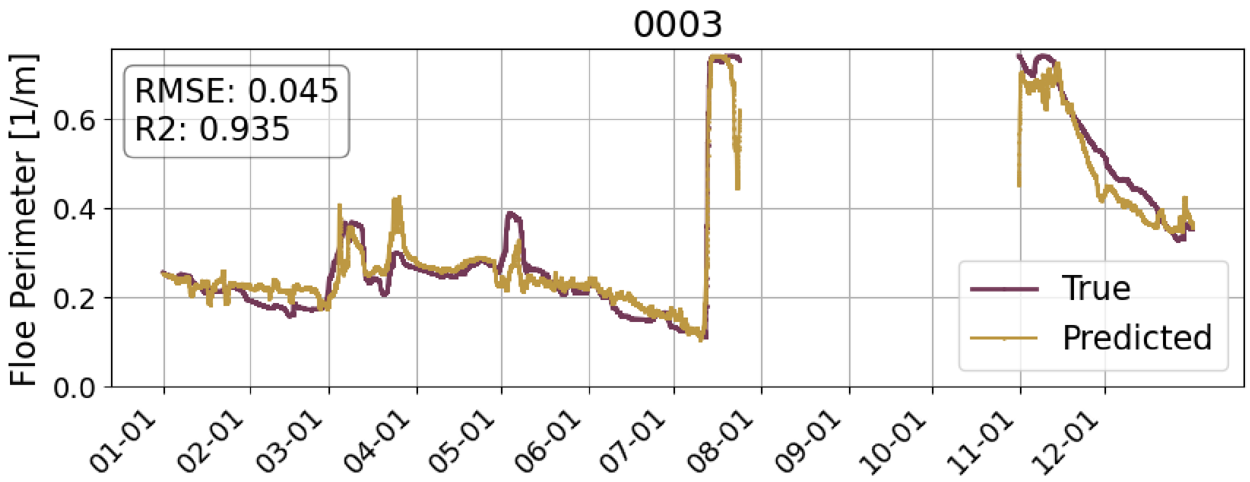
1. ITD ice fraction (mean)
2. Wave significant height
3. ITD ice volume per unit area (mean)
4. Ocean heat content
5. SST

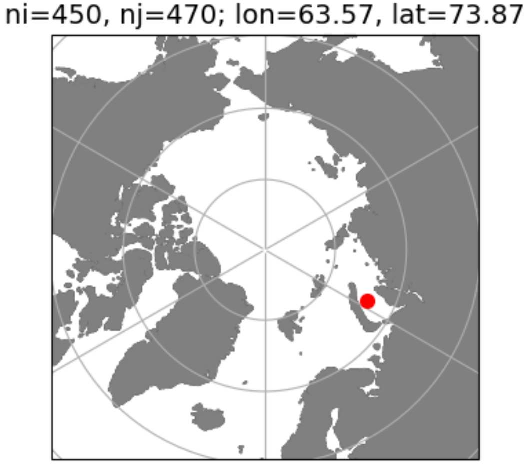
ITD: sub-grid scale ice thickness distribution

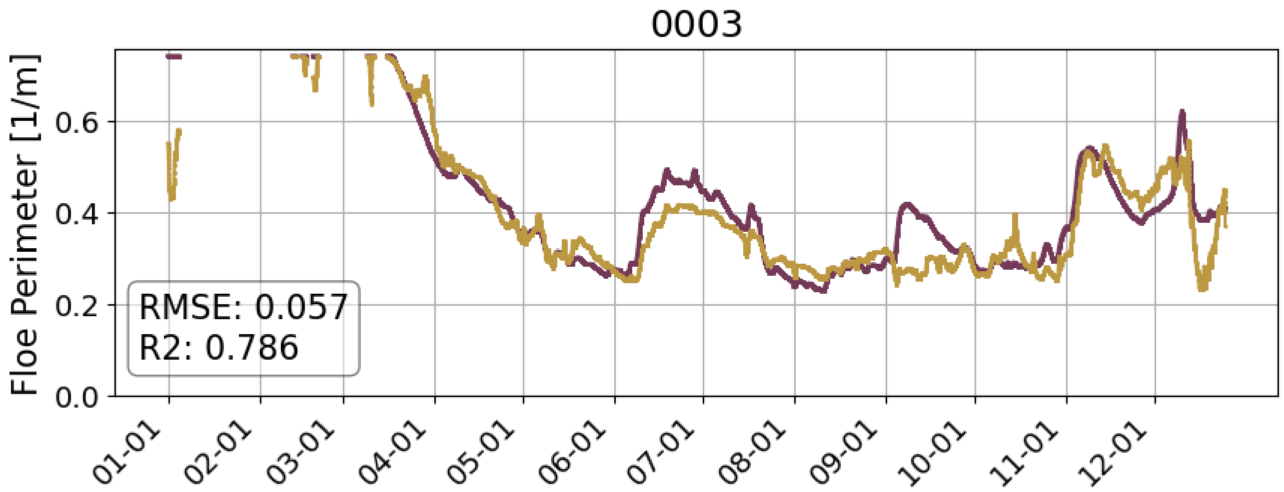
-> Subgrid scale information crucial for better NN prediction

