Sea-ice emulator in the Arctic region

Flavia Porro
C. Durand, G. De Cillis, T. Finn, M. Bocquet, A. Carrassi

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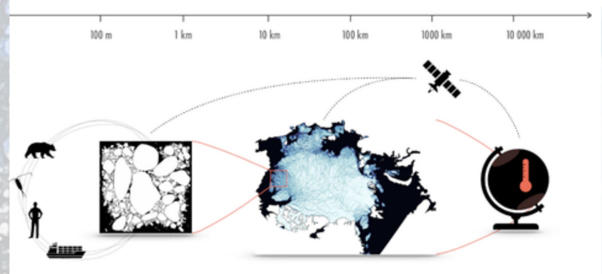
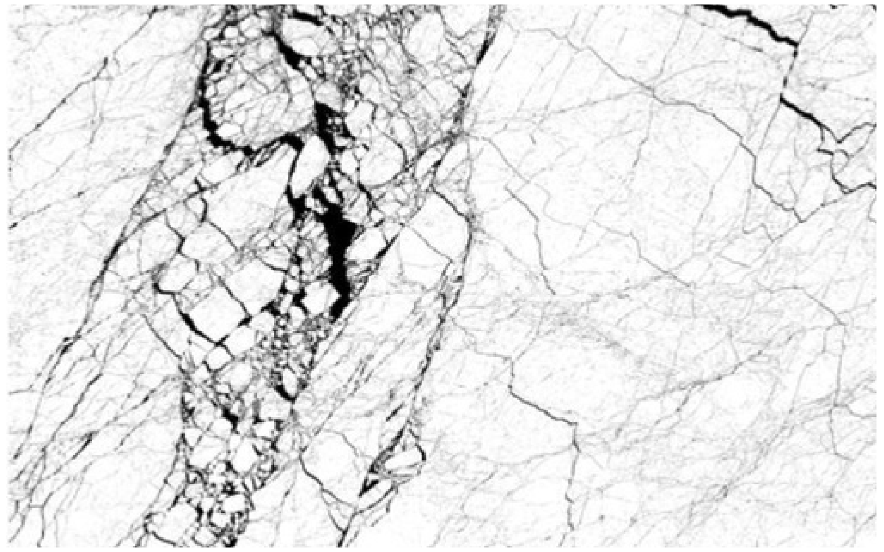
ECMWF - ESA workshop



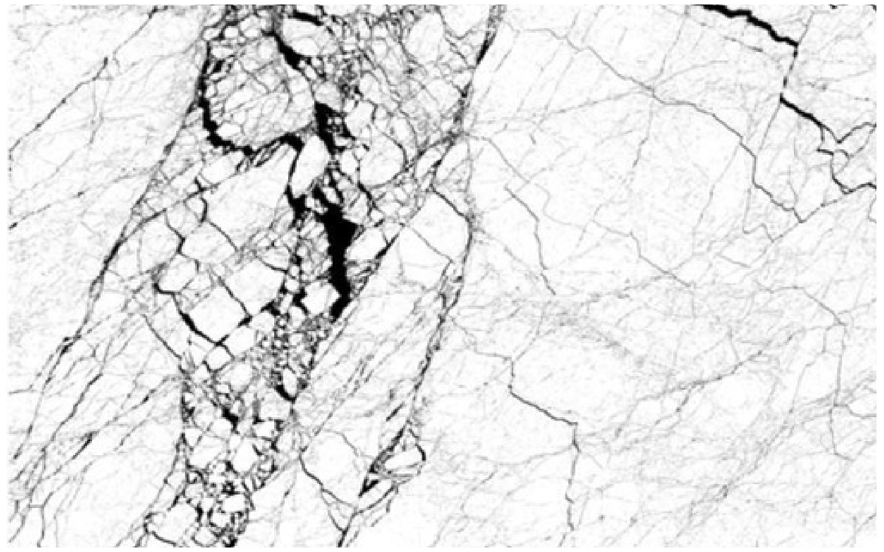
This project is supported by Schmidt Sciences, LLC

Where we stand



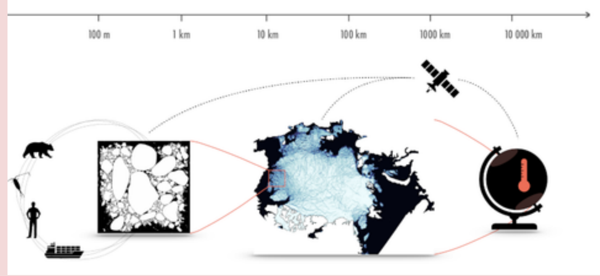
Where we stand

What kind of model can capture the complexity of such system?



neXtSIM

- **Dynamical** and **thermodynamical** sea ice model, fully Lagrangian coupled with ocean (Rampal et al. 2016)
- **Brittle Bingham-Maxwell** rheology (Olason, 2021).



The Scale-Aware Sea Ice Project

SASIP

The Cryosphere, 10, 1055–1073, 2016
www.the-cryosphere.net/10/1055/2016/
doi:10.5194/tc-10-1055-2016

The Cryosphere

neXtSIM: a new Lagrangian sea ice model

Pierre Rampal[1], Sylvain Bouillon[1], Einar Ólason[1], and Mathieu Morlighem[2]
[1]Nansen Environmental and Remote Sensing Center and Bjerknes Centre for Climate Research, Bergen, Norway
[2]Department of Earth System Science, University of California, Irvine, California, USA

Correspondence to: Pierre Rampal (pierre.rampal@nersc.no)

Received: 18 September 2015 – Published in The Cryosphere Discuss.: 30 October 2015
Revised: 22 April 2016 – Accepted: 3 May 2016 – Published: 20 May 2016

Symbol	Name	Meaning	Unit
h	sea ice thickness	volume of ice per unit area	m
h_s	snow thickness	volume of snow per unit area	m
A	sea ice concentration	surface of ice per unit area	–
d	sea ice damage	0 = undamaged; 1 = completely damaged	–
u, v	sea ice velocity	horizontal sea ice velocities	ms^{-1}
σ	sea ice internal stress	planer internal stress	Nm^{-2}

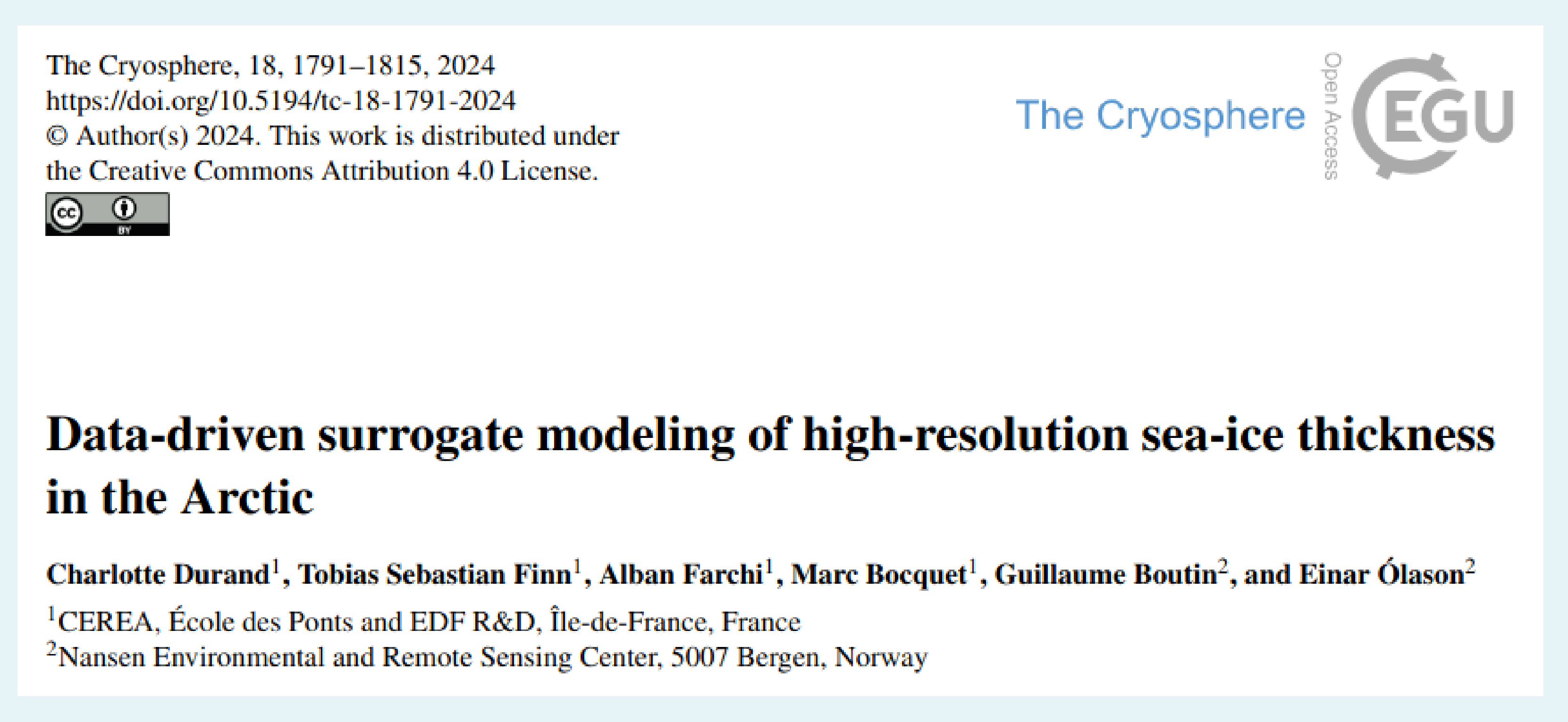
Motivation for my contribution

Physical based models, describe with great details some of the many complex processes occurring in the sea-ice.

