Climate feedback strength: no historical period pattern effect when using HadISST data

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Climate feedback & pattern effects

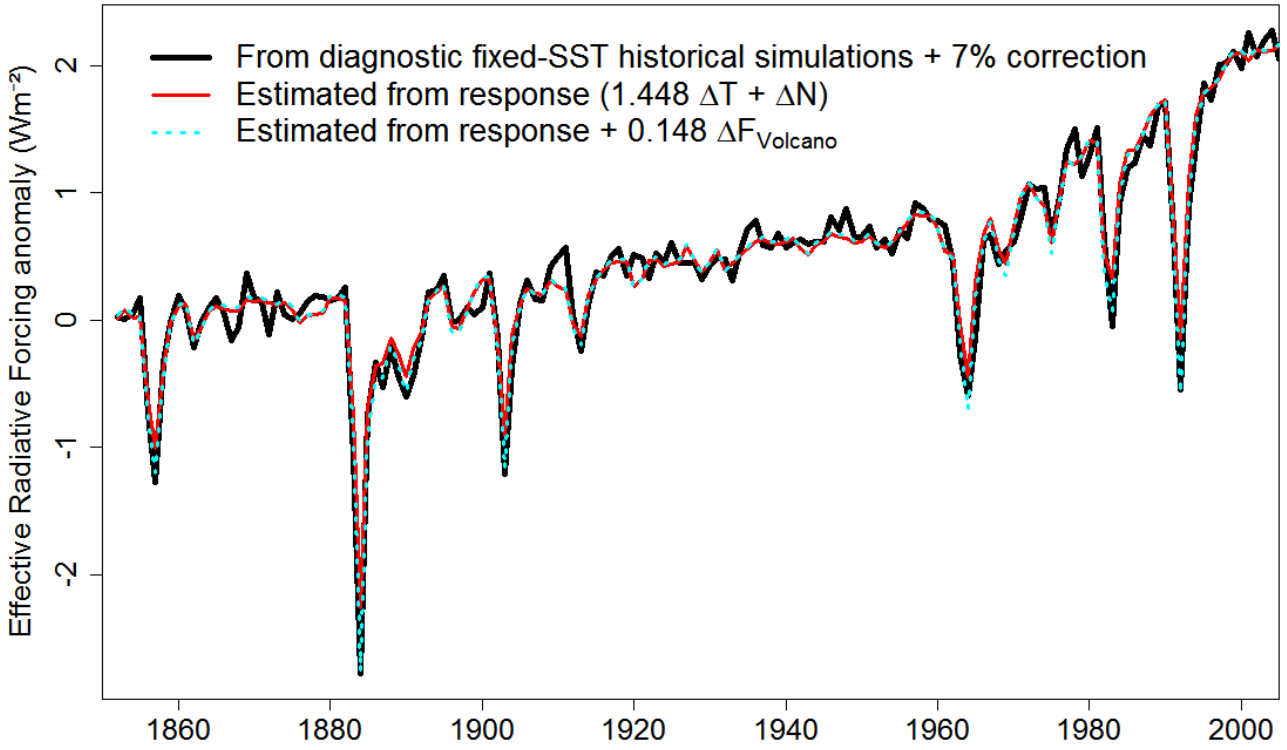
- Define climate feedback λ by $\Delta R = \lambda \Delta T + \varepsilon_R$ [random, 0-mean]
- $\Delta R = \Delta F - \Delta N$: change in *outgoing* radiation↑
- Effective sensitivity=F_{2xCO2}/λ: ECS per transient changes
- In AOGCMs λ ↘ over time, so ECS > Effective sensitivity
- Linked to changing warming patterns: 'Pattern effect'
- GMST impact v slow: Effective sensitivity OK for ≫100yrs
- Unforced historical period pattern effect alters λ estimate

Historical period $E_{ff}CS$ (ECS_{hist})

- $\lambda_{hist} = \Delta R/\Delta T = (\Delta F - \Delta N)/\Delta T$; Δ over last ~150 yr (not 30 yr)
- $ECS_{hist} = F_{2xCO2}/\lambda_{hist}$
- Mean CMIP5 model ECS_{hist} estimate ~3.0 K
- Mean CMIP5 model ECS estimate ~3.3 K
- CMIP5 median $ECS/ECS_{hist} \approx 1.10$
- ECS_{hist} best estimate from observations ~1.7–1.8 K
- Mauritsen's & Lewis's ECS_{hist} estimates now 2.3 K & 1.7-2 K
- Substantial pattern effect, bias or random errors for >3 K

