



GDNat: a global, daily, high-resolution, natural-forcing only temperature data set for attribution research

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Abstract.

Attribution studies quantify anthropogenic contributions to meteorological changes and commonly rely on approaches that compare historical observations with global climate model (GCM) simulations that are driven solely by natural forcing (Bindoff et al., 2013). However, GCM simulations have limited spatial resolution and are biased by parameterized climate processes and uninitialized conditions that lead to the lack of representation of historical meteorological events (Cannon et al., 2015; Eyring et al., 2016; Almazroui, 2021; Zhang et al., 2023). In addition, attributing climate extremes to human activity requires assessing these events in an unperturbed climate system. We address these gaps by developing a novel high-resolution dataset that provides daily average global temperatures over the past four decades without the influence of anthropogenic climate forcing. We use quantile delta mapping (QDM), a quantile trend-preserving bias adjustment method, to remove anthropogenic warming from the fifth generation of the European Centre for Medium-Range Weather Forecasts Reanalysis (ERA5) using historical and natural-forcing-only simulations from the Coupled Model Intercomparison Project Phase 6 (CMIP6). The resulting dataset consists of historical Global Daily Natural temperature (henceforth, GDNat) records at 0.25° x 0.25° spatial resolution from 1979–2020, providing a valuable resource for attributing extremes and their impacts to anthropogenic warming. We demonstrate a regional application of GDNat by assessing changes in the number of days in the year where daily average temperatures reach or exceed 35°C over North Africa, the Middle East, South Asia, and Australia. We find an average of an additional 15–30 days per year attributable to anthropogenic to warming over the 2000 to 2020 period.

1 Introduction

Since the industrial revolution, anthropogenic activity has substantially warmed the planet (Gulev et al., 2021; Eyring et al., 2021). Current estimates suggest that global mean surface temperatures have already increased by about 1.3°C above late



nineteenth century levels ((Chen et al., 2021)), and global climate models (GCMs) project about 3°C of planetary warming by the year 2100 under a moderate emission trajectory (Scafetta, 2023; Sung, 2021). The evidence that human activity is driving global warming is unequivocal (Eyring et al., 2021; Gillett et al., 2021; Li et al., 2021), but attributing the relative influence of anthropogenic warming to a single meteorological event has proven to be more challenging due to the short observational record, the rare nature of these events, and the difficulty in disentangling the effects of internal climate variability (e.g., El Niño-Southern Oscillation) from anthropogenic forcing (Stott et al., 2004; Sherman et al., 2023).

The challenge of isolating anthropogenic contributions spurred the development of climate attribution research, which aims to quantitatively identify the effects of anthropogenic emissions of greenhouse gases and aerosols on historical weather and climate. Attribution studies have relied on numerous techniques that compare observed climate patterns with GCM-simulated responses to specific forcings, and systematically separate the effects of anthropogenic forcing on the climate system from internal climate variability (Hegerl, 2011; Cummins, 2022; Hannart, 2019; Sai Ma, 2023). GCMs have been instrumental in attribution analysis and allow for the comparison of modeled simulations with and without human-caused forcing (e.g., land-use change, fossil energy emissions, etc.). The Detection and Attribution Model Intercomparison Project (DAMIP), in particular, was created within the broader Coupled Model Intercomparison Project (CMIP) modeling framework to specifically examine the role of natural forcings (e.g., from volcanic eruptions and solar cycles) in driving the spatiotemporal patterns and variability inherent to the climate system (Eyring et al., 2021; Gillett et al., 2021). DAMIP scenarios provide a critical baseline for understanding the climate system in the absence of human activity and with only human activity, allowing researchers to more easily evaluate and quantify the relative contributions of human activity to the observed changes in climatic events (Gillett et al., 2016). Using these tools and modeling approaches, it has been shown that human-driven climate change has doubled the risk of heat waves (Zeppetello et al., 2022; Stott et al., 2004), increased the risk of extreme precipitation (Estrada et al., 2023; Seung-Ki Min, 2011), and rapidly escalated the risk of heat-related mortality across the globe (Lüthi et al., 2023; Eyring et al., 2021). Despite these advances there is a need to continuously improve methods and data products to better capture extreme events, regional differences, and temporal variability which motivated the methodological approach and dataset we present here. Since many climate impact studies evaluate long term regional temperature trends and threshold extremes over relatively short observational windows, constructing a counterfactual that adjusts the full temperature distribution rather than only the mean is necessary, yet computationally demanding at the spatial and temporal resolutions for attribution and impacts studies. To address this limitation, we provide a daily, high-resolution counterfactual temperature dataset that includes removal of the full distribution of the anthropogenic signal from ERA5, not just the mean, for all global grid cells.

While GCMs are continuously improved with each CMIP release, their outputs are too spatially coarse for the needs of many climate impact studies, and some archived GCM outputs are limited in their temporal resolution (Eyring et al., 2016; Naveau and Thao, 2022; Wang et al., 2023). Participating GCMs also have large structural differences in their representation of the climate (Ramirez-Villegas et al., 2013), which can be attributed to simplified and incomplete geophysical processes, missing feedback processes, nonlinear earth system interactions, and their response to various radiative forcing mechanisms. (Knutti and Sedláček, 2012; Taylor et al., 2012; Eyring et al., 2016; Zhu and Yang, 2020; Srivastava et al., 2020; Fyfe et al., 2021; Illangasingha et al., 2023). Yet, although the performance of individual GCMs varies between regions and variables of interest,



they are able to adequately capture large-scale climate variability and change (Flato and Rummukainen, 2013). GCMs are also useful in simulating the evolution of the historical climate and the overall distribution of historical meteorology. Given these constraints, raw GCM projections can be limited in their usage in attribution research. Thus, GCMs are often bias-adjusted and statistically downscaled to align their output with the characteristics of observed or reanalysis data and improve their spatial resolution for regional analysis (Tabor and Williams, 2010). Yet while bias adjusting is an important step to match the data with the desired distribution, the methods used to perform these adjustments are not without challenges and can inadvertently introduce anomalous behaviors to the data, particularly at the tails of the data distribution, which capture extreme events (Cannon et al., 2015; Tabor and Williams, 2010; Watanabe et al., 2012). Additionally, GCMs are not initialized to replicate historical climate variability, and even after bias adjustment, will not reproduce individual observed weather events.

While impact assessments done in climate impact modeling are tied to the real world (Cucchi et al., 2020), our primary focus is to provide a climate dataset for attribution studies that serves as a counterfactual to the real world, in order to isolate the real-world impacts of anthropogenic warming. We therefore elected to use the 5th generation reanalysis (ERA5) product from the European Centre for Medium Range Weather Forecast (ECMWF) as the real world, and remove its anthropogenic signal using the difference between the historical and historical natural-only GCM simulations on a quantile basis. Previous attribution studies have used a range of methods to isolate and remove the anthropogenic signal from simulated or observed climate. For instance, some studies have done this by averaging global or regional temperatures in simulated projections that include and omit anthropogenic warming over a number of years, with the calculated difference then applied uniformly to a time series of spatially gridded data (Burke et al., 2018; Diffenbaugh and Burke, 2019; van Garderen, 2021). Although more simplistic methods like these may adequately adjust trends in the long-term mean, they assume that the temporal distribution does not change and therefore may not accurately represent the more extreme values in the adjusted climate. This has the effect of producing unrealistically inflated or truncated values and trends (Cannon et al., 2015). Some studies have addressed these limitations by adopting more advanced techniques, such as linear regression, Bayesian, and detrended approaches to account for the temporal variability observed in the data (Hegerl, 1996, 2011; Katzfuss, 2017; Franke, 2022). For example, Hegerl (1996) and Hegerl (2011) developed methods to better separate the anthropogenic signal using natural variability. Katzfuss (2017) introduced a framework estimating extreme event probabilities with temporal dependence, while Franke (2022) proposed detrended approaches that improve attribution of climate extremes by accounting for long-term trends and internal variability. Mengel et al. (2021) produce a complementary dataset to GDNat for use in attribution research, known as ATTRICI, that allows for the attribution of climate impacts to all climate change, not solely attributable anthropogenic climate change as in GDNat. ATTRICI was created using a detrending method at each grid point in which the long term component of a given climate variable that is conditional on global mean temperature change is removed from a reanalysis-like historical dataset to produce a counterfactual mean seasonal cycle. Quantile-mapping is then used to map daily values from the factual climate to the counterfactual to produce a daily timeseries. The ATTRICI approach is used to generate a counterfactual climate in the ISIMIP impact modeling framework (Hattermann and Krysanova, 2024; Frieler et al., 2024; Didovets et al., 2024). However, to our knowledge none of the existing attribution studies attempted to represent and remove the full distribution of the anthropogenic signal from a historical dataset at high resolution around the world, which we do using a quantile-based method.



Quantile-based adjustment methods, such as detrended quantile mapping (DQM) and standard quantile mapping (QM), have also been used to align changes in the quantiles with the target distribution in traditional bias adjustment contexts (Thrasher et al., 2012; Themeßl et al., 2011; Hempel et al., 2013). Although DQM and QM generally outperform simpler bias correction methods, these methods also often distort data trends and exaggerate changes in the distributional extremes (Cannon et al., 2015; Kim et al., 2021; Maraun, 2013). In our case, we were particularly interested in preserving the spatiotemporal patterns and temperature trends present in the distributional tails of ERA5 while solely removing the full distribution of the anthropogenic warming signal from the dataset. We therefore chose a quantile-based method that maps the distribution of ERA5 by quantile at each grid point location and time-step independently, called quantile delta mapping (QDM) (Cannon et al., 2015; Lehner, 2023), and use it in conjunction with historical natural-only simulations from DAMIP to calculate the anthropogenic component of CMIP6 historical simulations. Our attribution adjustment method subsequently removes the anthropogenic signal from ERA5 on a quantile-by-day-by-location basis while avoiding introducing biases inherent in the GCMs.

The QDM method has been found to better preserve changes in quantiles and extreme values (Gergel et al., 2023; Cannon et al., 2015; Lehner, 2023; Xavier, 2022; Tong, 2020), but it can be quite computationally expensive and complex to run at this spatiotemporal scale of 0.25 degrees for the globe (Gergel et al., 2023; Lehner, 2023). These computational and resource constraints have limited the broader application of QDM at the finer resolutions required for regional attribution analyses. To facilitate future attribution research, we produce a publicly available dataset using QDM as an attribution adjustment method to strip anthropogenic warming from ERA5. This novel dataset provides daily coverage over the period of 1979-2020 at quarter-degree resolution and has the potential for regional attribution studies, given its highly resolved spatiotemporal coverage.

2 Methods

2.1 Climate Data

To estimate the anthropogenic component of historical climate change, we use multiple realizations from the historical ("historical"), historical natural-only ("hist-nat"), and SSP2-4.5 ("ssp245") scenarios, and one realization from the long preindustrial control ("piControl") simulation, for six GCMs participating in the DAMIP exercise of CMIP6 (scenario details can be found in Tables A1 and A2). These six GCMs all have daily surface air temperature available for these four scenarios (Tables A1 and A2). We use these data and the ERA5 historical reanalysis to create the GDNat dataset. The dataset described here solely includes daily average surface air temperature (i.e., the variables *tas* and *t2m* in CMIP6 GCMs and ERA5, respectively). However, the methodology can be applied to other continuous variables (e.g., maximum and minimum daily temperature) and, with small method modifications (e.g., using a multiplicative rather than additive approach), non-continuous positive-definite variables (e.g., precipitation) found within the CMIP archive, so long as reference data exist. We expect to provide some of these additional data products along with new iterations of GDNat (e.g., using CMIP7 and ERA6) with subsequent releases.

In the CMIP6 experiments, the historical scenario covers the period 1850-2014 and includes anthropogenic forcings from greenhouse gases, aerosols, and land use. The hist-nat scenario covers 1850-2020 but only contains solar and volcanic forcing (Eyring et al., 2016). Because our methodology employs a 21-year rolling cumulative distribution function (CDF) (see Section



2.3), we extend the historical simulations with future projections from ssp245 and extend the hist-nat simulations with years
 125 extracted from piControl in order to generate global gridded time series through 2030.

The ssp245 scenario incorporates both natural and anthropogenic forcings and reflects a middle-of-the-road for the current
 climate trajectory (Meinshausen et al., 2020; Eyring et al., 2016; O'Neill et al., 2016). The DAMIP protocol also includes a
 scenario, ssp245-nat, that includes only natural forcings (Gillett et al., 2016). However, we used piControl rather than ssp245-
 nat to extend hist-nat simulations because ssp245-nat was not available for all the GCMs. The preindustrial control (piControl)
 130 experiment reflects Earth's radiative energy balance prior to 1850, and global greenhouse gases and land-use are held in a fixed
 state. The piControl scenario provides a long-term equilibrium state of the climate system and a robust baseline for internal
 variability (Gillett et al., 2016). Although differences exist between piControl and ssp245-nat, both simulations represent the
 Earth's climate without contemporary anthropogenic forcing, and result in a comparable planetary energy balance and climate
 variability. While ssp245-nat includes stratospheric aerosol forcing that initially aligns with 2014 observations, these levels
 135 are explicitly prescribed to approach piControl levels by 2025 (Gillett et al., 2016; O'Neill et al., 2016). We therefore found it
 reasonable to substitute ssp245-nat with piControl for the 2020-2030 period and use piControl for all GCMs for consistency.
 Ultimately, we identified six GCMs having piControl and at least three available ensemble members from each of the historical,
 ssp245, and hist-nat simulations, which we used to remove the anthropogenic signal from ERA5.

140 2.2 Adjustment Methodology

We develop a counterfactual dataset that retains the natural variability and extreme events observed in ERA5 while removing
 the GCM estimated anthropogenic forcing component. We use Quantile Delta Mapping (QDM) ((Cannon et al., 2015)) trained
 on the historical and hist-nat simulations from CMIP6, then apply the computed deltas to ERA5 on a time, location, and
 quantile basis. In the language of traditional bias adjustment, we are assuming that the reference climate is a world without
 145 anthropogenic climate change and treat the difference between historical and hist-nat simulations as a "bias" to be removed
 from ERA5, where the "bias" is the anthropogenically forced climate change. QDM was selected due to its ability to preserve
 the changes in distributional shape by preserving changes between the historical and hist-nat simulations at the quantile level
 (Bürger et al., 2013; Cannon et al., 2015), unlike single delta approaches that primarily modify the distributional mean (Ho
 et al., 2012; Hawkins et al., 2013).

