Lower Tropospheric Temperatures 1978-2016: The Role Played By Anthropogenic Global Warming

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The slowdown in tropospheric temperature increase between 1997-2016 led some commentators in Australia (and elsewhere) to repeat earlier assertions that there is an absence of any relationship between anthropogenic carbon dioxide increase and global air temperature. Here we test the null hypothesis that anthropogenic greenhouse forcing makes no contribution to global mean tropospheric temperature by analysing a satellite-derived lower tropospheric temperature record since 1978. A well-known heuristic model that separates variance in air temperature into components from different sources of climate variability is employed to determine what contribution anthropogenic greenhouse gases made to satellite-measured lower tropospheric temperature. Over the satellite record from December 1978 to the January 2016 the anthropogenic contribution to lower tropospheric temperature is estimated to be between +0.29 and +0.34K. Over the shorter segment of the record from December 1997 to January 2016 an anthropogenic contribution of +0.15K to the satellite-derived lower tropospheric air temperature was found. The slowdown in rate of temperature increase in that period is found simply to be a consequence of internal climate system variability that at other times has the opposite effect. The null hypothesis of no relationship between lower troposphere temperature and greenhouse gas increase is rejected.

1. Introduction

A recurrent theme within some public Australian commentary on the science of anthropogenically-forced climate change has been that there is an absence of correlation between trends in global air temperature (T) and trends in greenhouse gas concentrations. A particular focus for such commentary has been on the period beginning just prior to the very large 1997-98 El Niño event extending to the end of 2015. One example commentary in early 2016 that stated *"there has been another spike in the global mean temperature based on this satellite record. This signifies the end of "the pause"*" but then went on to state that "*the ....shorter satellite records for all of Australia, the northern hemisphere and the globe, are not consistent with carbon dioxide as a significant driver of temperature change.*" (Marohasy 2016).

Another recent example utilised linear regression applied to a satellite-derived global tropospheric temperature record to conclude that temperature trend had remained "*paused*", or less than ±0.01K per decade, for eighteen years and eight months since November 1997 (Stewart 2016). Previously the same commentator had stated (Stewart 2016) "*Greenhouse gas increase is anthropogenic; CO_2 increase has probably caused some small temperature increase; The relationship between CO_2 and temperature in the satellite era is weak, with 58 per cent of the CO_2 increase occurring while temperatures have paused; Therefore temperature change is probably caused mainly by natural factors*".

There are evident deficiencies in an implicit assumption that a simple bivariate plot of global tropospheric temperature against CO_2 concentration over a short time period is sufficient to define the relationship between these parameters when it is well known that many other factors also contribute to variability in temperature at decadal timescales (Masson-Delmotte

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et al. 2013). Moreover, because the claimants write blogs that sit outside the climate science community and the scientific journal publication environment their conclusions are not subject to quality assurance through any form of rigorous scientific peer review: the claims are not tested in that way.

A final problem that stems from operating outside the scientific community is that these writers are unaware of, do not acknowledge and do not incorporate contemporary peer-reviewed scientific debate into their analyses, so uninformed and biased conclusions are likely. Just a very few exemplars of the breadth of contemporary peer-reviewed discussion in the scientific literature regarding global temperatures in the period post-1997 are provided in the works of Held (2013), Nieves et al. (2015), Steinman et al. (2015), Fyfe et al. (2016) and Mann et. al. (2016). Lewandowsky et al. (2015) cite many more in their use of the post-1997 slowdown in temperature trend as a case-study exemplar in their analysis of the way in which framing of the public narrative around climate change scepticism has affected the scientific community.

Given the foregoing, the current work was undertaken to bridge the gap between the blog-based commentary and the scientific community by here framing the sceptical commentary as a null hypothesis and testing that hypothesis in a rigorous scientific manner for dispassionate evaluation in the normal way via a peer-reviewed scientific publication, this paper.

