IMPOSED AND NEGLECTED UNCERTAINTY IN THE GLOBAL AVERAGE SURFACE AIR TEMPERATURE INDEX

Patrick Frank
Email: pfrank830@earthlink.net

ABSTRACT
The statistical error model commonly applied to monthly surface station temperatures assumes a physically incomplete climatology that forces deterministic temperature trends to be interpreted as measurement errors. Large artefactual uncertainties are thereby imposed onto the global average surface air temperature record. To illustrate this problem, representative monthly and annual uncertainties were calculated using air temperature data sets from globally distributed surface climate stations, yielding ±2.7 C and ±6.3 C, respectively. Further, the magnitude uncertainty in the 1961-1990 global air temperature annual anomaly normal, entirely neglected until now, is found to be ±0.17 C. After combining magnitude uncertainty with the previously reported ±0.46 C lower limit of measurement error, the 1856-2004 global surface air temperature anomaly with its 95% confidence interval is 0.8±0.98 C, Thus, the global average surface air temperature trend is statistically indistinguishable from 0 C. Regulatory policies aimed at influencing global surface air temperature are not empirically justifiable.

INTRODUCTION

The work of Brohan, et al. [1], hereinafter B06, exemplifies the commonly accepted signal-averaging approach to uncertainty [2] in the global average surface air temperature record. In a previous publication [2], it was shown that this approach had incorrectly incorporated the statistics of random measurement error and had entirely neglected systematic error.

Further consequences of the signal averaging statistical model applied within B06 are assessed herein. In addition, the magnitude uncertainty of the 1961-1990 annual anomaly normal is evaluated here for the first time.

Section 1 below summarizes the standard scope of measurement uncertainty as applied to surface air temperatures. Section 2 uncovers an incorrect physical assumption that is hidden within the B06 statistical model of surface temperatures, while Section 3 demonstrates the artefactual uncertainties imposed by this model. Finally, Section 4 derives the magnitude uncertainty in the 1961-1990 annual climate normal, and briefly considers its impact.

RESULTS AND DISCUSSION

1. MEASUREMENT UNCERTAINTY IN SURFACE AIR TEMPERATURES

The total uncertainty in the measurement mean of a physical variable, such as air temperature, involves measurement error and magnitude uncertainty [2]. Measurement error includes both instrumental error and systematic error [3]. Instrumental error consists of electronic noise and the limits of instrumental resolution. Instrumental resolution is discussed in Section 2.2, below. However, systematic error entails the impact that uncontrolled environmental variables have on the measured observable, or on the instrument itself, or on both [4-6]. For example, solar loading on the shield of a temperature sensor can affect the internal air temperature proximate to the sensor, and is thus an uncontrolled variable that can migrate the observed temperature away from the true air temperature. Solar loading also affects the electronics of a modern sensor, and can cause a nonlinear instrumental response to temperature [7, 8].

Magnitude uncertainty stems from the variation in time and/or space of the inherent intensities of the measured observables. For example, the instantaneous magnitude of surface air temperature fluctuates due to local short-term weather effects. Additionally, air temperatures exhibit a trend of non-zero slope across a month, which can intrinsically vary across time and space. For any fluctuation or trend in air temperatures, the magnitude uncertainty in the mean temperature is given as

$$\pm s = \sqrt{\sum_{i=1}^{N} (\tau_i - \bar{T})^2 \Big/ (N-1)} \;, \tag{1}$$

where τ_i is the magnitude of the i^{th} temperature measurement, $\bar{T}$ is the mean of all the temperature magnitudes, and N is the number of observations. Over long times local temperature excursions due to "weather noise" may average away as $1/\sqrt{N}$ [2], but deterministic monthly temperature trends need not.

It was previously shown [2] that B06 classified station temperature normals as constants. B06 assumed that temperature measurement error is random and declines as $1/\sqrt{N}$, and disregarded magnitude uncertainty, $\pm s$, which should have followed the description of station normal error, ε_N. Magnitude uncertainty also made no appearance in any monthly or annual mean surface air temperature anomaly [1].

With the $1/\sqrt{N}$ decline in measurement error globally applied and with $\pm s$ entirely absent, the statistical uncertainty model in B06 follows the standard method for averaging repetitive measurements of a constant signal [9-12], (signal-averaging *Case 1* in Ref. [2]). The B06 statistical uncertainty model therefore implicitly imposes the physical condition that over any given month, the N station temperatures, τ_i, are inherently constant. That is, for any month, $\tau_1 = \ldots = \tau_i = \tau_j = \ldots = \tau_n \equiv \tau_c$, where τ_c is a constant.

More explicitly, B06 statistically imposed, but left unstated, the physical hypothesis that the local air temperature around any given surface station is of inherently constant magnitude during every day of any given month, deviated only by weather noise and measurement noise. Only by assuming repetitive measurement of a constant-magnitude signal can B06 justify both the $1/\sqrt{N}$ uncertainty reduction in the mean and the absence of ±*s* [2].

2. THE SIGNAL-AVERAGING MODEL IN B06

The full B06 signal-averaging model is that at any given surface station, each temperature measurement entering a monthly mean is given by,

$$t_i = \tau_c + w_i + n_i, \tag{2}$$

where t_i is the measured temperature, τ_c is the model-implied constant temperature, w_i is weather noise, and n_i is stationary random noise [1, 2]. This description exhausts the hypothesis of monthly temperature embedded in the B06 statistical model, and is physically non-innocent. It predicts that the *N* monthly Tmax and Tmin values should all be of inherently identical magnitude, and therefore that monthly temperature trends must be of zero slope. The implicit physical meaning entrained by the B06 statistical model impacts the uncertainty of station temperature measurements in ways that heretofore have not been recognized. This impact will be described next, by first introducing the idea of instrumental resolution.

2.2 Temperature Sensor Resolution

The reliability of any temperature measurement will be impacted, *inter alia*, by the sensor resolution imposed by instrumental design. Resolution is the convolution of a signal with the response width of an instrument [11], which limits measurement precision. The WMO defines resolution [13] as, "A quantitative expression of the ability of an indicating device to distinguish meaningfully between closely adjacent values of the quantity indicated". Temperature sensor resolution, $\pm\Delta\tau_r$, is distinct from random noise and represents the instrumental limits at which two temperatures, t_1 and t_2, can be observationally distinguished. When $\Delta t = |t_1 - t_2| < |\Delta\tau_r|$, the measurements are poorly resolved or unresolved. Full resolution requires that $\Delta t \geq 3\Delta\tau_r$.

