Predicting the future of ice sheets and sea level rise

Challenges and how ML might help

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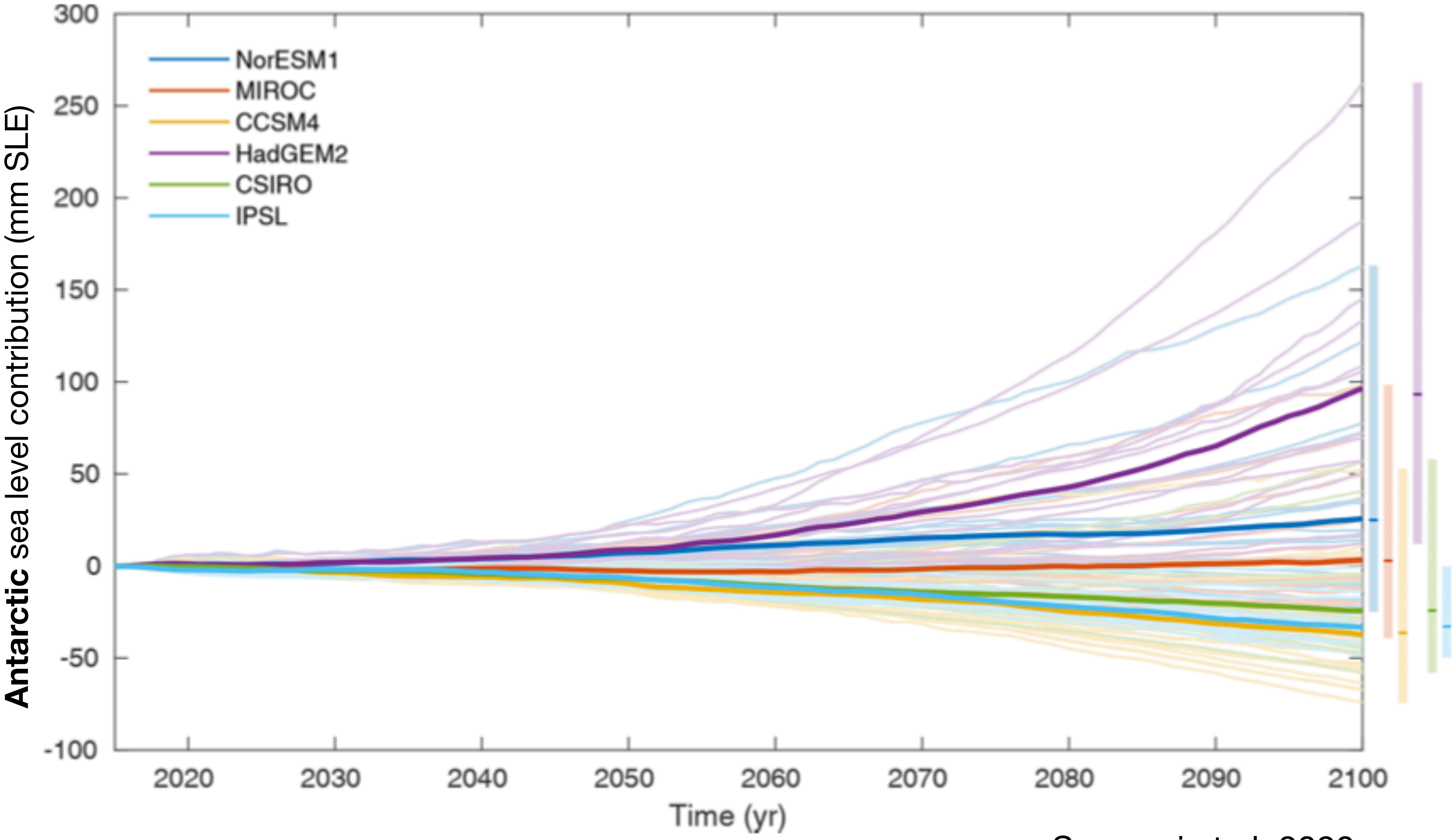
KITP Machine Learning for Climate - 8 Dec. 2021

Predictions of future ice sheet change are highly uncertain



Seroussi et al. 2020

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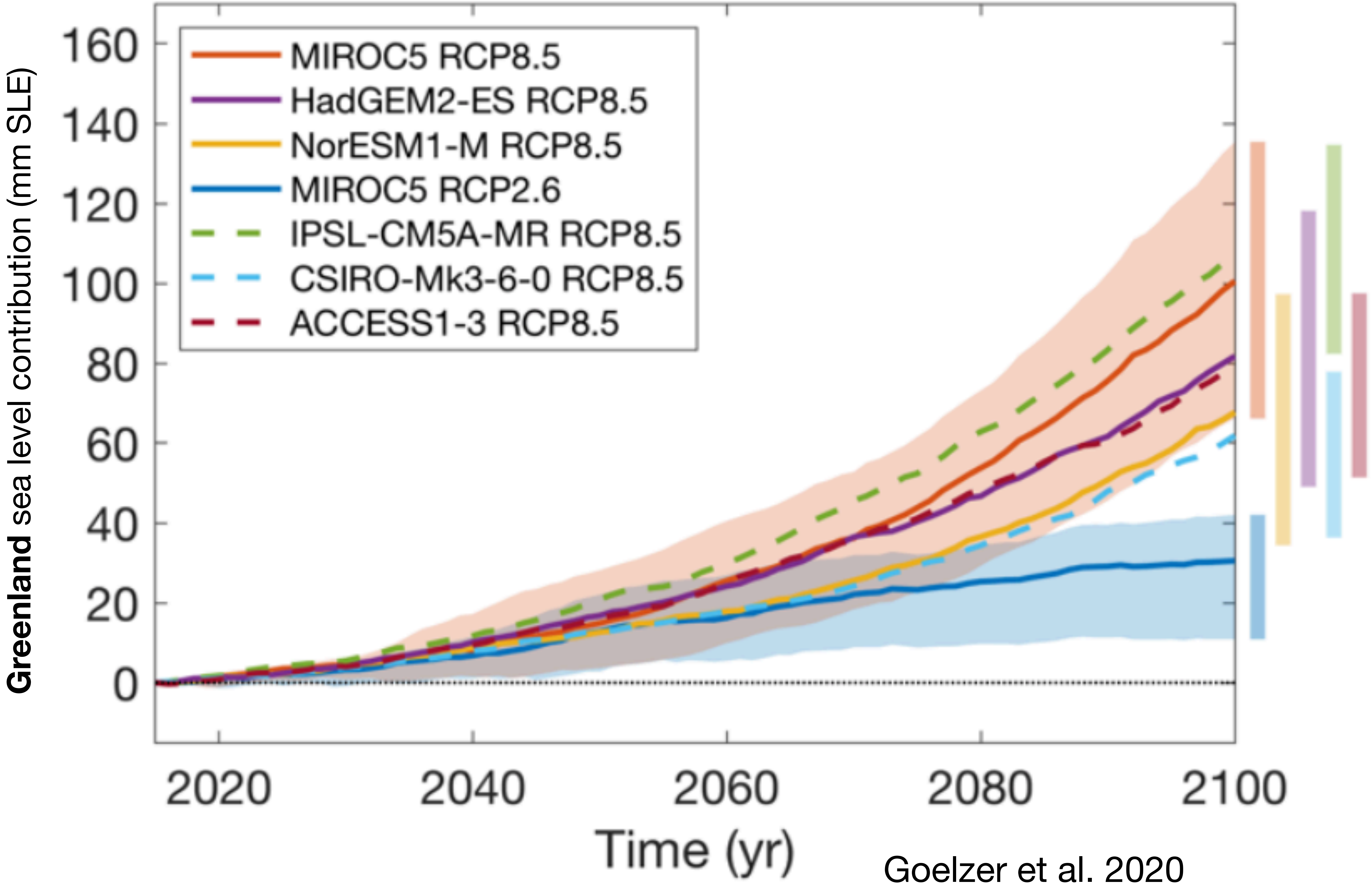


Goelzer et al. 2020

How are ice sheets different from typical modeling targets (e.g., atmosphere, ocean) you may be familiar with?

Ice sheets (i.e., not sea ice) interact with (mechanical, thermal, hydrology) with the solid Earth, the ocean and the atmosphere

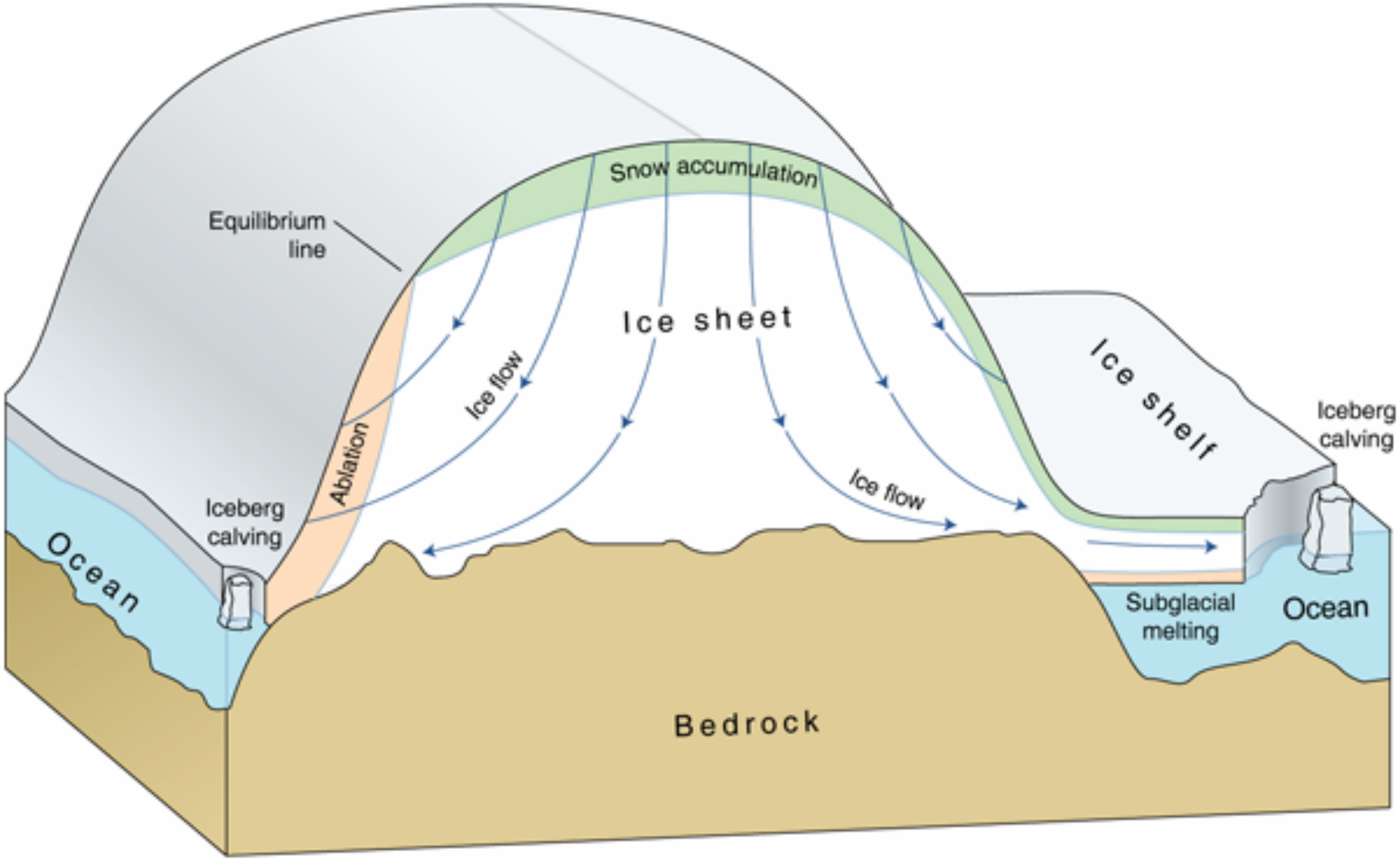


Image: NSIDC

$$Re \left[\frac{\partial \mathbf{u}}{dt} + (\mathbf{u} \cdot \nabla)\mathbf{u} \right] = \nabla \cdot \sigma + \mathbf{f}$$

