ADVANCING EARTH AND SPACE SCIENCES

Geophysical Research Letters

RESEARCH LETTER
10.1029/2025GL118804

Key Points:
- During the last decade, the rate at which Earth warmed increased substantially
- After removing the influence of known natural variability factors, the increase of the warming rate is statistically significant
- At the present rate, we will exceed the 1.5°C limit of the Paris Climate Accord by 2030

Correspondence to:
S. Rahmstorf,
rahmstorf@pik-potsdam.de

Citation:
Foster, G., & Rahmstorf, S. (2026). Global warming has accelerated significantly. *Geophysical Research Letters*, *53*, e2025GL118804. https://doi.org/10.1029/2025GL118804

Received 14 AUG 2025
Accepted 4 FEB 2026

Author Contributions:
Conceptualization: G. Foster, S. Rahmstorf
Data curation: G. Foster
Formal analysis: G. Foster
Methodology: G. Foster
Software: G. Foster
Validation: S. Rahmstorf
Visualization: G. Foster
Writing – original draft: S. Rahmstorf
Writing – review & editing: G. Foster, S. Rahmstorf

Global Warming Has Accelerated Significantly

G. Foster[2] and S. Rahmstorf[1]

[1]Potsdam Institute for Climate Impact Research, University of Potsdam, Potsdam, Germany, [2]Retired, Orono, ME, USA

Abstract Recent record-hot years have caused discussion over whether global warming has accelerated. Previous analysis found acceleration (i.e., increase in warming rate) has not yet reached a 95% confidence level, given natural temperature variability. We remove the estimated influence of three main natural variability factors: El Niño, volcanism, and solar variation. The resulting adjusted and thus less "noisy" data show that there has been acceleration with over 98% confidence, with faster warming over the last 10+ years than during any previous decade.

Plain Language Summary The rise in global temperature has been widely considered to be quite steady for several decades since the 1970s. Recently, however, scientists have started to debate whether global warming has accelerated since then. It is difficult to be sure of that because of natural fluctuations in the warming rate, and so far no statistical significance (meaning 95% certainty) of an acceleration (increase in warming rate) has been demonstrated. In this study we subtract the estimated influence of El Niño events, volcanic eruptions and solar variations from the data, which makes the global temperature curve less variable, and it then shows a statistically significant acceleration of global warming since about the year 2015. Warming proceeding faster is not unexpected by climate models, but it is a cause of concern and shows how insufficient the efforts to slow and eventually stop global warming under the Paris Climate Accord have so far been.

1. Introduction

The years 2023 and 2024 have been Earth's hottest on record, and in 2024 global temperature exceeded 1.5°C above pre-industrial temperatures, although to breach the 1.5°C limit of the Paris Climate Accord this level would need to be exceeded not for a single year but for an average over 20 years (Bevacqua et al., 2025).

Since the 1970s, global mean surface temperature (GMST) has followed a rather steady upward trend, rising at an average rate of about 0.2°C/decade, together with ubiquitous fluctuations about that trend. Random variations can be very suggestive of a change in the trend, which caused speculation in the early 2000s that global warming had slowed or even stopped (the infamous "pause"), but detailed analysis found that this slowing was at no point statistically significant (Risbey et al., 2018).

More recently, discussion has focused on whether global warming has accelerated. Past change point analysis showed a clear acceleration around 1970 (Cahill et al., 2015; Miniere et al., 2023), at the end of a plateau phase starting ~1940 usually attributed to a masking of the effects of increasing greenhouse gases by cooling aerosols in the atmosphere. This plateau is also the key reason robust acceleration is diagnosed for the period 1960–2020 (Beaulieu et al., 2024).

However, it remains unclear whether global warming has significantly accelerated further since the current upward trend started in the 1970s. A change point analysis (assuming stationary noise) performed on GMST data until 2023 did not find a significant change in warming trend after the 1970s (Beaulieu et al., 2024). We have reproduced this analysis and then included the year 2024, but that does not raise statistical significance to the 95% confidence level.

