**EES 445**: Global Climate Change

# Making climate projections conditional on historical observations

*Ribes et.al. 2021*

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# Introduction

# Introduction

- Why look at Historical Observations / Constraints?

- Early Constraining Methodologies:

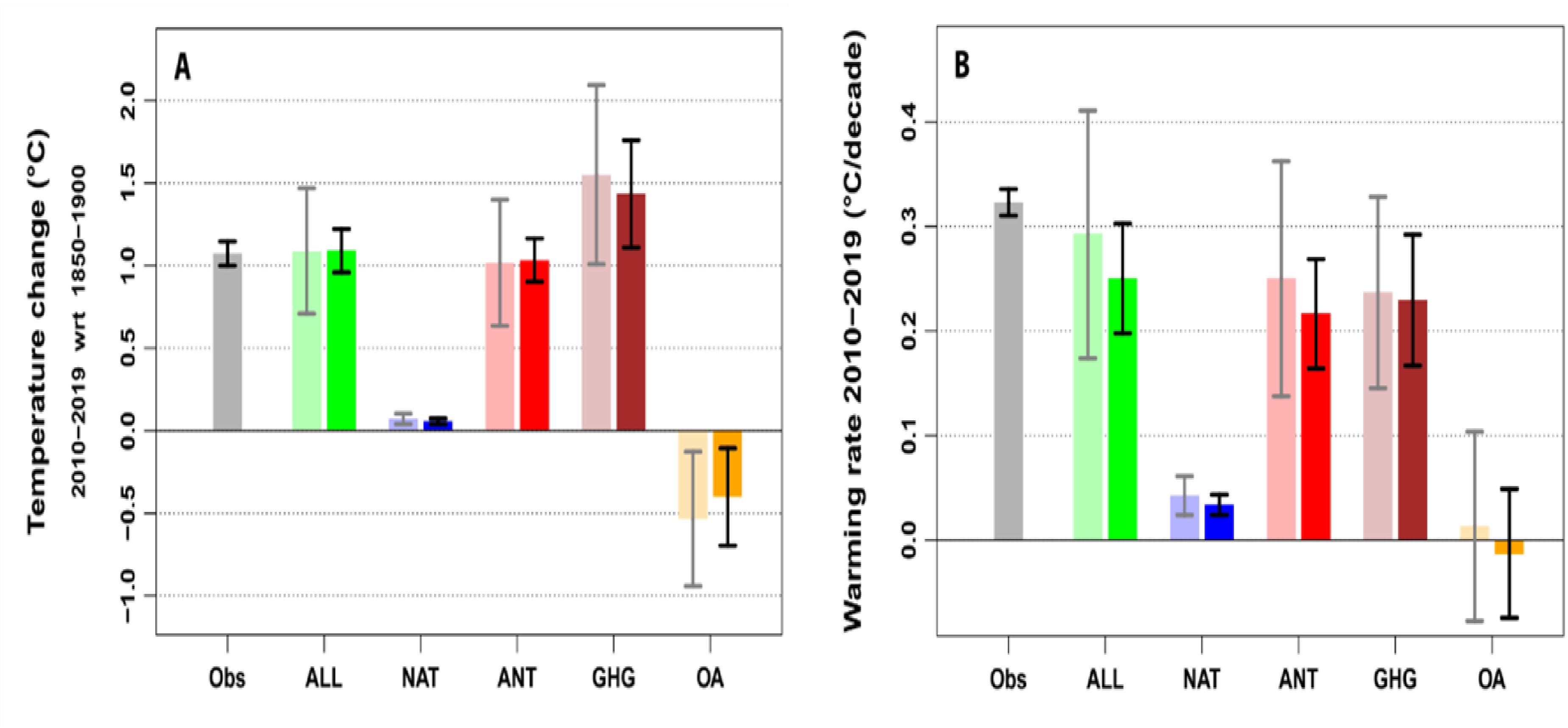
    - Detection and Attribution (**D&A**) techniques
    - Transient Climate Response (**TCR**)
    - Equilibrium Climate Sensitivity (**ECS**)
    - Energy Balance Models
    - Earth’s Energy Budget

