

Robust warming rates, marginal evidence of acceleration and unstable extrapolation: a reproducible reanalysis of statistical trend models for the Berkeley Earth global temperature record

Arav Mestry

Cornell University, Ithaca, New York, USA

Email: asm388@cornell.edu

ORCID: <https://orcid.org/0009-0001-6779-7144>

Peer review status:

This is a non-peer-reviewed preprint submitted to EarthArXiv.

Robust warming rates, marginal evidence of acceleration and unstable extrapolation: a reproducible reanalysis of statistical trend models for the Berkeley Earth global temperature record

Arav Mestry

Cornell University, Ithaca, New York, USA

ORCID: <https://orcid.org/0009-0001-6779-7144>

Correspondence: asm388@cornell.edu

Abstract

Simple trend fits to the global temperature record are widely used to summarise warming, but their uncertainty, their evidence for acceleration and their predictive value are often overstated. We re-analysed an earlier linear and quadratic analysis of the Berkeley Earth Land/Ocean record (1850–2024) that reported in-sample R^2 values of 0.74 and 0.90 and a post-1970 warming rate of 0.194 °C per decade. The original results reproduced exactly, but the parser averaged the two sea-ice versions contained in the data file, lowering recent anomalies by about 0.06 °C. With the recommended version, the 1970–2024 rate is 0.206 ± 0.022 °C per decade (95%, AR(1)-adjusted), consistent across HAC, GLS and monthly ARMA(1,1) estimates and with NASA GISTEMP (0.199) and HadCRUT5 (0.202). Berkeley Earth’s observational uncertainty and individual warm years change this rate by less than 0.015 °C per decade; the choice of start and end years matters more. A continuous hinge fitted to 1970–2024 places a rate increase of 0.176 °C per decade in 2013, but a sup- F test with a simulated AR(1) null gives $p = 0.064$; p was at least 0.23 for every end year from 2000 to 2023, and fixing the break at 2010 after inspecting the data gives a misleading nominal $p = 0.006$. With current noise levels, increases below about 0.20 °C per decade beginning in 2010 are not reliably detectable by 2024. In rolling-origin retrospective forecasts, every method under-predicted later warming and nominal 90% intervals from the quadratic and 30-year linear trends covered only 0.38–0.53 of 30-year outcomes. The quadratic’s extrapolated 2100 anomaly ranged from 1.58 to 3.69 °C depending on the last year fitted, and from 1.16 to 16.43 °C across polynomial degrees 1–5. Trend fits describe the observed record well but provide no defensible long-range forecast.

Keywords: global mean surface temperature; Berkeley Earth; warming rate; autocorrelation; change point; warming acceleration; forecast validation; extrapolation

1 Introduction

The global mean surface temperature record is the most widely used summary of observed climate change. Independent reconstructions from Berkeley Earth, NASA GISS, NOAA and the Met Office Hadley Centre agree closely on its long-term evolution (Rohde and Hausfather, 2020; Lenssen et al., 2019; Morice et al., 2021), and the Intergovernmental Panel on Climate Change assessed with high confidence that global surface temperature has increased faster since 1970 than in any other 50-year period over at least the last 2000 years (Gulev et al., 2021). None of these conclusions is in question here.

What is less settled is how much a simple statistical description of the record can support. Three questions recur. First, how precisely is the recent warming rate known once the serial correlation of year-to-year variability is taken into account (Santer et al., 2000; Foster and Rahmstorf, 2011)? Second, has the rate itself increased in the last decade or so? Some recent work argues for acceleration (Hansen et al., 2025), and indicator assessments report a human-induced warming rate of 0.27 °C per decade

over 2015–2024 (Forster et al., 2025). Formal change-point analyses, however, have so far found that a surge in observed warming is not yet statistically detectable (Cahill et al., 2015; Rahmstorf et al., 2017; Beaulieu et al., 2024). Third, what, if anything, can a curve fitted to the historical record say about future temperatures? Physical climate models have a documented record of projecting warming skilfully when forcings are accounted for (Hausfather et al., 2020), but a polynomial fitted to past temperatures has no physical constraint at all.

This paper started as a re-examination of an earlier technical report and dashboard by the author. That work fitted a straight line and a quadratic to annual Berkeley Earth anomalies from 1850 to 2024, reported in-sample R^2 values of 0.7372 and 0.8993, estimated a post-1970 warming rate of 0.194 °C per decade, and displayed a quadratic extrapolation to 2100. Re-running the original code reproduced every number, but an audit of the data file showed that the parser combined two different versions of the Berkeley Earth series. More importantly, in-sample fit statistics do not answer any of the three questions above.

We therefore re-analysed the same record with four aims: (i) to correct the data processing and quantify its effect; (ii) to estimate warming rates and their uncertainty under explicit treatment of autocorrelation, observational uncertainty, period choice and influential years; (iii) to ask whether the record through 2024 contains statistically detectable evidence of a recent increase in the warming rate, accounting for the fact that the timing of any change is estimated from the same data; and (iv) to evaluate trend models by genuine retrospective forecasting and to audit the stability of the dashboard’s polynomial extrapolation. The study is a reproducible methodological reanalysis. Its findings are largely confirmatory, and we state where they add to, rather than repeat, published work (Table 5).

2 Data

2.1 Berkeley Earth record

We used the Berkeley Earth Land/Ocean monthly global summary file distributed with the original project (Rohde and Hausfather, 2020). Its header states that the land analysis was run on 4 January 2025 and the ocean analysis published on 6 January 2025, that the series combines the Berkeley Earth land field with an interpolated HadSST4 ocean field, and that anomalies are relative to January 1951 to December 1980, with uncertainties given as 95% intervals for statistical, spatial-sampling and ocean-bias effects. The file has 4,293 lines (SHA-256 beginning e2d57dc0). It contains two complete monthly series from January 1850 to December 2024: one in which temperature anomalies over sea ice are inferred from air temperatures, which Berkeley Earth describes as its preferred version, and one in which they are inferred from sea-surface water temperatures. Each line reports the monthly anomaly and uncertainty, followed by centred 12-, 60-, 120- and 240-month moving averages.

2.2 Audit of the file and of the original processing

Each version has 2,100 monthly rows, with no missing values, no duplicated year-months and twelve months in every year (Supplementary Table S1). The original parser read every numeric line regardless of section, so it collected 4,200 rows and averaged 24 values, 12 from each version, in each calendar year. The resulting annual series is exactly the mean of the two versions. Because the versions diverge as Arctic sea ice declines, the air-minus-water difference averages 0.12 °C over 2011–2024 and peaks at 0.14 °C in 2016 (Fig. 1b). Over 2011–2024 the original series therefore differs from the recommended version by -0.058 °C on average (original minus air), which biases recent trends downwards. All analyses below use the recommended air-temperature version; the water version and the original mixed series are retained as sensitivity cases.

