Heat, Ocean, and Atmosphere

Origins of the Warming 'hiatus' Concept

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(draft)

1 How Heat Flows and Why It Matters

Heat is most often experienced as *energy density*, related to *temperature*. While technically temperature is only meaningful for a body in thermal equilibrium, temperature is the operational definition of heat content, both in daily life and as a scientific measurement, whether at a point or averaged. For the present discussion, it is taken as given that increasing atmospheric concentrations of carbon dioxide trap and re-radiate Earth blackbody radiation to its surface, resulting in a higher mean blackbody equilibration temperature for the planet, via *radiative forcing* [10, 88, 86, 85]. The question is, how does a given Joule of energy travel? Once entrained on Earth, does it remain in atmosphere? Warm the surface? Go into the oceans? And, especially, if it *does* go into the oceans, what is its *residence time* before released to atmosphere? These are important questions [66, 67]. Because of the miscibility of energy, questions of residence time are very difficult to answer. A Joule of energy can't be tagged with a radioisotope like matter sometimes can. In practice, energy content is estimated as a constant plus the time integral of energy flux across a well-defined boundary using a baseline moment.

Variability is a key aspect of natural systems, whether biological or large scale geophysical systems such as Earth's climate [103]. Variability is also a feature of statistical models used to describe behavior of natural systems, whether they be straightforward empirical models or models based upon *ab initio* physical calculations. Some of the variability in models captures the variability of the natural systems which they describe, but some variability is inherent in the mechanism of the models, an artificial variability which is not present in the phenomena they describe[1]. No doubt, there is always some variability in natural phenomena which no model captures. This variability can be partitioned into parts, at the risk of specifying components which are not directly observable. Sometimes they can be inferred.

Models of planetary climate are both surprisingly robust and understood well enough that appreciable simplifications are possible, such as setting aside fluid dynamism, without damaging their utility [88, Preface]. Thus, long term or asymptotic and global predictions of what consequences arise when atmospheric carbon dioxide concentrations double or triple are pretty solid. What is less certain are the dissipation and diffusion mechanisms for this excess energy and its behavior in time [63, 100, 101, 96]. There is keen interest in these mechanisms because of the implications differing magnitudes have for regional climate forecasts and economics [30, 104, 65]. Moreover, there is a natural desire to obtain empirical confirmation of physical calculations, as difficult as that might be, and as subjective as judgments regarding quality of predictions might be [99, 5, 80, 81, 7, 16, 37, 44, 45, 50, 102, 110, 79, 97, 53, 56, 57, 64].

Observed rates of surface temperatures in recent decades have shown a moderating slope compared with both long term statistical trends and climate model projections [32, 39, 99, 106, 110, 81, 37, 38, 5]. It's the purpose of this article to present this evidence, and report the research literature's consensus on where the heat resulting from radiative forcing is going, as well as sketch some implications of that containment.

[1] The nomenclature can be confusing. With respect to observations, variability arising due to choice of method is sometimes called *structural uncertainty* [79, 107].

2 On Surface Temperatures, Land and Ocean

Monitoring surface temperatures globally is a useful geophysical project. They are accessible, can be measured in a number of ways, permitting calibration and cross-checking, are taken at convenient boundaries, land-and-atmosphere or ocean-and-atmosphere, and coincide with the living space about which we most care. Nevertheless, like any large observational effort in the field, such measurements need careful assessment and processing before they can be properly interpreted. The Berkeley Earth Surface Temperature ("BEST") Project represents the most comprehensive such effort, but it was not possible without many predecessors, such as HadCRUT4, and works by Kennedy, *et al* and Rohde [92, 79, 53, 54, 93].

Surface temperature is a manifestation of four interacting processes. First, there is warming of the surface by the atmosphere. Second, there is lateral heating by atmospheric convection and latent heat in water vapor. Third, during daytime, there is warming of the surface by the Sun or *insolation* which survives reflection. Last, there is warming of the surface from below, either latent heat stored subsurface, or geologic processes. Roughly speaking, these are ordered from most important to least. These are all manifestations of *energy flows*, a consequence of equalization of different contributions of energy to Earth.

Physically speaking, the total energy of the Earth climate system is a time integral of the energy of non-reflected insolation less the energy of the long wave radiation or *blackbody radiation* which passes from Earth out to space, plus geothermal energy ultimately due to radioisotope decay within Earth's aesthenosphere and mantle, plus thermal energy generated by solid Earth and ocean tides, plus waste heat from anthropogenic combustion and power sources[2]. Both the degree of non-reflected insolation and the amount of long wave radiation leaving Earth for space vary with time, the former affected by time dependent albedo and the latter by water aloft, greenhouse gases, and other factors. Our understanding of this is improving rapidly, as can be seen by contrasting Kiehl, *et al* in 1997 with Trenberth, *et al* in 2009 and the IPCC's 2013 WG1 Report [58, 109, 47]. Steve Easterbrook has given a nice summary of radiative forcing at his blog, as well as provided a succinct recap of the 2013 IPCC WG1 Report and its take on energy flows elsewhere at the *Azimuth* blog. I refer the reader to those references for information about energy budgets, what we know about them, and what we do not.

What is of interest here is whether or not there is a physical science basis for the "moderation" in global surface temperatures and, if there is, how that might work. It is an interesting question, for such a conclusion is predicated upon observed temperature series being calibrated and used correctly, and, further, upon a lack of trust in climate model predictions. Hypothetically, it could be that the temperature models are not being used correctly and the models *are* correct, and which evidence we choose to believe depends upon our short-term goals. Surely, from a scientific perspective, what's wanted is a reconciliation of both, and that is where many climate scientists invest their efforts. This is also an

[2]There are tiny amounts of heating due to impinging ionizing radiation from space, and changes in Earth's magnetic field.

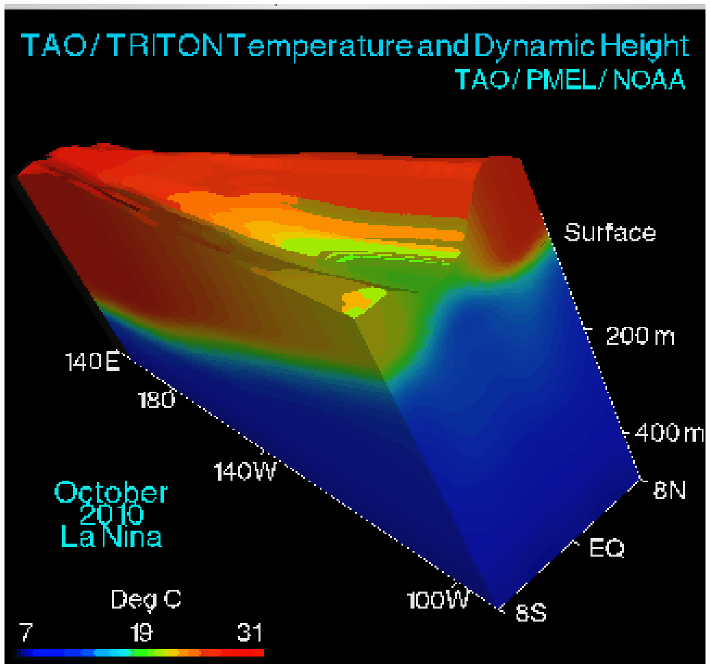
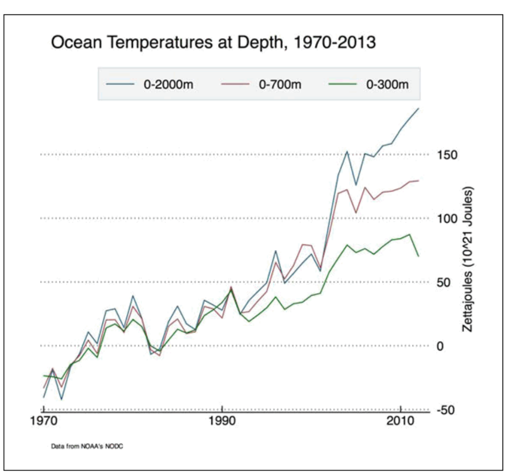


Figure 1.2: Oblique view of variability of Pacific equatorial region from *El Niño* to *La Niña* and back. Vertical heigh of ocean is exaggerated to show piling up of waters in the Pacific warm pool. **(Note that this will be replaced on the Web page with a GIF file.)**

interesting question because it is, at its root, a statistical one, namely, how do we know which model is better [111, 103, 102, 41, 14, 34, 8]?

The first graph depicting evidence of warming is quite remarkable, reproduced below as Figure 1.1. A similar graph is shown in the important series recapping the recent IPCC Report by Steve Easterbrook [29]. In short, a great deal of excess heat is going into the oceans. In fact, most of it is. This can happen in many ways, but one of the most dramatic is due to a phase of the *El Niño Southern Oscillation* ("ENSO").



Total ocean heat content has increased by around 170 Zettajoules since 1970, and about 255 Zettajoules since 1955. This increased temperature has caused the oceans (0-2,000 meters) to warm about 0.09 C over this period. As the UK's Met Office points out, if the same amount of energy had gone into the lower atmosphere it would of caused about 36 C (nearly 65 degrees F) warming! The oceans are by far the largest heat sink for the Earth, absorbing the vast majority of extra heat trapped in the system by increasing concentrations of greenhouse gases.

It's important to point out that overall deep-ocean heating (0-2,000 meters) shows no sign of a slow down in recent years, though shallower layers (0-300 meters and 0-700 meters) do. That the slowdown in surface warming has been concentrated in the ocean-surface (and shallow-ocean) temperatures has led a number of scientists (including the Met Office) to posit that the pause in ocean surface warming may be driven in part by increased heat uptake in the deep ocean.

Figure 1.1: Ocean temperatures at depth, from `http://www.yaleclimatemediaforum.org/2013/09/`

The trade winds along the Pacific equatorial region vary in strength. When they are weak, the phenomenon called *El Niño* is seen, affecting weather in the United States and in Asia. Evidence for *El Niño* includes elevated sea-surface temperatures ("SSTs") in the eastern Pacific. This short-term climate variation brings increased rainfall to the southern United States and Peru, and drought to east Asia and Australia, often triggering large wildfires there. The reverse phenomenon, *La Niña*, is produced by strong trades, and results in cold SSTs in the eastern Pacific, and plentiful rainfall in east Asia and northern Australia. Strong trades actually pile ocean water up against Asia, and these warmer-than-average waters push sur-

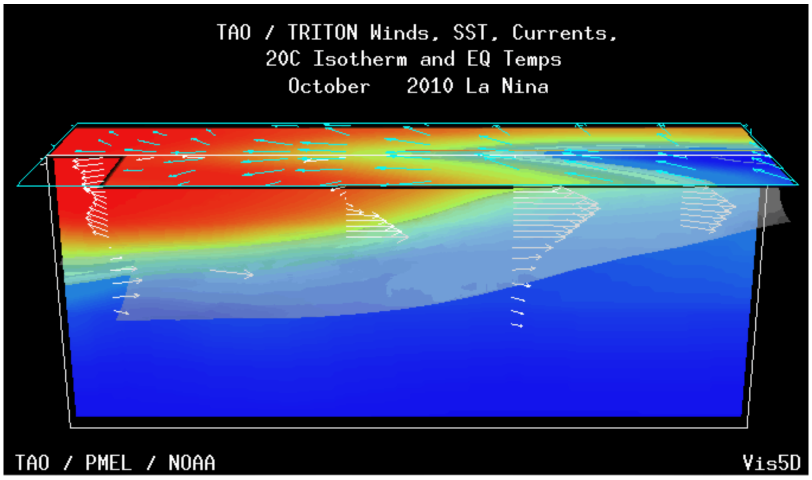


Figure 1.3: Trade winds vary in strength, having consequences for pooling and flow of Pacific waters and sea surface temperatures. **(Note that this will be replaced on the Web page with a GIF file.)**