Every instrument suffers from limited resolution, which introduces a measurement uncertainty that is not reduced by averaging. Resolution was not explicitly considered in B06, but is a standard uncertainty found in all instrumental methods [3]. Klaupinnen discussed resolution functions for infrared spectrophotometers [11], for example, but the presented ideas are universally adaptable to other instruments.

2.3 The Degraded Resolution Encrypted within the B06 Model

As noted above, deterministic non-zero trends in monthly temperatures are physically excluded from the B06 signal-averaging model, and are thus relegated to a non-climatological cause. As a consequence, such trends must be treated as systematic errors arising within the experimental process, including sensor resolution and uncontrolled variables. Systematic errors stemming from uncontrolled variables, and/or poor instrumental resolution, can produce a spurious scatter of points in a series of measurements.

To demonstrate that a spurious error arises naturally from the B06 signal-averaging model, the model is extended to recognize the possibility of systematic point scatter. For any single temperature measurement, t_i, let

$$t_i = \tau_c + w_i + n_i + r_i, \tag{3}$$

where τ_c is again the constant temperature implied by the B06 statistical model, w_i is weather noise, n_i is measurement noise, and r_i is measurement point scatter reflecting the effect of systematic errors. When $r_i = 0$, the original B06 model is recovered (cf. eqn. 2). Sensor noise = n_i = ±0.2 C in B06, so $n_i << w_i$ and can be neglected. Now, define:

$$\tau_i' = \tau_c + r_i, \tag{4}$$

where every τ_i' represents the implied constant monthly temperature plus its point-scatter deviation, r_i. Equations 3 and 4 can then be combined, so that

$$t_i = \tau_i' + w_i \tag{5}$$

Equation 5 maps onto eqn. 2, with the noise discounted and with r_i subsumed within τ_i'. Extracting all the terms in equations 4 and 5 will reveal the point scatter hidden within the B06 model.

If w_i has a constant variance and a mean of zero, then τ_i' can be estimated by interpolating a linear fit to the monthly set of t_i temperature measurements. When n_i is negligible, the fit residuals, $t_i - \tau_i'$, are estimates of w_i (eqn. 5). When the values of τ_i' are known, an adjusted mean temperature, $\bar{T}'$, can be derived from equation 4 as,

$$\bar{T}' = \frac{1}{N}\sum_{i=1}^{N}\tau_i' = \tau_c + \frac{1}{N}\sum_{i=1}^{N} r_i \text{, and } (\tau_i' - \bar{T}') = r_i. \tag{6}$$

$\bar{T}'$ is now the measurement mean of a constant monthly temperature, τ_c, biased only by the mean of the point-scatter, r_i. Appraising the r_i will reveal the systematic point scatter imposed by the limited physical climatology implicit in the statistics of B06.

2.4 The Uncertainty Entrained by Assuming a Physically Constant Monthly Temperature

Air temperature data sets for 1998 were obtained from surface stations, Nivala, Finland; Fair Isle, Scotland; NTUA Athens, Greece; Philadelphia PA, USA; Kahoolawe HI, USA; Henderson Park, New Zealand, and; Vanwyksvlei, South Africa. These stations represent high, mid- and tropical latitudes, sea level and montane elevations, and include both hemispheres. Station details are given in the Supporting Information. The year 1998 was arbitrarily chosen as an illustrative period.[1]

Figure 1 exemplifies how τ_i' and w_i, r_i and $\bar{T}'$ were extracted, following eqns. 4-6, using the sixty April 1998 Vanwyksvlei temperatures. Thus, for each month examined, separate linear least-squares fits were made to the monthly trends of *N/2* daily minimum (Tmin) or maximum (Tmax) temperatures (Figure 1a). The two linear fits were then interpolated to yield N estimates of τ_i'. Each τ_i' departs from τ_c only from the influence of r_i (eqn. 4). From eqn. 5, when n_i is comparatively negligible (~±0.2 C), the residuals of the linear fits are weather noise, i.e., $t_i - \tau_i' = w_i$ (Figure 1b).

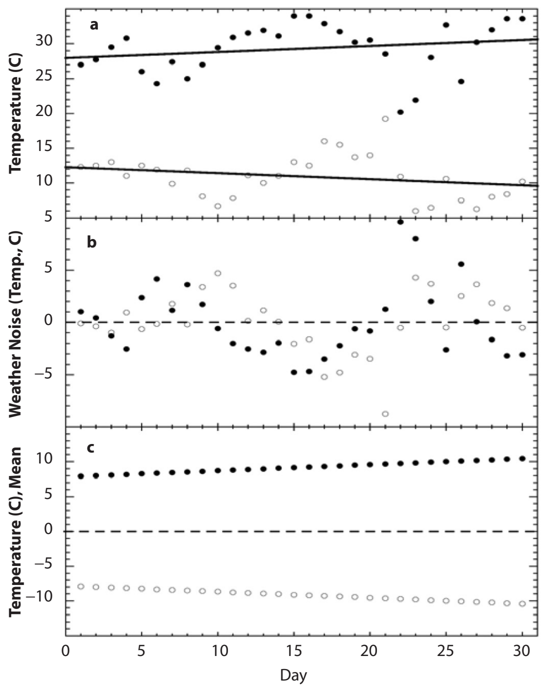

Figure 1: Panel a. (•), Tmax, and; (o), Tmin for April 1998, Vanwyskvlei, SA, representing the N values of daily station measurements which are the t_i of eqn. 3. The straight lines are the linear least squares fits to these data (Tmax = 27.94+0.0860x; r^2 = 0.0444, and; Tmin = 12.27-0.0866x; r^2 = 0.0598). Interpolation of these fits yielded N values of τ_i', eqn. 4. The average of the τ_i' yielded $\bar{T}'$, eqn. 6, which represents the constant monthly temperature normal. For April 1998 Vanwyksvlei, $\bar{T}'$ = 20.1 C. Panel b. Weather noise, represented by the $t_i - \tau_i'$ unfit residual from part 'a,' showing a mean of 0 C. Panel c. The sixty $\tau_i' - \bar{T}'$ bias temperatures, representing the resolution point scatter, r_i, as derived from equations 4 and 6.

