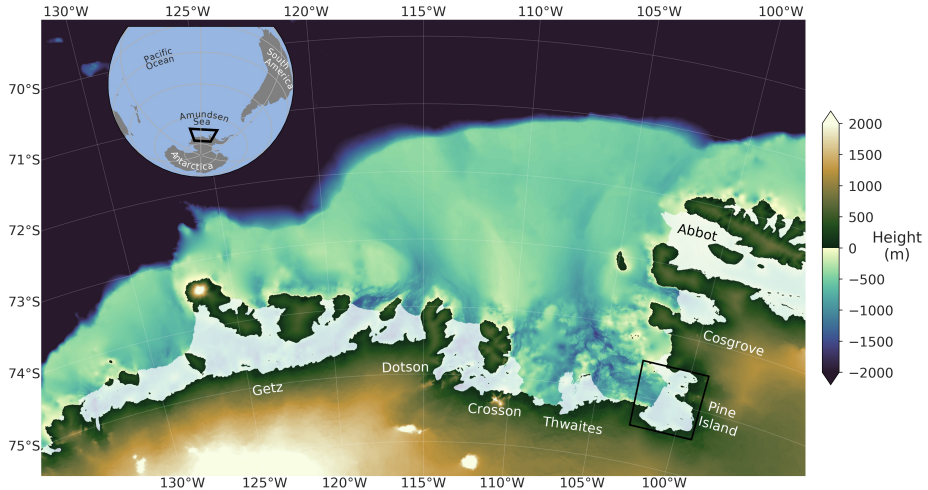


# Uncertainty Quantification of Ocean Driven Melting Under the Pine Island Ice Shelf

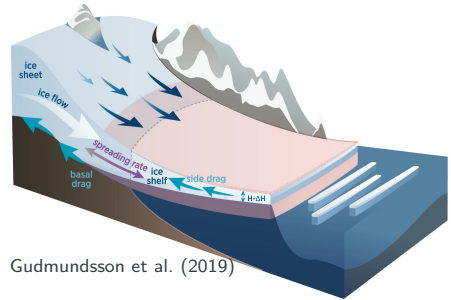
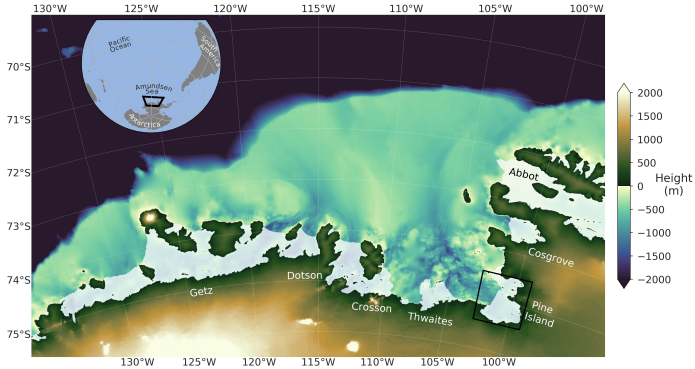
**Timothy Smith**  
Patrick Heimbach

ECCO Meeting  
Jan. 26, 2023

# The Amundsen Sea, West Antarctica

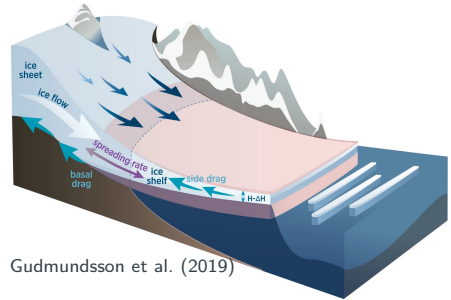
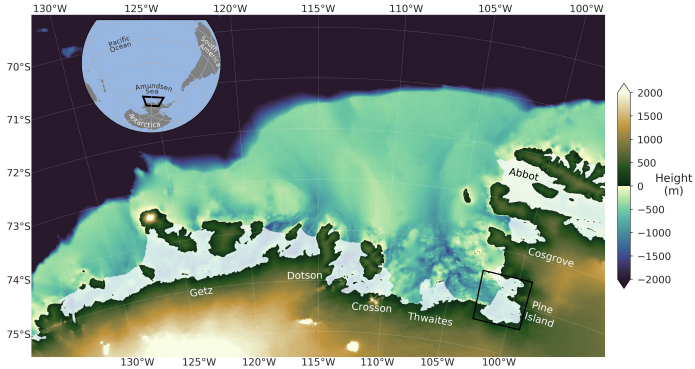


# The Amundsen Sea, West Antarctica



Gudmundsson et al. (2019)

