Response to Referee Report of 7 May 2015

L. M. W. Leggett and D. A. Ball*
*Global Risk Policy Group Pty Ltd, Townsville, Queensland, Australia

Abstract

Response to Referee Report of 7 May 2015 on amended manuscript of 8 April 2015 "First and second derivative atmospheric CO_2, global surface temperature and ENSO".

----

1 Overall Response

The referee's comments are again valued and we have attempted to follow up the points raised we hope to some degree comprehensively.

In our response we first provide the referee's comments in their entirety (pages 2 to 5).

We then (from page 5 onward) provide our responses to individual comments

2 Referee's Comments

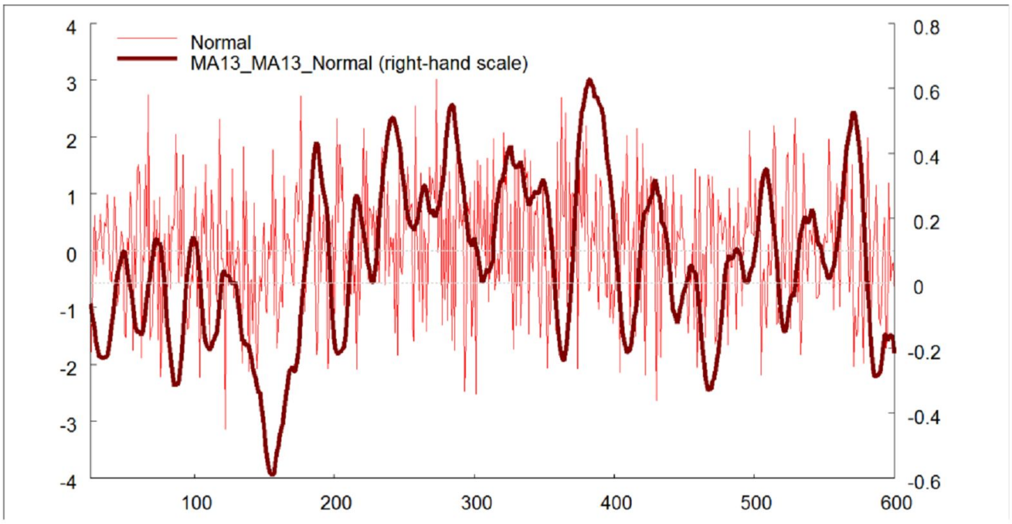
Referee's comments on
"Granger causality from the first and second derivatives of atmospheric CO2 to global surface temperature, ENSO and NDVI"
By L. M. W. Leggett and D. A. Ball

This is a rather different paper from the first version on which I have commented for ACP. It is much longer and there is a complete new section dealing with "NDVI", whose relationship with the second difference of CO_2 concentration is investigated.

My views are mixed. In principle these results are very interesting. In particular, the findings of various previous studies are re-iterated and confirmed, specifically that there is no relationship, in the relevant historical data, between surface temperature and the level of CO_2 concentration in the atmosphere, while a positive relation does exist between temperature and the difference of CO_2.

The significance of these facts (if they are facts) can hardly be underestimated, since they contradict the hypothesis on which (what we may call) "global warming alarmism" is predicated. , Evidently, the worst that *continuously* increasing CO_2 has done is to raise temperature by a fixed amount, which observation suggest is pretty small. If this pattern continues into the future it is, clearly, not an alarming prospect. Does this finding place the authors among the "97% of scientists who believe in anthropogenic global warming" (as President Obama and others have it) or the other 3%? I'm not clear about this, but these are interesting questions, to be sure.

The authors have developed their methodology with care, and their literature references show that they have a good knowledge of the relevant econometrics and time series literature. One can therefore put some faith in their empirical findings. Nonetheless there are some aspects of their analysis that worry me, in particular the "smoothing" of series by moving averages.



Note that although these are monthly series, smoothing is not the same thing as seasonal adjustment, and its effects on test outcomes are unclear. The attached plot, which I've prepared, shows 600 independent Gaussian drawings, and also the series obtained by applying two successive 13-point moving average transformations to these points. The time series properties of these two series can hardly be treated as equivalent, especially for testing sensitive questions such as phase shifts of one or two periods. In particular, the results of unit root tests are not going to be comparable. Smoothing exaggerates stochastic trends by suppressing high frequency components. I really don't think we can take tests based on these smoothed series at face value.

The authors must first explain coherently why they regard these transformations as necessary to the analysis. At best, they seem to be claiming that the effect is to make a nicer plot, which is hardly adequate. Second, if they convince at the first step they need to show the effects of their transformations by comparing their test results for the smoothed and unsmoothed series.

Something else that concerned me in these causality tests is that although the series in question are being treated as stationary (acceptably in my view) there are still "deterministic" upward drifts in the series. These need to be fitted separately from the higher frequency components, to capture the required "constant conjunction" specified in the definition of causality, and ensure that this is not spurious. (Note that every linear trends is correlated with every other, by construction!) The regressions ought to contain trend terms so that the data are, in effect, de-trended, before correlations are computed. This does not appear to have been done, and it should be.

My third major comment concerns the new section on NDVI. Interesting correlations for sure (subject to the caveats above), but the discussion goes far out on a limb and is, for my taste, unacceptably speculative. First, the series constructed as the difference of standardized CO_2 and standardized temperature is a proxy for anything only by a severe stretch of the imagination. Surely, GCMs must (at best) link temperature projections to a particular fraction of projected CO_2. (See comment 10 below.) Even if we accept the suggestion that GCM projections are linear in CO_2 concentration, the simple difference between CO_2 and temperature may or may not capture (in the "constant conjunction" sense) the true forecast discrepancy. Hence, the correlation with NDVI is either interesting by chance, or spurious. I would need firmer evidence to be convinced. The discussion in Section 5 reads like off-the-cuff theorising of the most casual sort. Of course, there is ample evidence, supported by sound theory, for the hypothesis that higher CO_2 concentrations are "greening" the planet. To that extent, the authors have a good point. However, it seems to me that their model (involving the second differences of CO_2, etc.) needs to be much more carefully derived and argued than it is at present. It's not good enough to simply report a curious correlation and extrapolate from it a whole theory of the biosphere, This seems like blatant data mining.

My suggestion to the authors is to subtract the section on NDVI, as ample material for a new paper although a good deal of additional work is called for. Then, to redraft the first part of the paper taking note of the various comments offered here.

I recommend in particular that plots of the raw data series are shown in the paper, so that the effects of the authors' manipulations can be judged (and also, ideally, the series be made available for download).

Detailed Comments

1. The paragraph in lines 19-25 on page 8 is incoherent. Please redraft. (There are various other places where the quality of exposition could be improved. Please redraft with careful attention to readability.)

2. Lines 13-21 on page 9 are a reworking of the preceding paragraph. Please delete whichever is the unintended version.

3. (Page 11, lines 26-27). The point about SOI versus ENSO could be better made. Is "more valid" a better reason for the preference than "simpler"? It would be very helpful to readers to give brief formal definitions of both these series. How is ENSO constructed? I don't know.

4. (Page 12, lines 9 and 30) The use of the term "derivative" as a synonym for "difference" is, to this reader, an irritating tic. "Derivative" suggests that the models in question are discrete approximations to continuous time relations, but nowhere are these relations specified or the approximations formalized. Indeed, the tests for Granger causality, of the form given, could not be formalized at all in a continuous time framework! Let's be clear that the models presented here are explicitly formulated for discrete sequences of observations. Differences, like lags, are an inherent feature of these models, not approximations to anything.

5. (Page 13, lines 7-16) Please see the main discussion above.

6. There are lots of missing references in the paper. See in particular pages 13, lines 30-31, and 14, lines 4-6, but there are others.

7. (Page 15, lines 9-10) Note that BLUE is a property pertaining to the classical (fixed regressor) regression model, which is not appropriate to time series.

Autocorrelated disturbances may result in bias when the model includes lagged endogenous variables among the regressors.

8. (Page 18) The discussion of the "I(d)" categorization of series on this page is totally muddled. Beenstock et al. find temperature to be I(1) and CO_2 (level) to be I(2). Please redraft with care.

9. The application of the Toda-Yamamoto result is most interesting, but it needs to be seen in context. These authors propose tests for a VAR in levels with an unknown number of unit roots. However, please note that in such a model, Granger causality of an I(1) series by an I(2) series is ruled out by construction. A model generating variables with different orders of integration can only embody long-run relations between variables transformed to have the *same* orders of integration: in particular, between the level of an I(1) and the differences of an I(2), or between the level of an I(0) and the differences of an I(1)). (To verify this statement, consider the VAR $A(L)x_t = u_t$ and verify the properties that $A(L)$ must satisfy to ensure that $A(L)^{-1}$ contains different powers of the factor $1-L$ appearing in different rows.) The outcome of the reported test is inevitable, given the other reported results. I guess it does not harm to report it, but with suitable caveats.

10. (Page 27, lines 11-13) The regression of (say) $x - ay$ on z is clearly different for different choices of constant a. It could be significant (or cointegrated in the nonstationary case) for some value of a, and not for others. The case that the projection error of a GCM can be captured as the simple difference of the two standardized series needs to be much more carefully argued.

11. My guess is that "the APCD paper" referred to in Page 30, line 20, and elsewhere refers to the first version of the present paper. If so, this needs to be made explicit.

3 Author Responses to Individual Comments

The comments are addressed as follows (specific Comments content quoted verbatim citing Comments page number and indented).

As they all relate to smoothing and seasonal adjustment we group the following points from the comments together and, for convenience for response, in the following order.

> Referee's comments page 1. Note that although these are monthly series, smoothing is not the same thing as seasonal adjustment…
>
> Page 2. The authors must first explain coherently why they regard these transformations as necessary to the analysis. At best, they seem to be claiming that the effect is to make a nicer plot, which is hardly adequate.
>
> Page 1. …(the) effects (of smoothing) on test outcomes are unclear.
>
> Page 2. …especially for testing sensitive questions such as phase shifts of one or two periods.

> Page 2. In particular, the results of unit root tests are not going to be comparable

> Page 2. I recommend in particular that plots of the raw data series are shown in the paper, so that the effects of the authors' manipulations can be judged (and also, ideally, the series be made available for download).

> Page 2. … they need to show the effects of their transformations by comparing their test results for the smoothed and unsmoothed series.

> Comment 5 from the initial review by the referee (C10403, 22 December 2014): The only legitimate way to conduct these kind of tests, where timing shifts of one or two months is critical, is on the raw observations, where extraneous data features such as seasonality have been accounted for by effective modelling. This may be tricky, but in the case of a seasonal pattern it might, for example, be effective to employ polynomial dummy variables to explain seasonal changes…

> Page 2. I really don't think we can take tests based on these smoothed series at face value.

> Page 2…especially for testing sensitive questions such as phase shifts of one or two periods.

> Page 2. Smoothing exaggerates stochastic trends by suppressing high frequency components.

These are now dealt with individually in the order listed above.

Referee comment page 1. *Note that although these are monthly series, smoothing is not the same thing as seasonal adjustment…*

It is noted that in the econometrics realm, the draft current update to Chapter 7. *Seasonal Adjustment* of the IMF Quarterly National Accounts Manual 2001 (Bloem et al., 2001) http://www.imf.org/external/pubs/ft/qna/ considers moving average smoothing to be an established form of seasonal adjustment, stating as follows (page 4):

> Several methods have been developed to remove seasonal patterns from a series. Broadly speaking, they can be divided into two groups: moving average methods and model-based methods.

Referee comment page 2. *The authors must first explain coherently why they regard these transformations as necessary to the analysis. At best, they seem to be claiming that the effect is to make a nicer plot, which is hardly adequate.*

Our explanation is as follows, again taken from the update to Bloem et al. (2001). Page 3:

> Seasonal adjustment of the QNA allows a timely assessment of the current economic conditions and identification of turning points in key macroeconomic variables, such as quarterly GDP. Economic variables are influenced by systematic and recurrent within-a-year patterns due to weather- and social- factors, commonly referred to as the seasonal pattern (or seasonality). When seasonal variations dominate period-to-period changes in the original series (or seasonally unadjusted series), it is difficult to identify non-seasonal effects, such as long-term movements, cyclical variations, or irregular factors, which carry the most important economic signals for QNA users.
>
> Seasonal adjustment is the process of removing seasonal and calendar effects from a time series. This process is performed by means of analytical techniques that break down the series into components with different dynamic features. These components are unobserved and have to be identified from the observed data based on a priori assumptions on their expected behavior. In a broad sense, seasonal adjustment comprises the removal of both within-a-year seasonal movements and the influence of calendar effects (such as the different number of working days, or moving holidays). By removing the repeated impact of these effects, seasonally adjusted data highlight the underlying long-term trend and short-run innovations in the series.

More details on the moving average methods and model-based methods are as follows (update to Bloem et al. (2001), Page 4):

> (Moving average methods) derive the seasonally adjusted data by applying a sequence of moving average filters to the original series and its transformations. These methods are all variants of the X-11 method, originally developed by the U.S. Census Bureau (Shiskin and others, 1967). The current version of the X-11 family is X-13ARIMA-SEATS (X-13A-S), which will often be referred to in this chapter. Model-based methods derive the unobserved components in accord with specific time series models, primarily autoregressive integrated moving average (ARIMA) models. The most popular model-based seasonal adjustment method is TRAMO-SEATS,[6] developed by the Bank of Spain (Gomez and Maravall, 1996).
>
> TRAMO is the acronym for *Time Series Regression with Autoregressive integrated moving average (ARIMA) Errors and Missing Observations*. SEATS stands for *Signal Extraction for ARIMA Time Series.*

Referee comment page 1. *...(the) effects (of smoothing) on test outcomes are unclear.*

Referee comment page 2. *In particular, the results of unit root tests are not going to be comparable.*

There is an extensive literature dealing with the effect that seasonal adjustment has on standard tests for unit roots. A short, but very clear discussion of the early part of this literature is provided by Maddala and Kim (1998, pp. 364-365). One important result is that, *in finite samples*: "the ADF and Philliups-Perron statistics for testing a unit root will be biased towards nonrejection of the unit root null if filtered data are used." (Here, the term "filtered" refers to "seasonally adjusted".)

In other words, these tests have lower power *in finite samples* when applied to seasonally adjusted data.

However the asymptotic (large sample) properties of the ADF and similar tests have been shown to be unaffected by seasonally adjusting the data.

What is a large sample? In assessing performance of unit root tests, Narayan and Popp (2010) used sample sizes of T = 50, 100, 300, and 500.They showed that over with 100 data points, key statistics start to become asymptotic. Our sample size is T = over 600.

Results below (Table 14) based on both adjusted and unadjusted data bear this out empirically.

One way of interpreting these results is that we have demonstrated that our sample size is sufficiently large for this potential loss of power of unit root tests to be a non-issue in our study.

Referee comments page 2. *I recommend in particular that plots of the raw data series are shown in the paper, so that the effects of the authors' manipulations can be judged (and also, ideally, the series be made available for download).*

Referee comments page 2. ... *they need to show the effects of their transformations by comparing their test results for the smoothed and unsmoothed series.*

Referee comment 5 from the initial review by the referee (C10403, 22 December 2014): *The only legitimate way to conduct these kind of tests, where timing shifts of one or two months is critical, is on the raw observations, where extraneous data features such as seasonality have been accounted for by effective modelling. This may be tricky, but in the case of a seasonal pattern it might, for example, be effective to employ polynomial dummy variables to explain seasonal changes…*

In response to the above three comments, in the following section the raw and then variously seasonally adjusted data (including by both moving averages and modelling), are both plotted (Figures 1 to 13) and then the core correlational analysis conducted in the paper carried out and statistically tested (Tables 1 to 13).

This analysis shows the results for various forms of adjustment, and in particular carries out (Figures 9 and 10; Tables 9 and 10) seasonal adjustment by modelling as discussed by the referee in the initial review (C10403, 22 December 2014). This seasonal adjustment using modelling is done by means of the TRAMO/SEATS model. It is run using raw monthly data on the levels of atmospheric CO_2.

For comparison, the result from a second, published, seasonal adjustment of atmospheric CO_2 time series by modelling is also presented (NOAA: seasonally adjusted CO2 data series from ftp://aftp.cmdl.noaa.gov/products/trends/co2/co2_mm_mlo.txt ; its modelling method is described in Thoning et al. (1989). Results are in Figures 7 and 8 and Tables 7 and 8.

Discussion of the results of the analyses in this section in connection with the referee's comments occur after Table 14: Summary of dynamic regression results.

Abbreviations used in figures and tables: FD - first difference; SD - second difference; HadGL - HadCrut4 global surface temperature; CO2_NOAAseascorr - seasonally corrected CO_2 data published by NOAA; TRAMO: seasonally corrected CO_2 data resulting from TRAMO/SEATS method.

Monthly data, ZFDCO2 no smoothing

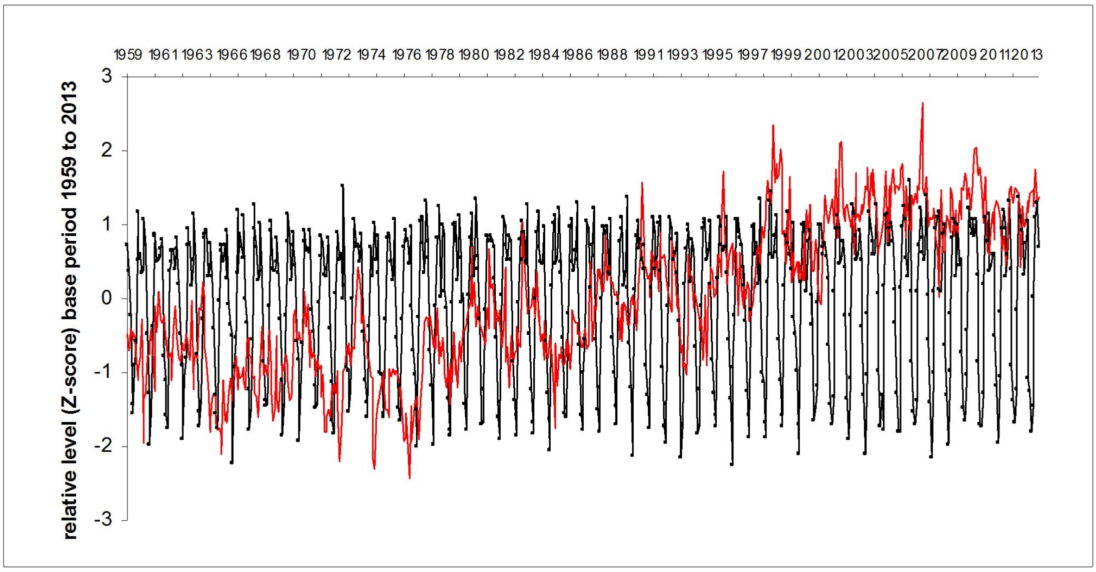


Figure 1. *Z* scored monthly data: First difference atmospheric CO_2 (black dotted curve) compared to global surface temperature (red curve)

Table 1: OLS, using observations 1-654
Dependent variable: ZHad4Gl

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	0.00464901	0.0144919	0.3208	0.74847	
led1mZHad4Gl	0.565413	0.0375822	15.0447	<0.00001	***

Led2mZHad4Gl	0.260223	0.0424148	6.1352	<0.00001	***
led4mZHad4Gl	0.131589	0.0337038	3.9043	0.00010	***
ZFDCO2	0.0265	0.014517	1.8254	0.06839	*

Mean dependent var	−0.006217	S.D. dependent var	0.998938
Sum squared resid	89.08538	S.E. of regression	0.370494
R-squared	0.863285	Adjusted R-squared	0.862442
F(4, 649)	1024.526	P-value(F)	1.0e-278
Log-likelihood	−276.1073	Akaike criterion	562.2147
Schwarz criterion	584.6302	Hannan-Quinn	570.9067
rho	−0.002069	Durbin-Watson	2.004137

LM test for autocorrelation up to order 11 -
Null hypothesis: no autocorrelation
Test statistic: LMF = 1.19088
with p-value = P(F(11,638) > 1.19088) = 0.289543

Monthly data, 13mmaZFDCO2 smooth

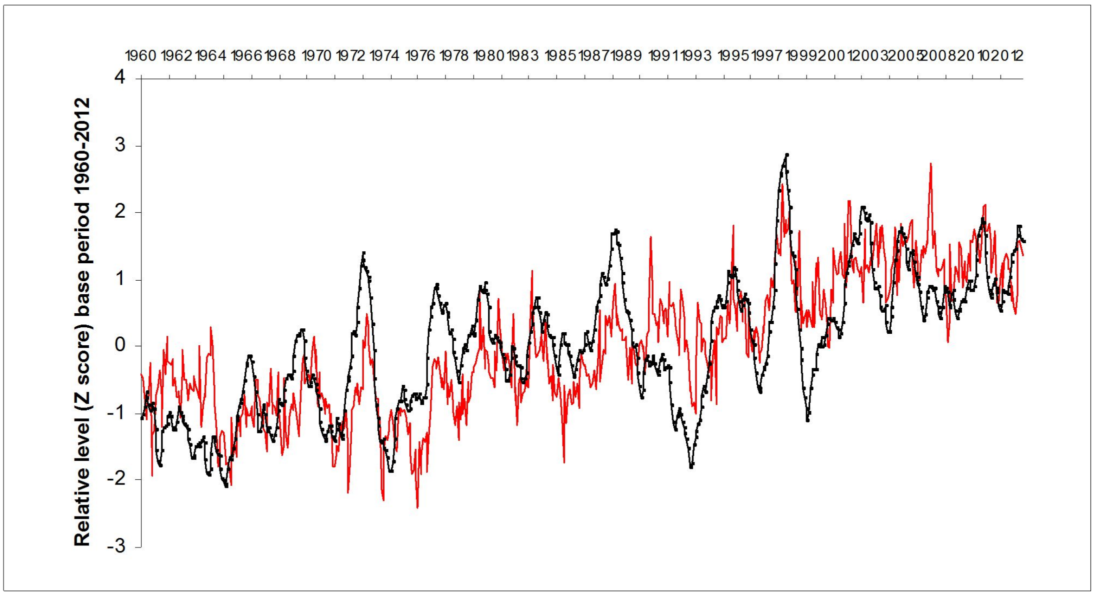


Figure 2. *Z* scored monthly data: First difference atmospheric CO_2 smoothed with two 13-month moving averages (black dotted curve) compared to global surface temperature (red curve)

Table 2: OLS, using observations 1-640
Dependent variable: ZHad4Gl

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	0.00428239	0.0147572	0.2902	0.77177	
led2mZ2x13mFD CO2	0.102015	0.0216835	4.7047	<0.00001	***
Led1mZHad4Gl	0.564726	0.0377431	14.9623	<0.00001	***
led2mZHad4Gl	0.306035	0.0374109	8.1804	<0.00001	***

Mean dependent var	0.003075	S.D. dependent var	1.002326
Sum squared resid	88.63759	S.E. of regression	0.373319
R-squared	0.861930	Adjusted R-squared	0.861279
F(3, 636)	1323.454	P-value(F)	6.7e-273
Log-likelihood	−275.5088	Akaike criterion	559.0175
Schwarz criterion	576.8634	Hannan-Quinn	565.9444
rho	−0.011403	Durbin-Watson	2.022743

LM test for autocorrelation up to order 20 -
Null hypothesis: no autocorrelation
Test statistic: LMF = 1.1028
with p-value = P(F(20,616) > 1.1028) = 0.34132

Annual data, FDCO2 and Had4Gl

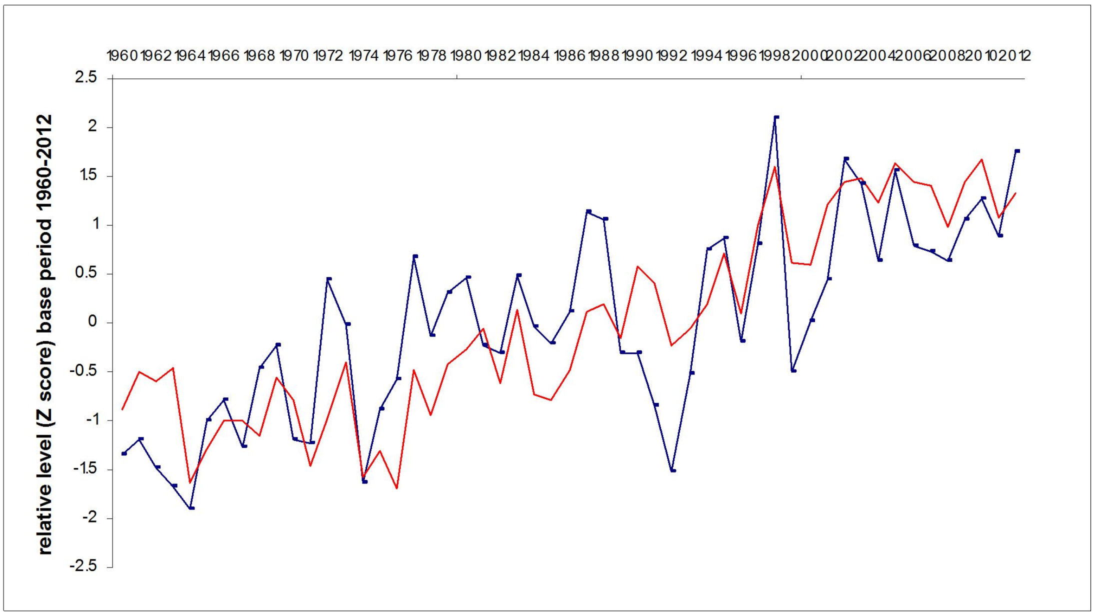


Figure 3. *Z* scored annual data: First difference atmospheric CO_2 smoothed with two 13-month moving averages (black dotted curve) compared to global surface temperature (red curve)

Table 3: OLS, using observations 1-52
Dependent variable: ZAnnHad4Gl

	Coefficient	Std. Error	t-ratio	p-value	
const	0.0215094	0.0504468	0.4264	0.67170	
ZAnn2x13mFDCO2	0.447195	0.0609389	7.3384	<0.00001	***
led1yZAnnHad4Gl	0.624044	0.0609126	10.2449	<0.00001	***

Mean dependent var	0.017148	S.D. dependent var	1.001857
Sum squared resid	6.465283	S.E. of regression	0.363242
R-squared	0.873699	Adjusted R-squared	0.868544
F(2, 49)	169.4814	P-value(F)	9.65e-23
Log-likelihood	−19.58008	Akaike criterion	45.16017
Schwarz criterion	51.01390	Hannan-Quinn	47.40435
rho	−0.099887	Durbin-Watson	2.147075

LM test for autocorrelation up to order 11 -
Null hypothesis: no autocorrelation
Test statistic: LMF = 0.894529
with p-value = P(F(11,38) > 0.894529) = 0.553897

Monthly data: Second difference CO2 and first difference temp, No smoothing

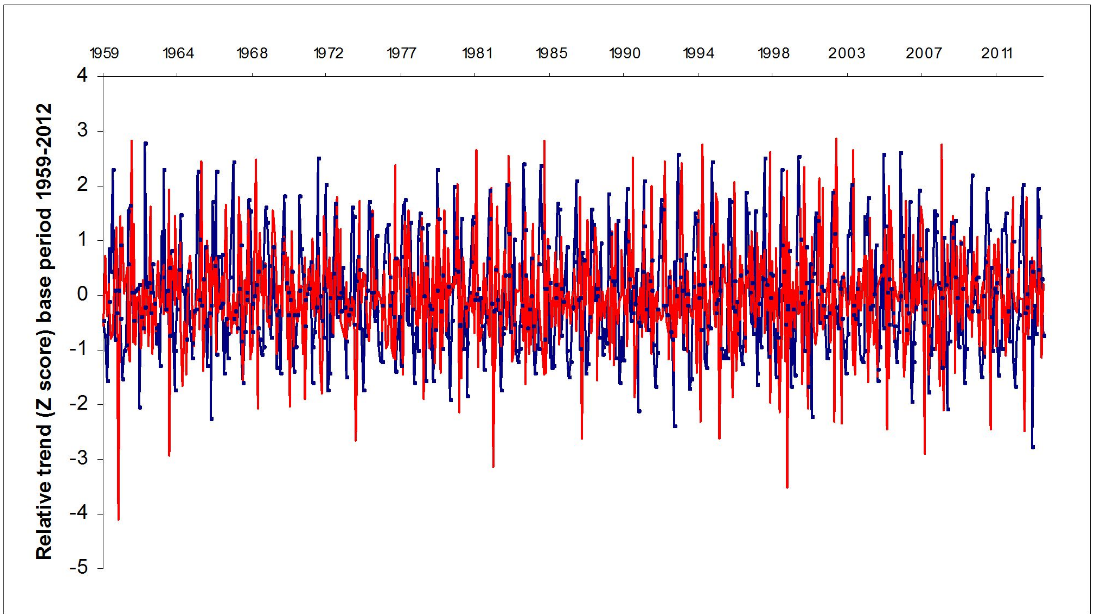


Figure 4. *Z* scored monthly data: second-difference atmospheric CO_2 (black dotted curve) compared to first-difference global surface temperature (red curve)

Table 4: OLS, using observations 1-650
Dependent variable: ZFDHad4GL

	Coefficient	Std. Error	t-ratio	p-value	
const	0.00276484	0.0359273	0.0770	0.93868	
Led3mZSDCO2	0.0986082	0.0359743	2.7411	0.00629	***

Led1mZFDHad4GL	−0.418447	0.0386966	-10.8135	<0.00001	***
Led2mZFDHad4GL	−0.146011	0.0415859	-3.5111	0.00048	***
Led3mZFDHad4GL	−0.140405	0.0387674	-3.6217	0.00032	***

Mean dependent var	0.002485	S.D. dependent var	1.003691
Sum squared resid	541.1463	S.E. of regression	0.915962
R-squared	0.172305	Adjusted R-squared	0.167172
F(4, 645)	33.56815	P-value(F)	1.84e-25
Log-likelihood	−862.7432	Akaike criterion	1735.486
Schwarz criterion	1757.871	Hannan-Quinn	1744.169
rho	−0.010671	Durbin-Watson	2.021077

LM test for autocorrelation up to order 11 -
Null hypothesis: no autocorrelation
Test statistic: LMF = 1.28767
with p-value = P(F(11,634) > 1.28767) = 0.227098

Monthly data: Second difference CO2 and first difference temp, 3x13mma smoothing

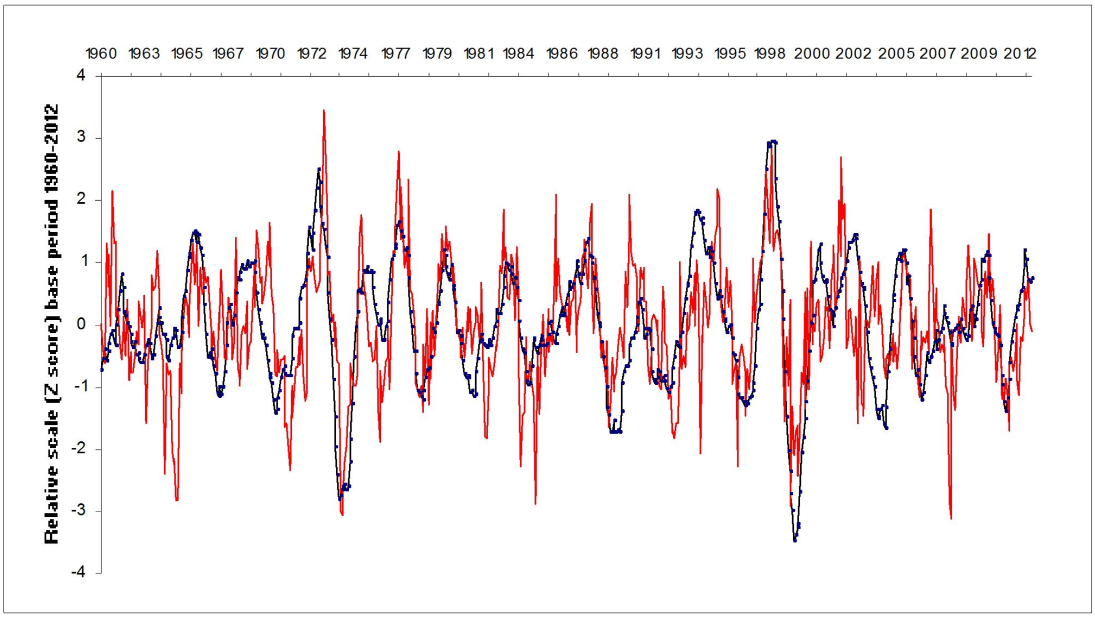


Figure 5. *Z* scored monthly data smoothed by 13-month moving average: second-difference atmospheric CO_2 (black dotted curve) compared to first-difference global surface temperature (red curve)

Table 5: OLS, using observations 1-650
Dependent variable: Z13mmaFDZHad4Gl

	Coefficient	Std. Error	t-ratio	p-value	
const	0.0201245	0.0260442	0.7727	0.43998	
Z13mmaSDZ2x13mCO2	0.166377	0.0299439	5.5563	<0.00001	***
led1mZ13mmaFDZHad4Gl	0.485095	0.038189	12.7025	<0.00001	***
led2mZ13mmaFDZHad4Gl	0.218271	0.0376337	5.7999	<0.00001	***

Mean dependent var	0.061759	S.D. dependent var	1.012336
Sum squared resid	288.7032	S.E. of regression	0.665429
R-squared	0.569909	Adjusted R-squared	0.56793
F(3, 652)	287.9859	P-value(F)	5.40E-119
Log-likelihood	−661.6138	Akaike criterion	1331.228
Schwarz criterion	1349.172	Hannan-Quinn	1338.185
rho	0.013684	Durbin-Watson	1.971948

LM test for autocorrelation up to order 11 -
Null hypothesis: no autocorrelation
Test statistic: LMF = 1.5184
with p-value = P(F(11,641) > 1.5184) = 0.120154

Annual data: Second difference CO_2 and first difference temp

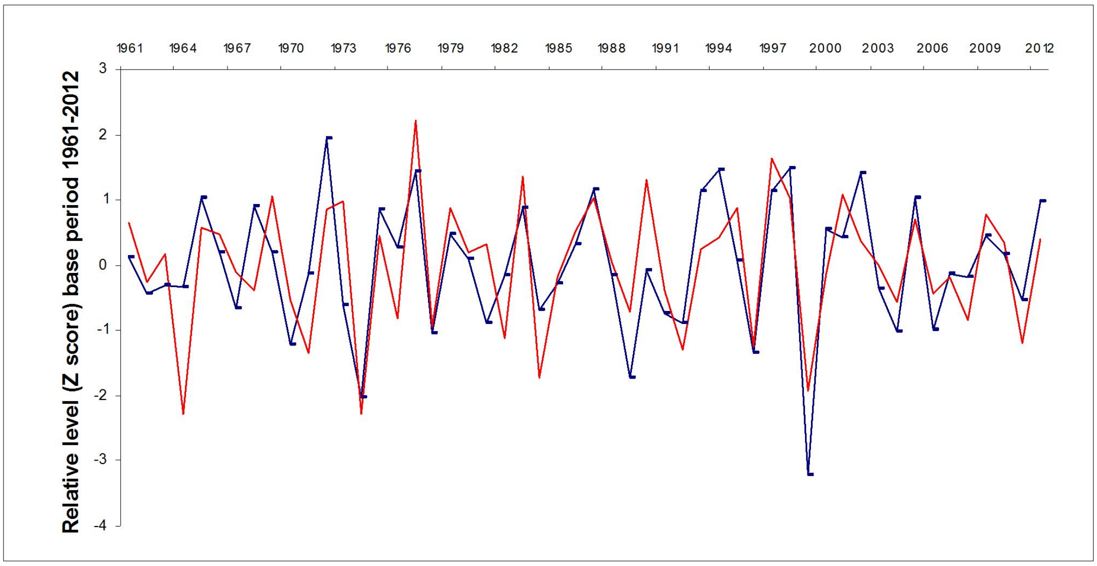


Figure 6. *Z* scored annual data: second-difference atmospheric CO_2 (black dotted curve) compared to first-difference global surface temperature (red curve)