The null hypothesis to be tested here is this: increasing levels of anthropogenic greenhouse gases make no contribution to global tropospheric temperature in the period of global tropospheric temperature measurement by satellite (since December 1978). This is generalised from reference to CO_2 forcing alone as it is overall anthropogenic forcing that will physically drive temperature response, not just CO_2. That said, CO_2 is the central player in anthropogenic forcing according to the Working Group 1 Report from the Intergovernmental Panel on Climate Change (see Figure 5 in the Summary for Policymakers): CO_2 contributed 1.68 Wm^{-2} of 2.29 Wm^{-2} estimated total net anthropogenic forcing in 2011 relative to 1750 (IPCC 2013).

2. Data and Methods

The global temperature record used here to test the null hypothesis is the satellite-derived record for the lower troposphere published by Spencer and Christy of the University of Alabama, Huntsville (UAH). The monthly-average temperature anomaly series is used. This represents a weighted average temperature over the lowest 10km of the atmosphere, with maximum weight at 3-4km altitude. Version 6.0 of the UAH Temperature Data Set was obtained from http://vortex.nsstc.uah.edu/data/msu/v6.0beta/tlt/uahncdc_lt_ac_6.0beta5. The series commences in December 1978.

To test the hypothesis that tropospheric temperature increase is unrelated to increase in anthropogenic greenhouse forcing a well known heuristic model is used. The model utilises an empirical multiple regression analysis method developed and applied to monthly global temperature anomaly series by Lean and Rind (2008) that has been applied and extended in various ways by others (Lean and Rind 2009; Lean 2010; Foster and Rahmstorf 2011; Kopp and Lean 2011; Zhou and Tung 2013; Tung and Zhou 2013; Chylek et al. 2014; Santer et al. 2014). The original technique models empirically the global temperature anomaly, ΔT, as a linear combination of contributions to temperature variability and trend from variations in El Niño-Southern Oscillation (ENSO), episodic cooling due to major volcanic eruptions (VOLC) injecting aerosol into the stratosphere, a quasi 11-year cycle of variability due to the small but regular cycles in total solar irradiance (TSI) and a trend in net anthropogenic forcing (ANTH; greenhouse gas warming offset to some degree by aerosol and cloud-mediated cooling). The regression equation used by Lean and Rind (2008) is:

$$\Delta T(t) = c0 + c1.ENSO(t-\Delta t_E) + c2.VOLC(t-\Delta t_V) + c3.TSI(t-\Delta t_T) + c4.ANTH(t-\Delta t_A) \quad (1)$$

where ΔT is the monthly T anomaly, the c's are the fitted coefficients, and Δt is a time lag in months specific to each explanatory variable, chosen to optimise the fit of the model by varying the lag to find the lag that maximised the multiple regression coefficient.

Zhou and Tung (2013) and Chylek et al. (2014) have suggested that the fit of the regression model to global temperature anomaly time-series is improved by adding the Atlantic Multidecadal Oscillation (AMO) as an explanatory variable. Elsewhere Rohde et al. (2013) found that a two parameter regression fit to annual average surface air temperature over land for the period 1753-2011 had a residual that strongly resembled the long-term AMO record. Thus the model here was tested with and without AMO leading to it being adopted as an additional term.

Additionally, the original model (Lean and Rind 2008) was later expanded by Kopp and Lean (2011) to improve variance explained by allowing for some broadening of the explanatory parameter responses through having the ENSO component incorporated three times each with a different lag, while VOLC was included twice with two different lags. That was the final form of the model applied to the UAH lower tropospheric temperature anomaly series.

The method here follows Lean and Rind (2008) in adoption of a relevant index for each independent variable. For ENSO the Multivariate ENSO Index (MEI) was adopted. For VOLC the stratospheric aerosol optical thickness series of Sato was used. For TSI the monthly series produced by Judith Lean (Lean 2010; Kopp and Lean, 2011) was used. For ANTH the IPCC's representative concentration pathways provide a single estimate of historical net anthropogenic forcing up to 2005, and projected forcings under different emissions and control scenarios post-2005, though the projected pathways post-2005 do not diverge significantly until beyond about 2020 (van Vuuren et al. 2011; IPCC 2013; Power et al. 2016). For the purpose here it thus makes no difference which pathway is used to describe historical forcing and the small extrapolation out to 2016. So a middle pathway, RCP4.5 was used. The final index employed in this work was the Atlantic Multidecadal Oscillation Index (AMO), obtained from NOAA/ESRL.