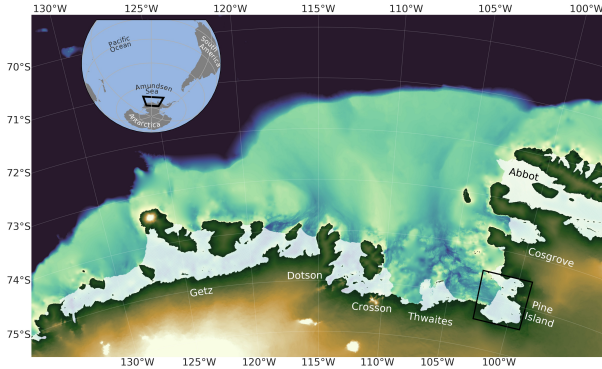
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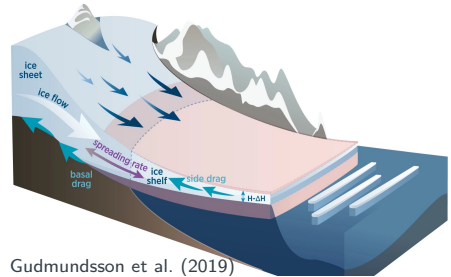
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Amundsen Sea ice shelves have some of the highest melt rates in Antarctica (Adusumilli et al., 2020).

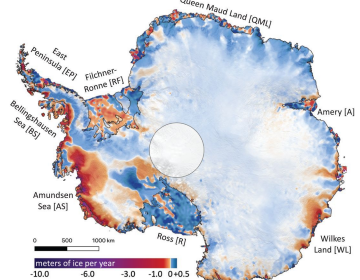
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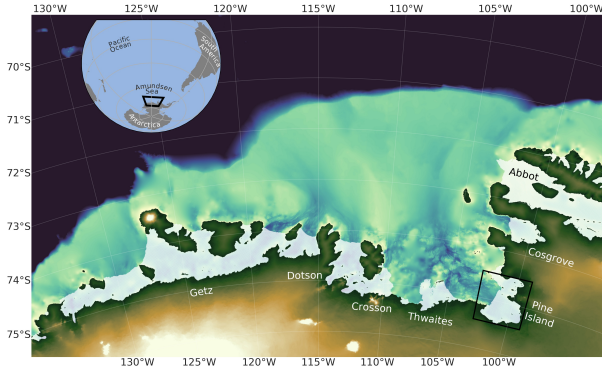


Gudmundsson et al. (2019)



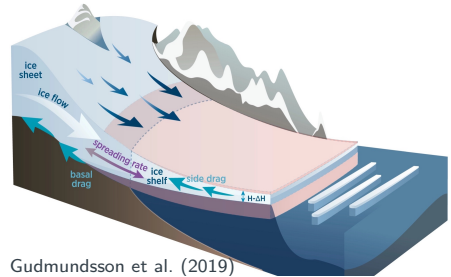
Smith et al. (2020)

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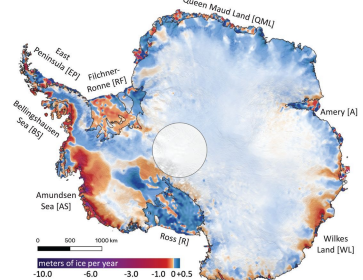


Amundsen Sea ice shelves have some of the highest melt rates in Antarctica (Adusumilli et al., 2020).

This leads to ice shelf thinning, glacial mass loss, and sea level rise (Fürst et al., 2016; Gudmundsson et al., 2019).

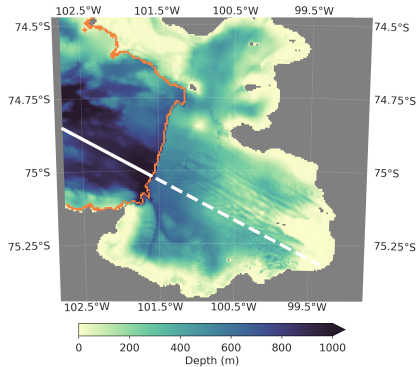
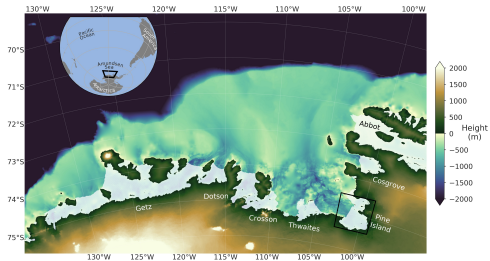


Gudmundsson et al. (2019)