150 The adjustment method follows from (Cannon et al., 2015) and (Gergel et al., 2023) and can be described as the following:
 For each GCM, cumulative distribution functions (CDFs) are used to align hist-nat and historical simulations and remove
 the anthropogenic signal from ERA5 by quantile. Let $F_{n,p}[\cdot]$, $F_{h,p}[\cdot]$, and $F_{r,p}[\cdot]$ denote the CDF from hist-nat simulation
 (reference data) n in period p , the CDF from historical simulation h in period p , and the CDF from the ERA5 reanalysis r
 in period p . Let $x_{r,p}(t)$ be a reanalysis value at time t (e.g., average temperature on September 1, 1990) and $x_{r,p}^*(t)$ be the
 155 adjusted value on that same date (in this study, x is the ERA5 value and x^* is the GDNat value). Then let $\tau_{r,p}(t)$ be the non-
 exceedance probability associated with $x_{r,p}(t)$ such that $\tau_{r,p}(t) = F_{r,p}[x_{r,p}(t)]$ and $x_{r,p}(t) = F_{r,p}^{-1}[\tau_{r,p}(t)]$ where $F^{-1}[\cdot]$ is the
 inverse CDF.



The training step involves calculating the adjustment factors between hist-nat and historical CDFs for the period p (Figure 1A shows illustrative training data), such that each quantile in the CDF is mapped to a temperature adjustment for that quantile (Figure 1B). Then, for a given time t , the adjusted value of ERA5, which is GDNat, is given by:

$$x_{r,p}^*(t) = x_{r,p}(t) + (F_{n,p}^{-1}[\tau_{r,p}(t)] - F_{h,p}^{-1}[\tau_{r,p}(t)]) \quad (1)$$

where $\tau_{r,p}(t) = F_{r,p}[x_{r,p}(t)]$. In other words, equation 1 states that on a given day t , the GDNat temperature $x_{r,p}^*$ (Figure 1C) is given by first finding the non-exceedance probability $\tau_{r,p}$ of that day's temperature in ERA5 in period p , $x_{r,p}$ (Figure 1D), and then adding the difference in temperature between the hist-nat and historical inverse CDFs at that same non-exceedance probability $F_{n,p}^{-1}[\tau_{r,p}(t)] - F_{h,p}^{-1}[\tau_{r,p}(t)]$ (AFs shown in Figure 1B).

Often in bias adjustment studies, the training step occurs one time such that the mapping from a simulated climate to a reference climate (e.g., adjustment factors) is fixed Gergel et al. (2023); Mengel et al. (2021); Cannon et al. (2015). In this study, we want to capture how the anthropogenic forcing changes in time so that the time-evolving signal can be accurately removed from ERA5. We therefore perform the training step (calculate adjustment factors), and the adjustment step, on a rolling basis throughout the dataset time period, as described in Section 2.3.

2.3 Pipeline implementation

Here we describe the implementation of the methodology described in Section 2.2, which is encapsulated in the "Data_Generation" section of the Python code repository at <https://github.com/ClimateImpactLab/gdnat>. While the adjustment method is relatively straightforward, working with GCM output, especially at a high resolution, is compute-intensive and can be cumbersome. The pipeline is organized to optimize for stability of the workflow rather than speed. We utilize the `dask` package on Google Cloud Platform to perform out-of-memory calculations for each step in the pipeline. The process for computing and saving GDNat can be summarized in the following steps, performed for each GCM and year: (1) prepare and clean input simulation data, (2) train QDM model on pooled data, (3) regrid the adjustment factors, and (4) apply QDM model adjustment factors to arrive at GDNat.

1. **Prepare and clean input simulation data:** We begin by concatenating historical and future simulations to cover the time period 1969–2030. Historical and ssp245 simulations that correspond to the same GCM and realization are concatenated to represent the climate including anthropogenic forcing from 1969 to 2030, while hist-nat and piControl simulations are concatenated to represent the naturally-forced counterfactual simulation over the same period. The temporal calendars are then harmonized across models to ensure consistency across each GCM simulation (e.g., the removal of leap days). Note that we perform this step at the the GCM's native (coarse) resolution for ease of computation, opting to regrid to the final 0.25 degree resolution after calculating the adjustment factors in step 2.
2. **Train QDM model:** Adjustment factors (AFs) are calculated for each day of the year and quantile annually from 1979 to 2020 on a rolling annual basis. We use the `xclim` package's implementation of QDM (Bourgault et al., 2023) to calculate the AFs. For each target year, data from three GCM ensemble members are pooled for that year to increase



the representation of internal variability and reduce the influence of a single GCM realization. Once data are pooled, CDFs are constructed by `xclim` for each day of the year with ± 10 years data centered on the target year and ± 15 days centered on the target day. For example, for July 15, 1990, the CDF is constructed from all July 1–July 30 days between the years 1980 and 2000 in all three ensemble members. This process yields 1953 data points from which to construct the CDF for each day of the year and year of GCM data (3 ensemble members $\times$ 31 days $\times$ 21 years) for each constructed temperature CDF.

Daily temperature CDFs are built for each time step and location, with each CDF divided into 100 equally sized quantile bins for the training calculation. The 100 adjustment factors are computed at the native horizontal resolutions of each GCM due to computational resource limitations and to preserve the empirical relationship between the historical and hist-nat GCM simulation. This constitutes the "training" step of the QDM model. For computational stability, we extract the AFs from the QDM model and save them to cloud storage for later use in the pipeline.

3. **Regrid adjustment factors:** Given that GCM resolution varies and is spatially coarse, the resulting AFs are too spatially coarse to be mapped directly to ERA5, which we obtained at 0.25 $\times$ 0.25 degree resolution. To align the spatial coordinates of the AFs with those of ERA5, we regrid the AFs to the ERA5 resolution on an annual basis using the bilinear interpolation method in the `xesmf` package (Zhuang et al., 2023). The fine resolution adjustment factors are very large (350GB per year) and are saved to scratch cloud storage for use in the adjustment step.

4. **Apply QDM model:** The fine resolution AFs are read from cloud storage and applied to ERA5 on an annual basis using `xclim`. To accomplish this, the QDM model calculates the CDF in ERA5 for each day in the year's timeseries (i.e., it finds each day's temperature quantile within the day and year windows), and adds the AF for each day's quantile to ERA5 to arrive at GDNat. This occurs for each grid point and time step in the year, and is repeated for all years in the final dataset.

These steps remove anthropogenic forcing from the climate system while avoiding introducing GCM biases, resulting in a fine-scale GDNat product that preserves the spatiotemporal variability, quantile structure, and statistical characteristics of ERA5, including the tails of the distribution that characterize extreme meteorological events. These steps are outlined in Figure A1 and were repeated for each GCM, resulting in a total of six GDNat ensemble members in the final dataset.

3 Results

To evaluate the GDNat dataset, the historical and hist-nat GCM simulations are compared with ERA5 and GDNat. A complete set of assessments is available on GDNat's GitHub repository (Fofrich Navarro et al., 2026b). The diagnostic evaluation focuses on specific years, assessing whether GDNat accurately preserves the anthropogenically forced spatial structure seen in model outputs. Figure 2 shows the average annual climatology over 2000–2010 in the historical and hist-nat simulations for MIROC6, ERA5, and GDNat. The coarse horizontal resolution of 2.5 degrees (250 km at the equator) in the raw model, MIROC6 in this case, is evident in Figure 2A and B, while GDNat's climatology reflects the higher resolution of ERA5 without adopting the



characteristics of the GCMs (Figure 2D and E). By construction, the spatial patterns of the differences in climatology between the GCMs (with and without anthropogenic forcing) are preserved between ERA5 and GDNat (Figure 2C and F), while the baseline climatologies are different.

225 Figure 3 shows an annual-mean, global-mean surface air temperature time series for each GDNat realization, alongside the original output for ERA5 and the historical and historical natural-only simulations from each GCM. By construction, interannual variation within each GDNat ensemble member closely mirrors that in ERA5 (Figure 3A). The magnitude of the temperature signal in each GDNat member reflects the degree of anthropogenic warming in its respective GCM, since higher projected warming in a particular GCM results in larger adjustments being applied to ERA5. For five of the six GDNat ensemble mem-
 230 bers, there is a relatively small change in global-mean temperature over 1980–2020, ranging from -0.082 to $0.040^{\circ}\text{C}/\text{decade}$ (Figure 3A), compared to $0.192^{\circ}\text{C}/\text{decade}$ in ERA5. The exception is the GDNat ensemble member derived from CanESM5, which exhibits a strong cooling trend ($-0.17^{\circ}\text{C}/\text{decade}$), comparable in magnitude to the historical warming trend in ERA5. This reflects an overly strong warming trend in CanESM5’s historical simulation compared to its hist-nat simulation (Figure 3B) likely due to the model’s underlying parameterizations and high equilibrium climate sensitivity (Cannon, 2024; Zelinka
 235 et al., 2020b; Swart et al., 2019). Consequently, caution is advised when using only the GDNat-CanESM5 data, recognizing that it may be overly sensitive to radiative forcing, especially when compared to other GCMs.

We show the spatial pattern of the time-average and quantile-average adjustment factors (Figure 4), which transform ERA5 to GDNat, by decade and GCM to show the range of anthropogenically forced changes predicted by the raw GCM simulations. These mean adjustments are close to, but not exactly, the mean climatological difference between historical and hist-nat
 240 simulations in these GCMs. Adjustment factors are larger in years with a greater magnitude of anthropogenic warming and in models with higher equilibrium climate sensitivity, and the greatest temperature adjustments occur in the Arctic, consistent with observed trends of anthropogenic warming (Taylor et al., 2022). In early years, many GCMs show regionally negative adjustment factors, indicating that the historical experiments predict cooler temperatures than the corresponding hist-nat experiments for those areas, which is to be expected when anthropogenic forcing is small and overwhelmed by internal variability.
 245 Looking across the days of the year and quantiles (Figure A2), we find that Northern Hemisphere-mean adjustment factors vary seasonally, generally reaching their highest values during Northern Hemisphere winter. We opted to solely look at the Northern Hemisphere to avoid averaging regions with opposite seasonal phases which would otherwise obscure the day of year dependent seasonal structure in the adjustment factors. The resulting pattern corresponds with the observed seasonality in anthropogenic warming trends documented over recent decades and is consistent with previous literature (Masson-Delmotte
 250 and Zhou, 2021; Marvel et al., 2023).

To compare the effectiveness of the QDM approach we use here with methods that quantify and apply a single adjustment over space and time to the climatological distribution, we evaluate the deviation of Northern Hemisphere-mean adjustment factors by the day of the year and across different quantiles from the median adjustment factor for each day for four climatological periods (Figure 5). The seasonal and quantile variations in these adjustment factors reveal that an adjustment using a single
 255 climatologically averaged factor would fail to account for the nuanced warming and cooling patterns present in the data. For instance, in some cases the adjustment factors at lower quantiles are smaller than the median (blue color in Figure 5), indicating



that quantifying and applying a single adjustment value would overestimate the effect of anthropogenic warming on the cool side of the distribution. In other cases, the adjustment factors exceed the median at higher quantile values, indicating a single adjustment value would underestimate the effect of anthropogenic warming on the warm side of the distribution. In fact, there is clear seasonal variation as seen also in Figure A2, which varies by GCM. However, in general, on relatively cooler days for a given day of year (i.e., lower quantiles), a single delta would overestimate the adjustments in the cold and shoulder seasons and underestimate in the hot season, whereas on relatively warmer days (higher quantiles), it would underestimate in the cold and shoulder seasons and overestimate in the hot season (Figure 5). As shown in the appendix figure A3, the resulting analysis using a simpler adjustment process would closely match those based of GDNat if only comparing the mean temperature but would generally underestimate the human-caused component of warming on the coolest and hottest days of the distribution. Additionally, annual mean temperature differences between the two methods shown in Figure A4 indicate that applying a single adjustment factor across all seasons and quantiles would miss important spatial variation and lead to varying degrees of underestimation of human-caused climate change over land.

As an example of the application of GDNat, Figure 6 shows the difference in the frequency of days exceeding 35°C over a 20 year climatological average from 2000-2020 relative to ERA5. We find that North Africa, the Middle East, South Asia, and Australia exhibit a notably smaller number of days above 35°C in GDNat compared to ERA5 with an additional 15-30 days per year (averaged from 2000 to 2020) reaching temperatures above 35°C directly attributable to anthropogenic warming. Interestingly, some regions have fewer days above this threshold in ERA5 compared to the GDNat ensemble. A notable example includes Northern India for NorESM2-LM (Figure 6F), which may be due to the removal of aerosol forcing within that GCM. In addition to Figure 6, we present a similar analysis but lower the threshold to 30°C and display the difference in days above 30°C between ERA5 and GDNat (Figure A5). Consistent with (Figure 6), the greatest differences are observed in North Africa, the Arabian Peninsula, South Asia, and Australia. Regions in the eastern half of South America, the southern part of North America, and across the southern Eurasian steppes also show large increases in days over 30°C due to anthropogenic warming.

4 Discussion and conclusion

Existing meteorological records only cover periods already substantially altered by anthropogenic activity, meaning the dynamics, frequency, and magnitudes of observed extreme meteorological events has been reflect a climate system already perturbed by past greenhouse gas emissions (Sherman et al., 2023; Swanson et al., 2009; Barnett et al., 1999). Recent efforts have been instrumental in generating counterfactual global climate model scenarios to study the behavior of the global climate system without anthropogenic forcing (Mengel et al., 2021; Bindoff et al., 2013; Ribes et al., 2016) and future attribution research depends on the availability of highly resolved credible counterfactual datasets. GDNat thus fills this need by systematically removing anthropogenic warming from the historical record, serving as a counterfactual dataset in impact attribution models to determine whether or not a recent meteorological event was the result of human activity or natural variability.