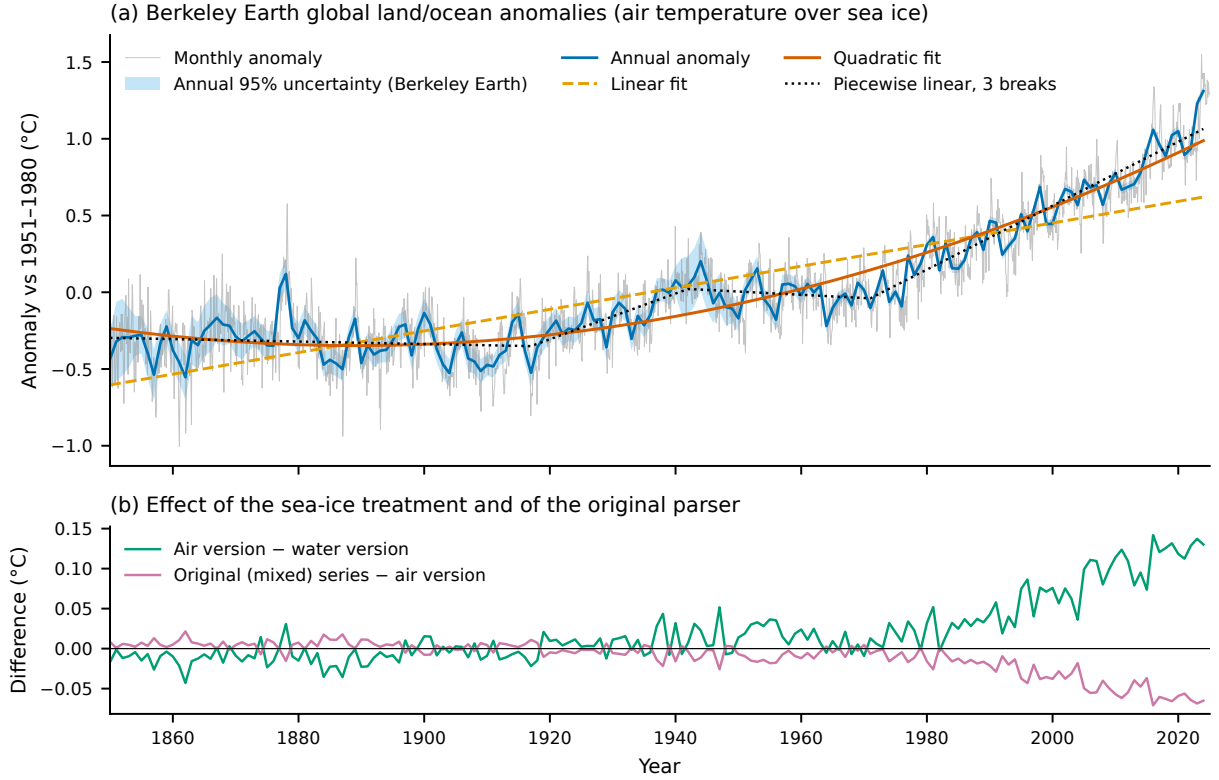


Figure 1: (a) Monthly and annual Berkeley Earth global anomalies (air temperature over sea ice) with Berkeley Earth’s annual 95% uncertainty, and ordinary least-squares linear, quadratic and three-break piecewise-linear fits to 1850–2024. (b) Annual differences between the air and water versions of the record, and between the series used in the original analysis (the mean of the two versions) and the air version.

Annual means were computed as the arithmetic mean of the twelve monthly anomalies. Because anomalies are taken relative to month-specific climatologies, this removes the seasonal cycle, and the result differs from Berkeley Earth’s own centred twelve-month average (reported at June of each year) by at most $0.0006\text{ }^{\circ}\text{C}$, consistent with rounding. The annual 95% uncertainty reported by Berkeley Earth falls from about $0.12\text{ }^{\circ}\text{C}$ in 1850–1900 to $0.03\text{ }^{\circ}\text{C}$ in 1970–2024. The mean annual anomaly of the air version over 1951–1980 is $0.017\text{ }^{\circ}\text{C}$ rather than exactly zero, a small offset that does not affect any trend or validation statistic.

2.3 Comparison datasets

For trend comparisons we used annual NASA GISTEMP v4 (Lenssen et al., 2019) and Met Office HadCRUT5.1.0.0 (Morice et al., 2021) series obtained from the `datasets/global-temp` repository on GitHub (commit 44571fe, 1 October 2026). That repository’s processing script downloads both series from the providers’ official URLs. GISTEMP annual values are computed there as the mean of twelve monthly values, and HadCRUT5 annual values are copied from the provider’s annual summary file. The provider websites could not be reached from the computing environment used for this study, so these values were not checked against the official files; they are used only for trend rates, which do not depend on the anomaly baseline, and only for complete years up to 2024.

3 Statistical methods

3.1 Trend models

Let y_t be the annual anomaly in year t . We considered the following descriptive models, all fitted by ordinary least squares (OLS) unless stated otherwise, with time centred and scaled to avoid the poor conditioning of raw-year polynomial designs.

- **Linear trend** over a window $[a, b]$: $y_t = \beta_0 + \beta_1 t + \varepsilon_t$. The slope β_1 , expressed in °C per decade, is the warming rate. It assumes a constant rate within the window.
- **Polynomial trends** of degree 2 to 5 over 1850–2024. In the quadratic $y_t = \beta_0 + \beta_1 t + \beta_2 t^2 + \varepsilon_t$, the implied rate $\beta_1 + 2\beta_2 t$ changes linearly with time and $2\beta_2$ is a constant acceleration. These models are flexible within the data and unconstrained outside them.
- **Continuous piecewise-linear (hinge) trends** with k break years $\tau_1 < \dots < \tau_k$: $y_t = \beta_0 + \beta_1 t + \sum_j \delta_j (t - \tau_j)_+ + \varepsilon_t$, where δ_j is the change in slope at τ_j . Break years were found by exhaustive search over integer years, with segments of at least 15 years. For the full record we compared $k = 0, \dots, 3$ using the Bayesian information criterion (BIC), counting each break year as a parameter.

The original analysis used scikit-learn (Pedregosa et al., 2011) with raw calendar years as predictors. The resulting quadratic design matrix has condition number 6.2×10^9 , compared with 5,136 after centring, but the fitted values agree to within 2×10^{-10} °C, so this caused no numerical error in the original results.

3.2 Uncertainty of warming rates

Annual residuals from trend fits are serially correlated (Supplementary Fig. S1), so OLS standard errors that assume independent errors are too small. For every period we report four 95% intervals for the slope: (i) the naive OLS interval; (ii) an interval inflated using the lag-one autocorrelation r_1 of the residuals through the effective sample size $n_{\text{eff}} = n(1 - r_1)/(1 + r_1)$ (Santer et al., 2000); (iii) a Newey–West heteroskedasticity- and autocorrelation-consistent (HAC) interval (Newey and West, 1987) with $\lfloor 4(n/100)^{2/9} \rfloor$ lags; and (iv) the interval from feasible generalized least squares with AR(1) errors (iterated Cochrane–Orcutt). As a check on the annual analysis, we also fitted the 1970–2024 monthly series with a linear trend and ARMA(1,1) errors by maximum likelihood, following the error model used by Foster and Rahmstorf (2011).

To assess Berkeley Earth’s own observational uncertainty, we perturbed each annual value with Gaussian noise whose standard deviation was the reported 95% half-width divided by 1.96, either independently across years or with strong year-to-year correlation (AR(1) with coefficient 0.9), and refitted the 1970–2024 slope 2,000 times. We also computed a weighted least-squares slope with inverse-variance weights. Sensitivity to individual years was checked by leave-one-year-out refits, by excluding the strong El Niño years 1998, 2016, 2023 and 2024 and the years after the 1991 Pinatubo eruption, and by the Theil–Sen median-of-slopes estimator. Finally, we computed the OLS slope for every window of at least 15 years in the record.

3.3 Testing for a recent change in warming rate

The central inferential question is whether the 1970– E record is better described by a single straight line or by a line whose slope changes at some year τ . Because τ is not known in advance, comparing a line with a hinge at the best-fitting year using standard F or t tests overstates significance. We therefore used the sup- F statistic, the largest F statistic for adding a hinge over all candidate years with at least 10 years

of data on each side, and simulated its null distribution by parametric bootstrap. Each of 2,000 replicates combined the fitted straight line with AR(1) noise whose lag-one coefficient and innovation variance were estimated from the residuals of that line. The same simulated replicates were used to obtain a null distribution for the coefficient of a quadratic term. The test was repeated for end years E from 2000 to 2024 to show how the evidence evolves as data accumulate.

For comparison we also report a hinge at the fixed year 2010, tested with a HAC standard error. This year was chosen with knowledge of published claims about recent acceleration and of the data, so its nominal p -value is not a valid confirmatory test; it is included to show how much the conclusion depends on whether the break year is treated as known.

The power of the sup- F test was estimated by simulating 1970–2024 (and 1970–2030) series consisting of a straight line, a step increase Δ in slope beginning in 2005, 2010 or 2015, and AR(1) noise with the parameters estimated from the observations. Because the sup- F statistic is invariant to the intercept and slope of the null line, the power depends only on Δ , the onset year, the series length and the noise parameters.

