NEGLIGENCE, NON-SCIENCE, AND CONSENSUS CLIMATOLOGY

by

Patrick Frank (USA)

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Patrick Frank
Palo Alto, CA , USA.
Email: pfrank830@earthlink.net

ABSTRACT
The purported consensus that human greenhouse gas emissions have causally dominated the recent climate warming depends decisively upon three lines of evidence: climate model projections, reconstructed paleo-temperatures, and the instrumental surface air temperature record. However, CMIP5 climate model simulations of global cloud fraction reveal theory-bias error. Propagation of this cloud forcing error uncovers a r.s.s.e. uncertainty $1\sigma \approx \pm 15$ C in centennially projected air temperature. Causal attribution of warming is therefore impossible. Climate models also fail to reproduce targeted climate observables. For their part, consensus paleo-temperature reconstructions deploy an improper 'correlation = causation' logic, suborn physical theory, and represent a descent into pseudo-science. Finally, the published global averaged surface air temperature record completely neglects systematic instrumental error. The average annual systematic measurement uncertainty, $1\sigma = \pm 0.5$ C, completely vitiates centennial climate warming at the 95% confidence interval. The entire consensus position fails critical examination and evidences pervasive analytical negligence.

Keywords: Climate, systematic error, GCM, proxy, air temperature, pseudoscience

1. INTRODUCTION

The modern concern about human-caused global warming dates approximately from the 1979 Charney Report to the US National Research Council. [1] The Charney committee described how carbon dioxide (CO_2) and other greenhouse gas (GHG) emissions may influence climate, but did not acknowledge the contemporary scientific debate about the magnitude of any effect. [2-10] In 1989, the US Environmental Protection Agency warned of myriad disasters to ostensibly follow CO_2 emissions; [11] a pessimism that has commandeered the modern consensus. [12, 13]

The consensus that human CO_2 emissions are dangerous rests upon three central elements of contemporary climatology: the climate modeling that imputes physical causality into recent air temperature trends, proxy reconstructions of paleo air temperatures, and the instrumental record that provides the surface air temperatures.

Results from all three have been combined to conclude that the rise in global averaged surface air temperature (GASAT) since about 1880 is unprecedented, is dangerous, and is caused by industrial GHG emissions. [12-16]

In this paper, climate models, proxy paleo-temperature reconstructions, and the surface air temperature record are critically examined in turn. They are each and all found to neglect physical error, or in the case of consensus paleo-temperature reconstructions to neglect physics itself. The normative certainties flourish on this neglect.

2. RESULTS AND DISCUSSION

2.1 General Circulation Models

On 23 June 1988 the US Senate Committee on Energy and National Resources hosted testimony on, "The Greenhouse Effect and Climate Change." Figure 1a shows a central element of this testimony: three alternative GASAT projections extending to the year 2020, simulated using the Goddard Institute for Space Studies (GISS) climate Model II. In scenario "A," surface air temperature was driven by a future rate of global CO_2 emission that was increased beyond the 1988 rate, in "B" the 1988 rate continued unabated, and in "C" the 1988 rate was drastically curtailed. Since then, whether the GISS Model II scenario B correctly predicted the post-1988 global air temperature trend has been a matter of discussion. [17-20]

Figure 1a, as it was presented to Congress and as it appeared in the original peer-reviewed paper, has no uncertainty bars. [21] However, "*even in high school physics, we learn that an answer without "error bars" is no answer at all.*" [22] The missing part of the GISS Model II answer is described next.

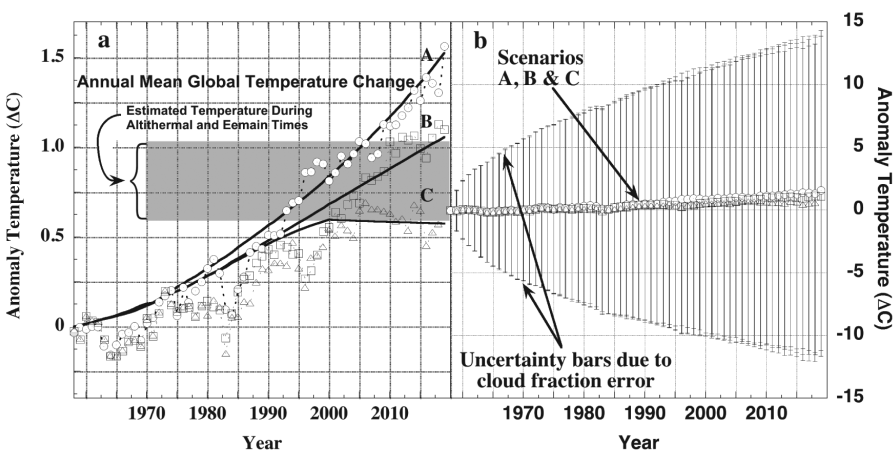

Figure 1: a. (points), the GISS Model II projections of future global averaged surface air temperature anomalies for scenario A, B, and C as presented in 1988 (see text). [21, 34] The lines were calculated using eq. 1 and the original forcings but without volcanic explosions (F_{CO2} = 0.42; F_0 = 33.946 Wm^{-2}). b. confidence intervals (CIs) obtained using eq. 1 to propagate the ±4 Wm^{-2} annual average CMIP5 tropospheric cloud forcing error through the same projected scenarios (see 2.1.3). [30]

2.1.1 Cloud error

It is very well known that climate models only poorly simulate global cloud fraction, [23-27] among other observables. [28] This simulation error is due to incorrect physical theory. [29, 30] Cloud error due to theory-bias means the models incorrectly partition the amount and distribution of energy in the atmosphere. This in turn means the air temperature is modeled incorrectly. The incorrectly simulated cloud fraction of state-of-the-art CMIP5 climate models produces an average annual theory-bias error in tropospheric thermal energy flux of ±4 Wm^{-2}, [27] which magnitude has not materially diminished between 1999 and 2012. [27, 29-33]

2.1.2 Theory-bias cloud error is a continually refreshed initial conditions error.

Climate is projected through time in a step-wise fashion. Each modeled time-step provides the initial conditions for the subsequent step. Because of theory-bias error, each calculational step delivers incorrectly calculated climate magnitudes to the subsequent step, so that every step initializes with incorrect magnitudes. These incorrect magnitudes are then further extrapolated, but again incorrectly. In a sequential calculation, calculational error builds upon initial error in every step, and the uncertainty accumulates with each step. [29, 30] However, no published model projection of terrestrial air temperatures has ever discussed or included propagated error. [30]

2.1.3 The propagated uncertainty due to theory-bias cloud error.

The GASAT anomaly projections of general circulation climate models (GCMs) can be accurately simulated using the linear equation:

$$\Delta T = f_{CO_2} \times 33K \times [(F_0 + \sum_{i=1}^{n} F_i) \Big/ F_0] \ , \qquad (1)$$

where ΔT is the GASAT anomaly (K), f_{CO_2} varies among GCMs and is the fraction of greenhouse warming due to water-vapor enhanced CO_2 forcing, *33 K* is the net unperturbed terrestrial surface greenhouse temperature, F_0 is the total GHG forcing of the zeroth projection year, and F_i is the annual change in GHG forcing in each of "*n*" projection years. [30, 35] The success of this equation shows that climate models project air temperature as a linear extrapolation of GHG forcing. [30] In a sequential linear calculation, the final uncertainty is the root-sum-square of the step-wise errors. [36-38] In a linear air temperature projection, the running total of uncertainty in the simulated GASAT due to theory-bias error is then $\pm\sigma_n^{Temp} = \pm\sqrt{\sum_{i=1}^{n}\varepsilon_i^2}$, where e_i is the error in the i^{th} step, across a simulation of "*n*" steps. It is a standard of physics that predictive reliability is evaluated by propagating error. Entering the average ±4 Wm^{-2} of CMIP5 cloud forcing error into eq. 1 allows calculation of confidence intervals (CI) for the GASAT projection of any climate model.

Figure 1b shows the CI from ±4 Wm^{-2} of thermal flux error propagated through the 1988 GISS Model II global air temperature projections (f_{CO_2} = 0.42). The CI uncertainty increases much faster than the projected GASAT because the ±4 Wm^{-2} of flux error is ±110× larger than the 0.036 Wm^{-2} average annual increase in GHG forcing since 1979. [39]

Scenarios A, B, and C are completely submerged within the strongly overlapping CIs. Therefore, they are not distinguishable. None of them can be tested by comparison against any conceivable trend in global air temperatures. Therefore, they are not falsifiable. As the projections are neither predictive nor falsifiable, they are physically meaningless. Analogous "error bars" will attend any CMIP5 projection. Applying the standard criterion of physics, CMIP5 climate models are predictively unreliable.

2.1.4 Tests of climate model simulations.

Advanced GCMs express the physical theory of climate. All meaning in science derives from a falsifiable theory. The 2007 "Summary for Policymakers," of the UN Intergovernmental Panel on Climate Change (the IPCC) says, "*Most of the observed increase in globally averaged temperatures since the mid-20th century is* ***very likely*** *due to the observed increase in anthropogenic greenhouse gas concentrations*." (original emphasis), where "*very likely*" means more than 90% probable. [40] The IPCC continues, "*There is considerable confidence that climate models provide credible quantitative estimates of future climate change, particularly at continental scales and above*." [13] As the assignment of causality for present and future climate change rests entirely on the physical accuracy of climate model simulations, then clearly the IPCC judges GCMs able to produce accurate and quantitative estimates of future climate changes.

