Statistical constraints on climate sensitivity

Aurélien Ribes

ENS Lyon, 21 Septembre 2022

Disclaimer

- Background in statistics.
- Key research in detection and attribution (long term + extreme events).
- Not an expert of *sensitivity* (ECS, TCR, others).

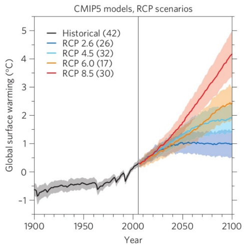
Sensitivity

- ECS: Equilibrium Climate Sensitivity
  GSAT Warming at 2x [CO_2] (equilibrium)
  Variations between S, ECS, ESS (cf Jean-Louis, Sherwood et al.).

- TCR : Transient Climate Response
  GSAT warming at 2x [CO_2] in 1%CO_2 runs (out of equilibrium).

- TCRE : Transient Climate Response to Emissions
  GSAT warming induced by 1000 $GtCO_2$.
  Concentration based vs emission based points of view.

- Hydrological sensitivity,
  e.g., Allan et al., 2020



Réchauffement global moyen
(2081-2100 vs 1986-2005)

RCP8.5 : 2.6°C – 4.8°C

RCP 6 : 1.4°C – 3.1°C

RCP4.5 : 1.1°C – 2.6°C

RCP2.6 : 0.3°C – 1.7°C

Graphique : Knuti & Sedlacek, 2012
Chiffres : GIEC, 2013

GSAT: Global mean Surface Air Temperature

Estimating ECS

- Purely Models (GCMs):
  model estimates, process based estimates
- Purely Observations:
  - Historical period: energy budget approach (Benoit),
  - Paleoclimate (Pascale).
- Constraints (emerging / observational)
  narrow model range using some observations,
  1. Processes-based,
  2. Historical warming (incl. attribution studies),
- Syntheses – combining all lines of evidence.

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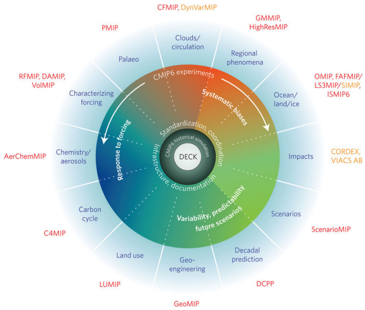
Constraints use the (limited) CMIP ensemble as a training sample.
So, all constraints rely on the underlying models somehow.

The CMIP ensembles

Coordinated experiments involving $\sim$ 40 models worldwide.
Large international effort!



Outline

1. Review of constraints
2. Historical warming and TCR
3. Statistical syntheses
   a. Sherwood et al. (2020)
   b. IPCC AR6
4. Conclusion

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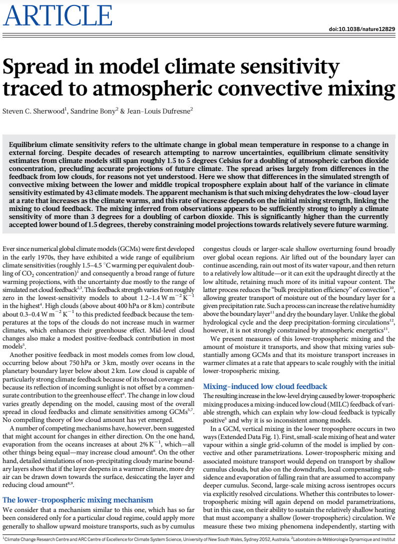
Example



ARTICLE

doi:10.1038/nature12829

Spread in model climate sensitivity traced to atmospheric convective mixing

Steven C. Sherwood[1], Sandrine Bony[2] & Jean-Louis Dufresne[2]

Equilibrium climate sensitivity refers to the ultimate change in global mean temperature in response to a change in external forcing. Despite decades of research attempting to narrow uncertainties, equilibrium climate sensitivity estimates from climate models still span roughly 1.5 to 5 degrees Celsius for a doubling of atmospheric carbon dioxide concentration, precluding accurate projections of future climate. The spread arises largely from differences in the feedback from low clouds, for reasons not yet understood. Here we show that differences in the simulated strength of convective mixing between the lower and middle tropical troposphere explain about half of the variance in climate sensitivity estimated by 43 climate models. The apparent mechanism is that such mixing dehydrates the low-cloud layer at a rate that increases as the climate warms, and this rate of increase depends on the initial mixing strength, linking the mixing to cloud feedback. The mixing inferred from observations appears to be sufficiently strong to imply a climate sensitivity of more than 3 degrees for a doubling of carbon dioxide. This is significantly higher than the currently accepted lower bound of 1.5 degrees, thereby constraining model projections towards relatively severe future warming.

Ever since numerical global climate models (GCMs) were first developed in the early 1970s, they have exhibited a wide range of equilibrium climate sensitivities (roughly 1.5–4.5 °C warming per equivalent doubling of CO_2 concentration)[1] and consequently a broad range of future warming projections, with the uncertainty due mostly to the range of simulated net cloud feedback[2,3]. This feedback strength varies from roughly zero in the lowest-sensitivity models to about 1.2–1.4 $W\,m^{-2}\,K^{-1}$ in the highest[4]. High clouds (above about 400 hPa or 8 km) contribute about 0.3–0.4 $W\,m^{-2}\,K^{-1}$ to this predicted feedback because the temperatures at the tops of the clouds do not increase much in warmer climates, which enhances their greenhouse effect. Mid-level cloud changes also make a modest positive-feedback contribution in most models[5].