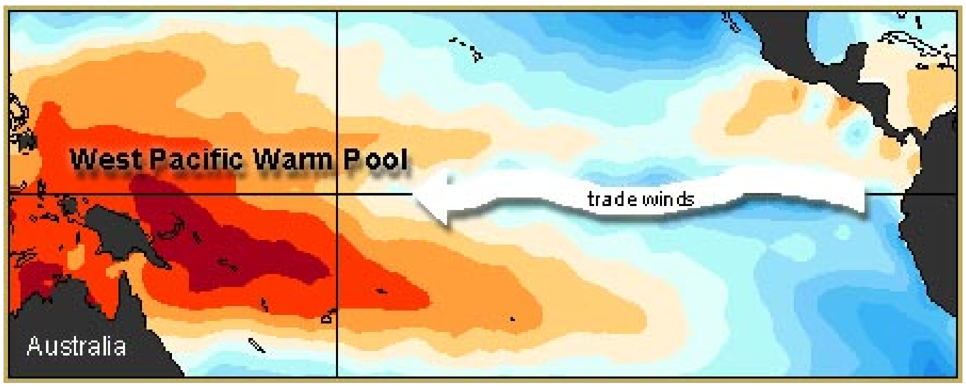


Figure 1.4: Strong trade winds cause the warm surface waters of the equatorial Pacific to pile up against Asia.

face waters there down, creating a cycle of returning cold waters back to the eastern Pacific. This process is depicted in Figures 1.2 and 1.3. At its peak, a *La Niña* causes waters to accumulate in the *Pacific warm pool*, and this results in surface heat being pushed into the deep ocean. To the degree to which heat goes into the deep ocean, it is not available in atmosphere. To the degree to which the trades do not pile waters into the Pacific warm pool and, ultimately, into the depths, that warm water is in contact with atmosphere [76]. Moreover, there are suggestions warm waters at depth rise to the surface [77].

Documentation of land and ocean *surface* temperatures is done in variety of ways. There are several important sources, including Berkeley Earth, NASA GISS, and the Hadley Centre/Climatic Research Unit ("CRU") data sets [92, 43, 79]. The three, referenced here as BEST, GISS, and HadCRUT4, respectively have been compared by Rohde [93]. They differ in duration and extent of coverage, but allow comparable inferences. For example, a linear regression establishing a trend using July monthly average temperatures from 1880 to 2012 for Moscow from GISS and BEST agree that Moscow's July 2010 heat was 3.67 standard deviations from the long term trend[3]. Nevertheless, there is an important difference between BEST and GISS, on the one hand, and HadCRUT4.

[3] 3.667 (GISS) versus 3.670 (BEST).

BEST and GISS attempt to capture and convey a single best estimate of temperatures on Earth's surface, and attach an uncertainty measure to each number. Sometimes, because of absence of measurements or equipment failures, there are no measurements, and these are clearly marked in the series. HadCRUT4 is different. With HadCRUT4 the uncertainty in measurements is described by a hundred member *ensemble* of 2592-by-1967 values. These correspond to observations from 2592 patches[4] with which it represents the surface of Earth and for each month from January 1850 to November 2013. This detail is important because it is the basis for a paper suggesting the pause in global warming is structurally inconsistent with climate models. It will be examined later.

[4] 36 in latitude, 72 in longitude.

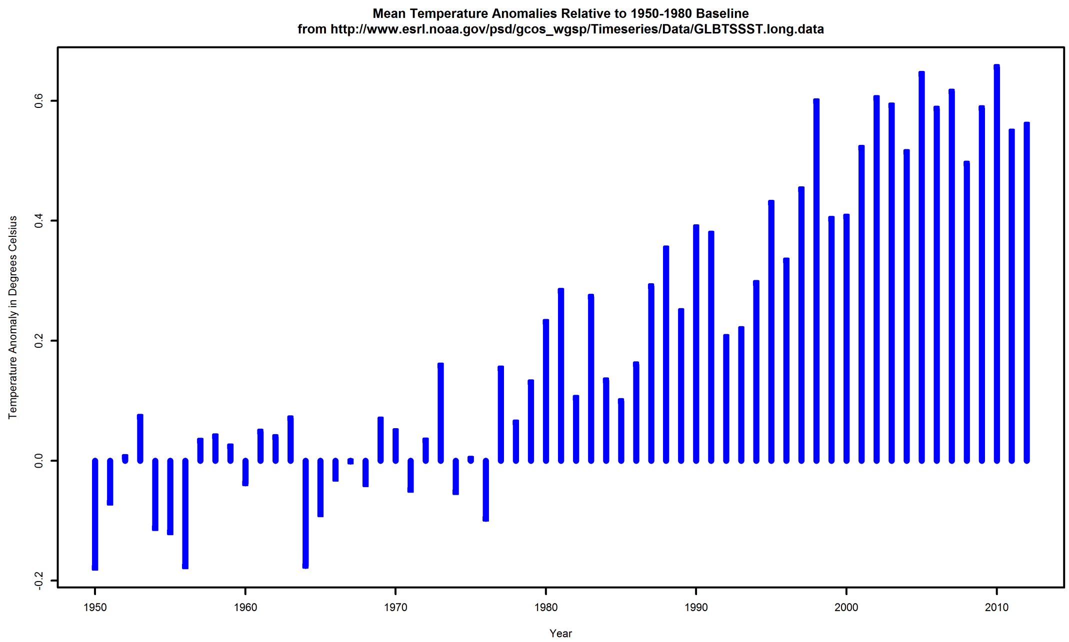


Figure 1.5: Global surface temperature anomalies relative to a 1950-1980 baseline.

3 Rumors of Pause

Figure 1.5 shows the global mean surface temperature *anomalies* relative to a standard baseline, 1950-1980. Before going on, consider that figure. Study it. What can you see in it?

Figure 1.6 shows the same graph, but now with two trendlines obtained by applying a *smoothing spline*, one smoothing more than another. One of the two indicates an uninterrupted uptrend. The other shows a peak and a downtrend, along with wiggles around the other trendline. Note the smoothing algorithm is the same in both cases, differing only in the setting of a smoothing parameter[5]. Which is correct? What is "correct"?

Figure 1.1 shows trend curves for ocean heat content over roughly the same period. Figure 1.7 shows a time series of anomalies for Moscow, in Russia. Do these all show the same trends? These are difficult questions, but there were, and are, those who take the kind of indication seen in Figure 1.6 as evidence of a warming "hiatus"[6] [28, 32]. Note that the best about it which can be said is that there is a reduction in the rate of temperature increase. That said, people have sought reasons, sought assessments of how severe this problem is. The answers have ranged from the conclusive "Global warming has stopped" to "Perhaps the slowdown is due to 'natural variability"', to "Perhaps it's *all* due to 'natural variability"' to "There is no statistically significant change". I'll get to how these might be teased apart in Section 4, but first let's see what some of the perspectives are.

It is hard to find a scientific paper which advances the proposal that climate might be or might have been cooling in recent history. The earliest I can find are repeated presentations by a single geologist

[5] Called "SPAR".

[6] The term *hiatus* has a formal meaning in climate science, as described by the IPCC itself [47, Box TS.3].

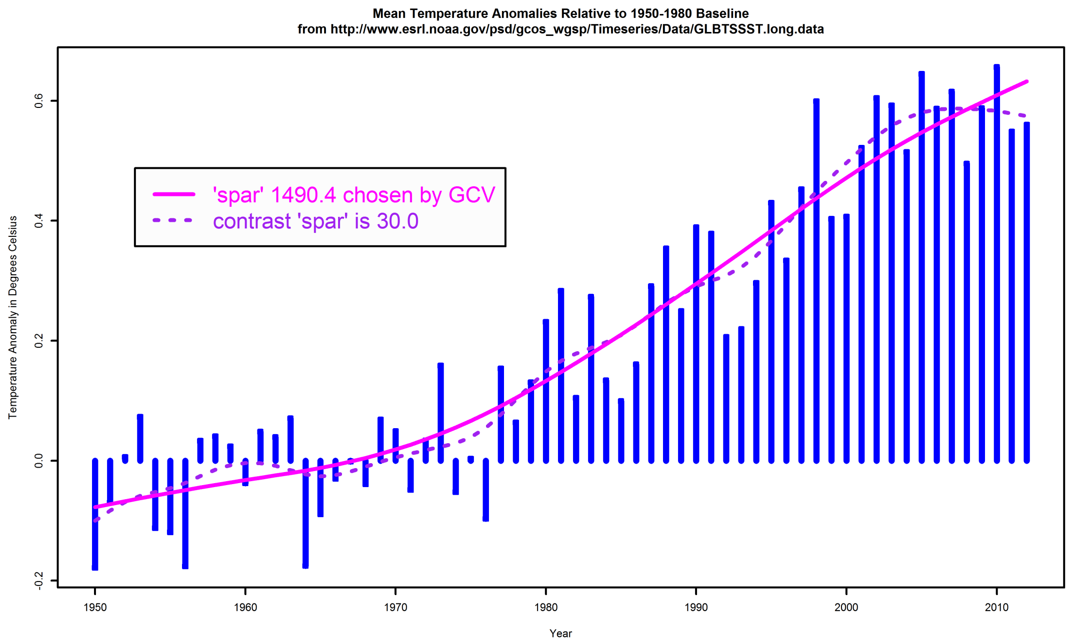


Figure 1.6: Global surface temperature anomalies relative to a 1950-1980 baseline, with two smoothing splines printed atop.

in the proceedings of the Geological Society of America, a conference which, like many, gives papers limited peer review [21, 21, 22, 23, 24, 25, 26, 27]. It is difficult to comment on this work since their full methods are not available for review. The abstracts appear to ignore the possibility of lagged response in any physical system.

These claims were summarized by Easterling and Wehner in 2009, attributing claims of a "pause" to cherry-picking of sections of the temperature time series, such as 1998-2008, and what might be called media amplification [28]. Further, technical inconsistencies within the scientific enterprise, perfectly normal in its deployment and management of new methods of measurement, were highlighted and abused to parlay claims of global cooling [116, 91, 87]. Based upon subsequent papers, climate science seemed to not only need to explain such variability is to be expected, but to provide a specific explanation for what could be seen as a recent moderation in the abrupt warming of the mid-late 1990s, appealing to oceanic capture, as described in Section 2 [76, 110, 32]. The reader might note that, given the overall temperature anomaly series, such as Figure 1.6, and specific series, such as the one for Moscow in Figure 1.7, moderation in warming is not definitive.

Certainly there was not and is not any problem with accounting for the Earth's energy budget overall, even if one grants energy distribution could not be specifically explained [58, 109, 88]. In my opinion, an interesting discrepancy is presented in a pair of papers in 2013 and 2014. The first, by Fyfe, Gillet, and Zwiers, has the (somewhat provocative) title "Overestimated global warming over the past 20 years" [37, 38]. It has been followed by another paper by Fyfe and Gillet applying the same methods to argue that even with the Pacific surface temperature anomalies and accommodating the coverage bias in the HadCRUT4 dataset there are discrepancies between the surface temperature record and climate model ensemble runs [60, 16, 39]. How this pair of papers presents that challenge and its possible significance is a story unto itself.