2.1.4.1 Perfect Model Tests.

In a perfect model test, a GCM is used to project a reference climate, and then evaluated by its ability to predict that very same climate. These conditions are most favorable to the model because a GCM is a perfect model of its own reference climate. Typically, the predictive test starts with small offsets of the original initial conditions to mimic imperfectly known input observables.

The CMIP3-level HadCM3 was subjected to a perfect model test in 2002. [41] Figure 2 shows one outcome: the correlation between the predicted and reference air temperatures dropped to ~0.25 after one year. By projection year eight, the correlation was zero.

The dashed line in Figure 2 shows the air temperature predictions of a random persistence model, which compared favorably with the HadCM3 through the nine projection years.

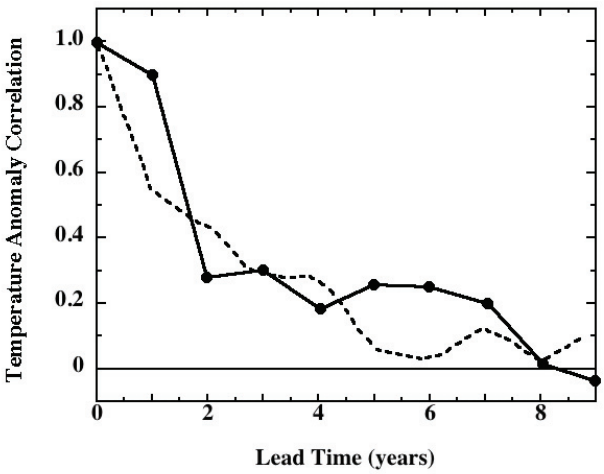

Figure 2. Full line: the HadCM3 perfect model test, re-predicting its own global mean surface air temperature across nine years. Dashed line: the random persistence model. The data are from Figure 6a in [41].

The HadCM3 was also unsuccessful predicting its own global average precipitation, and its own El Niños. Once again, the random persistence model did as well. Nevertheless, the HadCM3 was subsequently employed in the 2007 IPCC 4AR to predict climate futures.

In 2000, a similar perfect model test proved that the Canadian CCCma climate model was unable to predict its own global air temperatures. [42] Both studies concluded that even with perfect climate models, the ability to predict global climate would be non-existent. To this writing, GCMs have invariably failed perfect model reliability tests.

2.1.4.1.1 The general significance of a failed perfect model test.

This insight into the impact of initial-value errors is of general significance because in a step-wise climate projection the magnitudes of each prior climate state provide the initial conditions of the subsequent state. The theory-bias errors of climate models means that prior states are incorrectly represented. Therefore, subsequent states will initialize with incorrect physical variables. Theory bias ensures the erroneous variables will be again projected incorrectly. That is, when theory-bias error is present an initial conditions error of unknown magnitude is propagated into and through every single simulation time-step. The theory-bias initial condition error can never be removed using model equilibration or spin-up, because initial condition errors are sequentially produced and propagated within the model itself at every single simulation step.

2.1.4.1.2 Perfect Model Tests in the IPCC 4AR.

Chapters 8 and 9 of the 4AR discuss the physics of climate and evaluate whether climate models are reliable enough to attribute recent air temperature warming to human GHG emissions. [13, 43] Chapters 10 and 11 make model-based predictions about the effects of GHG emissions on future climate.

IPCC 4AR chapters 8 and 9 should have acknowledged the failed HadCM3 and CCCma perfect model tests. However, they are nowhere mentioned. The author of the 2002 HadCM3 perfect model study is cited 15 times in AR4 chapters 8-11, but the perfect model paper itself is never cited. The reported failure of the CCCma model is also never cited, even though Boer's other work is extensively referenced. The very 4AR chapters that purported to evaluate climate models was completely silent about failed perfect model tests.

In 2008, twenty-one CMIP3-level GCMs were subjected to perfect model tests that included, "*8850 years of simulated data from the control runs of 21 coupled climate models*." [44] These were the very same climate models the IPCC claimed could produce, "*credible quantitative estimates of future climate change*." As perfect models, the CMIP3 GCMs proved able to predict global air temperatures for five years, but not for twenty-five years. Precipitation was immediately unpredictable.

2.1.4.2 Real World Tests.

The 2007 4AR presented CMIP3-level hindcasts of 20th century temperatures and precipitation simulated at the points of a global grid. In a test comparison with known real-world observables, the 20th century hindcasts of six GCMs were evaluated against the known 20th century climate at 58 locations scattered across the globe. [45, 46]

From the four grid-points surrounding each of the 58 locales, a linear combination of the hindcasted trends in temperature or precipitation of the 20th century were fitted to the observational record. For the temperature trends at the four surrounding grid points, *i, j, k, m*, the hindcasted GCM $T_{i,j,k,m}^{GCM}$ were to fitted to the observed local temperature trend, as,

$$T_l^{obs'd} = aT_i^{GCM} + bT_j^{GCM} + cT_k^{GCM} + dT_m^{GCM} \tag{2}$$

where *a, b, c*, and *d* are fitted coefficients and always sum to unity. Eq. 2 describes an iteratively adjusted fit calculated to make a closest possible match to the observed local temperature. Each fit-reconstructed local temperature trend is then,

$$T_l^{fitted} = a_i T_i^{GCM} + b_j T_j^{GCM} + c_k T_k^{GCM} + d_m T_m^{GCM} \tag{3}$$

where a_i, b_j, c_k, d_m represent the final best-fit coefficients. The 20th century trends of T_l^{fitted} and $T_l^{obs'd}$ were then compared. The methodology is valid because measured air temperatures correlate $R \geq 0.5$ across 1200 km. [47-49] If the climate models were reliable, then the outcome should be $T^{fitted} \approx T^{obs'd}$.

Figure 3 shows the results for Vancouver, British Columbia, which warmed by a full degree in the 20 years after 1900, then cooled by 2 degrees for 40 years, and finally warmed again to finish almost where it started. None of the six tested climate models reproduced this variability. Further, although each model used the same physical theory to represent the same climate, the projected trends spread across nearly 2.5 C.

The usual strategy of climate prediction is to represent temperatures as anomalies. The assumption behind this strategy is that climate model error is constant. [50-52] Thus, constructing anomalies should subtract away the errors and uncover a physically reliable temperature change.

The right panel of Figure 3 shows the anomaly trends for Vancouver, BC. Once again, the observed variability of Vancouver's climate is not reproduced. Low-error anomalies should show similar trends. However, the simulation anomalies disagree by nearly a full degree. The inset shows that the HadCM3 anomaly wanders about without any particular correspondence to the observed temperature, as expected from the failed 2002 perfect model test.

Although Vancouver cooled at an average rate of -0.05 C per decade during the 20th century, all the climate models predicted increasing 20th century temperatures (Table 1). These results are typical of the entire study, which found that the 20th century CMIP3 model hindcasts were inaccurate in every region tested.

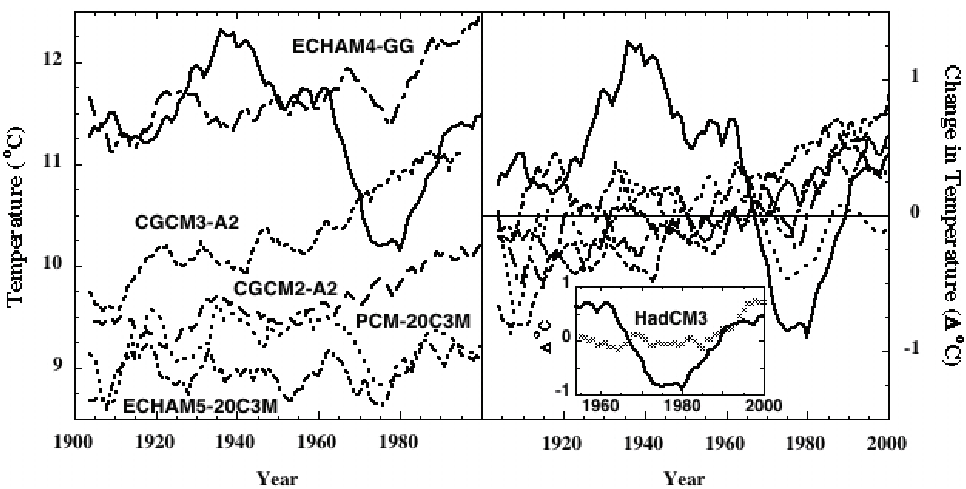

Figure 3: Left panel: (—), the 20th century temperature trend observed at Vancouver, British Columbia. Dashed and dotted lines: the Vancouver hindcasts by five CMIP3 climate models (see labels). Right panel, the 20th century observed and predicted anomaly trends for Vancouver (1951-1980 mean). Right panel inset: HadCM3 hindcast for the years 1950-2000. (11-year smoothing throughout.)