The list of indices used and the data source locations are given in Table 1.

Date Series	*Source*
ENSO	http://www.esrl.noaa.gov/psd/data/correlation/mei.data
VOLC	http://data.giss.nasa.gov/modelforce/strataer/
TSI	Lean (2010); Kopp and Lean (2011); J. Lean, personal communication
ANTH	http://tntcat.iiasa.ac.at:8787/RcpDb/dsd?Action=htmlpage&page=welcome
AMO	http://www.esrl.noaa.gov/psd/data/correlation/amon.us.long.data

Table 1 Independent variables used and data sources.

These independent variable data were all available with an anomaly reference period of 1961-1990, while UAH has the reference period 1981-2010. That difference has no effect on the regression results, simply adding a small component to the regression’s constant term.

3. Results

The heuristic model was applied to the UAH monthly anomaly data from December 1978 to January 2016 yielding the regression coefficients given in Table 2, with 71 per cent of variance explained. A visual model-data comparison is shown in panel (a) of Figure 1, from which it is evident that the UAH monthly data contain significantly more high frequency components, or noise, than the explanatory independent variables (Figure 2). Thus a second regression was performed with the UAH data series subject to a simple low-pass filter, a twelve month running mean tapering at each end, to filter out higher frequency components of the UAH signal. This second regression explained just under 90 per cent of variance, yielding the second set of coefficients in Table 2 and the visual model-data comparison shown in panel (b) of Figure 1.

Two implications follow from the visual comparisons in Figure 1. First, that the heuristic model based on just the five variables listed in Table 1 provides a very good explanation of variability in the UAH temperature data, particularly at annual and greater timescales when noise at monthly frequencies in the UAH data has been removed by the simple low pass filter. Second, while it would be possible to break the record into a number of short segments showing a variety of short-term trends as has been done by some public commentators, it is evident that taken over the full length of the data record the strong positive and negative variability at annual to inter-decadal timescales sits on a consistent upwards trend in temperature well characterised by the linear fit to the data included in each panel in Figure 1 (see also Table 3).

Forcing/CO_2 data set		*AMO*	*ANTH*	*TSI*	*VOLC(7)*	*VOLC(0)*	*ENSO(8)*	*ENSO(4)*	*ENSO(0)*	*intercept*
RCP4.5	coefficient	0.209	0.271	0.052	-1.99	-1.71	0.060	0.064	0.028	-0.156
$r^2 = 0.709$	std error	0.040	0.023	0.014	0.33	0.32	0.009	0.011	0.008	0.016
RCP4.5 (filtered)	coefficient	0.193	0.280	0.049	-2.18	-1.09	0.058	0.051	0.014	-0.159
$r^2 = 0.894$	std error	0.020	0.011	0.007	0.17	0.16	0.004	0.005	0.004	0.008
CO_2 (filtered)	coefficient	0.180	0.0050	0.050	-2.18	-1.10	0.058	0.051	0.015	-1.808
$r^2 = 0.897$	std error	0.020	0.0002	0.007	0.16	0.16	0.004	0.004	0.004	0.072
No-ANTH (filtered)	coefficient	0.475		0.023	-2.00	-1.10	0.038	0.042	0.013	0.014
$r^2 = 0.746$	std error	0.026		0.010	0.26	0.25	0.007	0.008	0.006	0.006

Table 2 Regression model coefficients with standard errors. The top two rows are for the model applied to the monthly UAH data for the lower troposphere (December 1978-January 2016), the next two rows are from the model applied to the same data after it was low-pass filtered. In both cases the ANTH index used was RCP4.5. The third set of two rows is for an additional case discussed later in the text where the regression applied to the low-pass filtered UAH data used monthly mean measured CO_2 levels from Mauna Loa, Hawaii, for ANTH in place of RCP4.5, while the final rows were for a regression with no ANTH component (see Discussion section for further details). The parenthetic numbers for ENSO and VOLC components reflect lag, in months

