

Uncertainty Analysis with Hector

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Overview of the Project

- Overarching goal is to improve Hector capabilities for probabilistic climate assessment
- Improve Hector model physics, including updating Hector's energy balance module to a diffusive ocean and incorporation of a sea-level rise module (accounting for thermal expansion, Antarctic/Greenland Ice sheets, and glaciers)
- Develop/Adapt new MCMC approaches for model calibration, parameter estimation, and uncertainty quantification
- Construct probabilistic projections of key climate change variables (e.g. global temperature, sea-level rise, etc.)

Project represents cross-disciplinary collaboration between JGCRI, University of Illinois, and Penn State University

- **emphasizing graduate student (B. Vega-Westhoff) and postdoctoral (T. Wong) research**

Climate impacts/damages closely linked to extreme (low probability) events



source: AP/Seth Perlman



National Climate Assessment, 2014

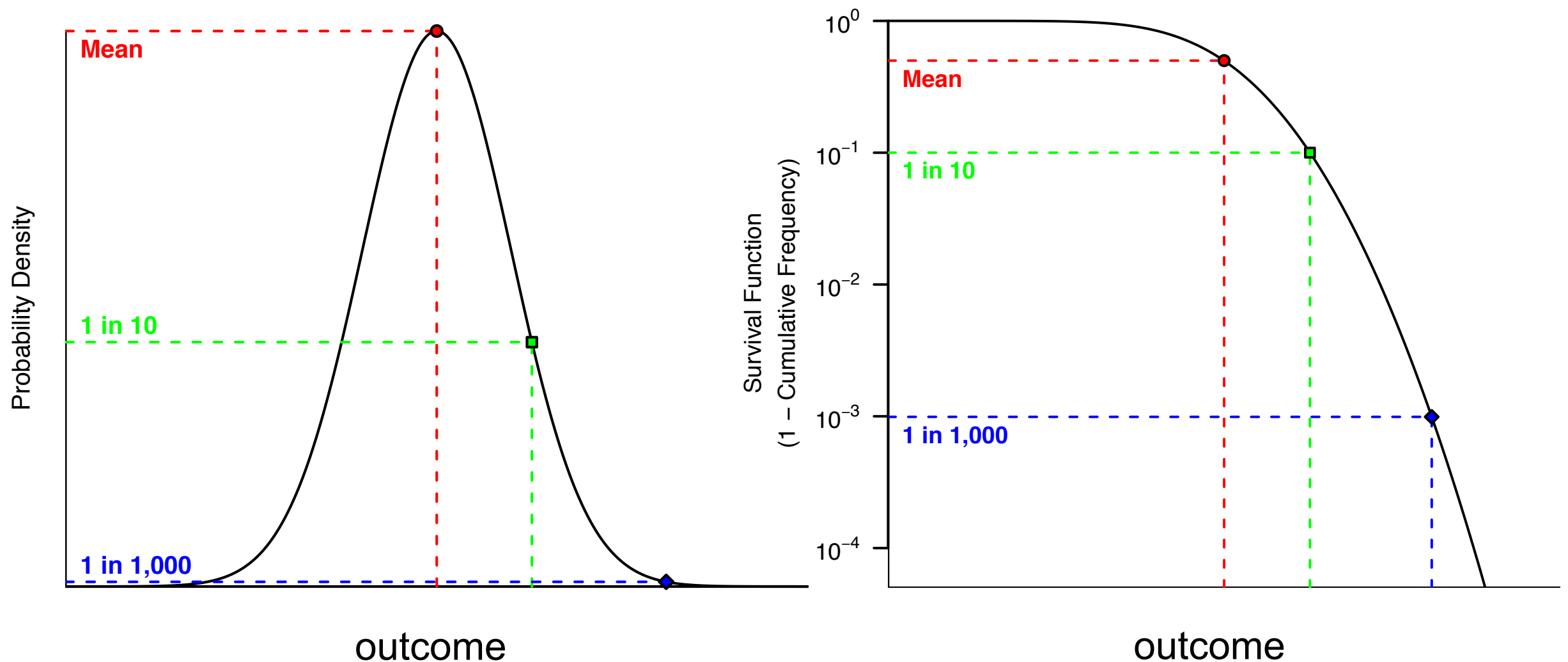
source: NOAA



Shifts in mean climate and changes in the tails can potentially lead to large increases in damages