Samset et al. (2023) adjusted global temperatures for the effect of El Niño/Southern Oscillation (ENSO) and concluded there had been a modest increase in 20-year warming rate from about 0.17 to 0.21°C/decade (their Figure 2b), suggesting a "step-up in warming rate since around 1990" but without an objective change point analysis. Jenkins, Povey, et al. (2022) looked at two subsequent 10-year trends in GMST and discussed an increase from +0.18°C/decade in 2000–2009 to 0.35°C/decade in 2010–2019, arguing this could partly be due to reduced cooling effect of atmospheric aerosols.

Richardson (2022) discusses the acceleration rate for the period 1980–2020 by way of quadratic fits to two versions of GMST data: before and after adjusting the observations for ENSO, volcanism and solar activity following Foster and Rahmstorf (2011, hereafter referred to as FR11). He concludes that for 4 out of 5 GMST data sets considered, the adjusted data show a 95% significant acceleration of 0.036 ± 0.030°C/decade^2, and one data set (GISTEMP) even for the unadjusted data. However, he provides arguments based on climate model ensemble simulations for the standard uncertainty range estimates being too small, so that the finding of significant acceleration would be premature, and he estimates that robust detection would be possible only from around the year 2026.

Finally, Hansen et al. (2025) have recently argued that global warming has accelerated, pointing to a diagram of the GISTEMP data, however without discussing the statistical significance of this claim.

We use two methods to test the null hypothesis of no change in the warming rate since 1970: fitting a quadratic function of time, and fitting a continuous piecewise-linear function which allows for a slope change at a time selected objectively by changepoint analysis, a model we call PLF-changepoint. This is exactly the method used by Beaulieu et al. (2024). As short-term natural variability in the data reduces the statistical significance of any changes in warming rate, we also applied the method of FR11 to estimate and remove variability due to volcanism, ENSO, and variations of solar luminosity. All three variability mechanisms can be quantified by independent measurements and their effect on global temperature established by a lagged correlation analysis using monthly data.

2. Methods

We use five established global temperature data sets: NASA, NOAA, HadCRU, Berkeley, and ERA5 as detailed in Data Availability Statement section below, and we remove these three exogenous factors from them.

2.1. Influence of Exogenous Factors: Difference From FR11

The influence of ENSO, volcanic eruptions, and solar variations was estimated with modification of the method of FR11, which modeled temperature x as a function of time t

$$x(t) = c_o + c_1\, t + c_V\, V_{k1}(t) + c_N\, N_{k2}(t) + c_S\, S_{k3}(t) + \varepsilon. \tag{1}$$

The constants c_o and c_1 are the intercept and slope of the best-fit straight line, which mimics the global warming trend from 1979 to 2010. The other constants c_V, c_N, and c_S are coefficients for $V_{k1}(t)$, aerosol optical depth from volcanic eruptions lagged by k_1 months, $N_{k2}(t)$, the multivariate El Niño index MEI lagged by k_2 months, and $S_{k3}(t)$, total solar irradiance lagged by k_3 months, while ε is a stationary noise process. Coefficients and lags are determined by the method of least squares.

Although the global warming signal was excellently approximated by a straight line during that time, if we wish to extend the method to prior times (in our case, back to 1950 and forward to the present), then we already know that a straight line is a poor model for the trend in global temperature apart from fluctuations, in view of the warming plateau lasting from the 1940s to 1970s (Figure 1). Therefore we here used an additive model, treating the GMST trend as a general function of time $g(t)$ which we expect to be strongly band-limited, that is, not to show rapid fluctuations. Our model is therefore

$$x(t) = g(t) + c_V\, V_{k1}(t) + c_N\, N_{k2}(t) + c_S\, S_{k3}(t) + \varepsilon. \tag{2}$$

Here, $g(t)$ is a general function of time, the other constants and functions are as before, except that we indicate ENSO with the NINO3.4 index rather than MEI because data are available covering a longer time span (otherwise this change makes little difference), and we use sunspot number as a proxy for solar irradiance. These choices enable us to acquire data extending back in time as far as 1880.