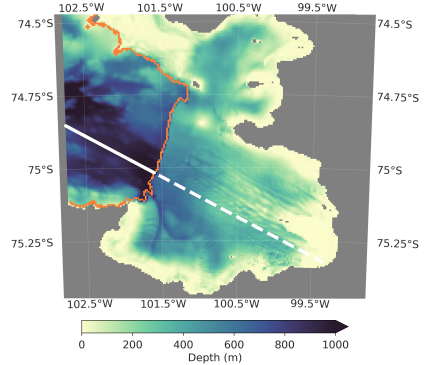
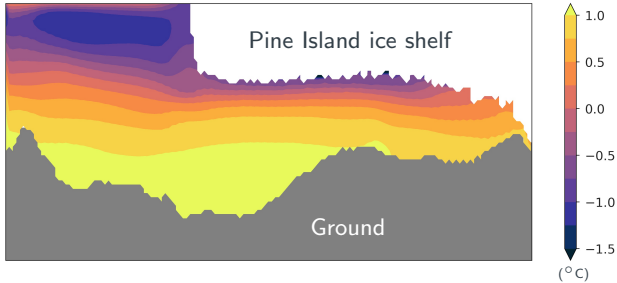
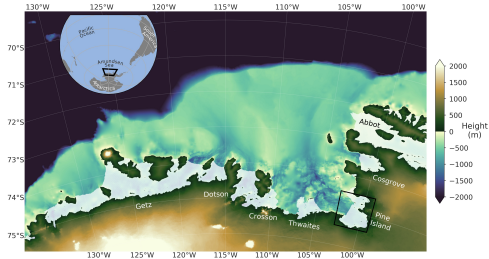


Smith et al. (2020)

# The Pine Island Ice Shelf

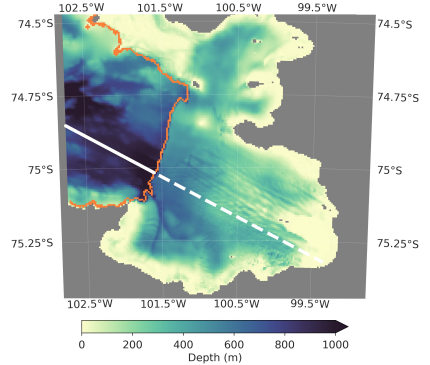
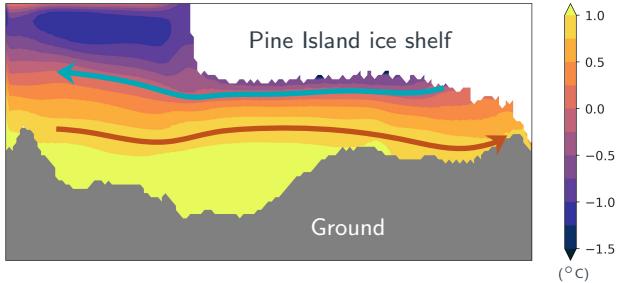
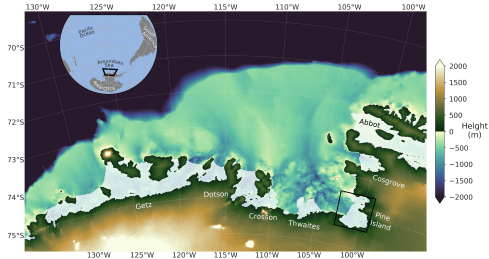


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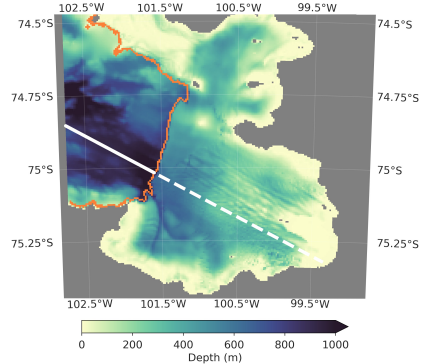
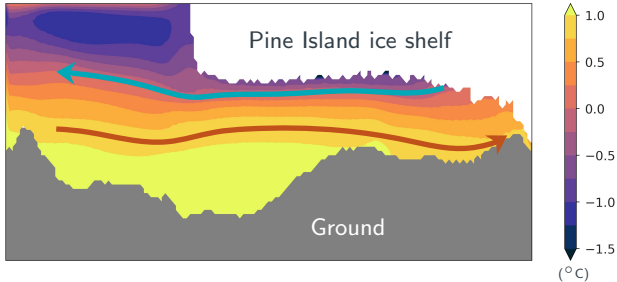
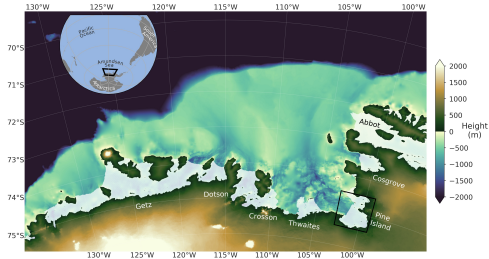