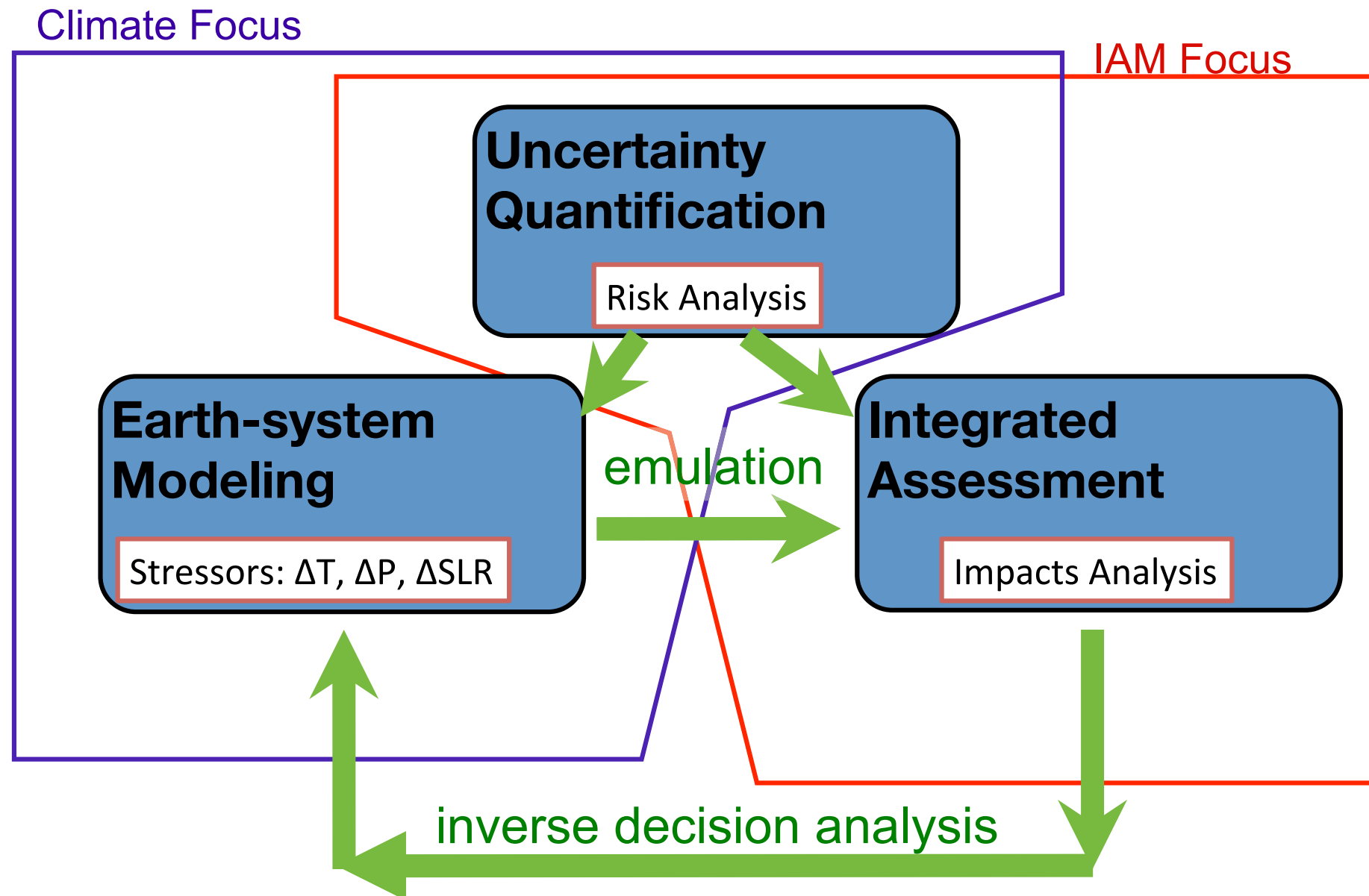
Understanding how tails may be changing is a major challenge

High reliabilities require information about the upper tail of the probability density function.



How robust are these tails?

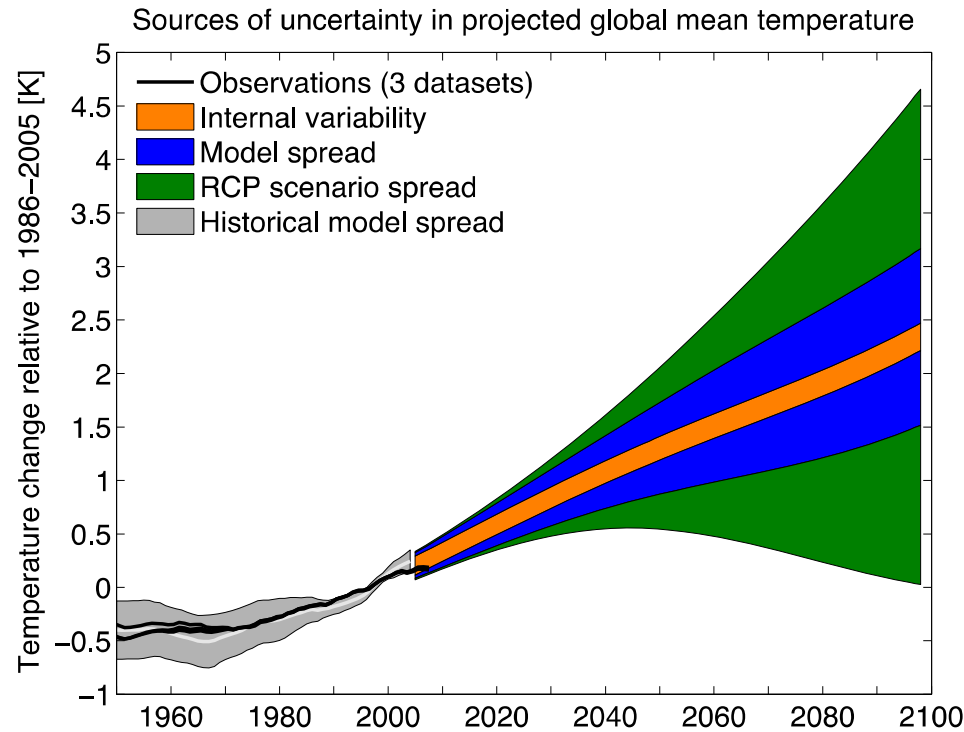
Uncertainty Quantification provides an important link between Earth-system modeling and Integrated Assessment, Risk Analysis and Impacts Analysis



Questions:

1. What uncertainties are important (decision-relevant)?
2. What drives the uncertainties?
3. How do the uncertainties affect climate metrics related to impacts?

