

Super-resolution of satellite observations of sea ice thickness using diffusion models and physical modeling

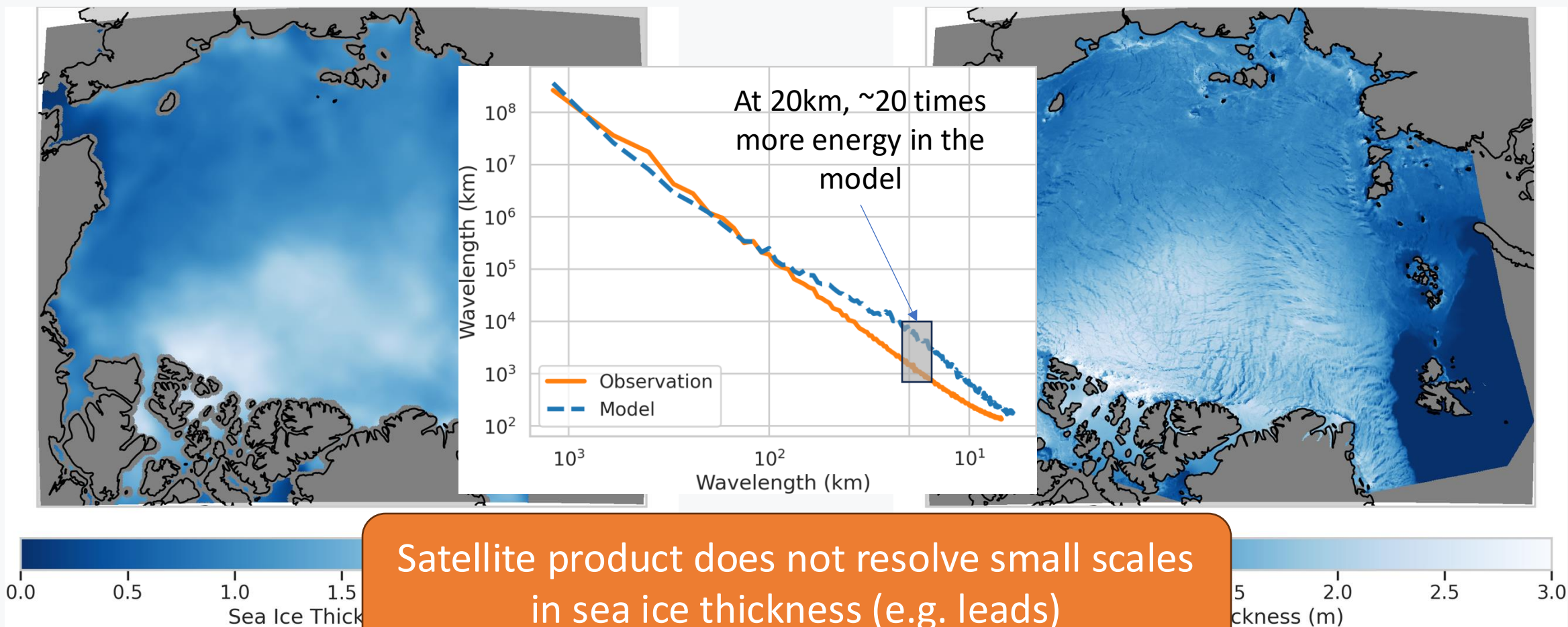
Julien Brajard, Fabio Mangini, Anton Korosov, Yiguo Wang, Richard Davy



Motivation

Satellite observation product (CS2SMOS)

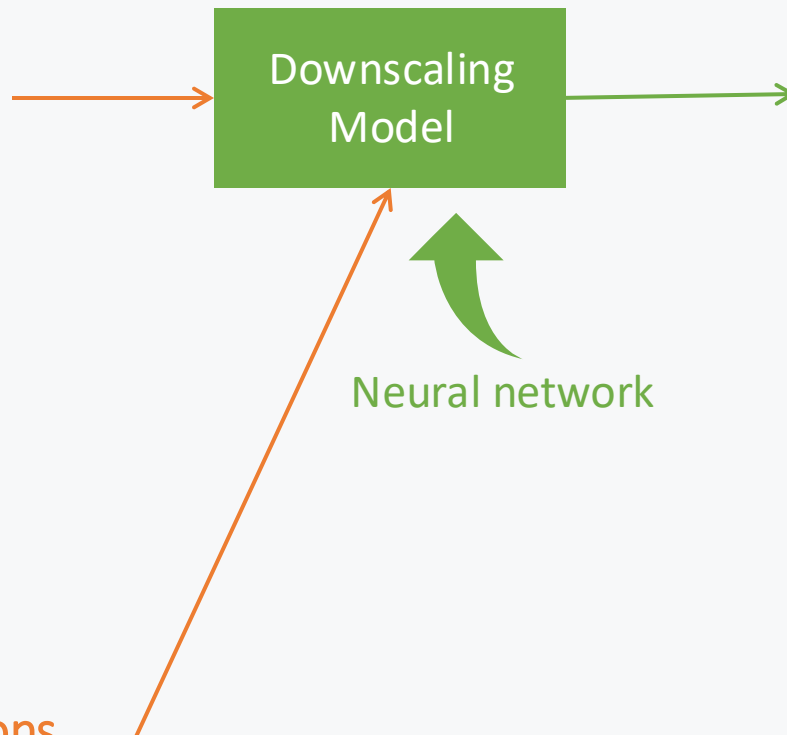
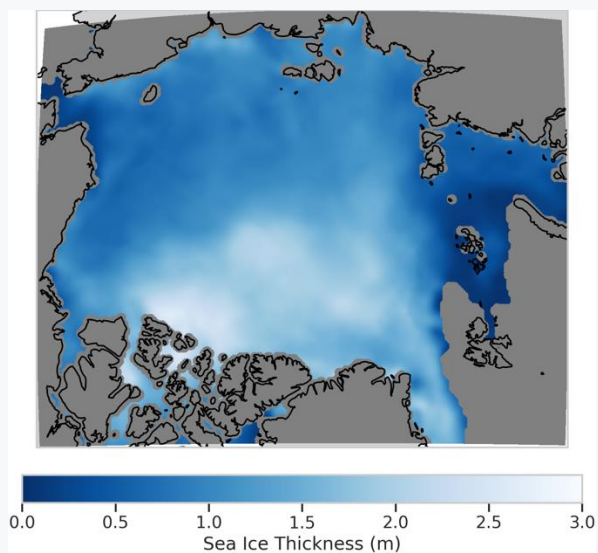
Physical model (NeXtSIM) forecast



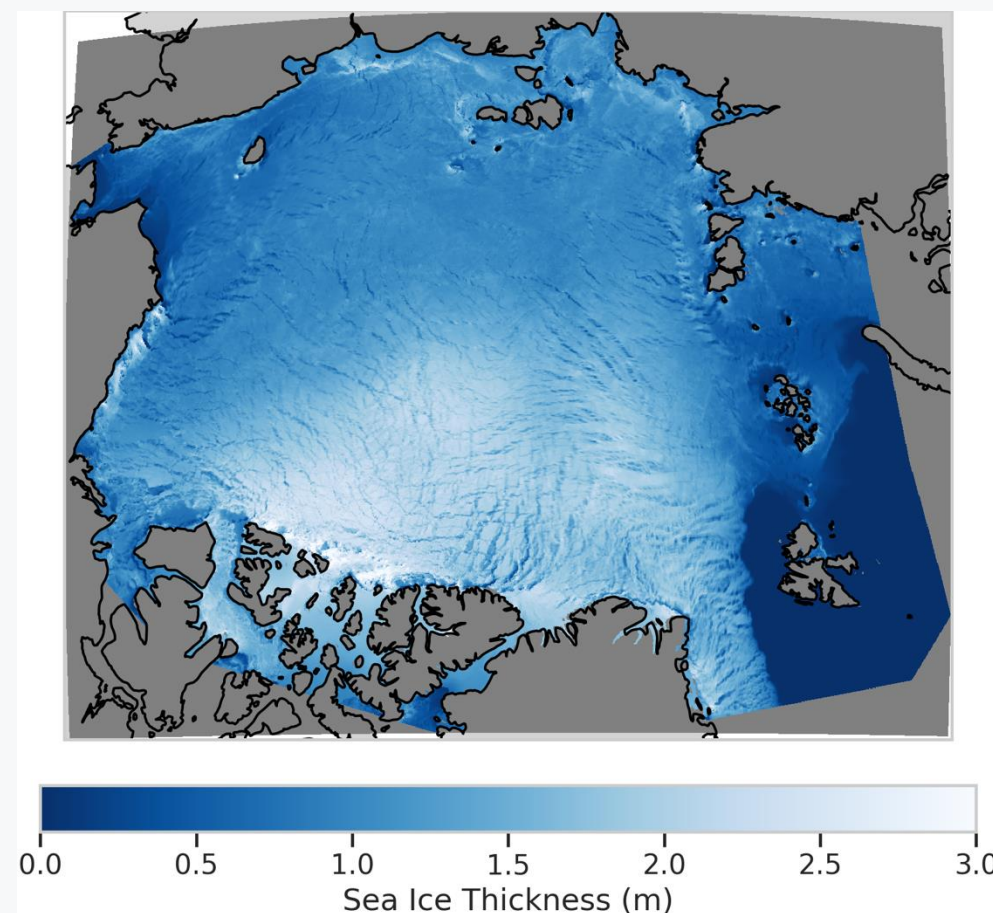
Satellite product does not resolve small scales in sea ice thickness (e.g. leads)