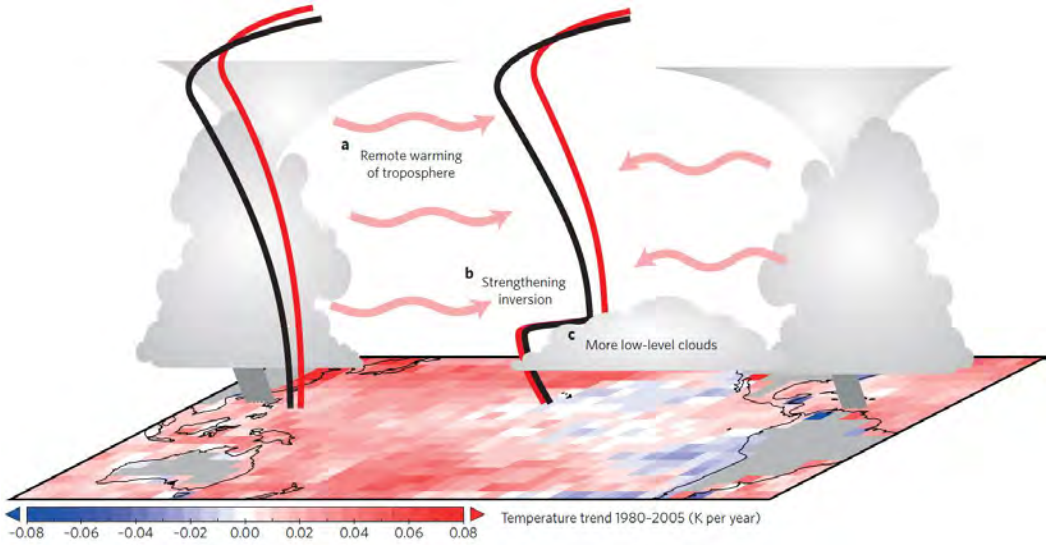
Historical forcing mix: no estimation bias

MPI-ESM1.1: $\lambda_{historical} = \lambda_{CO2}$ for same timescale



So is model–obs ECS_{hist} due to different *warming patterns*?

How/why does λ depend on ΔT pattern?

