Parameterising melt at the base of Antarctic ice shelves with a feedforward neural network

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Introduction and Motivation forcing for forcing for ocean models ice-sheet models to better simulate to project future Southern Ocean sea-level rise properties Ice shelf Ocean Sub-shelf cavities Temperature typically not resolved in ocean or coupledand Salinity climate models Grounding line Bedrock

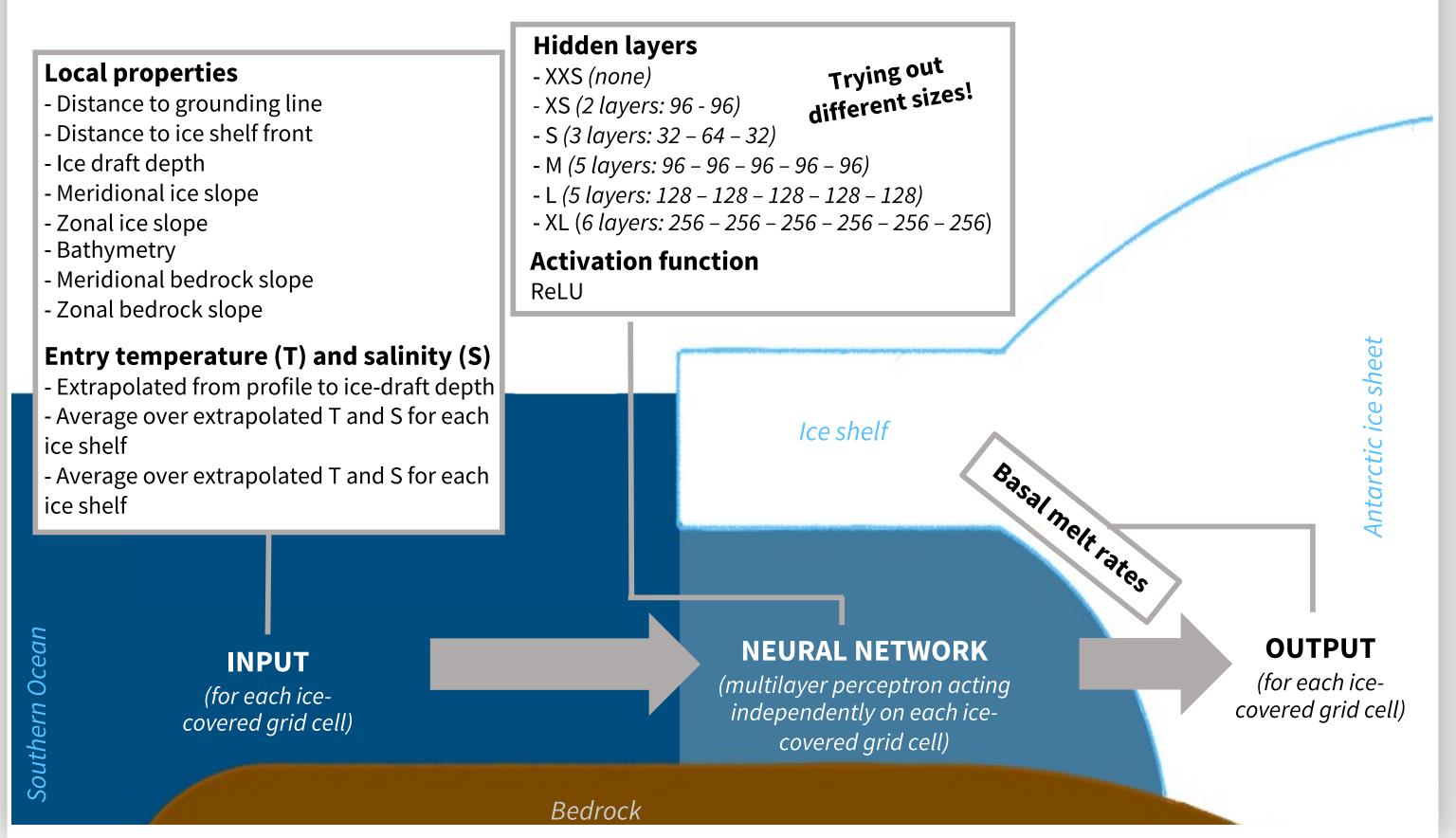
Existing physics-based parameterisations struggle to represent the link between open ocean and basal melt

Idea: Train a neural network to emulate the melt as simulated by a cavity-resolving ocean model (NEMO)

The neural network(s)

