

Quantifying Uncertainty in Climate Sensitivity Metrics Using Large Ensemble Observational Datasets

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Abstract.

Gridded surface temperature observational datasets are an important line of evidence for estimating climate sensitivity metrics. Climate sensitivity metrics are often derived from comparing historical warming in these observations against climate model simulations, an approach that is known to be sensitive to the choice of observational dataset. With observational products now providing large ensembles that sample their own methodological uncertainty, we use these large ensembles, together with a spatial-temporal model-observation framework, to assess the sensitivity of climate sensitivity metrics to observational uncertainty. We find that the uncertainty within a single dataset is now the dominant source of observational uncertainty, five to six times larger than the typical uncertainty captured when only the median estimate from each data product is considered. The additional datasets from these observational products further allow us to isolate where this uncertainty originates in the construction of a dataset. Uncertainty in how the land record is constructed contributes at least seven times more than uncertainty in the construction of the ocean record for climate sensitivity metrics, and we find that the choice of whether to spatially infill the observational record shifts estimates by about 0.2 °C. Applying the large ensembles to a global, time-mean energy balance framework, we find that uncertainty from a single dataset can produce a difference of about 1.1 °C in the median estimate of equilibrium climate sensitivity.

1 Introduction

Equilibrium Climate Sensitivity (ECS)—representing the equilibrium global mean surface temperature change in response to a doubling of atmospheric carbon dioxide (CO₂) concentration—and Transient Climate Response (TCR)—the global mean surface temperature change at the time of CO₂ doubling in a scenario where CO₂ increases at 1% per year—are fundamental climate sensitivity metrics important for understanding Earth’s climate response to increasing CO₂ concentrations. To constrain ECS specifically, recent assessments have used multiple lines of evidence including historical evidence, paleoclimate reconstructions, and process evidence (Sherwood et al., 2020; Forster et al., 2021). Within the historical evidence, there exists a subset of studies that constrain climate sensitivity metrics by systematically comparing observed historical warming patterns against climate model simulations—an approach we henceforth term model-observation frameworks (Forest et al., 2000, 2002, 2006; Sansó and Forest, 2009; Libardoni and Forest, 2011; Aldrin et al., 2012; Skeie et al., 2014; Johansson et al., 2015; Skeie et al., 2018). Studies using model-observation frameworks typically use emulator models (Sansó and Forest, 2009; Olson et al., 2012) or reduced-complexity Earth system models (Forest et al., 2002; Aldrin et al., 2012; Skeie et al., 2018), allowing them to efficiently explore relationships between key model parameters and observed historical warming. The model-observation framework has long been known to be highly sensitive to the choice of observational datasets (Libardoni and Forest, 2011; Sherwood et al., 2020), with different temperature reconstructions yielding climate sensitivity estimates that can differ by up to 1 °C. While the effect of observational uncertainty on climate sensitivity has been addressed in model-observation frameworks by using multiple datasets (Aldrin et al., 2012; Skeie et al., 2014) or select combinations of them (Olson et al., 2012), the underlying sources of observational uncertainty on climate sensitivity metrics have not been systematically analyzed.

Simultaneously, observational datasets themselves have evolved in how they characterize uncertainty. Previously, data centers that created gridded temperature reconstructions provided only a single realization of past historical warming. With recent updates, these data centers now provide large ensembles that sample the uncertainty in their methodology of generating gridded datasets. Specifically, the National Oceanic and Atmospheric Administration provides NOAA GlobalTemp version 5 (NOAA) with a 1000-member ensemble, the Met Office Hadley Centre/Climatic Research Unit provides Global Surface Temperature Dataset Version 5 (HadCRUT5) with a 200-member ensemble, the Goddard Institute for Space Studies provides Surface Temperature (GISTEMP) with a 200-member ensemble, and Berkeley Earth Surface Temperature (BerkeleyEarth) provides uncertainty estimates for their reconstructions (details in Methods). Additionally, NOAA partitions its ensemble uncertainty between land surface air temperature (LSAT) and sea surface temperature (SST) components, while HadCRUT5 provides versions with and without spatial infilling.

With the availability of updated observational datasets and their large ensembles along with source-specific decompositions, we can systematically assess how different uncertainty sources in observational datasets propagate to climate sensitivity estimates in model-observation frameworks. Specifically, we address:

1. How do different versions of observational datasets compare, and how do the different observed temperature estimates impact the values of ECS and TCR?
2. Data centers now provide large ensembles that quantify uncertainty in their methodology for creating gridded data products, but how does this uncertainty compare to differences that originate from using entirely different methodologies?
3. How much do partitioned uncertainties in the creation of LSAT and SST contribute to climate sensitivity estimates, and what is the impact of spatial infilling techniques on ECS and TCR?
4. How do the estimates of ECS derived from global energy balance frameworks to the uncertainty in the creation of these observational datasets?

We address these questions using the Massachusetts Institute of Technology Earth System Model (MESM) as our Earth system model (Sokolov et al., 2018) within a model-observation comparison framework. Our approach applies a variant of the optimal fingerprinting method (Allen and Tett, 1999) combined with Bayesian updating to estimate climate sensitivity metrics. By systematically propagating the full ensemble spreads from multiple observational datasets, we aim to provide insights into how uncertainties in observational datasets affect climate sensitivity metrics derived from model-observation frameworks.

2 Methods

2.1 Overview of MESM

We use the MESM as our climate model, notable for its capacity to conduct an extensive array of simulations. MESM's strength lies in its capability to dynamically adjust key climate parameters, thus altering the feedback mechanisms of the Earth

system. This unique capability allows us to explore a spectrum of climate states, extending beyond the usual practice with general circulation models (GCMs), which typically test various forcing scenarios within a fixed climate state (Sokolov and Stone, 1998). Within this framework, we specifically tune three key climate parameters: climate sensitivity (S), effective ocean diffusivity (K_v), and the net aerosol scaling factor (F_{aer}). The S is modulated through the strength of the cloud feedbacks at different vertical levels in the model (Sokolov, 2006; Sokolov and Monier, 2012). K_v is set to represent the vertical diffusion of heat anomalies into the deep ocean, accounting for all mixing processes. This value tends to exceed those for typical ocean diffusivity, which are limited to heat diffusion alone (Sokolov et al., 2003). F_{aer} is characterized by a geographically varying pattern that differs over land and ocean. While this pattern is constant in its spatial distribution, it is dynamically scaled over time in line with the evolving emissions of sulfur dioxide (Langner and Rodhe, 1991), and also as a proxy for all unmodeled forcings in our simulations (Forest et al., 2000).

The MESM is comprised of three main components: an atmospheric model incorporating dynamic, physical, and chemical processes; an ocean model with an integrated carbon cycle; and a suite of land models that simulate ecosystems and biogeochemical cycles. The atmospheric component of MESM, a zonally averaged statistical-dynamical model, is derived from the GISS three-dimensional climate model, first described by Hansen et al. (1984). The model utilizes a latitude-height coordinate system to calculate zonal-mean temperatures. Simulations are conducted at a 4° latitudinal resolution with 11 vertical layers. Each latitude band is subdivided into four surface types: land, ocean, sea-ice, and land-ice, with zonal values determined as the weighted average of these types. The atmosphere interacts with a mixed-layer ocean model, with heat anomaly diffusion across the interface linking the two components. In MESM, the ocean model comprises a mixed-layer model with a horizontal resolution of 4° in latitude and 5° in longitude, and a 3,000-meter-deep Anomaly-Diffusing Ocean Model (ADOM) below. The depth of the mixed layer is determined by latitude and time, derived from observations (Hansen et al., 1983). The land component of MESM is designed to capture the spatial and temporal dynamics of heat, water, carbon, and nitrogen fluxes, not only within land ecosystems but also in their exchanges with the atmosphere. This coupled land-atmosphere-ocean system is driven by both natural and anthropogenic forcings, detailed in Forest et al. (2006). Natural sources include solar irradiance variations and volcanic aerosols, while anthropogenic sources encompass greenhouse gas concentrations, sulfate aerosol emissions, and changes in stratospheric and tropospheric ozone levels.

2.2 Observational Datasets

2.2.1 Berkeley Earth Surface Temperature (BerkeleyEarth)

We used estimates of monthly surface temperature anomaly from BerkeleyEarth (Rohde and Hausfather, 2020), available in a $1^\circ \times 1^\circ$ grid from 1850 to the present. This dataset integrates the Hadley Centre Sea Ice and Sea Surface Temperature data set (HADSST3) (Kennedy et al., 2011a, b) with the BerkeleyEarth Land temperature record (Muller et al., 2013; Rohde et al., 2013). The HADSST3 component of this dataset undergoes several adjustments, most notably the replacement of the gridded data with an interpolated field using a kriging-based approach. We use the BerkeleyEarth version that treats areas with sea ice as air temperature over sea ice. BerkeleyEarth's anomaly base period is 1951-1980. Notably, the ocean-average

uncertainty in BerkeleyEarth’s ocean reconstruction aligns with the model adopted by HadSST3, which combines sampling, bias, and measurement error uncertainties. For BerkeleyEarth’s land data, the analysis utilizes over 40,000 stations, offering a more extensive dataset compared to some other products. The uncertainty assessment for the combined record assumes independence between uncertainties in LSAT and SST time series, combining these in proportion to the relative area of land and ocean (Rohde and Hausfather, 2020). Statistical uncertainties in BerkeleyEarth’s Land record are estimated using a “jackknife” statistical method, which involves subdividing the stations into smaller sets and comparing the results (Muller et al., 2013). Spatial sampling uncertainties for the land are assessed by simulating poorly sampled periods with modern data, measuring the departure from the full site average using only the limited spatial regions available at early times (especially prior to 1850). It is important to note that unlike the HADCRUT5, which provides 200 samples of sampling, bias and measurement error uncertainty, the BerkeleyEarth dataset only presents minimum and maximum uncertainty estimates. Gridded uncertainty estimates for BerkeleyEarth were obtained through personal communication with Zeke Hausfather and Robert Rodhe. The monthly estimates of surface temperature anomaly can be downloaded from <https://berkeleyearth.org/data/>.

2.2.2 Goddard Institute for Space Studies Surface Temperature (GISTEMP)

In our analysis, we utilized median estimates of monthly surface temperature anomalies from the Goddard Institute for Space Studies Surface Temperature with 250 km Smoothing (GISTEMP250), available from 1880 to the present in a $2^\circ \times 2^\circ$ grid (Lenssen et al., 2019). GISTEMP250 combines GISTEMP v4’s land temperature data with the Extended Reconstruction Sea Surface Temperature (ERSST v5) (Huang et al., 2017), and employs the 1951-1980 period as its anomaly base. The dataset, accessible at <https://data.giss.nasa.gov/gistemp/>, is distinct in its use of an equal-area grid system developed by Hansen and Lebedeff (1987), which divides the Earth into 80 equal-area boxes in bands of constant latitude. This arrangement provides a consistent representation across diverse geographical regions. GISTEMP250’s methodology includes radial basis function interpolation with a 250 km radius of influence for each station, enabling effective data infilling, especially for data-scarce periods before 1960. Additionally, the station averaging process in GISTEMP250 integrates a new station if it overlaps with existing data for at least 20 years, applying an offset to maintain the mean over this common period unchanged for each calendar month.

In addition to the operational median GISTEMP version 4 analysis, a 200-member GISTEMP version 4 uncertainty ensemble is available, spanning 1880–2020 at $2^\circ \times 2^\circ$ resolution. This ensemble differs from the median product by using a broader spatial influence radius of approximately 1200 km for interpolation, enhancing coverage in data-sparse regions. Land LSAT data from the Global Historical Climatology Network monthly version 4 (GHCNm v4) (Menne et al., 2018), with SST data from ERSSTv5 (Huang et al., 2020), are incorporated. Similar to HadCRUT5 and BerkeleyEarth, LSAT uncertainties are partitioned into sampling, bias, and measurement error components. A 100-member GHCN-ERSST-GISTEMP intermediate ensemble is first generated by applying the standard GISTEMP analysis steps—converting station and grid cell data into monthly anomalies, merging LSAT and SST fields, and performing spatial interpolation—to monthly LSAT and SST realizations. Each of these 100 members is then combined with two independent LSAT sampling uncertainty realizations, producing the final 200-member

130 GISTEMP observational uncertainty ensemble. GISTEMP median estimates and ensembles are accessible at <https://data.giss.nasa.gov/gistemp/>

2.2.3 National Oceanic and Atmospheric Administration Global Temperature version 5 (NOAA)

We used median estimates of monthly surface temperature anomaly from NOAA Global Temp V5 (Huang et al., 2020), available in a 5° x 5° latitude-longitude grid from 1850 to the present. NOAA Global Temp V5 incorporates Sea Surface
135 Temperature data from ERSSTv5 (Huang et al., 2017) and Land Surface Air Temperature data from the Global Historical Climatological Network monthly version 4 (Menne et al., 2018), with 1961-1990 as its anomaly base period. In addition to median estimates, we utilized uncertainty estimates from NOAA Global Temp V5, which include 1000-member realizations of surface temperature anomaly, encompassing the various uncertainties inherent in dataset creation. Total uncertainty in NOAA Global Temp V5 comprises of parametric and reconstruction uncertainties. Reconstruction uncertainty addresses errors from
140 using limited empirical orthogonal teleconnection modes in SST and LSAT reconstructions, while parametric uncertainty relates to selecting internal parameters in these reconstructions. This approach implicitly includes sampling uncertainty within the parametric uncertainty framework.