Navier-Stokes Equation

$$0 = \nabla \cdot \sigma + \rho \mathbf{g}$$

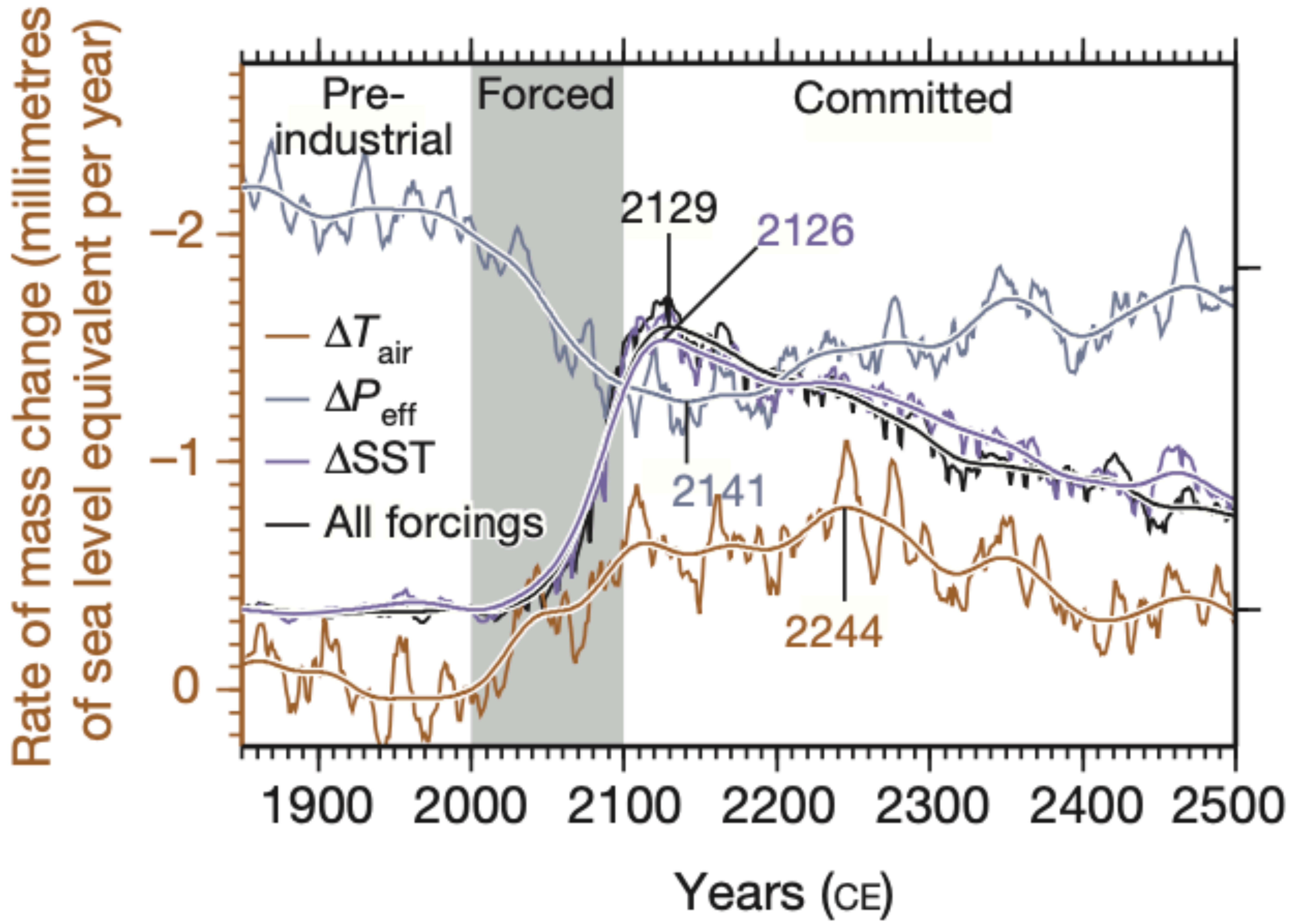
Stokes Equation

$$\sigma = \mu \frac{\partial u_i}{\partial x_j}$$

$$\mu = A\sigma_E^{1-n}$$

Effective viscosity of ice

Ice sheet response time scales are hundreds to thousands of years

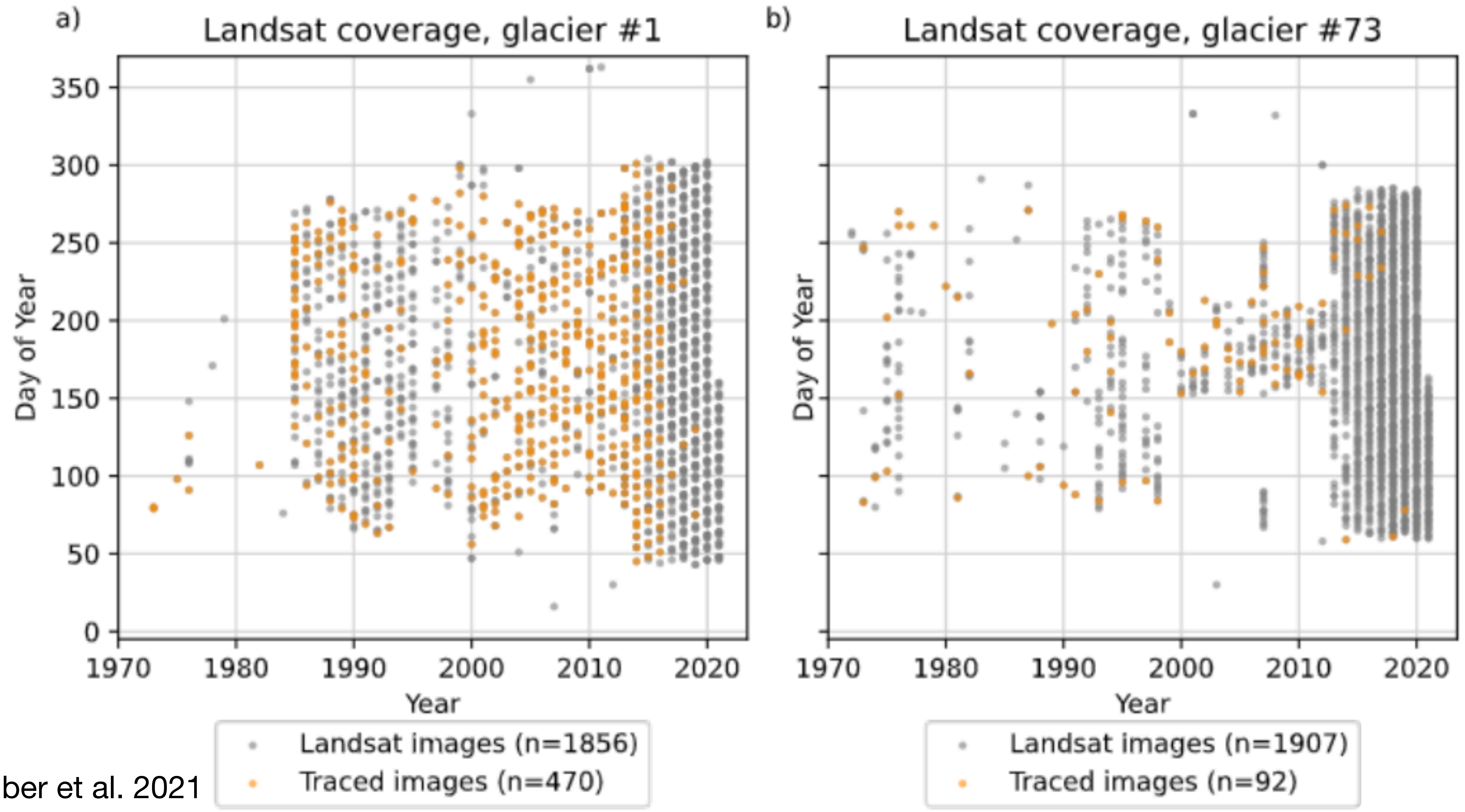


Golledge et al. 2015

Ice breaks

Where does sea level projection uncertainty come from?

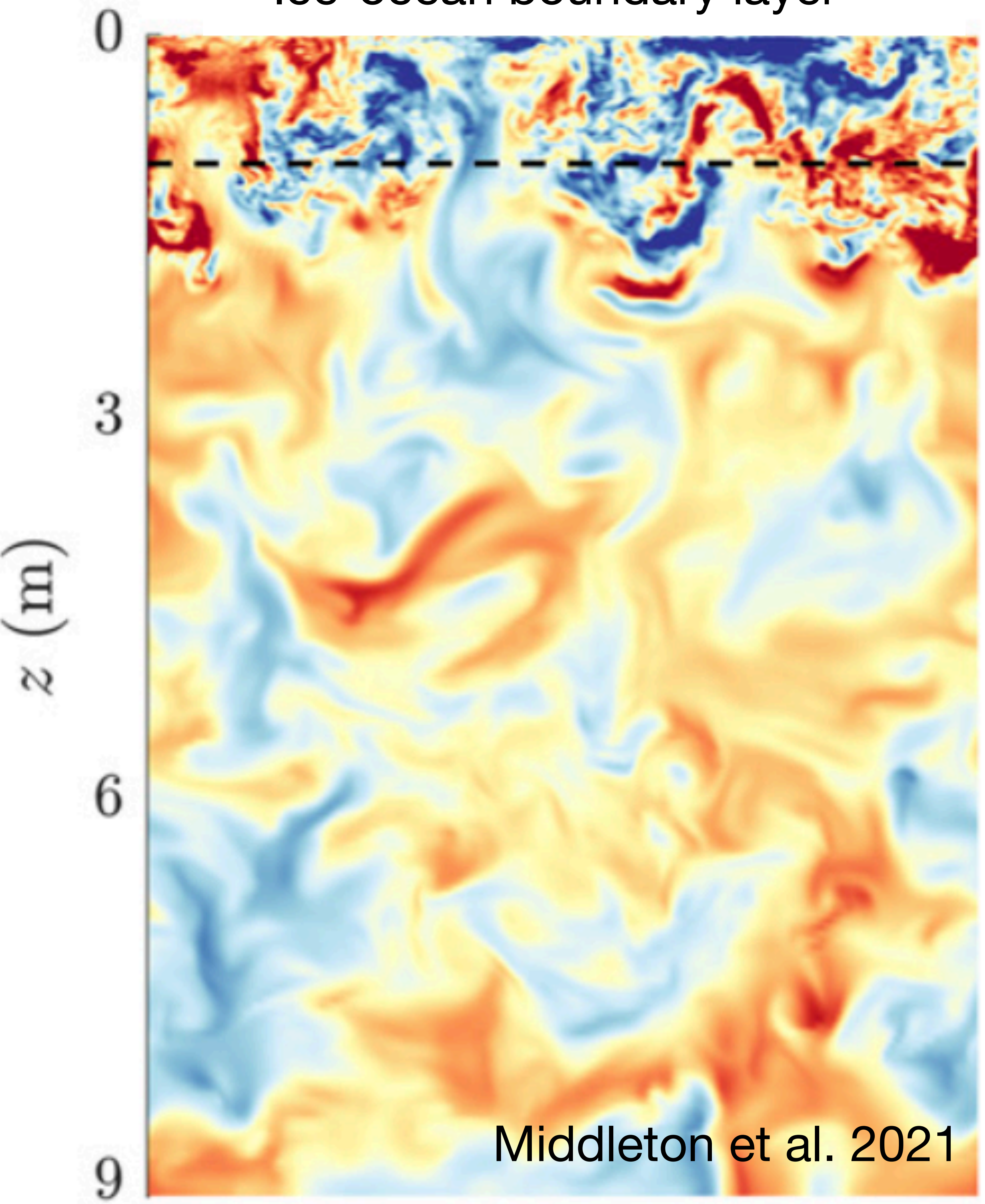
Data sparsity: almost all glacier measurements have been gathered in the last 40 years



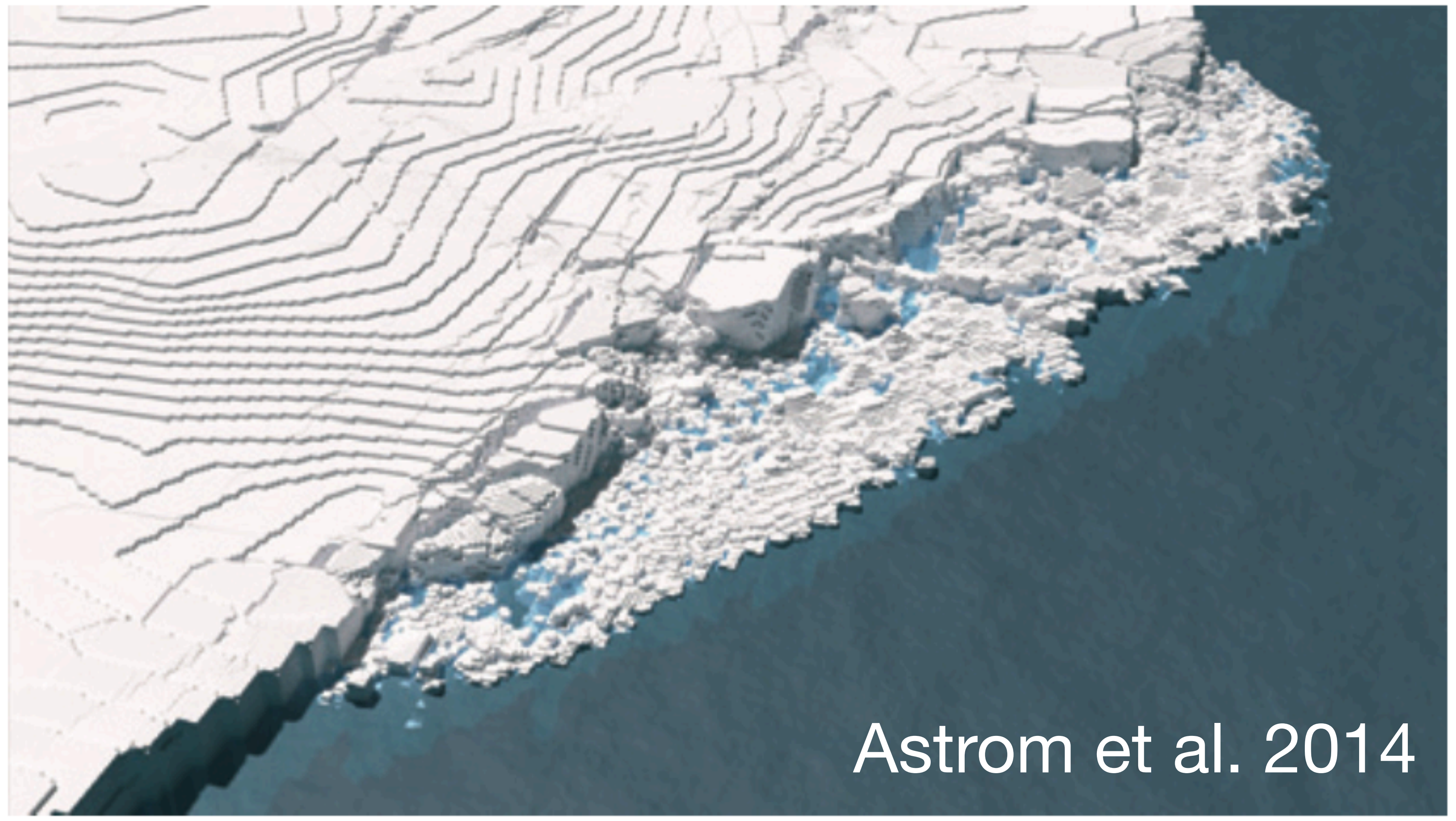
Goliber et al. 2021

Unresolved processes: ice sheets are a multi-phase, multi-rheology, multi-scale problem

