27.05.2022

ESA Living Plant Symposium - Bonn

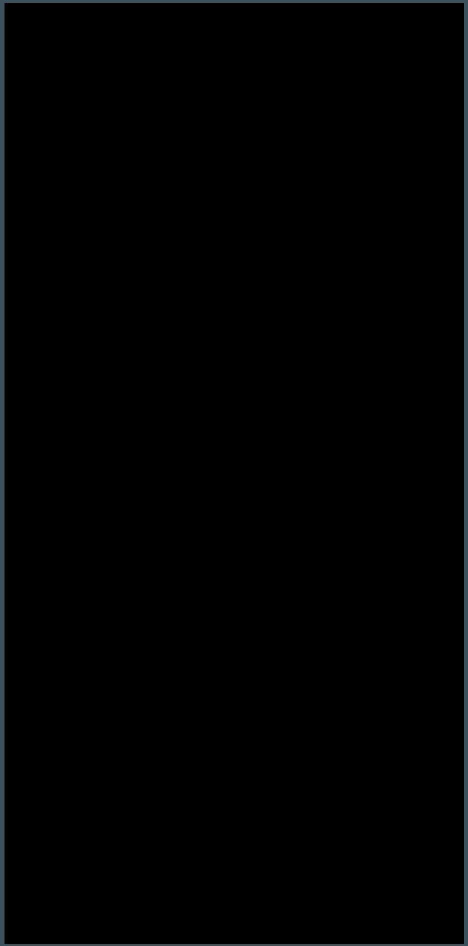
Learning and screening of neural networks for sub-grid-scale parametrisations of sea-ice dynamics

Tobias Sebastian Finn

Charlotte Durand, Alban Farchi, Marc Bocquet,
Yumeng Chen, Alberto Carrassi, Veronique Dansereau

For the first time, one blink away from predicting sea-ice

These advanced geophysical sea-ice models are not perfect



27.05.2022

Enhance these advanced models with neural networks

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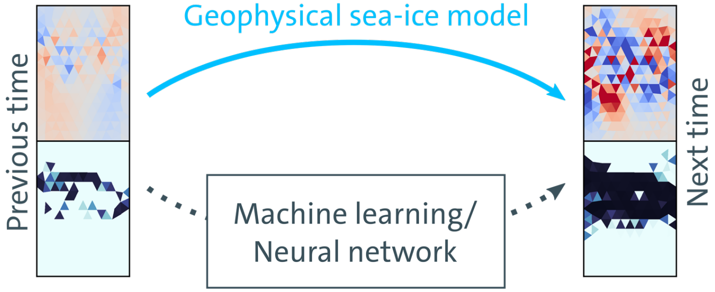
Correct forecast errors of sea-ice dynamics with machine learning before they appear



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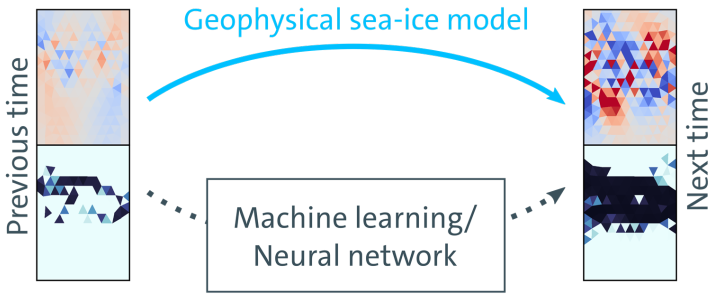

<u>Already possible (not exclusive):</u>

Cloud convection (Rasp et al., 2018)

Atmospheric boundary layer (Chen et al., 2022)

Ocean turbulence (Bolton and Zanna, 2020)

Enhance these advanced models with neural networks

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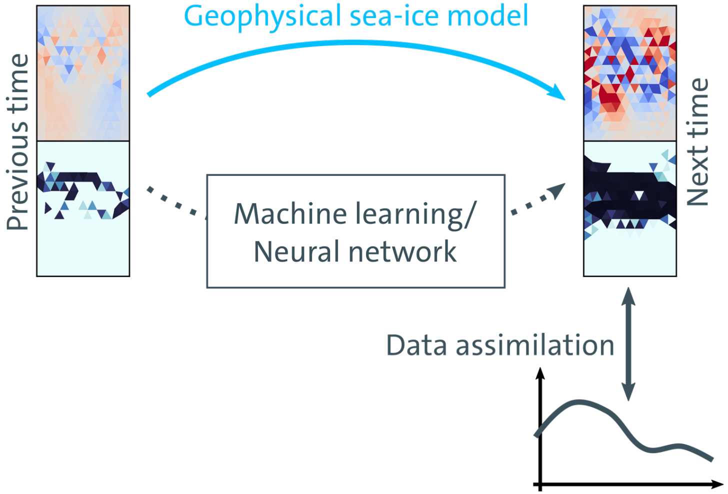

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Ocean turbulence (Bolton and Zanna, 2020)

We can even learn the dynamics from observations

(Bocquet et al. 2020, Gottwald and Reich 2021, Farchi et al. 2021)

How can we use similar approaches for the sea-ice dynamics?

Sea-ice imposes new challenges for neural networks

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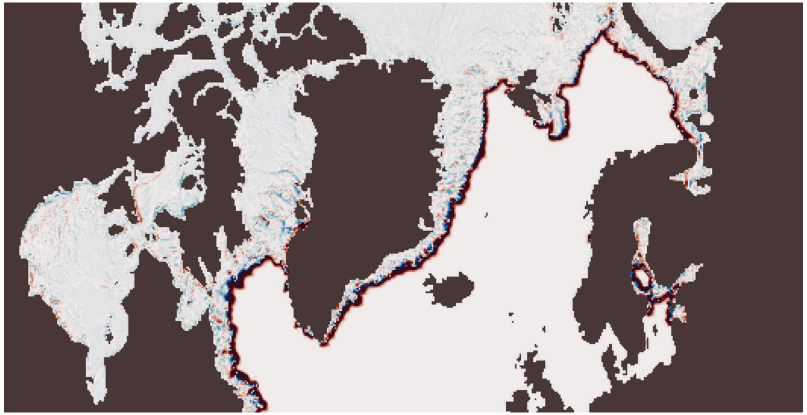
Marginal ice zone



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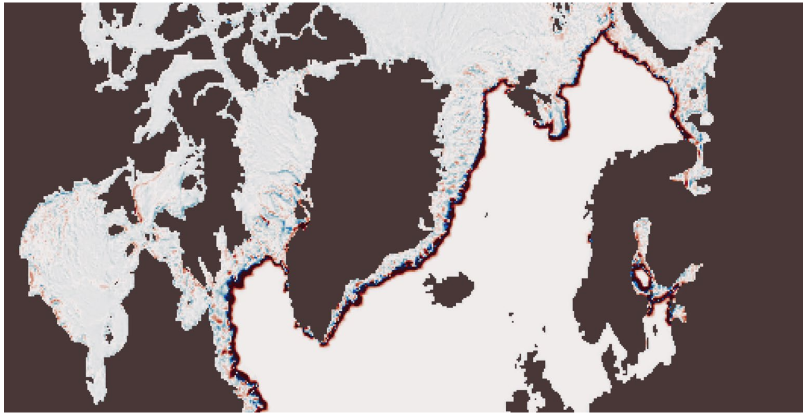
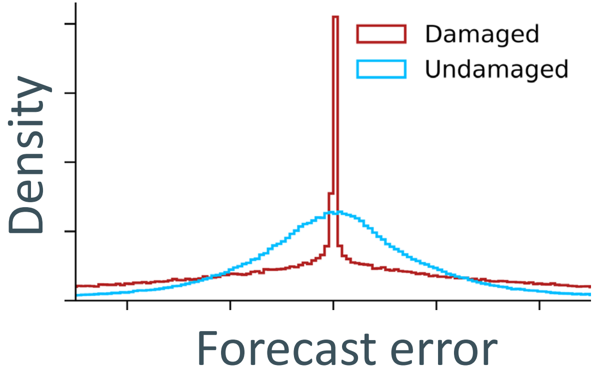


Damage



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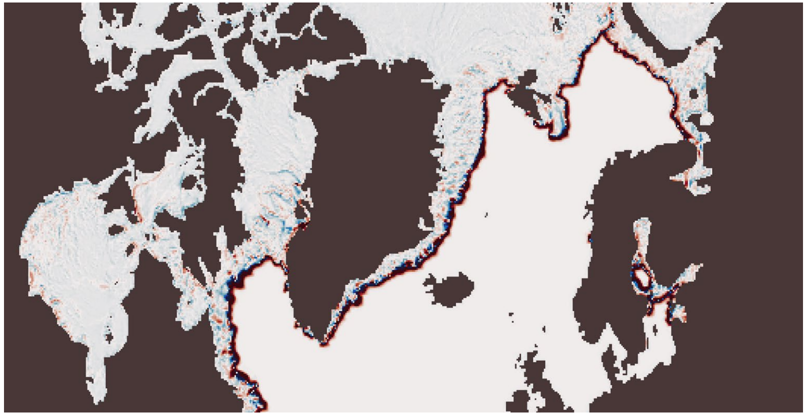

