Improving the Representations of Sea-level Rise and Ice-Sheet Responses in Integrated Assessment Models

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with inputs from
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Outline

1. Why are sea-level rise and ice-sheet responses important for IAMs?

2. What are methodological challenges for a sound representation of ice-sheets and sea-level rise in IAMs?

3. How has our work contributed to overcoming these challenges and enabled improved analyses?

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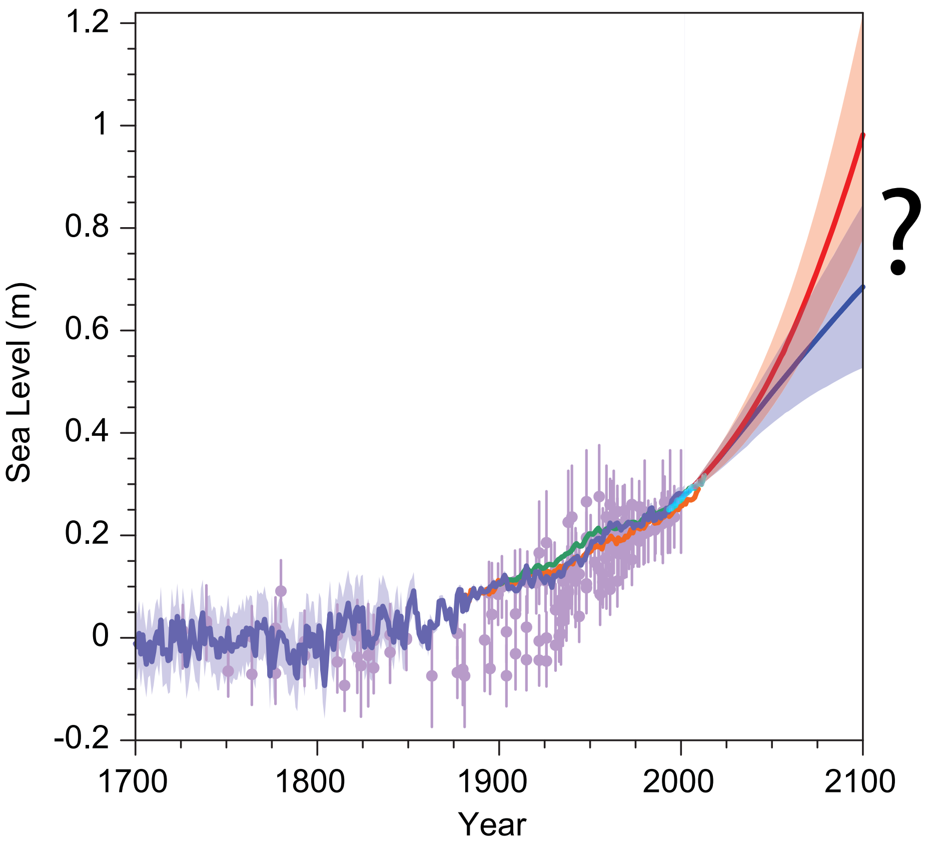
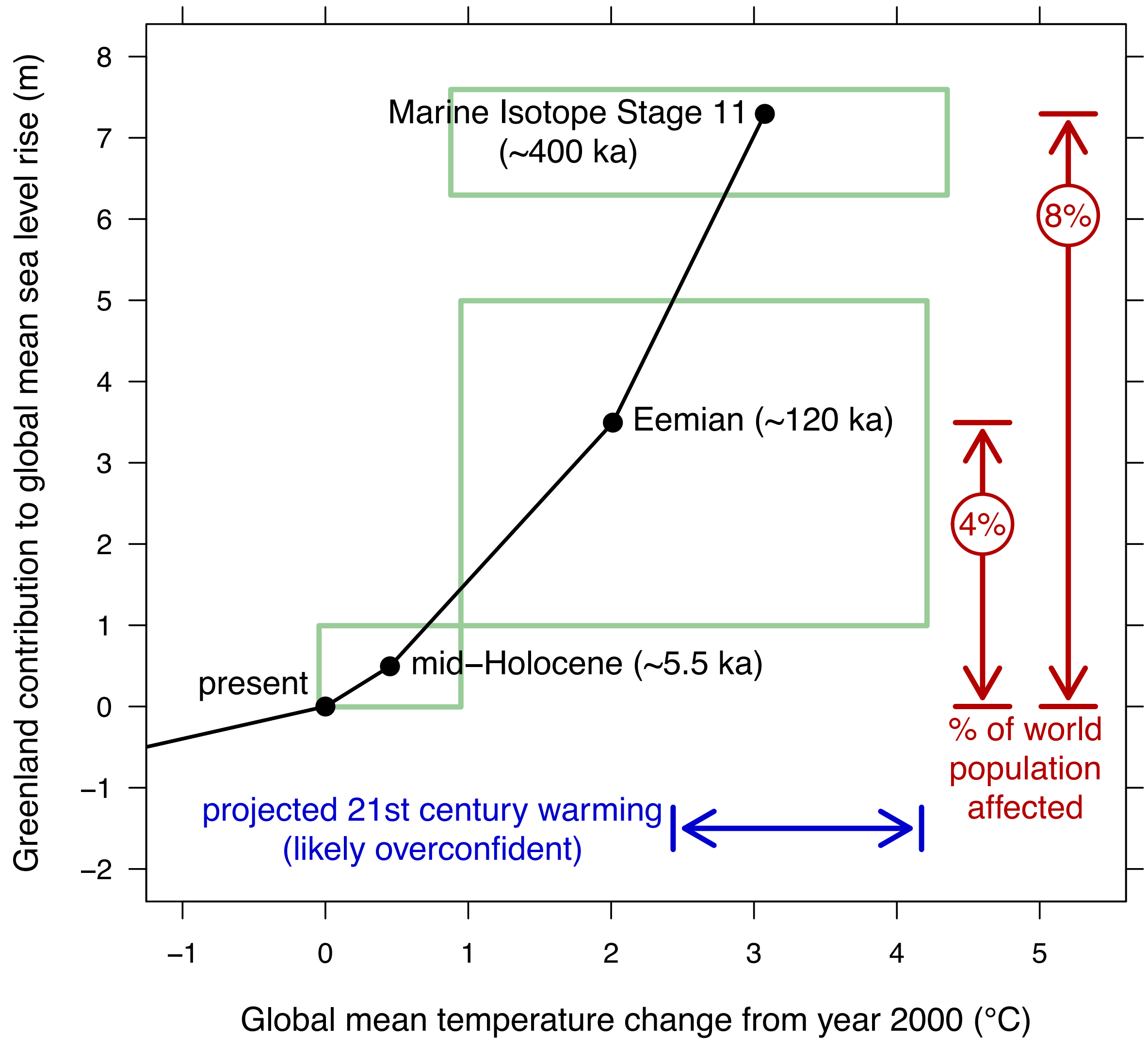
Future sea-level rise is uncertain and imposes risks



Figures: annotated from IPCC AR5 WG 1, Fig 13.27, U.S. Coast Guard, Petty Officer 2nd Class Kyle Niemi

The paleo-record and simple physics suggest that anthropogenic climate forcings cause considerable risks driven by a potential Greenland Ice Sheet disintegration.