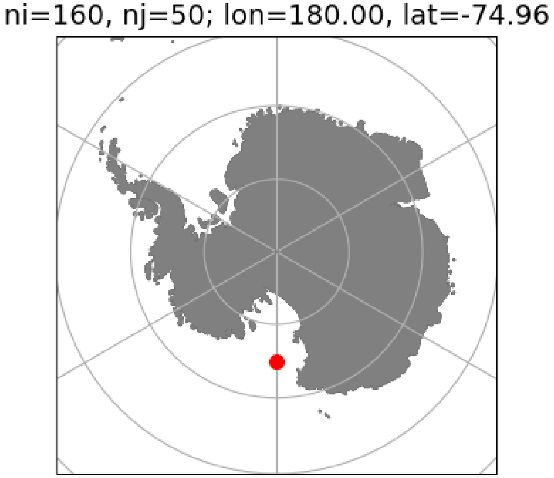


Time series – SFS5 predictions

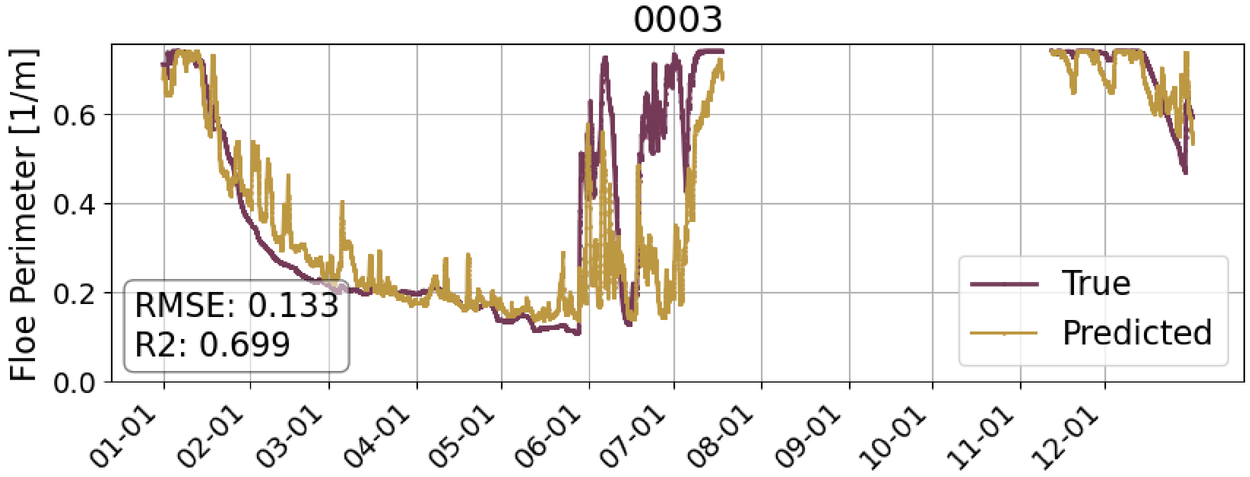








Time series – SFS5 predictions



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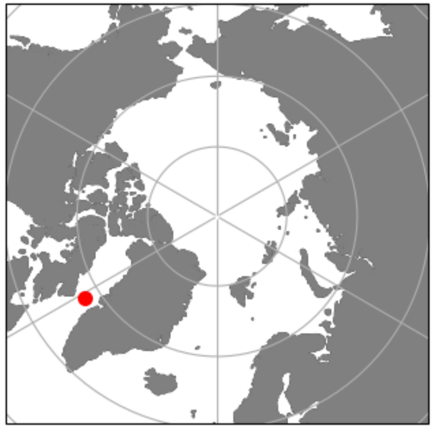

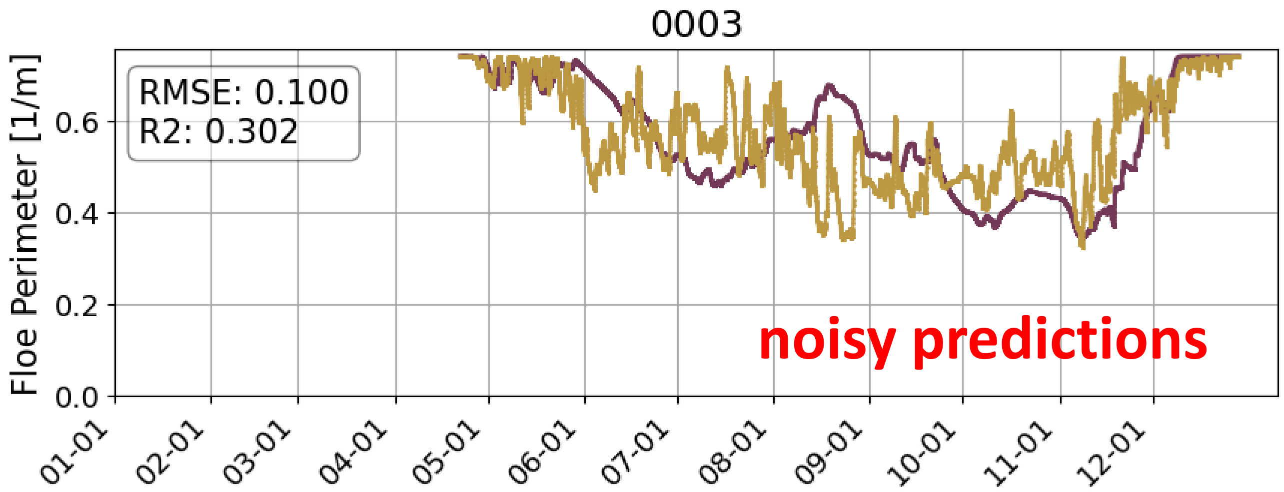

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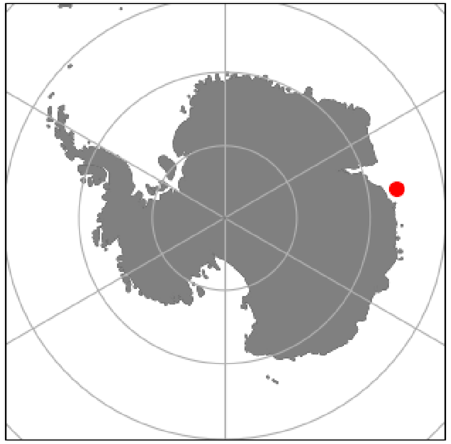

Online coupling – Computational costs

cesm3_0_alpha07f (2 months of simulation)

CICE timing

- FSD turned off: 4.997 sec/mday
- FSD turned on: 6.517 sec/mday
- ML perimeter: 5.698 sec/mday

+1.52 sec/mday

-0.82 sec/mday

FTorch

Fortran-PyTorch bridge developed at ICCS Cambridge
Standard library in CESM-MLe (also in ICON-XPP-MLe)

ML-based parameterization is faster!

