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Recent Structural Breaks in Global Temperature Series: Evidence from a Changepoint Analysis

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Highlights

What are the main findings?

- Since 2013-2014, the rate of global warming has increased significantly.
- We find this 'shift in pace' of global warming with a robust statistical method.

What are the implications of the main findings?

- Our findings call for immediate action to counter this new rapid rise in temperatures.

Abstract

Recent studies have investigated whether the rate of global warming has changed since the 1970s, with particular attention to the role of natural variability and its removal from temperature time series. In particular, Foster and Rahmstorf (2026) analyzed global mean surface temperature series, adjusted for natural variability. However, their procedure might produce spurious changepoints, since it does not appropriately handle the autocorrelation present in the residuals of the models considered. In this study, we revisit the same adjusted temperature series using a different methodology (the Quandt likelihood ratio test) while properly accounting for the presence of autocorrelation. We find evidence that global temperature has departed from its previous path since around 2013-2014. Our results provide a robust proof of a clear recent increase in the temperature trend, at a rate of warming that has doubled since that date.

Keywords: global temperatures; warming trend; changepoint analysis; Quandt likelihood ratio test

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1. Introduction

The time series of global average temperature currently available (of which five will be considered in this study) show an initial rise in temperature in the early 20th century, due to the first significant anthropogenic emissions of greenhouse gases [1]. This was followed by a plateau from the Second World War onwards, generally attributed to the 'masking effect' of high sulphate cooling emissions [1,2]. Finally, when environmental legislation limited these emissions, the temperature began to rise more markedly from the '1970s onwards and a change point in the timeseries has been clearly identified around 1970 [3,4].

More recently, prompted by the fact that the last few years have been particularly hot, a number of studies has sought to determine whether global warming has accelerated further over the last decade. Beaulieu et al. [5] did not find any significant change in warming trend after 1970s. Otherwise, Hansen et al. [6] argued that a change in warming rate can be recently detected in the data of GISTEMP time series, but no statistical significance of this claim has been supplied.

As a matter of fact, it is very difficult to establish statistical significance in time series where natural variability plays a significant role, enhance the variance of the signal and can partially mask the anthropogenic trend. Thus, a key contribution to the study of whether human-induced global warming is accelerating was made when researchers began to filter out the components of the time series attributable to natural variability, such as solar radiation, volcanic ash and El Niño-Southern Oscillation (ENSO). Following the pioneering study by Foster and Rahmstorf in 2011 [7], further attempts to address the issue were made by Samset et al. [8], Jenkins et al. [9] and Richardson [10]. However, in each case, it proved difficult to determine the statistical significance of any change in the trend value and to pinpoint the exact timing of the changing point.

More recently, in 2026, Foster and Rahmstorf [11], hereafter FR26, conducted a comprehensive analysis of this issue using time series 'stripped' of natural variability and employing the method described in [5] to test the null hypothesis that there has been no change point since the 1970s. In this paper, we draw on this study, using the same time series but a different methodology for their analysis (the Quandt likelihood ratio test).

According to FR26, the appropriate model for describing the evolution of global temperature is a continuous piecewise-linear function that allows for a change in slope at a certain point in time, a model they call the PLF-changepoint. If we denote global mean surface temperature (GMST) by y and time by t, the model can be written as follows:

$$y = \begin{cases} \alpha + \beta t + u_t, t \leq t_c \\ \alpha + \beta t + \gamma(t - t_c) + u_t, t \geq t_c \end{cases} \tag{1}$$

FR26 use five established global temperature datasets: NASA, NOAA, HadCRU, Berkeley, and ERA5. The series are analyzed at the monthly time scale. From each series, they remove natural variability due to volcanism, ENSO, and changes in solar activity. Using the changepoint analysis proposed in [5], FR26 obtained an estimated changepoint date for each of the five monthly series considered (see Table 1 on page 4 of FR26).