Table 6: OLS, using observations 1-52
Dependent variable: ZFDAnnHad4Gl

	Coefficient	Std. Error	t-ratio	p-value	
const	0	0.100406	0	1	
ZSDAnnCO2	0.697174	0.101385	6.8765	<0.00001	***

Mean dependent var	0	S.D. dependent var	1
Sum squared resid	26.21139	S.E. of regression	0.724036
R-squared	0.486051	Adjusted R-squared	0.475772
F(1, 50)	47.28595	P-value(F)	9.36E-09
Log-likelihood	−55.97351	Akaike criterion	115.947
Schwarz criterion	119.8495	Hannan-Quinn	117.4431
rho	−0.289599	Durbin-Watson	2.561752

LM test for autocorrelation up to order 10 -
Null hypothesis: no autocorrelation
Test statistic: LMF = 1.83677
with p-value = P(F(10,40) > 1.83677) = 0.0850608

Monthly data, FDCO2 NOAA seascorr, no further smoothing

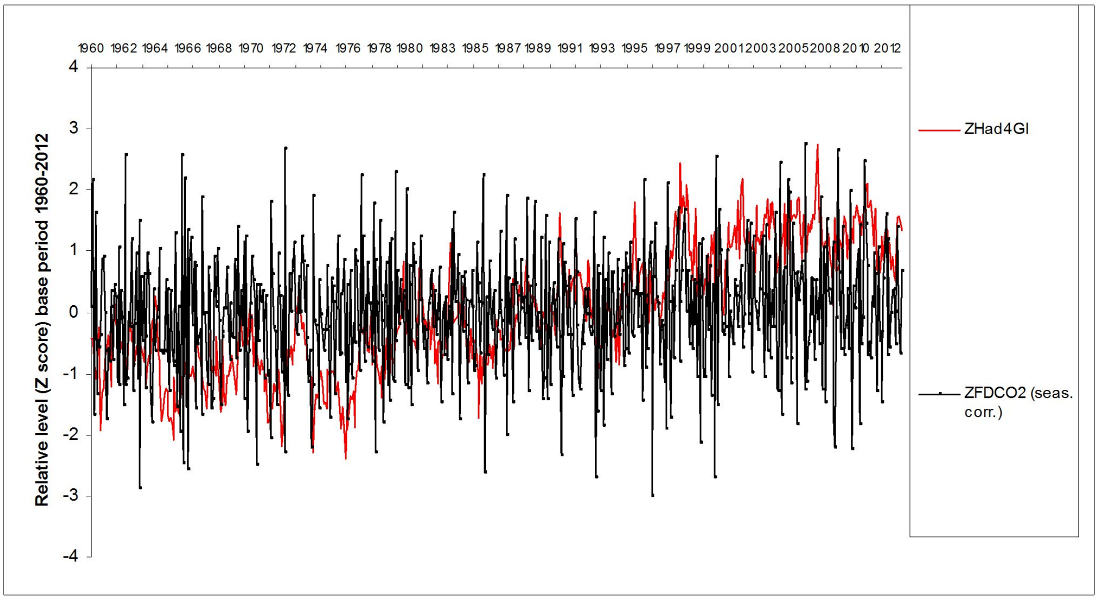


Figure 7. *Z* scored monthly data, : first-difference atmospheric CO_2 (NOAA seasonally corrected) (black dotted curve) compared to level of global surface temperature (red curve)

Table 7: OLS, using observations 1-649
Dependent variable: ZHad4Gl

	Coefficient	Std. Error	t-ratio	p-value

const	0.00164552	0.0164019	0.1003	0.92012	
Led5mZFDCO2 seascorr	0.0337206	0.0164708	2.0473	0.04103	**
led1mZHad4Gl	0.685278	0.0380884	17.9918	<0.00001	***
Led1mZHad4Gl	0.237719	0.0381737	6.2273	<0.00001	***

Mean dependent var	0.005216	S.D. dependent var	1.006416
Sum squared resid	112.5346	S.E. of regression	0.417699
R-squared	0.828542	Adjusted R-squared	0.827745
F(3, 645)	1038.955	P-value(F)	1.90E-246
Log-likelihood	−352.3114	Akaike criterion	712.6229
Schwarz criterion	730.5246	Hannan-Quinn	719.567
rho	0.009035	Durbin-Watson	1.959372

LM test for autocorrelation up to order 11 -
Null hypothesis: no autocorrelation
Test statistic: LMF = 3.38672
with p-value = P(F(11,634) > 3.38672) = 0.000142093

Monthly data, FDCO2seascorr 4x3mma smooth

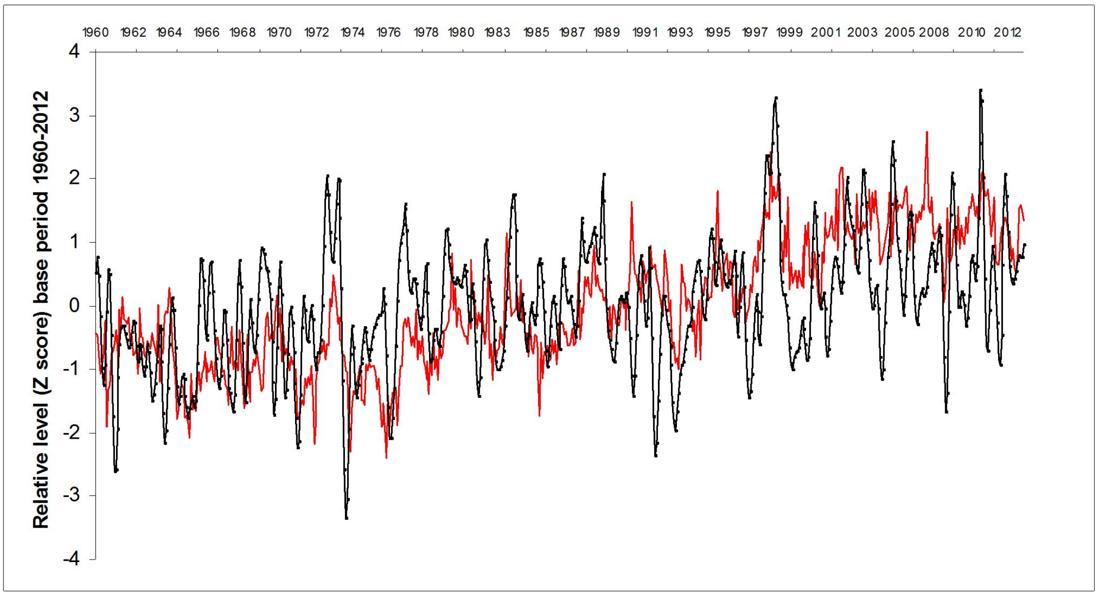


Figure 8. *Z* scored monthly data: first-difference atmospheric CO_2 (NOAA seasonally corrected) smoothed by 4 3month moving averages (black dotted curve) compared to level of global surface temperature (red curve)

Table 8: OLS, using observations 1-632
Dependent variable: ZHad4Gl

	Coefficient	Std. Error	t-ratio	p-value	
const	0.00607628	0.0149984	0.4051	0.68552	
Z4x3mmaFDCO2seascorr	0.0377393	0.0173021	2.1812	0.02954	**

l1ZHad4Gl	0.565126	0.0396178	14.2644	<0.00001	***
l2ZHad4Gl	0.255092	0.0456426	5.5889	<0.00001	***
l3ZHad4Gl	−0.0148978	0.0456096	-0.3266	0.74405	
l4ZHad4Gl	0.130828	0.0394726	3.3144	0.00097	***

Mean dependent var	0.004336	S.D. dependent var	1.001443
Sum squared resid	88.96325	S.E. of regression	0.37698
R-squared	0.859418	Adjusted R-squared	0.858295
F(5, 626)	765.3852	P-value(F)	6.70E-264
Log-likelihood	−277.1987	Akaike criterion	566.3974
Schwarz criterion	593.0907	Hannan-Quinn	576.7643
rho	−0.008269	Durbin-Watson	2.016528

LM test for autocorrelation up to order 11 -
Null hypothesis: no autocorrelation
Test statistic: LMF = 1.38344
with p-value = P(F(11,615) > 1.38344) = 0.176079

Monthly data, FDCO2 TRAMO seasonal adjustment no further smooth

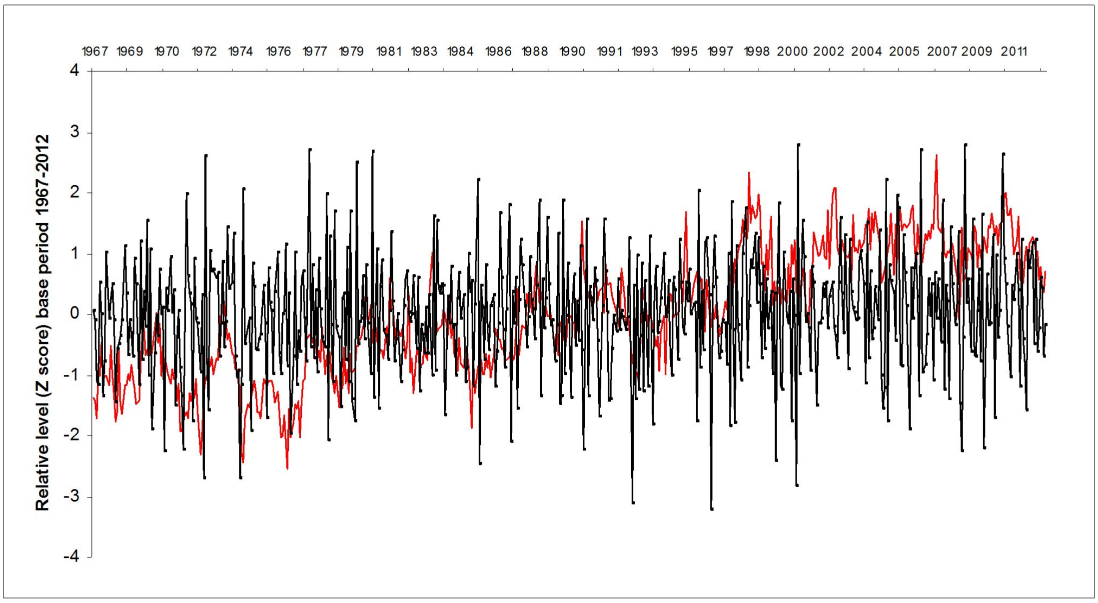


Figure 9. *Z* scored monthly data: first-difference atmospheric CO_2 (TRAMO seasonally corrected) (black dotted curve) compared to level of global surface temperature (red curve)

Table 9: OLS, using observations 1-541
Dependent variable: ZHad4Gl

	Coefficient	Std. Error	t-ratio	p-value
const	0.00580134	0.0165292	0.351	0.72574
Led1ZFDCO2_TRAMO	0.0169459	0.016621	1.0195	0.3084

L1ZHad4Gl	0.594865	0.0405482	14.6706	<0.00001	***
L2ZHad4Gl	0.342522	0.0404153	8.4751	<0.00001	***

Mean dependent var	0.008321	S.D. dependent var	0.996424
Sum squared resid	79.36784	S.E. of regression	0.384446
R-squared	0.851966	Adjusted R-squared	0.851139
F(3, 537)	1030.179	P-value(F)	3.00E-222
Log-likelihood	−248.4681	Akaike criterion	504.9361
Schwarz criterion	522.1098	Hannan-Quinn	511.6522
rho	−0.020425	Durbin-Watson	2.035772

LM test for autocorrelation up to order 11 -
Null hypothesis: no autocorrelation
Test statistic: LMF = 1.65967
with p-value = P(F(11,526) > 1.65967) = 0.0792997

Monthly data, FDCO2 TRAMO seasonal adjustment plus further 4X3mma smoothing

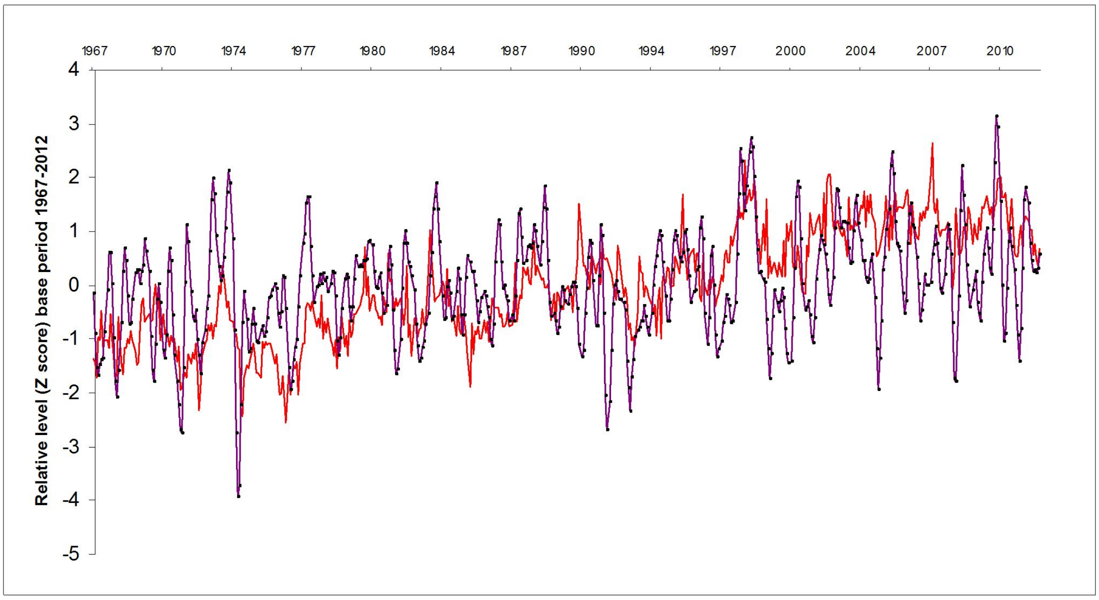


Figure 10. *Z* scored monthly data: first-difference atmospheric CO_2 (TRAMO seasonally corrected) smoothed by three 3-month moving averages (black dotted curve) compared to level of global surface temperature (red curve)

Table 10: OLS, using observations 1-540
Dependent variable: ZHad4Gl

	Coefficient	Std. Error	t-ratio	p-value	
const	−0.0518209	0.0345242	-1.501	0.13394	
Led1m3x3mmaFDCO2_TRAMO	0.50309	0.238916	2.1057	0.03569	**
Led1mZHad4Gl	0.589466	0.040646	14.5024	<0.00001	***

Led2mZHad4Gl	0.333687	0.0404246	8.2545	<0.00001	***

Mean dependent var	0.133697	S.D. dependent var	0.988703
Sum squared resid	77.36309	S.E. of regression	0.379913
R-squared	0.853171	Adjusted R-squared	0.852349
F(3, 536)	1038.164	P-value(F)	8.70E-223
Log-likelihood	−241.6008	Akaike criterion	491.2016
Schwarz criterion	508.3678	Hannan-Quinn	497.9152
rho	−0.021301	Durbin-Watson	2.041103

LM test for autocorrelation up to order 11 -
Null hypothesis: no autocorrelation
Test statistic: LMF = 1.65475
with p-value = P(F(11,525) > 1.65475) = 0.0805097

Monthly data, ZFDHad4Gl and reverse SOI, no smoothing

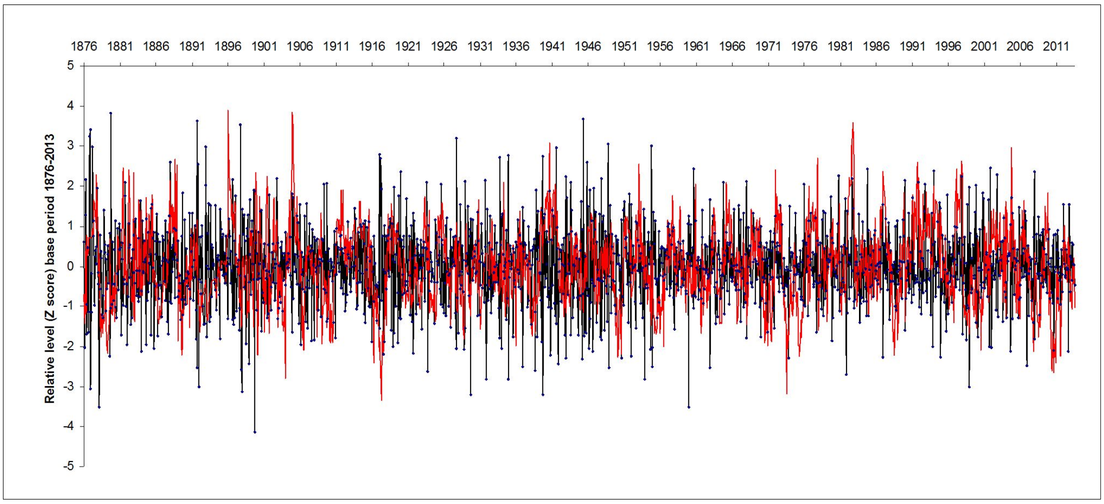


Figure 11. *Z* scored monthly data: first-difference atmospheric CO_2 (TRAMO seasonally corrected) smoothed by three 3-month moving averages (black dotted curve) compared to level of global surface temperature (red curve)

Table 11: OLS, using observations 1-1647
Dependent variable: ZReverseSOI

	Coefficient	Std. Error	t-ratio	p-value	
const	0.000821969	0.0182354	0.0451	0.96405	
ZFDZHad4Gl	0.0551914	0.018288	3.0179	0.00258	***
L1ZReverseSOI	0.47422	0.0244903	19.3636	<0.00001	***
L2ZReverseSOI	0.187349	0.0266996	7.0169	<0.00001	***

L3ZReverseSOI	0.0874809	0.0244789	3.5737	0.00036	***

Mean dependent var	0.002695	S.D. dependent var	1.000409
Sum squared resid	899.2797	S.E. of regression	0.74005
R-squared	0.454104	Adjusted R-squared	0.452774
F(4, 1642)	341.4746	P-value(F)	5.50E-214
Log-likelihood	−1838.678	Akaike criterion	3687.356
Schwarz criterion	3714.39	Hannan-Quinn	3697.38
rho	−0.007240	Durbin-Watson	2.01295

LM test for autocorrelation up to order 11 -
Null hypothesis: no autocorrelation
Test statistic: LMF = 1.69657
with p-value = P(F(11,1631) > 1.69657) = 0.0685144

Monthly data, ZFDHad4Gl smoothed by 13mma, and reverse SOI

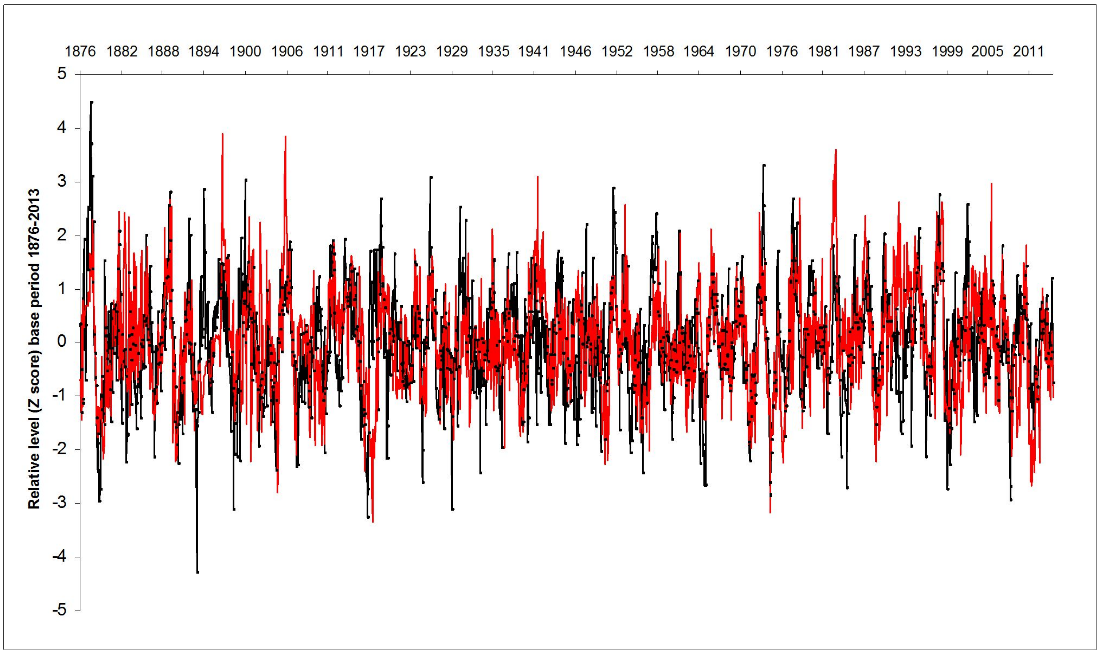


Figure 12. *Z* scored monthly data: led 3 month first-difference global surface temperature smoothed by a 13-month moving average (black dotted curve) compared to level of (reverse) Southern Oscillation Index (red curve)

Table 12 : OLS, using observations 1-1648
Dependent variable: ZReverseSOI

	Coefficient	Std. Error	t-ratio	p-value

const	0.000305	0.0179903	0.017	0.98646	
Led3mZ13mmaFDHad4Gl	0.14137	0.019169	7.374	<0.00001	***
L1ZReverseSOI	0.442205	0.0245285	18.028	<0.00001	***
L2ZReverseSOI	0.172003	0.0264475	6.5036	<0.00001	***
L3ZReverseSOI	0.0818258	0.0241703	3.3854	0.00073	***

Mean dependent var	0.002074	S.D. dependent var	1.0004
Sum squared resid	876.331	S.E. of regression	0.7303
R-squared	0.468372	Adjusted R-squared	0.4670
F(4, 1643)	361.8771	P-value(F)	1.50E-2
Log-likelihood	−1817.994	Akaike criterion	3645.9
Schwarz criterion	3673.024	Hannan-Quinn	3656.0
rho	−0.006071	Durbin-Watson	2.010102

LM test for autocorrelation up to order 11 -
Null hypothesis: no autocorrelation
Test statistic: LMF = 1.15483
with p-value = P(F(11,1632) > 1.15483) = 0.31415

Annual data, ZFDHad4Gl and reverse SOI

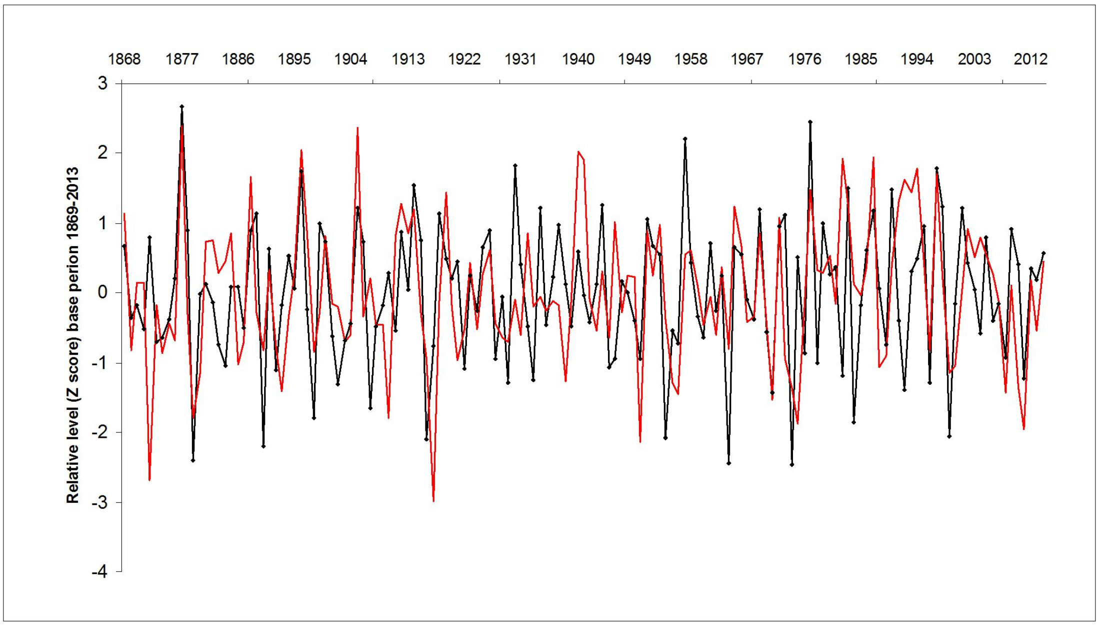


Figure 13. *Z annual* data: first-difference global surface temperature (black dotted curve) compared to level of (reverse) Southern Oscillation Index (red curve)

Table 13: OLS, using observations 1-147
Dependent variable: reverseAnnSOI

	Coefficient	Std. Error	t-ratio	p-value	
const	0	0.0738511	0	1	
FDAnnHad4Gl	0.451394	0.0741036	6.0914	<0.00001	***

Mean dependent var	0	S.D. dependent var	1
Sum squared resid	116.2516	S.E. of regression	0.895397
R-squared	0.203756	Adjusted R-squared	0.198265
F(1, 145)	37.10503	P-value(F)	9.57E-09
Log-likelihood	−191.3353	Akaike criterion	386.6706
Schwarz criterion	392.6514	Hannan-Quinn	389.1007
rho	0.121635	Durbin-Watson	1.750504

LM test for autocorrelation up to order 11 -
Null hypothesis: no autocorrelation
Test statistic: LMF = 0.669798
with p-value = P(F(11,134) > 0.669798) = 0.764953

Table 14: Summary of dynamic regression results

	Condition	FDCO2 or FDHad4GI partial regression coefficient	Significance of independent variable (FDCO2, etc.) partial regression coefficient (p-value)	Adjusted R-square of entire model	LMF p-value (green indicates no significant auto-correlation at order tested)
Monthly: FDCO2 and temperature (Hadcrut4GI)	Monthly, no filter	0.027	0.0684 *	0.862	0.290
	Monthly, filtered (2x13mma)	0.102	<0.00001 ***	0.861	0.341
Monthly: FDCO2_NOAAseascorr and Hadcrut4GI	Monthly, no filter	0.034	0.0410 **	0.828	0.00014
	Monthly, filtered (4x3mma)	0.038	0.02954 **	0.858	0.176
Monthly: FDCO2_TRAMO and Had4GI	Monthly, no filter	0.017	0.308	0.851	0.079
	Monthly, filtered (4x3mma)	0.503	0.0357 **	0.852	0.081
Annual (no seasonality to filter) FDCO2 and Hadcrut4GI		0.447	<0.00001 ***	0.862	0.554
SDCO2 and FDHad4GI	Monthly, no filter	0.099	0.00629 ***	0.167	0.227
	Monthly, filtered (2x13mma)	0.166	<0.00001 ***	0.568	0.120
	Annual (no seasonality to filter)	0.697	<0.00001 ***	0.476	0.085

	Monthly, no filter	0.057	0.00189 ***	0.453	0.053
	Monthly, filtered (2x13mma)	0.141	<0.00001 ***	0.466	0.239
FD temperature and (reverse) SOI	**Annual (no seasonality to filter)**	0.451	<0.00001 ***	0.198	0.562

Comment:
Thirteen analyses are summarised in the table. In all but one case, models were achieved with no significant autocorrelation remaining. The green highlighting shows results which are both statistically significant and show differenced CO2 correlated with temperature, or differenced temperature correlated with the SOI.
Of the 12 cases without significant autocorrelation, 10 are green highlighted, and one is light green. In other words, most of the approaches assessed above (i) support the findings of the paper, and (ii) the use of its particular seasonal smoothing method.

In more detail, it is seen firstly that, *even using raw data*, in three of the four instances assessed, the findings made in the paper using its smoothed data are supported.

Secondly, the highest partial regression coefficient p-value is seen for the smoothing for first-difference CO_2 used in the paper, 2x13mma.

The question of the best method to use is explored further using cross-correlogram analysis in Table 15 and Figure 15.

Table 15 also enables further assessment of the question of whether first difference CO2 leads or lags global surface temperature. (Re Referee comment Page 2. "…especially for testing sensitive questions such as phase shifts of one or two periods.")

Table 15: Cross-correlogram analyses. Maximum correlation achieved for each analysis is highlighted in green

	Correlation between:					
Lag	**ZFDCO2 and Had4Gl**	**ZFDCO2 NOAA seas corr and Had4gl**	**Z4x3mmaFDCO2 NOAA seas corr and had4gl**	**Z2x13mFDCO2 and Had4gl**	**FDCO2_TRAMO and Had4Gl**	**4x3mmaFDCO2_TRAMO and Had4Gl**
-60	0.017	0.070	0.235	0.420	0.058	0.156
-59	0.011	0.058	0.246	0.434	0.046	0.165
-58	0.013	0.059	0.266	0.449	0.036	0.178
-57	0.015	0.079	0.291	0.466	0.061	0.196
-56	0.005	0.077	0.317	0.483	0.062	0.215
-55	0.002	0.102	0.335	0.501	0.084	0.230
-54	0.004	0.090	0.342	0.517	0.069	0.240

-53	0.021	0.093	0.344	0.534	0.067	0.249
-52	0.037	0.067	0.347	0.548	0.052	0.261
-51	0.053	0.104	0.357	0.560	0.089	0.276
-50	0.042	0.102	0.372	0.567	0.075	0.288
-49	0.024	0.096	0.386	0.571	0.077	0.297
-48	0.020	0.105	0.396	0.574	0.085	0.303
-47	0.023	0.114	0.401	0.576	0.107	0.308
-46	0.024	0.099	0.402	0.576	0.081	0.309
-45	0.026	0.106	0.399	0.575	0.092	0.306
-44	0.018	0.101	0.390	0.570	0.080	0.295
-43	0.007	0.104	0.375	0.564	0.081	0.277
-42	0.009	0.098	0.355	0.556	0.072	0.256
-41	0.020	0.081	0.335	0.552	0.053	0.240
-40	0.034	0.068	0.322	0.549	0.049	0.234
-39	0.051	0.093	0.317	0.545	0.072	0.240
-38	0.038	0.079	0.316	0.537	0.066	0.249
-37	0.022	0.088	0.317	0.528	0.075	0.256
-36	0.014	0.075	0.315	0.520	0.063	0.256
-35	0.016	0.083	0.314	0.514	0.071	0.250
-34	0.021	0.083	0.308	0.510	0.076	0.234
-33	0.024	0.090	0.301	0.507	0.068	0.215
-32	0.006	0.059	0.296	0.504	0.034	0.200
-31	-0.001	0.075	0.302	0.503	0.050	0.198
-30	0.003	0.075	0.318	0.505	0.047	0.209
-29	0.023	0.103	0.335	0.510	0.087	0.223
-28	0.042	0.100	0.342	0.516	0.079	0.229
-27	0.048	0.079	0.338	0.518	0.065	0.228
-26	0.040	0.089	0.327	0.517	0.074	0.224
-25	0.021	0.080	0.318	0.513	0.059	0.225
-24	0.014	0.072	0.316	0.511	0.052	0.232
-23	0.016	0.087	0.323	0.512	0.073	0.242
-22	0.020	0.084	0.333	0.513	0.069	0.250
-21	0.022	0.096	0.340	0.514	0.069	0.253
-20	0.012	0.092	0.338	0.514	0.080	0.247
-19	-0.001	0.092	0.328	0.514	0.077	0.234
-18	-0.001	0.081	0.315	0.515	0.060	0.220
-17	0.011	0.061	0.306	0.521	0.041	0.214
-16	0.041	0.088	0.306	0.531	0.057	0.221
-15	0.052	0.076	0.312	0.542	0.067	0.237
-14	0.047	0.091	0.322	0.552	0.080	0.254
-13	0.022	0.072	0.333	0.559	0.053	0.267
-12	0.019	0.102	0.345	0.571	0.086	0.278
-11	0.019	0.092	0.354	0.584	0.085	0.287
-10	0.026	0.093	0.361	0.598	0.091	0.294
-9	0.028	0.094	0.366	0.614	0.084	0.299
-8	0.018	0.094	0.377	0.629	0.084	0.308
-7	0.004	0.094	0.395	0.646	0.076	0.325
-6	0.008	0.098	0.422	0.662	0.088	0.353
-5	0.030	0.142	0.451	0.681	0.125	0.386
-4	0.047	0.117	0.471	0.698	0.114	0.415
-3	0.064	0.132	0.483	0.711	0.118	0.435
-2	0.052	0.122	0.487	0.715	0.131	0.446

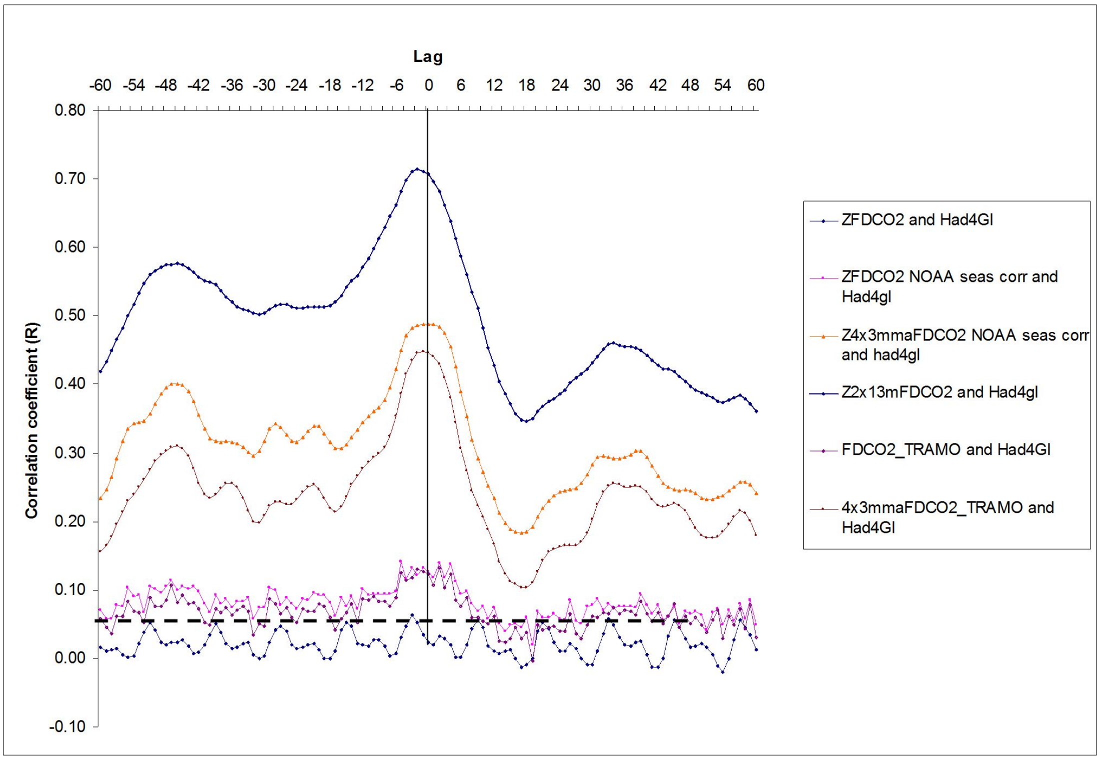
-1	0.034	0.133	0.488	0.712	0.126	0.448
0	0.023	0.127	0.488	0.707	0.123	0.447
1	0.020	0.118	0.487	0.696	0.107	0.440
2	0.032	0.139	0.485	0.682	0.133	0.431
3	0.030	0.118	0.475	0.663	0.103	0.411
4	0.019	0.137	0.456	0.639	0.124	0.381
5	0.002	0.112	0.426	0.612	0.085	0.344
6	0.002	0.093	0.390	0.587	0.076	0.307
7	0.021	0.098	0.353	0.561	0.089	0.273
8	0.044	0.080	0.320	0.536	0.059	0.245
9	0.056	0.068	0.293	0.511	0.060	0.224
10	0.045	0.076	0.271	0.482	0.055	0.207
11	0.019	0.057	0.252	0.453	0.050	0.189
12	0.011	0.075	0.233	0.427	0.061	0.167
13	0.007	0.051	0.213	0.404	0.026	0.142
14	0.010	0.040	0.197	0.386	0.024	0.123
15	0.012	0.049	0.188	0.372	0.029	0.112
16	0.000	0.051	0.184	0.358	0.046	0.108
17	-0.014	0.045	0.182	0.348	0.029	0.103
18	-0.009	0.060	0.185	0.346	0.038	0.103
19	0.000	0.020	0.192	0.350	-0.003	0.110
20	0.039	0.069	0.206	0.361	0.049	0.126
21	0.053	0.059	0.219	0.369	0.041	0.143
22	0.043	0.060	0.230	0.375	0.046	0.155
23	0.024	0.066	0.237	0.380	0.048	0.160
24	0.010	0.058	0.242	0.385	0.040	0.163
25	0.011	0.057	0.245	0.393	0.040	0.164
26	0.022	0.085	0.247	0.402	0.066	0.165
27	0.015	0.055	0.249	0.410	0.036	0.165
28	0.000	0.050	0.256	0.416	0.030	0.170
29	-0.010	0.076	0.268	0.422	0.048	0.183
30	-0.009	0.078	0.283	0.431	0.061	0.204
31	0.011	0.087	0.293	0.441	0.059	0.225
32	0.037	0.070	0.296	0.451	0.068	0.242
33	0.058	0.080	0.294	0.458	0.066	0.252
34	0.049	0.075	0.292	0.460	0.075	0.255
35	0.030	0.075	0.292	0.458	0.065	0.253
36	0.019	0.077	0.294	0.456	0.071	0.250
37	0.019	0.076	0.298	0.455	0.070	0.250
38	0.023	0.074	0.302	0.453	0.063	0.251
39	0.025	0.095	0.302	0.450	0.084	0.250
40	0.005	0.078	0.295	0.443	0.065	0.244
41	-0.013	0.066	0.282	0.435	0.054	0.233
42	-0.013	0.079	0.267	0.428	0.068	0.223
43	0.000	0.057	0.256	0.423	0.050	0.221
44	0.033	0.062	0.250	0.422	0.062	0.224
45	0.057	0.076	0.247	0.419	0.079	0.226
46	0.045	0.051	0.245	0.411	0.046	0.223
47	0.029	0.069	0.247	0.405	0.062	0.215
48	0.016	0.065	0.245	0.397	0.051	0.203
49	0.018	0.069	0.241	0.392	0.059	0.190
50	0.022	0.064	0.235	0.389	0.049	0.180

51	0.016	0.042	0.232	0.385	0.038	0.176
52	0.005	0.067	0.233	0.381	0.057	0.175
53	-0.011	0.073	0.235	0.375	0.070	0.179
54	-0.020	0.049	0.238	0.374	0.029	0.184
55	0.000	0.071	0.244	0.378	0.062	0.196
56	0.027	0.055	0.250	0.382	0.048	0.207
57	0.055	0.080	0.257	0.384	0.073	0.216
58	0.045	0.057	0.257	0.379	0.043	0.212
59	0.034	0.086	0.253	0.371	0.079	0.201
60	0.013	0.049	0.241	0.362	0.030	0.180

Table 15 shows, first, that, while there are some differences in the precise number of periods by which first-difference CO_2 leads temperature, the key point in this aspect of our study is supported - that in none of the six cases assessed does temperature lead first-difference CO_2. Two of these cases are new to the study – NOAA and TRAMO.

