Warming caused by cumulative carbon emissions: the trillionth tonne

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Myles Allen

Department of Physics, University of Oxford

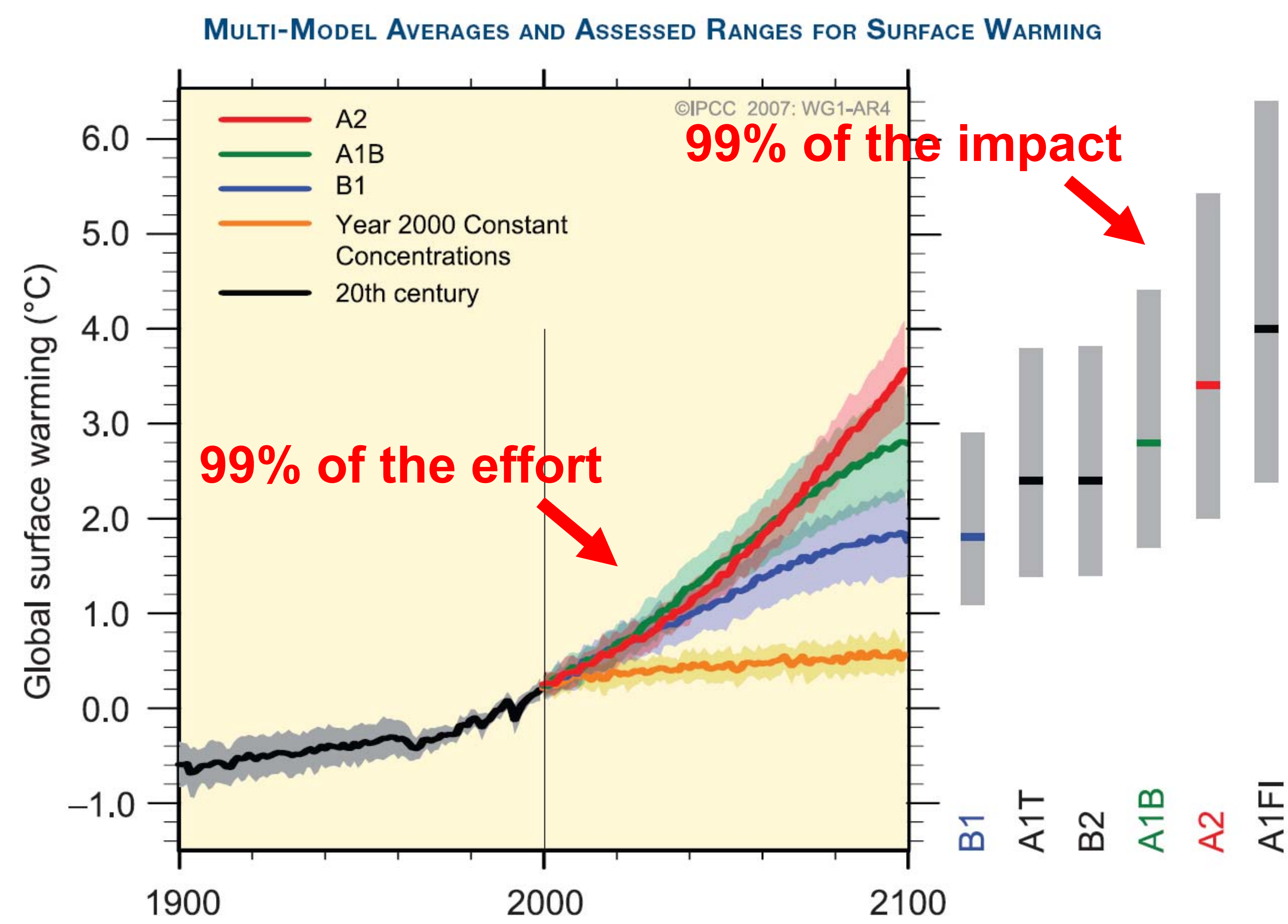
myles.allen@physics.ox.ac.uk

David Frame, Chris Huntingford, Chris Jones, Jason Lowe, Malte Meinshausen & Nicolai Meinshausen

Sources of uncertainty in climate forecasting

- **Initial condition uncertainty:**
  - Technically irrelevant to *climate* forecasts, but important because distinction between internal state and boundary conditions is fuzzy: is the Greenland ice cap part of the weather, or a boundary condition on the climate?
- **Boundary condition uncertainty:**
  - Natural (solar and volcanic) forcing: poorly known, but conceptually straightforward.
  - Anthropogenic (mostly greenhouse gas emissions): all muddled up in politics, but Somebody Else's Problem.
- **Response uncertainty, or "model error":**
  - The subject of this lecture.

A recent failure of climate modelling



What is the aim of climate modeling?

- Recent Reading conference called for $1bn "revolution in climate modeling".
- How do we know when the revolution is over?
  - When we have a 25km resolution global climate model.
  - When we have a 1km resolution global climate model.
  - When we don't need to parameterize clouds.
  - When we have a bigger computer than the weapons developers.
- Or:
  - When, no matter how we perturb our climate models, the distribution of future climates consistent with observations of past and current climate is the same.

The conventional Bayesian approach to probabilistic climate forecasting

$$P(S \mid y) = \int_\theta P(S \mid \theta)\, P(\theta \mid y)\, d\theta$$

$$= \int_\theta P(S \mid \theta)\, \frac{P(y \mid \theta)\, P(\theta)}{P(y)}\, d\theta$$

S **quantity predicted by the model, e.g. "climate sensitivity"**

θ **model parameters, e.g. diffusivity, entrainment coefficient etc.**

y **observations of model-simulated quantities e.g. recent warming**

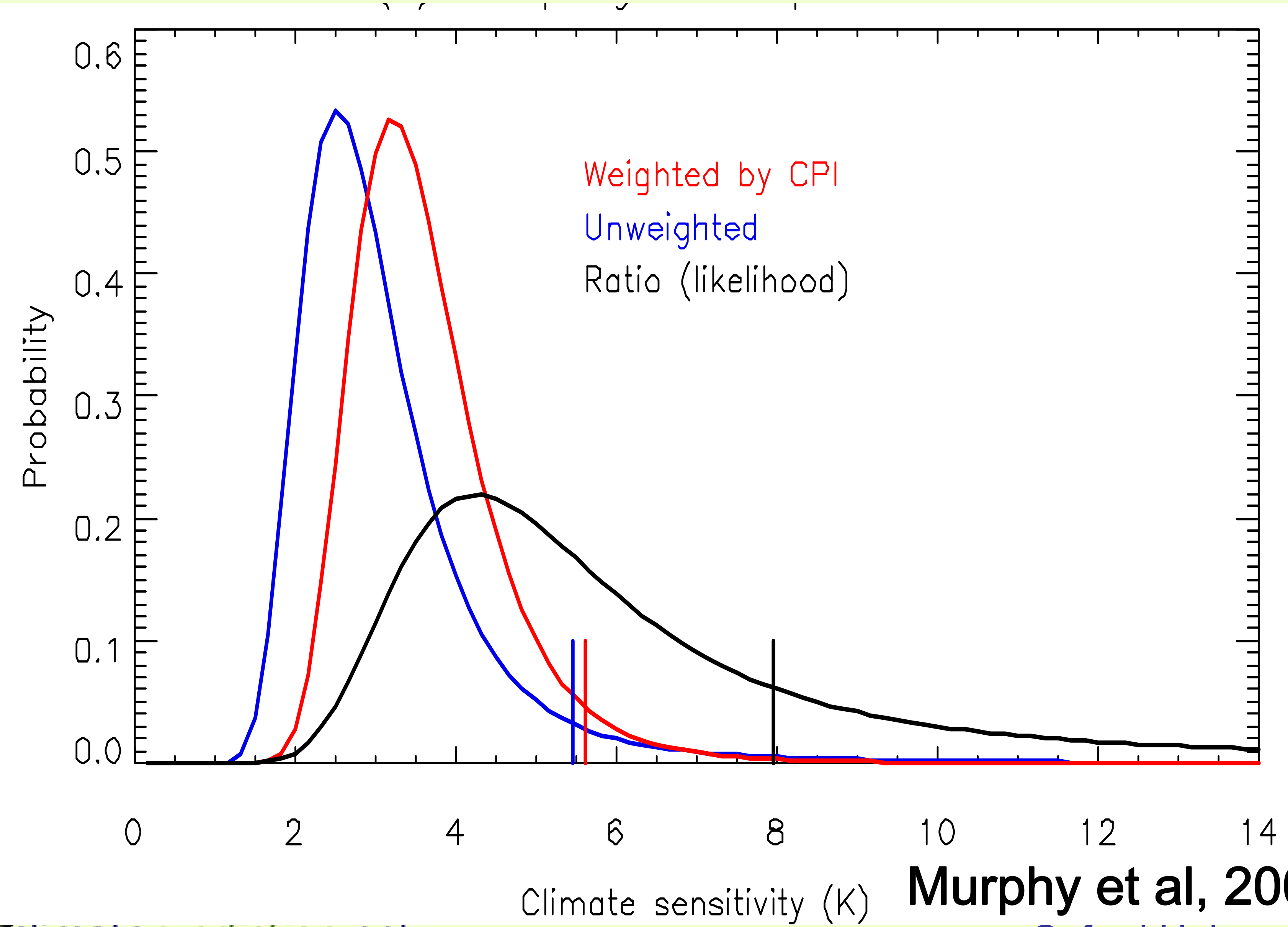
$P(y|\theta)$ **likelihood of observations y given parameters θ**