Another positive feedback in most models comes from low cloud, occurring below about 750 hPa or 3 km, mostly over oceans in the planetary boundary layer below about 2 km. Low cloud is capable of particularly strong climate feedback because of its broad coverage and because its reflection of incoming sunlight is not offset by a commensurate contribution to the greenhouse effect[6]. The change in low cloud varies greatly depending on the model, causing most of the overall spread in cloud feedbacks and climate sensitivities among GCMs[5,7]. No compelling theory of low cloud amount has yet emerged.

A number of competing mechanisms have, however, been suggested that might account for changes in either direction. On the one hand, evaporation from the oceans increases at about 2% K^{-1}, which—all other things being equal—may increase cloud amount[8]. On the other hand, detailed simulations of non-precipitating cloudy marine boundary layers show that if the layer deepens in a warmer climate, more dry air can be drawn down towards the surface, desiccating the layer and reducing cloud amount[8,9].

The lower-tropospheric mixing mechanism

We consider that a mechanism similar to this one, which has so far been considered only for a particular cloud regime, could apply more generally to shallow upward moisture transports, such as by cumulus congestus clouds or larger-scale shallow overturning found broadly over global ocean regions. Air lifted out of the boundary layer can continue ascending, rain out most of its water vapour, and then return to a relatively low altitude—or it can exit the updraught directly at the low altitude, retaining much more of its initial vapour content. The latter process reduces the "bulk precipitation efficiency" of convection[10], allowing greater transport of moisture out of the boundary layer for a given precipitation rate. Such a process can increase the relative humidity above the boundary layer[11] and dry the boundary layer. Unlike the global hydrological cycle and the deep precipitation-forming circulations[12], however, it is not strongly constrained by atmospheric energetics[11].

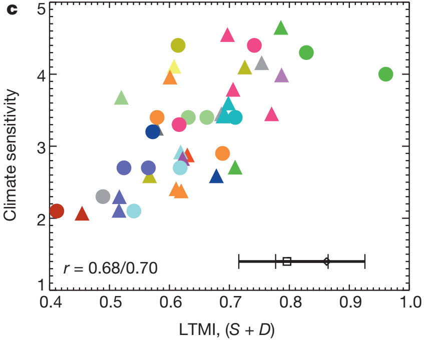
We present measures of this lower-tropospheric mixing and the amount of moisture it transports, and show that mixing varies substantially among GCMs and that its moisture transport increases in warmer climates at a rate that appears to scale roughly with the initial lower-tropospheric mixing.

Mixing-induced low cloud feedback

The resulting increase in the low-level drying caused by lower-tropospheric mixing produces a mixing-induced low cloud (MILC) feedback of variable strength, which can explain why low-cloud feedback is typically positive[5] and why it is so inconsistent among models.

In a GCM, vertical mixing in the lower troposphere occurs in two ways (Extended Data Fig. 1). First, small-scale mixing of heat and water vapour within a single grid-column of the model is implied by convective and other parametrizations. Lower-tropospheric mixing and associated moisture transport would depend on transport by shallow cumulus clouds, but also on the downdrafts, local compensating subsidence and evaporation of falling rain that are assumed to accompany deeper cumulus. Second, large-scale mixing across isentropes occurs via explicitly resolved circulations. Whether this contributes to lower-tropospheric mixing will again depend on model parametrizations, but in this case, on their ability to sustain the relatively shallow heating that must accompany a shallow (lower-tropospheric) circulation. We measure these two mixing phenomena independently, starting with

[1]Climate Change Research Centre and ARC Centre of Excellence for Climate System Science, University of New South Wales, Sydney 2052, Australia. [2]Laboratoire de Météorologie Dynamique and Institut



Sherwood et al. (2014) Spread in model climate sensitivity traced to atmospheric convective mixing, *Nature*.

Principle

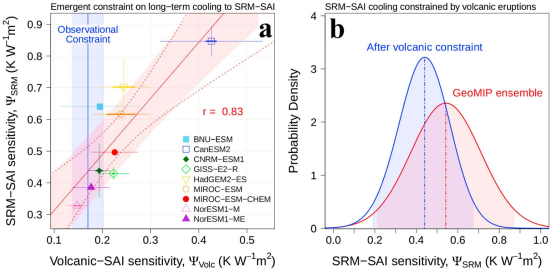
- Find a variable X related to the ESC S, e.g.

$$S = aX + b + \varepsilon$$

- Estimate (a, b) from an ensemble of models (CMIP),
- Take an observed value for X (+ uncrty): $X_o \pm \varepsilon_o$,
- Derive a revised estimate for real worl sensitivity:

$$\widehat{S} = \widehat{a}X_o + \widehat{b} \pm (\varepsilon + \widehat{a}\varepsilon_o).$$

People often neglect uncertainty in $(\widehat{a}, \widehat{b})$.