We also utilized the separated uncertainties associated with the LSAT and SST components of NOAA Global Temp V5. LSAT uncertainties arise primarily from methods used in homogenizing and gridding station data, nonstandard instrument
145 exposures, and variations in station distributions within grid boxes. A 100-member ensemble of GHCN monthly version 4 data was employed to estimate these uncertainties. SST uncertainties are quantified at both local grid and global scales, taking into account the limited number of statistical modes used in analysis. These uncertainties are larger in the early period (1880s–1910s) and during the world wars due to sparse observations, decreasing significantly in the modern period (1950s–2010s) due to improved data coverage.

150 Uncertainties at the global scale in NOAA Global Temp V5 are substantially smaller than at the local grid scale due to error cancellations through averaging. SST uncertainties are generally smaller than LSAT uncertainties, attributed to less variabilities in SST. NOAA Global Temp V5 datasets can be downloaded from <https://www.ncei.noaa.gov/data/noaa-global-surface-temperature/v5/>.

2.2.4 Met Office Hadley Centre/Climatic Research Unit Global Surface Temperature Dataset Version 5 (HadCRUT5)

155 We utilized monthly surface temperature anomaly estimates from HadCRUT5 (Morice et al., 2021), available in a 5° x 5° latitude-longitude grid covering the period from 1850 to 2018. HadCRUT5 uses Climatic Research Unit Temperature version 5 (CRUTEM5) (Osborn et al., 2021) for land temperature estimates and HADSST4 (Kennedy et al., 2019) for sea surface temperatures. HADCRUT5 offers two variations: one with temperature anomaly data on grids based on available measurement data and another using a Gaussian process-based statistical method for spatially complete temperature anomaly estimates. Each
160 variant is provided as a 200-member ensemble, accompanied by comprehensive uncertainty information.

The uncertainties in HadCRUT5 are categorized into measurement and sampling uncertainties, bias uncertainty, and coverage uncertainty. Measurement and sampling uncertainties combine uncorrelated uncertainties in the land station record with

correlated uncertainties in sea-surface temperatures. Bias-related uncertainties encompass contributions from both CRUTEM5 and HADSST4, including homogenization adjustments, long-term average calculations for the 1961 to 1990 reference period, effects of urbanization, sensor exposure changes, and sea-surface temperature bias adjustments. These bias uncertainties, due to their strong spatial correlation, significantly contribute to the total uncertainty in the global average temperature anomaly time series. Coverage uncertainty in HadCRUT5 represents the potential errors in regional averages due to the spatial incompleteness of the dataset, affecting the reliability of regional average temperature anomaly estimates. HadCRUT5 datasets, including median estimates and their ensembles, are accessible at <https://www.metoffice.gov.uk/hadobs/hadcrut5/data/current/download.html>.

2.3 Standardization of Observational Data

For our analysis, we used data from four different data centers, each providing surface temperature anomaly data in a gridded format. However, these datasets differ in their anomaly base years. To standardize our approach, we converted this gridded global data into four equal-area zonal estimates of surface temperature anomaly. Our standardization process involved using 1906-1995 as the base period for temperature anomaly estimation. We then transformed the monthly datasets into decadal averages for the period 1940-2010. We based this transformation on selecting grid points with more than 8 months of data per year and at least 8 years of data within each decade. We uniformly applied this procedure across all the different versions of datasets acquired from the data centers.

2.4 Bayesian Estimation of Climate Sensitivity Metrics

We follow the methodology established by Forest et al. (2002, 2006) and Libardoni and Forest (2011); Libardoni et al. (2018, 2019) to derive probability distributions for key model parameters in our analysis, focusing on Transient Climate Response and Climate Sensitivity. This process involves running historical climate change simulations using the MESM model. We compare the output of each simulation, defined by a distinct set of model parameters, against past climate observations to assess how effectively it represents the climate system.

In terms of model parameters, we sample Climate Sensitivity from 0.5 to 10.0 °C in increments of 0.5 °C, the square root of effective ocean diffusivity from 0 to 8 cm²/s in increments of 1 cm²/s, and the net aerosol forcing scaling parameter from -1.75 to 0.5 W/m² in increments of 0.25 W/m². These ranges allow for a comprehensive exploration of climate system responses within the model.

For model performance evaluation, we utilize two temperature diagnostics. Firstly, the time series of decadal mean surface temperature anomalies across four equal-area zonal bands, calculated with respect to a chosen base period. Secondly, the linear trend in global mean ocean heat content in the 0-2000 m layer. We rely on observations from Levitus et al. (2012) for ocean heat content data. In this study, we use multiple observational datasets from different data-centers but use the same ocean heat content data for each calculation.

To quantify the fit between model output and observed diagnostics, we compute a goodness-of-fit statistic, r^2 , for each model run. This statistic is based on the weighted sum of squared residuals between observed diagnostics and corresponding

model outputs. Weights are derived from unforced climate variability from 25 Coupled Model Intercomparison Project Phase 5 (CMIP5) models based on their pre-industrial control run simulations (Libardoni et al., 2019). The goodness-of-fit statistics are then converted to probability distribution functions (PDFs) for model parameters using the likelihood function as described by Forest et al. (2006) and modified by Libardoni and Forest (2011) and Lewis (2013). We apply Bayes' Theorem to combine
200 likelihoods and estimate a joint PDF for the model parameters. An expert prior for S , as derived by Webster and Sokolov (2000), and uniform priors for K_v and F_{aer} are utilized. We calculate probability distributions for individual parameters by integrating the joint PDF over the two other parameter dimensions. Following this, we focus on deriving probability distributions specifically for TCR. To achieve this, we utilize the joint probability distributions obtained from the MESM ensemble. From each of these distributions, we draw a 1000-member Latin Hypercube Sample, as outlined by McKay et al. (1979). This
205 sampling technique allows us to systematically explore the parameter space, ensuring a comprehensive representation of the model's variability and response characteristics.

2.5 Recreation of Sherwood et al. (2020) Climate Sensitivity Distribution with Large Ensembles from Observational Datasets

We reproduce the climate sensitivity distribution from Sherwood et al. (2020) (their Figure 11b, black line) and then apply
210 large ensemble observational temperature datasets to examine how the distribution varies across large ensemble estimates. We briefly describe the Sherwood et al. (2020) methodology below.

For the historical estimate of climate sensitivity (defined as Historical-No-Pattern-Effect in their paper), Sherwood et al. (2020) use the global energy balance framework (listed as Equation 19 in their paper):

$$S_{\text{hist}} = \frac{\Delta F_{2 \times \text{CO}_2} \times \Delta T}{\Delta F - \Delta N}$$

215 where S_{hist} is climate sensitivity, $\Delta F_{2 \times \text{CO}_2}$ is the CO_2 doubling forcing, ΔT is the observed warming, ΔF is total radiative forcing, and ΔN is the change in top-of-atmosphere energy imbalance.

For their baseline calculation, Sherwood et al. (2020) used $\Delta F_{2 \times \text{CO}_2} = 4.0$ (3.51, 4.49) W/m^2 , $\Delta F = 1.83$ (−0.03, 2.71) W/m^2 , and $\Delta N = 0.6$ (0.3, 0.9) W/m^2 , with values in parentheses representing 5–95% uncertainty ranges. These forcing estimates are taken from Bellouin et al. (2020). For ΔT , they used the Cowtan and Way (2014) temperature reconstruction
220 with baseline period 1861–1880, recent period 2006–2018, yielding $\Delta T = 1.03$ (0.89, 1.17) $^{\circ}\text{C}$ with a standard deviation of ± 0.14 $^{\circ}\text{C}$. They use a uniform prior distribution on S_{hist} from 0 to 20 $^{\circ}\text{C}$.

The key methodological difference involves replacing Sherwood et al. (2020)'s single temperature reconstruction ($\Delta T = 1.03$ K) with ensemble-specific warming estimates from three large ensemble observational datasets: NOAA, GISTEMP, and HadCRUT5 (200 members each), yielding 600 different ΔT values. We maintain consistency with Sherwood et al. (2020)'s
225 baseline and anomaly period but modify them slightly given data availability constraints. Specifically, for HadCRUT5 we use the identical 1861–1880 to 2006–2018 periods, while for NOAA we use 1861–1880 to 2006–2015 as the ensemble terminates in

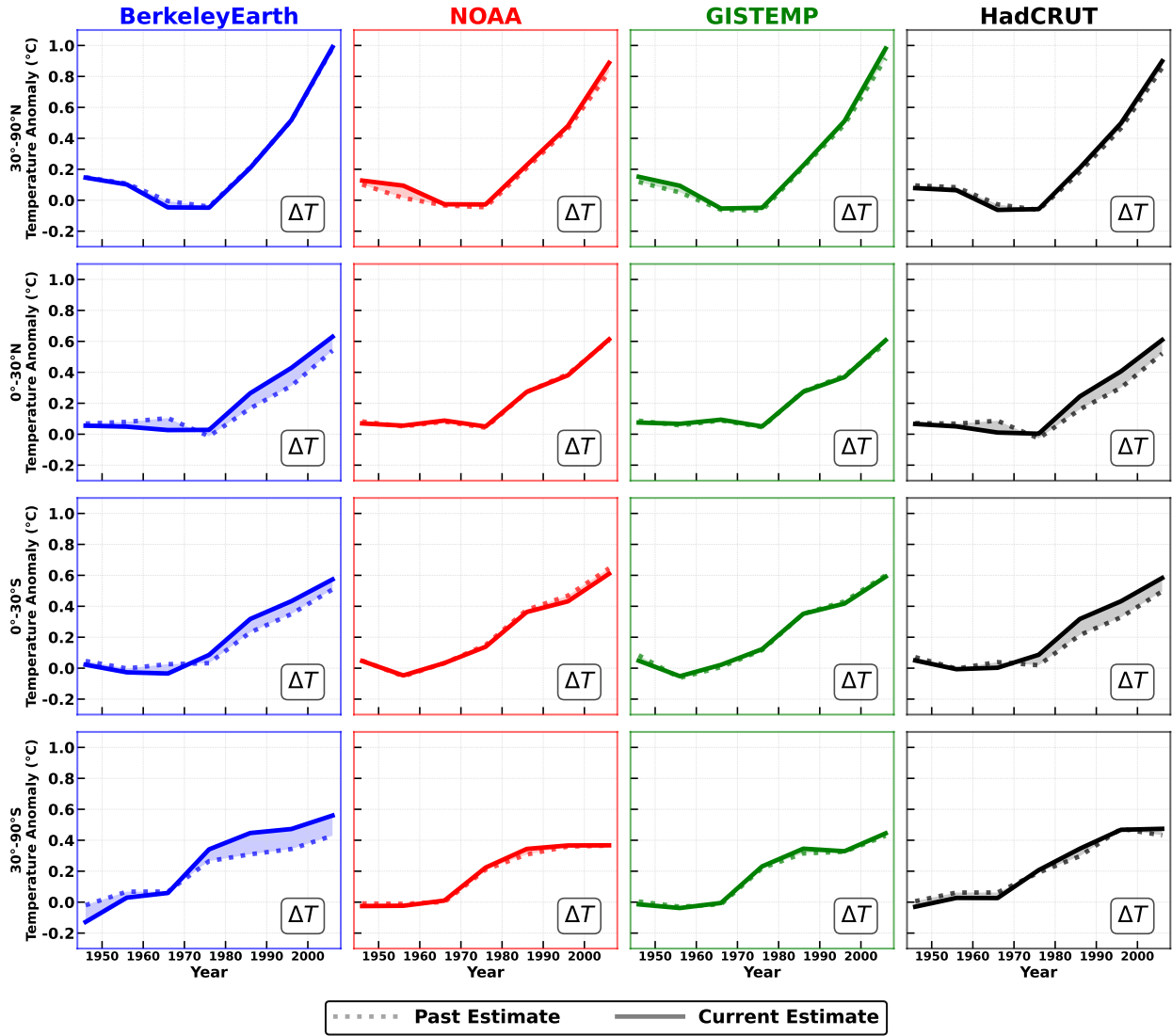


Figure 1. Decadal zonal temperature anomalies calculated relative to the 1906-1995 climatology for four observational datasets (BerkeleyEarth, NOAA, GISTEMP, and HadCRUT) across four equal-area latitudinal zones: 30°-90°N (top row), 0°-30°N (second row), 0°-30°S (third row), and 30°-90°S (bottom row). Solid lines represent the current version of each dataset, while dotted lines represent past versions. The shaded area indicates the difference between the current and past versions.