However, the IPCC claim that climate models produce more quantitatively reliable results "*at continental scales and above*." [13] This claim was also tested by extending the CMIP3 comparison to the continental USA. [45, 53] The result was that the hindcasts "*[did] not correspond to reality any better*" on the continental scale than they did at the 58 local scales. [54]

Table 1: Simulated and Observed 20th Century Trends for Vancouver, BC

Data Set	Temperature Trend per Decade (C)	Anomaly % Error[a]
	Years 1900-2000	
Observed	-0.05	---
CGCM2-A2	+0.09	280
CGCM3-A2	+0.15	400
ECHAM4-GG	+0.10	300
ECHAM5-20C3M	+0.03	160
PCM-20C3M	+0.01	120
	Years 1950-2000	
Observed	-0.03	---
HadCM3-A2	+0.11	467

a. *Anomaly % error* = $[(T_{obs} - T_{GCM})/T_{obs}]\times 100$, where T is the anomaly temperature.

The CIs of Figure 1b, the failed perfect model tests (Figure 2), and the failed hindcasts (Figure 3) demonstrate that advanced GCMs are neither predictive nor falsifiable, and are not reliable. Their air temperature projections have no obvious physical meaning. [55] Any attribution of the GASAT increase to human GHG emissions has been and remains without any scientific warrant.

2.2 Proxy paleo-temperature reconstructions

Paleo-temperature reconstruction — paleo-thermometry — estimates the temperature of past climates. As measurements are not available from distant times, the recovery of ancient temperatures requires proxies. Tree-ring series dominate air temperature proxies but proxy series typically include other annually layered temperature-sensitive bio- and geo-structures.

2.2.1 The methodological basis of tree-ring paleo-thermometry.

Trees growing in a sub-optimum thermal climate produce annual growth rings that are narrow and/or of low density. Climates closer to the optimum growth temperature produce trees with relatively thicker or denser annual rings. A relationship of temperature with tree growth is apparent, [56-58] and in principle annual tree rings should record significant transitions of local growth conditions, including those of climate.

Candidate trees used to reconstruct past temperatures are those growing in a cold climate at high latitudes or high altitudes. The candidate trees are judged to be suffering from 'temperature limited' growth, following a qualitative assessment of the surrounding environment. [58-61] This qualitative judgment entrains an untested assumption that temperature stress has continuously dominated the growth of the chosen trees over their mature lifetime. This assumption is absolutely central to the entire method and rests upon the standard argument that the, "*biological bases of tree growth are essentially immutable*." [57]

However, it is known that the genome of every tree confers highly mutable responses to stress. [62-64] This mutability allows individual trees to survive the great variety of environmental challenges, any of which may affect tree ring metrics. The entire field of tree-ring paleo-thermometry is based on an insupportable claim of immutability projected for centuries into the past to support qualitative judgments taken in the present.

To be physically valid, a judgment of temperature-limited growth must be based on a falsifiable physical theory of tree-growth. Such a theory will specify the observables that are dependent upon seasonal temperatures. In addition, the specific extraction of temperatures from tree rings requires a physical relation, i.e., an equation that converts tree ring metrics into degrees centigrade. However, no such theory is in evidence. Nor is any such equation.

Failing those criteria, semi-empirical physics might suffice. For example, controlled environment growth experiments might establish that tree-ring isotope ratios, such as $^{13}C/^{12}C$ or $^{18}O/^{16}O$, are strongly correlated with contemporaneous air temperature. Empirically established correlation equations might permit extracting historical air temperatures from living and dead trees. However, a specific and reliable empirical correlation between air temperatures and tree ring isotope ratios does not yet exist. [65-68]

It is clear, therefore, that tree-ring proxy paleo-temperatures are grounded in judgments that are invariably qualitative. Thus the "temperature" in tree-ring paleo-thermometry has no quantitative physical basis. It reduces to an assigned physical label, "Celsius," that has no physical meaning.

2.2.2 Applied proxy paleo-thermometry.

In any proxy paleo-temperature study, standard statistical methods are applied to time-series metrics obtained from tree rings, corals, speleothems, ice cores, or other physical surrogates. [69-71] External temperature can impact the development of each physical system, and each is therefore termed a temperature proxy.

However, no proxy is grounded in a reliable physical theory. Even climatological ∂O^{18}, the temperature proxy with the best grounding in physical theory, is confounded by the unknown variability in the seasonal strengths and tracks of ancient monsoons. [72, 73] Therefore, proxy series extending from the past into the present are typically validated by statistical comparisons with their local temperature record. [74] Local temperature records generally cover little more than the most recent 130 years. This defines the record length over which any proxy correlation can be tested. Proxy series that correlate with this 130-year range are assumed to be reliable temperature indicators. Temperature indication is then assumed to extend uniformly into the past, using the argument of constant developmental forces.

Tree ring metrics from old dead trees (snags) can be "wiggle-matched" in overlap regions with modern tree-ring series and added in to produce a composite extending back centuries. Wiggle-matching is also used to produce long-term series from other proxies. In the absence of physical theory, and sometimes despite physical theory [75], chosen proxy series are processed statistically, typically normalized to unit standard deviation, and then combined, scaled into coincidence with the 20th century temperature record, and finally awarded the label, Celsius.

The assignment of Celsius takes its entire justification from the prior judgments of temperature-limited development. Various statistical correlations are demonstrated to encourage a grant of confidence that a causal connection exists between proxies and recent local temperatures. Statistics is thus substituted for physics, is used to assign causality, and is made to pose material time series as temperature. In a classic of scientific non-sequiturs, the entire field of consensus proxy paleo-thermometry has decided that correlation equals causation, and also that correlation in the present proves causation in the past. This is physics by fiat.

2.2.3 A promising extension of consensus paleo-science.

Perhaps an analogy can demonstrate the scientific void that is a consensus proxy paleo-temperature reconstruction. To this end, a hypothesis is proposed that is as qualitatively plausible as an expert judgment of temperature limited formation, and that can likewise be justified by the full rigor of consensus statistics. The hypothesis that attains the statistical merit of a consensus proxy paleo-thermometric reconstruction attains the same level of causal meaning.

Beginning with the constancy assumption analogous to consensus proxy-thermometry: to first-order, atmospheric CO_2 should be constant in an unperturbed Holocene climate; an assumption that can be referenced to and supported by published studies. [76, 77]

Following from the foregoing, excursions in an otherwise constant Holocene atmospheric CO_2 imply the intensity of human inputs from agriculture, industry, and use of fire. [43, 78, 79] This supposition can be rationalized into the distant past in a manner directly analogous to the consensus extrapolations of temperature proxies into past times. For example, paleo-atmospheric CO_2 may be impacted by the stunning growth of fire used in paleo-hunting [80, 81], by the historical trend in paleo-slash-and-burn agriculture, [82] and by the documented increase in paleo-ore smelting and lime calcining. [83-87] The spread of farming, [88] also opened virgin paleo-soils to colonization by aerobic CO_2-producing paleo-bacteria. [89, 90]

It is plausible to deduce, therefore, that perturbations in paleo-atmospheric CO_2 may reflect the history and intensity of human paleo-industriousness. [91] Current human industriousness is reflected in Gross Domestic Product (GDP). If a correlation is found to exist between modern CO_2 and modern GDP, then paleo-CO_2 can obviously be used to infer a paleo-GDP. This construct expresses the full analytical rigor of consensus proxy paleo-thermometry, namely that proxy correlations of today immutably extrapolate to the temperatures of yesterday.

Figure 4 displays the relationship between the US Gross Domestic Product (US GDP) and the recent trend in atmospheric CO_2. The first and all-important supposition is clearly verified: US GDP and atmospheric CO_2 display a highly significant correlation (0.995, $P < 0.0001$) over the years 1929 through 2012. Global GDP also produced a very good correlation with CO_2 (1913-2003; R = 0.997, P < 0.0001), thereby exhibiting its own statistical paleo-thermometric-like power. However, only one 20th century world GDP datum is available prior to 1950, [92] severely reducing the methodological calibration and verification ranges.

The plausibility argument plus the strong statistical association establishes as much causality between modern GDP and modern atmospheric CO_2 as there is between modern air temperatures and modern proxy series.

The consensus methodological authority that extends causality deep into the past is calibration and verification of the proxy in the present. The standard approach, [69] is to divide the measurement data into the 'calibration range' and the 'verification range.'

Under this protocol, 1929-1979 was chosen as the US GDP calibration range. The proxy (atmospheric CO_2) was then regressed against the target (US GDP) over the calibration years, producing the calibration line (Figure 4, inset a; US GDP = $0.171\times[CO_2]_{ppmv} - 51.49$). The correlation ($R^2$=0.98, P < 0.0001) is well within the halleluiah norm of consensus paleo-thermometry.

The calibration line must now predict the verification half of the target data (US GDP, 1980-2012). With a successful verification, GDP-CO_2 causality will be demonstrated to the professional rigor of a consensus proxy paleo-temperature reconstruction. One can then just as confidently elaborate the relationship off into past time.

