Super-resolution of sea ice thickness using diffusion models

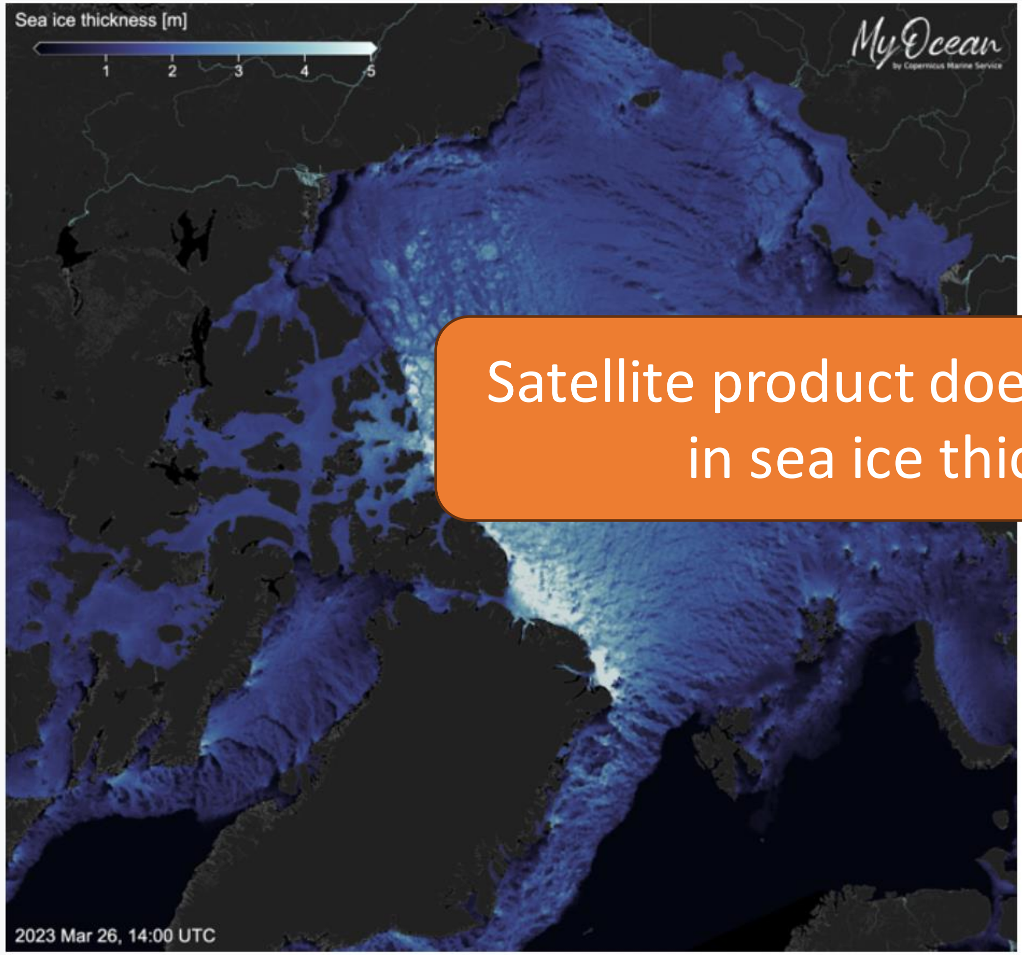
Julien Brajard, Anton Korosov, Yiguo Wang, Richard Davy

NERSC
STIFTELSEN NANSEN SENTER
FOR MILJØ OG FJERNMÅLING
NANSENSENTERET · BERGEN · NORGE

esa

Motivation

Physical model (NeXtSIM) forecast



Satellite observation product (CS2SMOS)

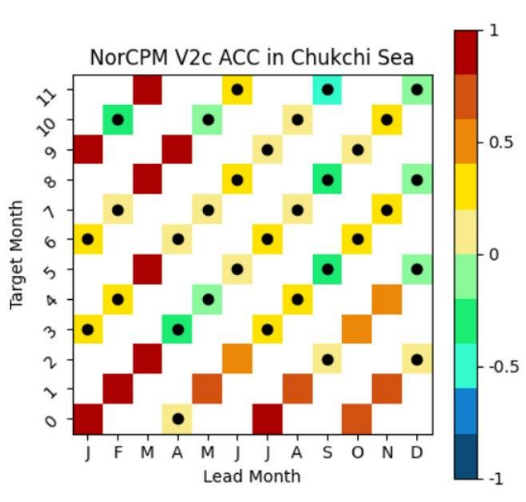
Satellite product does not resolve small scales in sea ice thickness (e.g. leads)

Why is it important?