The first step of computing the additive model is to fit a lowess smooth (Cleveland, 1981) to the raw data, as a first approximation of the smooth function $g(t)$. This requires choosing the proportion of points in the plot which influence the smooth at each value, which we chose so that it would cover 20 years. We then compute residuals as the data minus the smoothed values. We are now prepared to fit those residuals to the exogenous factors $V_{k1}(t)$,

10.1029/2025GL118804

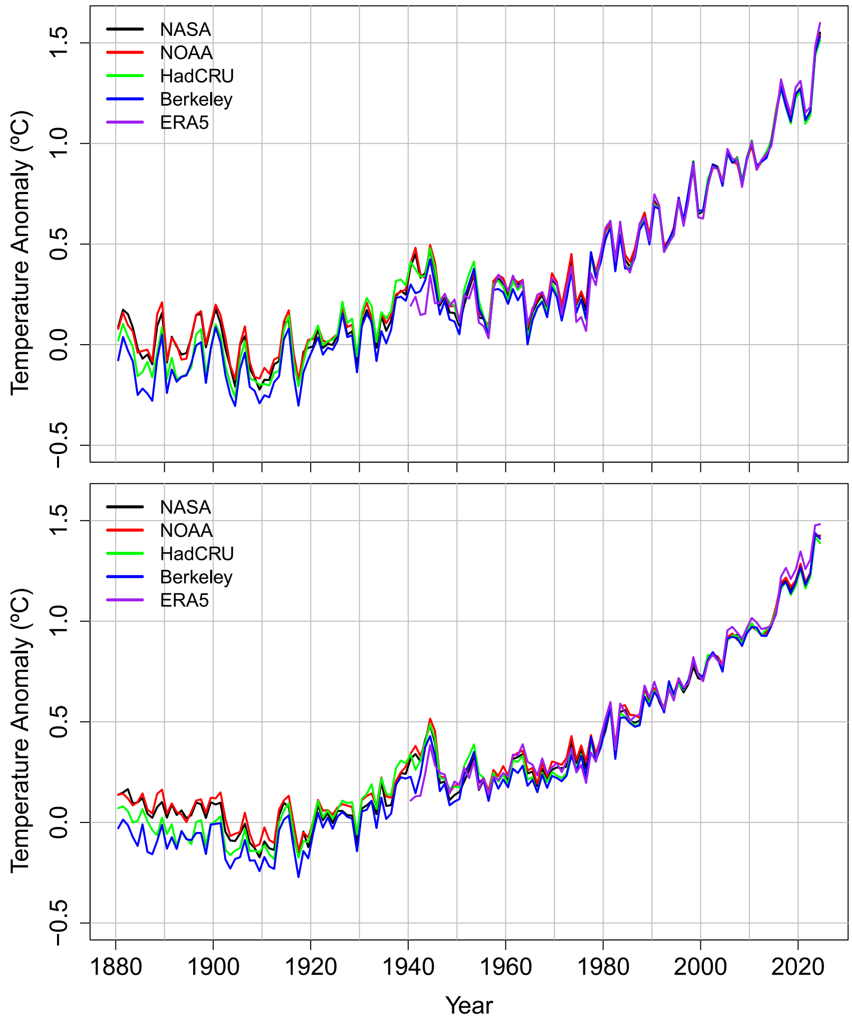

Figure 1. Yearly average global mean surface temperature from five data sources, in two versions: (top) unadjusted, (bottom) adjusted for El Niño/Southern Oscillation, volcanism, and solar variation. All are aligned so that the average from 1991 to 2020 equals 0.88°C, to approximate warming since pre-industrial.

$N_{k2}(t)$, and $S_{k3}(t)$, yielding a first approximation of the coefficients c_V, c_N, c_S and lags k_1, k_2, k_3. The fit itself is subtracted from the original data, defining the first approximation of *adjusted* data.

The next step is *backfitting*. A lowess smooth is fit to the adjusted (rather than raw) data and that is subtracted from the raw (rather than adjusted) data to define new residuals. They are fit to the exogenous factors, defining new coefficients c_V, c_N, c_S and lags k_1, k_2, k_3, and when the fit is subtracted from the raw data it defines the next iteration of adjusted data. The backfitting procedure can be repeated as often as desired; we found that four repetitions of backfitting converged well, with the final step modifying the adjustments by less than 0.01°C.

We originally computed the fit procedure using the data from 1950 to 2024. Extending further back to 1940 (the limit of the ERA5 data) degraded the fit slightly, although it did not change any of the essential conclusions. We stayed with the 1950–2024 period due to the large disagreement between data sets during the war years (1940–1945) and possible bias in sea surface temperatures at that time (Cowtan et al., 2018). This defines a model which can then be applied to any time for which the necessary input data are available, and so starting in 1880 for all sources of global temperature (except ERA5). Therefore we have estimates of adjusted data since 1880, based on the model defined by the data since 1950.