Our Objective: downscaling

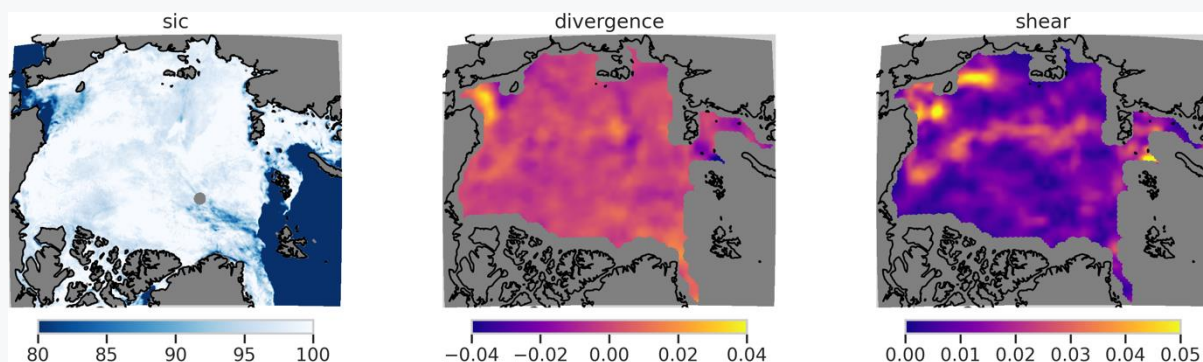
Low-resolution observation



High-resolution sea ice thickness



+ Other low-resolution observations



Our Objective: downscaling

probabilistic



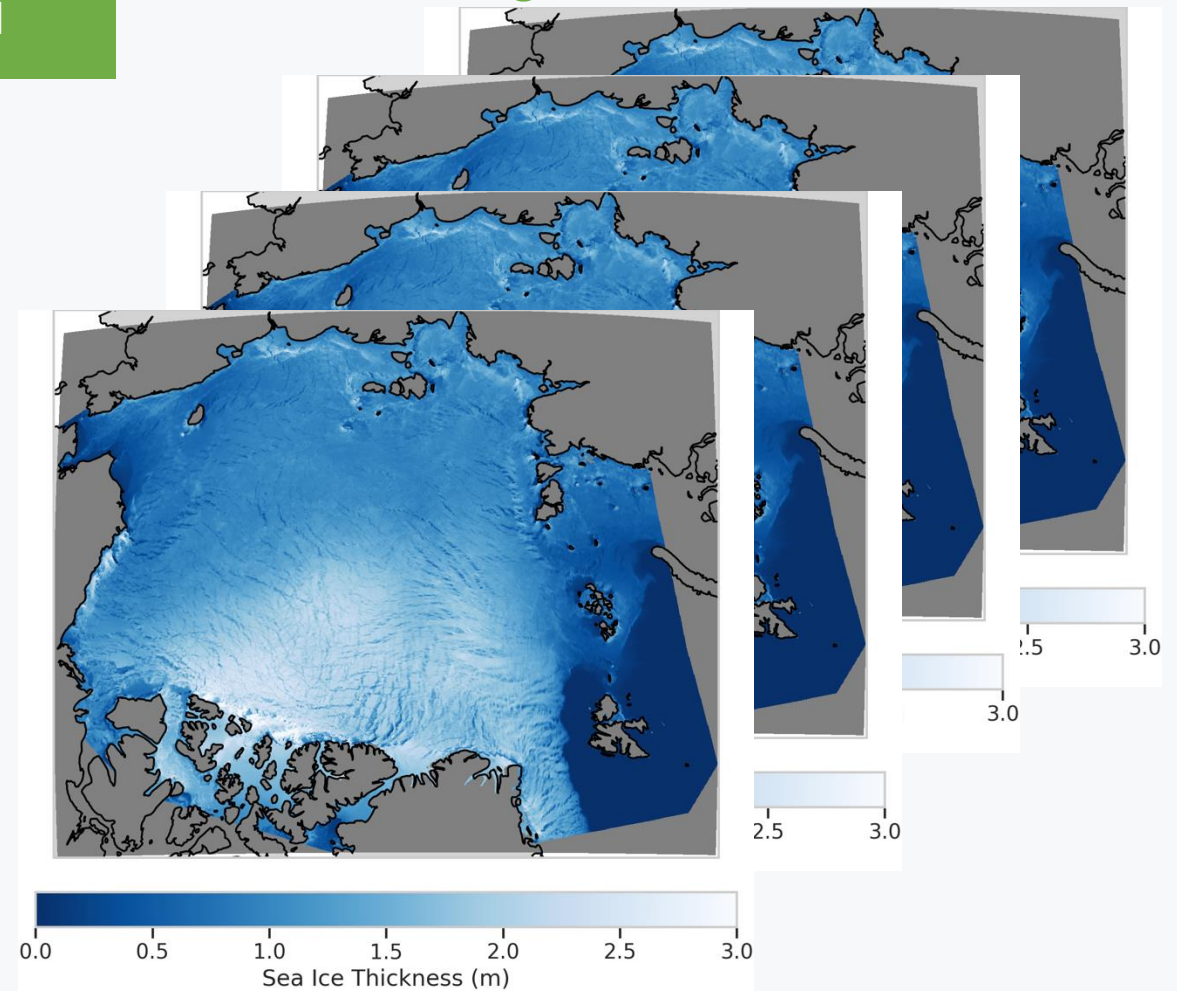
x
Low-resolution observations



y
High-resolution sea ice thickness

Deterministic downscaling: $y = f(x)$

Probabilistic downscaling: $P(y|x)$



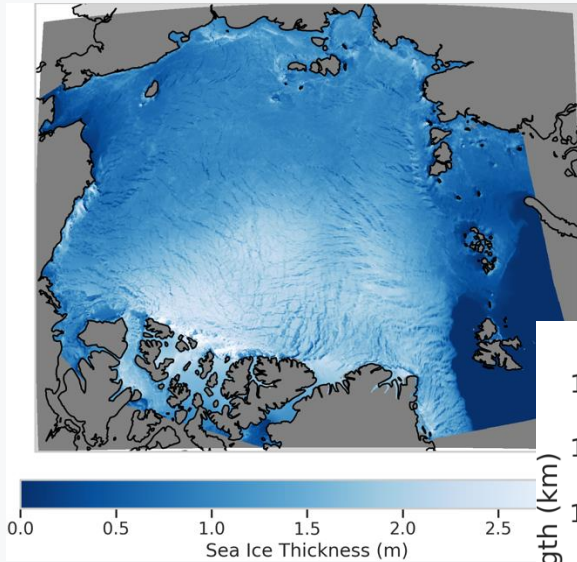
What do we need?

- ✓ A training set of matching pairs of low-resolution/high-resolution fields
- ✓ A probabilistic model
- ✓ Relevant metrics for validation
- ✓ Apply to observation

Dataset constitution

Principle: Using **high-resolution NeXtSIM simulations** [Ólason et al., 2022] and process them to match the resolution of **the observations**.

NeXtSIM sea ice thickness (res ~3km)

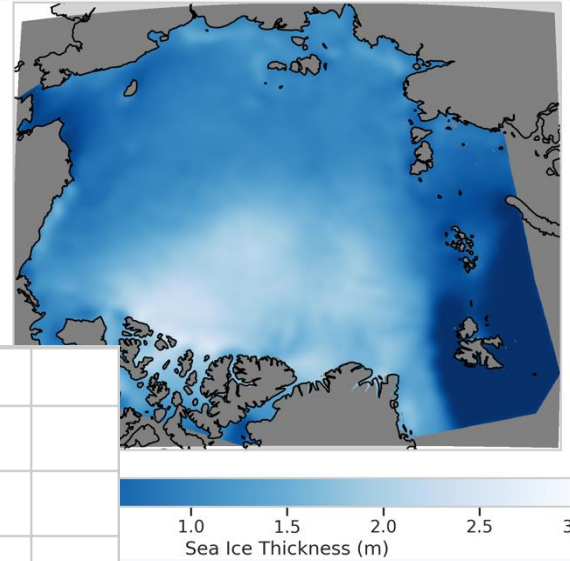


y

Smoothing with a Gaussian kernel
(size 33 km)

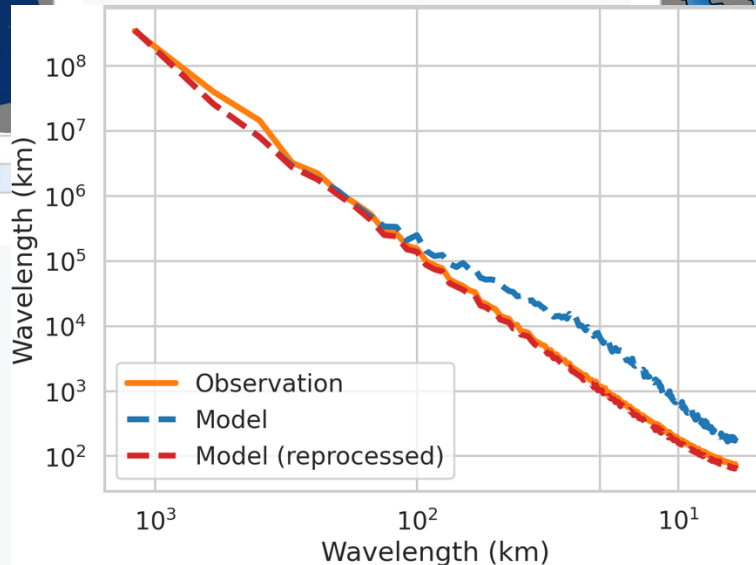
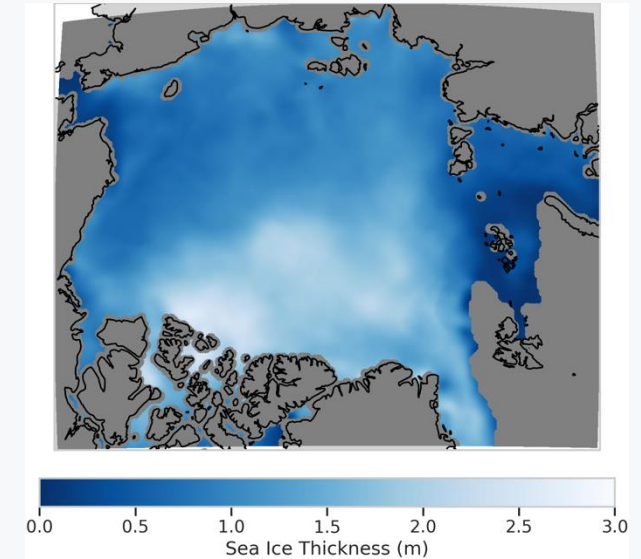


Reprocessed neXtSIM



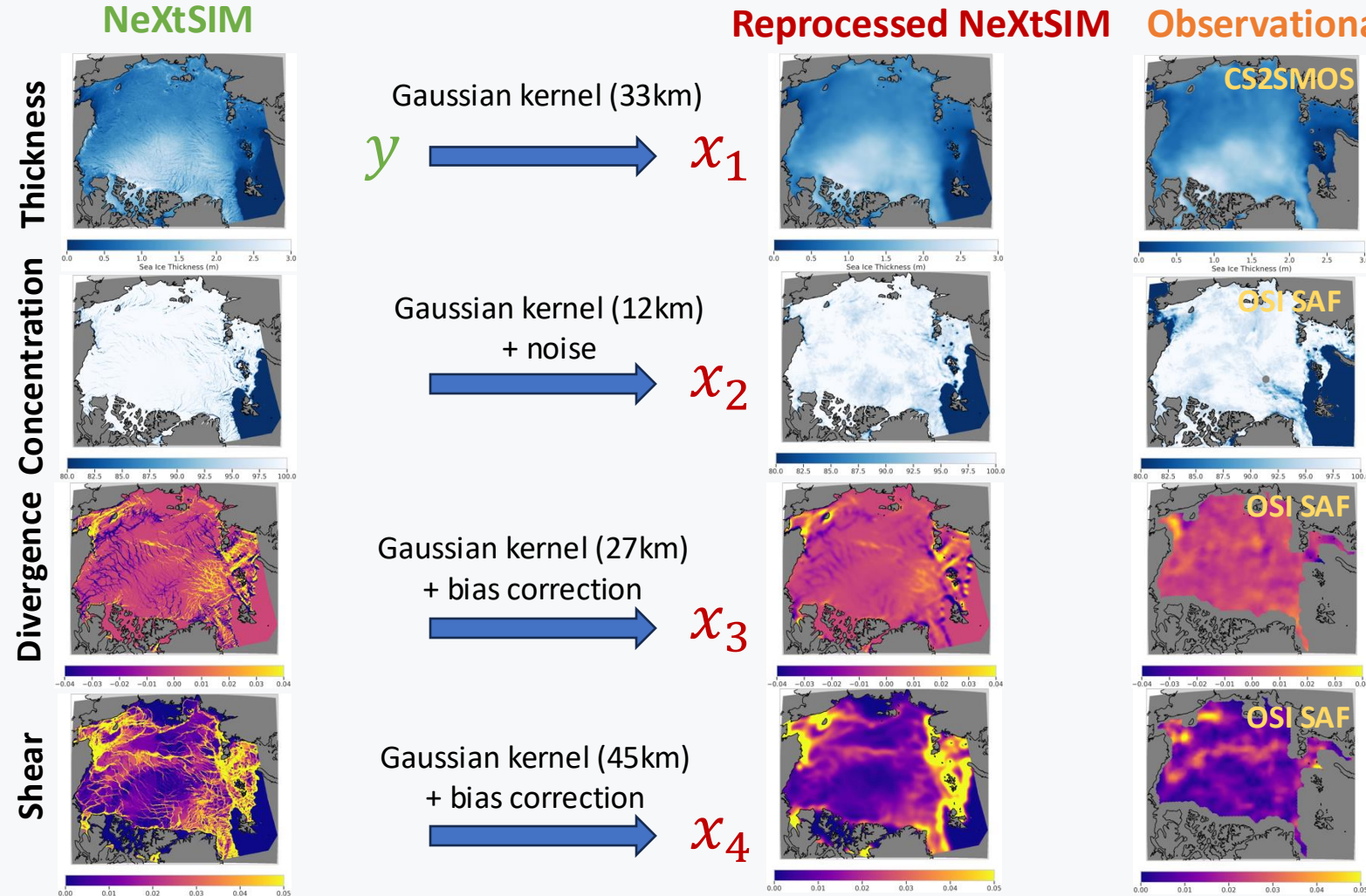
x

CS2SMOS (observational product)



Dataset constitution

Same procedure for Sea Ice concentration, divergence and shear (to be used as input feature)



Dataset: $([x_1, x_2, x_3, x_4], y)$

- ✓ Divergence and Shear are transformed into the total deformation
- ✓ A land mask is added
- ✓ Samples in freezing season:
 - ✓ Training: 2013-2020 (1157 samples)
 - ✓ Validation: 2020-2022 (360 samples)
 - ✓ Test: 2022-2023 (180 samples)

Download the dataset 

What do we need?

- ✓ A training set of matching pairs of low-resolution/high-resolution fields
- ✓ A probabilistic model
- ✓ Relevant metrics for validation
- ✓ Apply to observation

Generative machine learning



Probabilistic downscaling: $P(y|x)$

Generate an ensemble of realization of high-resolution sea ice thickness y

knowing low-resolution fields x

x : condition, context, prompt

Diffusion models!



Used by DALL-E, Midjourney, ...

Example of a prompt:

"Realistic image of a ship navigating in the Arctic sea-ice"

<https://openart.ai>



Generative machine learning

Probabilistic downscaling: $P(y|x)$

Generate an ensemble of realization of high-resolution sea ice thickness y

knowing low-resolution fields x

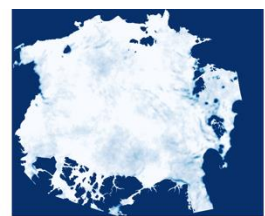
x : condition, context, prompt

Diffusion models!

Used by DALL-E, Midjourney, ...

