Emulating present and future simulations of melt rates at the base of Antarctic ice shelves with neural networks

OCEAN:ICE workshop
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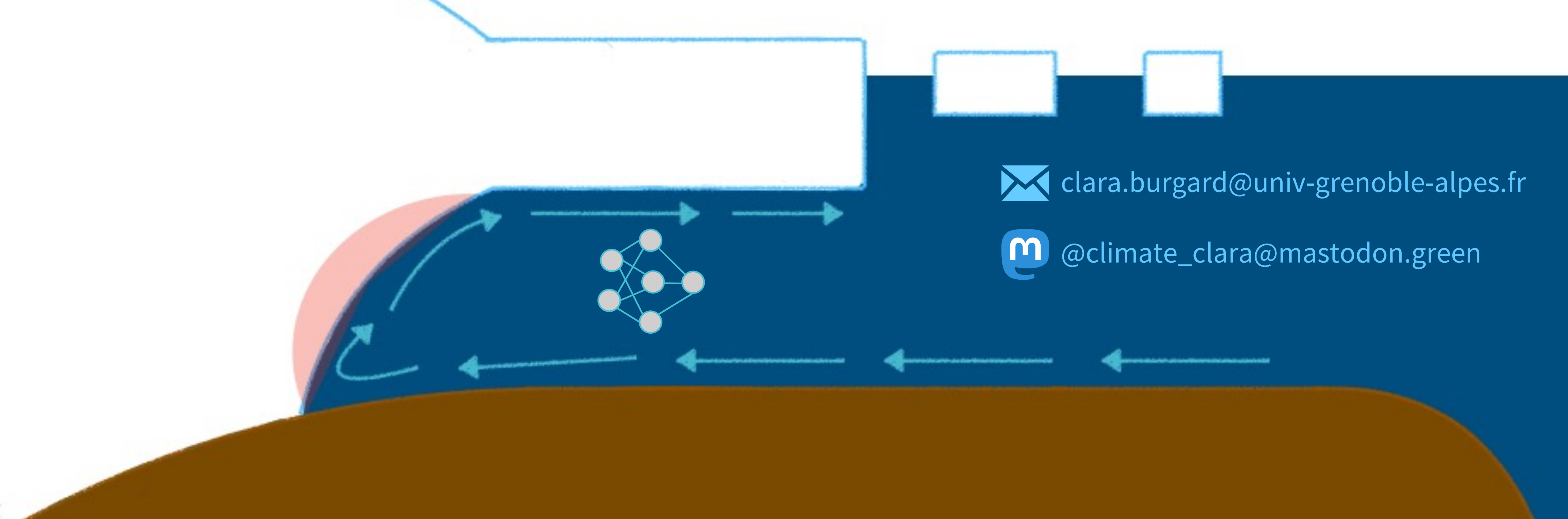

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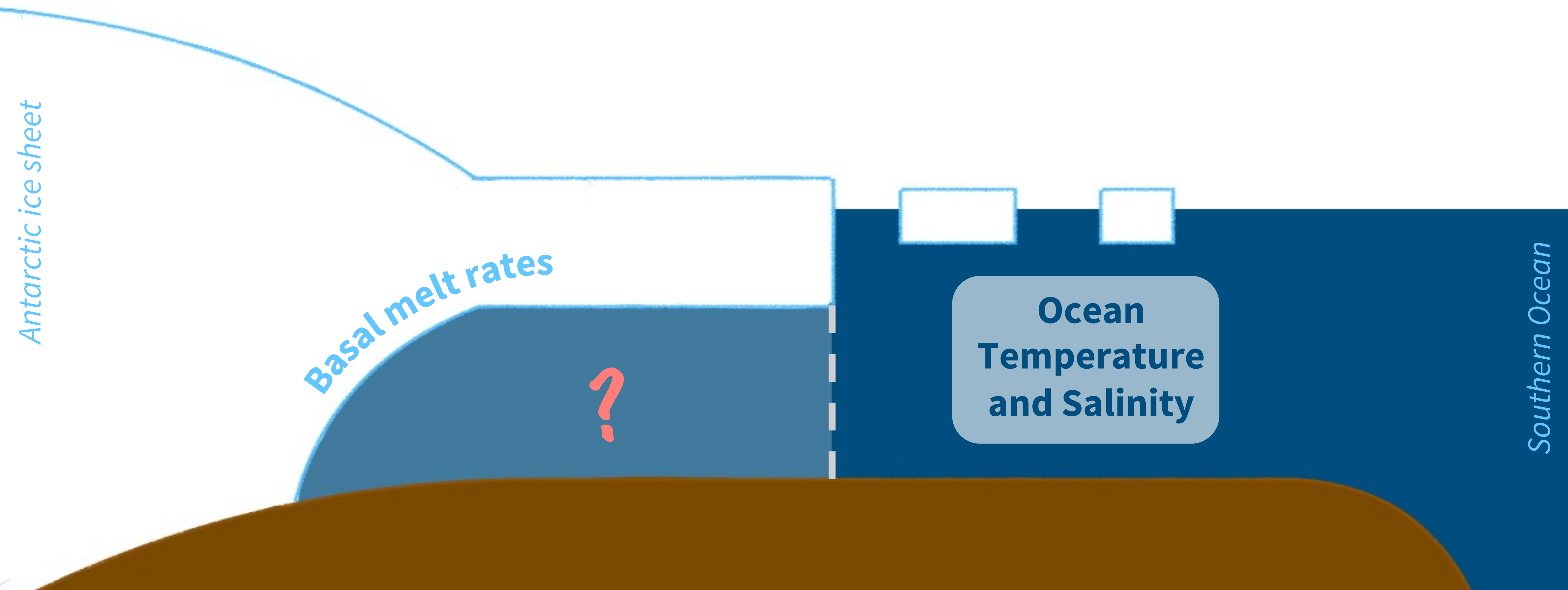
The problem: Representing sub-shelf melt in (uncoupled) ice-sheet and ocean models

Ice-sheet models need information about ocean-induced melt at the base of the ice shelves…



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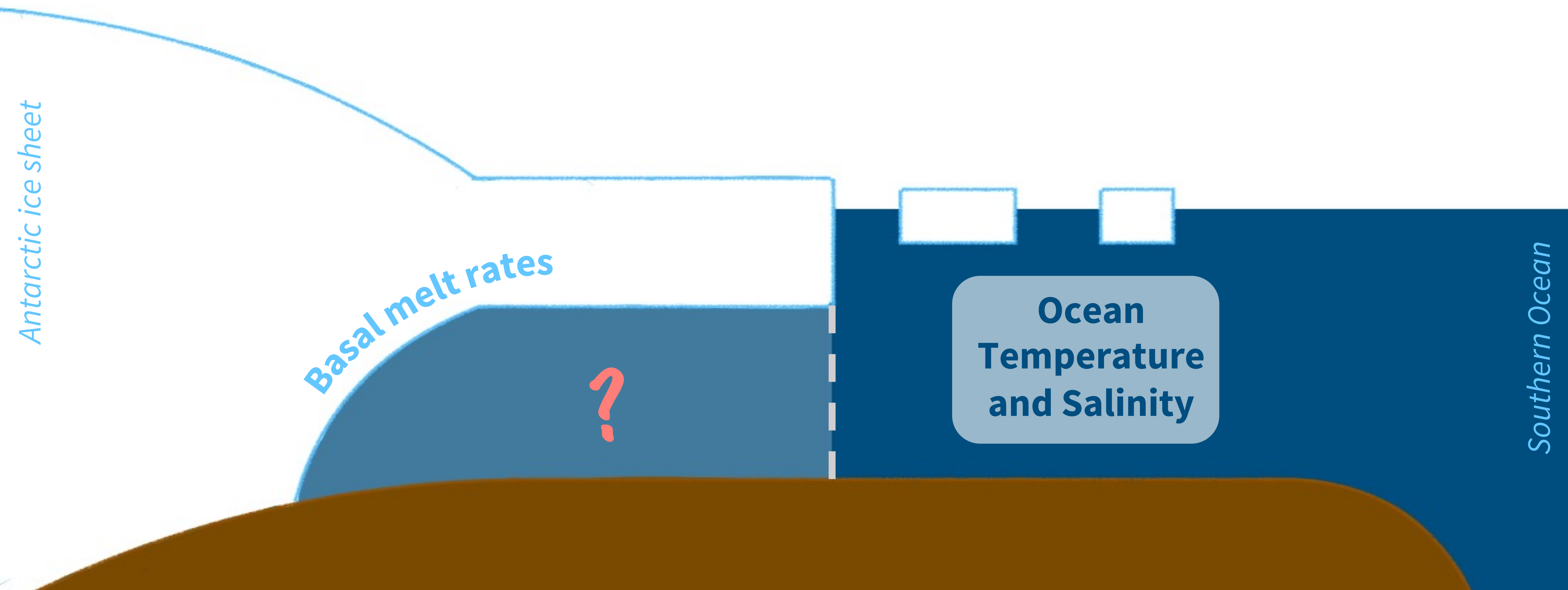
Ocean models need information about the melt as it affects the water properties



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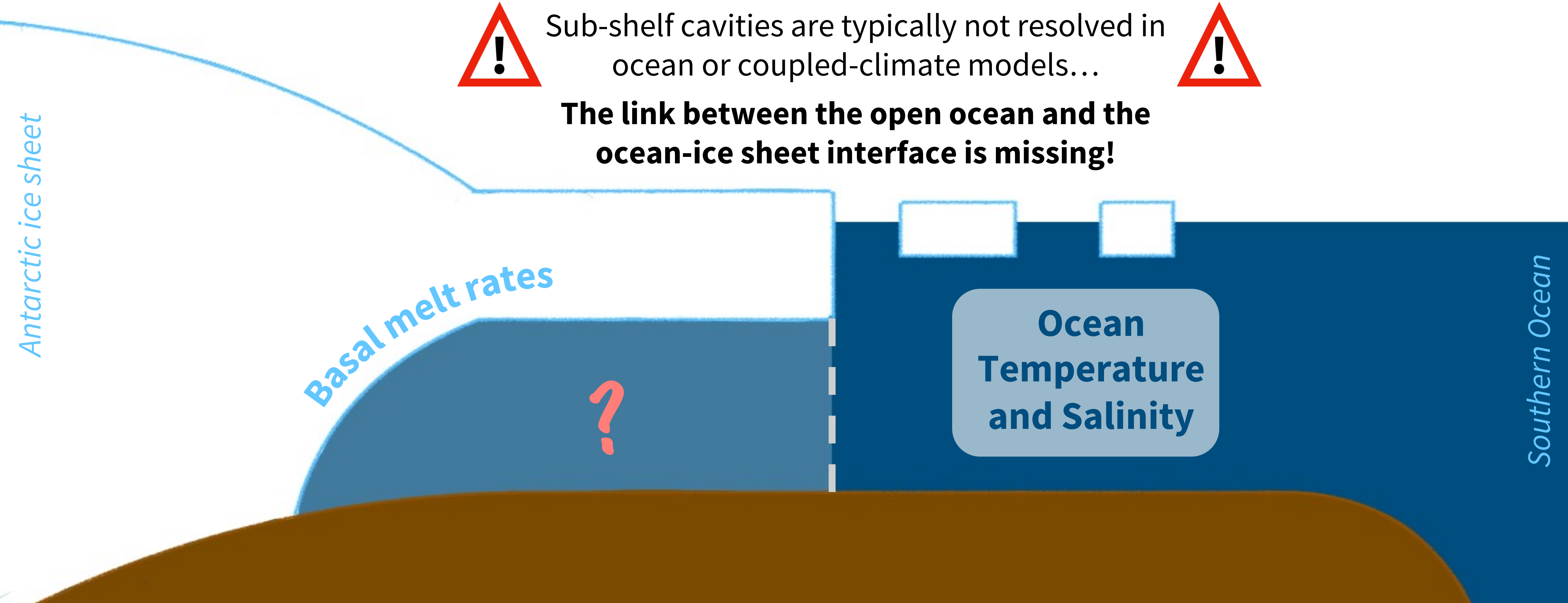
Ice-sheet models need information about ocean-induced melt at the base of the ice shelves…

