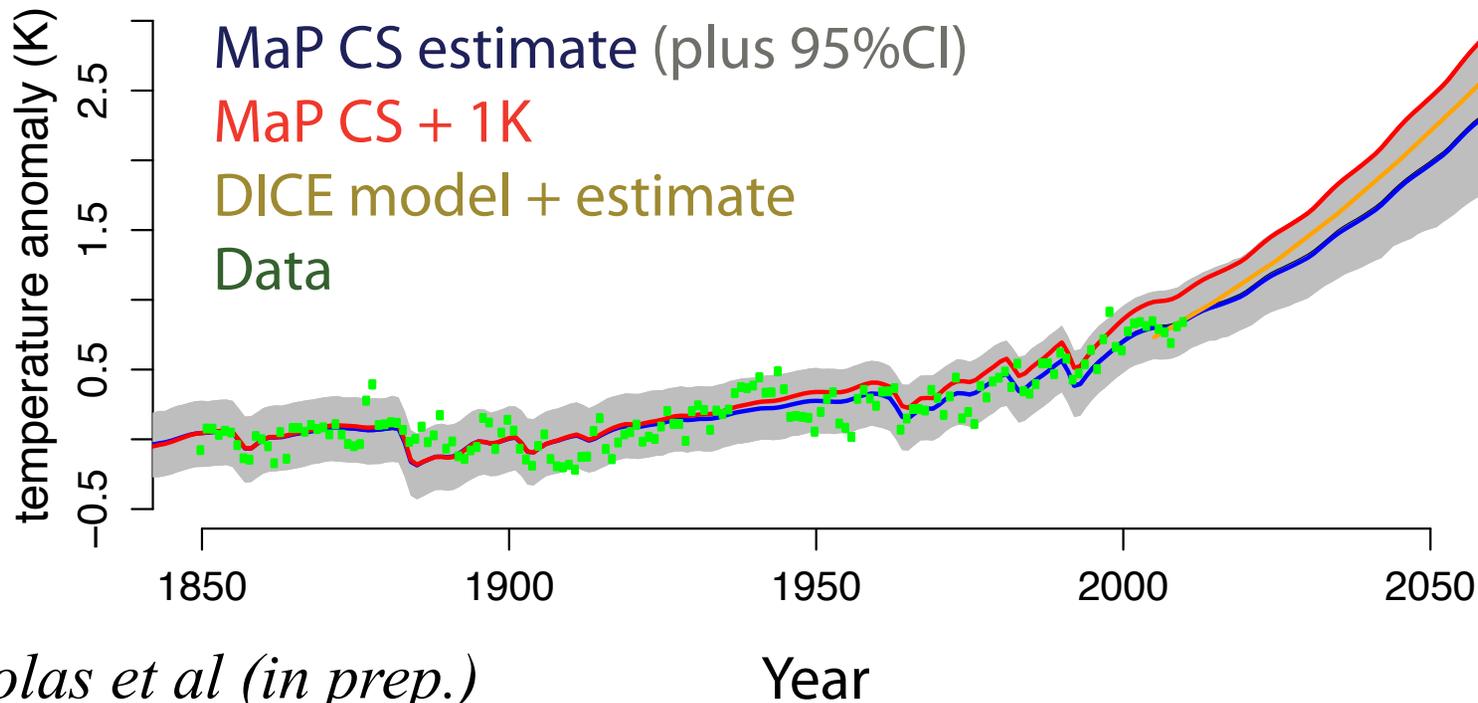


Uncertainty and Sensitivity Analyses in Integrated Assessments: Many obvious and a few new things..

Klaus Keller (presenter)

With inputs from David Anthoff, Patrick Applegate, Nathan Urban, Robert Nicholas, Jacob Haqq-Misra, Roman Olson, and Brian Tuttle