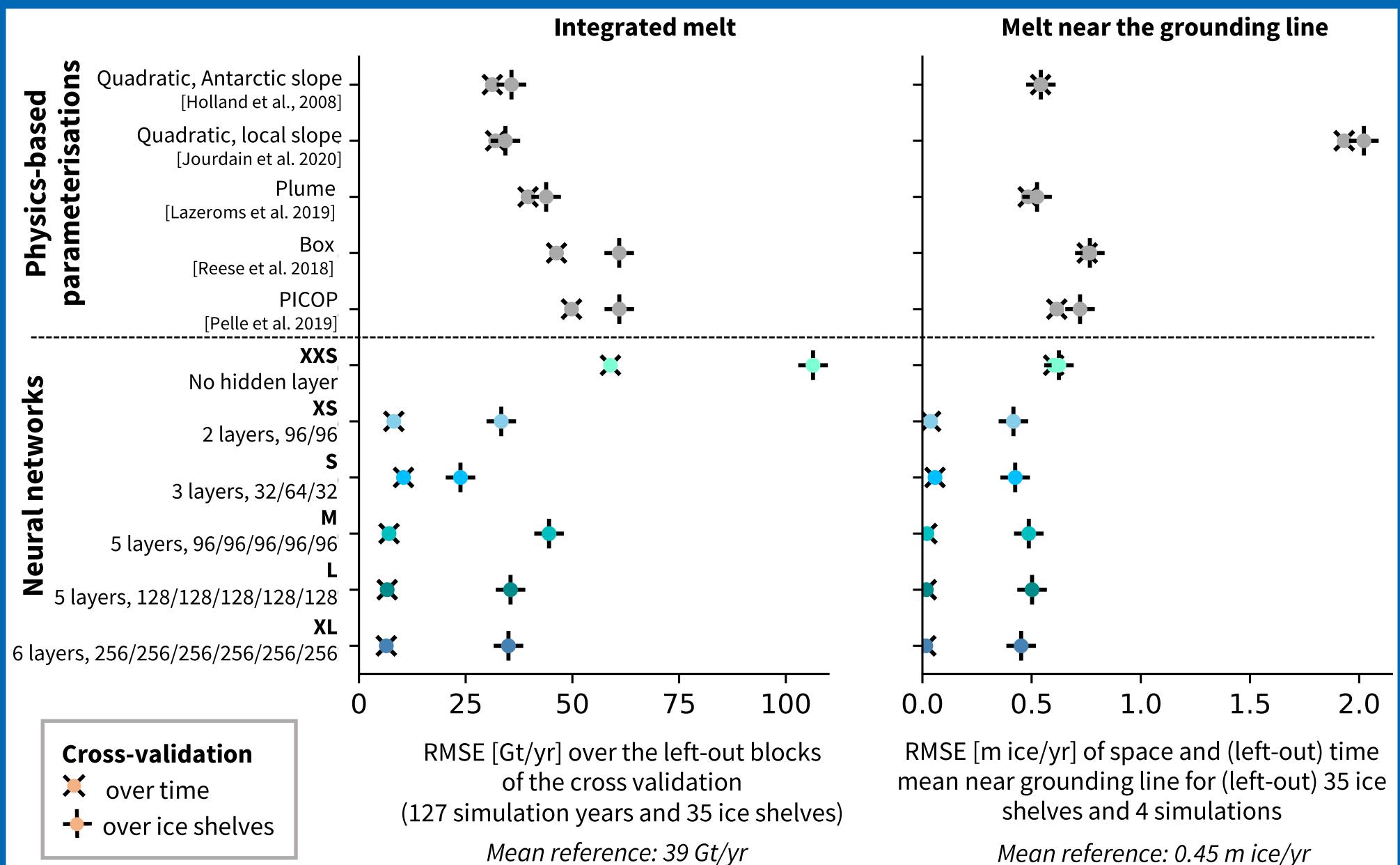
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"Simple" multilayer perceptron acting on the grid-cell level (in opposition to the convolutional approach from Rosier et al. 2023)