Figure 15 plots the data in Table 15.

Figure 15: Cross-correlograms between variously seasonally-adjusted first difference CO_2 time series and the Hadcrut4 global surface temperature time series. The dashed line shows the 0.05 level of statistical significance



The figure shows the following. First, it is of interest that there is very close conjunction between the two (NOAA and TRAMO) model-based methods of seasonal adjustment. Secondly, the 2x13mma FDCO2 series displays the highest correlation with temperature. Thus this observation, along with its displaying the highest statistical significance in the dynamic regression analyses (see Table 14 above) is support for its continued use as the method of seasonal adjustment in the paper.

We propose including these results in their entirety in a Supplement, and making this reference to the Supplement in the text of the manuscript (Page 14, line 23):

> Finally, seasonally adjusting the data by a range of alternative approaches did not qualitatively change the results discussed in the paper. Results of these analyses are given in the Supplement.

Referee comment page 2: *Something else that concerned me in these causality tests is that although the series in question are being treated as stationary (acceptably in my view) there are still "deterministic" upward drifts in the series. These need to be fitted separately from the higher frequency components, to capture the required "constant conjunction" specified in the definition of causality, and ensure that this is not spurious. (Note that every linear trend is correlated with every other, by construction!) The regressions ought to contain trend terms so that the data are, in effect, de-trended, before correlations are computed. This does not appear to have been done, and it should be.*

This question is addressed by running and comparing vector autoregression (VAR) analyses with and without trend terms.

It is noted that the lag lengths required for the VARs are chosen using the AIC criterion. This is a conservative test. As Lutkepohl and Kratzig (2004) note (pages 152-153):

> The larger number of lagged differences … is always the number suggested by AIC, whereas the lower number is the proposal of the HQ criterion. Recall that choosing the order too small can lead to size distortions for the tests while selecting too large an order may imply reductions in power.

In what follows unit root and lag detection pre-tests required for the two VARs are first carried out. These are followed by the two VARS themselves. Results are then discussed. In the tables highlighting is used to indicate key results.

Table 16: Augmented Dickey-Fuller tests for unit root for first-difference CO_2

Augmented Dickey-Fuller test for Z2x13mmaFDCO2
including 16 lags of (1-L)Z2x13mmaFDCO2
(max was 17, criterion modified AIC)

sample size 641
unit-root null hypothesis: a = 1

test without constant
model: (1-L)y = (a-1)*y(-1) + ... + e
1st-order autocorrelation coeff. for e: -0.002
lagged differences: F(16, 624) = 93.524 [0.0000]
estimated value of (a - 1): -0.00942986
test statistic: tau_nc(1) = -2.36994
asymptotic p-value 0.0172

test with constant
model: (1-L)y = b0 + (a-1)*y(-1) + ... + e
1st-order autocorrelation coeff. for e: -0.002
lagged differences: F(16, 623) = 93.354 [0.0000]
estimated value of (a - 1): -0.00939305
test statistic: tau_c(1) = -2.35964
asymptotic p-value 0.1535

with constant and trend
model: (1-L)y = b0 + b1*t + (a-1)*y(-1) + ... + e
1st-order autocorrelation coeff. for e: 0.000
lagged differences: F(16, 622) = 95.210 [0.0000]
estimated value of (a - 1): -0.0313915
test statistic: tau_ct(1) = -4.26113
asymptotic p-value 0.003549

The ADF test indicates that for the first-difference CO_2 data, VARS can be run straightforwardly for tests without constant and for tests with constant and trend but not for tests with constant alone.

Table 17: Augmented Dickey-Fuller test for ZHad4Gl
including 7 lags of (1-L)ZHad4Gl
(max was 17, criterion modified AIC)
sample size 650
unit-root null hypothesis: a = 1

test without constant
model: (1-L)y = (a-1)*y(-1) + ... + e
1st-order autocorrelation coeff. for e: 0.002
lagged differences: F(7, 642) = 15.533 [0.0000]
estimated value of (a - 1): -0.0350251
test statistic: tau_nc(1) = -2.24541
asymptotic p-value 0.02387

test with constant
model: (1-L)y = b0 + (a-1)*y(-1) + ... + e
1st-order autocorrelation coeff. for e: 0.002

lagged differences: F(7, 641) = 15.536 [0.0000]
estimated value of (a - 1): -0.0348952
test statistic: tau_c(1) = -2.23534
asymptotic p-value 0.1938

with constant and trend
model: (1-L)y = b0 + b1*t + (a-1)*y(-1) + ... + e
1st-order autocorrelation coeff. for e: 0.002
lagged differences: F(7, 640) = 8.542 [0.0000]
estimated value of (a - 1): -0.163601
test statistic: tau_ct(1) = -5.11451
asymptotic p-value 0.0001075

As for the first-difference CO_2 data, the ADF test indicates that for the Hadcrut4GL temperature data VARS can be run straightforwardly for tests without constant and for tests with constant and trend but not for tests with constant alone.

VAR analysis 1 – no constant or trend

Table 18: Optimum lag length for VAR

VAR system, maximum lag order 36 – no constant or trend

The asterisks below indicate the best (that is, minimized) values of the respective information criteria, AIC = Akaike criterion, BIC = Schwarz Bayesian criterion and HQC = Hannan-Quinn criterion.

lags	loglik	p(LR)	AIC	BIC	HQC
1	7.18572		-0.010243	0.018264	0.000836
2	235.29686	0.00000	-0.730858	-0.673843	-0.708699
3	248.28923	0.00003	-0.759772	-0.674249	-0.726534
4	257.57998	0.00095	-0.776784	-0.662754	-0.732466
5	261.97150	0.06676	-0.778043	-0.635505	-0.722646
6	277.88264	0.00000	-0.816343	-0.645297	-0.749866
7	282.70818	0.04673	-0.818997	-0.619444	-0.741441
8	299.89548	0.00000	-0.861400	-0.633339	-0.772764
9	300.92326	0.72554	-0.851843	-0.595274	-0.752128
10	307.05981	0.01543	-0.858713	-0.573637	-0.747918
11	313.15046	0.01605	-0.865436	-0.551851	-0.743561
12	335.85323	0.00000	-0.925573	-0.583481	-0.792619
13	336.91819	0.71188	-0.916136	-0.545536	-0.772102
14	427.84019	0.00000	-1.195628	-0.796520	-1.040515
15	438.41452	0.00030	-1.216767	-0.789152	-1.050574
16	455.90637	0.00000	-1.260149	-0.804027	-1.082877
17	461.74444	0.01993	-1.266059	-0.781429	-1.077708
18	466.49280	0.04981	-1.268466	-0.755328	-1.069034

19	469.52362	0.19459	-1.265349	-0.723704	-1.054839
20	475.38505	0.01954	-1.271335	-0.701182	-1.049744
21	482.05851	0.00970	-1.279931	-0.681270	-1.047261
22	485.15055	0.18582	-1.277011	-0.649843	-1.033262
23	492.11321	0.00754	-1.286538	-0.630862	-1.031709
24	509.98611	0.00000	-1.331145	-0.646961	-1.065237
25	539.07116	0.00000	-1.411804	-0.699113	-1.134817
26	541.08460	0.40238	-1.405417	-0.664218	-1.117350
27	612.09531	0.00000	-1.620885	-0.851179*	-1.321739
28	619.09157	0.00732	-1.630520	-0.832305	-1.320293
29	627.34628	0.00241	-1.644200*	-0.817478	-1.322895*
30	630.89450	0.13088	-1.642748	-0.787518	-1.310362
31	633.62100	0.24389	-1.638653	-0.754915	-1.295188
32	638.37697	0.04950	-1.641084	-0.728839	-1.286539
33	641.66155	0.16048	-1.638783	-0.698031	-1.273159
34	644.21450	0.27660	-1.634130	-0.664870	-1.257427
35	645.51207	0.62769	-1.625441	-0.627673	-1.237658
36	653.29252	0.00367	-1.637597	-0.611321	-1.238734

Table 19. VAR analysis 1 - no constant or trend

VAR system, lag order 29
OLS estimates, observations 30-658 (T = 629)
Log-likelihood = 636.06379
Determinant of covariance matrix = 0.00045363642
AIC = -1.6536
BIC = -0.8340
HQC = -1.3352
Portmanteau test: LB(48) = 217.173, df = 76 [0.0000]

Equation 1: Z2x13mmaFDCO2

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
Z2x13mmaFDCO2_1	1.72593	0.0413617	41.7277	<0.00001	***
Z2x13mmaFDCO2_2	−0.781579	0.0821668	-9.5121	<0.00001	***
Z2x13mmaFDCO2_3	0.0661491	0.0834604	0.7926	0.42835	
Z2x13mmaFDCO2_4	−0.0260817	0.076265	-0.3420	0.73249	
Z2x13mmaFDCO2_5	0.0693752	0.0762971	0.9093	0.36359	
Z2x13mmaFDCO2_6	−0.0421609	0.0758172	-0.5561	0.57837	
Z2x13mmaFDCO2_7	−0.0711063	0.0757778	-0.9384	0.34846	

Z2x13mmaFDCO2_8	0.047906	0.0759431	0.6308	0.52841	
Z2x13mmaFDCO2_9	−0.00711034	0.0761064	-0.0934	0.92560	
Z2x13mmaFDCO2_10	−0.0289113	0.0760203	-0.3803	0.70386	
Z2x13mmaFDCO2_11	0.246549	0.076003	3.2439	0.00125	***
Z2x13mmaFDCO2_12	0.127804	0.0766581	1.6672	0.09602	*
Z2x13mmaFDCO2_13	−1.26186	0.0769009	-16.4089	<0.00001	***
Z2x13mmaFDCO2_14	1.46629	0.0934632	15.6884	<0.00001	***
Z2x13mmaFDCO2_15	−0.680634	0.108196	-6.2908	<0.00001	***
Z2x13mmaFDCO2_16	0.0806417	0.0933387	0.8640	0.38797	
Z2x13mmaFDCO2_17	0.0557084	0.0767349	0.7260	0.46815	
Z2x13mmaFDCO2_18	0.0416344	0.0766399	0.5432	0.58717	
Z2x13mmaFDCO2_19	−0.0486445	0.0760808	-0.6394	0.52283	
Z2x13mmaFDCO2_20	−0.0407226	0.0762461	-0.5341	0.59348	
Z2x13mmaFDCO2_21	0.0343481	0.0762676	0.4504	0.65262	
Z2x13mmaFDCO2_22	−0.0170778	0.0762014	-0.2241	0.82275	
Z2x13mmaFDCO2_23	0.0426641	0.0762064	0.5598	0.57580	
Z2x13mmaFDCO2_24	0.24763	0.0764245	3.2402	0.00126	***
Z2x13mmaFDCO2_25	0.0518783	0.0771286	0.6726	0.50146	
Z2x13mmaFDCO2_26	−0.793164	0.0771768	-10.2772	<0.00001	***
Z2x13mmaFDCO2_27	0.673644	0.0839021	8.0289	<0.00001	***
Z2x13mmaFDCO2_28	−0.324441	0.0819737	-3.9579	0.00009	***
Z2x13mmaFDCO2_29	0.138495	0.0412347	3.3587	0.00084	***
ZHad4Gl_1	0.0101494	0.00794208	1.2779	0.20179	
ZHad4Gl_2	0.00118148	0.00873495	0.1353	0.89245	
ZHad4Gl_3	−0.00784056	0.00888824	-0.8821	0.37808	
ZHad4Gl_4	−0.00435003	0.00889417	-0.4891	0.62497	
ZHad4Gl_5	−0.0123628	0.00890794	-1.3878	0.16573	
ZHad4Gl_6	0.00349266	0.00885988	0.3942	0.69357	

ZHad4Gl_7	−0.00876787	0.00885169	-0.9905	0.32233	
ZHad4Gl_8	0.00456575	0.00886092	0.5153	0.60657	
ZHad4Gl_9	−0.00234467	0.0088358	-0.2654	0.79083	
ZHad4Gl_10	−0.00883043	0.00880715	-1.0026	0.31646	
ZHad4Gl_11	0.000844746	0.00881626	0.0958	0.92370	
ZHad4Gl_12	0.00781879	0.0087901	0.8895	0.37411	
ZHad4Gl_13	−0.0148777	0.00879569	-1.6915	0.09129	*
ZHad4Gl_14	0.0112028	0.00887775	1.2619	0.20750	
ZHad4Gl_15	0.00806641	0.00889173	0.9072	0.36469	
ZHad4Gl_16	−0.005193	0.00886845	-0.5856	0.55840	
ZHad4Gl_17	0.00226975	0.0088638	0.2561	0.79799	
ZHad4Gl_18	0.000249724	0.00879491	0.0284	0.97736	
ZHad4Gl_19	−0.00607713	0.0087459	-0.6949	0.48743	
ZHad4Gl_20	0.0112006	0.00875814	1.2789	0.20146	
ZHad4Gl_21	−0.000869594	0.00876724	-0.0992	0.92102	
ZHad4Gl_22	−0.000875013	0.00874311	-0.1001	0.92032	
ZHad4Gl_23	−0.00620297	0.00873374	-0.7102	0.47785	
ZHad4Gl_24	−3.40208e-05	0.00873703	-0.0039	0.99689	
ZHad4Gl_25	0.00197494	0.00878987	0.2247	0.82231	
ZHad4Gl_26	−0.00316451	0.0087708	-0.3608	0.71838	
ZHad4Gl_27	−0.00881157	0.0087779	-1.0038	0.31588	
ZHad4Gl_28	0.0146304	0.00860441	1.7003	0.08961	*
ZHad4Gl_29	0.0159557	0.00787513	2.0261	0.04322	**

Mean dependent var	0.052991	S.D. dependent var	0.989697
Sum squared resid	2.544154	S.E. of regression	0.066750
R-squared	0.995876	Adjusted R-squared	0.995464
F(58, 571)	2377.275	P-value(F)	0.000000
rho	−0.017482	Durbin-Watson	2.032816

F-tests of zero restrictions:

All lags of Z2x13mmaFDCO2F(29, 571) = 1994.8 [0.0000]

All lags of ZHad4Gl F(29, 571) = 1.0698 [0.3692]

All vars, lag 29 F(2, 571) = 8.1696 [0.0003]

Equation 2: ZHad4Gl

	Coefficient	*Std. Error*	*t-ratio*	*p-value*
Z2x13mmaFDCO2_1	0.351762	0.218073	1.6130	0.10729
Z2x13mmaFDCO2_2	−0.160469	0.433212	-0.3704	0.71121
Z2x13mmaFDCO2_3	0.0183659	0.440032	0.0417	0.96672
Z2x13mmaFDCO2_4	−0.297947	0.402096	-0.7410	0.45901
Z2x13mmaFDCO2	0.560611	0.402265	1.3936	0.16397

_5					
Z2x13mmaFDCO2_6	−0.144199	0.399735	-0.3607	0.71843	
Z2x13mmaFDCO2_7	−0.423575	0.399527	-1.0602	0.28951	
Z2x13mmaFDCO2_8	0.295925	0.400398	0.7391	0.46016	
Z2x13mmaFDCO2_9	−0.260102	0.401259	-0.6482	0.51711	
Z2x13mmaFDCO2_10	0.230741	0.400805	0.5757	0.56505	
Z2x13mmaFDCO2_11	−0.200734	0.400714	-0.5009	0.61661	
Z2x13mmaFDCO2_12	0.528353	0.404168	1.3073	0.19165	
Z2x13mmaFDCO2_13	−1.10078	0.405448	-2.7150	0.00683	***
Z2x13mmaFDCO2_14	1.10679	0.492771	2.2461	0.02508	**
Z2x13mmaFDCO2_15	−0.243162	0.570447	-0.4263	0.67007	
Z2x13mmaFDCO2_16	0.00763635	0.492114	0.0155	0.98762	
Z2x13mmaFDCO2_17	−0.606518	0.404573	-1.4992	0.13439	
Z2x13mmaFDCO2_18	0.397971	0.404072	0.9849	0.32509	
Z2x13mmaFDCO2_19	0.326914	0.401124	0.8150	0.41541	
Z2x13mmaFDCO2_20	−0.384669	0.401996	-0.9569	0.33902	
Z2x13mmaFDCO2_21	0.420224	0.402109	1.0450	0.29644	
Z2x13mmaFDCO2_22	−0.360486	0.40176	-0.8973	0.36996	
Z2x13mmaFDCO2_23	0.230553	0.401787	0.5738	0.56632	
Z2x13mmaFDCO2_24	−0.284056	0.402937	-0.7050	0.48112	
Z2x13mmaFDCO2_25	0.195071	0.406649	0.4797	0.63162	
Z2x13mmaFDCO2_26	−0.534194	0.406903	-1.3128	0.18977	
Z2x13mmaFDCO2_27	0.514871	0.442361	1.1639	0.24494	
Z2x13mmaFDCO2_28	0.0404195	0.432194	0.0935	0.92552	
Z2x13mmaFDCO2_29	−0.12579	0.217404	-0.5786	0.56309	
ZHad4Gl_1	0.459533	0.0418734	10.9743	<0.00001	***

ZHad4Gl_2	0.228872	0.0460537	4.9697	<0.00001	***
ZHad4Gl_3	−0.0136179	0.0468619	-0.2906	0.77147	
ZHad4Gl_4	0.0681717	0.0468932	1.4538	0.14656	
ZHad4Gl_5	0.00674787	0.0469658	0.1437	0.88581	
ZHad4Gl_6	−0.0438299	0.0467124	-0.9383	0.34849	
ZHad4Gl_7	0.0379334	0.0466692	0.8128	0.41666	
ZHad4Gl_8	0.0743408	0.0467178	1.5913	0.11210	
ZHad4Gl_9	−0.0259374	0.0465854	-0.5568	0.57790	
ZHad4Gl_10	0.0402099	0.0464344	0.8660	0.38688	
ZHad4Gl_11	−0.00953732	0.0464824	-0.2052	0.83750	
ZHad4Gl_12	−0.0105286	0.0463444	-0.2272	0.82036	
ZHad4Gl_13	0.0221907	0.0463739	0.4785	0.63247	
ZHad4Gl_14	−0.0191303	0.0468066	-0.4087	0.68291	
ZHad4Gl_15	−0.0239415	0.0468803	-0.5107	0.60976	
ZHad4Gl_16	−0.0267643	0.0467576	-0.5724	0.56727	
ZHad4Gl_17	0.0192374	0.046733	0.4116	0.68075	
ZHad4Gl_18	0.00459367	0.0463698	0.0991	0.92112	
ZHad4Gl_19	0.0720049	0.0461114	1.5615	0.11895	
ZHad4Gl_20	−0.0257433	0.0461759	-0.5575	0.57740	
ZHad4Gl_21	0.0172551	0.046224	0.3733	0.70907	
ZHad4Gl_22	−0.0212647	0.0460967	-0.4613	0.64475	
ZHad4Gl_23	0.0197747	0.0460473	0.4294	0.66776	
ZHad4Gl_24	0.124019	0.0460647	2.6923	0.00730	***
ZHad4Gl_25	0.0307578	0.0463433	0.6637	0.50715	
ZHad4Gl_26	−0.0435799	0.0462427	-0.9424	0.34638	
ZHad4Gl_27	−0.0885494	0.0462802	-1.9133	0.05621	*
ZHad4Gl_28	0.0259696	0.0453654	0.5725	0.56724	
ZHad4Gl_29	0.0257739	0.0415204	0.6208	0.53501	

Mean dependent var	0.020080	S.D. dependent var	1.005738
Sum squared resid	70.72152	S.E. of regression	0.351931
R-squared	0.888712	Adjusted R-squared	0.877602
F(58, 571)	78.61760	P-value(F)	1.6e-234
rho	0.000459	Durbin-Watson	1.998971

F-tests of zero restrictions:

All lags of Z2x13mmaFDCO2F(29, 571) = 2.3595 [0.0001]

All lags of ZHad4Gl F(29, 571) = 40.83 [0.0000]

All vars, lag 29 F(2, 571) = 0.33815 [0.7132]

For the system as a whole

Null hypothesis: the longest lag is 28

Alternative hypothesis: the longest lag is 29

Likelihood ratio test: Chi-square(4) = 18.6029 [0.0009]

VAR analysis 2 – trend included

Table 20. VAR analysis 2 - detection of optimal lag

VAR system, maximum lag order 36 – trend included

The asterisks below indicate the best (that is, minimized) values of the respective information criteria, AIC = Akaike criterion, BIC = Schwarz Bayesian criterion and HQC = Hannan-Quinn criterion.

lags	loglik	p(LR)	AIC	BIC	HQC
1	36.70207		-0.092290	-0.035274	-0.070131
2	253.77638	0.00000	-0.777416	-0.691893	-0.744177
3	267.15165	0.00002	-0.807562	-0.693531	-0.763244
4	275.59926	0.00203	-0.821863	-0.679324	-0.766465
5	281.21406	0.02410	-0.827055	-0.656009	-0.760578
6	299.10682	0.00000	-0.871726	-0.672173	-0.794170
7	303.50594	0.06635	-0.873009	-0.644948	-0.784373
8	317.09842	0.00002	-0.903853	-0.647285	-0.804138
9	318.76870	0.50253	-0.896362	-0.611286	-0.785567
10	327.97361	0.00103	-0.913098	-0.599514	-0.791224
11	336.76348	0.00149	-0.928500	-0.586408	-0.795546
12	364.32016	0.00000	-1.004245	-0.633645	-0.860211
13	367.92961	0.12476	-1.002989	-0.603882	-0.847876
14	444.46876	0.00000	-1.236234	-0.808619	-1.070041
15	456.36771	0.00009	-1.261632	-0.805510	-1.084360
16	470.70653	0.00001	-1.294876	-0.810246	-1.106525
17	474.44426	0.11280	-1.294033	-0.780895	-1.094602
18	477.57257	0.18079	-1.291230	-0.749585	-1.080719
19	480.23258	0.25601	-1.286921	-0.716768	-1.065331
20	484.88749	0.05381	-1.289027	-0.690367	-1.056358
21	491.75400	0.00820	-1.298244	-0.671076	-1.054495
22	495.61201	0.10255	-1.297788	-0.642112	-1.042959
23	503.76590	0.00263	-1.311144	-0.626961	-1.045236
24	523.01402	0.00000	-1.360174	-0.647482	-1.083186
25	557.15012	0.00000	-1.457074	-0.715875	-1.169007
26	559.18176	0.39751	-1.450745	-0.681039	-1.151599
27	622.54853	0.00000	-1.641635	-0.843421*	-1.331409*
28	628.88984	0.01294	-1.649163	-0.822442	-1.327858
29	635.36967	0.01147	-1.657137*	-0.801908	-1.324752
30	638.03464	0.25509	-1.652845	-0.769107	-1.309380
31	640.48257	0.29815	-1.647854	-0.735609	-1.293310
32	645.59597	0.03678	-1.651434	-0.710681	-1.285810
33	648.43487	0.22454	-1.647701	-0.678440	-1.270997
34	651.36807	0.20935	-1.644270	-0.646502	-1.256488
35	652.64971	0.63334	-1.635530	-0.609254	-1.236667
36	661.06225	0.00209	-1.649718	-0.594935	-1.239776

Table 20. VAR analysis 2 – trend included

VAR system, lag order 29
OLS estimates, observations 30-658 (T = 629)
Log-likelihood = 637.61808
Determinant of covariance matrix = 0.00045140003
AIC = -1.6522
BIC = -0.8185
HQC = -1.3283
Portmanteau test: LB(48) = 219.26, df = 76 [0.0000]

Equation 1: Z2x13mmaFDCO2

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
Z2x13mmaFDCO2_1	1.72161	0.0413889	41.5958	<0.00001	***
Z2x13mmaFDCO2_2	−0.778323	0.0820744	-9.4831	<0.00001	***
Z2x13mmaFDCO2_3	0.066736	0.0833424	0.8007	0.42361	
Z2x13mmaFDCO2_4	−0.0263525	0.0761566	-0.3460	0.72945	
Z2x13mmaFDCO2_5	0.0688404	0.0761892	0.9035	0.36662	
Z2x13mmaFDCO2_6	−0.0418151	0.0757095	-0.5523	0.58095	
Z2x13mmaFDCO2_7	−0.0709658	0.07567	-0.9378	0.34873	
Z2x13mmaFDCO2_8	0.0474232	0.0758355	0.6253	0.53200	
Z2x13mmaFDCO2_9	−0.00693413	0.0759981	-0.0912	0.92733	
Z2x13mmaFDCO2_10	−0.0286644	0.0759122	-0.3776	0.70587	
Z2x13mmaFDCO2_11	0.245987	0.0758956	3.2411	0.00126	***
Z2x13mmaFDCO2_12	0.128783	0.0765513	1.6823	0.09306	*
Z2x13mmaFDCO2_13	−1.26004	0.0767996	-16.4068	<0.00001	***
Z2x13mmaFDCO2_14	1.46186	0.0933702	15.6566	<0.00001	***
Z2x13mmaFDCO2_15	−0.678441	0.10805	-6.2789	<0.00001	***
Z2x13mmaFDCO2_16	0.0814008	0.093207	0.8733	0.38285	
Z2x13mmaFDCO2_17	0.0549384	0.0766271	0.7170	0.47369	
Z2x13mmaFDCO2	0.0412421	0.0765312	0.5389	0.59017	

_18					
Z2x13mmaFDCO2_19	−0.0482152	0.0759729	-0.6346	0.52592	
Z2x13mmaFDCO2_20	−0.0409021	0.0761376	-0.5372	0.59133	
Z2x13mmaFDCO2_21	0.0339944	0.0761593	0.4464	0.65551	
Z2x13mmaFDCO2_22	−0.0171144	0.0760929	-0.2249	0.82213	
Z2x13mmaFDCO2_23	0.0428004	0.076098	0.5624	0.57404	
Z2x13mmaFDCO2_24	0.247376	0.0763159	3.2415	0.00126	***
Z2x13mmaFDCO2_25	0.0529869	0.0770218	0.6879	0.49177	
Z2x13mmaFDCO2_26	−0.791654	0.0770726	-10.2715	<0.00001	***
Z2x13mmaFDCO2_27	0.670938	0.0837993	8.0065	<0.00001	***
Z2x13mmaFDCO2_28	−0.324589	0.0818571	-3.9653	0.00008	***
Z2x13mmaFDCO2_29	0.139405	0.0411799	3.3853	0.00076	***
ZHad4Gl_1	0.00991418	0.0079321	1.2499	0.21186	
ZHad4Gl_2	0.00110205	0.00872266	0.1263	0.89950	
ZHad4Gl_3	−0.00784665	0.00887558	-0.8841	0.37703	
ZHad4Gl_4	−0.00443465	0.00888167	-0.4993	0.61776	
ZHad4Gl_5	−0.0124287	0.00889535	-1.3972	0.16289	
ZHad4Gl_6	0.00344782	0.00884731	0.3897	0.69690	
ZHad4Gl_7	−0.00882284	0.00883915	-0.9982	0.31863	
ZHad4Gl_8	0.00445706	0.00884856	0.5037	0.61466	
ZHad4Gl_9	−0.00241577	0.00882333	-0.2738	0.78434	
ZHad4Gl_10	−0.00893226	0.00879484	-1.0156	0.31024	
ZHad4Gl_11	0.000694529	0.00880419	0.0789	0.93715	
ZHad4Gl_12	0.00770992	0.00877784	0.8783	0.38013	
ZHad4Gl_13	−0.0149396	0.00878325	-1.7009	0.08950	*
ZHad4Gl_14	0.0109846	0.00886614	1.2389	0.21588	
ZHad4Gl_15	0.00790526	0.00887963	0.8903	0.37370	
ZHad4Gl_16	−0.00527712	0.00885598	-0.5959	0.55149	
ZHad4Gl_17	0.00215937	0.00885144	0.2440	0.80735	
ZHad4Gl_18	0.00018374	0.00878249	0.0209	0.98332	
ZHad4Gl_19	−0.00617904	0.00873368	-0.7075	0.47955	
ZHad4Gl_20	0.0111163	0.00874582	1.2710	0.20423	
ZHad4Gl_21	−0.00089272	0.00875477	-0.1020	0.91882	
ZHad4Gl_22	−0.000808518	0.00873076	-0.0926	0.92625	
ZHad4Gl_23	−0.00613741	0.00872141	-0.7037	0.48190	
ZHad4Gl_24	−7.91095e-05	0.00872464	-0.0091	0.99277	
ZHad4Gl_25	0.00193099	0.0087774	0.2200	0.82595	

ZHad4Gl_26	−0.00313812	0.00875833	-0.3583	0.72025	
ZHad4Gl_27	−0.00884439	0.00876543	-1.0090	0.31340	
ZHad4Gl_28	0.0146501	0.00859216	1.7051	0.08873	*
ZHad4Gl_29	0.0162128	0.00786551	2.0613	0.03973	**
time	1.24186e-05	7.6587e-06	1.6215	0.10546	

Mean dependent var	0.052991	S.D. dependent var	0.989697
Sum squared resid	2.532473	S.E. of regression	0.066655
R-squared	0.995895	Adjusted R-squared	0.995477
F(59, 570)	2343.695	P-value(F)	0.000000
rho	−0.018122	Durbin-Watson	2.033779

F-tests of zero restrictions:

All lags of Z2x13mmaFDCO2 F(29, 570) = 1952.6 [0.0000]

All lags of ZHad4Gl F(29, 570) = 1.0738 [0.3639]

All vars, lag 29 F(2, 570) = 8.3406 [0.0003]

Equation 2: ZHad4Gl

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
Z2x13mmaFDCO2_1	0.344439	0.218668	1.5752	0.11577	
Z2x13mmaFDCO2_2	−0.154957	0.433619	-0.3574	0.72096	
Z2x13mmaFDCO2_3	0.0193596	0.440318	0.0440	0.96495	
Z2x13mmaFDCO2_4	−0.298405	0.402354	-0.7416	0.45861	
Z2x13mmaFDCO2_5	0.559706	0.402526	1.3905	0.16493	
Z2x13mmaFDCO2_6	−0.143613	0.399992	-0.3590	0.71970	
Z2x13mmaFDCO2_7	−0.423337	0.399783	-1.0589	0.29009	
Z2x13mmaFDCO2_8	0.295107	0.400657	0.7366	0.46169	
Z2x13mmaFDCO2_9	−0.259804	0.401517	-0.6471	0.51786	
Z2x13mmaFDCO2_10	0.231159	0.401063	0.5764	0.56459	
Z2x13mmaFDCO2_11	−0.201686	0.400975	-0.5030	0.61517	
Z2x13mmaFDCO2_12	0.530009	0.404439	1.3105	0.19056	
Z2x13mmaFDCO2_13	−1.09769	0.405751	-2.7053	0.00703	***
Z2x13mmaFDCO2_14	1.09929	0.493297	2.2284	0.02624	**

Z2x13mmaFDCO2_15	−0.23945	0.570856	-0.4195	0.67504	
Z2x13mmaFDCO2_16	0.00892138	0.492435	0.0181	0.98555	
Z2x13mmaFDCO2_17	−0.607821	0.40484	-1.5014	0.13381	
Z2x13mmaFDCO2_18	0.397307	0.404333	0.9826	0.32621	
Z2x13mmaFDCO2_19	0.327641	0.401384	0.8163	0.41468	
Z2x13mmaFDCO2_20	−0.384973	0.402254	-0.9570	0.33895	
Z2x13mmaFDCO2_21	0.419625	0.402368	1.0429	0.29744	
Z2x13mmaFDCO2_22	−0.360548	0.402017	-0.8968	0.37018	
Z2x13mmaFDCO2_23	0.230784	0.402044	0.5740	0.56618	
Z2x13mmaFDCO2_24	−0.284486	0.403196	-0.7056	0.48074	
Z2x13mmaFDCO2_25	0.196948	0.406925	0.4840	0.62858	
Z2x13mmaFDCO2_26	−0.531638	0.407193	-1.3056	0.19221	
Z2x13mmaFDCO2_27	0.510289	0.442732	1.1526	0.24956	
Z2x13mmaFDCO2_28	0.040169	0.432471	0.0929	0.92603	
Z2x13mmaFDCO2_29	−0.12425	0.217563	-0.5711	0.56816	
ZHad4Gl_1	0.459135	0.0419072	10.9560	<0.00001	***
ZHad4Gl_2	0.228737	0.0460839	4.9635	<0.00001	***
ZHad4Gl_3	−0.0136282	0.0468919	-0.2906	0.77144	
ZHad4Gl_4	0.0680285	0.046924	1.4498	0.14768	
ZHad4Gl_5	0.00663623	0.0469963	0.1412	0.88776	
ZHad4Gl_6	−0.0439058	0.0467425	-0.9393	0.34797	
ZHad4Gl_7	0.0378404	0.0466994	0.8103	0.41811	
ZHad4Gl_8	0.0741568	0.0467491	1.5863	0.11323	
ZHad4Gl_9	−0.0260578	0.0466158	-0.5590	0.57639	
ZHad4Gl_10	0.0400376	0.0464653	0.8617	0.38923	
ZHad4Gl_11	−0.00979162	0.0465147	-0.2105	0.83335	
ZHad4Gl_12	−0.0107129	0.0463755	-0.2310	0.81740	
ZHad4Gl_13	0.0220859	0.0464041	0.4759	0.63429	
ZHad4Gl_14	−0.0194998	0.046842	-0.4163	0.67736	
ZHad4Gl_15	−0.0242143	0.0469133	-0.5162	0.60595	
ZHad4Gl_16	−0.0269067	0.0467883	-0.5751	0.56547	
ZHad4Gl_17	0.0190505	0.0467643	0.4074	0.68389	
ZHad4Gl_18	0.00448196	0.0464	0.0966	0.92308	
ZHad4Gl_19	0.0718324	0.0461421	1.5568	0.12008	
ZHad4Gl_20	−0.0258862	0.0462063	-0.5602	0.57554	

ZHad4Gl_21	0.0172159	0.0462536	0.3722	0.70988	
ZHad4Gl_22	−0.0211521	0.0461267	-0.4586	0.64672	
ZHad4Gl_23	0.0198857	0.0460773	0.4316	0.66622	
ZHad4Gl_24	0.123943	0.0460944	2.6889	0.00738	***
ZHad4Gl_25	0.0306834	0.0463731	0.6617	0.50845	
ZHad4Gl_26	−0.0435352	0.0462724	-0.9408	0.34718	
ZHad4Gl_27	−0.0886049	0.0463099	-1.9133	0.05621	*
ZHad4Gl_28	0.026003	0.0453945	0.5728	0.56699	
ZHad4Gl_29	0.0262092	0.0415554	0.6307	0.52849	
time	2.10237e-05	4.04628e-05	0.5196	0.60356	

Mean dependent var	0.020080	S.D. dependent var	1.005738
Sum squared resid	70.68804	S.E. of regression	0.352156
R-squared	0.888764	Adjusted R-squared	0.877446
F(59, 570)	77.19086	P-value(F)	1.2e-233
rho	0.000443	Durbin-Watson	1.998998

F-tests of zero restrictions:

All lags of Z2x13mmaFDCO2F(29, 570) = 2.2811 [0.0002]

All lags of ZHad4Gl F(29, 570) = 39.45 [0.0000]

All vars, lag 29 F(2, 570) = 0.3401 [0.7118]

For the system as a whole

Null hypothesis: the longest lag is 28

Alternative hypothesis: the longest lag is 29

Likelihood ratio test: Chi-square(4) = 18.9972 [0.0008]

These results show that when trend is included in the VAR it is insignificant; and that models both with and without trend, as in the paper, show causality from first-difference CO_2 to temperature, and not from temperature to first-difference CO_2.