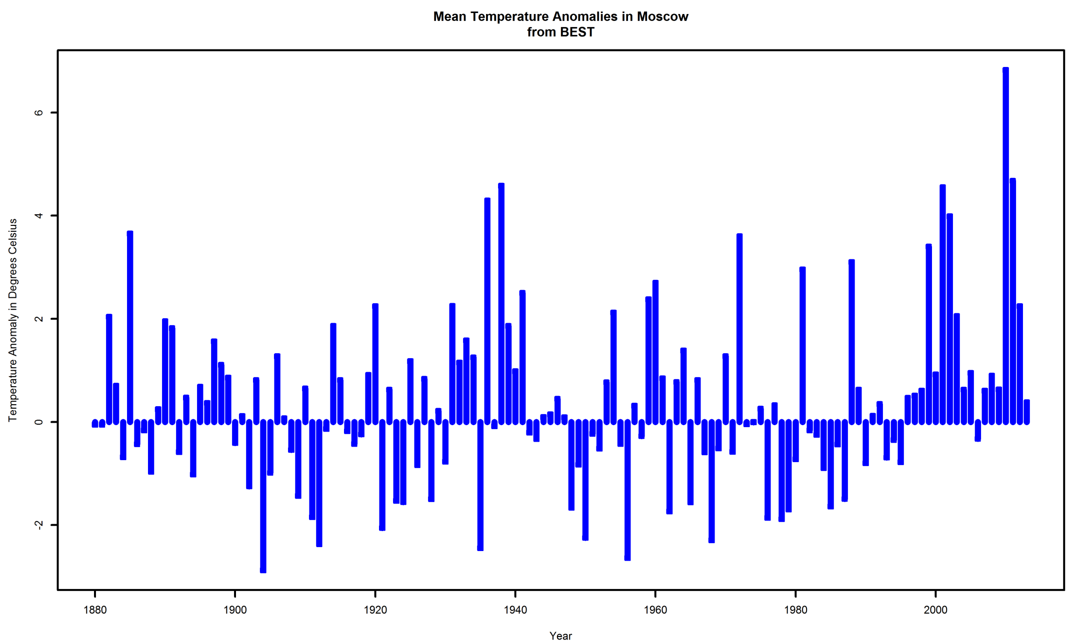


Figure 1.7: Temperature anomalies for Moscow, Russia.

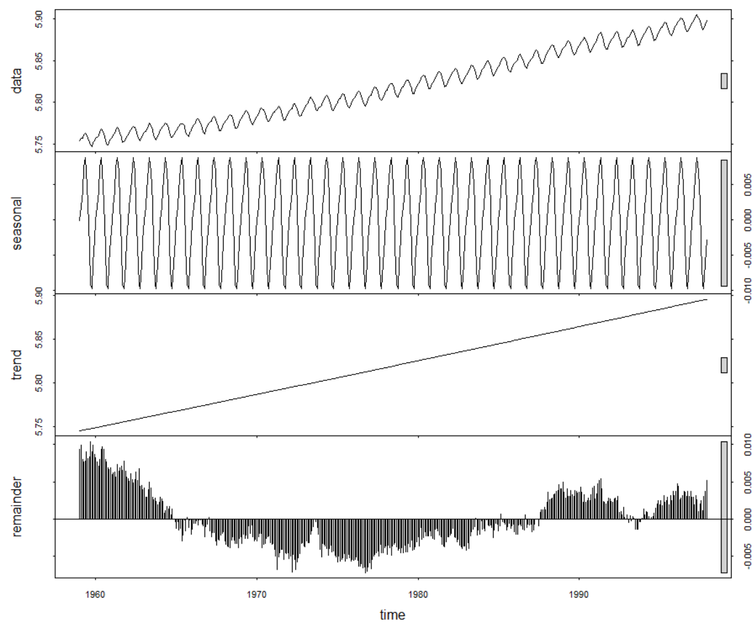


Figure 1.8: Keeling CO_2 concentration curve at Mauna Loa, Hawaii, showing original data and its decomposition into three parts, a sinusoidal annual variation, a linear trend, and a stochastic residual.

4 Trends Are Tricky

Trends as a concept are easy. Trends as an objective measure, however, are slippery. Consider the Keeling Curve, the record of atmospheric carbon dioxide concentration first begun by Charles Keeling in the 1950s and continued in the face of great obstacles [52]. This curve is reproduced in Figure 1.8, and there presented in its original, and then decomposed into three parts, an annual sinusoidal variation, a linear trend, and a stochastic remainder. The question is, which component represents the true trend, long term or otherwise? Are linear trends superior to all others?

Consider the global surface temperature anomalies of Figure 1.5 again. What are some ways of determining trends? Apart from a single long term trend, such as Figure 1.9, local linear trends can be estimated, depicted in Figure 1.11. These can be averaged, if you like, to obtain an overall trend. There is a question of what to do if local intervals for fitting the little lines overlap, since these are not independent of one another. There are a number of ways of making them independent. One way is to shrink the intervals until they are infinitesimally small, and, so, necessarily independent. That's just the point slope of a curve going through the data, or its *first derivative*. Numerical methods exist of estimating these, one involving a *smoothing spline* and estimating the derivative(s) of *that* [112]. Such an estimate is shown in Figure 1.12 where the instantaneous slope is plotted atop the data of Figure 1.5. The spline is a cubic spline and the smoothing parameter[7] is determined by *generalized cross-validation* [17].

What else might we do? We could go after a *really good* approximation to the data of Figure 1.5. One possibility is to use the Bayesian Rauch-Tung-Striebel ("RTS") smoother to get a good approximation

[7] Basically the weight of the penalty term for the second derivative of curvature.

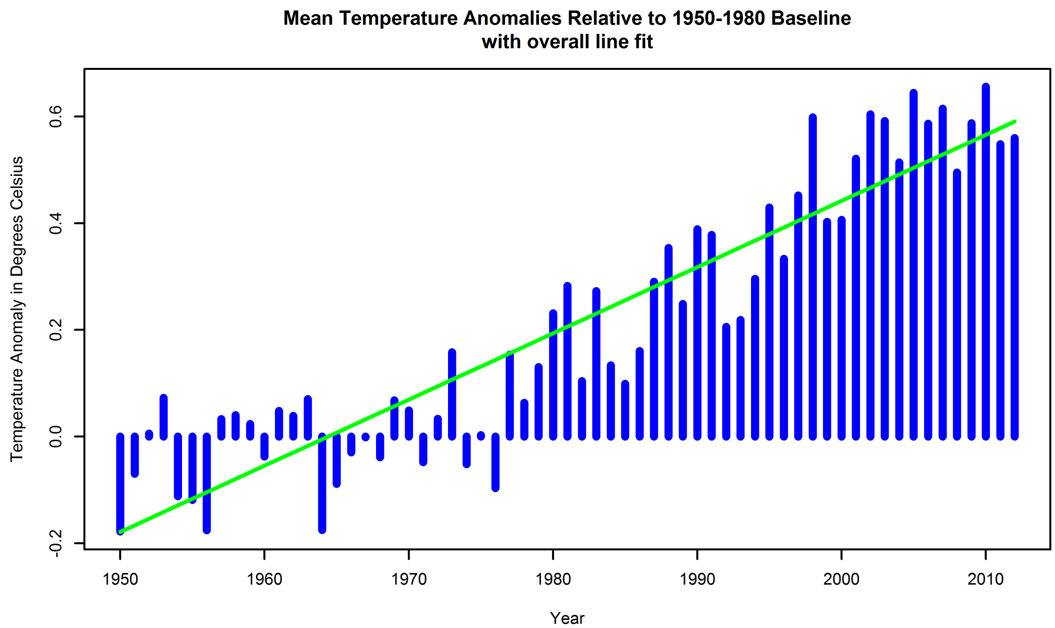


Figure 1.9: Global surface temperature anomalies relative to a 1950-1980 baseline, with long term linear trend atop.

for the underlying curve and estimate the derivatives of *that* [98]. There is a problem in that the *prior variance* of the signal needs to be estimated, and the larger it is, the smoother the RTS [8]. The RTS smoother result for two variance values of 0.156 and high 0.0.312 is shown in Figure 1.13. These are 4 and 8 times the decorrelated variance value for the series of 0.039.

Combining all these, Figure 1.14 shows the overprinted densities of slopes obtained using the six methods proposed. To be sure no slope of trend is favored, 30 randomly selected trends were chosen from each of the kinds of trends, and these are plotted. Note the spread of possibilities given by the local linear fits. Such fits are what were used by Fyfe, Gillet, and Zwiers in their 2013 paper [37, 38].

[8] The prior variance of the process evolution also needs to be estimated, and it was taken here to be $\frac{1}{300}$ of the observations variance. This ratio assures a smooth curve.

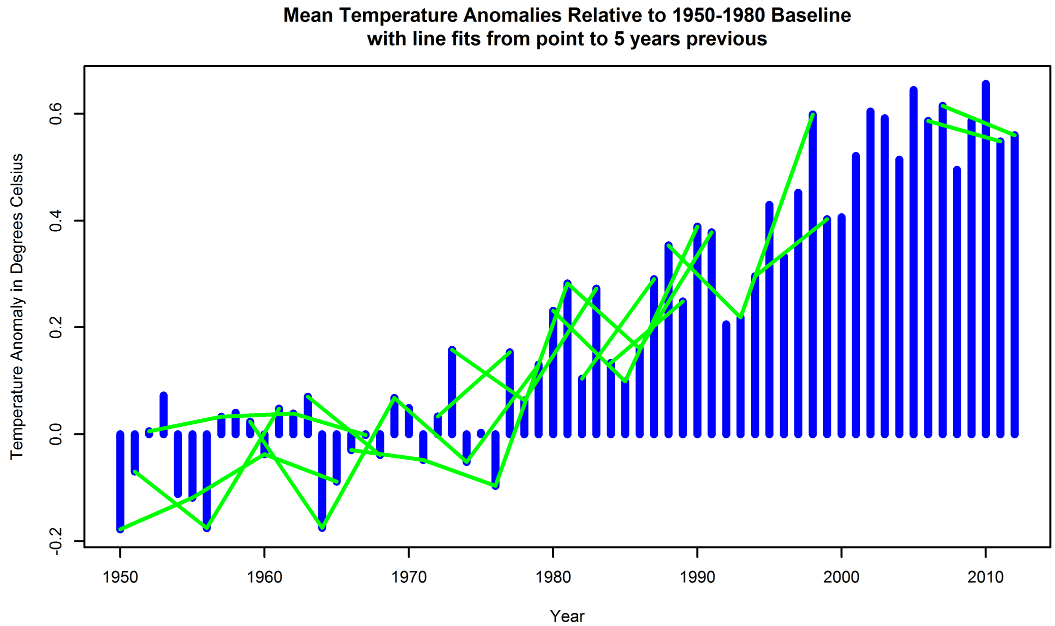


Figure 1.10: Global surface temperature anomalies relative to a 1950-1980 baseline, with randomly placed trends from local linear having 5 year support atop.