$P(\theta)$ **prior distribution of parameters θ**

Simple models: $P(S|\theta)=1$ **if parameters θ gives sensitivity S**

$P(S|\theta)=0$ **otherwise**

Bayesian approach: sample parameters, run ensemble, “emulate” & weight by fit to observations



Murphy et al, 2004

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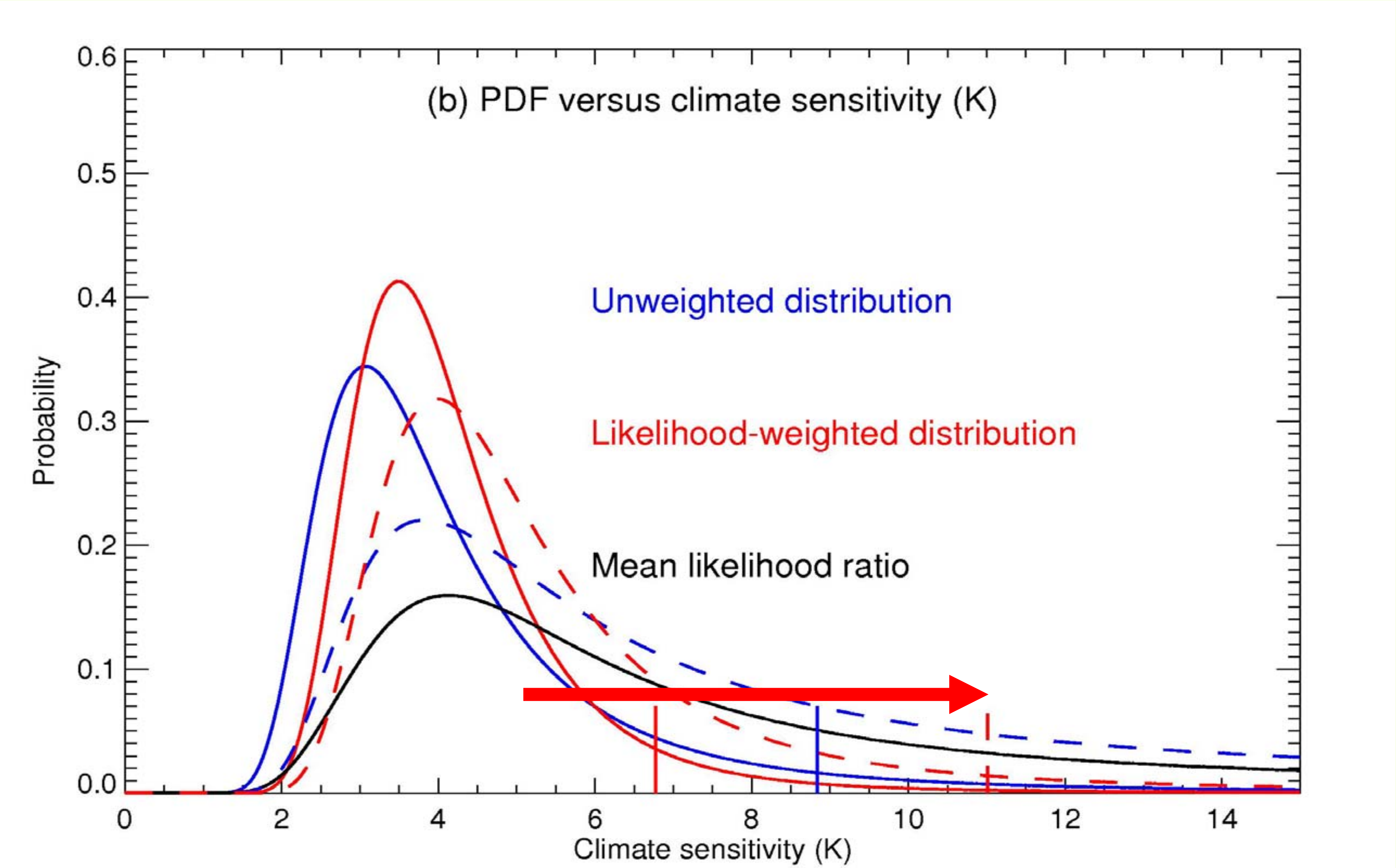
Adopting alternative plausible parameter sampling designs has a big impact on results



Why the standard Bayesian approach won't *ever* work

- Sampling a distribution of "possible models" requires us to define a distance between two models in terms of their input parameters & structure, a "metric for model error".
- As long as models contain "nuisance parameters" that do not correspond to any observable quantity, this is impossible in principle: definition of these parameters in the model is arbitrary.

Why we need a different approach

- There's no such thing as a neutral or uninformative prior in this problem.
- Very difficult to avoid impression that investigators are subject to external pressures to adopt the "right" prior (the one that gives the answer people want).
- Highly informative priors obscure the role of new observations, making it very difficult to make "progress" (the 1.5-4.5K problem).
- So what is the alternative?

A more robust approach: compute *maximum* likelihood over all models that predict a given S

$$L_1(S \mid y) = \max_\theta P(S \mid \theta)\, P(y \mid \theta)$$

$P(S|\theta)$ picks out models that predict a given value of the forecast quantity of interest, e.g. climate sensitivity.

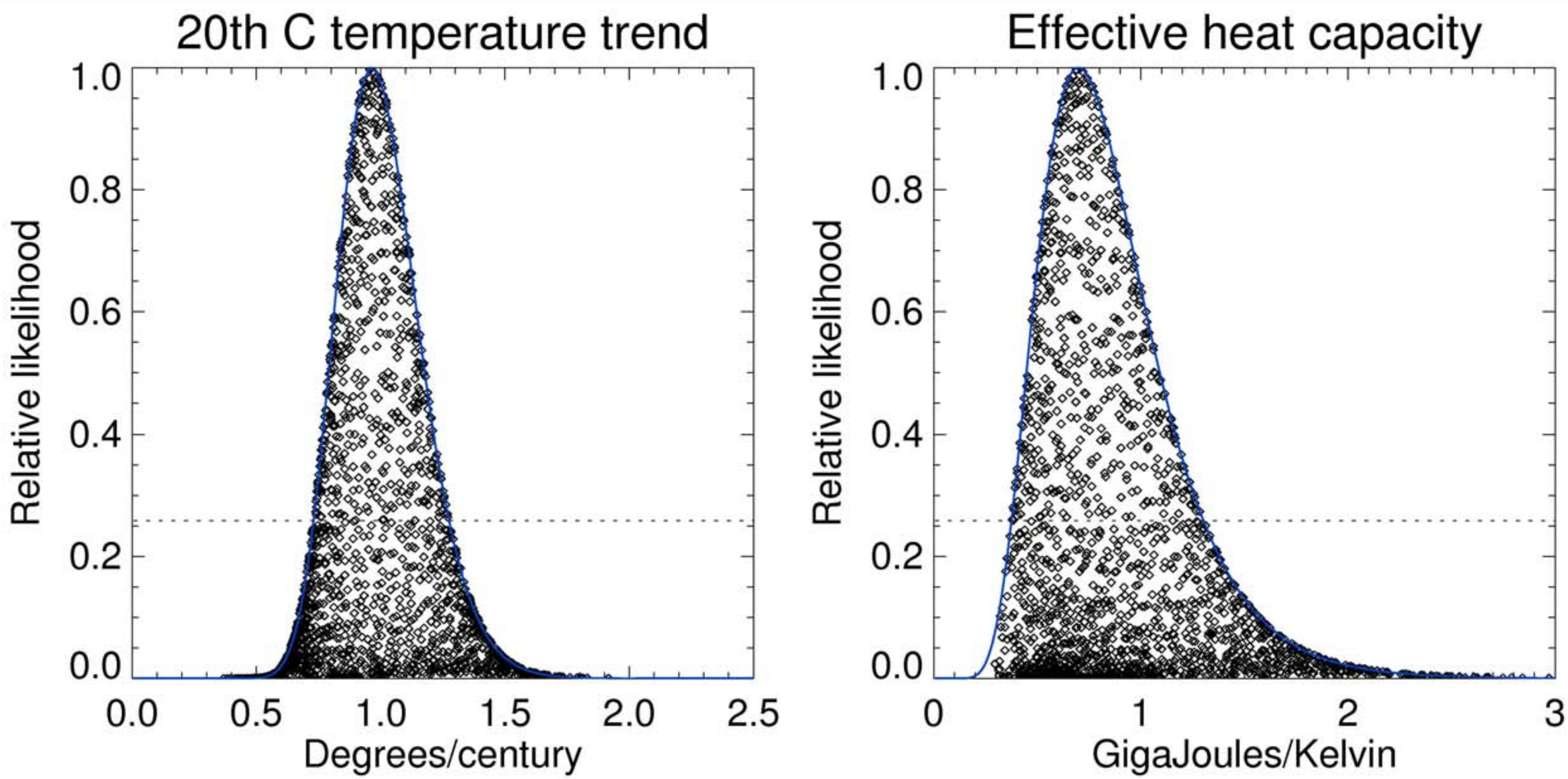
$P(y|\theta)$ evaluates their likelihoods.