Sources of climate uncertainty



Internal Variability

- natural (unforced) variability of the system

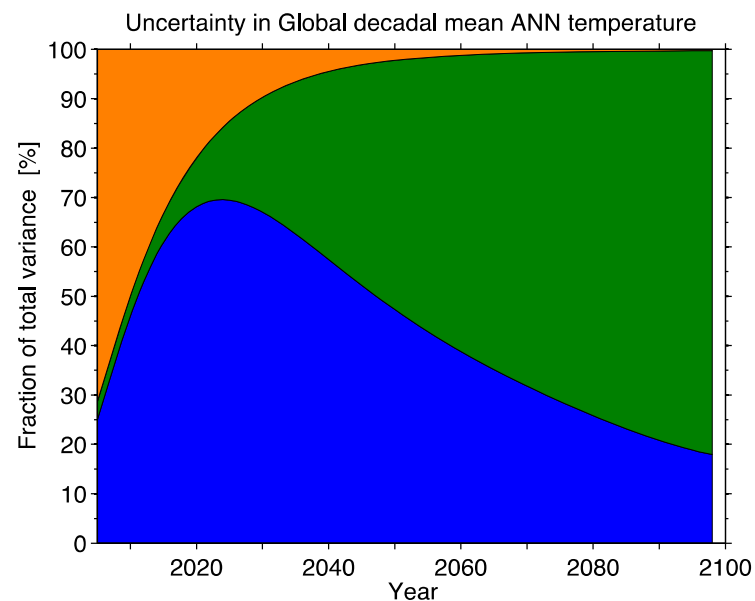
Model (structural) uncertainty

- different physics and numerical formulations lead to different responses to a given forcing