[1] This study began with a request sent to the Royal Botanic Garden of Edinburgh, Scotland, for an arbitrary monthly temperature record derived from the surface station located on their grounds. They chose to send October 1998, and the subsequent analysis followed the year of their choice. There is no reason to suspect any unique statistical artifact arising because 1998 happened to be a powerful El Niño year. Edinburgh was chosen to be the first record investigated because the University of Edinburgh is home to the strong program of post-modern relativism, of which this study is yet one more definitive refutation. Falsifiable scientific statements fully refute post-modern theory because their meanings are invariant in time, impervious to subjective interpretation, and independent of culture [14-16]. Any science journal is replete with such refutations.

The mean magnitude of the invariant monthly temperature required by the B06 model was estimated as $\bar{T}' = \frac{1}{N}\sum_{i=1}^{N}\tau_i'$, (eqn. 6), and $\tau_i' - \bar{T}'$ yields the hidden point-scatter, r_i (eqn. 6, Figure 1c). The uncertainty reflecting the imperfect resolution caused by point scatter is then,

$$\pm\sigma_r = \sqrt{\sum_{i=1}^{N}(\tau_i' - \bar{T}')^2 \Big/ (N-1)} = \sqrt{\sum_{i=1}^{N} r_i^2 \Big/ (N-1)}. \qquad (7)$$

The analysis in Figure 1 was carried out on October 1998 air temperature data sets from all seven surface stations.

The mean constant temperature, $\bar{T}' \approx \tau_c$, plus the weather noise, w_i, exhaust the climatological physics allowed by the B06 statistical model. Within this model, each one of the sixty points in Figure 1a must represent one April 1998 measurement of τ_i at Vanwyksvlei, SA, deviated from τ_c only by a weather noise fluctuation.

Therefore, in B06, the non-zero slopes of the fits to Tmin and Tmax in Figure 1a have no external physical meaning. Consequently, the non-zero trends in the $\tau_i' - \bar{T}'$ bias temperatures, Figure 1c, must be assigned to a source of error internal to the experiment. From eqn. 6, the B06 model leaves these departures to be treated as point-scatter that reflects systematic error [4]. A spurious point scatter artefactually degrades measurement resolution. This is demonstrated next.

3. ARTEFACTUAL IMPRECISION ENTRAINED BY THE B06 MODEL

Gaussian fits were employed to estimate the resolution uncertainty represented by the spurious point scatter of the *N* monthly bias-temperatures, or by the *N* values of weather noise, in the data sets from the seven globally distributed surface stations. In this analysis, the empirical resolution uncertainty in the estimated mean temperature due to point scatter was calculated as,

$$\pm\sigma_r = \sqrt{\sum_{i=1}^{N}(\tau_i' - \bar{T}')^2 \Big/ (N-1)} = \sqrt{\sum_{i=1}^{N} r_i^2 \Big/ (N-1)}\,, \qquad (8)$$

where the τ_i' are the *N* temperature values interpolated from the linear fits, and $\bar{T}'$ is the mean of those values. Likewise, the empirical standard deviation of the weather noise was calculated as,

$$\pm\sigma_w = \sqrt{\sum_{i=1}^{N}(t_i - \tau_i')^2 \Big/ (N-1)}\,, \qquad (9)$$

These empirical standard deviations were then used to set frequency bin-ranges for the Gaussian fits to the bias temperatures ($r_i = \tau_i' - \bar{T}$) or to the weather noise ($w_i = t_i - \tau_i'$), described below.

Three bins were constructed on each side of the zero mean. Bin-ranges were set to the nearest round-up integer of three times the empirical sample standard deviation (eqns. 8 and 9), allowing a statistical spread of $\pm 3\sigma_{r,w}$. The bin-points were centered in each of the six standard deviation windows and are near $\pm 0.5\sigma$, $\pm 1.5\sigma$, and $\pm 2.5\sigma$. The standard deviations of the Gaussian fits estimate the resolution uncertainty, $\pm\sigma_r$, or the uncertainty due to weather noise, $\pm\sigma_w$, respectively, derived from the B06 model.

Figure 2 shows Gaussian fits to the frequencies of the bias temperature point-scatter and weather noise for 1998 September data from the NTUA surface station in Athens, Greece. The standard deviation of the bias temperatures reflects the spurious systematic error created by the B06 statistical model.

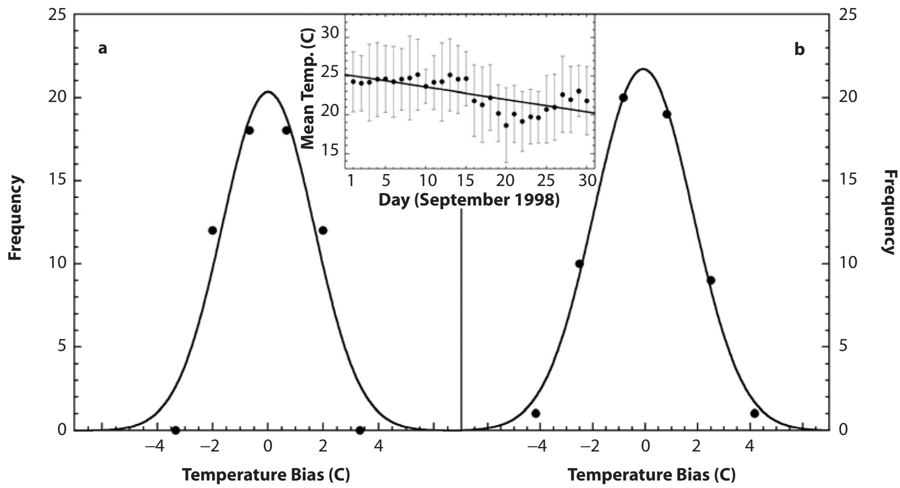

Figure 2: Gaussian fits to the binned frequency of occurrence of: a. bias temperature values ($r^2 = 0.925$), and; b. weather noise excursions ($r^2 = 0.994$), for 1998 September at the National Technical University of Athens, Athens, Greece. Inset: (•), 1998 September daily mean temperature, with Tmin and Tmax (vertical bars). The line is a linear least squares fit ($y = 25.2\text{-}0.16x;\ r^2 = 0.484$).