From Plazzotta et al., 2018, GRL

Requirements:

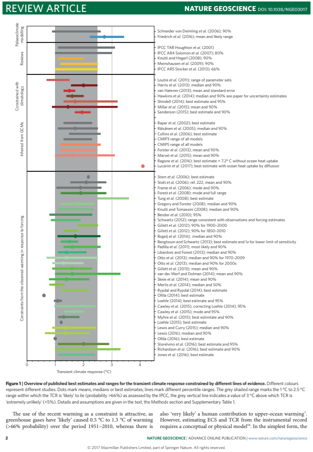
- Relationship between (X, S) [+ phys. underst.]
- Observational estimate of X (not too uncertain).

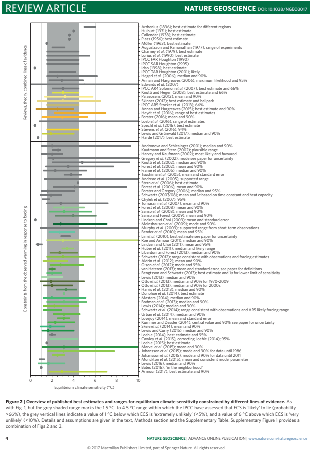
Catalog

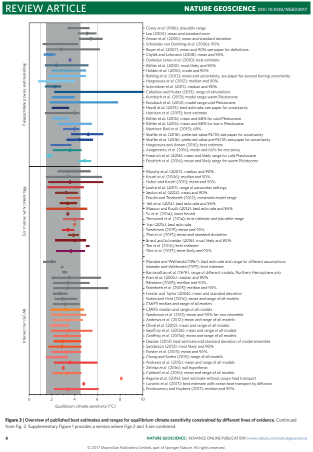
Large diversity of observational constraints – see e.g., IPCC AR6, Ch7, 7.5.4 (and earlier studies).

- Mean climate characteristics e.g. seasonal cycle in surface temperature (Knutti et al., 2006, JClim),
- Feedback processes, e.g., tropical low-clouds, albedo, etc (Sherwood et al., 2014, Brient et al., 2016, Zhai et al., 2015),
- Interannual variability (Cox et al., 2018),
- Observed temperature change, historical or paleo (see later).

Catalog (2) – Knutti et al. (2017)







From Knutti et al., 2017, NGeo.

But...

Some constraints found in CMIP5 do not hold in CMIP6.

Schlund et al., 2020, ESD
"*CMIP6 data shows a decrease in skill and statistical significance of the emergent relationship for nearly all constraints, with this decrease being large in many cases.*" Also Caldwell et al., 2018.

Why this happened?

Stats point of view:

- High dimension problem.
- Small training set.
- Risk of cherry picking – which maybe actually occurred.
- Solutions could include a more comprhensive exploration of uncertainties.

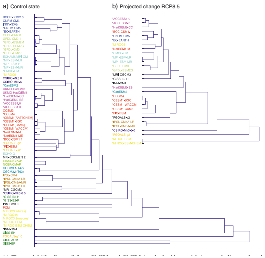
Phys. point of view:

- Need of “independently verifiable physical mechanism”,
- Many constraints apply to one single process / feedback.

The dark side of CMIP:

- Too small
- non-independent (cousin)
- no effort to sample uncertainty

See ’Ensemble of opportunity’ literature.



In IPCC AR6

- Cloud feedbacks: *not taken into account*
  Constraints usually applies to one process / feedback / type of clouds; other feedbacks can be biased too...
- Climatology: *not taken into account*
  “the physical relevance [...] is unclear”
  “these constraints are not considered reliable”
- Historical warming [next]: *taken into account :-)*

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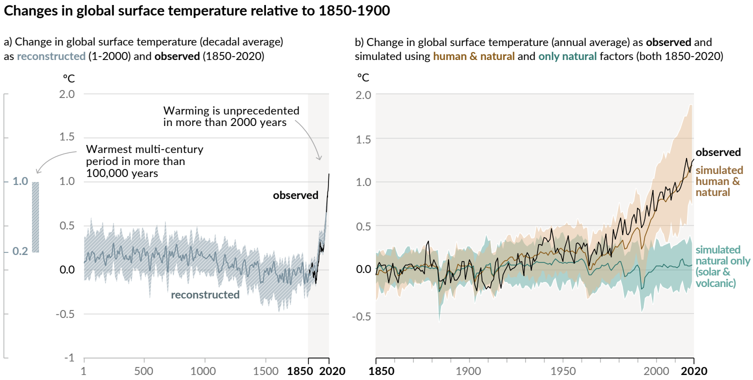
About historical warming



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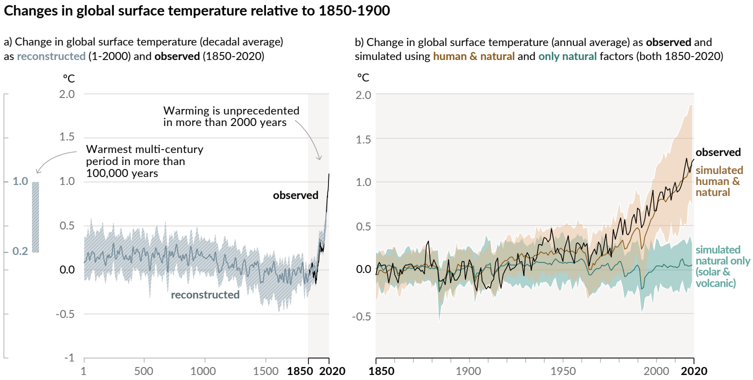

Issues: various forcings (**GHGs vs AER**, various GHGs); out of equilibrium state.