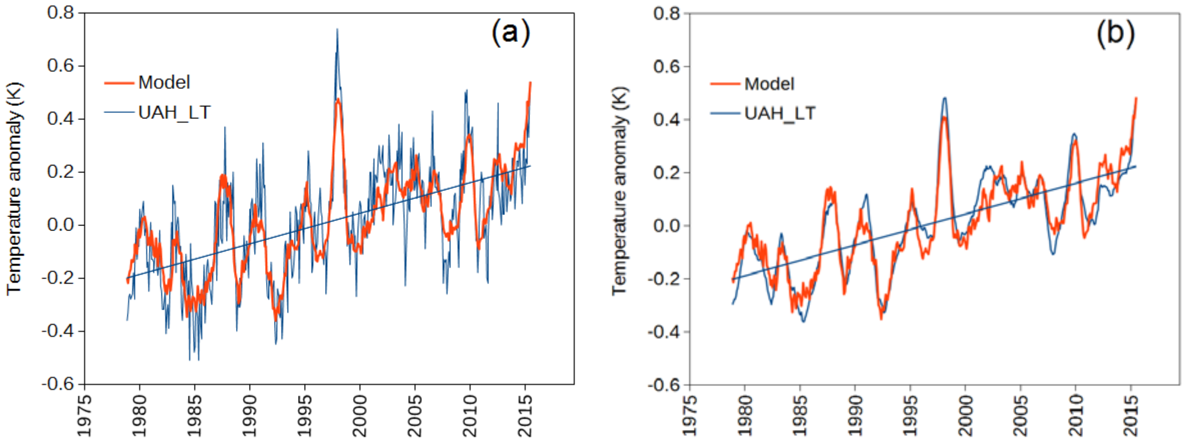

Figure 1 UAH global lower tropospheric (LT) temperature anomaly (blue lines), overlaid with the fitted regression model (orange lines). Panel (a): model fitted to monthly UAH data. Panel (b) model fitted to monthly UAH data low-pass filtered via a 12 month running mean. The straight lines are trend lines fitted to the UAH data series

To address the specific hypothesis that increases in greenhouse gases make no contribution to global air temperature consideration is now given to the individual components of the UAH signal determined by the regression analysis, remembering that only one of the explanatory variables, ANTH, represents the anthropogenic increase in net greenhouse forcing over the data analysis period. Figure 2 contains plots of each of the modelled components of both the unfiltered and low-pass filtered UAH signals shown in Figure 1. The results are close to identical. All coefficients differ from zero by more than 2 standard errors which based on the student t test implies statistical significance at $p < 0.05$.

Of specific interest here is what contribution to the UAH T trend can be attributed to each component. A simple empirical analysis is achieved by fitting a linear regression to the UAH T data in Figure 1 panel (b), doing likewise to each of the related component series in Figure 2, and comparing the UAH trend with the sum of the component trends. This is done in Table 3, revealing that the component trends sum to fully explain the T trend in the UAH T data series, and that the largest contribution to the observed trend is provided by ANTH, the index representing net anthropogenic greenhouse warming.