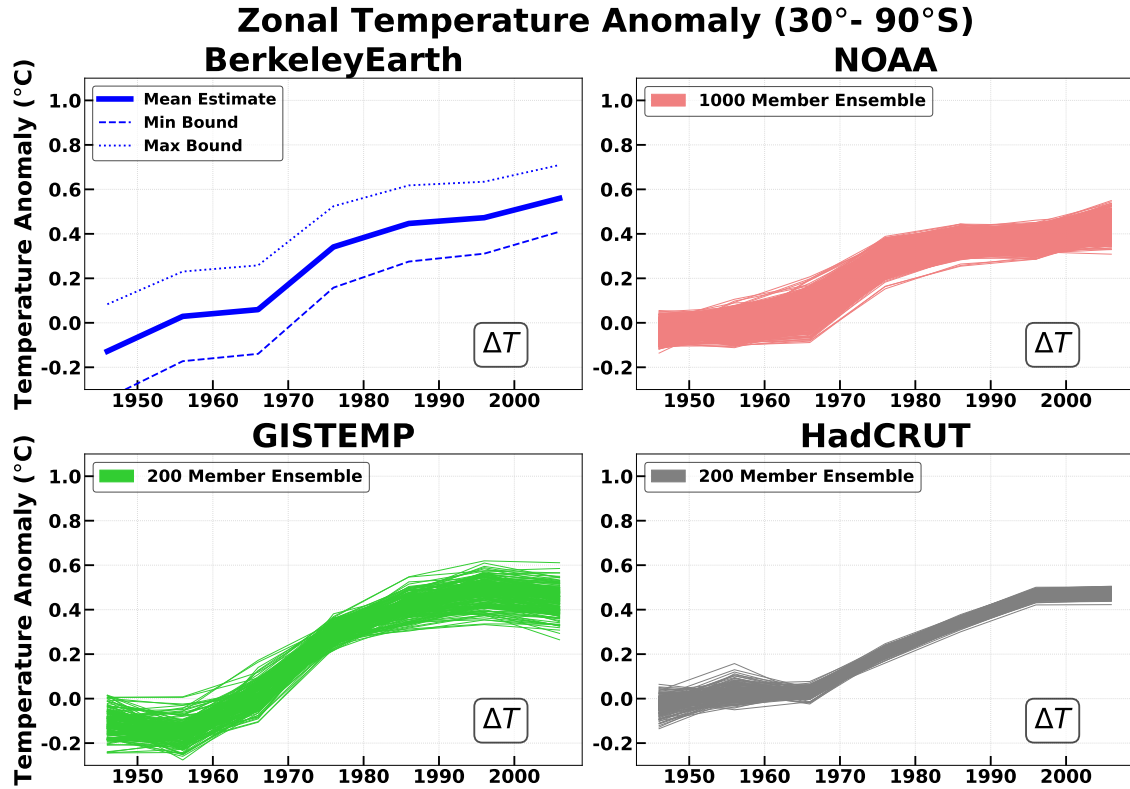


Figure 2. Decadal zonal temperature anomaly calculated relative to the 1906-1995 climatology for four observational datasets (30°-90°S) – BerkeleyEarth (min, median, max), NOAA (1000-member ensemble), GISTEMP (200-member ensemble), and HadCRUT (200-member ensemble).

2015, and for GISTEMP we use 1880–1900 to 2006–2018 as the dataset starts in 1880. All other values used in the calculation are identical to Sherwood et al. (2020), including the ± 0.14 °C standard deviation for ΔT and the uniform prior on S_{hist} .

3 Results

230 3.1 Systematic Uncertainty in Observational Temperature Datasets

Systematic uncertainty, also termed structural uncertainty (Thorne et al., 2005), arises from methodological differences in how independent data centers construct gridded observational temperature records. These differences originate from choices in data selection, quality control methods, spatial interpolation techniques, and selection of baseline climatology for anomaly calculation, etc. (see Table A2). The impact of systematic uncertainty on climate sensitivity estimates has been well-documented in
 235 observational constraint studies (Otto et al., 2013; Lewis and Curry, 2018). In model-observation comparison frameworks like ours, the choice of observational dataset can alter median climate sensitivity estimates by up to 1 °C (Libardoni and Forest,

2011). In this section, we quantify how the magnitude of systematic uncertainty has evolved between successive versions of gridded temperature datasets and examine the resulting impacts on climate sensitivity metrics.

Figure 1 illustrates how systematic differences appear across four equal-area latitude bands for current and previous dataset versions. The largest inter-dataset spread occurs in the Southern Hemisphere high latitudes (30°-90°S), where sparse observations amplify the impact of different spatial interpolation choices. In contrast, the Northern Hemisphere high latitudes (30°-90°N) show the strongest agreement among datasets, benefiting from dense station networks over land. The 30°-90°S band remains the region of greatest divergence even in current versions, though the spread has decreased substantially, with current dataset versions (solid lines) demonstrating markedly improved agreement compared to their predecessors (dotted lines).

With the updated observational datasets, median S estimates now range from 3.26 °C to 3.46 °C (a range of 0.20 °C), compared to 2.93 °C to 3.37 °C in older versions (a range of 0.44 °C), representing a 54.6% decrease in the range of median values (see Figure A1). Similarly, TCR median estimates have converged, spanning 1.79 °C to 1.98 °C (a range of 0.19 °C) versus 1.63 °C to 1.96 °C previously (a range of 0.33 °C), indicating a 42.4% decrease in the range of median values. Along with the medians, the 5th and 95th percentile values have also shifted higher. S 5th percentile values increased from 2.35–2.66 °C to 2.50–2.77 °C, while the 95th percentiles shifted from 4.13–4.77 °C to 4.35–4.73 °C. TCR 5th percentiles rose from 1.34–1.67 °C to 1.51–1.70 °C, and 95th percentiles from 1.99–2.27 °C to 2.13–2.30 °C.

The differences between the newer and older datasets can be attributed to updated methodologies (Fig. A2). BerkeleyEarth and HadCRUT5, which previously yielded lower S and TCR estimates, now show higher values compared to NOAA and GISTEMP250. BerkeleyEarth uses more land meteorological stations, resulting in higher temperature anomalies due to improved coverage in earlier decades (Rohde and Hausfather, 2020). HadCRUT5 now uses spatial infilling, unlike HadCRUT4 which did not infill any spatial data for missing grids (Morice et al., 2021). NOAA and GISTEMP250 maintain similar best estimates to their previous versions, both having updated to ERSST5 from ERSST4 for sea-surface temperatures. Compared to older versions, the updated datasets show improved coverage in high southern latitudes, both due to bias corrections implemented for the SST datasets and all datasets now applying some form of spatial infilling. This reduction in systematic uncertainty has important implications for climate sensitivity assessment for methodologies similar to ours. As structural differences between datasets converge, the dominant source of uncertainty shifts from differences between independent datasets to uncertainties within each individual dataset, which we examine in the following section.

3.2 Parametric Uncertainty

Parametric uncertainty (as defined here) represents the quantifiable uncertainties within each data-center’s methodology arising mostly from bias, coverage, measurement, and sampling uncertainties. Unlike systematic uncertainty, which captures differences between independent methodological approaches, parametric uncertainty quantifies how these sources of error propagate through a given data-center’s methodology. Most data centers now provide large ensemble realizations (200-1000 members) that sample these uncertainties, enabling our assessment of how parametric uncertainty propagates into uncertainty in climate sensitivity metrics.

270 We convert the large ensemble temperature datasets into decadal zonal temperature anomalies used in our framework (Figures 3 and A2-A4). The general pattern of parametric uncertainty in terms of zonal variation is similar to systematic uncertainty—highest agreement in the Northern Hemisphere and greatest spread in the Southern Hemisphere (30-90°S). An important difference is how both types of uncertainty propagate in our framework: systematic uncertainty differs in the temporal patterns between datasets (e.g., different warming rates), while parametric uncertainty mostly varies the amplitude but
 275 keeps the same temporal evolution. The reason it manifests this way is a limitation of our use of decadal-zonal averaging. While decadal-zonal data provides more constraints than global mean data (28 points vs 1), it compresses the full spatial variability that distinguishes ensemble members in their native gridded form. This has the highest impact when comparing the uncertainties arising from ocean data compared to CMIP6 estimates discussed in Section 3.3.1.

Using our model-observation comparison framework, we observe how parametric uncertainty propagates into climate sensi-
 280 tivity estimates. Figure 4a shows that the spread within each data center dwarfs the systematic uncertainty between data centers (cyan, 0.2 °C). NOAA’s 1000-member ensemble produces a 1.1°C spread in median S estimates, followed by GISTEMP and Berkeley Earth (1.0 °C each), while HadCRUT5 shows 0.7°C. This difference persists not just in median estimates but across all percentiles. Hence, considering parametric uncertainty in our framework leads to substantially wider probabilistic estimates of S and TCR. Table A2 shows the complete distribution: NOAA’s 1,000-member ensemble yields median S estimates ranging
 285 from 2.82 to 3.97 °C, with 5th percentile values from 2.16 to 3.20° C and 95th percentile from 4.18 to 6.00 °C. The spread at the 95th percentile (1.82 °C for NOAA) particularly exceeds the entire systematic uncertainty range at that percentile (4.63–4.73°C, a range of only 0.10 °C), while the 5th percentile spread (1.04 °C) similarly dwarfs the systematic range of 0.25 °C (2.52–2.77 °C).

An important note is that since the methodologies to calculate gridded surface temperature differ between data centers, the
 290 methodologies to estimate parametric uncertainty and hence the large ensembles from each data center are different as well. NOAA utilizes a parametric approach by constructing a statistical model that accounts for reconstruction errors and parametric errors (Huang et al., 2020). HadCRUT5 differentiates between various types of bias such as urbanization and sensor exposure, while also considering measurement and sampling errors (Morice et al., 2021). Berkeley Earth’s uncertainty model follows a similar decomposition to HadCRUT5 but includes a higher number of land-based stations and uses its own interpolation
 295 algorithm (Rohde and Hausfather, 2020). GISTEMP’s uncertainty model interpolates individual station anomalies onto an equal-area grid, using distance-weighted averaging where weights decrease with station distance (Lenssen et al., 2019).

In summary, for our framework for estimation of climate sensitivity, parametric uncertainty now exceeds systematic uncertainty. For S , the parametric uncertainty ranges up to 1.15 °C (NOAA: 2.82–3.97 °C at the median), while systematic uncertainty covers only 0.20 °C (3.26–3.46 °C)—parametric uncertainty exceeds systematic by a factor of five to six. For TCR,
 300 parametric uncertainty ranges up to 0.78 °C (NOAA: 1.48–2.26 °C) versus systematic uncertainty of 0.19 °C (1.79–1.98 °C), a factor of four higher. This finding indicates that model-observation comparison studies which estimate climate sensitivity metrics, having traditionally focused on systematic differences between datasets, should expect substantially larger sensitivity to parametric uncertainties. We also compare the effect of parametric uncertainty in a traditional global-mean framework, which is discussed in Section 3.4.

3.3.1 Relative Contributions of Land and Ocean Uncertainties

To understand the relative contributions of land versus ocean observational uncertainties to our climate sensitivity estimates, we use NOAA’s 1000-member parametric ensembles (Huang et al., 2020), which provides separate uncertainty quantification for land surface air temperature (LSAT) and sea surface temperature (SST). NOAA creates these ensembles by varying parameters in their statistical model—28 parameters for SST and 6 parameters for LSAT. From the individual 1000-member ensembles for land and ocean, we create two experimental datasets: one varying the 1000 LSAT ensemble members while holding SST at its median estimate, and another varying the 1000 SST ensemble members while holding LSAT at its median estimate.

Similar to our systematic and parametric uncertainty calculations, we convert these gridded datasets into our framework, computing decadal-zonal temperature anomalies for each of the 1000 members. The spread in temperature anomalies for the LSAT-varying and SST-varying datasets aligns with NOAA’s global-scale uncertainty estimates, showing consistently larger uncertainties in LSAT compared to SST. This difference between LSAT-varying and SST-varying datasets reflects the relative reliability of measurements from land versus ocean. LSAT measurements are less reliable compared to ocean measurements because of: (i) heterogeneous station environments, (ii) changes in instrumentation over time, and (iii) larger diurnal and seasonal cycles, among others. Ocean measurements benefit from the ocean’s thermal inertia, which dampens temperature variability, and from more consistent measurement techniques over time (bucket measurements, engine room intake, and modern Argo floats). In terms of spatial distribution of LSAT and SST uncertainties, we observe larger variation in the high latitudes compared to the Southern Ocean due to the sparsity of observations in both land and ocean regions at these latitudes.

When propagated through our framework for estimating climate sensitivity, we observe substantial differences between LSAT-varying and SST-varying datasets (Figure 5). As expected from the larger observational uncertainties, the LSAT-varying dataset shows much greater spread in climate sensitivity estimates. For S , the LSAT-varying ensemble yields median estimates ranging from 2.52 to 4.30 °C (spread of 1.78 °C), while the SST-varying ensemble produces 3.83 to 3.99 °C (0.16 °C spread)—11 times larger. Similarly for TCR, we observe medians ranging from 1.24 to 2.81 °C for LSAT-varying (spread of 1.57 °C) versus 1.98 to 2.20 °C for SST-varying (spread of 0.22 °C), approximately 7 times larger.

An important limitation of this quantification of ocean’s contribution to climate sensitivity is that it cannot capture the pattern effect—the phenomenon where different spatial patterns of SST warming produce different top-of-atmosphere radiative responses through their influence on climate feedbacks. Our framework compresses the full observational dataset (approximately 840 months $\times$ 36 latitude bands $\times$ 72 longitude bands) into just 28 constraint points (7 decades $\times$ 4 zonal bands). While this dimensional reduction provides more spatial information than global-mean energy balance frameworks, it cannot capture the detail required to quantify the pattern effect of SSTs. For a full assessment of pattern effects in a model-observation comparison framework, analysis on the full latitude-longitude grid would be required, which is beyond the scope of this framework.

In summary, we find that LSAT observational uncertainties contribute approximately 11 times more to S uncertainty and 7 times more to TCR uncertainty than SST observational uncertainties in our framework. This quantifies the propagation

of uncertainties arising from the creation and processing of gridded datasets, not the relative impact of land versus ocean
340 temperature patterns on climate feedback processes.