The aim of this note is twofold. First, we wish to emphasize that the procedure adopted by FR26 might produce spurious changepoints, since it does not appropriately handle the autocorrelation present in the residuals of the models considered. Second, we propose the adoption of a changepoint dating procedure by which we can address this problem in an appropriate and simple manner.

2. Materials and Methods

We analyze the same time series considered in FR26:

- NASA, the NASA GISTemp series version 4 [12,13].
- NOAA, NOAA GlobalTemp version 6.0.0 [14].
- HadCRU, HadCRUT5 from the Hadley Centre/Climate Research Unit in the UK [15].
- Berkeley, from the Berkeley Earth Surface Temperature project [16].
- ERA5, from the European Center for Medium-range Weather Forecasting [17,18].

Both adjusted and un-adjusted monthly global temperature anomalies can be found in [19].

In this paper we adopt the Quandt Likelihood Ratio (QLR) test [20] for our analyses. It is a procedure used to detect the presence of a structural break at an unknown date in a regression model. It extends the traditional Chow test, which requires a pre-specified break date, by searching across a range of possible dates and identifying the most likely point of instability.

The basic idea is the following. Suppose that a regression model is estimated over a sample of size T and suppose that under the null hypothesis the coefficients are constant throughout the sample. Under the alternative hypothesis, however, the coefficients may change at some unknown break date. If the break date were known, one could simply perform a standard Chow test for parameter stability at that date. The difficulty is that in most practical applications the break date is not known. The QLR test addresses this problem by computing a sequence of F statistics, one for each admissible candidate break date. More precisely, for each candidate τ, an F-statistic $F(\tau)$ is computed. The QLR statistic is then defined as the supremum of these values:

$$QLR = \sup_{\tau \in T} F(\tau) \tag{2}$$

Here T denotes the set of candidate break dates considered in the analysis. In practice, the search is restricted to an interior portion of the sample, excluding observations too close to the beginning or the end. This is called trimming. For example, with a trimming parameter of 15%, the break date is allowed to vary only between $0.15T$ and $0.85T$. Trimming is necessary because tests based on very small subsamples at the boundaries are unstable and may produce unreliable results.

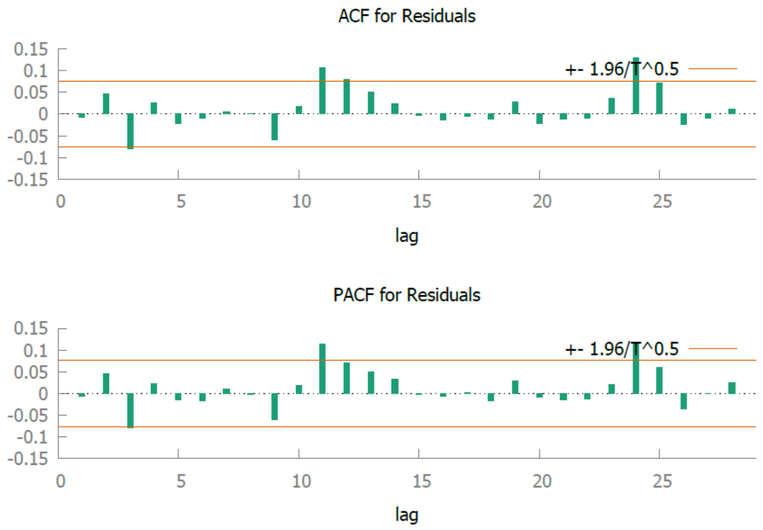
It is important to note that the QLR statistic does not follow a standard F distribution. Instead, its asymptotic distribution was derived by Andrews [21]. If the QLR statistic exceeds the Andrews critical value, we reject the null hypothesis of constant parameters and conclude that a structural break occurred. The estimated break date is the τ that yielded the maximum F-statistic.