Table 1
Ending Rate (°C/decade) According to the Quadratic and the PLF-Changepoint Models, and the Year to Cross 1.5°C Forecast From the Latter

Data source	Quadratic rate	PLF-changepoint rate	Changepoint time	Cross 1.5°C
NASA	0.27(3)	0.36(3)	2013/APR	2028
NOAA	0.27(3)	0.36(3)	2013/FEB	2028
HadCRU	0.25(3)	0.34(4)	2014/JAN	2029
Berkeley	0.25(3)	0.36(4)	2014/FEB	2028
ERA5	0.29(4)	0.42(5)	2014/FEB	2026

Note. Subscripts in parentheses are standard errors of the final digits.

2.2. Testing for Acceleration

We tested for acceleration by attempting to negate the null hypothesis that GMST since 1970 is the sum of a linear trend over time, and a stationary noise process, using two choices of alternate hypothesis. First, we adopted the model that temperature since 1970 is a quadratic function of time plus stationary noise. Second, we fit a continuous piecewise-linear function of time, with a single moment of slope change chosen by changepoint analysis.

The first test would be trivial were it not for the fact that the noise is autocorrelated. In fact, as FR11 show, the usual practice of approximating it as an AR(1) process is insufficient; hence we adopt the more severe test of FR11, treating the noise as an ARMA(1,1) process. When applied to the unadjusted data (either monthly or yearly averages), the test fails to reach 95% confidence. But for adjusted data, this test confirms acceleration at better than 98% confidence for each of the five data sets.

The null hypothesis (a linear fit) depends on two parameters, the intercept α and slope β. Our second alternate hypothesis is a PLF model which includes two additional parameters, the change in slope $\Delta\beta$ at some critical time, and the critical time t_c at which that slope change occurs. The model is therefore:

$$
\begin{aligned}
x &= \alpha + \beta t \text{ when } t <= t_c \\
& \alpha + \beta t + \Delta\beta\,(t - t_c) \text{ when } t >= t_c.
\end{aligned}
\tag{3}
$$

If the critical time t_c were known, statistical testing would be the simple application of a t-test (corrected for autocorrelation) to the coefficient $\Delta\beta$ (the null hypothesis being $\Delta\beta = 0$). But the freedom to choose t_c alters significance testing dramatically. Fortunately, we still have a straightforward solution because realistic critical values can be established by Monte Carlo simulation. This still requires accounting for autocorrelation when generating simulated data, which we do as Beaulieu et al. (2024) did, treating the noise as an AR(1) process.

On the unadjusted data this gives the same result as Beaulieu et al. (2024), failing to reach 95% confidence despite the fact that we include an additional year. But for adjusted data, the test finds a significant change point in 2013 or 2014 with over 99% confidence in all five data sets (Table 1). Even when leaving out 2023 and 2024 we still get 95% confidence using NASA and NOAA data, but not for HadCRU, Berkeley, or ERA5, so the past 2 years have clearly increased the significance of acceleration.

2.3. Estimating Warming Rates

Because both tests confirm acceleration of global temperature, it behooves us to estimate how the rate has changed over time. In addition to the models used for hypothesis testing, we also fit a piecewise-linear model allowing slope changes every 10 years from 1895 to 2015, that is, *linear spline* with knots spaced 10 years apart, a model we call PLF10.

Estimated standard errors, for the quadratic, PLF-changepoint, and PLF10 models, are corrected for autocorrelation using the ARMA(1,1) noise model as in FR11.

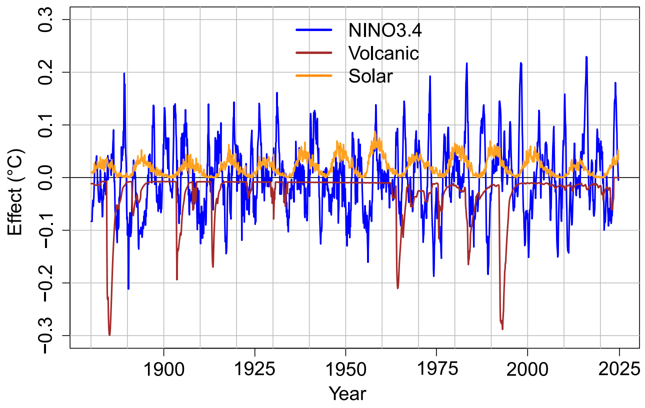

Figure 2. Effect on global temperature of El Niño/Southern Oscillation, volcanism, and solar variation, estimated from the Berkeley Earth data.