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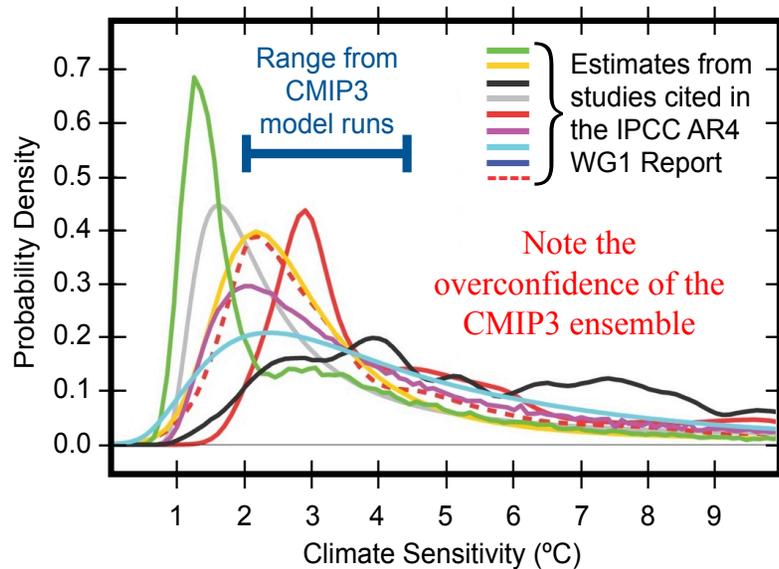
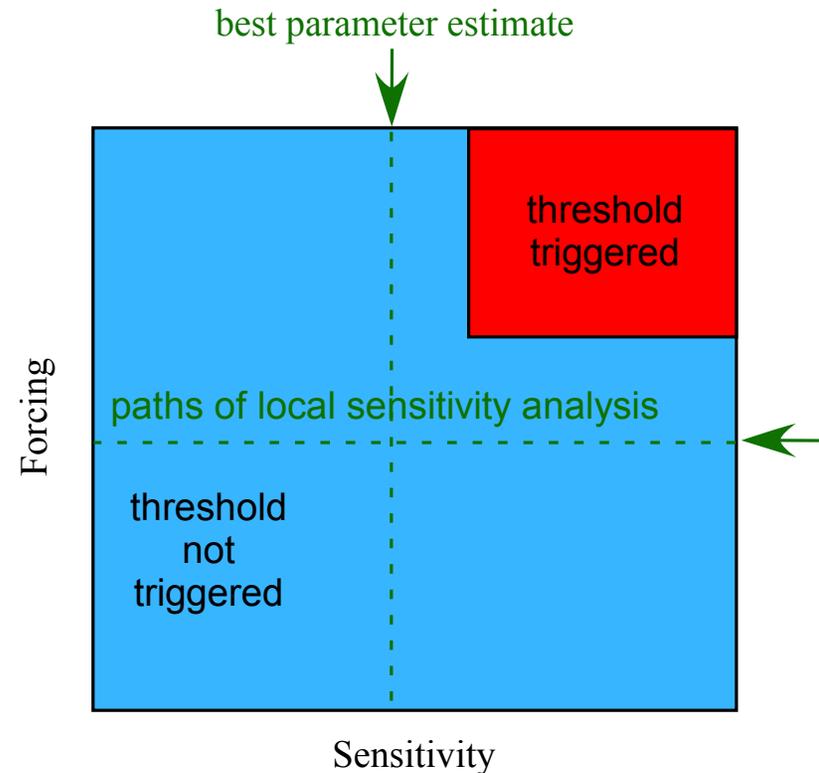
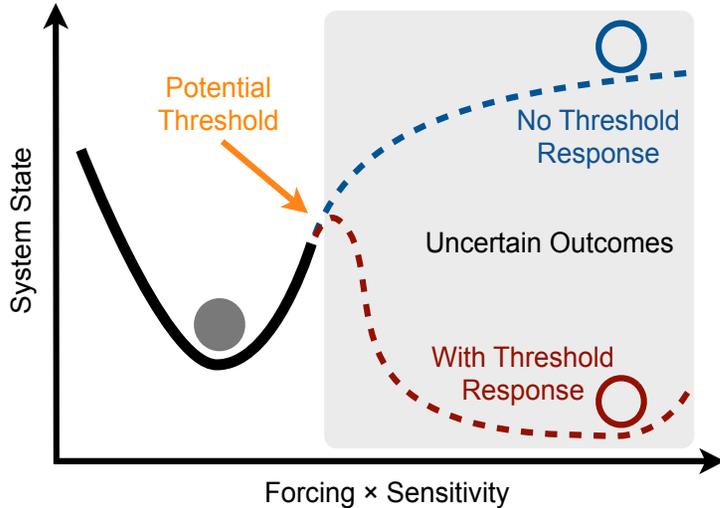


Nicholas et al (in prep.)

Outline

1. Why perform uncertainty and sensitivity analysis?
2. What is the current state-of-the-art?
3. What about future learning?
4. Research needs
5. Conclusions and recommendations for MUG

Why perform uncertainty and sensitivity analysis of IAMs?



- Are there nonlinear and persistent (threshold) responses?
- What are the (deeply uncertain) risks?
- What controls the risks?
- How brittle are the results with respect to improved representations of uncertainties

How brittle are conclusions based on the best-guess parameters?