However, these models are computationally very costly.

We aim to emulate sea-ice process with **data-driven model**.

Starting from


The Cryosphere, 18, 1791–1815, 2024
https://doi.org/10.5194/tc-18-1791-2024

The Cryosphere

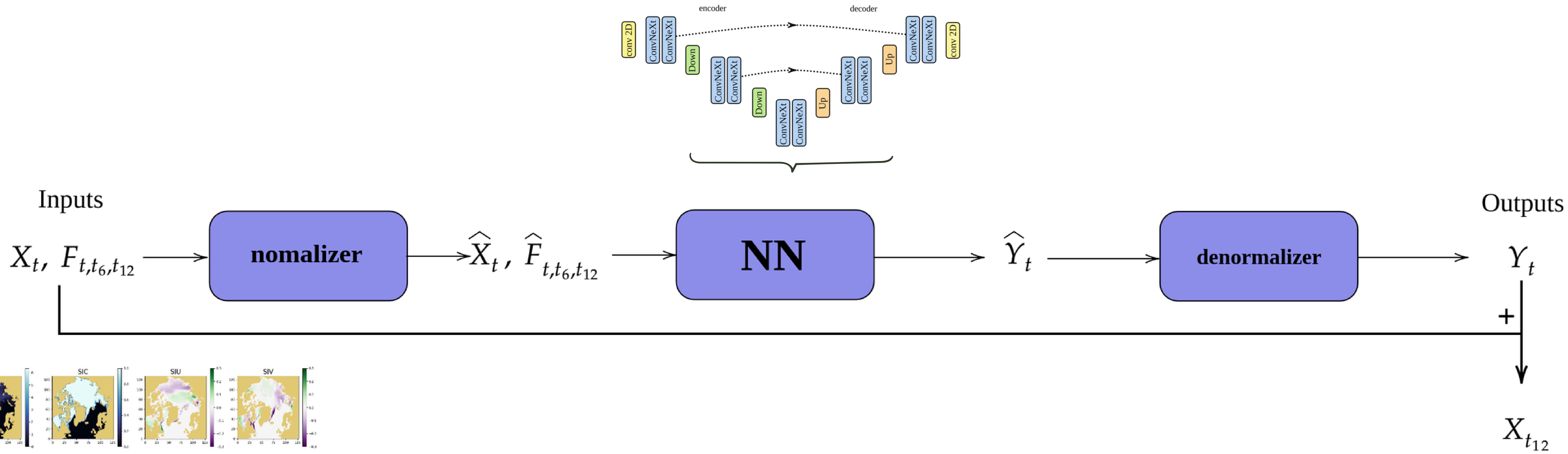
Data-driven surrogate modeling of high-resolution sea-ice thickness in the Arctic

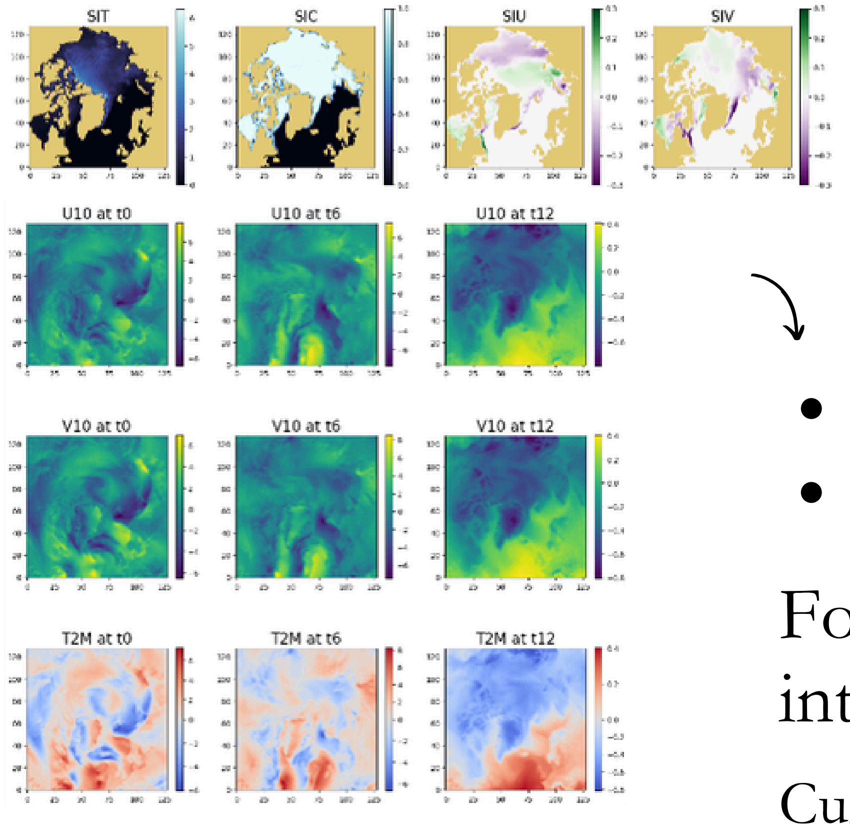
Charlotte Durand[1], Tobias Sebastian Finn[1], Alban Farchi[1], Marc Bocquet[1], Guillaume Boutin[2], and Einar Ólason[2]
[1]CEREA, École des Ponts and EDF R&D, Île-de-France, France
[2]Nansen Environmental and Remote Sensing Center, 5007 Bergen, Norway

We now build a **multi-variate emulator** including also sea-ice concentration (**SIC**) and sea-ice velocities (**SIU**, **SIV**).

Final goal: **create an emulator for sea-ice system** that can be a useful tool for faster simulation and data assimilation application.

Neural network architecture and training setup

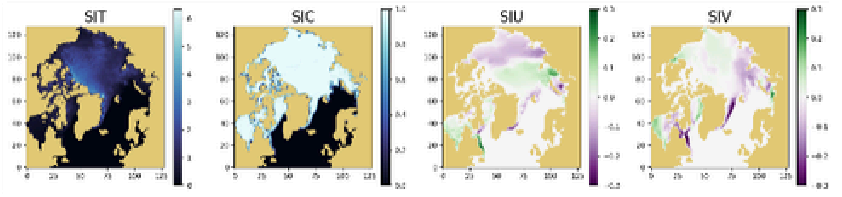




- neXtSIM outputs,
- atmospheric forcing from ERA5 reanalysis

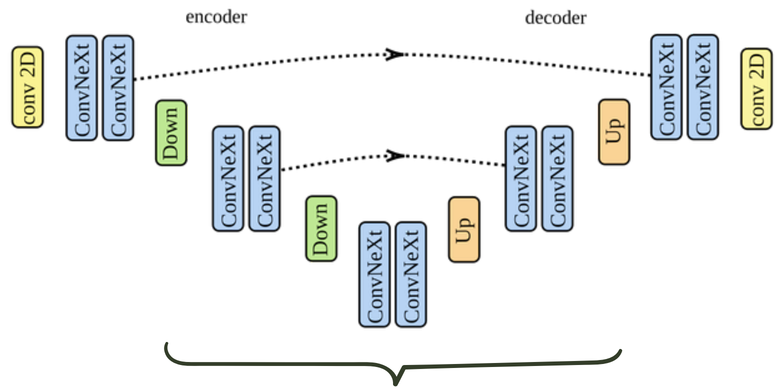
Forcing are given at different times, and they are interpolated from ERA5 grid to neXtSIM grid.

Current resolution: 48 km



Dataset
Training: from 2001 to 2014
Validation: 2015
Test: form 2016 to 2018

Neural network architecture and training setup



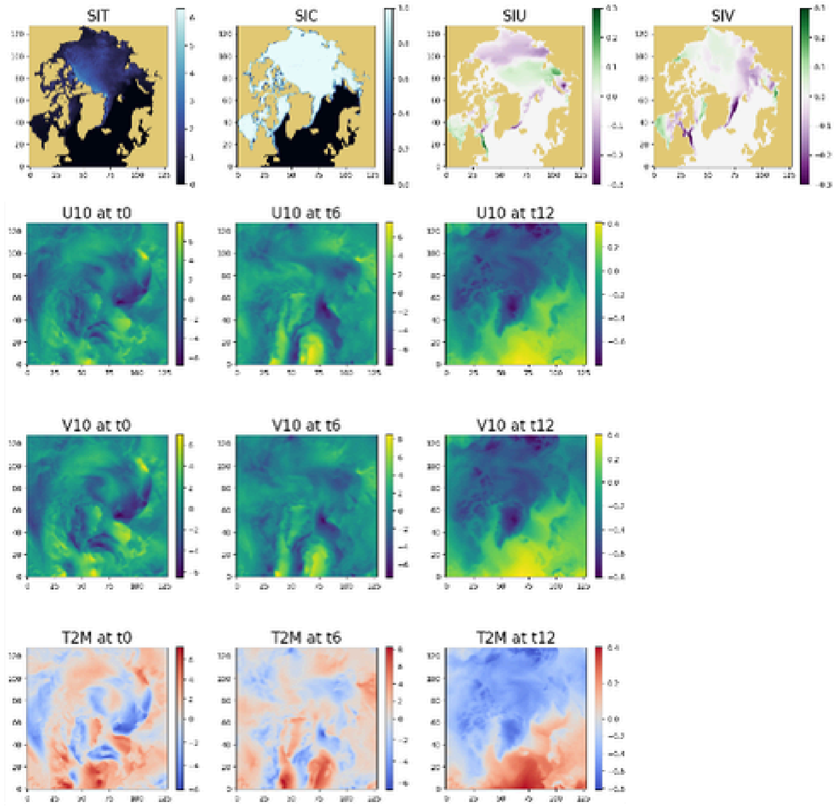
Inputs

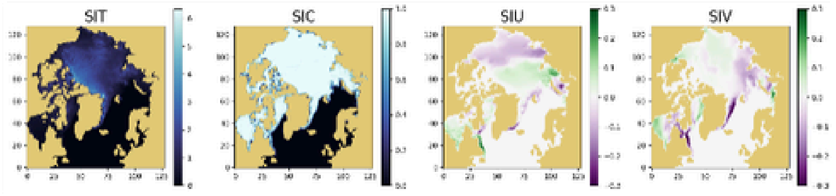
$X_t,\ F_{t,t_6,t_{12}}$ → **nomalizer** → $\widehat{X}_t,\ \widehat{F}_{t,t_6,t_{12}}$ → **NN** → $\widehat{Y}_t$ → **denormalizer** → Y_t