Referee third major comment: *My third major comment concerns the new section on NDVI. Interesting correlations for sure (subject to the caveats above), but the discussion goes far out on a limb and is, for my taste, unacceptably speculative. First, the series constructed as the difference of standardized CO_2 and standardized temperature is a proxy for anything only by a severe stretch of the imagination. Surely, GCMs must (at best) link temperature projections to a particular fraction of projected CO_2. (See comment 10 below.) Even if we accept the suggestion that GCM projections are linear in CO_2 concentration, the simple difference between CO_2 and temperature may or may not capture (in the "constant conjunction" sense) the true forecast discrepancy. Hence, the correlation with NDVI is either interesting by chance, or spurious. I would need firmer evidence to be convinced. The discussion in Section 5 reads like off-the-cuff theorising of the most casual sort. Of course, there is ample evidence, supported by sound theory, for the hypothesis that higher CO_2 concentrations are "greening" the planet. To that extent, the authors have a good point. However, it seems to me that their model (involving the second differences of CO_2, etc.) needs to be much more carefully derived and argued than it is at present.*

It's not good enough to simply report a curious correlation and extrapolate from it a whole theory of the biosphere, This seems like blatant data mining.

My suggestion to the authors is to subtract the section on NDVI, as ample material for a new paper although a good deal of additional work is called for. Then, to redraft the first part of the paper taking note of the various comments offered here.

Response: The points made are valued and the suggestion is accepted.

The NDVI section is redone and simplified in an attempt to be the minimum necessary to illustrate the point that further NDVI research could be conducted; and the Discussion is amended accordingly.

The two proposed new sections are as follows:

4.4 Normalized Difference Vegetation Index (NDVI)

Using the Normalized Difference Vegetation Index (NDVI) time series as a measure of the activity of the land biosphere**,** this section now investigates the land biosphere as a candidate mechanism for the issue, identified in the Introduction, of the increasing difference between the observed global surface temperature trend and that suggested by general circulation climate models.

The trend in the terrestrial CO_2 sink is estimated annually as part of the assessment of the well-known global carbon budget (Le Quere at al. 2014). It is noted that there is a risk of circular argument concerning correlations between the terrestrial CO_2 sink and interannual (first-difference) CO_2 because the terrestrial CO_2 sink is defined as the residual of the global carbon budget (Le Quere at al. 2014). By contrast, the Normalized Difference Vegetation Index (NDVI) involves direct (satellite-derived) measurement of terrestrial plant activity. For this reason and because, of the two series, only NDVI is provided in monthly form, we will use only NDVI in what follows.

4.4.1. Preparation of the global NDVI series used in this paper

Globally aggregated GIMMS NDVI data from the Global Land Cover Facility site is available from 1980 to 2006. This dataset is referred to here as NDVIG.

Spatially disaggregated GIMMS NDVI data from the GLCF site is available from 1980 to the end of 2013. An analogous global aggregation of this spatially disaggregated GIMMS NDVI data – from 1985 to end 2013 – was obtained from the Institute of Surveying, Remote Sensing and Land Information, University of Natural Resources and Life Sciences, Vienna. This dataset is abbreviated to NDVIV.

Pooling the two series enabled the longest time span of data aggregated at global level. The two series were pooled as follows. Figure 10 shows the appearance of the two series. Each series is Z-scored by the same common period of overlap (1985-2006). The extensive period of overlap can be seen, as can the close similarity in trend between the two series. The figure also shows that the seasonal adjustment smoothings vary between the two series. Seasonality was removed for the NDVIV series using the 13 month moving average smoothing used throughout this paper. This required two passes using the 13 month moving average, which leads to a smoother result than seen for the NDVIG series.

Pretis and Hendry (2013) observe that pooling data (i) from very different measurement systems and (ii) displaying different behaviour in the sub-samples can lead to errors in the estimation of the level of integration of the pooled series.

The first risk of error (from differences in measurement systems) is overcome here as both the NDVI series are from the same original disaggregated data set. The risk associated with the sub-samples displaying different behaviour and leading to errors in levels of integration is considered in the following section by assessing the order of each input series separately, and then the order of the pooled series.

Table 14 provides order of integration test results for the three NDVI series. The analysis shows all series are stationary (I(0)). It is, therefore, valid to pool the two series. Pooling was done by appending the Z-scored NDVIV data to the Z-scored NDVIG data at the point where the Z-scored NDVIG data ended (in the last month of 2006).

As discussed in the Introduction, Figure 1 shows that since around the year 2000 there is an increasing difference between the temperature projected by a mid-level IPCC model and that observed. Any cause for this increasing difference must itself show an increase in activity over this period.

The purpose of this section is, therefore: (i) to derive an initial simple indicative quantification of the increasing difference between the temperature model and observation; and (ii) to assess whether global NDVI is increasing. If NDVI is increasing, this is support for NDVI being a candidate for the cause of the temperature model-observation difference. If there is a statistically significant relationship between the two increases, this is further support for NDVI being a candidate for the cause of the model-observation difference, and hence worthy of further detailed research. A full analysis of this question is beyond the scope of the present paper.

4.4.2 Preparation of the indicative series for the difference between the temperature projected from a mid-level IPCC model and that observed

A simple quantification of the difference between the temperature projected from a mid-level IPCC model and that observed can be derived by subtracting the (Z-scored) temperature projected from the IPCC mid-range scenario model (CMIP3, SRESA1B scenario run for the IPCC fourth assessment report (IPCC 2007)) shown in Figure 1, from the observed global surface temperature also shown in Figure 1. This quantification is depicted in Figure 13 for monthly data and, to reduce the influence of noise and seasonality, in Figure 14 for the same data pooled into three-year bins.

4.4.3. Comparison of the pooled NDVI series with the difference between projected and observed global surface temperature

Figure 13, displaying monthly data, compares NDVI with the difference between the temperature projected from an IPCC mid-range scenario model (CMIP3, SRESA1B scenario run for the IPPC fourth assessment report (IPCC 2007)) and global surface temperature (red dotted curve). Both curves rise in more recent years.

The trends for the 36-month pooled data in Figure 14 show considerable commonality. OLS regression analysis of the relationship between the curves in Figure 14 shows that the best fit between the curves involves no lead or lag. The correlation between the curves displays an adjusted R-squared value of 0.86. This is statistically significant ($p = 0.00185$). As expected with such aggregated multi-year data, the relationship shows little or no autocorrelation (Test statistic: LMF = 1.59 with p-value = $P(F(5,3) > 1.59) = 0.37$). The similarity between the trend in the NDVI and the difference between IPCC temperature modelling and observed temperature is evidence supporting the possibility that the NDVI may contribute to the observed global surface temperature departing from the IPCC modelling.

5 Discussion

The results in this paper show that there are clear links – at the highest standard of non-experimental causality – that of Granger causality – between first- and second-difference CO_2 and the major climate variables of global surface temperature and the Southern Oscillation Index, respectively.

Relationships between first- and second-difference CO_2 and climate variables are present for all the time scales studied, including temporal start points situated as long ago as 1500. In the instances where time series analysis accounting for autocorrelation could be successfully conducted, the results were always statistically significant. For the further instances (for those studies using data series commencing before 1877) the data was not amenable to time series analysis – and therefore also not amenable to testing for Granger causality – due to the strongly smoothed nature of the temperature data available which made removal of the autocorrelation impossible (see Section 4.3). Nonetheless, the scale of the non-corrected correlations observed was of the same order of magnitude as those of the instances that were able to be corrected for autocorrelation.

Given the time scales over which these effects are observed, the results taken as a whole clearly suggest that the mechanism observed is long term, and not, for example, a creation of the period of the steepest increase in anthropogenic CO_2 emissions, a period which commenced in the 1950s (IPCC 2014).

Taking autocorrelation fully into account in the time series analyses demonstrates the major role of immediate past instances of the dependent variable (temperature, and SOI) in influencing its own present state. This was found in all cases where time series models could be prepared. This was not to detract from the role of first- and second-difference CO_2 – in all relevant cases, they were significant in the models as well.

According to Wilks (1995) and Mudelsee (2010), such autocorrelation in the atmospheric sciences also called persistence or "memory" is characteristic for many types of climatic fluctuations.

In the specific case of the temperature and first-difference CO_2 relationship, the significant autocorrelation for temperature occurred with present temperature being affected by the immediately prior month and the month before that. As mentioned above, for atmospheric CO_2 and global surface temperature, others (Sun and Wang 1996; Triacca 2005; Kodra et al. 2011; Attanasio and Triacca 2011; Attanasio 2012; Stern and Kaufmann 2014) have conducted Granger causality analyses involving the use of lags of both dependent and independent variables. These studies, however, are not directly comparable with the present study. Firstly, while reporting the presence or absence of Granger causality, the studies did not report lead or lag information. Secondly, the studies used annual data, so could not investigate the dynamics of the relationships at the interannual (monthly) level where our findings were greatest.

The anthropogenic global warming (AGW) hypothesis has two main dimensions (IPCC 2007; Pierrehumbert 2011): (i) that increasing CO_2 causes increasing atmospheric temperature (via a radiative forcing mechanism) and (ii) that most of the increase in atmospheric CO_2 in the last hundred years has been due to human causes.

The results presented in this paper are supportive of the AGW hypothesis for two reasons: firstly, increasing atmospheric CO_2 is shown to drive increasing temperature; and secondly, the results deepen the evidence for a CO_2 influence on climate in that second-difference CO_2 is shown to drive the SOI.

The difference between this evidence for the effect of CO_2 on climate and that of the standard AGW hypothesis is that the standard model proposes that temperature will rise roughly linearly with atmospheric CO_2, whereas the present results show that the climate effects result from persistence of previous effects and from *rates of change* of CO_2.

On the face of it, then, this model seems to leave little room for the linear radiative forcing aspect of the AGW hypothesis.

However more research is needed in this area.

Reflection on Figure 1 shows that the radiative mechanism would be supported if a second mechanism existed to cause the difference between the temperature projected for the radiative mechanism and the temperature observed. The observed temperature would then be seen to result from the addition of the effects of these two mechanisms.

As discussed in the Introduction, Hansen et al. (2013) have suggested that the mechanism for the pause in the global temperature increase since 1998 may be the planetary biota, in particular the terrestrial biosphere. As an initial indicative quantified characterisation of this possibility, Section 4.4 derived a simple measure of the increasing difference between the global surface temperature trend projected from a mid-range scenario climate model and the observed trend. This depiction of the difference displayed a rising trend. The time series trend for the globally aggregated Normalized Difference Vegetation Index – which represents the changing levels of activity of the terrestrial biosphere was also presented. This was shown also to display a rising trend.

If by further research, for example by Granger causality analysis, the global vegetation can be shown to embody the second mechanism, this would be evidence that the observed global temperature does result from the effects of two mechanisms in operation together – the radiative, level-of-CO_2 mechanism, with the biological first-difference of CO_2 mechanism.

Hence the biosphere mechanism would supplement, rather than replace, the radiative mechanism.

Further comprehensive time series analysis of the NDVI data and relevant climate data, beyond the scope of the present paper, could throw light on these questions.

Detailed Comments: 1. *The paragraph in lines 19-25 on page 8 is incoherent. Please redraft. (There are various other places where the quality of exposition could be improved. Please redraft with careful attention to readability.)*

We propose to replace the paragraph in question:

A number of Granger causality studies have been carried out on climate time series (see review in Attanasio 2012). Of papers we have found which assessed atmospheric CO_2 and global surface temperature – some six (Sun and

Wang 1996; Triacca 2005; Kodra et al., 2011; Attanasio and Triacca, 2011; Attanasio (2012); Stern and Kaufmann 2014) –while all but one (Triacca 2005) found Granger causality, it was not with CO_2 concentration but with CO_2 radiative forcing (lnCO_2 (Attanasio and Triacca, 2011).

With the following:

A number of Granger causality studies have been carried out on climate time series (see review in Attanasio 2012). We found six papers which assessed atmospheric CO_2 and global surface temperature (Sun and Wang 1996; Triacca 2005; Kodra et al. 2011; Attanasio and Triacca 2011; Attanasio (2012); Stern and Kaufmann 2014). Of these, while all but one (Triacca 2005) found Granger causality, it was not with CO_2 concentration as studied in this paper but with CO_2 radiative forcing (lnCO_2 (Attanasio and Triacca 2011)).

Detailed Comments: 2. *Lines 13-21 on page 9 are a reworking of the preceding paragraph. Please delete whichever is the unintended version.*

This has been done.

Detailed Comments: 3. (Page 11, lines 26-27). *The point about SOI versus ENSO could be better made. Is "more valid" a better reason for the preference than "simpler"? It would be very helpful to readers to give brief formal definitions of both these series. How is ENSO constructed? I don't know.*

On the existing manuscript we define

The Southern Oscillation is the atmospheric pressure component of ENSO, and is an oscillation in the surface air pressure between the tropical eastern and the western Pacific Ocean waters. It is calculated from normalized Tahiti minus Darwin sea level pressure. The SOI only takes into account sea level pressure. In contrast, the El Niño component of ENSO is specified in terms of changes in the Pacific Ocean sea surface temperature relative to the average temperature. It is considered to be more valid to conduct an analysis in which the temperature is an outcome (dependent variable) without also having (Pacific Ocean) temperature as an input (independent variable). The correlation between SOI and the other ENSO indices is high, so we believe this assumption is robust.

We suggest replacing the above with the following:

Concerning the El Nino-Southern Oscillation, according to IPCC (2014) the term El Niño was initially used to describe a warm-water current that periodically flows along the coast of Ecuador and Peru, disrupting the local fishery. It has since become identified with a basin-wide warming of the tropical Pacific Ocean east of the dateline. This oceanic event is associated with a fluctuation of a global-scale tropical and subtropical surface atmospheric pressure pattern called the Southern Oscillation. This atmosphere–ocean phenomenon is coupled, with typical time scales of two to about seven years, and known as the El Niño-Southern Oscillation (ENSO).

The El Nino (temperature) component of ENSO is measured by changes in the sea surface temperature of the central and eastern equatorial Pacific relative to the average temperature.The Southern Oscillation (pressure) ENSO component is often measured by the surface pressure anomaly difference between Tahiti and Darwin.

During an ENSO event, the prevailing trade winds weaken, reducing upwelling and altering ocean currents such that the sea surface temperatures warm, further weakening the trade winds. This event has a great impact on the wind, sea surface temperature and precipitation patterns in the tropical Pacific. It has climatic effects throughout the Pacific region and in many other parts of the world.

For the present study we choose the SOI component of ENSO to stand for ENSO as a whole. This is because it is considered to be more valid to conduct an analysis in which temperature is an outcome (dependent variable) without also having (Pacific Ocean) temperature as an input (independent variable). The correlation between SOI and the other ENSO indices is high, so we believe this assumption is robust.

Detailed Comments: 4. (Page 12, lines 9 and 30) *The use of the term "derivative" as a synonym for "difference" is, to this reader, an irritating tic. "Derivative" suggests that the models in question are discrete approximations to continuous time relations, but nowhere are these relations specified or the approximations formalized. Indeed, the tests for Granger causality, of the form given, could not be formalized at all in a continuous time framework! Let's be clear that the models presented here are explicitly formulated for discrete sequences of observations. Differences, like lags, are an inherent feature of these models, not approximations to anything.*

Response: Will change derivative to difference.

Detailed Comments: 5. (Page 13, lines 7-16) *Please see the main discussion above.*

Response provided above.

Detailed Comments: 6. *There are lots of missing references in the paper. See in particular pages 13, lines 30-31, and 14, lines 4-6, but there are others.*

Response: All references in body of newly amended manuscript have been checked with References section, missing references added and superfluous removed.

Detailed Comments: 7. (Page 15, lines 9-10) *Note that BLUE is a property pertaining to the classical (fixed regressor) regression model, which is not appropriate to time series. Autocorrelated disturbances may result in bias when the model includes lagged endogenous variables among the regressors.*

The OLS estimator is BLUE in the context of time-series data provided that the errors in the model satisfy the assumptions of a zero mean, no autocorrelation, and homoskedasticity; and provided that the regressors are non-random (or at least not correlated with the errors). "Fixed regressors" are not actually needed for OLS to be BLUE.

If the regressors include lagged values of the dependent variable, then OLS will be biased in small samples. However, this bias vanishes in very large samples, as OLS is still a consistent estimator in this situation. If, in addition to these lagged variables, we also have autocorrelated errors, the OLS will be inconsistent. By using a dynamic model specification (which typically includes using lagged values of the dependent variable as regressors) we can typically ensure that the model's errors are in fact serially independent. In this case there is a small-sample bias, but it will be negligible with samples of the size used in the paper.

Based on the above we propose to replace the text (page 15, line 30):

Notably and importantly this does not bias the OLS coefficient estimates.

With

Notably and importantly this does not bias the OLS coefficient estimates given the sample sizes used in this study.

Detailed Comments: 8. (Page 18) *The discussion of the "I(d)" categorization of series on this page is totally muddled. Beenstock et al. find temperature to be I(1) and CO_2 (level) to be I(2). Please redraft with care.*

Proposed redraft is as follows:

Both first-difference CO_2 being shown to lead temperature, and the two series displaying close correspondence, are considered a firm basis for the time series analysis of the statistical relationship between first-difference CO_2 and temperature which follows. For this further analysis, we choose global surface temperature as the temperature series because, while its maximum correlation is not the highest (Figure 5), its global coverage by definition is greatest.

The following sections provide the results of the time series analysis. (In this section, TEMP stands for global surface temperature ((HadCRUT4), and other block capital terms are those used in the modelling).

The order of integration, denoted I(d), is an important characteristic of a time series. It reports the minimum number of differences required to obtain a covariance stationary series. As stated above, all series used in a time series regression must be series which are stationary without further differencing (Greene 2012), that is, in the notation, display an order of integration of I(0). If a series has an order of integration greater than zero, it can be transformed by appropriate differencing into a new series which is stationary.

By means of the Augmented Dickey–Fuller (ADF) test for unit roots, Table 3 provides the information concerning stationarity for the level of, and first-difference of, CO_2, as well as for global surface temperature. Test results are provided for both monthly and annual data. The test was applied with an allowance for both a drift and deterministic trend in the data, and the degree of augmentation in the Dickey-Fuller regressions was determined by minimizing the Schwarz Information Criterion.

The results show that for both the monthly and annual series used, the variables TEMP and FIRST-DIFFERENCE CO_2 are stationary (I(0)); but level of CO_2 is not. Level of CO_2 is shown to be I(1) because (Table 3) its first differencefirst-difference is stationary .

In contrast to this result, however, Beenstock et al. (2012), using annual data, report that their series for the level of atmospheric CO_2 forcing is an *I (2)* variable and therefore is stationary in *second* differences.

With regard to the reconciliation of these two varying results, we refer to the study of Pretis and Hendry (2013) which reviewed Beenstock et al. (2012). Pretis and Hendry (2013) take issue with the finding of *I(2)* for the anthropogenic forcings studied – including CO_2 - and find evidence that this finding results from the combination of two different data sets measured in different ways which make up the 1850-2011 data set which Beenstock et al. test. Regarding this composite series Pretis and Hendry (2013) write:

> In the presence of these different measurements exhibiting structural changes, a unit-root test on the entire sample could easily not reject the null hypothesis of *I*(2) even when the data are in fact *I(1)*. Indeed, once we control for these changes, our results contradict the findings in Beenstock et al. (2012).

Pretis and Hendry (2013) give their results for CO_2 in their Table 1. Note that, in the table, level of CO_2 data is transformed into first-difference data (Beenstock et al claim the *level* of CO_2 is I(2); if that is the case, the first-difference of the level of CO_2 Pretis and Hendry (2013) should find would be I(1)).

Pretis and Hendry (2013) state:

> Unit-root tests are used to determine the level of integration of time series. Rejection of the null hypothesis provides evidence against the presence of a unit-root and suggests that the series is I(0) (stationary) rather than I(1) (integrated).
> …based on augmented Dickey–Fuller (ADF) tests (see Dickey and Fuller, 1981), the first differencefirst-difference of annual radiative forcing of CO_2 is stationary initially around a constant (over 1850–1957), then around a linear trend (over 1958–2011). Although these tests are based on sub-samples corresponding to the shift in the measurement system, there is sufficient power to reject the null hypothesis of a unit root.

Hence for annual data Pretis and Hendry (2013) find first-difference CO_2 to be stationary - I(0), not I(1) - as we do (Table 3).

With this question of the order of integration of the time series considered, we now turn to the next step of the time series analysis.

Detailed Comments: 9. *The application of the Toda-Yamamoto result is most interesting, but it needs to be seen in context. These authors propose tests for a VAR in levels with an unknown number of unit roots. However, please note that in such a model, Granger causality of an I(1) series by an I(2) series is ruled out by construction. A model generating variables with different orders of integration can only embody long-run relations between variables transformed to have the same orders of integration: in particular, between the level of an I(1) and the differences of an I(2), or between the level of an I(0) and the differences of an I(1)). (To verify this statement, consider the VAR ( ) A L x u t t and verify the properties that= A L ( ) must satisfy to ensure that A L ( )1− −contains different powers of the factor 1 L appearing in different rows.) The outcome of the reported test is inevitable, given the other reported results. I guess it does not harm to report it, but with suitable caveats.*

Our response is as follows:

In their text *Applied Time Series Econometrics*. Cambridge University Press, (2004), Lutkepohl and Kratzig state (page 148):

Because testing for Granger-causality requires checking whether specific coefficients are zero, standard tests for zero restrictions on VAR coefficients may be used here (χ 2- or *F*-tests based on the Wald principle are typically thought of in this context). Unfortunately, they may have nonstandard asymptotic properties if the VAR contains I(1) variables. In particular, Wald tests for Granger-causality are known to result in nonstandard limiting distributions depending on the cointegration properties of the system and possibly on nuisance parameters [see Toda & Phillips (1993)].

Fortunately, these problems can be overcome easily, as pointed out by Toda & Yamamoto (1995) and Dolado & Lutkepohl (1996). As mentioned in Section 3.3.1, the nonstandard asymptotic properties of the standard tests on the coefficients of cointegrated VAR processes are due to the singularity of the asymptotic distribution of the estimators. The singularity can be removed by fitting a VAR process whose order exceeds the true order, however. It can be shown that this device leads to a non-singular asymptotic distribution of the relevant coefficients. Thus, simply overfitting the VAR order and ignoring the extra parameters in testing for Granger-causality overcomes the problems associated with standard tests – at least if asymptotic properties are of interest.

Detailed Comments: 10. (Page 27, lines 11-13) *The regression of (say) $x - ay$ on z is clearly different for different choices of constant a. It could be significant (or cointegrated in the nonstationary case) for some value of a, and not for others. The* *case that the projection error of a GCM can be captured as the simple difference of the two standardized series needs to be much more carefully argued.*

Response: This point is valued. Will address in the new, separate paper.

Detailed Comments: 11. *My guess is that "the APCD paper" referred to in Page 30, line 20, and elsewhere refers to the first version of the present paper. If so, this needs to be made explicit.*

Response: this is correct – the term is not used in the present Author Response

References

Beenstock, M., Reingewertz, Y., and Paldor, N.: Polynomial cointegration tests of anthropogenic impact on global warming, Earth Syst. Dynam., 3, 173–188, doi:10.5194/esd-3-173-2012, 2012.

Bloem A.M., Dippelsman R.J., Maehle N.O.: *Quarterly National Accounts Manual: Concepts, Data Sources, and Compilation*. International Monetary Fund: Washington, DC, 2001.

Chatfield, C.: *The Analysis of Time Series*, 5th ed., Chapman & Hall, New York, NY, 1996.

Diebold, Francis X.: Discussion: The effect of seasonal adjustment filters on tests for a unit root, Journal of Econometrics, 55, pages 99-103, 1993.

Dolado, J.J. and Lutkepohl, H.: Making Wald tests for cointegrated VAR systems. Econometric Reviews 15, 369-386, 1996.

Gomez, V. and Maravall A.: Programs TRAMO and SEATS, Instruction for User. Banco de Espana, Working Paper 9628, 1996.

Ghysels, E. and Perron, P.: The effect of seasonal adjustment filters on tests for a unit root. Journal of Econometrics, 55, 57 98, 1993.

IPCC: 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., 2014.

Ladiray D. and Quenneville B.: Seasonal *Adjustment with the X-11 Method.* New York: Springer, 2001.

Lutkepohl H, Kratzig M.: *Applied Time Series Econometrics*. Cambridge University Press, Cambridge, 2004.

Maddala, G. S. and Kim, I. M.: *Unit Roots, Cointegration and Structural Change*, Cambridge University Press, Cambridge, 1998.

Narayan, P.K. and Popp S.: A new unit root test with two structural breaks in level and slope at unknown time. Journal of Applied Statistics 37: 1425-1438, 2010.

Pretis, F. and Hendry, D. F.: Comment on "Polynomial cointegration tests of anthropogenic impact on global warming" by Beenstock et al. (2012) - some hazards in econometric modelling of climate change. Earth System Dynamics 4, 375–384, 2013.

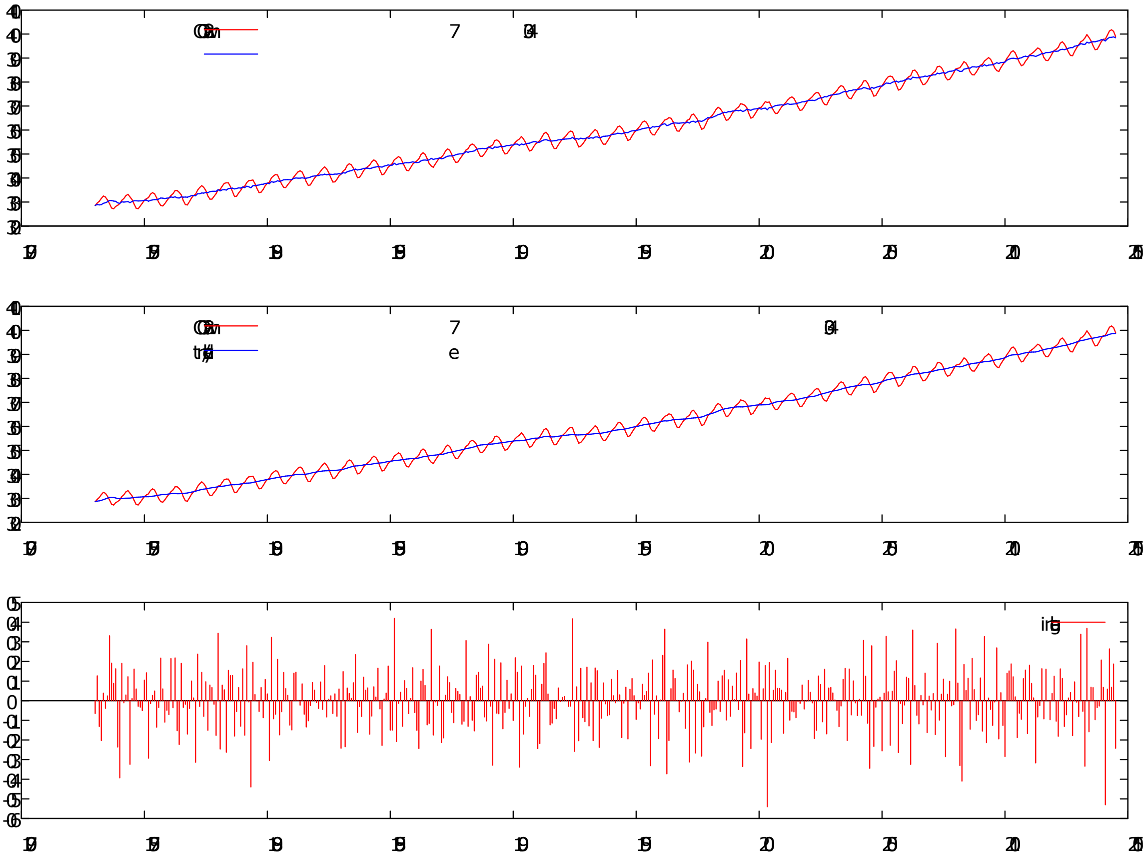
Sutcliffe, A.: Seasonal Adjustment: Comparison of Philosophies, Australian Bureau of Statistics Working Paper 99/2 (1999).

Thoning, K. W., Tans, P. P. and Komhyr, W.D.: Atmospheric carbon dioxide at Mauna Loa observatory. 2. Analysis of the NOAA GMCC data, 1974-1985. Journal of Geophysical Research-Atmospheres, 94, 8549-8565, 1989.

Toda, H. Y. and Yamamoto, T.: Statistical inferences in vector autoregressions with possibly integrated processes, Journal of Econometrics, 66, 225-250. 1995.