Summary

- Overall **good performance** of NN using five most informative input features: ITD ice fraction, wave significant height, ITD ice volume, ocean heat content and SST
- **Subgrid-scale information** (Ice Thickness Distribution) crucial for NN prediction
- NN predictions are **noisy**
- Coupling the ML-based parameterization using FTorch is **faster** than the FSD

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Next steps/ideas

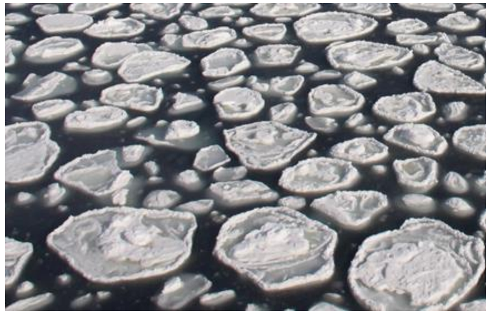
- Train binary classification

NN classification

Pancake ice?

fsdperim >= 0.7

Yes, fsdperim = 0.7/0.74?



fsdperim < 0.7

No, NN regression

- Train Generative Models, potentially overcoming noisy predictions
- Evaluation of online simulations

Thank you for your attention!

Supplementary Material

Why do we care about the size of floes?

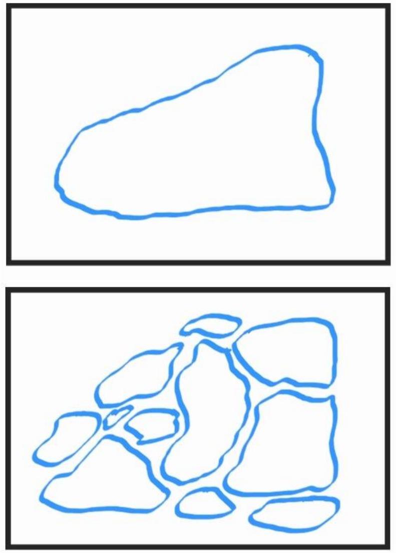
Steele (1992): Parameterization of lateral melting

Change in A due to lateral melting in each ice category n →

$$\left(\frac{dA}{dt}\right)_{\mathrm{lat},n} = G_r \frac{\pi}{\alpha \boxed{D}} A = G_r \boxed{P_i} A$$

in CICE: $\boldsymbol{D = 300\ \mathrm{m}}$
or $\boldsymbol{P_i = 0.0159\ \mathrm{m}^{-1}}$

A: Sea ice concentration
G_r: Lateral melting rate
$\alpha = 0.66$: Geometric factor
D: Floe diameter
P_i: Total perimeter of floes per area of sea ice



Same A, but higher P_i in lower figure.

The floe size determines the perimeter of sea ice floes exposed to the ocean and therefore the amount of lateral melting that occurs at floe edges.

Model setups

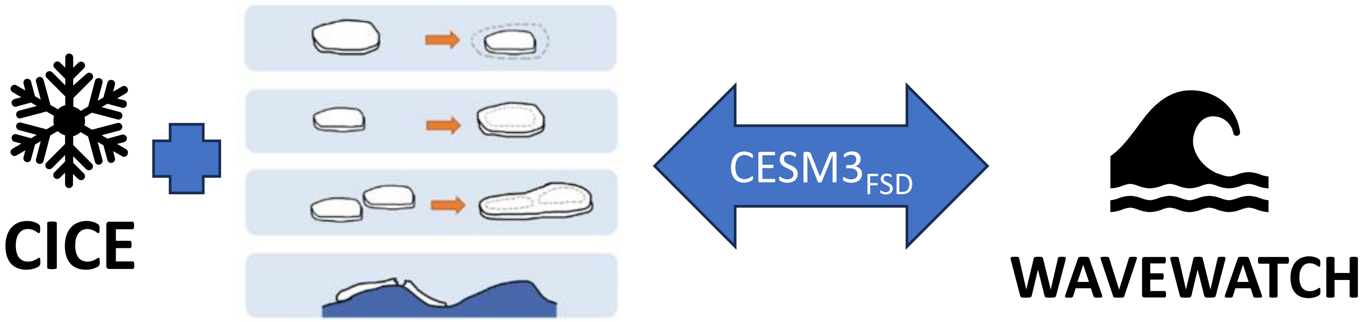
$\mathrm{CESM3}_{\mathrm{noFSD}}$: FSD turned off

- Constant floe perimeter value
- One-way interaction between sea ice and waves; waves receive sea ice information