# Introduction

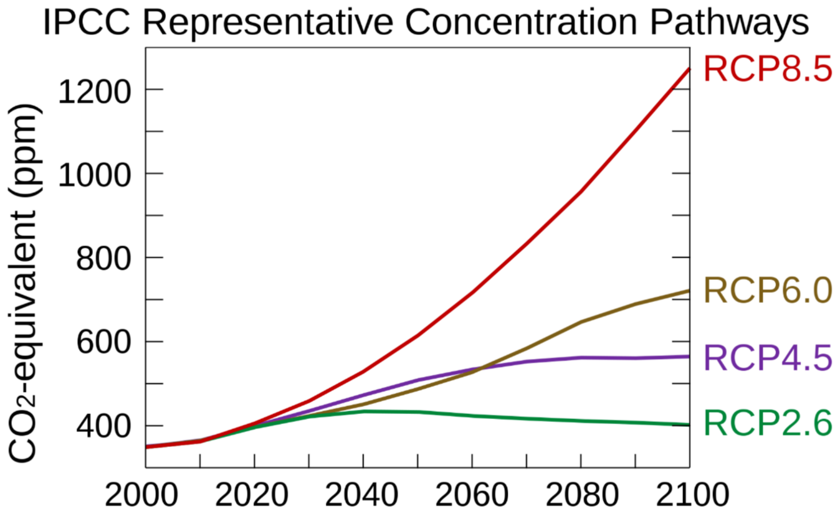
- Aim of the Study - Analyse warming range changes:
  - for the **temporal scale** (past, present and future)
  - across 3 new factors: Newly available climate models, improved observations, and a new statistical method.
- Latest Generation of Models: Coupled Model Intercomparison Project Phase 6 (CMIP6)
- Recent Improved Historical Observation Datasets
  - **SAT**: Near-Surface Atmospheric Temperature
  - **SST**: Sea Surface Temperature
- Newer Statistical Methods