Ocean models need information about the melt as it affects the water properties

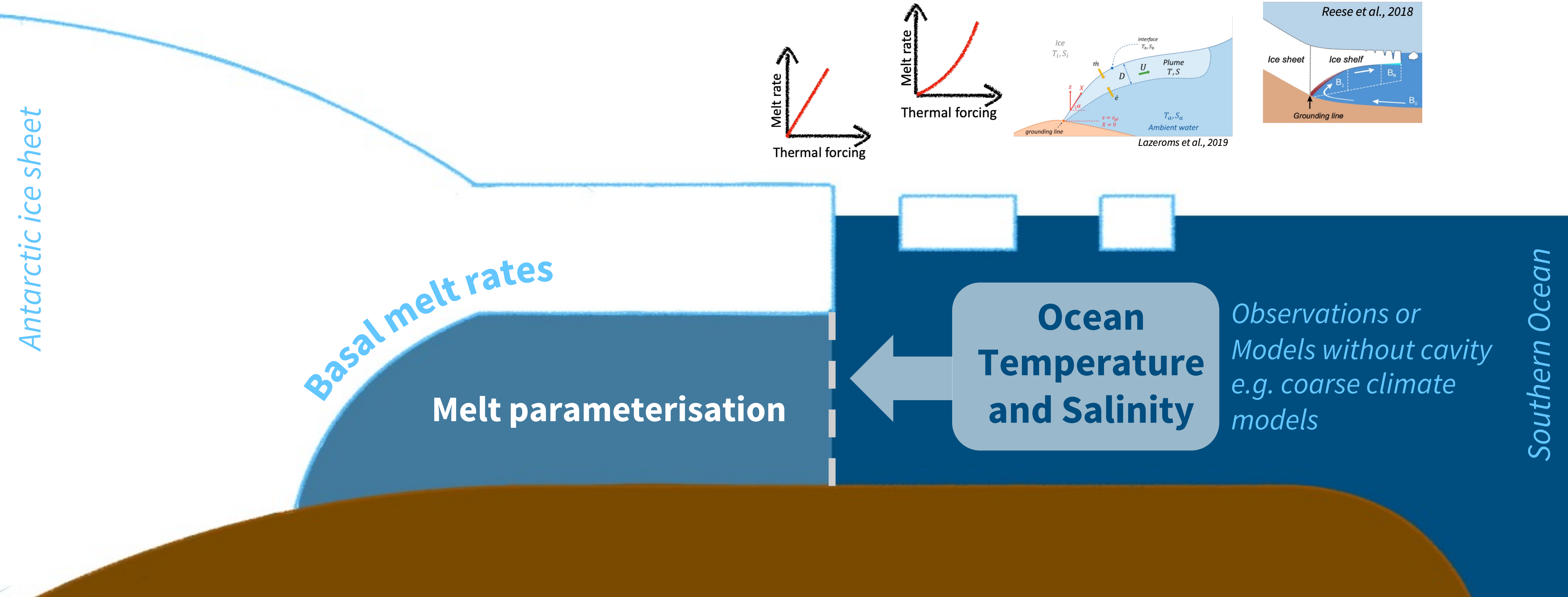
Sub-shelf cavities are typically not resolved in ocean or coupled-climate models…

The link between the open ocean and the ocean-ice sheet interface is missing!



Basal melt parameterisations bridge the gap between ocean and ice

Several parameterisations of various complexity developed in past decades
[e.g. Beckmann and Goosse (2002), Holland et al. (2008), Favier et al. (2019), Reese et al. (2018), Lazeroms et al. (2018 & 2019), Pelle et al. (2019)]



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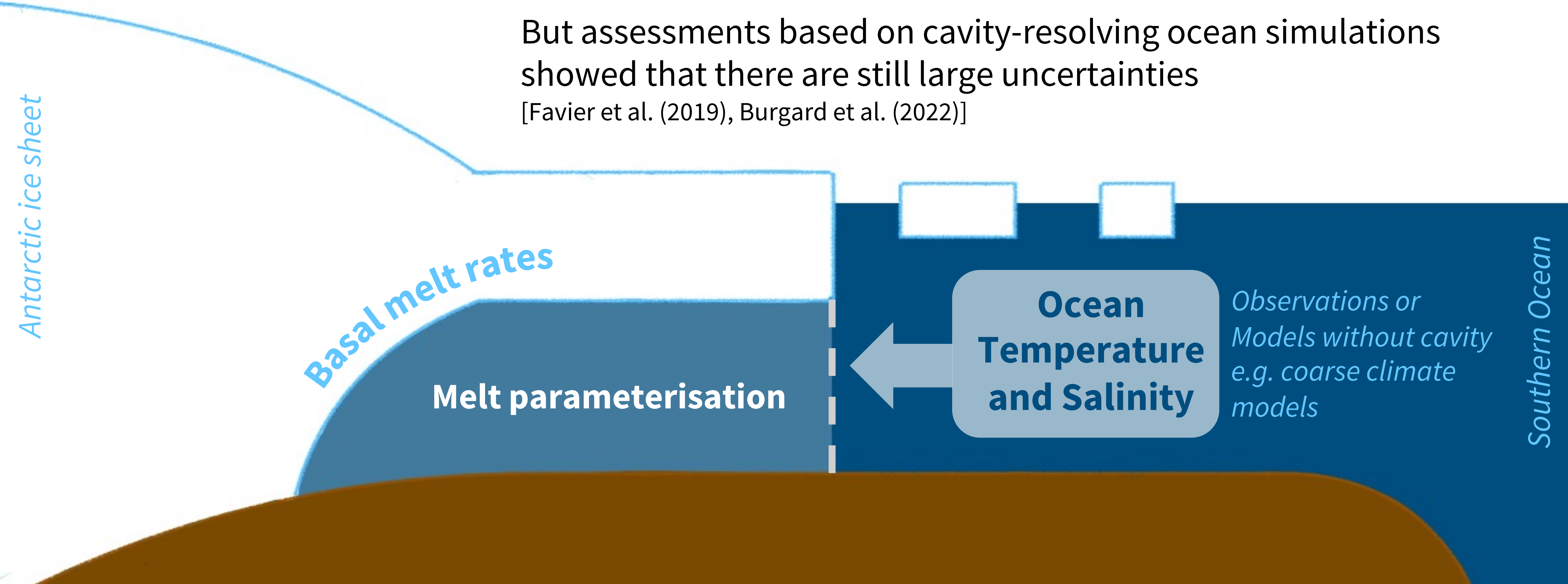
[e.g. Beckmann and Goosse (2002), Holland et al. (2008), Favier et al. (2019), Reese et al. (2018), Lazeroms et al. (2018 & 2019), Pelle et al. (2019)]

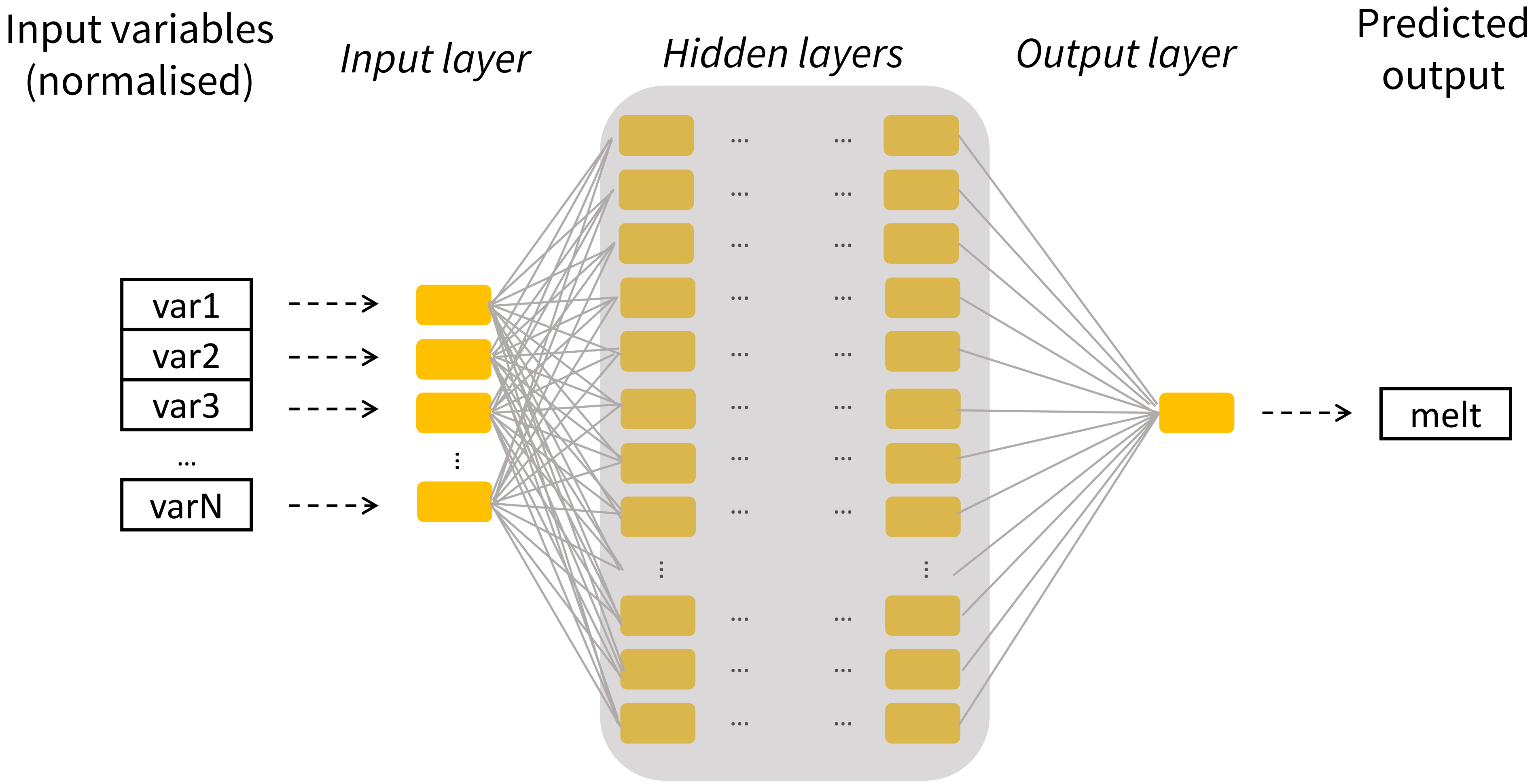
But assessments based on cavity-resolving ocean simulations showed that there are still large uncertainties
[Favier et al. (2019), Burgard et al. (2022)]



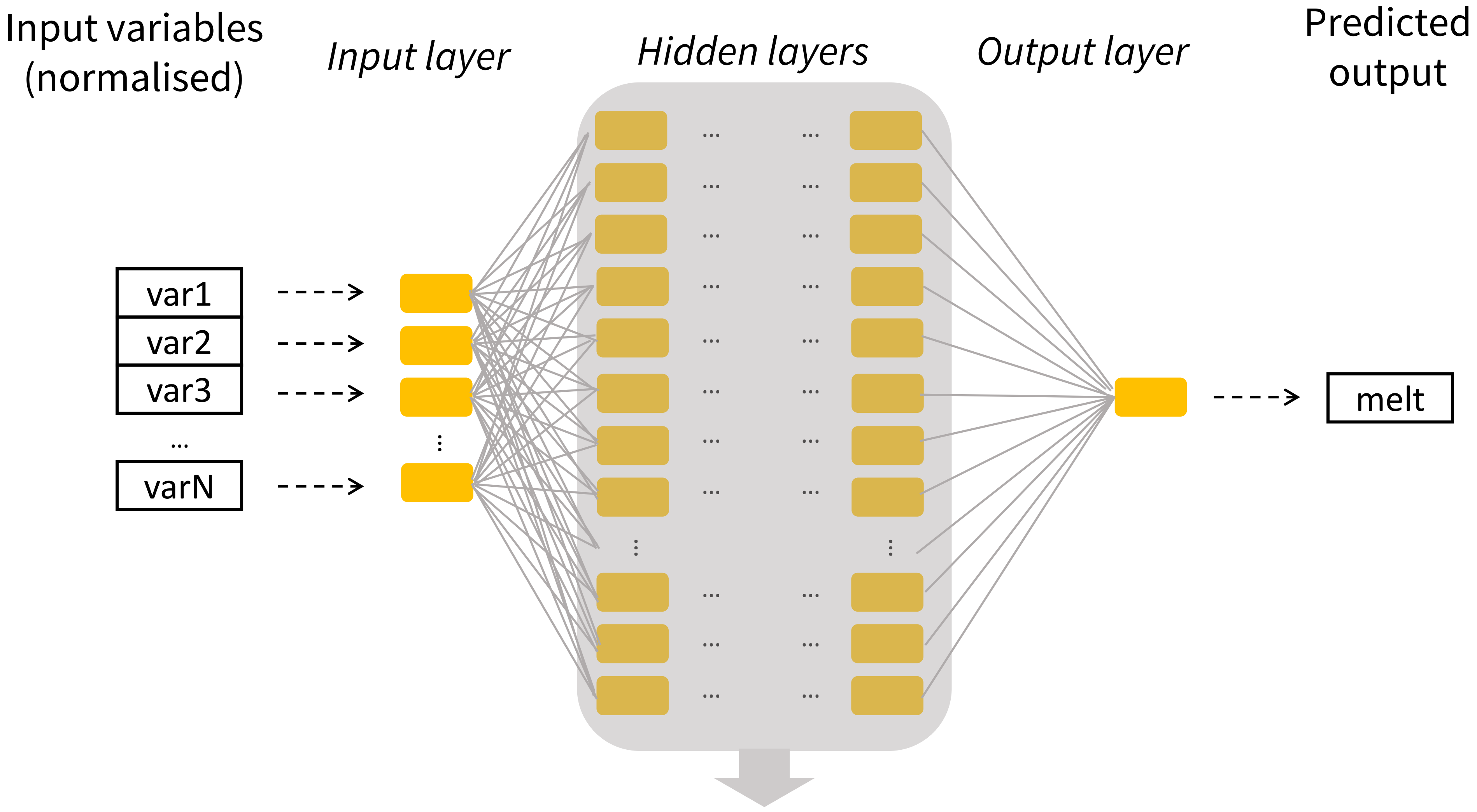
Our approach:

Explore the potential of a rather simple deep learning parameterisation

Feedforward neural network - 101

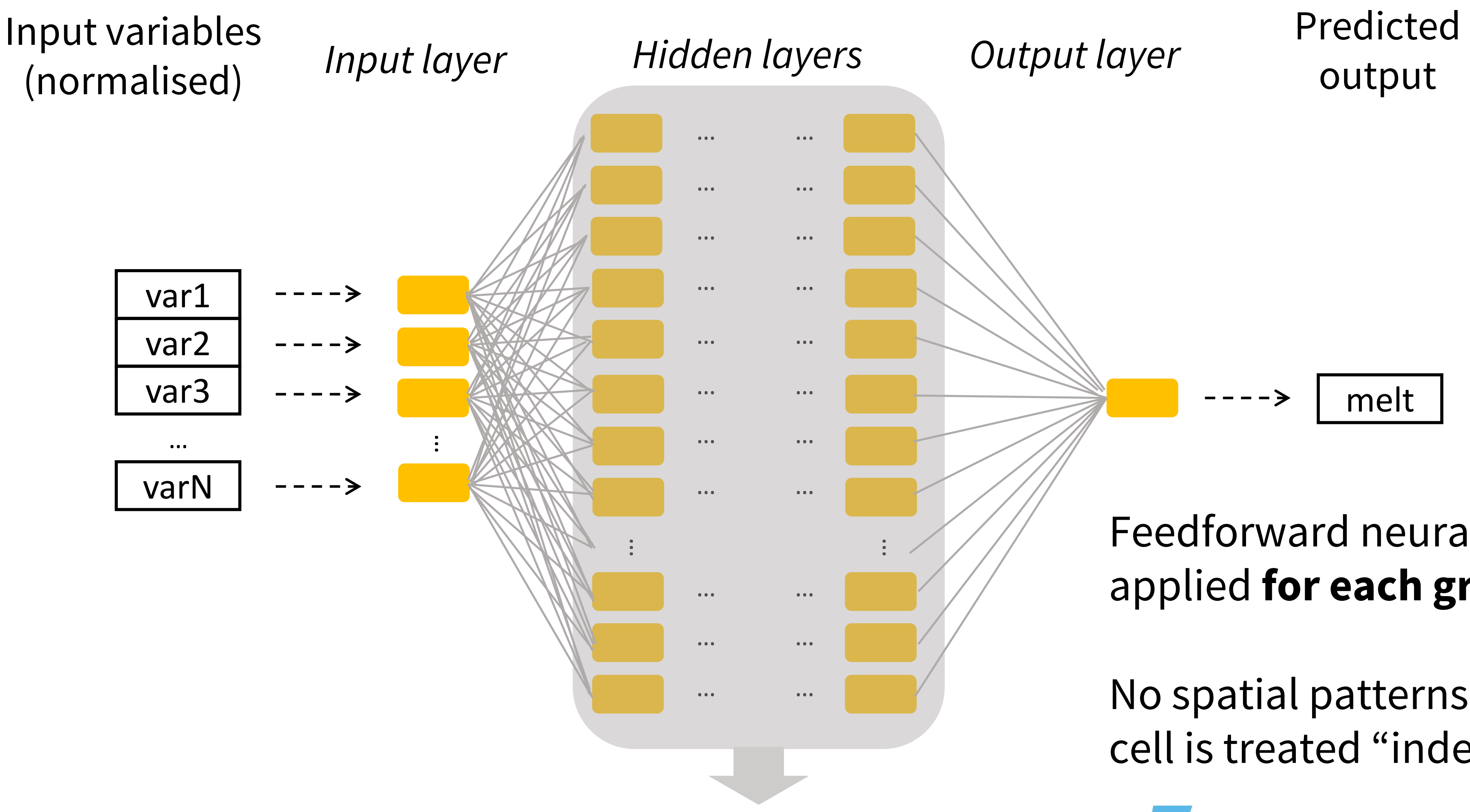


Feedforward neural network - 101



Weights and biases optimised during iterative training

Feedforward neural network - 101



Weights and biases optimised during iterative training

Feedforward neural network is applied **for each grid cell**

No spatial patterns, each grid cell is treated “independently”

Rosier et al. (2023), The Cryosphere
=> see next presentation

Our approach:

Explore the potential of a rather simple deep learning parameterisation

using cavity-resolving ocean simulations as a virtual reality

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PART I – TRAINING
PART II - TESTING

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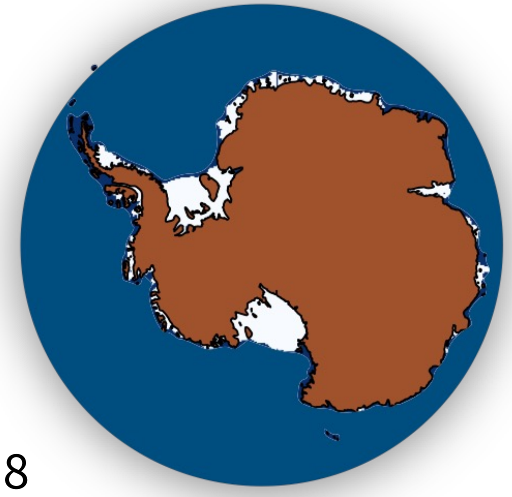
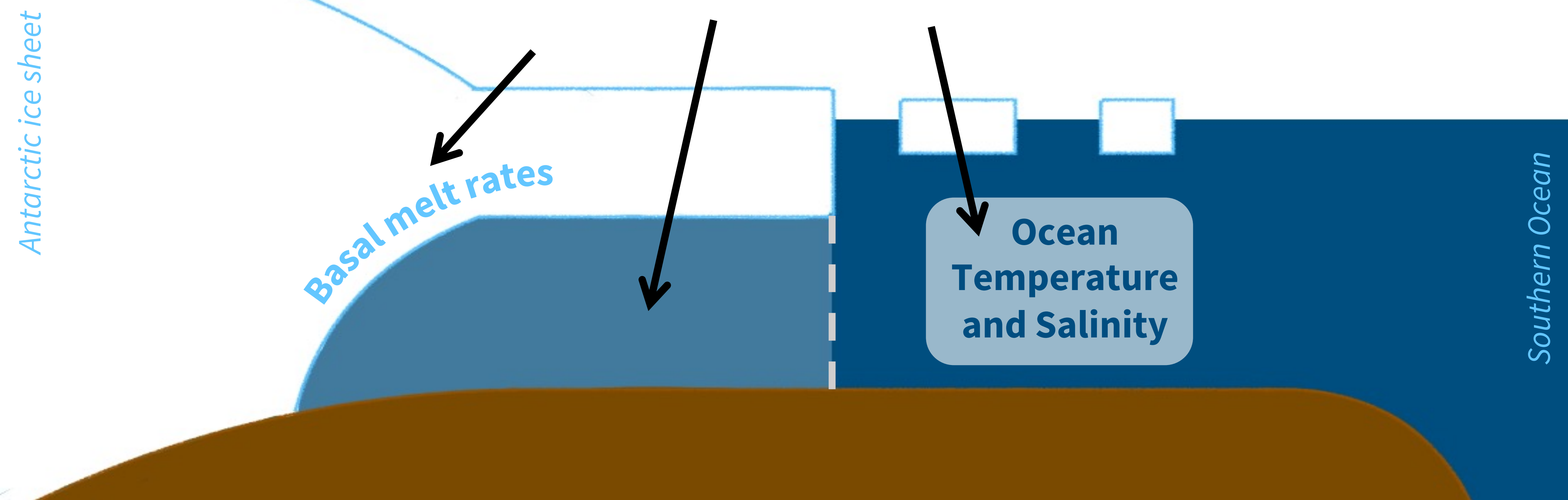
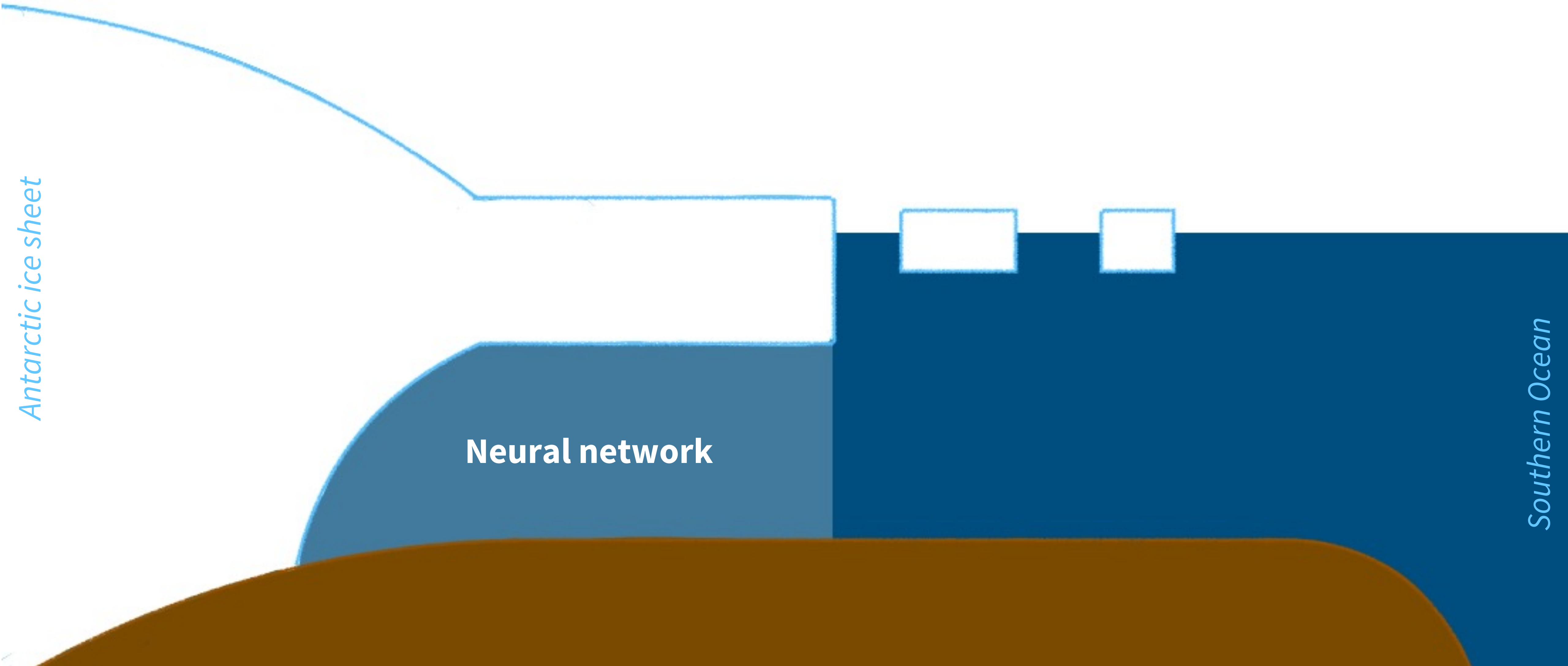
Our virtual reality for training



4 x NEMO global ocean simulations
[same as in Burgard et al. 2022]
0.25° grid
127 simulation years in total
representing varying conditions between 1980 and 2018
35 largest cavities resolved: ocean circulation and basal melt