GDNat complements existing counterfactual datasets such as ATTRICI v1.1 (Mengel et al., 2021). Unlike ATTRICI, GDNat allows explicit attribution of temperature-related impacts directly to anthropogenic climate change, whereas ATTRICI removes



290 signals correlated with global-mean surface-air temperature change regardless of driver. By deriving counterfactuals using multiple GCMs, GDNat includes a measure of uncertainty around the anthropogenic signal, whereas ATTRICI provides a single deterministic scenario. GDNat is also at a finer spatial resolution (0.25° versus ATTRICI's 0.5°), and carefully accounts for the rank-ordering of each day's temperature on a rolling basis, to maintain the fidelity of the observational variability, including extremes. However, GDNat currently models only surface air temperature, whereas ATTRICI includes more variables, including precipitation, wind speed, and surface air pressure. (Mengel et al., 2021; Frieler et al., 2024). While the ATTRICI approach of removing signals correlated with GSAT provides a tractable framework, the assumption that local or regional variables scale linearly with GSAT may not always hold, especially for extreme events and processes strongly influenced by local dynamics or non-GSAT drivers (Tebaldi and Arblaster, 2014; Wells et al., 2023; Grillakis et al., 2017). In contrast, GDNat was created using empirically derived adjustments that vary by location, time, and quantile. The result is a highly resolved counterfactual data product that removes the contributions of anthropogenic forcing yet captures these nuanced heterogeneous differences at the localized level. GDNat can also be used to quantify the effects of heat management measures by providing a baseline against which the effectiveness of interventions can be evaluated against natural conditions. Our findings further support the benefit of a quantile-based adjustment method used to create GDNat, which accounts for the spatiotemporal temperature nuances and ensures a more accurate data product for climate change attribution analysis.

305 Each GDNat member was generated using the same methodological framework, yielding consistent spatiotemporal patterns over time. However, differences in temperature values emerge across members due to differences in the initial conditions and anthropogenic response characteristics of the underlying GCMs. These variations result in a modest but noticeable spread among the six GDNat ensemble members. Data end users should treat individual GDNat simulations similarly to individual global climate model outputs and avoid relying too heavily on any single member. The inclusion of multiple GCMs in GDNat is intended to account for differences in how models simulate the climate system's response to anthropogenic forcing, helping to mitigate model-specific biases and uncertainties. As with analyses that rely on CMIP ensembles, researchers are strongly encouraged to leverage the full spread of GDNat members to enhance the robustness and credibility of their findings.

While we have taken extensive steps to ensure the robustness and quality of GDNat, several limitations should be noted. Most notably, at present GDNat solely includes daily mean surface air temperature. Nonetheless, the QDM methodology can be extended to other variables including maximum and minimum daily temperature or wet-bulb temperature, and modified to incorporate precipitation. Additionally, while QDM's fine-scale adjustments preserve the regional variability observed in ERA5, the adjustments to ERA5 were generated using the GCMs native resolution and later regridded to match ERA5's quarter-degree resolution. As a result, the adjustment factors used to create GDNat will not capture finer-scale processes that are missing in the source GCMs, particularly in areas with complex topographic terrain or in coastal regions. In addition, because no true counterfactual data product exists for direct comparison, GDNat cannot be validated against a ground-truth observational record. However, GDNat's construction is grounded in established methods (Cannon et al., 2015; Gergel et al., 2023), and its spatial and temporal patterns are consistent with ERA5 absent of anthropogenic warming. Thus, despite these limitations, GDNat is a useful tool for investigating the human influence on temperature-driven extremes and supports the growing field of impact attribution research.



325 As impact attribution studies increasingly inform policy, litigation, and financial risk assessments, the credibility, trans-
parency, and interpretability of counterfactual datasets becomes increasingly important. Yet, the methodological choices in
defining the anthropogenic signal and the removal of this signal can materially influence the resulting estimates. GDNat was
developed using a standardized, transparent, and reproducible framework used to isolate and remove anthropogenic warming
from a widely used global temperature data product (i.e., ERA5). By standardizing the counterfactual scenario at a daily and
330 quarter degree scale while retaining the internal variability of ERA5, GDNat supports more consistent evaluation of tempera-
ture metrics across regions, timescales, and applications. Still, GDNat is not a substitute for natural only model experiments,
but a complementary tool that preserves the observed sequence of events without the modeled anthropogenic forcing. As
methodological approaches to climate impacts and attribution continue to evolve, the availability of reproducible counterfac-
tual datasets will be essential for ensuring the comparability and interpretability of results across studies. Future iterations of
335 GDNat may be published to extend the dataset beyond 2020, incorporate new and improved climate data (e.g., ERA6), and
extend the data product to include additional climate variables critical to attribution studies.

5 Code and data availability

All data used for this study are publicly available. Historical and historical-natural temperature for the Coupled Model Inter-
comparison Project phase 6 (CMIP6) are available on the Earth System Grid Federation (ESGF) data archive [https://esgf-node.](https://esgf-node.llnl.gov/search/cmip6/)
340 [llnl.gov/search/cmip6/](https://esgf-node.llnl.gov/search/cmip6/). European Centre for Medium-Range Weather Forecasts Reanalysis v5 (ERA5) data is available at an
hourly time step at <https://cds.climate.copernicus.eu>.

Python was used for data processing and analysis. The code used to generate these findings is available on the Climate
Impact Lab GitHub repository <https://github.com/ClimateImpactLab/gdnat> (Fofrich Navarro et al., 2026b), and the underly-
ing data described in this manuscript is archived in the UChicago Knowledge repository <https://doi.org/10.6082/dqt5x-gxh81>
345 (Fofrich Navarro et al., 2026a).

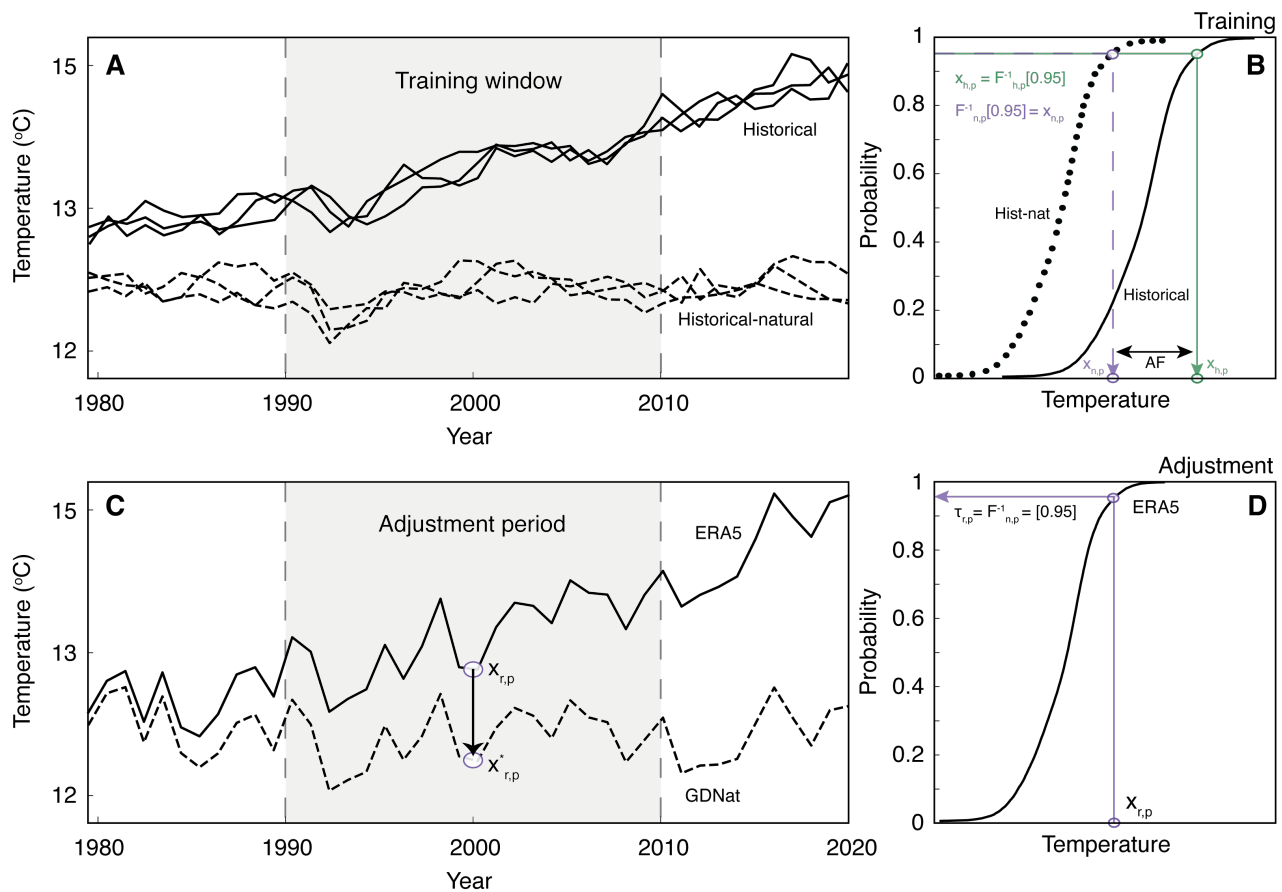


Figure 1. Idealized schematic of the Quantile Delta Mapping (QDM) method for one GCM. Panel A shows an annual time series of average temperature for a day of the year for 3 ensemble members of the historical and historical natural-only scenarios of one GCM. The 21-year training period p is shaded light gray. Panel B shows the GCM time series as CDFs for period p with the ensemble members pooled. The adjustment factors (AFs) are found by subtracting the historical temperature $x_{h,p}$ from the historical natural-only temperature $x_{n,p}$ at each quantile, using 0.95 as an illustration. Panel C shows the same day of the year time series for ERA5 with the target day and adjusted day marked respectively as $x_{r,p}$ and $x^*_{r,p}$. The adjustment period, also p , is shaded light gray. Panel D shows the CDF for ERA5 in period p and illustrates finding the non-exceedance probability for $x_{r,p}$, which is used to find the AF shown in Panel B, and applied in Panel C.

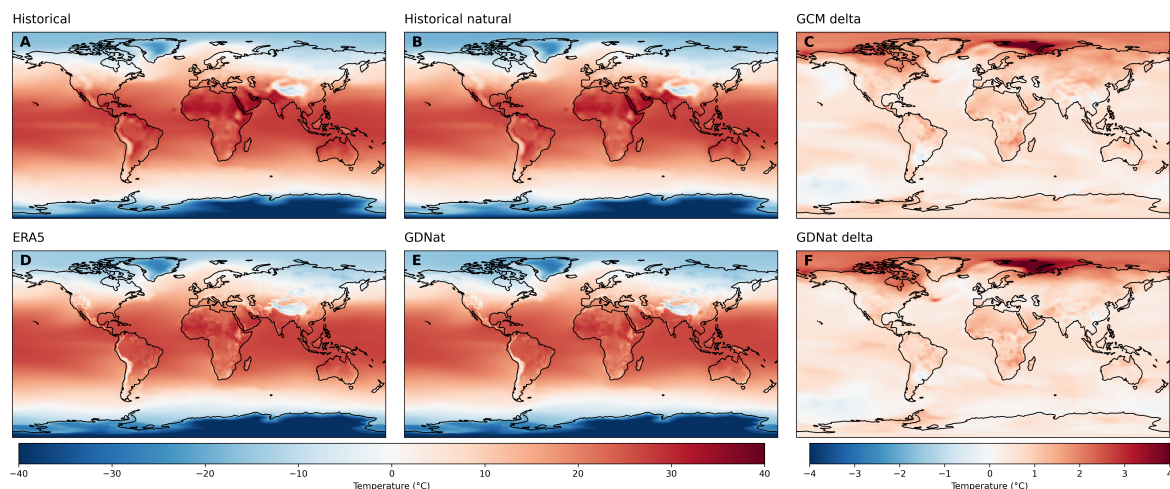


Figure 2. | Comparison of the historical, historical natural, ERA5, and GDNat temperature simulations, averaged over 2000–2010. Panels A and B show the average of three realizations from MIROC6, while panel E shows the corresponding GDNat ensemble. Panels C and F show the differences between the historical (A) and historical natural-only GCMs (B) and between ERA5 (D) and GDNat (E), respectively.

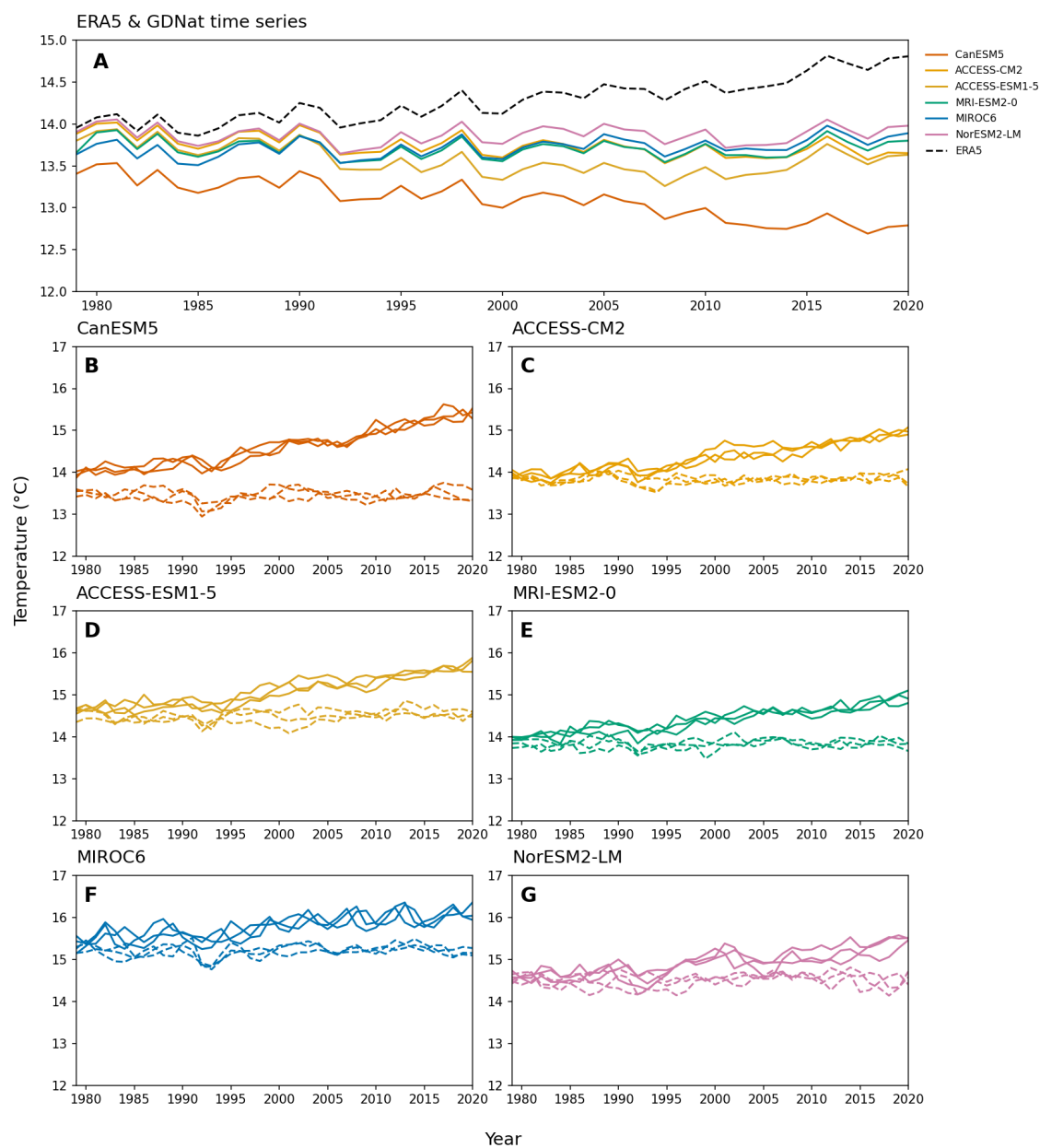


Figure 3. | Time series of global-mean surface air temperature for ERA5, global climate models, and GCMs. Colors denote different GCMs. Panel A shows the time series in ERA5 and GDNat members. (B-G) Global mean air surface temperature output for each GCM historical (solid lines) and historical natural (dashed lines) ensemble members used.