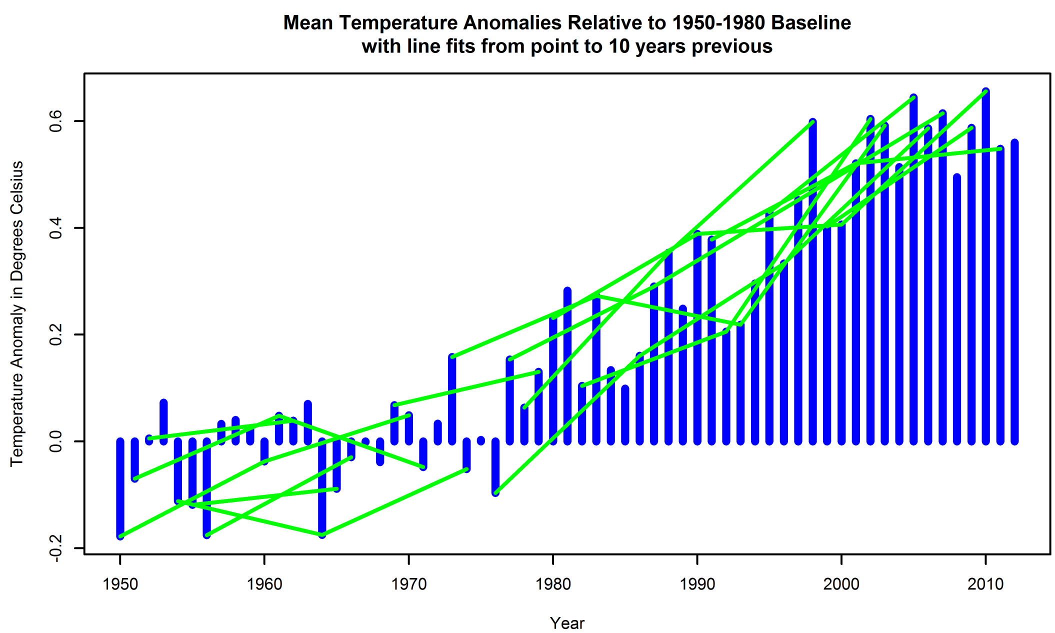


Figure 1.11: Global surface temperature anomalies relative to a 1950-1980 baseline, with randomly placed trends from local linear having 10 year support atop.

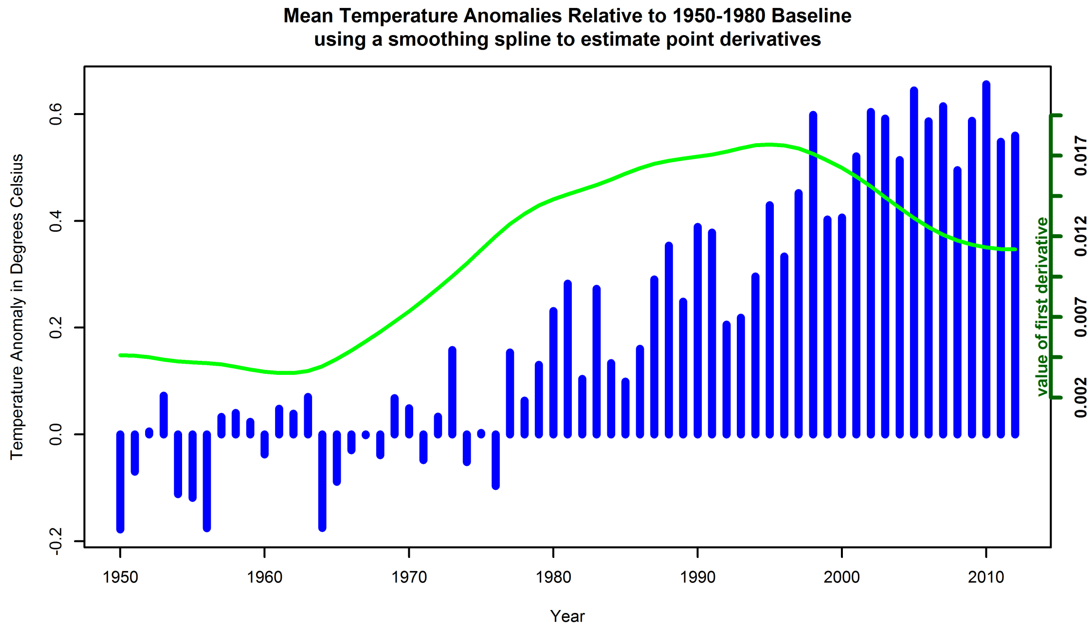


Figure 1.12: Global surface temperature anomalies relative to a 1950-1980 baseline, with instaneous numerical estimates of derivatives atop. Support for the smoothing spline used to calculate the derivatives is obtained using *generalized cross validation* [112]. Note how the value of the first derivative *never drops below zero* although its *magnitude* decreases as time approaches 2012.

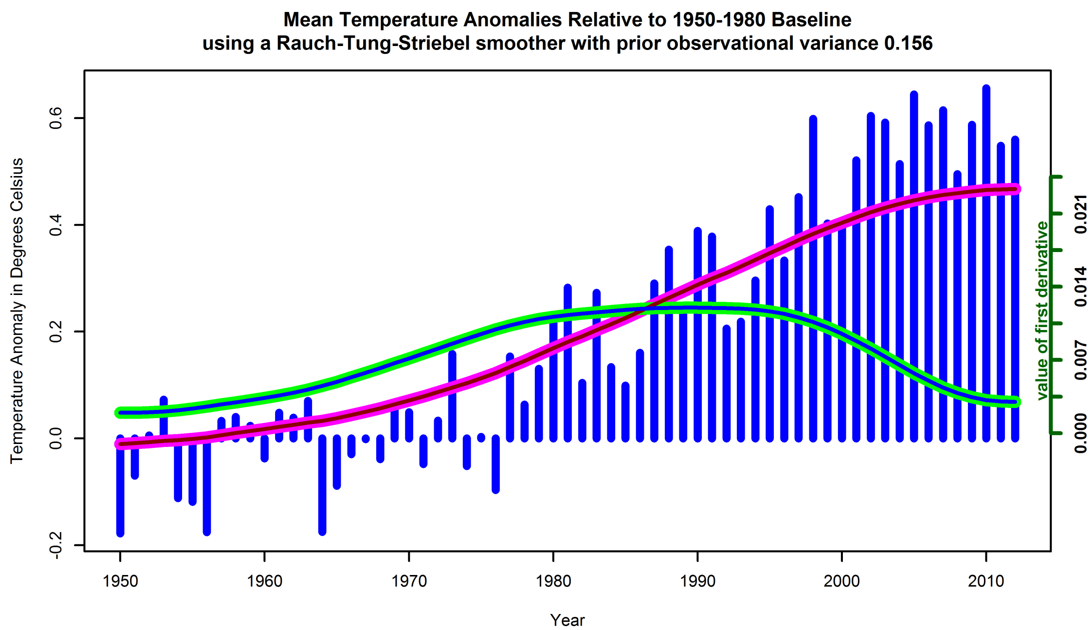


Figure 1.13: Global surface temperature anomalies relative to a 1950-1980 baseline, with fits using the Rauch-Tung-Striebel smoother placed atop, in magenta and dark red. The former uses a prior variance of 4 times that of the Figure 1.5 data corrected for serial correlation. The latter uses a prior variance of 4 times that. The instaneous numerical estimates derived from the two solutions are shown in green and blue, respectively. Note the two solutions are essentially identical.

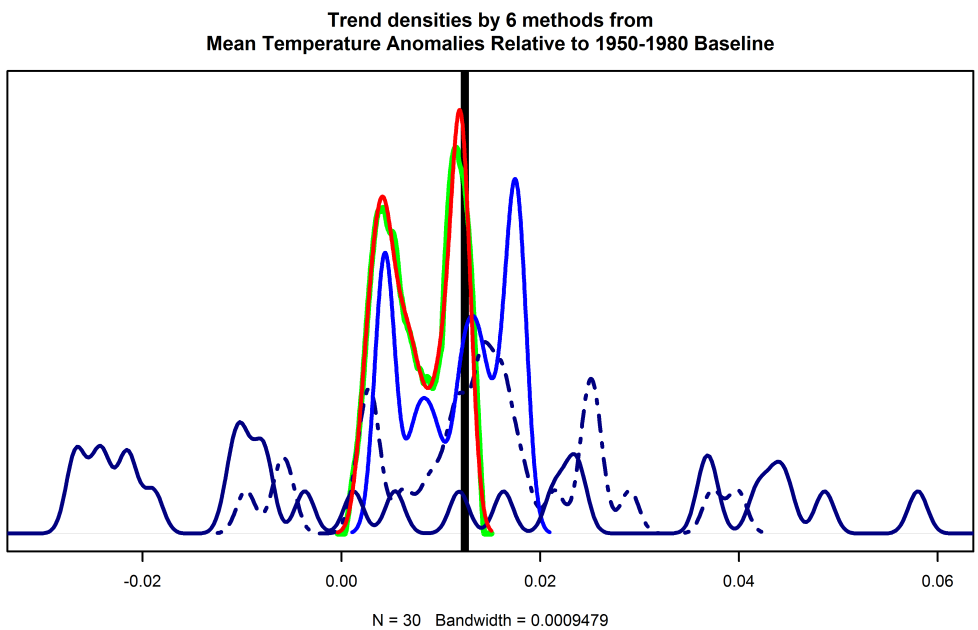


Figure 1.14: Composite of trends estimated using the long term linear fit (the vertical black line), the local linear fits with 5 years separation (navy blue trace), the local linear fits with 10 years separation (dashed navy blue trace), the smoothing spline (blue trace), the RTS smoother with variance 4 times the corrected estimate for the data as the prior variance (green trace), and the RTS smoother with eight times the corrected estimate for the data (red trace). 30 randomly chosen (without replacement) trends have densities estimated to construct this chart.

5 Internal Decadal Variability

The recent IPCC AR5 WG1 Report sets out the context [47, Box TS.3]:

> Hiatus periods of 10 to 15 years can arise as a manifestation of internal decadal climate variability, which sometimes enhances and sometimes counteracts the long-term externally forced trend. Internal variability thus diminishes the relevance of trends over periods as short as 10 to 15 years for long-term climate change (Box 2.2, Section 2.4.3). Furthermore, the timing of internal decadal climate variability is not expected to be matched by the CMIP5 historical simulations, owing to the predictability horizon of at most 10 to 20 years (Section 11.2.2; CMIP5 historical simulations are typically started around nominally 1850 from a control run). However, climate models exhibit individual decades of GMST trend hiatus even during a prolonged phase of energy uptake of the climate system (e.g., Figure 9.8; Easterling and Wehner, 2009; Knight et al., 2009), in which case the energy budget would be balanced by increasing subsurface-ocean heat uptake (Meehl et al., 2011, 2013a; Guemas et al., 2013).
>
> Owing to sampling limitations, it is uncertain whether an increase in the rate of subsurface-ocean heat uptake occurred during the past 15 years (Section 3.2.4). However, it is very likely[9] that the climate system, including the ocean below 700 m depth, has continued to accumulate energy over the period 1998-2010 (Section 3.2.4, Box 3.1). Consistent with this energy accumulation, global mean sea level has continued to rise during 1998-2012, at a rate only slightly and insignificantly lower than during 1993-2012 (Section 3.7). The consistency between observed heat-content and sea level changes yields high confidence in the assessment of continued ocean energy accumulation, which is in turn consistent with the positive radiative imbalance of the climate system (Section 8.5.1; Section 13.3, Box 13.1). By contrast, there is limited evidence that the hiatus in GMST trend has been accompanied by a slower rate of increase in ocean heat content over the depth range 0 to 700 m, when comparing the period 2003-2010 against 1971-2010. There is low agreement on this slowdown, since three of five analyses show a slowdown in the rate of increase while the other two show the increase continuing unabated (Section 3.2.3, Figure 3.2).
>
> During the 15-year period beginning in 1998, the ensemble of HadCRUT4 GMST trends lies below almost all model-simulated trends (Box 9.2 Figure 1a), whereas during the 15-year period ending in 1998, it lies above 93 out of 114 modelled trends (Box 9.2 Figure 1b; HadCRUT4 ensemble-mean trend $0.26\,^{\circ}\mathrm{C}$ per decade, CMIP5 ensemble-mean trend $0.16\,^{\circ}\mathrm{C}$ per decade). Over the 62-year period 1951-2012, observed and CMIP5 ensemble-mean trends agree to within $0.02\,^{\circ}\mathrm{C}$ per decade (Box 9.2 Figure 1c; CMIP5 ensemble-mean trend $0.13\,^{\circ}\mathrm{C}$ per decade). There is hence very high confidence that the CMIP5 models show long-term

[9] "In this Report, the following terms have been used to indicate the assessed likelihood of an outcome or a result: Virtually certain $99-100\%$ probability, Very likely $90-100\%$, Likely $66-100\%$, About as likely as not $33-66\%$, Unlikely 0-33%, Very unlikely 0-10%, Exceptionally unlikely 0-1%. Additional terms (Extremely likely: $95-100\%$, More likely than not $> 50-100\%$, and Extremely unlikely 0-5%) may also be used when appropriate. Assessed likelihood is typeset in italics, e.g., very likely (see Section 1.4 and Box TS.1 for more details)."