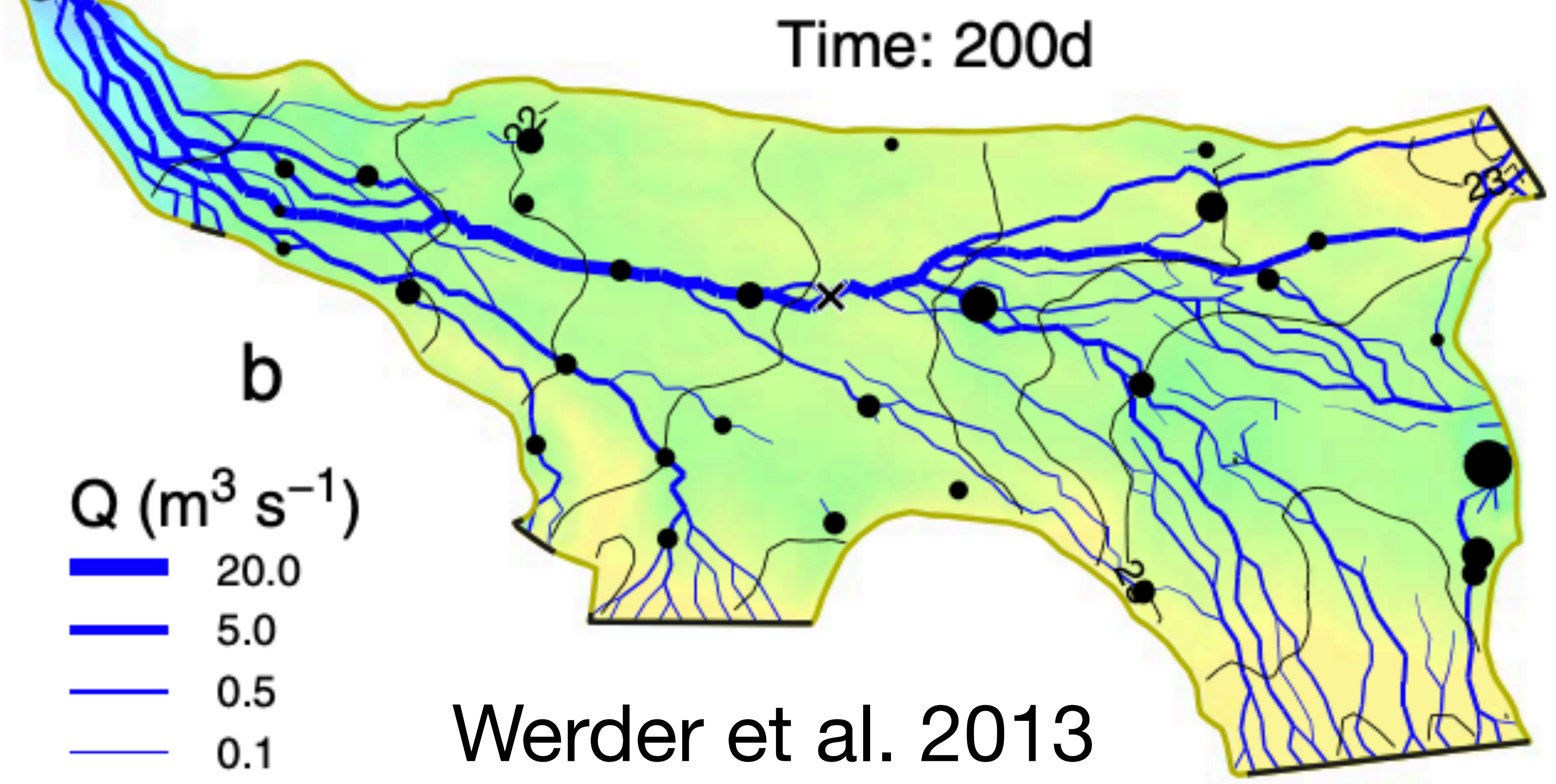
Ice-ocean boundary layer



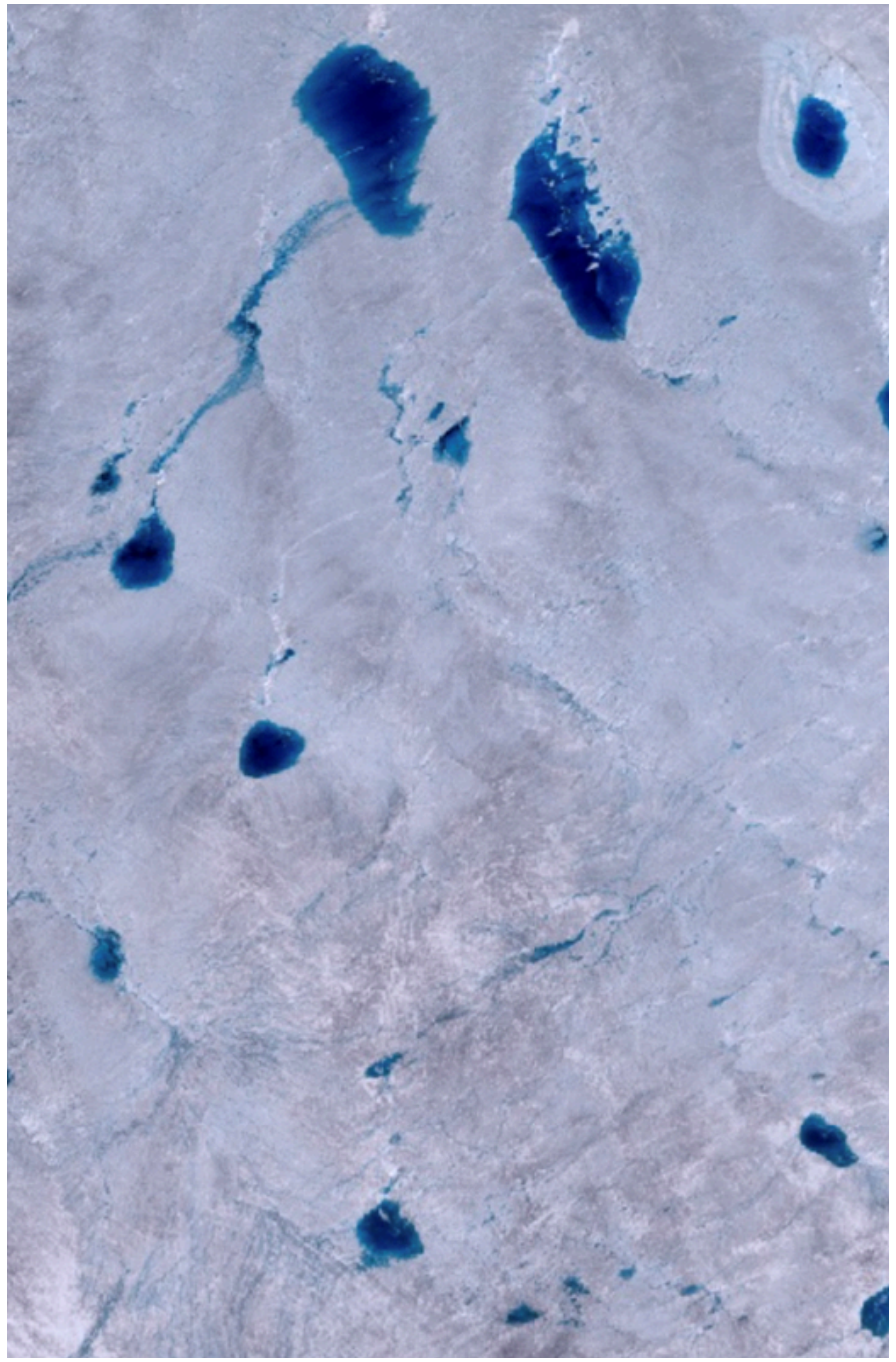
Ice fracture/calving



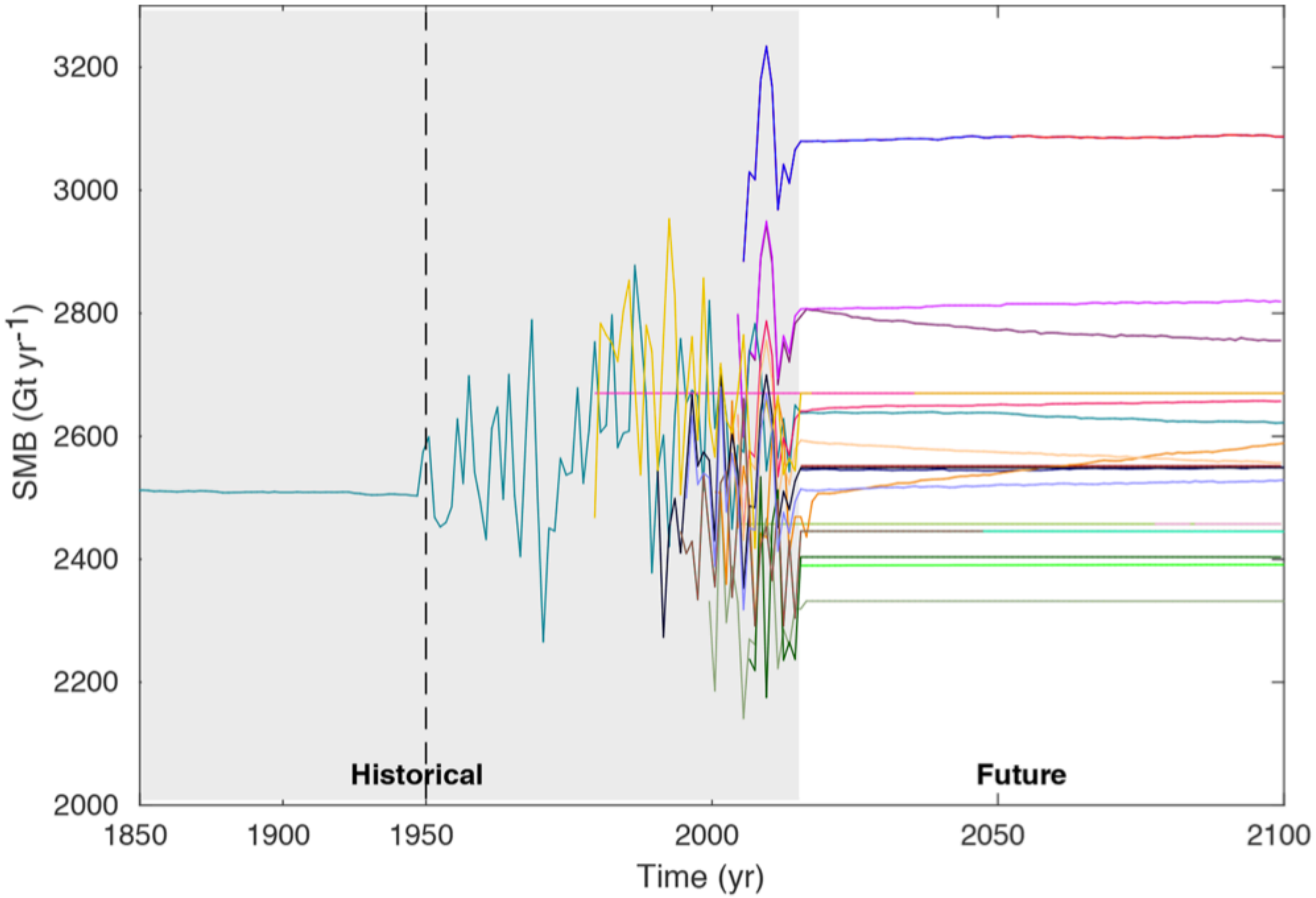
Subglacial hydrology

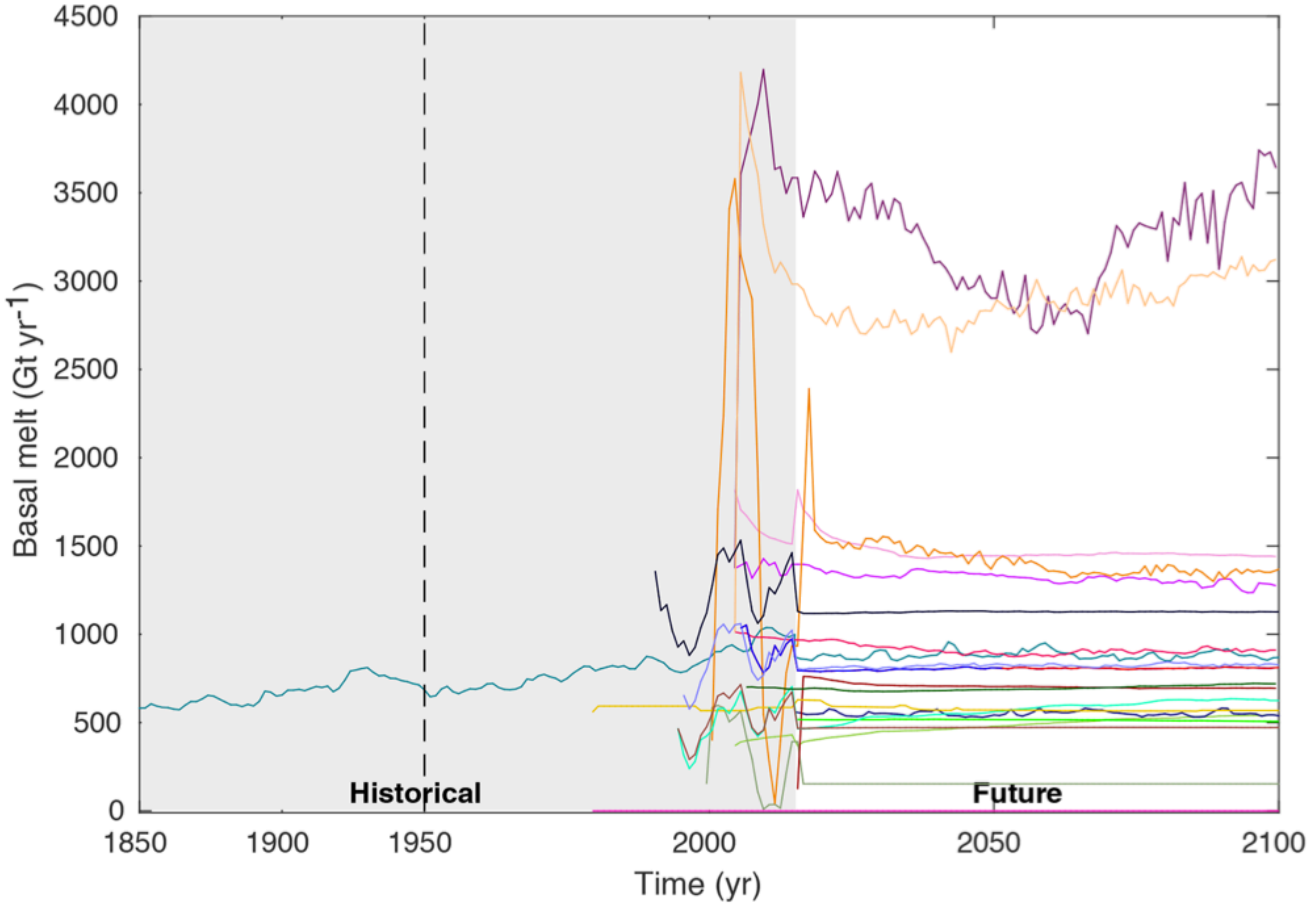


Surface hydrology



Atmosphere and ocean forcing is often from a single realization of a climate model and simplified





Coupling to the rest of the Earth System is computationally expensive and regions of ice sheet-climate interaction are small (individual glaciers)