The sea-level rise in the Eemian is one motivation for the max. 2 °C goal adopted by many countries.

Paleo-data from Alley et al (2010), population data from Li et al (2009), climate projections from Meehl et al (2007). Synthesis from Keller and Nicholas (2012)

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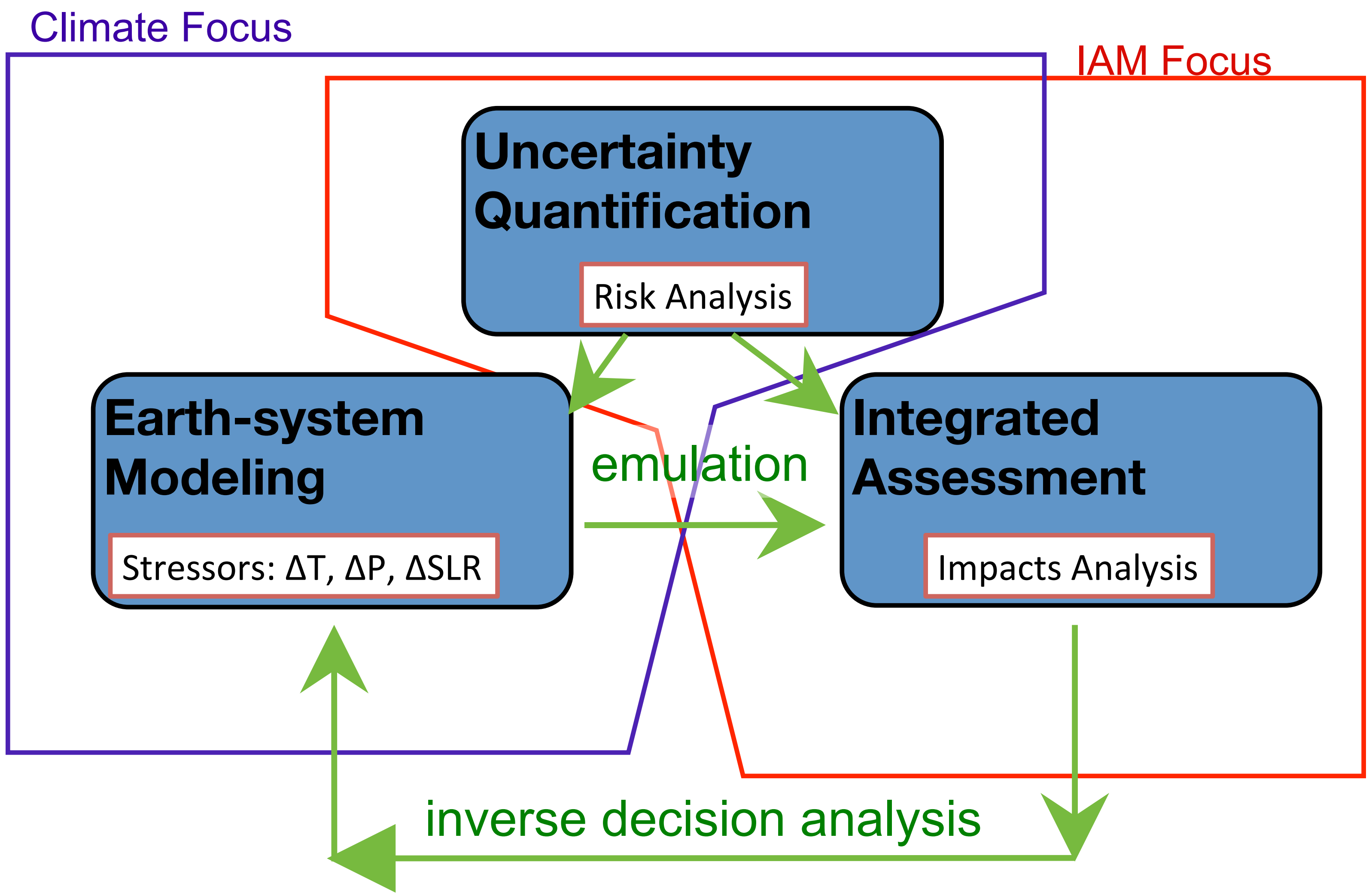

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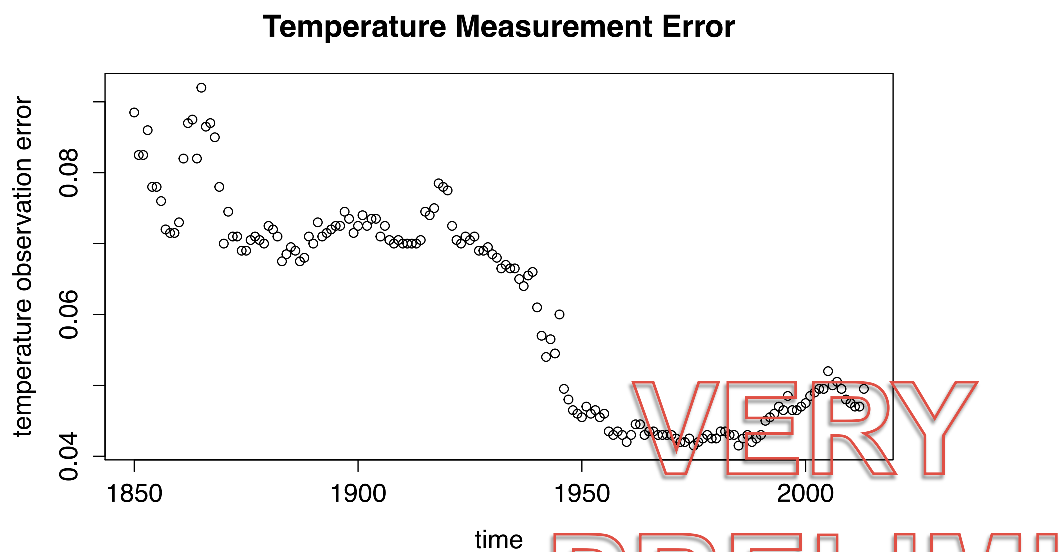
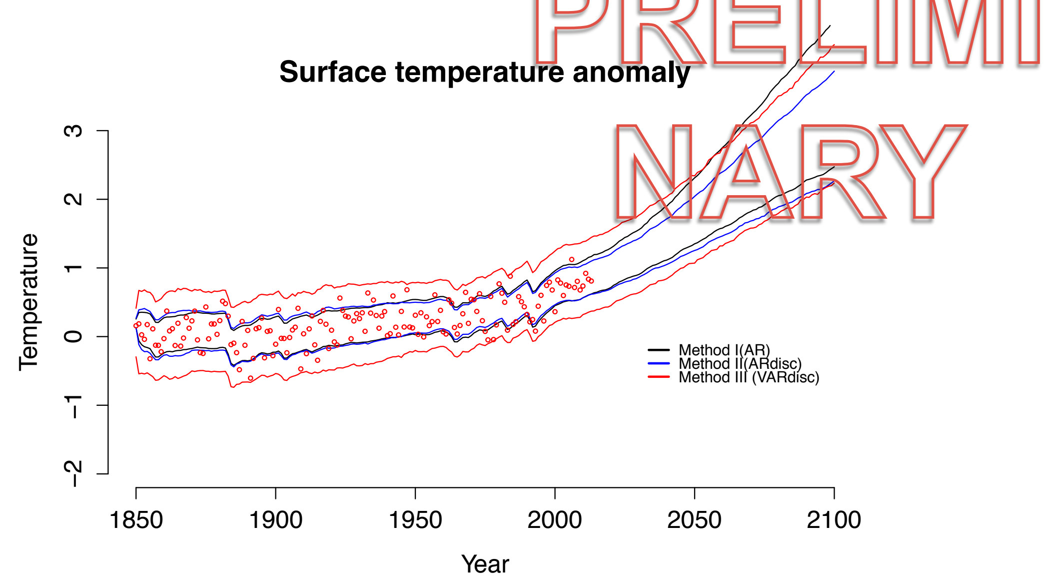
(1) Improving tools for uncertainty and risk-assessments