> GMST trends consistent with observations, despite the disagreement over the most recent 15-year period. Due to internal climate variability, in any given 15-year period the observed GMST trend sometimes lies near one end of a model ensemble (Box 9.2, Figure 1a, b; Easterling and Wehner, 2009), an effect that is pronounced in Box 9.2, Figure 1a, because GMST was influenced by a very strong El Niño event in 1998.

The contributions of Fyfe, Gillet, and Zwiers ("FGZ") are to (a) pin down this behavior for a 20 year period using the HadCRUT4 data, and, to my mind, more importantly, (b) to develop techniques for evaluating runs of ensembles of climate models like the CMIP5 suite without commissioning specfic runs for the purpose [37, 39]. This, if it were to prove out, would be an important experimental advance, since climate models demand expensive and extensive hardware, and the number of people who know how to program and run them is very limited[10], possibly a more limiting practical constraint than the hardware [59]. FGZ try to explicitly model trends due to internal variability [38]. They begin with two equations:

$$M_{ij}(t) = u^m(t) + \text{Eint}_{ij}(t) + \text{Emod}_i(t), i = 1, \ldots, N^m, j = 1, \ldots, N_i \tag{1.1}$$

$$O_k(t) = u^o(t) + \text{Eint}^o(t) + \text{Esamp}_k(t), k = 1, \ldots, N^o \tag{1.2}$$

with time explicitly indicated, unlike FGZ [38, page 2]. i is the model membership index. j is the index of the i^{th} model's j^{th} ensemble. Here, $M_{ij}(t)$ and $O_k(t)$ are trends calculated using models or observations, respectively. $u^m(t)$ and $u^o(t)$ denote the "true, unknown, deterministic trends due to external forcing" common to models and observations, respectively [38]. $\text{Eint}_{ij}(t)$ and $\text{Eint}^o(t)$ are the perturbations to trends due to internal variability of models and observations. $\text{Emod}_i(t)$ denotes error in climate model trends for model i. $\text{Esamp}_k(t)$ denotes the sampling error in the k^{th} sample. Notably FGZ assume $\text{Emod}_i(t)$ are exchangeable with each other as well, at least for the same time t. Note as well that while the internal variability of climate models $\text{Eint}_{ij}(t)$ varies from model-to-model, run-to-run, and time-to-time, the 'internal variability of observations', namely $\text{Eint}^o(t)$, is assumed to only vary with time.

The technical innovation FGZ use is to employ *bootstrap resampling* on the observations ensemble of HadCRUT4 and an ensemble of runs of 38 CMIP5 climate models to perform what is essentially a *two-sample comparison* [11, 18]. In doing so, they explicitly assume, in the framework above, *exchangeability of models*[11]. k runs over the bootstrap samples taken from HadCRUT4 observations.

So, what *is* a bootstrap? In its simplest form, a bootstrap is a nonparametric, often robust, frequentist technique for sampling the distribution of a function of a set of population parameters, generally irrespective of the nature or complexity of that function, or the number of parameters. Since estimates of the variance of that function, are themselves functions of population parameters, assuming the variance exists, the bootstrap can also be used to estimate the precision[12] of the first set of samples. In the case in question

[10]""It's great there's a new initiative," says modeler Inez Fung of DOE's Lawrence Berkeley National Laboratory and the University of California, Berkeley. "But all the modeling efforts are very short-handed. More brains working on one set of code would be better than working separately.""

[11]*Exchangeability* is a weaker assumption than *independence*. Random variables are *exchangeable* if their joint distribution only depends upon the set of variables, and not their order [19, 20, 94]. Note the caution in Coolen [**?**].

[12]The *precision* is the reciprocal of variance.

here, with FGZ, the bootstrap is being used to determine if the distribution of surface temperature trends as calculated from observations and the distribution of surface temperature trends as calculated from climate models for the same period have in fact similar means. This is done by examining *differences of paired trends*, one coming from an observation sample, one coming from a model sample, and assessing the degree of discrepancy based upon the variances of the observations trends distribution and of the models trends distribution.

The equations (1.1) and (1.2) can be re-written:

$$M_{ij}(t) - \text{Eint}_{ij}(t) = u^m(t) + \text{Emod}_i(t), i = 1, \ldots, N^m, j = 1, \ldots, N_i \tag{1.3}$$

$$O_k(t) - \text{Eint}^o(t) = u^o(t) + \text{Esamp}_k(t), k = 1, \ldots, N^o \tag{1.4}$$

moving the trends in internal variability to the left, calculated side. Both $\text{Eint}_{ij}(t)$ and $\text{Eint}^o(t)$ are *not* directly observable. Without some additional assumptions[13], such as

$$\text{Eint}_{ij}(t) \sim \mathcal{N}(0, \Sigma_{\text{model int}}) \tag{1.5}$$

$$\text{Eint}^o(t) \sim \mathcal{N}(0, \Sigma_{\text{obs int}}) \tag{1.6}$$

we can't really be sure we're seeing $O_k(t)$ or $O_k(t) - \text{Eint}^o(t)$, or at least $O_k(t)$ less the mean of $\text{Eint}^o(t)$. The same for $M_{ij}(t)$ and $\text{Eint}_{ij}(t)$.

[13]These may be implicit in the FGZ paper. They are not given explicitly. I don't see anything which says these must be true. Here $\Sigma_{\text{model int}}$ and $\Sigma_{\text{obs int}}$ are covariances among models and among observations. FGZ essentially say these are diagonal with their statement "An implicit assumption is that sampling uncertainty in [observation trends] is independent of uncertainty due to internal variability and also independent of uncertainty in [model trends]" [38]. They might not be so, but it is reasonable to suppose their diagonals are strong, and that there is a row-column exchange operator on these covariances which can produce banded matrices.

6 On Reconciliation

The centerpiece of the FGZ result is their Figure 1, reproduced here as Figure 1.15. Their conclusion, that climate models do not properly capture surface temperature observations for the given periods, is based upon the significant separate of the red density from the grey density, even measuring that separation using pooled variances. But, surely, a remarkable feature of these graphs is not only the separation of the means of the two densities, but the marked difference between the variance of the two densities. Why are climate models so less precise than HadCRUT4 observations? Conceivably, why do climate models

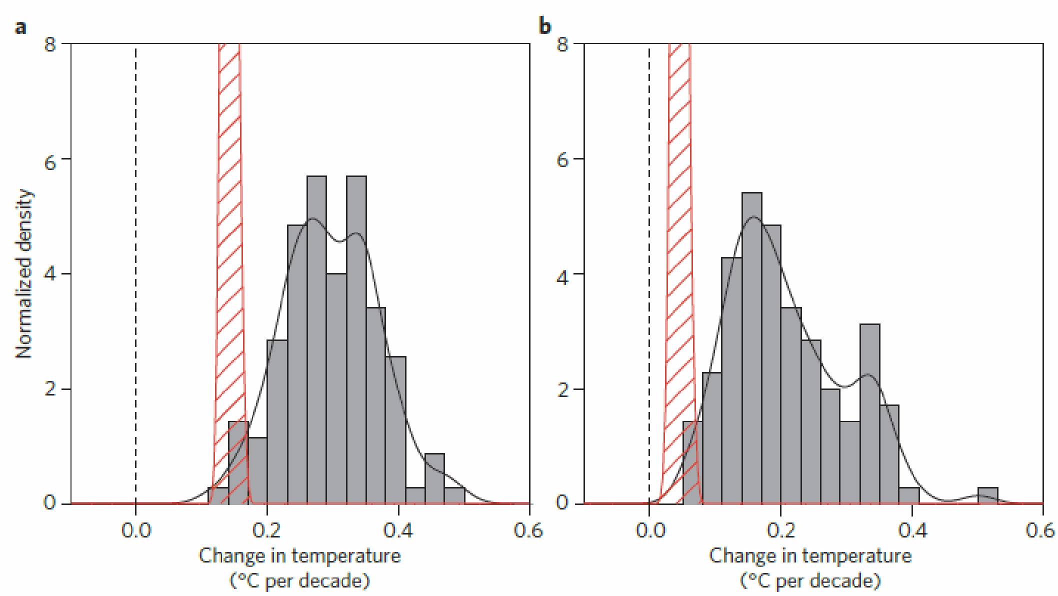


Figure 1 | Trends in global mean surface temperature. **a**, 1993–2012. **b**, 1998–2012. Histograms of observed trends (red hatching) are from 100 reconstructions of the HadCRUT4 dataset[1]. Histograms of model trends (grey bars) are based on 117 simulations of the models, and black curves are smoothed versions of the model trends. The ranges of observed trends reflect observational uncertainty, whereas the ranges of model trends reflect forcing uncertainty, as well as differences in individual model responses to external forcings and uncertainty arising from internal climate variability.

Figure 1.15: Figure 1 from Fyfe, Gillet, Zwiers [37].

not agree with one another so dramatically? We cannot tell without getting into CMIP5 details, but the same result could be obtained if the climate models came in three Gaussian populations, each with a variance 1.5x that of the observations, but mixed together. We could also obtain the same result if, for some reason, the variance of the HadCRUT4 was markedly understated.

That brings us back to the comments about HadCRUT4 made at the end of Section 2. HadCRUT4 is noted for "drop outs" in observations, where either the quality of an observation on a patch of Earth was poor or the observation was missing altogether for a certain month in history. It also has incomplete coverage [16]. Whether or not values for patches are *imputed* in some way, perhaps using *kriging*, or supports to calculate trends are adjusted to avoid these holes is an important question. As seen in Section 4, what trends you get depends a lot on how they are done. FGZ did linear trends. These are nice because means of trends have simple relationships with the trends themselves. On the other hand, using linear trends tends is equivalent to applying a low-pass filter to the density. This can produce a broad Gaussian shape from a multimodal one derived by estimating the density of a set of trends obtained using a good estimate of the local first derivative.