Appendix 1: Tramo model output

TRAMO



SIGNAL EXTRACTION IN 'ARIMA' TIME SERIES (BETA VERSION) (*)

BY

V. GOMEZ & A. MARAVALL,

with the programming assistance of G. CAPORELLO

Thanks are due to G. FIORENTINI and C. PLANAS for their research assistance

(Based on an original program developed by J.P.BURMAN at the Bank of England, version 1982)

REDUCED OUTPUT

SERIES TITLE: co2rawfr

PREADJUSTED WITH TRAMO : YES

NO OF OBSERVATIONS =499

YEAR	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
1973	328.54	329.56	330.3	331.5	332.48	332.07	330.87	329.31	327.51	327.18	328.16	328.64
1974	329.35	330.71	331.48	332.65	333.2	332.12	330.99	329.17	327.41	327.21	328.34	329.5
1975	330.68	331.41	331.85	333.29	333.91	333.4	331.74	329.88	328.57	328.36	329.33	330.59
1976	331.66	332.75	333.46	334.78	334.78	334.06	332.95	330.64	328.96	328.77	330.18	331.65
1977	332.69	333.23	334.97	336.03	336.82	336.1	334.79	332.53	331.19	331.21	332.35	333.47
1978	335.1	335.26	336.61	337.77	338.01	337.98	336.48	334.37	332.33	332.41	333.76	334.83
1979	336.21	336.65	338.13	338.94	339	339.2	337.6	335.56	333.93	334.12	335.26	336.78
1980	337.8	338.28	340.04	340.86	341.47	341.26	339.34	337.45	336.1	336.05	337.21	338.29

1981	339.36	340.51	341.57	342.56	343.01	342.49	340.68	338.49	336.92	337.12	
	338.59	339.9									
1982	340.92	341.69	342.86	343.92	344.67	343.78	342.23	340.11	338.32	338.39	
	339.48	340.88									
1983	341.64	342.87	343.59	345.25	345.96	345.52	344.15	342.25	340.17	340.3	
	341.53	343.07									
1984	344.05	344.77	345.46	346.77	347.55	346.98	345.55	343.2	341.35	341.68	
	343.06	344.54									
1985	345.25	346.06	347.66	348.2	348.92	348.4	346.66	344.85	343.2	343.08	344.4
	345.82										
1986	346.54	347.13	348.05	349.77	350.53	349.9	348.11	346.09	345.01	344.47	
	345.86	347.15									
1987	348.38	348.7	349.72	351.32	352.14	351.61	349.91	347.84	346.52	346.65	
	347.96	349.18									
1988	350.38	351.68	352.24	353.66	354.18	353.68	352.58	350.66	349.03	349.08	
	350.15	351.44									
1989	352.89	353.24	353.8	355.59	355.89	355.3	353.98	351.53	350.02	350.29	
	351.44	352.84									
1990	353.79	354.88	355.65	356.27	357.29	356.32	354.88	352.89	351.28	351.59	
	353.05	354.27									
1991	354.87	355.68	357.06	358.51	359.09	358.1	356.12	353.89	352.3	352.32	
	353.79	355.07									
1992	356.17	356.93	357.82	359	359.55	359.32	356.85	354.91	352.93	353.31	
	354.27	355.53									
1993	356.86	357.27	358.36	359.27	360.19	359.52	357.42	355.46	354.1	354.12	355.4
	356.84										
1994	358.22	358.98	359.91	361.32	361.68	360.8	359.39	357.42	355.63	356.09	
	357.56	358.87									
1995	359.87	360.79	361.77	363.23	363.77	363.22	361.7	359.11	358.11	357.97	359.4
	360.61										
1996	362.04	363.17	364.17	364.51	365.16	364.93	363.53	361.38	359.6	359.54	
	360.84	362.18									
1997	363.04	364.09	364.47	366.25	366.69	365.59	364.34	362.2	360.31	360.71	
	362.44	364.33									
1998	365.18	365.98	367.13	368.61	369.49	368.95	367.74	365.79	364.01	364.35	
	365.52	367.08									
1999	368.12	368.98	369.6	370.96	370.77	370.33	369.28	366.86	364.94	365.35	
	366.68	368.04									
2000	369.25	369.5	370.56	371.82	371.51	371.71	369.85	368.2	366.91	366.99	
	368.33	369.67									
2001	370.52	371.49	372.53	373.37	373.82	373.18	371.57	369.63	368.16	368.42	
	369.69	371.18									
2002	372.45	373.14	373.93	375	375.65	375.5	374	371.83	370.66	370.51	372.2
	373.71										
2003	374.87	375.62	376.48	377.74	378.5	378.18	376.72	374.31	373.2	373.1	
	374.64	375.93									
2004	377	377.87	378.73	380.41	380.63	379.56	377.61	376.15	374.11	374.44	
	375.93	377.45									
2005	378.47	379.76	381.14	382.2	382.47	382.2	380.78	378.73	376.66	376.98	
	378.29	379.92									
2006	381.35	382.16	382.66	384.73	384.98	384.09	382.38	380.45	378.92	379.16	
	380.18	381.79									
2007	382.93	383.81	384.56	386.4	386.58	386.05	384.49	382	380.9	381.14	
	382.42	383.89									
2008	385.44	385.73	385.97	387.16	388.5	387.88	386.42	384.15	383.09	382.99	
	384.13	385.56									
2009	386.94	387.42	388.77	389.44	390.19	389.45	387.78	385.92	384.79	384.39	386
	387.31										
2010	388.5	389.94	391.09	392.53	393.04	392.15	390.22	388.26	386.83	387.2	
	388.65	389.73									
2011	391.25	391.82	392.49	393.34	394.21	393.72	392.42	390.19	389.04	388.96	
	390.24	391.83									
2012	393.12	393.6	394.45	396.18	396.78	395.83	394.3	392.41	391.06	391.01	
	392.81	394.28									
2013	395.54	396.8	397.31	398.35	399.76	398.58	397.2	395.15	393.51	393.66	
	395.11	396.81									
2014	397.8	397.91	399.58	401.29	401.78	401.15	399				

TRANSFORMATION: Z -> Z

NONSEASONAL DIFFERENCING D= 1

SEASONAL DIFFERENCING BD= 1

TYPE OF ESTIMATION : FROM TRAMO

MODEL FITTED

NONSEASONAL P= 0 D= 1 Q= 1

SEASONAL BP= 0 BD= 1 BQ= 1

PERIODICITY MQ= 12

MEAN = 0.00000

SE = *******

ARIMA PARAMETERS

TH = -0.3766

SE = *****

BTH = -0.8978

SE = *****

RESIDUALS

YEAR	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
1973	-0.052	0.186	-0.185	-0.069	0.389	0.277	0.378	0.589	0.044	-0.288	-0.345	-0.873
1974	-0.682	0.268	-0.098	-0.066	-0.083	-0.584	0.095	0.177	-0.053	-0.164	-0.124	-0.034

1975	0.14	-0.106	-0.549	0.037	0.032	0.086	-0.215	0.006	0.345	-0.009	-0.219	0.029
1976	0.038	0.232	-0.099	0.062	-0.58	-0.362	0.192	-0.3	-0.175	-0.171	0.182	0.378
1977	0.137	-0.303	0.748	0.111	0.29	-0.02	0.087	-0.252	0.189	0.187	0.022	-0.064
1978	0.561	-0.487	0.201	0.022	-0.319	0.454	0.066	-0.08	-0.475	-0.015	0.161	-0.054
1979	0.255	-0.251	0.38	-0.255	-0.57	0.531	0.006	-0.022	0.002	0.258	0.036	0.361
1980	0.023	-0.263	0.607	-0.119	0.08	0.289	-0.385	-0.017	0.283	0.098	0.002	-0.127
1981	-0.099	0.389	0.081	-0.112	-0.09	-0.111	-0.376	-0.327	-0.083	0.211	0.358	0.25
1982	-0.002	0.002	0.052	-0.038	0.242	-0.348	-0.171	-0.161	-0.245	-0.005	-0.131	0.144
1983	-0.292	0.352	-0.272	0.446	0.359	0.191	0.216	0.215	-0.374	-0.003	0.023	0.322
1984	0.03	-0.084	-0.424	-0.017	0.234	0.008	0.073	-0.303	-0.293	0.214	0.252	0.316
1985	-0.233	-0.083	0.526	-0.444	-0.011	-0.026	-0.257	0.147	0.095	-0.123	0.047	0.157
1986	-0.247	-0.309	-0.296	0.492	0.366	0.008	-0.269	-0.093	0.571	-0.348	0.023	0.003
1987	0.237	-0.375	-0.202	0.346	0.352	0.116	-0.111	-0.084	0.272	0.267	0.159	-0.015
1988	0.176	0.63	-0.278	0.094	-0.065	-0.009	0.458	0.285	0.07	0.094	-0.152	-0.055
1989	0.392	-0.296	-0.574	0.332	-0.185	-0.146	0.139	-0.377	-0.056	0.26	0.01	0.116
1990	-0.086	0.309	-0.089	-0.711	0.174	-0.383	-0.09	0.041	-0.007	0.29	0.34	0.049
1991	-0.448	-0.142	0.372	0.362	0.092	-0.388	-0.637	-0.413	-0.156	-0.086	0.185	0.059
1992	0.104	0.013	-0.103	-0.11	-0.111	0.339	-0.803	-0.168	-0.453	0.164	-0.253	-0.125
1993	0.256	-0.277	-0.001	-0.334	0.182	-0.03	-0.477	-0.079	0.24	0.031	0.049	0.172
1994	0.387	0.16	-0.007	0.198	-0.209	-0.377	0.13	0.129	-0.139	0.335	0.349	0.139
1995	-0.038	0.159	0.049	0.248	0.019	0.069	0.16	-0.487	0.438	-0.088	0.127	-0.045
1996	0.332	0.49	0.195	-0.84	-0.273	0.273	0.343	0.078	-0.193	-0.219	-0.069	0.021
1997	-0.249	0.154	-0.552	0.412	-0.016	-0.539	0.163	0.025	-0.3	0.215	0.524	0.789
1998	0.056	-0.006	0.22	0.339	0.414	0.238	0.458	0.33	-0.044	0.218	-0.08	0.171
1999	0.038	0.05	-0.312	-0.007	-0.816	-0.134	0.44	-0.163	-0.352	0.148	0.07	0.007
2000	0.149	-0.522	-0.053	-0.021	-0.858	0.473	-0.191	0.403	0.521	0.118	0.067	-0.012
2001	-0.233	0.113	0.151	-0.364	-0.14	-0.178	-0.149	0.08	0.182	0.178	0.017	0.123
2002	0.261	-0.001	-0.153	-0.206	0.12	0.422	0.196	-0.034	0.423	-0.152	0.318	0.244
2003	0.175	0.036	-0.053	0.037	0.301	0.282	0.179	-0.269	0.35	-0.098	0.15	-0.052
2004	-0.035	0.08	-0.03	0.46	-0.109	-0.64	-0.665	0.397	-0.375	0.083	0.149	0.189
2005	0.007	0.507	0.657	0.051	-0.184	0.193	0.222	0.075	-0.473	0.013	-0.069	0.203
2006	0.429	0.134	-0.411	0.678	0.053	-0.364	-0.294	0.002	0.091	0.126	-0.309	0.069
2007	0.053	0.065	-0.14	0.465	-0.077	-0.014	0.004	-0.457	0.339	0.21	0.019	0.034
2008	0.447	-0.381	-0.801	-0.487	0.751	0.206	0.186	-0.122	0.453	-0.096	-0.23	-0.103
2009	0.181	-0.235	0.431	-0.524	0.051	-0.169	-0.176	0.171	0.442	-0.372	0.156	-0.076
2010	-0.021	0.68	0.522	0.351	0.115	-0.276	-0.465	-0.062	0.016	0.292	0.216	-0.269
2011	0.235	-0.164	-0.303	-0.566	0.132	0.163	0.367	-0.03	0.304	-0.079	-0.105	0.156

2012	0.131	-0.267	-0.137	0.423	0.199	-0.283	-0.062	0.165	0.145	-0.089	0.419	0.213
2013	0.115	0.539	-0.17	-0.328	0.722	-0.28	0.085	0.041	-0.2	-0.004	0.055	0.3
2014	-0.126	-0.752	0.542	0.637	0.079	0.084	-0.568					

RESIDUALS STATISTICS

MEAN= 0.1819E-01 (SE = 0.0130)

SKEWNESS= -0.2727E+00 (SE = 0.1097)

KURTOSIS= 0.3284E+01 (SE = 0.2193)

STANDARD DEVIATION= 0.2958E+00

Skewness is within approx 2.5 std. deviations from zero - essentially symmetric.

Kurtosis is within about 1 std. dev. from 3, so this also supports normality

AUTOCORRELATIONS OF RESIDUAL

	0.0275	-0.0809	-0.0056	-0.038	0.0301	0.0144
SE	0.0448	0.0448	0.0451	0.0451	0.0452	0.0452
	-0.08	0.0447	0.0096	-0.0327	-0.0134	-0.0066
SE	0.0452	0.0455	0.0456	0.0456	0.0456	0.0456
	-0.0323	0.093	0.0529	-0.0588	-0.0152	-0.0549
SE	0.0456	0.0457	0.0461	0.0462	0.0463	0.0463
	-0.068	0.0068	-0.0342	-0.0199	0.0219	-0.0082
SE	0.0465	0.0467	0.0467	0.0467	0.0467	0.0468
	-0.014	-0.0187	0.0307	0.0245	0.0367	-0.009
SE	0.0468	0.0468	0.0468	0.0468	0.0469	0.0469

	-0.0509	0.0473	-0.01	-0.0094	0.0774	-0.0691
SE	0.0469	0.047	0.0471	0.0471	0.0471	0.0474

Mark Leggett comment: Cannot reject randomness

THE LJUNG-BOX Q VALUE IS 22.82

IF RESIDUALS ARE RANDOM IT SHOULD BE DISTRIBUTED AS CHI-SQUARED (22)

AUTOCORRELATIONS OF SQUARED RESIDUAL

Mark Leggett comment: Cannot reject randomness

THE LJUNG-BOX Q VALUE IS 21.16

IF RESIDUALS ARE RANDOM IT SHOULD BE DISTRIBUTED AS CHI-SQUARED (22)

DERIVATION OF THE COMPONENT MODELS : OK

MODELS FOR THE COMPONENTS

TRENDS-CYCLE NUMERATOR

1	0.0089	-0.9911

TREND-CYCLE DENOMINATOR

1	-2	1

INNOV. VAR. (*) 0.08811

SEAS. NUMERATOR

1 1.4444 1.5374 1.4777 1.2869 1.04 0.7691 0.4978 0.2666 0.0486 -0.0932 -
0.3898
SEAS. DENOMINATOR

1 1 1 1 1 1 1 1 1 1 1 1

INNOV. VAR. (*) 0.00294

IRREGULAR

VAR. 0.42657

SEASONALLY ADJUSTED NUMERATOR

1 -1.3681 0.3736

SEASONALLY ADJUSTED DENOMINATOR

1 -2 1

INNOV. VAR. (*) 0.90798

(*) IN UNITS OF VAR(A)

DETERMINISTIC COMPONENT FROM TRAMO

NONE

DERIVATION OF THE FILTERS : OK

COMPONENTS (STATIONARY TRANSFORMATION) :SECOND MOMENTS

TREND-CYCLE ADJUSTED

LAG	COMPONENT ESTIMATE		ESTIMATOR		ESTIMATE		COMPONENT		ESTIMATOR
LAG	1	AUTCOR	0	0.399	0.385	-0.624	-0.624	-0.574	
LAG	12	AUTCOR	0	-0.051	-0.103	0	-0.051	0.01	
VAR.(*)	0.175	0.038	0.04	2.734	2.594	2.432			

IRREGULAR SEASONAL

LAG	COMPONENT ESTIMATE		ESTIMATOR		ESTIMATE		COMPONENT		ESTIMATOR
LAG	1	AUTCOR	0	-0.312	-0.263	0.921	0.742	0.818	
LAG	12	AUTCOR	0	-0.051	-0.029	0	0.924	0.945	
VAR.(*)	0.427	0.279	0.276	0.034	0.001	0.001			

(*) IN UNITS OF VAR(A)

ESTIMATION ERROR VARIANCE

(In units of Var(a))

		TREND-CYCLE	ADJUSTED
FINAL ERROR	ESTIMATION	0.142	0.034

REVISION IN CONCURRENT ERROR	0.117	0.034
TOTAL ESTIMATION ERROR (CONCURRENT ESTIMATOR)	0.259	0.069

PERCENTAGE REDUCTION IN THE STANDARD ERROR OF THE REVISION AFTER ADDITIONAL YEARS

(COMPARISON WITH CONCURRENT ESTIMATORS)

AFTER 1 YEAR	75.02	10.15
AFTER 2 YEAR	77.57	19.33
AFTER 3 YEAR	79.86	27.58
AFTER 4 YEAR	81.92	34.98
AFTER 5 YEAR	83.77	41.63

AVERAGE PERCENTAGE REDUCTION IN RMSE FROM CONCURRENT ADJUSTMENT 6.026

STANDARD ERROR OF THE CONCURRENT RATES OF ESTIMATORS

(In points of annualized percent growth. Linear approximations)

	TREND-CYCLE	SA SERIES	ORIGINAL SERIES
PERIOD TO PERIOD GROWTH OF THE SERIES (T11)	0.104	0.935E-01	
PERIOD GROWTH OF A 3-PERIOD OF THE CENTERED SERIES (T31)	0.223	0.294	

(CENTERED) ESTIMATOR	0.510	0.539	0.540
OF THE ANNUAL GROWTH			
(T 1 12)			

SEASONAL COMPONENT

YEAR	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
1973	-0.073	0.623	1.501	2.582	3.029	2.37	0.779	-1.346	-3.086	-3.228	-2.129	-1.022
1974	-0.069	0.623	1.504	2.586	3.028	2.37	0.775	-1.355	-3.093	-3.232	-2.131	-1.016
1975	-0.061	0.624	1.511	2.591	3.029	2.373	0.771	-1.367	-3.103	-3.237	-2.133	-1.01
1976	-0.052	0.624	1.521	2.598	3.03	2.378	0.768	-1.379	-3.116	-3.243	-2.135	-1.005
1977	-0.044	0.621	1.529	2.602	3.032	2.385	0.765	-1.39	-3.128	-3.247	-2.134	-0.998
1978	-0.036	0.62	1.536	2.604	3.033	2.392	0.759	-1.4	-3.14	-3.251	-2.134	-0.99
1979	-0.03	0.622	1.54	2.607	3.036	2.397	0.752	-1.412	-3.151	-3.254	-2.133	-0.981
1980	-0.027	0.627	1.542	2.61	3.045	2.4	0.744	-1.423	-3.161	-3.257	-2.132	-0.972
1981	-0.024	0.633	1.54	2.614	3.055	2.401	0.738	-1.434	-3.172	-3.262	-2.131	-0.962
1982	-0.02	0.639	1.535	2.617	3.064	2.402	0.734	-1.442	-3.181	-3.266	-2.131	-0.953
1983	-0.016	0.643	1.528	2.618	3.071	2.402	0.729	-1.45	-3.188	-3.268	-2.128	-0.943
1984	-0.008	0.648	1.524	2.619	3.076	2.4	0.721	-1.461	-3.194	-3.27	-2.125	-0.934
1985	0.001	0.653	1.521	2.622	3.08	2.398	0.712	-1.472	-3.197	-3.272	-2.122	-0.928
1986	0.01	0.659	1.516	2.626	3.084	2.395	0.704	-1.484	-3.202	-3.273	-2.12	-0.923
1987	0.021	0.669	1.513	2.63	3.086	2.39	0.695	-1.497	-3.211	-3.274	-2.118	-0.917
1988	0.032	0.681	1.515	2.634	3.086	2.384	0.687	-1.509	-3.221	-3.275	-2.115	-0.911
1989	0.043	0.693	1.519	2.639	3.088	2.379	0.677	-1.523	-3.234	-3.278	-2.113	-0.903
1990	0.052	0.703	1.527	2.644	3.091	2.377	0.666	-1.536	-3.247	-3.283	-2.112	-0.897
1991	0.061	0.713	1.534	2.651	3.094	2.377	0.656	-1.548	-3.258	-3.289	-2.112	-0.892
1992	0.072	0.722	1.54	2.655	3.092	2.375	0.649	-1.557	-3.266	-3.293	-2.112	-0.887
1993	0.083	0.733	1.543	2.658	3.087	2.368	0.643	-1.565	-3.272	-3.297	-2.111	-0.88
1994	0.093	0.743	1.546	2.662	3.081	2.36	0.641	-1.573	-3.276	-3.301	-2.11	-0.873
1995	0.101	0.753	1.548	2.664	3.074	2.352	0.64	-1.578	-3.28	-3.304	-2.108	-0.866
1996	0.109	0.762	1.548	2.665	3.066	2.345	0.638	-1.581	-3.283	-3.307	-2.107	-0.856
1997	0.117	0.767	1.546	2.668	3.06	2.337	0.634	-1.585	-3.287	-3.309	-2.105	-0.848
1998	0.126	0.771	1.545	2.671	3.052	2.331	0.628	-1.589	-3.286	-3.308	-2.103	-0.841
1999	0.137	0.776	1.546	2.673	3.045	2.326	0.62	-1.595	-3.285	-3.309	-2.101	-0.837
2000	0.146	0.78	1.547	2.674	3.043	2.323	0.61	-1.602	-3.282	-3.311	-2.101	-0.835
2001	0.153	0.785	1.549	2.677	3.048	2.323	0.602	-1.61	-3.281	-3.316	-2.104	-0.835

2002	0.159	0.789	1.548	2.68	3.056	2.323	0.596	-1.617	-3.281	-3.321	-2.107	-0.836
2003	0.164	0.793	1.548	2.687	3.068	2.323	0.589	-1.623	-3.283	-3.327	-2.112	-0.839
2004	0.169	0.796	1.549	2.695	3.08	2.322	0.582	-1.629	-3.286	-3.332	-2.118	-0.842
2005	0.174	0.799	1.548	2.7	3.091	2.322	0.578	-1.634	-3.285	-3.334	-2.122	-0.844
2006	0.18	0.799	1.544	2.701	3.101	2.321	0.573	-1.641	-3.28	-3.334	-2.123	-0.844
2007	0.187	0.799	1.54	2.696	3.111	2.319	0.568	-1.648	-3.274	-3.334	-2.122	-0.844
2008	0.194	0.798	1.54	2.69	3.119	2.318	0.563	-1.652	-3.269	-3.337	-2.121	-0.845
2009	0.197	0.797	1.543	2.689	3.129	2.316	0.556	-1.656	-3.268	-3.341	-2.12	-0.846
2010	0.198	0.796	1.545	2.69	3.138	2.315	0.552	-1.659	-3.268	-3.344	-2.118	-0.844
2011	0.201	0.793	1.542	2.688	3.145	2.314	0.549	-1.66	-3.268	-3.347	-2.118	-0.841
2012	0.203	0.79	1.541	2.69	3.153	2.314	0.546	-1.661	-3.271	-3.351	-2.119	-0.838
2013	0.203	0.786	1.541	2.693	3.161	2.317	0.544	-1.661	-3.273	-3.353	-2.119	-0.837
2014	0.202	0.78	1.541	2.696	3.165	2.319	0.543					

STANDARD ERROR OF SEASONAL

X 10.0D-1

YEAR	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
1973	0.77	0.766	0.764	0.762	0.761	0.761	0.761	0.761	0.761	0.759	0.757	0.737
1974	0.732	0.729	0.727	0.726	0.725	0.725	0.725	0.725	0.724	0.723	0.722	0.705
1975	0.701	0.698	0.696	0.695	0.694	0.694	0.694	0.694	0.694	0.693	0.691	0.677
1976	0.674	0.671	0.67	0.669	0.668	0.668	0.668	0.668	0.668	0.667	0.666	0.654
1977	0.651	0.649	0.648	0.647	0.647	0.647	0.647	0.647	0.646	0.646	0.645	0.635
1978	0.633	0.631	0.63	0.629	0.629	0.629	0.629	0.629	0.629	0.628	0.627	0.619
1979	0.617	0.616	0.615	0.614	0.614	0.614	0.614	0.614	0.614	0.613	0.613	0.606
1980	0.604	0.603	0.603	0.602	0.602	0.602	0.602	0.602	0.602	0.601	0.601	0.595
1981	0.594	0.593	0.592	0.592	0.592	0.592	0.592	0.592	0.592	0.591	0.591	0.586
1982	0.585	0.585	0.584	0.584	0.584	0.584	0.584	0.584	0.584	0.583	0.583	0.579
1983	0.578	0.578	0.577	0.577	0.577	0.577	0.577	0.577	0.577	0.577	0.576	0.573
1984	0.573	0.572	0.572	0.572	0.571	0.571	0.571	0.571	0.571	0.571	0.571	0.569
1985	0.568	0.568	0.567	0.567	0.567	0.567	0.567	0.567	0.567	0.567	0.567	0.565
1986	0.564	0.564	0.564	0.564	0.563	0.563	0.563	0.563	0.563	0.563	0.563	0.561
1987	0.561	0.561	0.561	0.561	0.561	0.561	0.561	0.561	0.56	0.56	0.56	0.559
1988	0.559	0.558	0.558	0.558	0.558	0.558	0.558	0.558	0.558	0.558	0.558	0.557

1989	0.557	0.556	0.556	0.556	0.556	0.556	0.556	0.556	0.556	0.556	0.556	0.555
1990	0.555	0.555	0.555	0.555	0.555	0.555	0.555	0.555	0.555	0.555	0.555	0.554
1991	0.554	0.554	0.554	0.553	0.553	0.553	0.553	0.553	0.553	0.553	0.553	0.553
1992	0.553	0.553	0.552	0.552	0.552	0.552	0.552	0.552	0.552	0.552	0.552	0.552
1993	0.552	0.552	0.552	0.552	0.552	0.552	0.552	0.552	0.552	0.552	0.552	0.552
1994	0.552	0.552	0.552	0.552	0.552	0.552	0.552	0.552	0.552	0.552	0.552	0.552
1995	0.552	0.552	0.552	0.552	0.552	0.553	0.553	0.553	0.553	0.553	0.553	0.553
1996	0.553	0.553	0.553	0.553	0.554	0.554	0.554	0.554	0.555	0.555	0.555	0.555
1997	0.555	0.555	0.555	0.555	0.555	0.555	0.555	0.555	0.556	0.556	0.556	0.556
1998	0.556	0.556	0.556	0.556	0.556	0.556	0.557	0.557	0.558	0.558	0.558	0.558
1999	0.558	0.558	0.558	0.558	0.558	0.558	0.559	0.559	0.56	0.56	0.56	0.561
2000	0.561	0.561	0.561	0.561	0.561	0.561	0.561	0.561	0.563	0.563	0.563	0.563
2001	0.563	0.563	0.563	0.564	0.564	0.564	0.564	0.565	0.567	0.567	0.567	0.567
2002	0.567	0.567	0.567	0.567	0.567	0.568	0.568	0.569	0.571	0.571	0.571	0.571
2003	0.571	0.571	0.571	0.572	0.572	0.572	0.573	0.573	0.576	0.577	0.577	0.577
2004	0.577	0.577	0.577	0.577	0.577	0.578	0.578	0.579	0.583	0.583	0.584	0.584
2005	0.584	0.584	0.584	0.584	0.584	0.585	0.585	0.586	0.591	0.591	0.592	0.592
2006	0.592	0.592	0.592	0.592	0.592	0.593	0.594	0.595	0.601	0.601	0.602	0.602
2007	0.602	0.602	0.602	0.602	0.603	0.603	0.604	0.606	0.613	0.613	0.614	0.614
2008	0.614	0.614	0.614	0.614	0.615	0.616	0.617	0.619	0.627	0.628	0.629	0.629
2009	0.629	0.629	0.629	0.629	0.63	0.631	0.633	0.635	0.645	0.646	0.646	0.647
2010	0.647	0.647	0.647	0.647	0.648	0.649	0.651	0.654	0.666	0.667	0.668	0.668
2011	0.668	0.668	0.668	0.669	0.67	0.671	0.674	0.677	0.691	0.693	0.694	0.694
2012	0.694	0.694	0.694	0.695	0.696	0.698	0.701	0.705	0.722	0.723	0.724	0.725
2013	0.725	0.725	0.725	0.726	0.727	0.729	0.732	0.737	0.757	0.759	0.761	0.761
2014	0.761	0.761	0.761	0.762	0.764	0.766	0.77					

TREND-CYCLE

YEAR	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
1973	328.678	328.81	328.931	329.121	329.413	329.738	330.067	330.326	330.405	330.32	330.127	329.898
1974	329.812	329.897	329.986	330.035	330.05	330.074	330.205	330.364	330.443	330.47	330.504	330.567
1975	330.636	330.644	330.631	330.713	330.854	330.978	331.104	331.281	331.456	331.537	331.572	331.649
1976	331.783	331.912	331.975	331.964	331.903	331.905	331.992	332.053	332.094	332.183	332.354	332.555
1977	332.72	332.923	333.203	333.457	333.644	333.795	333.929	334.071	334.238	334.39	334.502	334.645
1978	334.793	334.887	334.995	335.11	335.24	335.434	335.593	335.642	335.649	335.715	335.827	335.95

1979	336.078	336.203	336.31	336.339	336.403	336.608	336.817	336.973	337.136	337.307	337.48	337.653
1980	337.792	337.958	338.175	338.342	338.494	338.65	338.77	338.929	339.118	339.246	339.315	339.386
1981	339.533	339.737	339.885	339.944	339.978	340.003	340.011	340.058	340.195	340.406	340.629	340.809
1982	340.949	341.09	341.23	341.347	341.427	341.46	341.489	341.527	341.567	341.621	341.69	341.773
1983	341.898	342.079	342.297	342.567	342.852	343.106	343.33	343.465	343.52	343.598	343.738	343.893
1984	344.005	344.057	344.107	344.229	344.403	344.561	344.663	344.703	344.772	344.942	345.147	345.298
1985	345.399	345.557	345.72	345.786	345.853	345.959	346.078	346.22	346.335	346.417	346.511	346.58
1986	346.59	346.622	346.778	347.044	347.286	347.428	347.53	347.69	347.848	347.918	347.986	348.097
1987	348.182	348.244	348.396	348.663	348.933	349.128	349.274	349.449	349.669	349.876	350.046	350.217
1988	350.453	350.693	350.856	351.005	351.193	351.45	351.763	352.025	352.188	352.281	352.347	352.453
1989	352.56	352.575	352.609	352.74	352.866	352.987	353.11	353.196	353.314	353.464	353.592	353.708
1990	353.838	353.958	353.978	353.964	354.023	354.113	354.242	354.416	354.607	354.816	354.983	355.038
1991	355.053	355.186	355.442	355.669	355.752	355.689	355.587	355.552	355.597	355.701	355.837	355.967
1992	356.082	356.187	356.28	356.374	356.485	356.528	356.459	356.397	356.4	356.438	356.469	356.524
1993	356.606	356.666	356.725	356.815	356.936	356.999	357.014	357.114	357.281	357.433	357.588	357.792
1994	358.019	358.212	358.374	358.505	358.569	358.628	358.761	358.924	359.101	359.332	359.557	359.718
1995	359.865	360.048	360.264	360.483	360.67	360.821	360.919	361.019	361.182	361.343	361.484	361.669
1996	361.928	362.177	362.258	362.218	362.297	362.524	362.736	362.848	362.882	362.903	362.949	362.999
1997	363.063	363.14	363.236	363.38	363.475	363.519	363.624	363.74	363.879	364.152	364.535	364.88
1998	365.113	365.335	365.631	365.981	366.338	366.673	366.985	367.224	367.395	367.552	367.702	367.848
1999	367.978	368.063	368.099	368.083	368.06	368.167	368.345	368.421	368.469	368.597	368.742	368.854
2000	368.907	368.916	368.952	368.967	369.007	369.193	369.453	369.75	370.037	370.238	370.369	370.451
2001	370.533	370.663	370.766	370.792	370.826	370.915	371.055	371.244	371.455	371.656	371.836	372.017
2002	372.188	372.308	372.393	372.512	372.744	373.052	373.322	373.554	373.782	374	374.242	374.479
2003	374.666	374.824	374.981	375.185	375.459	375.749	375.966	376.136	376.322	376.499	376.651	376.779
2004	376.907	377.067	377.254	377.408	377.426	377.353	377.372	377.499	377.629	377.804	378.039	378.274
2005	378.552	378.923	379.264	379.455	379.606	379.831	380.052	380.16	380.209	380.327	380.528	380.785
2006	381.05	381.247	381.44	381.669	381.802	381.844	381.925	382.064	382.222	382.353	382.466	382.611
2007	382.79	382.976	383.192	383.412	383.568	383.698	383.812	383.933	384.142	384.376	384.568	384.755
2008	384.881	384.843	384.761	384.88	385.196	385.511	385.743	385.947	386.144	386.271	386.352	386.476
2009	386.627	386.777	386.9	386.965	387.048	387.178	387.349	387.582	387.789	387.926	388.08	388.282
2010	388.587	389.005	389.393	389.653	389.78	389.815	389.856	389.982	390.193	390.432	390.613	390.741
2011	390.869	390.939	390.933	390.969	391.148	391.431	391.708	391.942	392.148	392.308	392.455	392.634
2012	392.793	392.914	393.09	393.328	393.514	393.647	393.825	394.057	394.289	394.539	394.833	395.125
2013	395.418	395.676	395.823	395.991	396.231	396.422	396.587	396.744	396.879	397.048	397.256	397.44
2014	397.531	397.66	397.98	398.331	398.547	398.644	398.7					

STANDARD ERROR OF TREND-CYCLE

YEAR	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
1973	0.122	0.116	0.115	0.115	0.115	0.115	0.115	0.115	0.115	0.115	0.114	0.114
1974	0.114	0.114	0.114	0.114	0.114	0.114	0.114	0.114	0.114	0.114	0.114	0.114
1975	0.114	0.114	0.114	0.114	0.114	0.114	0.114	0.114	0.114	0.113	0.113	0.113
1976	0.113	0.113	0.113	0.113	0.113	0.113	0.113	0.113	0.113	0.113	0.113	0.113
1977	0.113	0.113	0.113	0.113	0.113	0.113	0.113	0.113	0.113	0.113	0.113	0.113
1978	0.113	0.113	0.113	0.113	0.113	0.113	0.113	0.113	0.113	0.113	0.112	0.112
1979	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112
1980	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112
1981	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112
1982	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112
1983	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112
1984	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112
1985	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112
1986	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112
1987	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112
1988	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112
1989	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112
1990	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112
1991	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112
1992	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112
1993	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112
1994	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112
1995	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112
1996	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112
1997	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112
1998	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112
1999	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112
2000	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112
2001	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112
2002	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112
2003	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112
2004	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112

2005	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112
2006	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112
2007	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112
2008	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.112	0.113	0.113	0.113
2009	0.113	0.113	0.113	0.113	0.113	0.113	0.113	0.113	0.113	0.113	0.113	0.113
2010	0.113	0.113	0.113	0.113	0.113	0.113	0.113	0.113	0.113	0.113	0.113	0.113
2011	0.113	0.113	0.113	0.113	0.113	0.113	0.113	0.113	0.113	0.113	0.114	0.114
2012	0.114	0.114	0.114	0.114	0.114	0.114	0.114	0.114	0.114	0.114	0.114	0.114
2013	0.114	0.114	0.114	0.114	0.114	0.114	0.114	0.114	0.114	0.115	0.115	0.115
2014	0.115	0.115	0.115	0.115	0.115	0.116	0.122					