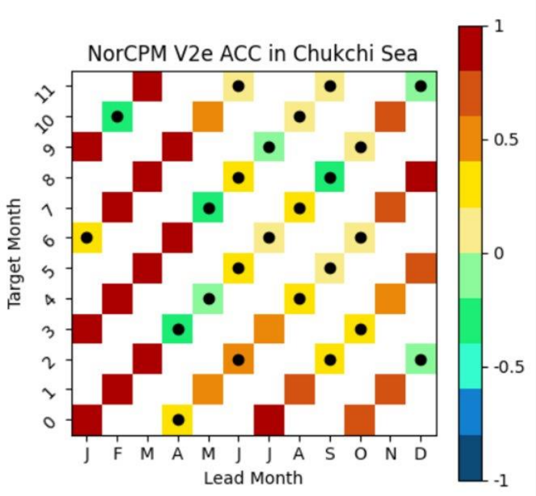
Case 1: Predictability

Forecast skill

Detrended correlation coefficient of Sea ice extent in Chukchi Sea



Initialization using Sea ice concentration observations only

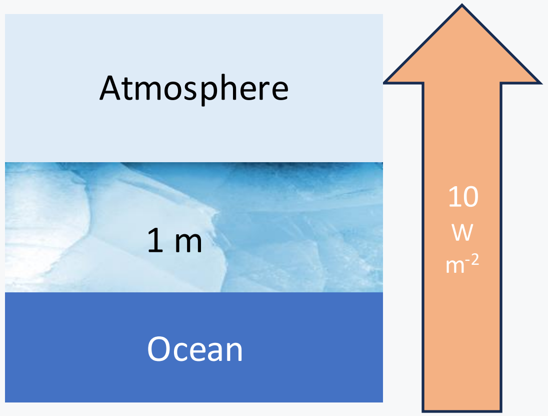


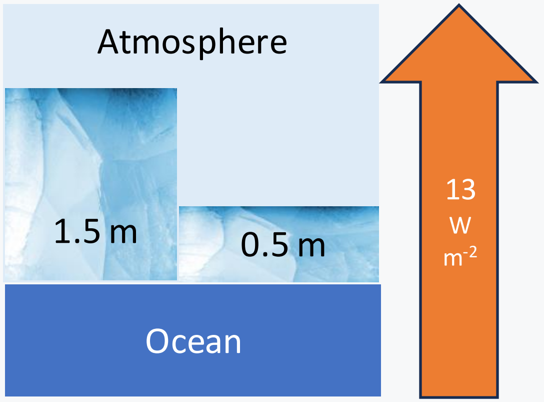
Initialization using Sea ice concentration observations + Sea ice thickness only