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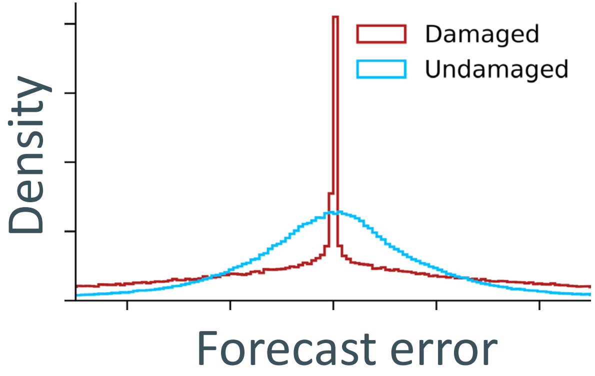
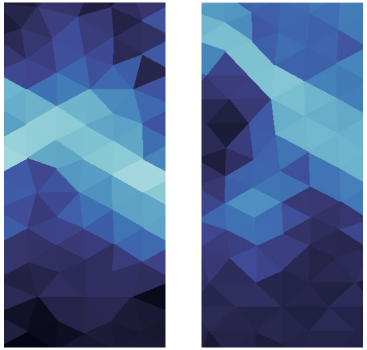


Multifractality



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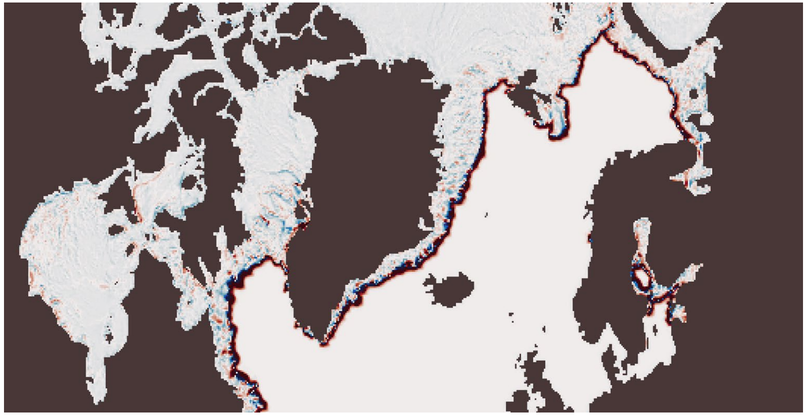

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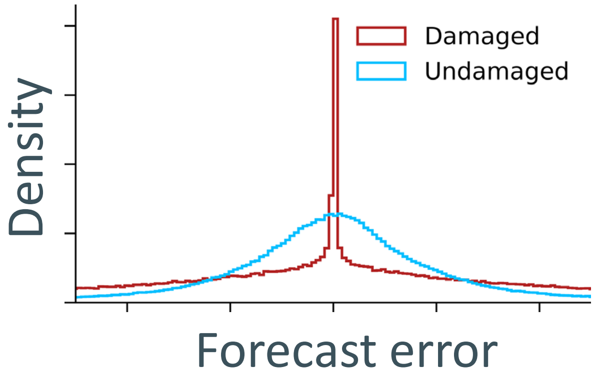

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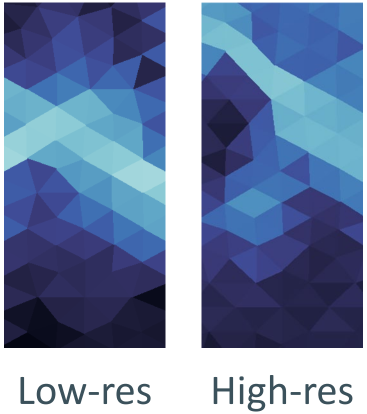

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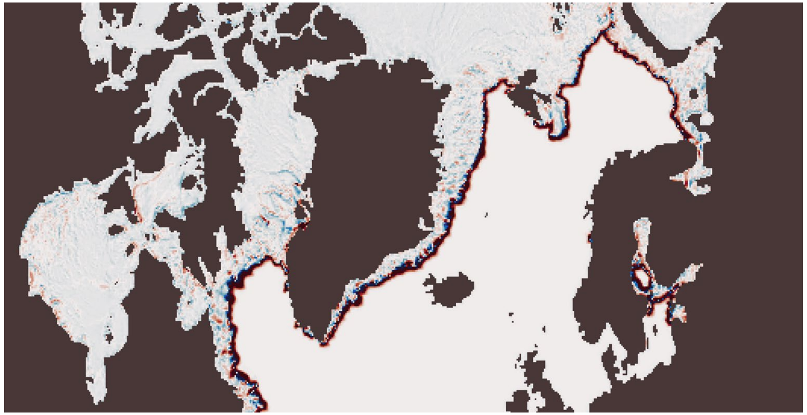

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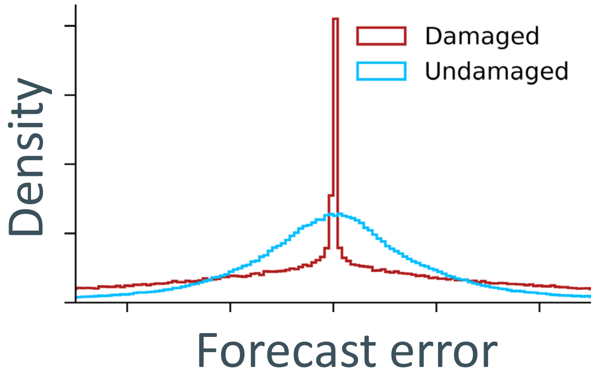

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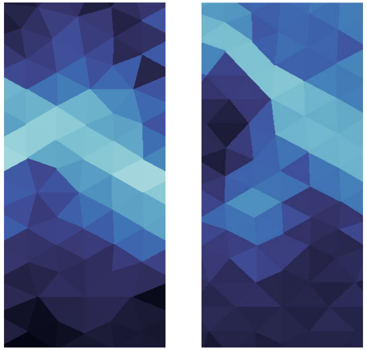

Low-res High-res

Scaling from small-scale model to Arctic-scale model

Sea-ice imposes new challenges for neural networks

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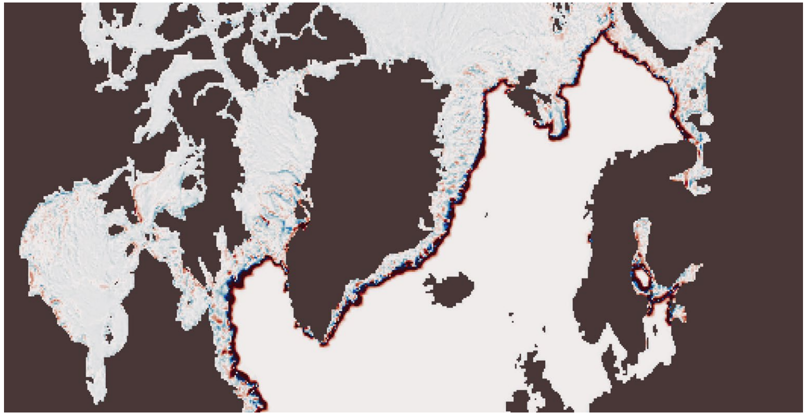

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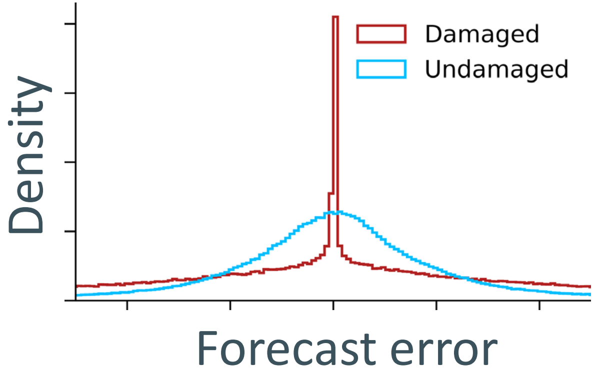

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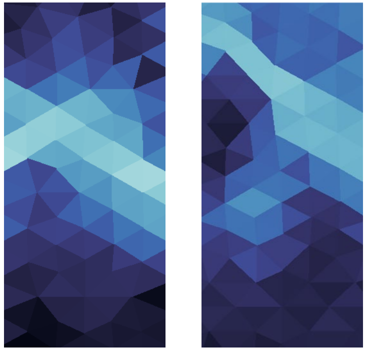