- DICE model with one simple climate threshold and four jointly uncertain parameters.
- Numerical stability of the conclusions requires here:
 - $O(10^4)$ SOW (see Figures)
 - $O(10^6)$ iterations over all SOW for optimization (not shown)
- > $O(10^{10})$ model runs
- > need fast models or large computers..

Fig. 2 Optimal abatement levels for $N_S = 1$ (circles), $N_S = 7$ (stars) and $N_S = 15$ (squares). These sampling densities correspond to 1, 2,401 and 50,625 states of the world respectively

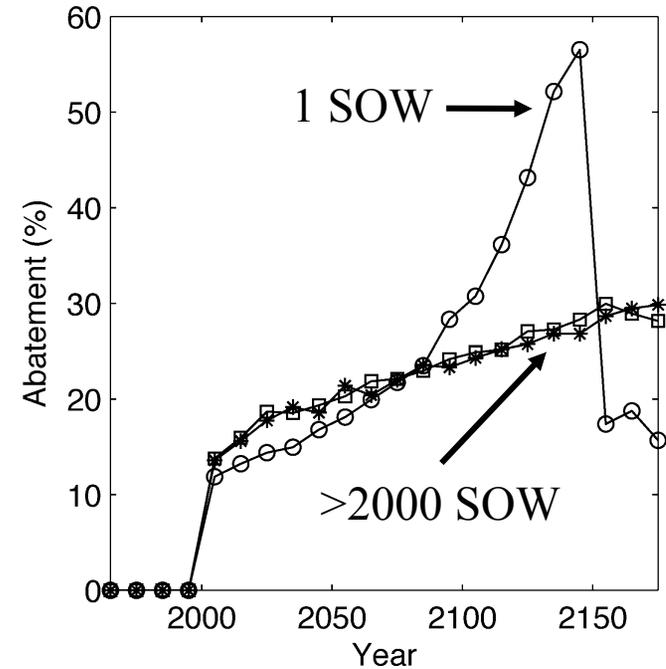
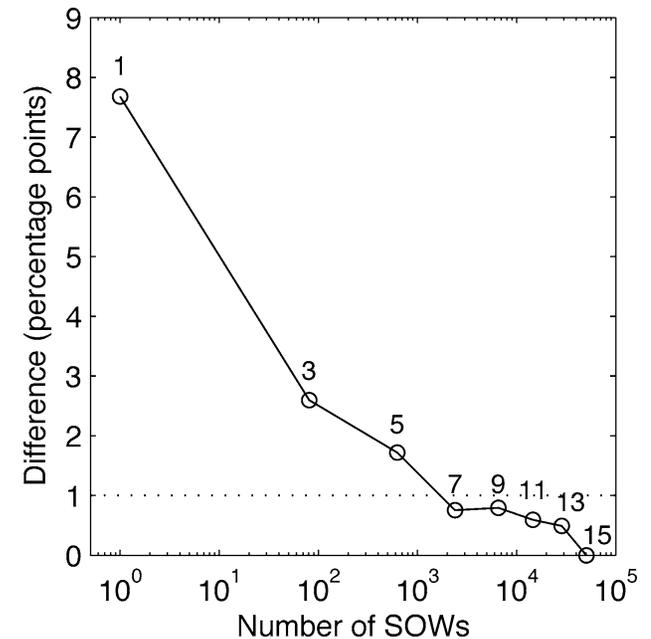


Fig. 3 Effects of increasing sampling resolution on approximation error. Shown are the mean difference (calculated from 2005 to 2155) between optimal abatement as a function of the numbers of states of the world (SOWs) compared with the optimal solution for 50,625 SOWs. The number of samples of each uncertain parameter are marked on the plot. The solution has practically converged beyond $7^4 = 2,401$ SOWs



McInerney and Keller (2008)

Approaches to Uncertainty and Sensitivity Analyses in IAMs

- 1. No formal inversion, “transfer pdfs”, neglect most correlations.**
 - Examples: McInerney and Keller et al (2008), Marten (2011), ...
 - Simple method with interesting (but limited) insights.
 - How to transfer pdfs?
 - Still the predominant approach.
- 2. Consider correlations along conditional maximum *a posterior* (MaP) estimates.**
 - Examples: Yohe et al (2004), Goes et al (2011),...
 - Improves hindcast consistency and tail area representation, but misses important uncertainties.
- 3. Full joint probabilistic analyses, without learning**
 - Examples: Pizer (1999), Urban and Keller (2009,2010).
 - Global sensitivity study (Butler et al, in prep)
- 4. Full joint probabilistic analyses, with learning**
 - Dynamic programming, agent based modeling, OSSE (Kelly and Kolstad, 1999, Keller et al, 2008, Peterson et al, 2003).