Likelihood profile, $L_1(S|y)$, is proportional to relative likelihood of most likely available model as a function of forecast quantity.

Likelihood profiles follow parameter combinations that cause likelihood to fall off as slowly as possible with S: the "least favourable sub-model" approach.

$P(\theta)$ does not matter. Use any sampling design you like as long as you find the likelihood maxima.

Generating models consistent with quantities we can observe…



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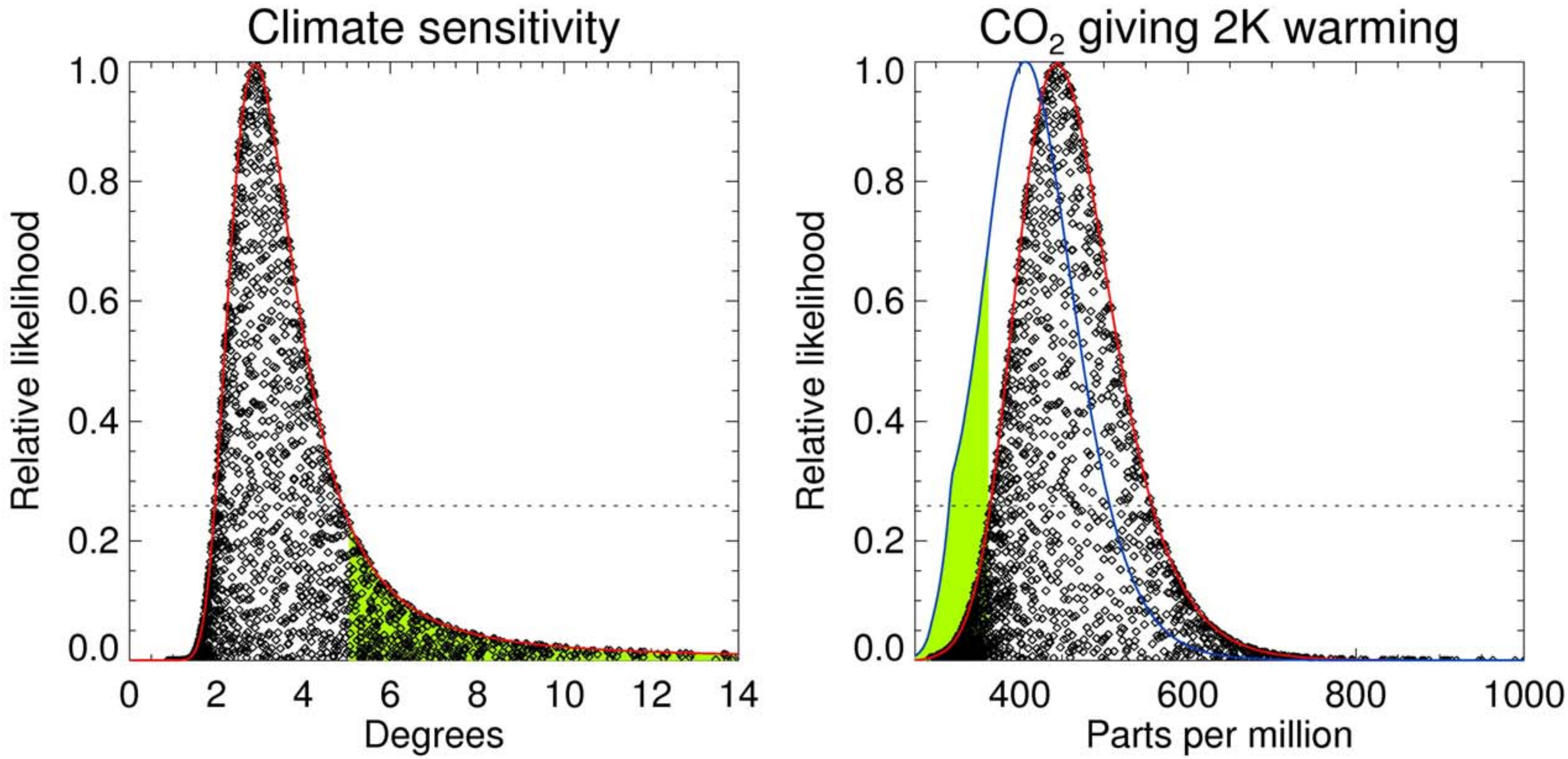
…and mapping their implications for quantities we wish to forecast.



Note: only the outline (likelihood profile) matters, not the density of models. Hence we avoid the metric-of-model-error problem.

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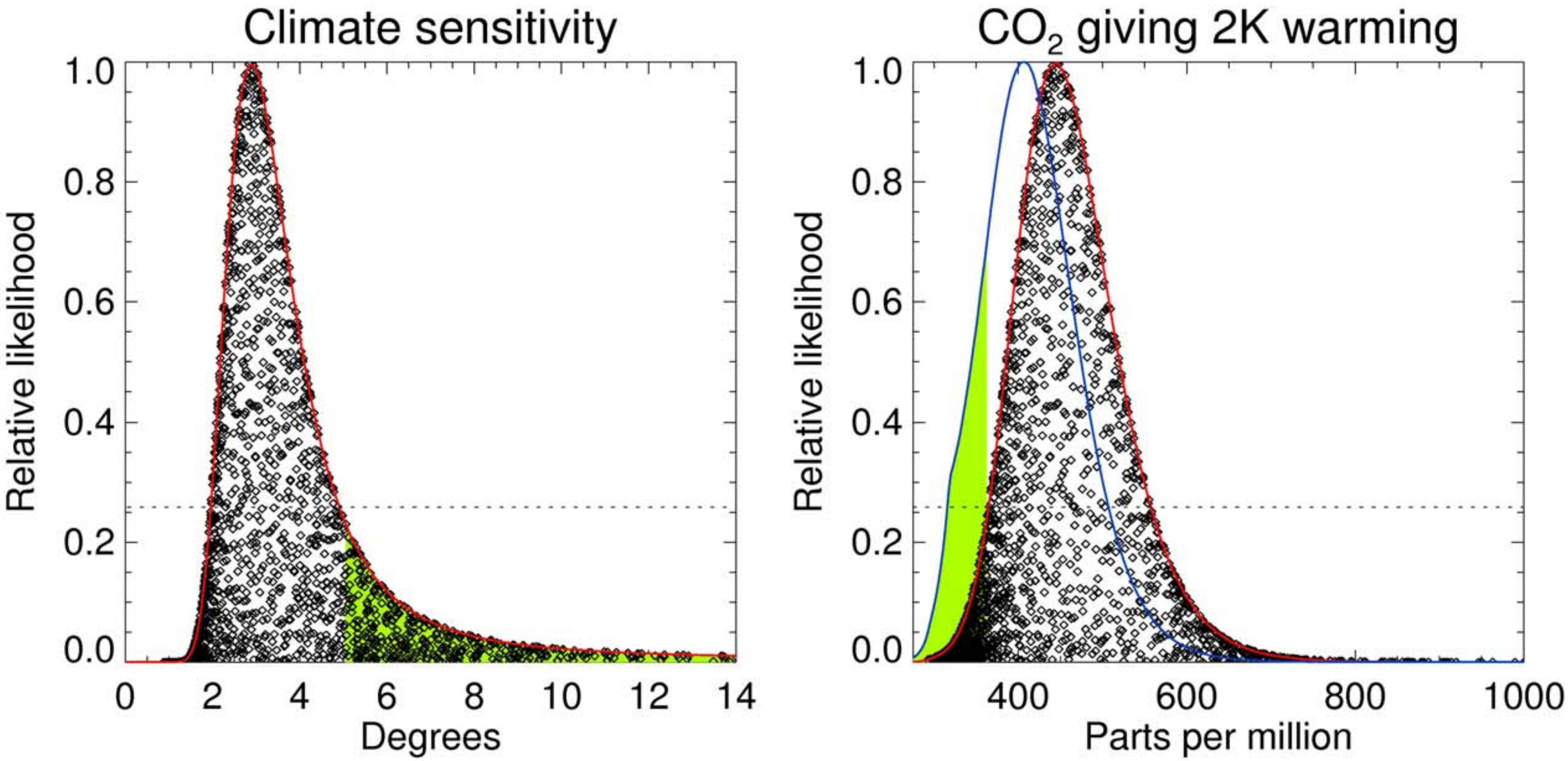
This gives confidence intervals, not PDFs



Non-linear relationship between climate sensitivity and CO_2 concentrations giving 2K warming.
Straightforward to generate conventional confidence intervals.
Consistent posterior PDFs require a consistent, and one-way-or-the-other informative, prior.

