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Key Points:
- The "pause" has a return period of 20–50 years (not unusual)
- Pre-pause (92–98) warming cancels the pause cooling
- The largest expected cooling event = 0.47 K: almost exactly the postwar cooling

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Return periods of global climate fluctuations and the pause

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Abstract An approach complementary to General Circulation Models (GCMs), using the anthropogenic CO_2 radiative forcing as a linear surrogate for all anthropogenic forcings [*Lovejoy*, 2014], was recently developed for quantifying human impacts. Using preindustrial multiproxy series and scaling arguments, the probabilities of natural fluctuations at time lags up to 125 years were determined. The hypothesis that the industrial epoch warming was a giant natural fluctuation was rejected with 99.9% confidence. In this paper, this method is extended to the determination of event return times. Over the period 1880–2013, the largest 32 year event is expected to be 0.47 K, effectively explaining the postwar cooling (amplitude 0.42–0.47 K). Similarly, the "pause" since 1998 (0.28–0.37 K) has a return period of 20–50 years (not so unusual). It is nearly cancelled by the pre-pause warming event (1992–1998, return period 30–40 years); the pause is no more than natural variability.

1. Introduction

A massive effort to prove anthropogenic warming has recently culminated in the conclusion that it is "extremely likely that human influence has been the dominant cause of the observed warming since the mid-20th century", with the term "extremely likely" referring to a 95–100% probability (International Panel on Climate Change, IPCC, Fifth Assessment Report, AR5). Yet this effort may be facing diminishing returns. It is surely significant that the 1979 National Academy of Science's climate sensitivity estimate (1.5–4.5 K/CO_2 doubling) was re-iterated in all the Assessment reports (with a minor variation in the AR4). More troubling, the models over-estimated the post-1998 El Nino global temperatures: they did not anticipate the "global slow-down" [*Guemas et al*., 2013], "hiatus" [*Fyfe et al*., 2013], or "pause" [*Slingo et al*., 2013]. Even if the ex-post facto reconciliations proposed by *Guemas et al*. [2013], *Schmidt et al*. [2014], or *Mann et al*. [2014] are correct, the damage has been done. Climate change deniers have been able to dismiss all the model results and attribute the warming to natural causes.

Whereas scientific theories can never be proven true "beyond reasonable doubt", they can be falsified by single decisive experiments. This was the approach taken in *Lovejoy* [2014] where a GCM-free methodology was proposed to determine the amount of the warming, the effective climate sensitivity, and—most importantly—the probability of the warming being due to natural causes. For the first two, the results were close to those of the AR5: for global temperature changes, compare 0.87 ± 0.11 K (1880–2004) with 0.85 ± 0.20 K (1880–2012), and for CO_2 doubling, 3.08 ± 0.58 with 3 ± 0.75 K (one standard deviation). However, the probability of a centennial scale giant fluctuation was estimated as ≤0.1%, a new result that allows a confident rejection of the natural variability hypothesis. At the moment, the necessary preindustrial centennial scale probabilities can only be reliably determined from multiproxy reconstructions (and for the extremes, with the help of some nonlinear geophysics theory). While the falsity of the natural variability hypothesis does not prove the veracity of the anthropogenic one, it certainly raises its credibility. The two most cogent remaining skeptic arguments—that the models are wrong and the variability is natural—are thus either irrelevant or are disproved by the new approach.

The key innovations were the use of the CO_2 radiative forcing as a linear surrogate for all the anthropogenic effects and the use of scaling fluctuation analysis on multiproxy temperatures to deduce bounds on the extreme probability tails of centennial scale fluctuation probability distributions. The first was justified by the tight relationship between global economic activity, emissions (both warming and cooling: greenhouse gases and aerosols) and other anthropogenic effects and confirmed by statistical analysis of the residuals. The second was justified by an empirical determination of probability distributions of fluctuations and the well documented scaling of preindustrial temperatures in the macroweather regime (≈10 days to ≈100 years, e.g., *Lovejoy and Schertzer* [1986], *Monetti et al*. [2003], *Pelletier* [1998], *Bunde et al*. [2004], *Huybers and Curry* [2006], *Rybski et al*. [2008], *Lennartz and Bunde* [2009], *Franzke* [2010], *Franzke* [2012], and *Fraedrich et al*. [2009]); for reviews, see *Lovejoy* [2013] and *Lovejoy and Schertzer* [2013].