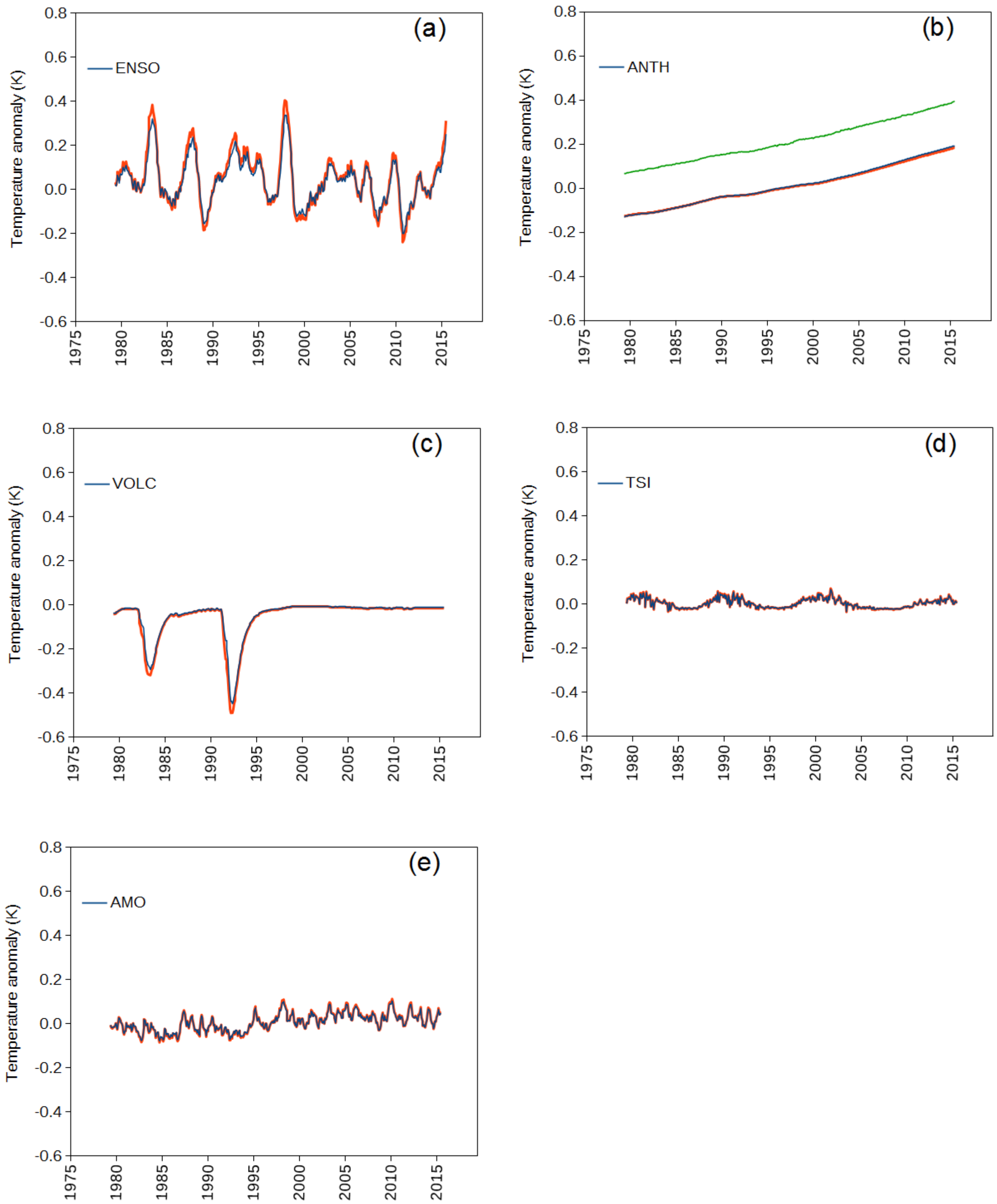

Figure 2 Regression component plots from the standard regression applied to the unfiltered (orange lines) and low-pass filtered (blue lines) UAH T anomaly series. In Panel (b) the green line depicts the ANTH contribution from the a regression applied to the low-pass filtered UAH data in an additional test in which RCP4.5 was replaced by the monthly mean CO_2 levels measured at Mauna Loa, Hawaii (see Discussion for details). The ANTH curve from that CO_2 regression sits exactly on top of the orange and blue curves so for clarity has been shifted upwards 0.2K

	K/decade
UAH_LT	0.11
ANTH	0.08
ENSO	-0.02
VOLC	0.03
TSI	0.00
AMO	0.02
Component Sum	0.11

Table 3 Linear T trend in the UAH data from Figure 1(b) (covering the period December 1978 - January 2016) and from the related regression components in Figure 2

4. Discussion

It is now possible to address the initial hypothesis: that increasing levels of anthropogenic greenhouse gases make no contribution to global tropospheric temperature in the period of global tropospheric temperature measurement by satellite (since December 1978). The results presented in Figure 2 and Table 3 makes it clear that this hypothesis cannot be sustained, so must be rejected. The analysis reveals that, in contradiction of that hypothesis, a sustained ANTH contribution of +0.08K per decade has been made to the UAH record over the period of its existence, with the magnitude of the overall UAH trend being determined by the ANTH trend added to or subtracted from by the smaller positive or negative trend contributions made by the other non-anthropogenic explanatory components, ENSO, VOLC, TSI and AMO.