Low-res High-res

Scaling from small-scale model to Arctic-scale model

→ Screening of possible approaches

How to learn parametrisations with twin experiments

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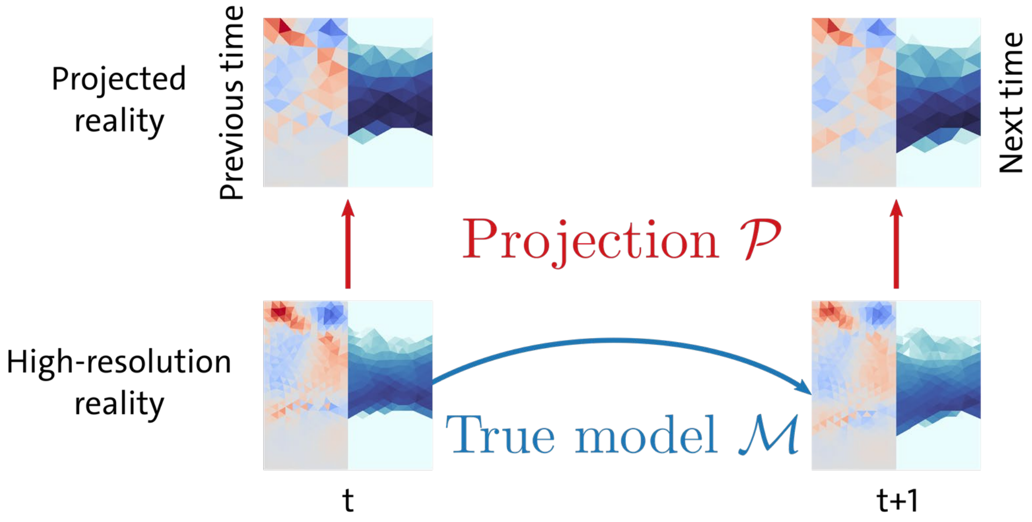
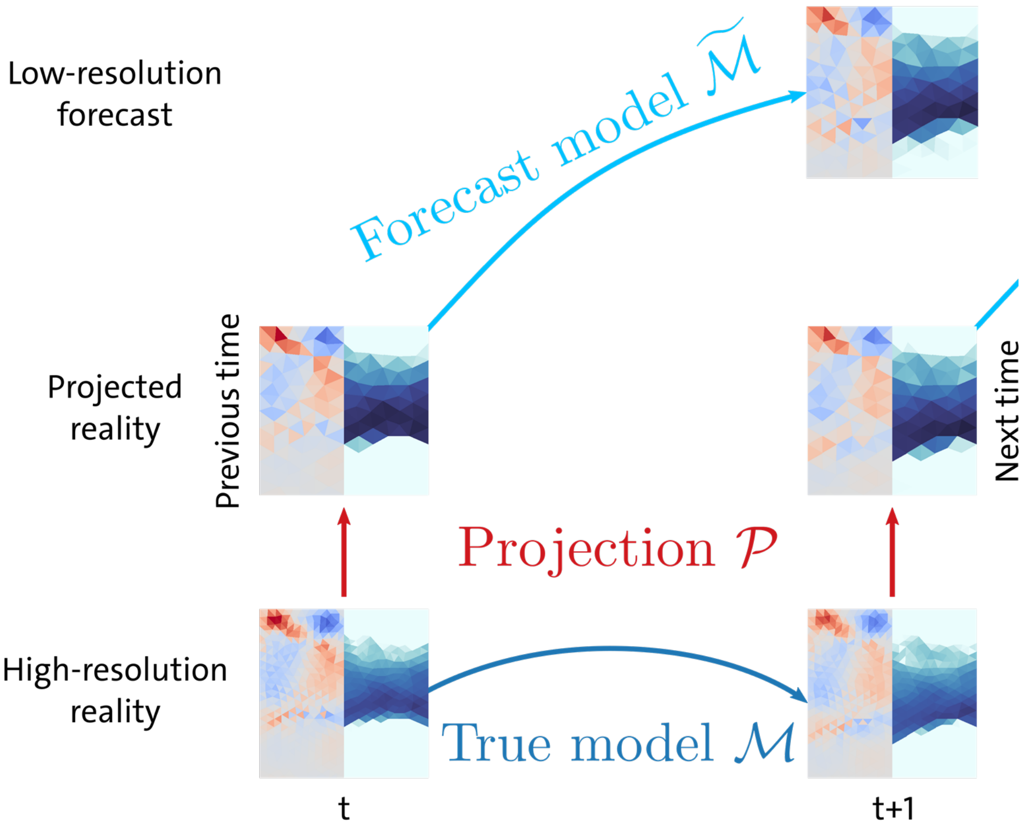


Projection by Lagrange interpolation as used in FEM solvers

How to learn parametrisations with twin experiments



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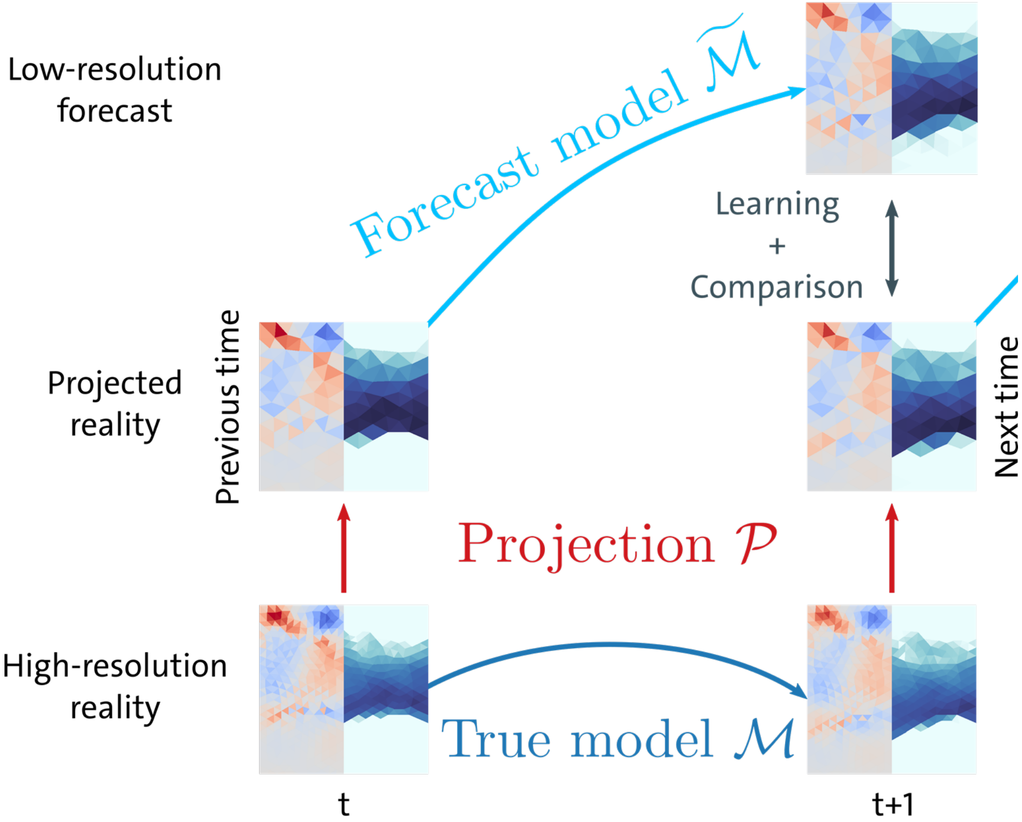

Projection by Lagrange interpolation as used in FEM solvers

Testbed based on a sea-ice dynamics-only model

Maxwell-Elasto-Brittle model (Dansereau et al. 2016; Dansereau et al. 2017)

based on discontinuous Galerkin finite elements and Rheolef solver (Saramito 2020)

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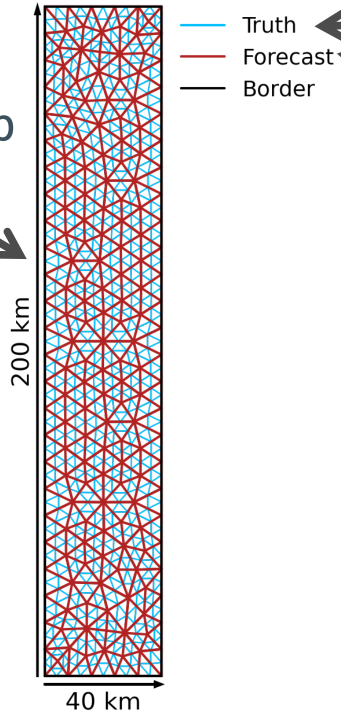
1D-like setup



$\sim 4\,\mathrm{km}$

$\sim 8\,\mathrm{km}$

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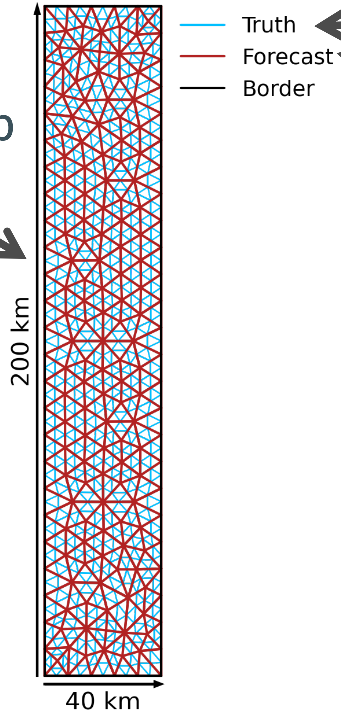