Observation errors are heteroskedastic

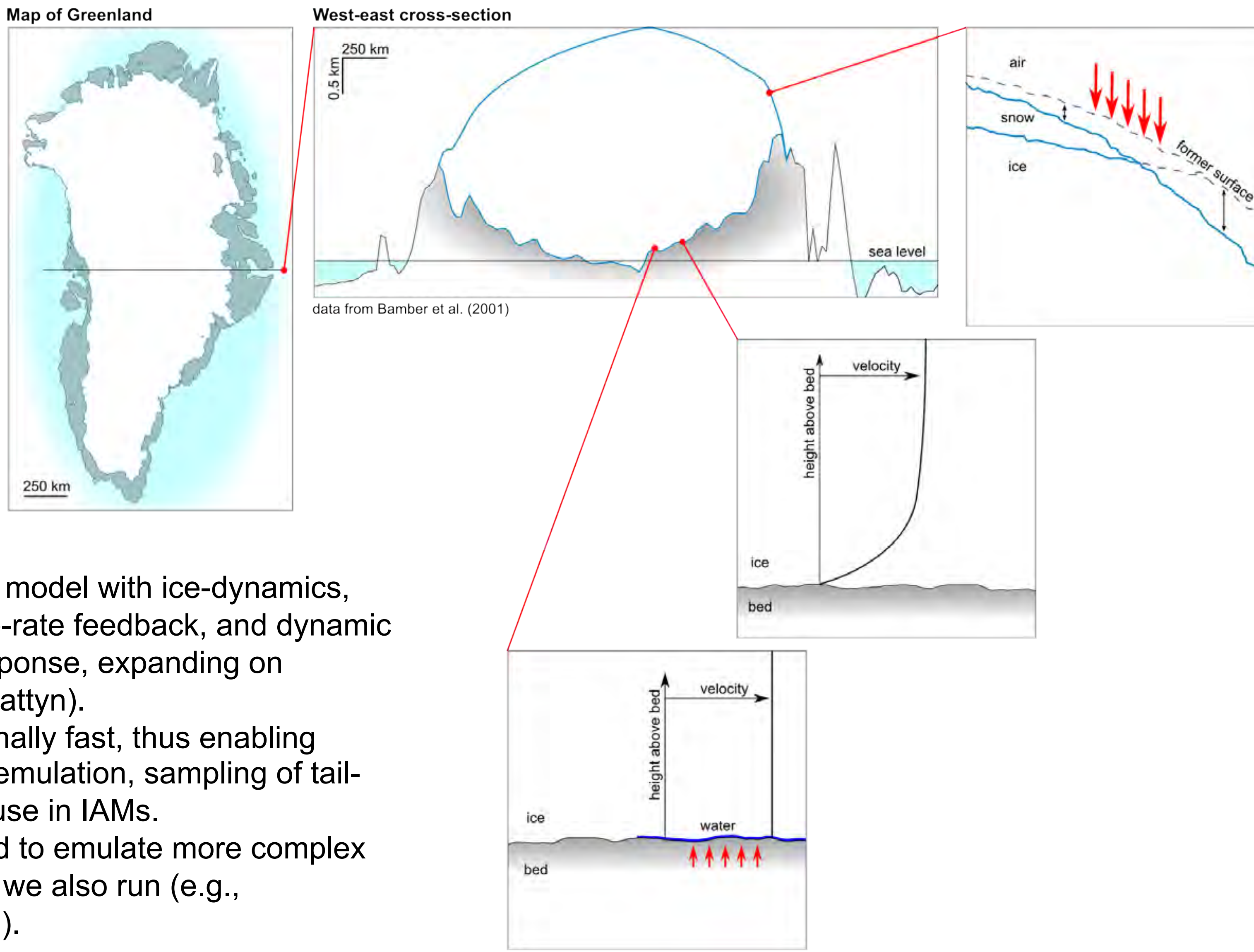


Accounting for heteroskedastic observation errors can change hindcasts, projections, and parameter estimates.



Guan et al (in prep)

(2) We have built a mechanistically based and computationally efficient model of the Greenland Ice Sheet