$\mathrm{CESM3}_{\mathrm{FSD}}$: FSD turned on

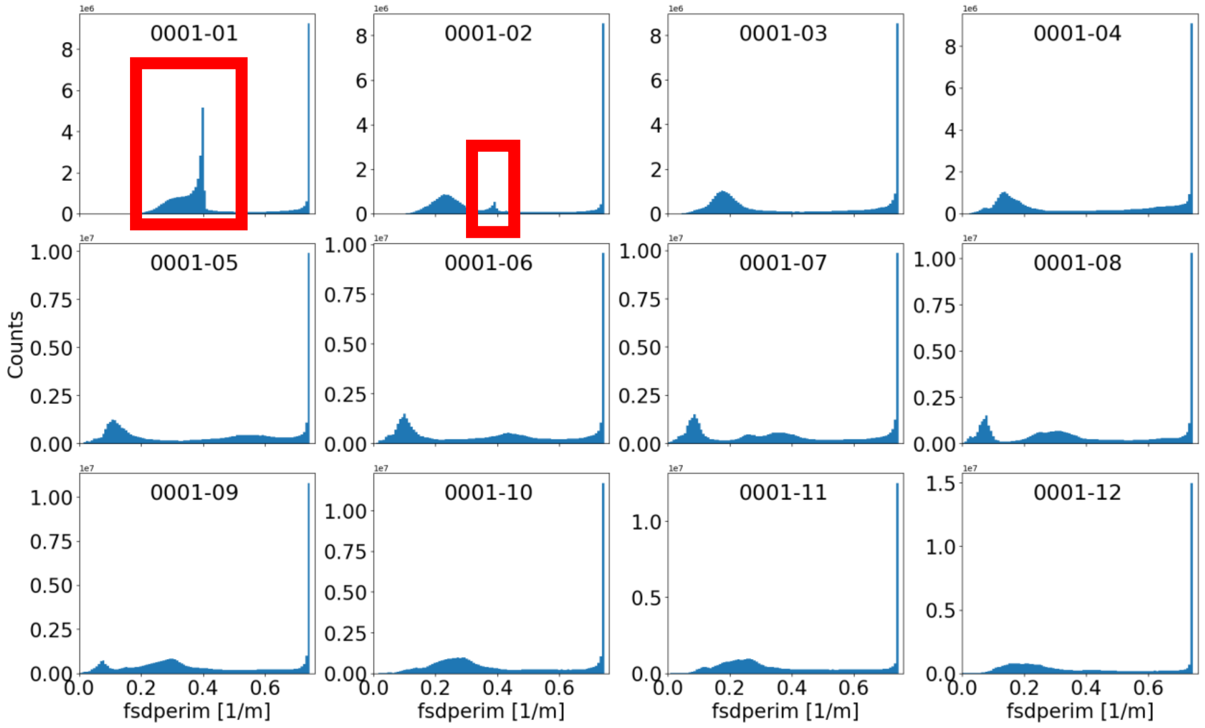
- Varying floe perimeter value subject to climate conditions
- Two-way interaction between sea ice and waves

Not included in any CMIP6 models, increasing interest in wave-sea ice interaction for sea ice forecasting