Outputs

$+$

$X_{t_{12}}$





Loss definition

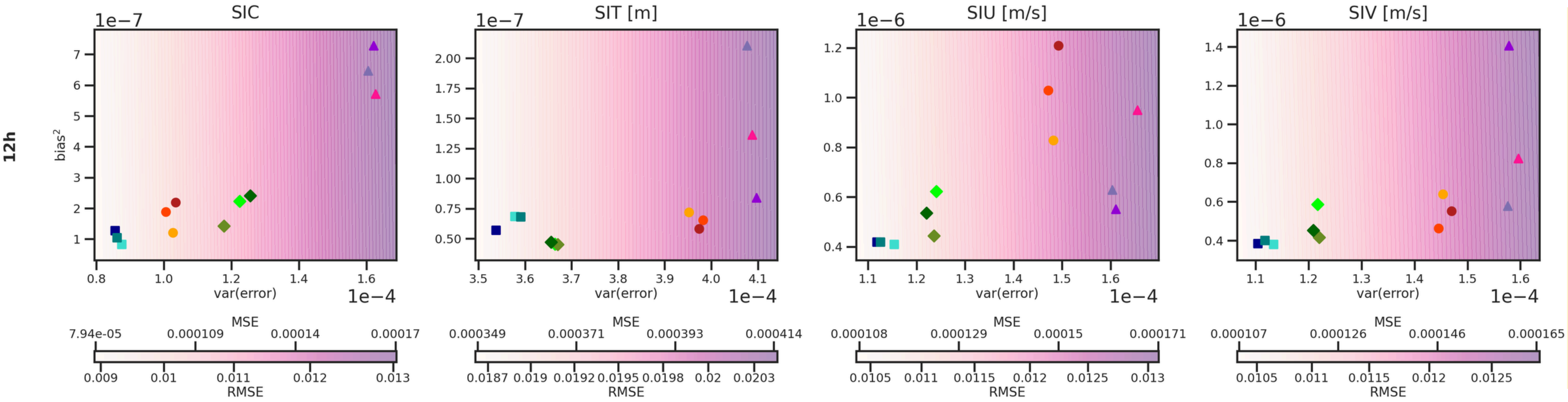
$$\mathcal{L} = \frac{1}{N_{var}} \sum_{i}^{N_{var}} \frac{1}{\sigma_i} (loss_i)$$

σ = std of each variable

Models

- A, MSE : SIC, SIT, SIU, SIV; MSE loss
- A, MAE SIC, SIT, SIU, SIV; MAE loss
- B, MSE : Vol, SIT, SIU, SIV; MSE loss
- B, MAE Vol, SIT, SIU, SIV; MAE loss

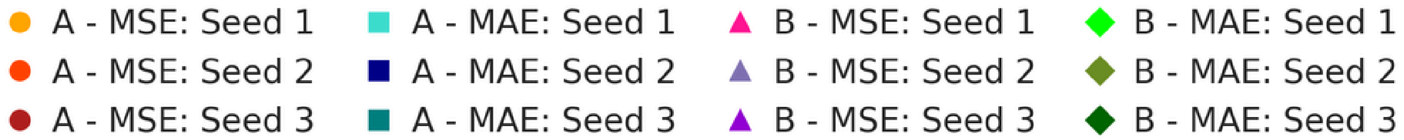
Robustness of the training



All configurations show **stable optimization**.

The effect of the **loss-variable choice** is most relevant.

The **bias** represents a subtle but structurally more complex component of the error.



A, MSE : SIC, SIT, SIU, SIV; MSE loss

A, MAE SIC, SIT, SIU, SIV; MAE loss

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B, MAE Vol, SIT, SIU, SIV; MAE loss

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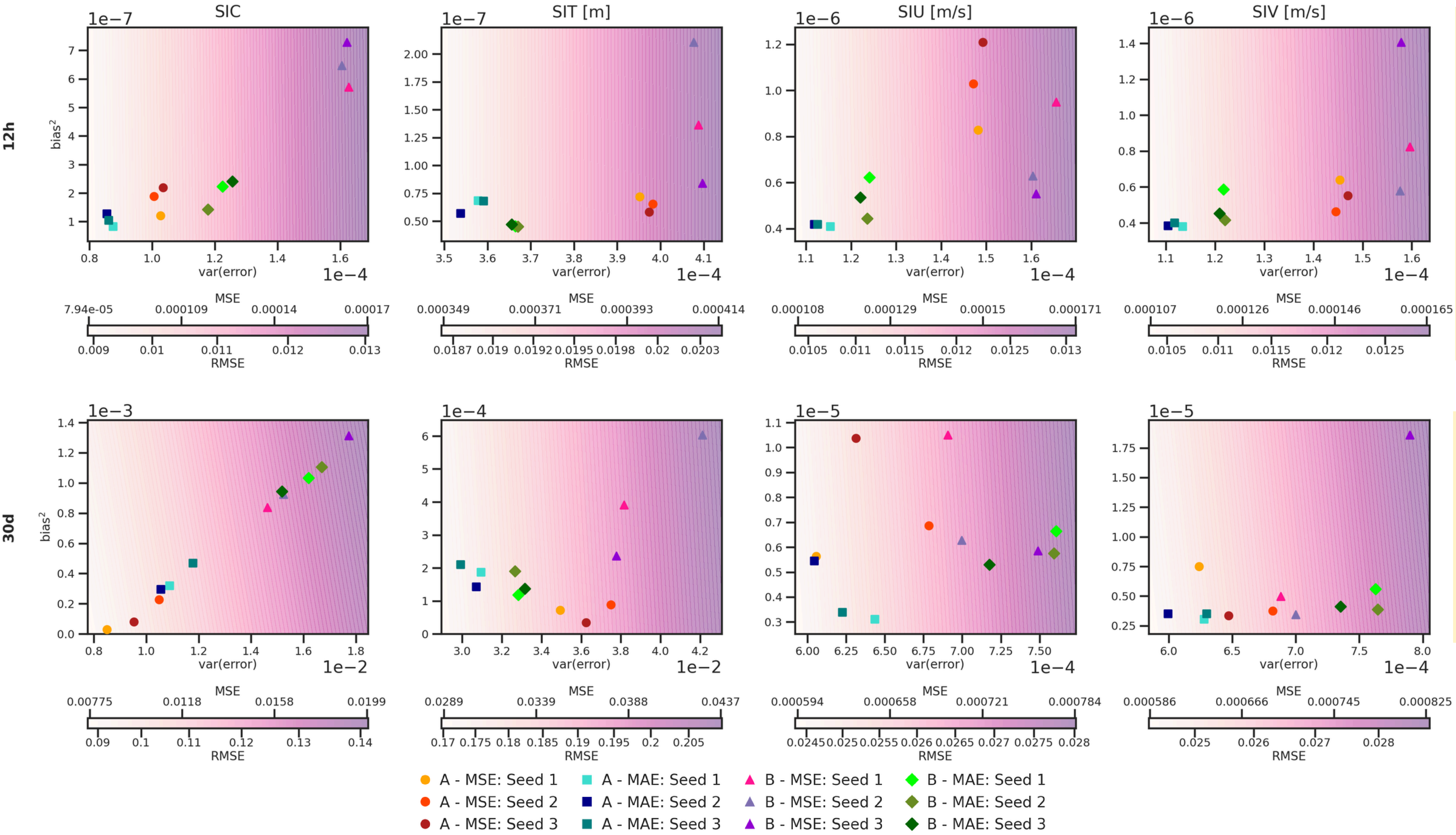


All configurations show **stable optimization**.

The effect of the **loss-variable choice** is most relevant.

The **bias** represents a subtle but structurally more complex component of the error.

The **autoregressive error accumulation** progressively **dominates** the forecast error. At 30 days, it is more difficult to distinguish between model configuration.

