

Observational-based estimates of climate sensitivity: impacts of aerosol evolution, natural variability and the recent temperature records

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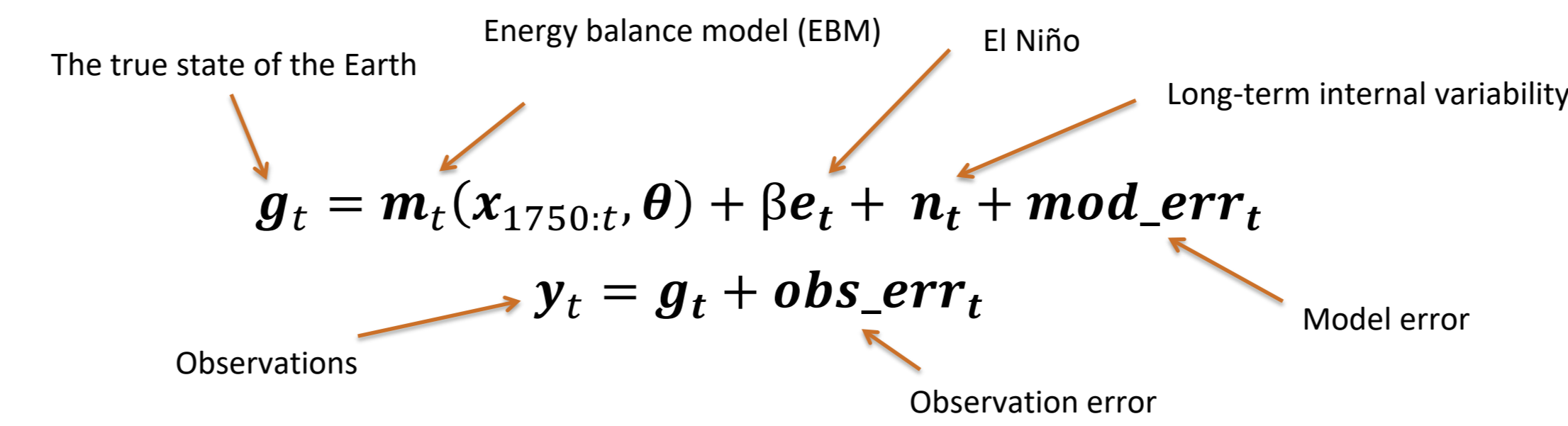
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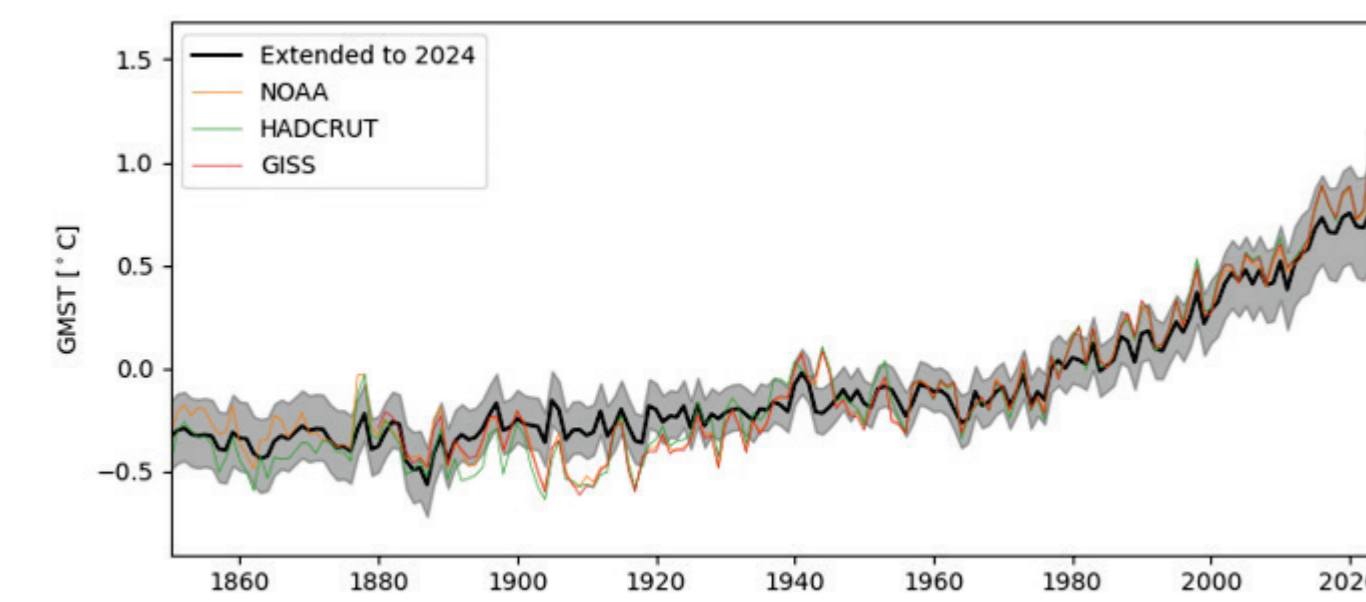