3. Results

Yearly averages of adjusted and unadjusted data are shown in Figure 1. Note how the variability is reduced in the adjusted data, and temperature peaks following strong El Niño events (e.g., 1998, 2016, 2024) are greatly reduced. The adjustments for the three natural variability factors in the Berkeley Earth data are shown in Figure 2; comparison to Figure 7 in FR11 shows that estimates based on the updated model are like those of the original model.

The models used for hypothesis testing are very different, and together they illustrate the fact that, in the framework of frequentist statistics, "statistical significance" is *not* confirmation of the test model, it is *negation of the null hypothesis*. The two test models cannot both be right; comparing their estimates of Earth's warming rate over time in Figure 3, they paint dramatically different pictures. The blue line is the rate according to the PLF-changepoint model (light blue shading its 95% confidence interval); for the quadratic model the rate is shown in brown (confidence interval in gray). Their estimates of Earth's warming rate over the last decade are incompatible.

Also included in Figure 3 is a red line showing the slope from windowed linear regression, a straight-line fit to moving 10-year time spans of the data. Each serves to estimate the warming rate at the midpoint of that time span; advancing by 1-year steps reveals the changing rate over time. This analysis agrees much better with the PLF-changepoint model than the quadratic. This suggests that the quadratic model, while a good choice to test for acceleration, is (in this case) a poor choice to estimate the present warming rate.

Table 1 lists the present warming rate according to both the quadratic and PLF-changepoint models; numbers in parentheses are standard errors of the final digits. It also gives the time of slope change for the PLF-changepoint model; like Beaulieu et al. (2024) we used annual averages for statistical testing, but here we list the year based on monthly data. Finally, we give the year in which global temperature will exceed 1.5°C if it follows the latter model into the near future, defined as the time when the model linear trend crosses 1.5°C. In case of a linear evolution, that corresponds to the mid-point of the 20-year period defined by IPCC as 1.5°C threshold. According to this, all data sets are near 1.5°C already and will cross that limit before 2030.

For a more general history of Earth's warming rate, for each data set we fit a piecewise-linear function with slope changes every 10 years from 1895 to 2015 (PLF10). Figure 4 reveals that all data sources agree: the warming rate has been far higher during the last decade than any previous. Whether such rapid warming will continue remains to be seen, but if it does, global temperature will cross the 1.5°C limit in the very near future.

The main limitation of our method is that the removal of El Niño, volcanism, and solar variations is empirically based, but approximate and imperfect. For example, it is possible that the effect of El Niño on the 2023 and 2024 temperature is not completely removed.

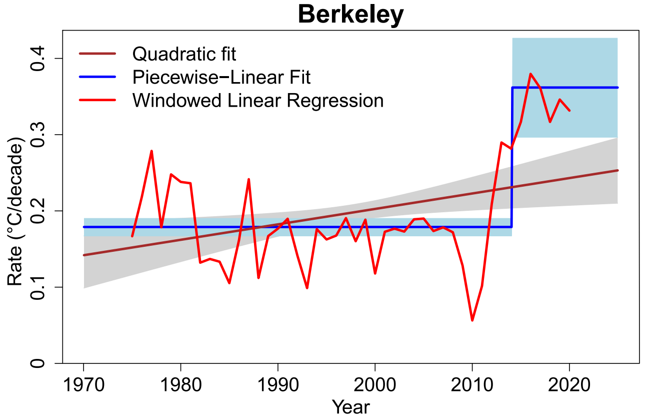

Figure 3. Warming rate (in °C/decade) estimated from the PLF-changepoint model (blue line with light blue shading for 95% confidence interval), quadratic fit (brown line with gray shading), and linear regression on moving 10-year windows of the data (red line).