4 Validation and extrapolation methods

4.1 Rolling-origin retrospective forecasts

In-sample R^2 describes how closely a curve follows the data it was fitted to and does not measure predictive skill. To evaluate prediction we used rolling-origin evaluation with an expanding window (Tashman, 2000). For each forecast origin T from 1950 to 2023, every model was fitted using only data from 1850 (or from a window ending in T) up to T , and was used to predict the annual anomaly in year $T + h$ for horizons $h \in \{1, 5, 10, 20, 30\}$ years whenever $T + h \leq 2024$. No information after T entered any fit, parameter estimate or break-year search. The number of forecasts per horizon ranges from 74 ($h = 1$) to 45 ($h = 30$, origins 1950–1994).

Eight forecasting methods were compared: the mean of the last 10 years (a no-trend reference); linear, quadratic and cubic trends fitted to the full record up to T ; a linear trend fitted to the last 30 years; a continuous piecewise-linear trend with one break year estimated from the training data and the last segment extrapolated; and Holt exponential smoothing with linear and with damped trends, with smoothing parameters estimated on the training data. For the three polynomial trends and the 30-year linear trend we also computed nominal 90% OLS prediction intervals and their empirical coverage. We report mean absolute error (MAE), root-mean-square error and mean bias. Forecasts from adjacent origins overlap heavily, especially at long horizons, so the 30-year results rest on a few effectively independent periods. We therefore present the comparison descriptively and do not attach significance tests.

4.2 Audit of polynomial extrapolation to 2100

The original dashboard extrapolated a quadratic fitted to 1850–2024 to the year 2100. We examined the 2100 value implied by quadratics fitted to 1850– E for every end year E from 1950 to 2024, by quadratics with start years from 1850 to 1980, and by polynomials of degree 1 to 5, and compared the spread with the naive OLS 90% prediction interval. These calculations describe the behaviour of the statistical method. They are not projections of future climate, which depend on future emissions and physical responses that a curve fitted to past temperatures does not represent, and they should not be compared with scenario-based projections.

All computations used Python 3.13 with NumPy 2.5.3, pandas 3.0.5, SciPy 1.18.1, statsmodels 0.15.0, scikit-learn 1.9.1 and Matplotlib 3.11.2. Random simulations used a fixed seed.

Table 1: Original results as reported, as reproduced by running the original code, and after correction (air-temperature version only). Full-record statistics are in-sample. MAE and RMSE in °C.

Model	Statistic	Reported	Reproduced	Corrected
Linear, 1850–2024	R^2 / MAE / RMSE	0.7372 / 0.1649 / 0.2025	0.7372 / 0.1649 / 0.2025	0.7376 / 0.1726 / 0.2120
Quadratic, 1850–2024	R^2 / MAE / RMSE	0.8993 / 0.0991 / 0.1254	0.8993 / 0.0991 / 0.1254	0.9009 / 0.1030 / 0.1303
Linear, 1970–2024	slope (°C/decade)	0.194	0.194	0.206

Table 2: OLS warming rates (°C per decade) for selected periods with four 95% interval half-widths. r_1 : lag-one autocorrelation of OLS residuals; n_{eff} : effective sample size. The last column gives the GLS-AR(1) slope and its interval.

Period	n	Slope	Naive	r_1	n_{eff}	AR(1)-adj.	HAC	GLS-AR(1)
1850–1900	51	0.007	± 0.023	0.47	19	± 0.044	± 0.021	0.006 ± 0.041
1901–1950	50	0.102	± 0.021	0.47	18	± 0.040	± 0.032	0.109 ± 0.033
1951–1980	30	0.041	± 0.049	0.25	18	± 0.067	± 0.063	0.052 ± 0.067
1850–2024	175	0.070	± 0.006	0.83	16	± 0.024	± 0.015	0.078 ± 0.020
1970–2024	55	0.206	± 0.017	0.17	39	± 0.022	± 0.020	0.209 ± 0.022
1979–2024	46	0.206	± 0.023	0.27	27	± 0.032	± 0.030	0.211 ± 0.032
1995–2024	30	0.231	± 0.045	0.27	17	± 0.063	± 0.043	0.246 ± 0.063
2000–2024	25	0.257	± 0.058	0.35	12	± 0.094	± 0.061	0.259 ± 0.088
2010–2024	15	0.355	± 0.138	0.29	8	± 0.225	± 0.124	0.431 ± 0.227

5 Results

5.1 Reproduction and correction of the original analysis

The original code reproduced every reported number exactly (Table 1). The in-sample R^2 values describe how much of the variance of the 1850–2024 annual series each curve follows; they are not forecast accuracy. Correcting the version mixing changed the full-record fit statistics only in the third decimal place, but increased the 1970–2024 OLS warming rate from 0.194 to 0.206 °C per decade. The water version gives 0.181 °C per decade.

5.2 Warming rates and their uncertainty

The 1970–2024 warming rate is 0.206 °C per decade (Table 2). Residuals of this fit have modest autocorrelation ($r_1 = 0.17$), and all four interval methods agree closely: ± 0.017 (naive), ± 0.022 (AR(1)-adjusted), ± 0.020 (HAC), and 0.209 ± 0.022 (GLS). The monthly ARMA(1,1) fit gives 0.206 °C per decade with a 95% interval of 0.184 to 0.228. Over 1979–2024 the rate is the same, 0.206 °C per decade. Shorter recent windows give higher central estimates with much wider intervals: 0.231 ± 0.063 for 1995–2024, 0.257 ± 0.094 for 2000–2024 and 0.355 ± 0.225 for 2010–2024. For the full 1850–2024 record a single straight line is a poor description; its residual autocorrelation is 0.83 and the naive interval (± 0.006) is a quarter of the AR(1)-adjusted one (± 0.024).

Berkeley Earth’s reported observational uncertainty contributes little to the uncertainty of the post-1970 rate. The Monte Carlo standard deviation of the slope was 0.0013 °C per decade with independent perturbations and 0.0042 °C per decade with strongly correlated perturbations, compared with a sampling standard error of 0.0106 °C per decade from year-to-year variability; the weighted least-squares slope is 0.204 °C per decade. The estimate is also insensitive to individual years. No single excluded year moved the slope by more than 0.005 °C per decade; excluding 2023–2024 gave 0.196, excluding the four El Niño years gave 0.193, and the Theil–Sen slope was 0.203 (95% interval 0.185 to 0.223; Supplementary