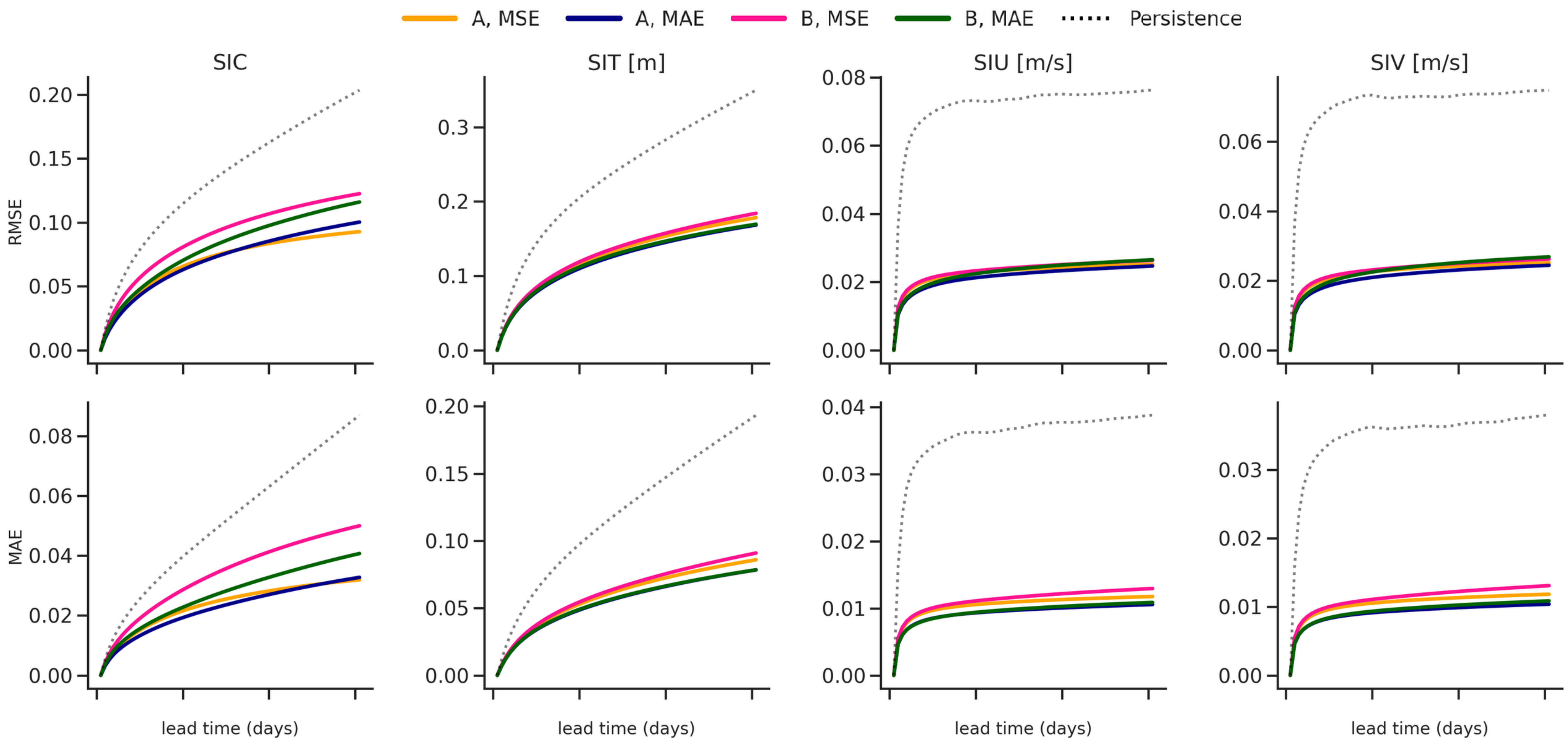
A, MSE : SIC, SIT, SIU, SIV; MSE loss

A, MAE SIC, SIT, SIU, SIV; MAE loss

B, MSE : Vol, SIT, SIU, SIV; MSE loss

B, MAE Vol, SIT, SIU, SIV; MAE loss

Emulator forecasting performances



A, MSE : SIC, SIT, SIU, SIV; MSE loss

A, MAE SIC, SIT, SIU, SIV; MAE loss

B, MSE : Vol, SIT, SIU, SIV; MSE loss

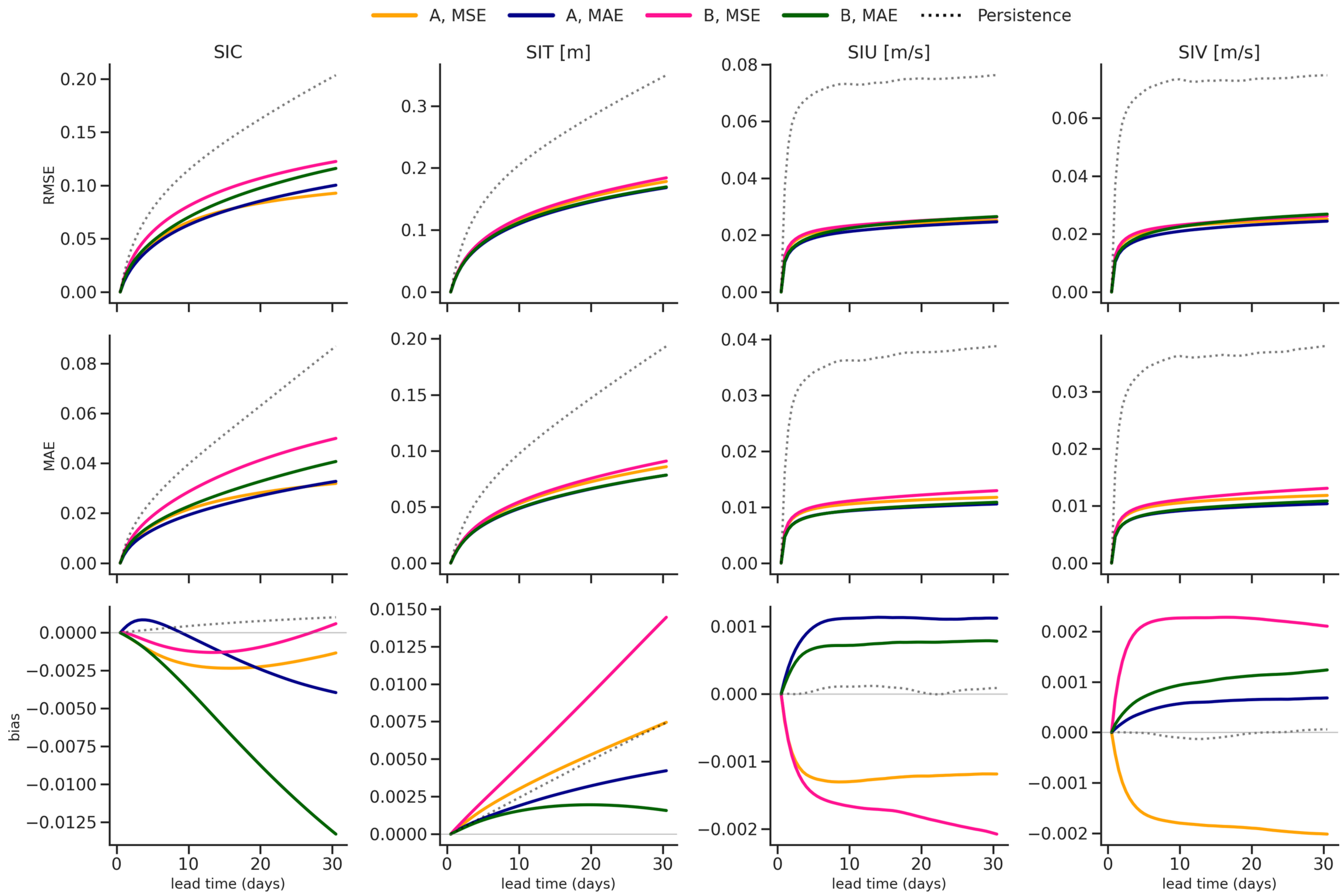
B, MAE Vol, SIT, SIU, SIV; MAE loss

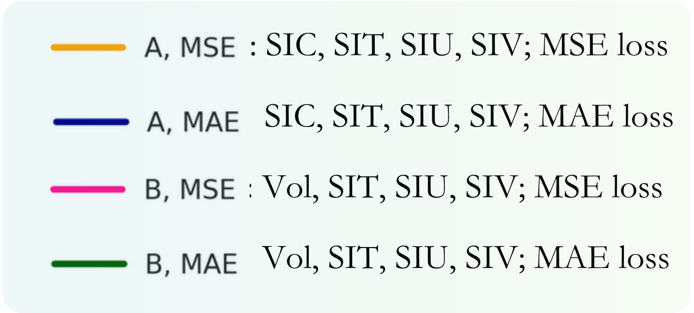
30 days forecast skills, averaged over the whole testing period.

The model performs **better than persistence** model in terms of the RMSE and MAE evaluation metrics.

Explicitly **supervising sea-ice concentration** is critical for accurate forecasts.