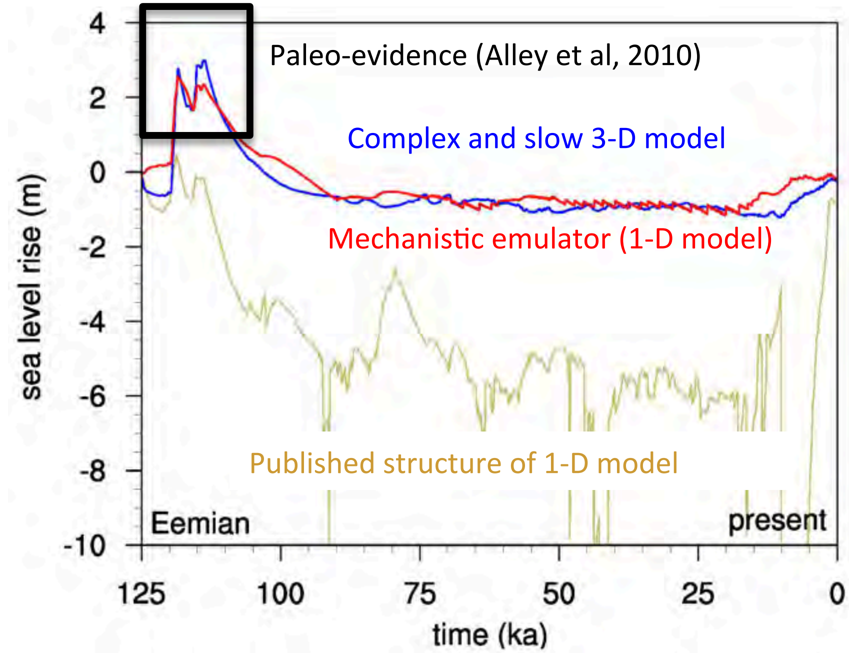
GLISTEN

- 1-D flowline model with ice-dynamics, height/lapse-rate feedback, and dynamic bedrock response, expanding on Grantism (Pattyn).
- Computationally fast, thus enabling calibration, emulation, sampling of tail-areas, and use in IAMs.
- Can be used to emulate more complex models that we also run (e.g., SICOPOLIS).
- Open source…

Applegate et al (2012)

The emulator enables a full, nonparametric and joint calibration that covers decision-relevant tail areas.

- Using paleo-observations to inform risk estimates requires many model runs in a feasible time window.
- Mechanistically based emulators enable this task.
- The new emulator hits the paleo-constraints and is fast enough for risk analyses.



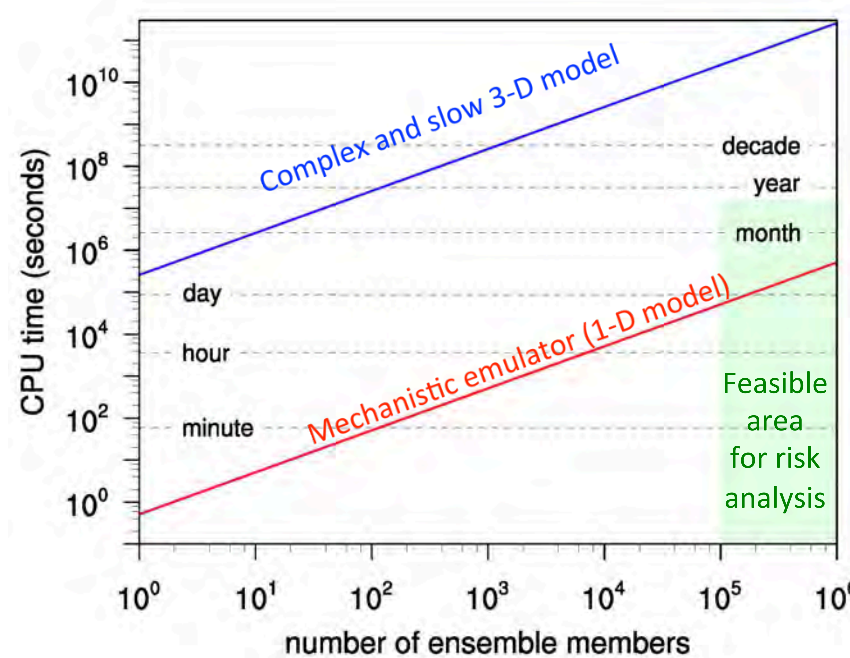


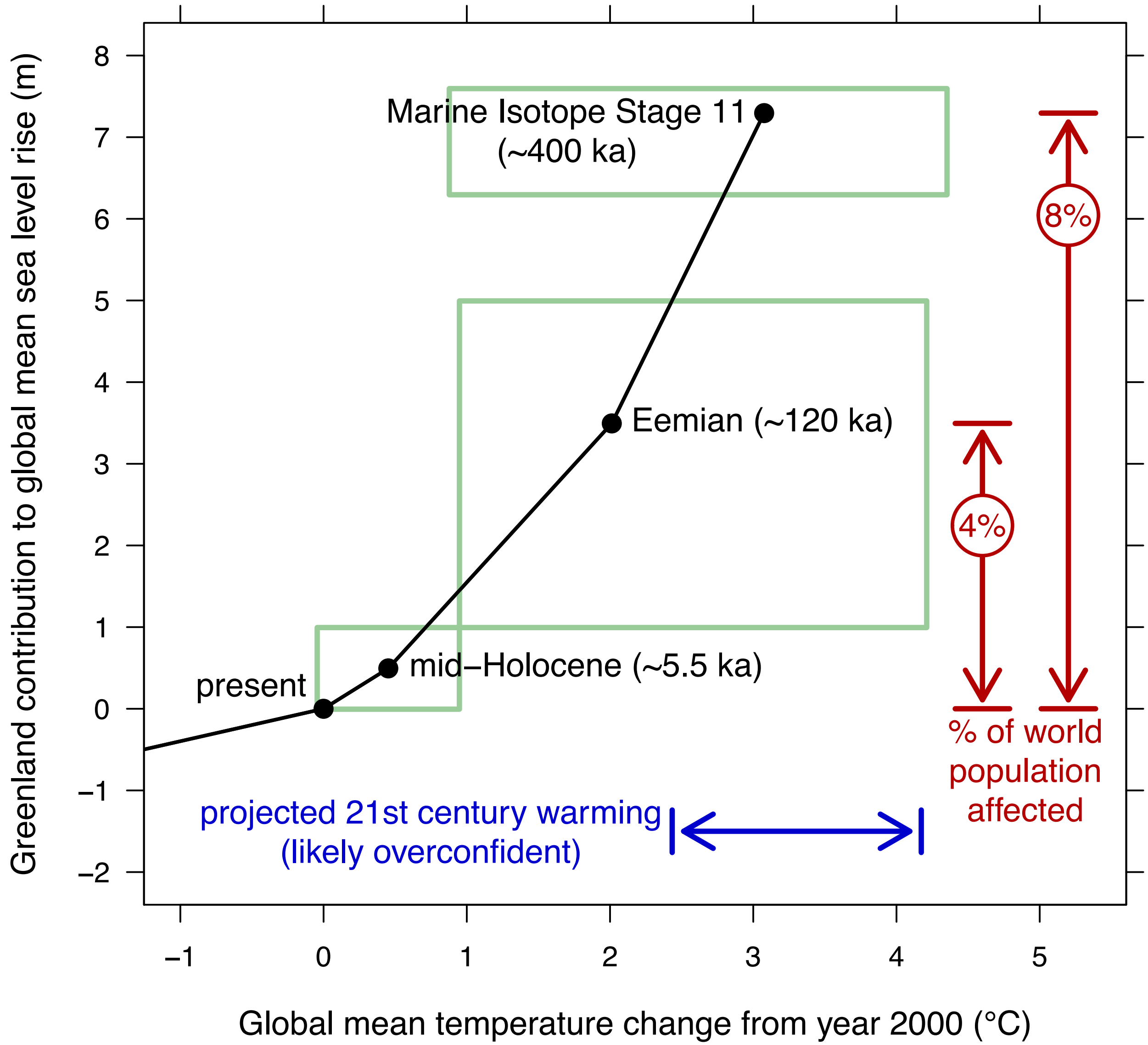
Figure annotated from Haqq-Misra et al (2012), 3-D model simulation is Applegate et al (2012), using the SICCOPOLIS model (Greve et al, 2011). Previously published 1D model is Pattyn (2006)

(3) What is the GIS response time scale?