Figure 4 inset b shows that the verification was successful: predicted US GDP correlated with observed US GDP at the 0.99 level. When carried out in reverse, calibrating on 1980-2012 and verifying on 1929-1979, equally good results were

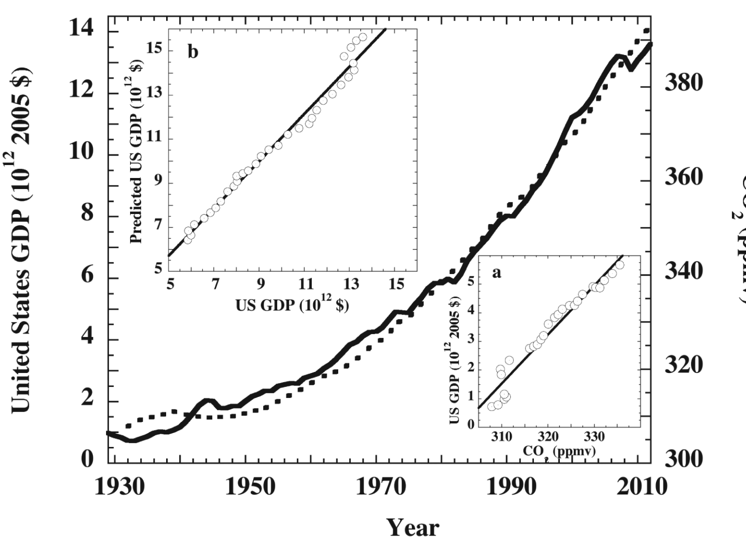

Figure 4. 1929-2012 trend in: (—), United States Gross Domestic Product, and; (····), atmospheric CO_2,; correlation R = 0.995. Inset a: (o), calibration 1929-1979, CO_2 *vs*. US GDP (see text); (—), linear least squares fit. Inset b: (o), verification 1980-2012, observed US GDP *vs*. predicted US GDP; correlation R = 0.99, P<0.0001; (—), linear least squares fit (R^2=0.95).

obtained (calibration R = 0.99, P<0.001; verification R = 0.98, P<0.0001). This correlation equals causation equation thus confers consensus paleo-thermometric stature on the relationship between atmospheric CO_2 and GDP.

This study is now in a strong position to analogize from the widely accepted logic of consensus proxy paleo-thermometry that, '*recent proxies correlate with recent temperatures therefore paleo-proxies measure ancient temperatures*.'

In the bright light of this science, Figure 4 implies just as strongly that, *recent CO_2 correlates with recent GDP, therefore paleo-CO_2 measures ancient GDP*. When the correlation equation is informed with recovered ancient CO_2 anomalies, a paleo-GDP covering past times is reconstructed. Following Mark Twain, [93] it is now possible to extrapolate GDP off into nether historical regions where no measureable GDP can possibly exist.

Announcing the new field of consensus paleo-economics: the intensity of economic activity of past continental-scale societies can now be statistically reconstructed during times when societal GDP went unrecorded. So, for example, the paleo-CO_2 from the ice cores of Alpine glaciers can be used to illuminate and track the paleo-economic activity of most of ancient Europe. Historians of the Roman Empire should note their breakthrough opportunities. [94] The snows of Kilimanjaro record equally well the economic level of the ancient and mysterious (until now) Kingdom of Meroe, and those of Mt. Ararat may as well reveal the economic climate experienced by Noah. Such is consensus proxy paleo-thermometry.

Clearly, the CO_2-GDP paleo-extrapolation is spurious. The global carbon cycle is not known to anywhere near the required resolution, and most importantly the physical theory of terrestrial CO_2 is incomplete. [95-97] These are the same failings that disqualify consensus proxy paleo-thermometry as science. Nevertheless, the methodological rigor of consensus proxy paleo-thermometry is fully in view. This light-hearted parody thus conveys a serious point: statistics is no substitute for physics. Statistical validity does not preclude causal vacuity. Correlation alone ***never*** equals causation. However, the entire purportedly *scientific* case for consensus paleo-thermometry rests upon correlation = causation. This diagnosis follows from the purely statistical methodology.

Even further, it is physically unwarrantable to assume a dominant and constant temperature-reflective response operates across deep time. In the case of tree-ring series, the purely qualitative judgment of temperature sensitivity is quantitatively fatal, and the further assumption of biological constancy is already refuted in the professional literature. [64, 98, 99] Absent any reliable physical theory at any stage of analysis, consensus proxy paleo-thermometry has no physical meaning.

This criticism is not vitiated by the use of principal component analysis (PCA) to extract numerically orthogonal series from proxies that have been qualitatively judged as temperature limited. [69, 100, 101] It is not controversial that the numerically orthogonal constructs of PCA have no distinct physical meaning. [102, 103] They are never known *a priori* to represent any physical magnitude. As far back as 1901, Spearman noted that, "*an estimate of the correlation between two things is generally of little scientific value if it does not depend unequivocally on the nature of the things...*" [104] Qualitative judgments filtered through numerical constructs are no route to physical orthogonality, and mere correlation with temperature does not establish a unique physical meaning.

Even the statistical validity of consensus proxy paleo-temperatures has been questioned, resulting in the following observation:

> "*Natural climate variability is not well understood and is probably quite large. It is not clear that the proxies currently used to predict temperature are even predictive of it at the scale of several decades let alone over many centuries.*" [105, 106]

Thus, the temperature "signal" in a physical proxy is invisible to statistical analysis. In the sense of climate physics, the "signal" is thus far unidentifiable. Consensus proxy-reconstructed global paleo-temperatures are often scaled in tenths of Celsius, e.g., refs. [107-110]. Both attribution and precision are utterly unjustifiable. As presently practiced, consensus proxy paleo-thermometry is pseudo-science. [111]

2.3 The global averaged surface air temperature (GASAT) record

The GASAT record is produced using the monthly temperature records from millions of individual land and sea surface temperatures (SSTs) distributed around the world. [112, 113] Despite that a 'globally averaged temperature' is physically meaningless, [114] it is nevertheless the metric widely accepted as proving that global climate has warmed since 1880. It is also widely agreed that the GASAT has increased by about 0.8±0.2 Celsius. [49, 115] In light of this, little doubt is expressed about the rate and magnitude of atmospheric warming, or that they are statistically significant. Any continued rise in the GASAT is itself taken as a proof that continued emission of GHGs is thermally dangerous.

However, a close examination of the global record reveals that the temperatures themselves have enjoyed a curious and unspoken canonization. That is, the reported monthly magnitudes are always taken at face value. The only argument booted about is whether they pristinely represent climate, or not. It's as though the measured values themselves, whether correct or incorrect, are nevertheless known with perfect accuracy.

Nevertheless, systematic instrumental error is always present because instruments are inevitably imperfect. [116] Systematic error is non-random, and a component of the temperature measurement itself. Solar heating, snow albedo, and variable winds inject instrumental errors into the modern land-based record because they impact the stability and response of temperature sensors. The consequent systematic error has been measured using ideal-condition calibration experiments. [117-120] The error produced by well-maintained and well-sited instruments is the minimal error to be expected under typical field conditions. Likewise, the sea-surface temperature (SST) measured by ships and buoys is also subject to large-scale systematic errors. [121-124] Despite this ubiquity, systematic sensor measurement error is completely neglected in the published record of global averaged surface air temperatures. [125]

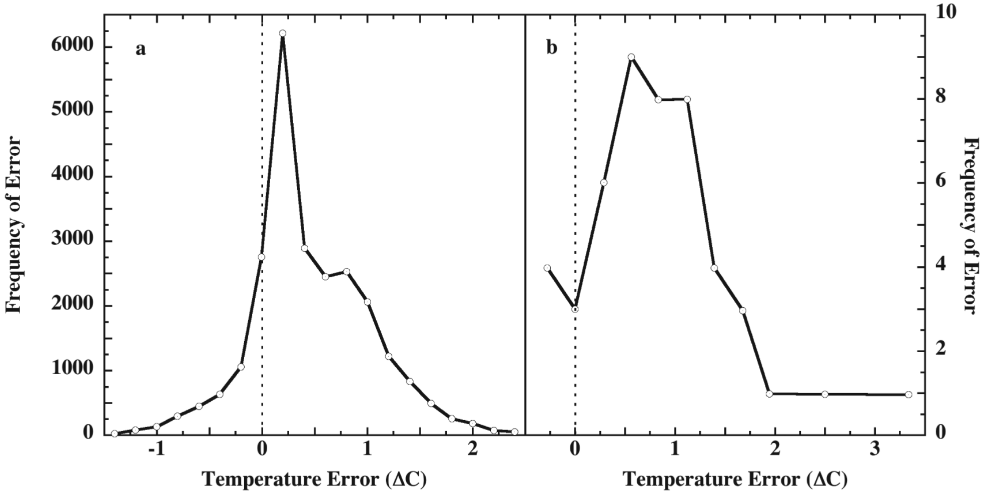

Figure 5: Systematic temperature measurement error found during calibration tests of: a. a platinum resistance thermometer inside a Cotton Regional Shelter (Stevenson Screen), σ = ±0.53 C, [117], and; b. a US military ship-board engine room intake thermometer, σ = ±1.1 C, [122]. The dashed vertical line marks zero error.

Figure 5 shows examples of error profiles in land-surface (5a) and SST (5b) temperature measurements. Figure 5b typifies the error that infects the ship engine-intake data sets, [126] which contribute by far the greatest part of the 20th century SST record.