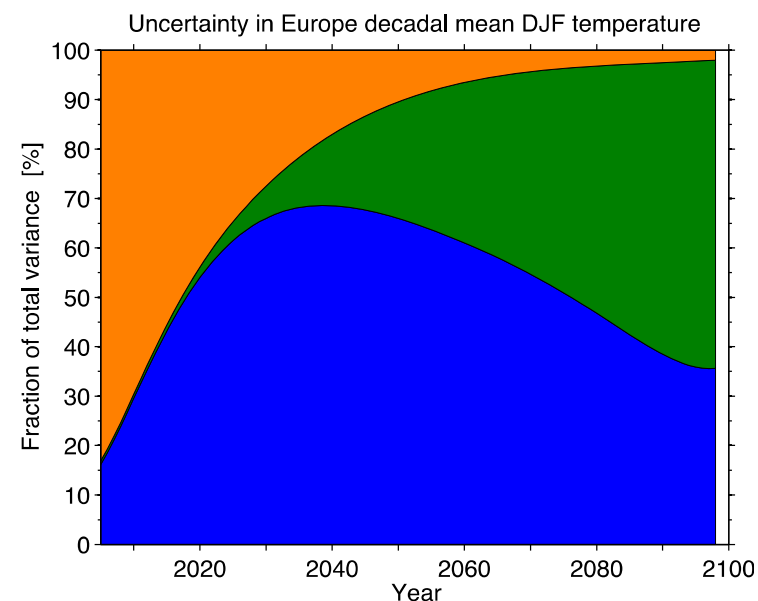
Forcing uncertainty

- incomplete knowledge about future emissions

Partitioning of uncertainties



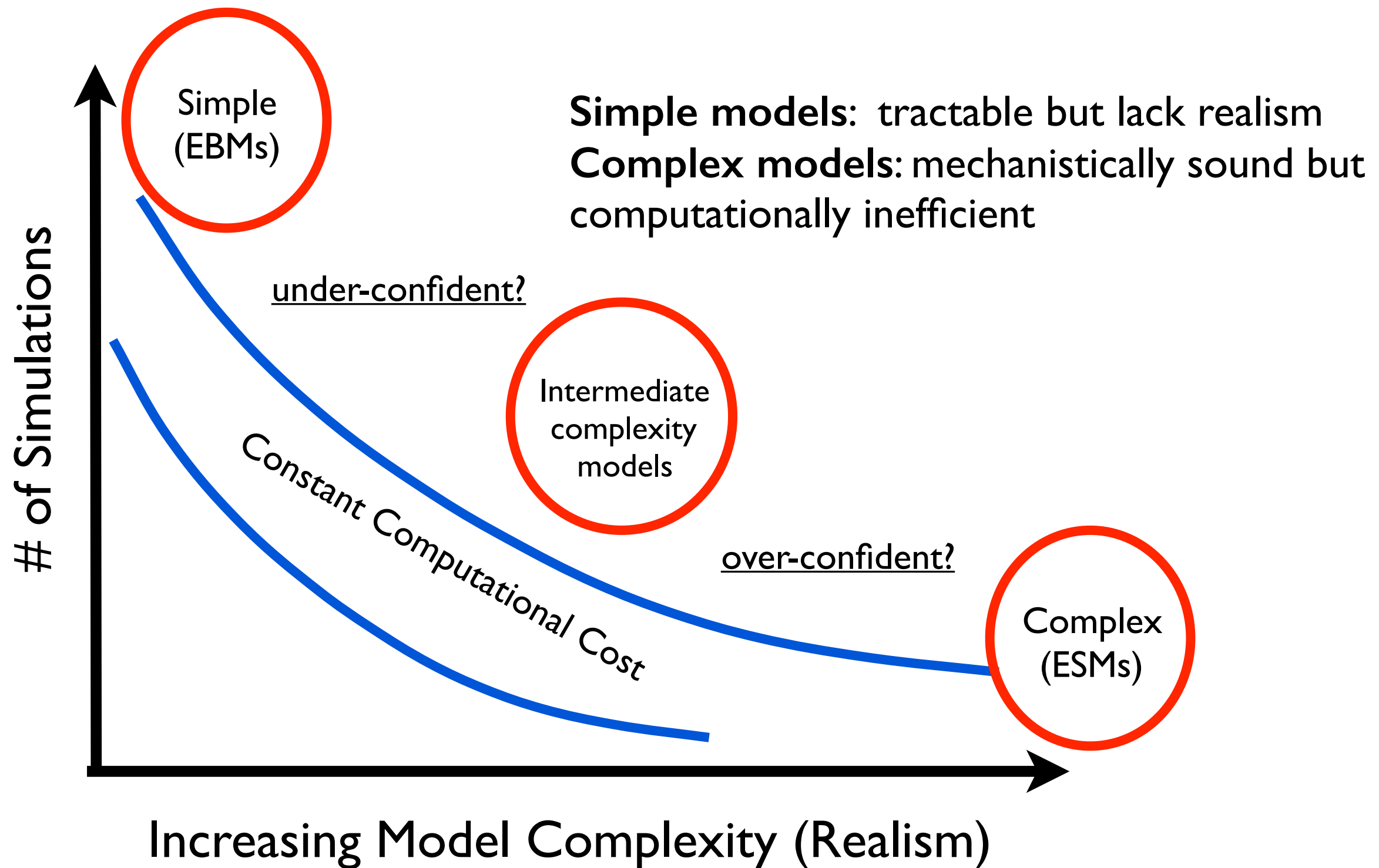
Global



Regional

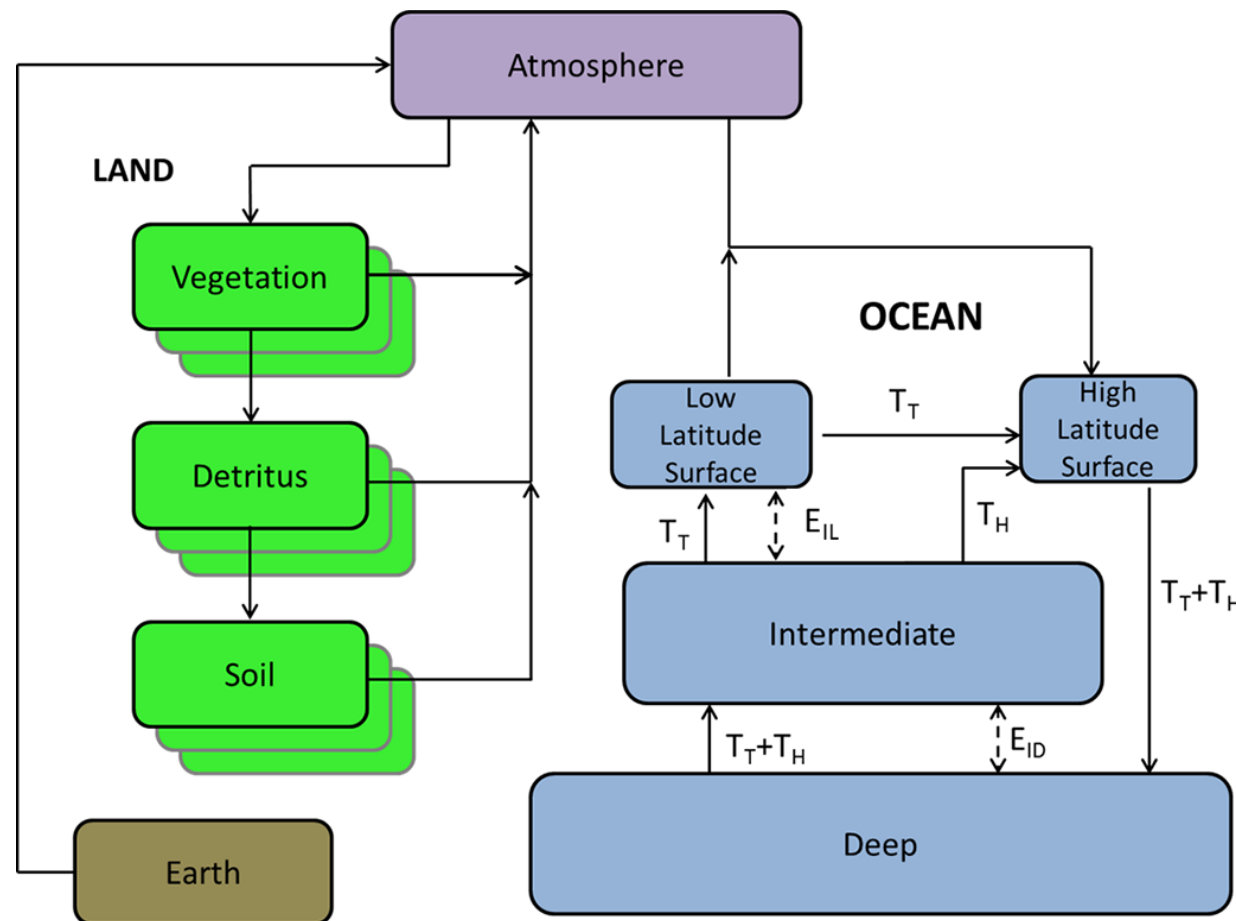
- Internal variability dominates on short timescales
 - Magnitude increases with decreasing spatial scale
- Forcing uncertainty increases with projection timescale (divergence in future scenarios)