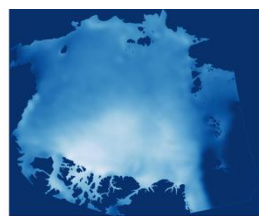


low-resolution context x



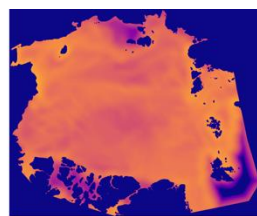
80 85 90 95 100

concentration



0 1 2 3

thickness



-2 0 2 4 6

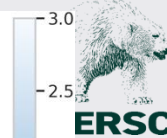
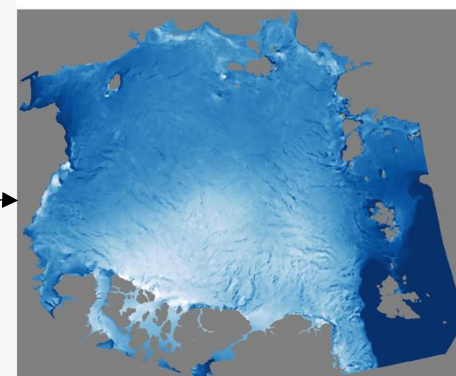
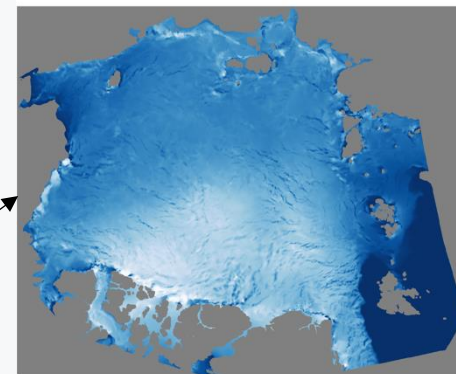
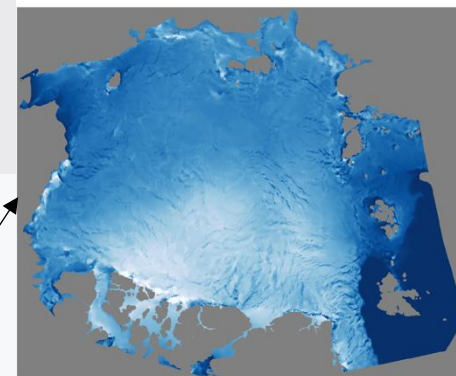
deformation



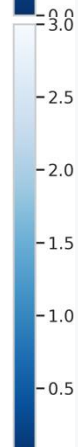
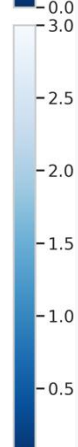
0.00 0.25 0.50 0.75 1.00

mask

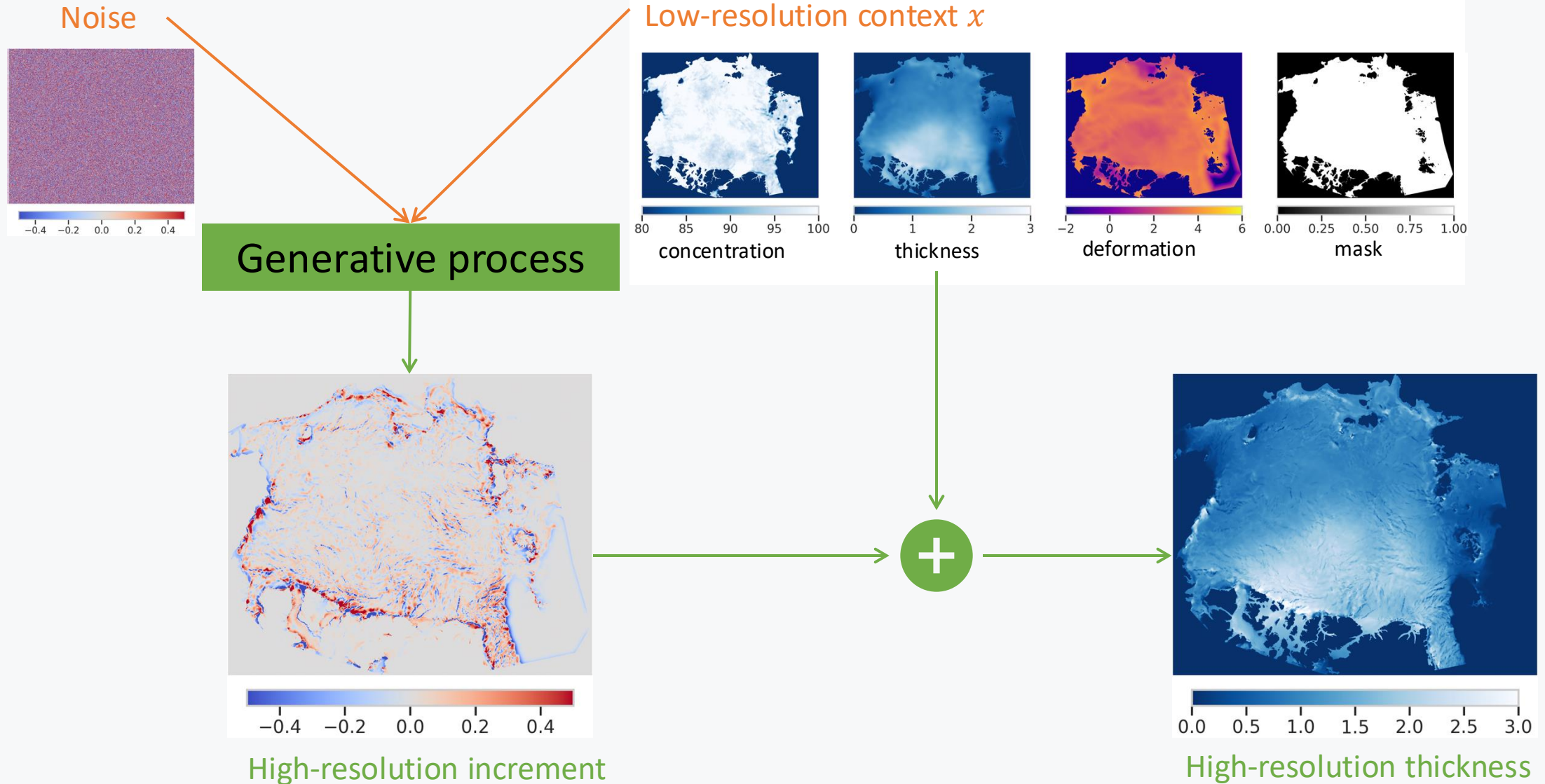
High-resolution sea ice thickness



ERSC

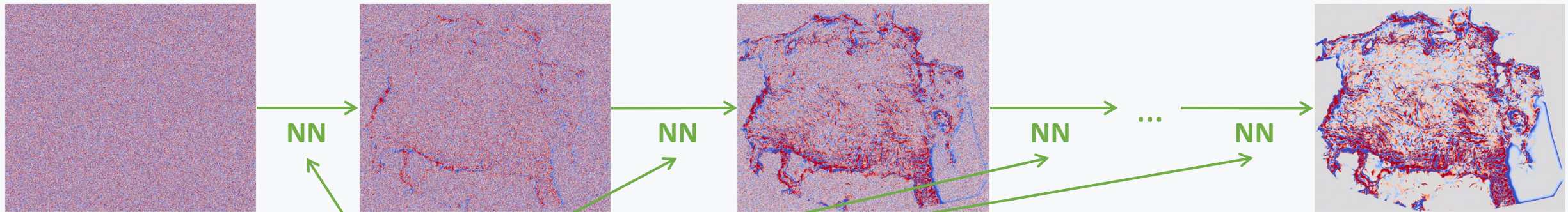


Applying the diffusion model to sea ice super-resolution

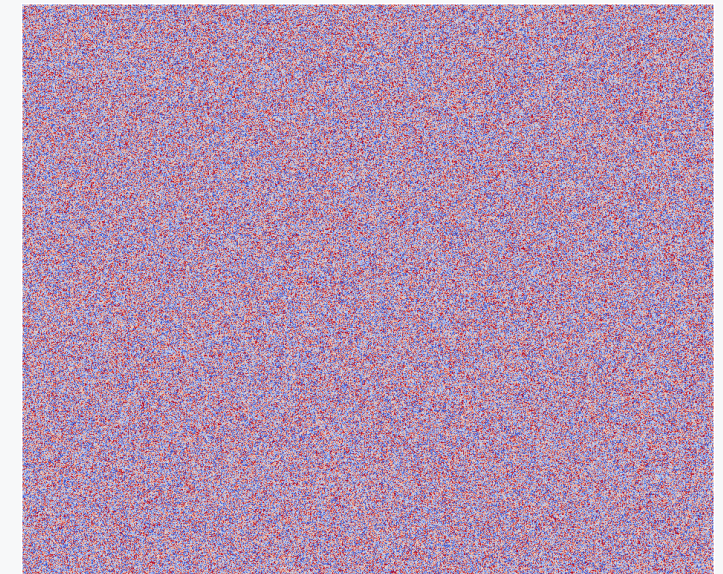
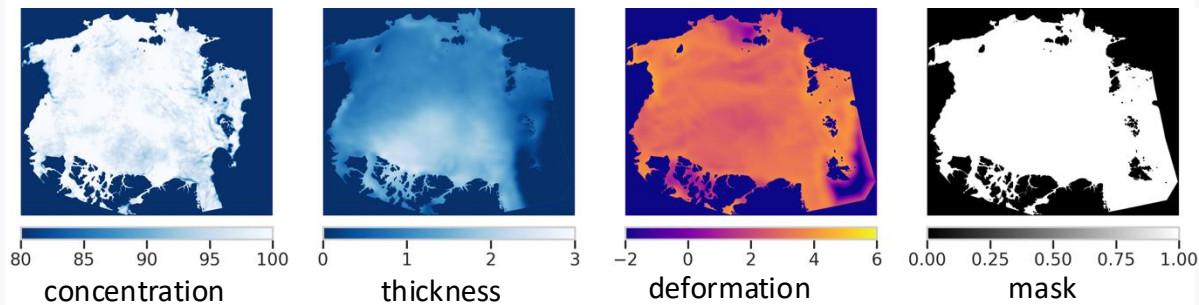


Diffusion models – how do they work?