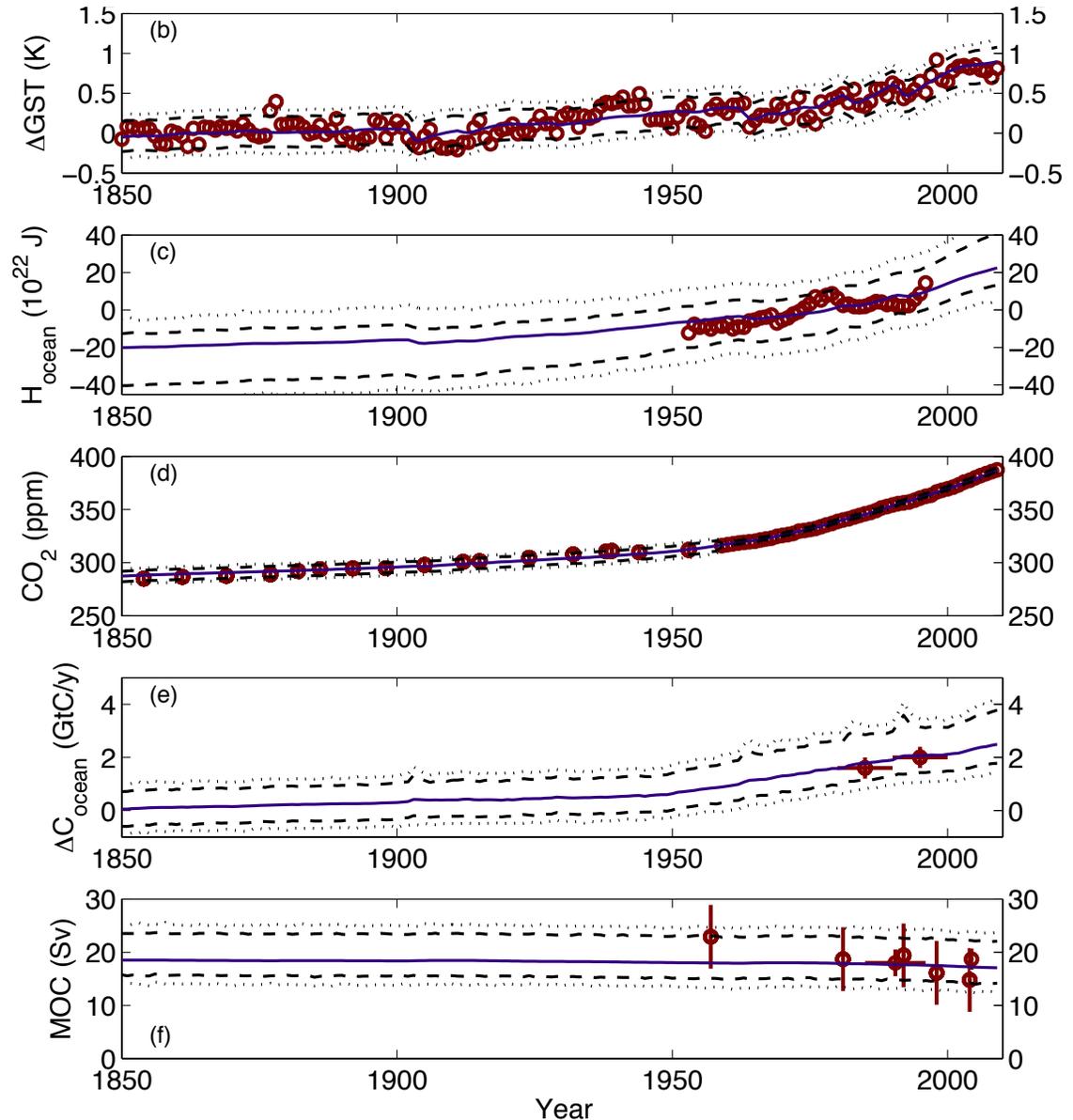
Increasing
power and
complexity

How does this work (or not) and why does this matter?

Two important tests:
 (i) Does the model represent key mechanisms?
 (ii) Do the hindcast credible intervals have appropriate coverage?