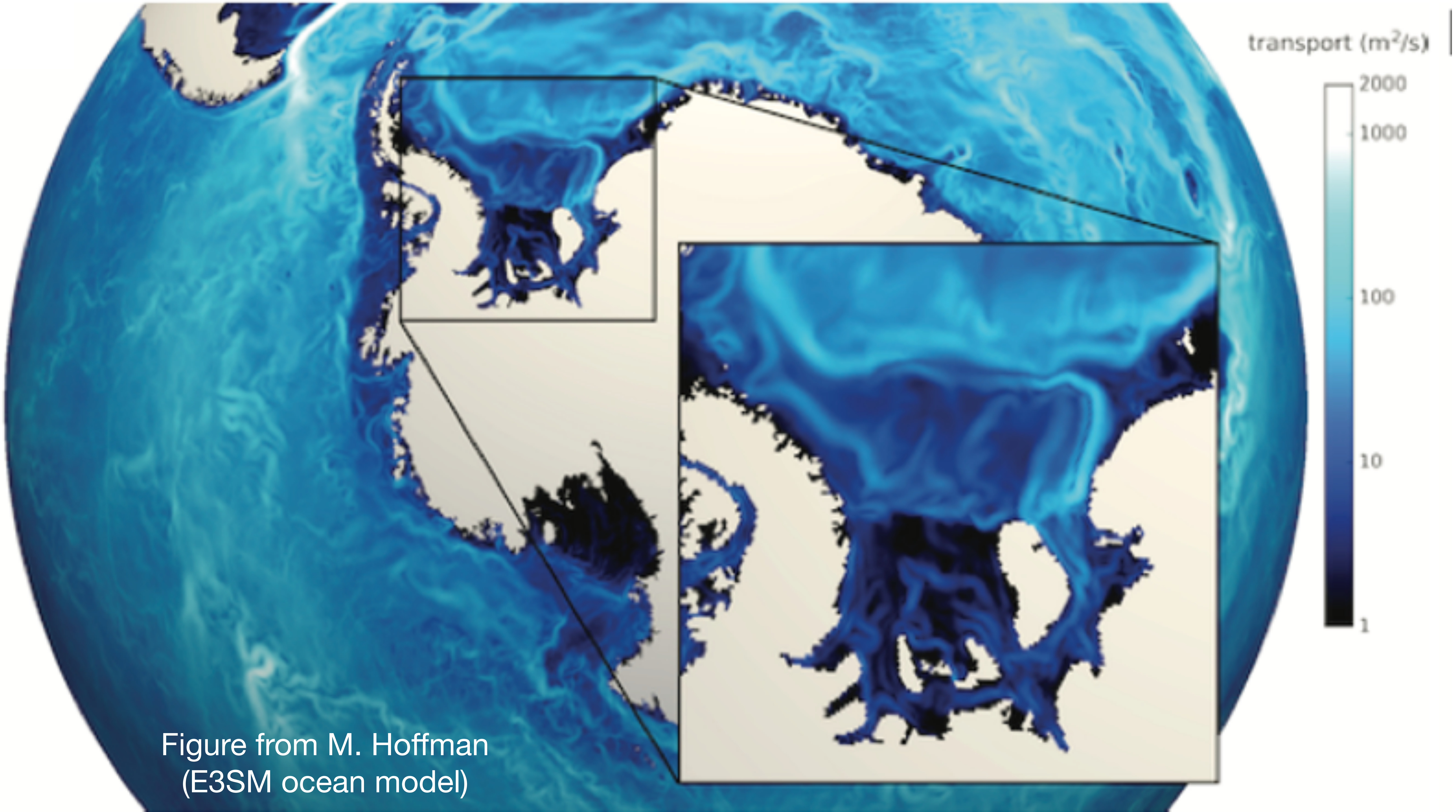
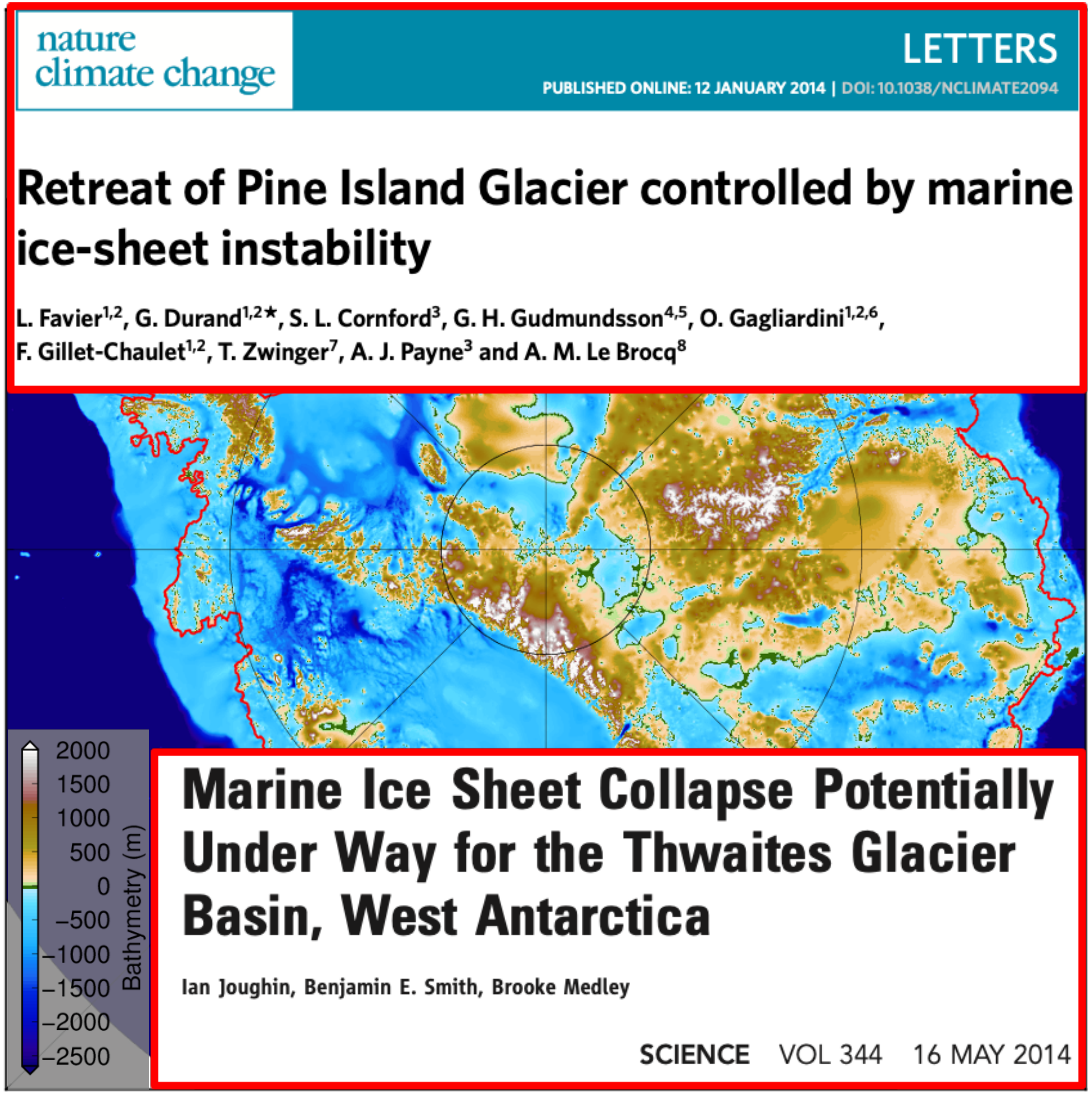


Figure from M. Hoffman
(E3SM ocean model)



nature climate change

LETTERS

PUBLISHED ONLINE: 12 JANUARY 2014 | DOI: 10.1038/NCLIMATE2094

Retreat of Pine Island Glacier controlled by marine ice-sheet instability

L. Favier[1,2], G. Durand[1,2*], S. L. Cornford[3], G. H. Gudmundsson[4,5], O. Gagliardini[1,2,6], F. Gillet-Chaulet[1,2], T. Zwinger[7], A. J. Payne[3] and A. M. Le Brocq[8]

Marine Ice Sheet Collapse Potentially Under Way for the Thwaites Glacier Basin, West Antarctica

Ian Joughin, Benjamin E. Smith, Brooke Medley

SCIENCE VOL 344 16 MAY 2014

Uncertainty may also originate from well-known instabilities inherent in ice sheet dynamics that can be initiated within the typical time range of predictions (2100-2300)

What is the role of unresolved (or expensive to resolve) variability of climate and ice sheet processes in the range of prediction uncertainty?

Consider a simple model of marine ice sheet dynamics

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$$h_g \frac{dL}{dt} = P - Q_g$$

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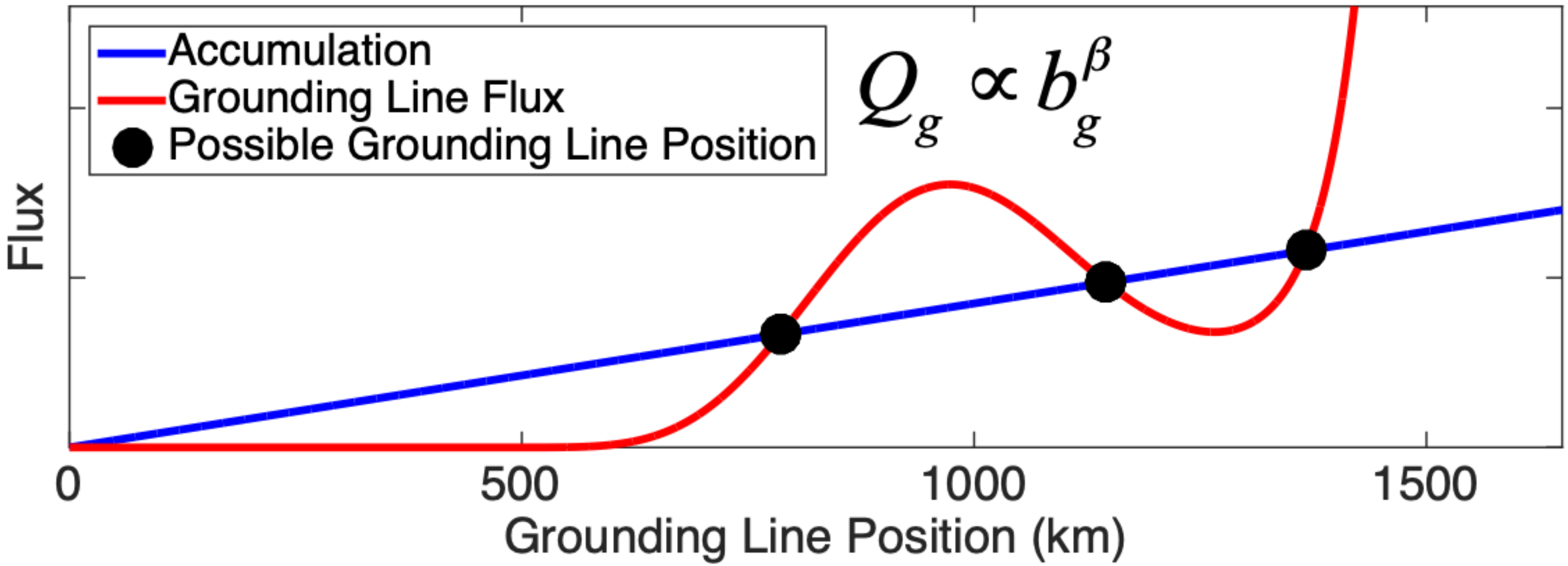

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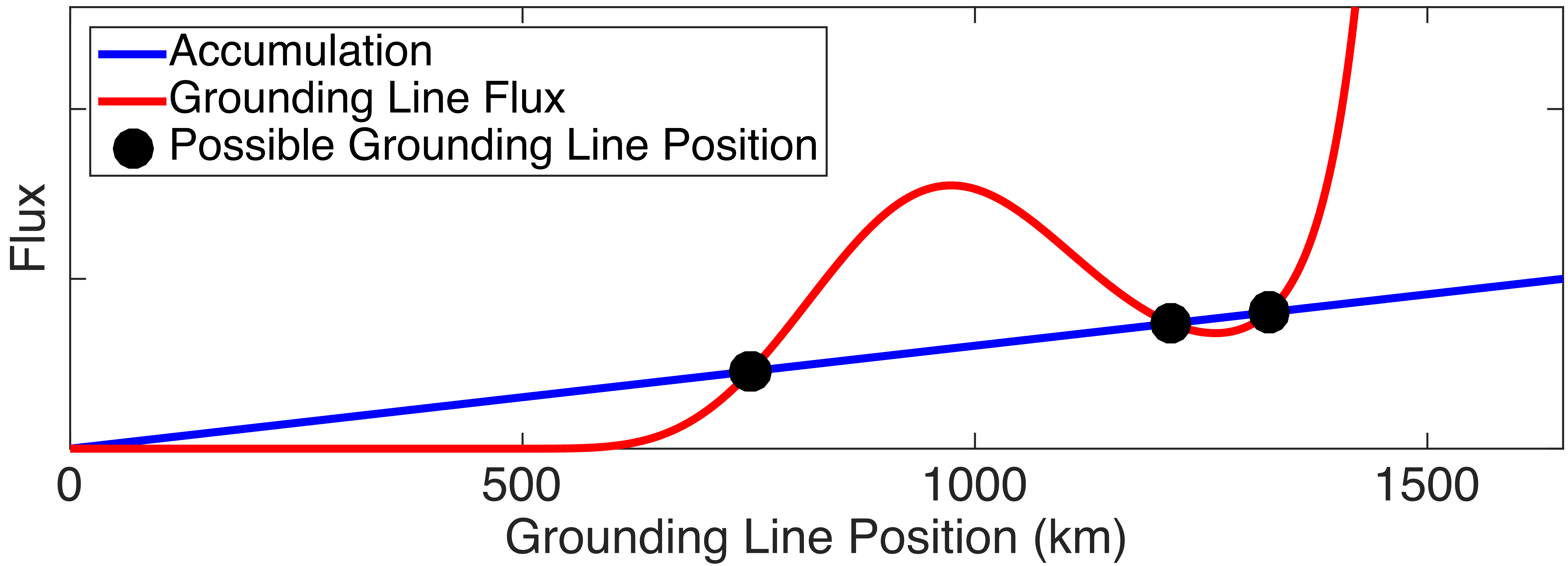