A **neural network** as a recursive denoiser



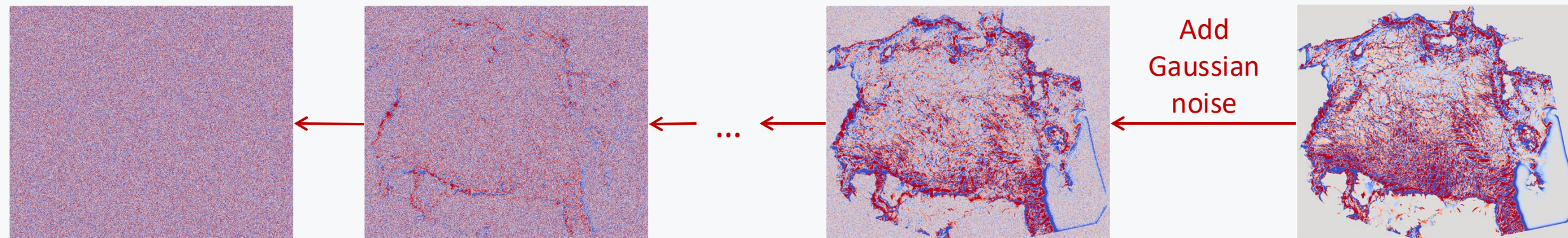
Low-resolution context x



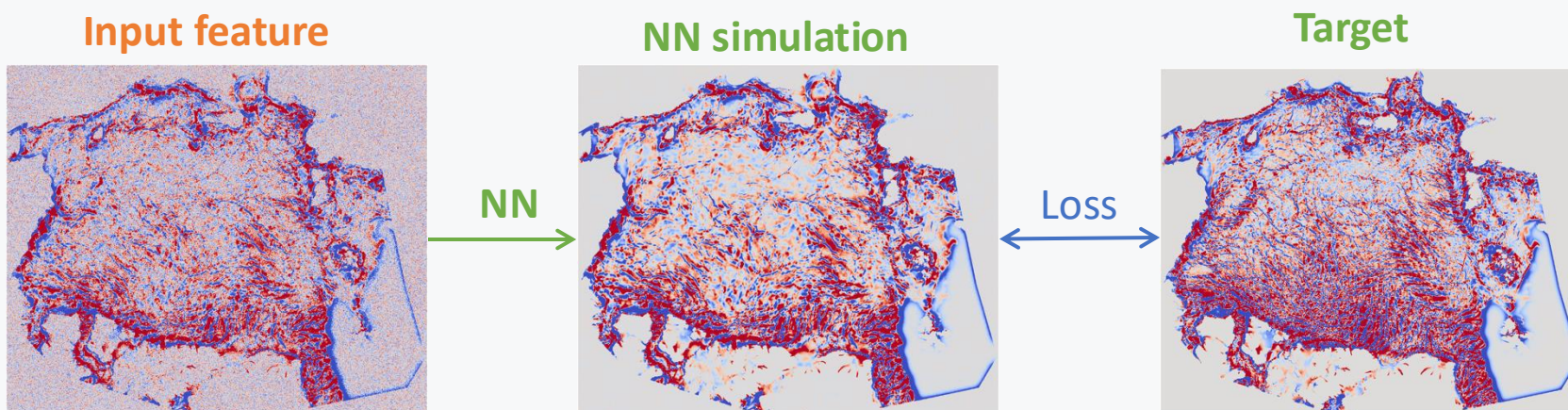
Training a diffusion model

The **noising process** is straightforward

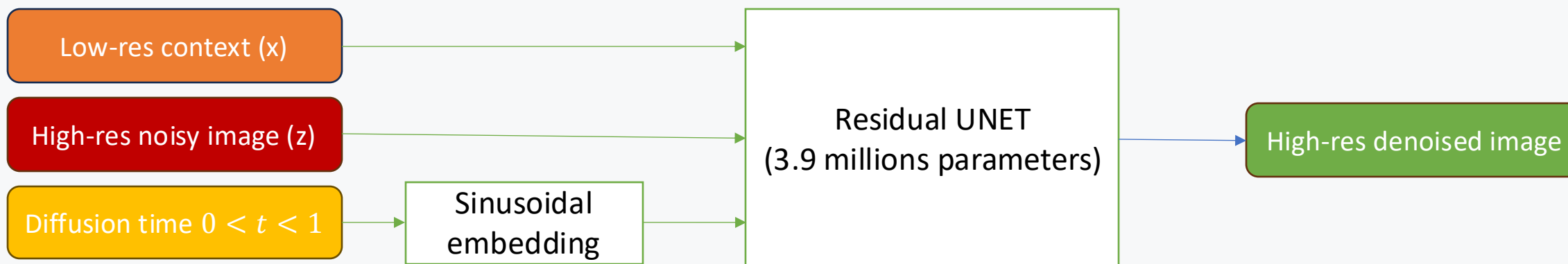
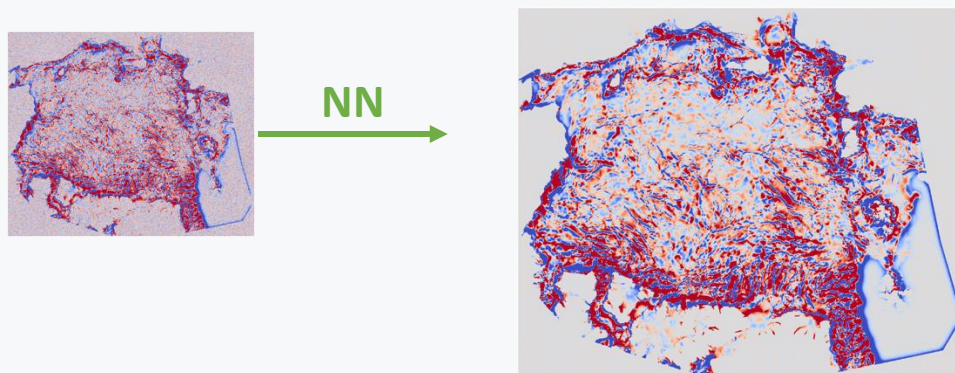
High-resolution increment
from the training set



One training sample (draw a level of noise between 0 and 1):

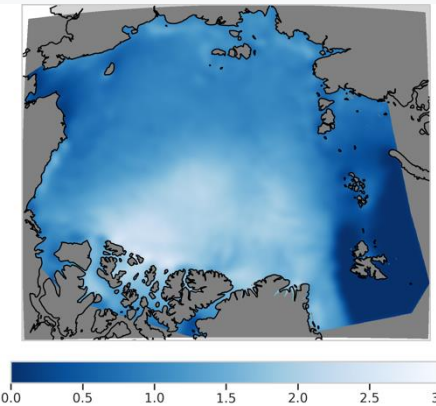
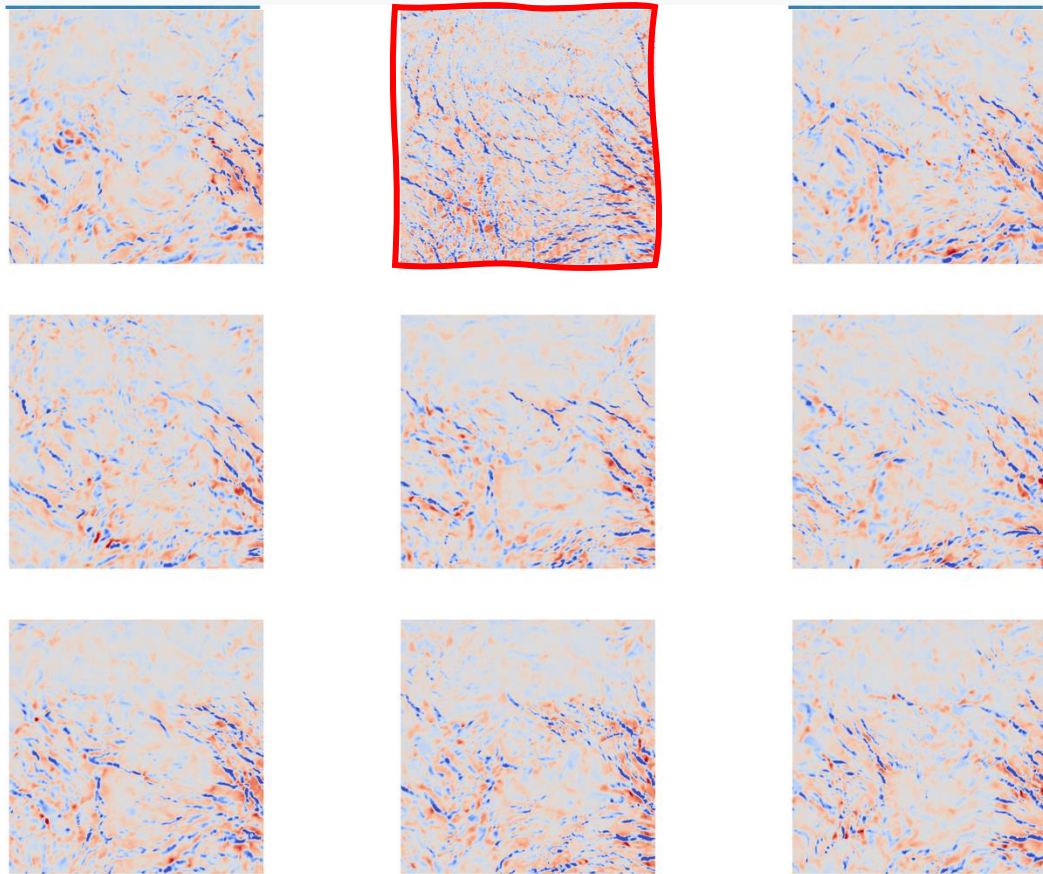


Implementation details



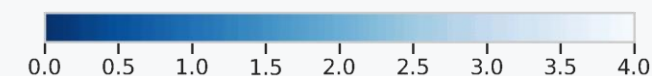
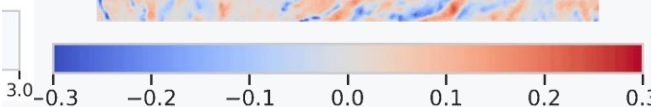
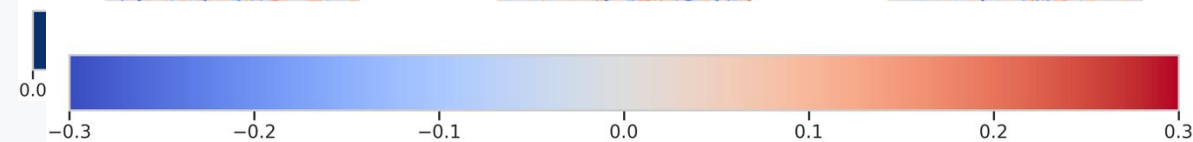
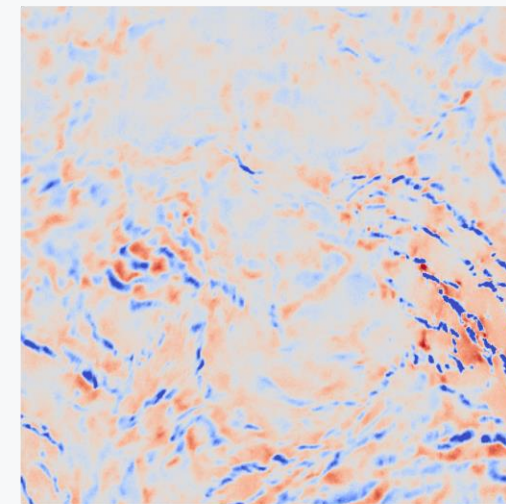
Generation January 1, 2021

Generated ensemble of sea ice thickness



From the low-resolution thickness

SIT mem 0 - 20210101

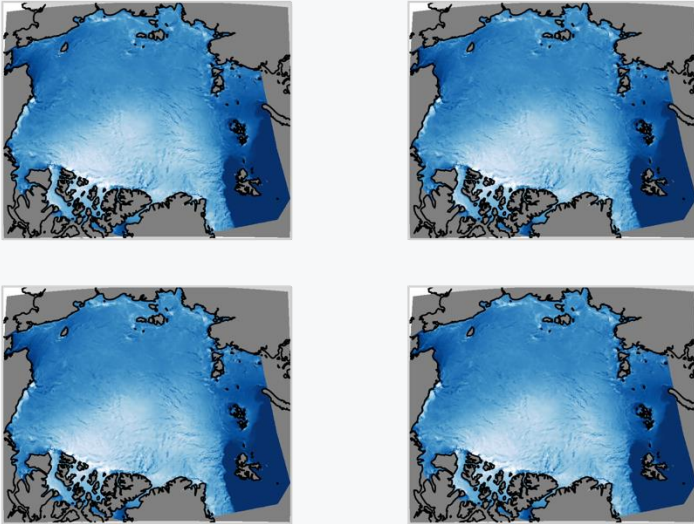


What do we need?

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- ✓ Apply to observation

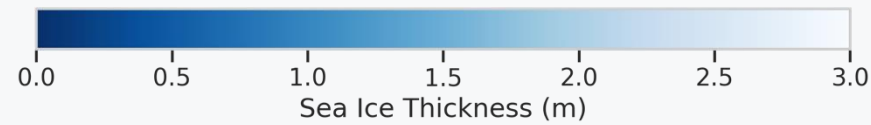
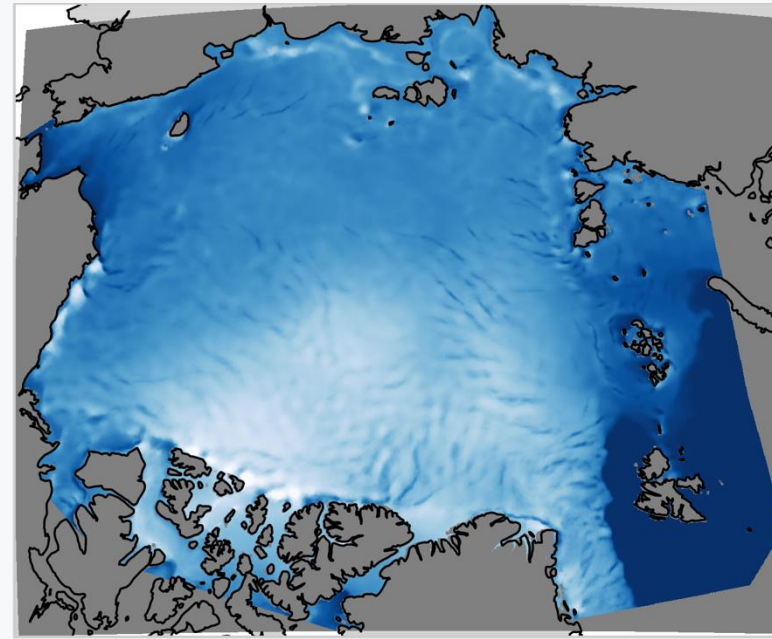
Different “products”

Individual members



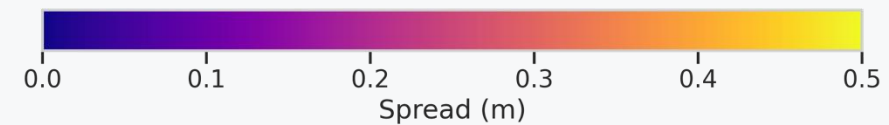
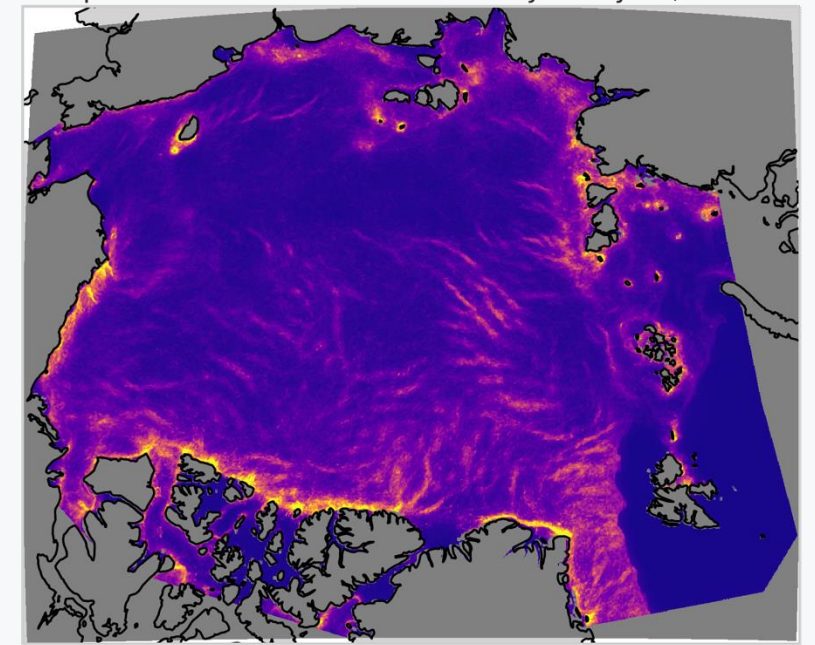
Used to assess
realism