Emulator forecasting performances



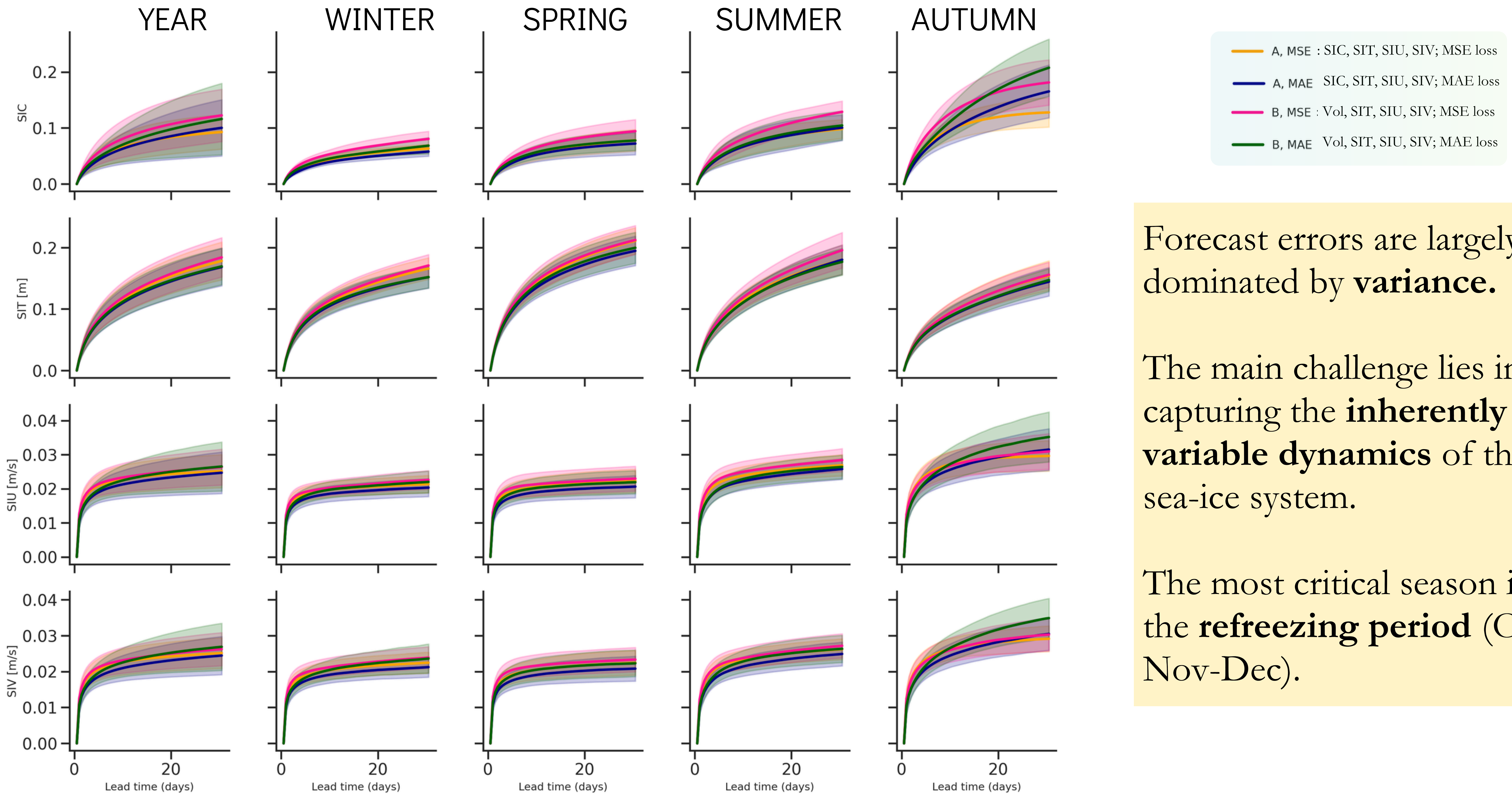


30 days forecast skills, averaged over the whole testing period.

The model performs **better than persistence** model in terms of the RMSE and MAE evaluation metrics.

Explicitly **supervising sea-ice concentration** is critical for accurate forecasts.

Emulator forecasting performances over seasons - RMSE

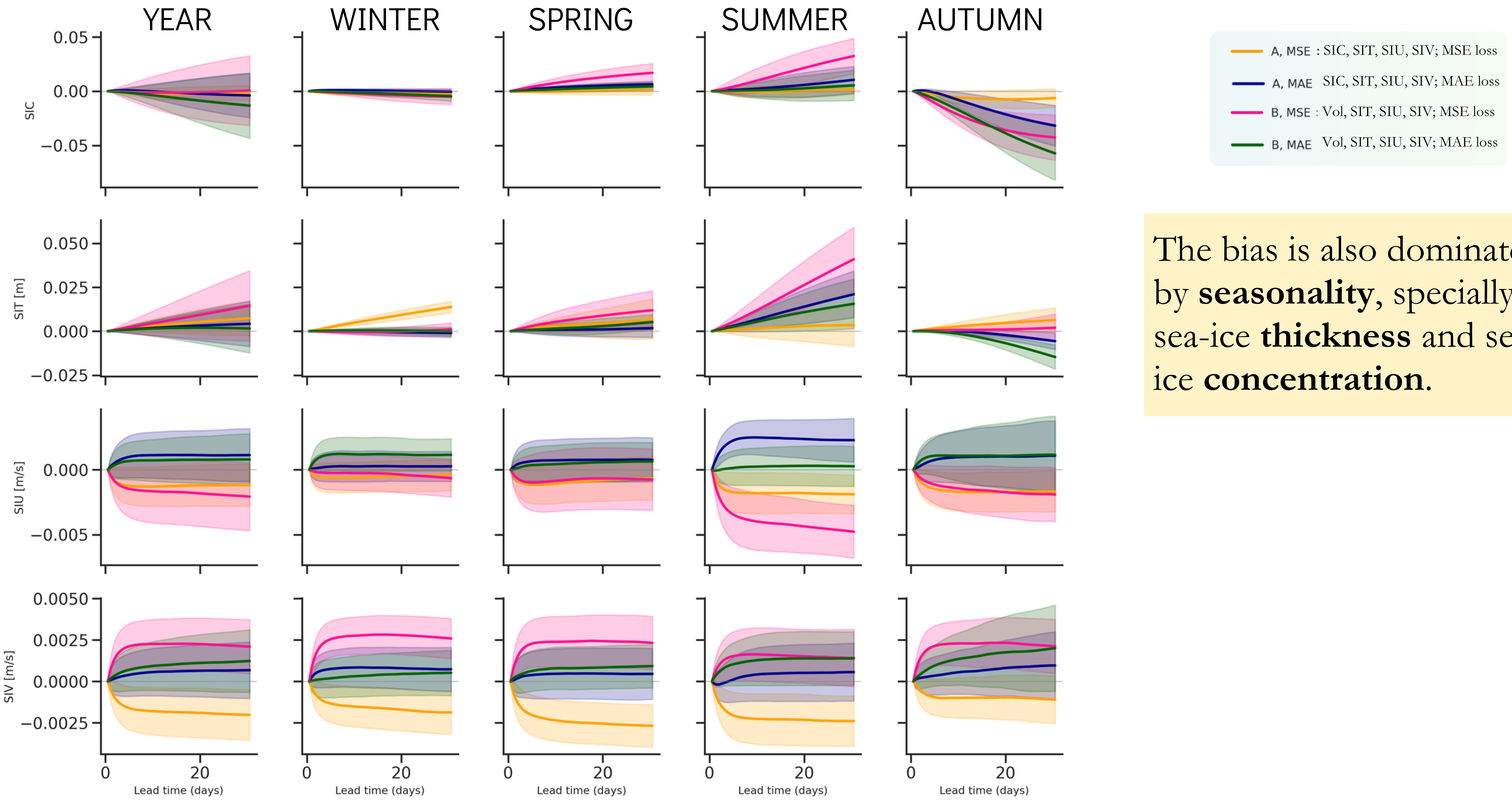


Forecast errors are largely dominated by **variance.**

The main challenge lies in capturing the **inherently variable dynamics** of the sea-ice system.

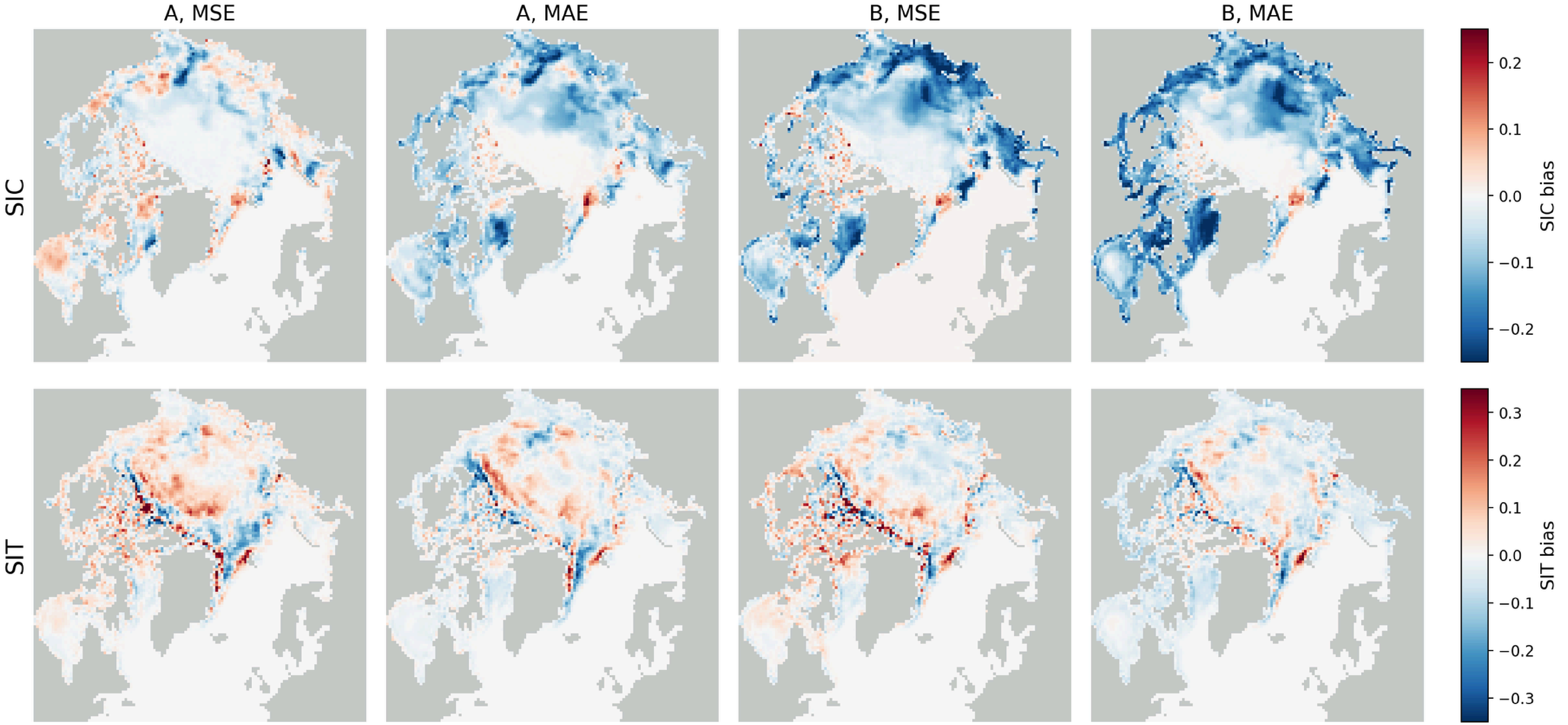
The most critical season is the **refreezing period** (Oct-Nov-Dec).