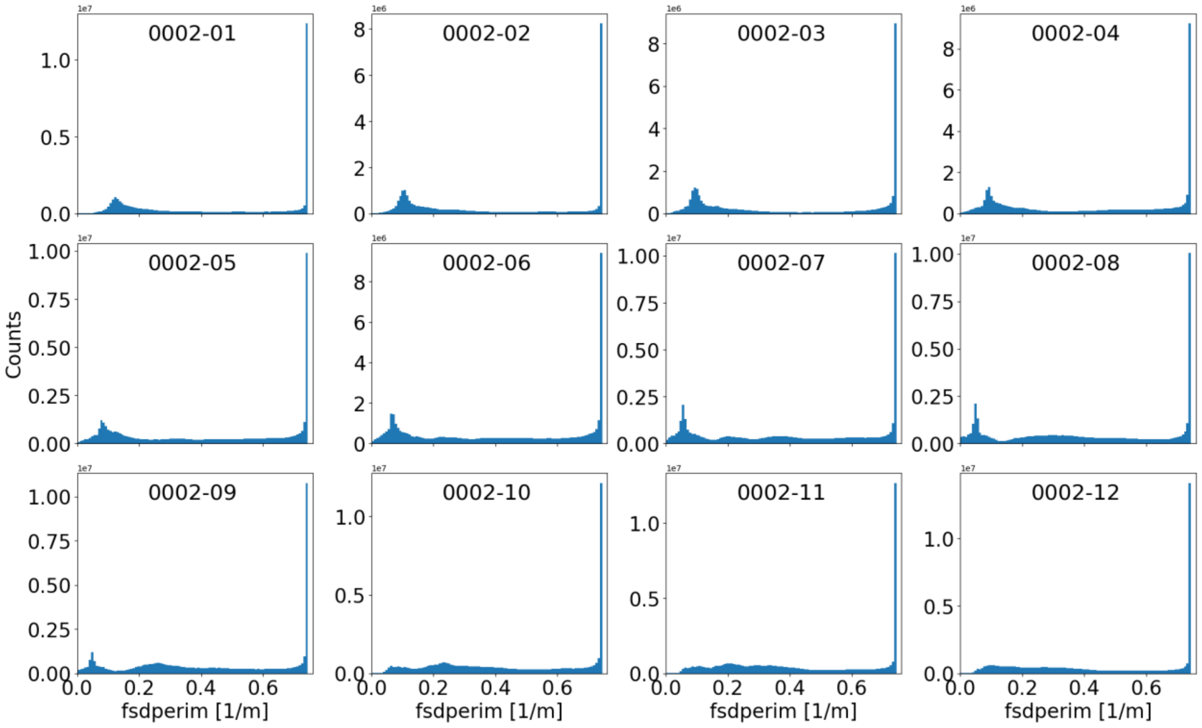


Differences in monthly distributions

0001



0002

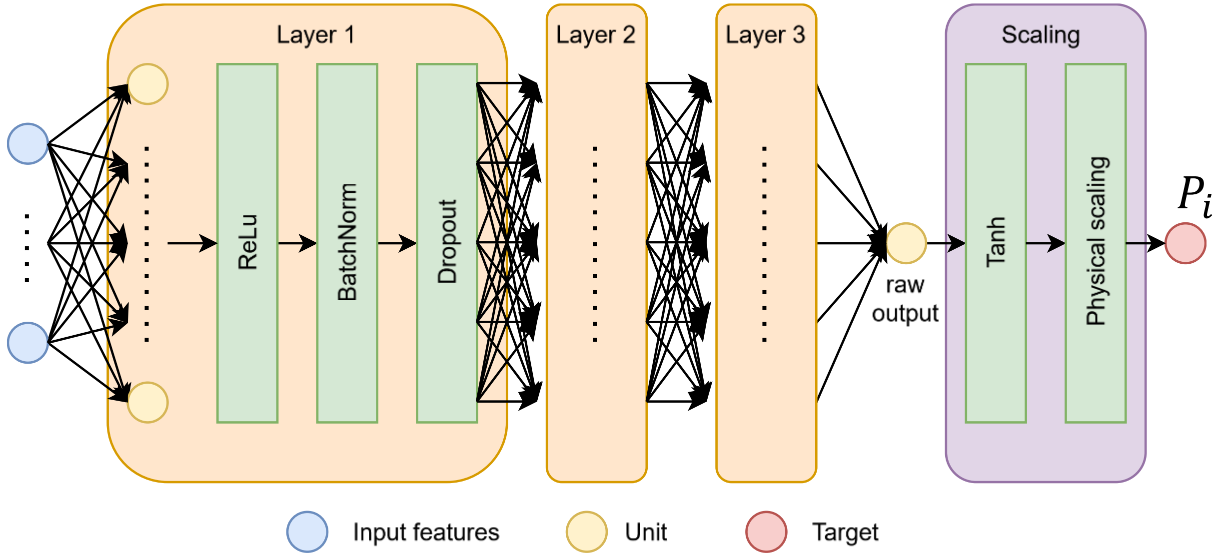


Machine learning pipeline

Baseline model

Sequential Feature Selection

Multilayer Perceptron Neural Network (MLP NN)




```
EPOCHS=100
BATCH_SIZE=1024
LEARNING_RATE=0.001
HIDDEN_SIZES="64 64 64"
DROPOUT_RATE=0.2
```

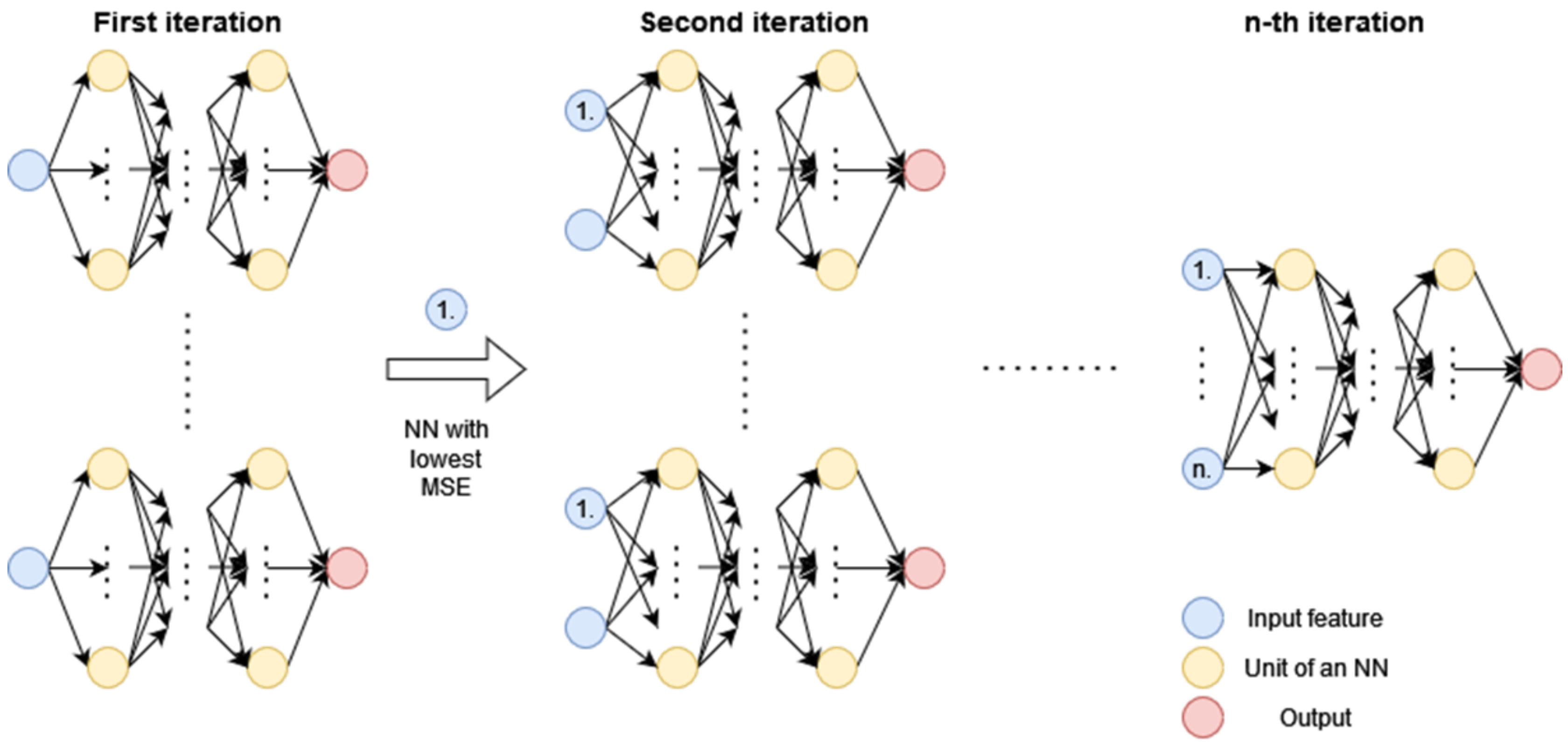
- Adam optimizer
- Loss function: Mean Squared Error (MSE) combined with boundary penalty