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The problem with equilibrium climate sensitivity…

- …is that it is not related linearly to anything we can observe, so any forecast distribution is inevitably dependent on arbitrary choices of prior.
- Conventional policy of specifying stabilization targets appears to require a distribution of climate sensitivity.
- Is there an alternative way of approaching the long-term climate forecast which is less sensitive to these issues?

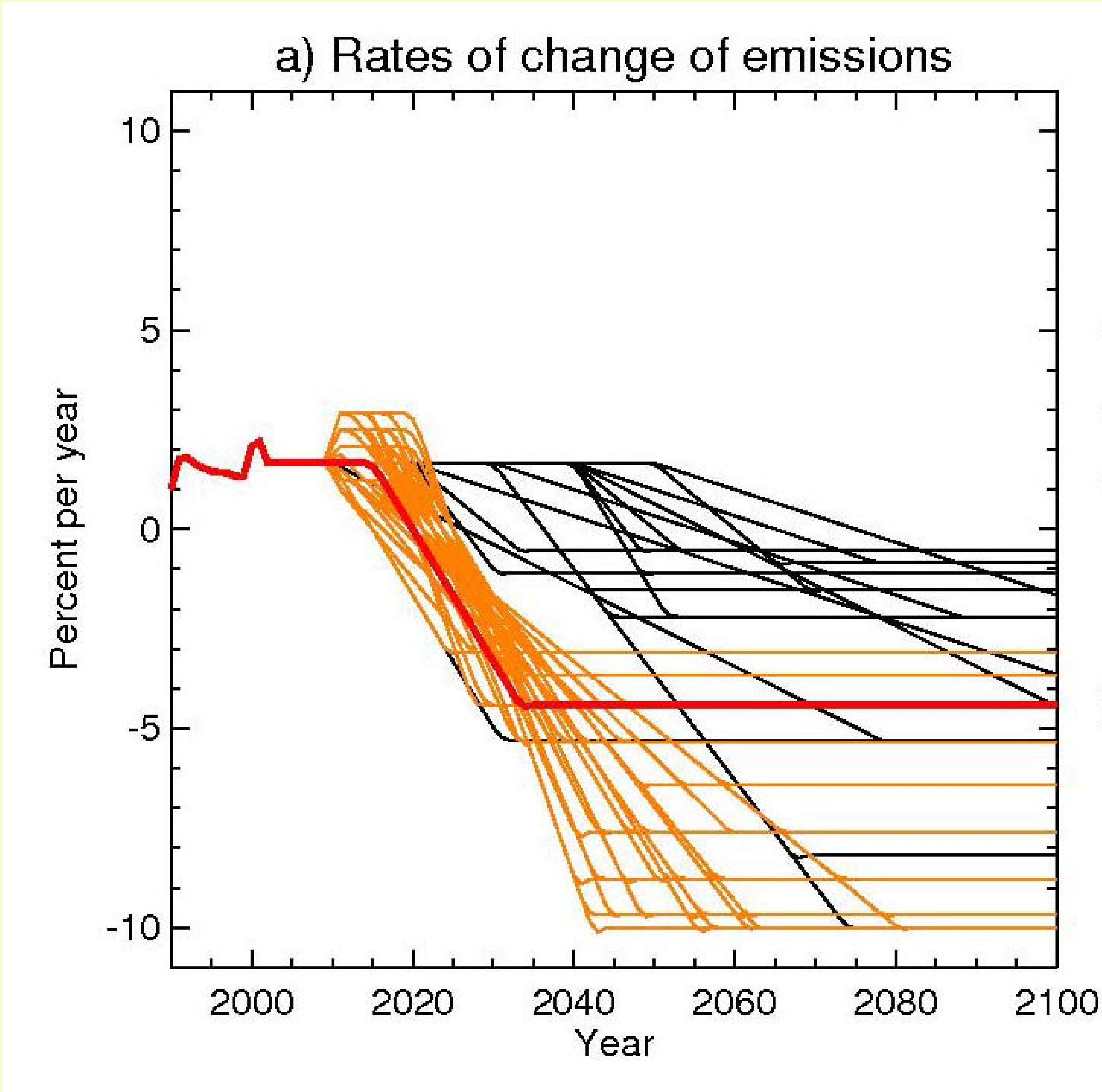
What would it take to avoid dangerous levels of warming?

Nature, April 30th 2009

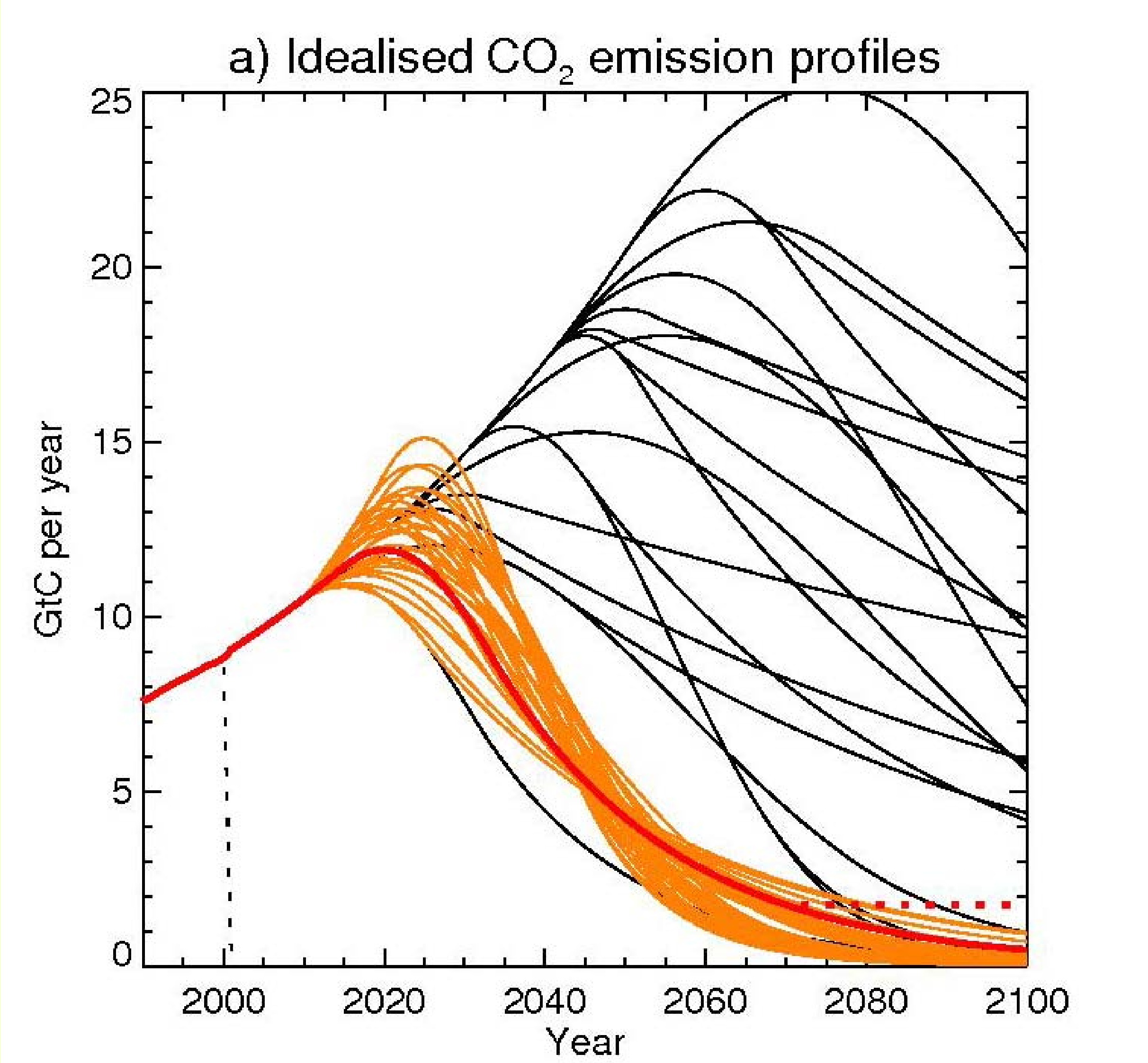
Summary of the study

- Generate idealised CO_2 emission scenarios varying:
  - Initial rate of exponential growth from 2010 (1-3%/year).
  - Year in which growth begins to slow down (2012 to 2050).
  - Rate at which growth slows and reverses.
  - Maximum rate of emission decline (up to -10%/year).
  - Exponential decline continues indefinitely (or until temperatures peak).
- Simulate response using simple coupled climate carbon-cycle models constrained by observations.
- Identify factors that determine “damage”, defined as:
  - Peak warming over pre-industrial (relevant to ecosystems).
  - Average warming 2000-2500 (relevant to ice-sheets).
  - Warming by 2100 (relevant to IPCC).

