Deep learning of subgrid-scale parametrisations for sea-ice dynamics

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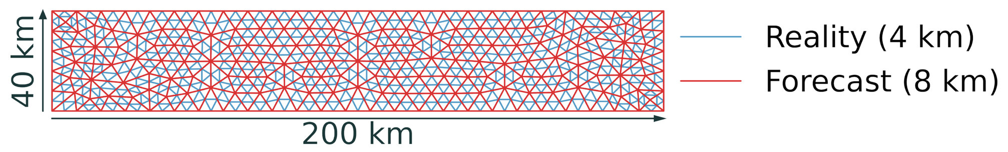
Motivation

Unresolved subgrid-scale processes make data assimilation difficult.

Sea ice induces new issues for deep learning methods by the marginal ice zone, multifractality, and anisotropy.

Method should be scalable to arctic-wide simulations with neXtSIM (Rampal et al., 2016).

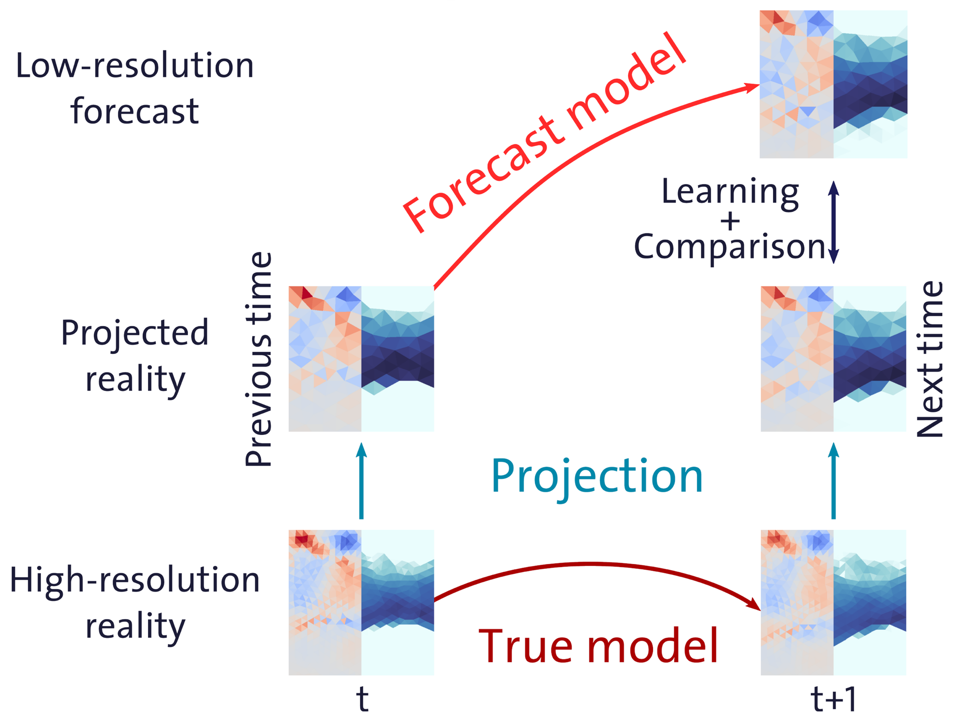
Model setup



Channel-like setup in a regional sea-ice model (Dansereau et al. 2016, 2017, 2021) that accounts for sea-ice dynamics only.

Examples of rapid transitions, by imposing a wave-like wind forcing.

Twin experiments



Training dataset with samples to correct forecast errors with lead time of around 10 minutes.