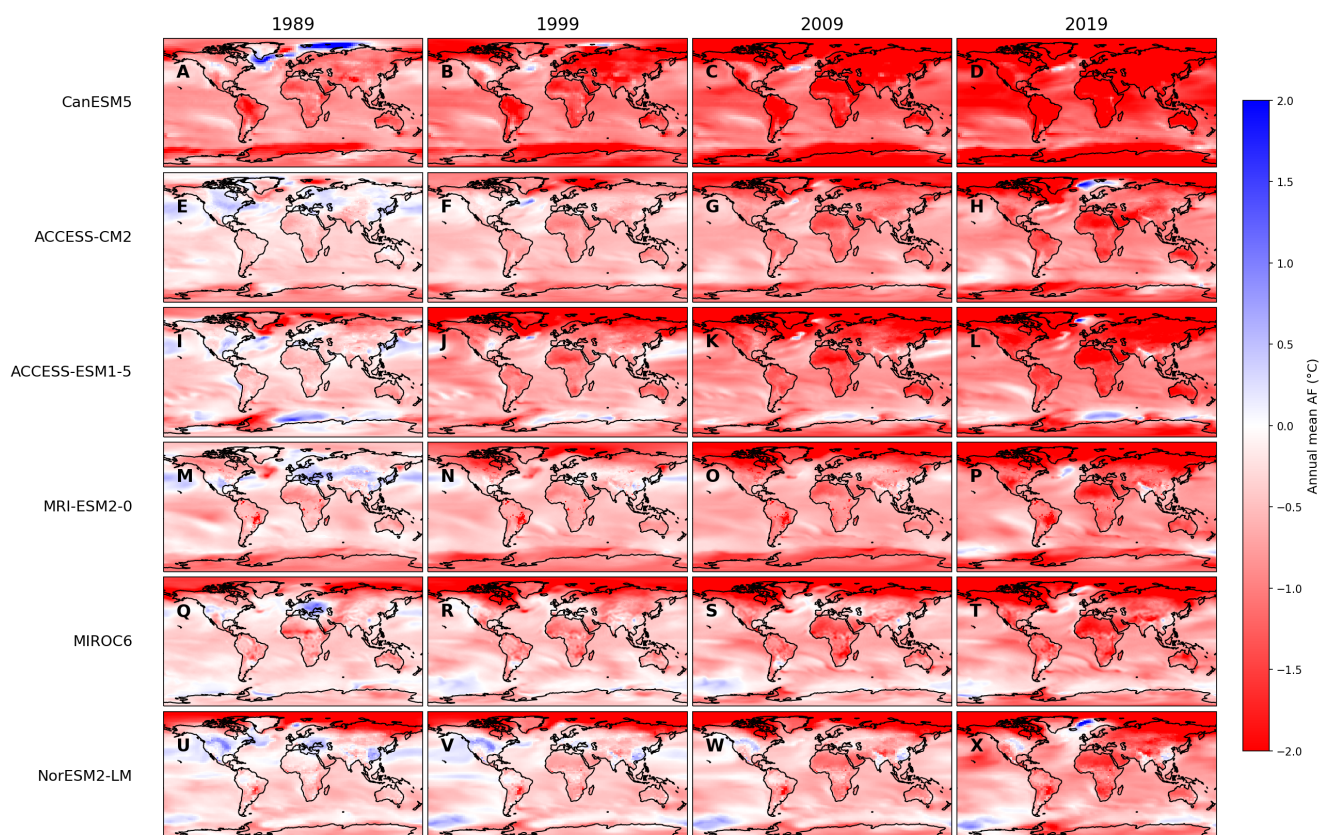


Figure 4. | Annual- and Quantile-Mean Adjustment Factors. Adjustment factors are averaged over quantile and the day of year for 1989 (left), 1999 and 2009 (middle), and 2019 (right). Positive values reflect places where the historical simulation is warmer than the historical natural simulation on average in the 21-year period centered on that year, while negative values reflect places that are cooler. Rows reflect the equilibrium climate sensitivity of the GCM, from the highest climate sensitivity on top to the lowest at the bottom.

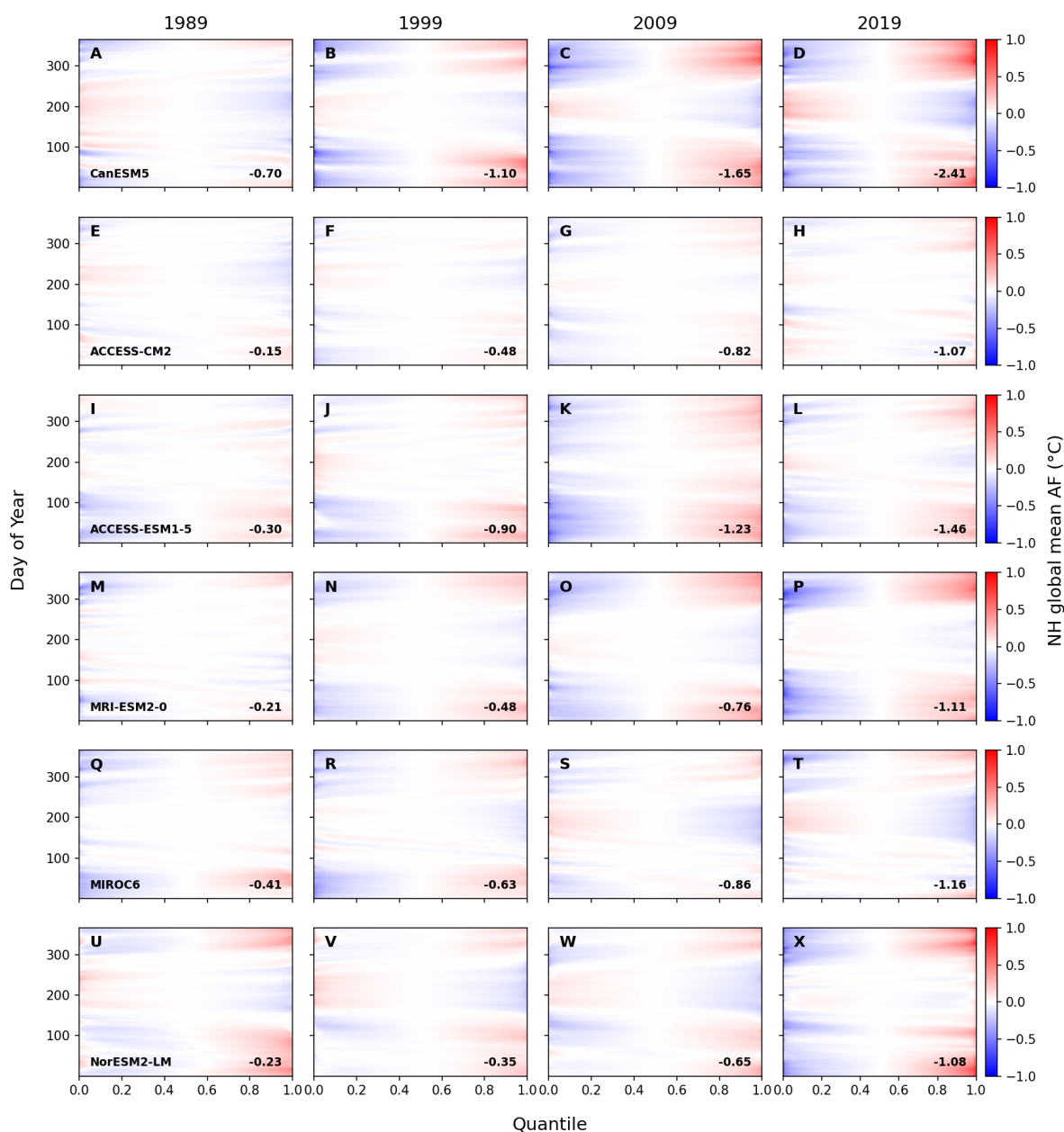


Figure 5. | Northern hemisphere mean adjustment factors by day-of-year and quantile, relative to the median adjustment factor for each day. Columns correspond to 1989 (left), 1999 and 2009 (middle), and 2019 (right) while rows correspond to different GCMs. Within each panel, the horizontal axis corresponds to quantile and the vertical axis to day of year (top to bottom). Blue colors illustrate greater warming at a given quantile than at the median for that day of year, while red colors represent less warming. The median adjustment factor across days and quantile is shown at the bottom right of each panel

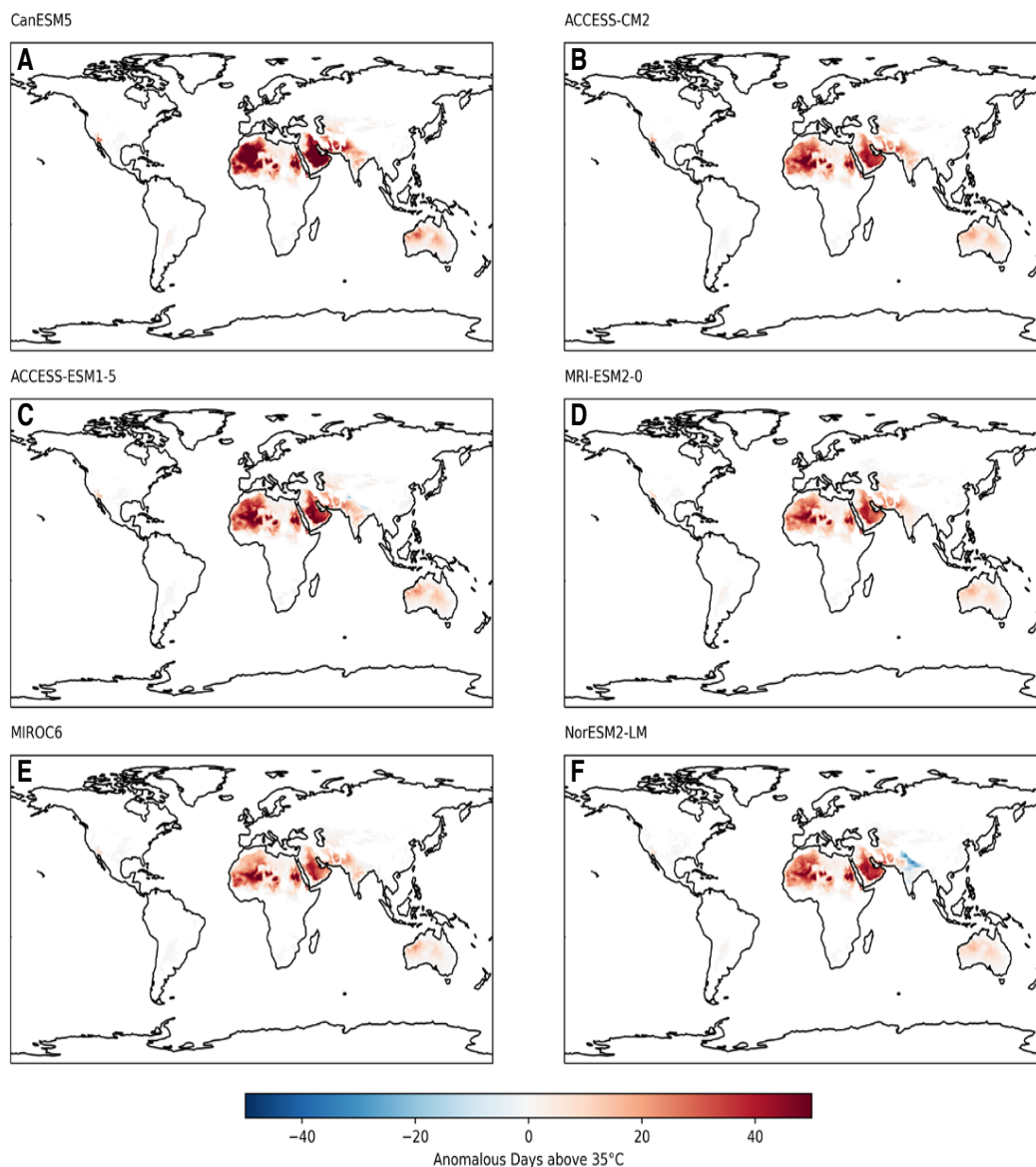


Figure 6. | Difference in number of days above 35°C in ERA5 relative to GDNat. The annual average difference in the number of days where average daily temperature values reach 35°C in ERA5 relative to each GCM in GDNat. Cooler colors indicate that ERA5 has fewer hot days than GDNat while warmer colors show a greater number of days above 35°C in ERA5 than GDNat.