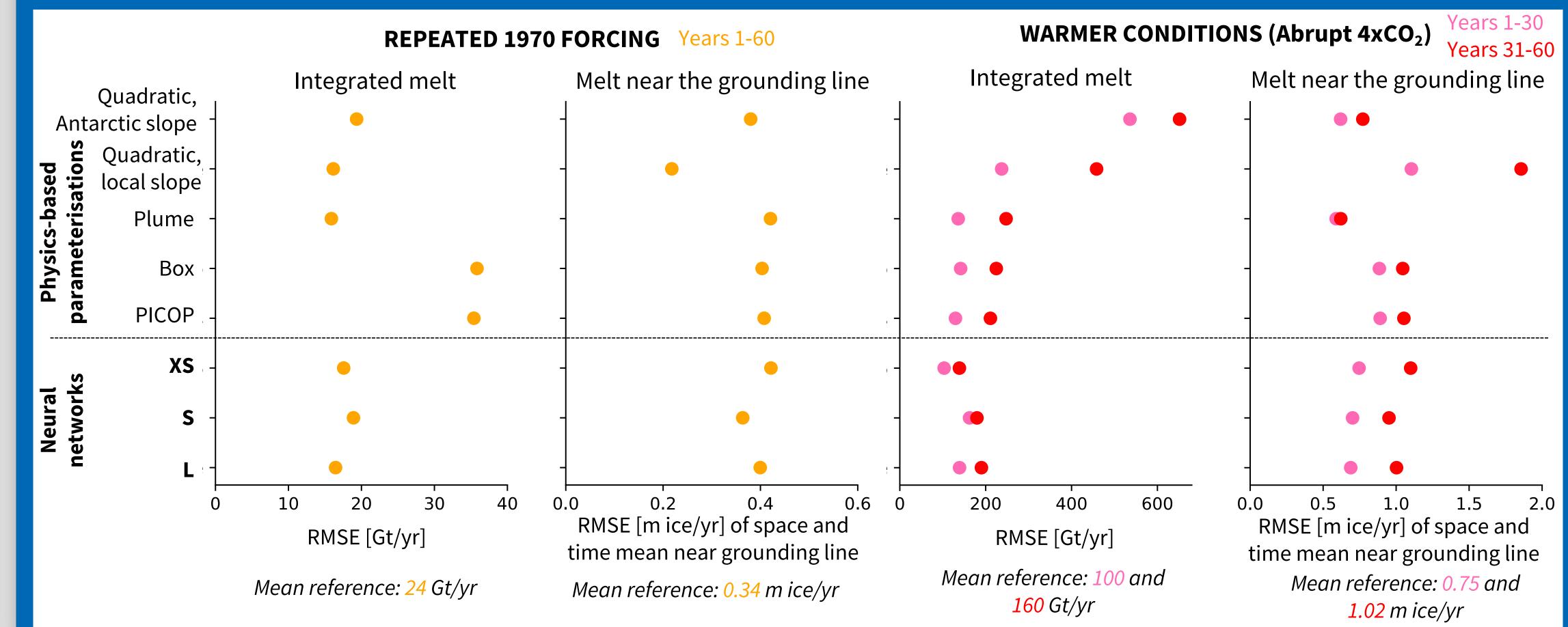


We show that a simple neural network acting on the grid-cell level can infer reasonable circum-Antarctic basal melt rates for ice shelves.

During cross-validation... [training on standalone ocean simulations - Burgard et al. 22] over time (127 years): trained over 12 ten-year blocks and validated over 1 ten-year block, repeated 13x over ice shelves (35 shelves): trained over 34 ice shelves and validated over 1 ice shelf, repeated 35x



In present and future conditions... [testing on coupled ocean-ice simulations - Smith et al. 21] Testing on changing ice-shelf geometries and temperature and salinity outside of training range