4800 / 960 /2400
Training/Validation/Test samples

Conclusion

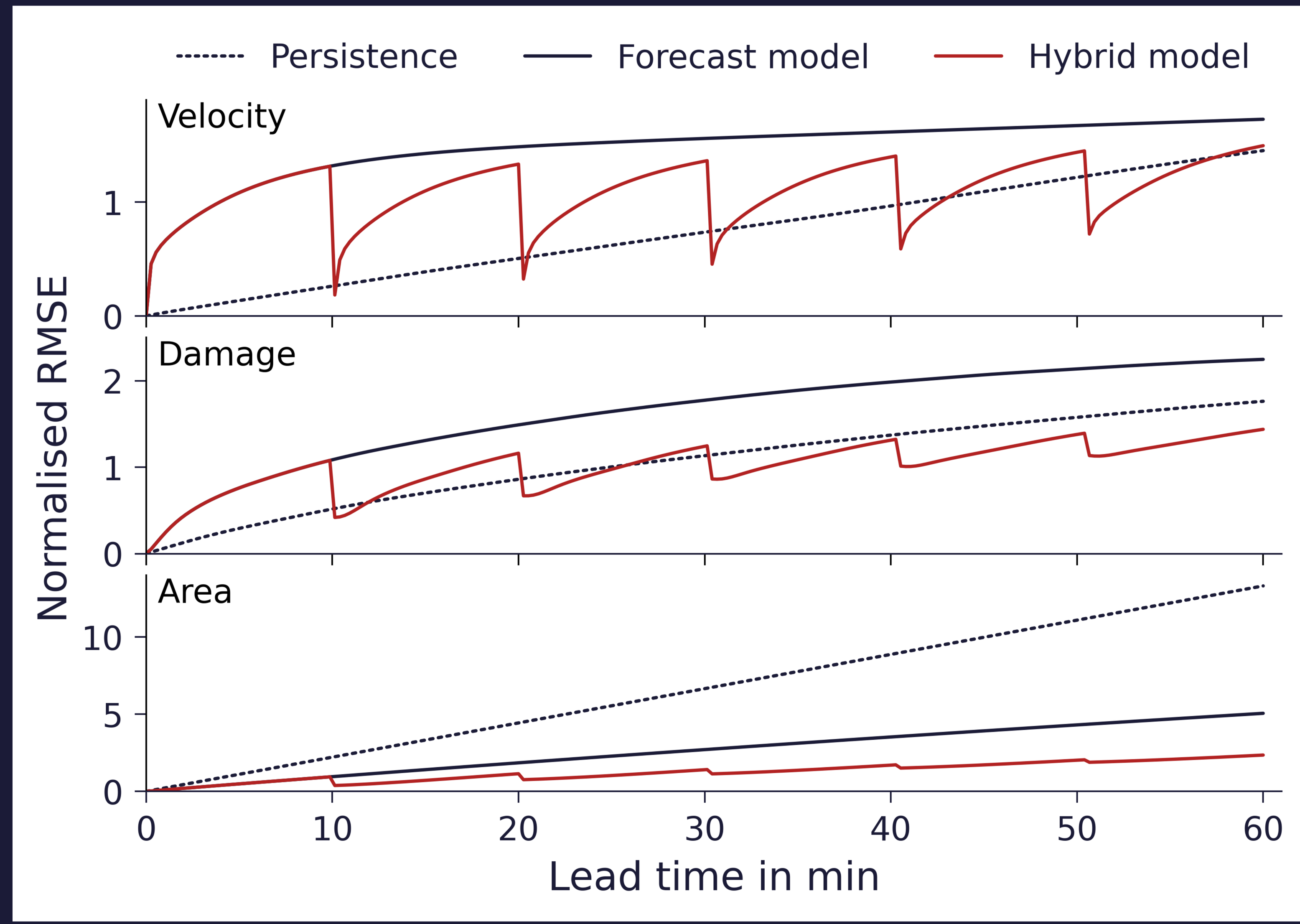
One deep neural network can parametrise subgrid-scale processes for all prognostic model variables at the same time.

Although only trained at first update, network can be cycled with model for continuous correction.