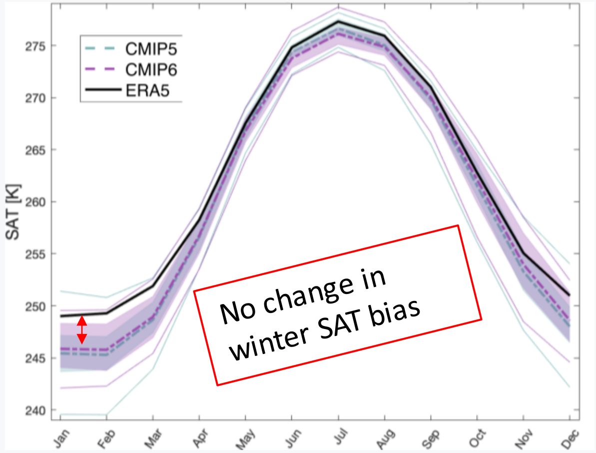
Black dot means not significant

Courtesy of N. Williams

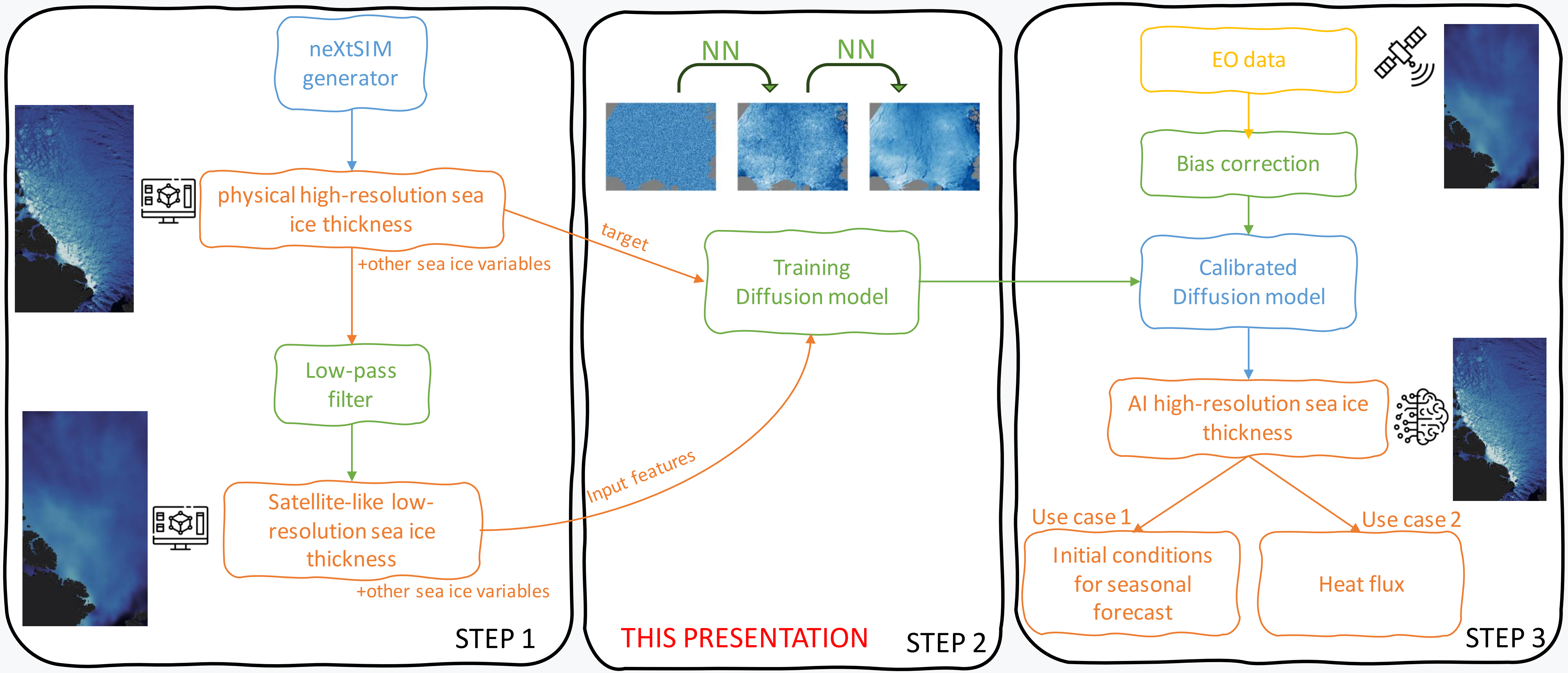
Case 2: Surface fluxes







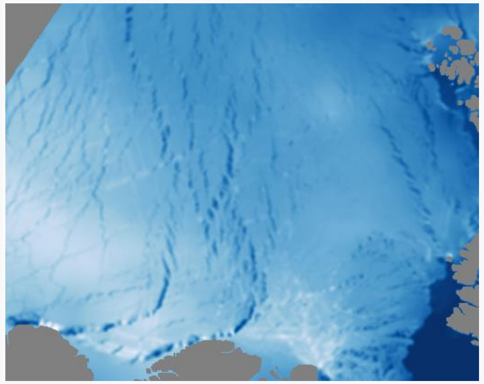
Steps of the project



Step 1: Dataset constitution

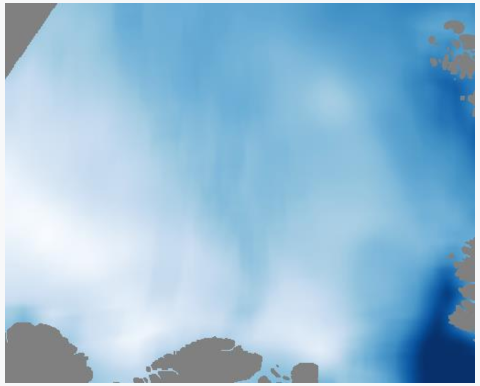
Principle: Filtering of NeXtSIM simulations

NeXtSIM sea ice thickness
11-01-2020 (res 4km)

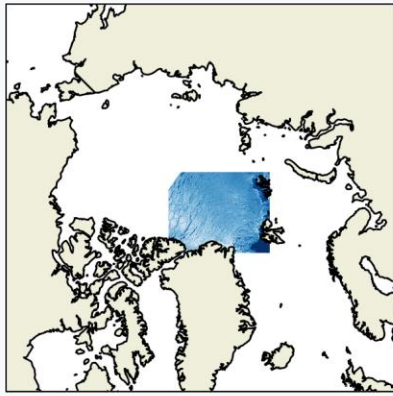


Convolution constant kernel (size 120 km)

Filtered sea ice thickness
(res ~ 120 km)

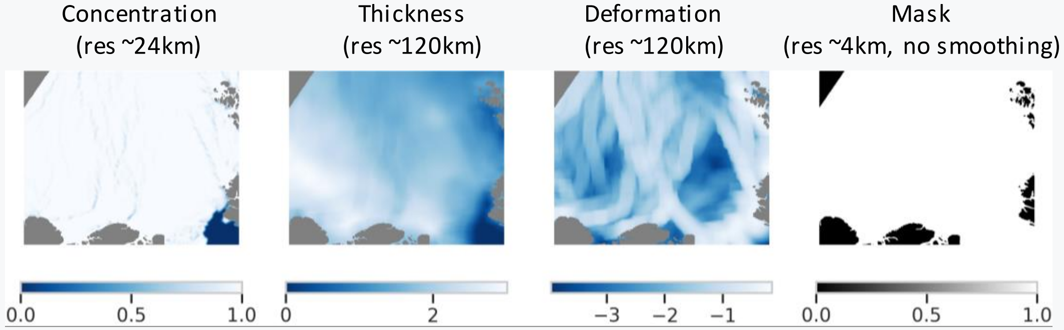


Observation product (CS2SMOS)
11-01-2021



Dataset:

- 4 input features (filtered)
- 529 samples, from 01-01-2020 to 30-09-2020
- Training: 10-10 -> 20-09 (509 samples)
- Validation 04-10-> 09-10 and 21-09->26-09 (12 samples)