3. Results and Discussion

3.1. Analysis of FR26 Method

Any changepoint analysis must address the issue of serial correlation with great care. It is important to account for autocorrelation in the model errors in climate changepoint analyses, because failure to do so can lead to the selection of a spurious changepoint. The most common method of compensating for autocorrelation in trend analysis is to treat the noise as a first-order autoregressive, or AR(1), process. However, FR26 conclude that the usual practice of treating the noise as an AR(1) process is inappropriate, suggesting instead that the noise should be modeled as an ARMA(1,1) process.

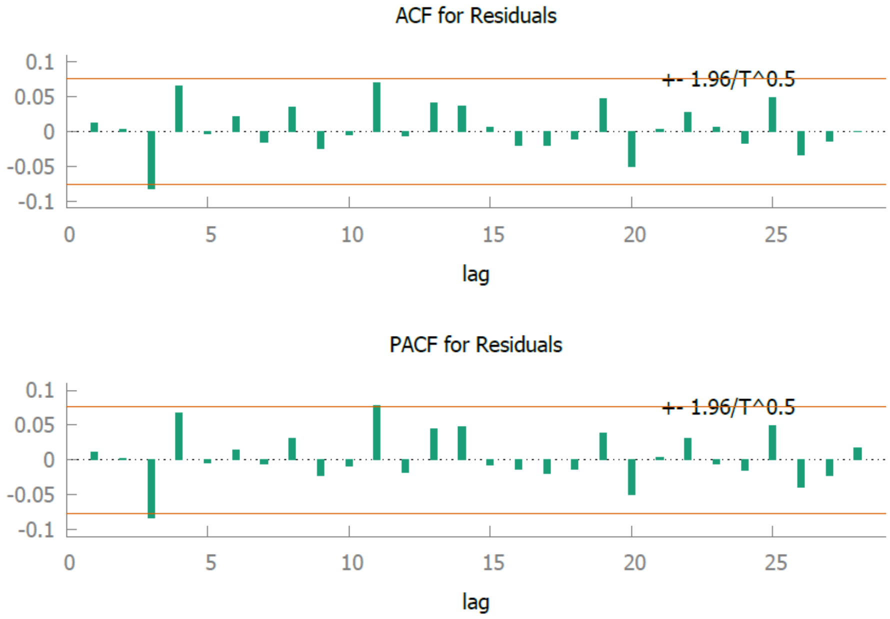
Unfortunately, even this specification does not appear to be adequate. The inadequacy of modeling the noise as an ARMA(1,1) process is evident from the analysis of the residual correlograms under the null hypothesis. Consider, for instance, the adjusted NASA time series. The residual correlograms (AutoCorrelation Function—ACF—and Partial AutoCorrelation Function—PACF) clearly indicates that the residual cannot be regarded as a realization of white noise. The residual dependence structure is mis specified (see Figure 1).


ACF for Residuals

PACF for Residuals

Figure 1. Sample ACFs (top) and sample PACFs (bottom) for ARMA(1,1).

A more flexible specification than an ARMA(1,1) process is therefore required. Despite the use of monthly anomalies, a seasonality signal remains in the data, so that a SARIMA model appears to be appropriate. In particular, we propose a $\text{SARIMA}(2,0,0)(2,0,0)_{12}$. Indeed, this model appears to be able to whiten the residuals (see the correlograms shown in Figure 2).


ACF for Residuals

PACF for Residuals

Figure 2. Sample ACFs (top) and sample PACFs (bottom) for SARIMA(2, 0, 0)(2, 0, 0)$_{12}$.

In short, to rule out the possibility that the changepoints identified by FR26 are spurious, the autocorrelation present in the noise must be addressed using more complex models. In particular, the presence of seasonality must be taken into account.

Extending the Beaulieu et al. [5] testing framework to a SARIMA error structure is feasible and conceptually straightforward. However, the implementation becomes substantially more demanding in practice, due to the repeated estimation of seasonal time-series models, possible convergence issues, and the need to simulate the null distribution under a correctly specified seasonal dependence structure. This fact prompts us to carry out an independent analysis of this important topic using a different method that properly addresses these issues.