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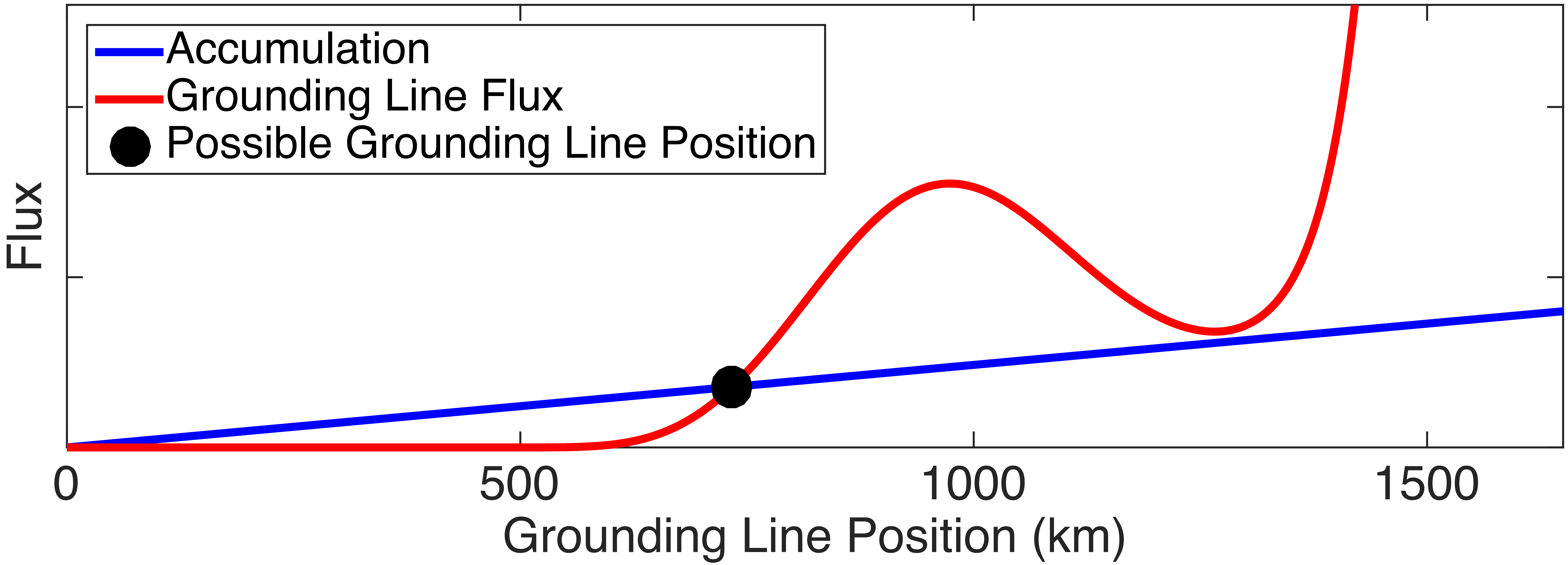

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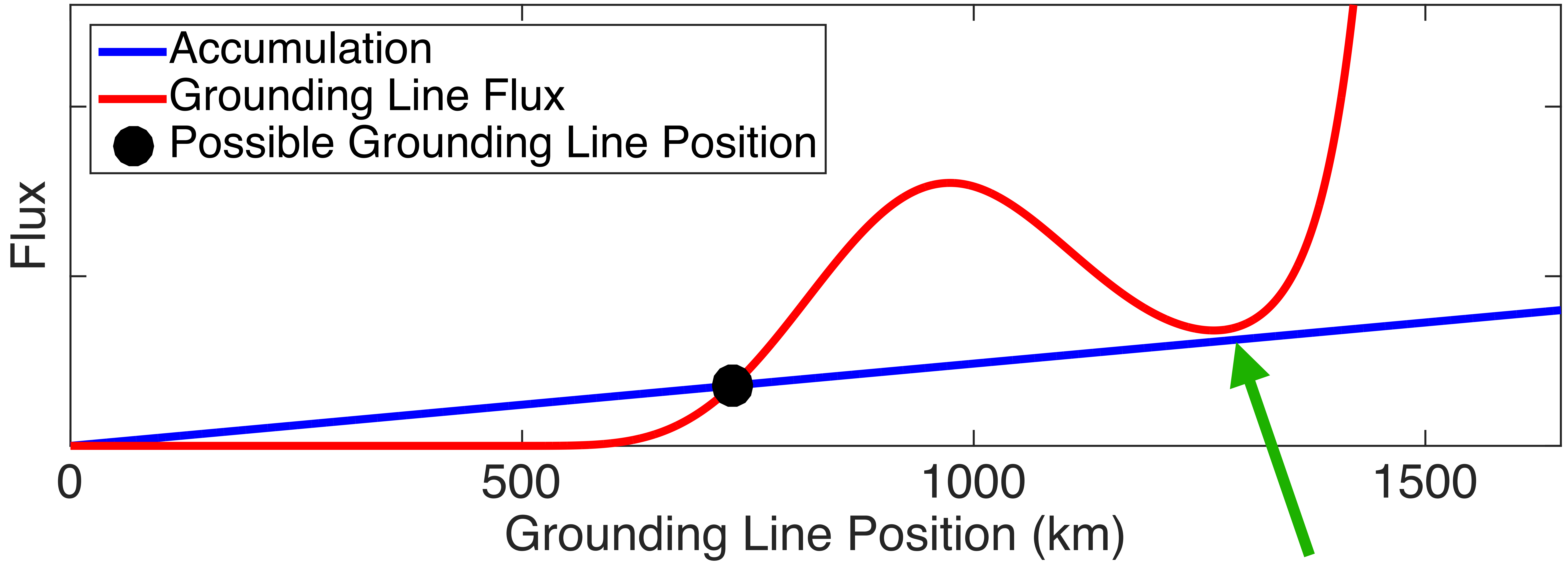


$$h_g \frac{dL}{dt} = P - Q_g$$

This saddle-node bifurcation is the "marine ice sheet instability"

How does this instability lead to the structure of uncertainty that we see in predictions of future ice sheet change/sea level rise?

$$\frac{dL}{dt} = f(L,t) + \sigma_F \xi(t)$$

Deterministic system dynamics

Noise amplitude

Wiener noise process

Stochastic perturbation theory cf. Moon & Wettlaufer 2013

We consider this simple version of the ice sheet problem as a stochastic differential equation (SDE)

Robel, Seroussi & Roe, *PNAS,* 2019

How does this instability lead to the structure of uncertainty that we see in predictions of future ice sheet change/sea level rise?

$$\frac{d\ell}{dt} = \left[\omega\ell + \kappa\ell^2 + \ldots\right] + \sigma_F \xi(t)$$

$$\omega(t) = \left.\frac{df}{dL}\right|_{L_d} \quad \text{and} \quad \kappa(t) = \left.\frac{1}{2}\frac{d^2 f}{dL^2}\right|_{L_d}$$

We expand the SDE about purely deterministic solutions

Robel, Seroussi & Roe, *PNAS,* 2019

How does this instability lead to the structure of uncertainty that we see in predictions of future ice sheet change/sea level rise?

$$\ell = \ell_0 + \sigma_F \ell_1 + \frac{\sigma_F^2}{2} \ell_2$$

$$\frac{d\ell_1}{dt} = \omega(t)\ell_1 + \xi$$

And then consider approximations to the solution of the full SDE in terms of the noise amplitude, assuming an initial steady-state and neglecting higher-order terms…leading to the Langevin equation

Robel, Seroussi & Roe, *PNAS*, 2019

How does this instability lead to the structure of uncertainty that we see in predictions of future ice sheet change/sea level rise?

Variance
(second moment)

$$\sigma_L^2 \propto \tau_F \left(e^{2\omega t} - 1\right)$$

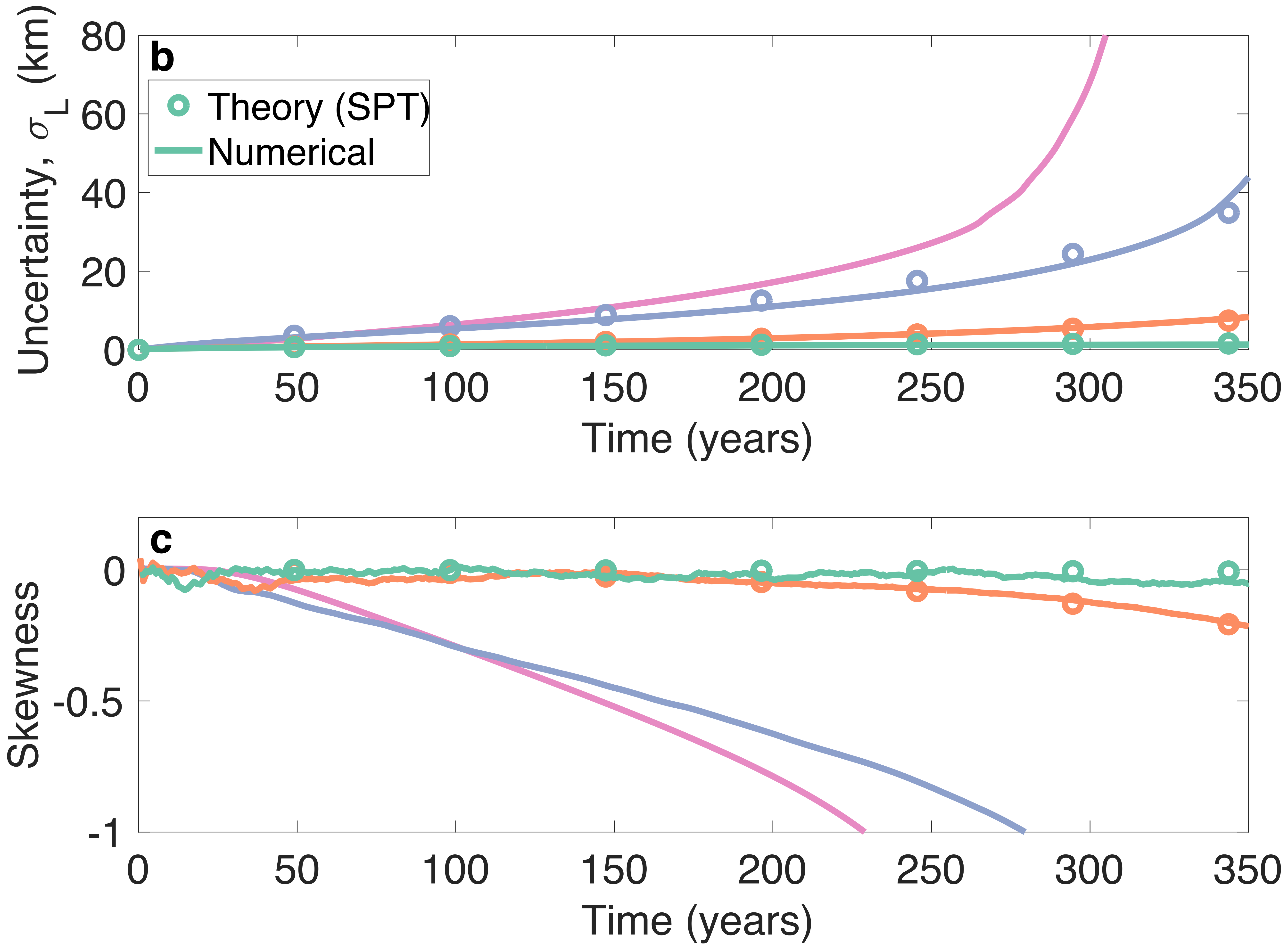
Skewness
(third moment)

$$Sk_L \propto \kappa \omega^3 \tau_F \left(e^{\omega t} - 1\right)^2$$

Ultimately, we find that the spread and skewness of ice sheet prediction uncertainty grow exponentially for unstable configurations