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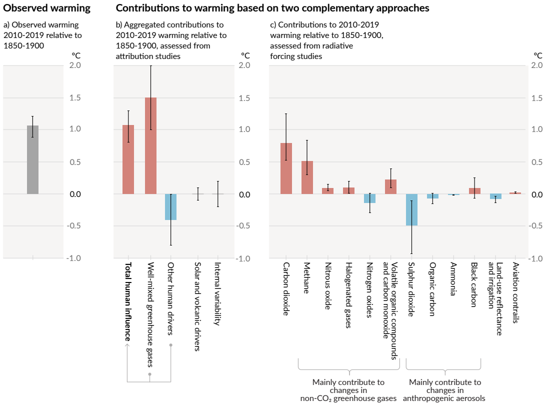

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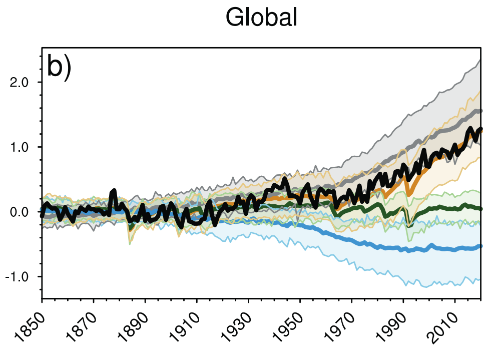
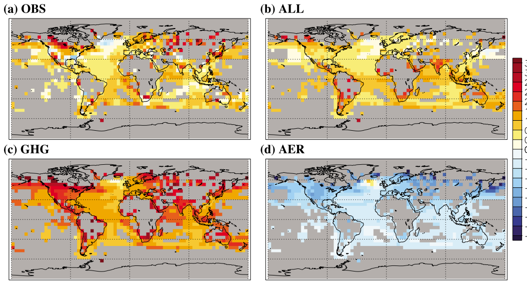




Issues: various forcings (**GHGs vs AER**, various GHGs); out of equilibrium state.

Attribution approaches

Try to estimate contributions from subsets of forcings, e.g., ANT/NAT, or better GHG/AER/NAT.

Key approach based on (variants of) linear regression:

$$Y_\ell = \sum_{i=1}^{k} \beta_i X_\ell^{(i)} + \varepsilon_\ell, \qquad Cov(\varepsilon) = \Sigma,$$

- ℓ: location (space-time),
- Y: observations (space-time vector),
- β_i: scaling factor (scalar), unknown,
- $X^{(i)}$: expected response to forcing i (space-time vector), known,
- ε: internal variability (space-time vector),
- Σ: IV covariance matrix (matrix).
- $k = 2$ or 3.

- Philosophy:
  The response patterns X are perfectly known.
  Amplitude of the responses are not
- $\widehat{\beta}_{GHG}$ can be use to correct (rescale) model results.
  ASK approach ; illustration
- But:
  - separating GHG and AER is hard (Ribes et al., 2013, IPCC AR5, etc).
  - linear regression model is questionable.

Simple constraint

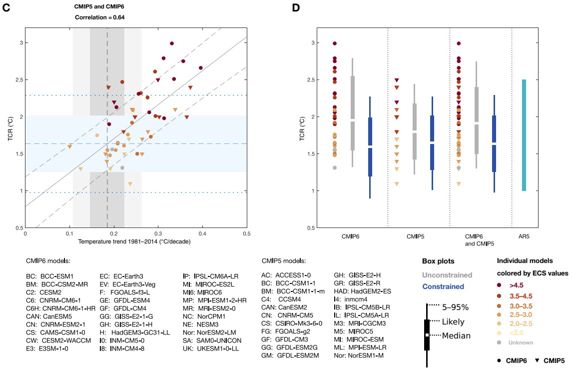
AR6 novelty: Post-1980 trends almost unaffected by AER.

CLIMATOLOGY

Past warming trend constrains future warming in CMIP6 models

Katarzyna B. Tokarska[1]*†, Martin B. Stolpe[1]*, Sebastian Sippel[1], Erich M. Fischer[1], Christopher J. Smith[2], Flavio Lehner[1], Reto Knutti[1]

Future global warming estimates have been similar across past assessments, but several climate models of the latest Sixth Coupled Model Intercomparison Project (CMIP6) simulate much stronger warming, apparently inconsistent with past assessments. Here, we show that projected future warming is correlated with the simulated warming trend during recent decades across CMIP5 and CMIP6 models, enabling us to constrain future warming based on consistency with the observed warming. These findings carry important policy-relevant implications: The observationally constrained CMIP6 median warming in high emissions and ambitious mitigation scenarios is over 16 and 14% lower by 2050 compared to the raw CMIP6 median, respectively, and over 14 and 8% lower by 2090, relative to 1995–2014. Observationally constrained CMIP6 warming is consistent with previous assessments based on CMIP5 models, and in an ambitious mitigation scenario, the likely range is consistent with reaching the Paris Agreement target.