3.3.2 Effect of Spatial Infilling

To examine how spatial infilling techniques affect climate sensitivity estimates, we compare two versions of the HadCRUT5 dataset: HadCRUT5 Analysis (the standard version with spatial infilling) and HadCRUT5 Non-infilled (without spatial infilling) (Morice et al., 2021). Spatial infilling refers to methods that fill temperature information in grid cells lacking sufficient
345 observations by using spatial and temporal correlations from nearby observed regions (Kennedy et al., 2011a). All major temperature datasets use some form of spatial infilling—GISTEMP uses distance-weighted averaging, NOAA uses Empirical Orthogonal Teleconnections, and Berkeley Earth uses kriging (see Table A2). However, only HadCRUT5 provides large ensembles both with and without infilling (200-member ensembles for each), allowing direct comparison of the effect of spatial infilling on climate sensitivity estimates.

350 We convert HadCRUT5 Analysis and HadCRUT5 Non-infilled to our zonal-temporal framework, computing decadal-zonal temperature anomalies for each of the 200 members. As expected, spatial infilling has the most impact in data-sparse regions. The zonal temperature anomalies show different trends in the Southern Ocean (30° – 90° S), where observational coverage has historically been sparse (Figure 6b). In this region, the non-infilled ensemble shows declining temperature anomalies during 2000–2010, while the infilled data remain relatively constant. In the high northern latitudes (30° – 90° N), infilled ensembles
355 show temperature anomalies approximately 0.1°C higher than non-infilled versions.

When propagated through our framework for estimating climate sensitivity, spatial infilling shifts the estimates to higher values for all percentiles for both S and TCR. For S , the spatially infilled dataset yields a median range of 2.98 to 3.70°C , while the non-infilled dataset produces a range of 2.90 to 3.41°C , indicating a shift of about 0.20°C on average. The S 5^{th} percentile range increases from 2.24 – 2.75°C to 2.29 – 2.98°C , and the 95^{th} percentile range rises from 4.09 – 4.70°C to 4.24 –
360 5.20°C . TCR estimates show a consistent increase across all percentiles, with the median range shifting from 1.68 – 2.07°C to 1.70 – 2.18°C , a change of approximately 0.08°C in both bounds (see Figure 6).

Previous studies have examined spatial infilling effects on climate sensitivity, notably Lewis (2013) who compared HadCRUT4 with Cowtan and Way (2014) (HadCRUT4 infilled using kriging method) using global-mean energy balance methods for estimating S and found similar $\sim 0.2^{\circ}\text{C}$ increases in S . Our analysis extends these findings by using 200-member ensembles for each version in a decadal-zonal framework, providing more robust quantification of how spatial infilling systematically
365 increases climate sensitivity estimates.

3.4 Comparison with Global Energy Balance Framework

To assess whether the large effect of parametric uncertainties that we observed in our model-observation comparison framework apply to global-mean observation-based frameworks, we apply the large ensembles to the Sherwood et al. (2020) global
370 energy balance framework (details in Methods). The key modification is replacing Sherwood et al. (2020)’s single temperature

reconstruction ($\Delta T = 1.03$ °C from Cowtan & Way 2014) with 600 ensemble members: 200 each from NOAA, GISTEMP, and HadCRUT5.

By treating each ensemble member as an equally valid realization of historical temperature anomalies, we find that parametric uncertainty still produces substantial spread in climate sensitivity estimates even in the global framework (Figure 7). The median S range across ensemble members spans 1.11 °C (2.47–3.59 °C) for the Sherwood et al. (2020) framework, compared to 1.38 °C (2.48–3.86 °C) for our zonal-temporal methodology. The 25th percentile range is 0.97 °C for the global framework versus 1.27 °C for our method, while the 75th percentile range is 1.05 °C versus 1.59 °C. Notably, we find much less variation in the 95th percentile ranges for the global energy framework. Hence, parametric uncertainty remains important even when applied to global-mean frameworks, although the effect is not as pronounced as when time-varying spatial information (as in our zonal-temporal methodology) is taken into account.

Our analysis here shows what additional uncertainty emerges when the full parametric ensemble spread is considered explicitly rather than through a single uncertainty parameter. We acknowledge that in the current Sherwood et al. (2020) framework, the standard deviation term (± 0.14 K) applied to ΔT already incorporates parametric uncertainty to some degree, and that utilizing each ensemble member as a distinct realization may not be directly applicable within the broader Sherwood et al. (2020) bayesian framework without modification.

4 Discussion

Observational datasets are an important component among the multiple lines of evidence used for estimating climate sensitivity metrics. Model-observation comparison frameworks were already known to be sensitive to observational dataset choices. Our results show that with decreasing systematic differences between datasets (54.6% reduction between decadal-zonal medians from old and new datasets), parametric uncertainty may now be the dominant source of observational uncertainty—up to 5–6 times higher than systematic uncertainty depending on the amount of spatial information used.

This shift has important implications across different methodological approaches. Studies using model-observation comparisons similar to ours should expect increased spread in their sensitivity estimates after accounting for parametric uncertainty. Additionally, studies such as (i) detection and attribution (Hegerl et al., 2001) and (ii) observational constraints on climate projections (Ribes et al., 2021) will benefit from incorporating parametric uncertainty into their frameworks by providing a more robust characterization of observational uncertainty.

To understand how parametric uncertainty scales with methodology, we performed a sensitivity test applying our large ensembles to the global energy balance framework. While the impact was smaller than in our zonal-decadal framework, it still had an appreciable effect ($\sim 25\%$ vs $\sim 40\%$ contribution), which demonstrates that the magnitude of parametric uncertainty scales with the amount of spatial information used. Incorporating observational uncertainty through full ensemble spreads rather than single standard deviation terms in global balance frameworks could better utilize these large ensemble observational datasets, though this would require methodological modifications to existing Bayesian frameworks to avoid double-counting uncertainty sources.

Our analysis of specific uncertainty sources further illustrates how methodological choices impact climate sensitivity estimates. Partitioning uncertainty components between land and ocean helps us understand how different sources of error propagate through climate sensitivity estimation frameworks. We show that LSAT uncertainties contribute at least 7 times more to climate sensitivity uncertainty than SST uncertainties. This partitioning is based on uncertainties in the creation of these data products and cannot account for the pattern effect of SST. For example, atmosphere-only global circulation models forced with different prescribed ocean warming patterns produce spreads in effective climate sensitivity ranging from 1.3 to 3.2 °C (Armour et al., 2024), demonstrating the impact of SST warming patterns on climate feedbacks, which our current framework cannot capture. Similarly, we quantify the effect of spatial infilling on climate sensitivity estimates by using 200-member ensembles for both infilled and non-infilled versions. We show spatial infilling shifts climate sensitivity estimates by ~ 0.2 °C. This suggests that the choice of interpolation method has smaller impact on sensitivity estimates compared to the sensitivity from parametric choices in land and ocean components (Section 3.3.1) or selection of baseline period (Rohde and Hausfather, 2020).

Data availability. Data used in this study can be accessed online : <https://doi.org/10.5281/zenodo.14543999> Sapkota and Forest (2024).

Appendix A

Author contributions. Conceptualization: V.S. Methodology: V.S. Investigation: V.S. Visualization: V.S. Supervision: C.E.F. Writing—original draft: V.S. Writing—review and editing: V.S. and C.E.F.

Competing interests. One of the authors is an Associate Editor at *ASCMO*.

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Table A1. Percentiles for Climate Sensitivity (S) and Transient Climate Response (TCR) in degrees Celsius ($^{\circ}\text{C}$) across the median of four observational datasets. Systematic Uncertainty (i.e. difference between the median of each datacenter) and parametric uncertainty for each datacenter: HadCRUT5 (200-member ensemble), GISTEMP (200-member ensemble), NOAA (1000-member ensemble), and the Berkeley Earth ensemble (Min, Max, Median) is shown.

Dataset	5%	50%	95%
Climate Sensitivity (S) ($^{\circ}\text{C}$)			
Systematic Uncertainty	2.52–2.77	3.26–3.46	4.63–4.73
HadCRUT5 (200 member ensemble)	2.29–2.98	2.98–3.70	4.24–5.20
GISTEMP (200 member ensemble)	1.82–2.76	2.48–3.52	3.76–5.00
NOAA (1000 member ensemble)	2.16–3.20	2.82–3.97	4.18–6.00
BerkeleyEarth (Min, Max)	2.08–3.23	2.77–3.85	4.23–5.46
Transient Climate Response (TCR) ($^{\circ}\text{C}$)			
Systematic Uncertainty	1.51–1.70	1.79–1.98	2.13–2.29
HadCRUT5 (200 member ensemble)	1.39–1.91	1.70–2.18	2.06–2.49
GISTEMP (200 member ensemble)	1.06–1.69	1.36–1.99	1.74–2.32
NOAA (1000 member ensemble)	1.21–1.98	1.48–2.26	1.83–2.58
BerkeleyEarth (Min, Max)	1.20–2.17	1.48–2.48	1.83–2.82

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Table A2. Key differences between past and current versions of four major observational temperature datasets in terms of data sources, spatial resolution, and interpolation methods

Dataset (Version)	Land Temp Source	SST Source	Spatial Resolution	Anomaly Base Period	Interpolation Method
GISTEMP (v3 → v4)	GHCN v3 → v4	ERSST v4 → v5	2° × 2°	1951-1980	Inverse distance weighting
HadCRUT (v4 → v5)	CRUTEM4 → CRUTEM5	HadSST3 → HadSST4	5° × 5°	1961-1990	Gaussian process regression (non-infilled version also available)
NOAAGlobalTemp (v4 → v5)	GHCN v3 → v4	ERSST v4 → v5	5° × 5°	1901-2000	Empirical Orthogonal Teleconnection (EOT)
Berkeley Earth	Berkeley Earth Land (continuous updates)	HadSST3 → HadSST4	1° × 1°	1951-1980	Kriging

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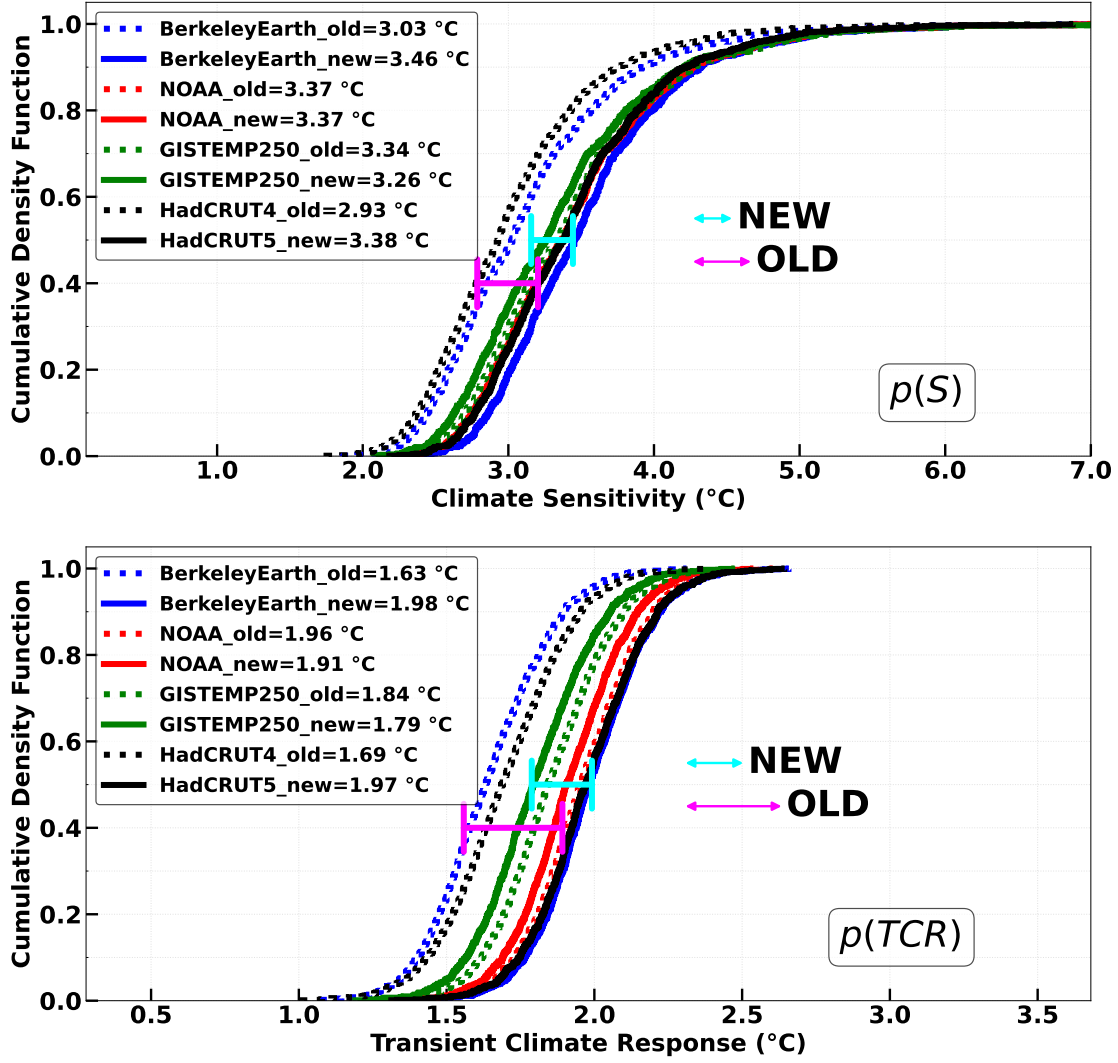


Figure 3. Cumulative Distribution Functions for Climate Sensitivity (S) and Transient Climate Response (TCR) for both old and new versions of observational datasets. The top panel displays the cumulative density functions for S (y-axis) for four observational datasets: BerkeleyEarth, NOAA, GISTEMP250, and HadCRUT (old and new versions), with S values in degrees Celsius (°C) on the x-axis. The bottom panel shows the cumulative density function for TCR, also in °C. For both panels, solid and dotted lines represent the new and old versions of the datasets, respectively. The horizontal error bars indicate the magnitude of systematic uncertainty for both old (magenta) and new (cyan) estimates. The numbers shown in the legend are the median S or TCR values for each dataset.