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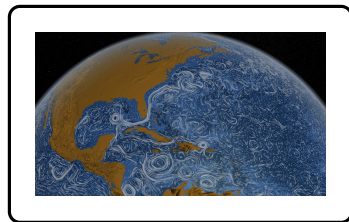
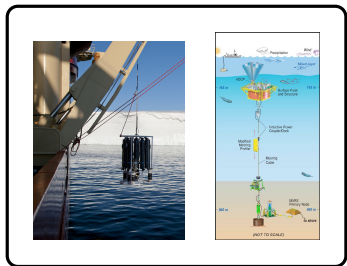


# The Pine Island Ice Shelf



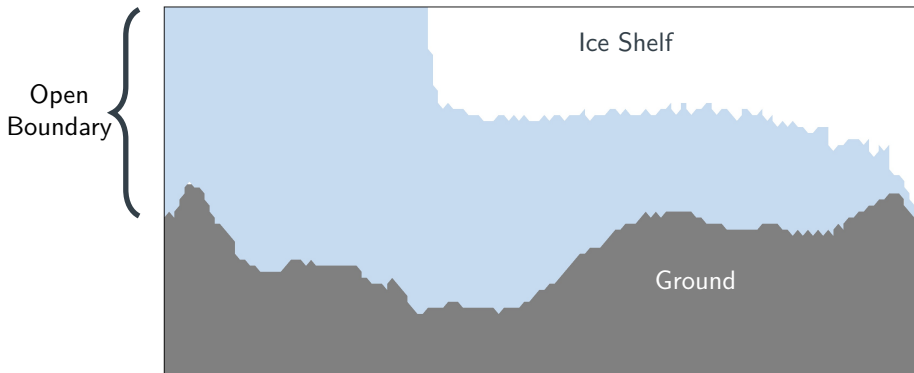
Warm waters access the deepest portions of the ice shelf and drive high meltrates

# Our Contribution: Physics Informed Bayesian Inference

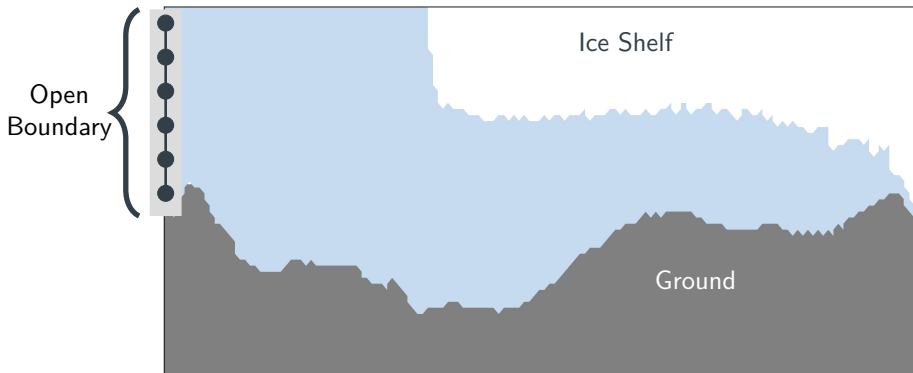


**Physics Informed Bayesian Inference**  
How much information do we gain in our estimate of melt rates from sparse ocean observations?

## A Two Stage Inference Problem for Open Boundary T, S, & U

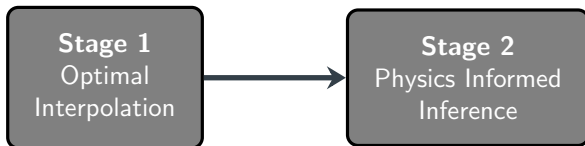
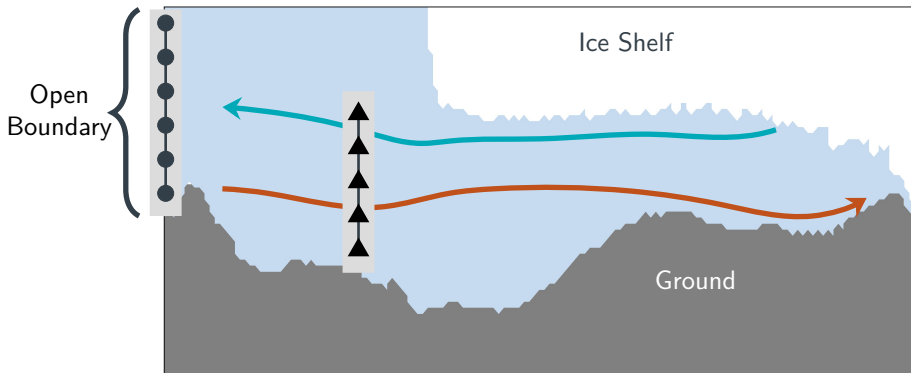