The minimal uncertainty in an individual land-surface temperature measurement coming from a standard temperature sensor, even while operating under ideal field conditions, has been evaluated as ±0.46 C. [125] Combining this ±0.46 C with the estimated ±0.2 C uncertainty due to site inhomogeneities [115, 127], the root-mean-square (r.m.s.) minimum uncertainty in the averaged global land-surface air temperature is $1\sigma = \pm 0.50$ C.

The SST measurement error profile shown in Figure 5b derived from a study employing twelve US military transport ships engaged off the US central Pacific coast, that included 6826 pairs of observations. The obviously skewed distribution of error in Figure 5b was called, “a typical distribution of the differences” between the measured and the true SST. The full data set over the entire fleet showed a mean bias error of 0.7 C, and $1\sigma_{\text{mean}} = \pm 0.9$ C systematic measurement error.

Land and SST systematic measurement errors have never been factored into the uncertainty reported for the GASAT record. The reason for this neglect is that measurement error is invariably assumed to be random, [115, 128-130] and that the Central Limit Theorem (CLT) applies carte blanche. [126] In brief, the CLT says that the distribution of points taken from an overall random process $X_N = \sum_{i=1}^{N} x_i$ will approach normality at the large N limit no matter the shapes of the data point distributions of the individual subsidiary processes, x_i. [131] When an overall error process is random, the error variance diminishes as σ_ε^2/N, where N is the number of measurements entering an average. When N is very large, as in the compilation of an annual global surface air temperature, the σ_ε^2 variance of sensor measurement error is reckoned to be negligible.

Variance reduction by appeal to the CLT is justified when the overall distribution of error is known to be random. However, there is no *a priori* reason to expect that systematic errors should be normally distributed at any N. [37, 132, 133] Further, the assumed global relevance of the CLT to the systematic measurement error of temperature sensors has never been empirically established. A recent comparison of ship SST measurements with equivalent SSTs measured using the Advanced Along-Track Scanning Satellite microwave radiometer aboard the European Envisat produced skewed non-random difference profiles. [126] Thus, neither the error profiles discussed here nor others in the published literature support the assumption of random measurement error. Invocation of the CLT to dismiss temperature sensor measurement error is therefore unjustified on any grounds.

For the present discussion let the minimal $1\sigma = \pm 0.5$ C land surface error also represent the minimum of uncertainty due to the systematic error inherent within the SST record. The typicality of the SST profile in Figure 5b ensures that the average 20th century SST systematic measurement error almost certainly exceeds ±0.5 C. More detailed analyses of these matters will be reported elsewhere.

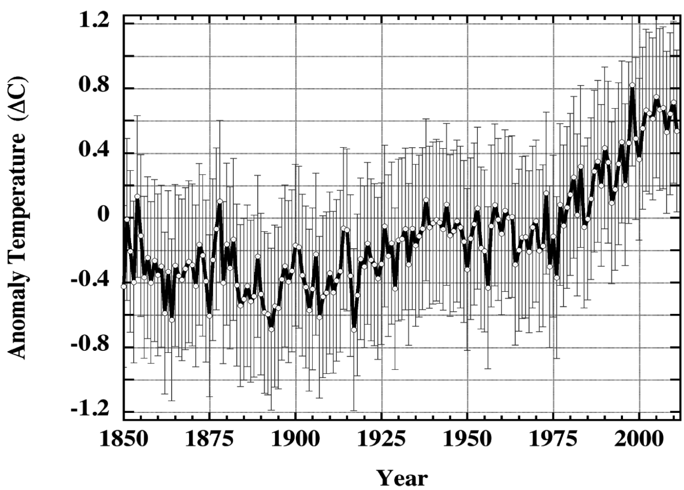

Figure 6. The 20th century GASAT record, HadCRUT3-gl. [112] The 1σ uncertainty bars extend across ±0.5 C. Thus, 2σ = ±1 C = 1.25 × the entire 160-year increase.

A lower limit of uncertainty due to systematic measurement error in the land plus SST GASAT record is then, $\pm 1\sigma_{global} = \pm\sqrt{0.3\times(0.5\,C)^2 + 0.7\times(0.5\,C)^2} = \pm 0.5\,C$. Figure 6 shows the effect of this uncertainty. The 20th century GASAT record is indistinguishable from zero at the 95% confidence interval. Thus, it is not knowable whether either the magnitude or the rate of air temperature warming since 1850 has been in any way unusual.

3. CONCLUSION

With the recovery of ignored systematic error in the GASAT record, it is found that scientific negligence has plagued all of consensus climatology. For 25 years the field has misrepresented its state of knowledge. Neither the scenarios produced using climate models, nor the consensus paleo-temperatures purported from proxies, nor the GASAT record can escape this judgment.

The following conclusions are entrained by the foregoing:

1. The poor resolution of present state-of-the-art CMIP5 GCMs means the response of the terrestrial climate to increased GHGs is far below any level of detection.
2. The poor resolution of CMIP5 GCMs means all past and present projections of terrestrial air temperature can have revealed nothing of future terrestrial air temperature.
3. The lack of any scientific content in consensus proxy paleo-temperature reconstructions means nothing has been revealed of terrestrial paleo-temperatures.
4. The neglected systematic sensor measurement error in the GASAT record means that neither the rate nor the magnitude of the change in surface air temperatures is knowable.

Therefore, 5: Detection and attribution of an anthropogenic cause to climate change can not have been nor presently can be evidenced in climate observables.

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5. REFERENCES

1. Charney, J.G., Arakawa, A., Baker, D.J., Bolin, B., Dickinson, R.E., Goody, R.M., Leith, C.E., Stommel, H.M. and Wunsch, C.I., Carbon Dioxide and Climate: A Scientific Assessment, *National Academy of Sciences*, USA, Washington, D.C. 1979 http://www.nap.edu/catalog.php?record_id=12181.

2. Möller, F., On the influence of changes in the CO_2 concentration in air on the radiation balance of the Earth's surface and on the climate, *Journal of Geophysical Research*, 1963, 68 (13), 3877-3886.

3. Möller, F., Reply [to "Comments on paper by F. Möller, 'On the influence of changes in the CO_2 concentrations in air on the radiation balance of the Earth's surface and on the climate'"], *Journal of Geophysical Research*, 1964, 69 (8), 1665-1665.

4. Plass, G.N., Effect of Carbon Dioxide Variations on Climate, *American Journal of Physics*, 1956, 24 (5), 376-387.

5. Plass, G.N., Comments on paper by F. Möller, 'On the influence of changes in the CO_2 concentrations in air on the radiation balance of the Earth's surface and on the climate', *Journal of Geophysical Research*, 1964, 69 (8), 1663-1664.

6. Sawyer, J.S., Man-made Carbon Dioxide and the "Greenhouse" Effect, Nature, 1972, 239 23-26; "[Against the background of climate variability,] a change of 0.6^o C by the end of the century will not be easy to distinguish from natural fluctuations and certainly is not a cause for alarm." Sawyer's calmly reasoned approach is almost entirely missing from the modern discussion.

7. Henderson-Sellers, A., Clouds and the long-term stability of the Earth's atmosphere and climate, *Nature*, 1979, 279 (5716), 786-788.

8. Henderson-Sellers, A., The Earth's environment-A uniquely stable system?, *Geophysical Surveys*, 1981, 4 (3), 297-329.

9. Hoyt, D.V., An empirical determination of the heating of the Earth by the carbon dioxide greenhouse effect, *Nature*, 1979, 282 (5737), 388-390.

10. Schneider, S.H., On the Carbon Dioxide-Climate Confusion, *J. Atmos. Sci.*, 1975, 32 (11), 2060-2066.

11. Smith, J.B. and Tirpak, D., The Potential Effects of Global Climate Change on the United States; EPA-230-05-89-050, Environmental Protection Agency (US), Washington, DC 1989 http://www.epa.gov/climatechange/effects/downloads/potential_effects.pdf.

12. IPCC, Climate Change 2001, Cambridge University, Cambridge, UK and New York, NY, USA 2001 http://www.grida.no/publications/other/ipcc_tar/?src=/climate/ipcc_tar/.

13. Solomon, S., Qin, D., Manning, M., Chen, Z., Marquis, M., Avery, K.B., Tignor, M. and Miller, H.L., Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, Cambridge University, Cambridge 2007 http://www.ipcc.ch/publications_and_data/ar4/wg1/en/contents.html.

14. Santer, B.D., Wigley, T.M.L., Simmons, A.J., Kållberg, P.W., Kelly, G.A., Uppala, S.M., Ammann, C., Boyle, J.S., Brüggemann, W., Doutriaux, C., Fiorino, M., Mears, C., Meehl, G.A., Sausen, R., Taylor, K.E., Washington, W.M., Wehner, M.F. and Wentz, F.J., Identification of anthropogenic climate change using a second-generation reanalysis, *J. Geophys. Res.: Atmospheres*, 2004, 109 (D21104).

15. Santer, B.D., Taylor, K.E., Gleckler, P.J., Bonfils, C., Barnett, T.P., Pierce, D.W., Wigley, T.M.L., Mears, C., Wentz, F.J., Brüggemann, W., Gillett, N.P., Klein, S.A., Solomon, S., Stott, P.A. and Wehner, M.F., Incorporating model quality information in climate change detection and attribution studies, *Proc. Natl Acad. Sci.* USA, 2009, 106 (35), 14778-14783.