If Earth's climate is thought of as a *dynamical system*, and take note the suggestion of Kharin that "There is basically one observational record in climate research", we can do the following thought experiment [56]. Suppose the total state of the Earth's climate system can be captured at one moment in time, no matter how, and the climate can be reinitialized to that state at our whim, again no matter how. What happens if this is done several times, and then the climate is permitted to develop for, say, exactly 100 years on each "run"? What are the resulting states? Suppose the dynamical "inputs" from the Sun, as a function of time, are held identical during that 100 years, as are dynamical inputs from volcanic forcings, as are human emissions of greenhouse gases. Are the resulting states copies of one another? No. Stochastic variability in the operation of climate means these end states will be each somewhat different than one another. Then of what use is the "one observation record"? Well, it is arguably better than no observational record.

In fact, FGZ's bootstrap approach to the HadCRUT4 ensemble is an attempt to imitate these various runs of Earth's climate. The trouble is, the frequentist bootstrap can only replicate values of observations actually seen, in this case, those of the HadCRUT4 ensembles. It will never produce values in-between and, as the parameters of temperature anomalies are in general continuous measures, that seems a reasonable thing to do. It may be possible to remedy this using a different kind of bootstrap, such as a *Bayesian bootstrap*, but I think there's another way. Suppose the $M_{ij}(t)$ are used to construct, for each time t, an *average model*, say, $\mathcal{M}(t)$ [35]. That construction also yields a time-varying variance, var$[\mathcal{M}](t)$ of this average model. And, while it can be done without the Gaussian assumption, suppose for example, deviations from that model are treated as Gaussian, so particular climate variable, like surface temperature, $\tau(t)$, abides a Gaussian density, per the usual:

$$\mathbf{n}(t, \tau(t)) = \frac{1}{\sqrt{2\pi \operatorname{var}[\mathcal{M}](t)}} \exp\left(-\frac{(\tau(t) - \mathcal{M}(t))^2}{2 \operatorname{var}[\mathcal{M}](t)}\right) \tag{1.7}$$

Such an expression can be interpreted as a *likelihood function*[14] of a particular $\tau(t)$ and therefore seen as the probability of having an excursion from the best known model average of $\tau(t) - \mathcal{M}(t)$. Such a reformulation would change the FGZ title of "Overestimated global warming over the past 20 years" to something like *Warming over the past 20 years is unusual*, which, by what's known of the science, seems more consistent.

More work needs to be done to assess the proper virtues of the FGZ technique. By rights, while climate models and observations might have different mean values in their estimates of variability for any time interval in the record, the widths of their distributions should broadly overlap. In my opinion, it is less the difference of their means that is interesting than the remarkably narrow distribution attributed to HadCRUT4 after processing. A device like that Rohde used to compare BEST temperature observations

[14] It is possible to develop an *empirical likelihood function* as well. See Owen [83].

with HadCRUT4 and GISS, one of supplying the FGZ procedure with synthetic data, would be perhaps the most informative regarding its character [93]. It would be worthwhile.

And regarding climate models, assessing *parametric uncertainty* hand-in-hand with the model builders seems to be a sensible route [68]. If the FGZ technique, or any other, can contribute to this process, it is most welcome. Lee reports how the GLOMAP model of aerosols was systematically improved using such careful statistical consideration [69]. It seems likely to be a more rewarding way than "black box" treatments. Incidently, Dr Lindsay Lee's article was runner-up in the *Significance*/Young Statisticians Section writers' competition. It's great to see bright young minds charging in to solve these problems!

7 Summary

Bibliography

[1] ACCCP, "ASA Advisory Committee on Climate Change Policy", *American Statistical Association*, 2013, `http://www.amstat.org/committees/ccpac/`, last visited 13^{th} September 2013.

[2] M. Aldrin, M. Holden, P. Guttorp, R. B. Skeie, G. Myhre, T. K. Berntsen, "Bayesian estimation of climate sensitivity based on a simple climate model fitted to observations of hemispheric temperatures and global ocean heat content", *Environmentrics*, 2012, **23**, 253-257, `http://dx.doi.org/10.1002/env.2140`.

[3] "ASA Statement on Climate Change", *American Statistical Association*, ASA Board of Directors, adopted 30^{th} November 2007, `http://www.amstat.org/news/climatechange.cfm`, last visited 13^{th} September 2013.

[4] L. M. Berliner, Y. Kim, "Bayesian design and analysis for superensemble-based climate forecasting", *Journal of Climate*, **21**, 1 May 2008, `http://dx.doi.org/10.1175/2007JCLI1619.1`.

[5] "Examining the recent "pause" in global warming", *Berkeley Earth Memo*, 2013, `http://static.berkeleyearth.org/memos/examining-the-pause.pdf`.

[6] S. P. Brooks, A. Gelman, "General methods for monitoring convergence of iterative simulations", *Journal of Computational and Graphical Statistics*, **7**, 1998, 434-455.

[7] P. Brohan, J. Kennedy, I. Harris, S. Tett, P. D. Jones, "Uncertainty estimates in regional and global observed temperature changes: A new data set from 1850", *Journal of Geophysical Research –Atmospheres*, 111(D12), 27 June 2006, `http://dx.doi.org/10.1029/2005JD006548`.

[8] K. P. Burnham, D. R. Anderson, *Model Selection and Multimodel Inference*, 2^{nd} edition, Springer-Verlag, 2002.

[9] P. M. Caldwell, Y. Zhang, S. A. Klein, "CMIP3 subtropical stratocumulus cloud feedback interpreted through a mixed-layer model", *Journal of Climate*, **26**, 2013, 1607-1625, `http://dx.doi.org/10.1175/JCLI-D-12-00188.1`.

[10] S. Carson, *Science of Doom*, a Web site devoted to atmospheric radiation physics and forcings, last accessed 7^{th} February 2014.

[11] M. R. Chernick, *Bootstrap Methods: A Guide for Practitioners and Researches*, 2^{nd} edition, 2008, John Wiley & Sons.

[12] C. Chivers, "Simudidactic", in *bayesianbiologist*, `http://bayesianbiologist.com/2013/11/23/simudidactic/`, last accessed 24^{th} November 2013.

[13] R. Christensen, W. Johnson, A. Branscum, T. E. Hanson, *Bayesian Ideas and Data Analysis: An Introduction for Scientists and Statisticians*, CRC Press, 2011.

[14] P. Congdon, *Bayesian Statistical Modelling*, 2^{nd} edition, John Wiley & Sons, 2006.

[15] F. P. A. Coolen, "On nonparametric predictive inference and objective Bayesianism", *Journal of Logic, Language and Information*, **15**, 2006, 21-47, http://dx.doi.org/10.1007/s10849-005-9005-7. ("Generally, though, both for frequentist and Bayesian approaches, statisticians are often happy to assume exchangeability at the prior stage. Once data are used in combination with model assumptions, exchangeability no longer holds post-data due to the influence of modelling assumptions, which effectively are based on mostly subjective input added to the information from the data.").

[16] K. Cowtan, R. G. Way, "Coverage bias in the HadCRUT4 temperature series and its impact on recent temperature trends", *Quarterly Journal of the Royal Meteorological Society*, 2013, http://dx.doi.org/10.1002/qj.2297.

[17] P. Craven, G. Wahba, "Smoothing noisy data with spline functions: Estimating the correct degree of smoothing by the method of generalized cross-validation", *Numerische Mathematik*, **31**, 1979, 377-403, http://www.stat.wisc.edu/~wahba/ftp1/oldie/craven.wah.pdf.

[18] A. C. Davison, D. V. Hinkley, *Bootstrap Methods and their Application*, first published 1997, 11^{th} printing, 2009, Cambridge University Press.

[19] P. Diaconis, "Finite forms of de Finetti's theorem on exchangeability", *Synthese*, **36**, 1977, 271-281.

[20] P. Diaconis, "Recent progress on de Finetti's notions of exchangeability", *Bayesian Statistics*, **3**, 1988, 111-125.

[21] D. J. Easterbrook, D. J. Kovanen, "Cyclical oscillation of Mt. Baker glaciers in response to climatic changes and their correlation with periodic oceanographic changes in the northeast Pacific Ocean", **32**, 2000, *Proceedings of the Geological Society of America*, Abstracts with Program, page 17, http://myweb.wwu.edu/dbunny/pdfs/dje_abstracts.pdf, abstract reviewed 23^{rd} April 2014.

[22] D. J. Easterbrook, "The next 25 years: global warming or global cooling? Geologic and oceanographic evidence for cyclical climatic oscillations", **33**, 2001, *Proceedings of the Geological Society of America*, Abstracts with Program, page 253, http://myweb.wwu.edu/dbunny/pdfs/dje_abstracts.pdf, abstract reviewed 23^{rd} April 2014.

[23] D. J. Easterbrook, "Causes and effects of abrupt, global, climate changes and global warming", *Proceedings of the Geological Society of America*, **37**, 2005, Abstracts with Program, page 41, http://myweb.wwu.edu/dbunny/pdfs/dje_abstracts.pdf, abstract reviewed 23^{rd} April 2014.

[24] D. J. Easterbrook, "The cause of global warming and predictions for the coming century", *Proceedings of the Geological Society of America*, 38(7), Astracts with Programs, page 235, http://myweb.wwu.edu/dbunny/pdfs/dje_abstracts.pdf, abstract reviewed 23^{rd} April 2014.

[25] D. J. Easterbrook, 2006b, "Causes of abrupt global climate changes and global warming predictions for the coming century", *Proceedings of the Geological Society of America*, **38**, 2006, Abstracts with Program, page 77, http://myweb.wwu.edu/dbunny/pdfs/dje_abstracts.pdf, abstract reviewed 23^{rd} April 2014.

[26] D. J. Easterbrook, "Geologic evidence of recurring climate cycles and their implications for the cause of global warming and climate changes in the coming century", *Proceedings of the Geological Society of America*, 39(6), Abstracts with Programs, page 507, http://myweb.wwu.edu/dbunny/pdfs/dje_abstracts.pdf, abstract reviewed 23^{rd} April 2014.

[27] D. J. Easterbrook, "Correlation of climatic and solar variations over the past 500 years and predicting global climate changes from recurring climate cycles", *Proceedings of the International Geological Congress*, 2008, Oslo, Norway.

[28] D. R. Easterling, M. F. Wehner, "Is the climate warming or cooling?", *Geophysical Research Letters*, **36**, L08706, 2009, http://dx.doi.org/10.1029/2009GL037810.

[29] S. Easterbrook, "What Does the New IPCC Report Say About Climate Change? (Part 4): Most of the heat is going into the oceans", 11^{th} April 2014, at the *Azimuth* blog, http://johncarlosbaez.wordpress.com/2014/04/11/what-does-the-new-ipcc-report-say-about-climate-change-part-4/.

[30] K. Emanuel, "Global warming effects on U.S. hurricane damage", *Weather, Climate, and Society*, **3**, 2011, 261-268, http://dx.doi.org/10.1175/WCAS-D-11-00007.1.

[31] "Guidance for the use of Bayesian statistics in medical device clinical trials", http://www.fda.gov/medicaldevices/deviceregulationandguidance/guidancedocuments/ucm071072.htm,5^{th} February 2010.