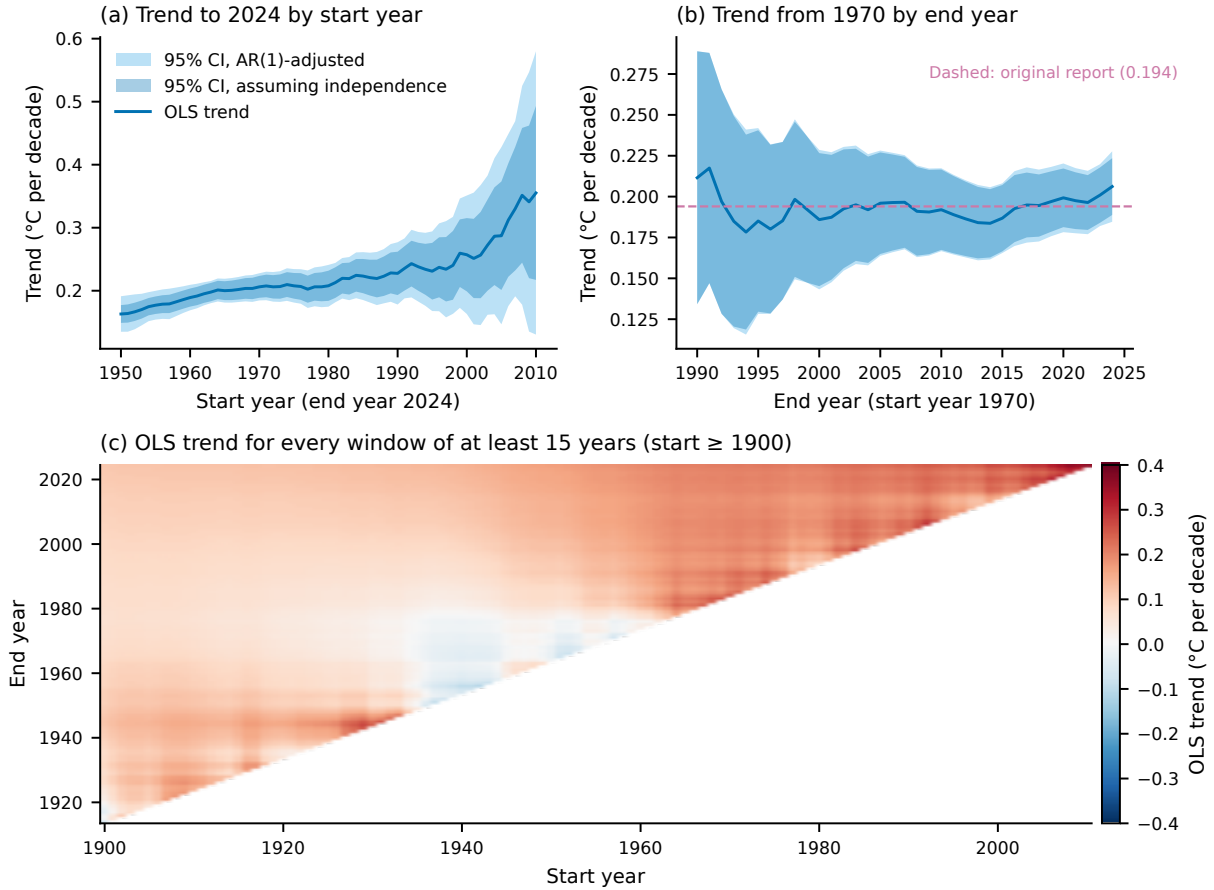


Figure 2: Sensitivity of OLS warming rates to the analysis period. (a) Trend ending in 2024 as a function of start year, with 95% intervals assuming independent errors and adjusted for AR(1) autocorrelation. (b) Trend starting in 1970 as a function of end year; the dashed line marks the value in the original report. (c) Trend for every window of at least 15 years beginning in or after 1900.

Table S2).

The choice of period matters more than any of these factors (Fig. 2). Trends ending in 2024 rise steadily as the start year moves later, from 0.163 °C per decade for a 1950 start to 0.257 for 2000 and 0.355 for 2010, while the uncertainty widens rapidly. For a fixed 1970 start, the trend ranged from 0.178 to 0.217 °C per decade for end years between 1990 and 2024, and between 0.184 (ending 2014) and 0.206 (ending 2024) for end years since 2000. The original value of 0.194 °C per decade thus lies inside the range of reasonable estimates, but it is lower than the corrected 2024 value for two reasons that should be kept separate: the data processing error and the inclusion of the 2023–2024 warm years.

The other datasets agree closely (Supplementary Table S4, Supplementary Fig. S2). For 1970–2024 the rate is 0.199 °C per decade in GISTEMP v4 and 0.202 °C per decade in HadCRUT5, compared with 0.206 for the Berkeley Earth air version and 0.181 for its water version. The differences between datasets are smaller than the AR(1)-adjusted uncertainty of any one of them. The air version has the highest 1970–2024 rate of the records compared, consistent with its use of air temperatures over the rapidly warming Arctic sea ice.

5.3 Change points in the full record

A continuous piecewise-linear model with three breaks gave the lowest BIC among $k = 0, \dots, 3$ (Supplementary Table S5). Its breaks are in 1917, 1942 and 1971, with segment slopes of -0.008 , 0.149 ,

Table 3: Tests for a change in warming rate in the 1970– E record. $\hat{\tau}$: best-fitting hinge year; slopes in $^{\circ}\text{C}$ per decade; Δ : slope change. Critical values and p -values come from 2,000 replicates of a straight line plus AR(1) noise fitted to each record.

E	$\hat{\tau}$	Before	After	Δ	sup- F	5% crit.	p (sup- F)	p (quadratic)
2014	2004	0.196	0.108	−0.088	1.58	6.54	0.495	0.347
2015	1980	0.247	0.178	−0.069	0.98	6.73	0.674	0.616
2016	1980	0.233	0.187	−0.047	0.41	6.99	0.909	0.838
2017	2007	0.186	0.258	0.071	1.00	7.34	0.714	0.653
2018	2008	0.186	0.258	0.072	1.04	7.78	0.716	0.727
2019	2009	0.185	0.288	0.103	2.23	8.00	0.450	0.536
2020	2010	0.185	0.315	0.130	3.70	7.99	0.251	0.364
2021	2011	0.187	0.285	0.098	2.08	7.43	0.480	0.530
2022	2012	0.189	0.260	0.071	1.12	8.07	0.685	0.630
2023	2012	0.187	0.305	0.118	3.69	7.31	0.233	0.302
2024	2013	0.186	0.362	0.176	8.11	9.03	0.064	0.129

−0.021 and 0.208 $^{\circ}\text{C}$ per decade (Fig. 1a). Cahill et al. (2015) likewise found that three change points were sufficient to describe four global records, with no detectable change in trend since about 1970. When the record was truncated at every second end year from 1990 to 2024, the three selected breaks moved by at most four years (sets found: 1917, 1942, 1968; 1917, 1942, 1971; 1917, 1943, 1967; 1917, 1943, 1968). The selection of three breaks rests on an information criterion that assumes independent errors and should be read as descriptive; the full-record residuals are autocorrelated, which tends to favour additional breaks.

5.4 Is there detectable evidence of recent acceleration?

With data to 2024, the best single hinge in the 1970–2024 record is in 2013, with slopes of 0.186 $^{\circ}\text{C}$ per decade before and 0.362 $^{\circ}\text{C}$ per decade after, an increase of 0.176 $^{\circ}\text{C}$ per decade (Fig. 3a). The sup- F statistic is 8.11 against a simulated 5% critical value of 9.03, giving $p = 0.064$ (Table 3). The quadratic term gives $p = 0.13$ against the same simulated null (HAC $p = 0.051$). The evidence is therefore suggestive but does not reach conventional significance once the search over break years is accounted for. It also depends heavily on the final year. With data ending in 2023 the sup- F p -value was 0.23, and for every end year from 2000 to 2023 it was at least 0.23 (Fig. 3b).

Treating 2010 as a known break year gives a slope increase of 0.129 ± 0.091 $^{\circ}\text{C}$ per decade with a nominal HAC $p = 0.006$. The contrast between this value and the sup- F result illustrates how strongly an apparently significant acceleration depends on choosing the break year with knowledge of the data.

The power simulations show what the test can detect (Fig. 3c, Supplementary Table S6). Under the estimated AR(1) noise ($\rho = 0.17$, innovation standard deviation 0.102 $^{\circ}\text{C}$), a slope increase beginning in 2010 would be detected by 2024 with at least 80% probability only if it were 0.20 $^{\circ}\text{C}$ per decade or larger. An increase of 0.15 $^{\circ}\text{C}$ per decade, similar to the point estimate above, would be detected with probability 0.57. With data through 2030, increases of 0.15 (onset 2010) or 0.20 $^{\circ}\text{C}$ per decade (onset 2015) would reach 80% power. The test’s false-positive rate in the simulations was 0.04, close to its nominal 5%.