Key implications for TCR and projections.

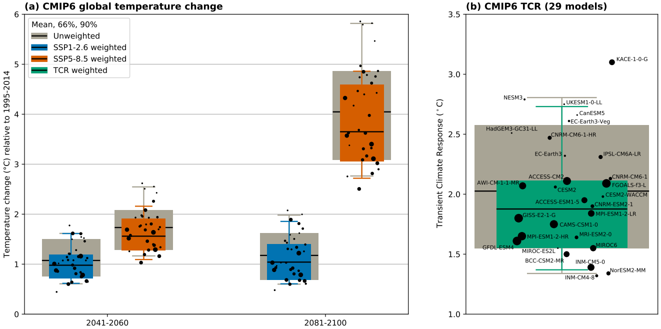
Tokarska et al., 2020, Sciences Advances.

Model weighting

Weight models according to independence and performance

Liang et al., 2020, GRL

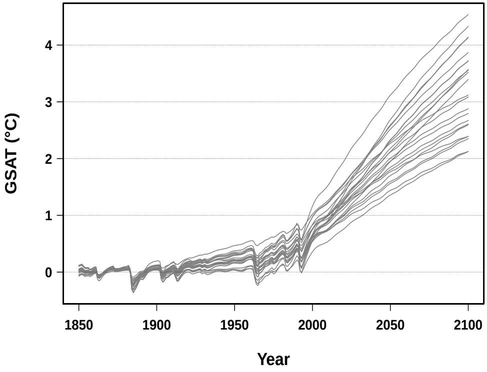
Brunner et al., 2020, ESD



Bayesian analysis (1)

Try to estimate the forced response “given observations”.

Ribes et al., 2021, Sci Adv.



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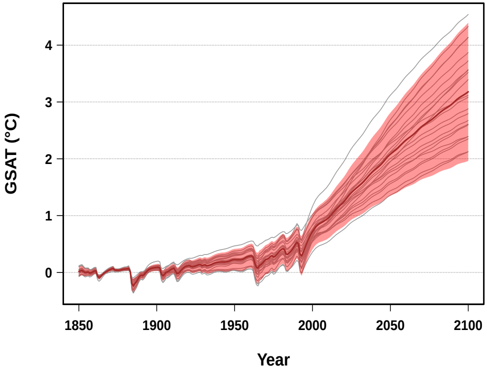

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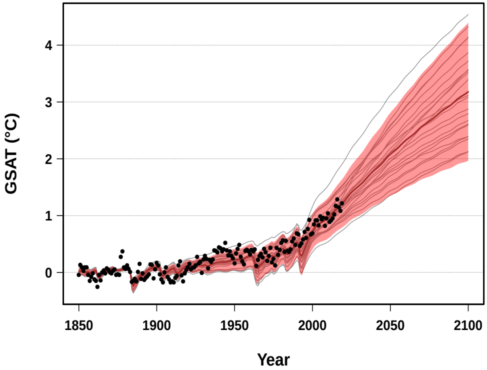

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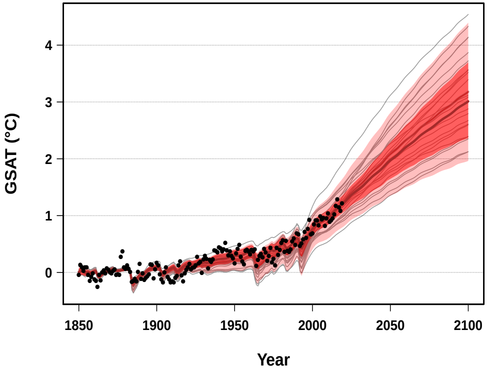


- Which pathways are consistent with observations?

Bayesian analysis (2)

$$\boldsymbol{x} = \begin{pmatrix} x_{1850}^{all} \\ \vdots \\ x_{2100}^{all} \end{pmatrix}, \qquad \boldsymbol{y} = \begin{pmatrix} y_{1850} \\ \vdots \\ y_{2019} \end{pmatrix}.$$

Prior:	$\boldsymbol{x} \sim N(\boldsymbol{\mu}, \boldsymbol{\Sigma}_{\text{mod}})$,
Obs:	$\boldsymbol{y} = \boldsymbol{H}\boldsymbol{x} + \boldsymbol{\varepsilon}$, with $\varepsilon \sim N(\boldsymbol{0}, \boldsymbol{\Sigma}_{\text{obs}})$,
We compute:	$p(\boldsymbol{x}\|\boldsymbol{y})$

$\boldsymbol{x}$: forced response (1850–2100), $\boldsymbol{y}$: observations, 1850–2019,
$\boldsymbol{\Sigma}_{\text{mod}}$: model error covariance, $\boldsymbol{\Sigma}_{\text{obs}}$: obs. error covariance,
$\boldsymbol{H}$: observation operator, $\boldsymbol{\varepsilon}$: error in obs. (i.v. + meas.),