3.2. Application of the Quandt Likelihood Ratio Test

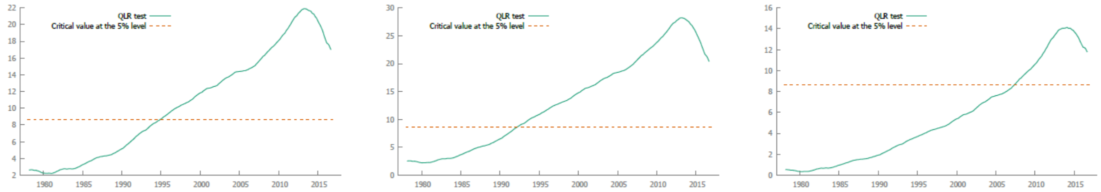
Consider a situation where we suspect that a break occurred sometime between two dates, t_0 and t_1. The well-known Chow test can be extended to handle this situation by testing for breaks at all possible dates t between t_0 and t_1 and then using the largest of the resulting F-statistics to test for a break at an unknown date. This modified Chow test is called the Quandt likelihood ratio (QLR) test [20]. For a comprehensive description of the QLR test, see Methods and [22].

We conducted the test by modeling the noise as a SARIMA(2,0,0)(2,0,0)$_{12}$ process. The results obtained are reported in Table 1 and Figure 3. It is striking to note that the results of changepoint estimations are very similar to those obtained by FR26, but now they derive by a correct consideration of autocorrelation, so that can be considered more reliable. Furthermore, all our results are significant at the 1% level (see p-values in Table 1).

Table 1. Estimated changepoints, p-values, and warming rates before and after the structural break for the adjusted temperature series. Warming rates are expressed in °C per decade.

Series	Changepoint	p-value	Pre-break warming rate	Post-break warming rate
NASA	April 2013	2.862×10^{-6}	0.17	0.36
NOAA	February 2013	4.044×10^{-6}	0.16	0.36
HadCRU	February 2014	0.003765	0.18	0.34
Berkeley	February 2014	0.003503	0.18	0.36
ERA5	February 2014	7.979×10^{-5}	0.18	0.42

Figure 3 reports the evolution of the *F*-statistic across candidate break dates for the five global temperature series considered here. A common pattern emerges across all datasets: the test statistic rises steadily over time, exceeds the 5% critical value, and reaches its maximum in the early 2010s, before declining slightly at the very end of the sample. The peaks in the curves (i.e., the QLR statistic) identify the dates of the changepoints. This provides strong evidence against the null hypothesis of no structural change in the warming trend and indicates that the most likely break date is located around 2013-2014, with only minor differences across datasets.