What gets into the neural network…



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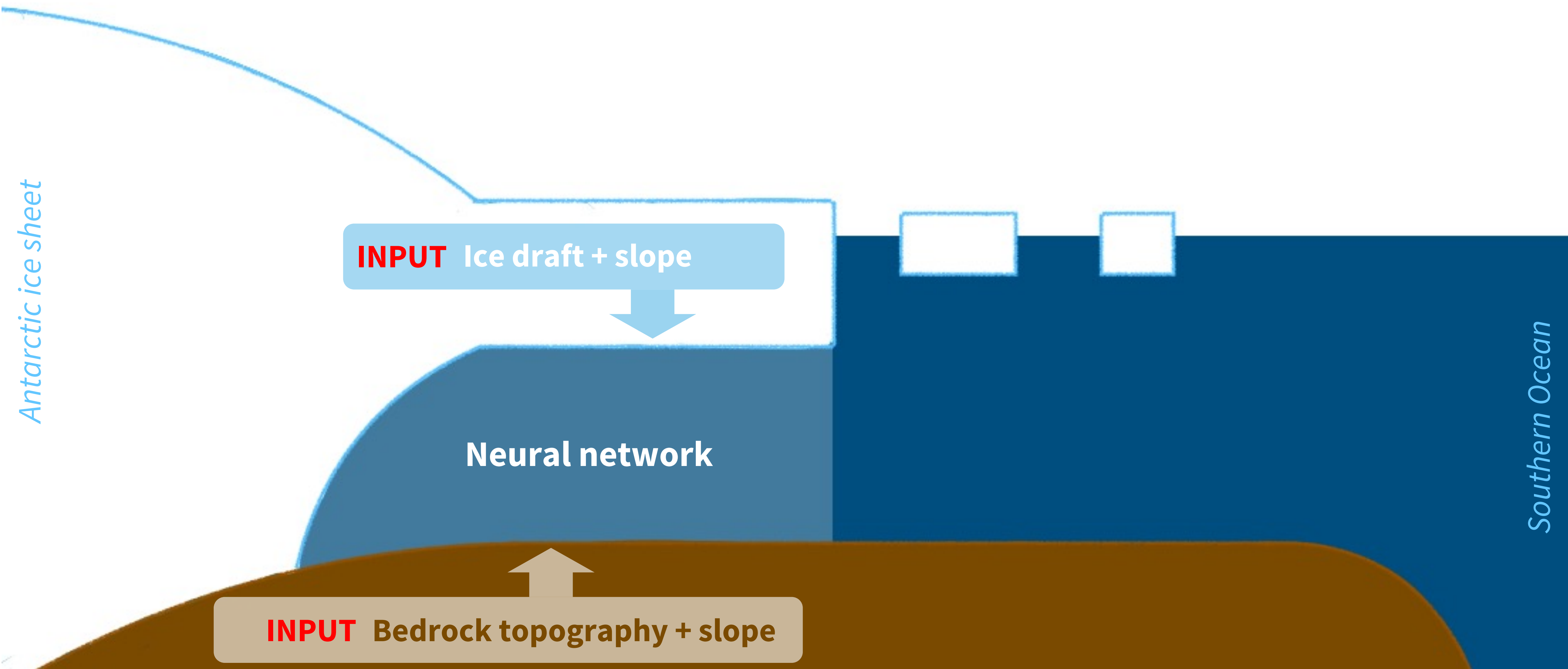

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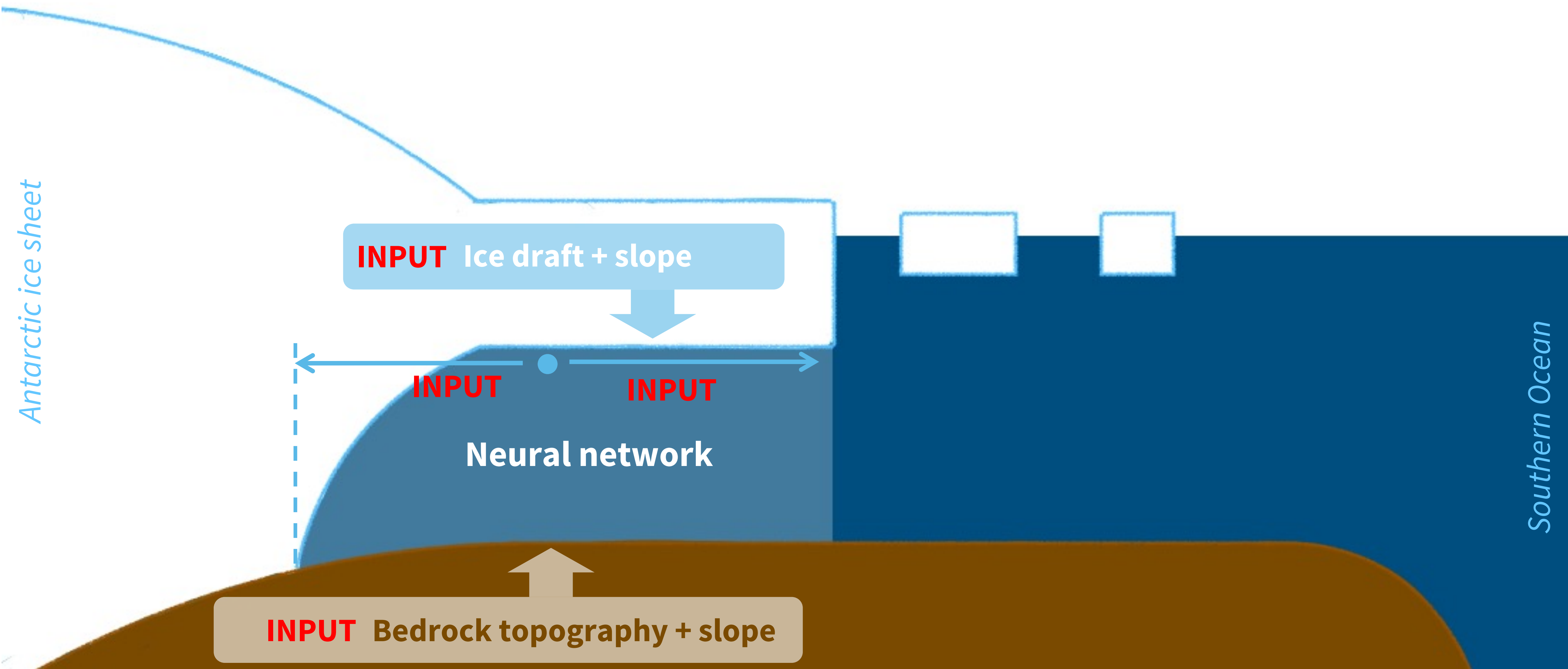

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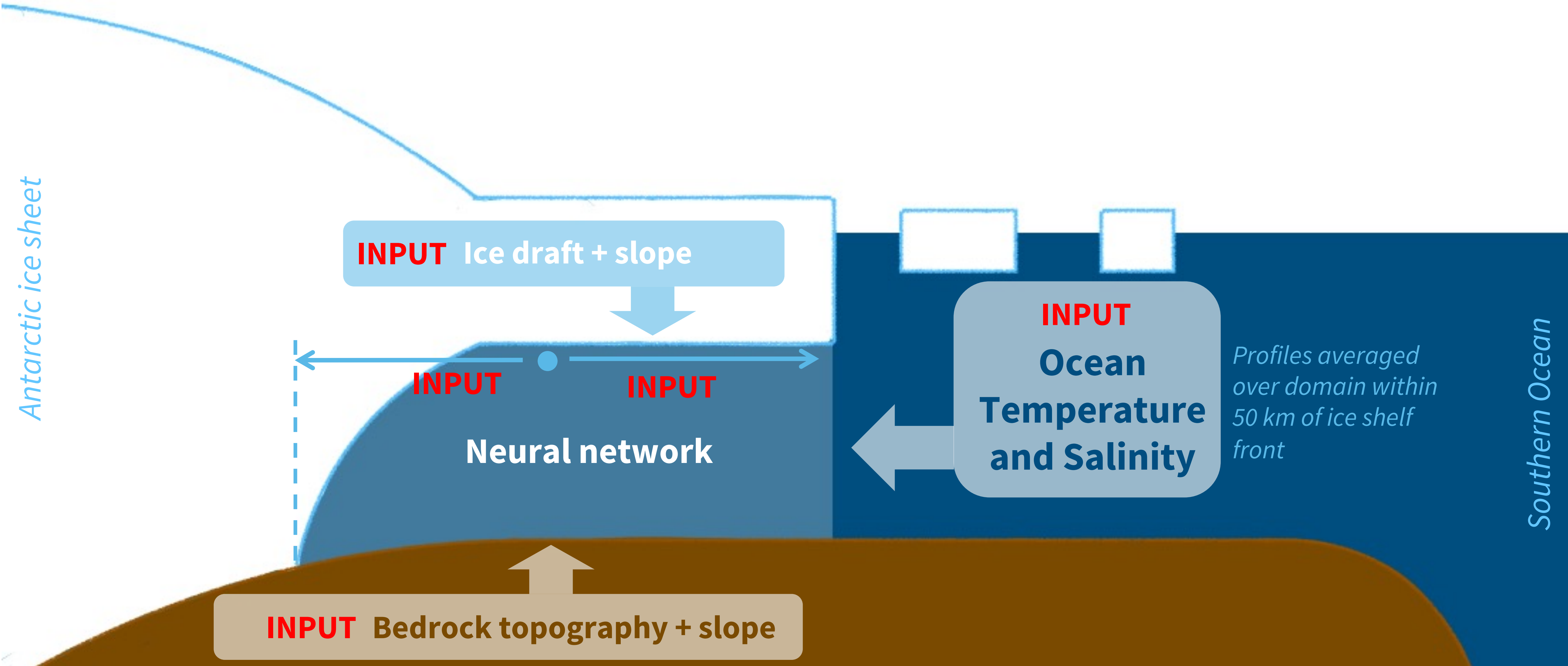
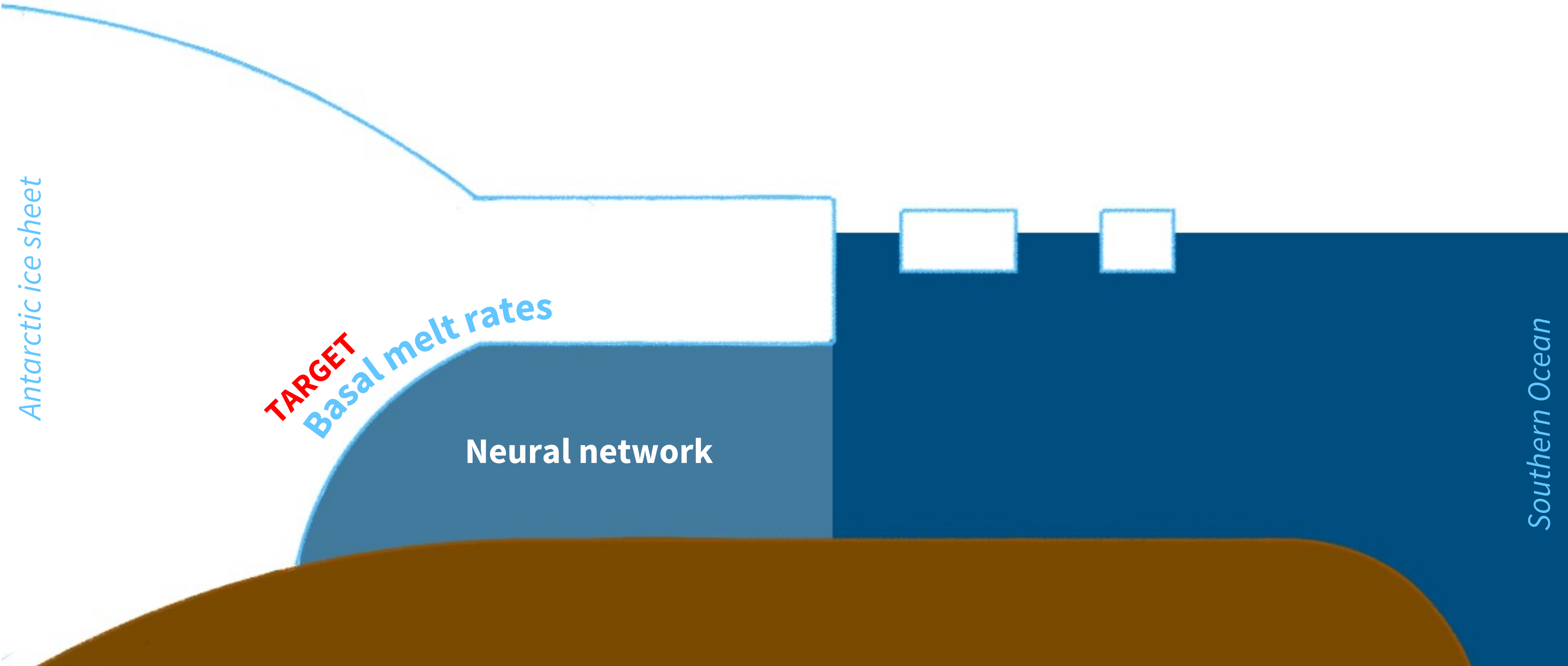