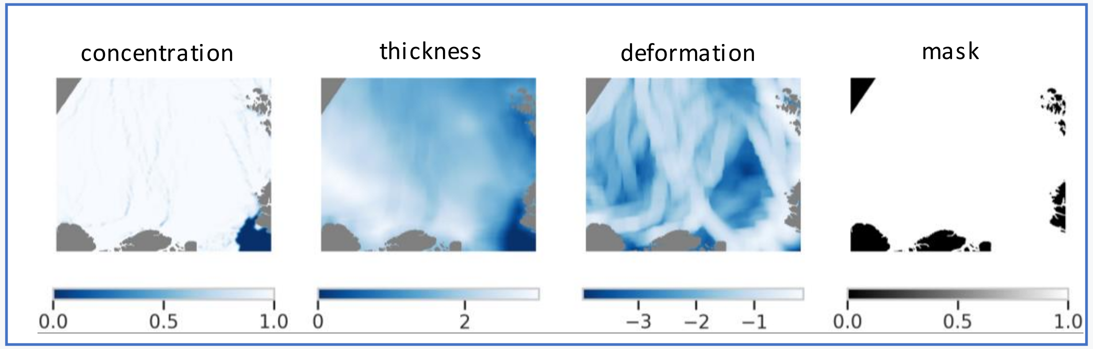


Apply diffusion model to sea ice thickness super-resolution

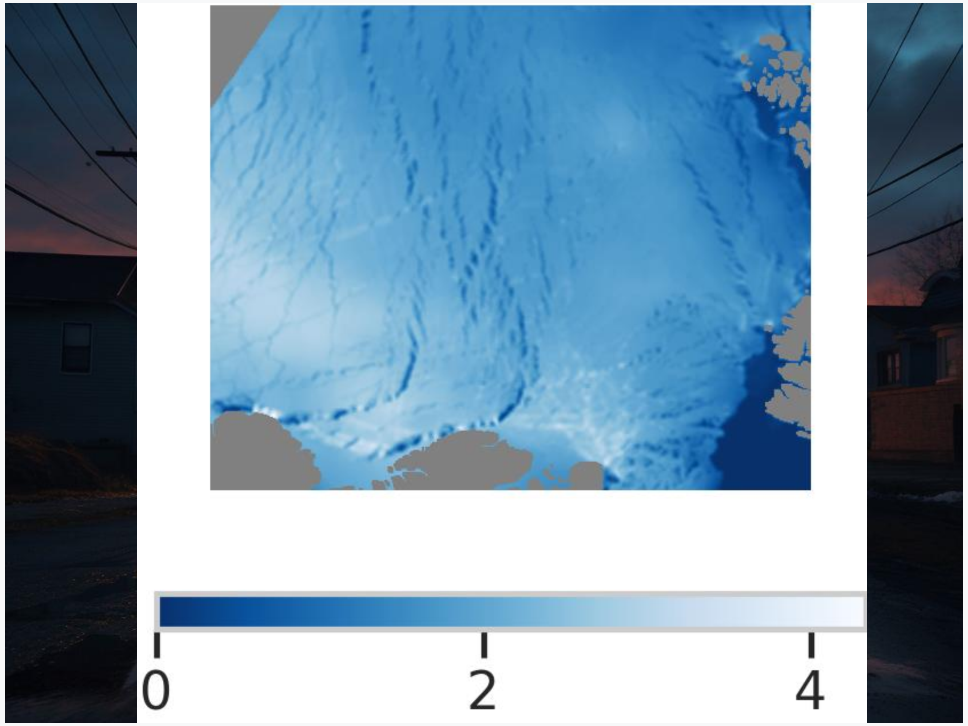
Used for AI image generator (Ex: Midjourney)