From Figure 2a, $1\sigma_r = \pm 1.7\pm 0.2$ C, representing the apparent resolution limit. Weather noise (± 1.88 C, Figure 2b) was treated as stationary, and for 60 measurements $\pm\sigma_w = \pm 1.88/\sqrt{60} = \pm 0.2\,C$. When these uncertainties were combined as their r.m.s. average, the 1998 September mean temperature for Athens, Greece was 22.7±1.7 C. The surface station at the National Technical University of Athens is excellently maintained and this uncertainty is therefore close to ideal with respect to non-systematic or faulty equipment error. Note that the final contribution from random weather noise for September 1998 is approximately 7× larger than the generalization of noise error allowed in B06. The model-induced resolution uncertainties in monthly temperature would not diminish in constructing a yearly average temperature anomaly [2].

The 1998 October temperature data from all seven surface stations, Table 1, display analogously large point scatter uncertainties. The aggregate mean temperature for October 1998 from these seven stations was 14.7 C, with an average magnitude uncertainty $\pm\overline{s} = \pm 6.5\,C$. The aggregated r.m.s. measurement uncertainty is $\overline{\sigma} = \pm 2.7\,C$, which does not subtract away when calculating an anomaly [17, p. 43]. The large magnitude uncertainty, $\pm\overline{s}$, indicates heterogeneity and that the mean temperature is a poor measure of the state of the system [18]. This caution should be applied to the significance of global average surface air temperature anomalies (see Section 4).

Figure 3 shows the 30-year average October temperature series from Anchorage, Alaska. Comparison of Figure 3 with Figure 2 shows that weather noise has almost completely averaged away in the 30-year data, consistent with the assumed stationarity. Similar results were found in 9-year averaged May temperatures from

Table 1: Gaussian Fits to October 1998 Binned Bias Temperatures and Weather Noise

Surface	October	Point Scatter			Weather Noise		
Station	Mean (C)	Mean (C)	$\pm\sigma$ (C)	r^2	Mean (C)	$\pm\sigma$ (C)	r^2
Nivala[a]	4.0	0.0±0.4	3.6±0.4	0.940	0.00±0.02	3.38±0.02	0.9999
KPHL[b]	14.7	–0.1±1.1	6.4±1.1	0.889	0.3±0.6	2.9±0.6	0.875
NTUA[c]	18.3	0.1±0.8	5.7±0.8	0.930	–0.13±0.09	2.14±0.09	0.994
Fair Isle[d]	8.0	0.06±0.29	2.4±0.3	0.943	–0.01±0.12	1.6±0.1	0.978
Kahhoolawe[e]	22.3	0.1±0.2	2.0±0.3	0.958	–0.08±0.04	0.48±0.05	0.980
HRP[f]	15.8	–0.6±0.7	3.3±1.0	0.870	–0.01±0.08	3.09±0.08	0.997
Vanwyksvlei[g]	19.7	–0.1±2.1	11.8±2.2	0.870	0.7±0.4	3.5±0.4	0.953

a. Finland; b. Philadelphia, PA, USA; c. National Technical University, Athens, Greece; d. Scotland; e. Kahoolawe, HI, USA, COOP 512558; f. Henderson River Park 1423 A64863, New Zealand; g. Vanwyksvlei 0193561A8, South Africa. See the Supporting Information for station details.

Kahoolawe, Hawaii (not shown). The non-zero trend in Figure 3, inset, tests and invalidates the B06 model prediction that a monthly temperature trend should have zero slope in the absence of weather noise. The uncertainty in the 30-year average trend at Anchorage will be found in the distribution of the 30 individual monthly slopes about the mean slope, and not by the vertical bars in Figure 3, inset.

Supporting Information Tables S1-S4 show the large systematic errors produced in all the 1998 monthly temperature means by the B06 signal-averaging model. The aggregate uncertainties in annual means were: Nivala, Finland, ±5.8 C; Kahoolawe, Hawaii, ±2.9 C; Henderson Park, New Zealand ±5.4 C, and; Vanwyksvlei, South Africa, ±9.3 C. Presently, there is no reason to suppose these large uncertainties do not reflect general outcomes. The total uncertainty in the combined 1998 average temperature was ±6.3 C. Under the B06 model, such uncertainties must be carried into any index of global average surface air temperature anomalies. When including both weather noise and point-scatter, the uncertainty imposed by the B06 statistical model is likely to be ~±4-10× larger than the nominal 20^{th} century global average surface air temperature anomaly increase of 0.7 C. It is clear, therefore, that the 'constant mean plus weather noise' measurement model is unable to sustain the prior uncertainty claim of ~±0.2 C in the global average surface air temperature anomaly trend.

Doubtless, it is unreasonable to interpret physically real monthly temperature trends as systematic error and point-scatter. However, the interpretative physical