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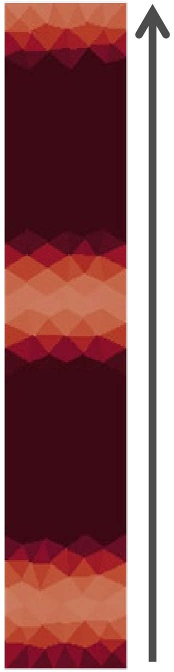

Wave-like forcing in y-direction

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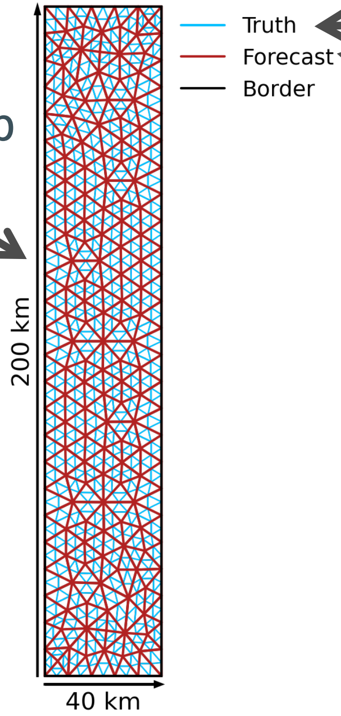

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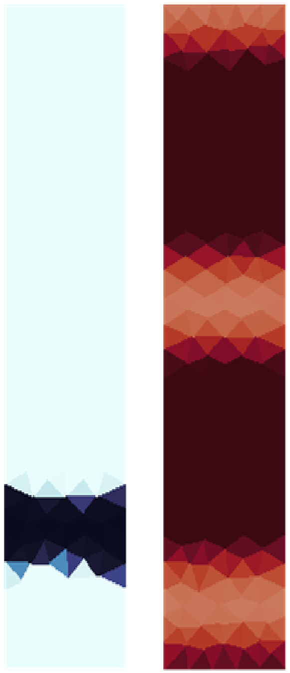
Marginal ice zones



Wave-like forcing in y-direction

How to train for all nine variables at the same time?

$$\mathcal{L}_{tot} = \lambda_1 \mathcal{L}_1 + \lambda_2 \mathcal{L}_2 + \cdots + \lambda_9 \mathcal{L}_9$$

Use maximum likelihood approach

$$\mathcal{L}_{tot} = \lambda_1 \mathcal{L}_1 + \lambda_2 \mathcal{L}_2 + \cdots + \lambda_9 \mathcal{L}_9$$

Maximum likelihood approach $\Big\downarrow$ Global per-variable uncertainty

$$\mathcal{L}_{tot} \approx \frac{1}{\mathrm{scale}_1}\mathcal{L}_1 + \log(2\,\mathrm{scale}_1) + \cdots + \frac{1}{\mathrm{scale}_9}\mathcal{L}_9 + \log(2\,\mathrm{scale}_9)$$

Training based on an ensemble of trajectories

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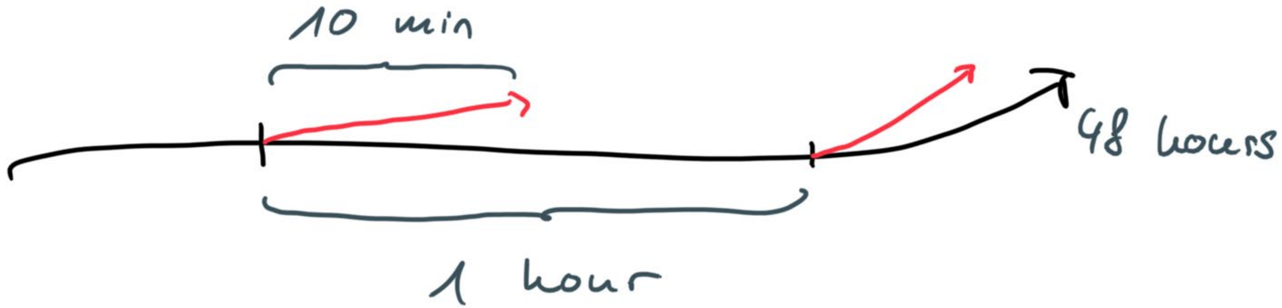

Ensemble of forcing parameters and initial cohesion

Training based on an ensemble of trajectories

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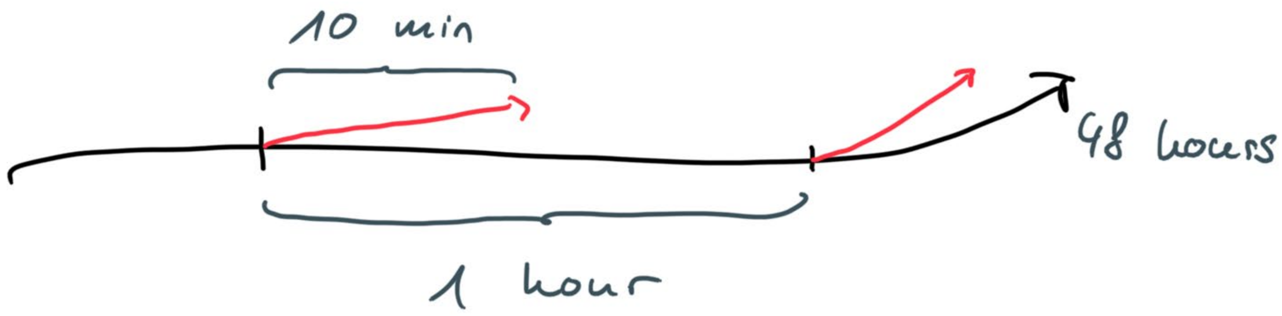


Ensemble of forcing parameters and initial cohesion

4800/960/2400 training/validation/test samples

How to make use of inductive bias for triangular data?

Input

Prediction

Project into Cartesian space

Input

Interpolate

Prediction

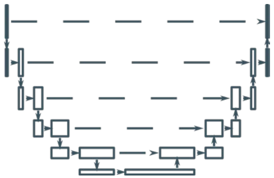
Project into Cartesian space and apply convolutional neural network

Input

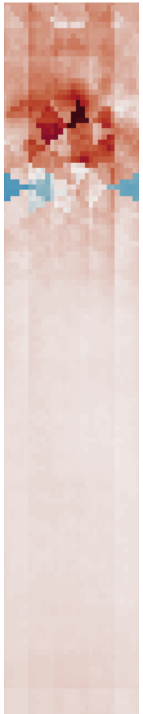
Interpolate

U-Net backbone

(Ronneberger et al. 2015)



+ dilation



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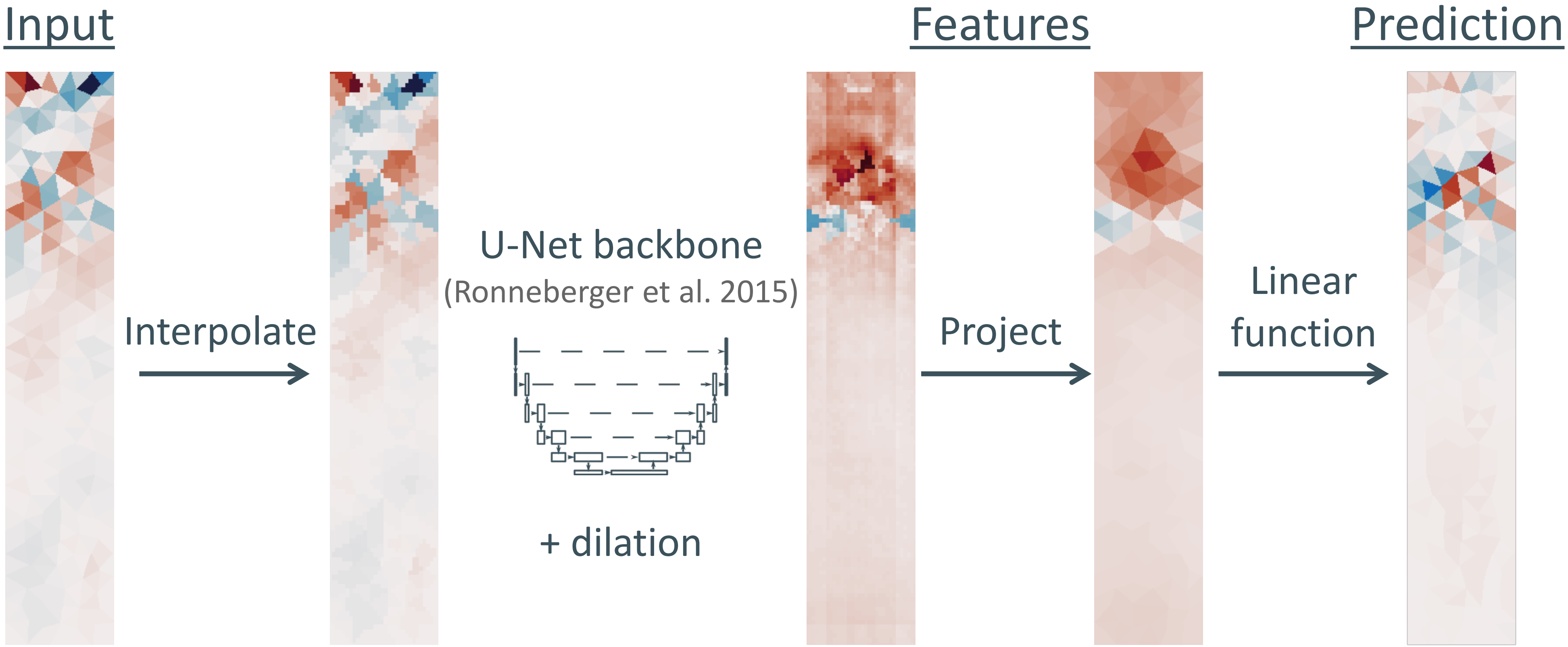
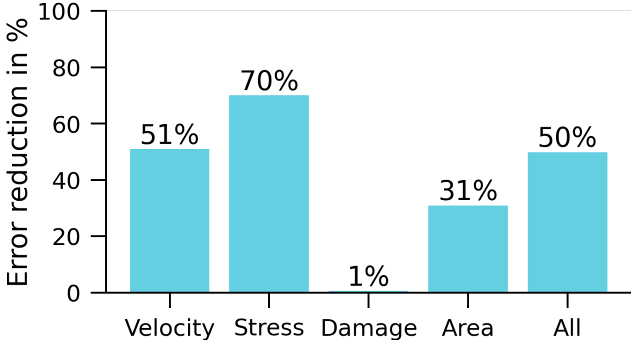