# Results

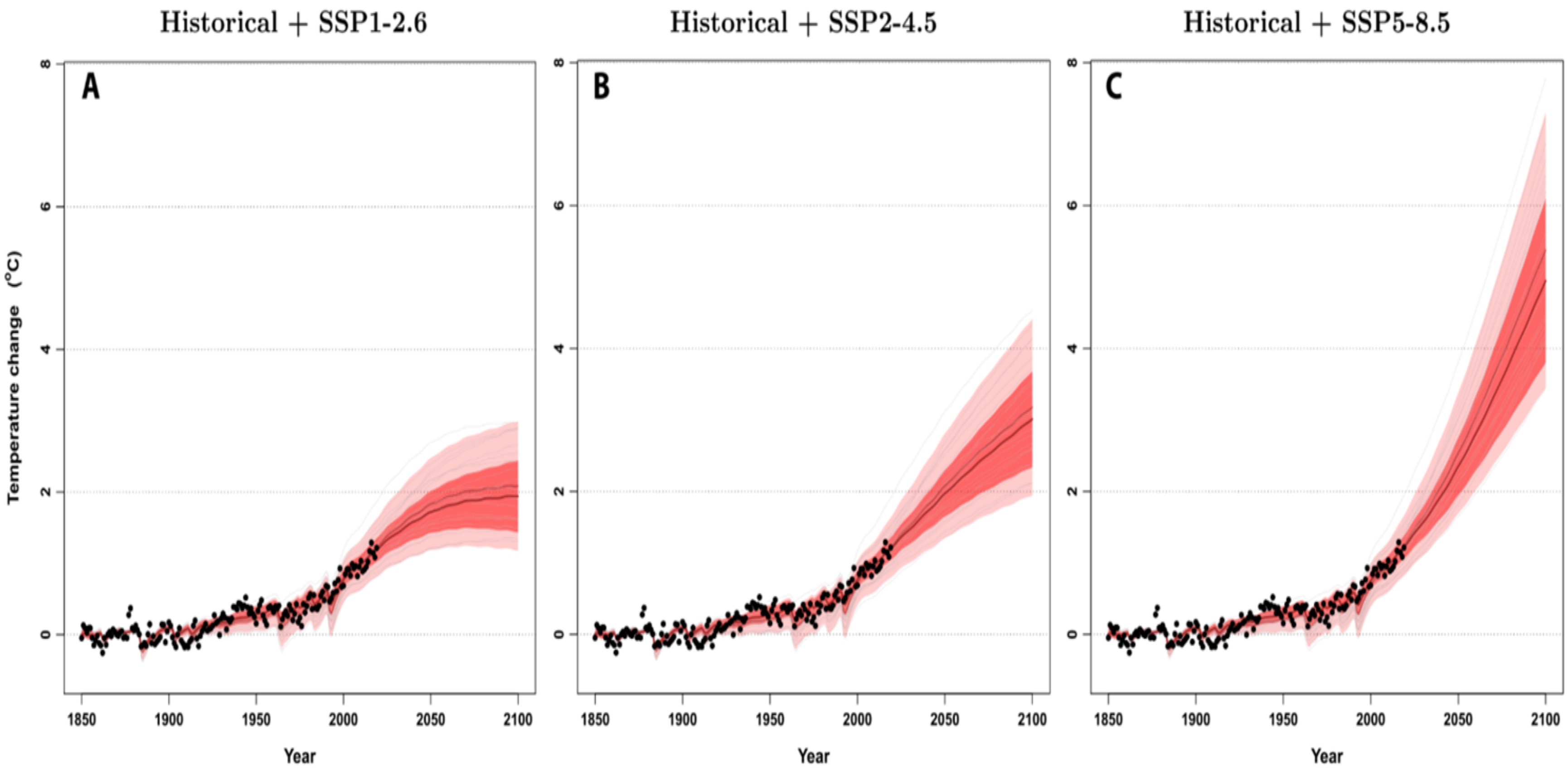
# Attributing Recent Warming



# Constraining Projections

# Constraining Projections



# Implications for Climate Sensitivity

- Using CMIP6 models, the climate sensitivity metrics (TCR and ECS)  in the cases of:

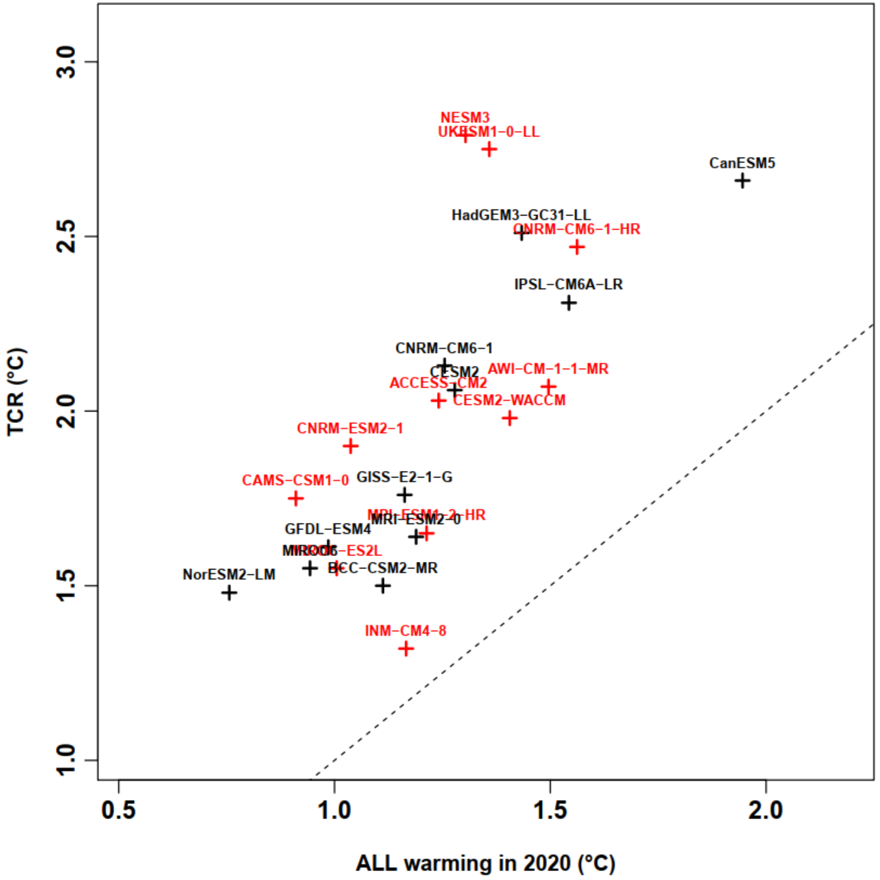
| | TCR | ECS |
|---|---|---|
| **Constrained** | 1.33 °C - 2.35 °C | 2.3 °C - 4.6 °C |
| **Unconstrained** | 1.24 °C - 2.72 °C | 2.1 °C - 6.1 °C |