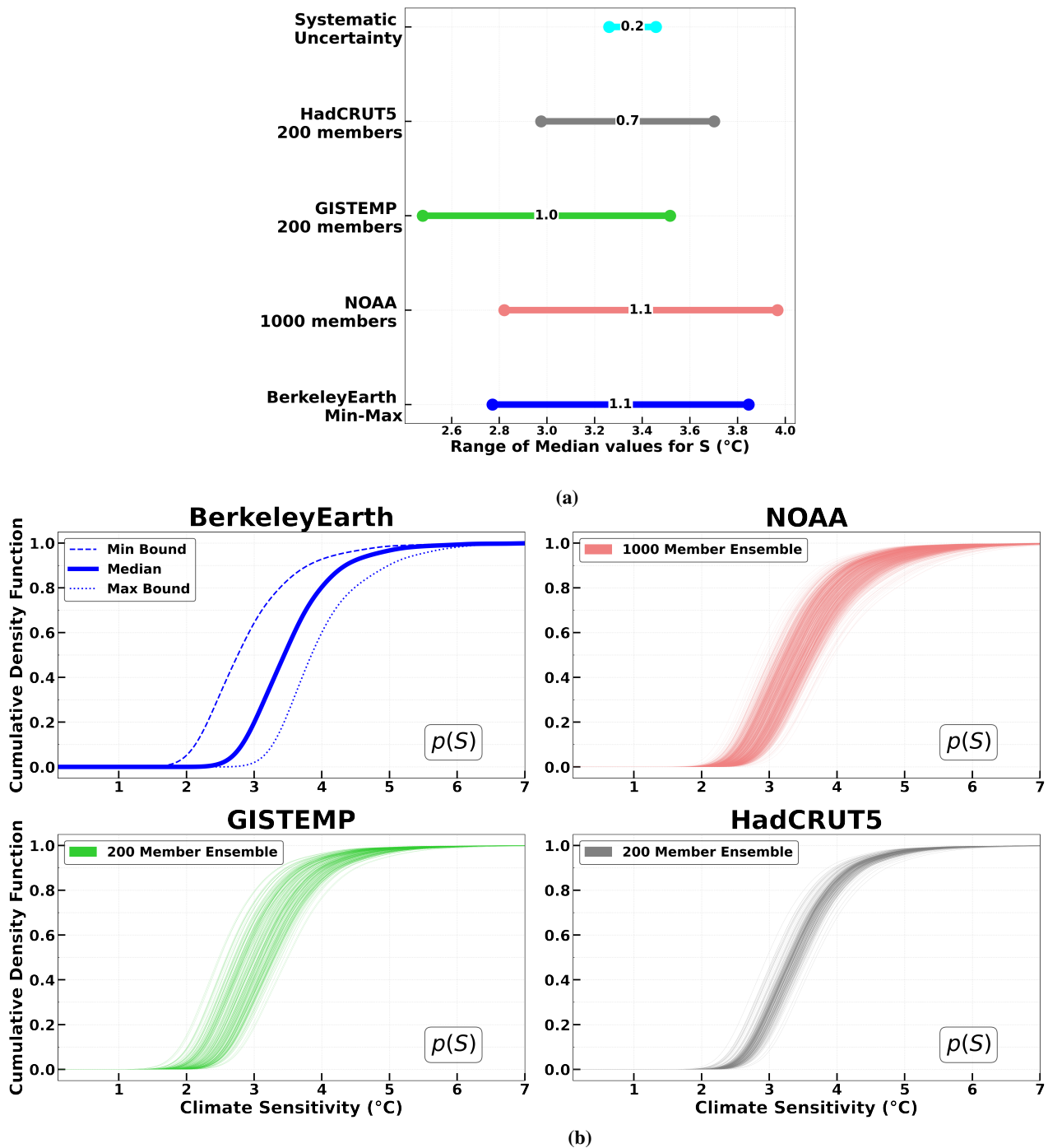


Figure 4. (a) Range of median Climate Sensitivity (S) values ($^{\circ}\text{C}$) across multiple datasets: BerkeleyEarth, HadCRUT5, GISTEMP, NOAA, alongside the systematic uncertainty range. Each dataset shows results from their large ensemble or the max-min uncertainty bounds. b) Cumulative Distribution Functions (CDFs) for Climate Sensitivity (S) in $^{\circ}\text{C}$ from four observational datasets: BerkeleyEarth (blue), NOAA (red), GISTEMP (green), and HadCRUT5 (gray). Each CDF represents a sample from the large ensemble or the min-median-max range.

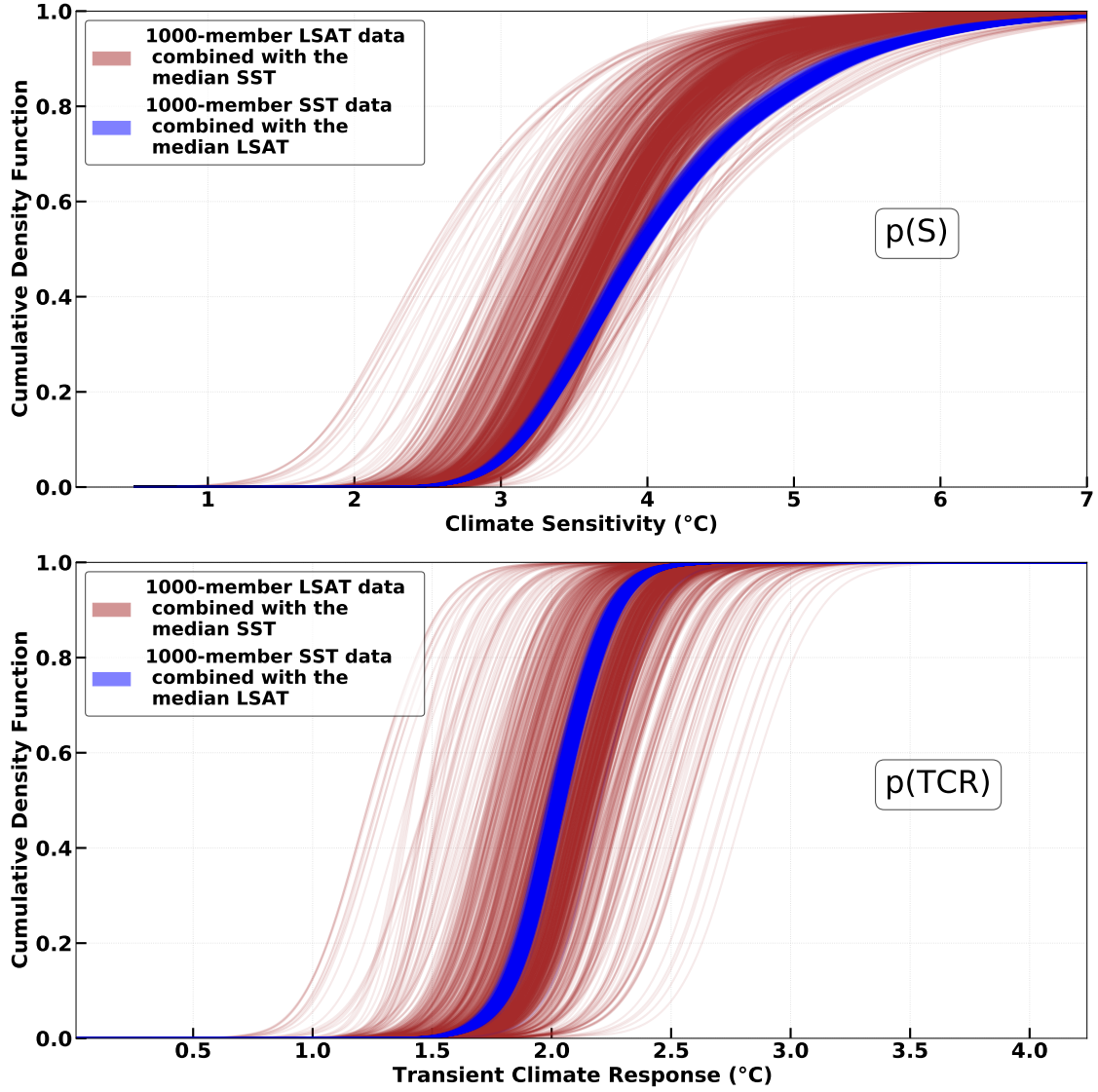


Figure 5. Cumulative Distribution Functions (CDFs) for Climate Sensitivity (S) and Transient Climate Response (TCR) for large ensemble of land and ocean partitioned datasets. The top panel displays the CDFs for S ($^{\circ}\text{C}$) from 1000-member ensembles, with Land Surface Air Temperature (LSAT) shown in brown and Sea Surface Temperature (SST) shown in blue. The bottom panel shows the CDFs for TCR ($^{\circ}\text{C}$), also based on 1000-member ensembles, with the same color scheme (blue for LSAT and brown for SST). Each line represents individual ensemble members, capturing the uncertainty in S and TCR across the simulations.

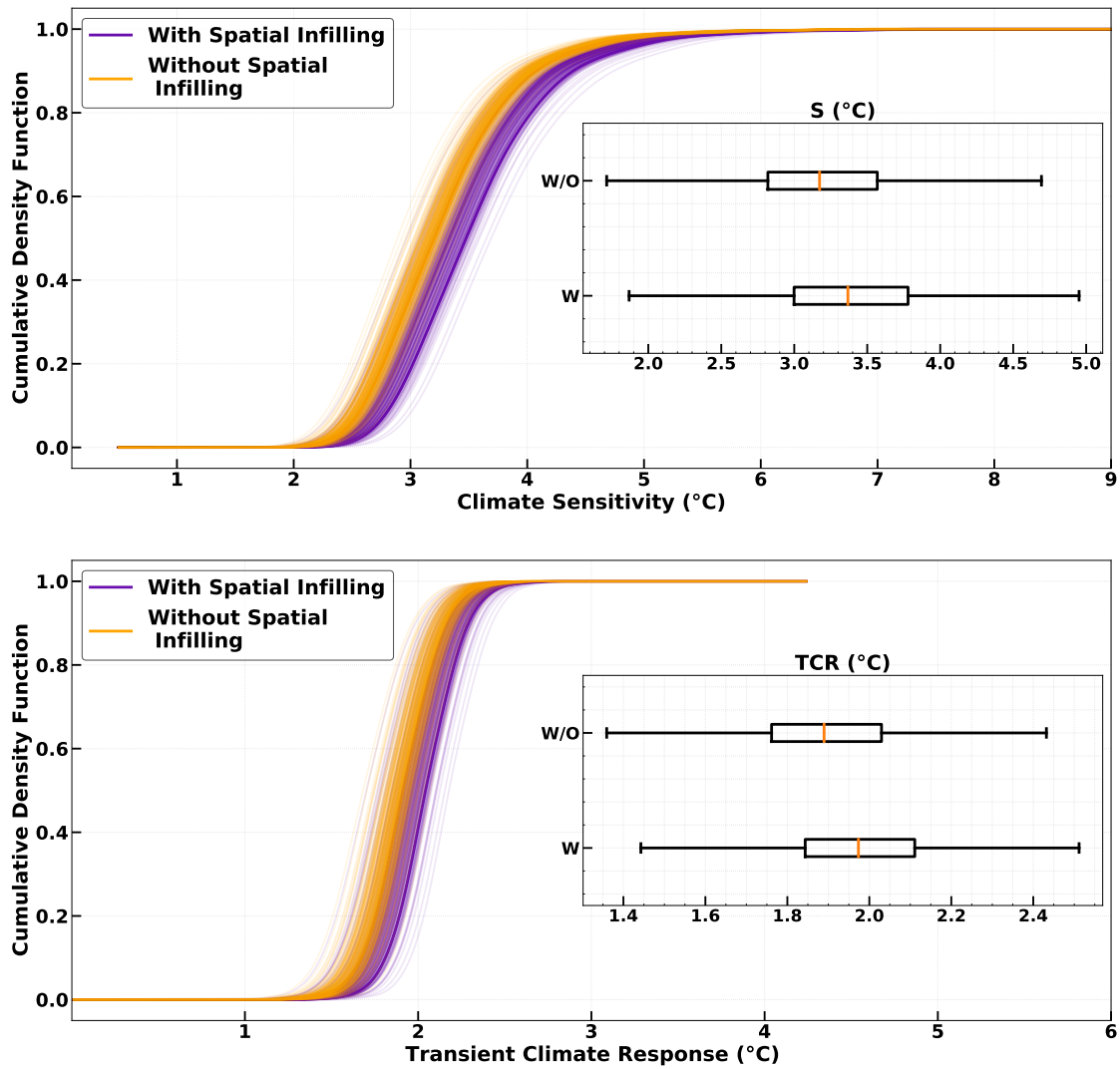


Figure 6. Cumulative Distribution Functions (CDFs) for Climate Sensitivity (S) and Transient Climate Response (TCR) for large ensemble, with and without spatial infilling. The top panel displays the CDFs for S ($^{\circ}\text{C}$) from 200-member ensembles, with and without spatial infilling. The bottom panel shows the CDFs for TCR ($^{\circ}\text{C}$), also based on 200-member ensembles. Each line represents individual ensemble members, capturing the uncertainty in S and TCR across the simulations. The boxplots on each panel represent all distributions aggregated together and binned, with the horizontal lines showing the spread of S and TCR values for the infilled (W) and non-infilled (W/O) cases.