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Appendix A

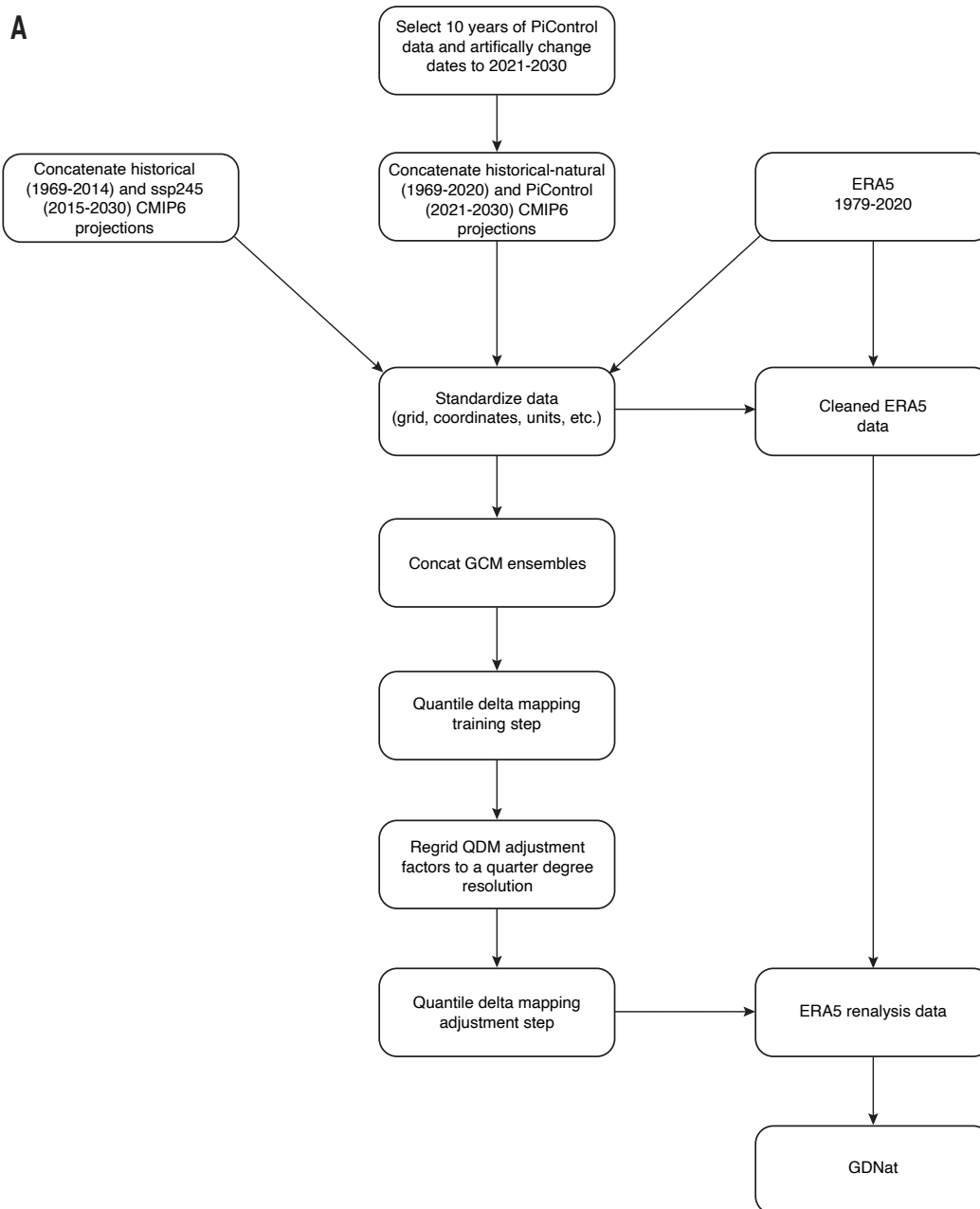


Figure A1. Methodological pipeline. Overview of the steps used to construct GDNat. We first harmonize the GCM and ERA5 inputs. The QDM framework is then trained using GCM output with a 30-day rolling window, 10 pooled years of data, and 100 quantiles. The resulting adjustment factors are regridded and subsequently applied to ERA5 on the corresponding temporal basis.

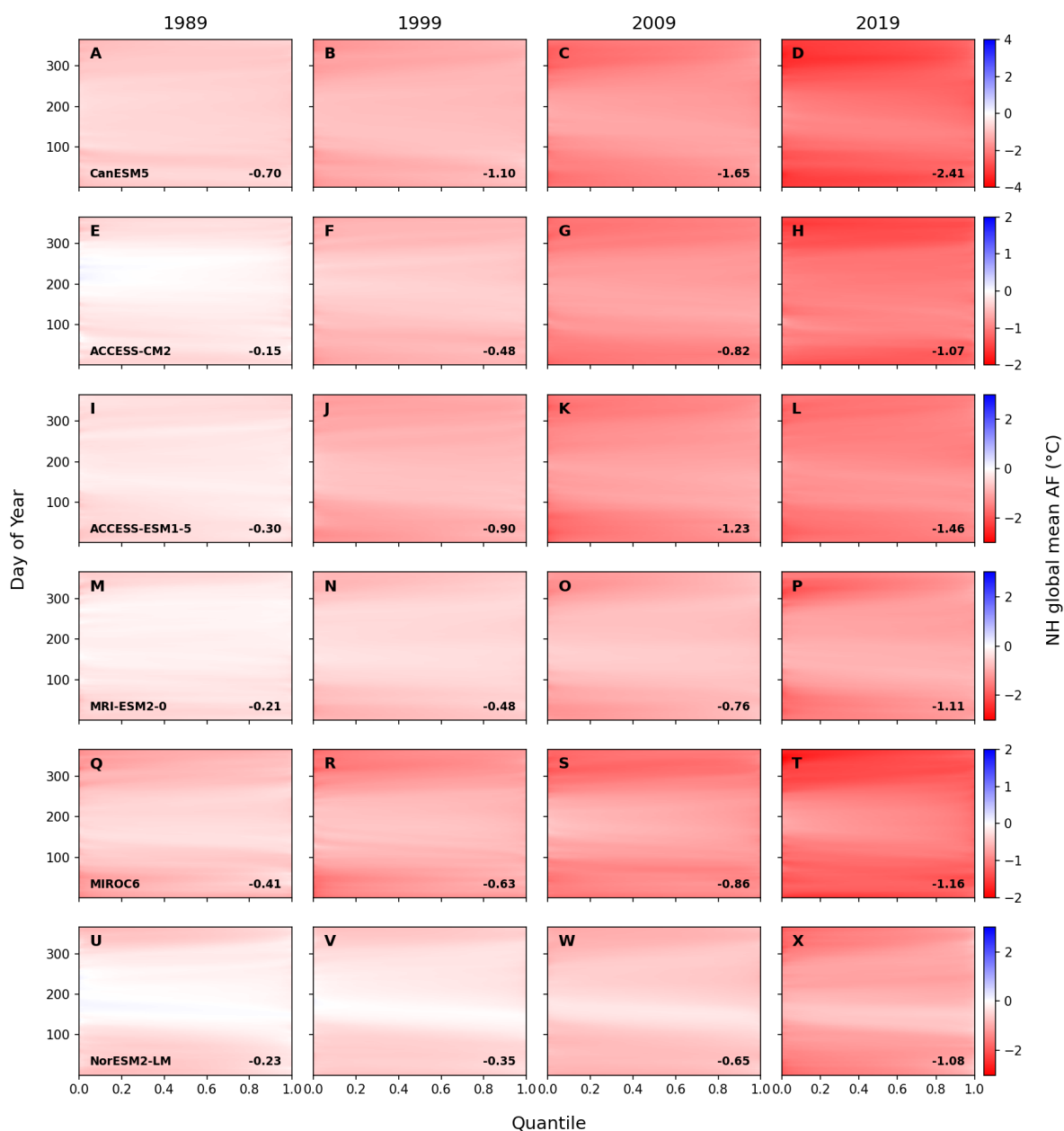


Figure A2. | Northern Hemisphere Mean Adjustment Factors. Northern Hemisphere mean adjustment factors for each quantile (y-axis) and day of the year (x-axis) are shown for each GCM. The Northern Hemisphere mean was taken over the GCM's native resolution before regridding to 0.25deg resolution. Here, we display the QDMs in descending order following the model's Equilibrium Climate Sensitivity. GCMs are arranged from highest sensitivity (top) to lowest sensitivity (bottom) and progress through time from left to right. Warm colors indicate warmer adjustment factors while bluer hues suggest a cooling pattern

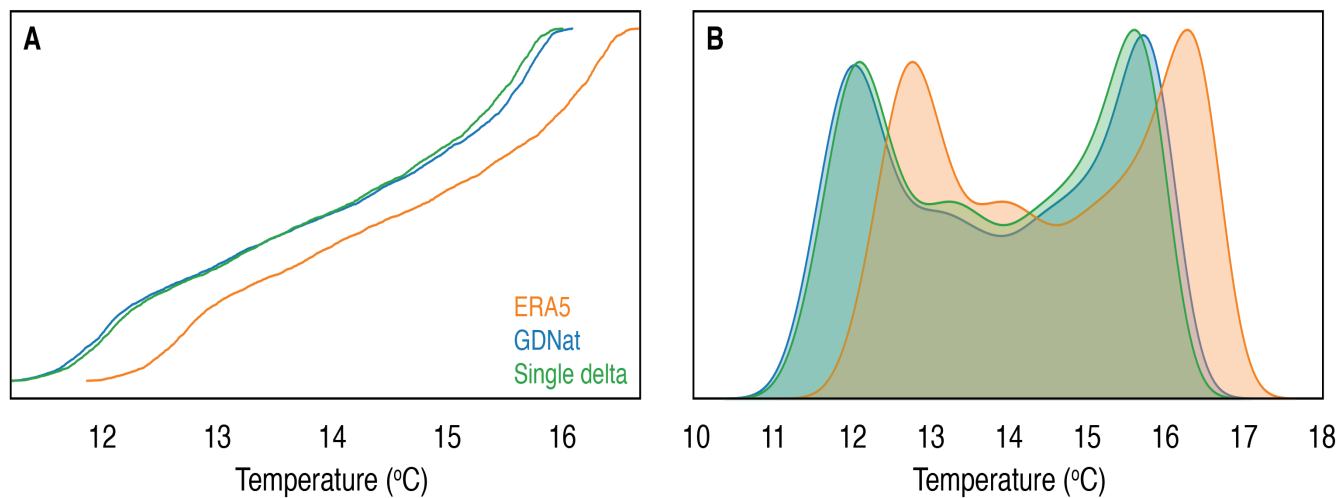


Figure A3. |Comparison of global mean temperature distributions from ERA5 using two bias correction methods (QDM and single delta). Cumulative distribution functions (left) and probability density functions (right) of Northern Hemisphere, area-weighted mean daily near-surface air temperature from ERA5 (orange), ERA5 corrected using a single-delta bias-correction approach (green), and GDNat (blue), over the period 2000–2010

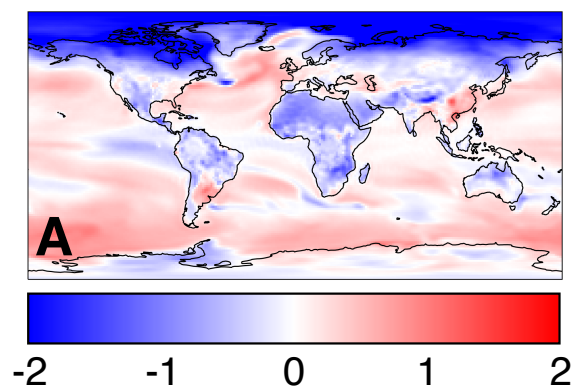


Figure A4. | Map comparing different bias correction method temperature outputs for MIROC6 using a ten-year climatology (2000-2010). Figure shows the differences between these two methods, calculated by subtracting the single delta results from the GDNat results.

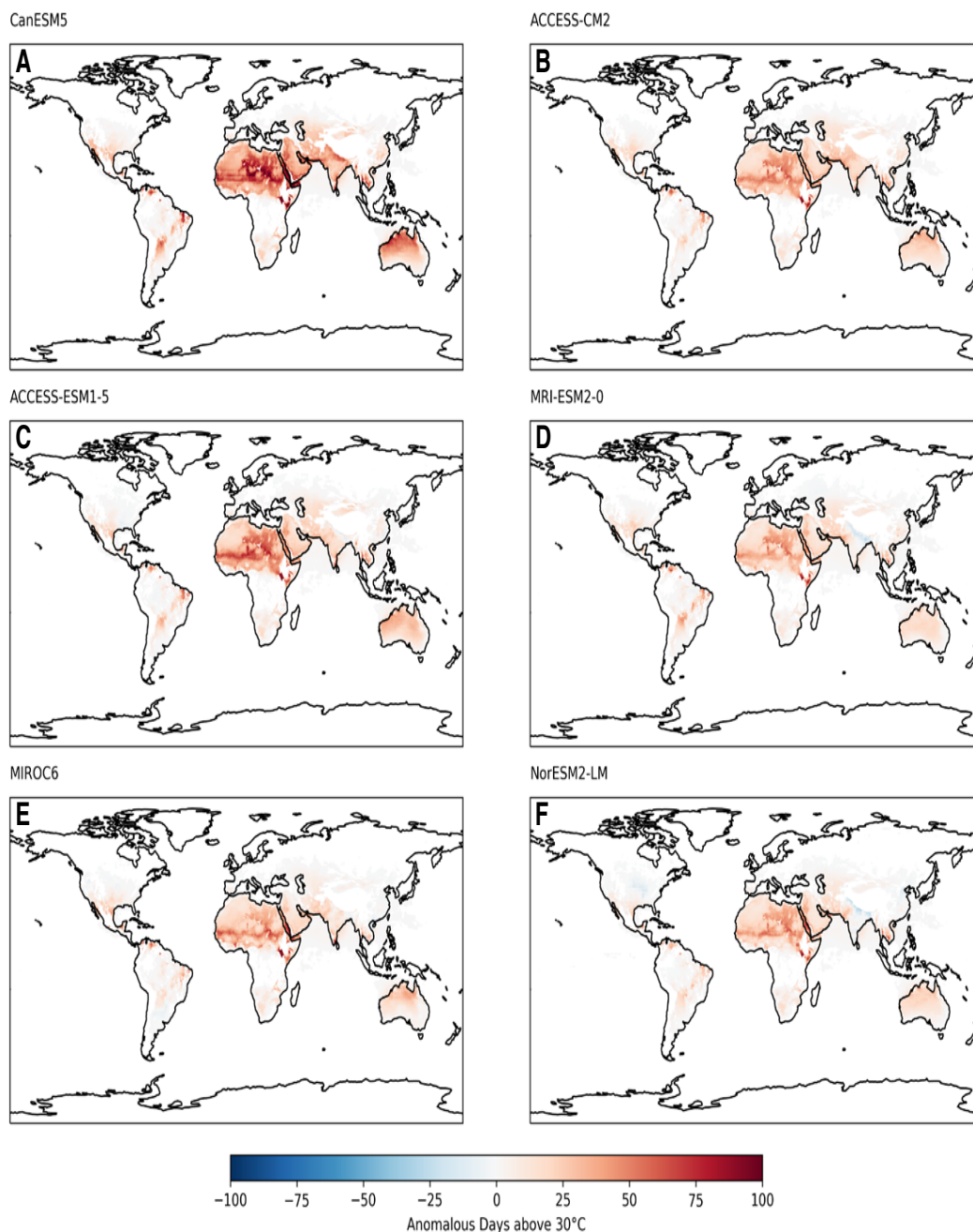


Figure A5. | The difference between the days above 30 degrees Celsius in ERA5 and GDNat. The figure shows the difference in days above the temperature threshold between ERA5 and GDNat ensemble members (colors). Warmer colors illustrating a higher number of days surpassing the threshold in GDNat compared to ERA5 while bluer colors suggest more warm days in ERA5. The names of the GCM used to create GDNat are shown on the top left of each panel.