Background: Climate sensitivity and aerosol forcing are two of the most central, but uncertain, quantities in climate science - crucial for understanding past climate changes and future projections.

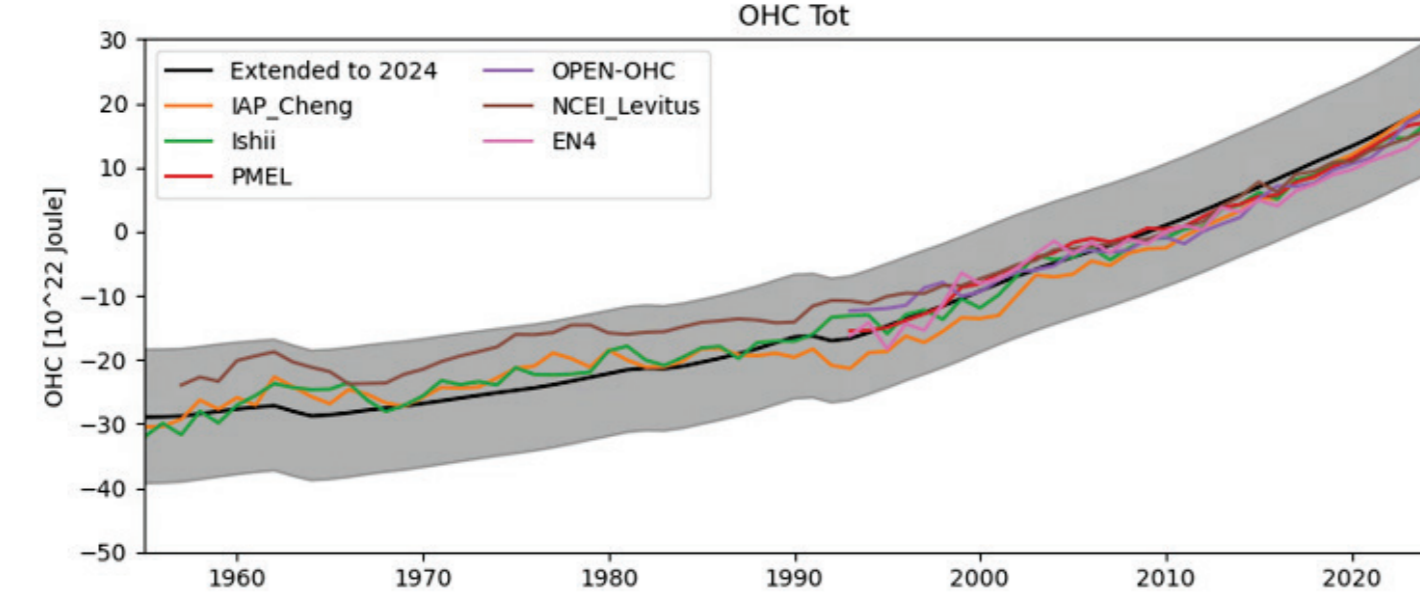
Method: Estimate inferred climate sensitivity (ECS_{inf}) using observations of surface temperature and ocean heat content (OHC) combined with prior knowledge of effective radiative forcing over the industrial period, within a Bayesian framework (Aldrin et al. 2012, Skeie et al. 2014, 2018, 2024).