There are 4 inputs: $\boldsymbol{y}, \boldsymbol{\mu}, \boldsymbol{\Sigma}_{\text{mod}}, \boldsymbol{\Sigma}_{\text{obs}}$. *#Kriging, #KalmanFiltering*

Can be extended to TCR / ECS

$$\begin{pmatrix} \boldsymbol{X}^{all} \\ F \\ \log(-\lambda) \end{pmatrix} \sim N(\mu, \boldsymbol{\Sigma}_{\text{mod}}).$$

- TCR: 1.33 ℃ – 2.36 ℃
- ECS: 2.2 ℃ – 4.6 ℃

IPCC AR6 Synthesis (projections)

- IPCC AR6 WG1 published in August 2021,
- GSAT[a] projections are model results constrained by observations
- Various methods used, incl. previous constraints, EBMs, and others.

- Results on TCR / ECS rely on a statistical relationship with $\mathbf{x}^{\mathbf{ALL}}$ accross (CMIP) climate models.
- This relationship could be questioned – see *pattern effect* issue.

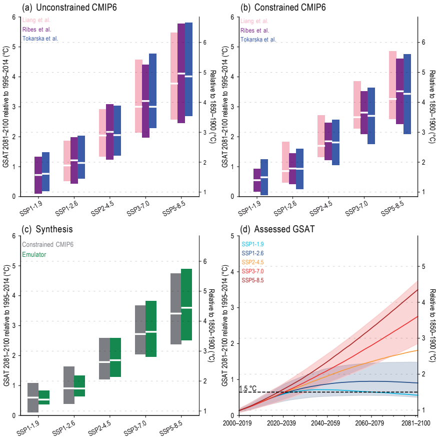
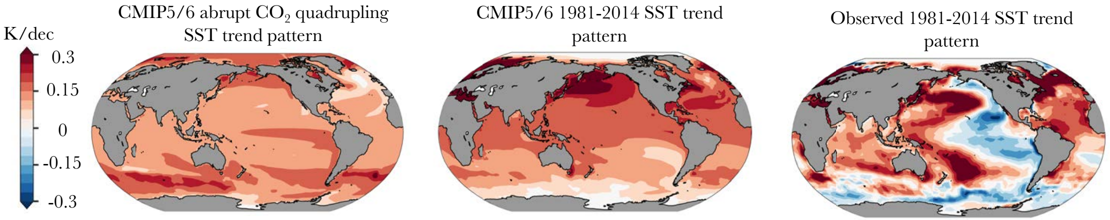


Fig 4.11 from IPCC AR6 (2021)

[a] Global mean Surface Air Temperature

But... How about the pattern?

Turns out that...



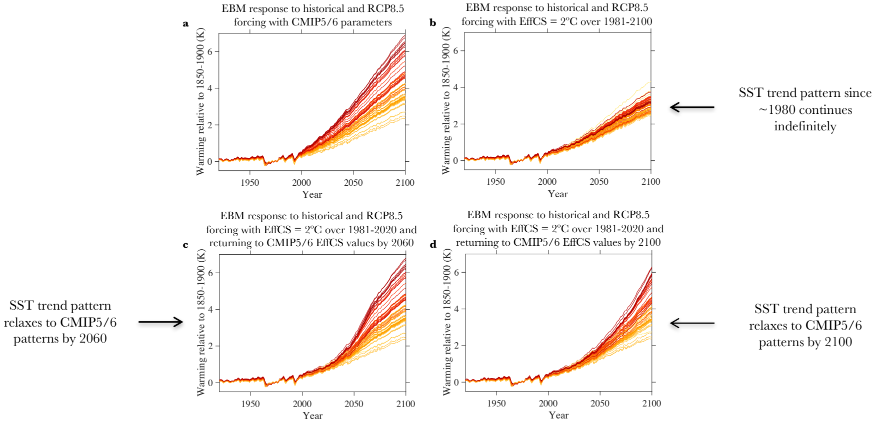
- The observed pattern of warming is very different from that expected / simulated by models,
- What causes this pattern: forced response? (low-frequency) variability?

How does the pattern effect impact future warming?

© Kyle Armour

Models miss the recent SST trend.

ECS vs historical warming relationship potentially wrong.



Pattern effect Workshop, May 10–13, 2022
`https://usclivar.org/meetings/pattern-effect-workshop-agenda`

Outline

Check for updates

AGU ADVANCING EARTH AND SPACE SCIENCE

Reviews of Geophysics

REVIEW ARTICLE
10.1029/2019RG000678

An Assessment of Earth's Climate Sensitivity Using Multiple Lines of Evidence

S. C. Sherwood[1], M. J. Webb[2], J. D. Annan[3], K. C. Armour[4], P. M. Forster[5], J. C. Hargreaves[3], G. Hegerl[6], S. A. Klein[7], K. D. Marvel[8,9], E. J. Rohling[10,11], M. Watanabe[12], T. Andrews[2], P. Braconnot[13], C. S. Bretherton[4], G. L. Foster[11], Z. Hausfather[14], A. S. von der Heydt[15], R. Knutti[16], T. Mauritsen[17], J. R. Norris[18], C. Proistosescu[19], M. Rugenstein[20], G. A. Schmidt[9], K. B. Tokarska[6,16], and M. D. Zelinka[7]