Emulator forecasting performances over seasons - bias



The bias is also dominated by **seasonality**, specially for sea-ice **thickness** and sea-ice **concentration**.

Sea-ice concentration at 30-day lead time during Oct-Nov-Dec



Bias computed as **(surrogate - neXtSIM)**

- **blue**: underestimation of the surrogate (in central pack and marginal zone for SIC);
- **red**: overestimation of the surrogate (boundary with land for SIT for both SIT and SIC).

A, MSE : SIC, SIT, SIU, SIV; MSE loss

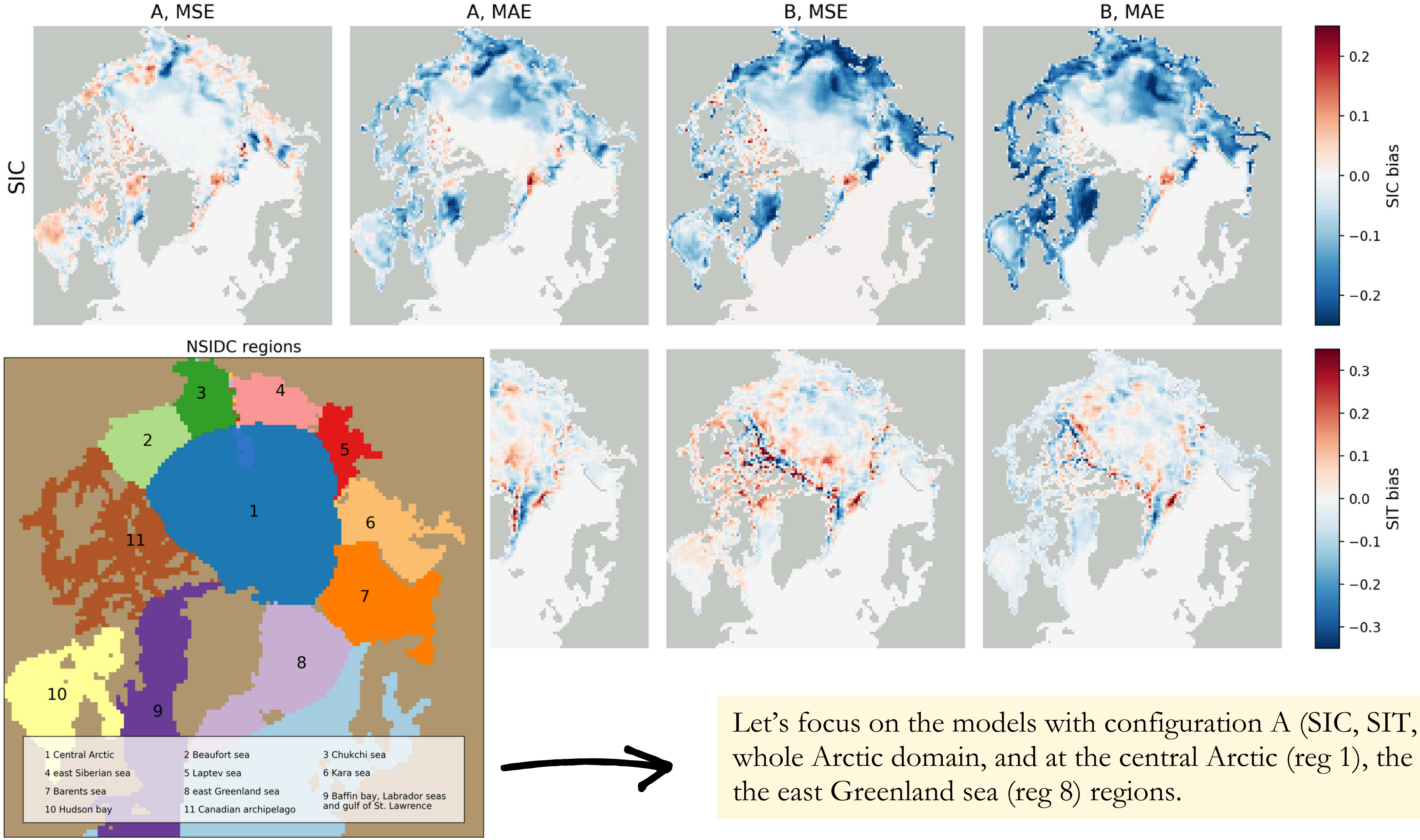
A, MAE SIC, SIT, SIU, SIV; MAE loss

B, MSE : Vol, SIT, SIU, SIV; MSE loss

B, MAE Vol, SIT, SIU, SIV; MAE loss

The bias for SIC and SIT show high locals values (up to 20% for SIC).

Sea-ice concentration at 30-day lead time during Oct-Nov-Dec

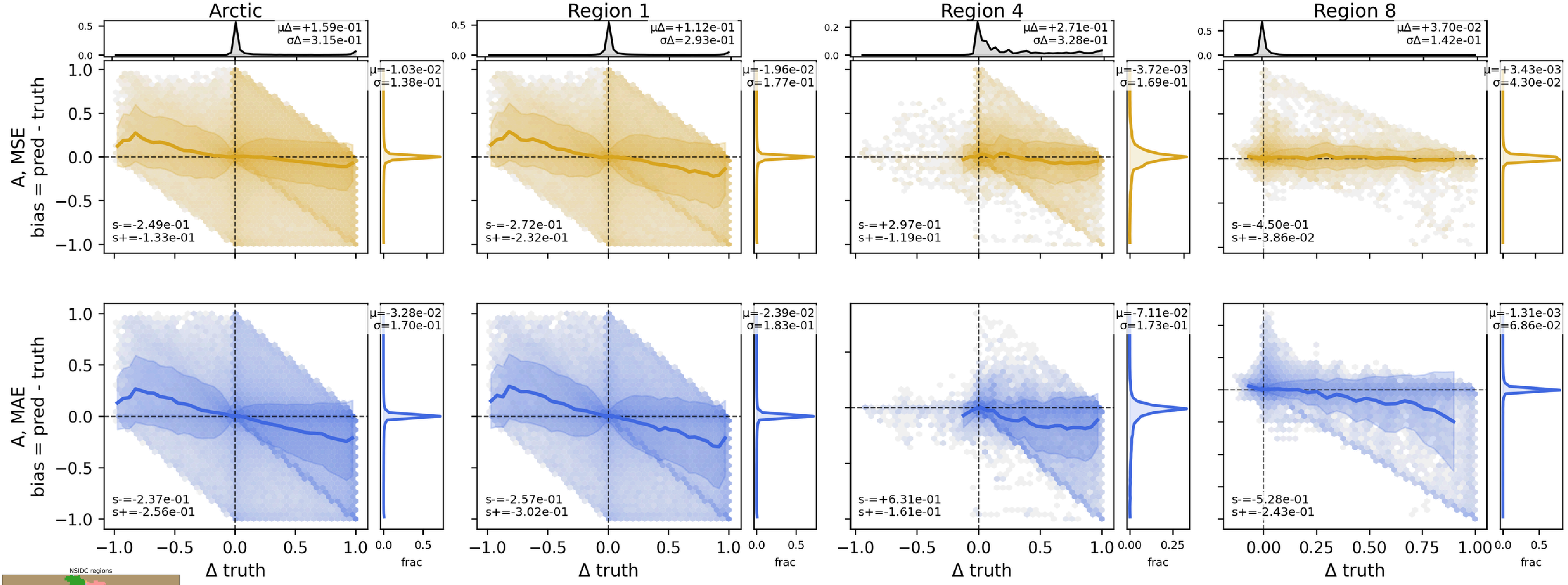


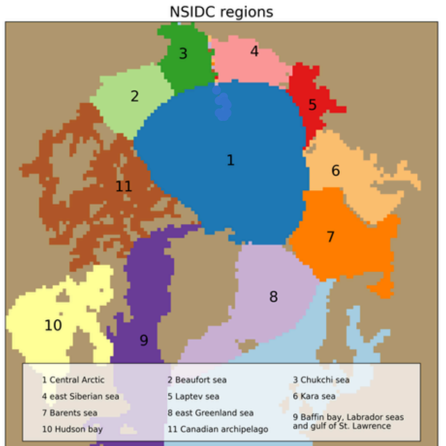
Bias computed as **(surrogate - neXtSIM)**

- **blue**: underestimation of the surrogate (in central pack and marginal zone for SIC);
- **red**: overestimation of the surrogate (boundary with land for SIT for both SIT and SIC).

Let's focus on the models with configuration A (SIC, SIT, SIU, SIV). Let's look at the whole Arctic domain, and at the central Arctic (reg 1), the east Siberian sea (reg 4), and the east Greenland sea (reg 8) regions.

Does the bias correlate with the temporal variability?



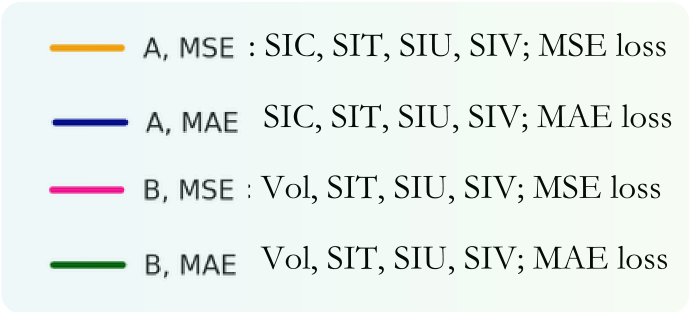


The central Arctic regions show a stronger correlation, for both models. The model A, MAE is generally slower than A, MSE in representing the refreezing process.