Lenton et al (2008) states:
“> 300 years”.

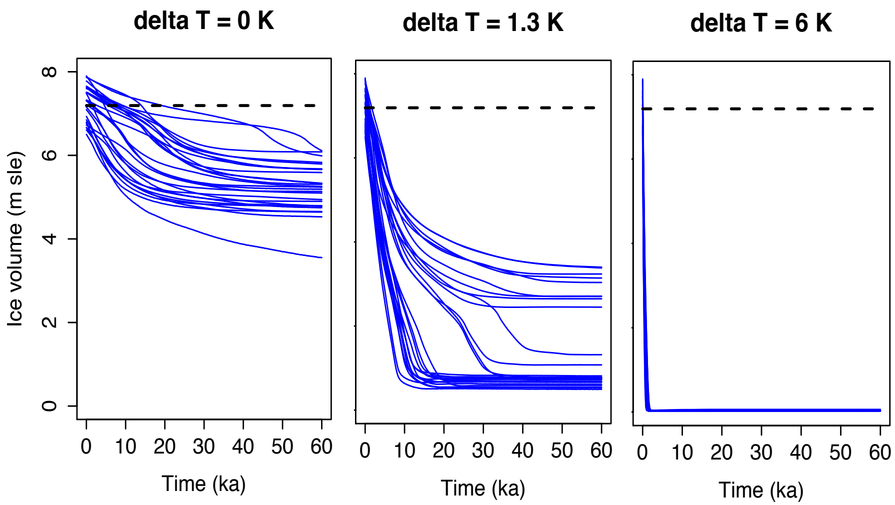
Is “>300 years” a good model?

What are sensitivities and uncertainties?

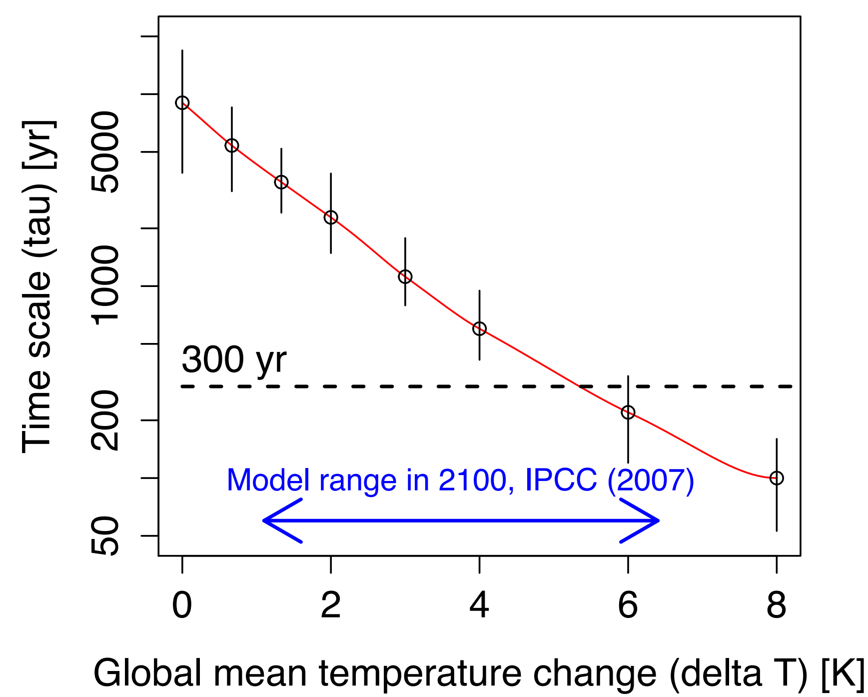


Paleo-data from Alley et al (2010), population data from Li et al (2009), climate projections from Meehl et al (2007).

“>300 years” (Lenton et al, 2008) is missing key sensitivities and uncertainties. The situation can be more pressing.



Applegate, Parizek, Nicholas, and Keller (in prep)



Applegate et al (AGU, this week)
ms in preparation

New work: How to account for regional patterns?

A. B. A. Slangen et al.: Towards regional projections of twenty-first century sea-level change

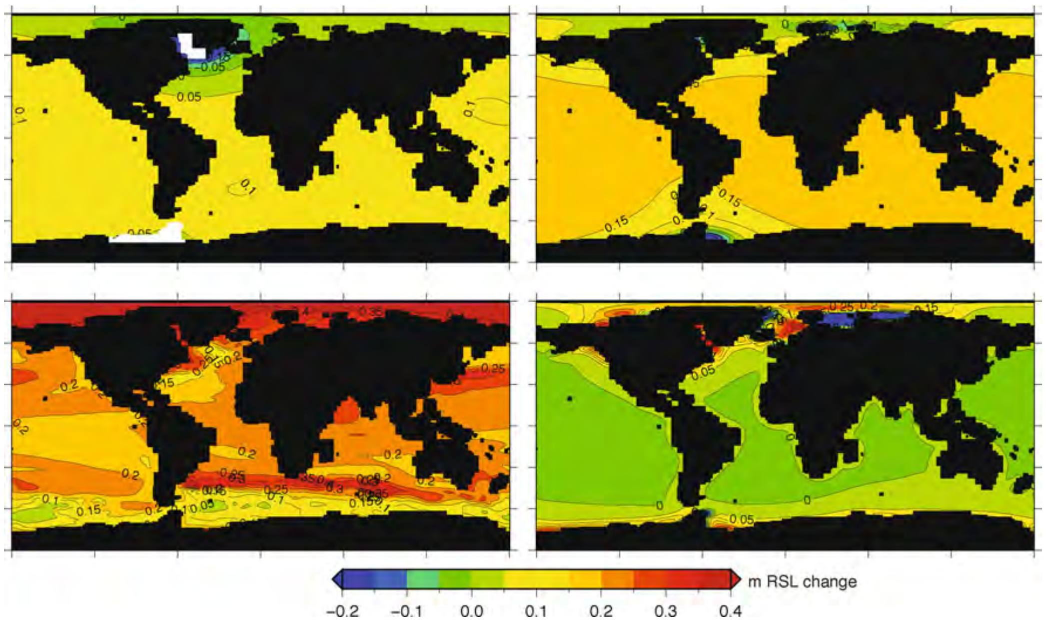


Fig. 2 Ensemble mean RSL contribution (m) of ice sheets (*upper left*), glaciers (*upper right*), steric changes (*lower left*) and GIA (*lower right*) for scenario A1B between 1980–1999 and 2090–2099. *White shading* in *upper left* panel indicates the mass loss regions on AIS and GIS