Tradeoff between model realism and computational tractability



- Integrated Assessment requires probabilistic predictions with full treatment of uncertainty
- How do we achieve this given the tradeoffs between realism and tractability?

Hector Model



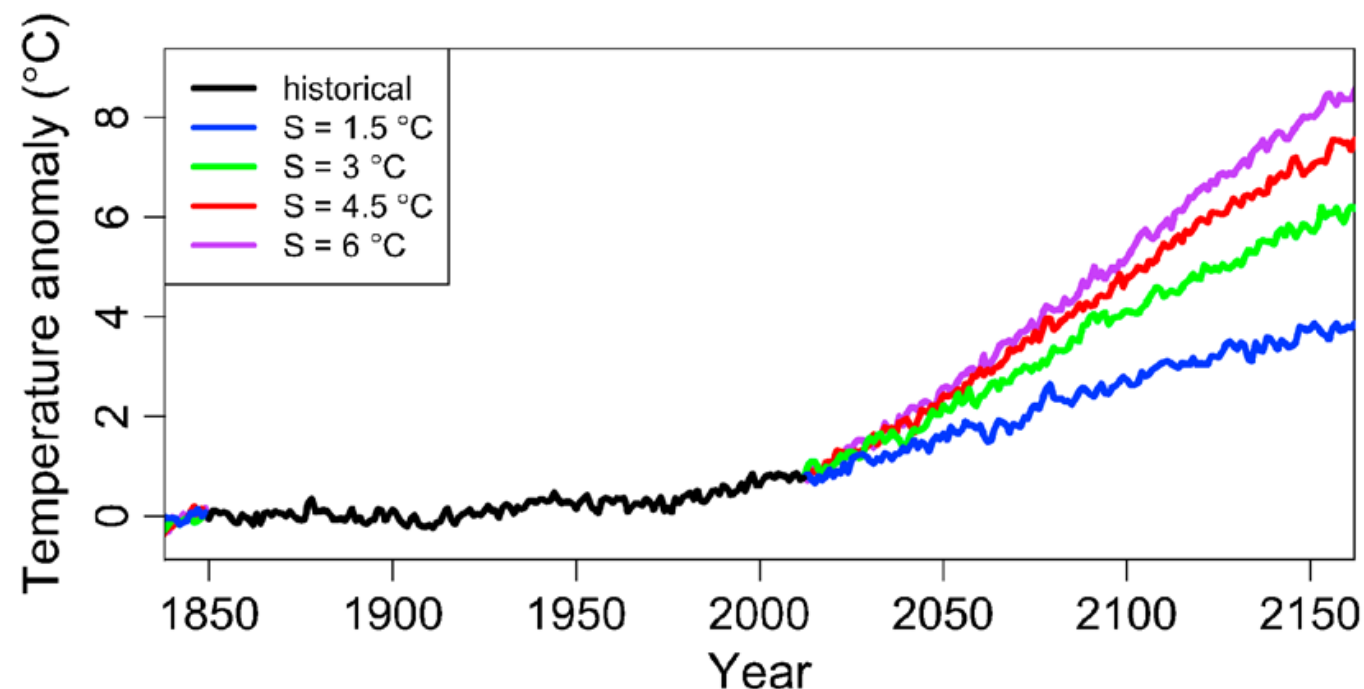
Open source, object- oriented, simple global climate carbon-cycle model

- Flexible and fast (runs in less than 1 second)
- Modular design with sub-components connected by a central coupler
- Three part carbon cycle: land, ocean, atmosphere
- Ocean consists of 4 separate boxes with transports and exchanges similar to thermohaline circulation