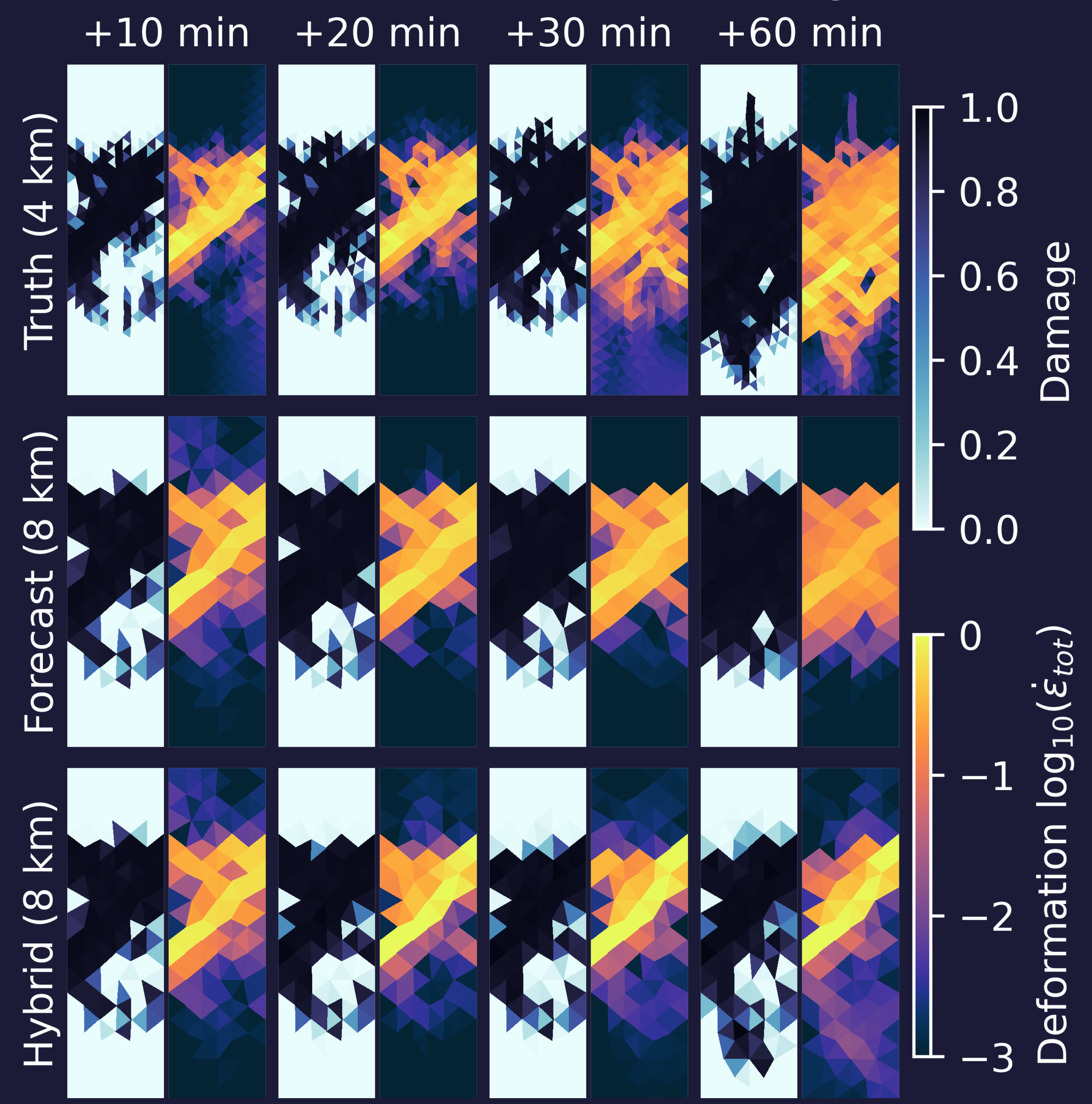
Next steps: Learn correction to NeXtSIM
Stochastic parametrisation

Deep learning can correct model errors from the subgrid-scale **for sea-ice dynamics**