GCM and GCM-free approaches are thus complementary; in this paper, we further demonstrate the potential of the latter by estimating the return periods for natural fluctuations of the global scale atmospheric temperature, in particular for the industrial epoch warming, the postwar cooling (1944–1976), the pre-pause warming (1992–1998), and the "pause" (1998–2013).

2. Estimating the Post Industrial Natural Variability

The basic hypothesis is that the global temperature anomaly ($T_{globe}(t)$) is the sum of an anthropogenic component—assumed proportional to the observed CO_2 forcing—and a residual representing the natural variability ($T_{nat}(t)$):

$$T_{globe}(t) = \lambda_{2xCO2,eff} log_2\left(\rho_{CO_2}(t)/\rho_{CO_{2,pre}}\right) + T_{nat}(t) \tag{1}$$

$\lambda_{2xCO2,eff}$ is the "effective" sensitivity of the climate to a CO_2 doubling, ρ_{CO2} is the global mean CO_2 concentration, and $\rho_{CO2,pre}$ is the preindustrial value (277 ppm). The logarithmic form is a basic semi-analytic result [*Arrhenius*, 1896]. The hypothesis is that while the actual series $T_{nat}(t)$ *does* depend on the forcing, its statistics do *not*. From the point of view of numerical modeling, this is plausible since the anthropogenic effects primarily change the boundary conditions not the type of internal dynamics and responses. This is consistent with *Nicolis* [1988] who investigated the relationship between the temperature variability and increasing CO_2 levels in stochastically forced energy balance models. She found that unless the noise is multiplicative, the temperature variance is insensitive to CO_2.

Two things should be noted: first, T_{nat} includes any temperature variation that is not anthropogenic in origin, i.e., it includes both "internal" variability and responses to any natural (including solar and volcanic) forcings. This is thus different from approaches that attempt to separate internal variability from external natural and anthropogenic forcings such as *Lean and Rind* [2008] and *Rohde et al*. [2013]. Second, $\lambda_{2xCO2,eff}$ is the "effective climate sensitivity," i.e., it is the sensitivity to the actual (historical) doubling of CO_2; it is thus conceptually different from the theoretical/model notions of "equilibrium" and "transient" sensitivity. Our approach is thus different from empirical approaches that attempt to infer the "equilibrium" climate sensitivities (e.g., *Gregory et al*. [2002], *Gregory and Forster* [2008], and *Bengtsson and Schwartz* [2013]) or "transient" sensitivities (e.g., *Dufresne and Bony* [2008], *Held et al*. [2010], *Padilla et al*. [2011], and *Schwartz* [2012]) and that require additional (and different) assumptions and interpretations. Note that it is only the effective climate sensitivity that permits one to estimate the natural variability during the industrial epoch (as a residue); this is the key to the estimates presented here.

The relatively accurate CO_2 concentration (ρ_{CO2}) reconstructions from [*Frank et al*., 2010] were used to determine $\log_2 \rho_{CO2}$. Since the reconstruction was only up to 2004, we extended it to 2013 using annually averaged Mauna Loa (i.e., local) concentrations and subtracted 5.3 ppm in order to estimate the global average concentration in optimal accord with the CO_2 reconstruction over their common period, 1959–2004.

For the temperature series, we used the annually averaged global and northern hemisphere series from NASA GISS [*Hansen et al*., 2010]. Spectral analysis showed that the northern hemisphere series had a slight excess variability at the highest frequencies—presumably associated with imperfect removal of the annual cycle—this was removed using a 1-2-1 running filter (equivalent to using the data at a 2 year resolution).