Observable low-resolution images

A generated high-resolution image

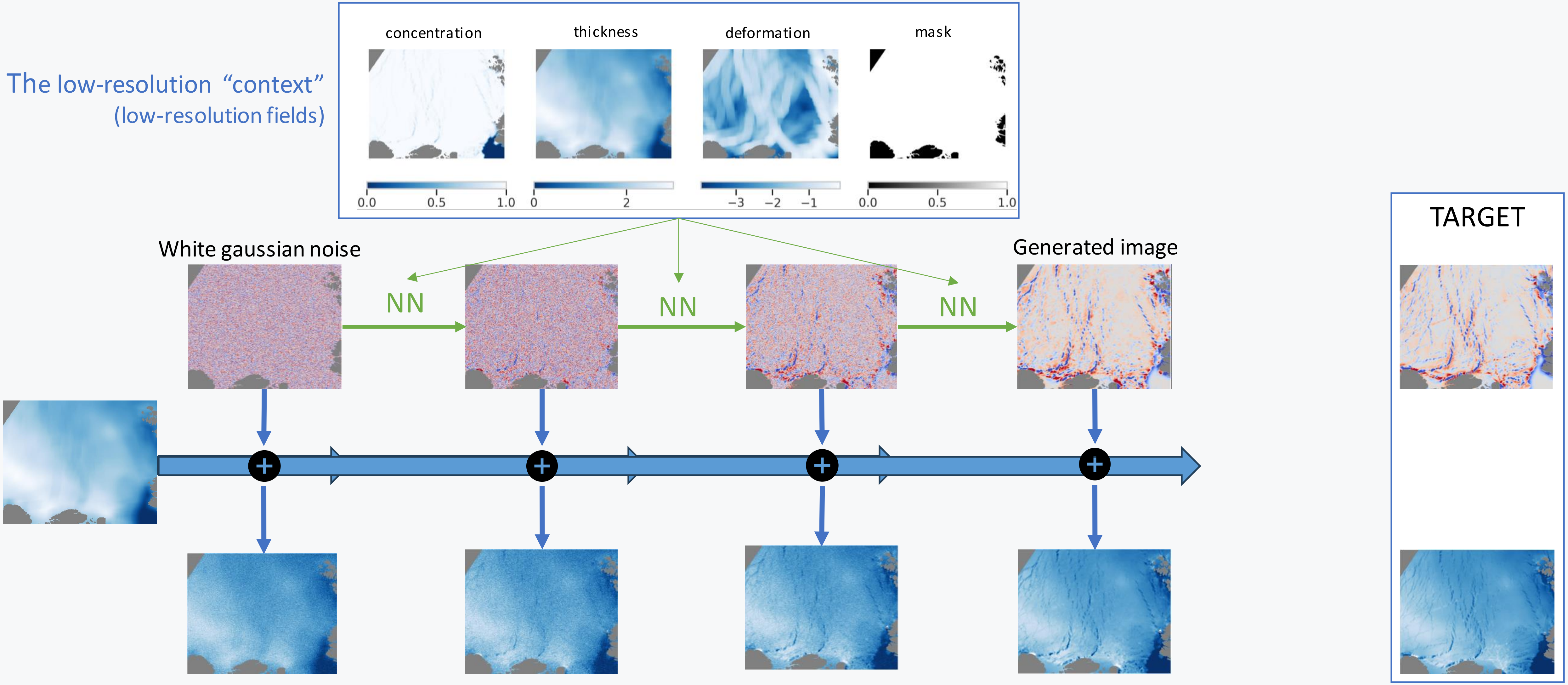


Generative diffusion model

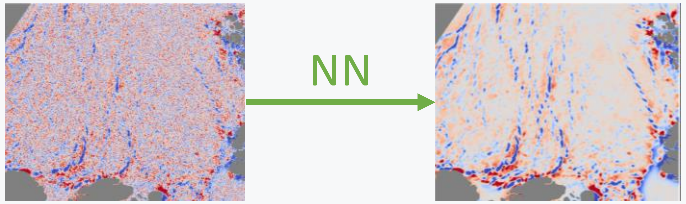


Source: https://aituts.com/midjourney-camera-prompts/

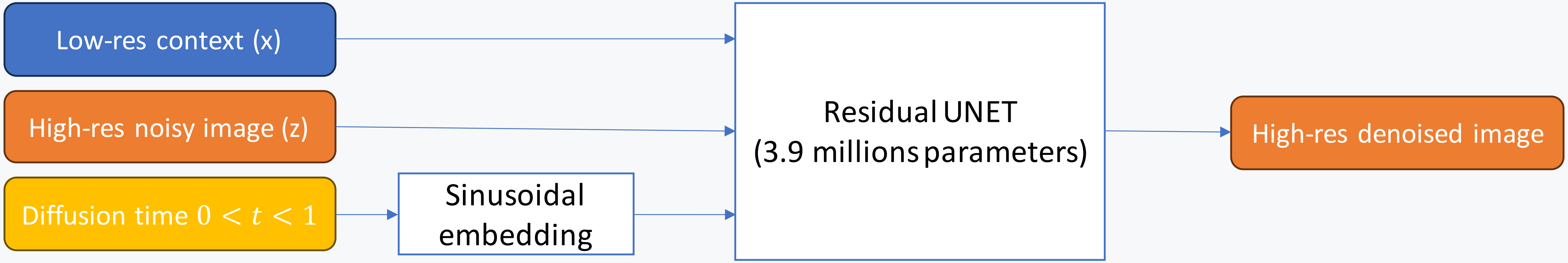
Principle of the diffusion model



Implementation details

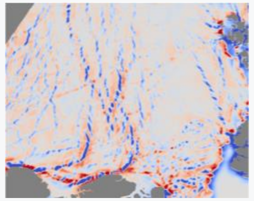


Model Residual Neural network f(x,z,t)

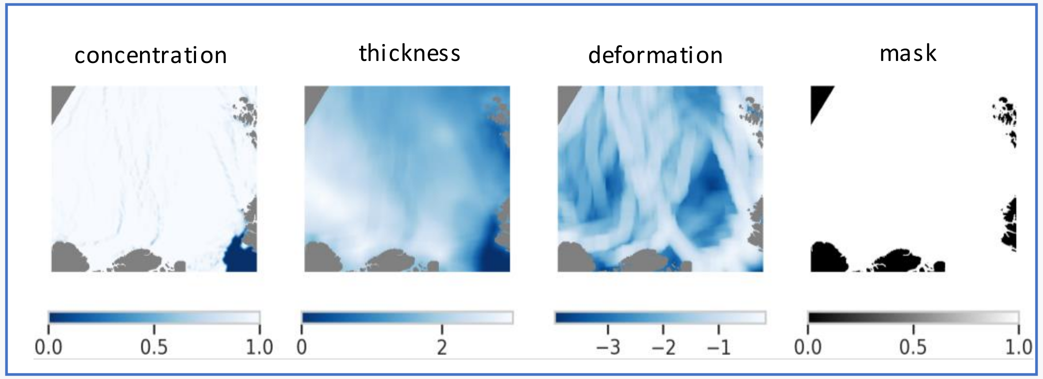


Training algorithm

1 y



x

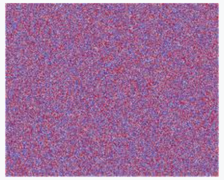


For one sample

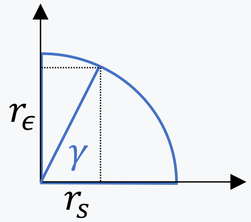
1. Draw a HR image y and a LR context x in the training set
2. Draw a diffusion time t between 0 (full signal) and 1 (full noise)
3. Draw a white Gaussian noise ϵ
4. Compute diffusion angle: $\gamma = \gamma_{min} + t.(\gamma_{max} - \gamma_{min})$
5. Compute the signal and noise rate: $r_s = \cos\gamma$, $r_\epsilon = \sin\gamma$
6. Compute the noisy image: $z_t = r_s \,.\, y + r_\epsilon . \epsilon$
7. Predict the noise by the NN: $\hat{\epsilon} = f_\theta(z_t, t, x)$
8. Predict the image: $\hat{z}_{t-1} = (z_t - r_\epsilon . \hat{\epsilon}) \,/\, r_s$
9. Compute the loss on the noise: = $L(\theta) = \|\epsilon - \hat{\epsilon}\|^2$
10. Minimize L