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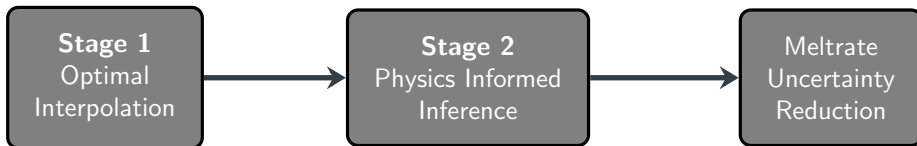
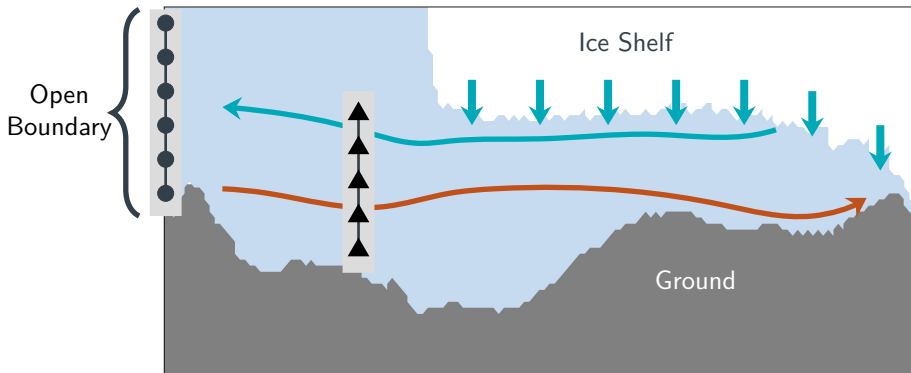


**Stage 1**  
Optimal  
Interpolation

## A Two Stage Inference Problem for Open Boundary T, S, & U



## A Two Stage Inference Problem for Open Boundary T, S, & U



# Two Stages of Uncertainty Propagation

Optimization:

$$\text{Optimal OBCS Stage 1} := \arg \min \left\{ \text{CTD/ADCP Misfit} + \text{Prior Deviation \& Uncertainty} \right\}$$

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Uncertainty Reduction / Info Gain

$$\underbrace{\Gamma_{\text{post}}}_{\text{Posterior Uncertainty}} = \underbrace{\Gamma_{\text{prior}}}_{\text{Prior Uncertainty}} - \underbrace{\sum_i \lambda_i \tilde{\mathbf{v}}_i \tilde{\mathbf{v}}_i^T}_{\text{Stage 1 Info Gain}} - \underbrace{\sum_j \mu_j \tilde{\mathbf{u}}_j \tilde{\mathbf{u}}_j^T}_{\text{Stage 2 Info Gain}}$$

- Eigenvalues and Eigenvectors  $(\lambda_i, \tilde{\mathbf{v}}_i)$ ,  $(\mu_j, \tilde{\mathbf{u}}_j)$  represent Hessian of each cost function