Physical range: (0, 0.74]

- Training on both hemispheres, pointwise prediction (no spatial or temporal information)
- Training/validation/test: 20/5/last days of each month
- Each month, downsample from $\sim 10^8$ to 10^6 samples
- Filter: $A \geq 0.05$
- Baseline model includes all input features (full-set)

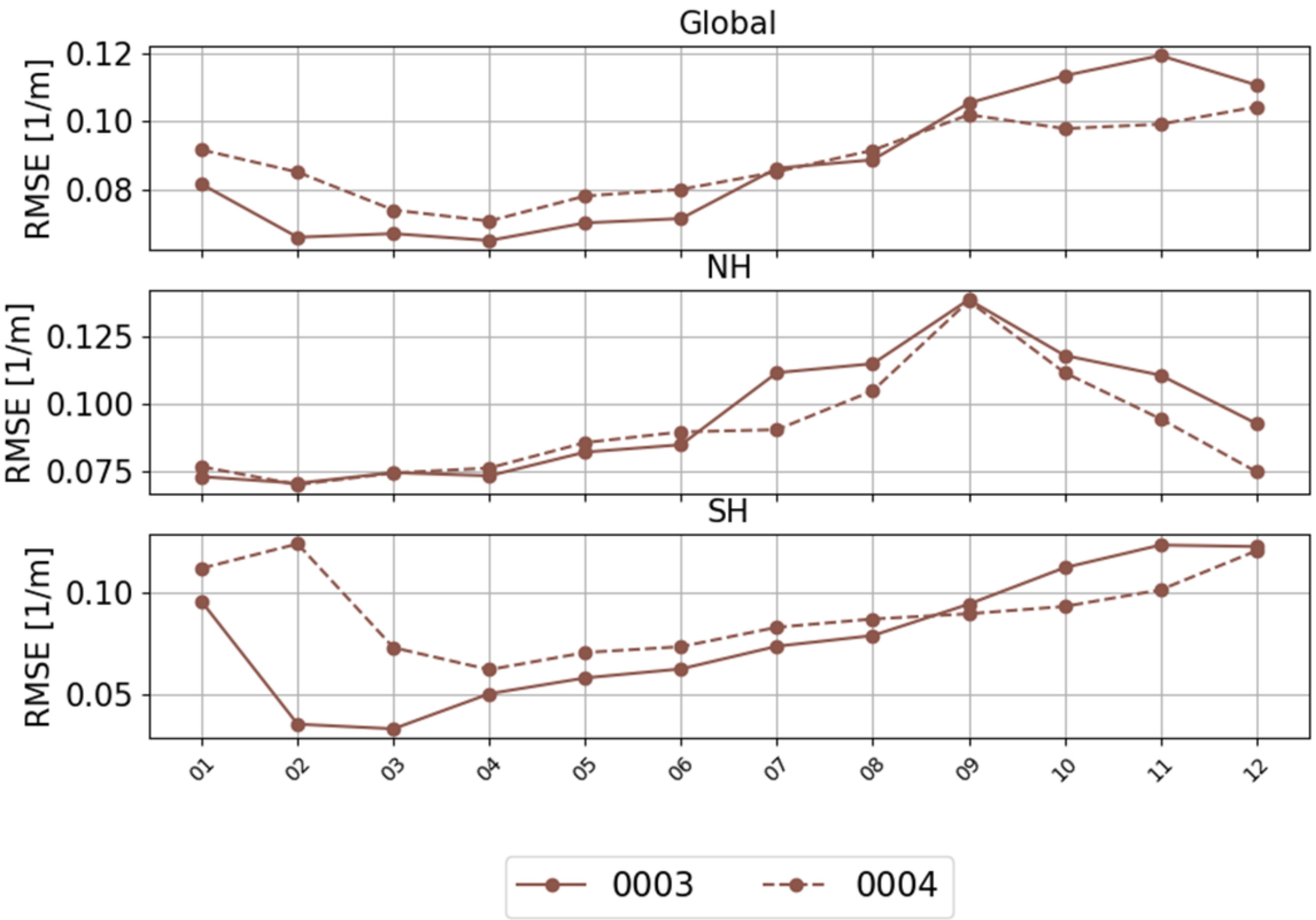
Sequential Feature Selection (SFS)