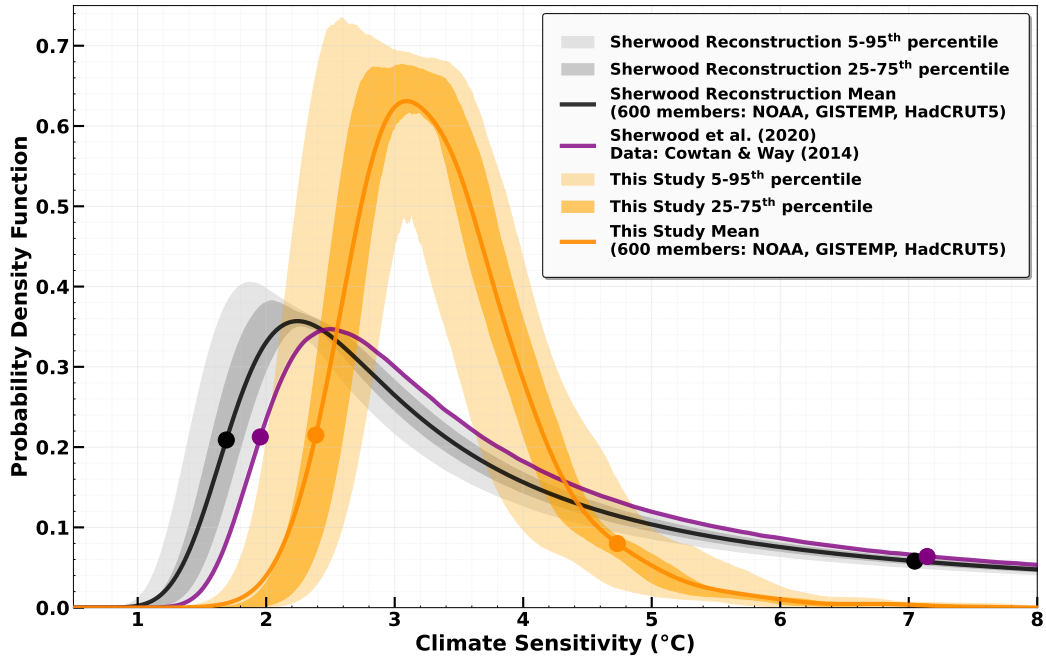


Figure 7. Comparison of Climate Sensitivity probability distribution functions (PDF) derived from large ensemble approaches. The solid orange line represents this study’s mean aggregated ensemble PDF, computed by equally weighting 600 ensemble members (200 each from NOAA, GISTEMP, and HadCRUT5 observational datasets). Orange shaded areas indicate the 25th-75th and 5th-95th percentile ranges across this study’s ensemble members. The solid black line shows the Sherwood et al. (2020) methodology for historical-with-no-pattern-effect applied to the same large ensemble reconstruction (600 members from NOAA, GISTEMP, and HadCRUT5), with gray shaded areas representing the corresponding percentile ranges. The purple line shows the original Sherwood et al. (2020) estimate using Cowtan & Way (2014) temperature dataset. Dots on each mean line indicate the 5th and 95th percentiles of the respective distributions.

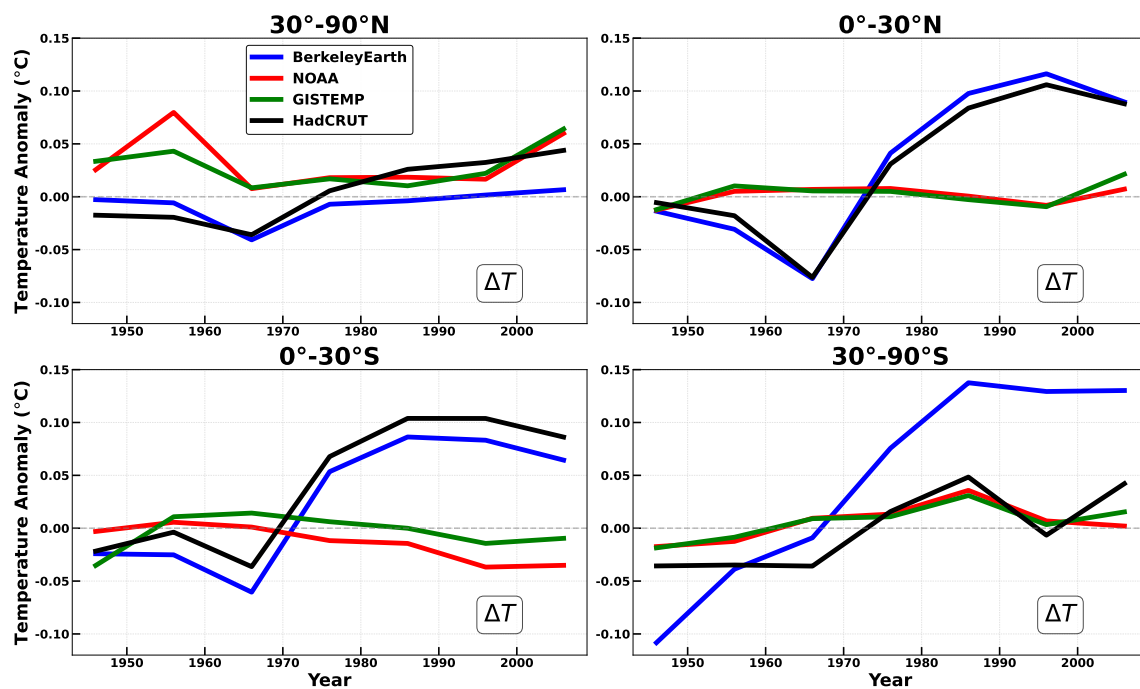


Figure A1. Difference in decadal zonal temperature anomalies between current and past versions for four observational datasets (BerkeleyEarth, NOAA, GISTEMP, and HadCRUT) across four equal-area latitudinal zones. Temperature anomalies are calculated relative to the 1906-1995 climatology.

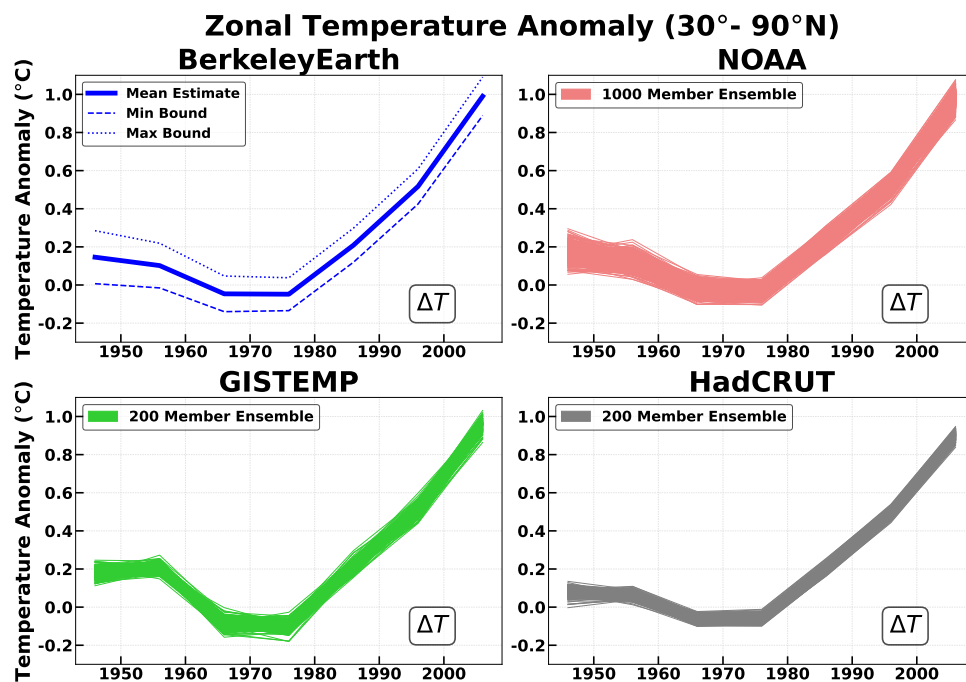


Figure A2. Decadal zonal temperature anomaly calculated relative to the 1906-1995 climatology for four observational datasets (30°-90°N).

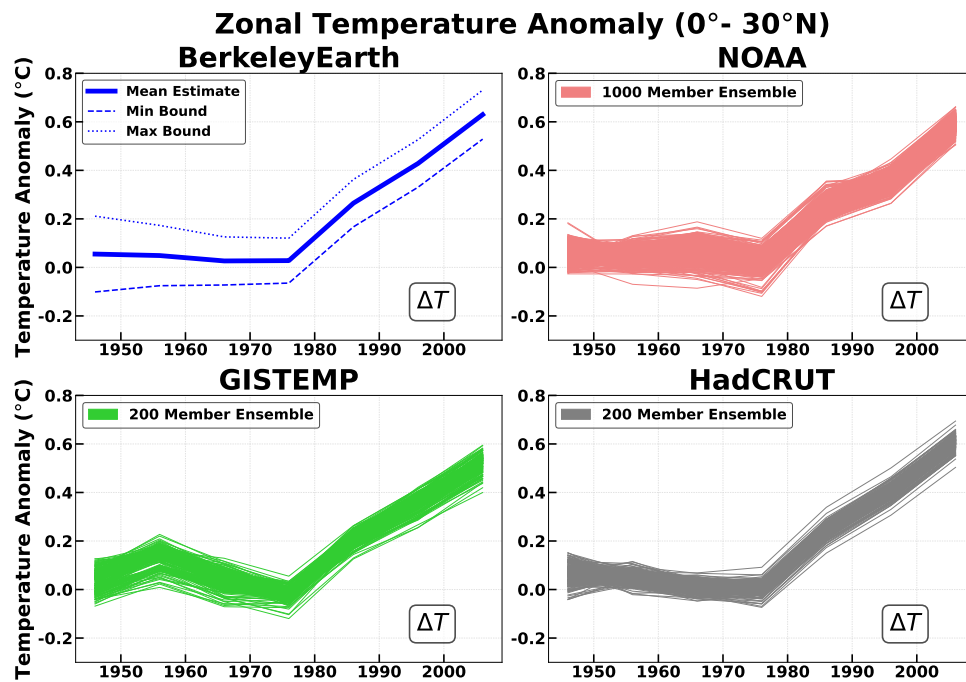


Figure A3. Decadal zonal temperature anomaly calculated relative to the 1906-1995 climatology for four observational datasets (0°-30°N).

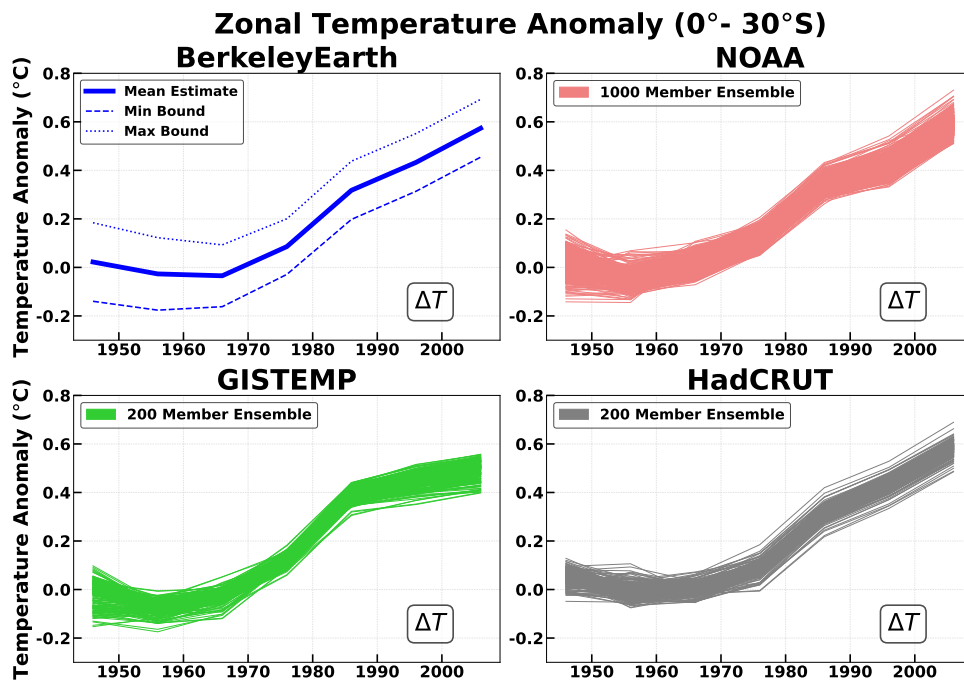


Figure A4. Decadal zonal temperature anomaly calculated relative to the 1906-1995 climatology for four observational datasets (0°-30°S).