- SNEASY (Simple Nonlinear Earth SYstem model): coupled nonlinear carbon cycle, climate, and MOC models.
- We are adding a dynamic Greenland ice sheet flow model.
- Full nonparametric posterior joint parameter pdf through Bayesian data-model fusion (MCMC).
- SNEASY is open source and is being integrated into DICE and FUND.
- SNEASY passes the laugh-test of roughly appropriate past credible intervals.

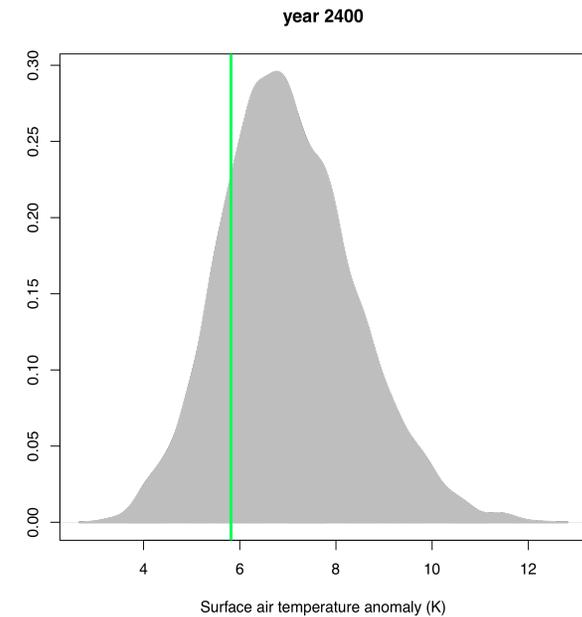
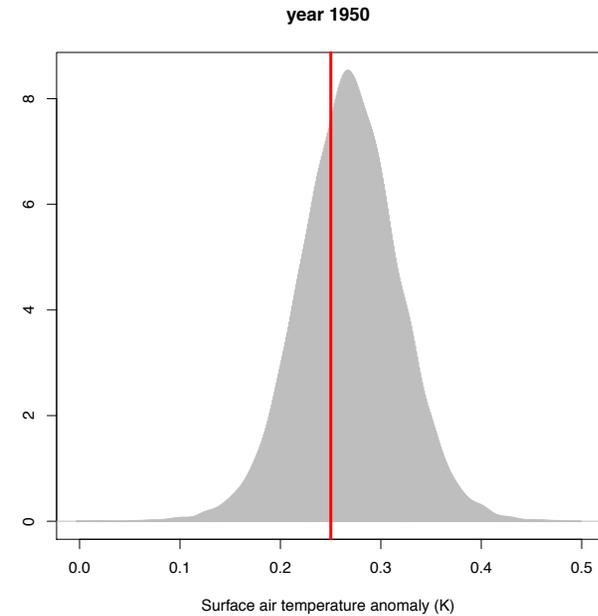
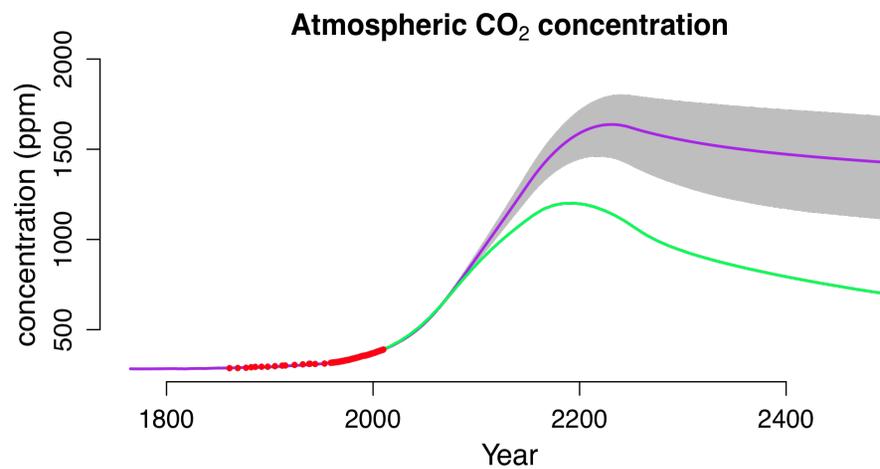
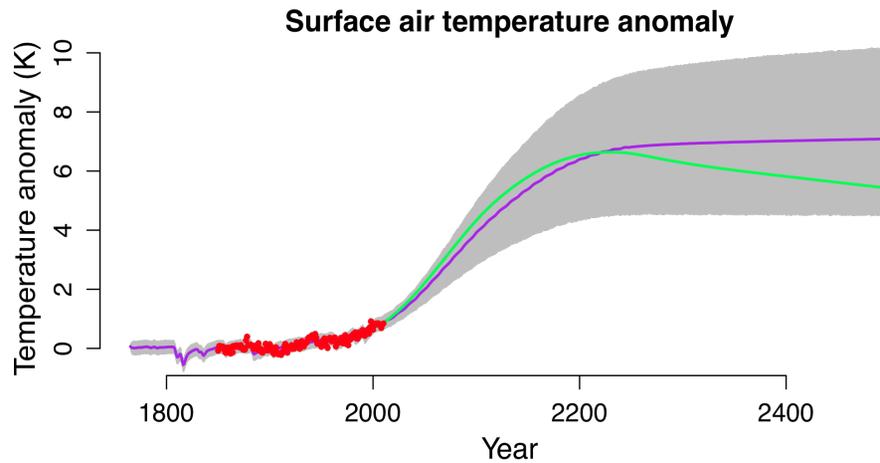
Urban and Keller (2010)