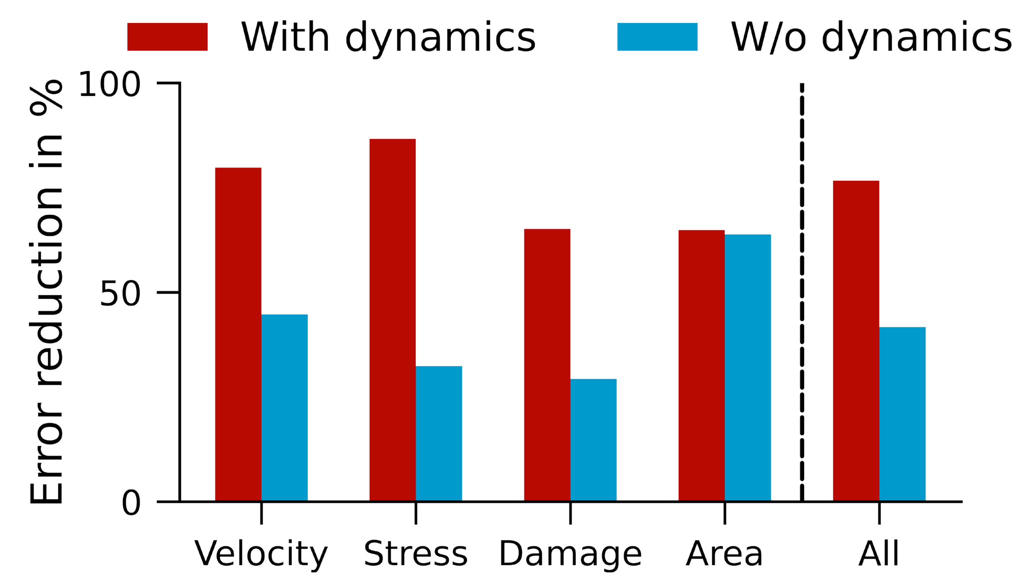
Cycling improves the short-term forecast