We used the same three annual resolution multiproxies as in *Lovejoy* [2014] over the more reliable recent (but mostly preindustrial) period 1500–1900 [*Huang*, 2004; *Moberg et al*., 2005; *Ammann and Wahl*, 2007]. The exact choice is not important since as shown in *Lovejoy and Schertzer* [2012] (eight multiproxies were analyzed)—although multiproxy statistics often differ substantially at long time lags Δt—over the macroweather regime ($\Delta t \approx <125$ years) of interest here—multiproxy statistics are very close to each other (to within ±0.09 K, unpublished analyses). It is worth noting that the *Huang* [2004] series is based on boreholes and is thus independent of the usual paleo calibration issues.

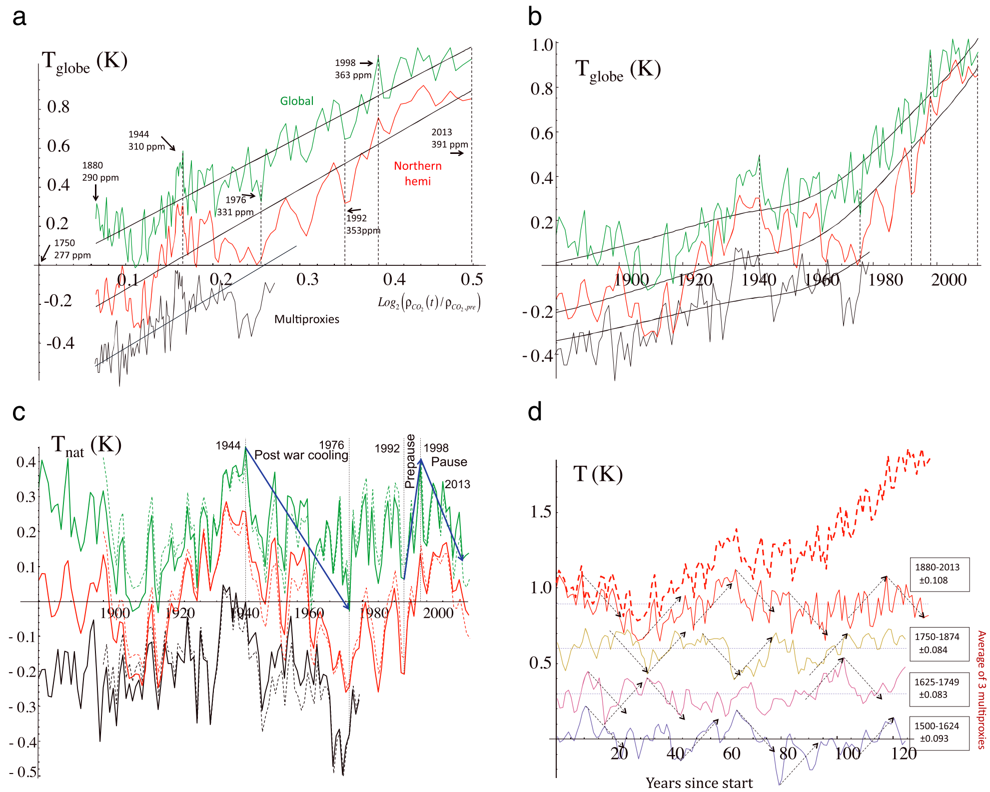

Figure 1. (a) Global (top, green), northern hemisphere (middle, red) temperature anomalies (NASA, GISS, 1880–2013) and (bottom, black) the average of the three multiproxies discussed in the text (1880–1979) as functions of radiative forcing using the CO_2 forcing as a linear surrogate. Each curve has been displaced in the vertical by 0.3 K for clarity, and the regressions have slopes 2.33, 2.55, and 1.98 (top to bottom). Some of the dates and corresponding annually, globally averaged CO_2 concentrations are indicated for reference; the dashed vertical lines indicate the beginning and end of the events discussed in the text (1944, 1976, 1992, and 1998). (b) T_{globe} as a function of date with the smooth line corresponding to the regression in Figure 1a with the same vertical dashed lines. Each curve has been displaced in the vertical by 0.2 K for clarity. (c) The residuals from figure 1b (solid) and from the corresponding curves with a 20 year lag (dashed). Green is global, red is northern hemisphere, and black is the multiproxy average. Each curve has been displaced in the vertical by 0.2 K for clarity. The vertical dashed lines are the same as in Figure 1a. The arrows indicate the events discussed in the paper. (d) The bottom three series are the average multiproxy temperatures for the indicated 125 year preindustrial periods, each with the mean removed and displaced in the vertical by 0.3 K for clarity. The top (red) curves are the global average for 1880–2013 (dashed) and residuals from Figure 1c (no lag). The dashed arrows are vectors 15 years wide, ±0.28 K in amplitude corresponding to positive or negative “pause” events. Several are shown; from their number we may roughly deduce that the return period of unsigned “pauses” is about 25–30 years, for a signed pause (double: 50–60 years).