Goal: ranking of the most informative input features



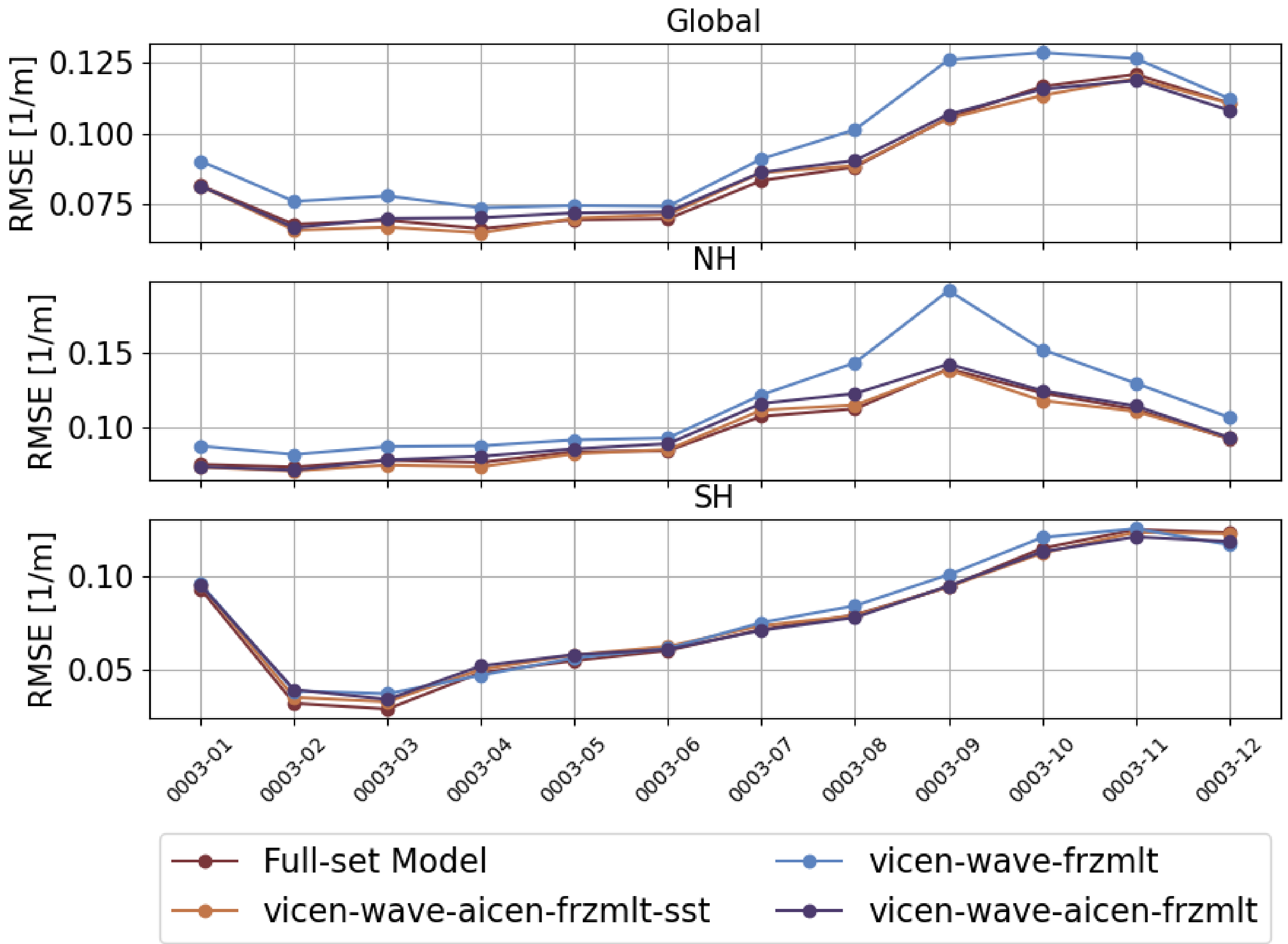
Comparison SFS5: 0003 and 0004

- Similar NN performance in both years



Reduced input set

- Both vicen and aicen needed



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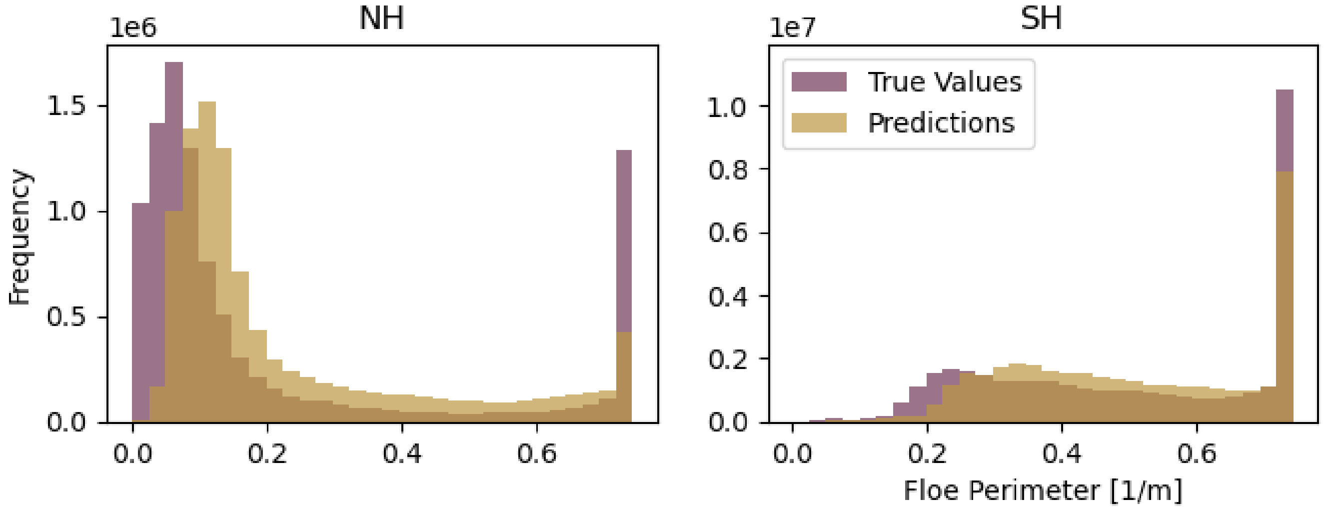
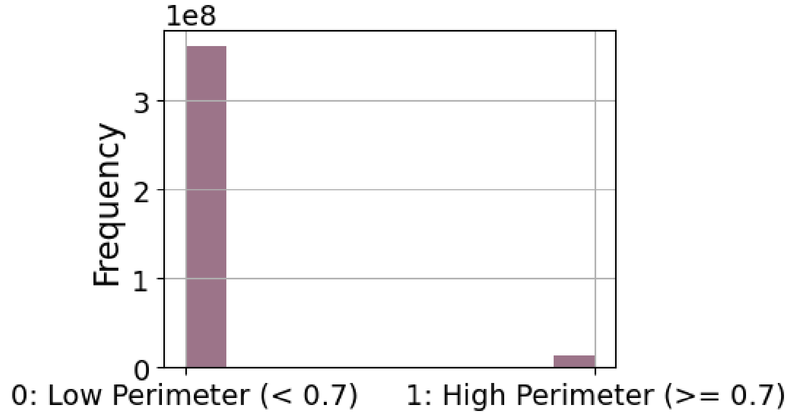
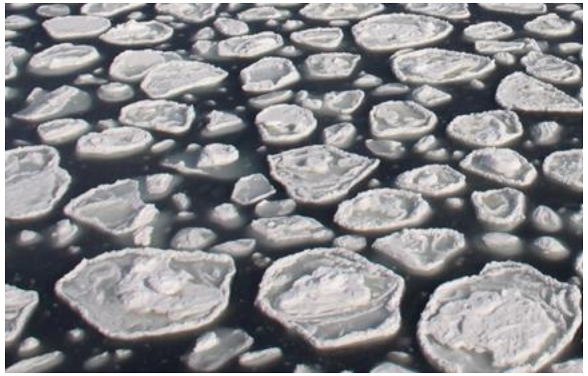
0003-09, SFS5 predictions