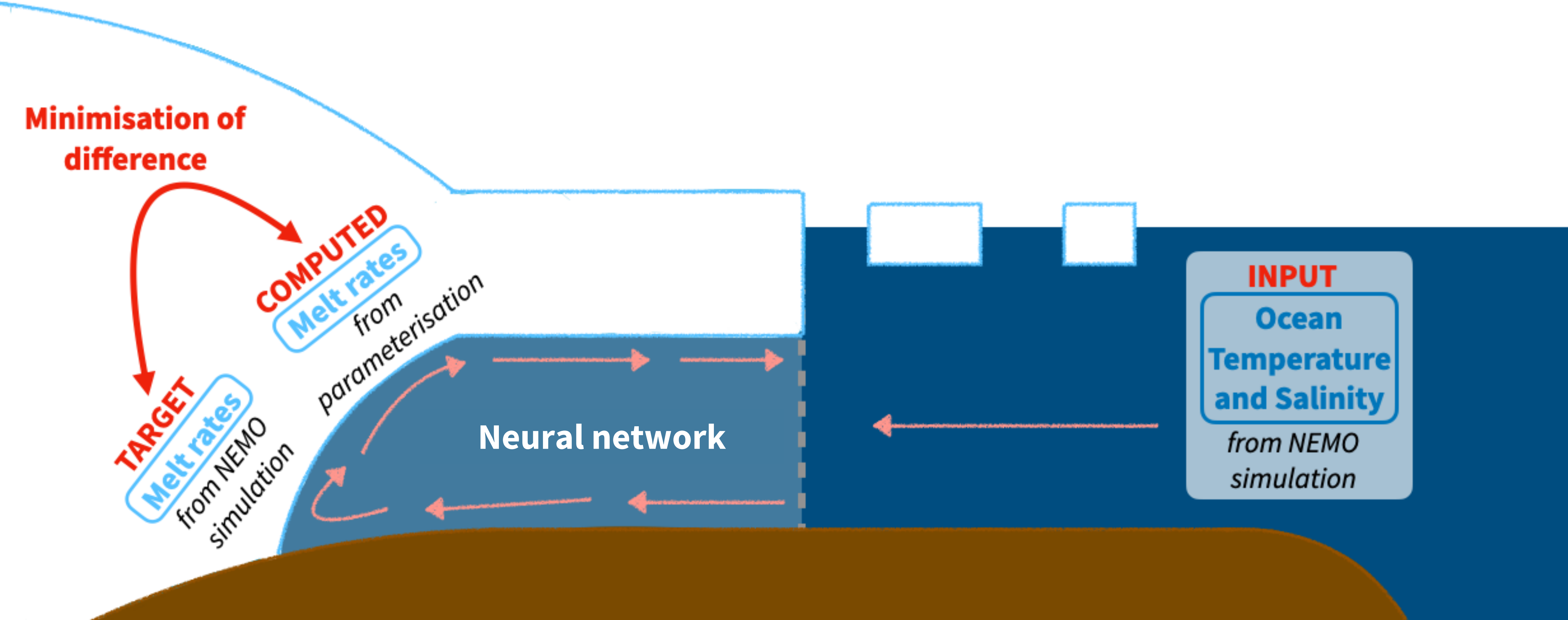
What gets out of the neural network…



The training process

Training

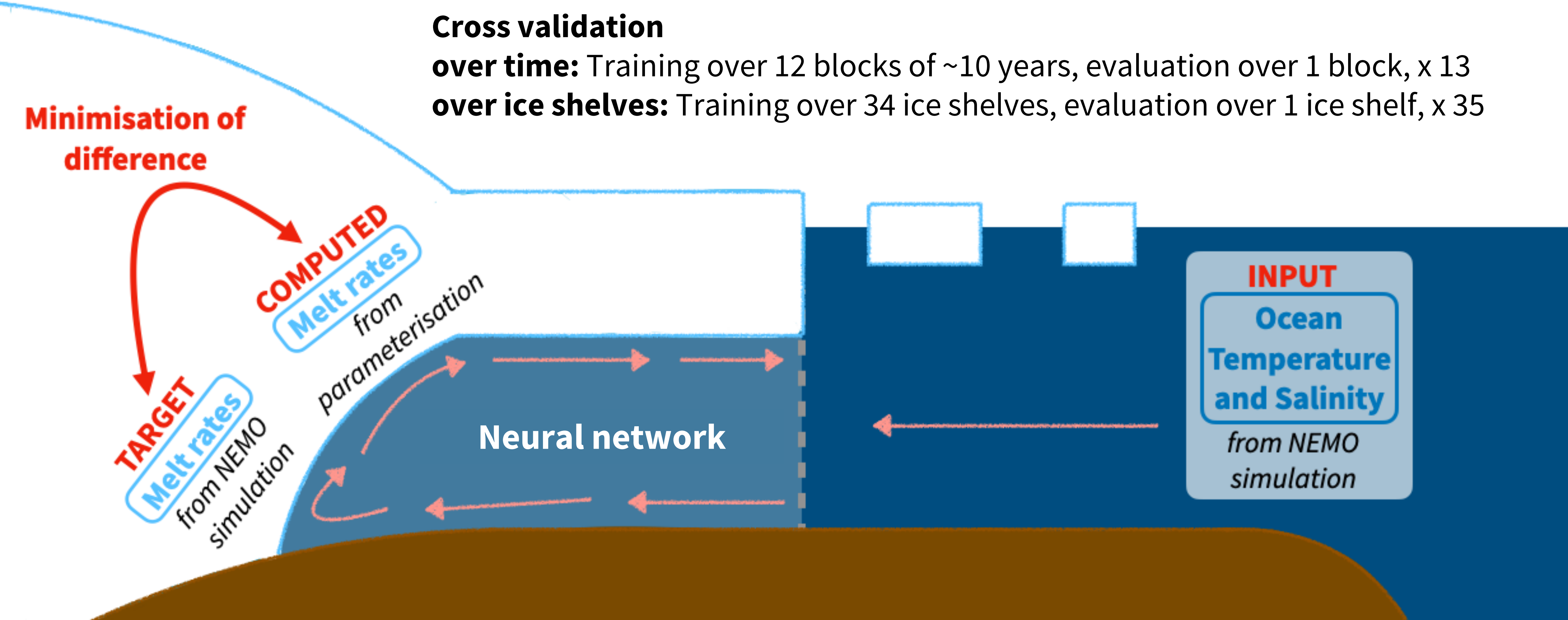
Minimisation of the mean squared error (MSE) between the parameterised and reference yearly melt for each grid cell



The training process

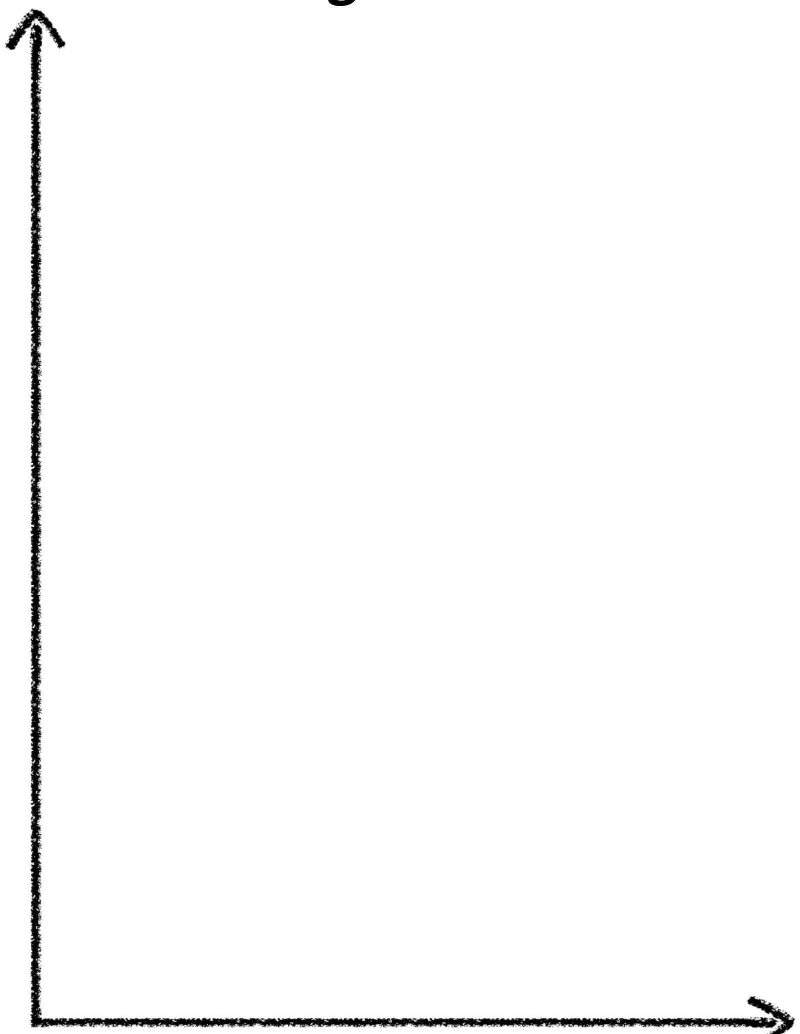
Training
Minimisation of the mean squared error (MSE) between the parameterised and reference yearly melt for each grid cell

Cross validation
over time: Training over 12 blocks of ~10 years, evaluation over 1 block, x 13
over ice shelves: Training over 34 ice shelves, evaluation over 1 ice shelf, x 35



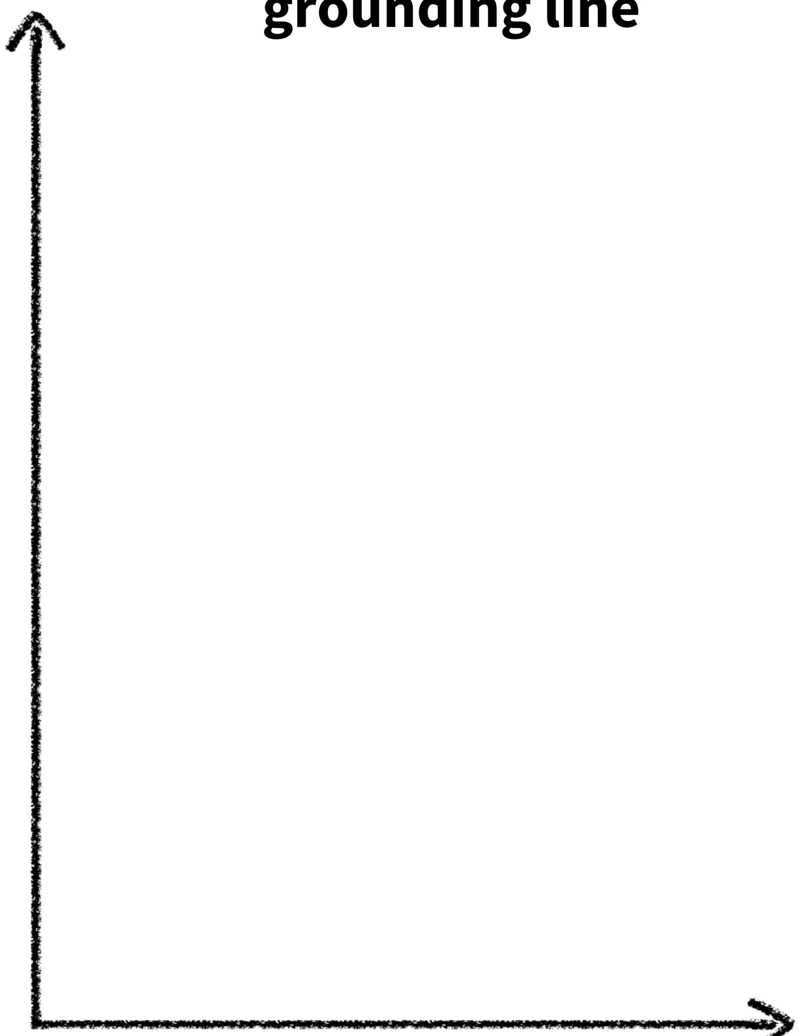
Assessing two different aspects

Integrated melt



RMSE [Gt/yr] over the left-out blocks of the cross validation
(127 simulation years and 35 ice shelves)

Melt near the grounding line



RMSE [m ice/yr] of space and (left-out) time mean near grounding line for (left-out) 35 ice shelves and 4 simulations