The linearity of Figure 1a confirms equation (1) and shows that the sensitivities (slopes) for the global and northern hemisphere curves (2.33, 2.55; see Table 1) are close to those determined in *Lovejoy* [2014] for three (different) surface series from 1880 to 2004 (which yielded 2.33 and 2.59, respectively); in Figure 1a, we also considered the mean of the multiproxies over their period of overlap, 1880–1979. As in *Lovejoy* [2014] scaling, fluctuation analysis was used to confirm that the statistics of $T_{nat}(t)$ were nearly the same as those of preindustrial multiproxies, and this is up to centennial scales.

However, the strongest immediate effect of anthropogenic forcings is to heat the oceans, and only after some delay does this in turn heat the atmosphere; cross correlation analysis showed that the corresponding lag was between 0 and 20 years, see Table 1 where we note that whereas the sensitivities are significantly different, the correlations and residuals (Figure 1c) are hardly changed (the lagged and unlagged residuals differ by ±0.046 K compared to the temperature measurements accuracy ≈ ±0.03 K, [*Lovejoy et al.*, 2013]).

Figure 1b plots T_{globe} in the familiar way as a function of time with the (regression based) anthropogenic contribution superposed (Figure 1b) and Figure 1c the residual, natural fluctuations, T_{nat}. Figure 1c directly displays any unusual natural fluctuations, events. Consider the postwar cooling (1944–1976); it stands out at magnitude ≈0.4–0.5 K depending somewhat on the lag and the series (Table 1). In comparison, the pause

Table 1. The Top Two Rows Show the Effective Climate Sensitivity to CO_2 Doubling and the Correlation Coefficient® With no Lag and With a 20 Year Lag Between the Temperature and the CO_2 Forcing[a]

		Global			Northern Hemisphere			Multiproxy		
Lag		0		20 years	0		20 years	0		20 years
Sensitivity (K/CO_2 doubling)		2.33 ± 0.08		3.73 ± 0.13	2.55 ± 0.097		3.96 ± 0.160	1.98 ± 0.197		3.32 ± 0.27
Correlation (*r*)		0.928		0.940	0.916		0.924	0.712		0.812
Postwar (1944–1976) (K)	O		−0.26			−0.26			−0.22	
	N	−0.47		−0.42	−0.50		−0.44	−0.33		−0.38
	A	0.21		0.16	0.24		0.18	0.11		0.16
Prepause (1992–1998) (K)	O		+0.42			+0.46		–		–
	N	+0.33		+0.30	+0.34		+0.32	_		_
	A	0.09		0.12	0.12		0.14	–		–
Pause (1998–2013) (K)	O		−0.01			+0.10		–		–
	N	−0.28		−0.37	−0.20		−0.28	_		_
	A	0.27		0.36	0.30		0.38	–		–

[a]Below, the amplitudes of the postwar cooling, the pre-pause warming, and the pause as estimated by the various series; "O" is for the observed temperature change, "N" is the "natural variability" contribution (from the residues), and "A" is the anthropogenic contribution (O = N + A). The accuracy is estimated as ±0.03 K.