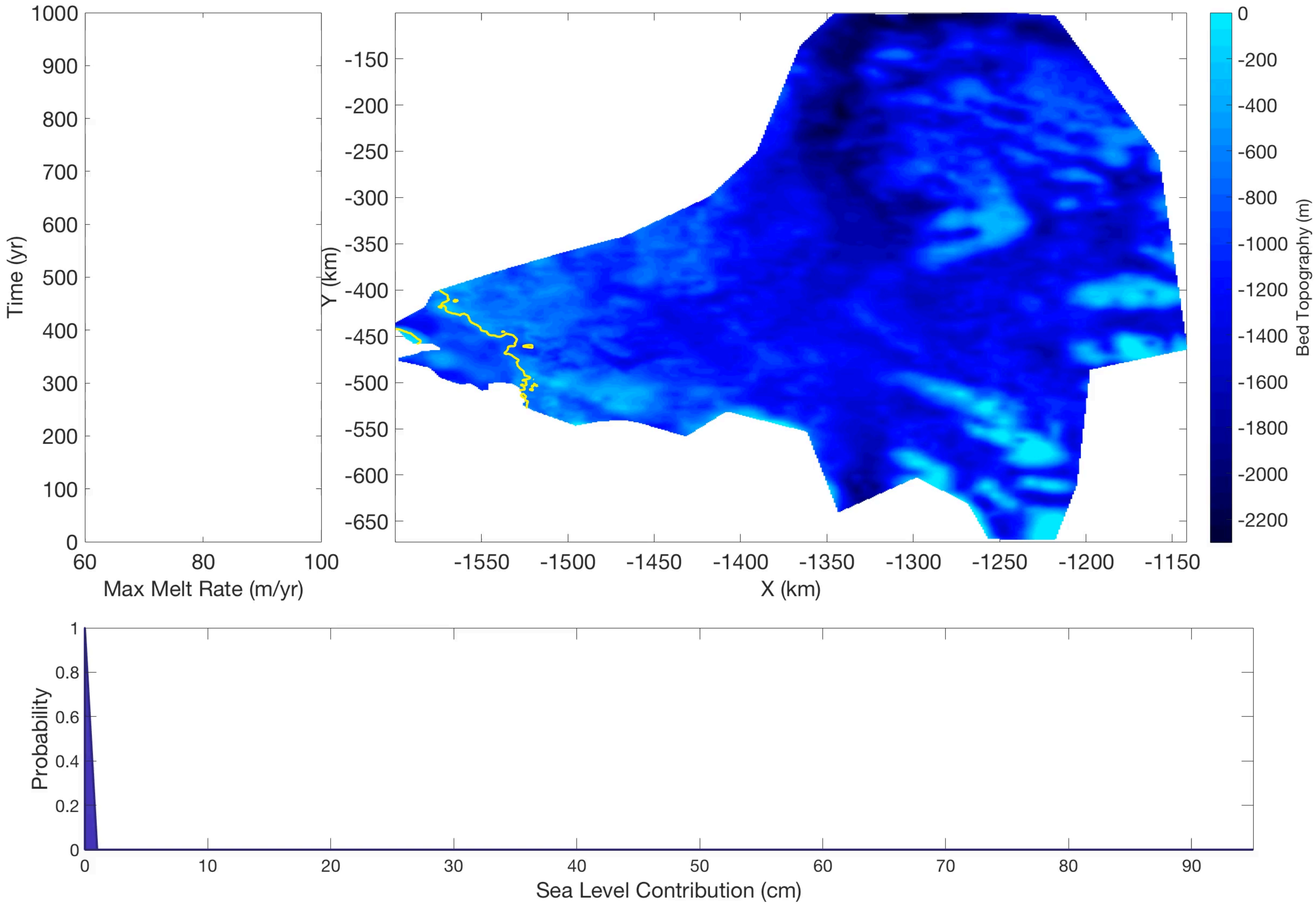
Robel, Seroussi & Roe, *PNAS,* 2019

Theory is verified in large ensembles with simple models



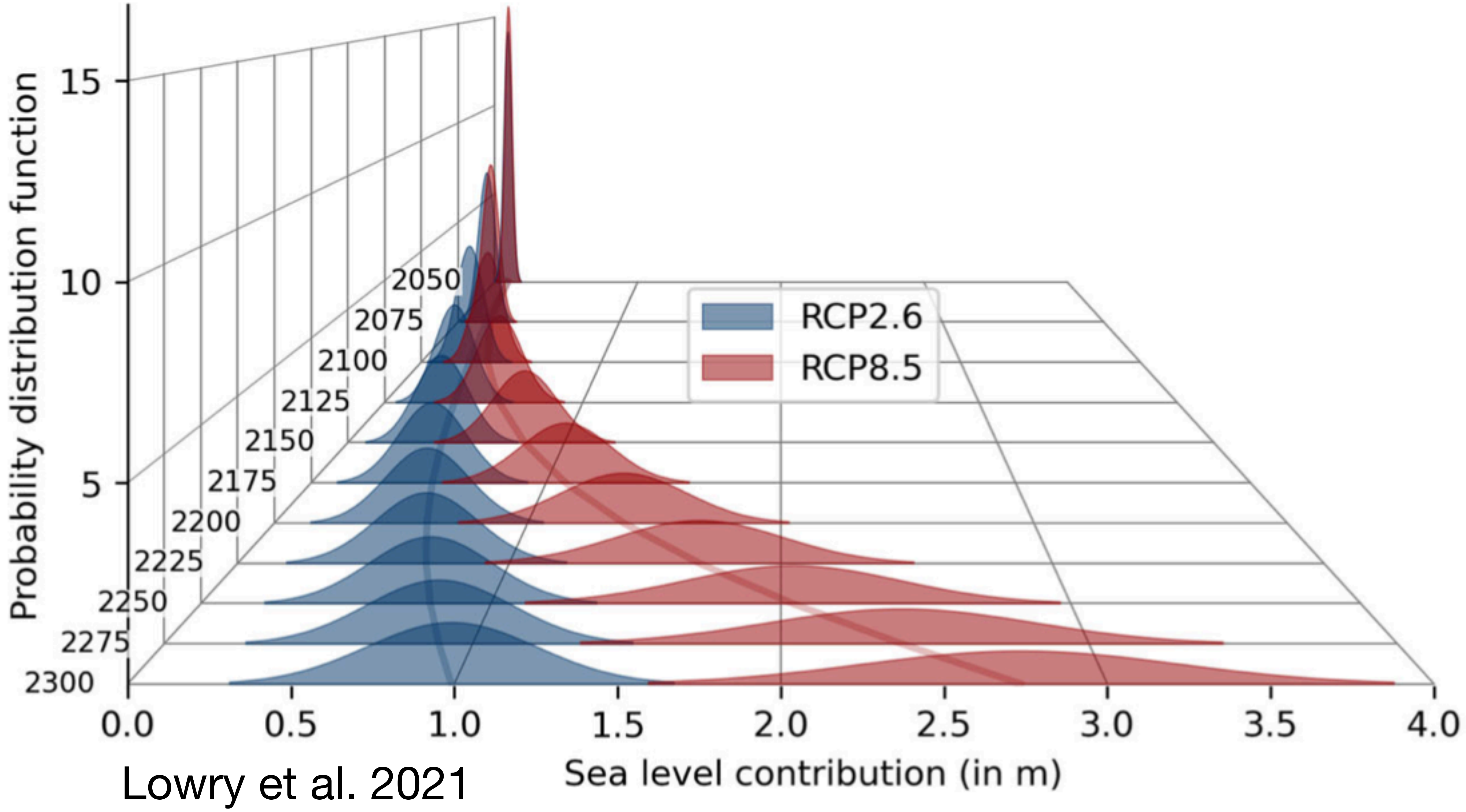
Robel, Seroussi & Roe, *PNAS*, 2019

…and in IPCC-class models of West Antarctic Glaciers

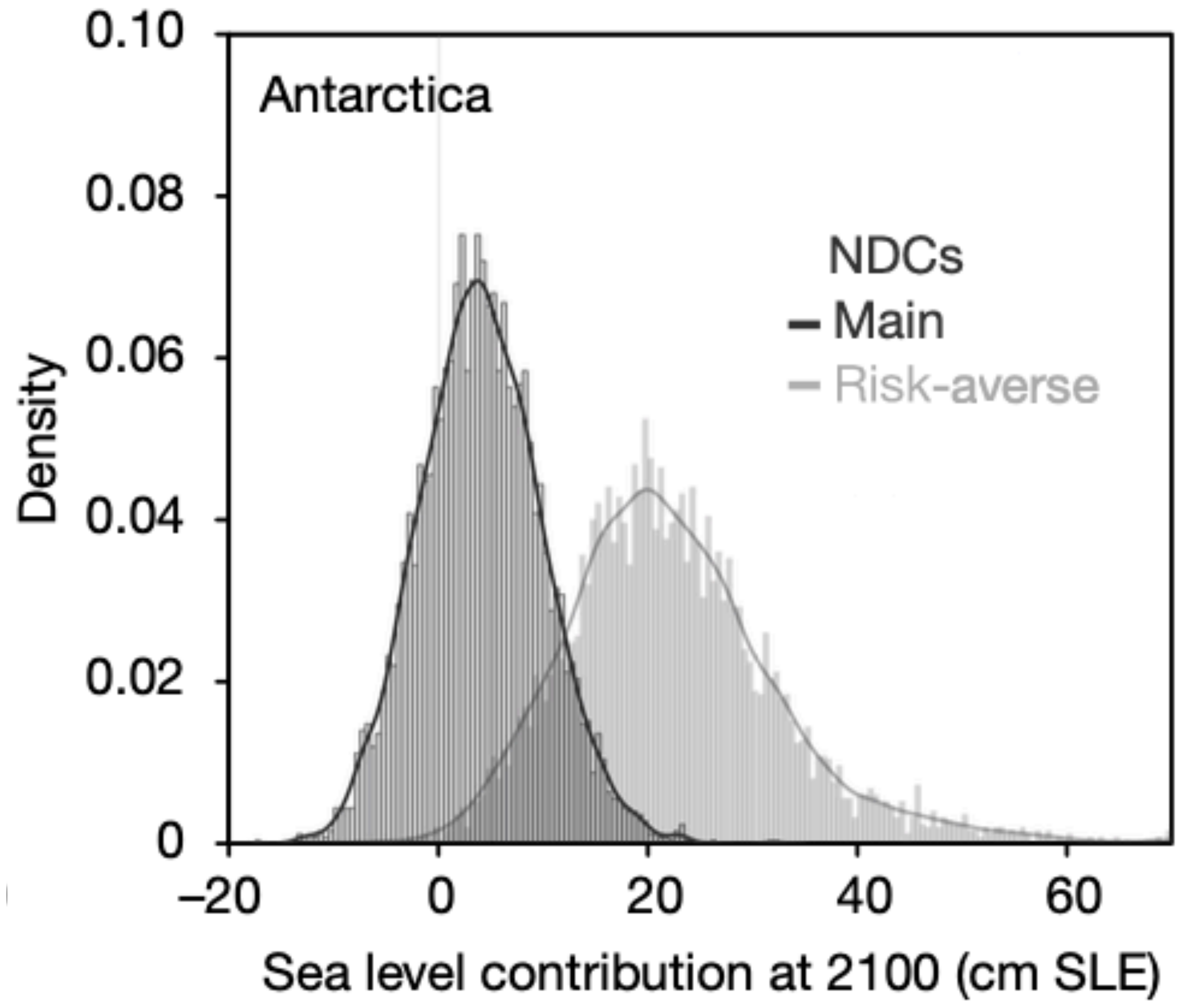


Robel, Seroussi & Roe, *PNAS,* 2019

Parameter uncertainty in sea level predictions tends to have either bimodal structure or "long tails" toward bad outcomes



Lowry et al. 2021

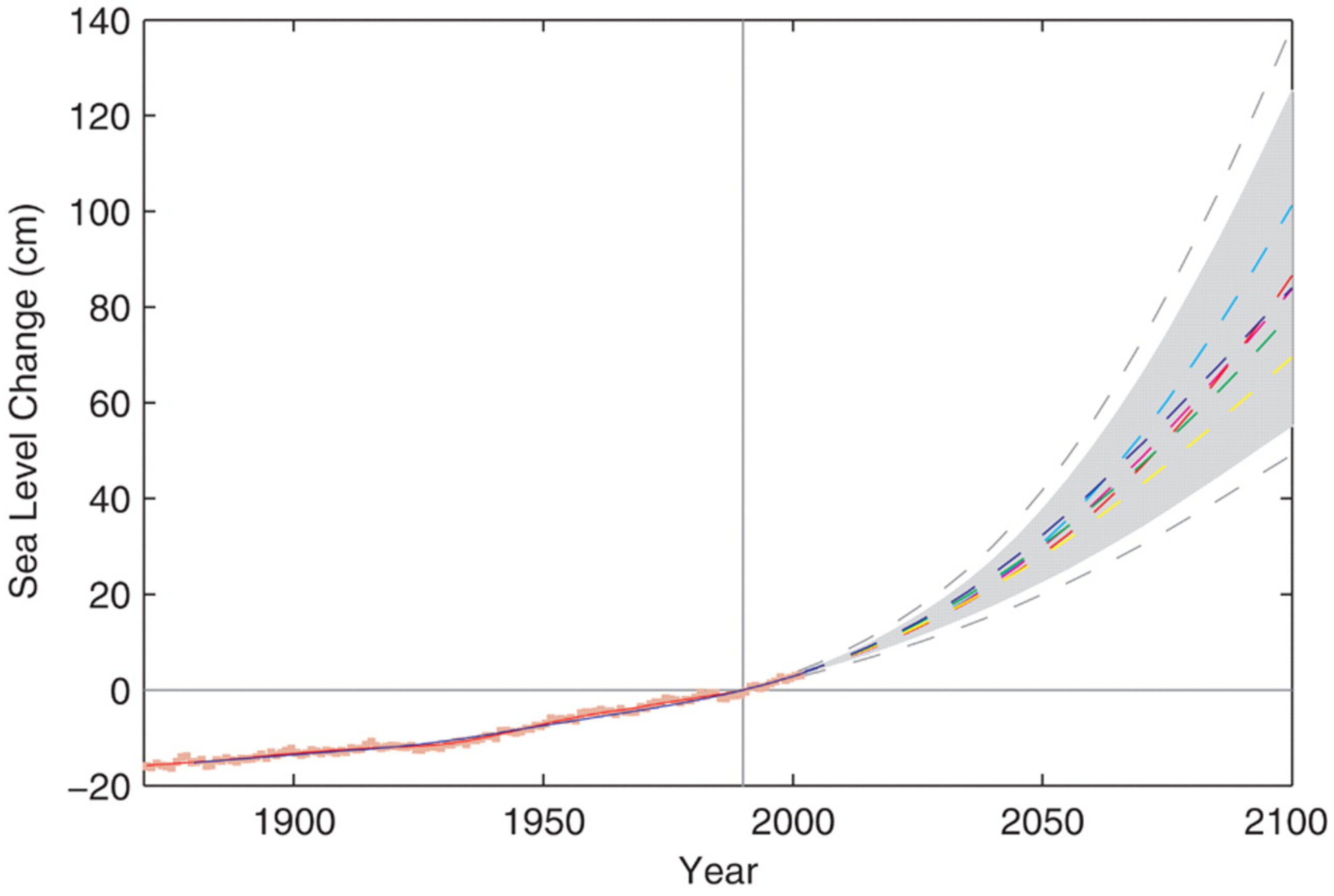


Edwards et al. 2021

Adaptation costs rise rapidly with "long tail" uncertainty

Next steps: how to include uncertainty from climate variability and parameterize unresolved processes directly within large-scale ice sheet models?