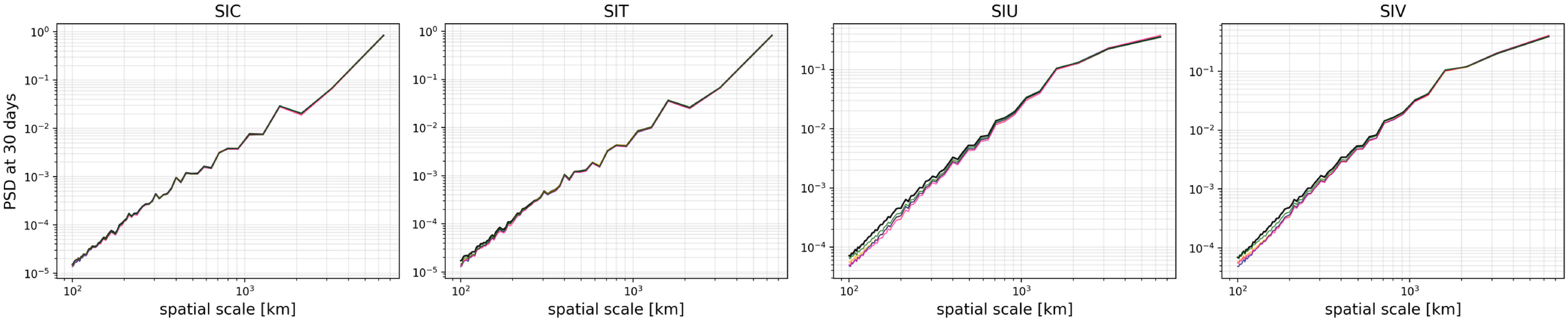
filter
$\Delta \neq 0$

Power spectrum density

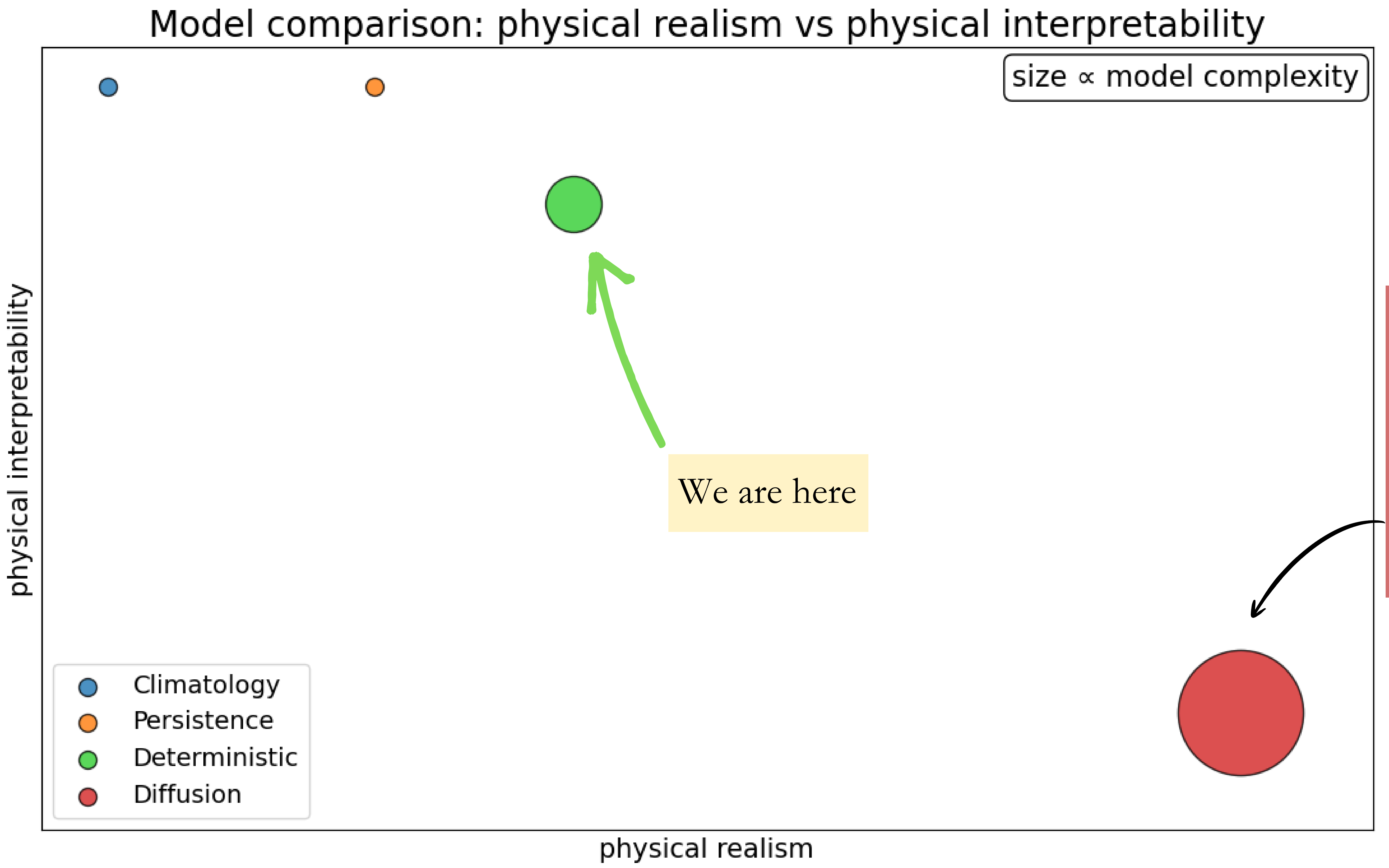
The **predicted fields are smoothed** compared with ground truth, due to the minimization of the MSE/MAE during training. This effect is measured with the **power spectrum density** analysis.

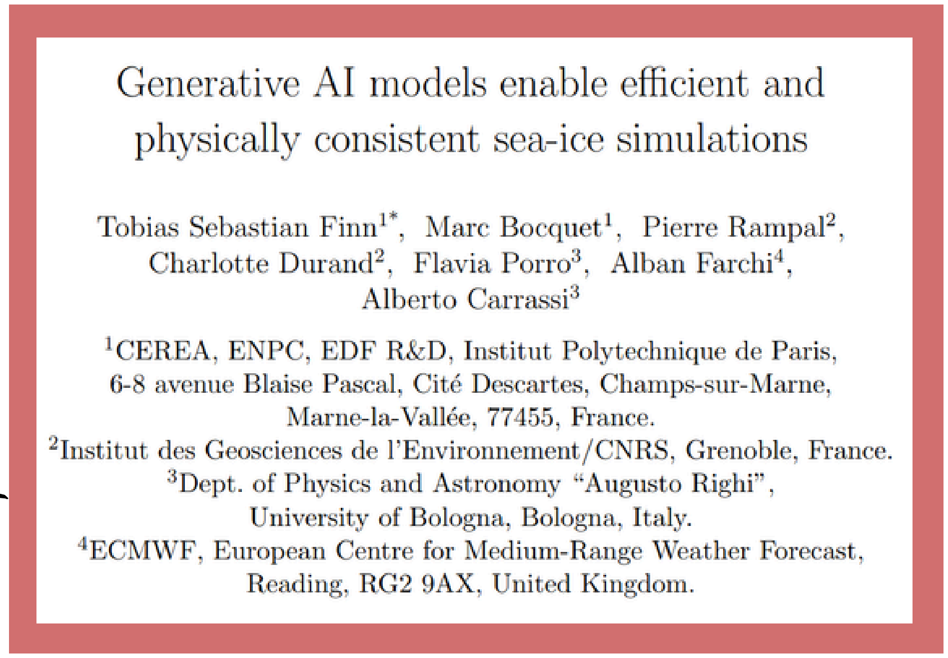


Here, the PSD is averaged over all the forecast cycles.