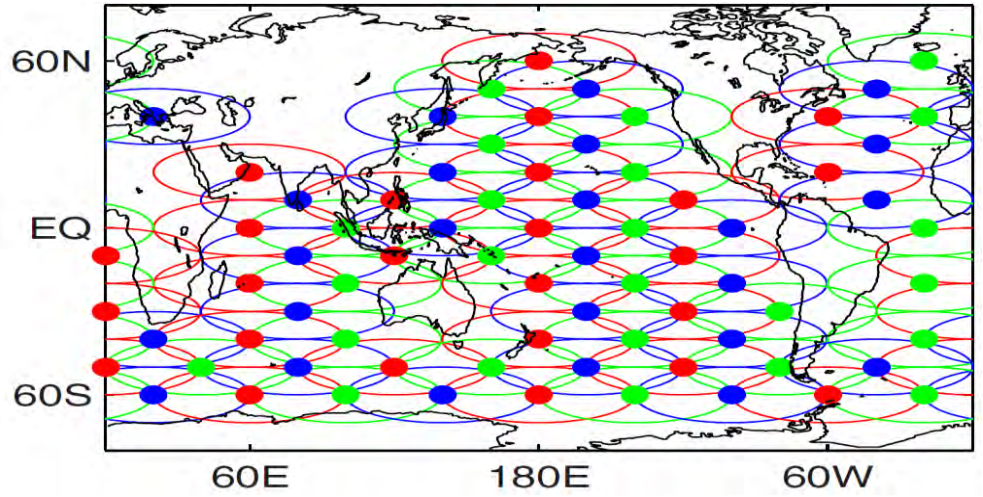


Source: Mauritsen 2016

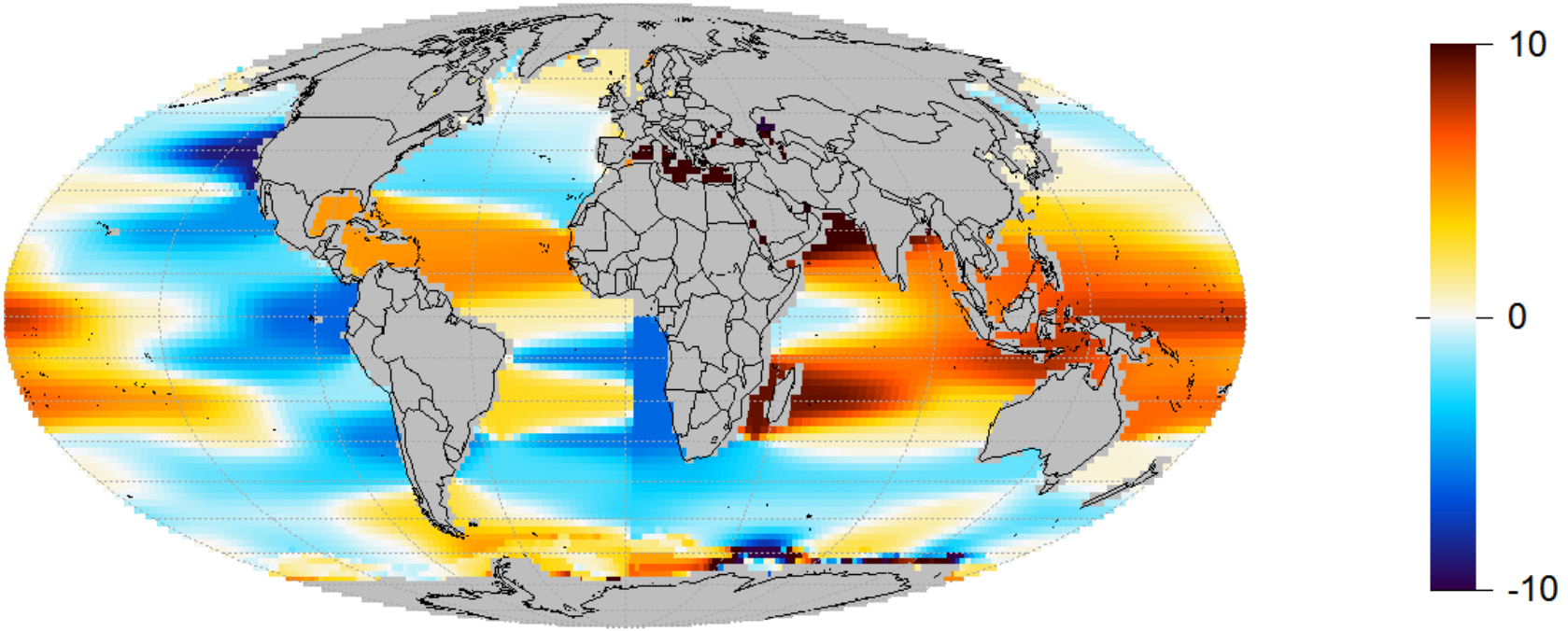
- Temperature in tropical troposphere set by convection
- Indian ocn/W Pacific warm-pool (IPWP) convects strongly
- Inversion strength (EIS) affects low cloud cover
- EIS affected by remote warming of tropical troposphere
- So, warm-pool–elsewhere *T* differentials affect *R*
- Also, λ weak where forced warming delayed: S Ocn + N Atl

Emulating effect in GCMs of Δ*T* patterns

- Green's functions (GFs) approach: linear superposition
- Use multiple fixed SST simulations to derive GFs
- For each, apply *local* Δ*T* to different ocean patch
- Find *global* Δ*T* and Δ*R* caused by each grid cell Δ*T*
- Σ(GFs x warming pattern) gives global Δ*T* & Δ*R*
- Zhou et al 2017: CAM5.3, 74 patches, good results



CAM5 GFs: $\Delta R_{global}/\Delta Ts_{global}$ by location



Strong feedback over IPWP and other tropical ascent regions

Global feedback in many other areas is destabilising: $R\downarrow$ as $Ts\uparrow$

Key region: Indo-Pacific warm pool

- Indo-Pacific Warm Pool ~ 45E–195E, 15S–15N
- Climate feedback λ ($\Delta R/\Delta Ts$) very strong in IPWP
- Higher IPWP ΔSST relative to elsewhere strengthens λ
- In CO_2-only runs, IPWP relative warming ↓ over time
- Claimed that IPWP has warmed faster to date, so $\lambda\uparrow$
- λ in 1870-on AMIP runs > λ in historical & 1pctCO2 runs
- Did internal var^y bias energy budget ECS_{hist} estimates low?
- Was IPWP relative ΔSST high over historical period?

Feedback and excess IPWP warming $_2$

SST/*Ts* data source and analysis period	Excess warm pool vs 30S-30N SST trend %	Excess warm pool vs 60S-60N SST trend %	Greens's function feedback on *Ts* estimate $Wm^{-2}K^{-1}$	Actual feedback on *Ts* in simulation $Wm^{-2}K^{-1}$
CAM5.3 AMIPF1850 amipPiForcing simulation 1871–2010	8	–4	1.73	1.70
CESM1-CAM5 1pctCO2 simulation – first 70 years	7	11	1.62	1.60
CESM1-CAM5 Historical/RCP8.5 simulation 1871–2010	10	4	1.62	-