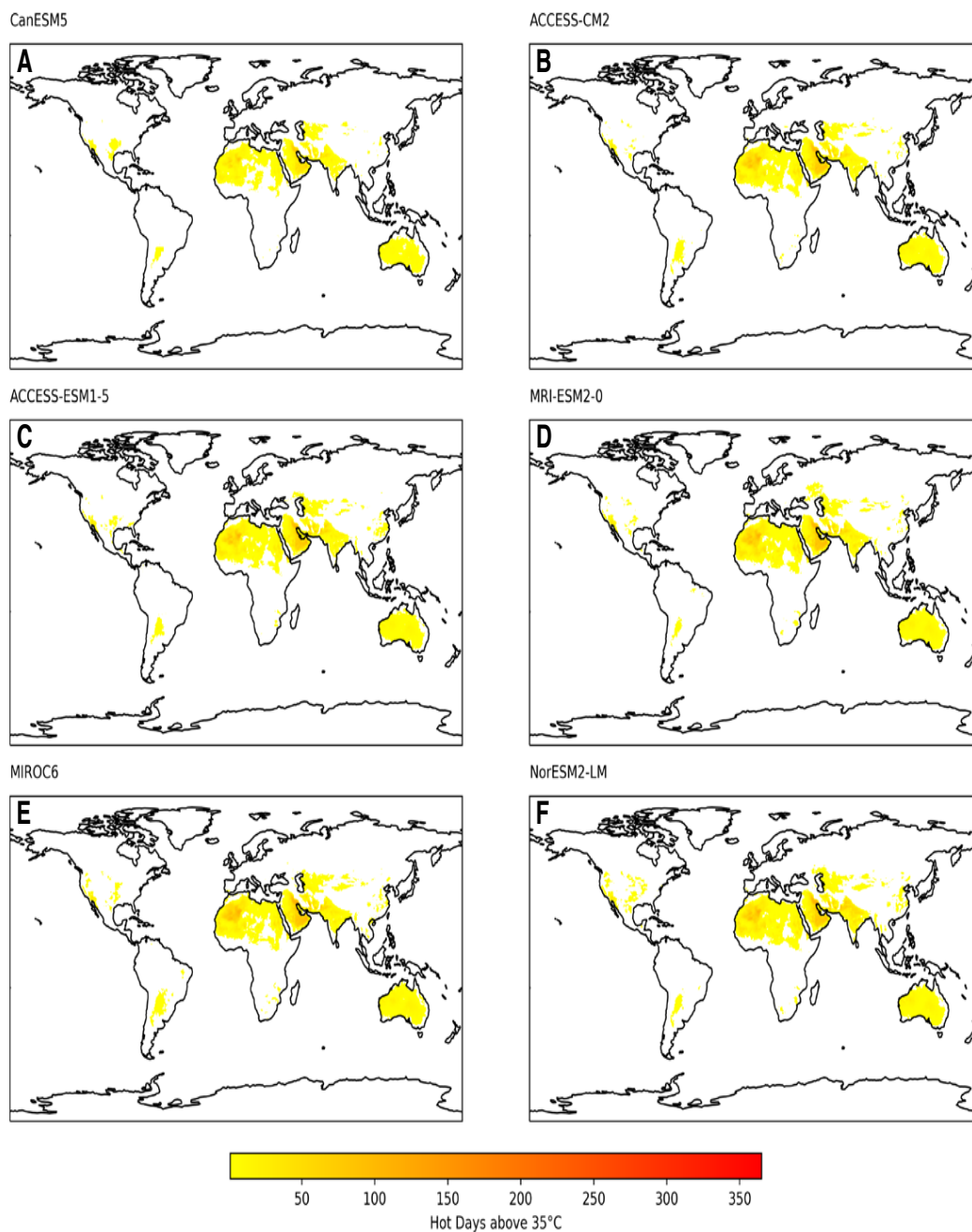


Figure A6. | Average annual occurrence of Days with Mean Surface Temperature Exceeding 35°C (2010-2020). We display the frequency of days where the mean surface temperature surpasses 35°C in GDNat (colors).

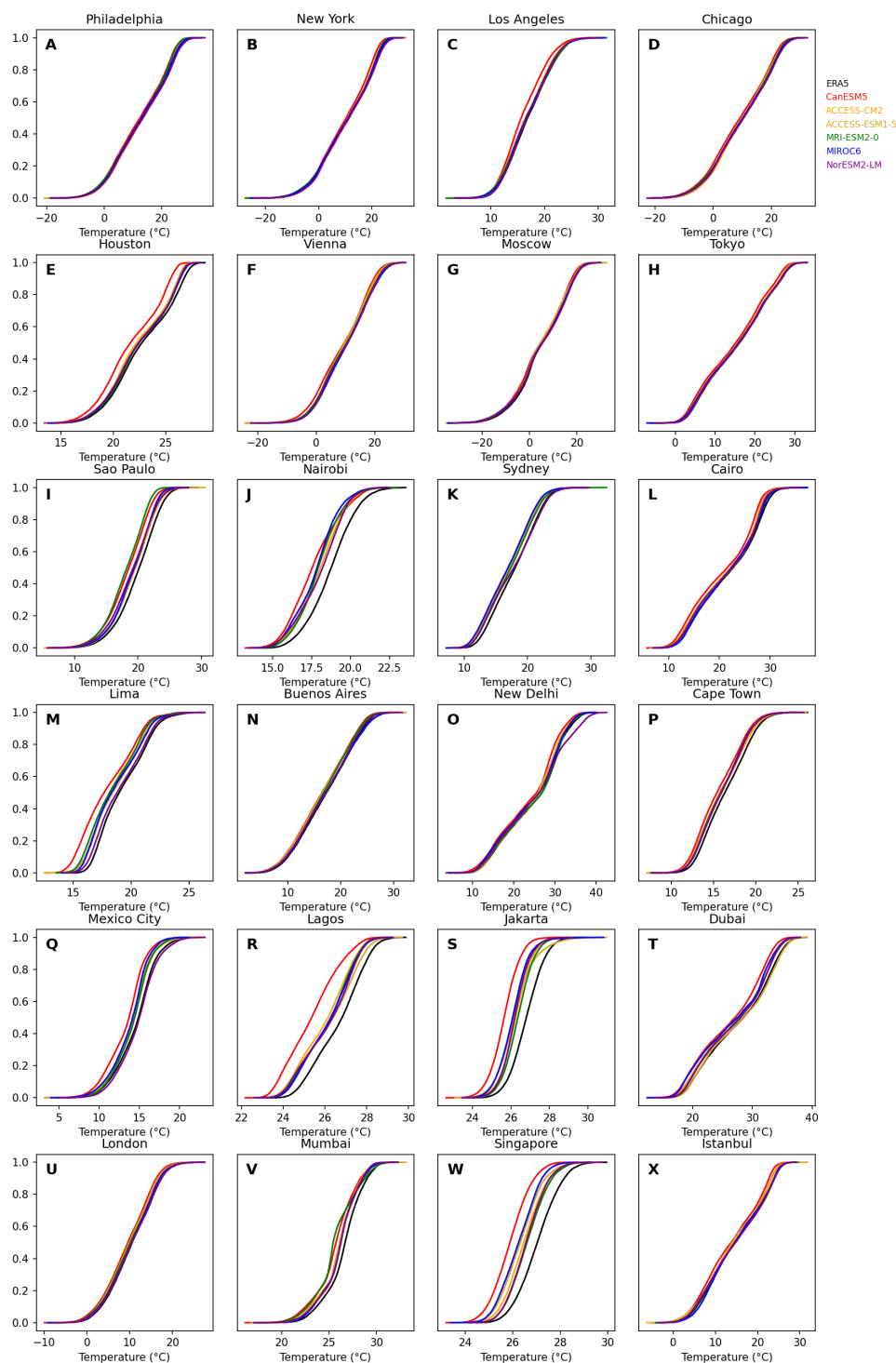


Figure A7. | Cumulative distribution functions of temperature for selected cities The figure depicts temperature cumulative distribution functions for individual GDNat ensembles (represented by various colors) alongside ERA5 data (shown as a black line).

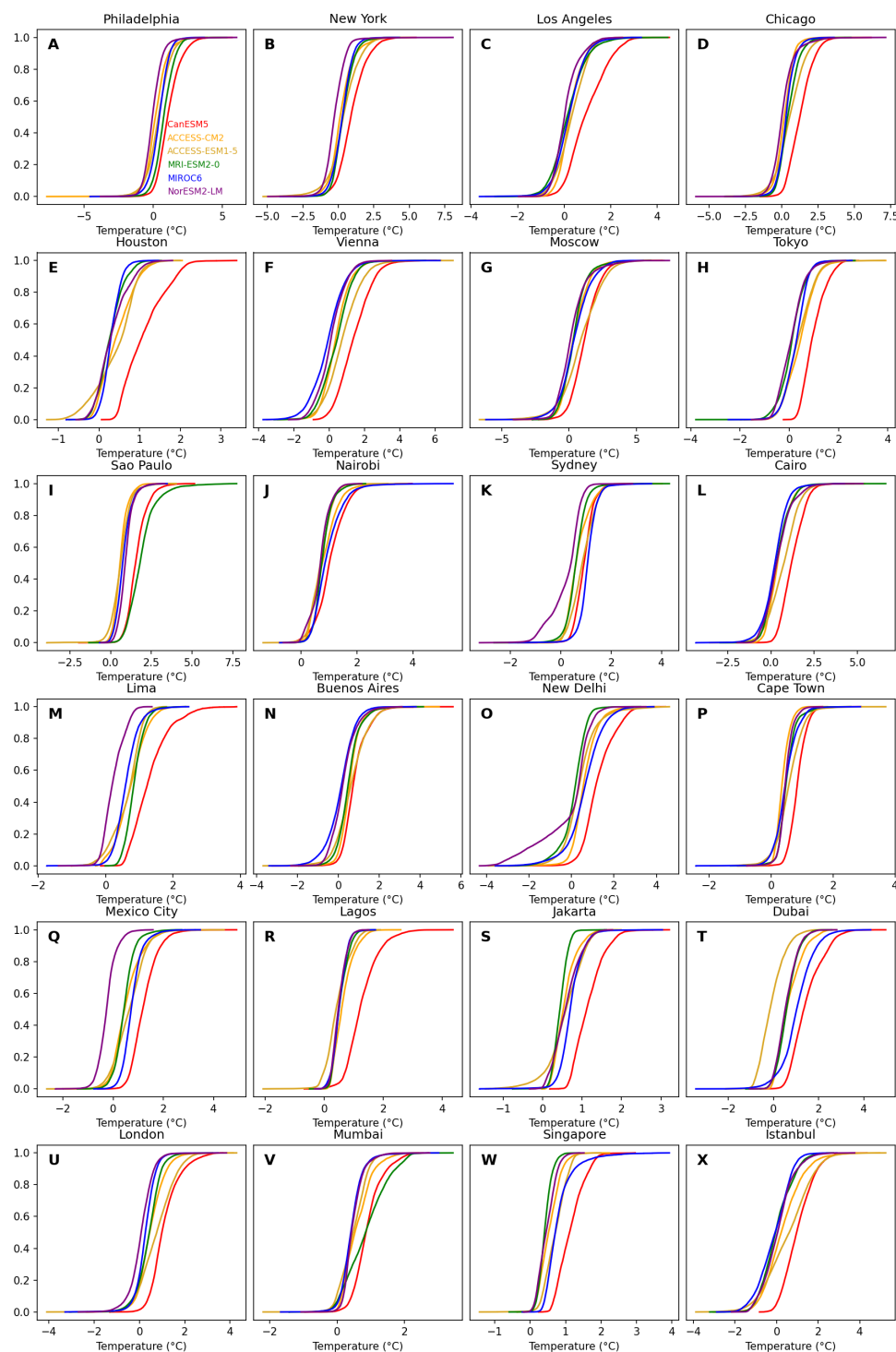


Figure A8. | Cumulative distribution functions of temperature differences for selected cities Figure shows the CDFs of the temperature difference (GDNat minus ERA5) for each ensemble member (colored lines).