Cross-validation
- over time
- over ice shelves

Assessing different neural network sizes

Integrated melt

Melt near the grounding line

Neural networks

No hidden layer : **XXS**

2 layers, 96/96 neurons : **XS**

3 layers, 32/64/32 : **S**

5 layers, 96/96/96/96/96 : **M**

5 layers, 128/128/128/128/128 : **L**

6 layers, 256/256/256/256/256/256 : **XL**

Cross-validation

over time

over ice shelves

RMSE [Gt/yr] over the left-out blocks of the cross validation (127 simulation years and 35 ice shelves)

RMSE [m ice/yr] of space and (left-out) time mean near grounding line for (left-out) 35 ice shelves and 4 simulations

Assessing different neural network sizes

“traditional” parameterisations

Quadratic, local, Ant slope

Quadratic, local, local slope

Plume

Box, 10 boxes

PICOP, PICO boxes

Neural networks

No hidden layer : **XXS**

2 layers, 96/96 neurons : **XS**

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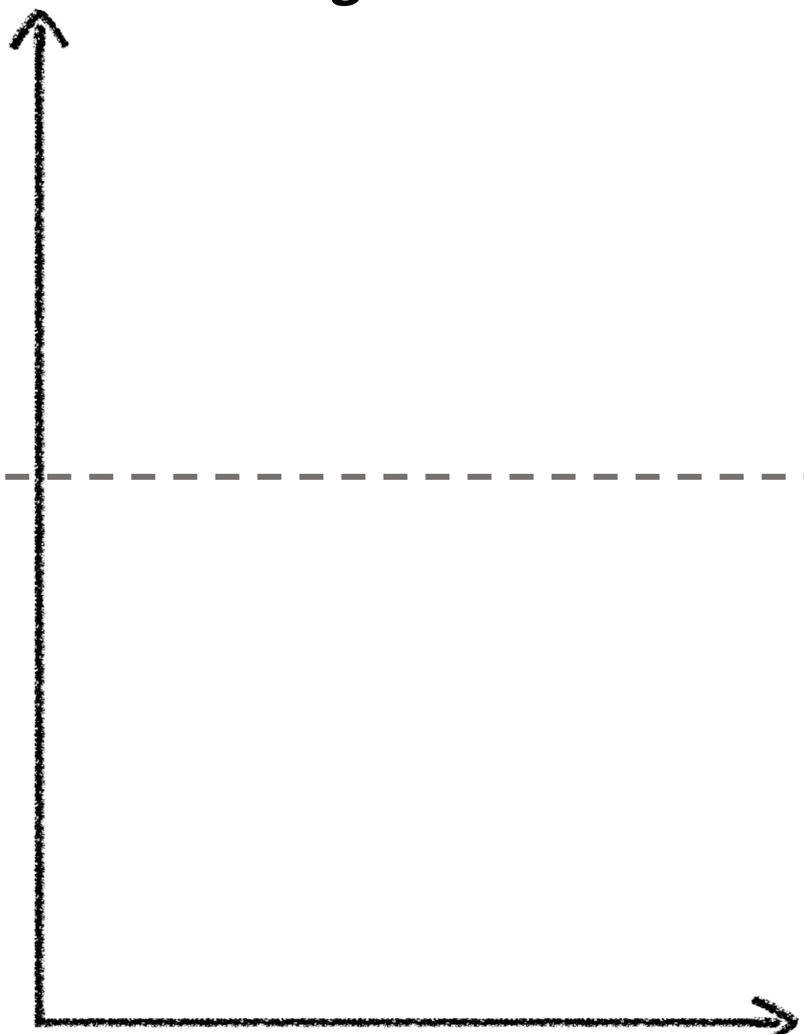
Cross-validation

over time

over ice shelves

Integrated melt



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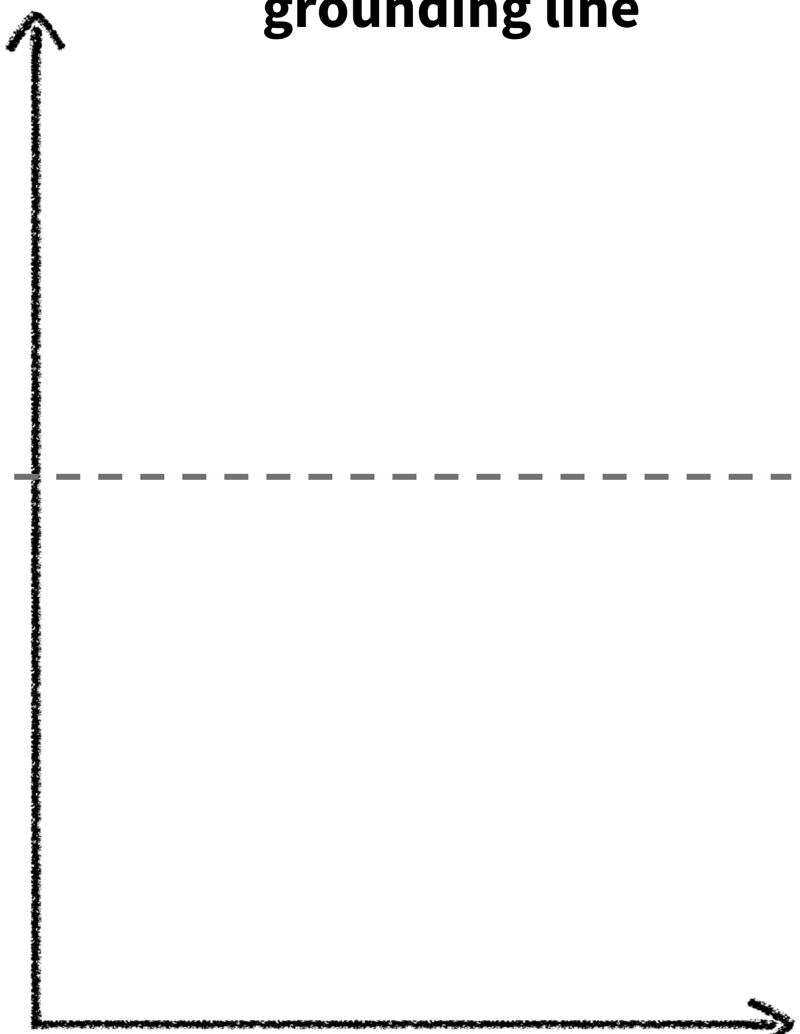
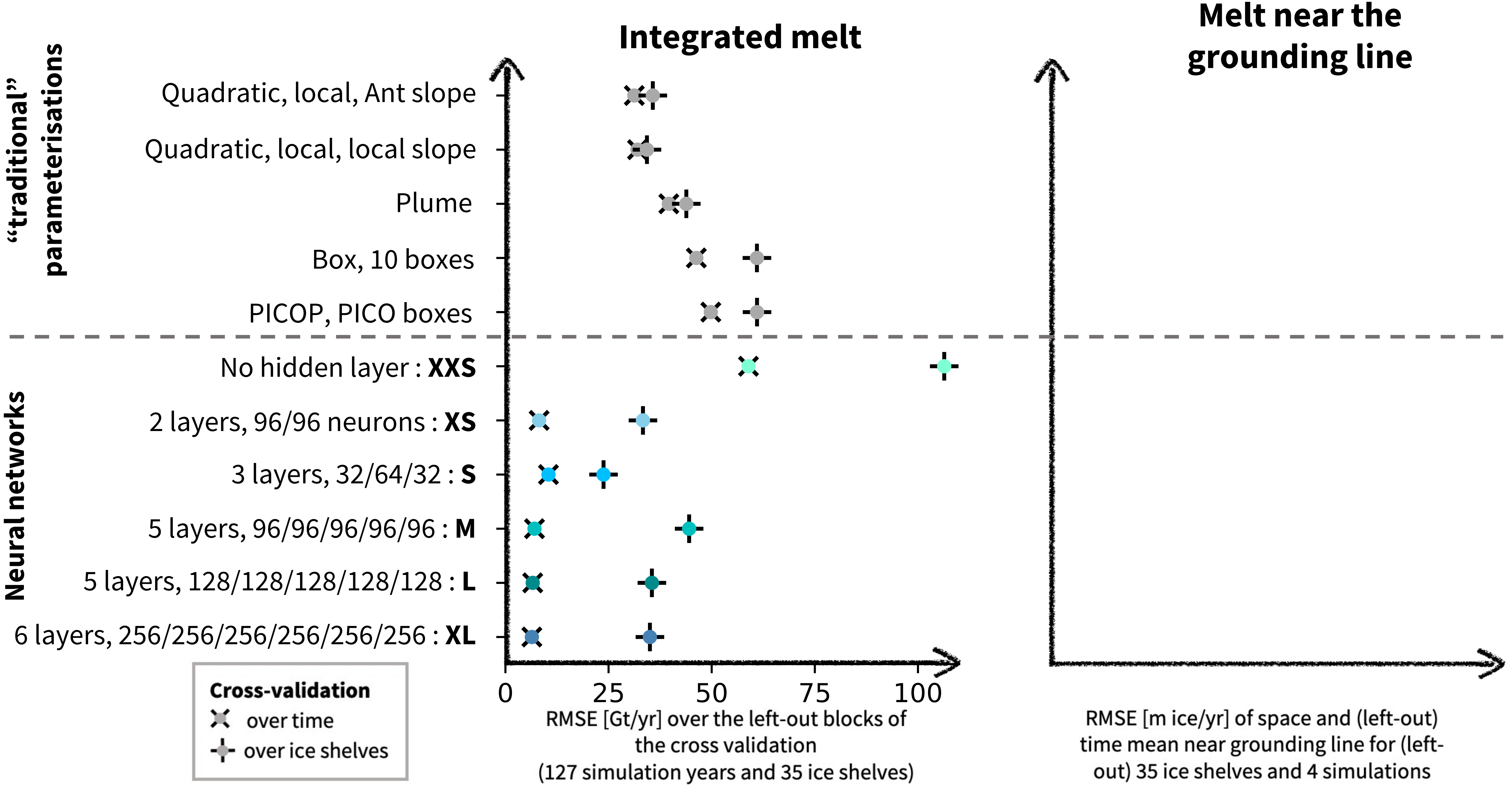
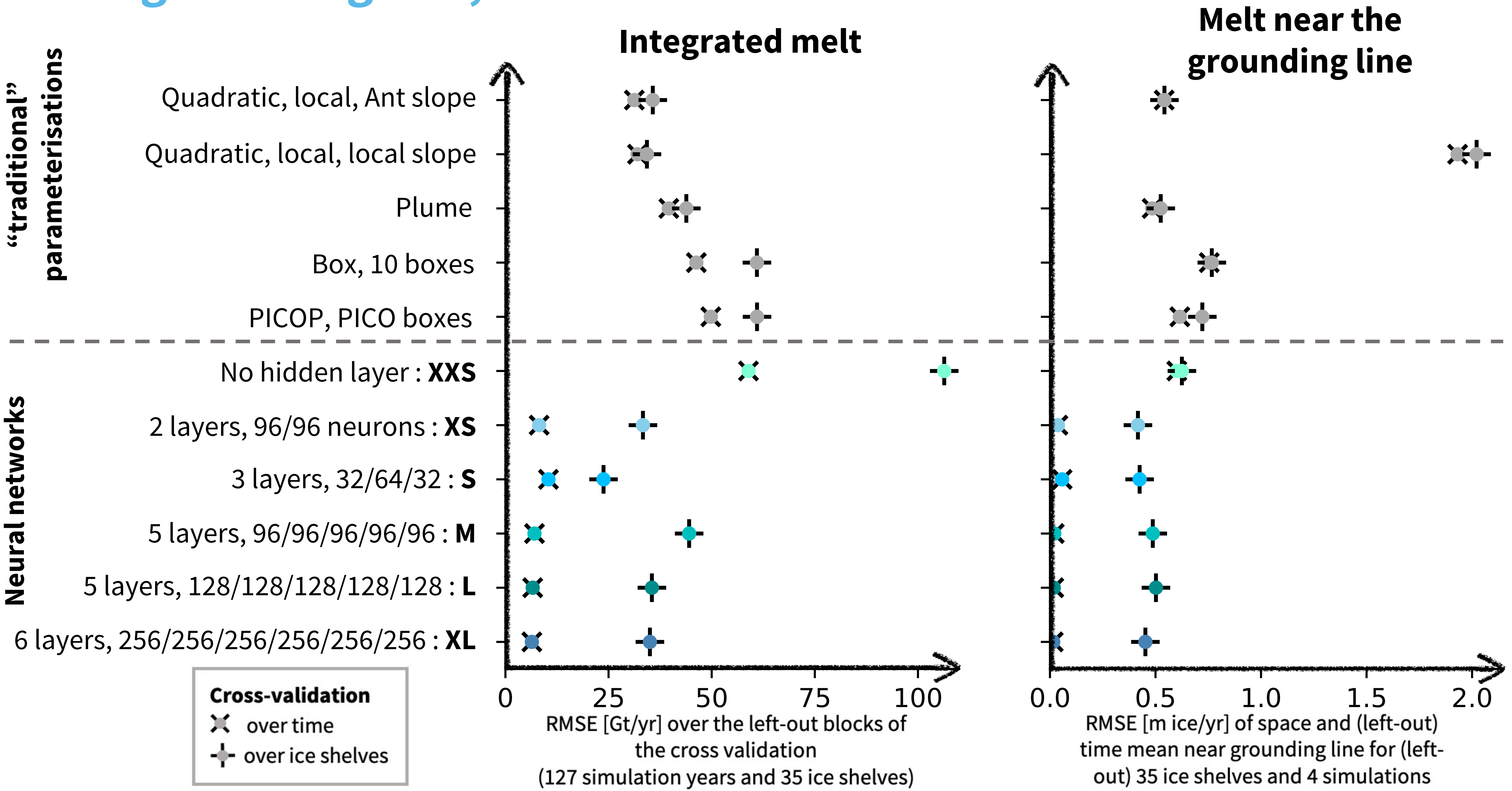