4. Discussion

We have focused here on a pure data analysis to establish whether the observed global temperature changes reveal a statistically significant acceleration, when adjusted for the empirical effects of key natural variability contributions. We do not analyze the possible causes of the acceleration found in the data. Some acceleration of global warming is expected in the standard global warming scenarios as presented in the 6th IPCC Assessment Report, and the observed data are within the range of model predictions. Note that model differences are large given that ENSO variability is random and thus different in each model, while the observations just represent one particular realization of this stochastic process.

10.1029/2025GL118804

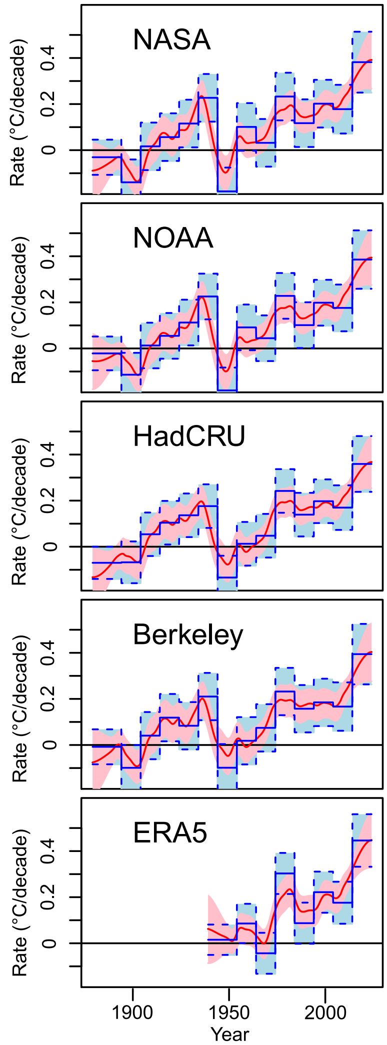

Figure 4. Warming rate (in °C/decade) from PLF10 (linear spline with slope changes every 10 years from 1895 to 2015). Light blue shading indicates the 95% confidence interval. Note that the high rate before 1945 and low rate after 1945 are likely due to a warm bias in sea surface temperature measurements during World War 2 (Cowtan et al., 2018).

A number of other studies looked at possible specific drivers that could cause a strong recent warming acceleration. The leading hypothesis is the reduced load of cooling aerosols in the atmosphere, as a result of effective reduction in emissions. Aerosol cooling has declined by an estimated 0.1–0.3 W/m^2 since the year 2000–2011. The trend in anthropogenic effective radiative forcing (ERF), the cause of global warming, has increased by 50% since 2000 (from 0.4 W/m^2 per decade in 2000–2009 to 0.6 W/m^2 per decade in 2010–2019), mainly driven by reduced aerosol cooling (Quaas et al., 2022). However, there is still substantial uncertainty regarding observations of aerosol loads and of their impact on global temperature, so that an expected acceleration for this reason is likely but not settled.

In conclusion, our analysis of GMST data after removing the best estimate of the influence of three natural variability factors reduces the noise level sufficiently to reveal a large and significant acceleration of global warming, regardless which statistical method is used. Note that the adjustments *reduce* the global temperature in 2024 and minimally in 2023 by removing effects of El Niño as well as the solar maximum. The evidence is thus strong that the statistical significance of warming acceleration is not due to outlier years in 2023 and 2024, but that global temperature has departed from its previous path since around 2015.

Stopping this trend is in our hands: studies show that global warming will stop around the time humanity reaches zero CO_2 emissions (Jenkins, Sanderson, et al., 2022), but it can hardly be reversed. In the current political climate, however, it is quite possible that warming may continue its fast pace or even accelerate further. This much is clear: if the warming rate of the past 10 years continues, the Paris Agreement 1.5°C warming limit will be breached by ~2030.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Data Availability Statement

The five global temperature anomaly data sets analyzed are:

- *NASA*, the NASA GISTemp series version 4 (GISTEMP Team, 2024; Lenssen et al., 2024).
- *NOAA*, NOAA GlobalTemp version 6.0.0 (Vose et al., 2021).
- *HadCRU*, HadCRUT5 from the Hadley Centre/Climate Research Unit in the UK (Morice et al., 2021).
- *Berkeley*, from the Berkeley Earth Surface Temperature project (Rohde & Hausfather, 2020).
- *ERA5*, from the European Center for Medium-range Weather Forecasting (Hersbach et al., 2017, 2020).