ϵ

3

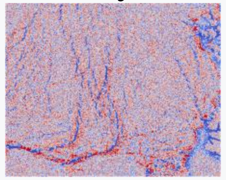


5



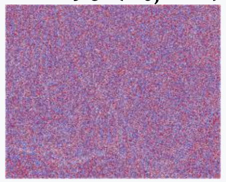
z_t

6



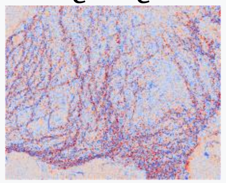
$\hat{\epsilon} = f_\theta(z_t, t, x)$

7



$\epsilon - \hat{\epsilon}$

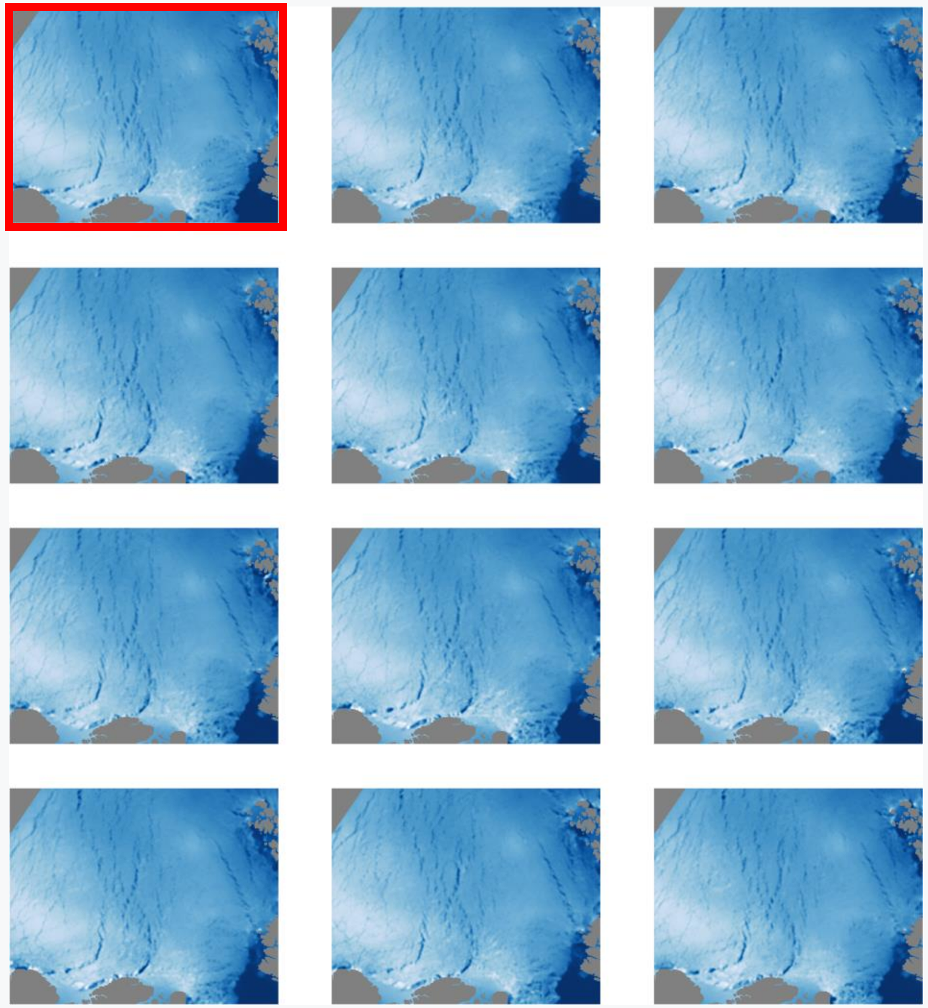
9

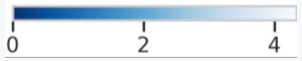


A stochastic generator

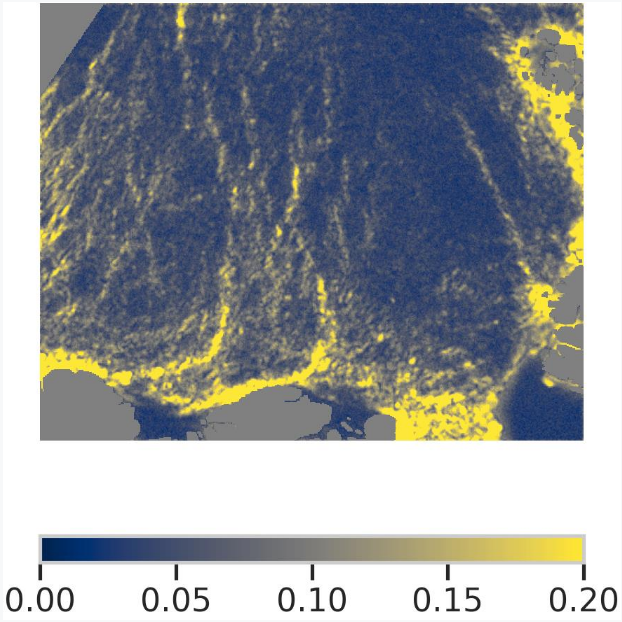
The generated process depends on the noise and enable to generate an ensemble of likely high-resolution images.