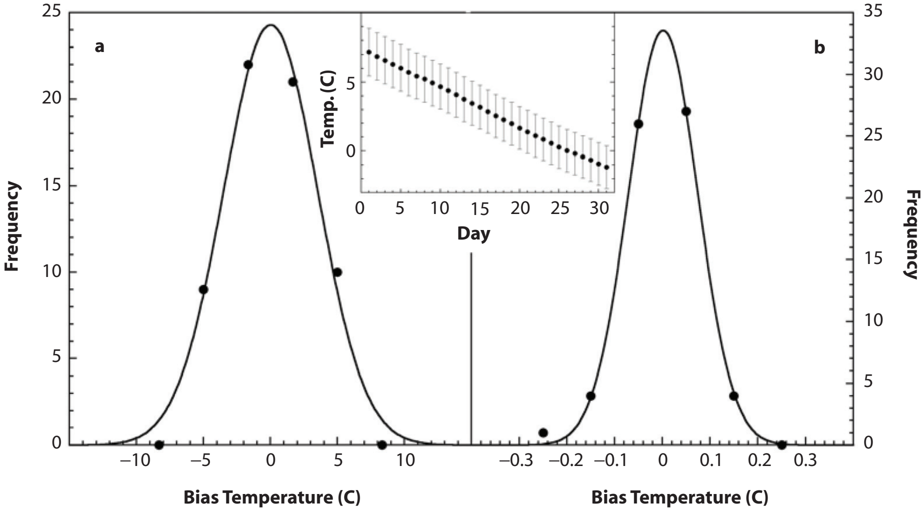

Figure 3: Thirty-year (1971-2000) average October temperatures for Anchorage, Alaska, showing Gaussian fits to frequencies of: a. the $\tau_i' - \bar{T}'$ bias temperatures, and; b. the residual weather noise. The fit values were (mean (C), σ (±C), r^2): a. 0.01±0.22 3.5±0.2, 0.987, and; b. 0.002±0.001, 0.073±0.002, 0.999. Inset: (•), The 30-year average daily October temperatures. The vertical bars show the mean values of Tmax and Tmin.

context here is necessarily confined within the commonly accepted B06 'constant mean plus weather noise' statistical model under examination. Within this model there is no climate process that allows systematic non-zero monthly temperature trends, because the available physics is exhausted by a constant monthly temperature plus weather noise. When any further external cause is excluded, only uncontrolled internal variables remain as major determinants of the bias temperature trend. A complete analysis of any model requires exhausting the implicate consequences. Thus, the full meaning of the B06 statistical model imposes very large artefactual uncertainties on averaged air temperatures. However, these large artefactual uncertainties in surface air temperature measurements are entirely avoidable [2].

4. MAGNITUDE UNCERTAINTY IN GLOBAL AVERAGE SURFACE AIR TEMPERATURE ANNUAL ANOMALIES

Finally, the neglected magnitude uncertainty, ±*s*, of the temperature anomaly normals is now assessed. Global average surface air temperature anomalies are commonly referenced to a 30-year mean [19, 20]. The magnitude uncertainty in a 30-year mean annual anomaly normal is the standard deviation calculated from the twelve sets of thirty months. The magnitude uncertainty for each of the twelve sets of monthly anomalies during the 30-year normal period, is,

$$\pm s_n = \sqrt{\sum_{i=1}^{N} (\overline{T}_i - \hat{T}) \Big/ (N-1)}, \tag{10}$$

where $\pm s_n$ is the magnitude uncertainty of any set of homologous months in the normal period, $\overline{T}_i$ is the mean temperature anomaly of that month in the i^{th} year, N is the number of years in the normal period, and $\hat{T}$ is the mean temperature anomaly of the N months. Each monthly standard deviation represents the variability of the monthly mean anomaly during the normal period. The variance of the mean annual normal anomaly is then determined from the monthly anomaly variances.

The magnitude uncertainty of the mean annual anomaly normal used to produce the 20th century global average surface air temperature anomaly trend in B06 is now evaluated using the 1856-2004 data set, as released in May 2005 by the Climate Research Unit (CRU) of the University of East Anglia [21]. The standard deviations of the monthly mean anomalies were calculated over the standard 1961-1990 normal interval using eqn. (10), and the results are shown in Table 2.

Table 2: Magnitude Uncertainties in the 1961-1990 CRU Monthly Normals[a]

Month	$\pm s_n$ (ΔC)	Month	$\pm s_n$ (ΔC)
January	0.194	July	0.128
February	0.212	August	0.133
March	0.199	September	0.126
April	0.137	October	0.155
May	0.144	November	0.154
June	0.132	December	0.200

a. May 2005 data set [21].

The magnitude uncertainties from each of the twelve monthly normals were then analogously combined (eqn. 10) to produce a magnitude uncertainty of $\overline{s}_{30} = \pm 0.17\,C$ in an annual mean anomaly normal. This ±0.17 C is the 1σ uncertainty estimating the intrinsic magnitude of variation in the annual mean anomaly normal used to set the zero line for the global average air temperature anomaly trend in the CRU data set. Over the entire 1856-2004 interval, the annual anomaly magnitude uncertainty is $\overline{s}_{149} = \pm 0.28\,C$.

The meaning of the magnitude uncertainty in an annual thirty-year global anomaly normal is that it estimates the magnitude width in the global mean annual temperature anomaly index due to spontaneous fluctuations in climate during the normal period. The global mean annual temperature anomaly statistic itself should fluctuate spontaneously within this magnitude width, presuming there is no significant change in the underlying forcings and feedbacks that drive climate phases. Formal realization of this meaning requires ~±0.1 C accuracy in the composite anomaly magnitudes. However, in practice this requirement is unlikely to have been met [2].

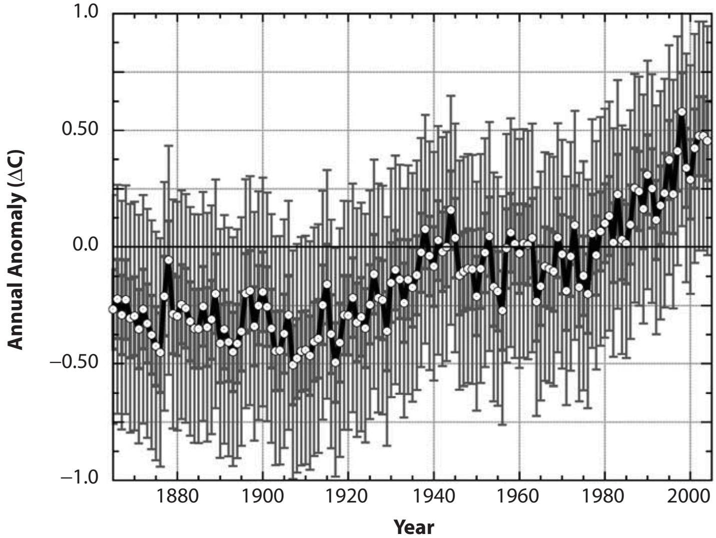

Figure 4: (–o–), The May 2005 global average air temperature anomaly trend as provided by the CRU of the University of East Anglia [21]. The 1σ uncertainty bars: (dark grey), the ±0.17 C magnitude uncertainty, and; (light grey), ±0.49 C, which is the magnitude uncertainty combined in quadrature with ±0.46 C, the previously reported [2] representative lower limit of uncertainty in annual surface air temperature amomalies.