A simple recipe for mitigation scenarios

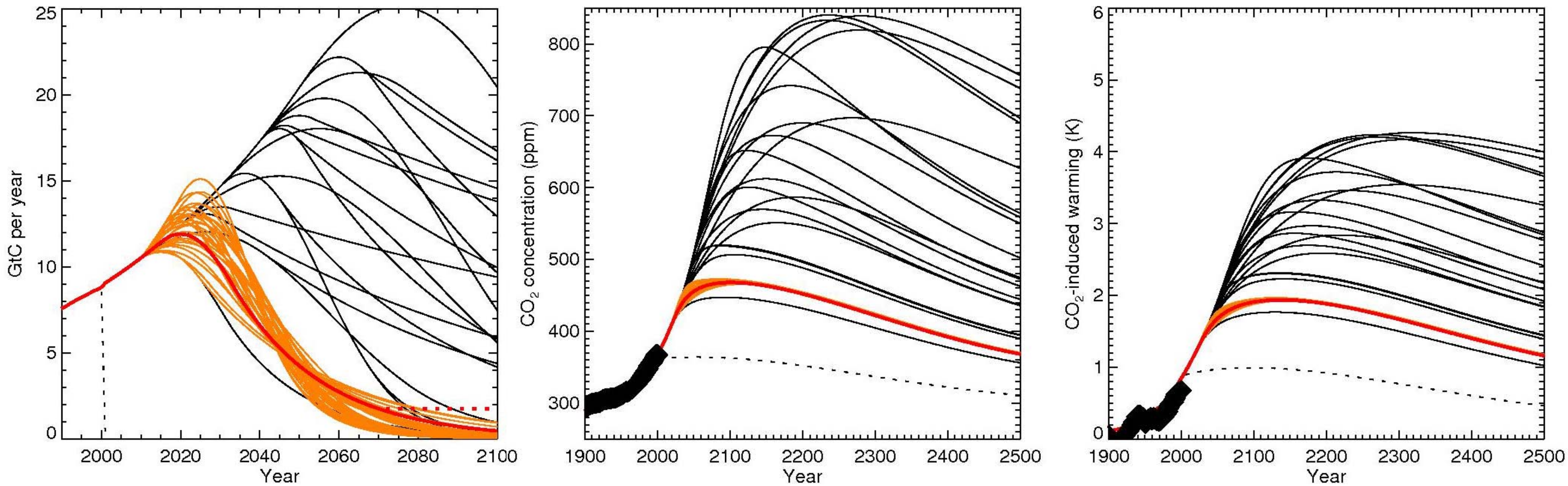


Red and orange scenarios all have cumulative emissions of 1TtC (=1EgC=3.7TtCO_2)



Timing and size of emission peak does not *in itself* determine peak warming

Emissions **CO_2 concentrations** **CO_2-induced warming**



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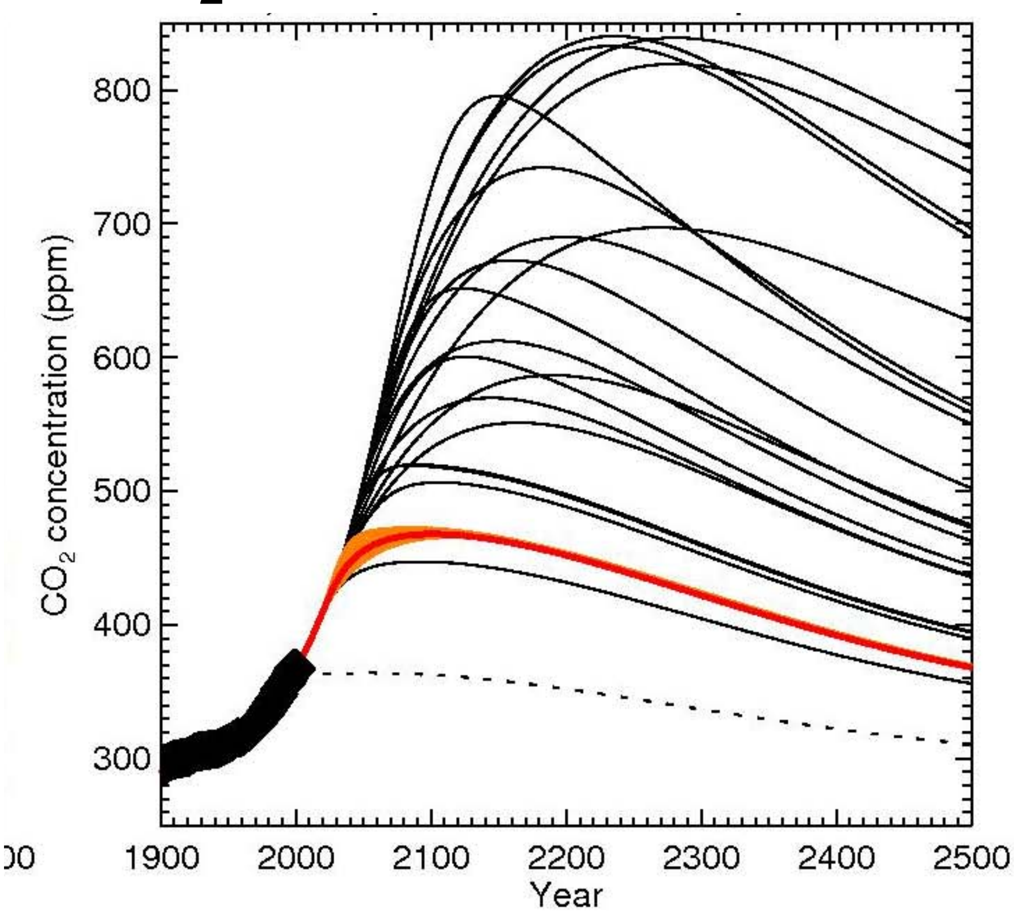
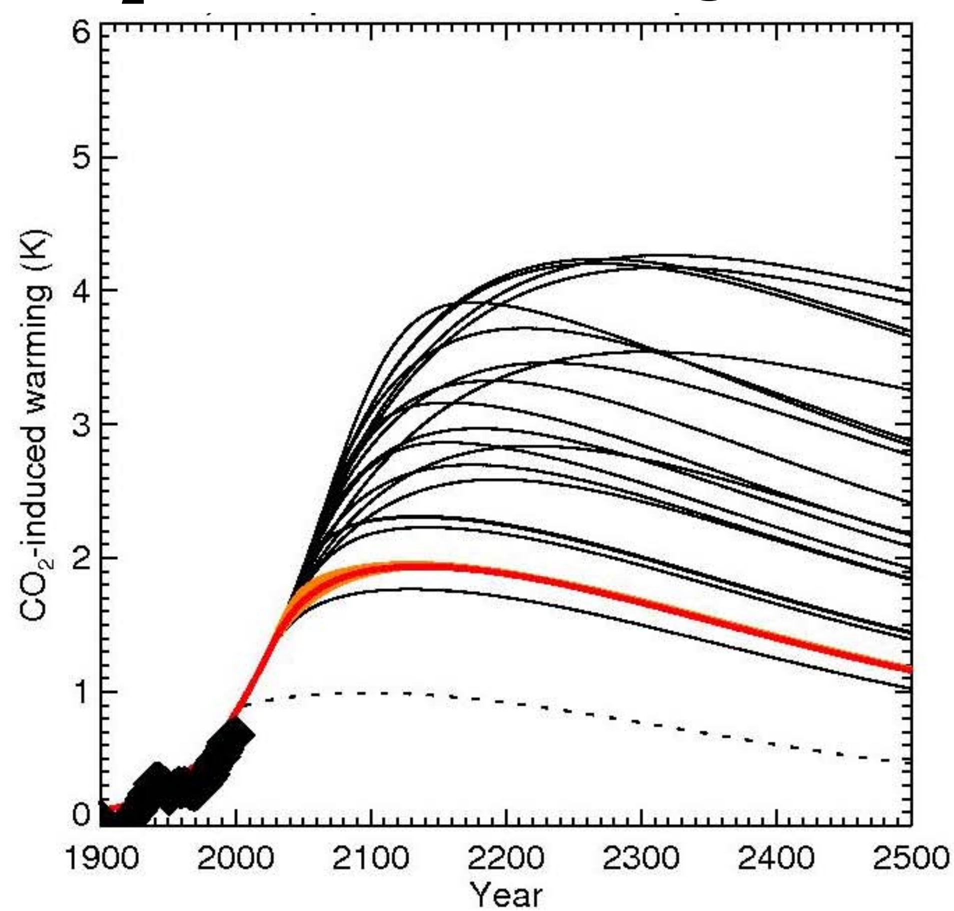
Response with best-fit model parameters