How is the performance of our neural network?

Forecast error reduced in offline testing dataset



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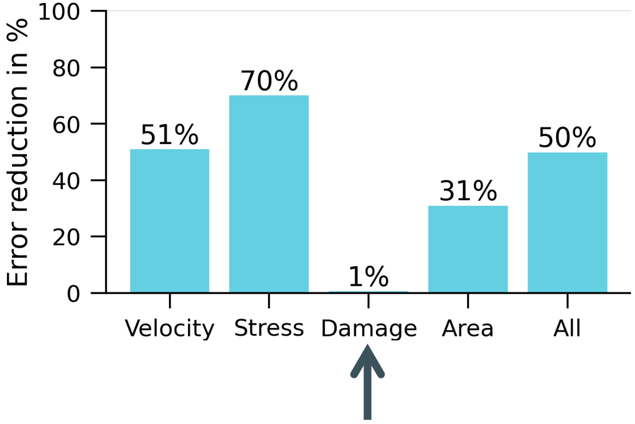
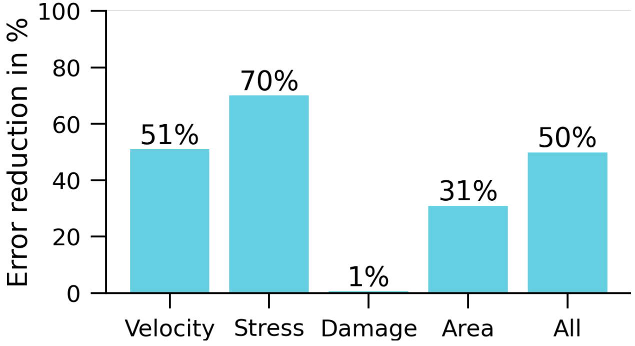
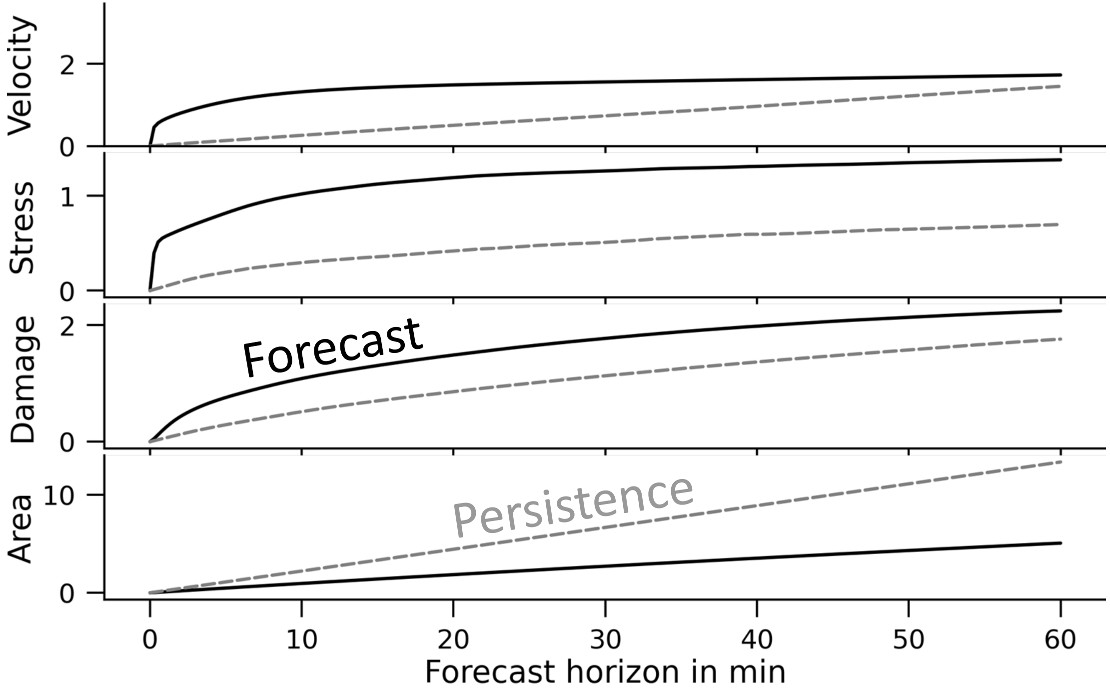


Multi-modality of damage

Forecast error reduced in offline testing dataset





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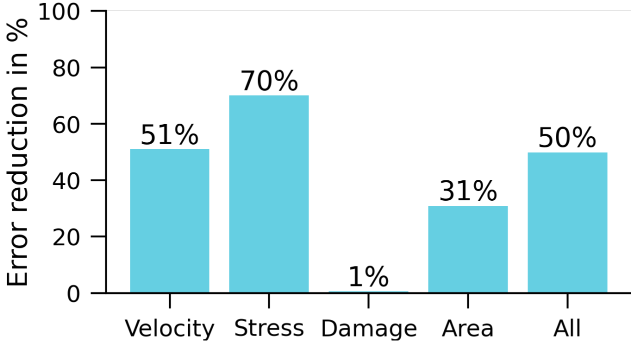