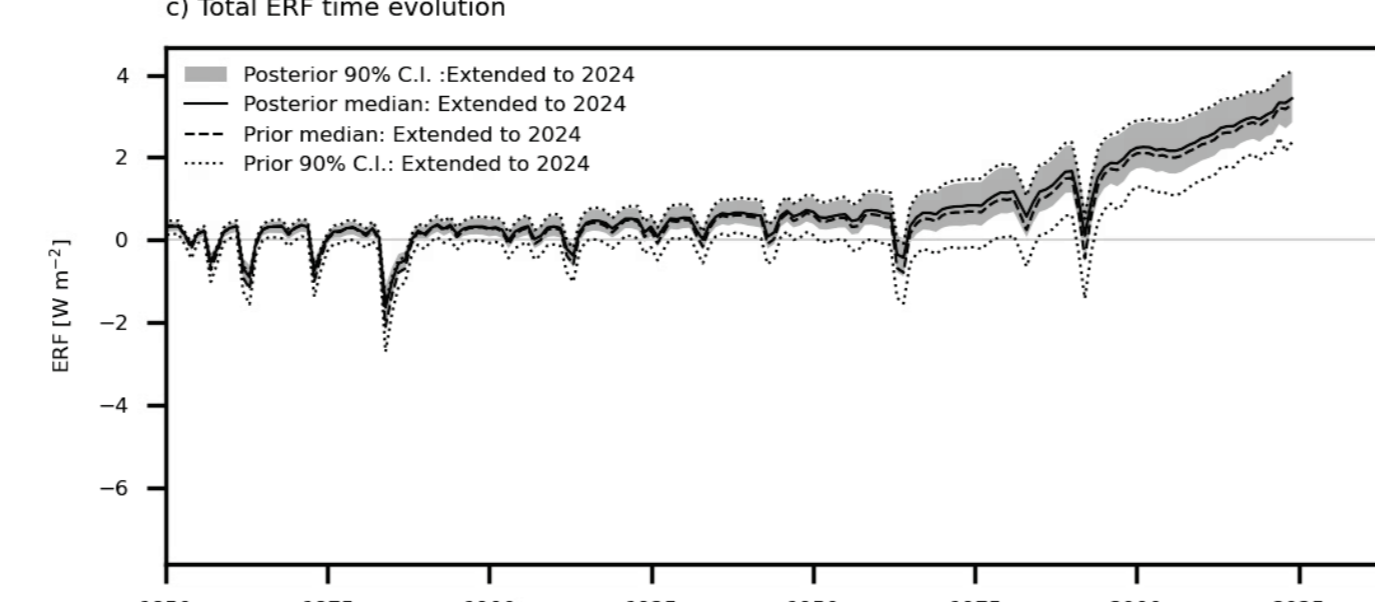
Estimated and observed global mean surface temperature (GMST) 1850 to 2024.



Estimated and observed ocean heat content (OHC) 1955 to 2024.