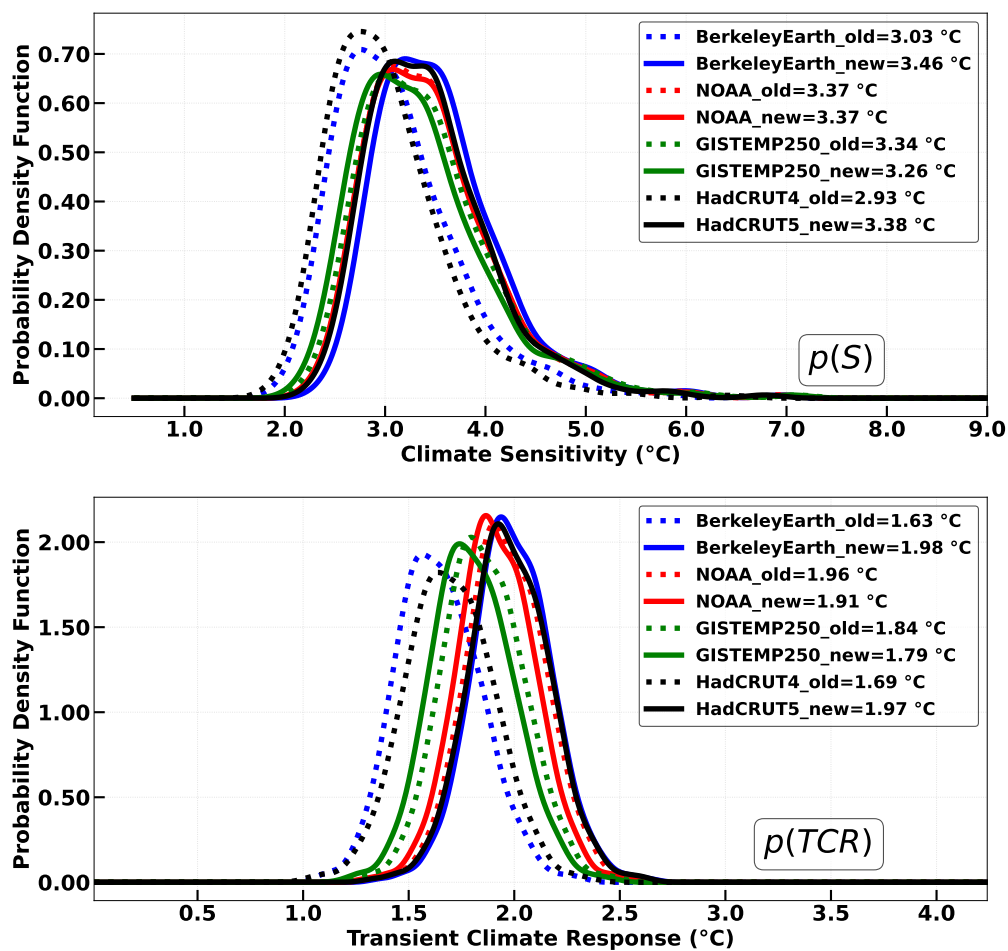


Figure A5. Probability Density Functions for Climate Sensitivity (S) and Transient Climate Response (TCR).

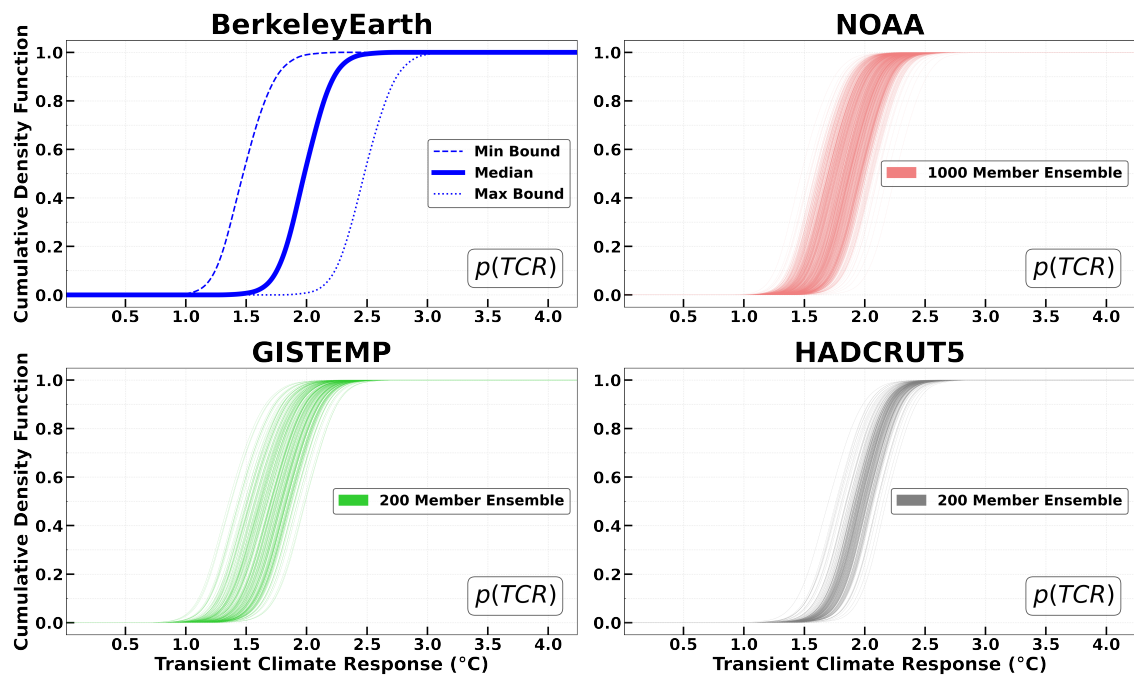


Figure A6. Cumulative density functions (CDFs) for Transient Climate Responses (TCR) in °C from four observational datasets: BerkeleyEarth (blue), NOAA (red), GISTEMP (green), and HadCRUT5 (gray). Each CDF represents a sample from the large ensemble or the min-median-max range.

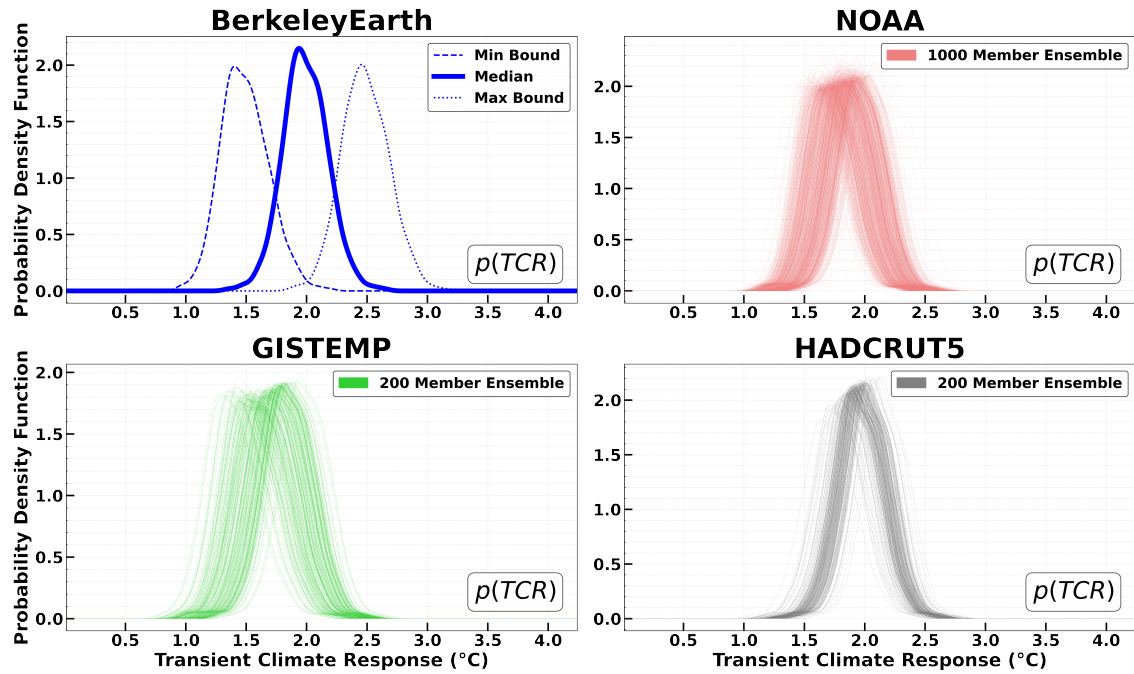


Figure A7. Probability Density Functions (PDFs) for Transient Climate Responses (TCR) in °C from four observational datasets: BerkeleyEarth (blue), NOAA (red), GISTEMP (green), and HadCRUT5 (gray). Each PDF represents a sample from the large ensemble or the min-median-max range.

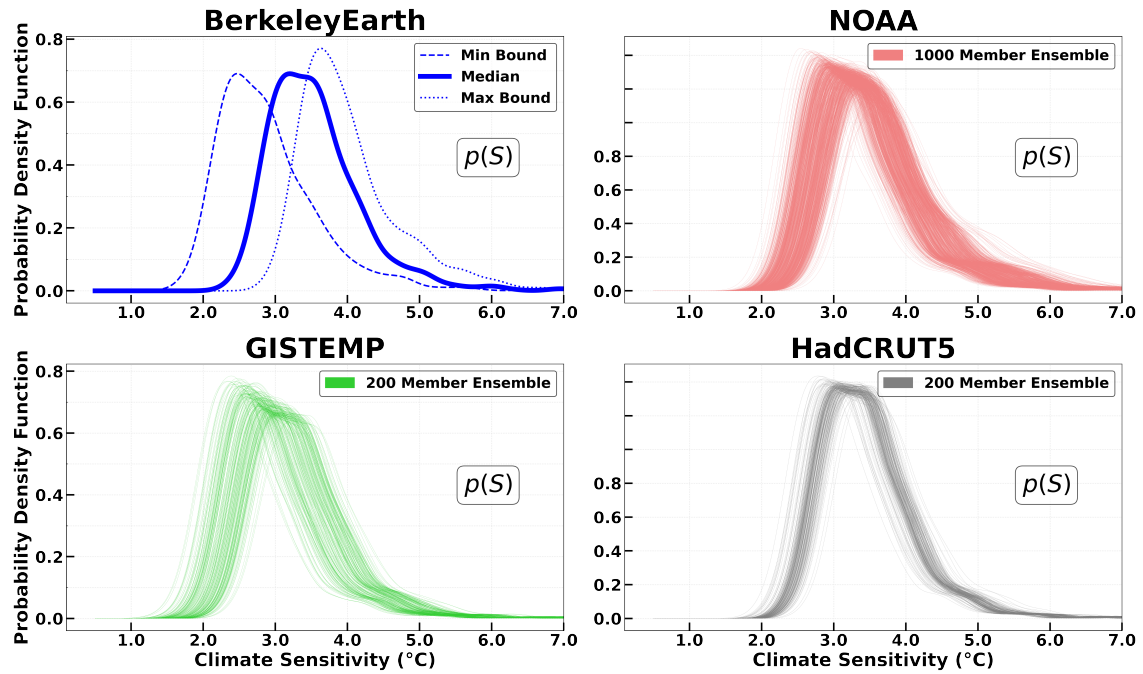


Figure A8. Probability Density Functions (PDFs) for Climate Sensitivity (S) in $^{\circ}\text{C}$ from four observational datasets: BerkeleyEarth (blue), NOAA (red), GISTEMP (green), and HadCRUT5 (gray). Each PDF represents a sample from the large ensemble or the min-median-max range.