To illustrate this point visually, Figure 3(a) displays the low-pass filtered UAH record contrasted with the same record after subtraction of the fitted ANTH contribution. For the full period removal of the ANTH contribution removes the majority of the UAH temperature trend. The small residual UAH trend can be attributed to the combination of small positive contributions to trend from VOLC and AMO offset partially by a small negative trend contribution from ENSO (Table 3).

Figure 3(a) also shows a line fitted to the UAH record for the shorter time period starting in November 1997. That period has been cited by various public commentators as demonstrating the absence of a relationship between anthropogenic greenhouse gases increase and global temperature, the rationale being that a linear regression to the UAH data for that chosen interval has zero slope, which is what that short-period fit reproduces (0.00K per decade) in Figure 3(a). The figure also shows a line fitted over the same period to the record having the ANTH contribution subtracted from the UAH record. With the ANTH contribution removed there is a negative temperature trend (-0.10K per decade) for the short period from November 1997. Far from the slowdown demonstrating an absence of greenhouse warming during that period, this analysis demonstrates that, had there not been a warming contribution from anthropogenic greenhouse gas increase in that period, a negative global temperature trend would have occurred.

Lean and Rind (2009) explored the prospects for just such an episodic decrease (or increase) in global T trend at sub-climatological timescales in a paper entitled *"How will Earth's surface temperature change in future decades?"*. Their conclusion was that variability associated with major influences on global temperature such as significant volcanic eruptions, large ENSO events and the regular cycle in total solar irradiance (to which we add here the AMO) must sum at different points in time to reduce or increase the overall temperature trend driven by anthropogenic global warming. They illustrated examples of both T trend decrease and trend increase in their Figure 1(a). Their work was prescient. The analysis presented here shows that the period 1997-2016 was one such period where the non-anthropogenic factors combined to offset anthropogenic global warming, leading to the apparent slowdown in global warming. We can conclude that in this period the planet continued to experience the ongoing global warming contribution from anthropogenic greenhouse gas increase, which enabled global temperature to remain flat rather than in decline by balancing out non-anthropogenic factors that otherwise would have combined to produce a phase of tropospheric cooling. The evidence is compelling that there was no cessation of anthropogenic greenhouse forcing in this period.

The disparate trend shown in Figure 3(a) for the post-1997 period in comparison with the trends calculated for the full dataset illustrate the dangers of drawing conclusions from too-short subsets of a data series containing multiple sources of both short and long-period variability.