The hybrid model represents the dynamics better

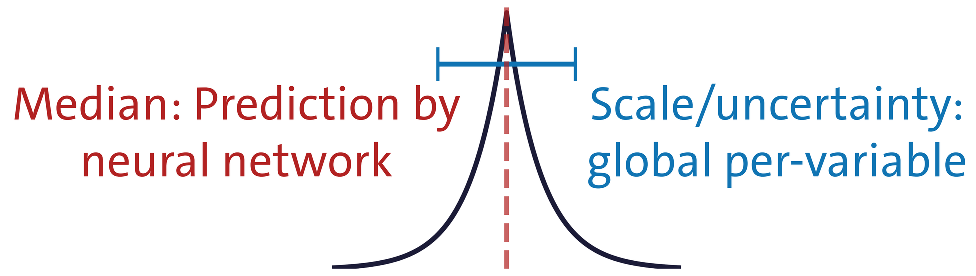


Results in testing dataset

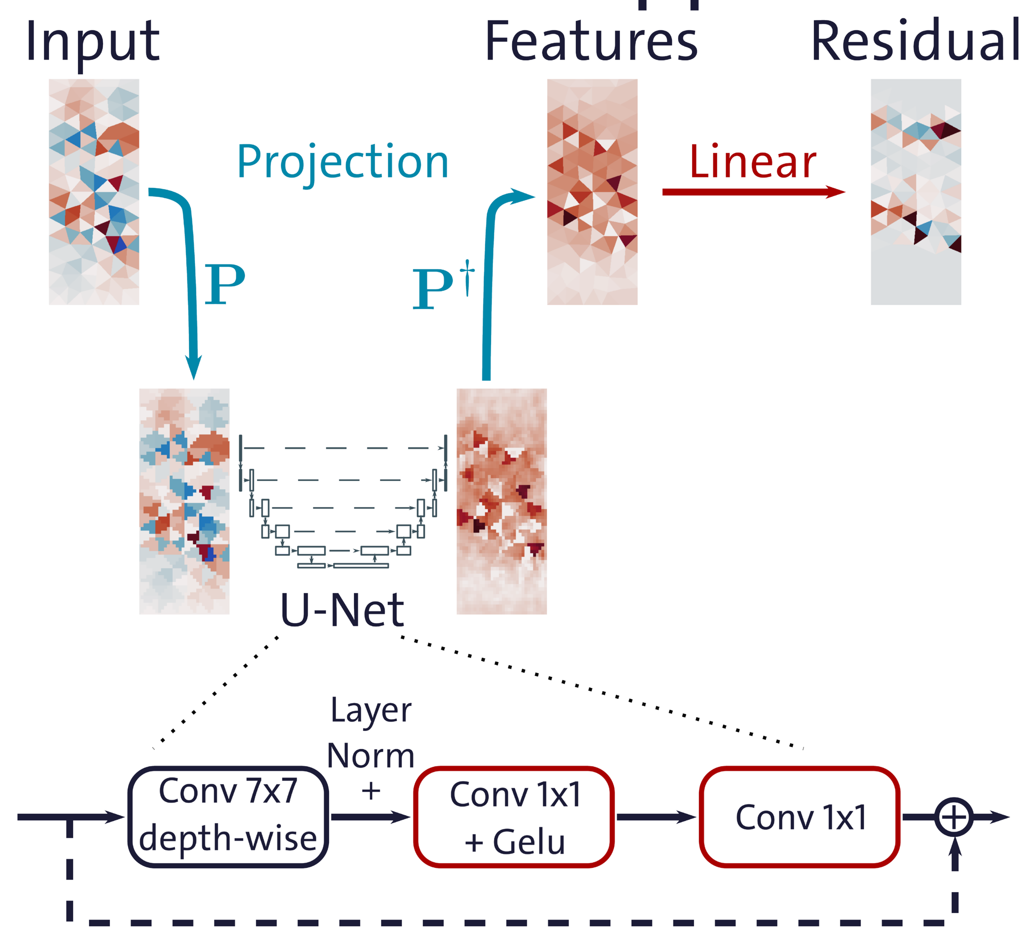


Maximum likelihood with Laplace distribution

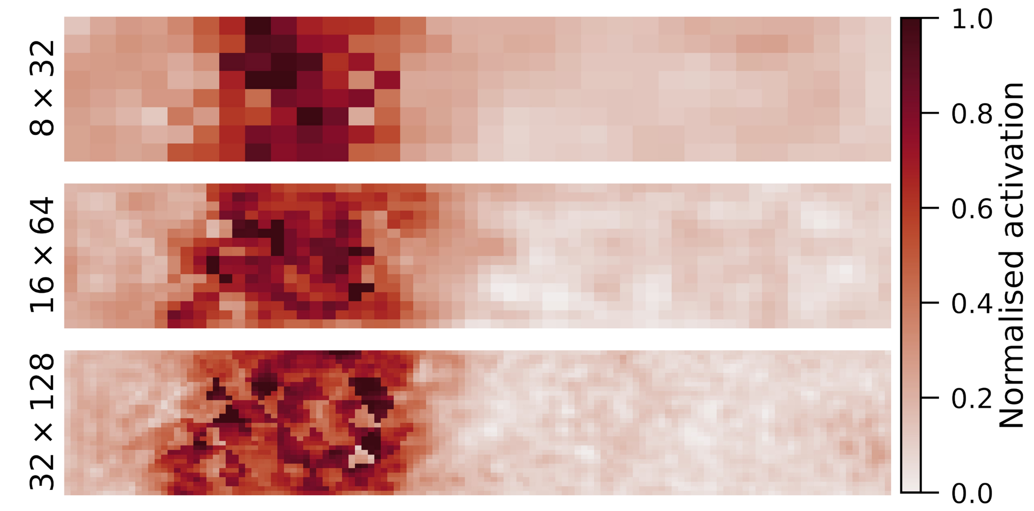
$$\mathcal{L}_{tot} = \sum_{i=1}^{9} \frac{1}{\text{scale}_i} \mathcal{L}_i + \log(2\,\text{scale}_i)$$



Efficient U-NeXt pipeline



Influence of Cartesian resolution



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The manuscript will be submitted to *The Cryosphere* soon

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