16. Blunden, J. and Arndt, D.S., State of the Climate in 2011, *Bulletin of the American Meteorological Society*, 2012, 93 (7), S1-S282.

17. Hansen, J., Sato, M., Ruedy, R., Lo, K., Lea, D.W. and Medina-Elizade, M., Global temperature change, *Proc. Natl Acad. Sci*. USA, 2006, 103 (39), 14288-14293.

18. Hargreaves, J.C., Skill and uncertainty in climate models, Wiley Interdisciplinary Reviews: *Climate Change*, 2010, 1 (4), 556-564.

19. Nuccitelli, D., Lessons From Past Predictions: Hansen 1981, ThinkProgress.org: Center for American Progress Action Fund, http://thinkprogress.org/climate/2012/05/08/479652/lessons-from-past-predictions-hansen-1981/?mobile=nc, Last accessed on: 11 August 2014.

20. Pielke Jr, R., Evaluating Jim Hansen's 1988 Climate Forecast, Cooperative Institute for Research in Environmental Sciences, http://cstpr.colorado.edu/prometheus/archives/climate_change/000836evaluating_jim_hanse.html, Last accessed on: 11 August 2014.

21. Hansen, J., Fung, I., Lacis, A., Rind, D., Lebedeff, S., Ruedy, R., Russell, G. and Stone, P., Global Climate Changes as Forecast by Goddard Institute for Space Studies Three-Dimensional Model, *J. Geophys. Res*., 1988, 93 (D8), 9341-9364.

22. Smith, L.A., What might we learn from climate forecasts?, *Proc. Natl. Acad. Sci*., USA, 2002, 99 2487-2492.

23. Stephens, G.L., Cloud Feedbacks in the Climate System: A Critical Review, *J. Climate*, 2005, 18 237-273.

24. Spencer, R.W. and Braswell, W.D., Potential Biases in Feedback Diagnosis from Observational Data: A Simple Model Demonstration, *Journal of Climate*, 2008, 21 (21), 5624-5628.

25. Cole, J., Barker, H.W., Loeb, N.G. and von Salzen, K., Assessing Simulated Clouds and Radiative Fluxes Using Properties of Clouds Whose Tops are Exposed to Space, *Journal of Climate*, 2011, 24 (11), 2715-2727.

26. Klein, S.A., Zhang, Y., Zelinka, M.D., Pincus, R., Boyle, J. and Gleckler, P.J., Are climate model simulations of clouds improving? An evaluation using the ISCCP simulator, *J. Geophys. Res.: Atmospheres*, 2013, 118 (3), 1329-1342.

27. Lauer, A. and Hamilton, K., Simulating Clouds with Global Climate Models: A Comparison of CMIP5 Results with CMIP3 and Satellite Data, *J. Climate*, 2013, 26 (11), 3823-3845.

28. Soon, W., Baliunas, S., Idso, S.B., Kondratyev, K.Y. and Posmentier, E.S., Modeling climatic effects of anthropogenic carbon dioxide emissions: unknowns and uncertainties, *Climate Res*., 2001, 18 259-275.

29. Frank, P., A Climate of Belief, *Skeptic*, 2008, 14 (1), 22-30.

30. Frank, P., Propagation of Error and the Reliability of Global Air Temperature Projections, submitted, 2015.

31. AchutaRao, K., Covey, C., Doutriaux, C., Fiorino, M., Gleckler, P., Phillips, T., Sperber, K. and Taylor, K., Report UCRL-TR-202550. An Appraisal of Coupled Climate Model Simulations, Lawrence Livermore National Laboratory, Livermore 2004 http://www-pcmdi.llnl.gov/appraisal.php.

32. Gates, W.L., Boyle, J.S., Covey, C., Dease, C.G., Doutriaux, C.M., Drach, R.S., Fiorino, M., Gleckler, P.J., Hnilo, J.J., Marlais, S.M., Phillips, T.J., Potter, G.L., Santer, B.D., Sperber, K.S., Taylor, K.E. and Williams, D.N., An Overview of the Results of the Atmospheric Model Intercomparison Project (AMIP I), *Bull. Amer. Met. Soc.*, 1999, 80 (1), 29-55.

33. Jiang, J.H., Su, H., Zhai, C., Perun, V.S., Del Genio, A., Nazarenko, L.S., Donner, L.J., Horowitz, L., Seman, C., Cole, J., Gettelman, A., Ringer, M.A., Rotstayn, L., Jeffrey, S., Wu, T., Brient, F., Dufresne, J.-L., Kawai, H., Koshiro, T., Watanabe, M., LÉcuyer, T.S., Volodin, E.M., Iversen, T., Drange, H., Mesquita, M.D.S., Read, W.G., Waters, J.W., Tian, B., Teixeira, J. and Stephens, G.L., Evaluation of cloud and water vapor simulations in CMIP5 climate models using NASA "A-Train" satellite observations, *J. Geophys. Res.*, 2012, 117 (D14), D14105.

34. Hansen, J., Statement of Dr. James Hansen, Director, NASA Goddard Institute for Space Studies, http://image.guardian.co.uk/sys-files/Environment/documents/2008/06/23/ClimateChangeHearing1988.pdf, Last accessed on: 11 August 2014.

35. Frank, P. (2013) invited poster: American Geophysical Union Fall Meeting, San Francisco, CA; Available from: http://meteo.lcd.lu/globalwarming/Frank/propagation_of_error_poster_AGU2013.pdf).

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

37. JCGM, Evaluation of measurement data — Guide to the expression of uncertainty in measurement, Bureau International des Poids et Mesures, Sevres, France 100:2008

38. Vasquez, V.R. and Whiting, W.B., Accounting for Both Random Errors and Systematic Errors in Uncertainty Propagation Analysis of Computer Models Involving Experimental Measurements with Monte Carlo Methods, *Risk Analysis*, 2005, 25 (6), 1669-1681.

39. Hofmann, D.J., Butler, J.H., Dlugokencky, E.J., Elkins, J.W., Masarie, K., Montzka, S.A. and Tans, P., The role of carbon dioxide in climate forcing from 1979 to 2004: introduction of the Annual Greenhouse Gas Index, *Tellus. Series B, Chemical and physical meteorology*, 2006, 58 (5), 614-619.

40. IPCC 2007, Summary for Policymakers, in: Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, Solomon, S., Qin, D., Manning, M., Chen, Z., Marquis, M., Averyt, K.B., Tignor, M. & Miller, H.L., eds. Cambridge University, Cambridge, United Kingdom and New York, NY, USA., 2007.

41. Collins, M., Climate predictability on interannual to decadal time scales: the initial value problem, *Clim. Dynam.*, 2002, 19 671-692.

42. Boer, G.J., A study of atmosphere-ocean predictability on long time scales, *Climate Dynam.*, 2000, 16 469-477.

43. Solomon, S., Qin, D., Manning, M., Chen, Z., Marquis, M., Averyt, K.B., Tignor, M. and Miller, H.L., Summary for Policymakers, Cambridge University, Cambridge 2007

44. Boer, G.J. and Lambert, S.J., Multi-model decadal potential predictability of precipitation and temperature, *Geophys. Res. Lett.*, 2008, 35 L05706.

45. Anagnostopoulos, G.G., Koutsoyiannis, D., Christofides, A., Efstratiadis, A. and Mamassis, N., A comparison of local and aggregated climate model outputs with observed data, *Hydrolog. Sci. J.*, 2010, 55 (7), 1094–1110.

46. Koutsoyiannis, D., Efstratiadis, A., Mamassis, N. and Christofides, A., On the credibility of climate predictions, *Hydrolog. Sci. J.*, 2008, 53 (4), 671-684.

47. Hansen, J. and Lebedeff, S., Global Trends of Measured Surface Air Temperature, *J. Geophys. Res.*, 1987, 92 (D11), 13345-13372.

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

49. Hansen, J., Ruedy, R., Sato, M., Imhoff, M., Lawrence, W., Easterling, D., Peterson, T. and Karl, T., A closer look at United States and global surface temperature change, *J. Geophys. Res.*, 2001, 106 (D20), 23947-23963; see http://data.giss.nasa.gov/gistemp/.

50. Krishnamurti, T.N., Kishtawal, C.M., Zhang, Z., LaRow, T., Bachiochi, D., Williford, E., Gadgil, S. and Surendran, S., Multimodel Ensemble Forecasts for Weather and Seasonal Climate, *Journal of Climate*, 2000, 13 (23), 4196-4216.

51. Kug, J.-S., Lee, J.-Y. and Kang, I.-S., Systematic Error Correction of Dynamical Seasonal Prediction of Sea Surface Temperature Using a Stepwise Pattern Project Method, *Monthly Weather Review*, 2008, 136 (9), 3501-3512.

52. Palmer, T.N., Brankovič, Č. and Richardson, D.S., A probability and decision-model analysis of PROVOST seasonal multi-model ensemble integrations, *Quart. J. Roy. Meteorolog. Soc.*, 2000, 126 (567), 2013-2033.