When the normal of the global mean annual temperature anomaly is subtracted from each individual global mean annual temperature anomaly, in order to normalize an annual anomaly trend about zero, the magnitude uncertainty must be propagated into the total uncertainty of each annual anomaly in the normalized trend [2, 17]. The impact of the ±0.17 C magnitude uncertainty itself on the annual anomaly trend is shown in Figure 4 as dark grey uncertainty bars. At the 95% confidence interval, the magnitude uncertainty alone discounts about 42% of the 149-year global surface air temperature anomaly trend of ~0.8 C.

The larger light grey uncertainty bars in Figure 4 show the effect of combining the magnitude uncertainty with the previously reported ±0.46 C representative lower limit of measurement uncertainty in an annual global air temperature anomaly [2]. Combining these uncertainties in quadrature yielded $1\sigma = \pm 0.49$ C. The 95% confidence interval of these two uncertainties alone equals ±0.98 C, discounting the entire global surface air temperature anomaly trend between 1856 and 2004. That is, from the perspective of uncertainty statistics, the dark line running along the zero axis in Figure 4 is as informative about Earth's 20th century thermal history as is the temperature anomaly trend itself.

5. CONCLUSION

Analysis of the statistical protocol commonly used to estimate uncertainty in the global average surface air temperature anomaly index shows it to be fatally flawed. It should be discarded in favor of one that explicitly reflects the lack of knowledge concerning the error variances in surface climate station temperature measurements. The magnitude uncertainty in the normals period of the global mean air temperature anomaly has rarely been evaluated. This temperature magnitude uncertainty represents the minimal variability one may expect in mean annual temperature over a given climate regime, presuming that the normals period is representative. Assuming the 1961-1990 normals period is representative, then ±0.51 C captures 99.7% of the 20th century global average air temperature variability. If the global climate has been in a single phase over the interval 1856-2004, then ±0.84 C captures 99.7% of the intrinsic climatological air temperature variability of the 20th century. These considerations imply that most or all of the variation in global average temperature observed over the 20th century can most parsimoniously be assigned to spontaneous climate fluctuations that also display the pseudo-trends reflecting persistence [22-25]. It appears that there is no particular evidence for an alarming causative agent in the 20th century global average surface air temperature trend. Therefore policies aimed at influencing this trend are empirically insupportable.

ACKNOWLEDGEMENTS:

Free provision of 1998 temperature data sets by Prof. Demetris Koutsoyiannis (NTUA, Athens), by the Finnish Meteorological Institute (Nivala station), by the National Institute of Water & Atmospheric Research Ltd, New Zealand (Henderson Park), by The South African Weather Service (Vanwyksvlei), by Mr. David Wheeler (UK Met office, Fair Isle, Scotland), and Dr. Gary Szatkowski (NOAA, Philadelphia KPHL 011028) are all gratefully acknowledged.

REFERENCES

1. Brohan, P., Kennedy, J.J., Harris, I., Tett, S.F.B. and Jones, P.D., Uncertainty estimates in regional and global observed temperature changes: A new data set from 1850, J. Geophys. Res., 2006, 111 D12106 1-21; doi:10.1029/2005JD006548; see http://www.cru.uea.ac.uk/cru/info/warming/.
2. Frank, P., Uncertainty in the Global Average Surface Air Temperature Index: A Representative Lower Limit, Energy & Environment, 2010, 21 (8), 969-989.
3. Willard, H.H., Merritt Jr., L.L., Dean, J.A. and Settle Jr., F.A., Instrumental Methods of Analysis, 7th edn., Wadsworth, Belmont, CA 1988.
4. Eisenhart, C., Expression of the Uncertainties of Final Results, Science, 1968, 160 1201-1204.
5. Rukhin, A.L., Weighted means statistics in interlaboratory studies, Metrologia, 2009, 46 323-331; doi: 10.1088/0026-1394/46/3/021.
6. Runnalls, K.E. and Oke, T.R., A Technique to Detect Microclimatic Inhomogeneities in Historical Records of Screen-Level Air Temperature, J. Climate, 2006, 19 (6), 959-978.
7. Hubbard, K.G., Lin, X., Baker, C.B. and Sun, B., Air Temperature Comparison between the MMTS and the USCRN Temperature Systems, J. Atmos. Ocean. Technol., 2004, 21 1590-1597.

8. Lin, X. and Hubbard, K.G., Sensor and Electronic Biases/Errors in Air Temperature Measurements in Common Weather Station Networks, J. Atmos. Ocean. Technol., 2004, 21 1025-1032.

9. Aunon, J.I., McGillum, C.D. and Childers, D.G., Signal Processing in Evoked Potential Research: Averaging and Modeling, CRC Crit. Rev. Bioeng., 1981, 5 (4), 323-367; cf. eqs. 10-18.

10. Leski, J., New Concept of Signal Averaging in the Time Domain, in, Nagel, J.H. & Smith, W.M., eds. Vol. 13: Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc., IEEE, Orlando, FL, 1991, pp. 367-369.

11. Kauppinen, J.K., Optimum Instrumental Resolution in Condensed Phase Infrared Spectroscopy, Appl. Spectrosc., 1984, 38 (6), 778-781.