CO_2 concentrations



CO_2-induced warming



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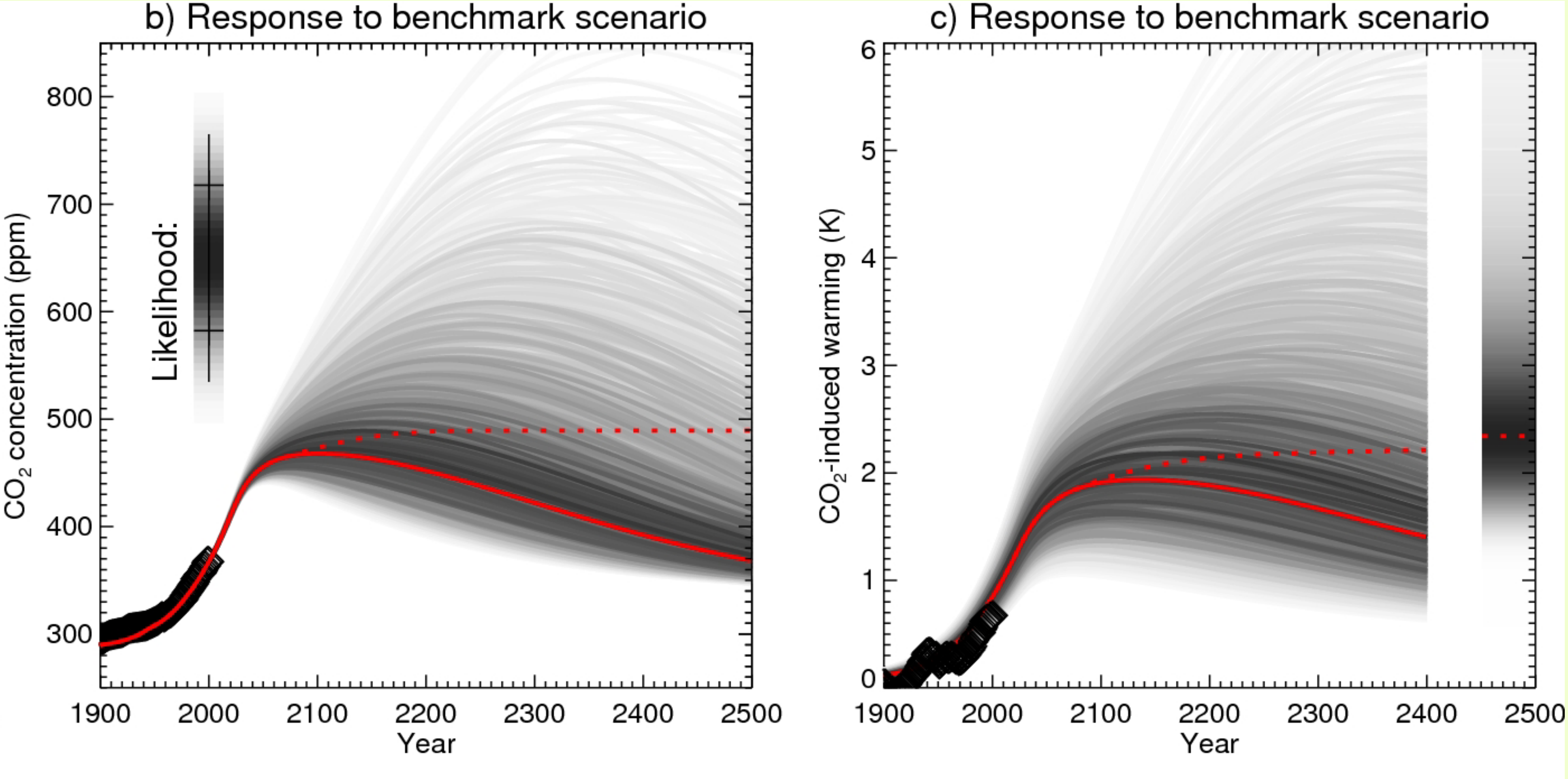
Uncertainty in the response dwarfs the impact of timing of emissions or size of emission peak



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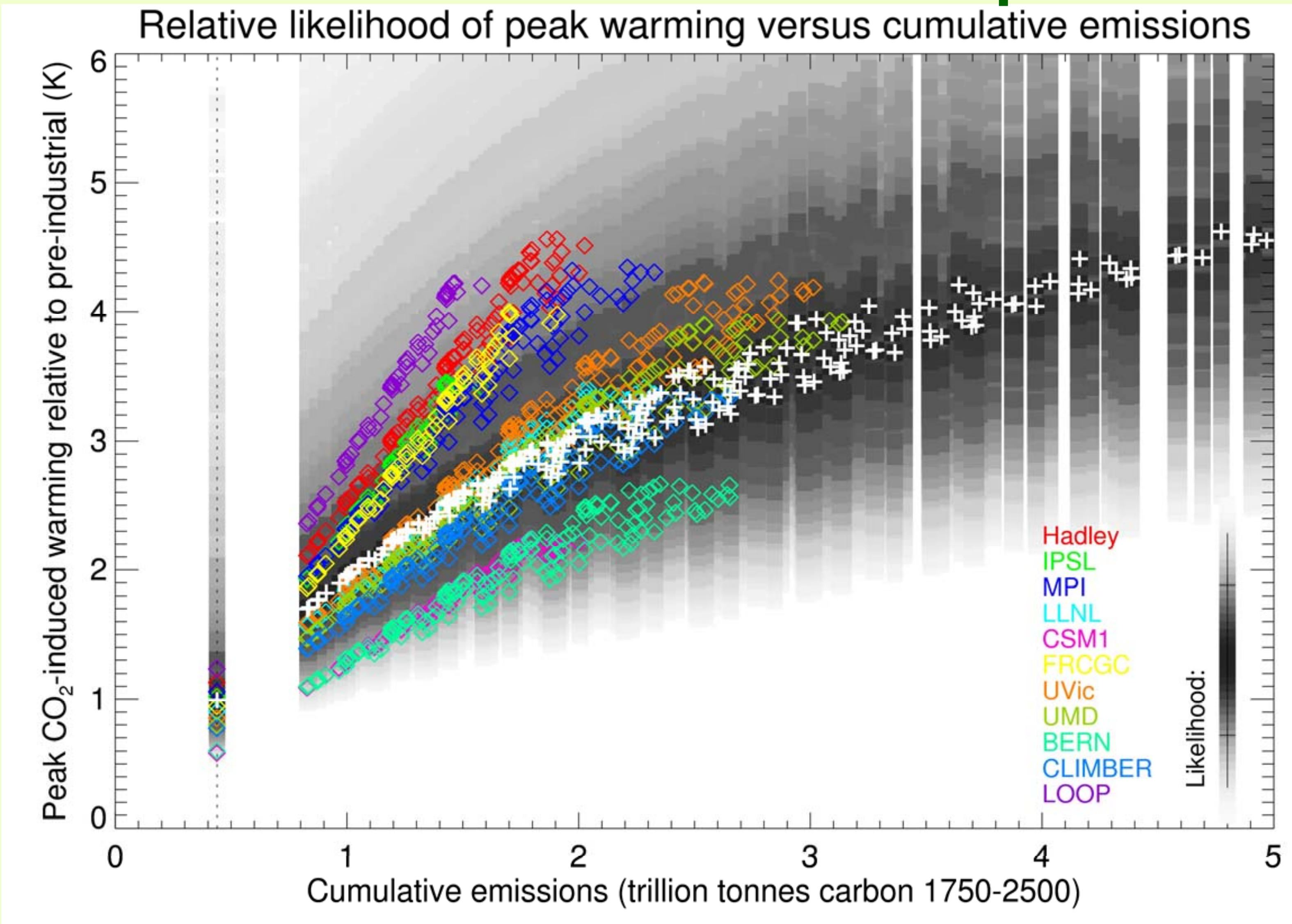
Peak warming is determined by total amount of carbon released into the atmosphere…