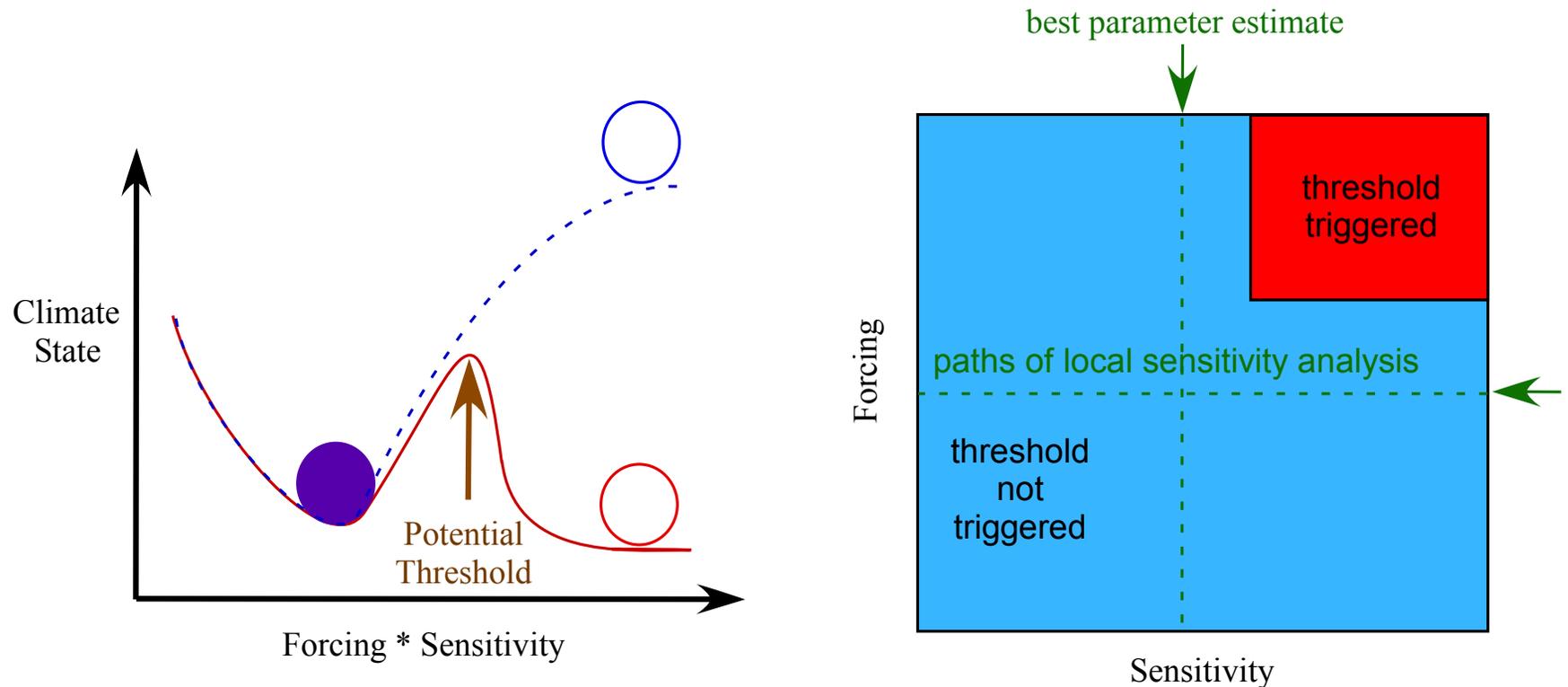
What are the projections?