5.5 Retrospective forecast skill

Out-of-sample errors were much larger than the in-sample fit statistics suggest, and every method underestimated later temperatures on average (Table 4, Fig. 4). Across origins 1950–2023, the linear trend over the last 30 years was most accurate at horizons of 1 to 10 years (MAE 0.092 to 0.146 $^{\circ}\text{C}$). At 20 and 30 years the full-record quadratic, the model of the original analysis, had the smallest errors (MAE 0.202

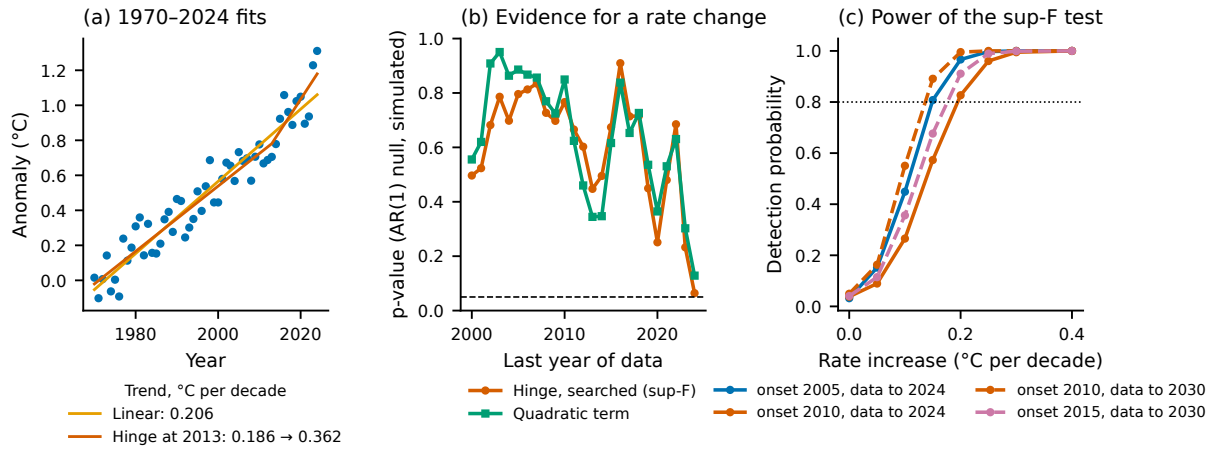


Figure 3: (a) Annual anomalies for 1970–2024 with the linear fit and the best-fitting continuous hinge. (b) Simulated p -values for the searched hinge (sup- F) and for a quadratic term as a function of the last year of data; the dashed line marks 0.05. (c) Probability that the sup- F test detects a slope increase of a given size beginning in the stated year, using data to 2024 (solid) or 2030 (dashed), under AR(1) noise estimated from the observations.

Table 4: Retrospective forecast mean absolute error (°C) by horizon for origins 1950–2023, with mean bias (forecast minus observed) at 20 and 30 years and empirical coverage of nominal 90% prediction intervals at 10 and 30 years. The smallest error at each horizon is in bold. Numbers of forecasts: 74, 70, 65, 55 and 45 for $h = 1, 5, 10, 20$ and 30.

Method	$h = 1$	5	10	20	30	Bias 20 / 30	Cov. 10 / 30
Mean of last 10 years	0.108	0.162	0.227	0.377	0.541	−0.370 / −0.541	–
Linear, full record	0.233	0.259	0.297	0.386	0.495	−0.380 / −0.495	0.40 / 0.16
Quadratic, full record	0.110	0.131	0.158	0.202	0.237	−0.082 / −0.125	0.78 / 0.53
Cubic, full record	0.108	0.143	0.188	0.301	0.475	−0.059 / −0.107	0.71 / 0.40
Linear, last 30 years	0.092	0.108	0.146	0.240	0.365	−0.171 / −0.341	0.72 / 0.38
Piecewise linear, 1 break	0.117	0.144	0.174	0.269	0.300	−0.176 / −0.247	–
Holt linear trend	0.098	0.117	0.160	0.267	0.400	−0.249 / −0.399	–
Holt damped trend	0.099	0.122	0.175	0.298	0.447	−0.285 / −0.447	–

and 0.237 °C, against 0.240 and 0.365 °C for the 30-year linear trend). The full-record straight line was the least accurate trend model at every horizon, and higher polynomial degree did not help: the cubic’s 30-year MAE was 0.475 °C.

This ranking depends on the evaluation period. For origins from 1980 onwards, the 30-year linear trend was more accurate than the quadratic at every horizon, including 30 years (0.307 versus 0.338 °C; Supplementary Table S7). The quadratic’s advantage at long horizons over the full evaluation period comes mainly from origins in the 1950s to 1970s. For those origins, a curve fitted to the whole record already bent upward, while trends fitted to the preceding decades of near-zero warming did not (Fig. 4c).

Nominal 90% prediction intervals were too narrow at all but the shortest horizons. For the quadratic, coverage was 0.78 at 10 years and 0.53 at 30 years; for the 30-year linear trend it was 0.72 and 0.38. In 30-year forecasts, every method under-predicted in at least 64% of cases.

5.6 Extrapolation to 2100

The original dashboard’s quadratic gives an anomaly of 2.77 °C relative to 1951–1980 in 2100; the corrected series gives 2.92 °C, with a naive 90% prediction interval of 2.63 to 3.20 °C (Fig. 5). That interval is narrow compared with the effect of choices that the data cannot resolve (Supplementary Table S8). Fitting the same quadratic to records ending in different years between 1950 and 2024 gave

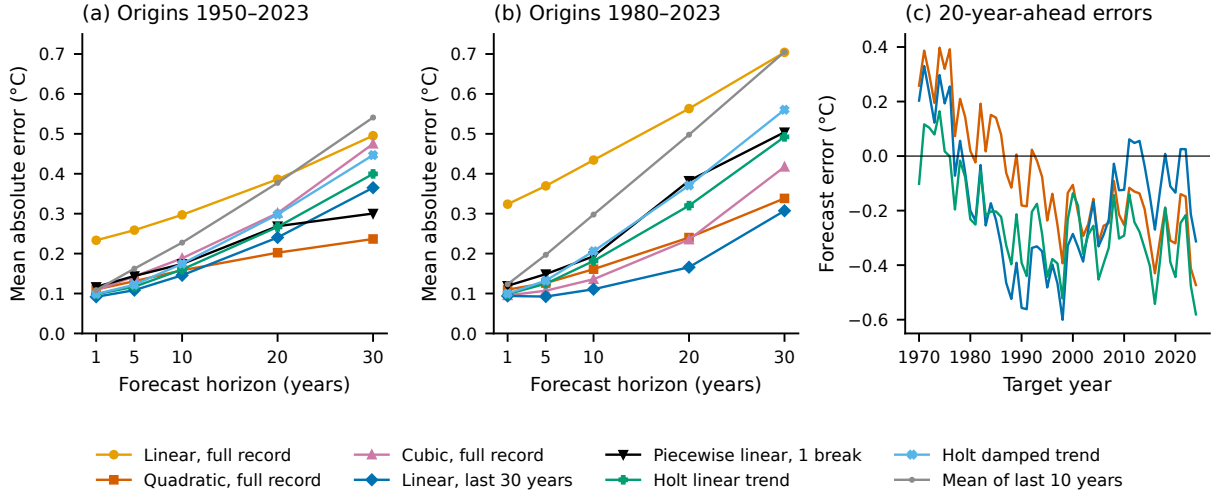


Figure 4: Rolling-origin retrospective forecasts. Mean absolute error by horizon for origins (a) 1950–2023 and (b) 1980–2023. (c) 20-year-ahead forecast errors by target year for the full-record quadratic (vermillion), the 30-year linear trend (blue) and Holt’s linear trend (green); negative values are under-predictions.

2100 values from 1.58 (end year 1976) to 3.69 °C (end year 1953); for the end years 1980 and 2000 the values were 1.78 and 2.29 °C. Changing the start year while ending in 2024 gave 2.92 to 5.20 °C. Changing the polynomial degree gave 1.16 (linear), 2.92 (quadratic), 4.37 (cubic), 6.60 (quartic) and 16.43 °C (quintic). The quadratic fitted to 1850–1994 predicted 0.72 °C for 2024 (90% interval 0.49 to 0.96), whereas the observed value was 1.31 °C. The quadratic also implies a constantly increasing warming rate, from 0.198 °C per decade in 2024 to 0.309 °C per decade in 2100. That is a consequence of the functional form, not an inference from the data.

6 Discussion

6.1 What the reanalysis adds

Table 5 summarises how these results relate to published work. Most of them confirm established findings: the post-1970 warming rate of about 0.2 °C per decade and its agreement across datasets (Rohde and Hausfather, 2020; Foster and Rahmstorf, 2011; Gulev et al., 2021); the need to account for autocorrelation in trend uncertainty (Santer et al., 2000); the instability of trends over short windows (Rahmstorf et al., 2017); the adequacy of three change points, with the most recent near 1970 (Cahill et al., 2015); and the absence, so far, of a statistically detectable surge in the warming rate (Beaulieu et al., 2024). The contributions here are narrower. We document a processing error that is easy to make with this widely used file and quantify its effect. We extend a sup- F detection test to the Berkeley Earth record through 2024 and show directly how the conclusion depends on the final year and on whether the break year is treated as known. We evaluate simple trend models by rolling-origin forecasting rather than in-sample fit. Finally, we show quantitatively how unstable polynomial extrapolation is. All of this is supported by a single executable package.