53. Koutsoyiannis, D. Christofides, A. Efstratiadis, A. Anagnostopoulos, G.G. and Mamassis, N., Scientific dialogue on climate: is it giving black eyes or opening closed eyes? Reply to “A black eye for the Hydrological Sciences Journal” by D. Huard, *Hydrolog. Sci. J.*, 2011, 56(7), 1334-1339.

54. Anagnostopoulos, G.G., Koutsoyiannis, D., Christofides, A., Efstratiadis, A. and Mamassis, N., A comparison of local and aggregated climate model outputs with observed data, Department of Water Resources and Environmental Engineering, NTUA, http://www.itia.ntua.gr/en/docinfo/978/, Last accessed on: 11 August 2014.

55. Green, K.C., Armstrong, J.S. and Soon, W., Validity of climate change forecasting for public policy decision making, *International Journal of Forecasting*, 2009, 25 (4), 826-832.

56. Fritts, H.C., Blasing, T.J., Hayden, B.P. and Kutzbach, J.E., Multivariate Techniques for Specifying Tree-Growth and Climate Relationships and for Reconstructing Anomalies in Paleoclimate, *Journal of Applied Meteorology*, 1971, 10 (5), 845-864.

57. Sheppard, P.R., Dendroclimatology: extracting climate from trees, *Wiley Interdisciplinary Reviews: Climate Change*, 2010, 1 343–352.

58. Tessier, L., Guibal, F. and Schweingruber, F.H., Research Stratagies in Dendroecology and Dendroclimatology in Mountain Environments, *Climatic Change*, 1997, 36 (3), 499-517.

59. D'Arrigo, R., Cook, E., Villalba, R., Buckley, B., Salinger, J., Palmer, J. and Allen, K., Trans-Tasman Sea climate variability since 1740 inferred from middle to high latitude tree-ring data, *Climate Dynamics*, 2000, 16 (8), 603-610.

60. Jacoby, G.C., D'Arrigo, R.D. and Davaajamts, T., Mongolian Tree Rings and 20th-Century Warming, *Science*, 1996, 273 (5276), 771-773.

61. Loehle, C., A mathematical analysis of the divergence problem in dendroclimatology, *Climatic Change*, 2009, 94 (3-4), 233-245.

62. Ettl, G.J. and Peterson, D.L., Extreme climate and variation in tree growth: individualistic response in subalpine fir (*Abies lasiocarpa*), *Global Change Biology*, 1995, 1 231-241. Ettl and Peterson point out (p. 232) that, "Variation in species growth response to climate suggests that predictions of uniform species responses to climate change may be inaccurate."

63. Jelinski, D.E., Associations between Environmental Heterogeneity, Heterozygosity, and Growth Rates of *Populus tremuloides* in a Cordilleran Landscape, *Arctic and Alpine Research*, 1993, 25 (3), 183-188.

64. Walbot, V., Sources and consequences of phenotypic and genotypic plasticity in flowering plants, *Trends in Plant Science*, 1996, 1 (1), 27-32.

65. Waterhouse, J.S., Cheng, S., Juchelka, D., Loader, N.J., McCarroll, D., Switsur, V.R. and Gautam, L., Position-specific measurement of oxygen isotope ratios in cellulose: Isotopic exchange during heterotrophic cellulose synthesis, *Geochimica et Cosmochimica Acta*, 2013, 112 (0), 178-191.

66. Sensuła, B. and Pazdur, A., Influence of climate change on carbon and oxygen isotope fractionation factors between glucose and α-cellulose of pine wood, *Geochronometria*, 2013, 40 (2), 145-152.

67. Kern, Z., Patkó, M., Kázmér, M., Fekete, J., Kele, S. and Pályi, Z., Multiple tree-ring proxies (earlywood width, latewood width and d13C) from pedunculate oak (*Quercus robur L.*), Hungary, *Quaternary International*, 2013, 293 257-267.

68. Gulbranson, E.L. and Ryberg, P.E., Paleobotanical and Geochemical Approaches to Studying Fossil Tree Rings: Quantitative Interpretations of Paleoenvironment and Ecophysiology, *PALAIOS*, 2013, 28 (3), 137-140.

69. Briffa, K.R., Jones, P.D., Wigley, T.M.L., Pilcher, J.R. and Baillie, M.G.L., Climate reconstruction from tree rings: Part 1, basic methodology and preliminary results for England, *Journal of Climatology*, 1983, 3 (3), 233-242.

70. Briffa, K.R., Osborn, T.J. and Schweingruber, F.H., Large-scale temperature inferences from tree rings: a review, *Global and Planetary Change*, 2004, 40 (1-2), 11-26.

71. Wilson, R., Tudhope, A., Brohan, P., Briffa, K., Osborn, T. and Tett, S., Two-hundred-fifty years of reconstructed and modeled tropical temperatures, *Journal of Geophysical Research: Oceans*, 2006, 111 (C10), C10007.

72. Stevenson, S., McGregor, H.V., Phipps, S.J. and Fox-Kemper, B., Quantifying errors in coral-based ENSO estimates: Toward improved forward modeling of δ18O, *Paleoceanography*, 2013, 28 1-17.

73. Wang, Y., Cheng, H., Edwards, R.L., He, Y., Kong, X., An, Z., Wu, J., Kelly, M.J., Dykoski, C.A. and Li, X., The Holocene Asian Monsoon: Links to Solar Changes and North Atlantic Climate, *Science*, 2005, 308 (5723), 854-857.
74. Jacoby, G.C. and D'Arrigo, R.D., Tree ring width and density evidence of climatic and potential forest change in Alaska, *Global Biogeochemical Cycles*, 1995, 9 (2), 227-234.
75. Frank, P., Proxy Science and Proxy Pseudo-Science, Watts Up With That http://wattsupwiththat.com/2012/04/03/proxy-science-and-proxy-pseudo-science/, Last accessed on: 11 August 2014.
76. Broecker, W.S. and Stocker, T.F., The Holocene CO_2 rise: Anthropogenic or natural?, *Eos*, *Transactions American Geophysical Union*, 2006, 87 (3), 27-27.
77. Etheridge, D.M., Steele, L.P., Langenfelds, R.L., Francey, R.J., Barnola, J.-M. and Morgan, V.I., Natural and anthropogenic changes in atmospheric CO_2 over the last 1000 years from air in Antarctic ice and firn, *J. Geophys. Res.*, 1996, 101 (D2), 4115-4128.
78. Pongratz, J. and Caldeira, K., Attribution of atmospheric CO_2 and temperature increases to regions: importance of preindustrial land use change, *Environmental Research Letters*, 2012, 7 (3), 034001 (8pp).
79. Boyle, J.F., Gaillard, M.-J., Kaplan, J.O. and Dearing, J.A., Modelling prehistoric land use and carbon budgets: A critical review, *The Holocene*, 2011, 21 (5), 715-722.
80. Bird, M., Fire, prehistoric humanity, and the environment, *Interdisciplinary Science Reviews*, 1995, 20 (2), 141-154.
81. Brncic, T.M., Willis, K.J., Harris, D.J., Telfer, M.W. and Bailey, R.M., Fire and climate change impacts on lowland forest composition in northern Congo during the last 2580 years from palaeoecological analyses of a seasonally flooded swamp, *The Holocene*, 2009, 19 (1), 79-89.
82. Naveh, Z., Ancient man's impact on the Mediterranean landscape in Israel - Ecological and evolutionary perspectives, in: Man's Role in Shaping the Eastern Mediterranean Landscape, Bottema, S., Entjes-Nieborg, G. & van Zeist, W., eds. Balkema, Rotterdam, 1990.
83. Craddock, P., Early Metal Mining and Production, Edinburgh University, Edinburgh 1995.
84. Forbes, R.J., Studies in Ancient Technology, E. J. Brill, Leiden 1971.
85. Kingery, W.D., Vandiver, P.B. and Prickett, M., The Beginnings of Pyrotechnology, Part II: Production and Use of Lime and Gypsum Plaster in the Pre-Pottery Neolithic Near East, *Journal of Field Archaeology*, 1988, 15 (2), 219-243.
86. Watkins, K.W., Lime, *J. Chem. Ed.*, 1983, 60 (1), 60-63.
87. Williams, R., Limekilns and Limeburning, CIT printing Services, Ltd., Haverfordwest 2004.
88. Mazoyer, M. and Roudart, L., A History of World Agricuture, Monthly Review, New York, NY 2006.

89. Reick, C.H., Raddatz, T., Pongratz, J. and Claussen, M., Contribution of anthropogenic land cover change emissions to pre-industrial atmospheric CO_2, *Tellus B*, 2010, 62 (5), 329-336.

90. Schlesinger, W.H. and Andrews, J.A., Soil respiration and the global carbon cycle, *Biogeochemistry*, 2000, 48 (1), 7-20.

91. Olofsson, J. and Hickler, T., Effects of human land-use on the global carbon cycle during the last 6,000 years, *Vegetation History and Archaeobotany*, 2008, 17 (5), 605-615.

92. Maddison, A., Table B-18 World GDP, 20 Countries and Regional Totals, 0-1998 A.D., This data set has since been updated: http://www.ggdc.net/maddison/maddison-project/home.htm see Maddison Project Database, Last accessed on: 11 August 2014.