Using hindcasts to assess probabilistic projections: Data vs DICE vs SNEASY

Nicholas et al (in prep.)



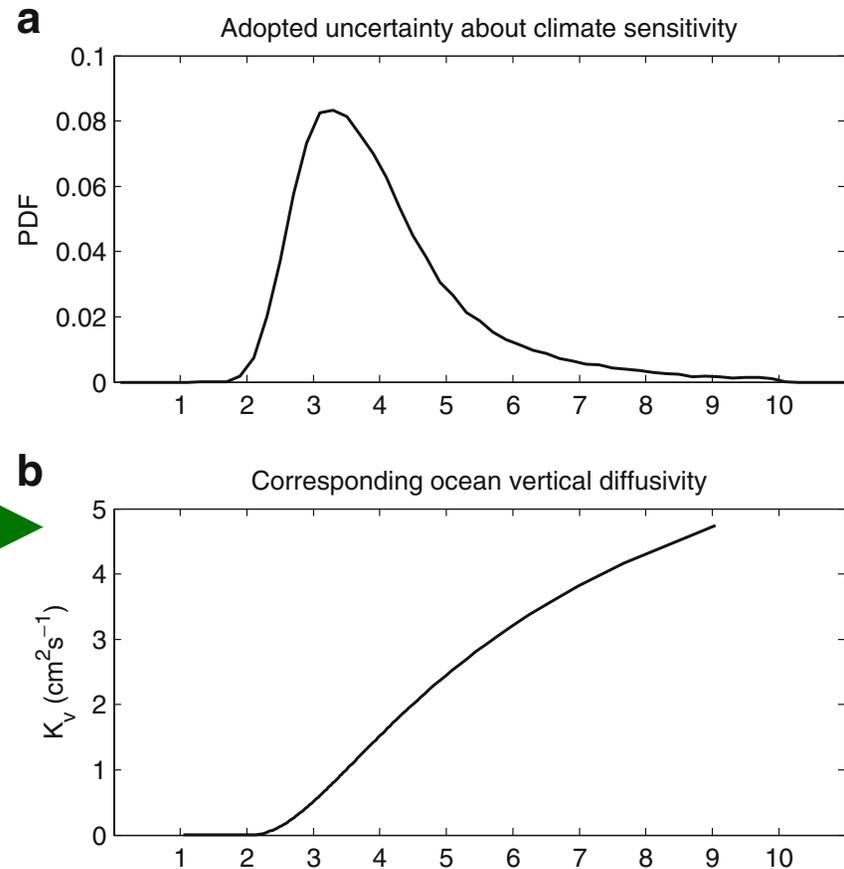
Which uncertainty matters the most?



The sensitivity analysis should resolve the effects of **important interactions within the reasonable parameter range.** **=> We need the joint pdf with correlations.**

How to implement these correlations in IAMs?