12. Mark, H. and Workman jr., J., Statistics in Spectroscopy, 2nd edn., Elsevier; cf. Chapter 11, Amsterdam 2003.

13. Artz, R., Ball, G., Behrens, K., Bonnin, G.M., Bower, C.A., Canterford, R., Childs, B., Claude, H., Crum, T., Dombrowsky, R., Edwards, M., Evans, R.D., Feister, E., Forgan, B.W., Hilger, D., Holleman, I., Hoogendijk, K., Johnson, M., Klapheck, K.-H., Klausen, J., Koehler, U., Ledent, T., Luke, R., Nash, J., Oke, T., Painting, D.J., Pannett, R.A., Qiu, Q., Rudel, E., Saffle, R., Schmidlin, F.J., Sevruk, B., Srivastava, S.K., Steinbrecht, W., Stickland, J., Stringer, R., Sturgeon, M.C., Thomas, R.D., Van der Meulen, J.P., Vanicek, K., Wieringa, J., Winkler, P., Zahumensky, I. and Zhou, W., WMO GUIDE TO METEOROLOGICAL INSTRUMENTS AND METHODS OF OBSERVATION: Part 1. MEASUREMENT OF METEOROLOGICAL VARIABLES, World Meteorological Organization, Geneva 2008 http://www.wmo.int/pages/prog/www/IMOP/publications/CIMO-Guide/CIMO_Guide-7th_Edition-2008.html.

14. Popper, K.R., Conjectures and Refutations: the growth of scientific knowledge, Harper Torchbooks, New York 1965.

15. Miller, D., Critical Rationalism, Open Court, Chicago 1994.

16. Frank, P. and Ray, T.H., Science is not Philosophy, Free Inquiry, 2004, 24 (6), 40-42.

17. Bevington, P.R. and Robinson, D.K., Data Reduction and Error Analysis for the Physical Sciences, 3rd edn., McGraw-Hill, Boston 2003.

18. Esper, J. and Frank, D., The IPCC on a heterogeneous Medieval Warm Period, Climatic Change, 2009, 94 267-273; doi: 10.1007/s10584-008-9492-z.

19. Hansen, J., Ruedy, R., Glascoe, J. and M. Sato, M., GISS analysis of surface temperature change, J. Geophys. Res., 1999, 104 (D24), 30997–31022.

20. Jones, P.D., Hemispheric Surface Air Temperature Variations: A Reanalysis and an Update to 1993, J. Climate, 1994, 7 (11), 1794-1802; doi: 10.1175/1520-0442(1994)007<1794:HSATVA>2.0.CO;2.

21. Jones, P.D., Osborn, T.J., Briffa, K.R. and Parker, D.E., Global Monthly and Annual Temperature Anomalies (degrees C), 1856-2004 (Relative to the 1961-1990 Mean), CRU, University of East Anglia, and Hadley Centre for Climate Prediction and Research,

http://cdiac.ornl.gov/ftp/trends/temp/jonescru/global.txt, Last accessed on: 27 November 2010.

22. Koutsoyiannis, D., The Hurst phenomenon and fractional Gaussian noise made easy, Hydrolog. Sci. J., 2002, 47 (14), 573-595.

23. Fatichi, S., Barbosa, S.M., Caporali, E. and Silva, M.E., Deterministic versus stochastic trends: Detection and challenges, J. Geophys. Res., 2009, 114 (D18), D18121.

24. Koutsoyiannis, D. and Montanari, A., Statistical analysis of hydroclimatic time series: Uncertainty and insights, Water Resour. Res., 2007, 43 (5), W05429.

25. Koutsoyiannis, D., A random walk on water, Hydrol. Earth Syst. Sci., 2010, 14 (3), 585-601.

Supporting Information For "Imposed And Neglected Uncertainty In The Global Average Surface Air Temperature Index," by Patrick Frank

I. UNCERTAINTY IN MEAN TEMPERATURES ENTRAINED BY THE B06 SIGNAL-AVERAGING MODEL.

In the Tables below, "Sample" is the empirical standard deviation, and "Parent" is the standard deviation from the Gaussian fit, of correlation "r^2." Column "RMS" = $\frac{\textit{weather noise sample}\ \sigma}{\sqrt{2n}}$, where n = days per month.

Row "RMS mean" = $\sqrt{\frac{\sum_{i=1}^{N} \sigma_i^2}{N-1}}$, where σ_i^2 = monthly variance, and N = months per year. Climate station provenances follow the Tables.

Table S1: Uncertainty in 1998 Mean Monthly Temperature for Nivala, Finland

Month	Mean Measurement σ (±C)			Weather Noise σ (±C)			
	Sample	Parent	r^2	Sample	RMS	Parent	r^2
January	3.63	4.24±1.02	0.809	6.09	0.77	5.78±0.79	0.987
February	8.30	9.75±1.22	0.938	6.35	0.85	6.58±0.36	0.989
March	7.13	8.90±1.14	0.936	4.50	0.57	4.10±0.44	0.963
April	9.33	10.94±1.19	0.955	3.09	0.40	3.31±0.68	0.862
May	5.26	3.39±1.34	0.803	3.58	0.45	2.88±0.43	0.922
June	5.20	6.45±0.93	0.921	3.61	0.47	4.21±0.30	0.980
July	4.87	6.24±0.90	0.919	2.70	0.34	2.57±0.22	0.979
August	4.10	4.84±0.84	0.897	1.87	0.24	1.69±0.14	0.982
September	5.05	6.43±0.86	0.931	3.80	0.49	3.59±0.38	0.966
October	2.84	3.65±0.45	0.940	3.01	0.38	3.79±0.02	0.9999
November	2.31	2.97±0.47	0.900	4.63	0.60	4.47±0.43	0.967
December	4.27	4.14±0.87	0.852	5.53	0.70	6.29±0.82	0.939
RMS mean	5.82	6.80	—	4.47	0.57	4.54	—

Table S2: Uncertainty in 1998 Mean Monthly Temperature for Kahoolawe, Hawaii

Month	±Mean Measurement σ (±C)			±Weather Noise σ (±C)			
	Sample	Parent	r^2	Sample	RMS	Parent	r^2
January	3.28	3.65±0.77	0.861	0.93	0.12	0.98±0.07	0.981
February	3.08	3.13±0.51	0.925	1.17	0.16	1.14±0.06	0.991
March	3.16	2.18±0.76	0.838	1.25	0.16	1.23±0.08	0.988
April	2.78	2.72±0.06	0.999	0.74	0.10	0.83±0.09	0.973
May	2.68	2.96±0.24	0.978	0.72	0.09	0.79±0.03	0.998
June	2.31	2.97±0.47	0.900	0.58	0.07	0.54±0.02	0.995
July	2.65	1.62±0.74	0.765	0.72	0.09	0.75±0.04	0.995
August	2.89	1.94±0.45	0.942	0.82	0.10	0.72±0.15	0.890
September	2.81	0.79±0.02	0.999	0.68	0.09	0.56±0.02	0.997
October	2.54	2.01±0.30	0.958	0.56	0.07	0.48±0.05	0.980
November	2.24	2.66±0.32	0.948	0.70	0.09	0.80±0.05	0.990
December	2.47	2.38±0.23	0.974	0.84	0.11	0.76±0.08	0.973
RMS mean	2.88	2.64	—	0.87	0.11	0.86	—