- Consistent with projections, the constrained range primarily **revises the unconstrained model range downward** but excludes the lower end of the IPCC AR5-assessed likely range.
- Historical observations are expected to constrain ECS less effectively, and any such constraint must be taken with caution.
- The ECS range remains relatively wide suggesting observed GSAT changes do not constrain the long-term equilibrium (e.g., ECS/TCR ratio) very well.

# Implications for Climate Sensitivity

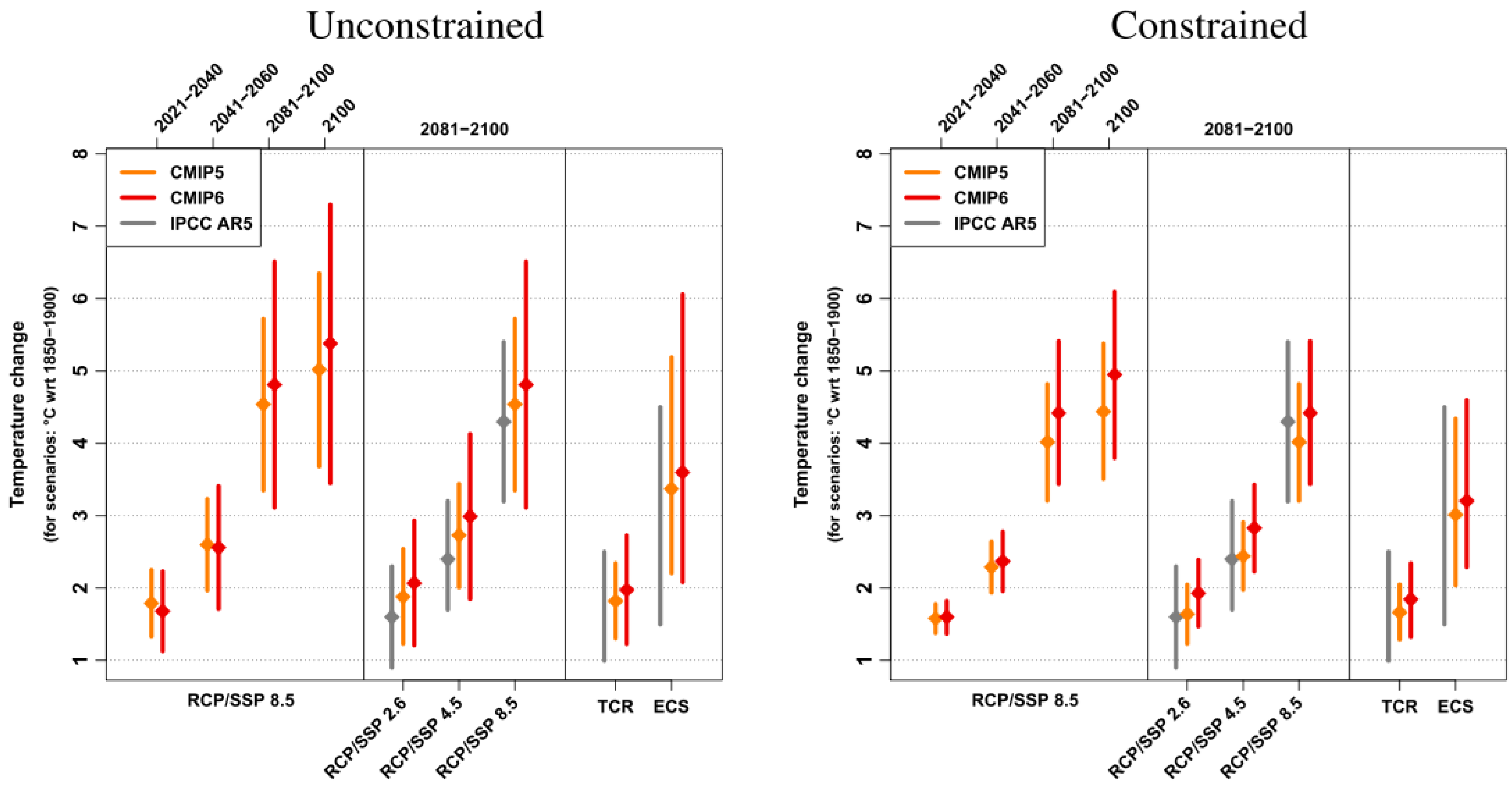
- The lower bound of TCR (Constrained) is consistent with some of the recent studies *[A.G. Libardoni et.al., 2019]* but is quite high compared to others *[Haustein K. et.al., 2019; Tokarska K. B. et.al., 2020]*.