GCM	Average temperature difference from 2015 - 2020 (°C)	ECS (°C)	TCR (°C)
CanESM5	1.15	5.64	2.71
ACCESS-CM2	0.53	4.72	1.96
ACCESS-ESM1-5	0.60	3.87	1.97
MIROC6	0.57	2.66	1.55
MRI-ESM2-0	0.58	3.13	1.67
NorESM2-LM	0.40	2.56	1.49

Table A1. CMIP6 climate models climate metrics. The table shows the average temperature difference between the GCM historical and historical natural-only simulations (averaged over all three model ensemble members and from 2015-2020), equilibrium climate sensitivity, and transient climate response estimates. ECS and TCR estimates were obtained from (Zelinka et al., 2020a) and (Cannon, 2024), respectively.



Global Climate Models		
GCM	Institution	Ensemble members
CanESM5	Canadian Centre for Climate Modelling and Analysis, Victoria, British Columbia, Canada	r1i1p1f1, r2i1p1f1, r3i1p1f1
ACCESS-CM2	Commonwealth Scientific and Industrial Research Organisation, Canberra, Australia	r1i1p1f1, r2i1p1f1, r3i1p1f1, r4i1p1f1, r6i1p1f1
ACCESS-ESM1-5	Commonwealth Scientific and Industrial Research Organisation, Canberra, Australia and Australian Research Council Centre of Excellence for Climate System Science, Sydney, Australia	r1i1p1f1, r2i1p1f1, r3i1p1f1
MIROC6	National Institute for Environmental Studies, Tsukuba, Ibaraki Prefecture, Japan, the Japan Agency for Marine-Earth Science and Technology, Yokohama, Japan and the University of Tokyo, Tokyo, Japan	r1i1p1f1, r2i1p1f1, r3i1p1f1
MRI-ESM2-0	Meteorological Research Institute, Tsukuba, Ibaraki Prefecture, Japan	r1i1p1f1, r2i1p1f1, r3i1p1f1
NorESM2-LM	Norwegian Climate Centre (NCC), Oslo, Norway	r1i1p1f1, r2i1p1f1, r3i1p1f1

Table A2. Global Climate Models (GCMs) included in this study Table shows which GCMs were included to create GDNat along with their respective institutions and ensemble members.



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Author contributions. R.F.N., K.M., and R.K. designed the study; R.F.N. compiled data with the assistance from S.B.M.; R.F.N. led the analysis in consultation with K.M. and R.K., and assistance from S.B.M; R.F.N. wrote the manuscript with input and revisions from all coauthors.

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Competing interests. The authors declare no competing interests



References

- Almazroui: Assessment of CMIP6 Performance and Projected Temperature and Precipitation Changes Over South America, *Earth Systems and Environment*, <https://doi.org/10.1007/s41748-021-00233-6>, 2021.
- 355 Barnett, T. P., Hasselmann, K., Chelliah, M., Delworth, T., Hegerl, G., Jones, P., Rasmusson, E., Roeckner, E., Ropelewski, C., Santer, B., and Tett, S.: Detection and Attribution of Recent Climate Change: A Status Report, *Bulletin of the American Meteorological Society*, 80, 2631 – 2660, [https://doi.org/10.1175/1520-0477\(1999\)080<2631:DAAORC>2.0.CO;2](https://doi.org/10.1175/1520-0477(1999)080<2631:DAAORC>2.0.CO;2), 1999.
- Bindoff, N., Stott, P., AchutaRao, K., Allen, M., Gillett, N., Gutzler, D., Hansingo, K., Hegerl, G., Hu, Y., Jain, S., Mokhov, I., Overland, J., Perlwitz, J., Sebbari, R., and Zhang, X.: Detection and Attribution of Climate Change: from Global to Regional., *Intergovernmental Panel on Climate Change*, 2013.
- 360 Bourgault, P., Huard, D., Smith, T. J., Logan, T., Aoun, A., Lavoie, J., Éric Dupuis, Rondeau-Genessee, G., Alegre, R., Barnes, C., Laperrière, A. B., Biner, S., Caron, D., Ehbrecht, C., Fyke, J., Keel, T., Labonté, M.-P., Lierhammer, L., Low, J.-F., Quinn, J., Roy, P., Squire, D., Stephens, A., Tanguy, M., and Whelan, C.: xclim: xarray-based climate data analytics, *Journal of Open Source Software*, 8, 5415, <https://doi.org/10.21105/joss.05415>, 2023.
- 365 Burke, M., Davis, W. M., and Diffenbaugh, N. S.: Large potential reduction in economic damages under UN mitigation targets, *Nature*, 557, 549–553, <https://doi.org/10.1038/s41586-018-0071-9>, 2018.
- Bürger, G., Sobie, S. R., Cannon, A. J., Werner, A. T., and Murdock, T. Q.: Downscaling Extremes: An Intercomparison of Multiple Methods for Future Climate, *Journal of Climate*, 26, 3429 – 3449, <https://doi.org/10.1175/JCLI-D-12-00249.1>, 2013.
- Cannon, A. J.: The Impact of “Hot Models” on a CMIP6 Ensemble Used by Climate Service Providers in Canada: Do Global Constraints Lead to Appreciable Differences in Regional Projections?, *Journal of Climate*, 37, 2141–2154, <https://doi.org/10.1175/JCLI-D-23-0459.1>, 2024.
- 370 Cannon, A. J., Sobie, S. R., and Murdock, T. Q.: Bias Correction of GCM Precipitation by Quantile Mapping: How Well Do Methods Preserve Changes in Quantiles and Extremes?, *Journal of Climate*, 28, 6938–6959, <https://doi.org/10.1175/jcli-d-14-00754.1>, 2015.
- Chen, D., Rojas, M., Samset, B., Cobb, K., Diongue Niang, A., Edwards, P., Emori, S., Faria, S., Hawkins, E., Hope, P., Huybrechts, P., Meinshausen, M., Mustafa, S., Plattner, G.-K., and Tréguier, A.-M.: Framing, Context, and Methods Supplementary Material, Available from <https://www.ipcc.ch/>, 2021.
- Cucchi, M., Weedon, G. P., Amici, A., Bellouin, N., Lange, S., Müller Schmied, H., Hersbach, H., and Buontempo, C.: WFDE5: bias-adjusted ERA5 reanalysis data for impact studies, *Earth System Science Data*, 12, 2097–2120, <https://doi.org/10.5194/essd-12-2097-2020>, 2020.
- Cummins, D. P.: Could detection and attribution of climate change trends be spurious regression?, *Climate Dynamics*, 59, 2785–2799, <https://doi.org/10.1007/s00382-022-06242-z>, 2022.
- 380 Didovets, I., Krysanova, V., Nurbatsina, A., Fallah, B., Krylova, V., Saparova, A., Niyazov, J., Kalashnikova, O., and Hattermann, F. F.: Attribution of current trends in streamflow to climate change for 12 Central Asian catchments, *Climatic Change*, 177, <https://doi.org/10.1007/s10584-023-03673-3>, 2024.
- Diffenbaugh, N. S. and Burke, M.: Global warming has increased global economic inequality, *Proceedings of the National Academy of Sciences*, 116, 9808–9813, <https://doi.org/10.1073/pnas.1816020116>, 2019.
- 385 Estrada, F., Perron, P., and Yamamoto, Y.: Anthropogenic influence on extremes and risk hotspots, *Scientific Reports*, 13, Not available, <https://doi.org/10.1038/s41598-022-27220-9>, 2023.



- Eyring, V., Bony, S., Meehl, G. A., Senior, C. A., Stevens, B., Stouffer, R. J., and Taylor, K. E.: Overview of the Coupled Model Intercomparison Project Phase 6 (CMIP6) experimental design and organization, *Geoscientific Model Development*, 9, 1937–1958, <https://doi.org/10.5194/gmd-9-1937-2016>, 2016.
- Eyring, V., Gillett, N., Achuta Rao, K., Barimalala, R., Barreiro Parrillo, M., Bellouin, N., Cassou, C., Durack, P., Kosaka, Y., McGregor, S., Min, S., Morgenstern, O., and Sun, Y.: Human Influence on the Climate System, p. 423–552, <https://doi.org/10.1017/9781009157896.005>, 2021.
- Flato, G., J. M. B. A. P. B. S. C. W. C. P. C. F. D. S. E. V. E. C. F. P. G. E. G. C. J. V. K. C. R. and Rummukainen, M.: Evaluation of Climate Models. In: *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, Cambridge University Press, 2013.
- Fofrich Navarro, R., McCusker, K., Malevich, B., and Kopp, R.: GDNat: a Global, Daily, High-resolution, Natural-Forcing Only Temperature Data Set, <https://doi.org/10.6082/dqt5x-gxh81>, 2026a.
- Fofrich Navarro, R., McCusker, K., Malevich, B., and Kopp, R.: GDNat - Replication and Validation Code Repository, <https://github.com/ClimateImpactLab/gdnat>, 2026b.
- Franke, J.: Climate change detection and attribution using observed and simulated tree-ring width, *Climate of the Past*, 18, 2583–2597, <https://doi.org/10.5194/cp-18-2583-2022>, 2022.
- Frieler, K., Volkholz, J., Lange, S., Schewe, J., Mengel, M., del Rocío Rivas López, M., Otto, C., Reyer, C. P. O., Karger, D. N., Malle, J. T., Treu, S., Menz, C., Blanchard, J. L., Harrison, C. S., Petrik, C. M., Eddy, T. D., Ortega-Cisneros, K., Novaglio, C., Rousseau, Y., Watson, R. A., Stock, C., Liu, X., Heneghan, R., Tittensor, D., Maury, O., Büchner, M., Vogt, T., Wang, T., Sun, F., Sauer, I. J., Koch, J., Vanderkelen, I., Jägermeyr, J., Müller, C., Rabin, S., Klar, J., Vega del Valle, I. D., Lasslop, G., Chadburn, S., Burke, E., Gallego-Sala, A., Smith, N., Chang, J., Hantson, S., Burton, C., Gädeke, A., Li, F., Gosling, S. N., Müller Schmied, H., Hattermann, F., Wang, J., Yao, F., Hickler, T., Marcé, R., Pierson, D., Thiery, W., Mercado-Bettín, D., Ladwig, R., Ayala-Zamora, A. I., Forrest, M., and Bechtold, M.: Scenario setup and forcing data for impact model evaluation and impact attribution within the third round of the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP3a), *Geoscientific Model Development*, 17, 1–51, <https://doi.org/10.5194/gmd-17-1-2024>, 2024.
- Fyfe, J. C., Kharin, V. V., Santer, B. D., Cole, J. N. S., and Gillett, N. P.: Significant impact of forcing uncertainty in a large ensemble of climate model simulations, *Proceedings of the National Academy of Sciences*, 118, Not available, <https://doi.org/10.1073/pnas.2016549118>, 2021.
- Gergel, D. R., Malevich, S. B., McCusker, K. E., Tenezakis, Fish, M. A., and Kopp, R. E.: Global downscaled projections for climate impacts research (GDPCIR): preserving extremes for modeling future climate impacts, *EGUsphere*, 2023, 1–35, <https://doi.org/10.5194/egusphere-2022-1513>, 2023.
- Gillett, N. P., Shiogama, H., Funke, B., Hegerl, G., Knutti, R., Matthes, K., Santer, B. D., Stone, D., and Tebaldi, C.: The Detection and Attribution Model Intercomparison Project (DAMIP v1.0) contribution to CMIP6, *Geoscientific Model Development*, 9, 3685–3697, <https://doi.org/10.5194/gmd-9-3685-2016>, 2016.
- Gillett, N. P., Kirchmeier-Young, M., Ribes, A., Shiogama, H., Hegerl, G. C., Knutti, R., Gastineau, G., John, J. G., Li, L., Nazarenko, L., Rosenbloom, N., Seland, Ø., Wu, T., Yukimoto, S., and Ziehn, T.: Constraining human contributions to observed warming since the pre-industrial period, *Nature Climate Change*, 11, 207–212, <https://doi.org/10.1038/s41558-020-00965-9>, 2021.
- Grillakis, M. G., Koutroulis, A. G., Daliakopoulos, I. N., and Tsanis, I. K.: A method to preserve trends in quantile mapping bias correction of climate modeled temperature, *Earth System Dynamics*, 8, 889–900, <https://doi.org/10.5194/esd-8-889-2017>, 2017.