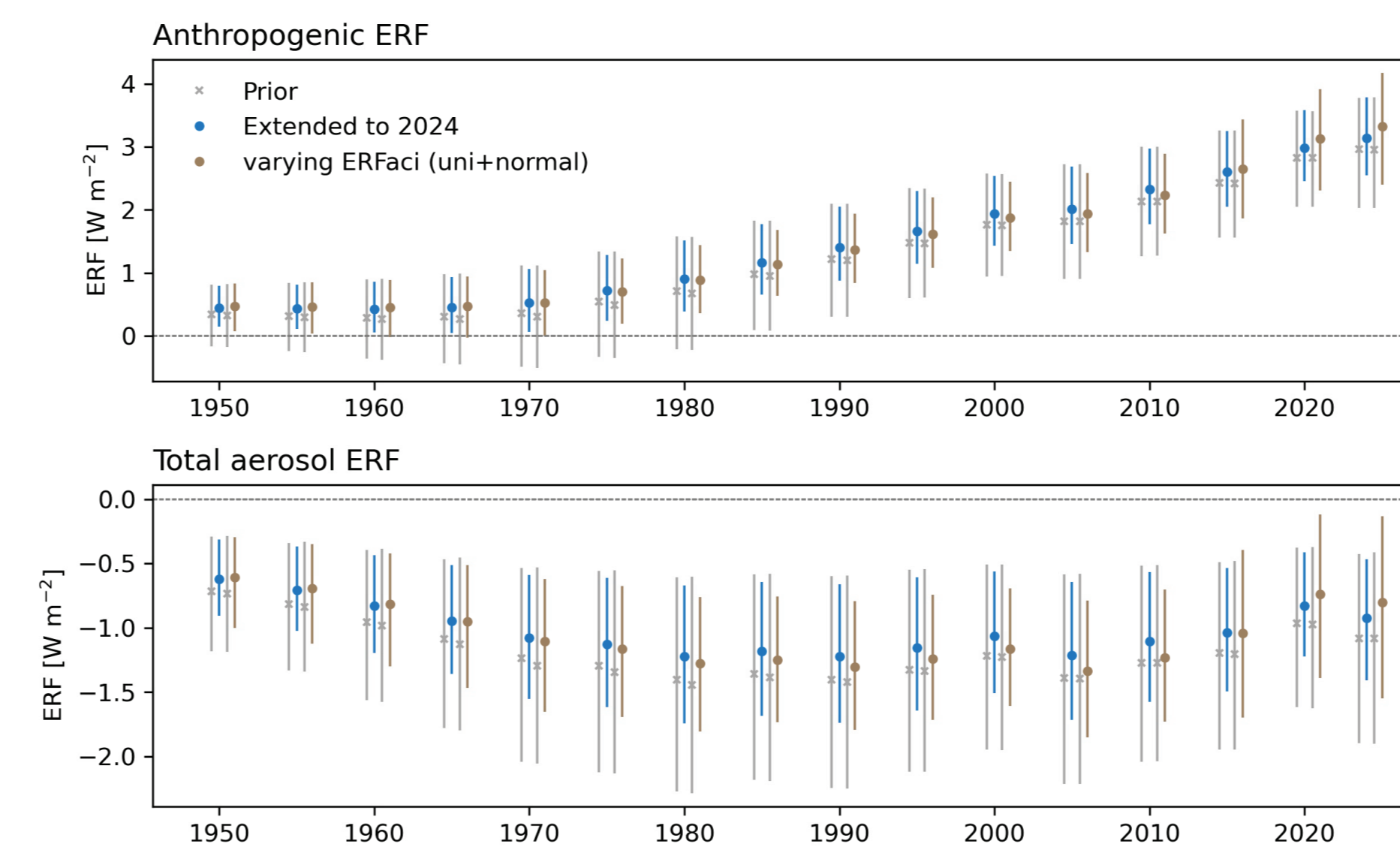


Prior and posterior ERF time evolution 1850 to 2024. Prior from Forster et al. (2025).