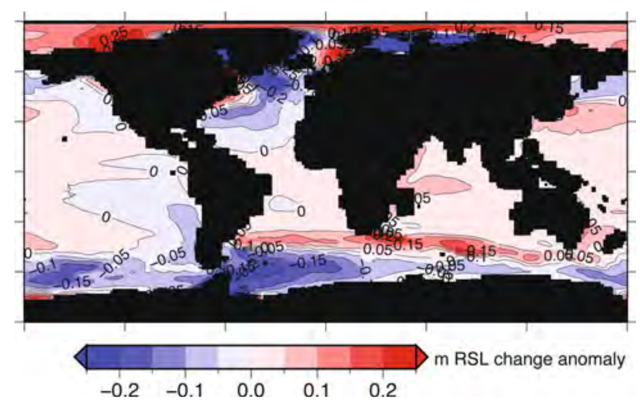
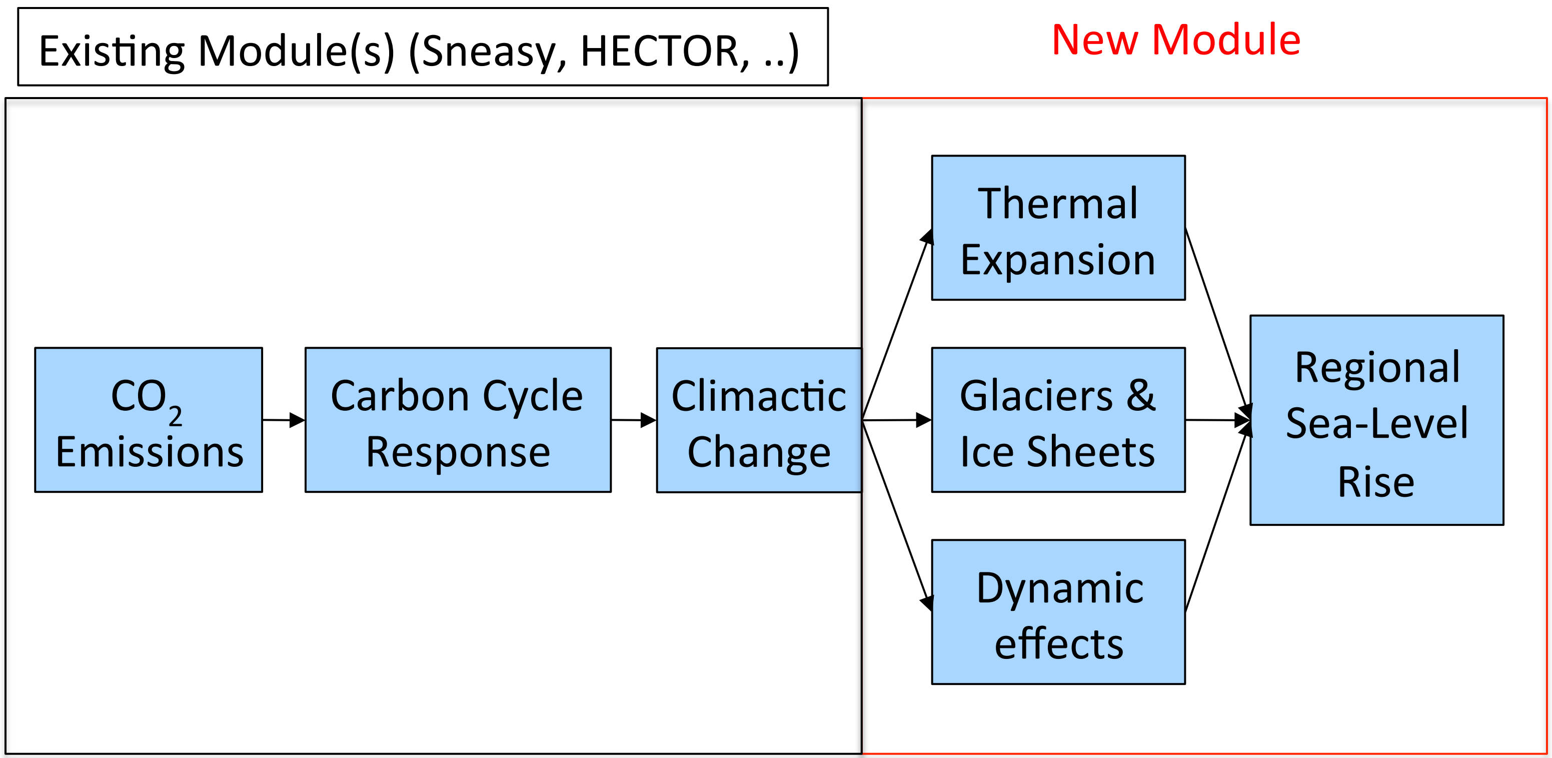


Fig. 5 Ensemble mean sea-level anomaly (m) w.r.t. global mean RSL change (0.47 m) for scenario A1B between 1980–1999 and 2090–2099

Slangen et al (2011)

What is the current design of the sea-level module?