True image

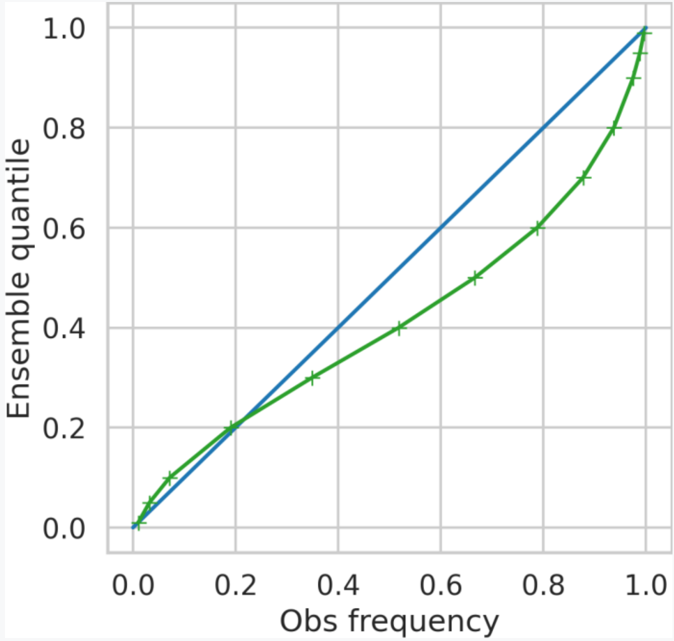




Spread



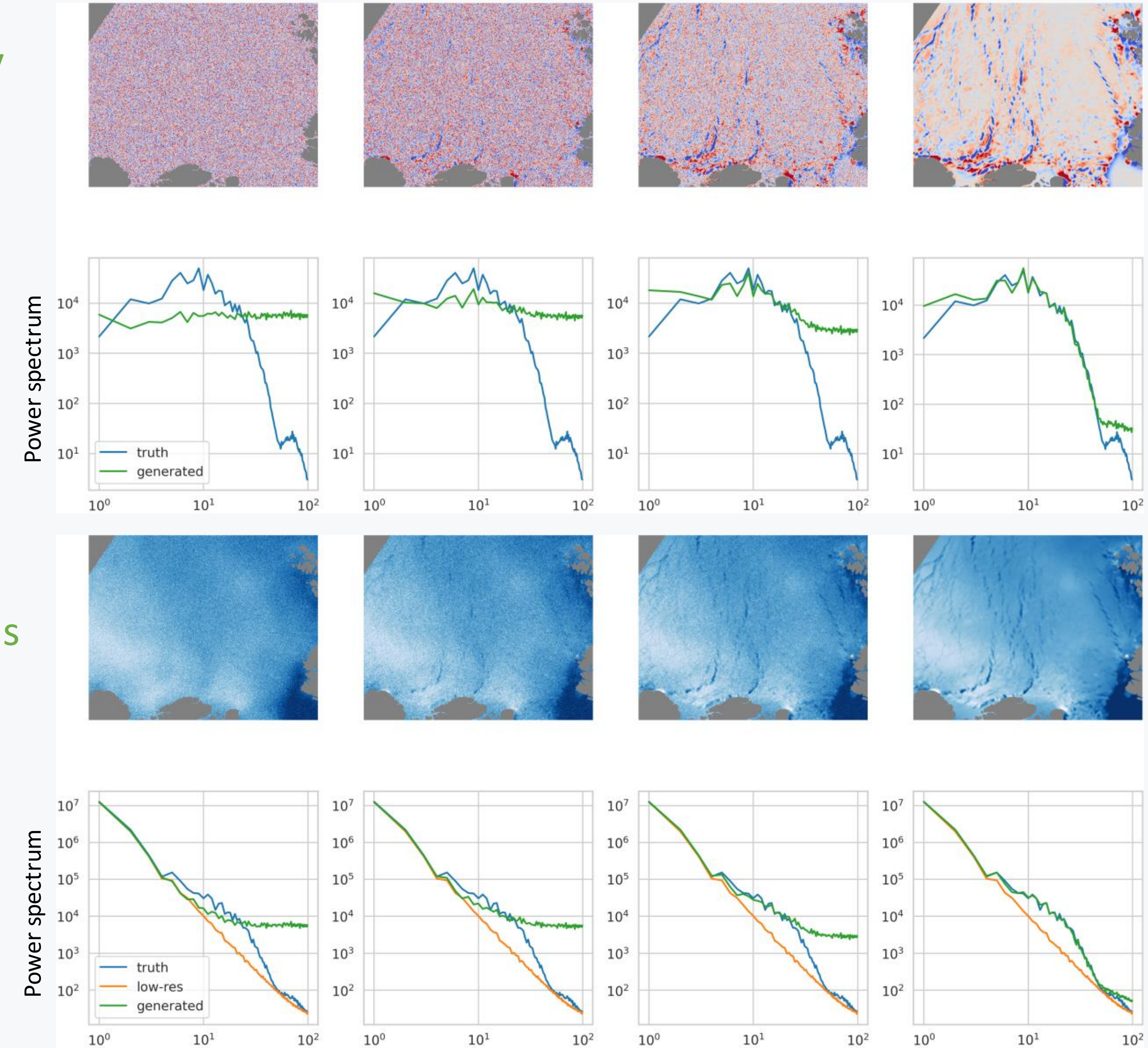
Reliability



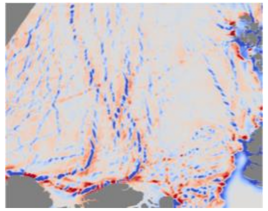
Preliminary result

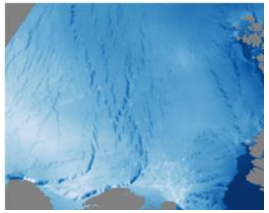
Generated field in anomaly
(SIT HighRes – SIT LowRes)