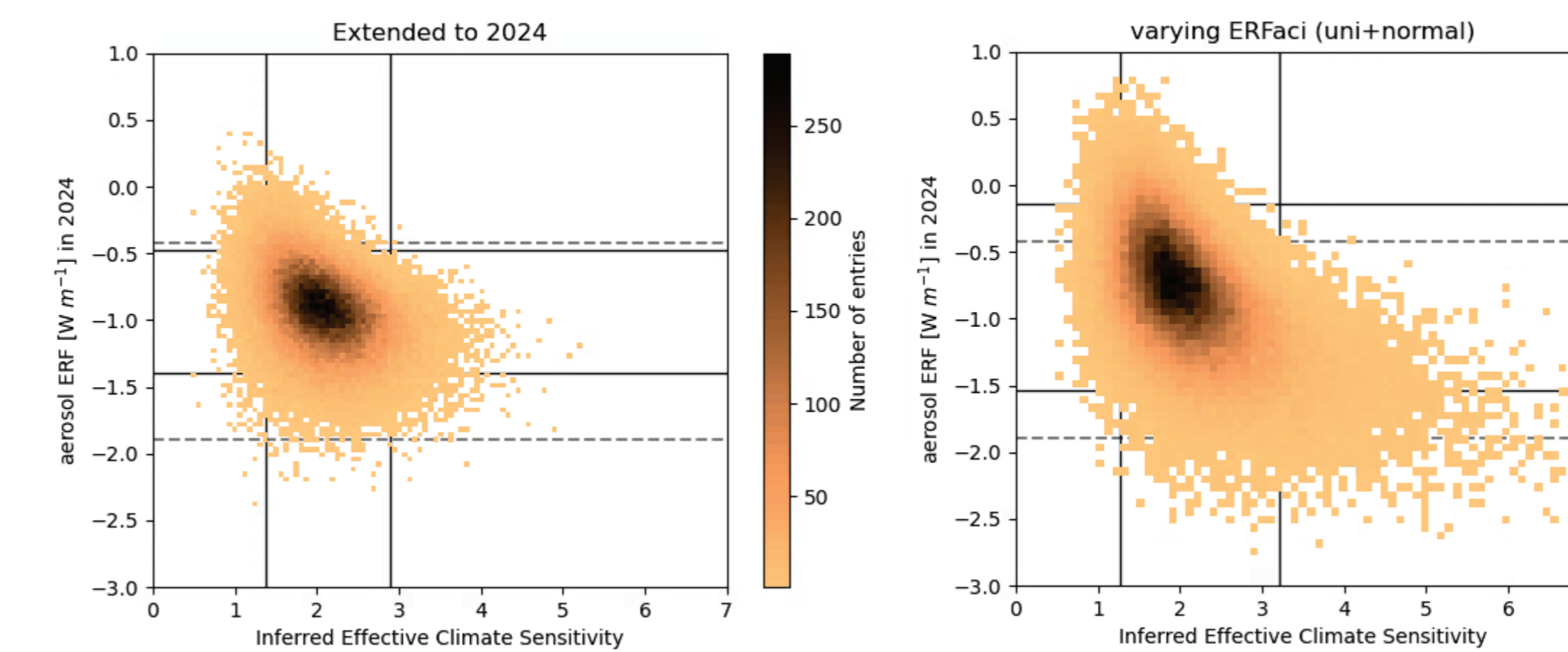


Aerosol ERF evolution

Another limitation in observational based estimates of climate sensitivity is the large uncertainty in the forcing of the Earth system, primarily due to the uncertain cooling effect from aerosols and its historical evolution.



Strong aerosol ERF in the 1960-1980s not supported by observations. Anthropogenic ERF > 0 W m⁻² over this period.



Idealized prior with aerosol forcing (ERFaci) independent in 1950, 2010, 2024 → stretch the upper tail of the ECS_{inf} distribution toward larger values.

Recent temperature records:

Include observations for the years 2023 and 2024:

Posterior mean ECS_{inf} [90% C.I.]:
End year 2022: 2.2 [1.5, 3.1] K
End year 2024: 2.1 [1.4, 2.9] K