SEASONALLY ADJUSTED SERIES

YEAR	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
1973	328.613	328.937	328.799	328.918	329.451	329.7	330.091	330.656	330.596	330.408	330.289	329.662
1974	329.419	330.087	329.976	330.064	330.172	329.75	330.215	330.525	330.503	330.442	330.471	330.516
1975	330.741	330.786	330.339	330.699	330.881	331.027	330.969	331.247	331.673	331.597	331.463	331.6
1976	331.712	332.126	331.939	332.182	331.75	331.682	332.182	332.019	332.076	332.013	332.315	332.655
1977	332.734	332.609	333.441	333.428	333.788	333.715	334.025	333.92	334.318	334.457	334.484	334.468
1978	335.136	334.64	335.074	335.166	334.977	335.588	335.721	335.77	335.47	335.661	335.894	335.82
1979	336.24	336.028	336.59	336.333	335.964	336.803	336.848	336.972	337.081	337.374	337.393	337.761
1980	337.827	337.653	338.498	338.25	338.425	338.86	338.596	338.873	339.261	339.307	339.342	339.262
1981	339.384	339.877	340.03	339.946	339.955	340.089	339.942	339.924	340.092	340.382	340.721	340.862
1982	340.94	341.051	341.325	341.303	341.606	341.378	341.496	341.552	341.501	341.656	341.611	341.833
1983	341.656	342.227	342.062	342.632	342.889	343.118	343.421	343.7	343.358	343.568	343.658	344.013
1984	344.058	344.122	343.936	344.151	344.474	344.58	344.829	344.661	344.544	344.95	345.185	345.474
1985	345.249	345.407	346.139	345.578	345.84	346.002	345.948	346.322	346.397	346.352	346.522	346.748
1986	346.53	346.471	346.534	347.144	347.446	347.505	347.406	347.574	348.212	347.743	347.98	348.073
1987	348.359	348.031	348.207	348.69	349.054	349.22	349.215	349.337	349.731	349.924	350.078	350.097
1988	350.348	350.999	350.725	351.026	351.094	351.296	351.893	352.169	352.251	352.355	352.265	352.351
1989	352.847	352.547	352.281	352.951	352.802	352.921	353.303	353.053	353.254	353.568	353.553	353.743
1990	353.738	354.177	354.123	353.626	354.199	353.943	354.214	354.426	354.527	354.873	355.162	355.167
1991	354.809	354.967	355.526	355.859	355.996	355.723	355.464	355.438	355.558	355.609	355.902	355.962
1992	356.098	356.208	356.28	356.345	356.458	356.945	356.201	356.467	356.196	356.603	356.382	356.417
1993	356.777	356.537	356.817	356.612	357.103	357.152	356.777	357.025	357.372	357.417	357.511	357.72
1994	358.127	358.237	358.364	358.658	358.599	358.44	358.749	358.993	358.906	359.391	359.67	359.743

1995	359.769	360.037	360.222	360.566	360.696	360.868	361.06	360.688	361.39	361.274	361.508	361.476
1996	361.931	362.408	362.622	361.845	362.094	362.585	362.892	362.961	362.883	362.847	362.947	363.036
1997	362.923	363.323	362.924	363.582	363.63	363.253	363.706	363.785	363.597	364.019	364.545	365.178
1998	365.054	365.209	365.585	365.939	366.438	366.619	367.112	367.379	367.296	367.658	367.623	367.921
1999	367.983	368.204	368.054	368.287	367.725	368.004	368.66	368.455	368.225	368.659	368.781	368.877
2000	369.104	368.72	369.013	369.146	368.467	369.387	369.24	369.802	370.192	370.301	370.431	370.505
2001	370.367	370.705	370.981	370.693	370.772	370.857	370.968	371.24	371.441	371.736	371.794	372.015
2002	372.291	372.351	372.382	372.32	372.594	373.177	373.404	373.447	373.941	373.831	374.307	374.546
2003	374.706	374.827	374.932	375.053	375.432	375.857	376.131	375.933	376.483	376.427	376.752	376.769
2004	376.831	377.074	377.181	377.715	377.55	377.238	377.028	377.779	377.396	377.772	378.048	378.292
2005	378.296	378.961	379.592	379.5	379.379	379.878	380.202	380.364	379.945	380.314	380.412	380.764
2006	381.17	381.361	381.116	382.029	381.879	381.769	381.807	382.091	382.2	382.494	382.303	382.634
2007	382.743	383.011	383.02	383.704	383.469	383.731	383.922	383.648	384.174	384.474	384.542	384.734
2008	385.246	384.932	384.43	384.47	385.381	385.562	385.857	385.802	386.359	386.327	386.251	386.405
2009	386.743	386.623	387.227	386.751	387.061	387.134	387.224	387.576	388.058	387.731	388.12	388.156
2010	388.302	389.144	389.545	389.84	389.902	389.835	389.668	389.919	390.098	390.544	390.768	390.574
2011	391.049	391.027	390.948	390.652	391.065	391.406	391.871	391.85	392.308	392.307	392.358	392.671
2012	392.917	392.81	392.909	393.49	393.627	393.516	393.754	394.071	394.331	394.361	394.929	395.118
2013	395.337	396.014	395.769	395.657	396.599	396.263	396.656	396.811	396.783	397.013	397.229	397.647
2014	397.598	397.13	398.039	398.594	398.615	398.831	398.457					

STANDARD ERROR OF SEASONALLY ADJUSTED SERIES

X 10.0D-1

YEAR	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
1973	0.77	0.766	0.764	0.762	0.761	0.761	0.761	0.761	0.761	0.759	0.757	0.737
1974	0.732	0.729	0.727	0.726	0.725	0.725	0.725	0.725	0.724	0.723	0.722	0.705
1975	0.701	0.698	0.696	0.695	0.694	0.694	0.694	0.694	0.694	0.693	0.691	0.677
1976	0.674	0.671	0.67	0.669	0.668	0.668	0.668	0.668	0.668	0.667	0.666	0.654
1977	0.651	0.649	0.648	0.647	0.647	0.647	0.647	0.647	0.646	0.646	0.645	0.635
1978	0.633	0.631	0.63	0.629	0.629	0.629	0.629	0.629	0.629	0.628	0.627	0.619
1979	0.617	0.616	0.615	0.614	0.614	0.614	0.614	0.614	0.614	0.613	0.613	0.606
1980	0.604	0.603	0.603	0.602	0.602	0.602	0.602	0.602	0.602	0.601	0.601	0.595
1981	0.594	0.593	0.592	0.592	0.592	0.592	0.592	0.592	0.592	0.591	0.591	0.586

1982	0.585	0.585	0.584	0.584	0.584	0.584	0.584	0.584	0.584	0.583	0.583
	0.579										
1983	0.578	0.578	0.577	0.577	0.577	0.577	0.577	0.577	0.577	0.577	0.576
	0.573										
1984	0.573	0.572	0.572	0.572	0.571	0.571	0.571	0.571	0.571	0.571	0.571
	0.569										
1985	0.568	0.568	0.567	0.567	0.567	0.567	0.567	0.567	0.567	0.567	0.567
	0.565										
1986	0.564	0.564	0.564	0.564	0.563	0.563	0.563	0.563	0.563	0.563	0.563
	0.561										
1987	0.561	0.561	0.561	0.561	0.561	0.561	0.561	0.561	0.56	0.56	0.56
	0.559										
1988	0.559	0.558	0.558	0.558	0.558	0.558	0.558	0.558	0.558	0.558	0.558
	0.557										
1989	0.557	0.556	0.556	0.556	0.556	0.556	0.556	0.556	0.556	0.556	0.556
	0.555										
1990	0.555	0.555	0.555	0.555	0.555	0.555	0.555	0.555	0.555	0.555	0.555
	0.554										
1991	0.554	0.554	0.554	0.553	0.553	0.553	0.553	0.553	0.553	0.553	0.553
	0.553										
1992	0.553	0.553	0.552	0.552	0.552	0.552	0.552	0.552	0.552	0.552	0.552
	0.552										
1993	0.552	0.552	0.552	0.552	0.552	0.552	0.552	0.552	0.552	0.552	0.552
	0.552										
1994	0.552	0.552	0.552	0.552	0.552	0.552	0.552	0.552	0.552	0.552	0.552
	0.552										
1995	0.552	0.552	0.552	0.552	0.552	0.553	0.553	0.553	0.553	0.553	0.553
	0.553										
1996	0.553	0.553	0.553	0.553	0.554	0.554	0.554	0.554	0.555	0.555	0.555
	0.555										
1997	0.555	0.555	0.555	0.555	0.555	0.555	0.555	0.555	0.556	0.556	0.556
	0.556										
1998	0.556	0.556	0.556	0.556	0.556	0.556	0.557	0.557	0.558	0.558	0.558
	0.558										
1999	0.558	0.558	0.558	0.558	0.558	0.558	0.559	0.559	0.56	0.56	0.56
	0.561										
2000	0.561	0.561	0.561	0.561	0.561	0.561	0.561	0.561	0.563	0.563	0.563
	0.563										
2001	0.563	0.563	0.563	0.564	0.564	0.564	0.564	0.565	0.567	0.567	0.567
	0.567										
2002	0.567	0.567	0.567	0.567	0.567	0.568	0.568	0.569	0.571	0.571	0.571
	0.571										
2003	0.571	0.571	0.571	0.572	0.572	0.572	0.573	0.573	0.576	0.577	0.577
	0.577										
2004	0.577	0.577	0.577	0.577	0.577	0.578	0.578	0.579	0.583	0.583	0.584
	0.584										
2005	0.584	0.584	0.584	0.584	0.584	0.585	0.585	0.586	0.591	0.591	0.592
	0.592										
2006	0.592	0.592	0.592	0.592	0.592	0.593	0.594	0.595	0.601	0.601	0.602
	0.602										
2007	0.602	0.602	0.602	0.602	0.603	0.603	0.604	0.606	0.613	0.613	0.614
	0.614										
2008	0.614	0.614	0.614	0.614	0.615	0.616	0.617	0.619	0.627	0.628	0.629
	0.629										
2009	0.629	0.629	0.629	0.629	0.63	0.631	0.633	0.635	0.645	0.646	0.646
	0.647										
2010	0.647	0.647	0.647	0.647	0.648	0.649	0.651	0.654	0.666	0.667	0.668
	0.668										
2011	0.668	0.668	0.668	0.669	0.67	0.671	0.674	0.677	0.691	0.693	0.694
	0.694										
2012	0.694	0.694	0.694	0.695	0.696	0.698	0.701	0.705	0.722	0.723	0.724
	0.725										
2013	0.725	0.725	0.725	0.726	0.727	0.729	0.732	0.737	0.757	0.759	0.761
	0.761										
2014	0.761	0.761	0.761	0.762	0.764	0.766	0.77				

Mark Leggett comment: These are considered small relative to the seasonally adjusted series itself (above)

IRREGULAR COMPONENT

YEAR	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
1973	-0.065	0.127	-0.132	-0.203	0.039	-0.039	0.024	0.331	0.191	0.088	0.162	-0.236
1974	-0.393	0.19	-0.011	0.029	0.122	-0.324	0.011	0.161	0.06	-0.028	-0.033	-0.05
1975	0.105	0.142	-0.292	-0.014	0.027	0.049	-0.135	-0.034	0.217	0.06	-0.109	-0.049
1976	-0.071	0.215	-0.036	0.218	-0.153	-0.223	0.19	-0.034	-0.018	-0.17	-0.039	0.1
1977	0.014	-0.314	0.237	-0.029	0.144	-0.08	0.096	-0.151	0.08	0.067	-0.018	-0.177
1978	0.343	-0.246	0.079	0.056	-0.263	0.154	0.127	0.128	-0.18	-0.055	0.067	-0.13
1979	0.162	-0.175	0.28	-0.006	-0.439	0.195	0.031	-0.002	-0.055	0.067	-0.087	0.108
1980	0.035	-0.305	0.323	-0.092	-0.069	0.21	-0.174	-0.056	0.144	0.061	0.027	-0.124
1981	-0.149	0.14	0.145	0.002	-0.023	0.086	-0.069	-0.134	-0.102	-0.024	0.092	0.054
1982	-0.009	-0.039	0.095	-0.044	0.178	-0.082	0.007	0.025	-0.065	0.035	-0.079	0.06
1983	-0.242	0.148	-0.235	0.065	0.037	0.012	0.091	0.234	-0.161	-0.03	-0.08	0.12
1984	0.053	0.065	-0.17	-0.078	0.071	0.018	0.165	-0.042	-0.228	0.009	0.039	0.177
1985	-0.15	-0.15	0.419	-0.208	-0.013	0.043	-0.13	0.102	0.062	-0.065	0.011	0.168
1986	-0.061	-0.151	-0.244	0.1	0.159	0.077	-0.123	-0.116	0.364	-0.175	-0.006	-0.024
1987	0.177	-0.213	-0.189	0.027	0.122	0.092	-0.06	-0.112	0.062	0.047	0.032	-0.12
1988	-0.105	0.306	-0.131	0.021	-0.1	-0.154	0.13	0.144	0.063	0.074	-0.082	-0.103
1989	0.288	-0.027	-0.328	0.211	-0.064	-0.067	0.193	-0.143	-0.06	0.104	-0.039	0.035
1990	-0.101	0.219	0.145	-0.338	0.176	-0.17	-0.028	0.011	-0.08	0.057	0.179	0.13
1991	-0.244	-0.219	0.084	0.19	0.244	0.034	-0.123	-0.114	-0.04	-0.092	0.065	-0.004
1992	0.016	0.021	0.001	-0.029	-0.027	0.417	-0.258	0.07	-0.204	0.165	-0.087	-0.107
1993	0.171	-0.129	0.091	-0.204	0.167	0.153	-0.238	-0.089	0.091	-0.016	-0.076	-0.071
1994	0.108	0.025	-0.011	0.153	0.03	-0.188	-0.012	0.069	-0.195	0.058	0.113	0.026
1995	-0.095	-0.011	-0.042	0.084	0.026	0.046	0.14	-0.331	0.207	-0.068	0.024	-0.193
1996	0.004	0.231	0.364	-0.373	-0.203	0.061	0.156	0.113	0.001	-0.057	-0.002	0.037
1997	-0.14	0.182	-0.312	0.201	0.156	-0.266	0.083	0.045	-0.282	-0.133	0.011	0.298
1998	-0.059	-0.127	-0.047	-0.042	0.1	-0.055	0.127	0.154	-0.098	0.106	-0.079	0.074
1999	0.005	0.141	-0.045	0.204	-0.335	-0.164	0.315	0.034	-0.244	0.061	0.039	0.024
2000	0.197	-0.196	0.061	0.178	-0.54	0.194	-0.213	0.052	0.155	0.062	0.062	0.054
2001	-0.166	0.042	0.216	-0.099	-0.054	-0.057	-0.087	-0.004	-0.013	0.08	-0.042	-0.003
2002	0.103	0.042	-0.011	-0.193	-0.151	0.126	0.082	-0.107	0.16	-0.169	0.065	0.067
2003	0.039	0.004	-0.049	-0.132	-0.027	0.108	0.164	-0.203	0.161	-0.072	0.101	-0.011
2004	-0.076	0.007	-0.073	0.307	0.125	-0.115	-0.344	0.28	-0.233	-0.033	0.008	0.018
2005	-0.256	0.038	0.328	0.045	-0.227	0.048	0.15	0.203	-0.264	-0.013	-0.117	-0.022
2006	0.12	0.113	-0.324	0.36	0.077	-0.074	-0.118	0.027	-0.021	0.14	-0.163	0.023

2007	-0.047	0.036	-0.172	0.292	-0.099	0.033	0.11	-0.285	0.032	0.099	-0.026	-0.021
2008	0.366	0.09	-0.33	-0.409	0.184	0.052	0.114	-0.145	0.215	0.056	-0.101	-0.071
2009	0.116	-0.155	0.326	-0.214	0.013	-0.044	-0.126	-0.006	0.269	-0.195	0.041	-0.126
2010	-0.285	0.139	0.152	0.187	0.122	0.02	-0.188	-0.063	-0.095	0.112	0.156	-0.167
2011	0.181	0.088	0.014	-0.317	-0.083	-0.025	0.163	-0.092	0.16	-0.001	-0.097	0.037
2012	0.125	-0.104	-0.181	0.162	0.113	-0.131	-0.072	0.014	0.041	-0.178	0.096	-0.007
2013	-0.081	0.338	-0.054	-0.334	0.368	-0.158	0.068	0.067	-0.097	-0.035	-0.027	0.207
2014	0.068	-0.53	0.059	0.264	0.068	0.187	-0.242					

Mark Leggett comment: This should be essentially "white noise", and the TRAMO plots above suggests that it is

* * PROCESSING COMPLETED * *

Granger causality from the first and second differenc~~erivativ~~es of atmospheric CO_2 to global surface temperature and the El Niño–Southern Oscillation respectively

L.M.W. Leggett [1] and D.A. Ball [1]

(1) (Global Risk Policy Group Pty Ltd, Townsville, Queensland, Australia)

www.globalriskprogress.com

Correspondence to: L.M.W. Leggett (mleggett.globalriskprogress@gmail.com)

Abstract

A significant gap now of some 16 years in length has been shown to exist between the observed global surface temperature trend and that expected from the majority of climate simulations, and this gap is presently continuing to increase. For its own sake, and to enable better climate prediction for policy use, the reasons behind this mismatch need to be better understood. While an increasing number of possible causes have been proposed, the candidate causes have not yet converged.

The standard model which is now displaying the disparity has it that temperature will rise roughly linearly with atmospheric CO_2. However research also exists showing correlation between the interannual variability in the growth rate of atmospheric CO_2 and temperature. Rate of change of CO_2 had not been considered a causative mechanism for temperature because it was concluded that causality ran from temperature to rate of change of CO_2.

However more recent studies have found little or no evidence for temperature leading rate of change of CO_2 but instead evidence for simultaneity. With this background, this paper reinvestigates~~d~~ the relationship between rate of change of CO_2 and two of

the major climate variables, atmospheric temperature and the El Niño–Southern Oscillation (ENSO).

Using time series analysis in the form of dynamic regression modelling with autocorrelation correction, it is demonstrated that first-difference CO_2 leads temperature and that there is a highly statistically significant correlation between first-difference CO_2 and temperature. Further, a correlation is found for second-difference CO_2 with the Southern Oscillation Index, the atmospheric-pressure component of ENSO. This paper also demonstrates that both these correlations display Granger causality.

It is shown that the first-difference CO_2 and temperature model shows no trend mismatch in recent years.

These results may contribute to the prediction of future trends for global temperature and ENSO.

Interannual variability in the growth rate of atmospheric CO_2 is standardly attributed to variability in the carbon sink capacity of the terrestrial biosphere. The terrestrial biosphere carbon sink is created by the difference between photosynthesis and respiration (net primary productivity): a major way of measuring global terrestrial photosynthesis is by means of satellite measurements of vegetation reflectance, such as the Normalized Difference Vegetation Index (NDVI). In a preliminary analysis, this study finds a close correlation between an increasing NDVI and the increasing climate model/temperature mismatch (as quantified by the difference between the trend in the level of CO_2 and the trend in temperature).

~~It is believed that the results in this paper provide strong evidence that the global climate is the result of the combination of two mechanisms – one a physical mechanism based on the level of atmospheric CO_2, the other a mechanism embodied in the terrestrial biosphere and based on the rate of change of CO_2.~~

1 Introduction

Understanding current global climate requires an understanding of trends both in Earth's atmospheric temperature and the El Niño–Southern Oscillation (ENSO), a characteristic large-scale distribution of warm water in the tropical Pacific Ocean and the dominant global mode of year-to-year climate variability (Holbrook et al. 2009). However, despite much effort, the average projection of current climate models has become statistically significantly different from the 21st century global surface - temperature trend (Fyfe et al. 2013; Fyfe and Gillett 2014) and has failed to reflect the statistically significant evidence that annual-mean global temperature has not risen in the 21st century (Fyfe et al. 2013; Kosaka and Shang-Ping 2013). ~~temperature trend (Fyfe et al. 2013, 2014) and has failed to reflect the statistically significant evidence that annual-mean global temperature has not risen in the 21st century (Fyfe 2013; Kosaka 2013).~~

~~-~~The situation is illustrated visually in Figure 1 which shows the increasing departure over recent years of the global surface temperature trend from that projected by a representative mid-range global climate model (GCM) for global surface temperature - the CMIP3, SRESA1B scenario model (Meehl et al. 2007)~~KNMI 2013)~~. It is noted that the level of atmospheric CO_2 is a good proxy for the International Panel on Climate Change (IPCC) models predicting the global surface temperature trend: according to IPCC (2014), on decadal to interdecadal time scales and under continually increasing effective radiative forcing, the forced component of the global surface temperature trend responds to the forcing trend relatively rapidly and almost linearly.

Modelling also provides a wide range of predictions for future ENSO variability, some showing an increase, others a decrease, and some no change (Guilyardi et al. 2012; Bellenger 2013). The extremes of this ENSO variability cause extreme weather events (such as floods and droughts) in many regions of the world.
A wide range of physical explanations has now been proposed for the global warming slowdown. These involve proposals either for changes in the way the radiative mechanism itself is working or for the increased influence of other physical

mechanisms. Chen and Tung (2014) place these proposed explanations into two categories. The first involves a reduction in radiative forcing: by a decrease in stratospheric water vapour, an increase in background stratospheric volcanic aerosols, by 17 small volcano eruptions since 1999, increasing coal-burning in China, the indirect effect of time-varying anthropogenic aerosols, a low solar minimum, or a combination of these. The second category of candidate explanation involves planetary sinks for the excess heat. The major focus for the source of this sink has been physical and has involved ocean heat sequestration. However, evidence for the precise nature of the ocean sinks is not yet converging: according to Chen and Tung (2014) their study followed the original proposal of Meehl et al. (2011) that global deep-ocean heat sequestration is centred on the Pacific. However, their observational results were that such deep-ocean heat sequestration is mainly occurring in the Atlantic and the Southern oceans.

Alongside the foregoing possible physical causes, Hansen et al. (2013) have suggested that the mechanism for the pause in the global temperature increase since 1998 might be the planetary biota, in particular the terrestrial biosphere: that is (IPCC 2007), the fabric of soils, vegetation and other biological components, the processes that connect them and the carbon, water and energy that they store.

It is widely considered that the interannual variability in the growth rate of atmospheric CO_2 is a sign of the operation of the influence of the planetary biota. Again, IPCC (2007) states: “The atmospheric CO_2 growth rate exhibits large interannual variations. The change in fossil fuel emissions and the estimated variability in net CO_2 uptake of the oceans are too small to account for this signal, which must be caused by year-to-year fluctuations in land-atmosphere fluxes.”
In the IPCC Fourth Assessment Report, Denman et al. (2007) state (italics denote present author emphasis): “Interannual and inter-decadal variability in the growth rate of atmospheric CO_2 is dominated by the *response of the land biosphere to climate variations*. …. The terrestrial biosphere *interacts strongly with the climate*, providing both positive and negative feedbacks due to biogeophysical and biogeochemical processes. … Surface climate is determined by the balance of fluxes, which can be changed by radiative (e.g., albedo) or non-radiative (e.g., water cycle related

processes) terms. Both radiative and non-radiative terms *are controlled by details of vegetation*."

Denman et al. (2007) also note that many studies have confirmed that the variability of CO_2 fluxes is mostly due to land fluxes, and that tropical lands contribute strongly to this signal. A predominantly terrestrial origin of the growth rate variability can be inferred from (1) atmospheric inversions assimilating time series of CO_2 concentrations from different stations, (2) consistent relationships between δ13C and CO_2, (3) ocean model simulations, and (4) terrestrial carbon cycle and coupled model simulations. For one prominent estimate carried out by the Global Carbon Project, the land sink is calculated as the residual of the sum of all sources minus the sum of the atmosphere and ocean sinks (Le Quere et al. 2014).

The activity of the land sink can also be estimated directly. The terrestrial biosphere carbon sink is created by photosynthesis: a major way of measuring global land photosynthesis is by means of satellite measurements of potential photosynthesis from greenness estimates. The measure predominantly used ~~such measure~~ is the Normalized Difference Vegetation Index (NDVI) (Running et al. 2004; Zhang et al. 2014). NDVI data are available from the start of satellite observations in 1980 to the present. For this period the trend signature in NDVI has been shown to correlate closely with that for atmospheric CO_2 (Barichivich et al. 2013). This noted, we have not been able to find studies which have compared NDVI data with the difference between climate models and temperature.

2 Methodological issues and objectives of the study

2.1 Methodological issues

Before considering further material it is helpful now to consider a range of methodological issues and concepts. The first concept is to do with the notion of causality.

According to Hidalgo and Sekhon (2011) there are four prerequisites to enable an assertion of causality. The first is that the cause must be prior to the effect. The second prerequisite is "constant conjunction" between variables (Hume (1751), cited in Hidalgo and Sekhon (2011)) ~~between variables~~. This relates to the degree of fit between variables. The final requirements are those concerning manipulation and random placement into experimental and control categories. It is noted that each of the four prerequisites is necessary but not sufficient on its own for causality.

~~Concerning~~ With regard to the last two criteria, the problem for global studies such as global climate studies is that manipulation and random placement into experimental and control categories cannot be carried out.

One method using correlational data, however, approaches more closely the quality of information derived from random placement into experimental and control categories. The concept is that of Granger causality (Granger 1969). According to Stern and Kaufmann (2014), a time series variable "*x*" (e.g. atmospheric CO_2) is said to "Granger-cause" variable "*y*" (e.g. surface temperature) if past values of *x* help predict the current level of *y*, better than do just the past values of *y*, given all other relevant information.

Reference to the above four aspects of causality will be made to help structure the review of materials in the following sections.

2.2 Objectives of the study

What has been considered to influence the biota's creation of the pattern observed in the trend in the growth rate of atmospheric CO_2? The candidates for the influences on the biota have mainly been considered in prior research to be atmospheric variations, primarily temperature and/or ENSO (e.g., Kuo et al. 1990; Wang W. et al. 2013). Despite its proposed role in global warming overall, CO_2 (in terms of the initial state of atmospheric CO_2 exploited by plants at time *A*) has not generally been isolated and studied in detail through time series analysis as an influence in the way the biosphere influences the CO_2 left in the atmosphere at succeeding time *B*.

This ~~state of affairs~~lack of attention to the influence of the biosphere on climate variables seems to have come about for two reasons, one concerning ENSO, the other, temperature. For ENSO, the reason is that the statistical studies are unambiguous that ENSO leads rate of change of CO_2 (e.g., Lean and Rind 2008). On the face of it, therefore, this ruled out CO_2 as the first mover of the ecosystem processes. For temperature, the reason was that the question of whether atmospheric temperature leads rate of change of CO_2 or vice versa is less settled.

In the first published study on this question, Kuo et al. (1990) provided evidence that the signature of interannual atmospheric CO_2 (measured as its ~~first difference~~first-difference) fitted temperature (passing therefore one of the four tests for causality, of close conjunction).

The relative fits of both level of and ~~first difference~~first-difference of atmospheric CO_2 with global surface temperature up to the present are depicted in Figure 2. Attention is drawn to both signature (fine grained data structure) and, by means of polynomial smoothing, core trend for each data series.

Concerning signature, while clearly first-difference CO_2 and temperature are not identical, each is more alike than either is to the temperature model based on level of CO_2. As well, the polynomial fits show that the same likeness groupings exist for core trend.

Kuo et al. (1990) also provided evidence concerning another of the causality prerequisites – priority. This was that the signature of first-difference CO_2 *lagged* temperature (by 5 months). This idea has been influential. More recently, ~~despite~~ Adams and Piovesan (2005) noted~~ing~~ that climate variations~~,~~ acting on ecosystems~~,~~ are believed to be responsible for variation in CO_2 increment, but there are major uncertainties in identifying processes, including uncertainty concerning *instantaneous* (present authors' emphasis) versus lagged responses.~~;~~ ~~and~~ Wang ~~W.~~ et al. (2013) ~~observing~~ observed that the strongest coupling is found between the CO_2 growth rate and the *concurrent* (present authors' emphasis) tropical land temperature.~~,~~ Wang et al. (2013) nonetheless state in their conclusion that the strong temperature–CO_2 coupling they observed is best explained by the additive responses of tropical terrestrial respiration and primary production to temperature variations, which reinforce each other in enhancing *temperature's control* (present author emphasis) on tropical net ecosystem exchange.

Another perspective on the relative effects of rising atmospheric CO_2 concentrations on the one hand and temperature on the other has been provided by extensive direct experimentation on plants. In a large scale meta-analysis of such experiments, Dieleman et al. (2012) drew together results on how ecosystem productivity and soil processes responded to combined warming and CO_2 manipulation, and compared it with those obtained from single factor CO_2 and temperature manipulation. While the meta-analysis found that responses to combined CO_2 and temperature treatment showed the greatest effect, this was only slightly larger than for the CO_2-only treatment. By contrast, the effect of the CO_2-only treatment was markedly larger than for the warming-only treatment.

~~Concerning~~ In looking at leading and lagging climate series more generally, the first finding of correlations between the rate of change (in the form of the ~~first-difference~~first-difference) of atmospheric CO_2 and a climate variable was with the foregoing and the Southern Oscillation Index (SOI) component of ENSO (Bacastow 1976). Here evidence was presented that the SOI led first-difference atmospheric CO_2. There have been further such studies (see Imbers (2013) for overview) which, taken together, consistently show that the highest correlations are achieved with SOI leading temperature by some months (3-4 months).

In light of the foregoing, this paper reanalyses by means of time series regression analysis ~~the question of~~ which of first-difference CO_2 and temperature lead~~s which~~. The joint temporal relationship between interannual atmospheric CO_2, global surface temperature and ENSO (indicated by the SOI) is also investigated.

The foregoing also shows that a strong case can be made for further investigating the planetary biota influenced by atmospheric CO_2 as a candidate influence on (cause of) climate outcomes. This question is also explored in this paper.

~~A number of Granger causality studies have been carried out on climate time series (see review in Attanasio 2012). Of papers we have found which assessed atmospheric~~

~~CO_2 and global surface temperature – some six (Sun and Wang 1996; Triacca 2005; Kodra et al. 2011; Attanasio and Triacca 2011; Attanasio 2012; Stern and Kaufmann 2014) - while all but one (Triacca 2005) found Granger causality, it was not with CO_2 concentration but with CO_2 radiative forcing (lnCO_2 (Attanasio and Triacca 2011).~~

A number of Granger causality studies have been carried out on climate time series (see review in Attanasio 2012). We found six papers which assessed atmospheric CO_2 and global surface temperature (Sun and Wang 1996; Triacca 2005; Kodra et al. 2011; Attanasio and Triacca 2011; Attanasio 2012; Stern and Kaufmann 2014). Of these, while all but one (Triacca 2005) found Granger causality, it was not with CO_2 concentration as studied in this paper but with CO_2 radiative forcing (lnCO_2 (Attanasio and Triacca 2011)).

As well, all studies used annual not monthly data. Such annual data for each of atmospheric CO_2 and temperature is not stationary of itself but must be transformed into a new, stationary, series by differencing (Sun and Wang 1996). Further, data at this level of aggregation can "mask" correlational effects that only become apparent when higher frequency (e.g., monthly) data are used.

Rather than using a formal Granger causality analysis, a number of authors have instead used conventional multiple regression models in attempts to quantify the relative importance of natural and anthropogenic influencing factors on climate outcomes such as global surface temperature. These regression models use contemporaneous explanatory variables. For example, see Lean and Rind (2008, 2009); Foster and Rahmstorf (2011); Kopp and Lean (2011); Zhou and Tung (2013). This type of analysis effectively assumes a causal direction between the variables being modelled. It is incapable of providing a proper basis for testing for the presence or absence of causality. In some cases account has been taken of autocorrelation in the model's errors, but this does not overcome the fundamental weakness of standard multiple regression in this context. In contrast, Granger causality analysis that we adopt in this paper provides a formal testing of both the presence and direction of this causality (Granger 1969).

From such studies, a common set of main influencing factors (also called explanatory or predictor variables) has emerged. These are (Lockwood (2008); Folland (2013); Zhou and Tung (2013)): El Nino–Southern Oscillation (ENSO), or Southern Oscillation Index (SOI) alone~~ (SOI)~~; volcano aerosol optical depth; total solar irradiance; and the trend in anthropogenic greenhouse gas (the predominant anthropogenic greenhouse gas being CO_2). In these models, ENSO/SOI is the factor embodying interannual variation. Imbers et al. (2013) show that a range of different studies using these variables have all produced similar and close fits with the global surface temperature.

With this background, this paper first presents an analysis concerning whether the ~~first-difference~~first-difference of atmospheric CO_2 leads or lags global surface temperature. ~~That assessed~~After assessing this, questions of autocorrelation, strength of correlation, and of causality are then explored. Given this exploration of correlations involving first-difference atmospheric CO_2, the possibility of the correlation of second-~~-~~difference CO_2 with climate variables is also explored.

Correlations are assessed at a range of time scales to seek the time extent over which relationships are held, and thus whether they are a special case or possibly longer term in nature. The time scales involved are, using instrumental data, over two periods starting respectively from 1959 and 1877; and, using paleoclimate data, over a period commencing from 1515. The correlations are assessed by means of regression models explicitly incorporating autocorrelation using dynamic modelling methods. Granger causality between CO_2 and, respectively, temperature and SOI is also explored. Atmospheric CO_2 rather than emissions data is used, and where possible at monthly rather than annual aggregation. Finally, as noted, we have not been able to find studies which have compared the gap between climate models and temperature with NDVI data, so an assessment of this question is carried out. All assessments were carried out using the time series statistical software packages Gnu Regression, Econometrics and Time-series Library (GRETL) (Available from: http://gretl.sourceforge.net/ (~~[~~Accessed January 23, 2014)) and IHS Eviews (IHS EViews~~,~~ 2011).

3. Data and methods

We present results of time series analyses of climate data. The data assessed are global surface temperature, atmospheric carbon dioxide (CO_2) and the Southern Oscillation Index (SOI). The regressions are presented in several batches based on the length of data series for which the highest temporal resolution is available. The first batch of studies involves the data series for which the available high resolution series is shortest: this is for atmospheric carbon dioxide (CO_2) and commences in 1958. These studies are set at monthly resolution.

The second batch of studies is for data able to be set at monthly resolution not involving CO_2. These studies begin with the time point at which the earliest available monthly SOI data commences, 1877.

The final batch of analyses utilises annual data. These studies use data starting variously in the 16th or 18th centuries.

Data from 1877 and more recently ~~is~~ are from instrumental sources; earlier data ~~is~~ are from paleoclimate sources.

For instrumental data sources for global surface temperature, we used the Hadley Centre–Climate Research Unit combined land SAT and SST (HadCRUT) version 4.2.0.0 (Morice et al. 2012), for atmospheric CO_2, the U.S. Department of Commerce National Oceanic & Atmospheric Administration Earth System Research Laboratory Global Monitoring Division Mauna Loa, Hawaii, monthly CO_2 series (Keeling et al. 2009), and for volcanic aerosols the National Aeronautic and Space Administration Goddard Institute for Space Studies Stratospheric Aerosol Optical Thickness series (Sato et al. 1993). Southern Oscillation Index ~~(SOI)~~ data (Troup 1965) is from the Science Delivery Division of the Department of Science, Information Technology, Innovation and the Arts (DSITIA) Queensland, Australia. Solar irradiance data is from Lean, J. (personal communication 2012).

~~Concerning~~ With regard to the El Nino-Southern Oscillation, according to IPCC (2014) the term El Niño was initially used to describe a warm-water current that periodically flows along the coast of Ecuador and Peru, disrupting the local fishery. It has since become identified with a basin-wide warming of the tropical Pacific Ocean east of the dateline. This oceanic event is associated with a fluctuation of a global-scale tropical and subtropical surface atmospheric pressure pattern called the Southern Oscillation. This atmosphere–ocean phenomenon is coupled, with typical time scales of two to about seven years, and known as the El Niño-Southern Oscillation (ENSO).

The El Niñ~~n~~o (temperature) component of ENSO is measured by changes in the sea surface temperature of the central and eastern equatorial Pacific relative to the average temperature. The Southern Oscillation (atmospheric pressure) ENSO component is often measured by the surface pressure anomaly difference between Tahiti and Darwin.