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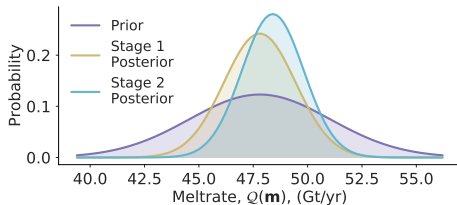
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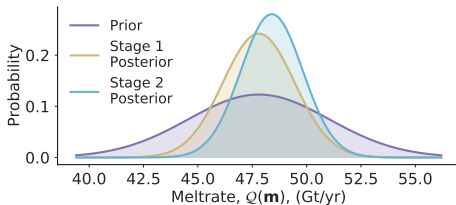
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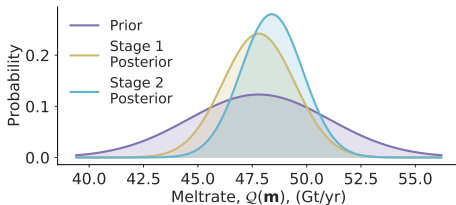
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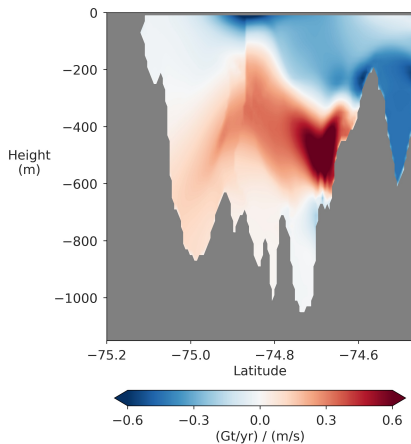
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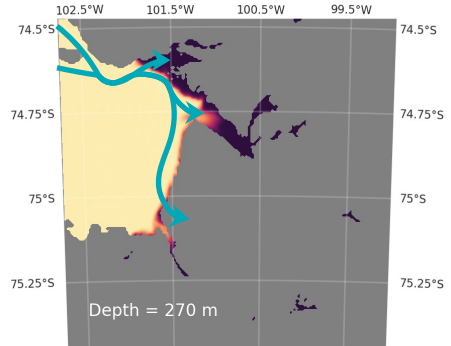
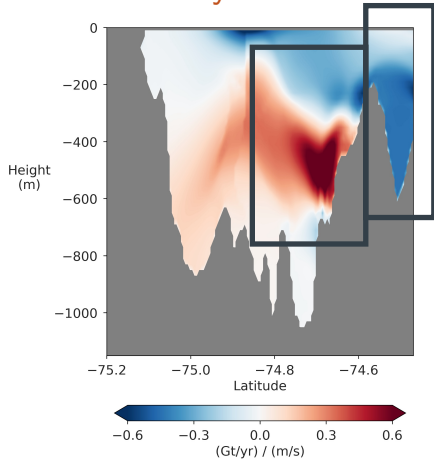
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  - Adjoint for efficiently uncertainty propagation
- Eigenvectors show regions informed by observations
  - Sensitivity shows important regions for meltrate

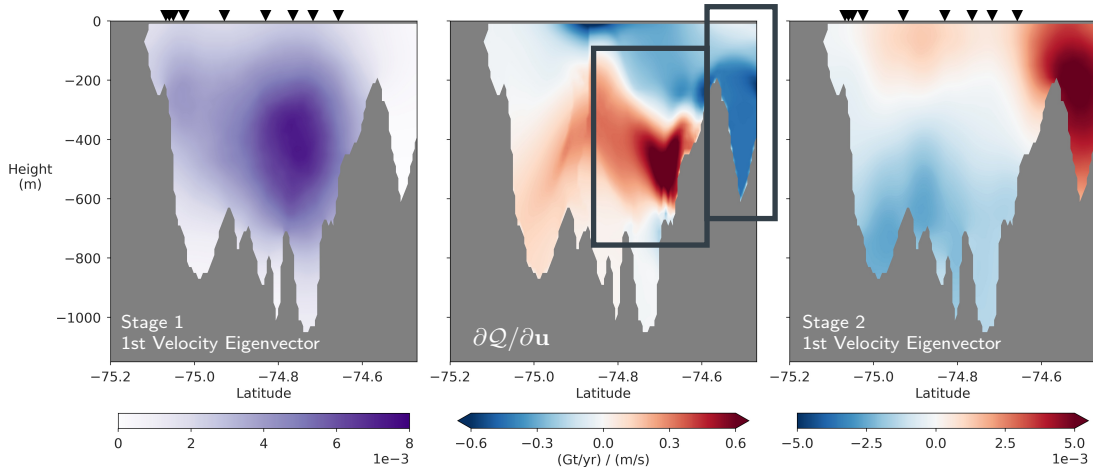
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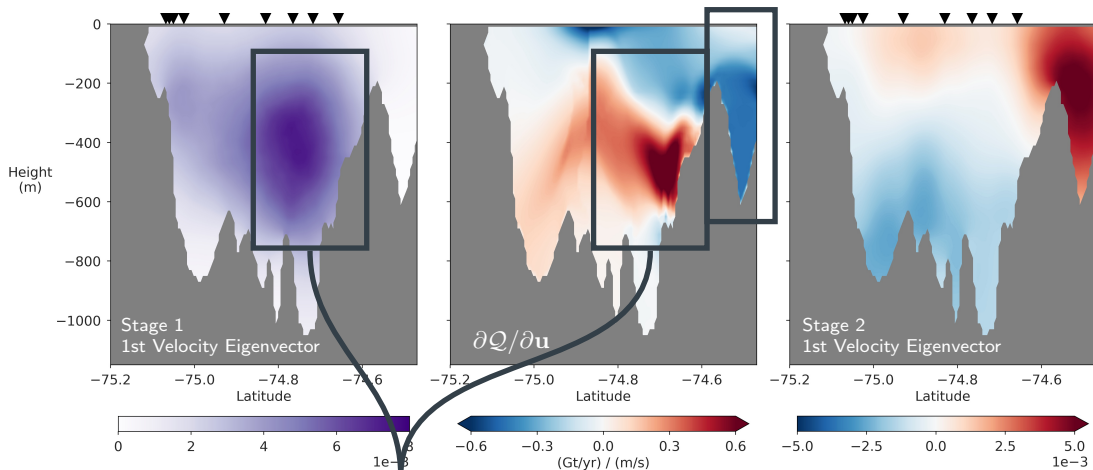