RMSE [m ice/yr] of space and (left-out) time mean near grounding line for (left-out) 35 ice shelves and 4 simulations

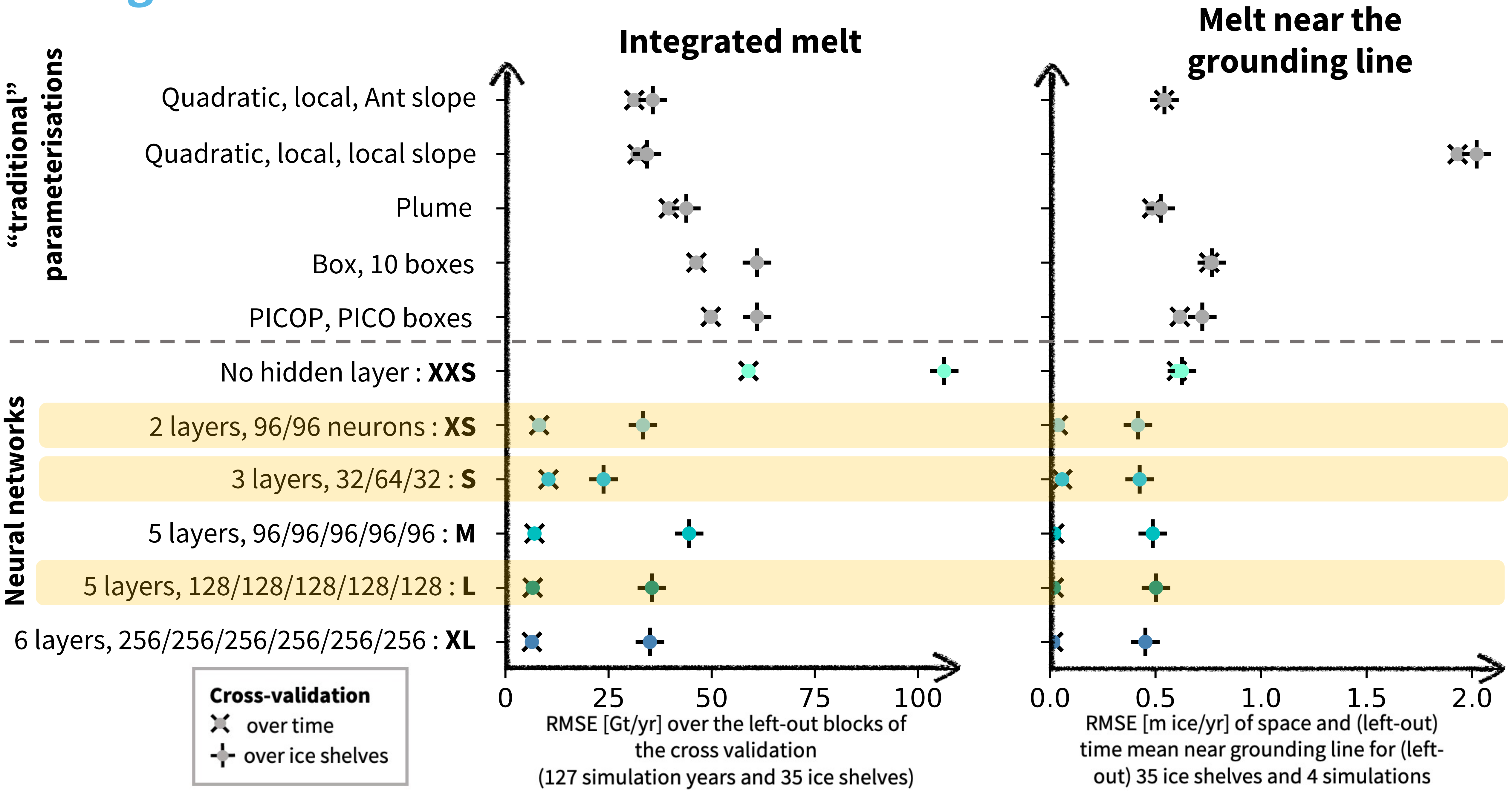
Neural networks closer to reference…



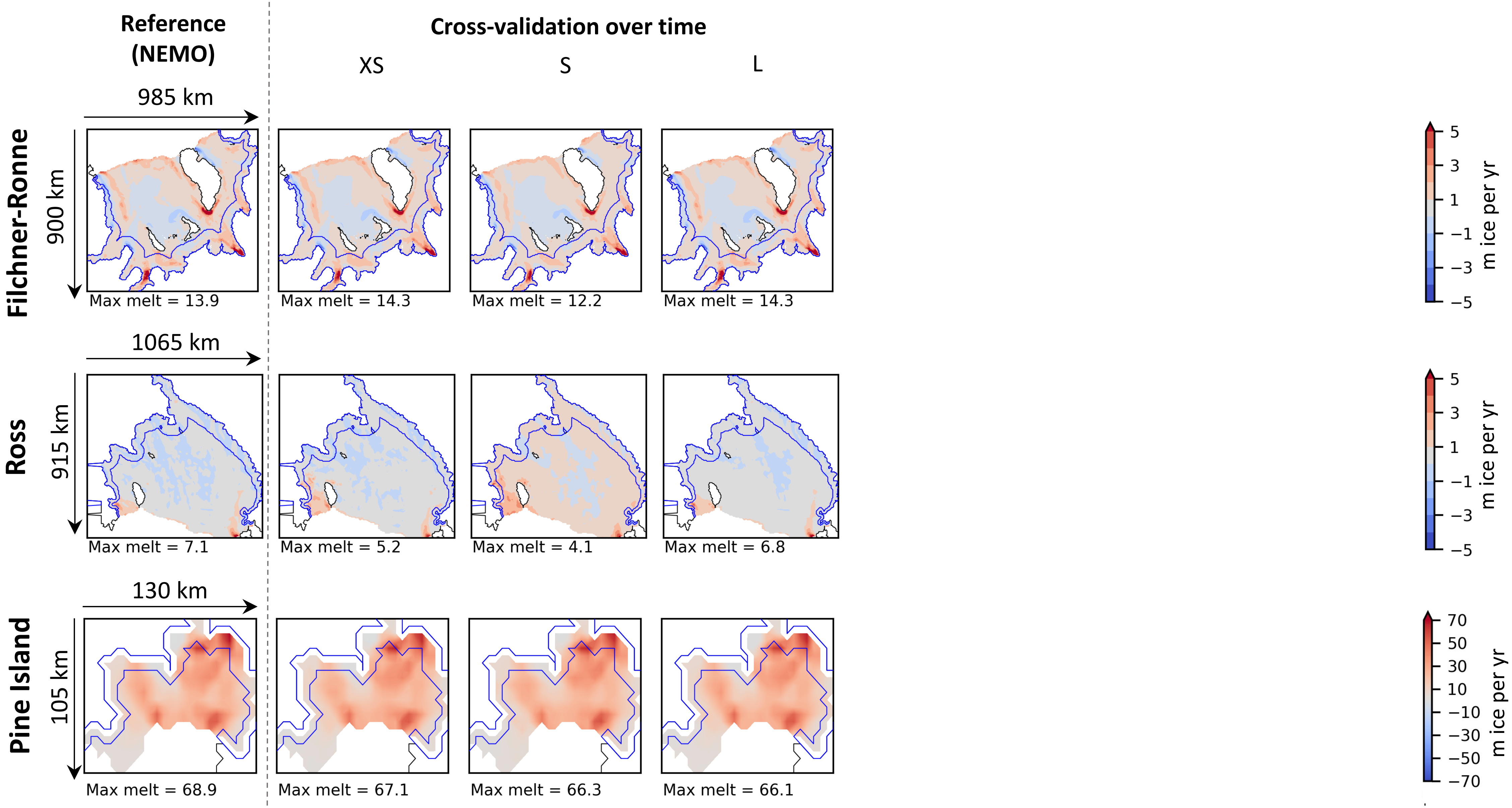
Near grounding line, less difference between them



Going forward



Spatial patterns promising !?



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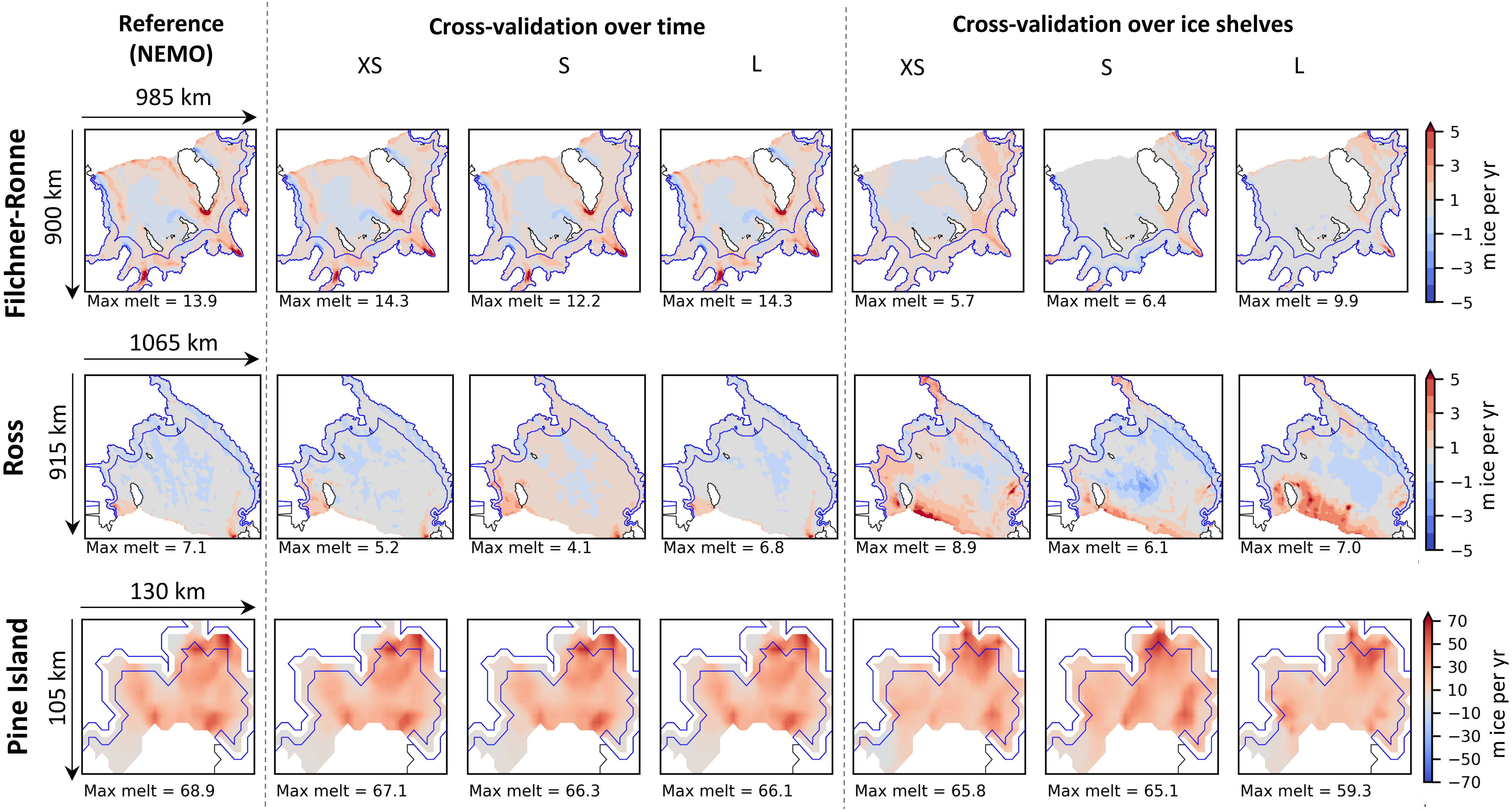

Two questions to explore during testing...