For the present study we choose the SOI atmospheric pressure component rather than the temperature component of ENSO to stand for ENSO as a whole. This is because it is considered to be more valid to conduct an analysis in which temperature is an outcome (dependent variable) without also having temperature as an input (independent variable). The correlation between SOI and the other ENSO indices is high, so we believe this assumption is robust.

~~The Southern Oscillation is the atmospheric pressure component of ENSO, and is an oscillation in the surface air pressure between the tropical eastern and the western Pacific Ocean waters. It is calculated from normalized Tahiti minus Darwin sea level pressure. The SOI only takes into account sea level pressure. In contrast, the El Niño component of ENSO is specified in terms of changes in the Pacific Ocean sea surface temperature relative to the average temperature. It is considered to be more valid to conduct an analysis in which the temperature is an outcome (dependent variable) without also having (Pacific Ocean) temperature as an input (independent variable). The correlation between SOI and the other ENSO indices is high, so we believe this assumption is robust.~~

Paleoclimate data sources are: Atmospheric CO_2, from 1500 – ice cores (Robertson et al. (2001)); (NH) temperature, from 1527 – tree ring data (~~:~~Moberg, A. et al. 2005; SOI, from 1706 – tree ring data (~~-~~Stahle et al. (1998)).

Normalized Difference Vegetation Index (NDVI) monthly data from 1980 to 2006 is from the GIMMS (Global Inventory Modeling and Mapping Studies) data set (~~,~~ Tucker et al. 2005)~~accessed via KNMI~~ ~~(2014)~~. NDVI data from 2006 to 2013 was provided by the Institute of Surveying, Remote Sensing and Land Information, University of Natural Resources and Life Sciences, Vienna.

Statistical methods used are standard (Greene 2012). Categories of methods used are: normalisation; differentiation (approximated by differencing); and time series analysis. Within time series analysis, methods used are: smoothing; leading or lagging of data series relative to one another to achieve best fit; assessing a prerequisite for using data series in time series analysis, that of stationarity; including autocorrelation in models by use of dynamic regression models; and investigating causality by means of a multivariate time series model, known as a vector autoregression (VAR) and its associated Granger causality test. These methods will now be described in turn.

To make it easier to ~~visually~~ assess visually the relationship between the key climate variables, the data were normalised using statistical Z scores or standardised deviation scores (expressed as “Relative level” in the figures). In a Z-scored data series, each data point is part of an overall data series that sums to a zero mean and variance of 1, enabling comparison of data having different native units. Hence, when several Z-scored time series are depicted in a graph, all the time series will closely superimpose, enabling visual inspection to clearly discern the degree of similarity or dissimilarity between them.

See the individual figure legends for details on the series lengths.

In the time series analyse~~i~~s, SOI and global atmospheric surface temperature are the dependent variables. ~~For these two variables, w~~We tested the relationship between each of these variables and (1) the change in atmospheric CO_2 and (2) the variability in its rate of change. We express these CO_2-related variables as finite differences~~, which is a convenient approximation to differences (Hazewinkel 2001; Kaufmann et al. 2006)~~. The finite differences used here are of both the first- and second-order types (we label these “first” and “second” differences in the text). Variability is explored using both intra-annual (monthly) data and interannual (yearly) data. The period covered in the figures is shorter than that used in the data preparation because of the loss of some data points due to calculations of differences and of moving averages (in monthly terms of up to 13 x 13), which commenced in January 1960.

Smoothing methods are used to the degree needed to produce similar amounts of smoothing for each data series in any given comparison. Notably, to achieve this outcome, series resulting from higher levels of differences require more smoothing. Smoothing is carried out initially by means of a 13-month moving average – this also minimises any remaining seasonal effects. If further smoothing is required, then this is achieved ~~(Hyndman 2010)~~ by taking a second moving average of the initial moving average (to produce a double moving average) (Hyndman 2010). Often, this is performed by means of a further 13 month moving average to produce a 13 x 13 moving average. ~~——~~For descriptive statistics to describe the long-term variation of a time series trend, polynomial smoothing is sometimes used.

It is important to consider what effects this filtering of our data may have on the ensuing statistical analysis. In these analyses, only the CO_2 series was smoothed and therefore requires assessment. To do this, we tested if the smoothed (2 x 13 month moving average) first-difference CO_2 series used here has different key dynamics to that of the original raw (unsmoothed) data from which the smoothed series was derived. Lagged correlogram analysis showed that the maximum, and statistically significant, correlation of the smoothed series with the unsmoothed series occurs when there is no phase shift. This suggests that the particular smoothing used should provide no problems in the assessment of which of ~~first difference~~first-difference CO_2 and temperature has priority.

Second, there is extensive evidence that while the effect that seasonal adjustment (via smoothing) on the usual tests for unit roots in time-series data is to reduce their power in small samples, this distortion is *not* an issue with samples of the size used in this study~~. For example, (~~see, e.g., Ghysels (1990), Frances (1991), Ghysels and Perron (1993), and Diebold (1993)). Moreover, Olekalns (1994) shows that seasonal adjustment by using dummy variables also impacts adversely on the finite-sample power of these tests, so there is little to be gained by considering this alternative approach. Finally, one of the results emerging from the Granger causality literature is that while such causality can be "masked" by the smoothing of the data, apparent causality cannot be "created" from non-causal data. For example, see Sims (1971), Wei (1982), Christiano and Eichenbaum (1987), Marcellino (1999), Breitung and Swanson (2002), and Gulasekaran and Abeysinghe (2002).

Finally, seasonally adjusting the data by a range of alternative approaches did not qualitatively change the results discussed in the paper. The results of these assessments are given in the Supplement.
This means that our results relating to the existence of Granger causality should not be affected adversely by the smoothing of the data that has been undertaken.

Variables are led or lagged relative to one another to achieve best fit. These leads or lags were determined by means of time-lagged correlations (correlograms). The correlograms were calculated by shifting the series back and forth relative to each other, 1 month at a time.

With this background, the convention used in this paper for unambiguously labelling data series and their treatment after smoothing or leading or lagging is depicted in the following example. The atmospheric CO_2 series is transformed into its second difference and smoothed twice with a 13 month moving average. The resultant series is then Z-scored. This is expressed as Z2x13mma2ndDerivCO_2.

~~As well, it is n~~Note~~d~~ that, to assist readability in text involving repeated references, atmospheric CO_2 is sometimes referred to simply as CO_2 and global surface temperature as temperature.

The time series methodology used in this paper involves the following procedures. First, any two or more time series being assessed by time series regression analysis must be what is termed stationary in the first instance, or be capable of being made stationary (by differencing). A series is stationary if its properties (mean, variance, covariances) do not change with time (Greene 2012). The (augmented) Dickey-Fuller test is applied to each variable. For this test, the null hypothesis is that the series has a unit root, and hence is non-stationary. The alternative hypothesis is that the series is integrated of order zero.

Second, the residuals from any time series regression analysis then conducted must not be significantly different from white noise. This is done seeking correct model specification for the analysis.

After Greene (2012): the results of standard ordinary least squares (OLS) regression analysis assume that the errors in the model are uncorrelated. Autocorrelation of the errors violates this assumption. This means that the OLS estimators are no longer the Best Linear Unbiased Estimators (BLUE). Notably and importantly this does not bias the OLS coefficient estimates. However statistical significance can be overestimated, and possibly greatly so, when the autocorrelations of the errors at low lags are positive.

Addressing autocorrelation can take either of two alternative forms: *correcting for it* (for example, for first order autocorrelation by the Cochrane-Orcutt procedure), or *taking it into account*.

In the latter approach, the autocorrelation is taken to be a consequence of an inadequate specification of the temporal dynamics of the relationship being estimated. The method of dynamic modelling (Pankratz 1991) addresses this by seeking to explain the current behavior of the dependent variable in terms of both contemporaneous and past values of variables. In this paper the dynamic modelling approach is taken.

To assess the extent of autocorrelation in the residuals of the initial non-dynamic OLS models run, the Breusch-Godfrey procedure is used. Dynamic models are then used to take account of such autocorrelation. To assess the extent to which the dynamic models achieve this, Kiviet's Lagrange multiplier F-test (LMF) statistic for autocorrelation (Kiviet 1986) is used.

Hypotheses related to Granger causality (see Introduction) are tested by estimating a multivariate time series model, known as a vector autoregression (VAR), for level of and first-difference CO_2 and other relevant variables. The VAR models the current values of each variable as a linear function of their own past values and those of the other variables. Then we test the hypothesis that x does not cause y by evaluating restrictions that exclude the past values of x from the equation for y and vice versa.

Stern and Kander (2011) observe that Granger causality is not identical to causation in the classical philosophical sense, but it does demonstrate the likelihood of such causation or the lack of such causation more forcefully than does simple contemporaneous correlation. However, where a third variable, z, drives both x and y, x might still appear to drive y though there is no actual causal mechanism directly linking the variables (any such third variable must have some plausibility - see Discussion and C~~c~~onclusions below).

4 Results

4.1. Relationship between first-difference CO_2 and temperature

4.1.1. Priority

Figure 2 showed that, while clearly first-difference CO_2 and temperature are not identical in signature, each is more alike than either is to the temperature model based on level of CO_2. As well the figure shows that the same likeness relationships exist for the core trend. The purpose of the forthcoming sections is to see the extent to which these impressions are statistically significant.

The first question assessed is that of priority: which of first-difference atmospheric CO_2 and global surface temperature leads the other. The two series are shown for the period 1959 to 2012 in Figure 3.

~~It is not possible to discern from the above plot which precise relative phasing of the two series leads to the best fit, and hence the answer to the question of which series leads which.~~ To quantify the degree of difference in phasing between the variables, time-lagged correlations (correlograms) were calculated by shifting the series back and forth relative to each other, one month at a time.

~~First, what does the above relationship look like in correlogram form, and what is the appearance of the correlograms for the other commonly used global temperature categories – tropical, Northern hemisphere and Southern hemisphere?~~ These correlograms are given in Figure 4 for global and regional data.

~~It can be seen that, f~~For all four relationships shown, first-difference CO_2 always leads temperature. The leads differ as quantified in Table 1.

It is possible for a lead to exist overall on average but for a lag to occur for one or other specific subsets of the data. This question is explored in Figure 5 and Table 2. Here the full 1959-2012 period of monthly data – some 640 months – for each of the temperature categories is divided into three approximately equal sub-periods, to provide 12 correlograms. It can be seen that in all 12 cases, first-difference CO_2 leads temperature. It is also noted that earlier sub-periods tend to display longer first-difference CO_2 leads. For the most recent sub-period the highest correlation is when the series are neither led nor lagged.

4.1.2 Correspondence between first-difference CO_2 and global surface temperature curves

Next, the second prerequisite for causality, close correspondence, is also seen between first-difference CO_2 and global surface temperature in Figure 3.

4.1.3 Time series analysis

Both first-difference CO_2 being shown to lead temperature, and the two series displaying close correspondence, are considered a firm basis for the time series analysis of the statistical relationship between first-difference CO_2 and temperature which follows. For this further analysis, we choose global surface temperature as the temperature series because, while its maximum correlation is not the highest (Figure 5), its global coverage by definition is greatest.

~~The following sections provide the results of the time series analysis.~~ (In this section, TEMP stands for global surface temperature ((HadCRUT4), and other block capital terms are ~~those~~ variable names used in the modelling).

The order of integration, denoted I(d), is an important characteristic of a time series. It reports the minimum number of differences required to obtain a covariance stationary series. As stated above, all series used in a time series regression must be series which are stationary without further differencing (Greene 2012);~~,~~ that is, ~~in the notation,~~ display an order of integration of I(0). If a series has an order of integration greater than zero, it can be transformed by appropriate differencing into a new series which is stationary.

By means of the Augmented Dickey–Fuller (ADF) test for unit roots, Table 3 provides the information concerning stationarity for the level of, and first-difference of, CO_2, as well as for global surface temperature. Test results are provided for both monthly and annual data. The test was applied with an allowance for both a drift and deterministic trend in the data, and the degree of augmentation in the Dickey-Fuller regressions was determined by minimizing the Schwarz Information Criterion.

The results show that for both the monthly and annual series used, the variables TEMP and FIRST-DIFFERENCE CO_2 are stationary (I(0)); but level of CO_2 is not. Level of CO_2 is shown to be I(1) because (Table 3) its ~~first difference~~first-difference is stationary .

In contrast~~ to this result, however~~, Beenstock et al. (2012), using annual data, report that their series for the level of atmospheric CO_2 forcing is an I(2) variable and therefore is stationary in *second* differences.

~~With regard t~~To ~~the reconciliation~~ reconcile ~~of~~ these two ~~varying~~ results, we refer to ~~the study of~~ Pretis and Hendry (2013), ~~(2013)~~ ~~which~~ who reviewed Beenstock et al. (2012). Pretis and Hendry (2013) ~~(2013)~~ take issue with the finding of I(2) for the anthropogenic forcings studied – including CO_2 – and find evidence that this finding results from the combination of two different data sets measured in different ways which make up the 1850-2011 data set which Beenstock et al. test. Regarding this composite series Pretis and Hendry (2013) write:

> In the presence of these different measurements exhibiting structural changes, a unit-root test on the entire sample could easily not reject the null hypothesis of *I*(2) even when the data are in fact *I(1)*. Indeed, once we control for these changes, our results contradict the findings in Beenstock et al. (2012).

Pretis and Hendry (2013) give their results for CO_2 in their Table 1. Note that, in the table, level of CO_2 data is transformed into first-difference data (Beenstock et al claim the *level* of CO_2 is I(2); if that is the case, the ~~first difference~~first-difference of the level of CO_2 Pretis and Hendry (2013) should find would be I(1)).

Pretis and Hendry (2013) state:

> Unit-root tests are used to determine the level of integration of time series. Rejection of the null hypothesis provides evidence against the presence of a unit-root and suggests that the series is I(0) (stationary) rather than I(1) (integrated).
> …based on augmented Dickey–Fuller (ADF) tests (see Dickey and Fuller, 1981), the ~~first difference~~first-difference of annual radiative forcing of CO_2 is stationary initially around a constant (over 1850–1957), then around a linear trend (over 1958–2011). Although these tests are based on sub-samples corresponding to the shift in the measurement system, there is sufficient power to reject the null hypothesis of a unit root.

Hence for annual data Pretis and Hendry (2013) find first-difference CO_2 to be stationary – I(0), not I(1) – as is found in this study (Table 3).

With this question of the order of integration of the time series considered, we now turn to the next step of the time series analysis. ~~This concerns the implications for time series analysis of, a~~As Table 3, above, and Pretis and Hendry (2013) show, ~~and Table 3 in this paper shows,~~ the variable of the level of CO_2 ~~being~~ is non-stationary (specifically, integrated of order one, i.e., I(1)). ~~Here an important methodological point arises: a~~Attempting to assess TEMP in terms of the level of CO_2 would result in an “unbalanced regression”, as the dependent variable (TEMP) and the explanatory variable (CO_2) have different orders of integration. It is well known (e.g., Banerjee et al. 1993, pp. 190-191, and the references therein) that in unbalanced regressions the t-statistics are biased away from zero. That is, one can appear to find statistically significant results when in fact they are not present. In fact, ~~that~~ this ~~occur~~occurrence ~~s~~ of spurious significance is found when we regress TEMP on CO_2. This ~~reason~~ is strong evidence that any analysis should involve the variables TEMP and FIRST-DIFFERENCE CO_2, and not TEMP and CO_2.

For TEMP and FIRST-DIFFERENCE CO_2, ~~then,~~ one must next assess the extent ~~if any of~~ to which autocorrelation affects~~ing~~ the time series model. This is done by obtaining diagnostic statistics from an OLS regression. This regression shows, by means of the Breusch-Godfrey test for autocorrelation (up to order 12 – that is, including all monthly lags up to 12 months), that there is statistically significant autocorrelation at lags of one and two months, leading to an overall Breusch-Godfrey Test statistic (LMF) = 126.901, with p-value = $P(F(12,626) > 126.901) = 1.$~~06e~~$06 \times 10^{-158}$.

~~The a~~Autocorrelation is ~~taken to be~~ a consequence of an inadequate specification of the temporal dynamics of the relationship being estimated. With this in mind, a dynamic model (Greene 2012) with two lagged values of the dependent variable as additional independent variables has been estimated.

Results are shown in Table 4. ~~There, t~~The LMF test shows that there is now no statistically significant unaccounted-for autocorrelation, thus supporting the use of this dynamic model specification.

~~Inspection of~~ Table 4 shows that a highly statistically significant model has been established. First it shows that the temperature in a given period is strongly influenced by the temperature of closely preceding periods (s~~S~~ee Discussion for a possible mechanism for this). Further, it provides evidence that there is also a clear, highly statistically significant role in the model for first-difference CO_2.

4.1.4 Granger causality analysis

We now can turn to assessing if first-difference atmospheric CO_2 may not only correlate with, but also contribute causatively to, global surface temperature. This is done by means of Granger causality analysis.

Recalling that both TEMP and FIRST-DIFFERENCE CO_2 are stationary, it is appropriate to test the null hypothesis of no Granger causality from FIRST-DIFFERENCE CO_2 to TEMP by using a standard Vector Autoregressive (VAR) model without any transformations to the data. The Akaike I~~i~~nformation C~~c~~riterion (AIC) and the Schwartz I~~i~~nformation C~~c~~riterion (SIC) were used to select an optimal maximum lag length (k) for the variables in the VAR. This lag length was then lengthened, if necessary, to ensure that:

(i) The estimated model was dynamically stable (i.e., all of the inverted roots of the characteristic equation lie inside the unit circle);

(ii) The errors of the equations were serially independent.

The relevant EViews output from the VAR model is entitled VAR Granger Causality/Block Exogeneity Wald Tests and documents the following summary results ~~:~~ — Wald Statistic (p-value): Null is there is No Granger Causality from FIRST-DIFFERENCE CO_2 to TEMP; Number of lags K=4; Chi-Square 26.684 (p-value = 0.000).

A p-value of this level is highly statistically significant and means the null hypothesis of No Granger Causality is very strongly rejected. That is, over the period studied there is strong evidence that FIRST-DIFFERENCE CO_2 Granger-causes TEMP.

Despite the lack of stationarity in the level of CO_2 time series (meaning it cannot be used to model temperature), one can still assess the answer to the question: “Is there evidence of Granger causality between level of CO_2 and TEMP?”

In answering this question, because the TEMP series is stationary, but the CO_2 series is non-stationary (it is integrated of order one, *I(1)*), the testing procedure is modified slightly. Once again, the levels of both series are used. For each VAR model, the maximum lag length (k) is determined, but then one additional lagged value of both TEMP and CO_2 is included in each equation of the VAR. However, the Wald test for Granger non-causality is applied only to the coefficients of the original k lags of CO_2. Toda and Yamamoto (1995) show that this modified Wald test statistic will still have an asymptotic distribution that is chi-square, even though the level of CO_2 is non-stationary.

Here the relevant Wald Statistic (p-value): Null is there is No Granger Causality from level of CO_2 to TEMP; Number of lags K= 4; Chi-Square 2.531 (p-value = 0.470) .

The lack of statistical significance in the p-value is strong evidence that level of CO_2 does not Granger-cause TEMP.

With the above two assessments done, it is significant that ~~concerning~~ with regard to global surface temperature we are able to discount causality involving the level of CO_2, but establish causality involving first-difference CO_2.

4.2 Relationship between second-difference CO_2 and temperature and Southern Oscillation Index

4.2.1 Priority and correspondence

Given the results of this exploration of correlations involving first-difference atmospheric CO_2, the possibility of the correlation of second-difference CO_2 with climate variables is also explored. The climate variables assessed are global surface temperature and the Southern Oscillation Index (SOI). In this section, data is from the full period for which monthly instrumental CO_2 data is available, 1958 to the present. For this period, the series neither led nor lagged appear as follows (Figure 6).~~:~~

~~Let us look (Figure 6) at the two key pairs of interannually varying factors.~~ For the purpose of this figure, to facilitate depiction of trajectory, second-difference CO_2 (left axis) and SOI (right axis) are offset so that all four curves display a similar origin in 1960.

~~The f~~Figure 6 shows that, alongside the ~~already demonstrated~~ close similarity between first-difference CO_2 and temperature already demonstrated, there is a second apparent distinctive pairing between second-difference CO_2 and SOI.

The figure shows that the overall trend, amplitude and phase – the signature – of each pair of curves is both matched within each pair and different from the other pair. The remarkable sorting of the four curves into two groups is readily apparent. Each pair of results provides context for the other – and highlights the different nature of the other pair of results.

Recalling that (even uncorrected for any autocorrelation)~~,~~ correlational data still holds information concerning regression coefficients, we initially use OLS correlations without assessing autocorrelation to provide descriptive statistics. Table 5 includes, ~~first~~ without any phase-shifting to ~~seek to~~ maximise fit, the ~~full~~ six pairwise correlations arising from all possible combinations of the four variables other than with themselves. Here it can be seen that the two highest correlation coefficients (in bold in the table) are~~,~~ firstly~~,~~ between first-difference CO_2 and temperature, and~~,~~ secondly~~,~~ between second-difference CO_2 and SOI.

In Table 6, phase shifting has been carried out to maximise fit (shifts shown in variable titles in the table). This results in an even higher correlation coefficient for second-difference CO_2 and SOI.

The link between all three variable realms – CO_2, SOI and temperature – can be further observed in Figure 7 and Table 7. Figure 7 shows SOI, second-difference atmospheric CO_2 and first-difference temperature, each of the latter two series phase-shifted for maximum correlation with SOI (as in- Table 5). ~~Concerning~~ Looking at priority, Table 6 shows that maximum correlation occurs when second-difference CO_2 leads SOI. It is also noted that the correlation coefficients for the correlations between the curves shown in Table 6 have all converged in value compared to those shown in Table 5.

~~Concerning~~ Looking at the differences between the curves shown in Figure 7, two of ~~what~~ the major departures ~~there are~~ between the curves ~~are~~ coincide with volcanic aerosols – from the El Chichon volcanic eruption in 1982 and the Pinatubo eruption in 1992 (Lean and Rind 2009). With t~~T~~hese volcanism-related factors taken into account, it is notable (when expressed in the form of the transformations in Figure 7) that the signatures of all three curves are so essentially similar that it is almost as if all three curves are different versions of – or responses to – the same initial signal.

So, a case can be made that first- and second-difference CO_2 and temperature and SOI respectively are all different aspects of the same process.

4.2.2 Time series analysis

~~Let us~~We now assess more formally ~~assess~~ the relationship between second-difference CO_2 and SOI. As for first-difference CO_2 and temperature above, stationarity has been established. Again, ~~similarly to first-difference CO_2 and temperature,~~ there is statistically significant autocorrelation at lags of one and two months, leading to an overall Breusch-Godfrey Test statistic (LMF) of 126.9, with p-value = P(F(12,626) > 126.901) = 1.~~06e~~06 x 10^{-158}.

Table 8 shows the results of a dynamic model with the dependent variable used at each of the two lags as further independent variables~~.~~

~~In Table 8 the results first show (LMF test) that~~; there is now no statistically significant ~~unaccounted-for~~ autocorrelation which has not been accounted for.

~~Further inspection of~~As Table 8 shows, ~~that~~ a highly statistically significant model has been established. As for temperature, it shows that the SOI in a given period is strongly influenced by the SOI of closely preceding periods. Again as for temperature, it provides evidence that there is a clear role in the model for second-difference CO_2.

With this established, it is noted that while the length of series in the foregoing analysis was limited by the start date of the atmospheric CO_2 series (January 1958), high temporal resolution (monthly) SOI goes back considerably further, to 1877. This long period SOI series (for background see Troup (1965)) is that provided by the Australian Bureau of Meteorology, sourced here from the Science Delivery Division of the Department of Science, Information Technology, Innovation and the Arts, Queensland, Australia. As equivalent temperature data is also available (the global surface temperature series already used above (Had~~AD~~CRUT4) goes back as far as 1850), these two longer series are now plotted in Figure 8.

~~What is immediately noted~~Notable is the continuation ~~over this longer period~~ of the striking similarity between the two signatures already shown in Figure 7 over this longer period.

Turning to regression analysis, as previously the Breusch-Godfrey procedure shows that, for lags up to lag 12, the ~~lion's share~~majority of autocorrelation is again restricted to the first two lags. Table 9 shows the results of a dynamic model with the dependent variable used at each of the two lags as further independent variables.

In comparison with Table 8, the extended time series modelled in Table 9 shows a remarkably similar R-squared statistic: 0.466 compared with 0.477. By contrast, the partial regression coefficient for second-difference CO_2 has increased, to 0.14 compared with 0.077. ~~These points made, tThe main finding is that there is little or no difference in the relationship when it is extended back to 1877. (~~It is beyond the scope of this study, but the relationship of SOI and second-difference CO_2 means it is now possible to produce a proxy for monthly atmospheric CO_2 from 1877 –~~:~~ a date approximately 75 years prior to the start ~~in January 1958~~ of the CO_2 monthly instrumental record in January 1958.~~)~~

4.2.3 Granger causality analysis

This section assesses whether second-difference CO_2 can be considered to Granger-cause SOI. This assessment is carried out using data for the period 1959 to 2012~~ data~~.

~~Test r~~Results o~~n~~f ~~the ~~stationarity ~~or otherwise~~tests for~~ of~~ each series are given in Table 10. Each series is shown to be stationary. These results imply that we can approach the issue of possible Granger causality by using a conventional VAR model, in the levels of the data, with no need to use a "modified" Wald test (as used in the Toda and Yamamoto (1995) methodology).

Simple OLS regressions of SOI against separate lagged values of second-difference CO_2 (~~DCO2 (~~including an intercept) confirm the finding that the highest correlation is when a two-period lag is used.

A 2-equation VAR model is needed for reverse-sign SOI and second-difference CO_2. ~~The first task is to determine~~Using SIC, the optimal maximum lag length~~ to be used for the variables. Using the SIC, this~~ is found to be 2 lags. When the VAR model is estimated with this lag structure ~~however ~~(Table 11), testing the null hypothesis that there is no serial correlation at lag order h, shows that there is evidence of autocorrelation in the residuals.

This suggests that the maximum lag length for the variables needs to be increased. The best results (in terms of lack of autocorrelation) were found when the maximum lag length is 3. (Beyond this value, the autocorrelation results deteriorated substantially, but the conclusions below, regarding Granger causality, were not altered.)

Table 12 shows that the preferred, 3-lag model, still suffers a little from autocorrelation. However, as we have a relatively large sample size, this will not impact adversely on the Wald test for Granger causality.

The relevant EViews output from the VAR model is entitled VAR Granger Causality/Block Exogeneity Wald Tests and documents the following summary results –~~:~~ Wald Statistic (p-value): Null is there is No Granger Causality from second-difference CO_2 to sign-reversed SOI; Chi-Square 22.554 (p-value = 0.0001). The forgoing Wald statistic shows that the null hypothesis is strongly rejected –~~:~~ in other words, there is very strong evidence of Granger Causality from second-difference CO_2 to sign-reversed SOI.

4.3 Paleoclimate data

So far, the time period considered in this study has been pushed back in the instrumental data realm to 1877. If non-instrumental paleoclimate proxy sources are used, CO_2 data now at annual frequency can be taken further back. The following example uses CO_2 and temperature data. The temperature reconstruction used here commences in 1500 and is that of Frisia et al. (2003), derived from annually laminated speliothem (stalagmite) records. A second temperature record (Moberg et al. 2005) is from tree ring data. The atmospheric CO_2 record (Robertson et al. ~~(~~2001) is from fossil air trapped in ice cores and from instrumental measurements. The trends for these series are shown in Figure 9.

Visual inspection of the figure shows that there is a strong overall likeness in signature between the two temperature series, and between them and first-difference CO_2. The similarity of signature is notably less with level of CO_2. It can be shown that level of CO_2 is not stationary and, even with the two other series which are stationary, the strongly smoothed nature of the temperature data makes removal of the autocorrelation ~~present~~ impossible. Nonetheless, noting that data uncorrected for autocorrelation still provides valid correlations (Greene 2012) – only the statistical significance is uncertain – it is simply noted that first-difference CO_2 displays a better correlation with temperature than level of CO_2 for each temperature series (Table 13).

4.4 Normalized Difference Vegetation Index (NDVI)

Using the Normalized Difference Vegetation Index (NDVI) time series as a measure of the activity of the land biosphere, this section now investigates the land biosphere as a candidate mechanism for the issue, identified in the Introduction, ~~that~~ of the increasing difference between the observed global surface temperature trend and that suggested by general circulation climate models ~~and that observed~~.

~~The level of atmospheric CO_2 is a good proxy for the IPCC models predicting the global surface temperature trend – : according to IPCC (2013), on decadal to interdecadal time scales and under continually increasing effective radiative forcing (ERF), the forced component of the global surface temperature trend responds to the ERF trend relatively rapidly and almost linearly. This trend can be taken to represent that expected from the operation of the standard anthropogenic global warming model, its mechanism being a physical one in which (IPCC, 2013, NASA 2015) about half of the light reaching Earth's atmosphere passes through the air and clouds to the surface, where it is absorbed and then radiated upward in the form of infrared heat. About 90 percent of this heat is then absorbed by the greenhouse gases and radiated back toward the surface, which is warmed. If greenhouse gases have been increasing (including because ofthrough increasing anthropogenic emissions), that contributes to an increase in the infrared radiation they emit (including that back toward the surface, which is warmed further). On this basis, an indicator of the difference between the climate model trend and the observed temperature is prepared by subtracting the Z-scored actual temperature trend from the Z-scored CO_2 trend. In the paper, this indicator is sometimes termed the climate model/temperature difference or the difference between the level-of-CO_2 model for temperature and the observed temperature.~~

The trend in the terrestrial CO_2 sink is estimated annually as part of the assessment of the well-known global carbon budget (Le Quere at al. 2014). It is noted that there is a risk of ~~involving a~~ circular argument concerning correlations between the terrestrial CO_2 sink and interannual (first-difference) CO_2 because the terrestrial CO_2 sink is defined as the residual of the global carbon budget (Le Quere at al. 2014). By contrast, the Normalized Difference Vegetation Index (NDVI) involves direct (satellite-derived) measurement of terrestrial plant activity. For this reason~~,~~ and because, of the two series, only NDVI is provided in monthly form, we will use only NDVI in what follows.

~~4.4.1. Issues of method concerning the NDVI-related analyses~~

~~Two issues of method arise from the NDVI-related analyses. These are: sensitivity of methods for detecting the order of integration of a time series; and, for the Granger Causality testing used, the optimal selection of the number of lags of the time series variables involved for use in the analysis.~~

~~These two matters issues will be dealt with in turn.~~

~~4.4.1.1. Determination of order of integration of time series~~

~~The data series used until now – the shortest monthly series starting in 1959 – have meant that, using the most commonly used test of series order of integration (the Augmented Dickey-Fuller test (Dickey and Fuller 1981)) it has been unambiguous as to the order of integration of each series.~~

~~The more recent start date arising from the use of the NDVI series – 1981 – has meant that the series used in the NDVI-related analyses have been made up of fewer observations, and are centred over a different period of history compared with the data commencing in 1959.~~

~~This has meant that one series – first-derivative CO_2 – for the data commencing in 1981 has displayed ADF unit root test results which place it on the cusp between *I(0)* and *I(1)*.~~

~~According to Zivot and Wang (2006), the ADF test and another test, the Phillips-Perron test (Phillips and Perron (1988)) have in general very low power to discriminate between *I(0)* and *I(1)* alternatives when the two alternatives are close together. Zivot and Wang (2006) recommend that for maximum power in these circumstances, the tests of Elliot, Rothenberg, and Stock (1996), and Ng and Perron (2001) should be used.~~

~~For this reason, the above – and some further – unit root tests for the order of integration of a time-series are used in this stage of the study. The full list of tests is:~~

- ~~the Augmented Dickey Fuller (ADF) test (Dickey and Fuller 1981); the Phillips-Perron test (Phillips and Perron 1988); the Elliott-Rothenberg-Stock Point Optimal test (Elliot et al. 1996); the Ng-Perron Modified Unit Root test (Ng and Perron 2001). The null hypothesis for the foregoing tests is non-stationarity.~~

- ~~The Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test (Kwiatkowski et al. 1992) is also used. The null hypothesis for this test is stationarity.~~

~~Use of both stationarity and non-stationarity hypotheses can add robustness to the assessment of the order of integration of a time-series.~~

~~For the KPSS and Phillips-Perron tests the bandwidth, b, was selected using the Newey-West method, with the Bartlett kernel. In the remaining unit root tests the Akaike Iinformation Ceriterion (AIC) and the Schwartz Iinformation Ceriterion (SIC) were used to select an optimal maximum lag length (k) for the variables.~~

~~4.4.1.2. Lag-length selection for Granger causality testing~~

~~We turn now to a matter concerning lag-length selection for Granger causality testing.~~

~~Thornton and Batten (1985) assessed the accuracy of Granger tests under a range of lag selection techniques ranging from arbitrarily chosen lags, lags chosen by three statistical criteria, and an extensive search of the lag space.~~

~~Thornton and Batten (1985) conclude:~~

> ~~As a generalization … there appears to be no substitute for selecting a model specification criterion ex ante or for an extensive search of the lag space if one is to ensure that the causality test results are not critically dependent on the judicious (or perhaps fortuitous) choice of the lag structure.~~

~~With this background, in the present study Granger causality testing of NDVI-related data series pairs was conducted as follows:~~

- ~~If hypothesis and the prior dynamic regression modelling used suggested a possible Granger link, tests were run based on model lags suggested from the results of the prior modelling;~~
- ~~If a Granger causality test set up as just described was positive at its default lag selection settings, that result was reported. If not, an extensive search of the lag space was carried out. That result was reported, positive or negative.~~

~~4.4.2. Results~~

~~Results are organised under the following headings:~~

~~4.4.2.1. Order of integration of series~~
~~4.4.2.2. Preparation of the pooled global NDVI series used~~
~~4.4.3. Relationship between climate variables and NDVI~~

~~4.4.2.1. Order of integration of series~~

~~As mentioned in Section 3,. *Data and methods,* of the ACPD paper, any two or more time series being assessed by time series regression analysis must be stationary in the first instance, or be capable of being transformed into a new stationary series (by differencing). A series is stationary if its properties (mean, variance, covariances) do not change with time (Greene 2012).~~

~~In the first instance, Augmented Dickey-Fuller (ADF) stationarity tests are calculated for each variable. Results and lag lengths chosen are given in Table 14.~~

~~The table shows that for this data from 1981, level of CO_2 and temperature are *I(0)*, as they were for the data from 1959. This is not the case for first-derivative CO_2.~~

~~As can be seen, the ADF test result for first-derivative CO_2 for data from 1981 to 2012 of 0.0895 shows that first-derivative CO_2 approaches the statistical significance level of 0.05 required to be *I(0),* but does not reach it. In other words, for first derivative CO_2, the two *I(0)* and *I(1)* alternatives are close together.~~

~~For the reasons given by Zivot and Wang (2006) above, the order of integration of first-derivative CO_2 is therefore assessed by the wider range of tests for order of integration listed above, including the two tests nominated by Zivot and Wang (2006) as more sensitive when *I(0)* and *I(1)* alternatives are close together.~~

~~The results are given in Tables 15 to 17. All tests were run at their automatic setting for lags. For all tests, the null hypothesis is that the series is *I(1)*, and the alternative is that it is *I(0)*; except for the KPSS test (where the null hypothesis is that the series is *I(0)*, and the alternative is that it is *I(1)*).~~

~~The ADF tests have been applied with an allowance for a drift and trend in the data, and the SIC was used to select degree of augmentation, k. For the KPSS tests the bandwidth, b, was selected using the Newey-West method, with the Bartlett kernel.~~

~~The significance level each test meets or surpasses is indicated by an asterisk in each column of the table.~~

~~Tables 15 to 17 show that the extra tests are not unanimous for the first-derivative CO_2 series.~~

~~The test using the alternative Schwartz or Akaike Information Criteria agree for two tests, DF-GLS and Ng-Perron. Here the *I(0)* statistical significance was between 0.05 and 0.1. For the other two tests, the Akaike Information Criterion gave lower probabilities: Elliott-Rothenberg-Stock Point Optimal between 0.05 and 0.1; ADF greater than 0.1. For the Schwartz Information Criterion the figures were p<.01 and statistical significance was between 0.05 and 0.1.~~

~~Finally, there were two tests – KPSS and Phillips-Perron – which used bandwidth criteria for the selection of an optimal lag length. Each of these tests characterised first-derivative CO_2 as *I(0)*: statistical significance was at 0.05 and 0.01 respectively.~~

~~One of the tests recommended by Zivot and Wang (2006) for a series on the cusp of *I(0)* and *I(1)* – that of Elliot, Rothenberg, and Stock (1996) – gives a result for first difference CO_2 from 1981 to 2012 of *I(0)* at better than the 1% level; however, the similarly recommended Ng and Perron test gives *I(0)* at between the 5% and 10% level. Overall, three of the ten tests displayed probabilities of 5% or better, a further remaining six of between 5% and 10%. One of the 10 tests, the ADF under the Akaike Information Criterion, gave a result of greater than 10%.~~

~~It can be argued that the foregoing tests overall lean towards CO_2 from 1981 being *I(0)*. To be conservative, however, in the following analyses first-derivative CO_2 is assessed separately both as *I(0)* and *I(1)*.~~

4.4.1. Preparation of the global NDVI series used in this paper

Globally aggregated GIMMS NDVI data from the Global Land Cover Facility site is available from 1980 to 2006. This dataset is referred to here as NDVIG. Spatially disaggregated GIMMS NDVI data from the GLCF site is available from 1980 to the end of 2013. An analogous global aggregation of this spatially disaggregated GIMMS NDVI data – from 1985 to end 2013 – was obtained from the Institute of Surveying, Remote Sensing and Land Information, University of Natural Resources and Life Sciences, Vienna. This dataset is abbreviated to NDVIV.