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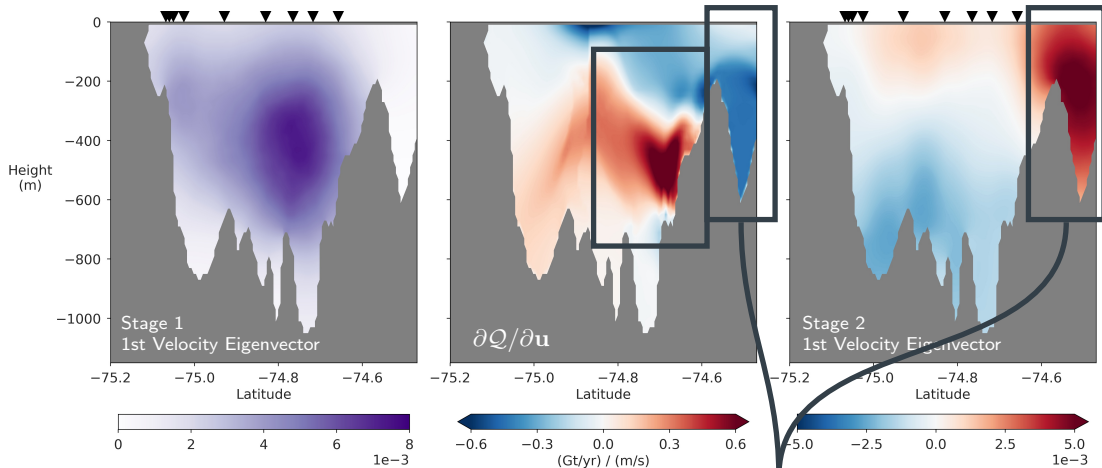
# Meltrate Uncertainty Reduction



$$\frac{\lambda_1}{\lambda_1 + 1} (\tilde{\mathbf{v}}_1^T \mathbf{q})^2$$

Stage 1 Info Gain

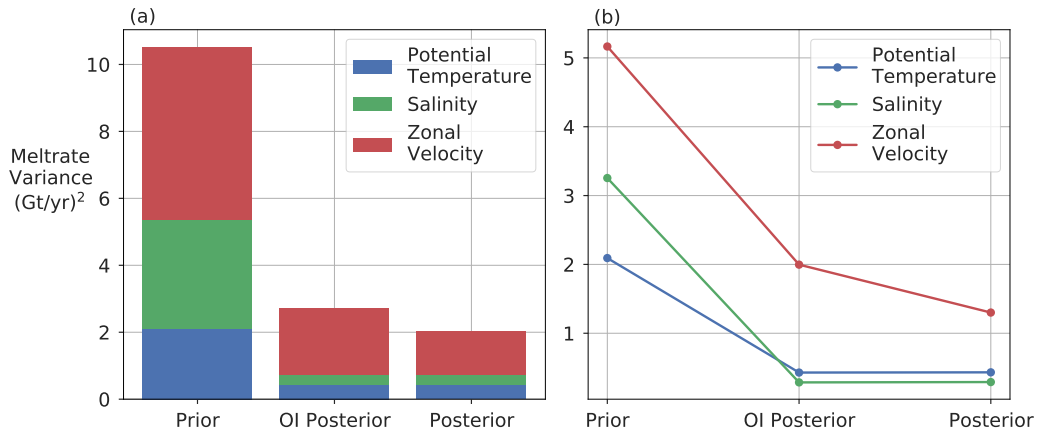
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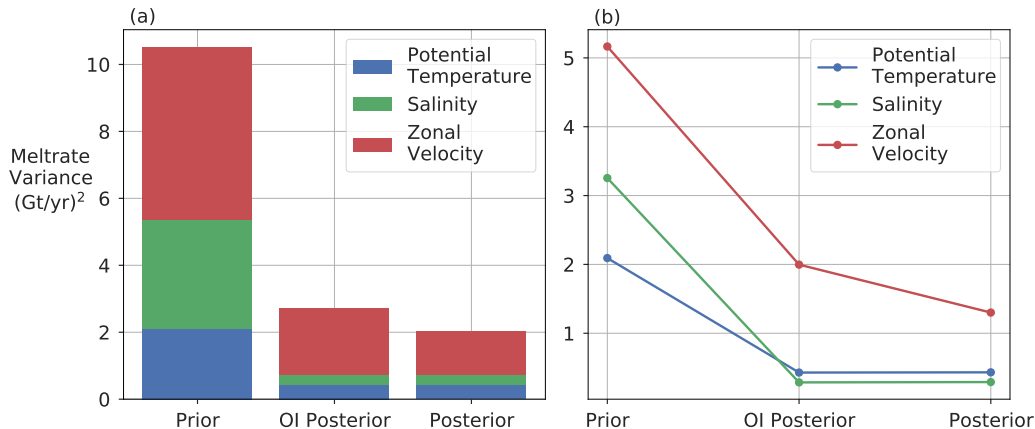
$$\frac{\mu_1}{\mu_1 + 1} (\tilde{\mathbf{u}}_1^T \mathbf{q})^2$$