Data were translated to warming since pre-industrial by offsetting each with a constant, chosen to ensure that its average value during the 30-year period from 1991 through 2020 was equal to 0.88°C.

To characterize the El Niño southern oscillation, we tried the multivariate El Niño index MEI, the Southern Oscillation Index SOI, and the NINO3.4 index. All three choices gave nearly identical final results; we selected NINO3.4 because it is available as far back as 1880. Data are from the HadISST data set (Rayner et al., 2003), acquired from www.metoffice.gov.uk/hadobs/hadisst (Met Office Hadley Centre, 2003), data for aerosol optical depth due to volcanism are from Sato et al. (1993), and as a proxy for solar irradiance we used monthly sunspot numbers from Solar Influences Data Analysis Center (2025).

All needed input data are part of a zip archive containing R code and data to reproduce calculation of the temperature adjustments, available at Foster (2025b), https://doi.org/10.5281/zenodo.15608929.

Both adjusted and un-adjusted monthly global temperature anomaly (offset to indicate difference from pre-industrial), suitable for reproducing Figure 1, can be downloaded from Foster (2025a), https://doi.org/10.5281/zenodo.15591644.

Acknowledgments
We do wish to acknowledge the very helpful comments from anonymous reviewers, which improved the clarity of the manuscript considerably. Open Access funding enabled and organized by Projekt DEAL.

References

Beaulieu, C., Gallagher, C., Killick, R., Lund, R., & Shi, X. (2024). A recent surge in global warming is not detectable yet. *Communications Earth & Environment*, *5*(1), 576. https://doi.org/10.1038/s43247-024-01711-1

Bevacqua, E., Schleussner, C.-F., & Zscheischler, J. (2025). A year above 1.5°C signals that Earth is most probably within the 20-year period that will reach the Paris agreement limit. *Nature Climate Change*, *15*(3), 262–265. https://doi.org/10.1038/s41558-025-02246-9

Cahill, N., Rahmstorf, S., & Parnell, A. C. (2015). Change points of global temperature. *Environmental Research Letters*, *10*(8), 6. https://doi.org/10.1088/1748-9326/10/8/084002

Cleveland, W. S. (1981). LOWESS: A program for smoothing scatterplots by robust locally weighted regression. *The American Statistician*, *35*(1), 54. https://doi.org/10.2307/2683591

Cowtan, K., Rohde, R., & Hausfather, Z. (2018). Evaluating biases in sea surface temperature records using coastal weather stations. *Quarterly Journal of the Royal Meteorological Society*, *144*(712), 670–681. https://doi.org/10.1002/qj.3235

Foster, G. (2025a). Adjusted global mean surface temperature anomaly [Dataset]. https://doi.org/10.5281/zenodo.15591644

Foster, G. (2025b). R code and data for method of Foster and Rahmstorf (2025) [Dataset] [Software]. https://doi.org/10.5281/zenodo.15608928

Foster, G., & Rahmstorf, S. (2011). Global temperature evolution 1979-2010. *Environmental Research Letters*, *6*(4), 044022. https://doi.org/10.1088/1748-9326/6/4/044022

GISTEMP Team. (2024). GISS surface temperature analysis (GISTEMP), version 4 [Dataset]. *NASA Goddard Institute for Space Studies*. Retrieved from https://data.giss.nasa.gov/gistemp/

Hansen, J. E., Kharecha, P., Sato, M., Tselioudis, G., Kelly, J., Bauer, S. E., et al. (2025). Global warming has accelerated: Are the United Nations and the public well-informed? *Environment: Science and Policy for Sustainable Development*, *67*(1), 6–44. https://doi.org/10.1080/00139157.2025.2434494

Hersbach, H., Bell, B., Berrisford, P., Hirahara, S., Horányi, A., Muñoz-Sabater, J., et al. (2017). Complete ERA5 global atmospheric reanalysis [Dataset]. *Copernicus Climate Change Service (C3S) Data Store (CDS)*. https://doi.org/10.24381/cds.143582cf

Hersbach, H., Bell, B., Berrisford, P., Hirahara, S., Horányi, A., Muñoz-Sabater, J., et al. (2020). The ERA5 global reanalysis. *Quarterly Journal of the Royal Meteorological Society*, *146*(730), 1999–2049. https://doi.org/10.1002/qj.3803