Ensemble mean



Used to assess
accuracy

Spread

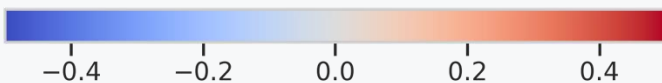
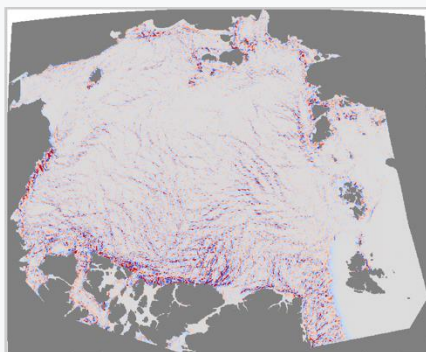
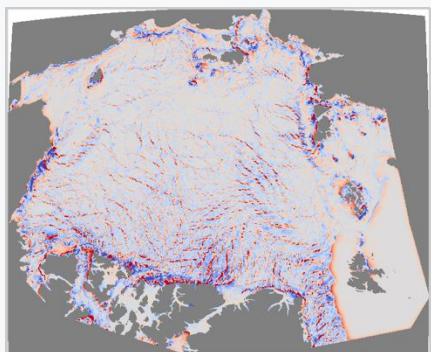


Used to assess
uncertainty

Accuracy of the super-resolution

Error low-resolution

Error AI ensemble mean

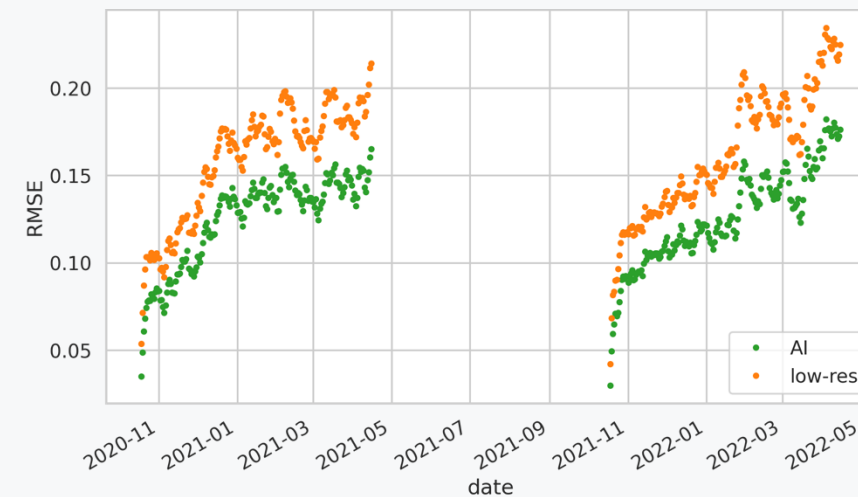


Root-mean square error (RMSE) of:

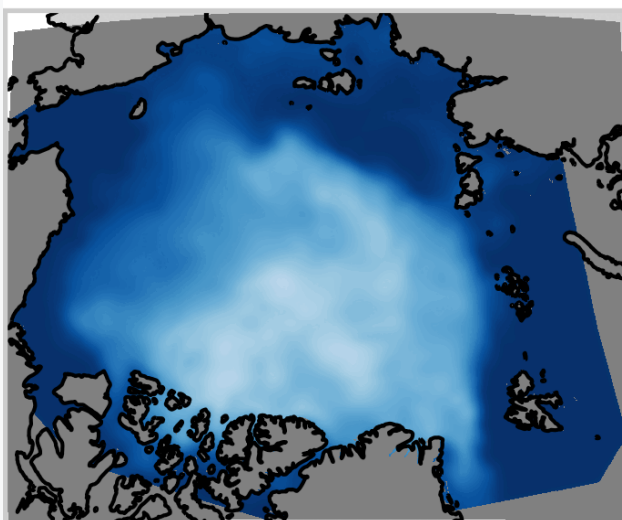
Low-resolution: 0.16 m

AI product: 0.13 m

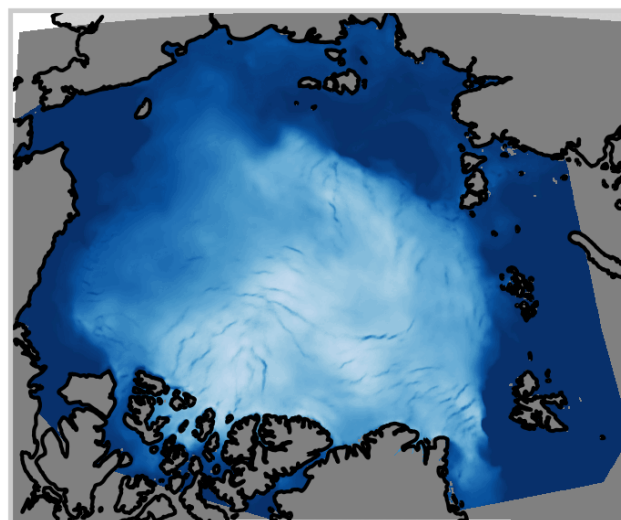
Improvement: 20%



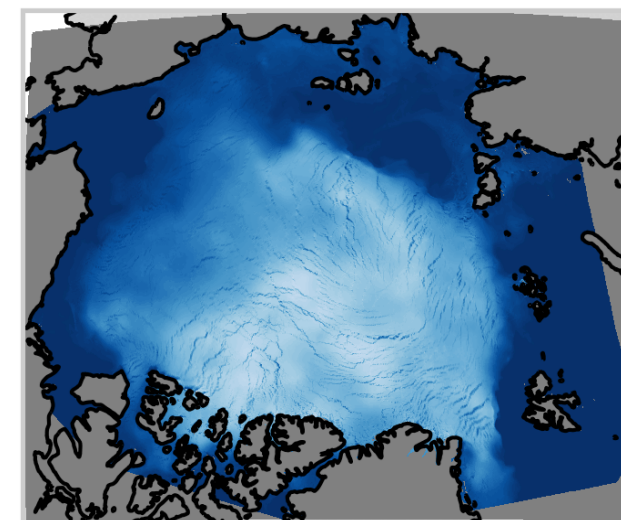
SIT low-res 20211022



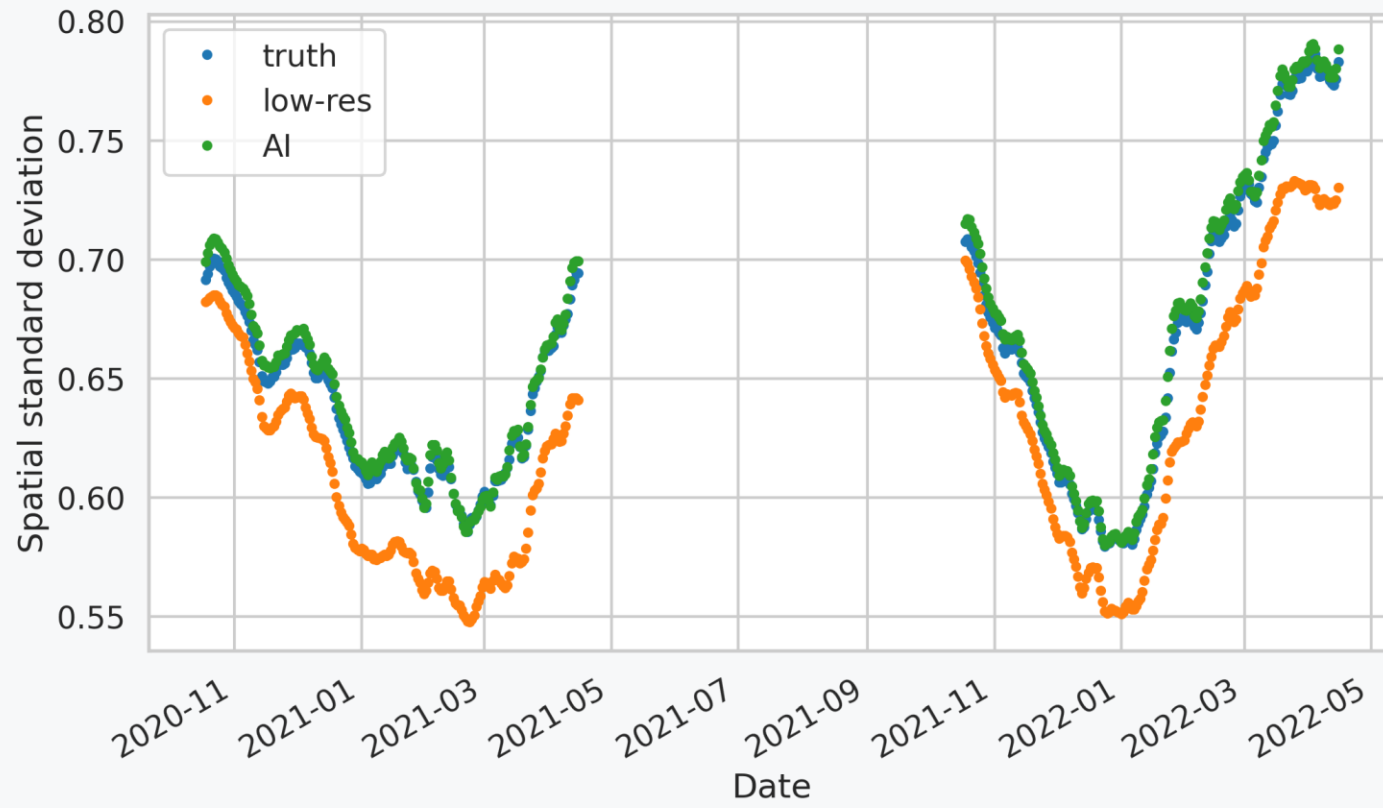
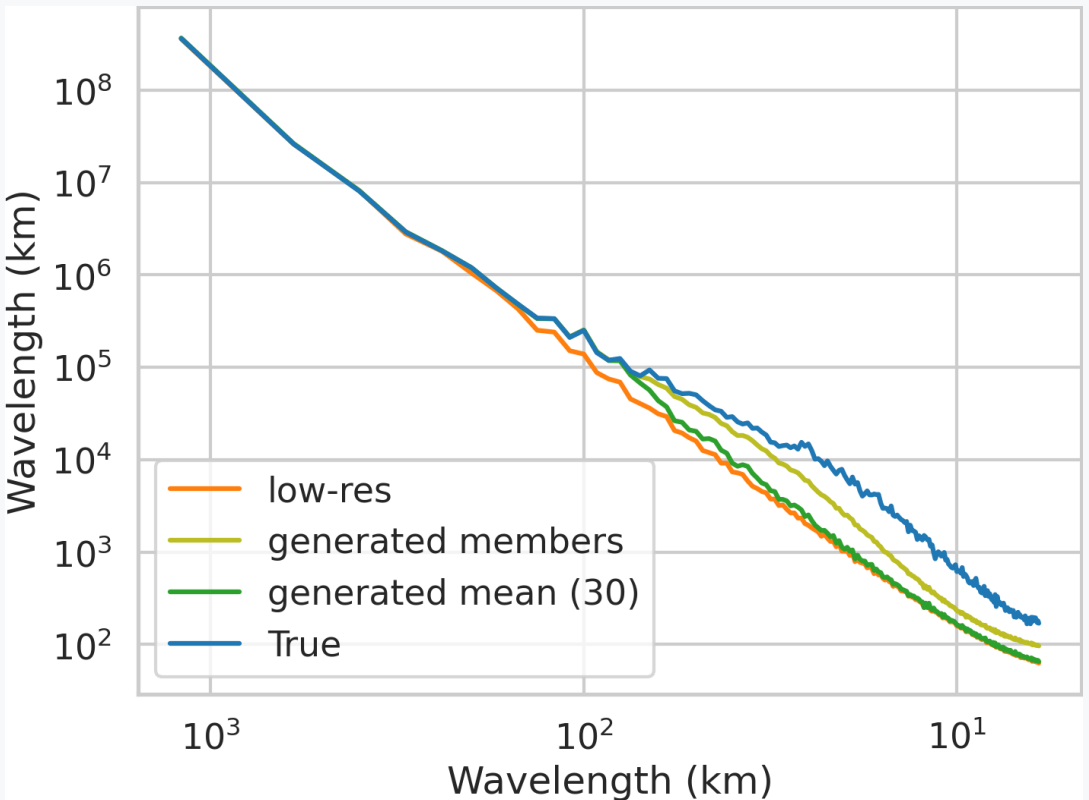
SIT AI 20211022



Ref 20211022



Realism



What do we need?