(1998–2013)—a natural cooling of ≈−0.3 K—is not exceptional. This impression is reinforced by considering the 1992–1998 "pre-pause" warming event, which is of nearly equal magnitude: to within the margin of error, they cancel each other out.

3. The Return Times

The multiproxies were used to directly determine the empirical probabilities $Pr(\Delta T(\Delta t) > s)$ of temperature changes ΔT exceeding a threshold s for over periods $\Delta t = 1$, 2, 4, 8, 16, 32, and 64 years. From the empirical probability distributions, we estimate the waiting times as inverse probabilities (e.g., an event with probability 0.01/year has a waiting time of 100 years) (Figure 2). The return times are waiting times conditioned on an event, but for extremes, the conditioning is typically weak, and we follow standard practice and take the two as equal (strictly speaking our results are for waiting times). However, due to the scaling, we may expect some clustering of extremes which could lead to differences between waiting and return times, although much larger preindustrial global scale temperature data sets would be needed to quantify this. See the discussion in *Schmitt and Nicolis* [2002], *Bunde et al.* [2004], and *Bunde et al.* [2005], although note that our extreme events are temperature changes so that these results do not directly apply. Due to the scale invariance of the climate dynamics over this range (and up to 100–125 years) there are long range statistical dependencies so that the distributions are virtually independent of the time scale Δt over which the differences were estimated (especially for $\Delta t \geq 4$ years), hence the near superposition of the curves in Figure 2.

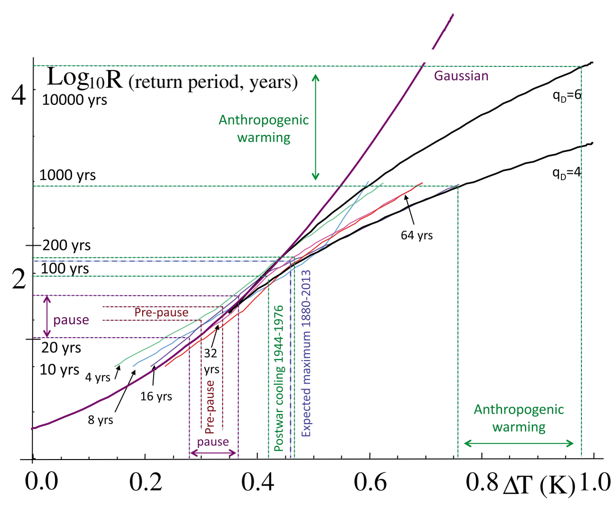

Figure 2. The return periods for signed fluctuations of the amplitude indicated on the abscissa. The colored curves are the empirical curves for various durations up to 64 years as determined directly from the preindustrial multiproxies. The black curves are the bounding hyperbolically tailed distributions, the brown is from the classical (Gaussian) distribution, and the standard deviation is 0.18 K. The dashed vertical lines correspond to various events, from right to left: global warming since 1880 (green range 0.76–0.98K), the largest event expected in the 134 years since 1880 (blue, 0.47 K), the postwar cooling (green, 0.42–0.47 K), the prepause 0.30–0.33 K (1992–1998), and pause 0.28–0.37 K (1998–2013). The horizontal lines indicate the corresponding return periods.

Since the warming from 1880 ($\approx$0.87 ± 0.11 K, [*Lovejoy*, 2014]) is much larger than any observed preindustrial fluctuations, in order to estimate its return period, the probabilities of the extreme fluctuations (the "tail") were bounded using (nonclassical) power law forms that are theoretically associated with scaling dynamics. This means that for low enough probabilities "*Pr*"—extreme enough fluctuations ΔT—we expect $Pr(\Delta T > s) \approx s^{-q_D}$ where s is a temperature threshold. It was found that $q_D \approx 5$ fit quite well but that in any case the actual tails were bounded: $4 \le q_D \le 6$ (the result $q_D \approx 5$ goes back to *Lovejoy and Schertzer* [1986] and was extended in *Lovejoy and Schertzer* [2013]; see also *Katz et al.* [2013]). Although only the tails (probabilities ≤0.03) were needed for testing global warming, a distribution with Gaussian shape for the high probability part that continuously merged with a power law with exponent q_D was found to be reasonable over most of the range (Figure 2); the Gaussian corresponds to $q_D = \infty$.