[1]Climate Change Research Centre and ARC Centre of Excellence for Climate Extremes, University of New South Wales Sydney, Sydney, New South Wales, Australia, [2]Met Office Hadley Centre, Exeter, UK, [3]Blue Skies Research Ltd, Settle, UK, [4]University of Washington, Seattle, WA, USA, [5]Priestley International Centre for Climate, University of Leeds, Leeds, UK, [6]School of Geosciences, University of Edinburgh, Edinburgh, UK, [7]PCMDI-LLNL, California, Berkeley, USA, [8]Department of Applied Physics and Applied Math, Columbia University, New York, NY, USA, [9]NASA Goddard Institute for Space Studies, New York, NY, USA, [10]Research School of Earth Sciences, Australian National University, Canberra, ACT, Australia, [11]Ocean and Earth Science, National Oceanography Centre, University of Southampton, Southampton, UK, [12]Atmosphere and Ocean Research Institute, The University of Tokyo, Tokyo, Japan, [13]Laboratoire des Sciences du Climat et de l'Environnement, unité mixte CEA-CNRS-UVSQ, Université Paris-Saclay, Gif sur Yvette, France, [14]Breakthrough Institute, Oakland, CA, USA, [15]Institute for Marine and Atmospheric Research, and Centre for Complex Systems Science, Utrecht University, Utrecht, The Netherlands, [16]Institute for Atmospheric and Climate Science, Zurich, Switzerland, [17]Department of Meteorology, Stockholm University, Stockholm, Sweden, [18]Scripps Institution of Oceanography, La Jolla, CA, USA, [19]Department of Atmospheric Sciences and Department of Geology, University of Illinois at Urbana-Champaign, Urbana, IL, USA, [20]Max Planck Institute for Meteorology, Hamburg, Germany

Key Points:

- We assess evidence relevant to Earth's climate sensitivity S: feedback process understanding and the historical and paleoclimate records
- All three lines of evidence are difficult to reconcile with $S < 2$ K, while paleo evidence provides the strongest case against $S > 4.5$ K
- A Bayesian calculation finds a 66% range of 2.6–3.9 K, which remains within the bounds 2.3–4.5 K under plausible robustness tests

Correspondence to:
S. Sherwood,
s.sherwood@unsw.edu.au

Citation:
Sherwood, S. C., Webb, M. J., Annan, J. D., Armour, K. C., Forster, P. M., Hargreaves, J. C., et al. (2020). An assessment of Earth's climate sensitivity using multiple lines of evidence.

How does it work?

Lines of evidence:

- Process understanding, E_{proc} (blue)
- Historical warming, E_{hist} (orange)
- Paleo records, E_{paleo} (red)

$$p(\lambda|E) \propto p(\lambda|E_{proc})p(E_{hist}|\lambda)p(E_{paleo}|\lambda)$$

Somehow: take the intersection of all lines of evidence.

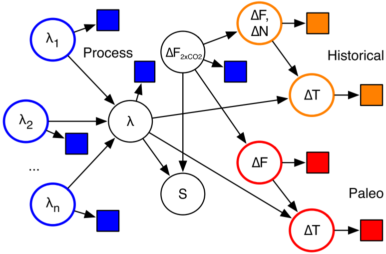


Figure 2. A Bayesian network diagram showing the dependence relationships between main variables in the inference model. Circles show uncertain variables, whose PDFs are estimated; squares show evidence (random effects on the evidence would appear as a second "parent" variable for each square and are omitted for simplicity). Colors distinguish the three main lines of evidence and associated variables (blue = process, orange = historical, and red = paleoclimate). For paleoclimate, only one $\Delta F/\Delta T$ climate change pair is shown but two independent ones are considered (see section 5).

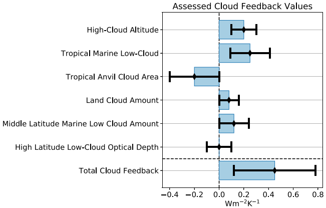
Process understanding

Quantify knowledge about each λ_i and ΔF_{2xCO_2}:

- CO_2 radiative forcing: ΔF_{2xCO_2},
  and the associated radiative adjustments
- Planck feedback: λ_{Planck},
- Water vapor and lapse rate: λ_{wv+lr},
- Surface albedo feedback: λ_a,
- Stratospheric feedback: λ_{strat},
- Other feedbacks (chemistry, aerosols): λ_{other},
- Clouds !!

The cloud feedback is decomposed into:

- High-cloud altitude feedback
- Tropical anvil cloud area feedback
- Tropical marine low-cloud feedbcak
- Midlatitude marine low-cloud feedback
- High-latitude low-cloud optical depth feedback
- Land cloud feeback



Prior on (S, λ)

Each $\lambda_i \sim N(\mu_i, \sigma_i^2)$; $\lambda \sim N(\sum \mu_i, \sum \sigma_i^2)$.

Dependence between ΔF_{2xCO_2} and λ: neglected.