Stage 2 Info Gain

# Uncertainty Quantification of Ocean Driven Melting



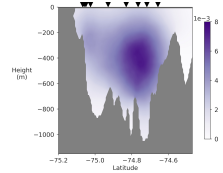
# Uncertainty Quantification of Ocean Driven Melting



- Second stage: information gain via propagation onto unobserved variable, and to meltrate
- Standard deviation reduced by  $\sim 90\%$  relative to prior 3.2 Gt/yr

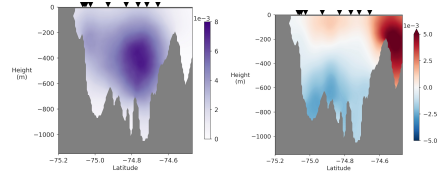
# Summary & Conclusions

- CTD & LADCP data provide good constraints on conditions across most of Pine Island Bay



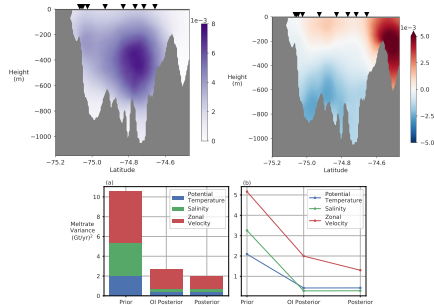
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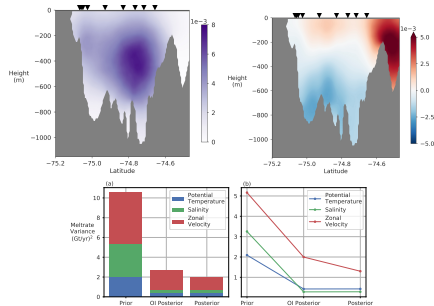
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- Unobserved regions informed via model dynamics, propagating hydrographic information onto the circulation and melt rate field
- Uncertainty in melt rate reduced by 90% relative to prior standard deviation of 3.2 Gt/yr
- To stay faithful to the math, **no adjustments** made to the framework once inference has begun!



## Limitations (a.k.a. Ongoing & Future Work)

- Total meltwater flux (48.4 Gt/yr) smaller than satellite observations
- Uncertainty estimate only accounts for open boundaries
- Linearity assumption behind sensitivity, uncertainty estimate is suspect
- Temporal variability not considered in modeling framework



## References I

- Adusumilli, S., Fricker, H. A., Medley, B., Padman, L., and Siegfried, M. R. (2020). Interannual variations in meltwater input to the Southern Ocean from Antarctic ice shelves. *Nature Geoscience*, pages 1–5. Publisher: Nature Publishing Group.
- Fürst, J. J., Durand, G., Gillet-Chaulet, F., Tavard, L., Rankl, M., Braun, M., and Gagliardini, O. (2016). The safety band of Antarctic ice shelves. *Nature Climate Change*, 6(5):479–482.  
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Publisher: Nature Publishing Group Subject\_term: Climate and Earth system modelling;Cryospheric science Subject\_term.id: climate-and-earth-system-modelling;cryospheric-science.
- Gudmundsson, G. H., Paolo, F. S., Adusumilli, S., and Fricker, H. A. (2019). Instantaneous Antarctic ice sheet mass loss driven by thinning ice shelves. *Geophysical Research Letters*, 46(23):13903–13909.  
\_eprint: <https://agupubs.onlinelibrary.wiley.com/doi/pdf/10.1029/2019GL085027>.

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Smith, B., Fricker, H. A., Gardner, A. S., Medley, B., Nilsson, J., Paolo, F. S., Holschuh, N., Adusumilli, S., Brunt, K., Csatho, B., Harbeck, K., Markus, T., Neumann, T., Siegfried, M. R., and Zwally, H. J. (2020). Pervasive ice sheet mass loss reflects competing ocean and atmosphere processes. *Science*.  
Publisher: American Association for the Advancement of Science Section: Report.