[32] M. H. England, S. McGregor, P. Spence, G. A. Meehl, A. Timmermann, W. Cai, A. S. Gupta, M. J. McPhaden, A. Purich, A. Santoso, "Recent intensification of wind-driven circulation in the Pacific and the ongoing warming hiatus", *Nature Climate Change*, **4**, 2014, 222-227, http://dx.doi.org/10.1038/nclimate2106. See also http://www.realclimate.org/index.php/archives/2014/02/going-with-the-wind/.

[33] X. Feng, T. DelSole, P. Houser, "Bootstrap estimated seasonal potential predictability of global temperature and precipitation", *Geophysical Research Letters*, **38**, L07702, 2011, http://dx.doi.org/10.1029/2010GL046511.

[34] D. Ferreira, J. Marshall, B. Rose, "Climate determinism revisited: Multiple equilibria in a complex climate model", *Journal of Climate*, **24**, 2011, 992-1012, http://dx.doi.org/10.1175/2010JCLI3580.1.

[35] C. Fraley, A. E. Raftery, T. Gneiting, "Calibrating multimodel forecast ensembles with exchangeable and missing members using Bayesian model averaging", *Monthly Weather Review*. **138**, January 2010, http://dx.doi.org/10.1175/2009MWR3046.1.

[36] P. Friedlingstein, M. Meinshausen, V. K. Arora, C. D. Jones, A. Anav, S. K. Liddicoat, R. Knutti, "Uncertainties in CMIP5 climate projections due to carbon cycle feedbacks", *Journal of Climate*, 2013, http://dx.doi.org/10.1175/JCLI-D-12-00579.1.

[37] J. C. Fyfe, N. P. Gillett, F. W. Zwiers, "Overestimated global warming over the past 20 years", *Nature Climate Change*, **3**, September 2013, 767-769, and online at http://dx.doi.org/10.1038/nclimate1972.

[38] Supplement to J. C. Fyfe, N. P. Gillett, F. W. Zwiers, "Overestimated global warming over the past 20 years", *Nature Climate Change*, **3**, September 2013, online at http://www.nature.com/nclimate/journal/v3/n9/extref/nclimate1972-s1.pdf.

[39] J. C. Fyfe, N. P. Gillett, "Recent observed and simulated warming", *Nature Climate Change*, **4**, March 2014, 150-151, http://dx.doi.org/10.1038/nclimate2111.

[40] M. H. DeGroot, S. Fienberg, "The comparison and evaluation of forecasters", *The Statistician*, 32(1-2), 1983, 12-22.

[41] J. Geweke, "Simulation Methods for Model Criticism and Robustness Analysis", in *Bayesian Statistics 6*, J. M. Bernardo, J. O. Berger, A. P. Dawid and A. F. M. Smith (eds.), Oxford University Press, 1998.

[42] D. M. Glover, W. J. Jenkins, S. C. Doney, *Modeling Methods for Marine Science*, Cambridge University Press, 2011.

[43] J. Hansen, R. Ruedy, M. Sato, and K. Lo, "Global surface temperature change", *Reviews of Geophysics*, 48(RG4004), 2010, `http://dx.doi.org/10.1029/2010RG000345`.

[44] E. Hawkins, "Comparing global temperature observations and simulations, again", *Climate Lab Book*, `http://www.climate-lab-book.ac.uk/2013/comparing-observations-and-simulations-again/`, 28^{th} May 2013.

[45] A. Hannart, A. Ribes, P. Naveau, "Optimal fingerprinting under multiple sources of uncertainty", *Geophysical Research Letters*, **41**, 2014, 1261-1268, `http://dx.doi.org/10.1002/2013GL058653`.

[46] T. J. Hoar, R. F. Milliff, D. Nychka, C. K. Wikle, L. M. Berliner, "Winds from a Bayesian hierarchical model: Computations for atmosphere-ocean research", *Journal of Computational and Graphical Statistics*, 12(4), 2003, 781-807, `http://www.jstor.org/stable/1390978`.

[47] IPCC, 2013: Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Stocker, T.F., D. Qin, G.-K. Plattner, M. Tignor, S.K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex and P.M. Midgley (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 1535 pp.

[48]

[49] V. E. Johnson, "Revised standards for statistical evidence", *Proceedings of the National Academy of Sciences*, 11^{th} November 2013, `http://dx.doi.org/10.1073/pnas.1313476110`, published online before print.

[50] R. W. Katz, P. F. Craigmile, P. Guttorp, M. Haran, Bruno Sans'o, M.L. Stein, "Uncertainty analysis in climate change assessments", *Nature Climate Change*, **3**, September 2013, 769-771 ("Commentary").

[51] J. Karlsson, J., Svensson, "Consequences of poor representation of Arctic sea-ice albedo and cloud-radiation interactions in the CMIP5 model ensemble", *Geophysical Research Letters*, **40**, 2013, 4374-4379, `http://dx.doi.org/10.1002/grl.50768`.

[52] C. D. Keeling, "Rewards and penalties of monitoring the Earth", *Annual Review of Energy and the Environment*, **23**, 1998, 2582, `http://dx.doi.org/10.1146/annurev.energy.23.1.25`.

[53] J. J. Kennedy, N. A. Rayner, R. O. Smith, D. E. Parker, M. Saunby, "Reassessing biases and other uncertainties in sea-surface temperature observations measured in situ since 1850, part 1: measurement and sampling uncertainties", *Journal of Geophysical Research: Atmospheres (1984-2012)*, 116(D14), 27 July 2011, `http://dx.doi.org/10.1029/2010JD015218`.

[54] J. J. Kennedy, N. A. Rayner, R. O. Smith, D. E. Parker, M. Saunby, "Reassessing biases and other uncertainties in sea-surface temperature observations measured in situ since 1850, part 2: Biases and homogenization", *Journal of Geophysical Research: Atmospheres (1984-2012)*, 116(D14), 27 July 2011, `http://dx.doi.org/10.1029/2010JD015220`.

[55] V. V. Kharin, F. W. Zwiers, "Climate predictions with multimodel ensembles", *Journal of Climate*, **15**, 1^{st} April 2002, 793-799.

[56] S. Kharin, "Statistical concepts in climate research: Some misuses of statistics in climatology", Banff Summer School, 2008, part 1 of 3. Slide 7, "Climatology is a one-experiment science. There is basically one observational record in climate."

[57] S. Kharin, "Climate Change Detection and Attribution: Bayesian view", Banff Summer School, 2008, part 3 of 3.

[58] J. T. Kiehl, K. E. Trenberth, "Earth's annual global mean energy budget", *Bulletin of the American Meteorological Society*, 78(2), 1997, `http://dx.doi.org/10.1175/1520-0477(1997)078<0197:EAGMEB>2.0.CO;2`.

[59] E. Kintsch, "Researchers wary as DOE bids to build sixth U.S. climate model", *Science*, 341(6151), 13^{th} September 2013, page 1160, `http://dx.doi.org/10.1126/science.341.6151.1160`.

[60] Y. Kosaka, S.-P. Xie, "Recent global-warming hiatus tied to equatorial Pacific surface cooling", *Nature*, **501**, 2013, 403407, `http://dx.doi.org/10.1038/nature12534`.

[61] J. K. Kruschke, *Doing Bayesian Data Analysis: A Tutorial with **R** and BUGS*, Academic Press, 2011.

[62] J. K. Kruschke, "Bayesian estimation supersedes the *t* test", *Journal of Experimental Psychology: General*, 142(2), 2013, 573-603, `http://www.indiana.edu/~kruschke/articles/Kruschke2013JEPG.pdf`, and video at `http://doingbayesiandataanalysis.blogspot.com/2012/11/video-bayesian-estimation-supersedes-t.html`. Academic Press, 2011.

[63] J. P. Krasting, J. P. Dunne, E. Shevliakova, R. J. Stouffer (2014), "Trajectory sensitivity of the transient climate response to cumulative carbon emissions", *Geophysical Research Letters*, **41**, 2014, `http://dx.doi.org/10.1002/2013GL059141`.

[64] T. C. K. Lee, F. W. Zwiers, G. C. Hegerl, X. Zhang, M. Tsao, "A Bayesian climate change detection and attribution assessment", *Journal of Climate*, **18**, 2005, 2429-2440.

[65] M. C. Lemos, R. B. Rood, "Climate projections and their impact on policy and practice", *WIREs Climate Change*, *1*, September/October 2010, `http://dx.doi.org/10.1002/wcc.71`.

[66] S. Levitus, J. I. Antonov, T. P. Boyer, O. K. Baranova, H. E. Garcia, R. A. Locarnini, A. V. Mishonov, J. R. Reagan, D. Seidov, E. S. Yarosh, and M. M. Zweng, "World ocean heat content and thermosteric sea level change (0-2000 m), 1955-2010", *Geophysical Research Letters*, **39**, L10603, 2012, `http://dx.doi.org/10.1029/2012GL051106`.

[67] S. Levitus, J. I. Antonov, T. P. Boyer, O. K. Baranova, H. E. Garcia, R. A. Locarnini, A. V. Mishonov, J. R. Reagan, D. Seidov, E. S. Yarosh, and M. M. Zweng, "World ocean heat content and thermosteric sea level change (0-2000 m), 1955-2010: supplementary information", *Geophysical Research Letters*, **39**, L10603, 2012, `http://onlinelibrary.wiley.com/doi/10.1029/2012GL051106/suppinfo`.

[68] L. A. Lee, K. J. Pringle, C. I. Reddington, G. W. Mann, P. Stier, D. V. Spracklen, J. R. Pierce, K. S. Carslaw, "The magnitude and causes of uncertainty in global model simulations of cloud condensation nuclei", *Atmospheric Chemistry and Physics Discussion*, **13**, 2013, 6295-6378, `http://www.atmos-chem-phys.net/13/9375/2013/acp-13-9375-2013.pdf`.

[69] L. A. Lee, "Uncertainties in climate models: Living with uncertainty in an uncertain world", *Significance*, 10(5), October 2013, 34-39, `http://dx.doi.org/10.1111/j.1740-9713.2013.00697.x`.

[70] X. R. Li, X.-B. Li, "Common fallacies in hypothesis testing", *Proceedings of the 11th IEEE International Conference on Information Fusion*, 2008, New Orleans, LA.

[71] J.-L. F. Li, D. E. Waliser, G. Stephens, S. Lee, T. LEcuyer, S. Kato, N. Loeb, H.-Y. Ma, "Characterizing and understanding radiation budget biases in CMIP3/CMIP5 GCMs, contemporary GCM, and reanalysis", *Journal of Geophysical Research: Atmospheres*, **118**, 2013, 8166-8184, `http://dx.doi.org/10.1002/jgrd.50378`.

[72] D. Lunn, C. Jackson, N. Best, A. Thomas, D. Spiegelhalter, *The BUGS Book: A Practical Introduction to Bayesian Analysis*, Chapman & Hall/CRC, 2013.

[73] D. Martin, P. Schwartz, E. Ng, S. Williams, S. Cornford, W. Lipscomb, S. Price, D. Ranken, "BISICLES for ice sheet in climate applications", Applied Numerical Algorithms Group, Lawrence Berkeley Laboratory, 2013, `http://crd.lbl.gov/groups-depts/ANAG/research/bisicles-for-ice-sheet-in-climate-applications/`, last visited 16^{th} September 2013.