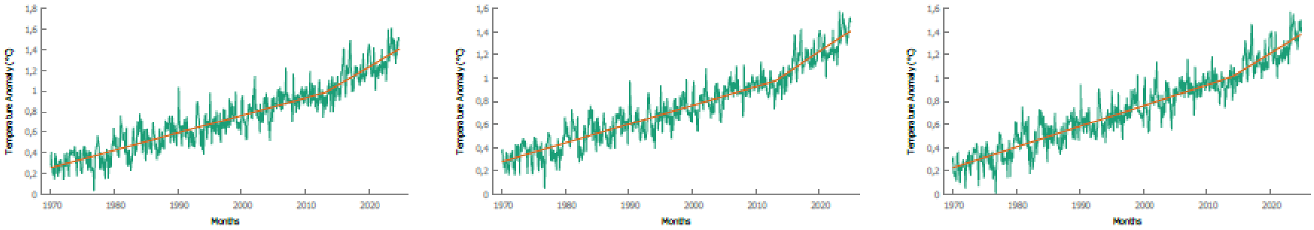


(a) NASA (b) NOAA (c) HadCRU

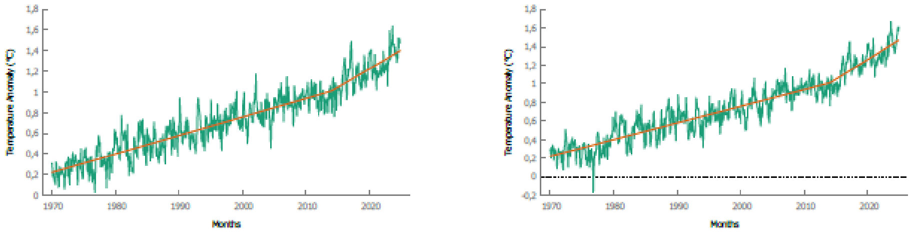
(d) Berkeley (e) ERA5

Figure 3. *F*-statistic across candidate break dates for the five adjusted temperature series.

In Figure 4 we show the adjusted temperature time series together with the broken linear fitting coming from our analysis. Consider the sensible increase in the rate of warming as shown in Table 1.



(a) NASA (b) NOAA (c) HadCRU



(d) Berkeley (e) ERA5

Figure 4. Monthly average adjusted global mean surface temperature from five data sources with superimposed continuous piecewise linear model fitted trends as found from our analysis.

Finally, what happens for unadjusted temperature series? Table 2 reports the estimated break dates and associated p-values for these series obtained by QLR test.

Table 2. Estimated break dates and associated p-values for the unadjusted temperature series.

Series	Changepoint	p-value
NASA	February 2012	0.068
NOAA	February 2012	0.037
HadCRU	March 2012	0.288
Berkeley	April 2013	0.199
ERA5	April 2013	0.098

A fairly consistent temporal pattern emerges across datasets, with the candidate break dates clustering between February 2012 and April 2013. In particular, NASA and NOAA identify February 2012 as the most likely break date, HadCRU points to March 2012, while Berkeley and ERA5 indicate April 2013. This concentration of estimated break dates within a relatively narrow time window suggests some cross-dataset agreement on the timing of a possible shift in the warming trajectory. However, the empirical evidence is not generally strong neither equal across series. Only the NOAA series yields a p-value below the conventional 5% significance threshold (p=0.037), while NASA and ERA5 provide only marginal evidence, significant at most at the 10% level. Furthermore, HadCRU and Berkeley do not provide sufficient evidence to reject the null hypothesis of no structural change.

Overall, the results suggest that, for the unadjusted series, the estimated timing of the potential break is relatively stable across datasets, whereas the empirical support for its existence remains weak to moderate and depends substantially on the temperature record considered.

4. Conclusions

In this paper, we have examined the issue of a possible 'shift' in the recent trend of global warming. Building on the work of FR26 and using the same temperature time series, adjusted to account for natural variability, we have seriously considered the existence of autocorrelation in the residuals of a broken-linear model using a different method from theirs. In our view, this has enabled us to obtain statistically more reliable results.

In any case, we find strong evidence for the existence of a changepoint around 2013-2014 in the adjusted series. Furthermore, by our method, also the un-adjusted NOAA series shows a significant changepoint in February 2012. Finally, heating rates for the adjusted time series have essentially doubled and range from 0.16-0.18 °C/decade (for the period before 2013-2014) to 0.34-0.42 °C/decade (for the last 10+ years).

We believe these findings contribute to the current scientific debate regarding the supposed 'acceleration' of global warming over the last decade or so. Furthermore, the significant increase in the rate of warming shows that our recent actions have not produced tangible results in terms of mitigation (quite the contrary). Therefore, we must raise our climate mitigation ambitions to remain below a safety threshold and avoid reaching a tipping point in global temperature.

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Data Availability Statement: Both adjusted and un-adjusted monthly global temperature anomalies can be downloaded from Foster (2025), https://doi.org/10.5281/zenodo.15591644. The script used for the Quandt likelihood ratio test is available at https://cnrsc-my.sharepoint.com/:t:/g/personal/antonello_pasini_cnr_it/IQCxkLYNothGR6IeFUJzk0KiAbqz__QwHLB6N-cpqusxzGE?e=9HweNB.

Conflicts of Interest: The authors declare no conflicts of interest.

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