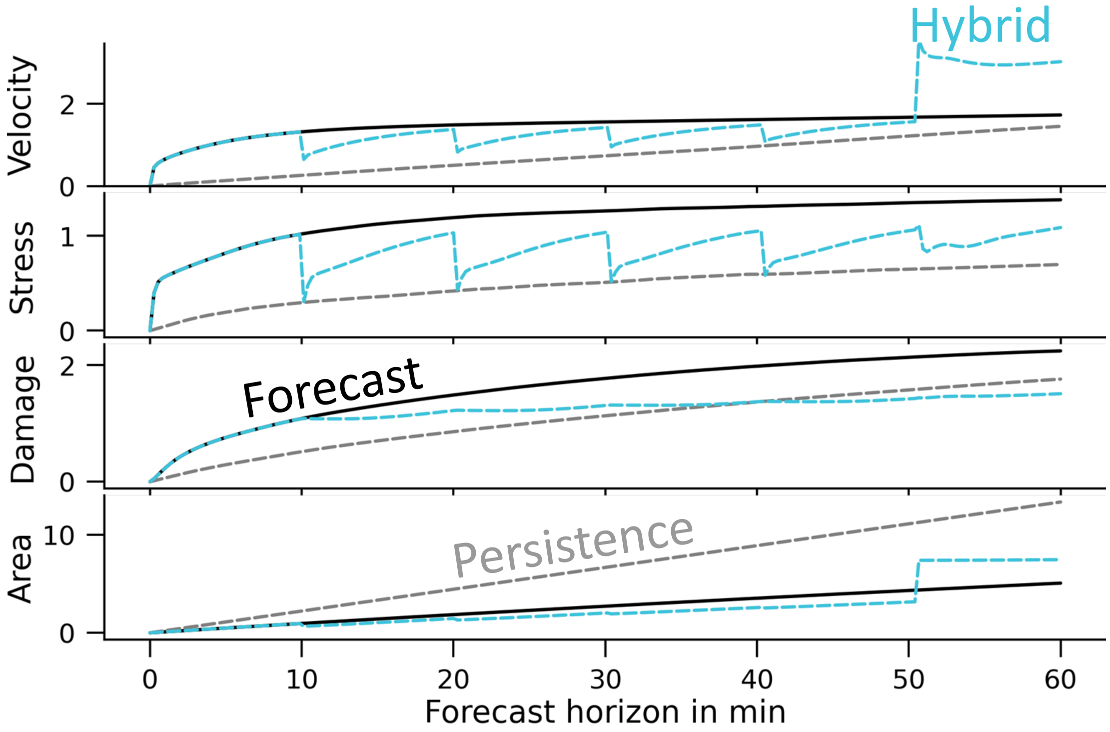

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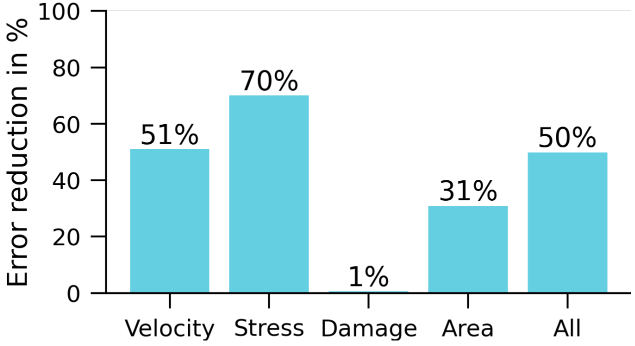

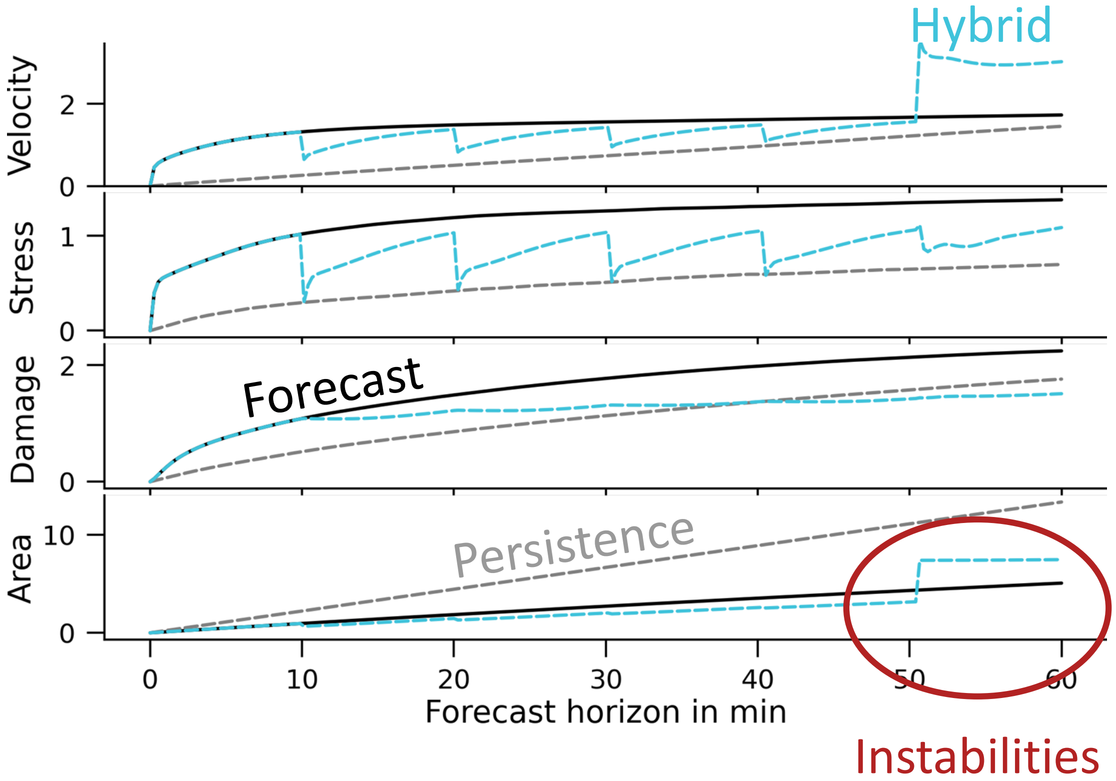

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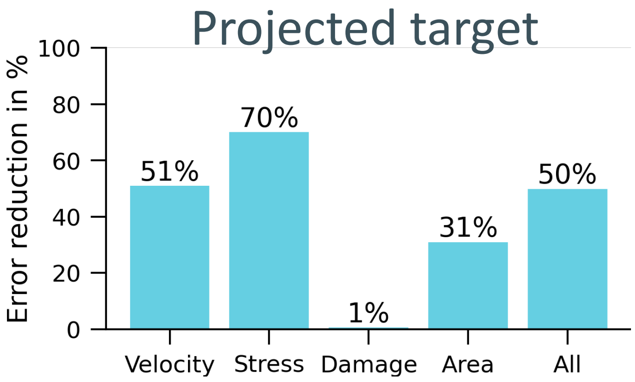
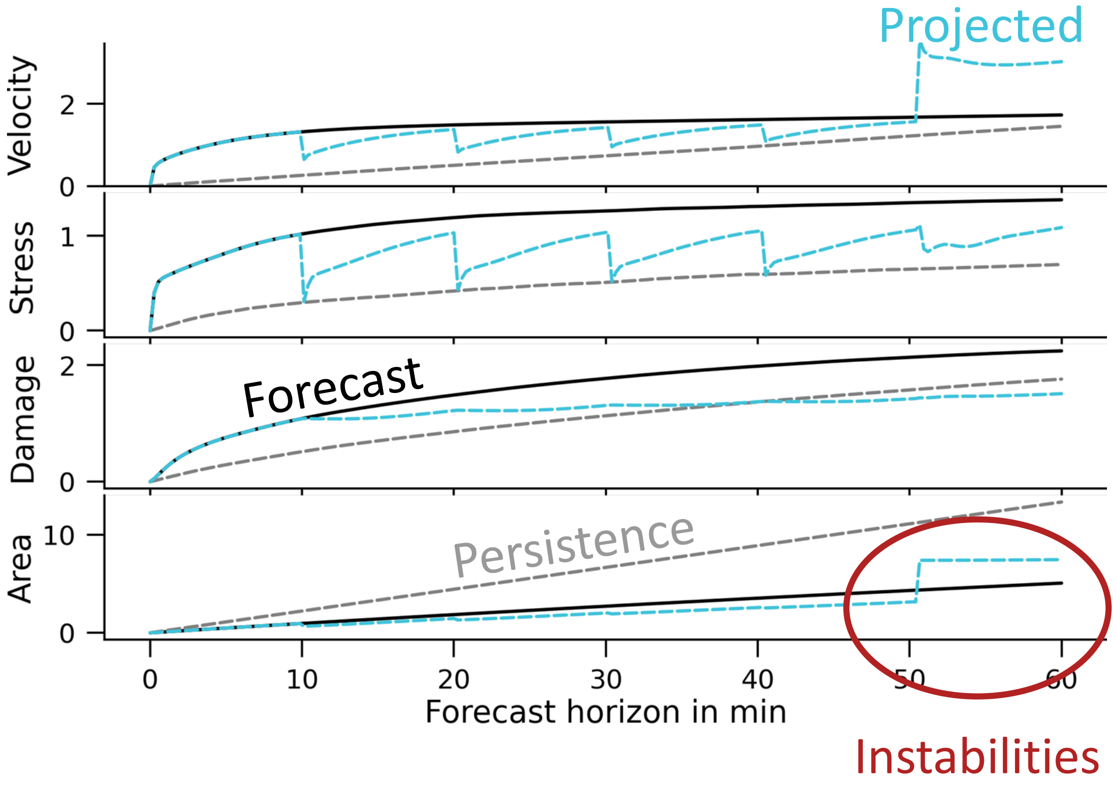
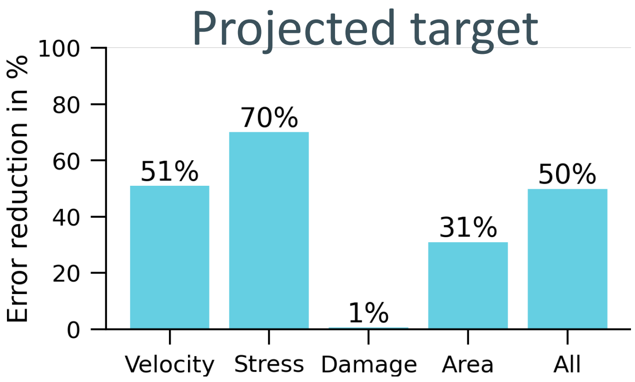
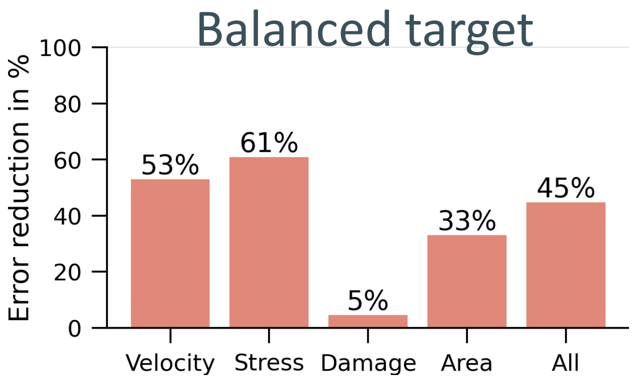