- Gulev, S., Thorne, P., Ahn, J., Dentener, F., Domingues, C., Gerland, S., Gong, D., Kaufman, D., Nnamchi, H., Quaas, J., Rivera, J., Sathyendranath, S., Smith, S., Trewin, B., von Schuckmann, K., and Vose, R.: Changing State of the Climate System, p. 287–422, Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, <https://doi.org/10.1017/9781009157896.004>, 2021.
- Hannart, A.: An improved projection of climate observations for detection and attribution, *Advances in Statistical Climatology, Meteorology and Oceanography*, 5, 161–171, <https://doi.org/10.5194/ascmo-5-161-2019>, 2019.
- Hattermann, F. F. and Krysanova, V.: Impact attribution: exploring the contribution of climate change to recent trends in hydrological processes—an editorial introduction, *Climatic Change*, 177, <https://doi.org/10.1007/s10584-024-03804-4>, 2024.
- Hawkins, E., Osborne, T. M., Ho, C. K., and Challinor, A. J.: Calibration and bias correction of climate projections for crop modelling: An idealised case study over Europe, *Agricultural and Forest Meteorology*, 170, 19–31, <https://doi.org/https://doi.org/10.1016/j.agrformet.2012.04.007>, agricultural prediction using climate model ensembles, 2013.
- Hegerl, G. C., F. Z.: Use of models in detection and attribution of climate change, *WIREs Climate Change*, 2, 570–591, <https://doi.org/10.1002/wcc.121>, 2011.
- Hegerl, G. C.: Detecting Greenhouse-Gas-Induced Climate Change with an Optimal Fingerprint Method, *Journal of Climate*, 9, 2281–2306, [https://doi.org/10.1175/1520-0442\(1996\)009<2281:dggicc>2.0.co;2](https://doi.org/10.1175/1520-0442(1996)009<2281:dggicc>2.0.co;2), 1996.
- Hempel, S., Frieler, K., Warszawski, L., Schewe, J., and Piontek, F.: A trend-preserving bias correction – the ISI-MIP approach, *Earth System Dynamics*, 4, 219–236, <https://doi.org/10.5194/esd-4-219-2013>, 2013.
- Ho, C. K., Stephenson, D. B., Collins, M., Ferro, C. A. T., and Brown, S. J.: Calibration Strategies: A Source of Additional Uncertainty in Climate Change Projections, *Bulletin of the American Meteorological Society*, 93, 21 – 26, <https://doi.org/10.1175/2011BAMS3110.1>, 2012.
- Illangasingha, S., Koike, T., Rasmy, M., Tamakawa, K., Matsuki, H., and Selvarajah, H.: A holistic approach for using global climate model (GCM) outputs in decision making, *Journal of Hydrology*, 626, 130 213, <https://doi.org/https://doi.org/10.1016/j.jhydrol.2023.130213>, 2023.
- Katzfuss, M.: A Bayesian hierarchical model for climate change detection and attribution, *Geophysical Research Letters*, 44, 5720–5728, <https://doi.org/10.1002/2017gl073688>, 2017.
- Kim, S., Joo, K., Kim, H., Shin, J.-Y., and Heo, J.-H.: Regional quantile delta mapping method using regional frequency analysis for regional climate model precipitation, *Journal of Hydrology*, 596, 125 685, <https://doi.org/10.1016/j.jhydrol.2020.125685>, 2021.
- Knutti, R. and Sedláček, J.: Robustness and uncertainties in the new CMIP5 climate model projections, *Nature Climate Change*, 3, 369–373, <https://doi.org/10.1038/nclimate1716>, 2012.
- Lehner, F.: Evaluating skills and issues of quantile-based bias adjustment for climate change scenarios, *Advances in Statistical Climatology, Meteorology and Oceanography*, 9, 29–44, <https://doi.org/10.5194/ascmo-9-29-2023>, 2023.
- Li, C., Wang, Z., Zwiers, F., and Zhang, X.: Improving the Estimation of Human Climate Influence by Selecting Appropriate Forcing Simulations, *Geophysical Research Letters*, 48, <https://doi.org/10.1029/2021gl095500>, 2021.
- Lüthi, S., Fairless, C., Fischer, E. M., Scovronick, N., Armstrong, B., Coelho, M. D. S. Z. S., Guo, Y. L., Guo, Y., Honda, Y., Huber, V., Kysely, J., Lavigne, E., Royé, D., Rytí, N., Silva, S., Urban, A., Gasparrini, A., Bresch, D. N., and Vicedo-Cabrera, A. M.: Rapid increase in the risk of heat-related mortality, *Nature Communications*, 14, Not available, <https://doi.org/10.1038/s41467-023-40599-x>, 2023.
- Maraun, D.: Bias Correction, Quantile Mapping, and Downscaling: Revisiting the Inflation Issue, *Journal of Climate*, 26, 2137–2143, <https://doi.org/10.1175/jcli-d-12-00821.1>, 2013.



- Marvel, K., Su, W., Delgado, R., Aarons, S., Chatterjee, A., Garcia, M. E., Hausfather, Z., Hayhoe, K., Hence, D. A., Jewett, E. B., Robel, A., Singh, D., Tripathi, A., and Vose, R. S.: Climate trends, chap. 2, U.S. Global Change Research Program, Washington, DC, USA, <https://doi.org/10.7930/NCA5.2023.CH2>, 2023.
- Masson-Delmotte, V., P. Z. A. P. S. C. C. P. S. B. N. C. Y. C. L. G. M. G. M. H. K. L. E. L. J. M. T. M. T. W. O. Y. R. Y. and Zhou, B.: Climate
 465 Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change, In Press, <https://doi.org/10.1017/9781009157896>, 2021.
- Meinshausen, M., Nicholls, Z. R. J., Lewis, J., Gidden, M. J., Vogel, E., Freund, M., Beyerle, U., Gessner, C., Nauels, A., Bauer, N., Canadell, J. G., Daniel, J. S., John, A., Krummel, P. B., Luderer, G., Meinshausen, N., Montzka, S. A., Rayner, P. J., Reimann, S., Smith, S. J., van den Berg, M., Velders, G. J. M., Vollmer, M. K., and Wang, R. H. J.: The shared socio-economic pathway (SSP) greenhouse gas concentrations
 470 and their extensions to 2500, *Geoscientific Model Development*, 13, 3571–3605, <https://doi.org/10.5194/gmd-13-3571-2020>, 2020.
- Mengel, M., Treu, S., Lange, S., and Frieler, K.: ATTRICI v1.1 – counterfactual climate for impact attribution, *Geoscientific Model Development*, 14, 5269–5284, <https://doi.org/10.5194/gmd-14-5269-2021>, 2021.
- Naveau, P. and Thao, S.: Multimodel Errors and Emergence Times in Climate Attribution Studies, *Journal of Climate*, 35, 4791 – 4804, <https://doi.org/https://doi.org/10.1175/JCLI-D-21-0332.1>, 2022.
- 475 O'Neill, B. C., Tebaldi, C., van Vuuren, D. P., Eyring, V., Friedlingstein, P., Hurtt, G., Knutti, R., Kriegler, E., Lamarque, J.-F., Lowe, J., Meehl, G. A., Moss, R., Riahi, K., and Sanderson, B. M.: The Scenario Model Intercomparison Project (ScenarioMIP) for CMIP6, *Geoscientific Model Development*, 9, 3461–3482, <https://doi.org/10.5194/gmd-9-3461-2016>, 2016.
- Ramirez-Villegas, J., Challinor, A. J., Thornton, P. K., and Jarvis, A.: Implications of regional improvement in global climate models for agricultural impact research, *Environmental Research Letters*, 8, 024 018, <https://doi.org/10.1088/1748-9326/8/2/024018>, 2013.
- 480 Ribes, A., Zwiers, F. W., Azaïs, J.-M., and Naveau, P.: A new statistical approach to climate change detection and attribution, *Climate Dynamics*, 48, 367–386, <https://doi.org/10.1007/s00382-016-3079-6>, 2016.
- Sai Ma, Tianying Wang, J. Y. X. Z.: Optimal Fingerprinting with Estimating Equations, *Journal of Climate*, 36, 7109–7122, <https://doi.org/10.1175/jcli-d-22-0681.1>, 2023.
- Scafetta, N.: CMIP6 GCM Validation Based on ECS and TCR Ranking for 21st Century Temperature Projections and Risk Assessment, *Atmosphere*, 14, <https://doi.org/10.3390/atmos14020345>, 2023.
- 485 Seung-Ki Min, Xuebin Zhang, F. W. Z. G. C. H.: Human contribution to more-intense precipitation extremes, *Nature*, 470, 378–381, <https://doi.org/10.1038/nature09763>, 2011.
- Sherman, P., Huybers, P., and Tziperman, E.: On the attribution of weather events to climate change using a fit to extreme value distributions, 2023.
- 490 Srivastava, A., Grotjahn, R., and Ullrich, P. A.: Evaluation of historical CMIP6 model simulations of extreme precipitation over contiguous US regions, *Weather and Climate Extremes*, 29, 100 268, <https://doi.org/https://doi.org/10.1016/j.wace.2020.100268>, 2020.
- Stott, P. A., Stone, D. A., and Allen, M. R.: Human contribution to the European heatwave of 2003, *Nature*, 432, 610–614, <https://doi.org/10.1038/nature03089>, 2004.
- Sung: Climate Change Projection in the Twenty-First Century Simulated by NIMS-KMA CMIP6 Model Based on New GHGs Concentration Pathways, *Asia-Pacific Journal of Atmospheric Sciences*, 57, 851–862, <https://doi.org/10.1007/s13143-021-00225-6>, 2021.
- 495 Swanson, K. L., Sugihara, G., and Tsonis, A. A.: Long-term natural variability and 20th century climate change, *Proceedings of the National Academy of Sciences*, 106, 16 120–16 123, <https://doi.org/10.1073/pnas.0908699106>, 2009.



- Swart, N. C., Cole, J. N. S., Kharin, V. V., Lazare, M., Scinocca, J. F., Gillett, N. P., Anstey, J., Arora, V., Christian, J. R., Hanna, S., Jiao, Y., Lee, W. G., Majaess, F., Saenko, O. A., Seiler, C., Seinen, C., Shao, A., Sigmond, M., Solheim, L., von Salzen, K., Yang, D., and Winter, B.: The Canadian Earth System Model version 5 (CanESM5.0.3), *Geoscientific Model Development*, 12, 4823–4873, <https://doi.org/10.5194/gmd-12-4823-2019>, 2019.
- Tabor, K. and Williams, J. W.: Globally downscaled climate projections for assessing the conservation impacts of climate change, *Ecological Applications*, 20, 554–565, <https://doi.org/10.1890/09-0173.1>, 2010.
- Taylor, K. E., Stouffer, R. J., and Meehl, G. A.: An Overview of CMIP5 and the Experiment Design, *Bulletin of the American Meteorological Society*, 93, 485 – 498, <https://doi.org/10.1175/BAMS-D-11-00094.1>, 2012.
- Taylor, P. C., Boeke, R. C., Boisvert, L. N., Feldl, N., Henry, M., Huang, Y., Langen, P. L., Liu, W., Pithan, F., Sejas, S. A., and Tan, I.: Process Drivers, Inter-Model Spread, and the Path Forward: A Review of Amplified Arctic Warming, *Frontiers in Earth Science*, 9, <https://doi.org/10.3389/feart.2021.758361>, 2022.
- Tebaldi, C. and Arblaster, J. M.: Pattern scaling: Its strengths and limitations, and an update on the latest model simulations, *Climatic Change*, 122, 459–471, <https://doi.org/10.1007/s10584-013-1032-9>, 2014.
- Thiemeßl, M. J., Gobiet, A., and Heinrich, G.: Empirical-statistical downscaling and error correction of regional climate models and its impact on the climate change signal, *Climatic Change*, 112, 449–468, <https://doi.org/10.1007/s10584-011-0224-4>, 2011.
- Thrasher, B., Maurer, E. P., McKellar, C., and Duffy, P. B.: Technical Note: Bias correcting climate model simulated daily temperature extremes with quantile mapping, *Hydrology and Earth System Sciences*, 16, 3309–3314, <https://doi.org/10.5194/hess-16-3309-2012>, 2012.
- Tong, Y.: Bias correction of temperature and precipitation over China for RCM simulations using the QM and QDM methods, *Climate Dynamics*, <https://doi.org/10.1007/s00382-020-05447-4>, 2020.
- van Garderen, L.: A methodology for attributing the role of climate change in extreme events: a global spectrally nudged storyline, *Natural Hazards and Earth System Sciences*, 21, 171–186, <https://doi.org/10.5194/nhess-21-171-2021>, 2021.
- Wang, L., Gu, X., Slater, L. J., Lai, Y., Zheng, Y., Gong, J., Dembélé, M., Tosunoğlu, F., Liu, J., Zhang, X., Kong, D., and Li, J.: Attribution of the Record-Breaking Extreme Precipitation Events in July 2021 Over Central and Eastern China to Anthropogenic Climate Change, *Earth's Future*, 11, e2023EF003613, <https://doi.org/10.1029/2023EF003613>, e2023EF003613 2023EF003613, 2023.
- Watanabe, S., Kanae, S., Seto, S., Yeh, P. J., Hirabayashi, Y., and Oki, T.: Intercomparison of bias-correction methods for monthly temperature and precipitation simulated by multiple climate models, *Journal of Geophysical Research: Atmospheres*, 117, Not available, <https://doi.org/10.1029/2012jd018192>, 2012.
- Wells, C. D., Jackson, L. S., Maycock, A. C., and Forster, P. M.: Understanding pattern scaling errors across a range of emissions pathways, *Earth System Dynamics*, 14, 817–834, <https://doi.org/10.5194/esd-14-817-2023>, 2023.
- Xavier, A. C. F.: Evaluation of Quantile Delta Mapping as a bias-correction method in maximum rainfall dataset from downscaled models in São Paulo state (Brazil), *International Journal of Climatology*, 42, 175–190, <https://doi.org/10.1002/joc.7238>, 2022.
- Zelinka, M. D., Myers, T. A., McCoy, D. T., Po-Chedley, S., Caldwell, P. M., Ceppi, P., Klein, S. A., and Taylor, K. E.: Causes of Higher Climate Sensitivity in CMIP6 Models, *Geophysical Research Letters*, 47, e2019GL085782, <https://doi.org/10.1029/2019GL085782>, e2019GL085782 10.1029/2019GL085782, 2020a.
- Zelinka, M. D., Myers, T. A., McCoy, D. T., Po-Chedley, S., Caldwell, P. M., Ceppi, P., Klein, S. A., and Taylor, K. E.: Causes of Higher Climate Sensitivity in CMIP6 Models, *Geophysical Research Letters*, 47, <https://doi.org/10.1029/2019gl085782>, 2020b.
- Zeppetello, L. R. V., Raftery, A. E., and Battisti, D. S.: Probabilistic projections of increased heat stress driven by climate change, *Communications Earth and Environment*, 3, Not available, <https://doi.org/10.1038/s43247-022-00524-4>, 2022.



Zhang, J., Wu, T., Li, L., Furtado, K., Xin, X., Xie, C., Zheng, M., Zhao, H., and Zhou, Y.: Constraint on regional land surface air temperature projections in CMIP6 multi-model ensemble, *npj Climate and Atmospheric Science*, 6, Not available, <https://doi.org/10.1038/s41612-023-00410-6>, 2023.

540 Zhu, Y.-Y. and Yang, S.: Evaluation of CMIP6 for historical temperature and precipitation over the Tibetan Plateau and its comparison with CMIP5, *Advances in Climate Change Research*, 11, 239–251, <https://doi.org/https://doi.org/10.1016/j.accre.2020.08.001>, including special topic on East Asian climate response to 1.5/2 °C global warming, 2020.

Zhuang, J., raphael dussin, Huard, D., Bourgault, P., Banihirwe, A., Raynaud, S., Malevich, B., Schupfner, M., Filipe, Levang, S., Jüling, A., Almansi, M., RichardScottOZ, RondeauG, Rasp, S., Smith, T. J., Stachelek, J., Plough, M., Pierre, Bell, R., and Li, X.: *pangeo-data/xESMF: v0.7.1*, <https://doi.org/10.5281/zenodo.7800141>, 2023.