Constraint on S and/or λ,
(interannual radiation variability and climatology):
discussed but not taken into account (compensates potential missing feedbacks λ_i).

+ Historical evidence

+ Paleoclimate evidence

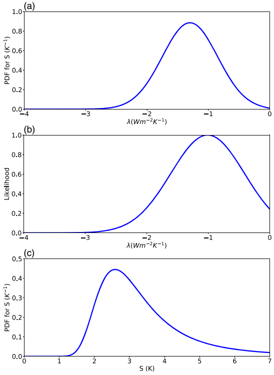
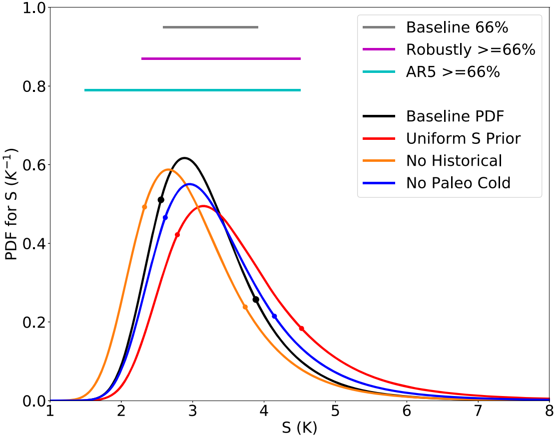


Figure 8. PDFs and likelihood functions based upon the assessment of individual climate feedbacks and the emergent constraint literature. (a) PDF for λ from combining evidence on individual feedbacks using the Baseline λ_i prior. (b) Emergent constraint likelihood for λ. Note that this likelihood is not a PDF. See section 3.6 for an explanation of how the parameters of this likelihood function were determined and why they differ from the parameters recorded in Table 2. (c) PDF for S from combining evidence on ΔF_{2xCO2} and individual feedbacks using uniform λ_i priors.

Synthesis



"*the paleoclimate record (in particular, the LGM) now provides the strongest evidence against very high S*"

"*all lines provide more similar constraints against low S (paleo slightly less than the others)*"

Still, the choice of the prior matters.

$$p(\lambda|E) \propto p(\lambda|E_{proc})p(E_{hist}|\lambda)p(E_{paleo}|\lambda)$$

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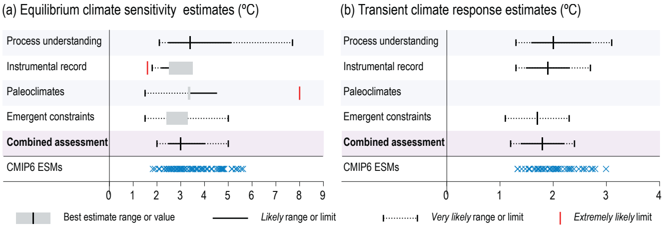
Another synthesis (more qualitative)

“*[Synthesis] can be done formally using Bayesian statistics, though such a process is complex and involves formulating likelihoods and priors*”



Equilibrium Climate Sensitivity (ECS)	Central Value	*Likely*	*Very likely*	*Extremely likely*
Process understanding (Section 7.5.1)	3.4°C	2.5°C to 5.1°C	2.1°C to 7.7°C	–
Warming over instrumental record (Section 7.5.2)	2.5°C to 3.5°C	>2.2°C	>1.8°C	>1.6°C
Paleoclimates (Section 7.5.3)	3.3°C to 3.4°C	<4.5°C	>1.5°C	<8°C
Emergent constraints (Section 7.5.4)	2.4°C to 3.3°C	–	1.5°C to 5.0°C	–
Combined assessment	3°C	2.5°C to 4.0°C	2.0°C to 5.0°C	–

Transient Climate Response (TCR)	Central Value	*Likely* Range	*Very likely* Range
Process understanding (Section 7.5.1)	2.0°C	1.6°C to 2.7°C	1.3°C to 3.1°C
Warming over instrumental record (Section 7.5.2)	1.9°C	1.5°C to 2.3°C	1.3°C to 2.7°C
Emergent constraints (Section 7.5.4)	1.7°C	–	1.1°C to 2.3°C
Combined assessment	1.8°C	1.4°C to 2.2°C	1.2°C to 2.4°C

Conclusions / Perspectives

- Statistical constraints contribute to knowledge of climate sensitivity.
- Constraint from historical (recent) warming is important... And expected to strengthen.
- Need of statistical methods (uncertainty quantification, sophisticated constraints, synthesis...).
- Key remaining issues include:
  - Limitation of the CMIP ensemble. *Use PPEs?* (Perturbed Physics Ensembles)
  - Pattern effect. *Revise the role of internal variability?*

Conclusions / Perspectives

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- Key remaining issues include:
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  - Pattern effect. *Revise the role of internal variability?*

Few personal thoughts: ECS has received very much attention, but...

- Highly idealized experiment
  Keeping constant [CO_2] on the long-term seems very unlikely
- Does not describe the response of the system that well...
  Transient resp., local resp. (pattern), extreme events, water cycle, carbon cycle (e.g. emissions based), etc
- Many other features to infer / monitor – come to the workshop.