  **Reason**: None of the CMIP6 models simulate TCR lower than their forced warming in 2020 (usually by a large margin).



# Comparing CMIP6 and CMIP5

- The same observational constraints were applied using CMIP5 models and RCPs.
- **Differences between unconstrained CMIP5 and CMIP6**: Higher warming, consistent with higher sensitivity, wider uncertainty ranges on CMIP6 leading to a relatively smaller lower bound.
- **Post-constraint application**: Ranges agree remarkably well in near-term (before 2040), suggesting that observations play a dominant role in this time frame.
- Both versions of ensemble models exhibit comparable width for all scenarios and periods considered. They diverge somewhat in the late 21st century.
- **Projected warming in 2100** is 10-15% higher using CMIP6 with the largest relative difference for the lowest emission scenarios. 0.3 °C to 0.5 °C difference in 2100, depending on the scenario.
- A smaller **discrepancy** is found in the case of **climate sensitivity metrics** i.e. TCR and ECS:
  - Range for TCR based on CMIP5 models is more narrower with lower upper bound
  - Range for ECS is shifted upward by about 0.2 °C from CMIP5 to CMIP6




**Comparison of warming ranges from the CMIP6 ensemble to CMIP5 and IPCC AR5**

# Comparing CMIP6 and CMIP5

- **Differences in scenarios** = A  more pronounced 21st century warming in CMIP6 relative to CMIP5. Although RCPs and SSPs have same forcing level in 2100, actual forcing levels are higher in SSPs.
- Scenario differences explain large gap in warming but can’t explain the reported discrepancies in TCR and ECS, => **CMIP6 models might exhibit a higher sensitivity than CMIP5 models** (unconstrained or constrained).
- The constrained time series of past changes using the CMIP5 or CMIP6 ensembles agree remarkably well.These two ensembles provide different estimates of future changes while they are in perfect agreement in the past.
  Possible reasons for this:
  - Substantial difference in the historical forcings used in both the ensembles (aerosols forcing in late 20th century, poor representation of RFs after 2005 in CMIP5)
  - Progress in the representation of atmospheric physics can affect how models respond to a given change in forcings.
- The **model sampling uncertainty** could also contribute to the reported gap.