Jenkins, S., Povey, A., Gettelman, A., Grainger, R., Stier, P., & Allen, M. (2022). Is anthropogenic global warming accelerating? *Journal of Climate*, *35*(24), 7873–7890. https://doi.org/10.1175/jcli-d-22-0081.1

Jenkins, S., Sanderson, B., Peters, G., Frölicher, T. L., Friedlingstein, P., & Allen, M. (2022). The multi-decadal response to net zero CO_2 emissions and implications for emissions policy. *Geophysical Research Letters*, *49*(23), e2022GL101047. https://doi.org/10.1029/2022gl101047

Lenssen, N., Schmidt, G. A., Hendrickson, M., Jacobs, P., Menne, M., & Ruedy, R. (2024). A GISTEMPv4 observational uncertainty ensemble. *Journal of Geophysical Research: Atmospheres*, *129*(17), e2023JD040179. https://doi.org/10.1029/2023JD040179

Met Office Hadley Centre. (2003). Hadley centre sea ice and sea surface temperature data set (HadISST) [Dataset]. Retrieved from https://www.metoffice.gov.uk/hadobs/hadisst/

Miniere, A., von Schuckmann, K., Sallee, J. B., & Vogt, L. (2023). Robust acceleration of Earth system heating observed over the past six decades. *Scientific Reports*, *13*(1), 22975. https://doi.org/10.1038/s41598-023-49353-1

Morice, C. P., Kennedy, J. J., Rayner, N. A., Winn, J. P., Hogan, E., Killick, R. E., et al. (2021). An updated assessment of near-surface temperature change from 1850: The HadCRUT5 dataset. *Journal of Geophysical Research: Atmospheres*, *126*(3), e2019JD032361. https://doi.org/10.1029/2019JD032361

Quaas, J., Jia, H., Smith, C., Albright, A. L., Aas, W., Bellouin, N., et al. (2022). Robust evidence for reversal of the trend in aerosol effective climate forcing. *Atmospheric Chemistry and Physics*, *22*(18), 12221–12239. https://doi.org/10.5194/acp-22-12221-2022

Rayner, N. A., Parker, D. E., Horton, E. B., Folland, C. K., Alexander, L. V., Rowell, D. P., et al. (2003). Global analyses of sea surface temperature, sea ice, and night marine air temperature since the late nineteenth century. *Journal of Geophysical Research*, *108*(D14), 4407. https://doi.org/10.1029/2002JD002670

Richardson, M. T. (2022). Prospects for detecting accelerated global warming. *Geophysical Research Letters*, *49*(2), e2021GL095782. https://doi.org/10.1029/2021gl095782

Risbey, J. S., Lewandowsky, S., Cowtan, K., Oreskes, N., Rahmstorf, S., Jokimäki, A., & Foster, G. (2018). A fluctuation in surface temperature in historical context: Reassessment and retrospective on the evidence. *Environmental Research Letters*, *13*(12), 123008. https://doi.org/10.1088/1748-9326/aaf342

Rohde, R. A., & Hausfather, Z. (2020). The Berkeley Earth land/ocean temperature record. *Earth System Science Data*, *12*(4), 3469–3479. https://doi.org/10.5194/essd-12-3469-2020

Samset, B. H., Zhou, C., Fuglestvedt, J. S., Lund, M. T., Marotzke, J., & Zelinka, M. D. (2023). Steady global surface warming from 1973 to 2022 but increased warming rate after 1990. *Communications Earth & Environment*, *4*(1), 400. https://doi.org/10.1038/s43247-023-01061-4

Sato, M., Hansen, J. E., McCormick, M. P., & Pollack, J. B. (1993). Stratospheric aerosol optical depths, 1850-1990. *Journal of Geophysical Research*, *98*(D12), 22987–22994. https://doi.org/10.1029/93JD02553

Solar Influences Data Analysis Center (SIDC). (2025). Solar influences data analysis center (SIDC) [Dataset]. *Royal Observatory of Belgium*. Retrieved from https://www.sidc.be

Vose, R. S., Huang, B., Yin, X., Arndt, D., Easterling, D. R., Lawrimore, J. H., et al. (2021). Implementing full spatial coverage in NOAA's global temperature analysis. *Geophysical Research Letters*, *48*(4), e2020GL090873. https://doi.org/10.1029/2020GL090873