Table S3: Uncertainty in 1998 Mean Monthly Temperature for Henderson River Park, New Zealand

Month	±Mean Measurement σ (±C)			±Weather Noise σ (±C)			
	Sample	Parent	r^2	Sample	RMS	Parent	r^2
January	6.14	7.52±1.26	0.898	2.70	0.34	2.96±0.28	0.969
February	6.43	7.95±1.12	0.926	2.28	0.30	2.38±0.17	0.983
March	5.29	7.00±1.28	0.870	2.56	0.33	2.76±0.21	0.977
April	5.11	5.19±0.32	0.988	3.24	0.42	3.47±0.45	0.943
May	4.59	2.83±1.30	0.765	2.83	0.36	2.01±0.29	0.944
June	4.25	5.09±0.53	0.958	3.97	0.51	4.27±0.30	0.982
July	4.03	2.70±0.50	0.972	2.60	0.33	2.94±0.26	0.968
August	4.81	4.45±0.44	0.974	2.86	0.36	2.61±0.19	0.984
September	5.46	6.85±0.99	0.921	2.25	0.29	2.08±0.19	0.973
October	4.79	3.31±1.04	0.870	2.76	0.35	3.09±0.08	0.997
November	5.44	3.75±1.22	0.859	2.28	0.29	2.80±0.31	0.951
December	5.44	6.89±0.93	0.930	2.21	0.28	2.37±0.10	0.993
RMS mean	5.42	5.85		2.88	0.36	3.00	

Table S4: Uncertainty in 1998 Mean Monthly Temperature for Vanwyksvlei, South Africa

Month	±Mean Measurement σ (±C)			±Weather Noise σ (±C)			
	Sample	Parent	r^2	Sample	RMS	Parent	r^2
January	8.73	5.72±2.26	0.803	3.18	0.40	2.94±0.16	0.990
February	8.18	7.52±2.30	0.783	2.91	0.39	3.35±0.25	0.977
March	8.09	9.86±1.10	0.952	3.23	0.41	3.12±0.48	0.929
April	9.28	12.21±2.17	0.877	3.25	0.41	3.07±0.53	0.902
May	8.79	9.56±2.19	0.843	4.24	0.54	4.30±1.36	0.735
June	10.65	8.09±1.33	0.962	3.16	0.40	2.20±0.26	0.977
July	8.38	11.47±2.60	0.807	3.99	0.51	5.60±1.09	0.830
August	8.99	12.10±2.44	0.843	4.35	0.55	3.58±0.92	0.801
September	9.16	6.06±222	0.824	3.42	0.43	3.60±0.66	0.891
October	8.86	11.81±2.16	0.870	3.60	0.46	3.50±0.41	0.953
November	8.93	11.77±2.09	0.877	4.18	0.53	4.53±0.39	0.973
December	8.45	10.54±1.42	0.930	2.44	0.31	2.80±0.56	0.868
RMS mean	9.29	10.43	—	3.70	0.47	3.82	—

II. SURFACE STATION PROVENANCES

Anchorage WSCMO AP, Alaska, station 500280; Latitude 61° 10' N, Longitude 150° 01' E, elevation 33.5 m. The 30-year average temperature data are freely available from http://www.wrcc.dri.edu/cgi-bin/cliMAIN.pl?akanch.

Kahoolawe 499.6, COOP number 512558; Latitude 20° 33' 25" N, Longitude 156° 34' 30" W, elevation 366 m. The temperature data for 1998 were purchased from the U.S. Western Regional Climate Center, Desert Research Institute, DRI; http:// www.dri.edu/. Nine-year average of daily May temperatures: Kahoolawe 499.6 512558-7, Hawaii, Latitude 20° 33' N, Longitude 156° 35' E, elevation 365.8 m. The full record nominally covers 1989 to 1999, but the nine years averaged were not specified. The data are available at http://www.wrcc.dri.edu/cgi-bin/cliMAIN.pl?hi2558.

Nivala Station 4302, Finland; Latitude 63°55'12" N, Longitude 24°57'36" E, elevation 69 m. The temperature data for 1998 Nivala were kindly provided by Dr. Niina Niinimäki, Niina.Ylimaki@fmi.fi, Finnish Meteorological Institute Climate Service, FMI.

Philadelphia: National Weather Service, NOAA, Mt. Holly, NJ. Station KPHL 011028; Latitude 39° 52' 5" N, Longitude 75° 14' 55" W, elevation 9 m. The original data are available at http://www.erh.noaa.gov/phi/climat/1998/101998l.htm.

National Technical University, Athens, Greece. NTUA; Latitude 37°58'26" N, Longitude 23°47'16" E, elevation 219 m. These data were kindly provided by Prof. Demetris Koutsoyiannis, dk@itia.ntua.gr.

Fair Isle Weather Station; Latitude 59° 32' N, Longitude 1° 38' W, elevation 61 m. Climate data are freely available from Mr. David Wheeler at Fair Isle weather station: http://www.zetnet.co.uk/sigs/weather/index.html.

Henderson River Park 1423 A64863; Latitude 36° 51' 19.4" S, Longitude 174° 37' 25.8" E, elevation 7 m. These data were provided by the National Institute of Water & Atmospheric Research Ltd, NIWA, New Zealand; http://www.niwa.cri.nz/.

Vanwyksvlei 0193561A8, Latitude 30° 21' 0" S, Longitude 21° 49' 12" E, elevation 962 m. These data were kindly provided by Ms. Charlotte McBride, Charlotte.McBride@weathersa.co.za, of the South African Weather Service.