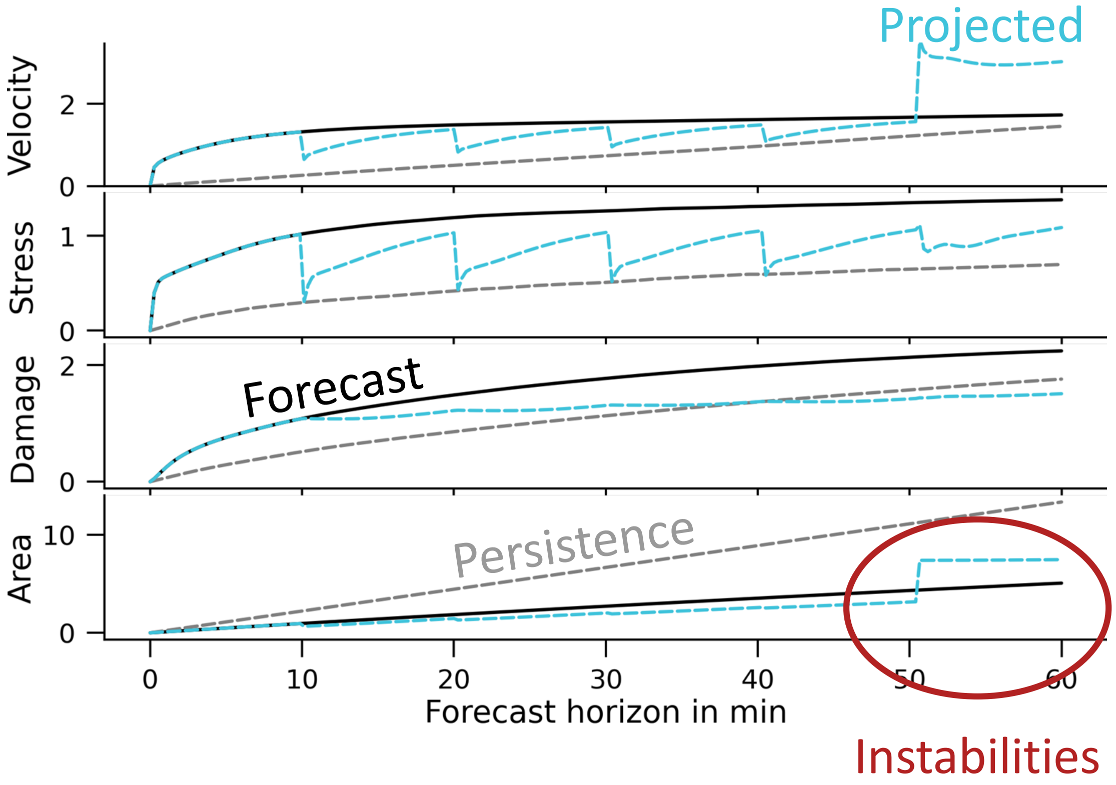


Might be caused by unbalanced training data

Balancing step has only little impact on offline performance

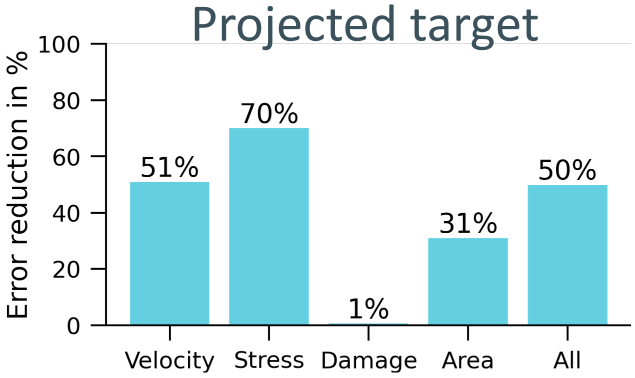


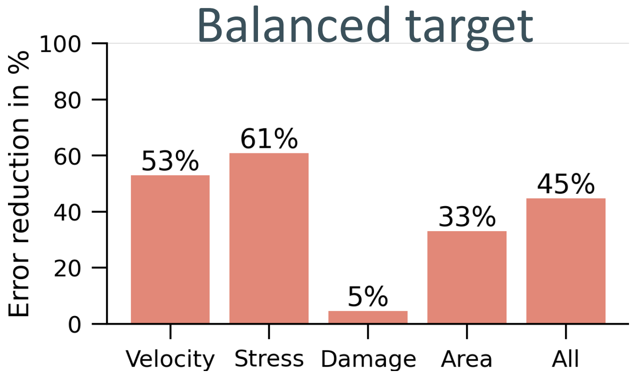


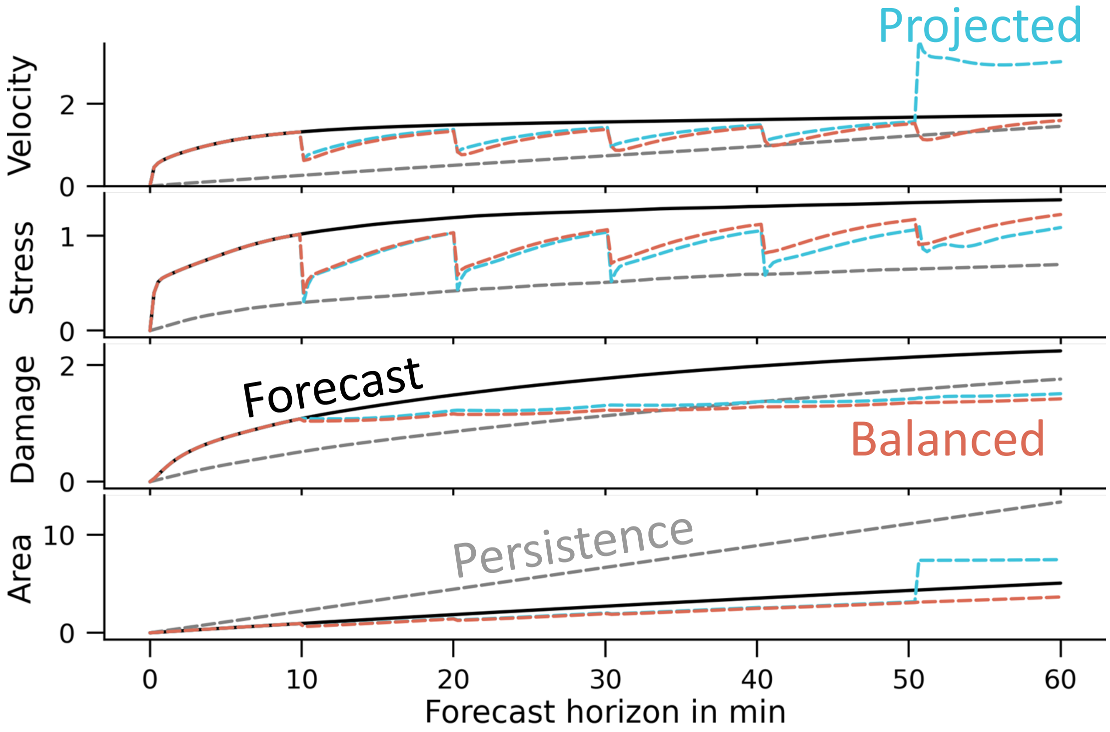


Might be caused by unbalanced training data

Balancing step within training data stabilises hybrid forecast







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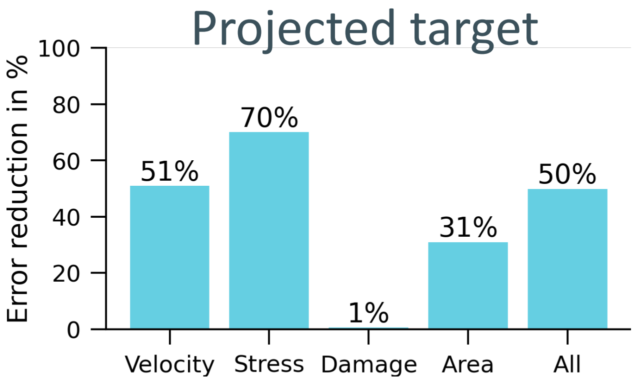