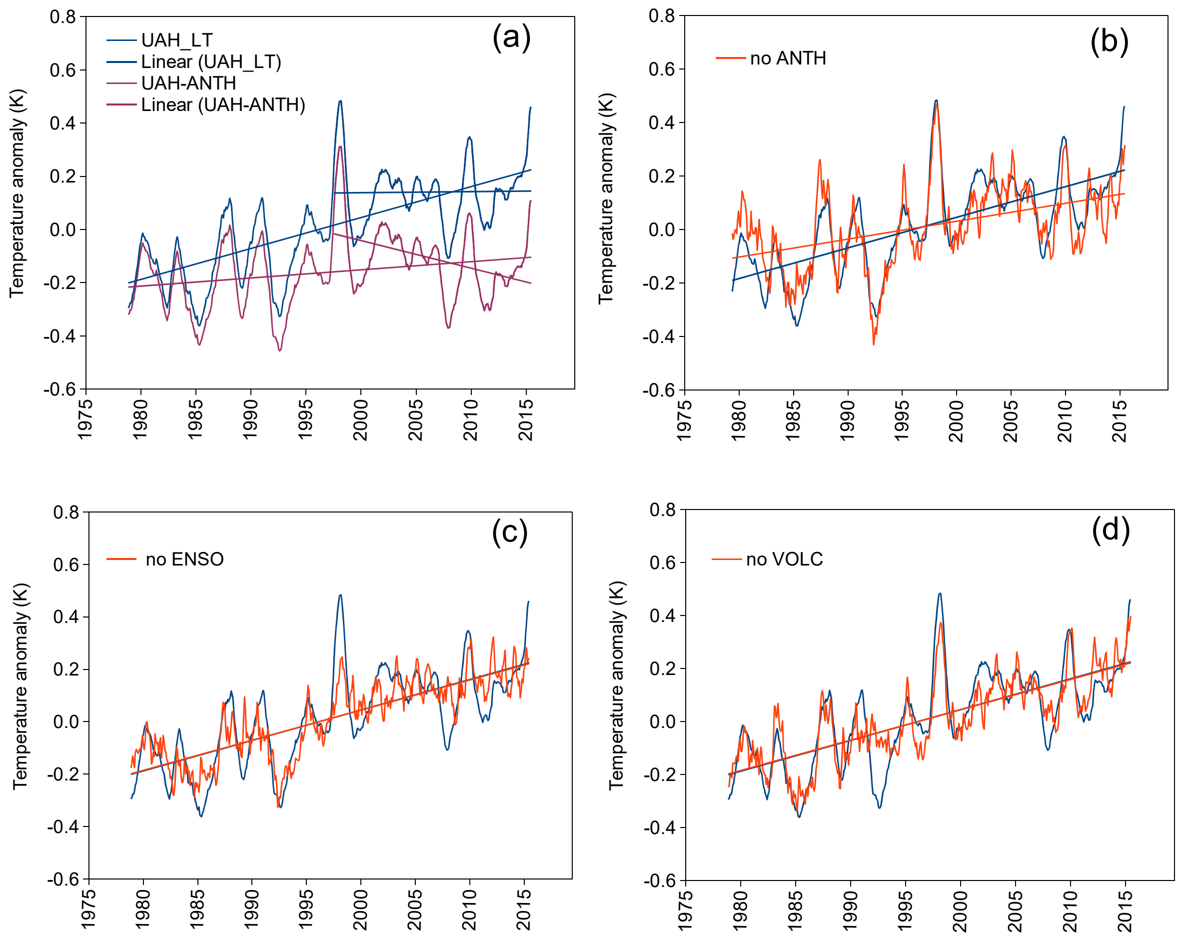

Figure 3 Panel (a): blue line: low-pass filtered UAH T anomaly series from December 1978 to January 2016, overlaid by one trend line fitted to the full record and a second to the subset of data commencing in December 1997; purple line: equivalent plots but for the UAH anomaly series from which the ANTH component determined by the heuristic multiple regression model has been subtracted. Panels (b) - (d) present results of model tests with one variable omitted from the regression in each case: (b) ANTH omitted; (c) ENSO omitted; (d) VOLC omitted. In (c) and (d) the model trend line (orange) lies right on top of the UAH data trend line (blue)

Santer et al. (2014) emphasise the importance of timescale in determination of trends in their analysis of a 32 year period of satellite-derived air temperature data. They demonstrated a major improvement in signal to noise going from ten year to 32 years trends, and concluded that a minimum of seventeen years was required for identification of human effects on temperature. Subsequently Santer et al. (2017) analysed the middle troposphere satellite record for the time period used here, concluding that the claim of no significant tropospheric warming over the last eighteen years is not correct. What is concluded in those analyses reinforces the conclusions reached here about the inappropriateness, in the face of internal climate variability, of trying to evaluate anthropogenic contributions to global temperature using truncated temperature data sets. To do so risks ‘cherry-picking’ the data in a manner that yields subset-based conclusions inconsistent with the conclusions reached from analysis of the full dataset. That is what has transpired in the case of the incorrect conclusions reached by public commentary as noted in the Introduction and elsewhere.

A potential criticism could be that for completeness in addressing the null hypothesis a model having no greenhouse gas-related variable should be considered. Thus another generalised set of tests was carried out with each independent variable removed in turn, in each case leaving just the other four independent variables, the purpose being to explore the effect on explanation of variance of any individual variable being omitted. Compared with the full model’s value of 0.894 for r^2 there was a decrease in r^2 in each case consistent with the extent to which the particular omitted variable contributed to overall explanation of variance: no-TSI, r^2 = 0.882; no-AMO r^2 = 0.872; no-VOLC, r^2 = 0.774; no-ANTH, r^2 = 0.746; no-ENSO, r^2 = 0.693. For the three most significant individual contributors, ANTH, ENSO and VOLC, the resultant regression models are compared with the UAH T series in Figure 3 (b) - (d). The decrease in goodness of fit corresponding to the reductions in r^2 is evident visually by comparing Figure 3(b) - (d) with Figure 1(b). In each case these regressions returned a model with an inferior explanation of variance compared with the full model, confirming the evidence from the regression coefficients that each of the five explanatory variables makes a statistically significant contribution to explanation of variance. Regarding T trend, all regressions that included ANTH reproduced exactly the T trend in the UAH data even though overall variance explained was diminished by the removal of any other variable (see Figures 3 (c), (d)). On the other hand, removal of ANTH led to a regression that could not reproduce T trend (Figure 3(b)), confirming the attribution of the majority of the trend to ANTH (Table 3).