- *Will the RMSE remain as low as for the cross-validation over time with an evolving geometry?*
- *How will the neural network perform with input data from a different distribution (climate change)?*

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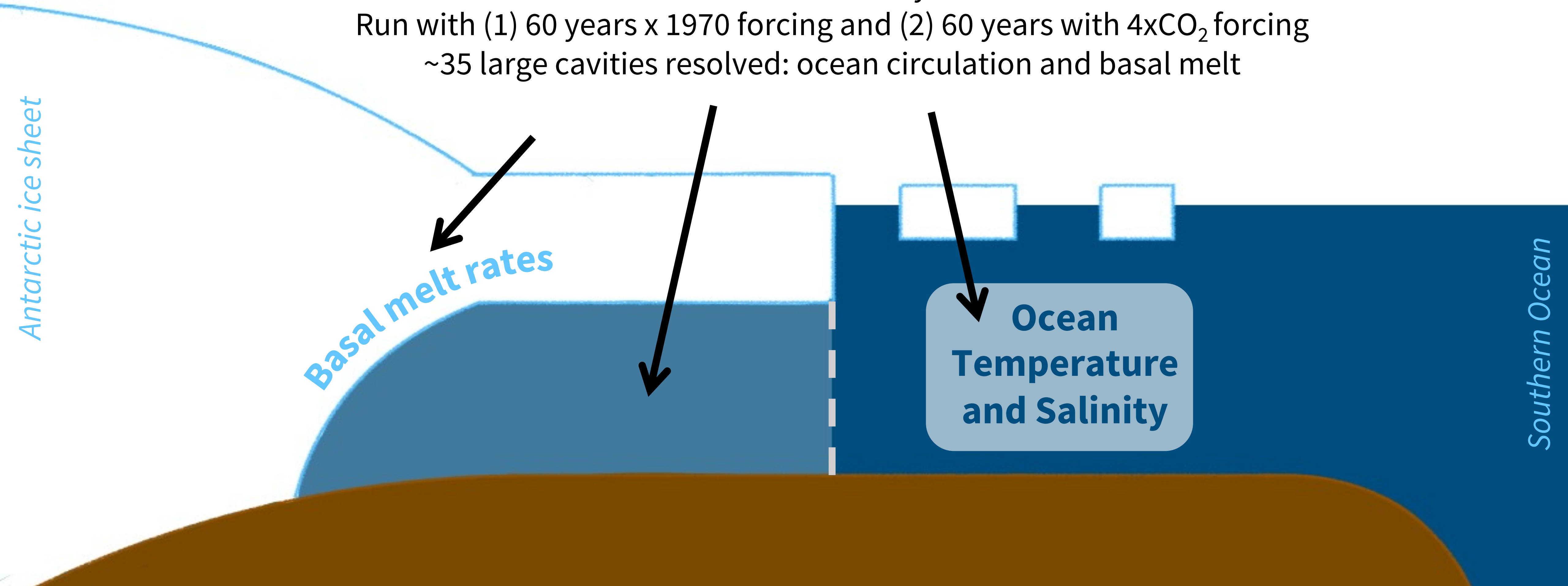
Our virtual reality for testing

2 x NEMO global ocean simulations
coupled with ice-sheet model within UKESM-ice
[from Smith et al. 2021]
0.25° grid
2 x 60 simulation years
Run with (1) 60 years x 1970 forcing and (2) 60 years with 4xCO_2 forcing
~35 large cavities resolved: ocean circulation and basal melt



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Apply to 60 years of 1970 forcing

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No large differences to cross-validation

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Two questions to explore…

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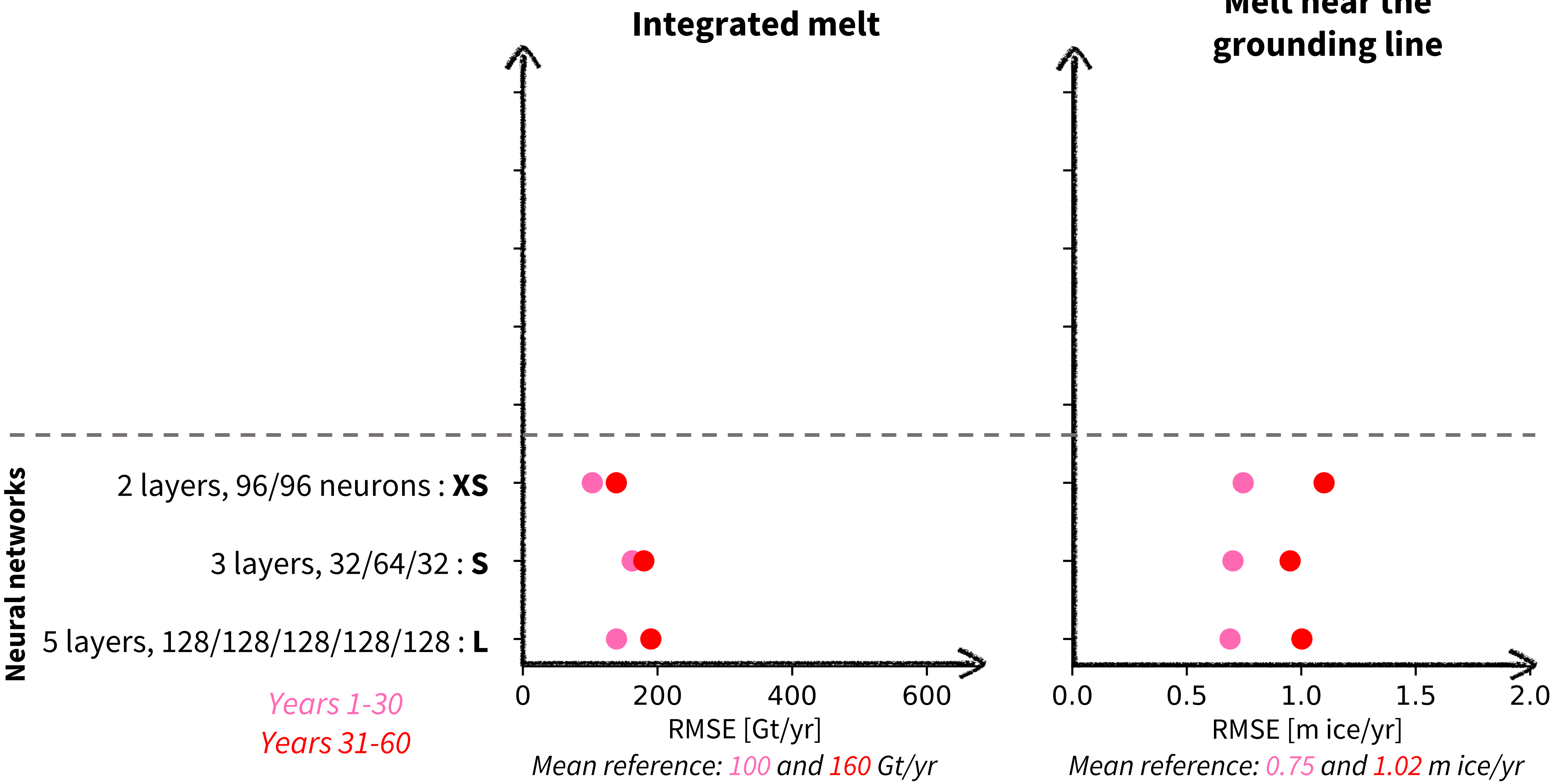
  → No large differences to cross-validation

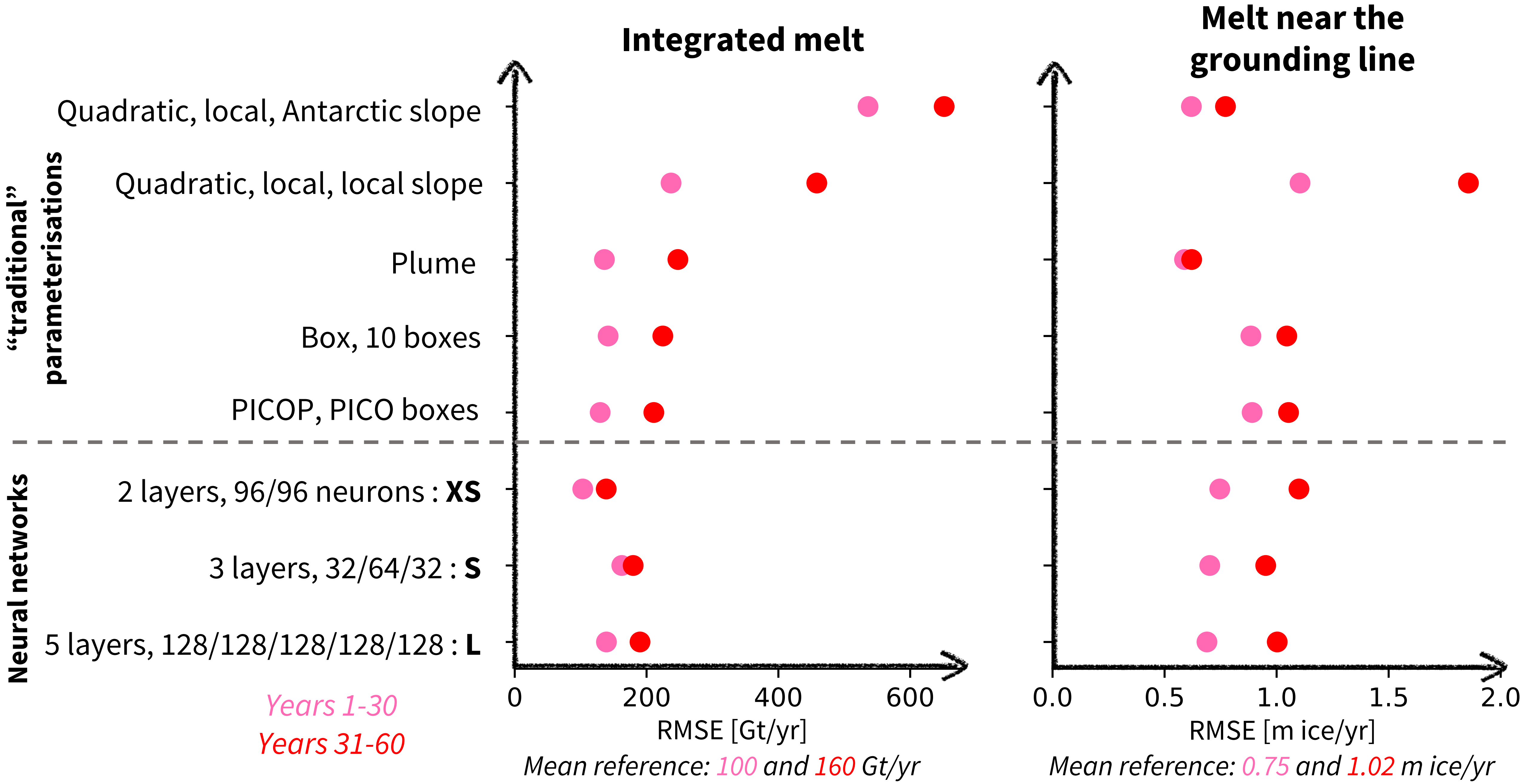
- *How will the neural network perform with input data from a different distribution (climate change)?*

  Apply to 60 years of 4xCO_2 forcing

The neural networks struggle…



… but the traditional ones too!



Two questions to explore…

- *Will the RMSE remain as low as for the cross-validation over time with an evolving geometry?*

  → No large differences to cross-validation

- *How will the neural network perform with input data from a different distribution (climate change)?*

  → Performance is not as good but still better as traditional parameterisations

What you should take home…

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We use an ensemble of cavity-resolving circum-Antarctic ocean simulations to explore neural network parameterisations

Comparably small neural networks applied on the grid-cell level perform well in:

- emulating basal melt rates in a cross-validation framework
- adapting to evolving geometries

For warmer conditions, both neural networks and traditional parameterisations struggle

- Include warmer simulations in training?

Promising results and food for thought for further development!

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Submitted to JAMES, contact me if interested!

THANK YOU FOR YOUR ATTENTION!

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Neural networks deal well with evolving geometries