6.2 Warming rate and acceleration

The 1970–2024 rate of about 0.21 °C per decade is well determined. Its uncertainty from interannual variability is about ± 0.02 °C per decade, Berkeley Earth’s observational uncertainty adds little, and the three global records agree within that range. Reported rates differ much more because of choices about

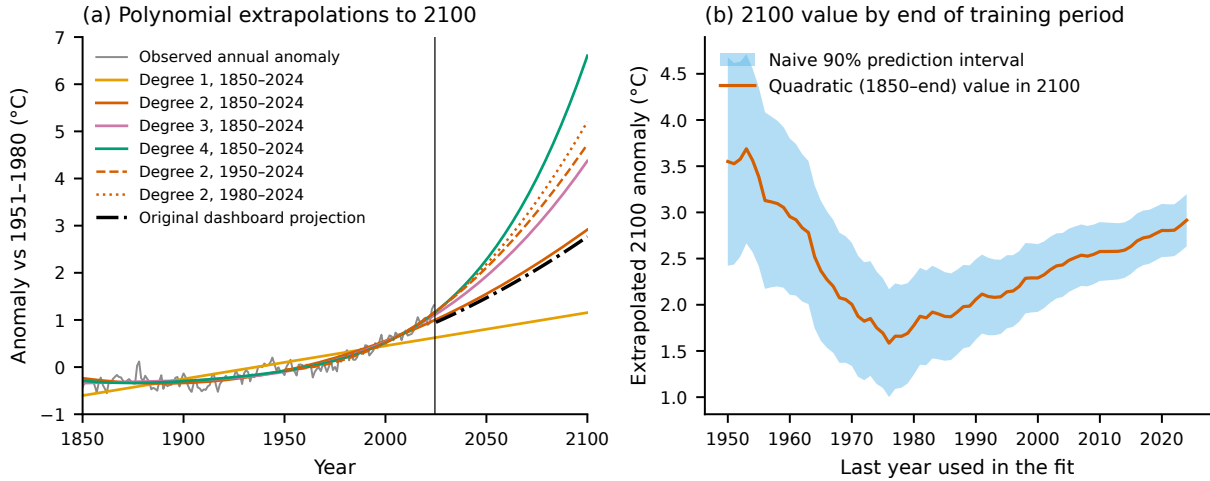


Figure 5: (a) Polynomial fits to the Berkeley Earth record extrapolated to 2100 for different degrees and start years, and the original dashboard projection. (b) The 2100 value implied by a quadratic fitted to 1850– E , as a function of the end year E , with its naive 90% OLS prediction interval. These curves illustrate the instability of statistical extrapolation and are not climate projections.

the period than because of statistical method.

Whether the rate has increased is a different and harder question. A 2024 p -value of about 0.06, after a decade of values above 0.2, is consistent with Beaulieu et al. (2024), who found no detectable surge in records through 2023, and it also shows how quickly the assessment can shift as exceptionally warm years are added. Two points follow. A test that fixes the break year after looking at the data, as in the 2010 hinge above, can produce a nominally significant result from the same evidence. And with only about 15 years of data after a plausible onset, the test can detect increases of roughly 0.2 °C per decade or more with high probability, so smaller increases, including one of the size suggested by Forster et al. (2025), may well be present but not yet statistically demonstrable in annual means. Removing variability associated with ENSO, volcanic aerosols and solar forcing, as in Foster and Rahmstorf (2011), would reduce the noise and increase power. We did not do so because it requires external indices and modelling choices beyond the scope of this reanalysis. None of these statistical results attributes any change in rate to a physical cause.

6.3 Fit, prediction and extrapolation

The original report’s statement that the quadratic “better represents” the record than a straight line is accurate as a description of in-sample fit. The rolling-origin results add two qualifications. First, which simple model forecasts best depends on the horizon and on the evaluation period. Recent 30-year linear trends were most accurate over horizons of up to a decade, and the quadratic’s advantage at longer horizons came largely from forecasts issued before 1980. Second, all methods systematically under-predicted, and their nominal prediction intervals were far too narrow. This happened because the record warmed faster during the test period than any of these models could anticipate from past temperatures alone. That is the expected behaviour of curve-fitting methods during a period of increasing radiative forcing, and it is why physically based projections, which take forcing as input, rather than trend extrapolation, are used to assess future warming (Hausfather et al., 2020; Gulev et al., 2021).

The extrapolation audit makes the same point more directly. The quadratic’s 2100 value moved by about two degrees depending on the end year of the data. Varying the start year or polynomial degree shifted it by similar or larger amounts. Its naive 90% prediction interval was narrower than any of these shifts. A statistically well-fitting curve therefore provides no defensible information about temperatures

Table 5: Relation of this reanalysis to prior work.

Topic	Established in prior work	This reanalysis
Dataset and recent warming	Berkeley Earth construction and uncertainty (Rohde and Hausfather, 2020); agreement among global records (Lenssen et al., 2019; Morice et al., 2021; Gulev et al., 2021)	Identifies and corrects mixing of the two sea-ice versions in a simple parser; confirms close agreement of 1970–2024 rates across three records
Trend uncertainty	AR(1) effective sample size (Santer et al., 2000); ARMA(1,1) errors and removal of ENSO, volcanic and solar signals (Foster and Rahmstorf, 2011)	Shows that AR(1), HAC, GLS and monthly ARMA intervals agree for 1970–2024, and that reported observational uncertainty adds little
Period choice	Short trends are unstable and easily misread (Rahmstorf et al., 2017)	Maps trends for all windows of at least 15 years and separates period effects from processing effects
Change points	Three change points suffice for four global records; no detectable trend change since about 1970 (Cahill et al., 2015)	Similar breaks (1917, 1942, 1971) in Berkeley Earth to 2024, stable to the end year
Recent acceleration	Argued from physical reasoning and recent data (Hansen et al., 2025); human-induced rate of 0.27 °C per decade over 2015–2024 (Forster et al., 2025); surge not yet detectable in records to 2023 (Beaulieu et al., 2024)	Searched-hinge test on Berkeley Earth to 2024 gives $p \approx 0.06$, with strong dependence on the final year and on whether the break year is pre-specified
Prediction	Rolling-origin evaluation (Tashman, 2000); physical models evaluated against observations (Hausfather et al., 2020)	Retrospective evaluation of simple trend models; demonstrates undercoverage of nominal intervals and instability of 2100 extrapolation

many decades ahead. We recommend that the dashboard either remove the 2100 projection or replace it with a clearly labelled illustration of this instability.

7 Limitations

Several limitations apply. (1) The analysis uses one global mean series, with two other records used only for trend comparison. The comparison series were obtained from a third-party mirror that could not be checked against the providers’ files from our computing environment. (2) We did not remove variability associated with ENSO, volcanic eruptions or solar changes, which lowers the power of the acceleration test relative to studies that do. (3) The AR(1) noise model is a simplification. The monthly ARMA(1,1) check agreed with the annual results, but long-memory behaviour was not examined. (4) The rolling-origin evaluation reuses a single realisation of the climate, and long-horizon forecasts from adjacent origins are strongly dependent, so the ranking of methods is descriptive. (5) The change-point selection uses BIC with independent errors, and the structural breaks are descriptive summaries rather than estimates of physical regime shifts. (6) The analysis plan was developed after the original results were known; the fixed-2010 hinge in particular is presented only as an illustration of selection effects. (7) Results were produced with one software environment; package versions are recorded, and a clean-environment rerun is described in the reproducibility package.

8 Conclusions

A reanalysis of the Berkeley Earth global record shows that the 1970–2024 warming rate, 0.206 ± 0.022 °C per decade after correcting a data-processing error, is robust to the treatment of autocorrelation, observational uncertainty, influential years and dataset choice, but sensitive to the choice of period. Evidence for a recent increase in the rate is suggestive ($p = 0.064$ with data to 2024) but not yet

statistically conclusive once the timing of the change is estimated from the data. It is also highly sensitive to the final year and could be made to look conclusive by fixing the break year after the fact. The original analysis reported in-sample R^2 , which is not a measure of predictive skill. In retrospective forecasts, all simple trend models under-predicted later warming, and their stated uncertainty was far too small. Polynomial extrapolation to 2100 changes by several degrees with defensible choices of period and degree. Statistical trend fits are useful for describing the observed record, but they should not be used as forecasts of future climate.