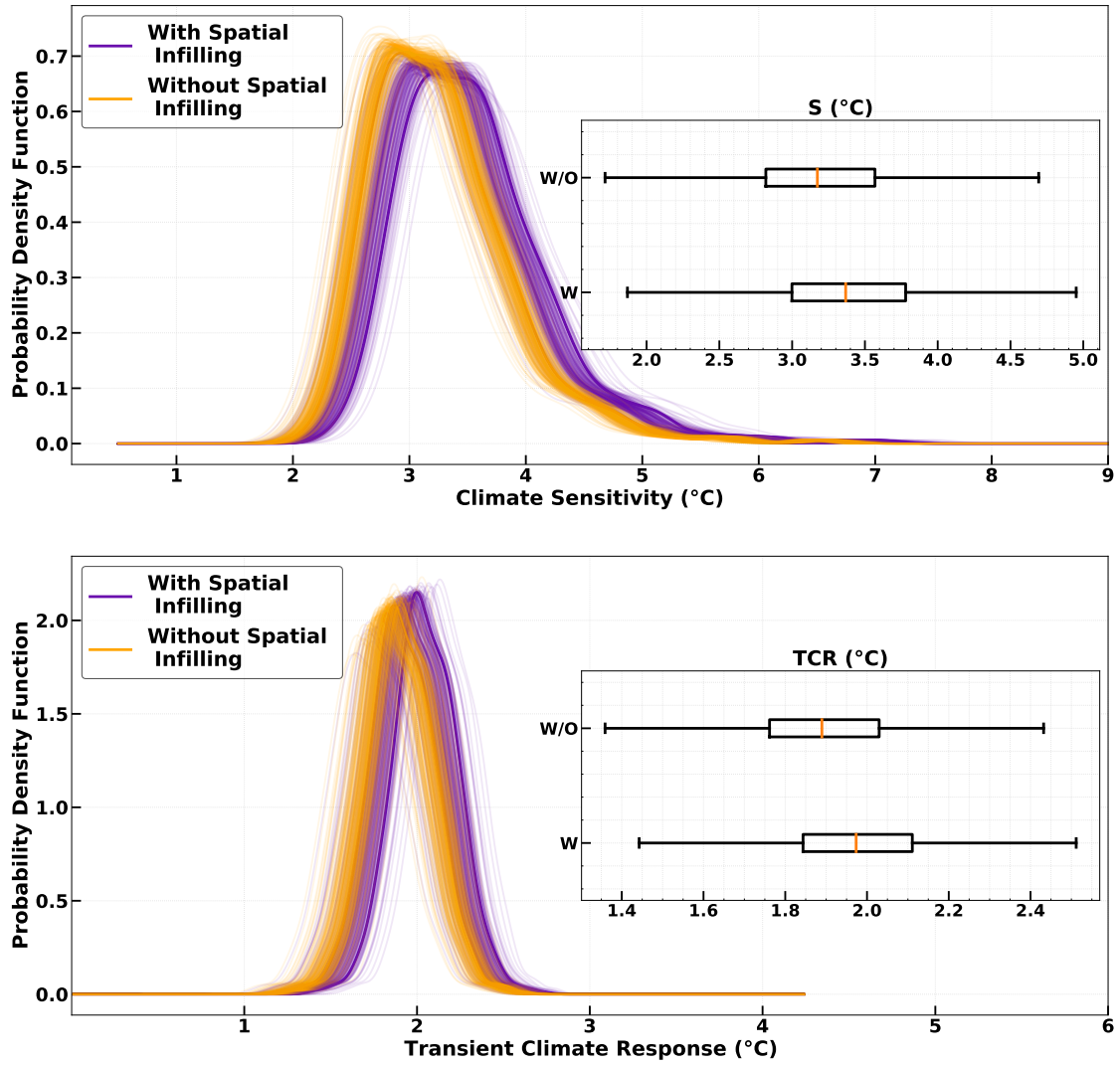


Figure A9. Decadal zonal temperature anomaly for the 1000 member data-products for both Land Surface Air Temperature (LSAT) and Sea Surface Temperature (SST) from NOAA for four different zones.

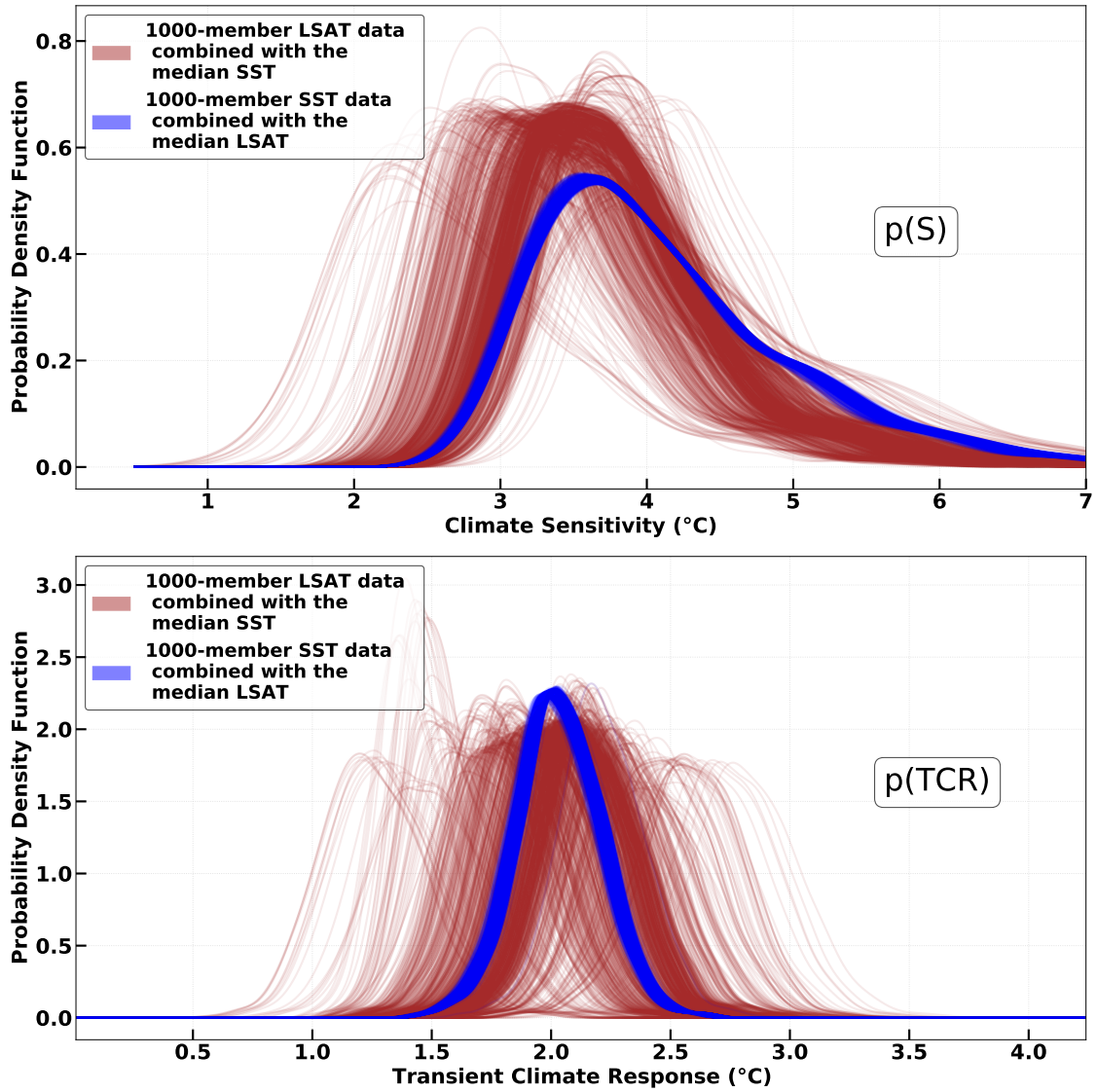


Figure A10. Probability Density Functions (PDFs) for Climate Sensitivity (S) and Transient Climate Response (TCR). The top panel displays the PDFs for S ($^{\circ}\text{C}$) from 1000-member ensembles, with Land Surface Air Temperature (LSAT) shown in brown and Sea Surface Temperature (SST) shown in blue. The bottom panel shows the PDFs for TCR ($^{\circ}\text{C}$), also based on 1000-member ensembles, with the same color scheme (brown for LSAT and blue for SST). Each line represents individual ensemble members, capturing the uncertainty in S and TCR across the simulations.

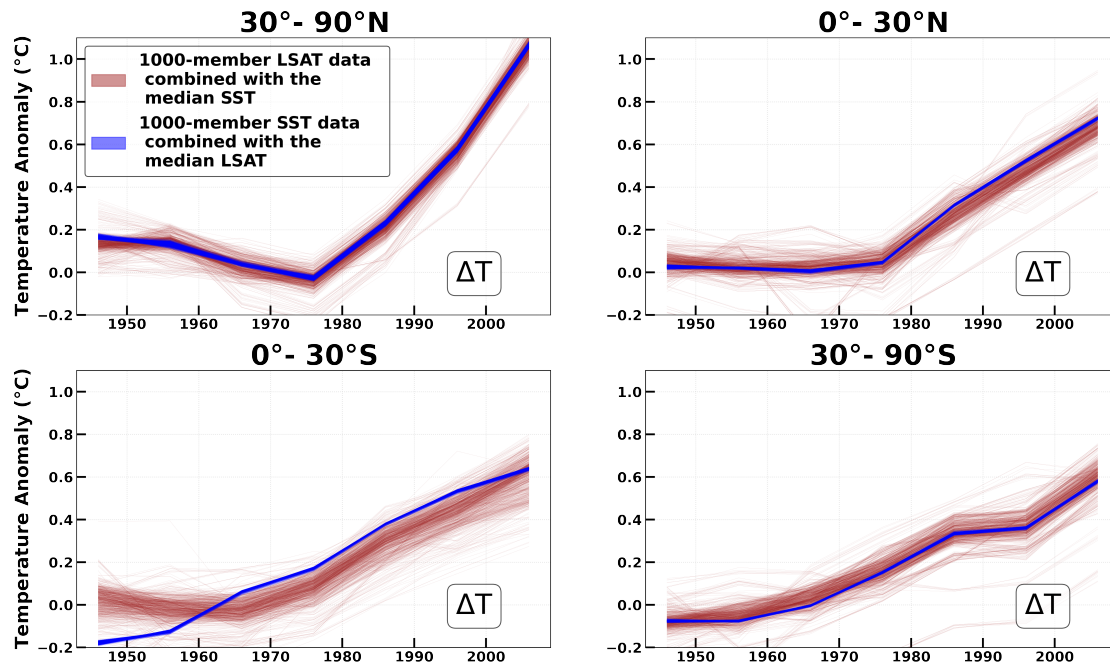


Figure A11. Probability Density Functions (PDFs) for Climate Sensitivity (S) and Transient Climate Response (TCR). The top panel displays the PDFs for S (°C) from 200-member ensembles, with and without spatial infilling. The bottom panel shows the CDFs for TCR (°C), also based on 200-member ensembles. Each line represents individual ensemble members, capturing the uncertainty in S and TCR across the simulations. The boxplots on each panel represent all distributions aggregated together and binned, with the horizontal lines showing the spread of S and TCR values for the infilled (W) and non-infilled (W/O) cases.

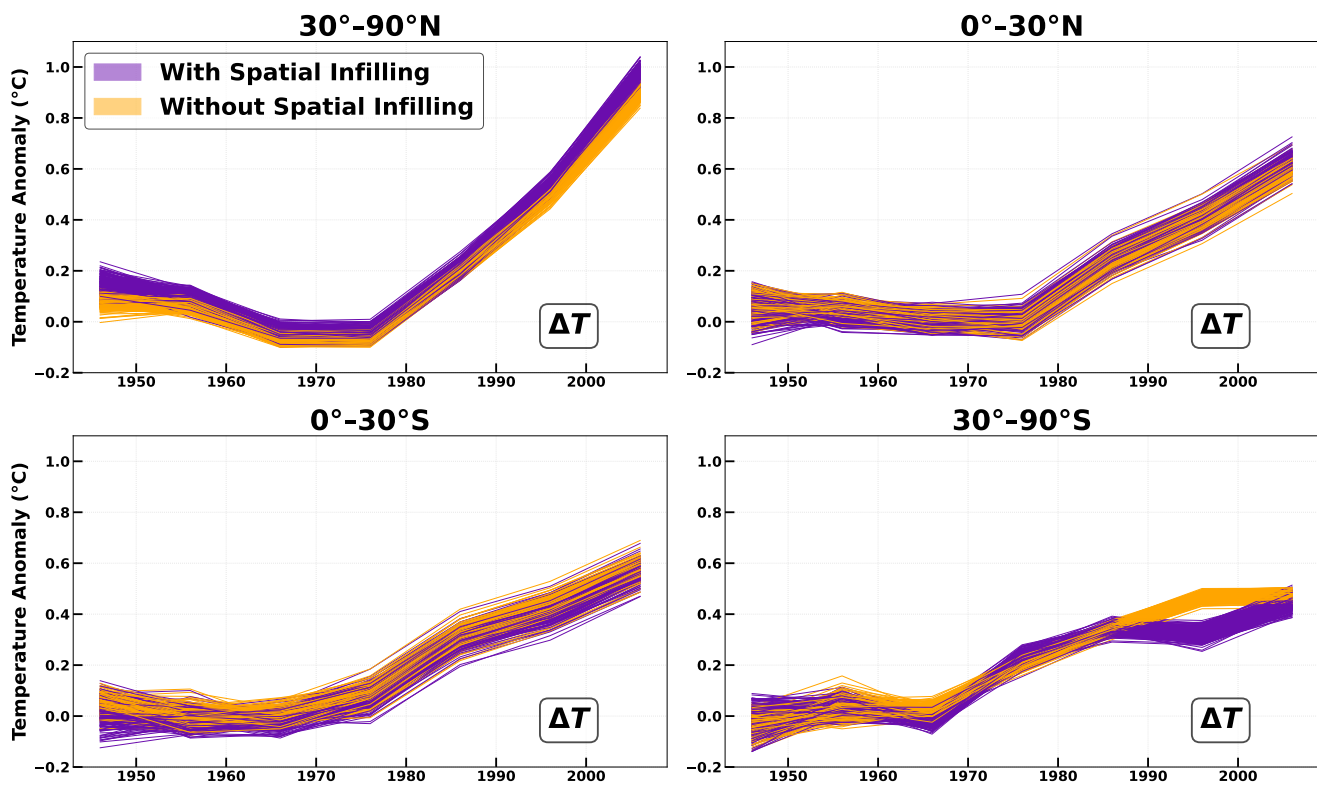


Figure A12. Decadal zonal temperature anomaly for the 2000 member data-products for HadCRUT5 for both Spatially Infilled (W) and non-infilled (W/O) cases.