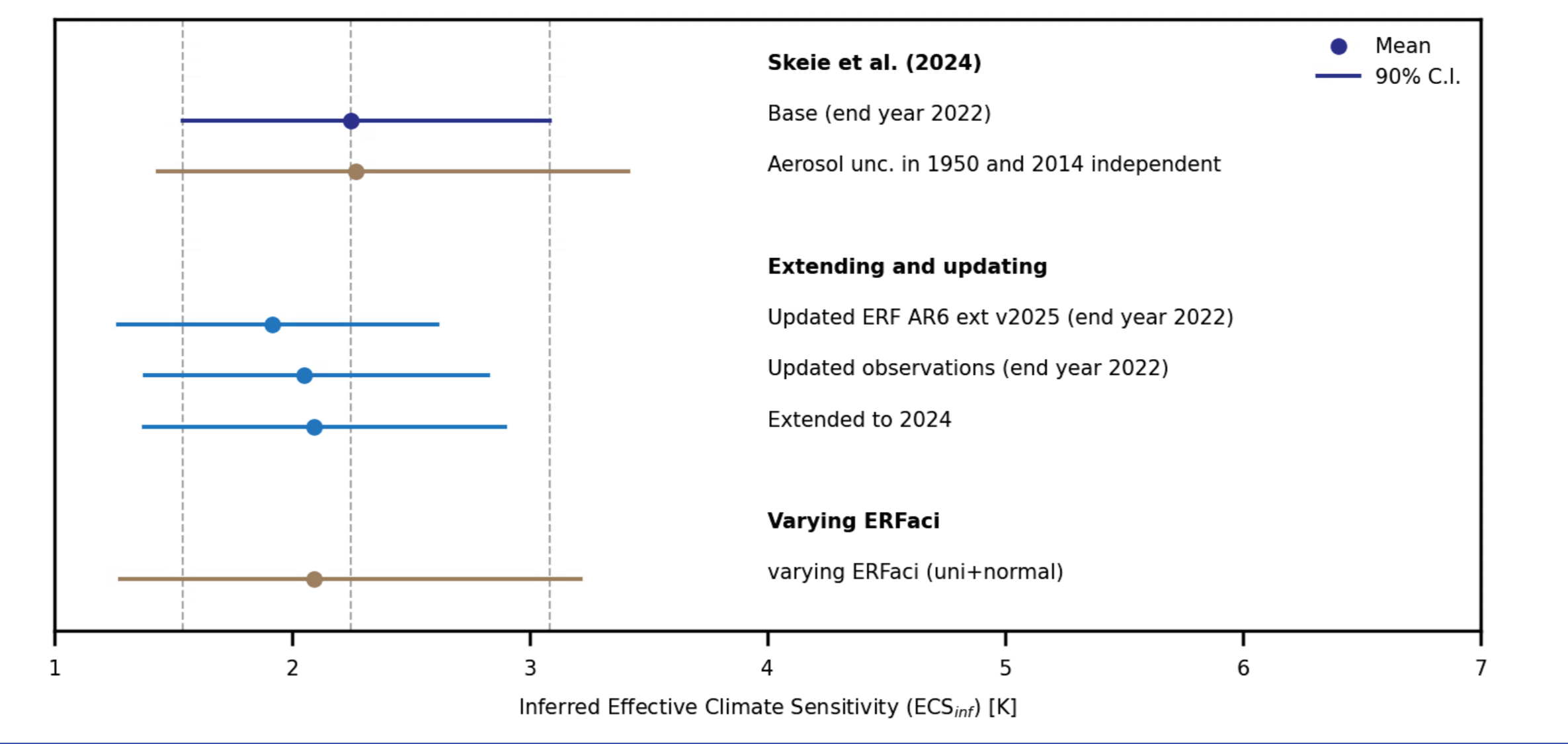
ECS_{inf} best estimate has remained stable from 1.9 K to 2.2 K where observations up to 2010, 2014, 2019 and 2022 were included (Skeie et al. 2014, 2018, 2024).

Pattern effect:

The posterior ECS_{inf} represents the mean climate feedbacks over the industrialized period. Pattern effect: The change in this feedback compared to 2xCO₂.

If a pattern effect of 0.5 Wm⁻²K⁻¹ (IPCC AR6 central estimate) is added → the climate sensitivity estimate is almost identical to the IPCC AR6 very likely range of 2 to 5 K, with a best estimate of 3K.

Inferred climate sensitivity (ECS_{inf})