Another potential criticism of this analysis is that the commentary on which the null hypothesis tested here was framed refers not to increasing net anthropogenic greenhouse forcing, but specifically to increase in CO_2 concentration. To test the validity of this potential criticism the heuristic model was re-run with ANTH represented not by RCP4.5's full anthropogenic forcing but by the de-seasonalised monthly atmospheric CO_2 concentration measured at Mauna Loa, Hawaii (data source: http://www.esrl.noaa.gov/gmd/ccgg/trends/data.html). Table 2 contrasts the resultant regression outputs from this case with those from the standard model run, while Figure 2(b) visually contrasts the fitted ANTH components. The results are essentially identical, and clearly independent of whether RCP4.5 anthropogenic forcing or CO_2 concentration is employed for ANTH. This is consistent with the results of Rohde et al. (2013) who were able to achieve a good fit to annual land surface air temperature from 1753 to 2001 using just a two-parameter model involving only CO_2 concentration and a parameter for volcanic activity.

One other test carried out initially was to test the Interdecadal Pacific Oscillation (IPO) as an alternative to the MEI as an index for ENSO. This was done in response to indications in the literature (e.g. Steinman et al. 2015) that longer-period variability in ENSO such as that represented by the IPO might underlie the slowdown in warming. Results were very similar to those obtained with the MEI but with slightly lower variance explained, so the MEI as used by Lean and Rind (2008) was retained in this work. However the near equivalence of MEI and IPO in this sort of empirical analysis is not surprising, given that these two indices are related manifestations of variability in ENSO (Power et al. 1999).

Finally, it is worth acknowledging the heuristic nature of the analysis carried out here. The model used is statistical in nature, it is not a physical model in which global atmospheric heat and momentum transfer processes are explicitly described and mathematically represented, for example by solving the Navier-Stokes and other equations. Therefore the discussion above is given in terms of imputed contributions to global temperature variability from two well-known modes of climate variability, ENSO and AMO, and from variations in three climate forcings, VOLC, TSI and ANTH. Discussion of the physical processes involved in fluctuations of energy transfer between the atmosphere and the ocean and within the depths of the ocean that are associated with global air temperature variability are to be found elsewhere in numerous papers in the literature, of which the works of Held (2013), Nieves et al. (2015), Steinman et al. (2015), Fyfe et al. (2016) and Mann et. al. (2016) were cited in the Introduction simply as a very small initial sample. A comprehensive, consolidated overview is provided by Masson-Delmotte et al. (2013).

5. Conclusions

Global-mean monthly temperature data from the lower troposphere measured by satellite since December 1978 have been analysed using a well-known heuristic model to characterise temperature variability associated with each of two modes of climate variability (ENSO, AMO) and each of three sources of variation in forcing (VOLC, TSI, ANTH). With data series variance apportioned into separate contributions from each of the five explanatory variables, the null hypothesis that there is no relationship between anthropogenic greenhouse gas increase and global-mean tropospheric temperature could be tested, resulting in the null hypothesis being rejected. Over the period December 1978 to January 2016 anthropogenic greenhouse gases contributed an estimated warming trend of +0.08K per decade to the satellite-derived global-mean temperature.

For the period November 1997 to January 2016 this corresponds to a contribution of +0.15K (0.155±0.012K with 95 per cent confidence). The slowdown in global mean temperature increase over that period occurred because this contribution was offset by strong internal climate variability that in the absence of the anthropogenic component would have produced cooling. Over the full period of satellite measurements from December 1978 to January 2016 the anthropogenic contribution to global mean lower tropospheric temperature is estimated to be between +0.29K and +0.34K with 95 per cent confidence.

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