Binary classification





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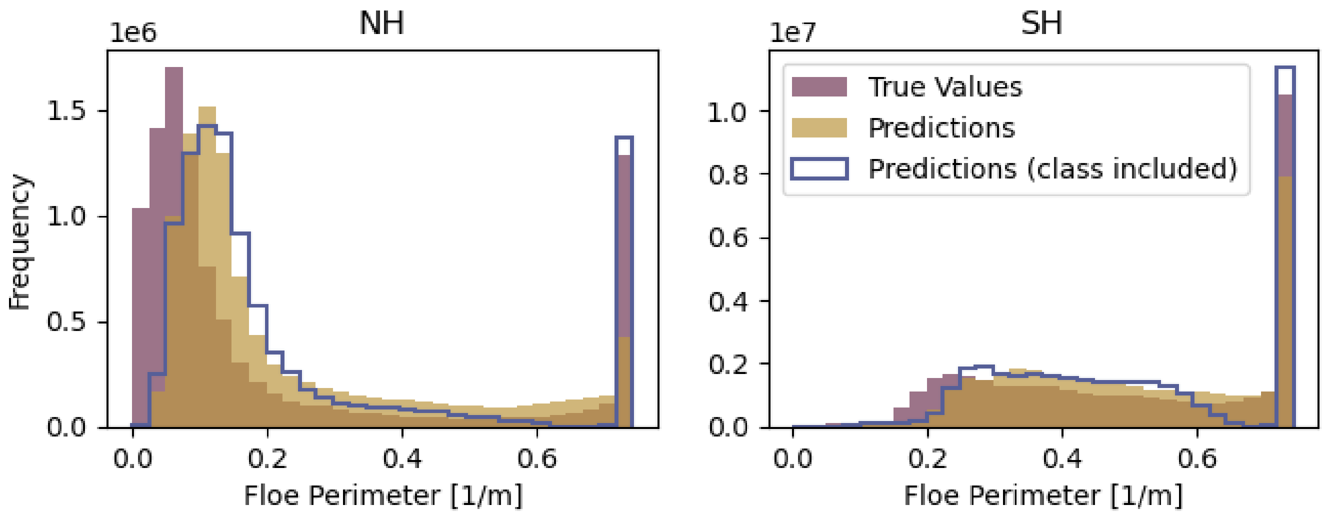
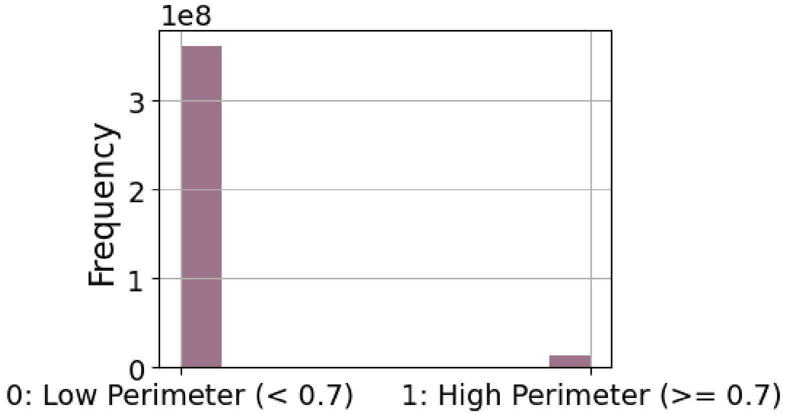
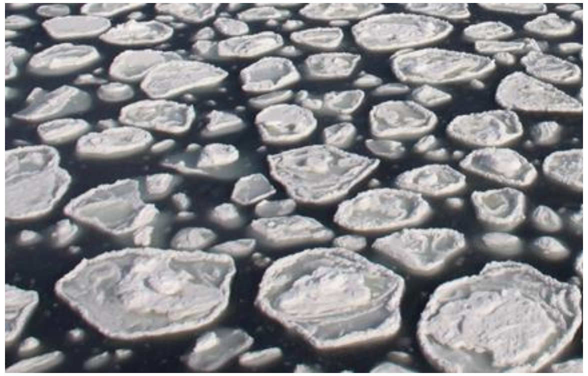
0003-09, SFS5 predictions



Binary classification



- Including binary class as input feature improves prediction of higher class (slight overestimation)
- No improvement of lower class



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