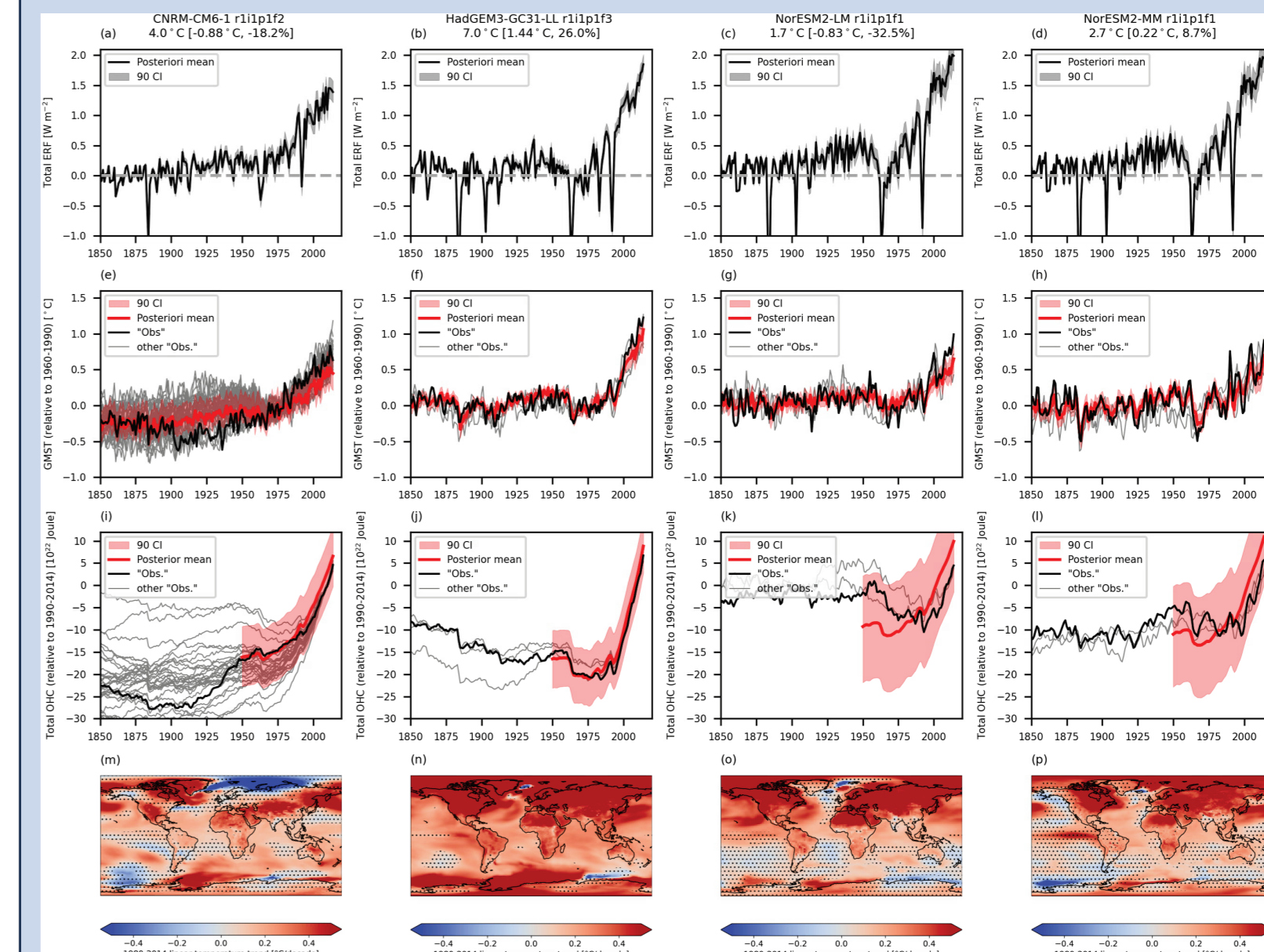
Take home:

- ECS_{inf} consistently end up in the lower ECS range in IPCC AR6 – with more years added and varying aerosol ERF evolution.
- Estimated ECS_{inf} (upper tail) sensitive to aerosol ERF pathway.
- Only feedbacks occurred over the industrial period included – which is a single realization of the Earth climate evolution.

Inferred effective climate sensitivity from a selection of CMIP6 models

1. Observed climate is only a single realization of the Earth's climate – How large is the spread in ECS_{inf} between different ensemble members?
2. How different is ECS and ECS_{inf} for these models?

Instead of observations, we use corresponding data from CMIP6 historical simulations to estimate ECS_{inf}



Historical ERF timeseries for the individual models, calculated from targeted simulations within CMIP6.

Temperature data for each ensemble member (gray, r1 in black). Posterior estimate for r1 in red.