Generated SIT fields

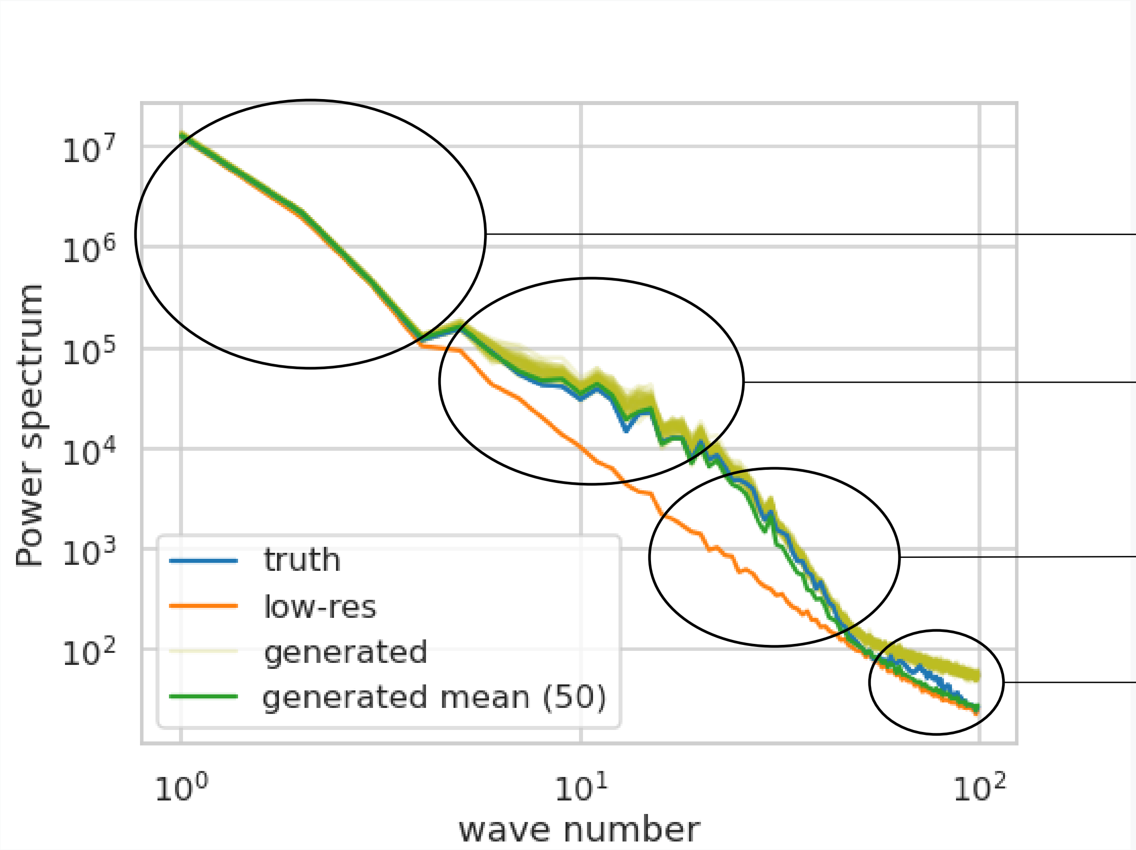


TARGET





More on power spectrums



Large-scale
Low-res = high-res

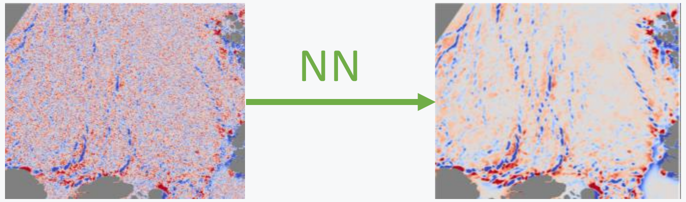
medium-scale (fully deterministic and predictable)
Ensemble mean > Ensemble members

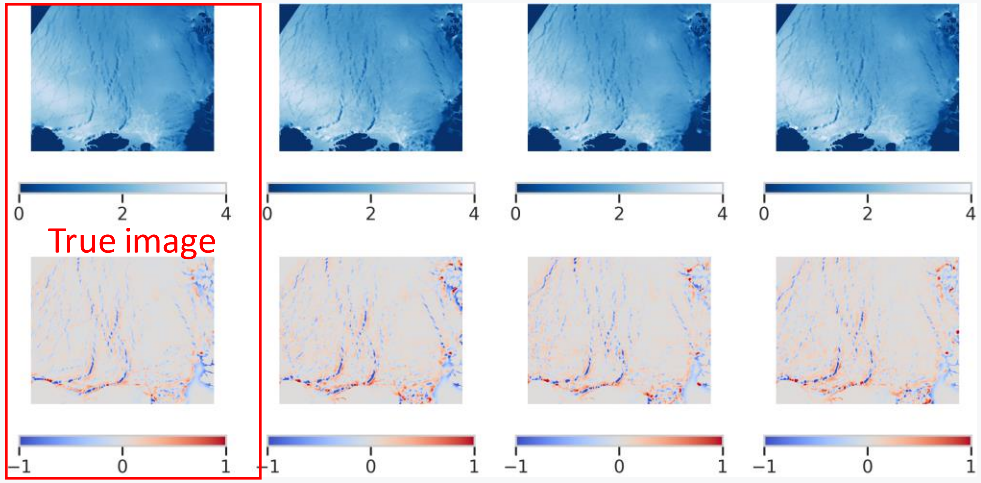
Fine-scale (probabilistic)
Ensemble members > Ensemble mean ?

Finest-scale (probabilistic and unpredictable)
Ensemble mean = Low-res

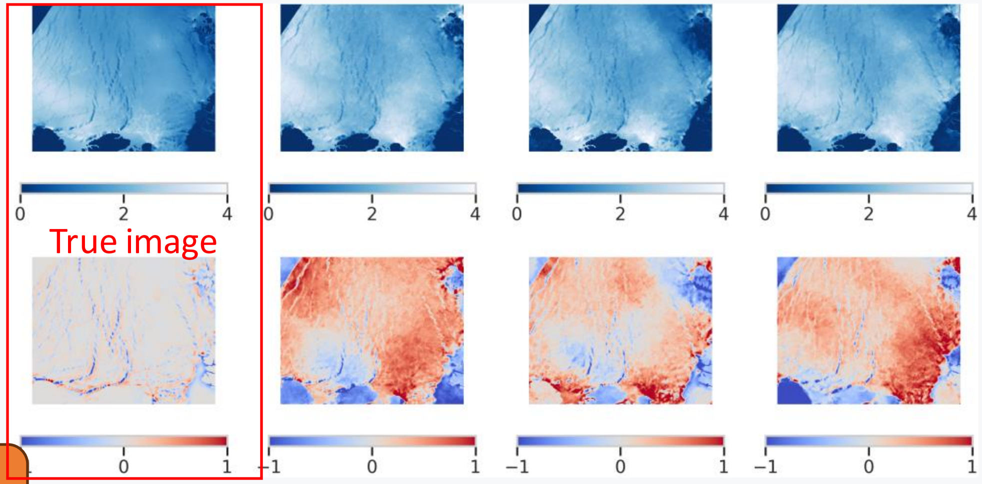
Anomaly Vs full field generation

Anomaly generation





Full-field generation



Full-field induces large-scale biases

Conclusion

- **Diffusion models can be used to generate a realistic sea ice thickness field**
- Many implementation choices have been made:
  - Dataset creation: smoothing
  - Choice of input features: guided by observable variables
  - Model architecture: Residual UNET
  - Diffusion type: continuous time
  - Training: Loss computed on the noise
  - Generation: deterministic generation (the noise is only drawn once)
  - Many hyperparameters
- What is the more sensitive choice?
- Next step: inference with observation data

Julien.brajard@nersc.no