Data availability

The Berkeley Earth Land/Ocean global summary file analysed here is included in the archived reproducibility package (<https://doi.org/10.5281/zenodo.23512341>; redistributed under Berkeley Earth's CC BY-NC 4.0 licence) and in the author's repository <https://github.com/aravmestry/global-temperature-trend-dashboard> (commit 3a38f36); current versions are distributed by Berkeley Earth (<https://berkeleyearth.org/data/>). The file used corresponds to analyses run in January 2025 and covers 1850–2024. Because Berkeley Earth updates its files in place, results obtained with later versions may differ slightly; the SHA-256 checksum of the file used is recorded in the package. GISTEMP v4 and HadCRUT5.1.0.0 annual series were taken from <https://github.com/datasets/global-temp> (commit 44571fe); the original providers are NASA GISS and the Met Office Hadley Centre.

Code availability

The original dashboard code and data file are publicly available at <https://github.com/aravmestry/global-temperature-trend-dashboard>. The corrected reproducibility package for this preprint is distinct from that repository. It contains all reanalysis scripts, logs, numerical outputs, figure and table generators, an unmodified copy of the original code, and a single entry point (`run_all.sh`). It is archived on Zenodo as version 1.0 at <https://doi.org/10.5281/zenodo.23512341>. The code is released under the MIT License and the other author-created material under CC BY 4.0, except the bundled Berkeley Earth data, which remain under CC BY-NC 4.0.

Author contributions

A.M. conceived the original project, built the original analysis and dashboard, and is responsible for the manuscript.

Funding

This research received no external funding.

Competing interests

The author declares no competing interests.

AI-assistance disclosure

AI-assisted tools, including Claude (Anthropic), were used to support code development, statistical analysis, literature verification, and manuscript preparation. The author directed the research, evaluated the methods and findings, and assumes full responsibility for the scientific content and conclusions.

References

- C. Beaulieu, C. Gallagher, R. Killick, R. Lund, and X. Shi. A recent surge in global warming is not detectable yet. *Communications Earth & Environment*, 5:576, 2024. doi: 10.1038/s43247-024-01711-1.
- N. Cahill, S. Rahmstorf, and A. C. Parnell. Change points of global temperature. *Environmental Research Letters*, 10(8):084002, 2015. doi: 10.1088/1748-9326/10/8/084002.
- P. M. Forster, C. Smith, T. Walsh, et al. Indicators of global climate change 2024: annual update of key indicators of the state of the climate system and human influence. *Earth System Science Data*, 17: 2641–2680, 2025. doi: 10.5194/essd-17-2641-2025.
- G. Foster and S. Rahmstorf. Global temperature evolution 1979–2010. *Environmental Research Letters*, 6(4):044022, 2011. doi: 10.1088/1748-9326/6/4/044022.
- S. K. Gulev, P. W. Thorne, J. Ahn, et al. Changing state of the climate system. In V. Masson-Delmotte, P. Zhai, A. Pirani, et al., editors, *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*, pages 287–422. Cambridge University Press, Cambridge, UK and New York, NY, USA, 2021. doi: 10.1017/9781009157896.004.
- J. E. Hansen, P. Kharecha, M. Sato, et al. Global warming has accelerated: Are the United Nations and the public well-informed? *Environment: Science and Policy for Sustainable Development*, 67(1):6–44, 2025. doi: 10.1080/00139157.2025.2434494.
- Z. Hausfather, H. F. Drake, T. Abbott, and G. A. Schmidt. Evaluating the performance of past climate model projections. *Geophysical Research Letters*, 47(1):e2019GL085378, 2020. doi: 10.1029/2019GL085378.
- N. Lenssen, G. Schmidt, J. Hansen, M. Menne, A. Persin, R. Ruedy, and D. Zyss. Improvements in the GISTEMP uncertainty model. *Journal of Geophysical Research: Atmospheres*, 124(12):6307–6326, 2019. doi: 10.1029/2018JD029522.
- C. P. Morice, J. J. Kennedy, N. A. Rayner, et al. An updated assessment of near-surface temperature change from 1850: the HadCRUT5 data set. *Journal of Geophysical Research: Atmospheres*, 126(3): e2019JD032361, 2021. doi: 10.1029/2019JD032361.
- W. K. Newey and K. D. West. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica*, 55(3):703–708, 1987. doi: 10.2307/1913610.
- F. Pedregosa et al. Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research*, 12: 2825–2830, 2011.
- S. Rahmstorf, G. Foster, and N. Cahill. Global temperature evolution: recent trends and some pitfalls. *Environmental Research Letters*, 12(5):054001, 2017. doi: 10.1088/1748-9326/aa6825.

- R. A. Rohde and Z. Hausfather. The Berkeley Earth land/ocean temperature record. *Earth System Science Data*, 12(4):3469–3479, 2020. doi: 10.5194/essd-12-3469-2020.
- B. D. Santer, T. M. L. Wigley, J. S. Boyle, D. J. Gaffen, J. J. Hnilo, D. Nychka, D. E. Parker, and K. E. Taylor. Statistical significance of trends and trend differences in layer-average atmospheric temperature time series. *Journal of Geophysical Research*, 105(D6):7337–7356, 2000. doi: 10.1029/1999JD901105.
- L. J. Tashman. Out-of-sample tests of forecasting accuracy: an analysis and review. *International Journal of Forecasting*, 16(4):437–450, 2000. doi: 10.1016/S0169-2070(00)00065-0.

Supplementary material

The supplementary material is included in this PDF as an appendix. It is also provided as a separate file in the reproducibility package.

S1. Data audit

Table S1: Audit of the Berkeley Earth file used in this study.

File SHA-256	e2d57dc0efc309e1...
Berkeley Earth analysis dates	land 04-Jan-2025, ocean 06-Jan-2025
Anomaly baseline	January 1951 to December 1980
Monthly rows per version	2,100 (air), 2,100 (water)
Years	1850–2024, 12 months in every year
Missing monthly anomalies; duplicate year-months	0; 0
Rows read by the original parser	4,200 (24 per year)
Max computed – official annual mean	0.0006 °C
Air – water version, 2011–2024 mean	0.116 °C
Original – air series, 2011–2024 mean	–0.058 °C
Mean annual 95% uncertainty, 1850–1900 / 1970–2024	0.116 / 0.030 °C

S2. Trend robustness

Table S2: Sensitivity of the 1970–2024 OLS slope (°C per decade) to excluded years and to a robust estimator. “Change” is relative to the full-sample slope.

Exclusion or estimator	Slope	Change
2023-2024	0.196	–0.010
1998, 2016, 2023, 2024	0.193	–0.013
1991-1993 (Pinatubo)	0.206	–0.001
none (Theil-Sen)	0.203 [0.185, 0.223]	–0.003
Largest single-year exclusion (2024)	–	–0.005

Table S3: Residual diagnostics for selected OLS trend fits: lag-one autocorrelation, Durbin–Watson statistic, Ljung–Box test at lag 10 and Breusch–Pagan test for heteroskedasticity.