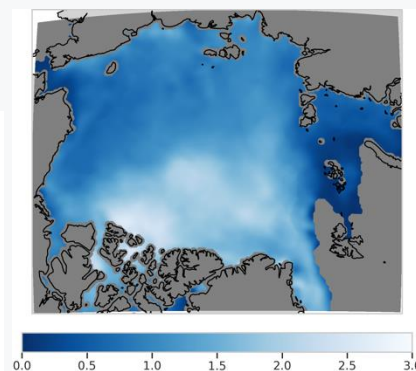
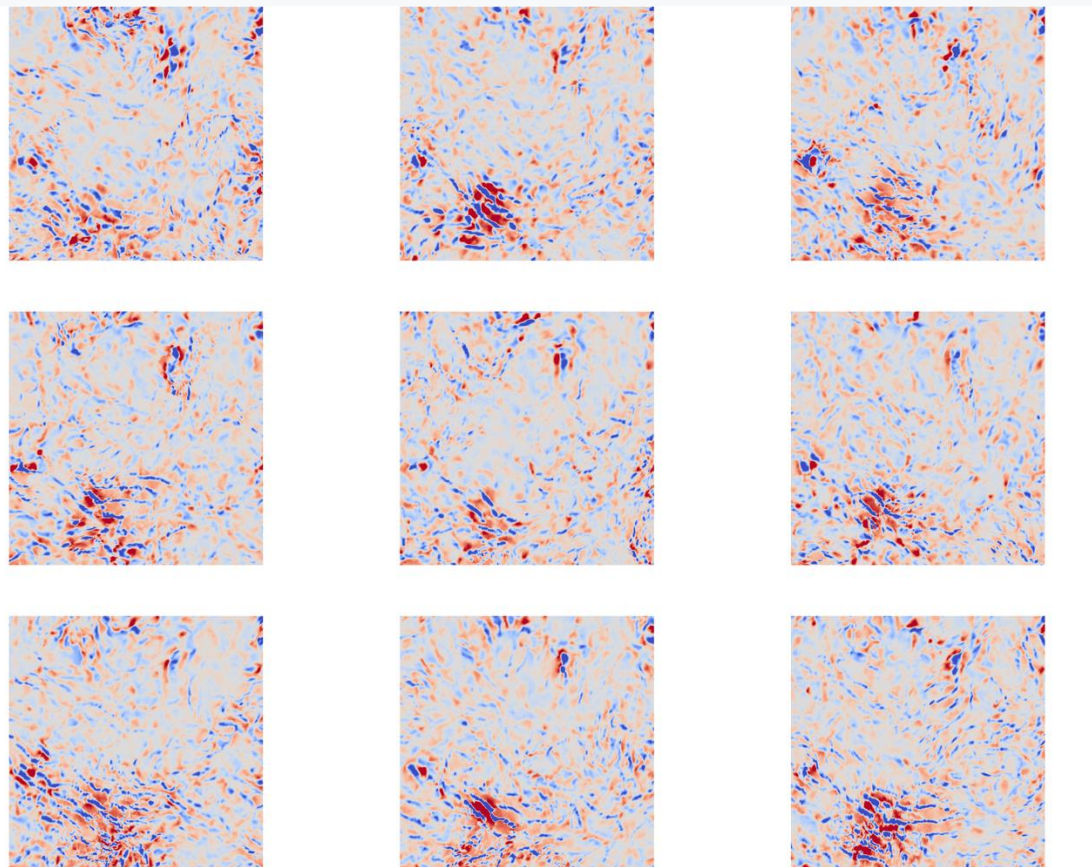
- ✓ A training set of matching pairs of low-resolution/high-resolution fields
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Generation from observations

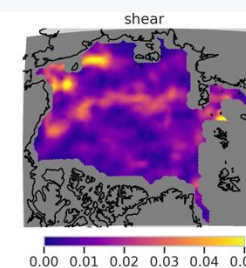
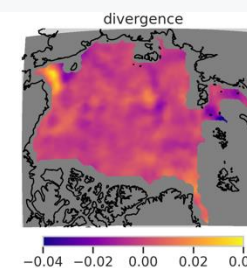
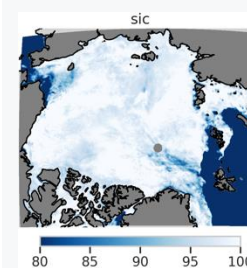
From the low-resolution
thickness (CS2SMOS)



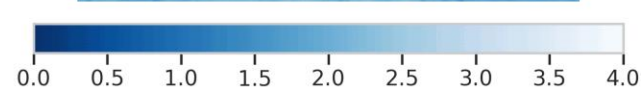
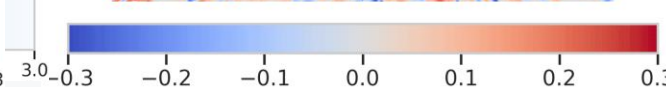
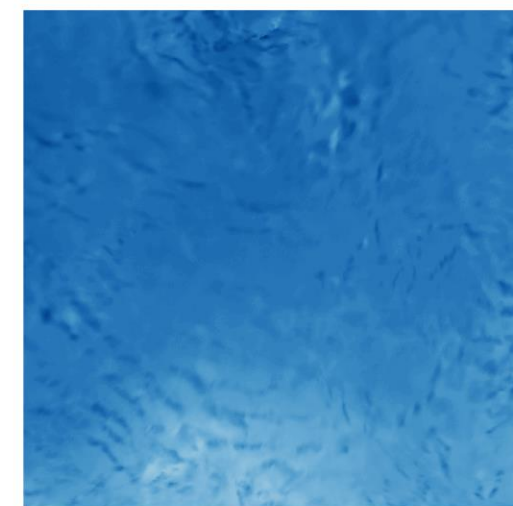
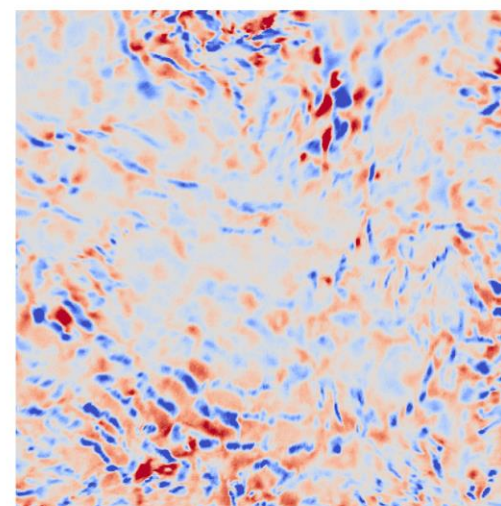
Generated ensemble of sea ice thickness



+ other observations

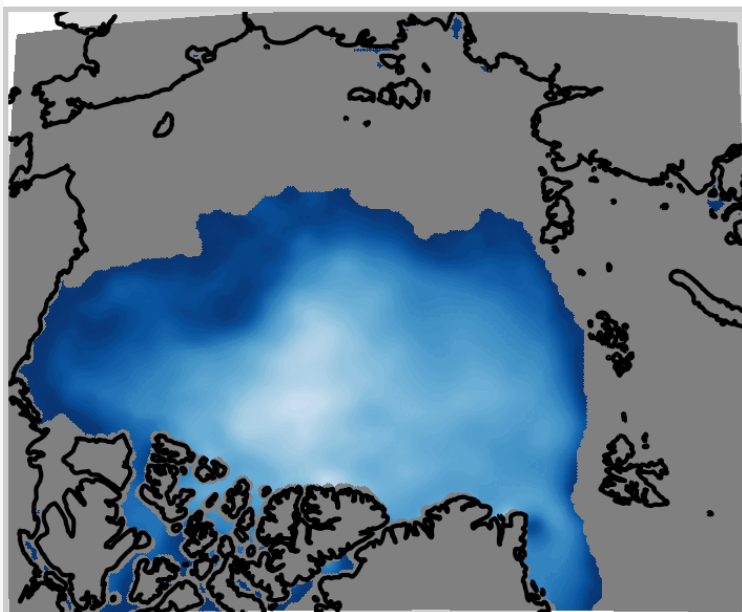


SIT mem 0 - 20210101

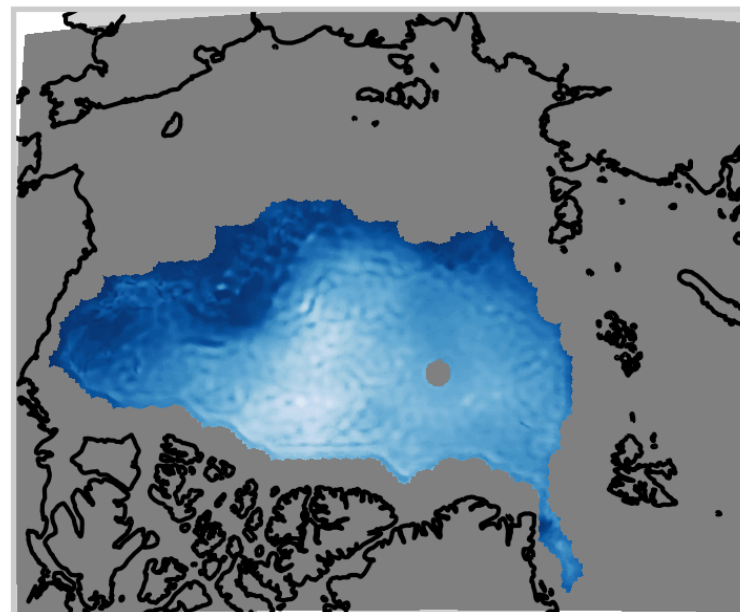


Observations 2020-2021

SIT low-res 20201022

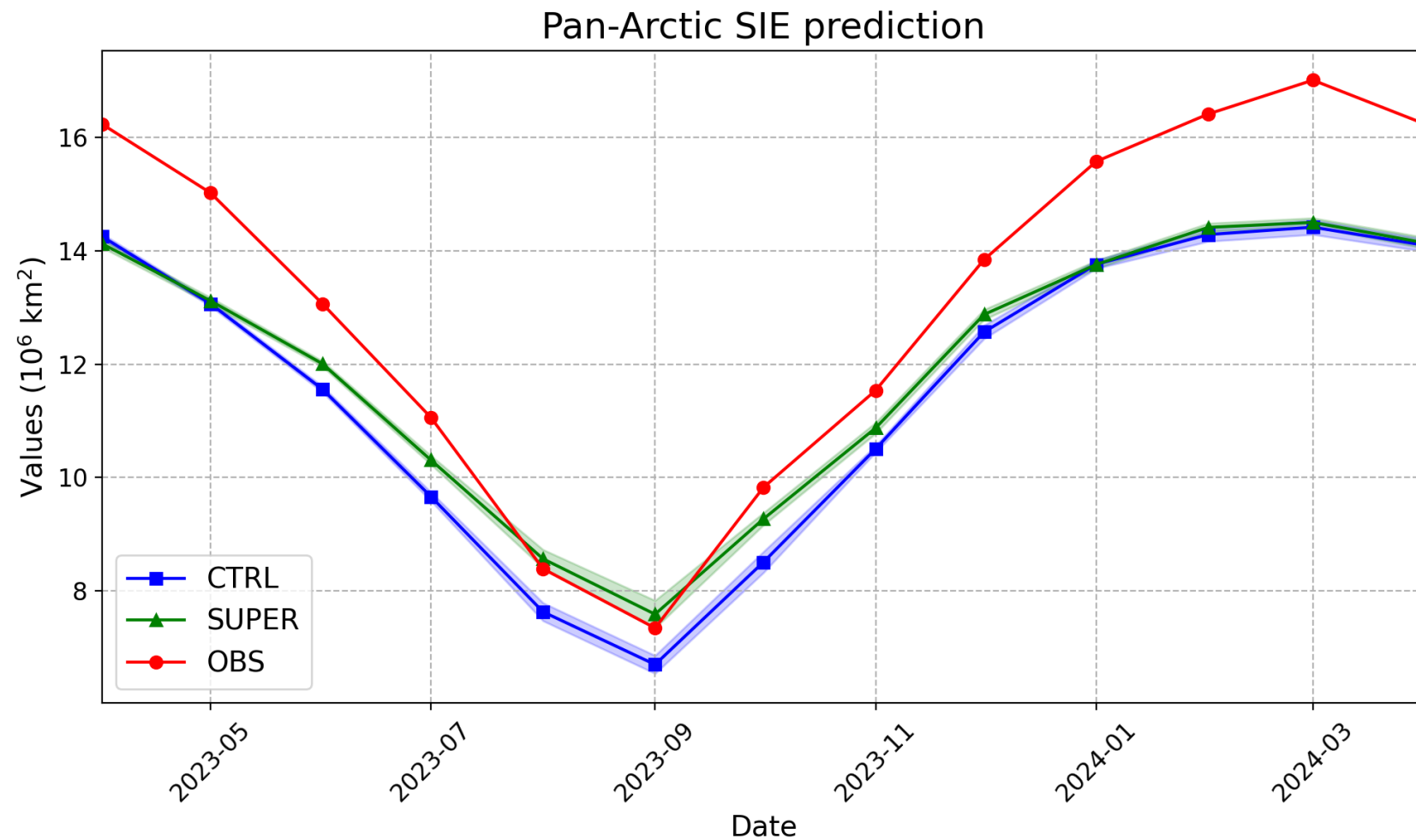


SIT AI 20201022



Case study for prediction from April 2023

CTRL: initialization with SIC and SIT observations (NOAA and CS2SMOS)
SUPER: initialization with category SI observations (SuperICE)
Obs: SIC observations (NOAA)