# Discussion

- Entire observational record was used to refine estimates of past and future climate change.
- The results suggest that the uncertainty in human induced warming can be reduced significantly: typically by a factor of x3, in the past and in the near term (i.e. by 2040) and by a factor of x2 in the long term (late 21st Century)
- Constrained estimates of attributable warming to date, future warming in response to a range of emission scenarios, and metrics of climate sensitivity, were derived and all of them consistently rejected the lower end of previous estimates.

*Comparison with a recent study [by Tokarska K.B. et.al., 2020] on similar lines*:

- Results of this paper agree with this recent study in rejecting the highest sensitivities from CMIP6
- This paper, however, reports larger reduction in uncertainty arising primarily from discrepancies in the lower bound of constrained ranges.[TCR ranges: 0.90° - 2.27°C (considering the 1981–2014 period), as opposed to 1.33 ° to 2.36°C here]
- This study’s constraints suggest a slightly higher future warming using CMIP6, while Tokarska et al. report consistent results with these two ensembles

*Limitations:*

- Prior distribution might not sample uncertainty comprehensively. The number of models could increase as the CMIP6 archive becomes more fully populated.
- Forcing uncertainty is also poorly sampled in the CMIP6 ensemble.
- CMIP models exhibit dependencies among themselves and from one generation to the next, further reducing the effective model sample size.

- Alternative approach to tackle model uncertainty sampling issue:  Perturbed Physics Ensembles (PPEs).

- Unlike techniques based on energy balance models, which are only suitable at the global or hemispheric scales, this technique could be easily adapted to constrain past and future changes at the regional scale

- Given that accurate climate projections with well-quantified uncertainties are essential for adaptation planning and mitigation policies, the authors believe and expect the results of this study and similar applications on smaller scales to be of great value to a range of stakeholders

# Materials and Methods

# Data

1. **Observational Data:**

- We use HadCRUT4-CW dataset with global coverage, which alleviates issues with missing data.
- From it, we compute global mean near-surface temperature(GMST).
- This dataset uses blending of sea surface temperatures(SSTs) and near-surface air temperature over land.
- HadCRUT4-CW dataset has measured uncertainties, through a set of equally plausible realizations.

*NOTE: We don’t use other dataset for GMST because they usually fall within uncertainty of HadCRUT4-CW.*

## 2. CMIP data:

- We make use of large set of models from CMIP6 and CMIP5.
- We take all models providing at least 200 years of pre industrial control simulations.
- One simulation model being of W m^-2 of scenario.
- Second being historical GHGs simulation.
- We use 22 models for CMIP6 and 17 models for CMIP5.

# Statistical Method

1. **Constraining projections:**

- Statistical approach works in two steps:
    - First, we consider an ensemble of climate models to derive a prior of real-world response from 1850-2100, denoted by $\pi(x)$.
    - Second we make use of GSAT observations (y) to derive the posterior $p(x|y)$.
- Then we derive $\pi(x)$ by estimating the GSAT response for each CMIP model for each scenario considered.
- Then we derive $p(x|y)$, as $\pi(x)$ follow normal laws.

## 2. Application to attribution

- To estimate attributable warming, the method is applied to a much longer vector.
- We consider the responses to ALL, NAT-only, or GHG-only forcings, respectively.
- The posterior distribution p(x | y) then provides information not only about the total forced response given y but also about the responses to NAT and GHG forcings specifically, still given y.
- Deriving the prior (x), in the case of attribution, requires an estimate of the responses of each climate model considered to the NAT and GHG forcings, specifically.

## 3. Application to TCR and ECS

- A key difficulty, in this case, is that there are several ways to relate TCR and ECS to the constrained temperature changes.
- Calculating ECS means the feedback parameter  is assumed constant; therefore, we consider an effective climate sensitivity rather than the real long-term ECS.

## 4. Discussion of the method and estimation of input parameters

- The model prior captures various facets of model uncertainty in a consistent way. This includes uncertainty in both the magnitude and the temporal pattern of the forced response, unlike usual D&A methods.
- Using the entire observed dataset avoids the arbitrary choice of a reference period, facilitates annual updates, and helps distinguish the responses to GHGs from OA factors.

# Thank you