Model	R^2	Resid. SD	r_1	DW	Ljung–Box p	Breusch–Pagan p
Linear 1850-2024	0.738	0.213	0.83	0.33	<0.001	0.016
Quadratic 1850-2024	0.901	0.131	0.56	0.87	<0.001	0.962
Linear 1970-2024	0.911	0.104	0.17	1.56	0.111	0.308

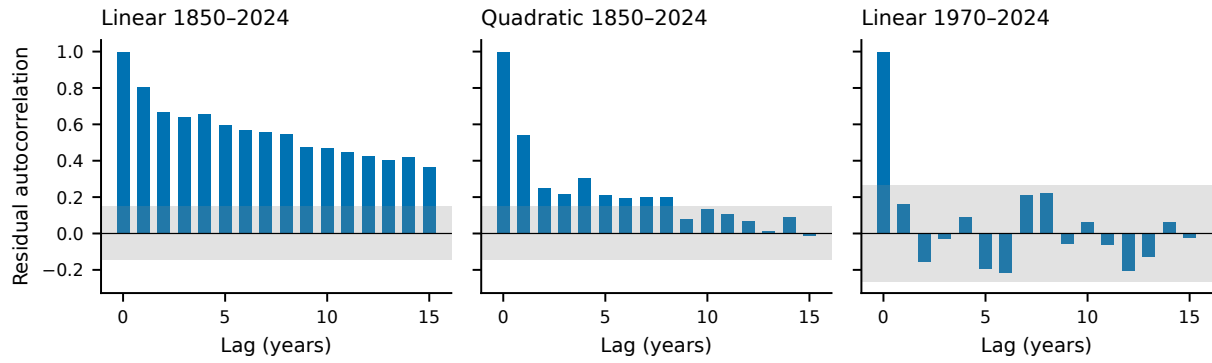


Figure S1: Autocorrelation of residuals from OLS trend fits. The grey band marks approximate 95% limits for independent errors.

Table S4: OLS trends ($^{\circ}\text{C}$ per decade) with AR(1)-adjusted 95% half-widths in five annual series. Comparison series were obtained from a third-party mirror of the providers' files (Section 2).

Series	1880–2024	1970–2024	1979–2024	2000–2024
Berkeley Earth (air, recommended)	0.092 ± 0.022	0.206 ± 0.022	0.206 ± 0.032	0.257 ± 0.094
Berkeley Earth (water)	0.084 ± 0.019	0.181 ± 0.022	0.179 ± 0.033	0.229 ± 0.104
Original mixed series	0.088 ± 0.020	0.194 ± 0.022	0.193 ± 0.033	0.243 ± 0.098
NASA GISTEMP v4	0.082 ± 0.028	0.199 ± 0.023	0.202 ± 0.035	0.259 ± 0.098
Met Office HadCRUT5.1	0.085 ± 0.022	0.202 ± 0.021	0.203 ± 0.032	0.249 ± 0.086

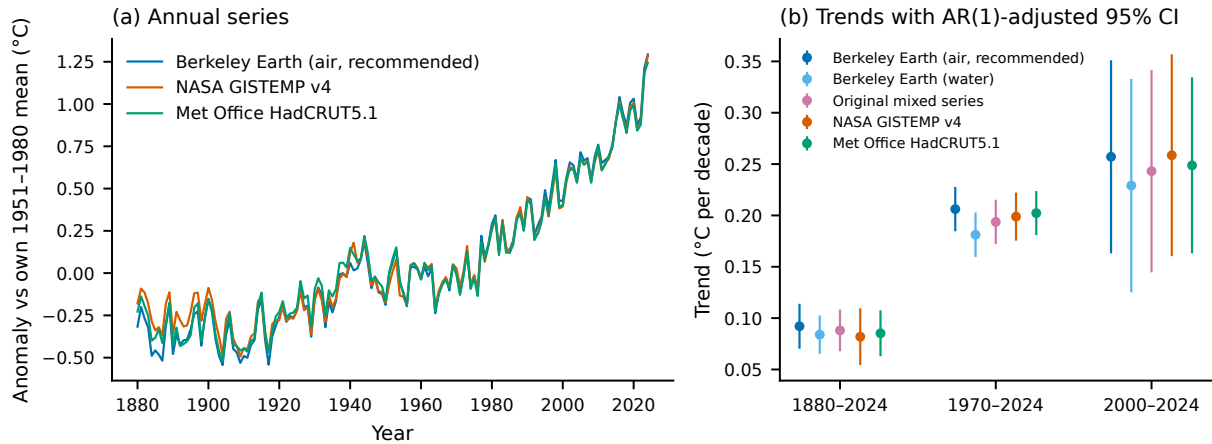


Figure S2: (a) Berkeley Earth, GISTEMP v4 and HadCRUT5 annual anomalies, each re-referenced to its own 1951–1980 mean. (b) Trends with AR(1)-adjusted 95% intervals.

S3. Change points and acceleration

Table S5: Continuous piecewise-linear fits to 1850–2024 with k breaks (segments of at least 15 years). Slopes in $^{\circ}\text{C}$ per decade. BIC counts each break year as a parameter and assumes independent errors.

k	Break years	Segment slopes	RSS	BIC
0	–	0.070	7.866	–532.6
1	1972	0.033, 0.207	2.844	–700.3
2	1908, 1978	–0.004, 0.063, 0.207	2.386	–720.7
3	1917, 1942, 1971	–0.008, 0.149, –0.021, 0.208	2.060	–736.0

Table S6: Simulated probability that the sup- F test (5% level) detects a step increase in warming rate ($^{\circ}\text{C}$ per decade) beginning in the onset year, for data from 1970 to the stated end year, under AR(1) noise estimated from the 1970–2024 observations (2,000 replicates per cell). The column for zero increase is the false-positive rate.

Onset	End	0.00	0.05	0.10	0.15	0.20	0.25	0.30
2005	2024	0.03	0.15	0.45	0.81	0.97	1.00	1.00
2010	2024	0.04	0.09	0.27	0.57	0.83	0.96	0.99
2005	2030	0.05	0.21	0.66	0.95	1.00	1.00	1.00
2010	2030	0.05	0.16	0.55	0.89	1.00	1.00	1.00
2015	2030	0.04	0.11	0.36	0.68	0.91	0.99	1.00

S4. Forecast evaluation and extrapolation

Table S7: As Table 4, for forecast origins 1980–2023 only.

Method	$h = 1$	5	10	20	30	Bias 20 / 30	Cov. 10 / 30
Mean of last 10 years	0.123	0.197	0.298	0.498	0.705	−0.498 / −0.705	–
Linear, full record	0.324	0.370	0.434	0.563	0.704	−0.563 / −0.704	0.06 / 0.00
Quadratic, full record	0.110	0.126	0.161	0.240	0.338	−0.240 / −0.338	0.77 / 0.27
Cubic, full record	0.095	0.107	0.136	0.235	0.417	−0.235 / −0.417	0.86 / 0.40
Linear, last 30 years	0.094	0.092	0.111	0.166	0.307	−0.148 / −0.306	0.83 / 0.33
Piecewise linear, 1 break	0.119	0.149	0.193	0.383	0.504	−0.383 / −0.504	–
Holt linear trend	0.098	0.125	0.182	0.320	0.492	−0.320 / −0.492	–
Holt damped trend	0.100	0.132	0.206	0.371	0.560	−0.371 / −0.560	–

Table S8: Polynomial extrapolation to 2100: anomaly relative to 1951–1980 ($^{\circ}\text{C}$), naive OLS 90% prediction interval, and the implied warming rate ($^{\circ}\text{C}$ per decade) in the last fitted year. These values describe the behaviour of the method and are not climate projections.

Fit	2100 value	90% PI	Rate at end of fit
Degree 2, 1880–2024	3.08	[2.77, 3.39]	0.210
Degree 2, 1900–2024	3.18	[2.81, 3.55]	0.217
Degree 2, 1920–2024	3.95	[3.54, 4.36]	0.266
Degree 2, 1950–2024	4.73	[4.11, 5.35]	0.315
Degree 2, 1970–2024	3.76	[2.67, 4.84]	0.265
Degree 2, 1980–2024	5.20	[3.63, 6.78]	0.327
Degree 1, 1850–2024	1.16	[0.79, 1.52]	0.070
Degree 2, 1850–2024	2.92	[2.63, 3.20]	0.198
Degree 3, 1850–2024	4.37	[3.76, 4.99]	0.272
Degree 4, 1850–2024	6.60	[4.64, 8.56]	0.334
Degree 5, 1850–2024	16.43	[9.88, 22.97]	0.465
Degree 2, 1850–1950	3.55	[2.42, 4.68]	0.111
Degree 2, 1850–1975	1.69	[1.10, 2.29]	0.080
Degree 2, 1850–2000	2.29	[1.92, 2.66]	0.130
Degree 2, 1850–2010	2.58	[2.26, 2.90]	0.158