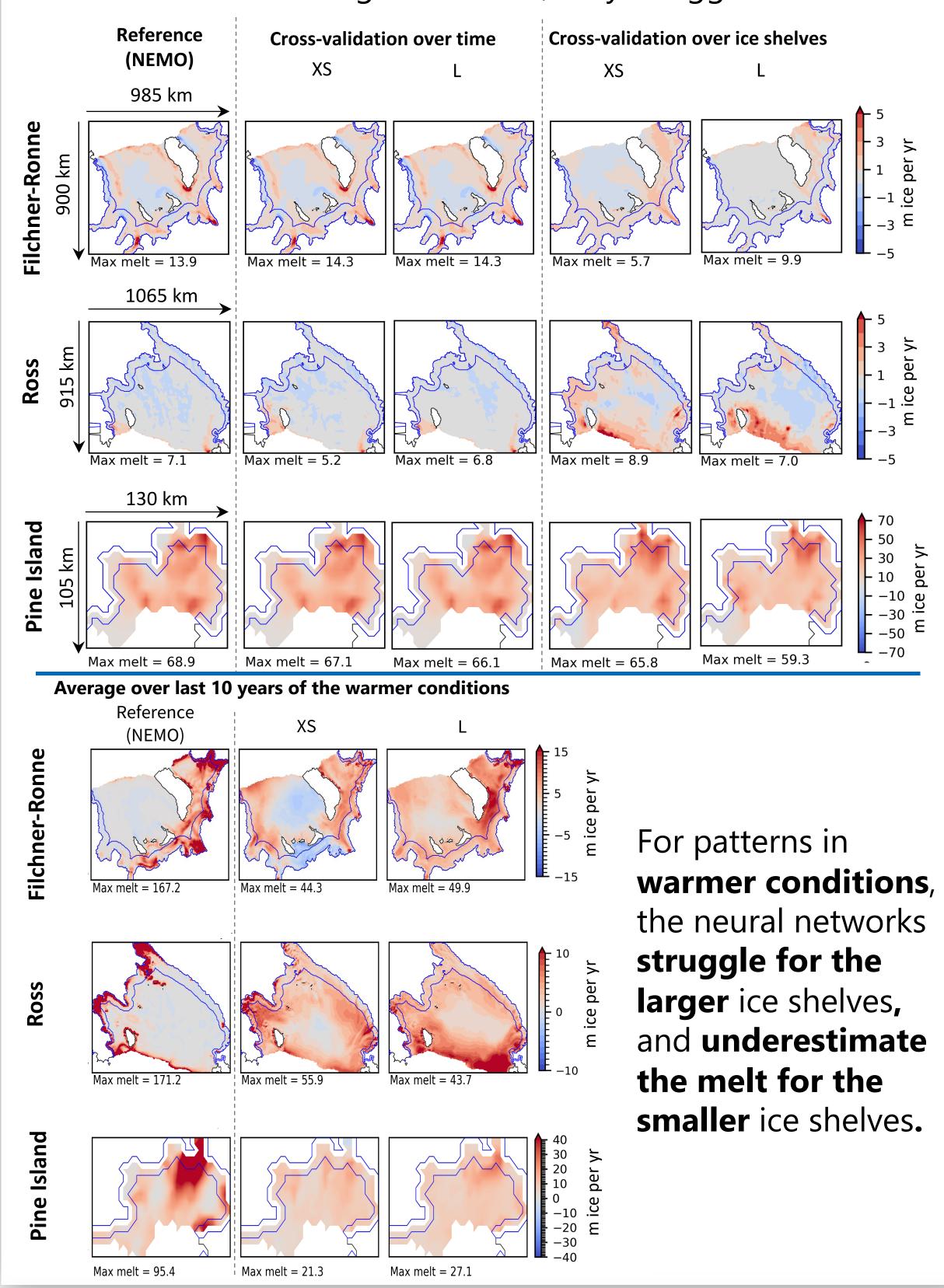




Mean reference: 0.45 m ice/yr

Look at the patterns!

Neural networks good at representing patterns if ice shelf was included in training! Otherwise, they struggle more...



Which input variables matter the most?

With a **permute-and-predict** approach, we explore the influence of the different input variables on the RMSE.

	Integrated melt [Gt/yr]		Melt near grounding line [m ice/yr]	
	XS	L	XS	L
Original RMSE	17.6	16.5	0.42	0.40
Water column	15.9	7.1	-0.03	-0.01
Position	13.9	13	-0.01	0
Slopes bed	0.5	0.1	-0	0
Slopes ice	1.1	0.9	0.04	0.05
Temperature info	330.6	266.5	0.21	-0.03
Salinity info	20.7	3.2	0.07	0.06
slope_ice_lon -	Difforence	potwoon the PMSE u	sing a random sa	mplo of input
slope_ice_lat -	⁰ f ¹⁷	Detween ^{0.45} -0.07 IxCO2 rung and the or	riginal dia nanuoni sa	$\frac{0.01}{0.01}$
theta_in -	1.8e+02	RCO2 run and the of		-0.04
Water coldinity_ini-	e draft debth and ba	athymetry <mark>1</mark> Position = c	distance to ice front	and grounding
	the second se	al bedroc®3lopes, Slop		
		ge and standard devia		
local, averag e_su d	standardideviation (of salinity13		0.02
S_std -	30	7.9	- 100	0.01

Outlook

Neural networks acting on the grid-cell level can infer similar or even better basal melt rates than physics-based parameterisations > very encouraging!

Improvements to explore in the future:

- Include warmer simulations in training
- Use Machine Learning to extract main temperature and salinity characteristics in front of the shelf (\neq only average)?
- Train without the larger ice shelves to improve patterns?