93. Twain, M., Extrapolation, Web page published by Donald Simanek, http://www.lhup.edu/~dsimanek/twain.htm Mr. Twain concluded that, "There is something fascinating about science. One gets such wholesale returns of conjecture out of such a trifling investment of fact.", Last accessed on: 11 August 2014.

94. Saller, R., Framing the Debate over Growth in the Ancient Economy, in: The Ancient Economy, Scheidel, W. & von Reden, S., eds. Edinburgh Readings on the Ancient World, Routledge, New York, NY, 2002.

95. Sabine, C.L., Heimann, M., Artaxo, P., Bakker, D.C.E., Chen, C.-T.A., Field, C.B., Gruber, N., Le Quéré, C., Prinn, R.G., Prichey, J.E., Lakao, P.R., Sathaye, J.A. and Valentini, R., Current status and past trends of the global carbon cycle, in: The Global Carbon Cycle: Integrating Humans, Climate, and the Natural World, Field, C.B. & Raupach, M.R., eds. Scope-Scientific Committee On Problems Of The Environment International Council Of Scientific Unions, Island Press, Washington, DC, 2004, pp. 17-44.

96. Michard, G., Can we explain atmospheric carbon dioxide oscillations during the past 400,000 years?, *Comptes Rendus Geoscience*, 2008, 340 (8), 483-494.

97. Canadell, J.G., Pataki, D.E., Gifford, R., Houghton, R.A., Luo, Y., Raupach, M.R., Smith, P. and Steffen, W., Saturation of the Terrestrial Carbon Sink, in: Terrestrial Ecosystems in a Changing World, Canadell, J.G., Pataki, D.E. & Pitelka, L.F., eds. Global Change - The IGBP Series, *Springer*, Berlin, Heidelberg, 2007, pp. 59-78.

98. Whitham, T.G. and Slobodchikoff, C.N., Evolution by individuals, plant-herbivore interactions, and mosaics of genetic variability: The adaptive significance of somatic mutations in plants, *Oecologia*, 1981, 49 (3), 287-292.

99. Walbot, V. and Cullis, C.A., Rapid Genomic Change in Higher Plants, *Ann. Rev. Plant Physiol.*, 1985, 36 367-396.

100. Mann, M.E., Bradley, R.S. and Hughes, M.S., Global-scale temperature patterns and climate forcing over the past six centuries, *Nature*, 1998, 392 779-787.

101. Mann, M.E., Rutherford, S., Wahl, E. and Ammann, C., Testing the Fidelity of Methods Used in Proxy-Based Reconstructions of Past Climate, *J. Climate*, 2005, 18 (20), 4097-4107.

102. Singh, A. and Harrison, A., Standardized principal components, *International Journal of Remote Sensing*, 1985, 6 (6), 883-896.

103. Wasserman, S., R., The Analysis of Mixtures: Application of Principal Component Analysis to XAS Spectra, *J. Phys.* IV France, 1997, 7 (C2), C2-203-C2-205.

104. Spearman, C., Correlation Calculated from Faulty Data, *British Journal of Psychology*, 1904-1920, 1910, 3 (3), 271-295.

105. McShane, B.B. and Wyner, A.J., A Statistical Analysis of Multiple Temperature Proxies: Are Reconstructions of Surface Temperature Over the Last 1000 Years Reliable?, *Ann. Appl. Stat.*, 2011, 5 (1), 5-44.

106. McShane, B.B. and Wyner, A.J., Rejoinder to A Statistical Analysis of Multiple Temperature Proxies: Are Reconstructions of Surface Temperature Over the Last 1000 Years Reliable?, *Ann. Appl. Stat.*, 2011, 5 (1), 99-123.

107. Luckman, B.H., Briffa, K.R., Jones, P.D. and Schweingruber, F.H., Tree-ring based reconstruction of summer temperatures at the Columbia Icefield, Alberta, Canada, AD 1073-1983, *The Holocene*, 1997, 7 (4), 375-389.

108. Crowley, T.J. and Lowery, T.S., How Warm Was the Medieval Warm Period?, *AMBIO*, 2000, 29 (1), 51-54.

109. Mann, M.E., Zhang, Z., Hughes, M.K., Bradley, R.S., Miller, S.K., Rutherford, S. and Ni, F., Proxy-based reconstructions of hemispheric and global surface temperature variations over the past two millennia, *Proc. Natl. Acad. Sci.* USA, 2008, 105 (36), 13252-13257.

110. D'Arrigo, R., Wilson, R. and Jacoby, G., On the long-term context for late twentieth century warming, *J. Geophys. Res.*, 2006, 111 (D3), D03103.

111. Turro, N.J., Toward a general theory of pathological science, http://www.columbia.edu/cu/21stC/issue-3.4/turro.html Last accessed on: 11 August 2014; "Junk science: methodologically sloppy research usually conducted to advance some extra-scientific agenda or to prevail in litigation".

112. Jones, P.D., Global Temperature Record (HadCRUT3), Climatic Research Unit, University of East Anglia, http://www.cru.uea.ac.uk/cru/data/temperature/HadCRUT3-gl.dat, Last accessed on: 11 August 2013.

113. Hansen, J., Ruedy, R., Sato, M. and Lo, K., Global Surface Temperature Change, *Rev. Geophys.*, 2010, 48 (4), RG4004 1-29.

114. Essex, C., McKitrick, R. and Andresen, B., Does a Global Temperature Exist?, *J. Non-Equilib. Thermo.*, 2007, 1–27.

115. 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; see http://www.cru.uea.ac.uk/cru/info/warming/.

116. Currie, L.A. and Devoe, J.R., Validation of the Measurement Process, in: Systematic Error in Chemical Analysis, Devoe, J., eds. Vol. 63: ACS Symposium Series, *American Chemical Society*, Washington, D.C., 1977, pp. 114-139.

117. Hubbard, K.G. and Lin, X., Realtime data filtering models for air temperature measurements, *Geophys. Res. Lett.*, 2002, 29 (10), 1425.

118. Hubbard, K.G., Lin, X. and Walter-Shea, E.A., The Effectiveness of the ASOS, MMTS,

Gill, and CRS Air Temperature Radiation Shields, *J. Atmos. Oceanic Technol.*, 2001, 18 (6), 851-864.

119. 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.

120. Lin, X., Hubbard, K.G. and Baker, C.B., Surface Air Temperature Records Biased by Snow-Covered Surface, *Int. J. Climatol.*, 2005, 25 1223-1236.

121. Brooks, C.F., Observing Water-Surface Temperatures at Sea, *Monthly Weather Review*, 1926, 54 (6), 241-253.

122. Saur, J.F.T., A Study of the Quality of Sea Water Temperatures Reported in Logs of Ships' Weather Observations, *J. Appl. Meteorol.*, 1963, 2 (3), 417-425.

123. Emery, W.J., Baldwin, D.J., Schlüssel, P. and Reynolds, R.W., Accuracy of in situ sea surface temperatures used to calibrate infrared satellite measurements, *J. Geophys. Res.*, 2001, 106 (C2), 2387-2405.

124. Tabata, S., Comparison of Observations of Sea Surface Temperatures at Ocean Station P and NOAA Buoy Stations and Those Made by Merchant Ships Traveling in Their Vicinities, in the Northeast Pacific Ocean, *Journal of Applied Meteorology*, 1978, 17 (3), 374-385.

125. Frank, P., Uncertainty in the Global Average Surface Air Temperature Index: A Representative Lower Limit, *Energy & Environment*, 2010, 21 (8), 969-989.

126. Kennedy, J.J., Smith, R.O. and Rayner, N.A., Using AATSR data to assess the quality of in situ sea-surface temperature observations for climate studies, *Remote Sensing of Environment*, 2012, 116 (0), 79-92.

127. Jones, P.D. and Wigley, T.M.L., Estimation of global temperature trends: what's important and what isn't, *Climatic Change*, 2010, 100 (1), 59-69.

128. Bottomley, M., Folland, C.K., Hsiung, J., Newell, R.E. and Parker, D.E., Global Ocean Surface Temperature Atlas "GOSSTA." 313 plates, Meteorological Office, UK and the Massachusetts Institute of Technology, Bracknell, UK and Boston, MA 1990

129. Folland, C.K. and Parker, D.E., Correction of instrumental biases in historical sea surface temperature data, *Quart. J. Roy. Met. Soc.*, 1995, 121 (522), 319-367.

130. Kennedy, J.J., Rayner, N.A., Smith, R.O., Parker, D.E. and Saunby, M., Reassessing biases and other uncertainties in sea surface temperature observations measured in situ since 1850: 1. Measurement and sampling uncertainties, *J. Geophys. Res.*, 2011, 116 (D14), D14103.

131. Emery, W.J. and Thomson, R.E., Data Analysis Methods in Physical Oceanography, 2nd edn., *Elsevier*; p. 211ff, Amsterdam 2004.

132. Eisenhart, C., Expression of the Uncertainties of Final Results, Science, 1968, 160 1201-1204.

133. Rukhin, A.L., Weighted means statistics in interlaboratory studies, Metrologia, 2009, 46 323-331.