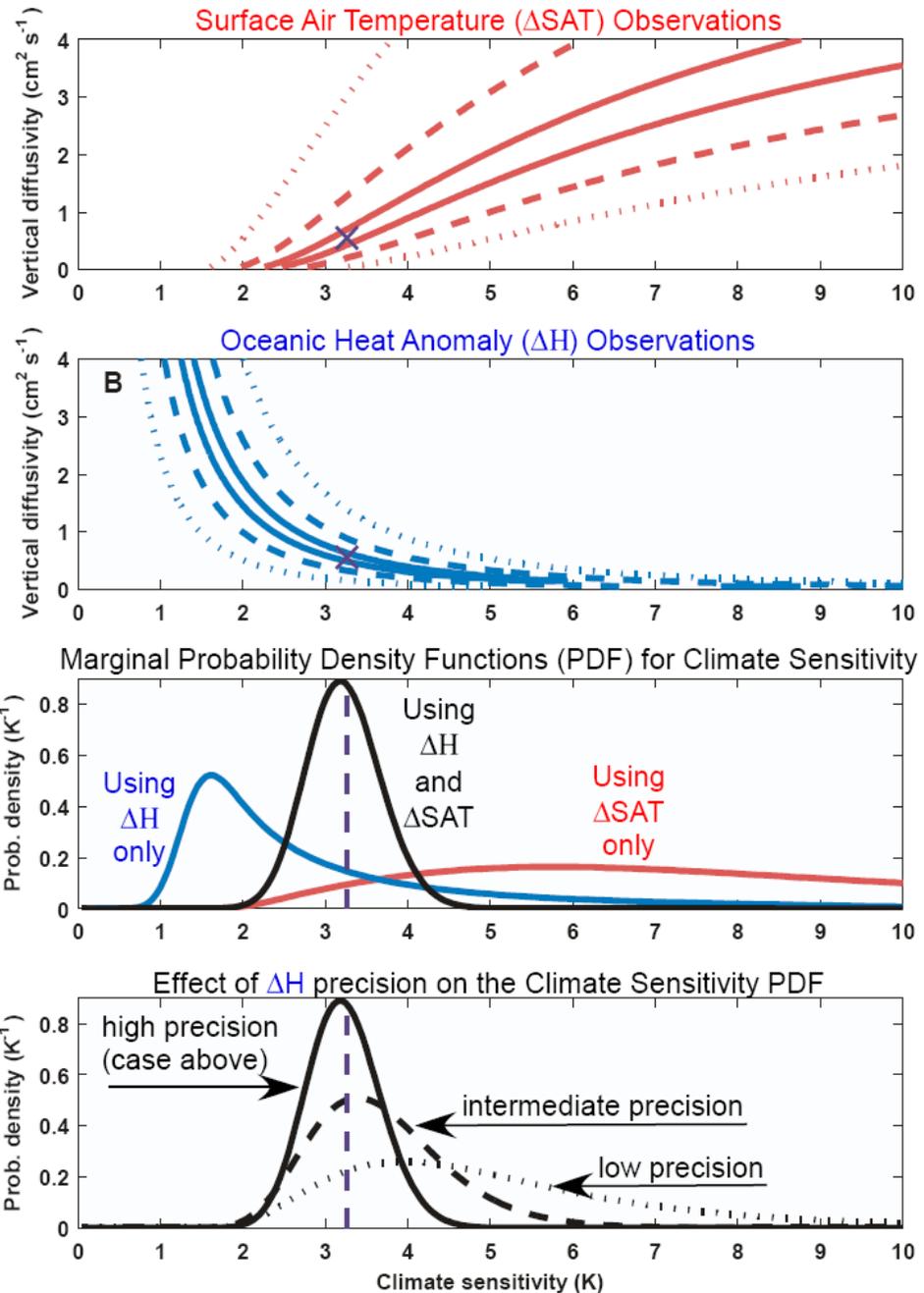
- **Simple:** Use a stratified sample of parameters and apply rejection sampling (cf. Sriviver et al, 2012).
- **Intermediate:** Sample along maximum *a posteriori* conditional parameter estimates (cf. Yohe et al, 2004, Goes et al, 2011).
- **Advanced:** Derive the full joint pdf using MCMC and then subsample the parameter chain (Anthoff et al, in prep.)



Goes, Tuana, and Keller (2011)

Marginal distributions miss important information

- High climate sensitivity estimates that would be consistent with the surface air temperature record are inconsistent with the oceanic heat uptake.
 - Likewise, low climate sensitivity estimates that would be consistent with the oceanic heat uptake are inconsistent with the surface air temperature observations.
 - Learning affects the joint pdf in complex ways.
 - The pdfs may be poorly approximated by multivariate and correlated normal distributions.
- > Arguably the easiest way to implement learning in IAMs is through the full joint pdf as a function of time.



Recommendations for MUG

1. Show probabilistic hindcasts over decision-relevant time-scales and check modeling assumptions with these hindcasts.
2. Use inversion methods with reasonable theoretical underpinning
 - a) Windowing is simple and gets many important aspects
 - b) Conditional MAP estimates improve the analysis, at some computational costs.
 - c) MCMC is powerful, state-of-the-art, but nontrivial.
3. Account for correlations and interaction effects
 - a) Uncertainty analysis:
-> Windowing, conditional MAP, and MCMC
 - b) Sensitivity analysis
=> Sobols' method or marginal projections
4. Choose sample size (and what you can sample) based on stability of the results (not what would like or hope to do).
5. We need to move to full joint inversion
 - a) Computationally and conceptually nontrivial, but the state-of-the-art in other fields.

Conclusions

1. The range of high-resolution climate model runs is often drastically overconfident and results in downwards biased risk estimates.
2. Model diagnosis and credible model projections hinge critically on (a) probabilistic hindcasts over decision-relevant time-scales and (b) the full joint parameter pdf.
3. Neglecting parameter correlations can strongly bias hindcasts, projections, and conclusions.
4. Formal model inversion techniques such as MCMC provide consistent and transparent avenues to probabilistic hindcasts and the full joint parameter pdf.

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All errors and opinions are mine (unless cited).