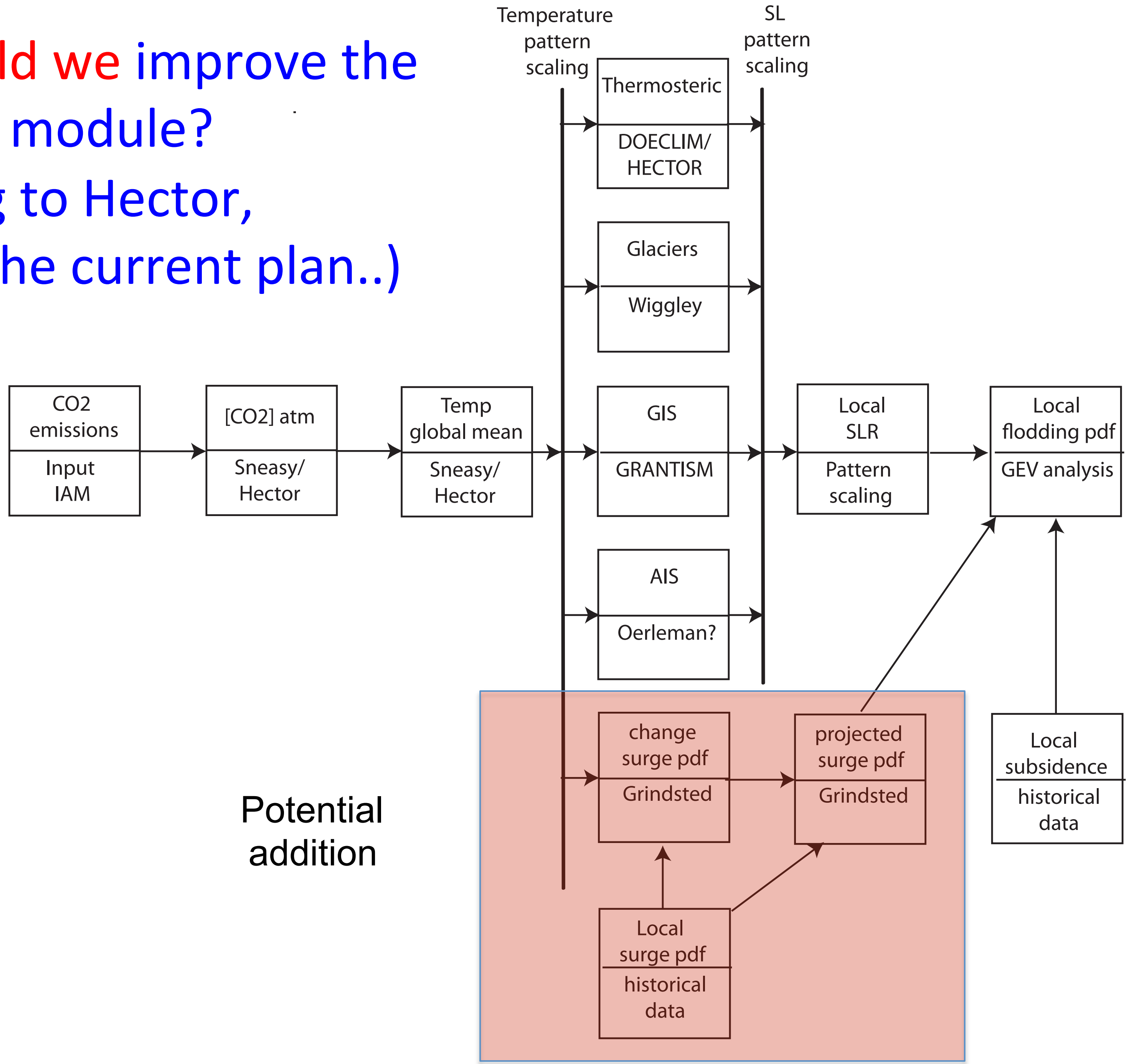


Main findings and next steps

- Linking climate models, uncertainty quantification, and integrated assessment requires a complex integration. Emulation and inverse decision analysis are key tools to support this integration.
- Ice-sheets responses pose nontrivial risks that are relevant for IAMs.
- We have developed and calibrated mechanistically based climate, carbon-cycle, and ice-sheet models that can serve as emulators.
- Improving the representation and uncertainty quantification of ice-sheet responses can drastically affect risk and decision-analyses.
- What are regional projections?
  - Mean functions (cf. Irvine et al 2012, Applegate et al, 2013) drive a pattern scaling (cf. Slangen et al 2011)
  - Emulator for iESM/CESM components (cf. Sriver et al, 2012)
- What are the effects of improved sea-level rise and climate projections on risk estimates?
  - IAM module (HECTOR if possible, SNEASY as a fallback)
  - IAM integration

Possible Project Extensions

How could we improve the sea-level module? (coupling to Hector, beyond the current plan..)



Potential addition

How to account for potential changes in storm surges?

Temperature depended GEV function fitted to historical observations

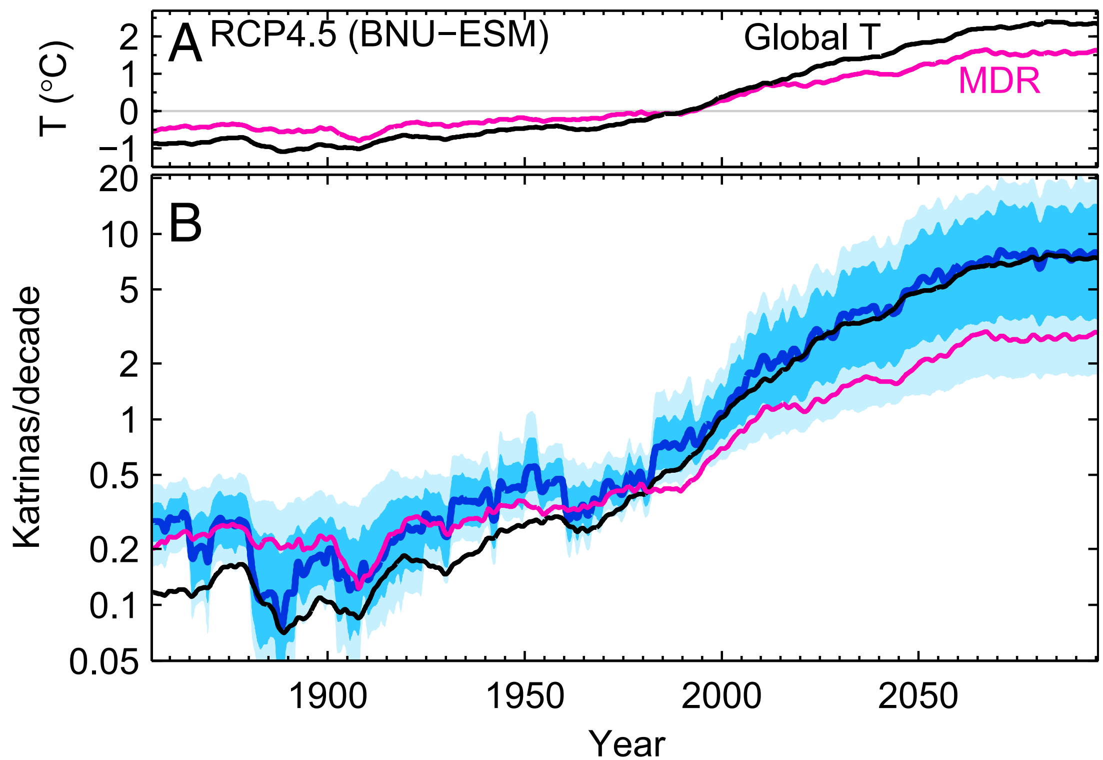


Fig. 3. Number of Katrina magnitude surge events per decade (*B*) hindcast and projected changes in temperatures from BNU-ESM under for RCP4.5 (*A*). The thick blue line shows the projection using the full spatial gridded temperatures and confidence interval (5–16–84–95%); magenta and black show the projections using only MDR and global average surface temperature. Confidence intervals for MDR and global *T* (not shown for clarity) are about the same size as for the gridded model.