According to Figure 2, the anthropogenic warming (1880–2004, estimated as 0.76–0.98 K shown by the dashed green lines to the right) has a return period of 1000–20,000 years (using the bounding distributions with exponents $q_D = 4$, 6). While this is a sufficiently long period that natural variability can confidently be rejected as an explanation for the warming, it is nevertheless much shorter than the 1–100 Myr return period obtained using the classical (Gaussian) assumption (the red line).

What is the largest fluctuation that we should expect over the period 1880–2013? Such an event would have a return period of 134 years; hence, according to Figure 2, an amplitude of ≈0.47 K (this may be a slight underestimate since beyond about 125 years, the distribution is no longer exactly independent of scale—see *Lovejoy* [2014]). Comparing this estimate with Table 1, we see that—as expected—it is comparable to the postwar (1944–1976) cooling event of 0.42–0.47 K. Turning to the "pause," we see that it is more of a global than a northern hemisphere fluctuation (the latter is ≈0.1 K smaller), so we only considered the global pause of 0.28–0.37 K. From the figure, we see that the return period for such an event is 20–50 years—in reasonable agreement with Figure 1d. While in themselves such cooling events are not unusual, they become altogether probable when they immediately follow comparable warming events. Figures 1a, 1b, 1c, and Table 1 confirm that there was indeed a 6 year "pre-pause" warming event of almost the same magnitude (≈+0.3 K) with a similar return period (30–40 years). Since in this "macroweather" regime—successive fluctuations tend to cancel (e.g., *Lovejoy* [2013]), this is already a statistical explanation for the pause; in a future publication, we show how it can be made more rigorous using stochastic simulations and conditional forecasts.

We can also obtain a rough estimate of the frequency with which "pause" sized events occur by comparing the estimated global natural fluctuations with preindustrial multiproxy series of comparable length. In Figure 1d we show the vectors (15 years, ±0.28 K) corresponding to a 15 year cooling or warming of 0.28 K (the positive and negative fluctuations have nearly the same probability distributions). We can see that in the preindustrial period pause events were relatively frequent—five or six per 125 years, i.e., a return period of about 20–30 years for an event of either sign.

4. Conclusions

As data and models have improved, the thesis of anthropogenic warming has become increasingly convincing, and today we appear to be reaching a state of small incremental improvements. Unless other approaches are explored, the AR6 may simply reiterate the AR5's "extremely likely" assessment (and possibly even the range 1.5–4.5 K). We may still be battling the climate skeptic arguments that the models are untrustworthy and that the variability is mostly natural in origin. To be fully convincing, GCM-free approaches are needed: we must quantify the natural variability and reject the hypothesis that the warming is no more than a giant century scale fluctuation. With the help of nonlinear geophysics ideas on fluctuations and scaling, this has been done. By lumping all sources of natural variability together (i.e., internal and external) and by using the CO_2 forcing as a surrogate for all anthropogenic effects, it is possible to avoid assumptions about the radiative effects of aerosols, cloud radiation feedbacks, and other difficult issues.

Since 1998, the warming has noticeably slowed down—and due to a lack of a convincing model based explanation—the IPCC AR5 resorted to the vague: "Due to natural variability, trends based on short records are very sensitive to the beginning and end dates and do not in general reflect long-term climate trends" (see *Hawkins et al*. [2014]). In this paper, we have shown that the pause has a short return time and that it follows an equal magnitude pre-pause warming event: the pause thus has a convincing statistical explanation.

This approach can profitably be extended to other fields—notably precipitation—and to the spatial domain—to regional variability. Finally, it is possible to make stochastic climate forecasts using multifractal models whose strengths and weaknesses will complement the GCMs. These applications promise to enrich both our understanding of the climate of its models.

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