Hector is well-suited for uncertainty quantification given its flexibility, efficiency (speed), coupled carbon cycle, and connections to integrated assessment (climate component of GCAM)

Enhancements to Hector

- **Link Hector to a 1-D energy balance model (DOECLIM)**
 - represents ocean heat uptake as a diffusive process
 - contains 3 tunable (uncertain) parameters: **climate sensitivity, vertical ocean diffusivity, and aerosol scaling**
 - fits well with Hector's modular design (can be easily exchanged with Hector's current ocean model)
 - well-documented and widely used in UQ



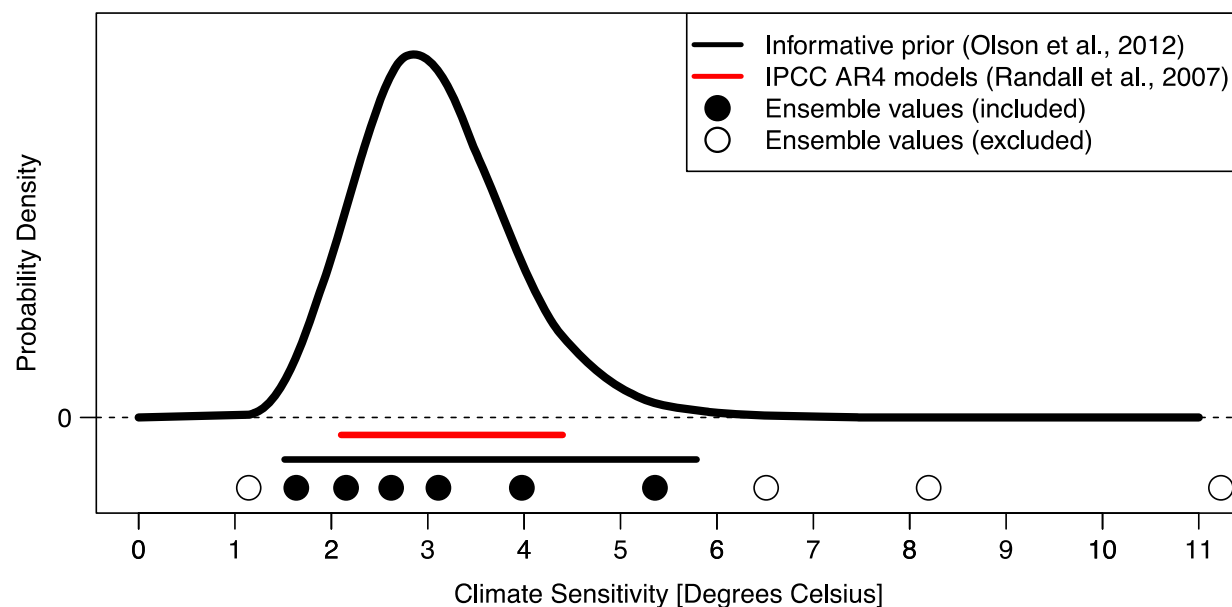
Parametric uncertainties can lead to divergence in climate projections, even when the model is fitted to historical observations

- Probabilistic assessments of climate change require careful consideration of parametric uncertainties, which are not adequately captured in CMIP

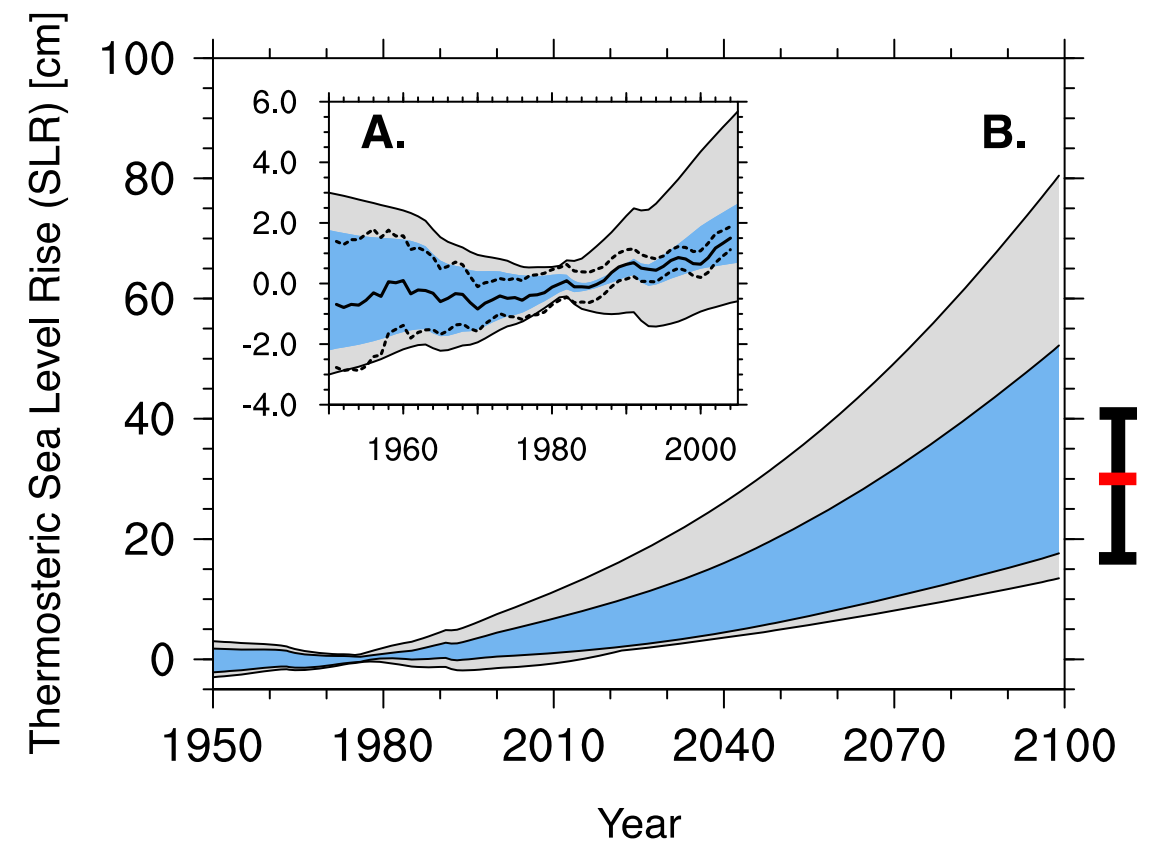
Uncertainty Quantification and model calibration