Grindsted et al (2013)

How to account for potential changes in storm surges?

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Grindsted et al (2013)

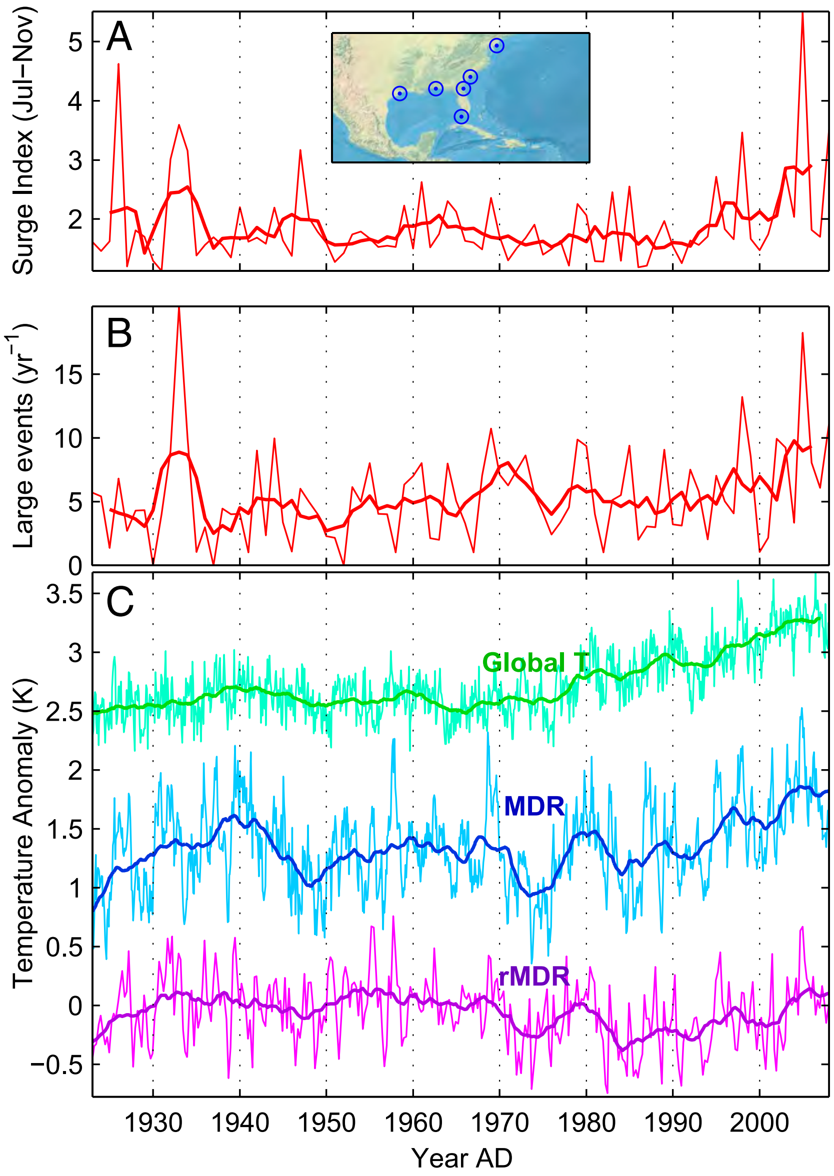

Fig. 1. (*A*) Average surge index over the cyclone season. (*B*) Observed frequency of surge events with surge index greater than 10 units per year (surge index > 10 units). (*C*) Global average temperature, MDR temperature, and rMDR temperature anomaly. *Inset* shows locations along the US coast of the six tide gauges used in the surge index (Fig. S1).

How to account for potential changes in storm surges?

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Table 2. Performance of alternative models expressed as an odds ratio relative to the model using global average temperature as the predictor

Predictor	Katrina sensitivity	Odds
Gridded temperatures (23)	2.1–6.6×	4:1
MDR SST (24)	1.8–5.5×	3:1
Global *T* (23)	1.5–6.6×	1:1
Linear increase	1.3–4.7×	1:5
Radiative forcing (25)		1:10
rMDR (24)	1.8–10×	1:75
Pacific Decadal Oscillation (26)		1:400
Quasi-Biennial Oscillation (27)		1:600
Southern Oscillation index (28)		1:700
North Atlantic Oscillation (29, 30)		1:800
Sahel rainfall index (31)		1:1,200

The average likelihood of each hypothesis is calculated from entire sample of models from the MCMC, while ensuring that the likelihood is calculated over the same time interval in the numerator and denominator of the ratio. The Katrina sensitivity is expressed as the relative frequency increase of Katrinas [5–95%] per degree Celsius. The linear trend sensitivity is given per century.

above mean sea level at New York have been shown to be sensitive to model choices and results range from a 10% reduction to

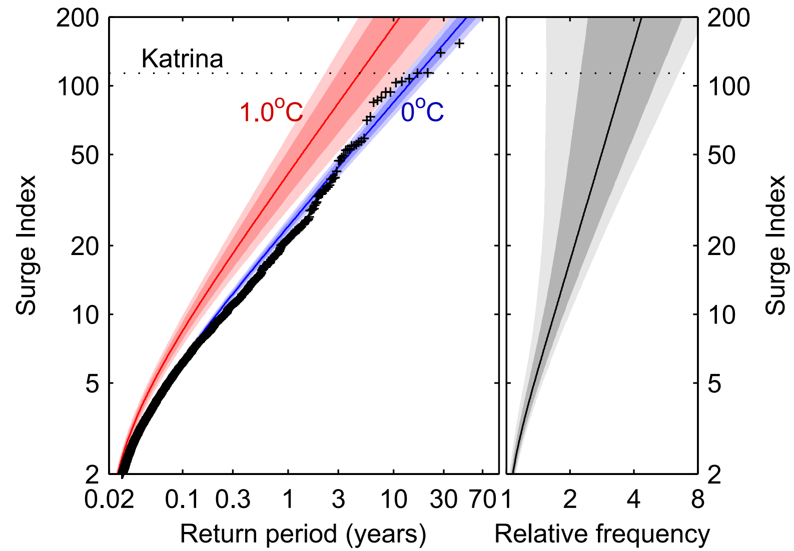

Fig. 4. (*Left*) Estimated return periods for global temperatures being 0 °C (blue) and 1 °C (red) warmer than present (1980–2000 average). The best-guess GEV distribution (lines) with confidence intervals (shading). Crosses show the empirically estimated return period assuming stationarity 1923 to present. (*Right*) Relative increase in frequency associated with a 1 °C warming in global temperatures (relative to a 1980–2000 baseline). (*Left* and *Right*) Light shading shows the 5–95% confidence intervals, and dark shading shows the 16–84%.

Grindsted et al (2013)