[74] E. Maloney, S. Camargo, E. Chang, B. Colle, R. Fu, K. Geil, Q. Hu, x. Jiang, N. Johnson, K. Karnauskas, J. Kinter, B. Kirtman, S. Kumar, B. Langenbrunner, K. Lombardo, L. Long, A. Mariotti, J. Meyerson, K. Mo, D. Neelin, Z. Pan, R. Seager, Y. Serra, A. Seth, J. Sheffield, J. Stroeve, J. Thibeault, S. Xie, C. Wang, B. Wyman, and M. Zhao, "North American Climate in CMIP5 Experiments: Part III: Assessment of 21st Century Projections", *Journal of Climate*, 2013, in press, `http://dx.doi.org/10.1175/JCLI-D-13-00273.1`.

[75] P. McCullagh, "Exchangeability and regression models", The University of Chicago, Department of Statistics, Technical Report No. 544, January 2004.

[76] G. A. Meehl, J. M. Arblaster, J. T. Fasullo, A. Hu.K. E. Trenberth, "Model-based evidence of deep-ocean heat uptake during surface-temperature hiatus periods", *Nature Climate Change*, **1**, 2011, 360364, `http://dx.doi.org/10.1038/nclimate1229`.

[77] G. A. Meehl, A. Hu, J. M. Arblaster, J. Fasullo, K. E. Trenberth, "Externally forced and internally generated decadal climate variability associated with the Interdecadal Pacific Oscillation", *Journal of Climate*, **26**, 2013, 72987310, `http://dx.doi.org/10.1175/JCLI-D-12-00548.1`.

[78] S.-K. Min, D. Simonis, A. Hense, "Probabilistic climate change predictions applying Bayesian model averaging", *Philosophical Transactions of the Royal Society*, *Series A*, **365**, 15^{th} August 2007, `http://dx.doi.org/10.1098/rsta.2007.2070`.

[79] C. P. Morice, J. J. Kennedy, N. A. Rayner, P. D. Jones, "Quantifying uncertainties in global and regional temperature change using an ensemble of observational estimates: The HadCRUT4 data set", *Journal of Geophysical Research*, **117**, 2012, `http://dx.doi.org/10.1029/2011JD017187`. See also `http://www.metoffice.gov.uk/hadobs/hadcrut4/data/current/download.html` where the 100 ensembles can be found.

[80] R. A. Muller, J. Curry, D. Groom, R. Jacobsen, S. Perlmutter, R. Rohde, A. Rosenfeld, C. Wickham, J. Wurtele, "Decadal variations in the global atmospheric land temperatures", *Journal of Geophysical Research: Atmospheres*, 118(11), 2013, 5280-5286, `http://dx.doi.org/10.1002/jgrd.50458`.

[81] R. Muller, "Has global warming stopped?", *Berkeley Earth Memo*, September 2013, `http://static.berkeleyearth.org/memos/has-global-warming-stopped.pdf`.

[82] N. Nicholls, "The insignificance of significance testing", *Bulletin of the American Meteorological Society*, **82**, 2001, 971-986.

[83] A. B. Owen, *Empirical Likelihood*, Chapman & Hall/CRC, 2001.

[84] G. Pennello, L. Thompson, "Experience with reviewing Bayesian medical device trials", *Journal of Biopharmaceutical Statistics*, 18(1), 81-115).

[85] G. W. Petty, *A First Course in Atmospheric Radiation*, 2^{nd} edition, Sundog Publishing, 2006.

[86] R. T. Pierrehumbert, "Infrared radiative and planetary temperature", *Physics Today*, January 2011, 33-38.

[87] R. Pielke, Sr, "The Lyman et al Paper 'Recent Cooling In the Upper Ocean' Has Been Published", blog entry, September 29, 2006, 8:09 AM, `https://pielkeclimatesci.wordpress.com/2006/09/29/the-lyman-et-al-paper-recent-cooling-in-the-upper-ocean-has-been-published/`, last accessed 24th April 2014.

[88] R. T. Pierrehumbert, *Principles of Planetary Climate*, Cambridge University Press, 2010, reprinted 2012.

[89] M. Plummer, "Just Another Gibbs Sampler", JAGS, 2013. Plummer describes this in greater detail at "JAGS: A program for analysis of Bayesian graphical models using Gibbs sampling", *Proceedings of the 3rd International Workshop on Distributed Statistical Computing* (DSC 2003), 20-22 March 2003, Vienna. See also M. J. Denwood, [in review] "runjags: An R package providing interface utilities, parallel computing methods and additional distributions for MCMC models in JAGS", *Journal of Statistical Software*, and `http://cran.r-project.org/web/packages/runjags/`. See also J. Kruschke, "Another reason to use JAGS instead of BUGS", `http://doingbayesiandataanalysis.blogspot.com/2012/12/another-reason-to-use-jags-instead-of.html`, 21st December 2012.

[90] D. N. Politis, J. P. Romano, "The Stationary Bootstrap", *Journal of the American Statistical Association*, 89(428), 1994, 1303-1313, `http://dx.doi.org/10.1080/01621459.1994.10476870`.

[91] N. Rayner, P. Brohan, D. Parker, C. Folland, J. Kennedy, M. Vanicek, T. Ansell, S. Tett, "Improved Analyses of Changes and Uncertainties in Sea Surface Temperature Measured In Situ since the Mid-Nineteenth Century: The HadSST2 Dataset", *Journal of Climate*, **19**, 1 February 2006, `http://dx.doi.org/10.1175/JCLI3637.1`.

[92] R. Rhode, R. A. Muller, R. Jacobsen, E. Muller, S. Perlmutter, A. Rosenfeld, J. Wurtele, D. Groom, C. Wickham, "A new estimate of the average Earth surface land temperature spanning 1753 to 2011", *Geoinformatics & Geostatistics: An Overview*, 1(1), 2013, `http://dx.doi.org/10.4172/2327-4581.1000101`.

[93] R. Rohde, "Comparison of Berkeley Earth, NASA GISS, and Hadley CRU averaging techniques on ideal synthetic data", *Berkeley Earth Memo*, January 2013, `http://static.berkeleyearth.org/memos/robert-rohde-memo.pdf`.

[94] J.C. Rougier, M. Goldstein, L. House, "Second-order exchangeability analysis for multi-model ensembles", *Journal of the American Statistical Association*, **108**, 2013, 852-863, `http://dx.doi.org/10.1080/01621459.2013.802963`.

[95] C.-E. Särndal, B. Swensson, J. Wretman, *Model Assisted Survey Sampling*, Springer, 1992.

[96] B. M. Sanderson, B. C. ONeill, J. T. Kiehl, G. A. Meehl, R. Knutti, W. M. Washington, "The response of the climate system to very high greenhouse gas emission scenarios", *Environmental Research Letters*, **6**, 2011, 034005, `http://dx.doi.org/10.1088/1748-9326/6/3/034005`.

[97] B. D. Santer, J. F. Painter, C. A. Mears, C. Doutriaux, P. Caldwell, J. M. Arblaster, P. J. Cameron-Smith, N. P. Gillett, P. J. Gleckler, J. Lanzante, J. Perlwitz, S. Solomon, P. A. Stott, K. E. Taylor, L. Terray, P. W. Thorne, M. F. Wehner, F. J. Wentz, T. M. L. Wigley, L. J. Wilcox, C.-Z. Zou, "Identifying human infuences on atmospheric temperature", *Proceedings of the National Academy of Sciences*, (*PNAS*), 29th November 2012, `http://dx.doi.org/10.1073/pnas.1210514109`.

[98] S. Särkkä, *Bayesian Filtering and Smoothing*, Cambridge University Press, 2013.

[99] G. A. Schmidt, D. T. Shindell, K. Tsigaridis, "Reconciling warming trends", *Nature Geoscience*, **7**, 2014, 158-160, `http://dx.doi.org/10.1038/ngeo2105`.

[100] D. T. Shindell, "Inhomogeneous forcing and transient climate sensitivity", *Nature Climate Change*, **4**, 2014, 274-277, http://dx.doi.org/10.1038/nclimate2136.

[101] D. T. Shindell, "Shindell: On constraining the Transient Climate Response", *RealClimate*, http://www.realclimate.org/index.php?p=17134, 8^{th} April 2014.

[102] J. Slingo, "Statistical models and the global temperature record", *Met Office*, May 2013, http://www.metoffice.gov.uk/media/pdf/2/3/Statistical_Models_Climate_Change_May_2013.pdf.

[103] R. L. Smith, C. Tebaldi, D. Nychka, L. O. Mearns, "Bayesian modeling of uncertainty in ensembles of climate models", *Journal of the American Statistical Association*, 104(485), March 2009.

[104] L. A. Smith, N. Stern, "Uncertainty in science and its role in climate policy", *Philosophical Transactions of the Royal Society A*, **269**, 2011 369, 1-24, http://dx.doi.org/10.1098/rsta.2011.0149.

[105] K. E. Taylor, R.J. Stouffer, G.A. Meehl, "An overview of CMIP5 and the experiment design", *Bulletin of the American Meteorological Society*, **93**, 2012, 485-498, http://dx.doi.org/10.1175/BAMS-D-11-00094.1.

[106] "Tamino", "el Niño and the Non-Spherical Cow", *Open Mind* blog, http://tamino.wordpress.com/2013/09/02/el-nino-and-the-non-spherical-cow/, 2^{nd} September 2013.

[107] P. W. Thorne, D. E. Parker, J. R. Christy, C. A. Mears, "Uncertainties in climate trends: Lessons from upper-air temperature records", *Bulletin of the American Meteorological Society*, **86**, 2005, 1437-1442, http://dx.doi.org/10.1175/BAMS-86-10-1437.

[108] A. Toreti, P. Naveau, M. Zampieri, A. Schindler, E. Scoccimarro, E. Xoplaki, H. A. Dijkstra, S. Gualdi, J, Luterbacher, "Projections of global changes in precipitation extremes from CMIP5 models", *Geophysical Research Letters*, 2013, http://dx.doi.org/10.1002/grl.50940.

[109] K. Trenberth, J. Fasullo, J. T. Kiehl, "Earth's global energy budget", *Bulletin of the American Meteorological Society*, **90**, 2009, 311323, http://dx.doi.org/10.1175/2008BAMS2634.1.

[110] K. Trenberth, J. Fasullo, "An apparent hiatus in global warming?", *Earths Future*, 2013, http://dx.doi.org/10.1002/2013EF000165.

[111] A. Vehtari, J. Ojanen, "A survey of Bayesian predictive methods for model assessment, selection and comparison", *Statistics Surveys*, **6** (2012), 142-228, http://dx.doi.org/10.1214/12-SS102.

[112] G. Wahba, *Spline Models for Observational Data*, Society for Industrial and Applied Mathematics (SIAM), 1990.

[113] World Climate Research Programme (WCRP), "CMIP5: Coupled Model Intercomparison Project", http://cmip-pcmdi.llnl.gov/cmip5/, last visited 13^{th} September 2013.

[114] M. B. Westover, K. D. Westover, M. T. Bianchi, "Significance testing as perverse probabilistic reasoning", *BMC Medicine*, 9(20), 2011, http://www.biomedcentral.com/1741-7015/9/20.

[115] D. S. Wilks, *Statistical Methods in the Atmospheric Sciences*, 3^{rd} edition, 2011, Academic Press.

[116] J. K. Willis, J. M. Lyman, G. C. Johnson, J. Gilson, "Correction to 'Recent Cooling of the Upper Ocean'", *Geophysical Research Letters*, **34**, L16601, 2007, http://dx.doi.org/10.1029/2007GL030323.

[117] F. W. Zwiers, H. Von Storch, "On the role of statistics in climate research", *International Journal of Climatology*, **24**, 2004, 665-680.