Take-home message

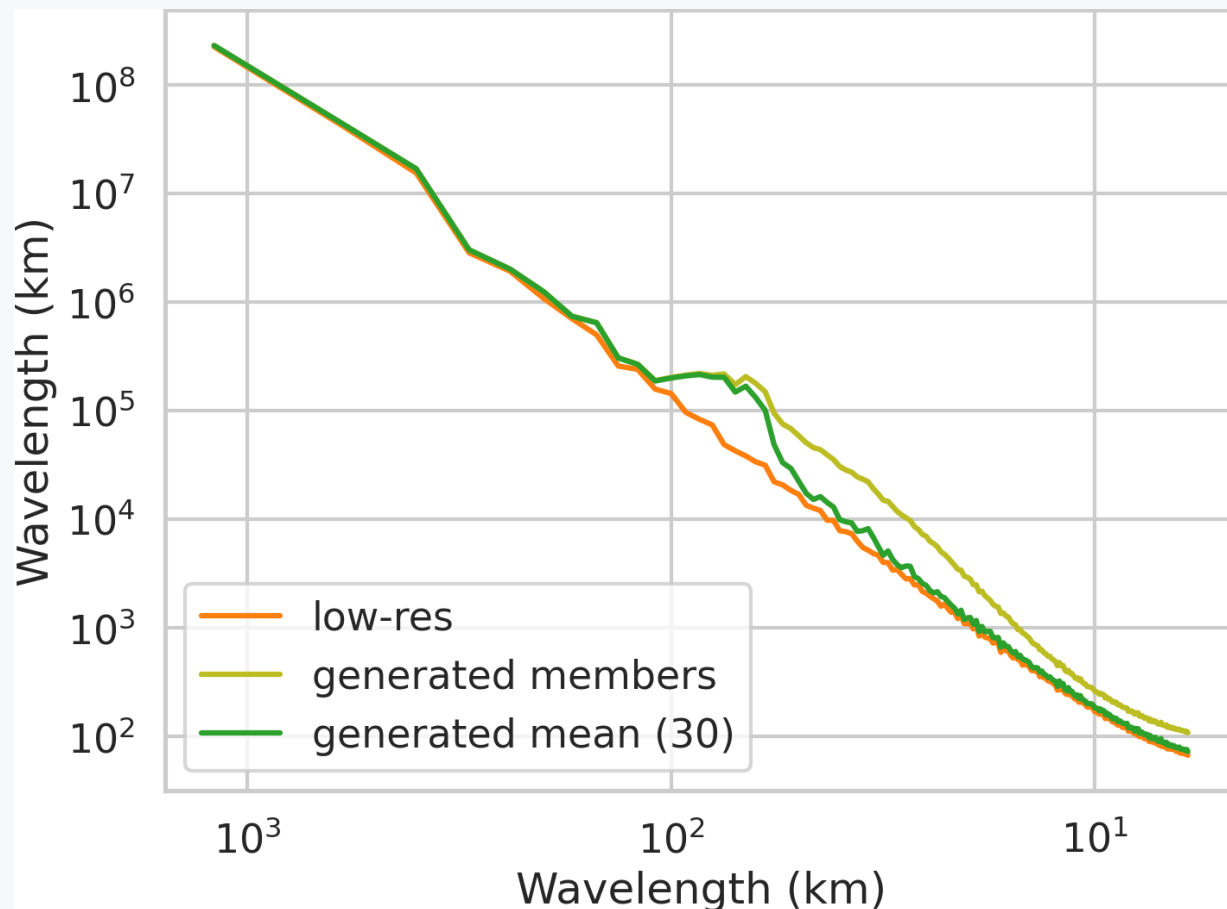


- **Diffusion models** can be used to generate **accurate** and **realistic** high-resolution sea ice thickness fields
 - Better accuracy and better realism compared with low-resolution field
- A model trained on a **realistic physical simulations** can be applied, **without retraining**, on observations (a few artifacts can appear)
- Super-resolution using diffusion models can be applied **to other sea ice variables** (actually, any geophysical variable)
- The dataset (both physical simulations and AI generation) is **available** for download