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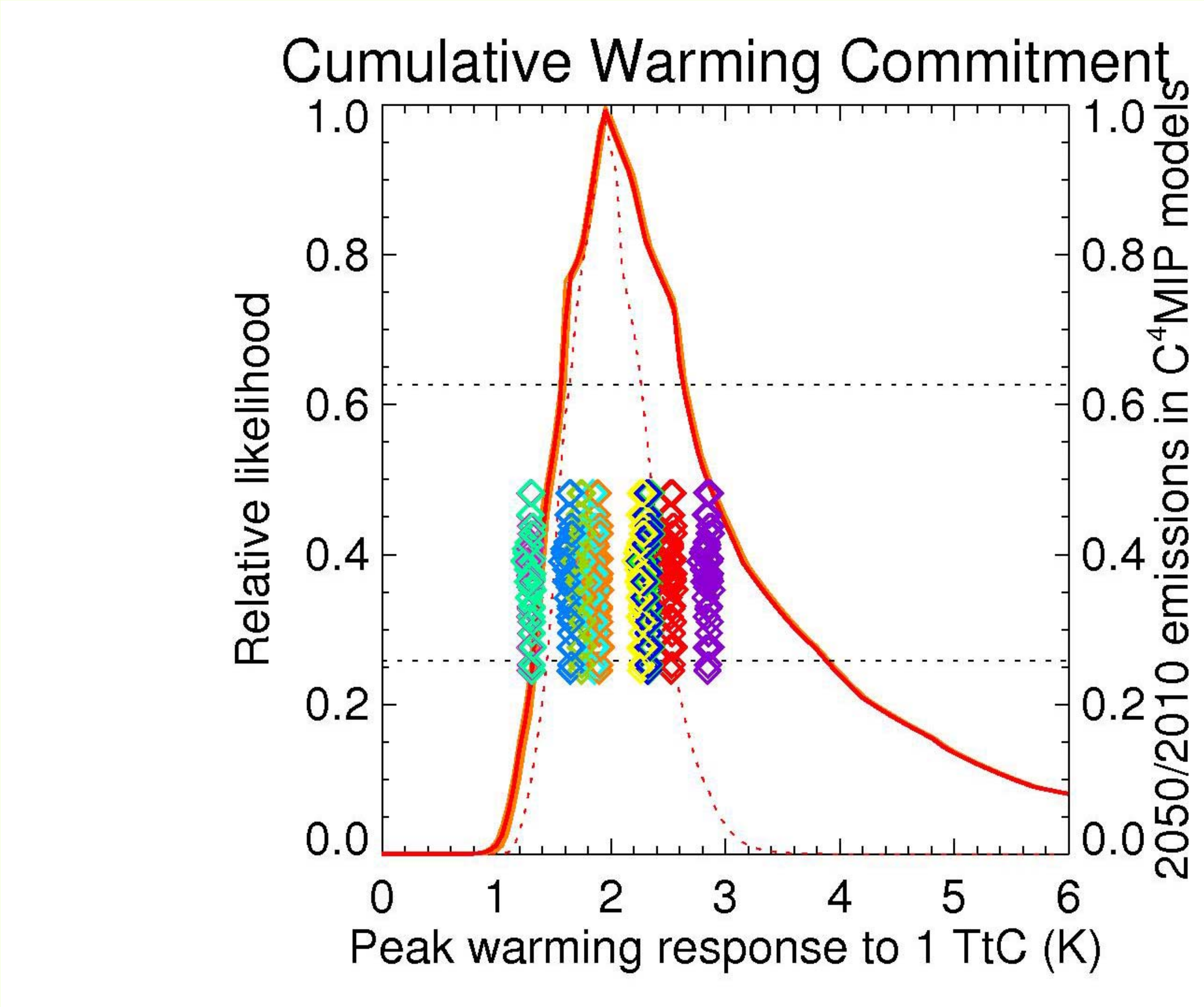
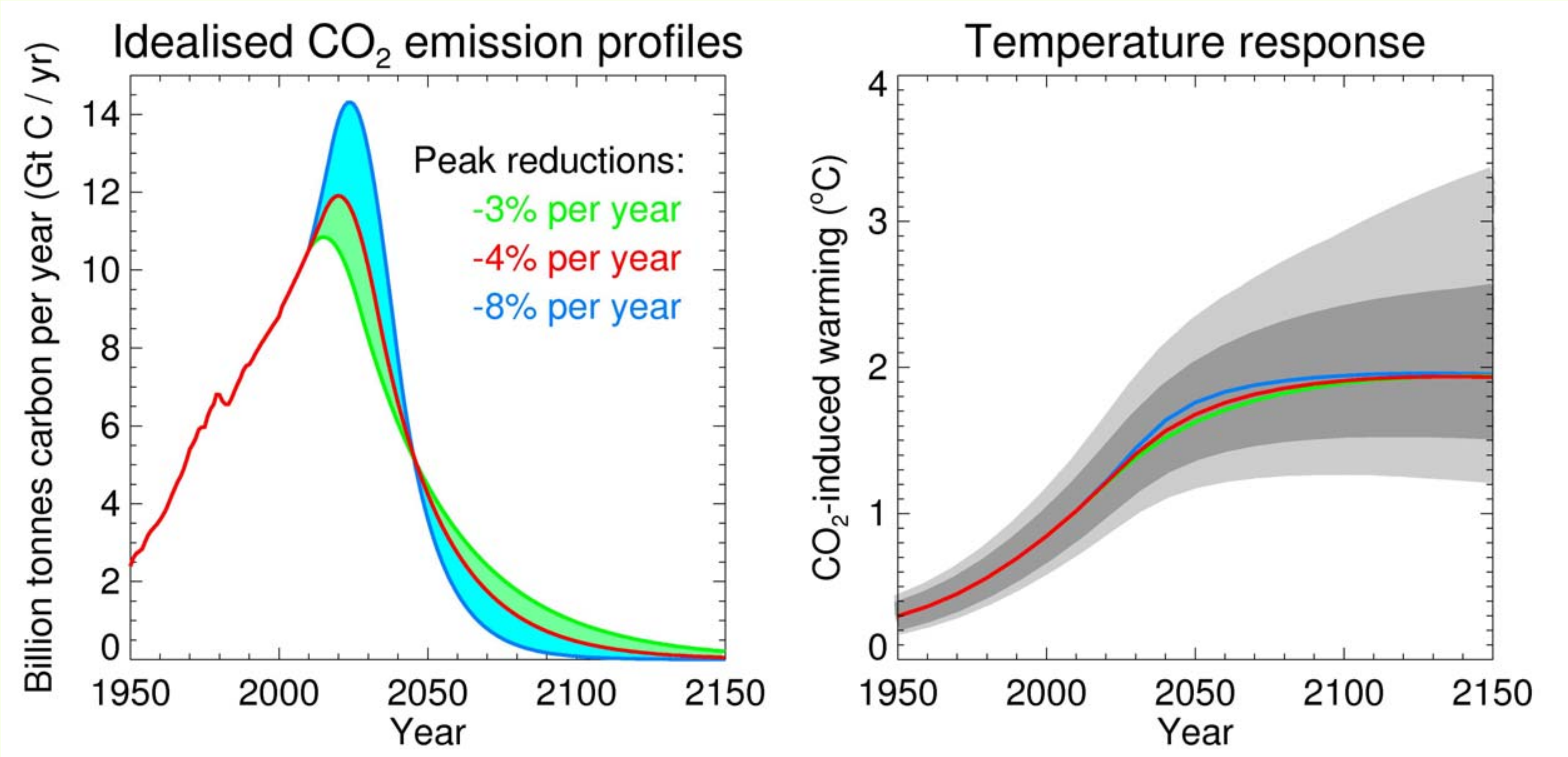
…not by emissions in 2050