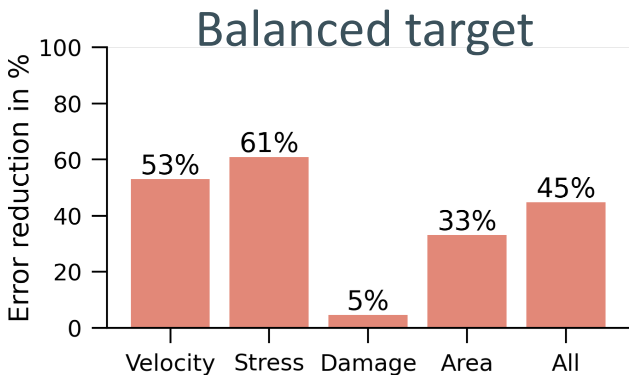

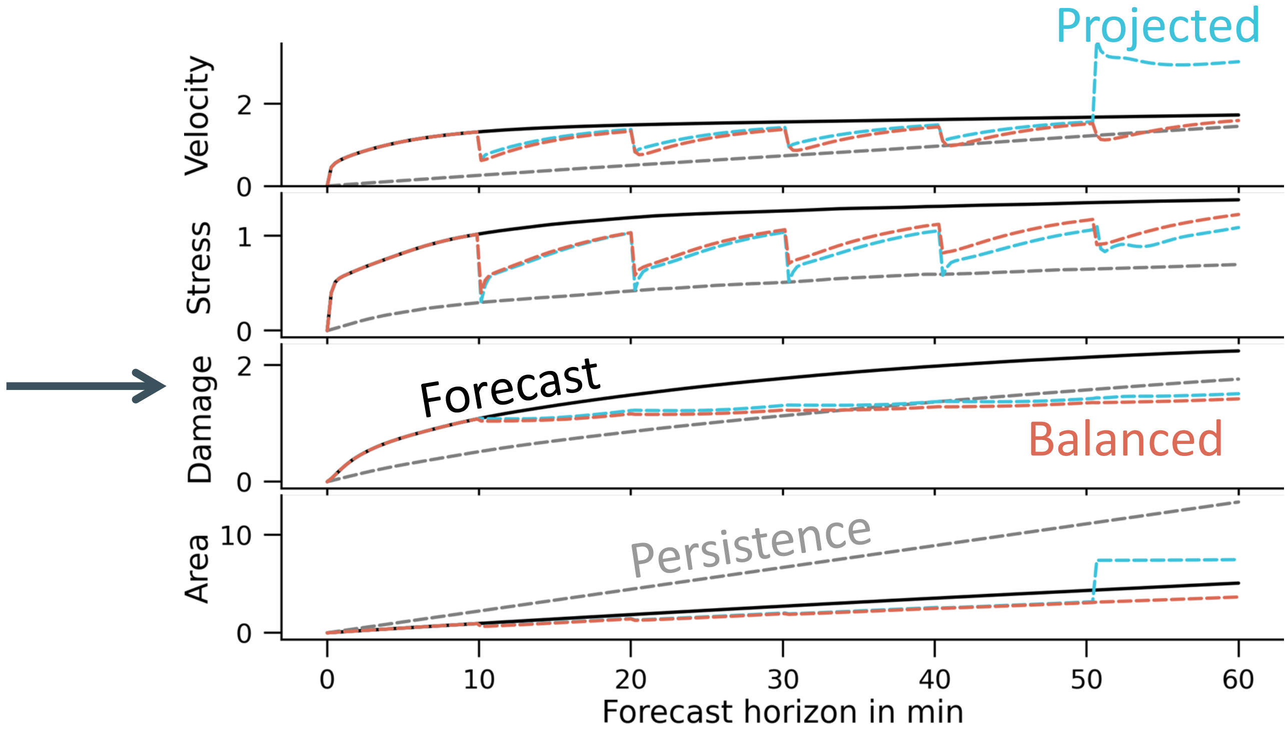

First promising results for hybrid modelling

Network is trained after spin-up

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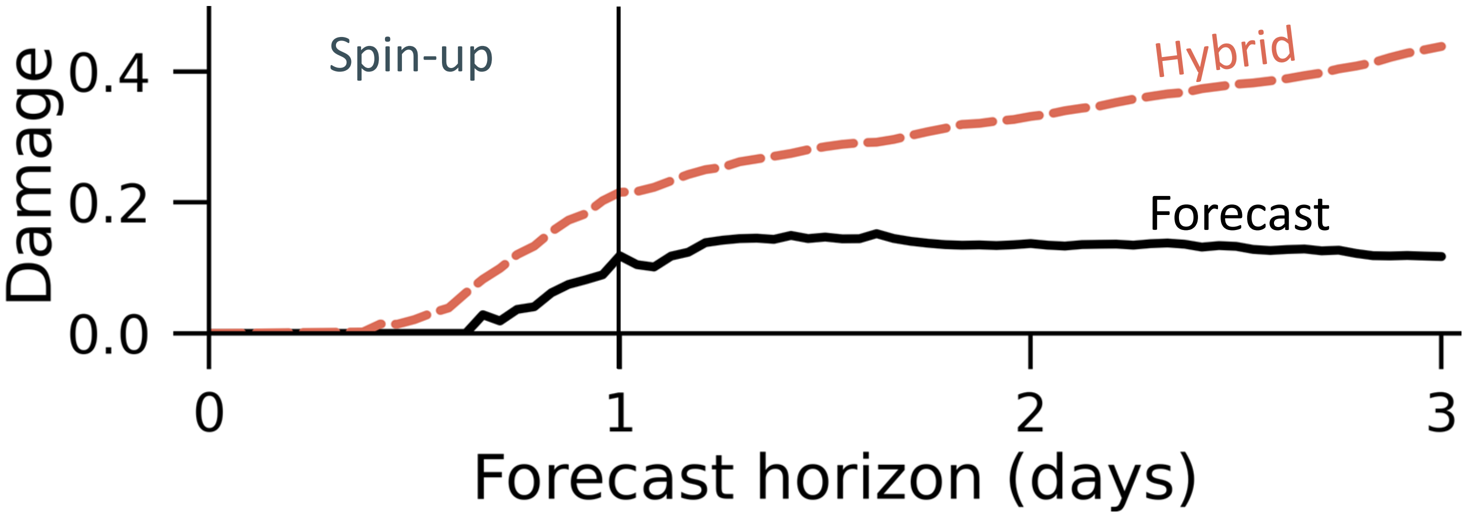
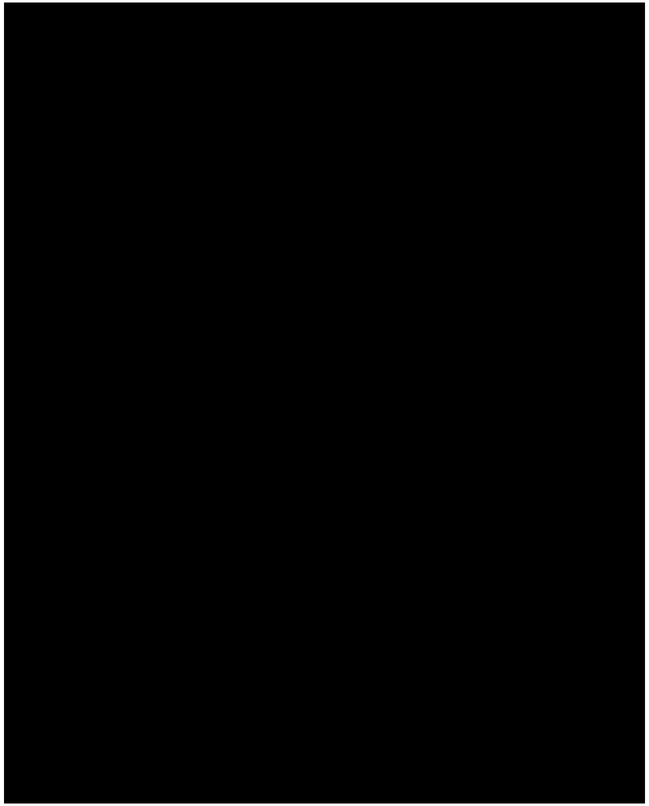
→ at the moment problems with spin-up



Network is trained after spin-up
$\longrightarrow$ at the moment problems with spin-up



Again encouraging results for hybrid modelling

Take home messages

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Subgrid-scale sea-ice dynamics **can be** parameterised
with neural networks

Take home messages

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Efficient feature mapping in projected Cartesian space with U-Nets + learning of all variables with maximum likelihood

Take home messages

Subgrid-scale sea-ice dynamics **can be** parameterised
with neural networks

Efficient feature mapping in projected Cartesian space with U-Nets
+ learning of all variables with maximum likelihood

Forecast errors reduction by around 45% in a 1D MEB model setup
+ first promising results in the hybrid modelling setup

Take home messages

Subgrid-scale sea-ice dynamics **can be** parameterised with neural networks

Efficient feature mapping in projected Cartesian space with U-Nets + learning of all variables with maximum likelihood

Forecast errors reduction by around 45% in a 1D MEB model setup + first promising results in the hybrid modelling setup

Do you have questions?

Feel free to also write me an email: tobias.finn@enpc.fr