Pre-Calibration:

- Vary model parameters based on mechanistically-motivated prior parameter ranges
- Constrain projections using windowing approach based on observations
- Useful to identify parametric sensitivities/correlations and provides first-order bounds on climate projections



Sampling from a prior climate sensitivity pdf



Projections of thermometric sea-level rise using windowing (emphasizing upper bounds)

Uncertainty Quantification using Bayesian Inference

- We can characterize the joint uncertainty in model parameters using Bayesian inference
- Assigns probabilities to different combinations of model parameters based on how well those settings cause the model to reproduce the observed data

$$f(\theta | x) \sim f(x | \theta) f(\theta)$$

Probability of the
parameter given
the data
(posterior)

Probability of the
data given the
parameter
(likelihood)

Probability of the
parameter based
on prior info
(prior)

- We can sample the parameter posterior distribution using Markov Chain Monte Carlo (MCMC)
 - using a likelihood function based on the data and a prior distribution based on our prior knowledge about the parameter

Markov Chain Monte Carlo (MCMC)

Markov Chain:

- Mathematical system that undergoes random state changes
- Each state depends only on the previous state
 - random walk (example of brownian motion)

Monte Carlo:

- Computational algorithm using random resampling

General Method to MCMC:

- Choose initial set of model parameter settings
- Randomly perturb the parameters and calculate the posterior
- If the new combination of parameters yields a better fit to the data, keep those settings
- If the new combination of parameters yields a worse fit to the data, then either keep the settings or perturb the parameters and try again
 - likelihood of keeping the settings depends on how much worse the model fits the data from previous combination
- Repeat steps 2 through 4

MCMC chains will “converge” to yield a random sampling of the posterior distributions of model parameters

MCMC Advantages and Disadvantages

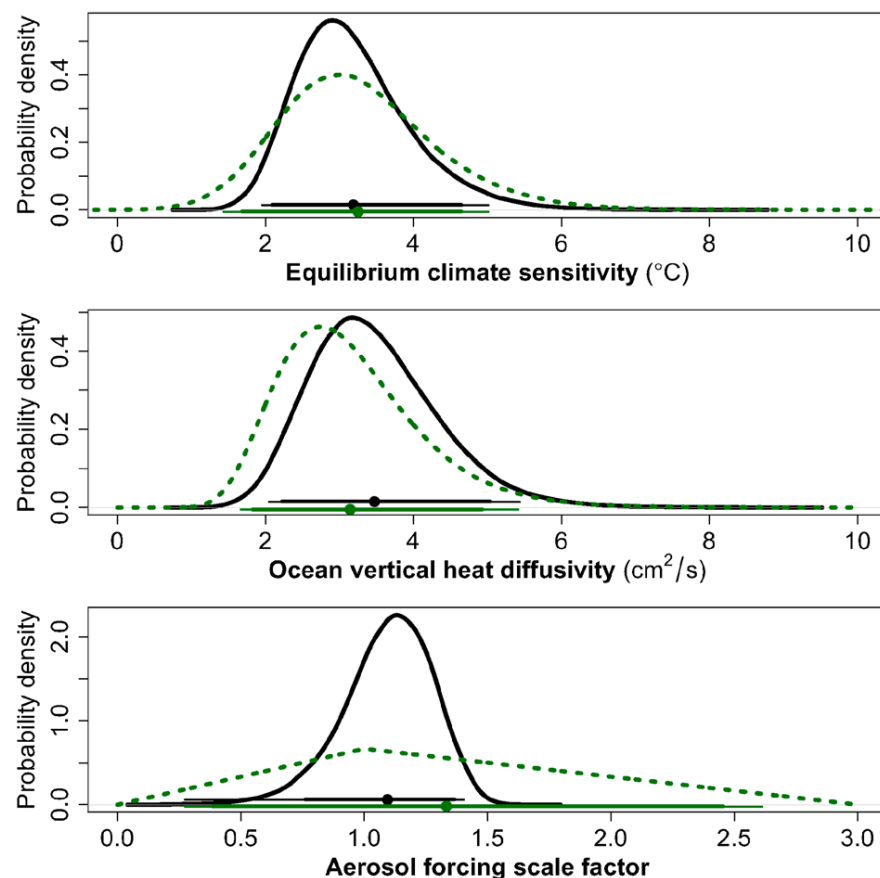
Advantages:

- multi-dimensional
- applicable to joint pdf or marginals
- simple to implement

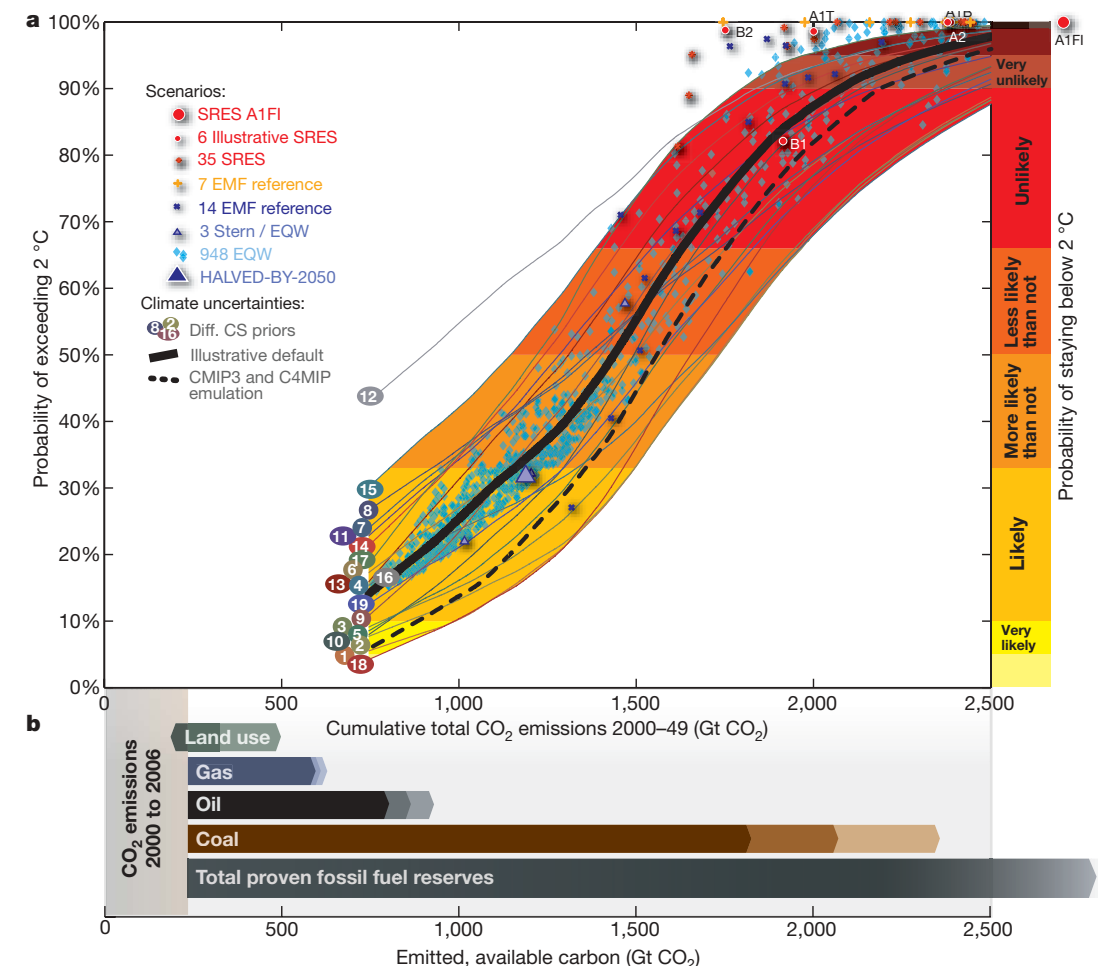
Challenges:

- computationally intensive
- can be difficult to assess convergence
- constructing the likelihood function
- how to choose the prior?
- multi-modal pdfs?

Bayesian parameter estimation enables probabilistic constraints on climate projections



Urban et al., 2014



Meinshausen et al., 2009

Final Thoughts

This project centers on Hector model development, uncertainty quantification, and probabilistic climate projections, at the interface of climate science and integrated assessment

Some projected outcomes:

- New enhancements to Hector featuring incorporation of a diffusive ocean module and sea-level rise module that accounts for thermometric and land ice contributions
- Expanded modeling framework utilizable for perturbed physics ensemble studies
 - building from recent work by Corinne Hartin et al.
- Incorporation of new MCMC tools for model calibration, parameter estimation, and probabilistic projections (**characterizing the tails**)

Some potential applications:

- Intercomparisons with other intermediate complexity climate models (Magicc, MIT IGSM, etc.) including carbon cycle uncertainties and feedbacks
- Broader-scale connections within GCAM