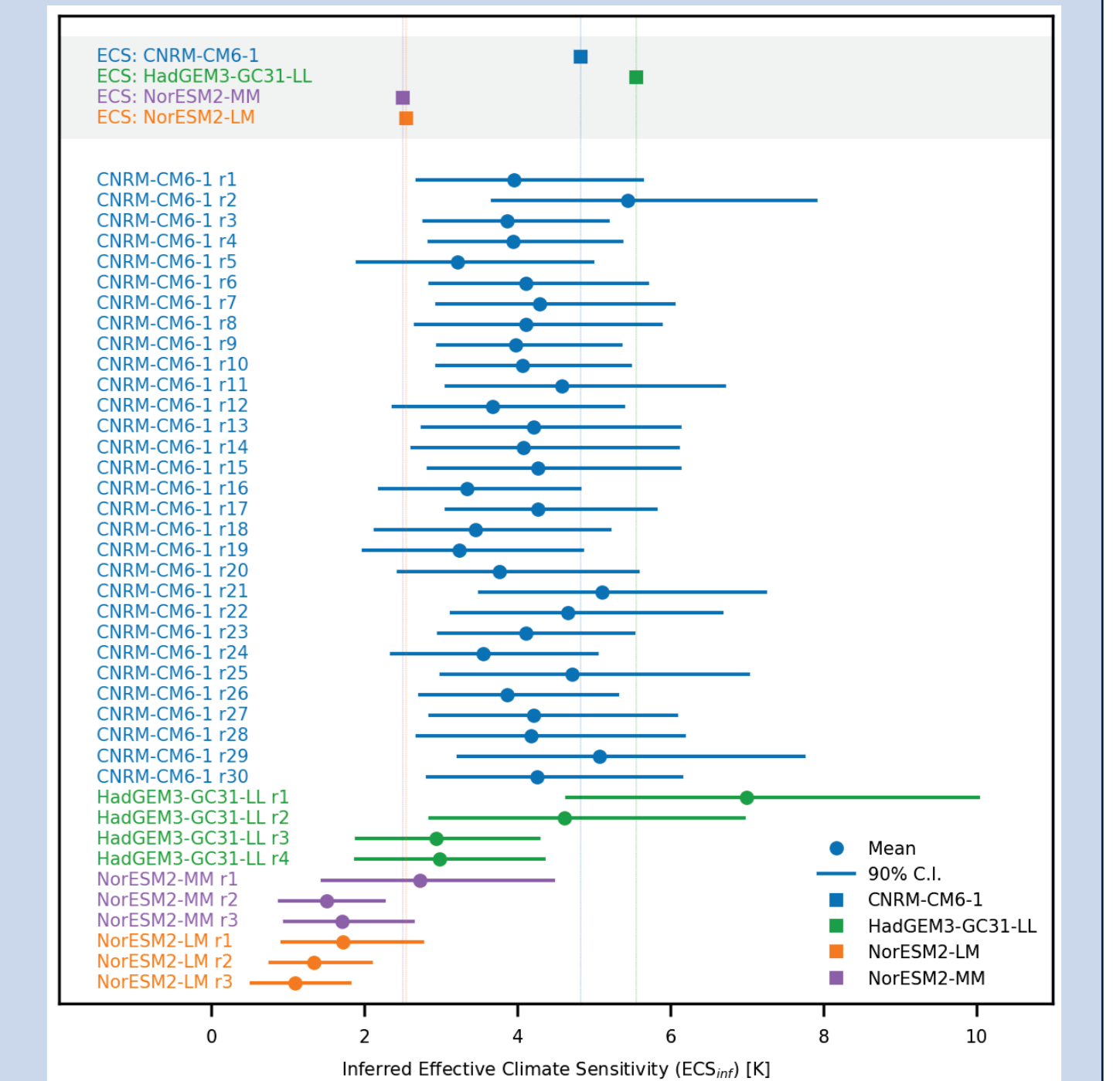
Total OHC for each ensemble member (gray, r1 in black). Posterior estimate for r1 in red.

Temperature trend pattern in ensemble r1. Large variability between different ensemble members for a given model.

Results:

The posterior mean ECS_{inf} varies by 0.6 K, 1.2 K, 2.1 K and as much as 4.1 K across ensemble members.

→ **Highlights** importance of natural variability in observational based estimates.



$ECS_{inf} < ECS$ (for most ensemble members)

Limitations: Structural limitations with the simplified energy balance model in capturing ocean-circulation driven variations in heat uptake and changes in feedbacks over time.

References:

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Acknowledgements:

This work was funded through the Norwegian Research Council project (grant number 314997). We kindly acknowledge all the observational data providers and climate modeling groups for their efforts and for making data available.