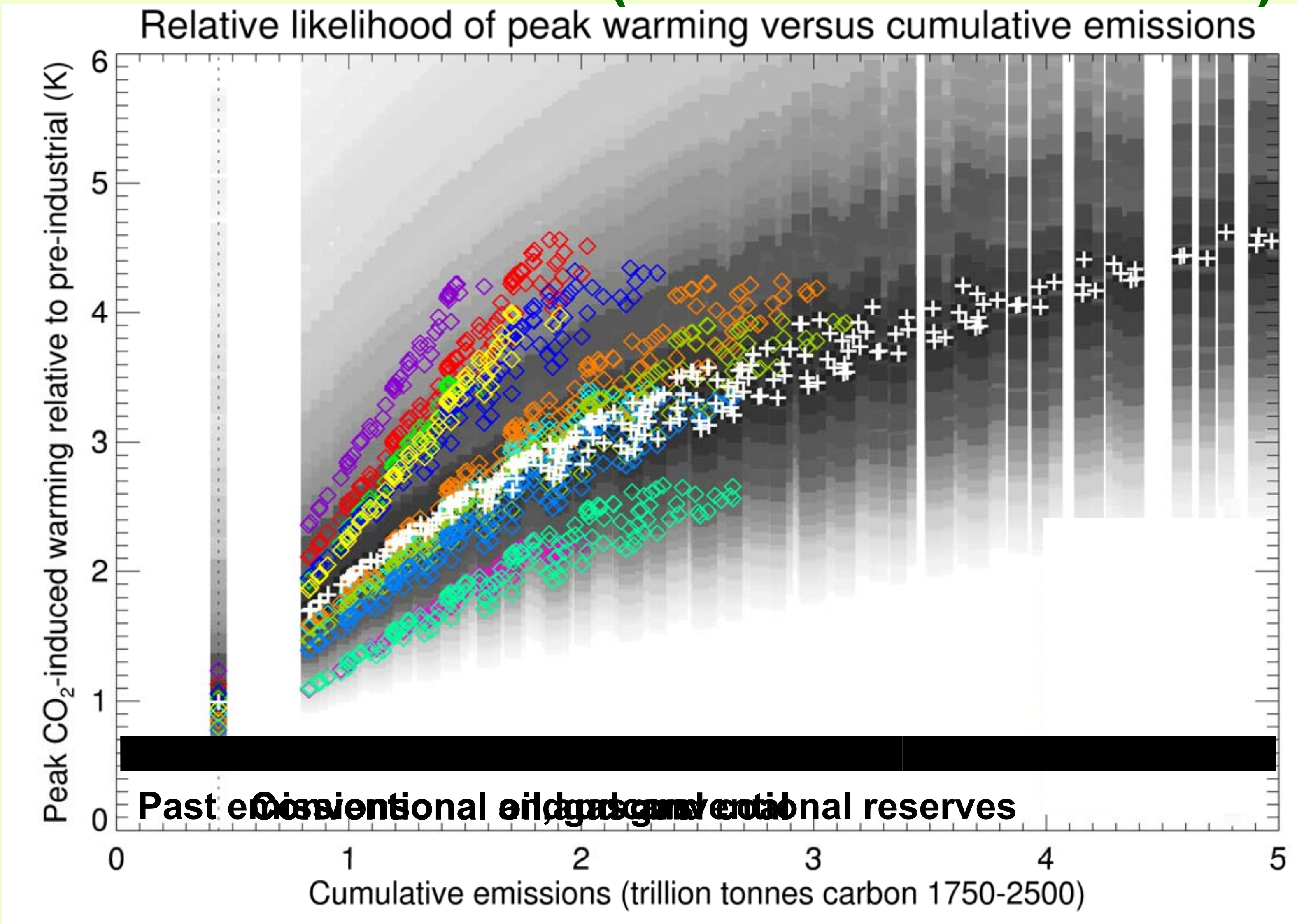


Implications: are we debating the wrong thing?

- **Warming caused by CO_2 depends on cumulative emissions, not emissions in 2020 or 2050.**
- **Releasing carbon slower makes little difference to climate (but a big difference to cost of mitigation).**



How cumulative emissions stack up against fossil fuel reserves (IPCC AR4 estimates)



Conclusions & links to other studies

- Cumulative CO_2 emissions over the entire anthropocene determine peak CO_2-induced warming.
- Warming response to cumulative emissions is constrained by past CO_2 increase and CO_2-induced warming. You do *not* need to know the:
  - Equilibrium climate sensitivity.
  - Long term target GHG stabilisation level.
  - Date and size of emission peak, or details of emission path (2000-2050 emissions determine total for most low scenarios).
- 1TtC gives most likely CO_2-induced warming of 2°C.

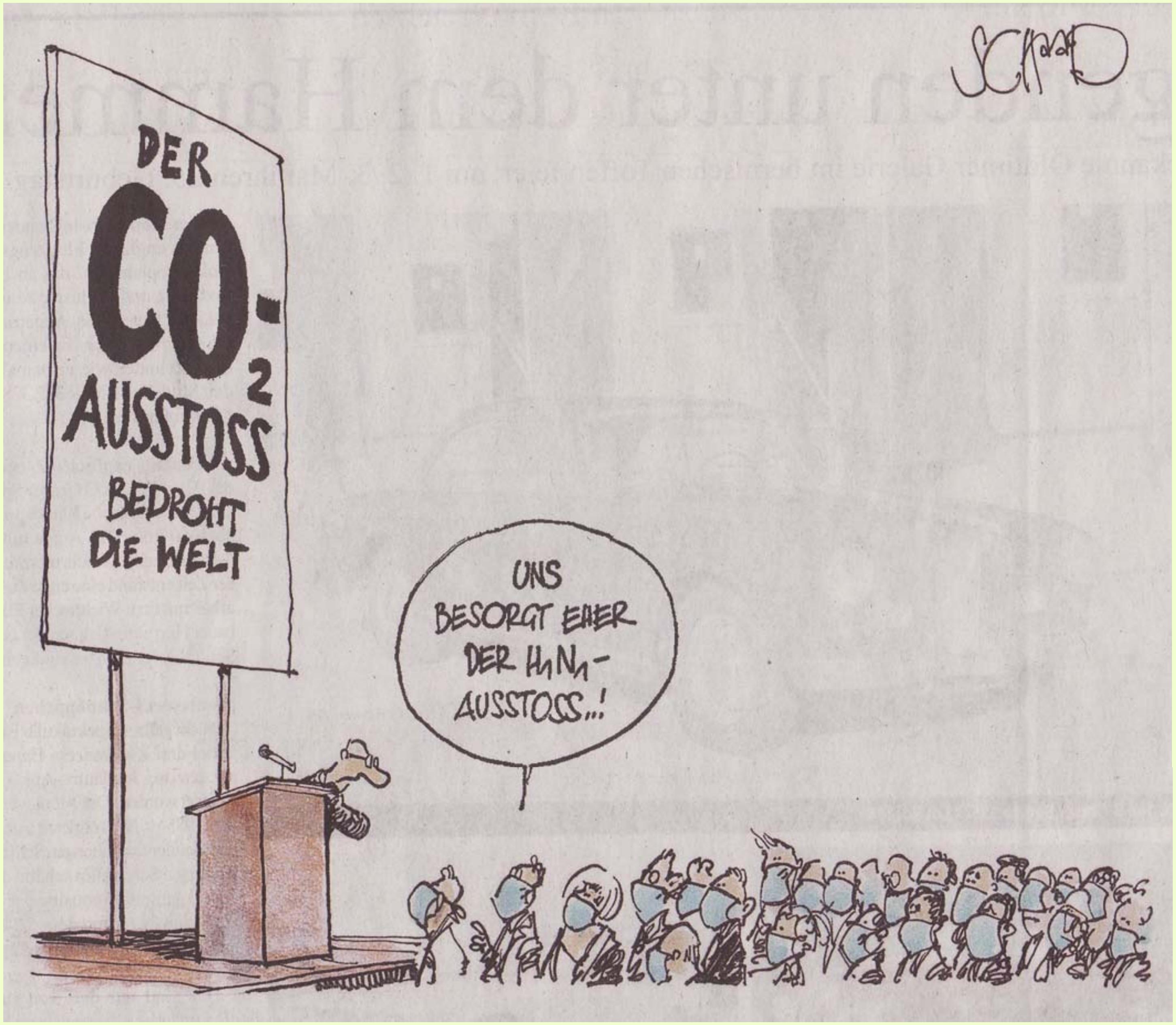
"Very likely" between 1.3-3.9°C, "Likely" between 1.6-2.6°C.

M09: 1,440 $GtCO2_{(2000-2050)}$ ≈0.9 $TtC_{(1750-2500)}$ → 50% risk of >2°C.

M09: 1,000 $GtCO2_{(2000-2050)}$ ≈0.71$TtC_{(1750-2500)}$ → 25% risk of >2°C.

UKCCC: 2,500 $GtCO2e_{(1990-2050)}$ ≈0.96$TtC_{(1750-2500)}$ → 50% risk of >2°C.

Long-term targets in a short-term world



Felix Schaad, *Tagesanzeiger,* (Swiss national newspaper), April 30, 2009

The model

- **Simple mixed-layer/diffusive energy balance model:**

$$a_1 \frac{dT}{dt} = a_3 \ln\left(\frac{C_1 + C_2 + C_3}{C_0}\right) - a_0 T - a_2 \int_0^t \frac{dT(t')}{dt'} \frac{dt'}{\sqrt{t - t'}}$$

- **"Revelle accumulation" of long-term equilibrium CO_2:**

$$\frac{dC_3}{dt} = b_3 E$$

- **Slow advection of "active CO_2" into deep ocean:**

$$\frac{dC_2}{dt} = b_1 E - b_0 C_2$$

- **Diffusive uptake by mixed layer and biosphere:**

$$\frac{dC_1}{dt} = b_4 E - b_2 \int_0^t \frac{dC_1(t')}{dt'} \frac{dt'}{\sqrt{t - t'}}$$

- **C-T feedback linear in ΔT above preceding century:**

$$E = E_a + b_5 T'$$

- **Emissions scaled to give correct 1960-2000 CO_2.**

The constraints

- Warming attributable to greenhouse gases over the 20th century.
- Effective ocean-troposphere-land heat capacity over 1959-98.
- CO_2 airborne fraction over 1960-2000 (uncertain due to uncertainty in land-use emissions).
- Contribution of C-T feedback to 2100 airborne fraction under A2 scenario (constrain with C4MIP).
- Rate of advection of active CO_2 into deep ocean (constrain with available EMICs).

Constraints on Cumulative Warming Commitment

Climate system property, *X*	Most likely value of *X*	5-95% confidence interval	Reduction in fractional uncertainty in CWC due to reducing fractional uncertainty $\sigma_{\log(X)}$ by	
			0.05	50%
20th century warming trend attributable to GHGs	0.97 °C/century	0.73-1.27 °C/century	18%	29%
Effective heat capacity 1955-98	0.70 GJ/°C	0.38-1.30 GJ/°C	1%	3%
Net airborne fraction (AF) 1960-2000	0.43	0.39-0.47	5%	0%
Contribution of temp. feedback to net AF 1766-2100	0.17	0.07-0.39	5%	13%
Rate constant for advection of CO-$_2$ into deep ocean	200 years	133-302 years	0%	0%

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