Standard methods limit probabilistic projections



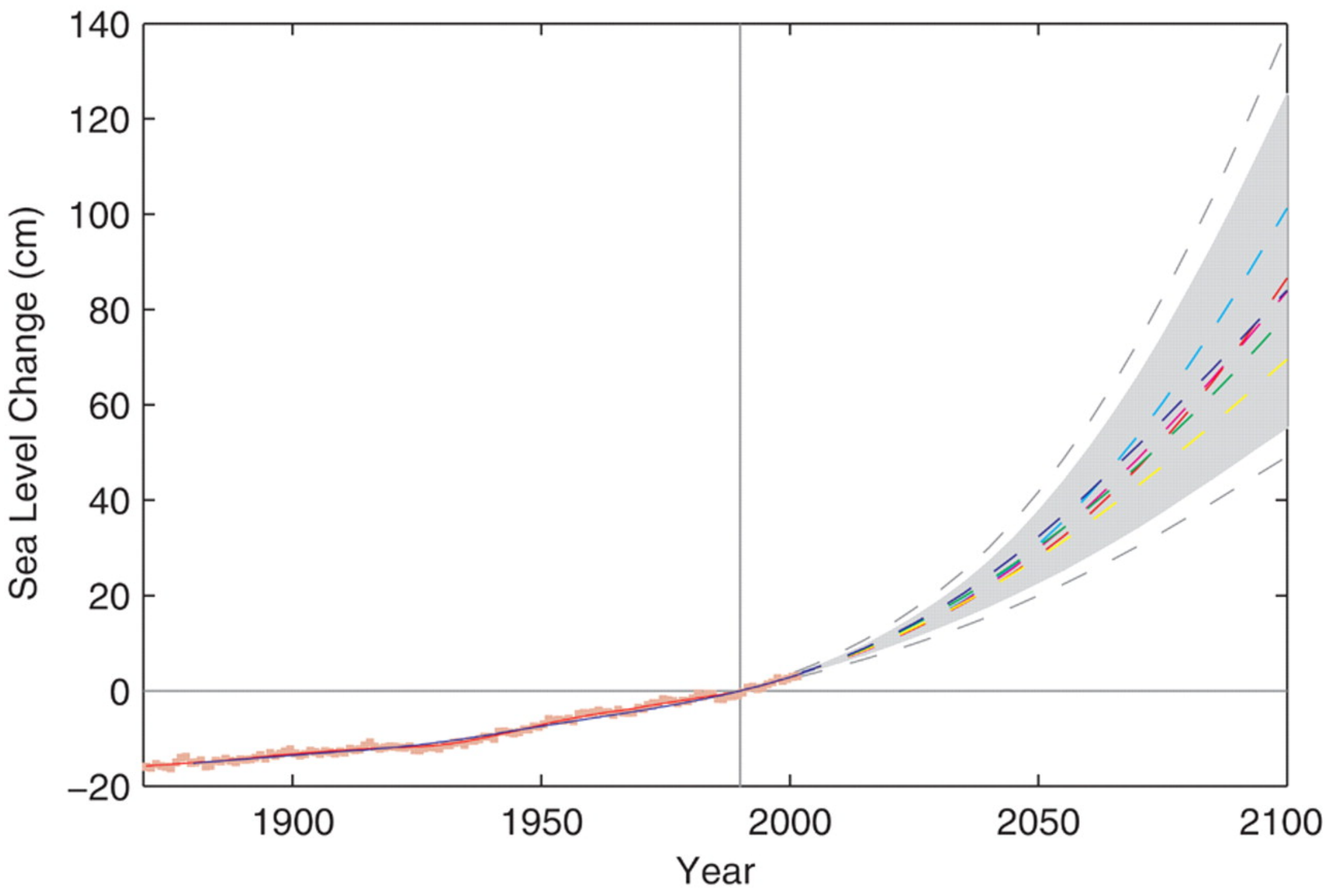
Semi-empirical: many simulations possible, SLR(T) similar to past

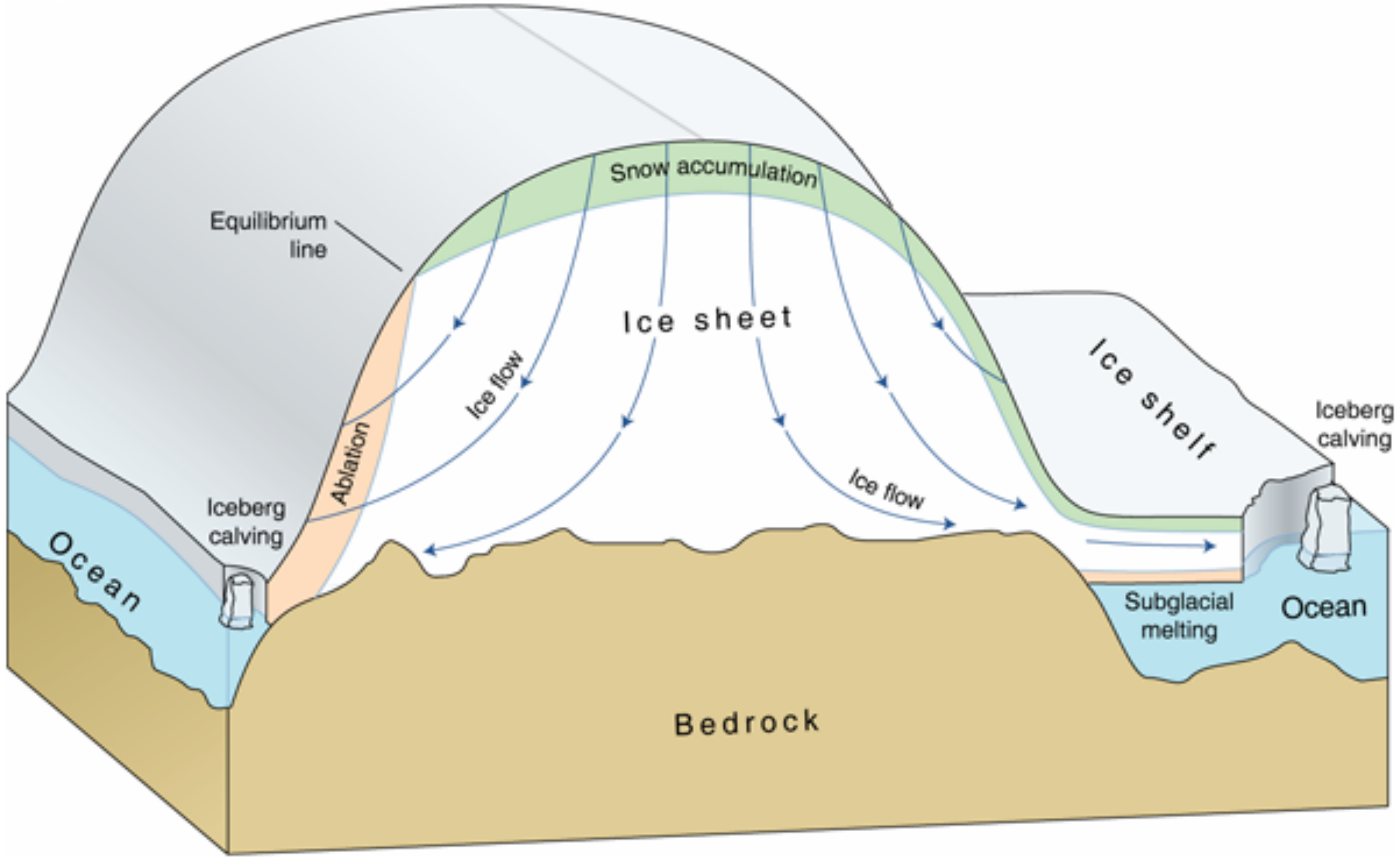
Simpler

More complex

Images: Rahmstorf 2007, NSIDC

Standard methods limit probabilistic projections





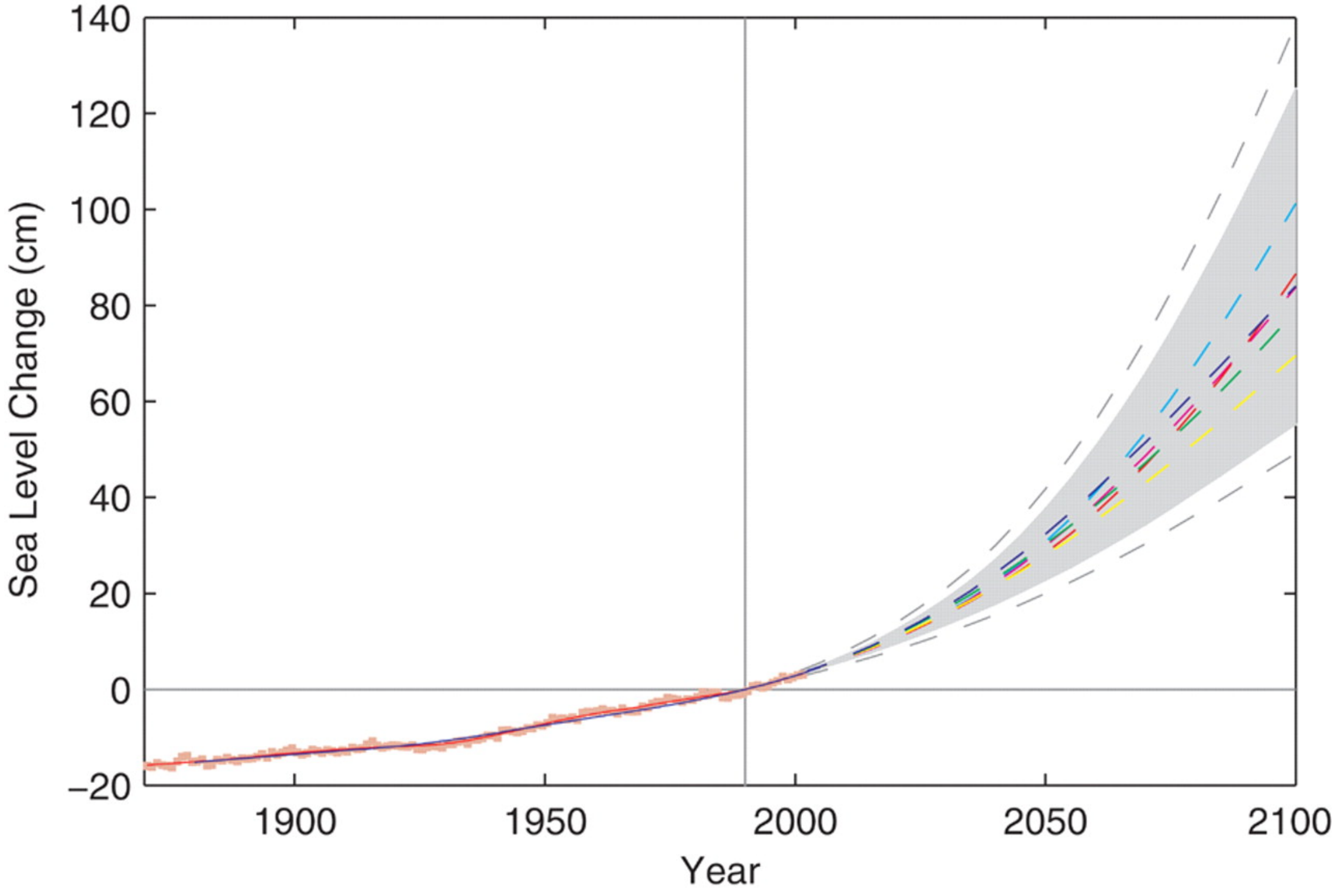
Semi-empirical: many simulations possible, SLR(T) similar to past

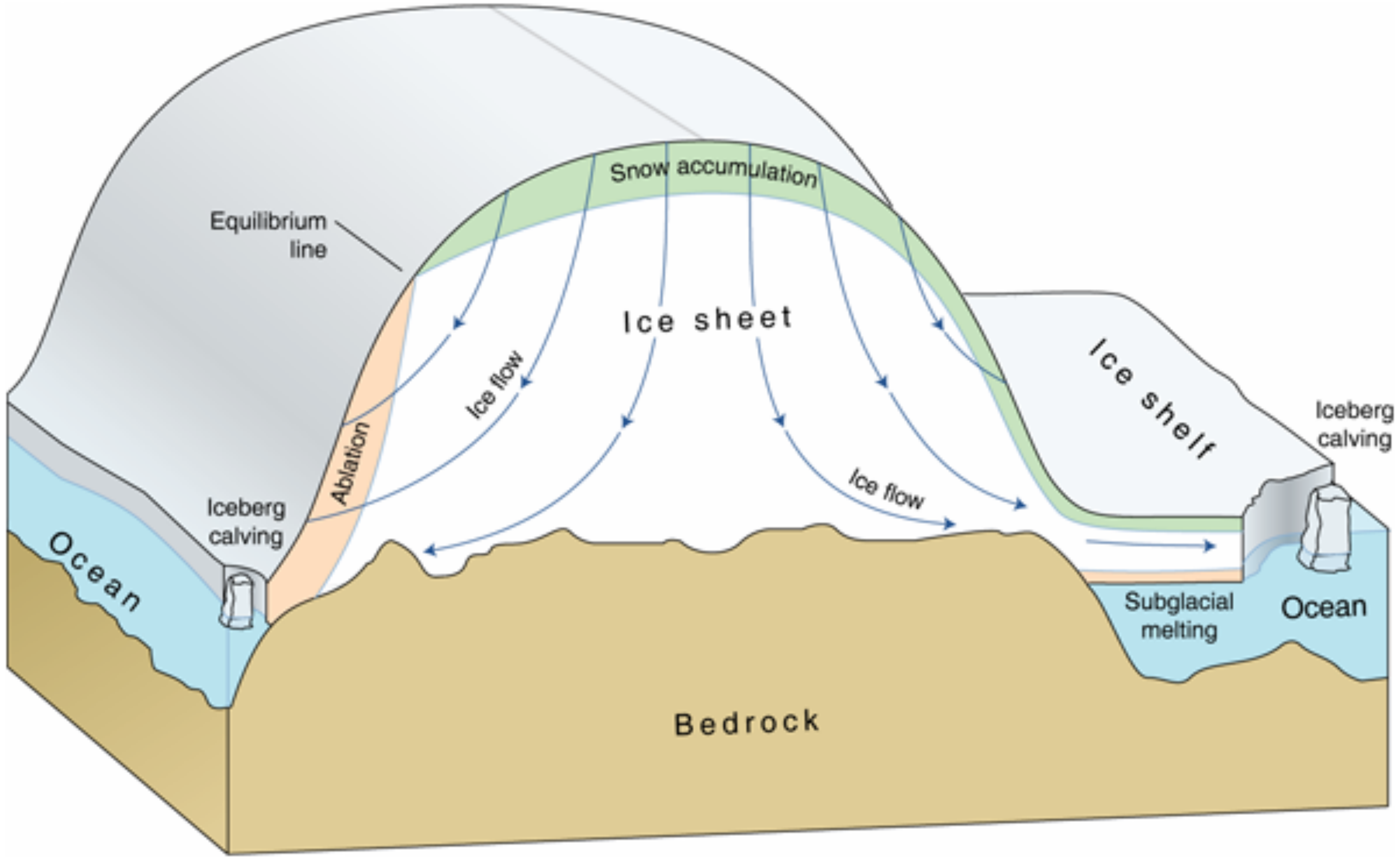
Process model: evolving dynamics, computational expense limits simulations