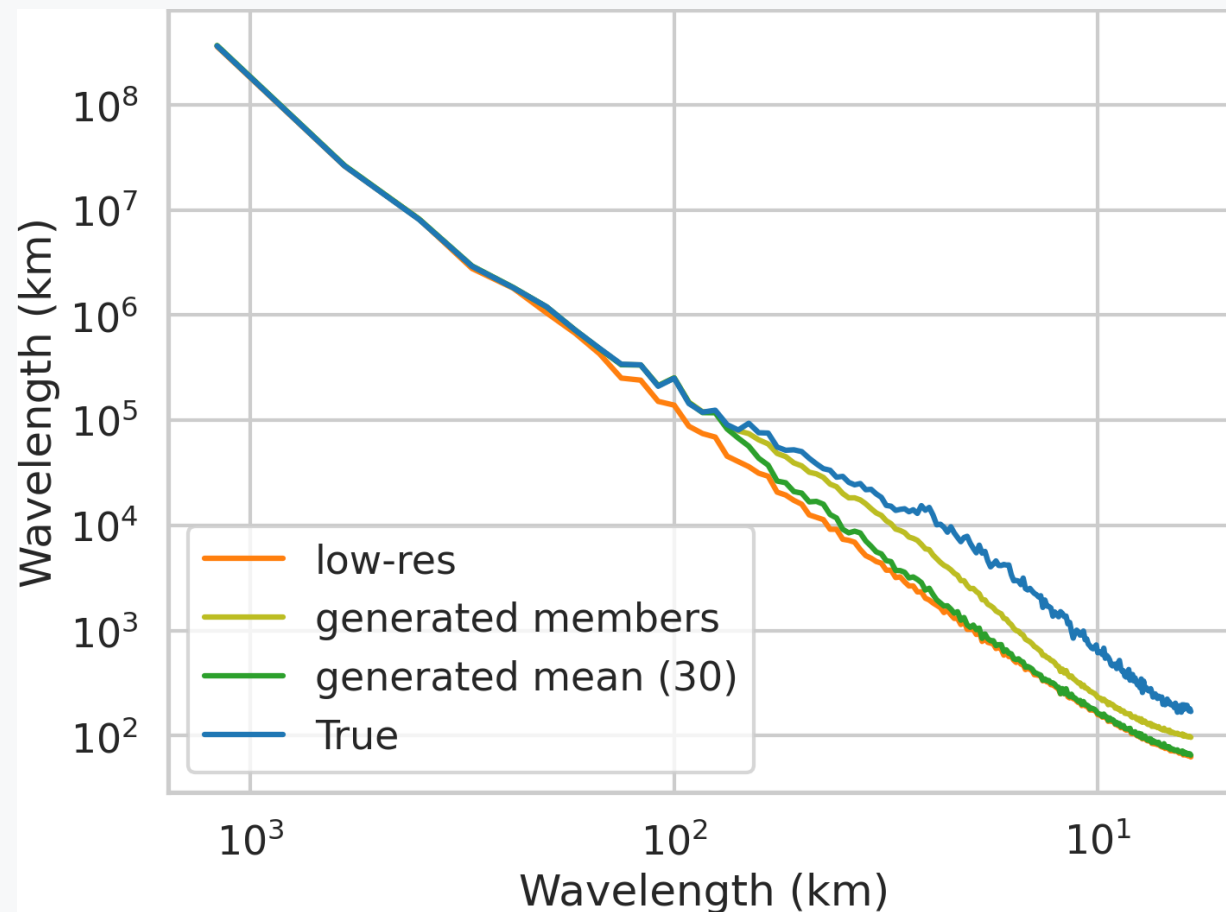
Contact me!  Julien.brajard@nerisc.no

Observation spectrum

Spectrum of the observations reconstruction

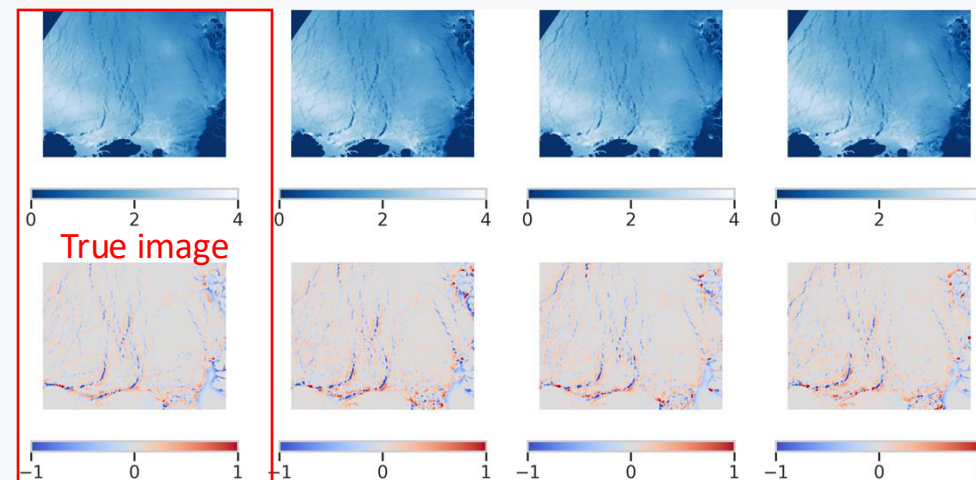


Spectrum of the NeXtSIM reconstruction

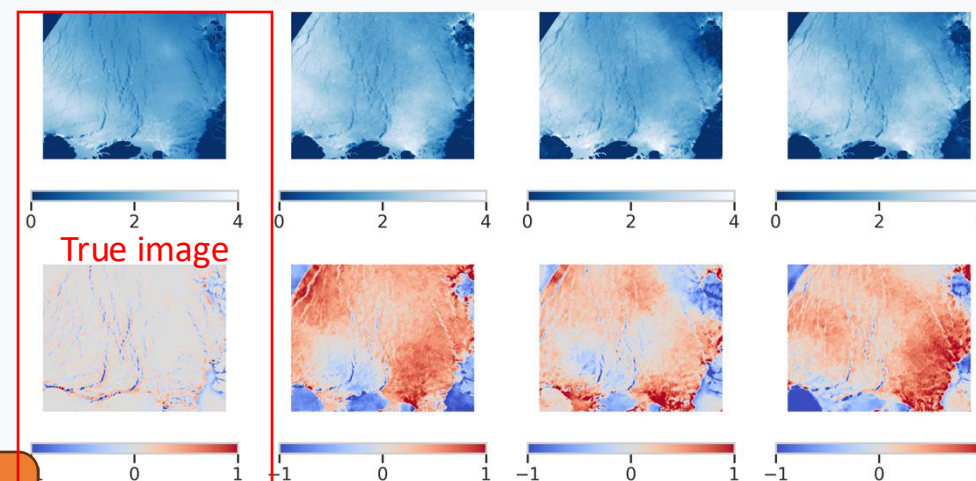


Anomaly Vs full field generation

Anomaly generation



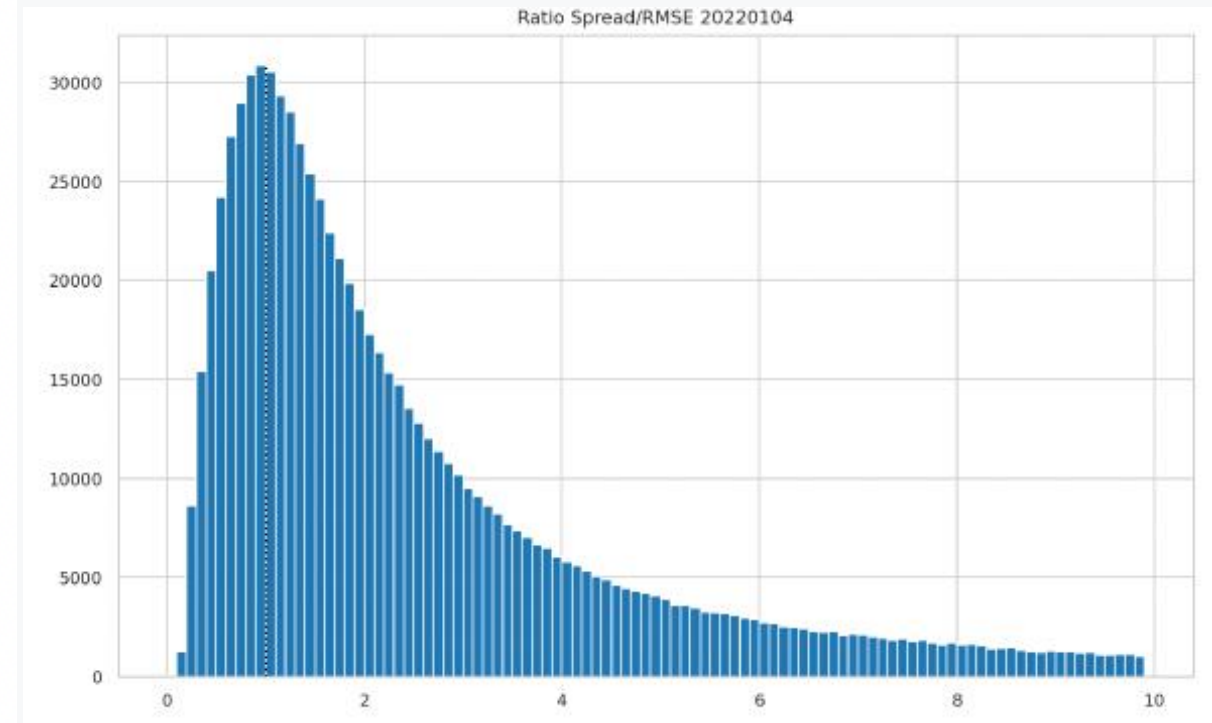
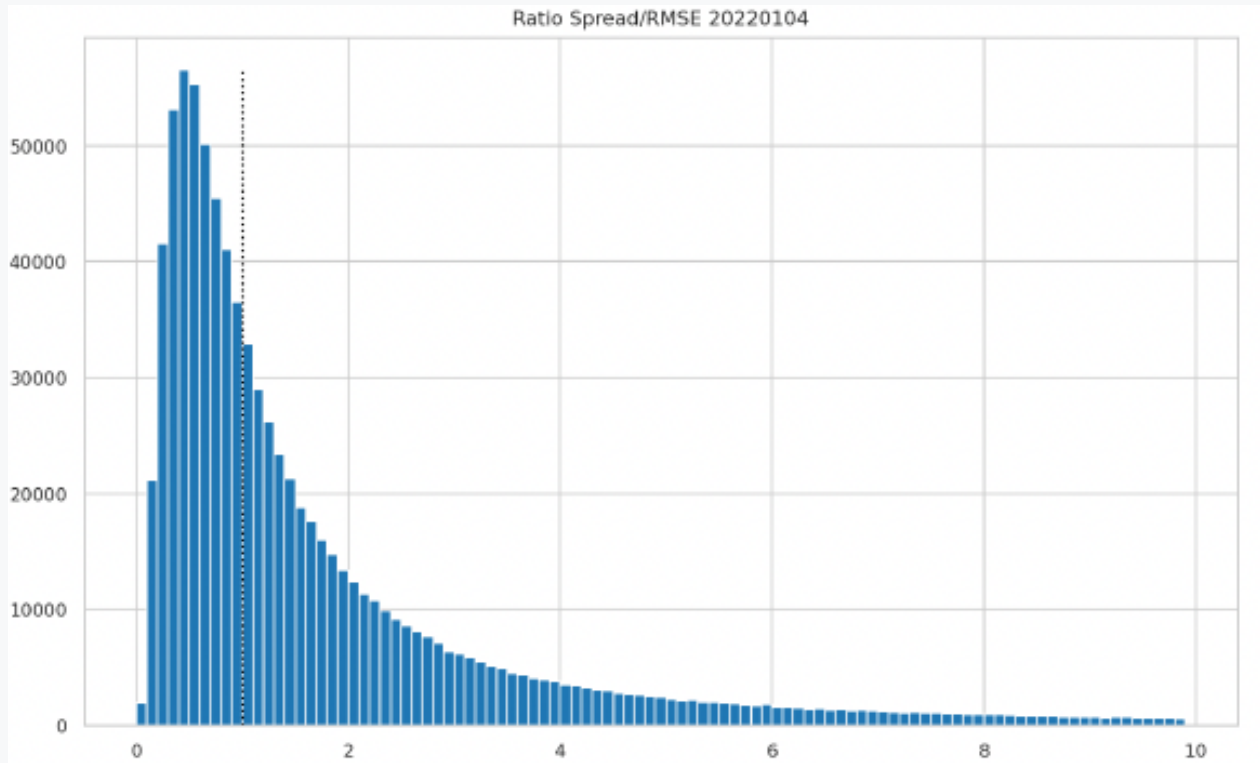
Full-field generation



Full-field induces large-scale biases

Ensemble score

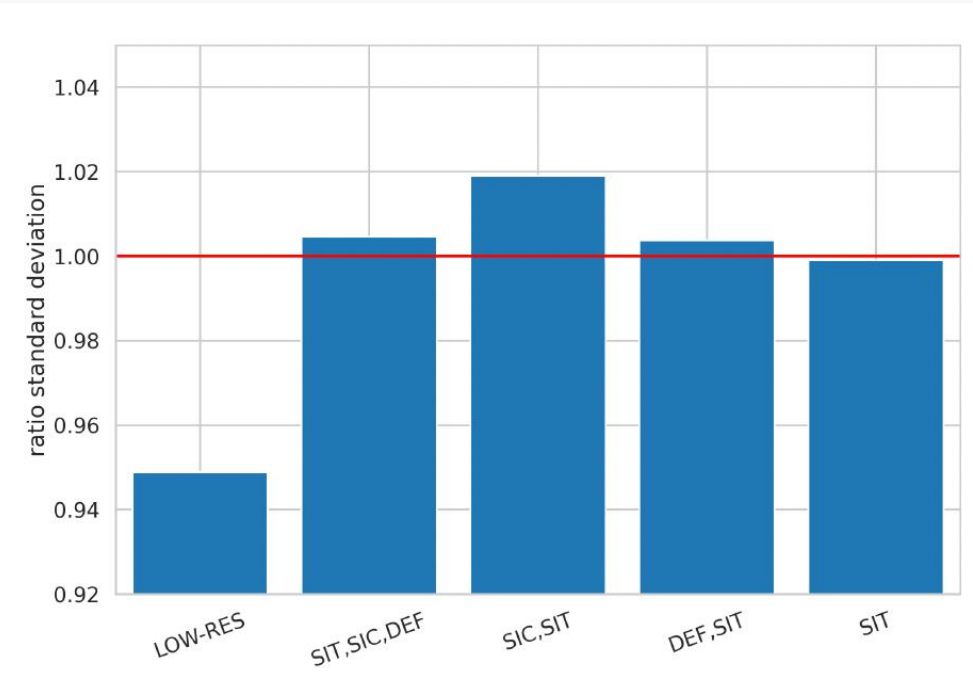
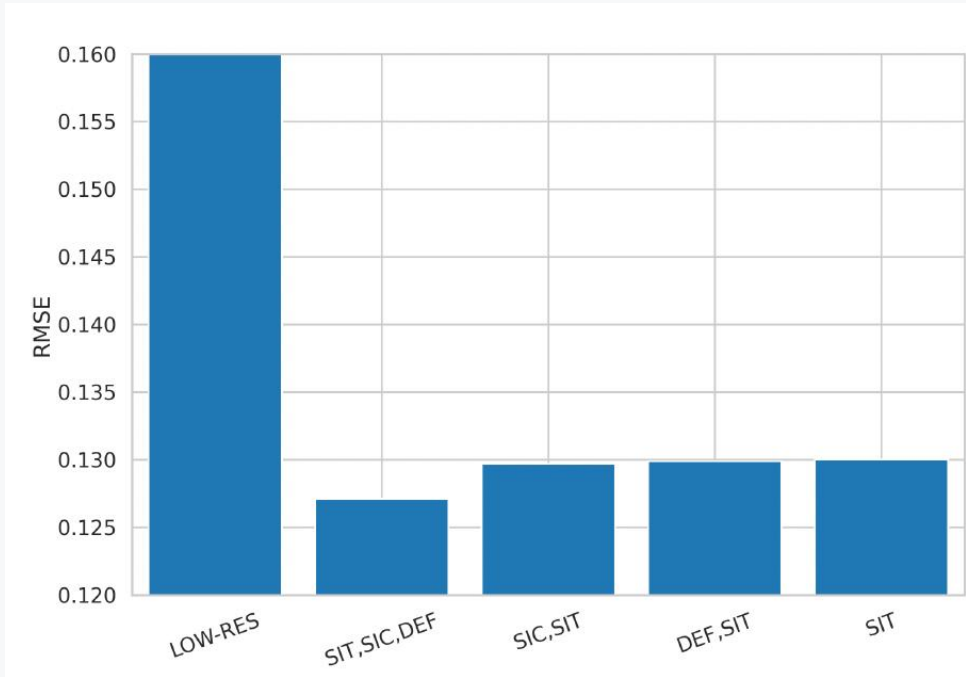
Ratio Spread / RMSE



Another training with only thickness and concentration in the context

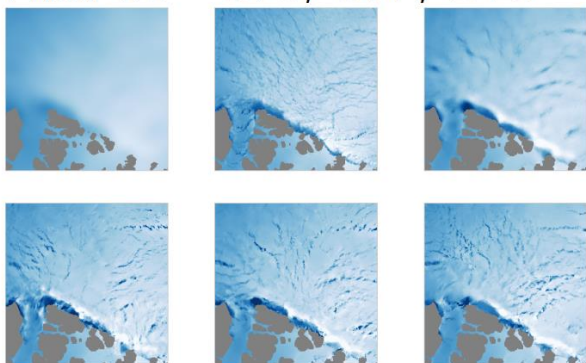
Input features

Trial	inputs
11	SIC, SIT, DEF
6	SIC, SIT
7	DEF, SIT
8	SIT

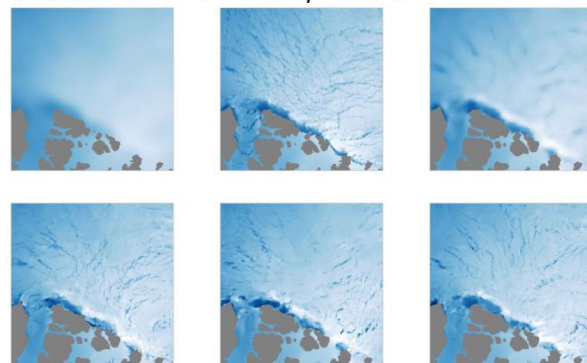


Input features

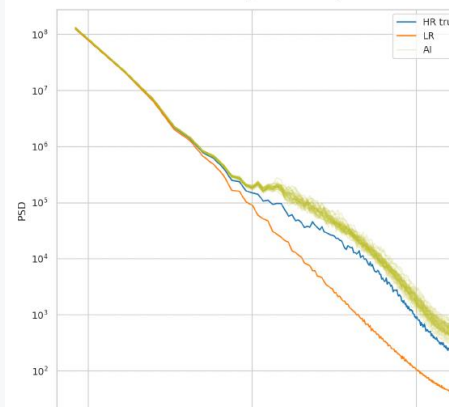
Trial 11 - SIC, SIT, DEF



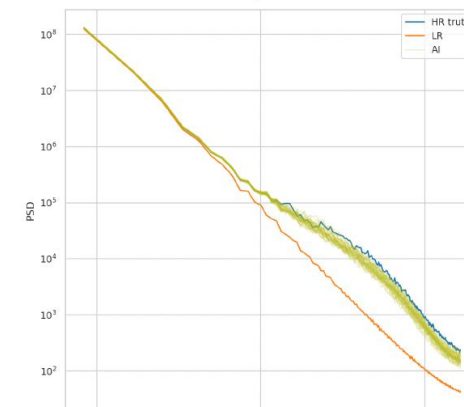
Trial 7 - DEF, SIT



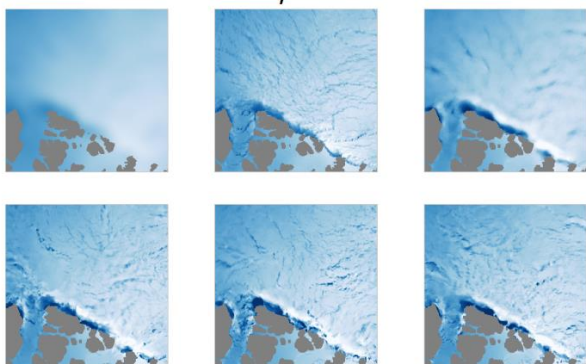
Trial 11 - SIC, SIT, DEF



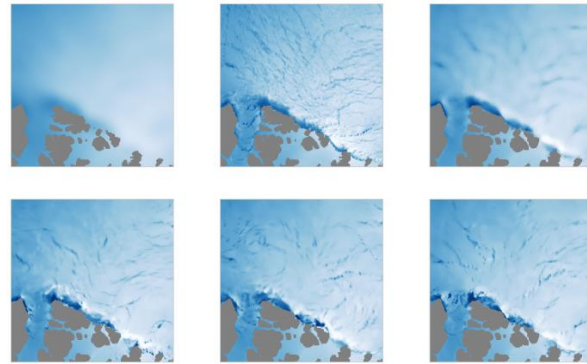
Trial 7 - DEF, SIT



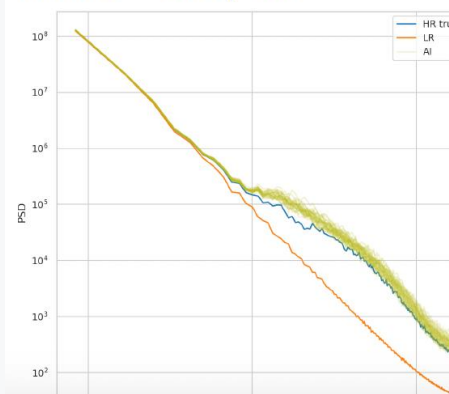
Trial 6 - SIC, SIT



Trial 8 - SIT



Trial 6 - SIC, SIT



Trial 8 - SIT