Where we are



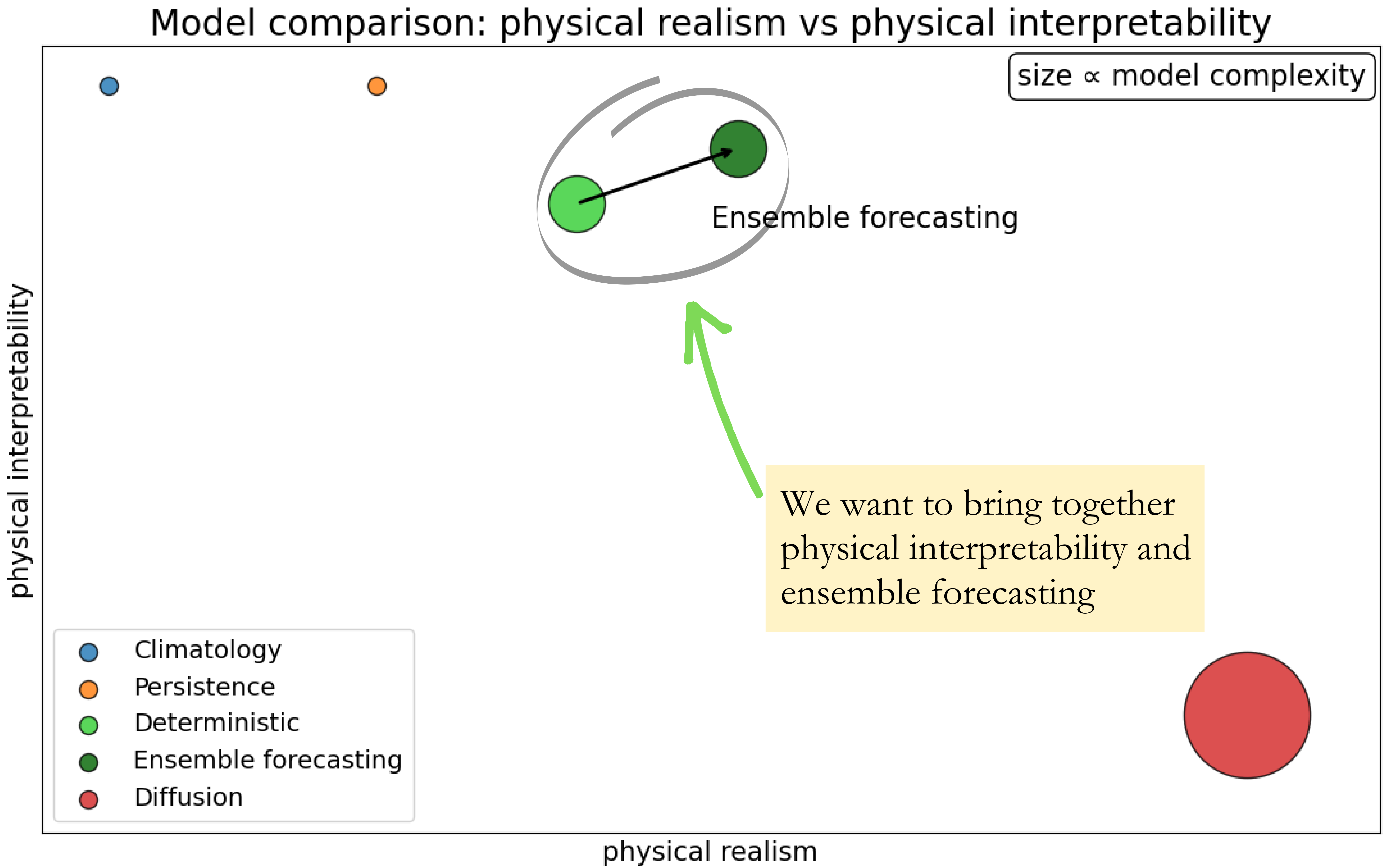


Generative AI models enable efficient and physically consistent sea-ice simulations

Tobias Sebastian Finn[1*], Marc Bocquet[1], Pierre Rampal[2], Charlotte Durand[2], Flavia Porro[3], Alban Farchi[4], Alberto Carrassi[3]

[1]CEREA, ENPC, EDF R&D, Institut Polytechnique de Paris, 6-8 avenue Blaise Pascal, Cité Descartes, Champs-sur-Marne, Marne-la-Vallée, 77455, France.
[2]Institut des Geosciences de l'Environnement/CNRS, Grenoble, France.
[3]Dept. of Physics and Astronomy "Augusto Righi", University of Bologna, Bologna, Italy.
[4]ECMWF, European Centre for Medium-Range Weather Forecast, Reading, RG2 9AX, United Kingdom.

Future prospective: towards probabilistic model



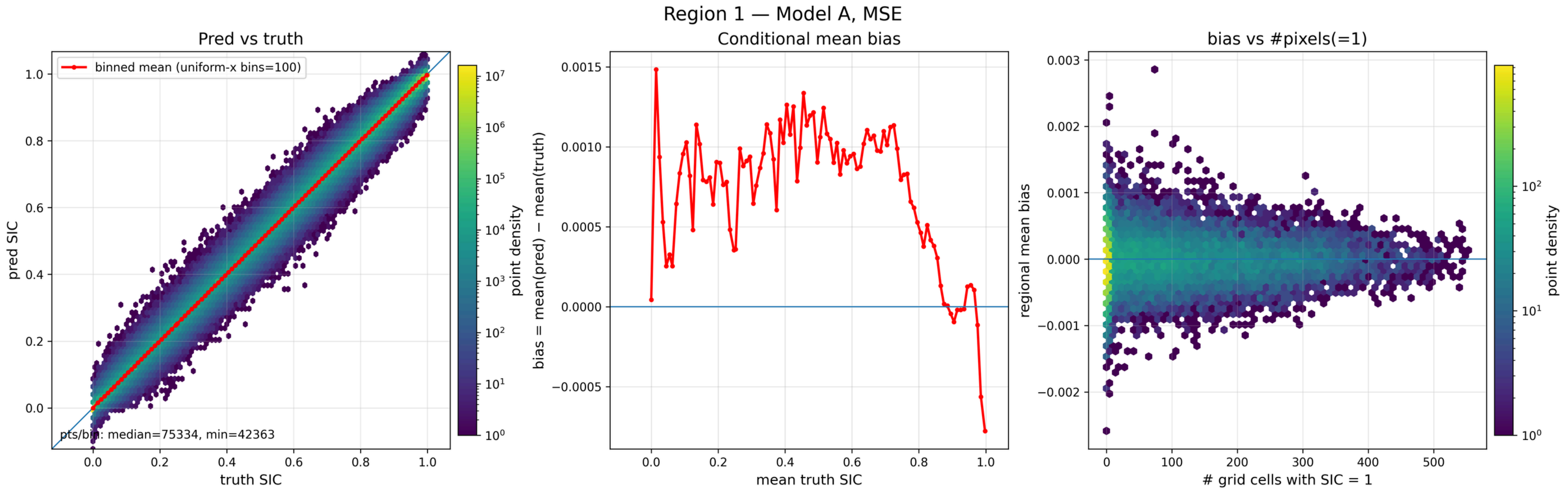
We want to bring together physical interpretability and ensemble forecasting

Thank you!

Does the bounded nature of SIC induce bias?

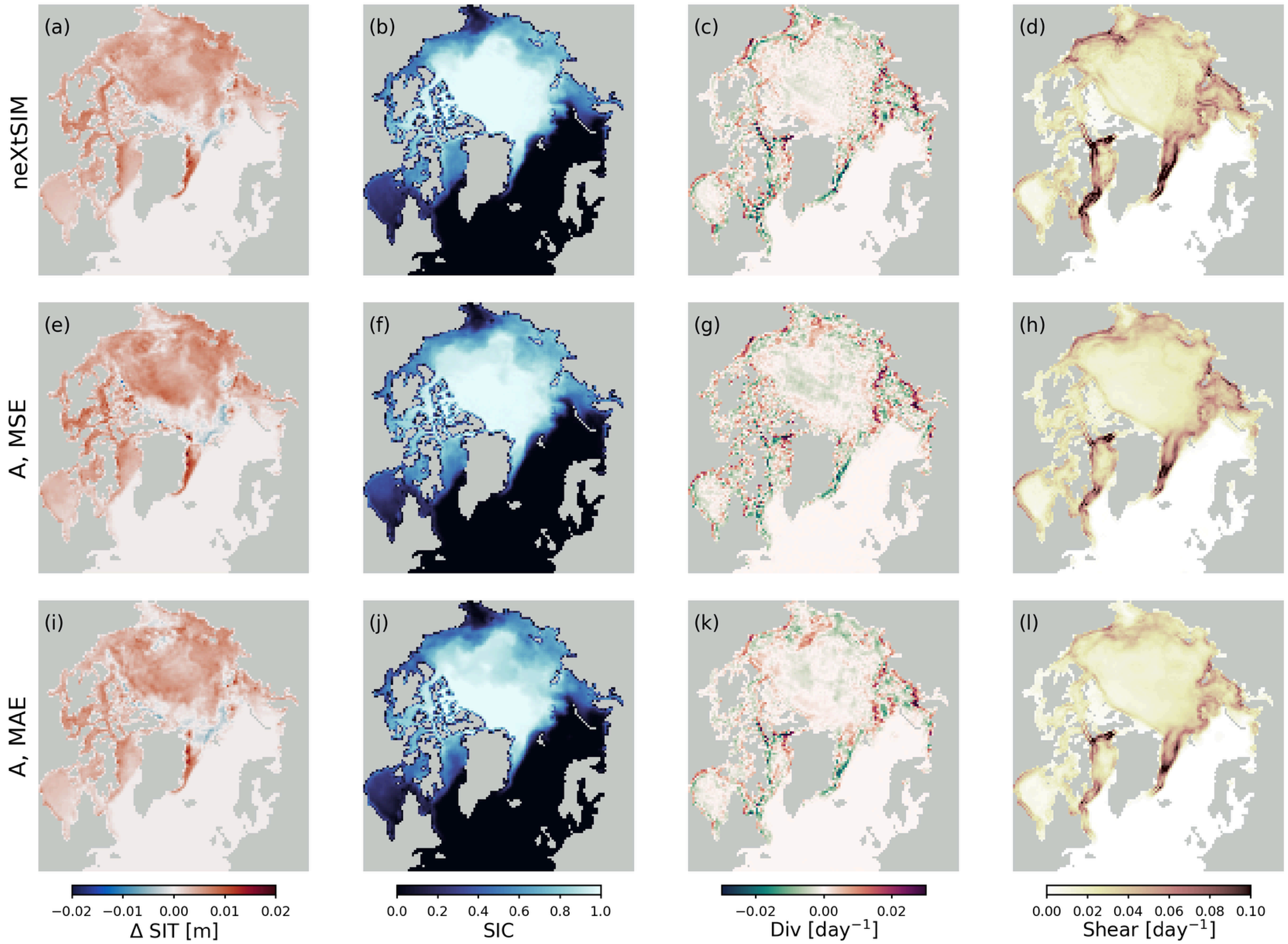
Towards diffusion models for large-scale sea-ice modelling

Tobias Sebastian Finn [1] **Charlotte Durand** [1] **Alban Farchi** [1] **Marc Bocquet** [1] **Julien Brajard** [2]



We do not observe a significant underestimation of the SIC at the upper bound.

Sea-ice deformation Oct-Nov-Dec



Sea ice deforms where sea-ice is weaker.

Convergence leads to ridging and divergence to further thinning of sea ice.

Yet, the surrogate shows **loss of small-scale information**.

The divergence and shear show fewer pixels with weak and strong deformation.