Simpler → More complex

Images: Rahmstorf 2007, NSIDC

Stochastic models can help





Semi-empirical: many simulations possible, SLR(T) similar to past

Process model: evolving dynamics, computational expense limits simulations

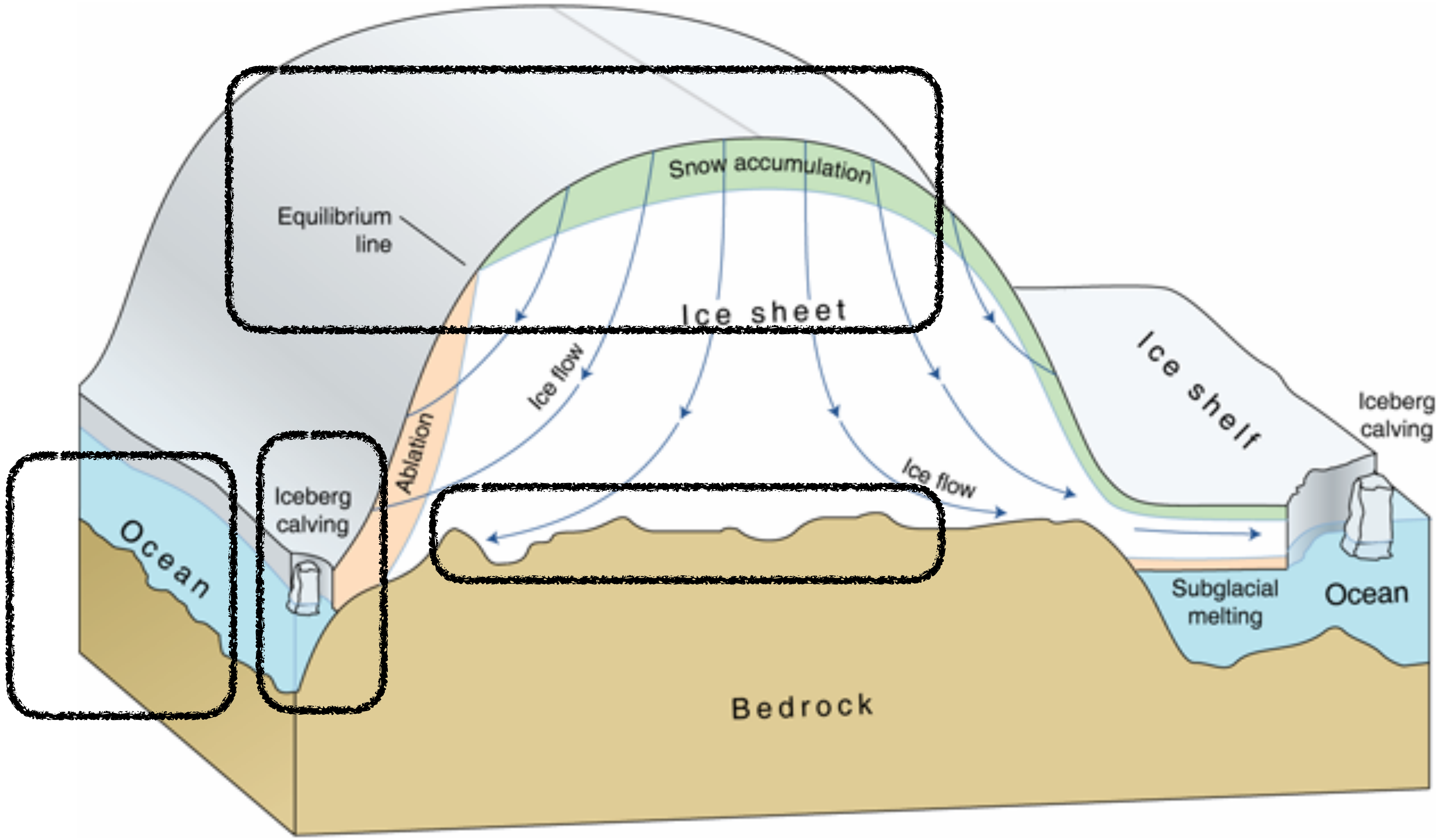
Simpler

More complex

Stochastic model: sample variability from process model, simulate many future scenarios

Images: Rahmstorf 2007, NSIDC

The Stochastic Ice Sheet Project



In Progress

- Adding stochastic integration capability to Ice-Sheet and Sea-Level System Model (ISSM)
- Surface mass balance
- Ocean thermal forcing
- Iceberg calving
- Subglacial hydrology

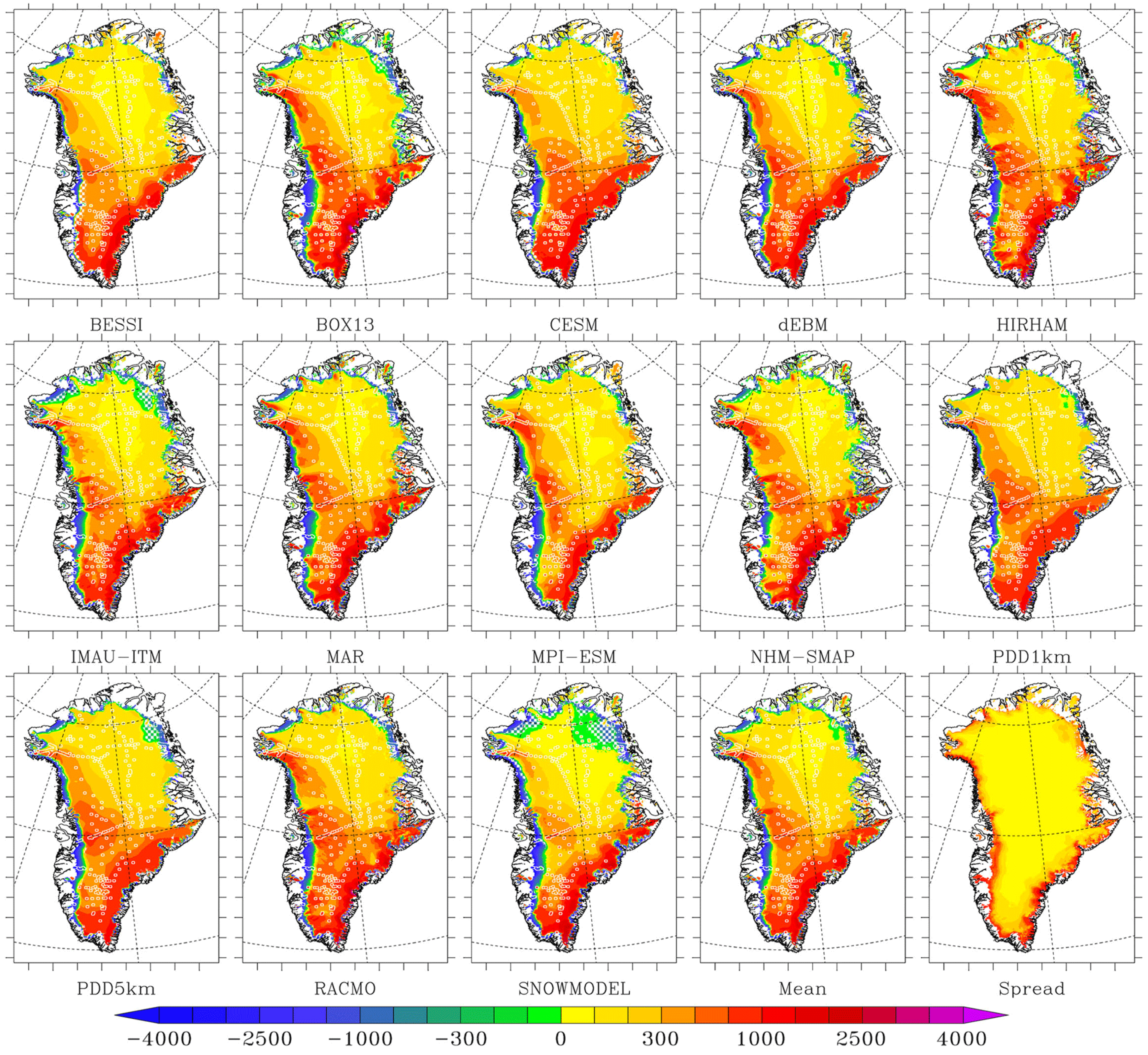
Image: NSIDC

HEISING-SIMONS FOUNDATION

ISSM

Georgia Tech

Stochastic Surface Mass Balance (SMB)



- 13 surface mass balance models simulated Greenland SMB 1980-2012

- Results interpolated onto common ice sheet mask with 1 km resolution

Ultee, Robel, and Castruccio, In Prep

Stochastic Surface Mass Balance (SMB)

$$SMB(t) = \beta_0 + \beta_1 t + \sum_{k=1}^{K} \gamma_k s_k + \sum_{i=1}^{p} \varphi_i \, SMB(t-i) + \epsilon(t)$$

β_0 constant

$\beta_1 t$ linear trend

$\sum_{k=1}^{K} \gamma_k s_k$ seasonal cycle

$\epsilon(t)$ residual
(more on this later)

$\sum_{i=1}^{p} \varphi_i \, SMB(t-i)$ dependence on past values (autoregression)

Ultee, Robel, and Castruccio, In Prep

Stochastic Surface Mass Balance (SMB)

$$\epsilon(t) \overset{iid}{\sim} \mathcal{N}(0, \sigma^2)$$

- If we've done our job, the residual, $\epsilon(t)$ consists of independent and identically distributed draws from a normal distribution with variance σ^2
- Temporal fits and variance may be different for each catchment
- Spatial correlation matrix *C* captures these differences

$$\sigma^2 = DCD$$

Per-catchment standard deviations — Inter-catchment correlations

Castruccio et al (2019); Hu & Castruccio (submitted 2021); Ultee et al., In Prep

Identifying correlation matrix C for construction

- Empirical correlation matrix C: correlation of the residuals of temporal fits between all catchments
    - 200x200 symmetric matrix: 20 000 data points
- Our problem is under-sampled (30 years of data) so we must control singularity of this matrix

Image: Correlation of residuals with residual of Kangerlussuaq AR(n) fit

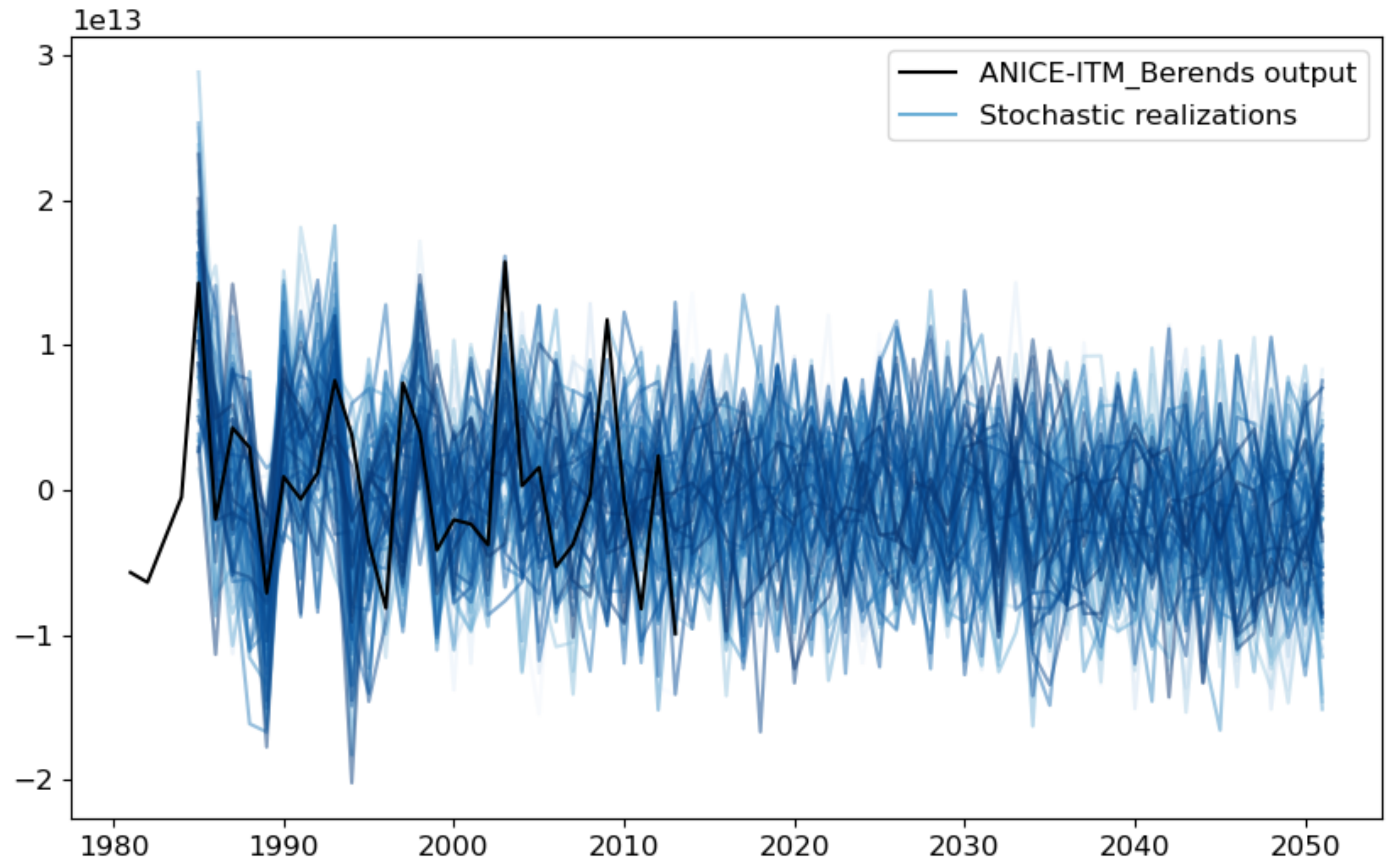
Stable construction of a spatially varying field

Sparse correlation matrix estimated with GraphicalLasso controls the singularity of C

Stable construction of a spatially varying field

Sparse correlation matrix estimated with GraphicalLasso controls the singularity of C

Efficient generation of random realizations of spatiotemporal variability



Pros

- AR models are simple, easily interpretable and seems to do a decent job reproducing statistics of SMB
- Training and generation require trivial computation
- Based on widely-used open-source packages (e.g., scikit-learn)

Cons

- Heavy with assumptions about gaussianity, structure of variability, spatial covariances
- Still requires downscaling from catchment (~100 km) to fine ice sheet model grid-scale (1 km)
- Not obviously extensible to other processes (e.g., sub-grid fracturing)

Takeaways

- Ice sheets change slowly (decades-millennia), but have the intrinsic capacity for instability on prediction-relevant time scales
- Many important internal and forcing processes are not represented within models, or are represented in a deterministic single realization in predictions
- Theory shows that instabilities intrinsic in marine ice sheet dynamics (i.e. West Antarctica, parts of Greenland) tend to produce heavily skewed or bimodal uncertainty in predictions
- Statistical methods can be used to represent such processes/forcing within ice sheet models, but require strong assumptions

Open questions related to ML in ice sheet modeling

- Which AI/ML methods work best with limited training data? What are the tradeoffs associated with more supervision and more a priori assumptions?
- How can we best use high-fidelity, computationally expensive models of ice sheet or climate processes to generate training data?
- What level of inaccuracy can we accepted in our learned parameterizations if the prediction of interest is an integrated quantity (i.e. ice sheet mass loss)?

Questions? Email: robel@eas.gatech.edu