Green's function emulations give accurate λ estimates

Feedback and excess IPWP warming [3]

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HadISST1 1871–2010	**2**	**–7**	**1.61**	**-**
HadISST2 1871–2010	**1**	**–3**	**1.60**	**-**

HadISST1/2 have lowest IPWP relative SST trends, and estimated $\lambda \approx \lambda$ in Historical & 1pctCO2 CAM5 simulations

Same findings in direct simulations

ECHAM6.3/MPI-ESM1.1 simulation data	Excess warm pool vs 30S-30N SST trend %	Excess warm pool vs 50S-50N SST trend %	Feedback on *Ts* in simulation (pentadal regression) $Wm^{-2}K^{-1}$
AMIPII SST amipPiForcing simulation 1871–2010	7	0	1.92
1pctCO2 coupled simulations years 1–100	5	7	1.54
HadISST1 amipPiForcing simulation 1871–2010	**2**	**–7**	**1.51**

Same findings in direct simulations

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1pctCO2 coupled simulations years 1–100	5	7	1.54
HadISST1 amipPiForcing simulation 1871–2010	**2**	**–7**	**1.51**
AMIPII SST amipPiForcing simulation 1871–2005	5	–3	1.85
Historical coupled simulations 1871–2005	7	12	1.58
HadISST1 amipPiForcing simulation 1871–2005	**0**	**–10**	**1.42**

HadISST1 IPWP relative SST trends are low and estimated λ is < λ for AMIPII & ≈ Historical & 1pctCO2 simulations λ

Conclusions

- Long term pattern effect: CMIP5 (coupled) ECS/ECS_{hist} ~1.1
- Historical pattern effect: 6 models $ECS_{hist}^{\text{coupled SST}}/ECS_{hist}^{\text{AMIPII SST}} \sim 1.4$
- But <u>no historical pattern effect</u> when using HadISST1, per CAM5 Green's functions and ECHAM6.3 model runs
- HadISST2 as for HadISST1, ex its stronger sea-ice feedback
- Historical period IPWP relative Δ*SST* appears *low,* not high
- No evidence that observational ECS_{hist} estimates biased low
- IPWP relative Δ*SST* may not dominate estimated λ in GCMs

References

Andrews, T., Gregory, J.M. and Webb, M.J., 2015. The dependence of radiative forcing and feedback on evolving patterns of surface temperature change in climate models. *Jnl of Climate*, *28*(4), pp.1630-1648.

Andrews, T., Gregory, J.M., Paynter, D., Silvers, L.G., Zhou, C., Mauritsen, T., Webb, M.J., Armour, K.C., Forster, P.M. and Titchner, H., 2018. Accounting for changing temperature patterns increases historical estimates of climate sensitivity. *Geophysical Research Letters*, *45*(16), pp.8490-8499.

Armour, K.C., 2017. Energy budget constraints on climate sensitivity in light of inconstant climate feedbacks. *Nature Climate Change*, *7*(5), p.331.

Dong, Y., Proistosescu, C., Armour, K.C. and Battisti, D.S., 2019. Attributing Historical and Future Evolution of Radiative Feedbacks to Regional Warming Patterns using a Green's Function Approach: The Preeminence of the Western Pacific. *Journal of Climate*, 32, pp.5471-5491

Kohyama, T., Hartmann, D.L. and Battisti, D.S., 2017. La Niña–like mean-state response to global warming and potential oceanic roles. *Journal of Climate*, *30*(11), pp.4207-4225

Lewis, N. and Curry, J., 2018. The impact of recent forcing and ocean heat uptake data on estimates of climate sensitivity. *Jnl of Climate*, *31*(15), pp.6051-6071.

Mauritsen, T., 2016. Clouds cooled the Earth. Nature Geoscience, 9(12), p.865

Mauritsen, T. and Pincus, R., 2017. Committed warming inferred from observations. *Nature Climate Change*, *7*(9), p.652.

Proistosescu, C. and Huybers, P.J., 2017. Slow climate mode reconciles historical and model-based estimates of climate sensitivity. *Science Advances*, *3*(7), p.e1602821

Zhang, L., Han, W., Karnauskas, K.B., Meehl, G.A., Hu, A., Rosenbloom, N. and Shinoda, T., 2019. Indian Ocean Warming Trend Reduces Pacific Warming Response to Anthropogenic Greenhouse Gases: An Interbasin Thermostat Mechanism. *Geophysical Research Letters*.

Zhou, C., Zelinka, M.D. and Klein, S.A., 2017. Analyzing the dependence of global cloud feedback on the spatial pattern of sea surface temperature change with a Green's function approach. *Journal of Advances in Modeling Earth Systems*, *9*(5), pp.2174-89