~~The Normalized Difference Vegetation Index (NDVI) involves direct (satellite-derived) measurement of terrestrial plant activity.~~

~~To provide the full temporal span of the global NDVI data set used in this study, two NDVI series aggregated to global level were pooled. Each of the two series is derived from the same underlying spatially disaggregated Global Inventory Modeling and Mapping Studies (GIMMS) data set provided by the Global Land Cover Facility (GLCF) of the University of Maryland. This data is derived from imagery obtained from the Advanced Very High Resolution Radiometer (AVHRR) instrument carried by NOAA meteorological satellites.~~ Pooling t~~T~~he two series enabled the longest time span of data aggregated at global level.

~~Globally aggregated GIMMS NDVI data from the Global Land Cover Facility (GLCF) site is available from 1980 to 2006. This dataset is referred to here as NDVIG. Spatially disaggregated GIMMS NDVI data from the Global Land Cover Facility (GLCF) site is available from 1980 to end 2013. An analogous global aggregation of this spatially disaggregated GIMMS NDVI data – from 1985 to end 2013 – was obtained from the Institute of Surveying, Remote Sensing and Land Information, University of Natural Resources and Life Sciences, Vienna. This dataset is abbreviated to NDVIV.~~

The~~se~~ two serie~~dataset~~s were pooled as follows.

Figure 10 shows the appearance of the two series. Each series is Z-scored by the same common period of overlap (1985-2006). The extensive period of overlap can be seen, as can the close similarity in trend between the two series.

The figure also shows that the seasonal adjustment smoothings vary between the two series. Seasonality was removed for the NDVIV series using the 13 month moving average smoothing used throughout this paper. This required two passes using the 13 month moving average, which leads to a smoother result than seen for the NDVIG series.

Pretis and Hendry (2013)~~ (2013)~~ observe that pooling data (i) from very different measurement systems and (ii) displaying different behaviour in the sub-samples can lead to errors in the estimation of the level of integration of the pooled series.

The first risk of error (from differences in measurement systems) is overcome here as both the NDVI series are from the same original disaggregated data set. The risk associated with the sub-samples displaying different behaviour and leading to errors in levels of integration is considered in the following section by assessing the order of each input series separately, and then the order of the pooled series.

Table 14 provides order of integration test results for the three NDVI series. The analysis shows all series are stationary (*I(0)*).

~~Because of the comparability of the NDVI series specified above, it was~~It is, therefore, valid to pool the two ~~sreeis~~series. ~~This~~Pooling was done ~~the series were pooled~~ by ~~adding~~ appending the Z-scored NDVIV data to the Z-scored NDVIG data at the point where the Z-scored NDVIG data ended (in the last month of 2006).

~~of the~~

~~of this question~~ As discussed ~~above~~in the Introduction, Figure 1 shows that ~~there~~ since around the year 2000 there is an increasing difference between the temperature projected by a mid-level IPC~~P~~C model and that observed.

Any cause for this increasing difference must itself show an increase in activity over this period.

The purpose of this section is, therefore: (i) to derive an initial simple indicative quantification of the increasing difference between the temperature model and ~~observation~~ observation; and (ii) to assess whether global NDVI is increasing. If NDVI is increasing, this is support for NDVI being a candidate for the cause of the temperature model-observation difference. If there is a statistically significant relationship between the two increases, this is further support for NDVI being a candidate for the cause of the model-observation difference, and hence worthy of further detailed research. A full analysis of this question is beyond the scope of the present paper.

4.4.2 Preparation of the indicative series for the difference between the temperature projected from a mid-level IPC~~P~~C model and that observed

A simple quantification of the difference between the temperature projected from a mid-level IPC~~P~~C model and that observed can be derived by subtracting the (Z-scored) temperature projected from the IPCC mid-range scenario model (CMIP3, SRESA1B scenario~~)~~ run for the IPC~~P~~C fourth assessment report (IPCC~~,~~ 2007)) shown in Figure 1, from the observed global surface temperature also shown in Figure 1. This quantification is depicted in Figure 13 for monthly data and, to reduce the influence of noise and seasonality, in Figure 14 for the same data pooled into three-year bins.

4.4.3. Comparison of the pooled NDVI series with the difference between projected and observed global surface temperature

Figure 13, displaying monthly data, compares NDVI with the difference between the temperature projected from an IPCC mid-range scenario model (CMIP3, SRESA1B scenario~~)~~ run for the IPPC fourth assessment report (IPCC 2007)) and global surface temperature (red dotted curve). Both curves rise ~~towards~~in more recent years.

~~To assess the nature of the core trends in each series, in x Figure 14 information on short- term changes in the series is removed by pooling the monthly data shown in Figure 14 into 36-month bins.14~~

The trends for the ~~curves~~36-month pooled data in Figure 14 show considerable commonality. OLS regression analysis of the relationship between the curves in Figure 14 shows that the best fit between the curves involves no lead or lag. The correlation between the curves displays an adjusted R-squared value of 0.86. This is statistically significant ($p = 0.00185$). As expected with such aggregated multi-year data, the relationship shows little or no autocorrelation (Test statistic: LMF = 1.59 with p-value = $P(F(5,3) > 1.59) = 0.37$).

The ~~foregoing~~ similarity between the trend in the NDVI and the difference between IPCC temperature modelling and observed temperature is evidence supporting the possibility that the NDVI may contribute to the observed global surface temperature departing from the IPCC modelling.

~~The process we follow in this section is outlined below.:~~

~~Relevant correlations involving first-derivative CO_2 characterised as *I(1)* are first assessed because of the near-stationarity of first-derivative CO_2 for the period 1981 to 2012.~~

~~As a check, we assess whether first-derivative CO_2 for the period from 1981 to 2012 has similar relationships to global surface temperature to those seen for the period 1959 to 2012.~~

~~We then explore remaining questions from our hypothesis concerning Granger causality and NDVI. These are firstly that there is Granger causality from first-derivative CO_2 to NDVI, and secondly from temperature to NDVI.~~

~~Finally, we ask whether NDVI is Granger-causal for the difference between the level-of-CO_2 model for temperature and the observed temperature.~~

~~Where each series in a series pair is stationary, assessments are done for each of the questions above both by OLS dynamic regression modelling, and by Granger causality testing. The dynamic modelling is informative in itself, but as outlined above also informs correct model specification in terms of optimising model independent-variable lag for Granger causality testing (Thornton and Batten 1985).~~

~~The following information is relevant to each of the instances of OLS dynamic regression modelling which follow. As described in Section 4.1.3, *Time series*~~

~~*analysis,* of the ACPD paper, for OLS dynamic regression modelling, one must assess the extent (if any) of autocorrelation affecting the time series model. This is done by obtaining diagnostic statistics from an OLS regression. This regression shows, by means of the Breusch-Godfrey test for autocorrelation (up to order 20 – that is, including all monthly lags up to 20 months), .~~

~~If autocorrelation is found, it is taken to be a consequence of an inadequate specification of the temporal dynamics of the relationship being estimated. With this in mind, a dynamic model (Greene 2012) with sufficient lagged values of the dependent variable as additional independent variables is estimated.~~

~~If the autocorrelation can be removed, this will be shown by the use of the LMF test, supporting the use of this dynamic model specification.~~

~~4.4.3.1. First-derivative CO_2 as *I(1)*~~

~~Characterising first-derivative CO_2 as *I(1)* means dynamic regression modelling of the type presented above cannot be used. As in Section 4.1.4, *Granger causality analysis,* of the ACPD paper, one can still assess the answer to the question: "Is there evidence of Granger causality between first-derivative CO_2 characterised as *I(1)* and relevant variables?" In this case the variables are global surface temperature and NDVI.~~

~~4.4.3.1.1 Does first-derivative CO_2 as *I(1)* display Granger causality of global surface temperature ?~~

~~In answering this question, because the TEMP series is stationary, but the first-difference CO_2 series is being treated as non-stationary (as integrated of order one, *I(1)*), the testing procedure is modified slightly. Once again, the levels of both series are used. This time a standard Vector Autoregressive (VAR) model is used. For each VAR model, the maximum lag length is determined, but then one additional lagged value of both TEMP and first-difference CO_2 is included in each equation of the VAR. However, the Wald test for Granger non-causality is applied only to the coefficients of the original k lags of first-difference CO_2. Toda and Yamamoto (1995) show that~~

~~this modified Wald test statistic will still have an asymptotic distribution that is chi-square, even though the level of CO_2 is non-stationary.~~

~~Here the relevant Wald Statistic for the null hypothesis – that is there is no Granger causality from first-derivative CO_2 as *I(0)* to temperature – is shown in Table 19 to produce a Chi-Square of 32.79 (p=0.0001).~~

~~The high statistical significance in the p-value is strong evidence that first-derivative CO_2, even treated as *I(1),* still displays Granger causality of temperature.~~

~~4.4.3.1.2 Does first-derivative CO_2 as *I(1)* display Granger causality of NDVI?~~

~~The identical steps to those in the previous section are used. Here the relevant Wald Statistic (Null hypothesis that is there is No Granger Causality from first-derivative CO_2 as *I(1)* to temperature) is shown in Table 20 to produce a Chi-Square of 3.184 (p=0.9223).~~

~~Hence in contrast with temperature, for the *I(1)* characterisation first-derivative CO_2 does *not* display Granger causality of NDVI.~~

~~4.4.3.2 Characterising first-derivative CO_2 as *I(0)*~~

~~4.4.3.2.1. Does first-derivative CO_2 as *I(0)* still display Granger causality of temperature for the 1981 to 2012 period?~~

~~A key finding earlier in the paper is that for the period 1959 to 2012, first-derivative CO_2 leads global surface temperature, is significant in an OLS dynamic regression model, and is Granger-causal of global surface temperature. This section repeats that analysis (characterising first-derivative CO_2 as *I(0)*) for the period used for the NDVI data, 1981 to 2012.~~

~~Figure 11 displays the data series, and shows the similarity between the Z-scored curves.~~

~~Inspection of Table 21 shows that a highly statistically significant model has been established. First it shows that the temperature in a given period is strongly influenced by the temperature of closely preceding periods. Further it provides evidence that there is also a clear, highly statistically significant role in the model for first-derivative CO_2 for the period from 1981 to 2012, just as for the period from 1959 to 2012.~~

~~The next section assesses whether first-derivative CO_2 can be considered to display Granger causality for global surface temperature for the 1981 to 2012 period.~~

~~The relevant EViews output is from the Pairwise Granger Causality Test. Table 22 documents the following summary results: F-statistic 5.02 (p-value = 0.01). The forgoing statistic shows that the null hypothesis is rejected : in other words, there is strong evidence of Granger Causality from first-derivative CO_2 to global surface temperature for the shorter 1981 to 2012 period.~~

~~The table shows that the same first-derivative CO_2 which, characterised as *I(1)*, displayed Granger causality for temperature (Table 19), characterised as *I(0)* also displays Granger causality for temperature.~~

~~4.4.3.3. Granger causality of NDVI~~

~~4.4.3.3.1 Does first-derivative CO_2 as *I(0)* display Granger causality of NDVI ?~~

~~Figure 12 shows Z-scored values for first-derivative CO_2 and NDVI. Considerable similarity between the signatures is seen.~~

~~An OLS dynamic regression model is set up using the procedure outlined in Section 3.2 above. Results are given in Table 23.~~

~~Inspection of Table 23 shows that a highly statistically significant model has been established. First it shows that, as seen for temperature, the NDVI in a given period is strongly influenced by the NDVI of closely preceding periods. Further it provides evidence that there is also a statistically significant role in the model for first-derivative CO_2.~~

~~The next sections assess whether first-derivative CO_2 can be considered to display Granger causality of NDVI. Two assessments are made using different criteria for lag selection: the first using the Akaike Information Criterion; the second using the method of extensive search of the lag space (Thornton and Batten 1985).~~

~~The relevant EViews output is from the Pairwise Granger Causality Test and Table 24 documents the following summary results: F-statistic 3.01 (p-value = 0.05).~~
~~This statistic shows that using the Akaike Information Criterion for lag selection, the null hypothesis is very slightly accepted – in other words, for the AIC there is (by a very narrow margin) an absence of evidence of Granger Causality from first-derivative CO_2 to NDVI.~~

~~Given the above result, what is the result from the extensive search method? The relevant EViews output is again from the Pairwise Granger Causality Test and Table 25 provides the following results: F-statistic 5.11 (p-value = 0.024).~~
~~This statistic shows that using the extensive search method for lag selection, the null hypothesis is rejected by a greater amount than for the AIC method, which reaches statistical significance – in other words, there is evidence of Granger Causality from first-derivative CO_2 to NDVI.~~

~~In summary, under the *I(0)* characterisation, first-derivative CO_2 displays Granger causality of NDVI, while under *I(1)*, it does not.~~

~~4.4.3.3.2 Does TEMP display Granger causality of NDVI?~~

~~Figure 13 shows Z-scored values for first-derivative CO_2 and NDVI. With the exception of the period 2003-2004, considerable similarity between the signatures is seen.~~

~~An OLS dynamic regression model is set up using the procedure outlined in Section 3.2 above. Results are given in Table 26.~~

~~Inspection of Table 26 shows that a highly statistically significant model has been established. First it shows that, as seen for first-derivative CO_2, the NDVI in a given period is strongly influenced by the NDVI of closely preceding periods. Further it provides evidence that there is also a highly statistically significant role in the model for temperature.~~

~~The next section assesses whether temperature can be considered to display Granger causality of NDVI. The relevant EViews output is again from the Pairwise Granger Causality Test and is shown in Table 27.~~

~~Table 27 documents the following summary results: F-statistic 11.59 (p-value =1.00E-05). This statistic shows that the null hypothesis is rejected, by a highly statistically significant amount – in other words, there is strong evidence of Granger causality from temperature to NDVI.~~

~~4.4.3.43 Does NDVI display Granger causality of the difference between the level-of-CO_2 model for temperature and the observed temperature?~~

~~Figure 14 shows Z-scored values for f NDVI and the difference between the Z-scored level of atmospheric CO_2 (standing for the level-of-CO_2 model for temperature) and the Z-scored observed temperature. Considerable similarity between the signatures is seen.~~

~~An OLS dynamic regression model is set up using the procedure outlined in Section 3.2 above. Results are given in Table 28.~~

~~Inspection of Table 28 shows that a highly statistically significant model has been established. First it shows that the difference between the level-of-CO_2 model for temperature and the observed temperature in a given period is strongly influenced by that of closely preceding periods. Further it provides evidence that there is also a clear, highly statistically significant role in the model for NDVI.~~

~~With these results, Figure 15 is as for Figure 14 but with the NDVI series led indicated by the OLS dynamic regression modelling in Table 25.~~

~~A marked overall similarity between the two series is seen, both in core trend (as illustrated by polynomial curves of best fit) and in details of signature.~~

~~The next sections assess whether NDVI can be considered to display Granger causality of the difference between the level-of-CO_2 model for temperature and the observed temperature. As for first-derivative CO_2 and NDVI in Section 3.2.2.1 above, two assessments are made using different criteria for lag selection: the first using the Akaike Information Criterion; the second using the method of extensive search of the lag space (Thornton and Batten 1985).~~

~~The relevant EViews output is from the Pairwise Granger Causality Test and Table 29 documents the following summary results: F-statistic 1.03 (p-value = 0.36). This statistic shows that using the Akaike Information Criterion for lag selection, the null hypothesis is rejected – in other words, for the AIC there is an absence of evidence of Granger causality from NDVI to the difference between the level-of-CO_2 model for temperature and the temperature observed.~~

~~The relevant EViews output from the extensive search method is again from the Pairwise Granger Causality Test and Table 30 documents the following summary results: F-statistic 1.81 (p-value = 0.03). This statistic shows that using the extensive~~

~~search method for lag selection, the null hypothesis is rejected – in other words, there is evidence of Granger causality from first-derivative CO_2 to NDVI.~~

~~The way in which the search reveals the statistically significant lag is depicted visually in Figure 16. Note the statistical significance of results of tests based on lags 14 to 16.~~

~~Considering the results of Section 4.4 overall, the following analysis is made.~~

~~Even considering first-derivative CO_2 as possibly being *I(1)* for the period 1981 to 2012, it is believed that there is sufficient redundancy in the range of data series and relationships used in the NDVI section to answer the question as to whether vegetation at global scale causes the difference between the linear CO_2-temperature model and observed temperature.~~

~~The redundancy comes about as follows. The Granger-causality with Toda-Yamamoto procedure results presented in Tables 16 and 17 show that, while first-derivative CO_2 as *I(1)* does not display Granger causality of NDVI, first-derivative CO_2 as *I(1)* does display Granger causality of temperature. And temperature characterised as *I(0)* – as it is unambiguously is shown to be (Table 11) – is shown to display Granger causality of NDVI (Table 14).~~

~~So whichever level of integration first-difference CO_2 is characterised as, adequate dynamic-regression and Granger-causality linkages are in place for the flow of causality from first-derivative CO_2 and temperature to NDVI.~~

~~It is also shown, in this case without ambiguities concerning the *I(0)* nature of series, that NDVI displays Granger causality of the difference between the linear CO_2-temperature model and observed temperature.~~

~~In conclusion, it is considered that the results in this section show a Granger-causal chain from first-derivative CO_2 and temperature to NDVI, and from NDVI to the difference between the linear CO_2-temperature model and observed temperature.~~

5 Discussion

~~Firstly it is noted that t~~The results in this paper show that there are clear links – ~~-~~ at the highest standard of non-experimental causality~~:~~ — that of Granger causality —— between first- and second-difference CO_2 and the major climate variables of global surface temperature and the Southern Oscillation Index, respectively.

~~Concerning The results show that r~~Relationships between first- and second-difference CO_2 and climate variables are present for all the time scales studied~~: that is~~, including temporal start points situated as long ago as 1500. In the instances where time series analysis accounting for autocorrelation could be successfully conducted, the results were always statistically significant. For the further instances (for those studies using data series commencing before 1877) the data was not amenable to time series analysis – ~~-~~ and therefore also not amenable to testing for Granger causality – ~~-~~ due to the strongly smoothed nature of the temperature data available which made removal of the autocorrelation impossible (see Section 4.3). Nonetheless, the scale of the non-corrected correlations observed was~~ere~~ of the same order of magnitude as those of the instances that were able to be corrected for autocorrelation.

Given the time scales over which these effects are observed, ~~taken as a whole~~ the results taken as a whole clearly suggest that the mechanism observed is long term, and not, for example, a creation of the period of the steepest increase in anthropogenic CO_2 emissions, a period which commenced in the 1950s (IPCC 2014). Taking autocorrelation fully into account in the time series analyses demonstrates the major role of immediate past instances of the dependent variable (temperature, and SOI) in influencing its own present state. This was found in all cases where time series models could be prepared. This was not to detract from the role of first- and second-difference CO_2 – in all relevant cases, they were significant in the models as well.

According to Wilks (1995) and Mudelsee (2010), such autocorrelation in the atmospheric sciences also called persistence or "memory" is characteristic for many types of climatic fluctuations.

In the specific case of the temperature and first-difference CO_2 relationship, the significant autocorrelation for temperature occurred with present temperature being affected by the immediately prior month and the month before that. As mentioned above, for atmospheric CO_2 and global surface temperature, others (Sun and Wang 1996; Triacca 2005; Kodra et al. 2011; Attanasio and Triacca 2011; Attanasio 2012; Stern and Kaufmann 2014) have conducted Granger causality analyses involving the use of lags of both dependent and independent variables. These studies, however, are not directly comparable with the present study. Firstly, while reporting the presence or absence of Granger causality, the studies did not report lead or lag information. Secondly, the studies used annual data, so could not investigate the dynamics of the relationships at the interannual (monthly) level where our findings were greatest.

The anthropogenic global warming (AGW) hypothesis has two main dimensions (IPCC 2007; Pierrehumbert 2011): (i) that increasing CO_2 causes increasing atmospheric temperature (via a radiative forcing mechanism) and (ii) that most of the increase in atmospheric CO_2 in the last hundred years has been due to human causes.

The results presented in this paper are supportive of the AGW hypothesis for two reasons: firstly, increasing atmospheric CO_2 is shown to drive increasing temperature; and secondly, the results deepen the evidence for a CO_2 influence on climate in that second-difference CO_2 is shown to drive the SOI.

The difference between this evidence for the effect of CO_2 on climate and that of the standard AGW hypothesis is that the standard model proposes that temperature will rise roughly linearly with atmospheric CO_2, whereas the present results show that the climate effects result from persistence of previous effects and from *rates of change* of CO_2.

On the face of it, then, this model seems to leave little room for the linear radiative forcing aspect of the AGW hypothesis.

However more research is needed in this area.

Reflection on Figure 1 shows that the radiative mechanism would be supported if a second mechanism existed to cause the difference between the temperature projected for the radiative mechanism and the temperature observed. The observed temperature would then be seen to result from the addition of the effects of these two mechanisms.

As discussed in the Introduction, Hansen et al. (2013) have suggested that the mechanism for the pause in the global temperature increase since 1998 may be the planetary biota, in particular the terrestrial biosphere. As an initial indicative quantified characterisation of this possibility, Section 4.4 derived a simple measure of the increasing difference between the global surface temperature trend projected from a mid-range scenario climate model and the observed trend. This depiction of the difference displayed a rising trend. The time series trend for the globally aggregated Normalized Difference Vegetation Index – which represents the changing levels of activity of the terrestrial biosphere was also presented. This was shown also to display a rising trend.

If by further research, for example by Granger causality analysis, the global vegetation can be shown to embody the second mechanism, this would be evidence that the observed global temperature does result from the effects of two mechanisms in operation together – the radiative, level-of-CO_2 mechanism, with the biological first-difference of CO_2 mechanism.

Hence the biosphere mechanism would supplement, rather than replace, the radiative mechanism.

Further comprehensive time series analysis of the NDVI data and relevant climate data, beyond the scope of the present paper, could throw light on these questions.

~~A further notable finding T demonstratesis the major role of immediate past instances of the dependent variable in influencing its own present state. This was found in all cases where time series models could be prepared, and was true for temperature, and~~

~~SOI. This was not to detract from the role of first- and second-difference CO_2 – in all relevant cases, they were significant in the models as well.~~

~~Tthe anthropogenic global warming hypothesis states that increased global warming is caused in part by increased atmospheric carbon dioxide, and that, especially since the 1950s, the increased human burning of fossil fuel has been a major contributor to the increased atmospheric CO_2 content which has come about.~~

~~Tthe results presented in this paper are supportive of the anthropogenic global warming hypothesis in its aspect of which states that CO_2 affects temperature. This is simply because (first-difference) atmospheric CO_2 is shown to drive global temperature. The results also deepen the evidence for a CO_2 influence on climate in that second-difference CO_2 is shown to drive the SOI.~~

~~The difference between this evidence for the effect of CO_2 on climate and that of the standard AGW hypothesis is that the standard model has it that temperature will rise roughly linearly with atmospheric CO_2, whereas as the present results show the climate effects are from autocorrelation and rates of change of CO_2 .~~

~~However, concerning temperature, as stated at the outset there is now a significant gap now of some 16 years in length between the projections from the linear CO_2 model and the observed global surface temperature trend, whereas there is no such gap between projection and observation from the first-difference CO_2 model.~~

~~Turning to potential mechanisms for the effect, it was noted above that Hansen et al. (2013) have suggested that the mechanism for the pause in the global temperature increase since 1998 might be the planetary biota, in particular the terrestrial biosphere.~~

~~As an initial indicative quantified characterisation of this possibility, Section 4.4 derives a simple measure of the increasing difference between the global surface temperature trend projected from a mid-range scenario climate model and the trend observed. This depiction of the difference displays a rising trend. The time series trend for the globally aggregated Normalized Difference Vegetation Index – which represents the changing levels of activity of the terrestrial biosphere - is also presented.~~

~~This is shown also to display a rising trend. The relationship between the two trends, for pooled data, is substantial and statistically significant.~~

~~Further comprehensive time series analysis of this data is beyond the scope of the present paper, but the above result provides further evidence that the terrestrial biosphere mechanism should be considered a candidate cause of the departure of temperature from that predicted by the level-of-CO_2 mechanism alone.~~

References

Adams, J. M. and Piovesan, G.: Long series relationships between global interannual CO_2 increment and climate: Evidence for stability and change in role of the tropical and boreal-temperate zones. Chemosphere, 59, 1595 – 1612, 2005.

Attanasio, A. and Triacca, U.: Detecting human influence on climate using neural networks based Granger causality," Theor. Appl. Climatol., 103,1-2,103-107, 2011.

Attanasio, A.: Testing for linear Granger causality from natural/anthropogenic forcings to global temperature anomalies Theor. Appl. Climatol. 110:281–289, 2012.

Bacastow, R. B.: Modulation of atmospheric carbon dioxide by the southern oscillation, Nature, 261, 116–118, 1976.

Banerjee, A. Dolado, J. Galbraith, J.W. and Hendry, D.F.: Co-integration, error-correction, and the econometric analysis of non-stationary data. Oxford University Press, Oxford, 1993.

Barichivich, J., Briffa, K. R., Myneni, R. B., Osborn, T. J., Melvin, T. M., Ciais, P., Piao, S., and Tucker, C.: Large-scale variations in the vegetation growing season and annual cycle of atmospheric CO_2 at high northern latitudes from 1950 to 2011, Glob. Change Biol., 19, 3167–3183, 2013.

Beenstock, M., Reingewertz, Y., and Paldor, N.: Polynomial cointegration tests of anthropogenic impact on global warming, Earth Syst. Dynam., 3, 173–188, doi:10.5194/esd-3-173-2012, 2012.

Bellenger, H., Guilyardi, E., Leloup, J., Lengaigne, M., and Vialard, J.: ENSO representation in climate models: from CMIP3 to CMIP5, Clim. Dynam., 42, 1999-2018, 2014.

Breitung, J. and Swanson, N. R.: Temporal aggregation and spurious instantaneous causality in multiple time series models. Journal of Time Series Analysis, 23, 651-665, 2002.

Canty, T., Mascioli, N. R. Smarte, M. D. and Salawitch R. J. An empirical model of global climate – part 1: A critical evaluation of volcanic cooling, Atmos. Chem. Phys. 13 3997–4031 2013.

Chen, X., and Tung, K. Varying planetary heat sink led to global-warming slowdown and acceleration. Science 345, 897, DOI: 10.1126/science.1254937, 2014.

Christriano, L. J. and Eichenbaum, M.: Temporal aggregation and structural inference in macroeconomics. Carnegie-Rochester Conference Series on Public Policy, 26, 63-130, 1987.

Denman, K.L., G. Brasseur, G. Chidthaisong, A. Ciais, P. P.M. Cox, P.M. Dickinson, R.E. Hauglustaine, D. Heinze, Holland, C.E, Jacob, D. Lohmann, U. Ramachandran, S. da Silva Dias, P.L. Wofsy, S.C. and Zhang, X.: Couplings between changes in the climate system and biogeochemistry, Climate Change 2007: The physical science basis. Contribution of working group I to the fourth assessment report of the intergovernmental panel on climate change [Solomon, S. Qin,D. Manning, M. Chen, Z. MMarquis, M. Avery, K.B. Tignor, M. and Miller, H.L. (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 2007.

Dickey, D.A. and Fuller, W.A.: Distribution of the estimators for autoregressive time series with a unit root, Journal of the American Statistical Association, 74, 427–431, 1979.

Dickey, D. A. and Fuller, W. A.: Likelihood ratio statistics for autoregressive time series with a unit root, Econometrica, 49, 1057–1072, 1981.

Diebold, F. X.: Discussion: Effect of seasonal adjustment filters on tests for a unit root. Journal of Econometrics, 55, 99-103, 1993.

Dieleman, W. I. J. Vicca, S. Dijkstra, F. A. Hagedorn, F. Hovenden, M. J. Larsen, K. S. Morgan, J. A.,Volder, A. Beier, C. Dukes, J. S. King, J. Leuzinger, S. Linder, S. Luo, Y. Oren, R. De Angelis, P. Tingey, D. Hoosbeek, M. R. and Janssens, I. A. Simple additive effects are rare: a quantitative review of plant biomass and soil process responses to combined manipulations of CO_2 and temperature, Glob. Change Biol., 18, 2681–2693, 2012.

Elliott, G., Rothenberg T. J.. and Stock J. H.: Efficient tests for an autoregressive unit root, Econometrica, 64, 813-836, 1996.

Folland C.K., Colman A.W., Smith D.M., Boucher O., Parker D.E., and Vernier J.P. : High predictive skill of global surface temperature a year ahead, Geophys. Res. Lett., 40, 761–767, 2013.

Foster, G. and Rahmstorf, S.: Global temperature evolution 1979–2010, Environ. Res. Lett., 6, 044022, 2011.

Franses, P. H.: Moving average filters and unit roots. Economics Letters, 37, 399-403., 1991.

Frisia, S., A. Borsato, N. Preto, and F. McDermott.: Late Holocene annual growth in three Alpine stalagmites records the influence of solar activity and the North Atlantic Oscillation on winter climate, Earth and Planetary Science Letters, 216, 411–424, 2003.

Fyfe, J. C., Gillett, N.P, and Zwiers, F. W.: Overestimated global warming over the past 20 years, Nature Climate Change, 3 767–769, 2013.

Fyfe J.C and Gillett, N.P.: Recent observed and simulated warming, Nature Climate Change, 4, 150-151, 2014.

Ghysels, E.: Unit root tests and the statistical pitfalls of seasonal adjustment: The case of U.S. postwar real gross national product. Journal of Business and Economic Statistics, 8, 145-152, 1990.

Ghysels, E. and Perron, P.: The effect of seasonal adjustment filters on tests for a unit root. Journal of Econometrics, 55, 57-98, 1993.

Granger, C.W.J.: Investigating causal relations by econometric models and cross-spectral methods, Econometrica, 37, 3, 424-438, 1969.

Greene, W. H.: Econometric Analysis (7th ed.), Prentice Hall, Boston, 2012.

Gnu Regression, Econometrics and Time-Series Library. GRETL 1.7.5. Available from: *http://gretl.sourceforge.net/*[Accessed April 23, 2008

Gribbons, B. and Herman, J.: True and quasi-experimental designs. Practical assessment, research and evaluation, 5, http://PAREonline.net/getvn.asp?v=5&n=14, 1997.

Guemas V., Doblas-Reyes F.J., Andreu-Burillo I. and Asif M.: Retrospective prediction of the global warming slowdown in the past decade, Nature Climate Change, 3, 649–653, 2013.

Guilyardi, E., Bellenger H., Collins M., Ferrett S., Cai, W., and Wittenberg A.: A first look at ENSO in CMIP5, Clivar. Exch., 17, 29–32, 2012.

Gulasekaran, R. and Abeysinghe,T.: The distortionary effects of temporal aggregation on Granger causality. Working Paper No. 0204, Department of Economics, National University of Singapore, 2002.

Ghosh, S. and Rao, C. R. eds.: Design and Analysis of Experiments, Handbook of Statistics, 13, North-Holland, 1996.

Hansen, J., Kharecha, P., and Sato, M.: Climate forcing growth rates: doubling down on our Faustian bargain, Environ. Res. Lett., 8, 2013.

Hidalgo, F. and Sekhon, J.: Causality. In Badie, B., Berg-Schlosser, D., and Morlino, L. (Eds.), International encyclopedia of political science, 204-211, 2011.

Holbrook, N.J. Davidson, J. Feng, M. Hobday, A.J. Lough, J.M. McGregor, S. and Risbey, J.S.: El niño-southern oscillation, In: A marine climate change impacts and adaptation report card for Australia 2009, (Eds. Poloczanska, E.S. Hobday, A.J. and Richardson, A.J.) NCCARF Publication, 05/09, 2009.

Hume D.: An enquiry into human understanding (1751) cited in: Hidalgo, F., & Sekhon, J.: Causality. In Badie, B., Berg-Schlosser, D. & Morlino, L. (Eds.) International encyclopedia of political science, 204-211, 2011.

Hyndman, R.J.: Moving averages. in Lovirc, M. (ed.), International encyclopedia of statistical science. 866-869 Springer, New York, 2010.

IHS EViews: *EViews 7.2*, Irvine CA. , 2011.

Imbers, J., Lopez, A., Huntingford, C., and Allen M. R.: Testing the robustness of the anthropogenic climate change detection statements using different empirical models, J. Geophys. Res.-Atmos., 118, 3192–3199, 2013.

IPCC: Climate Change 2007: The physical science basis. Contribution of working group I to the fourth assessment report of the intergovernmental panel on climate change [IPCC, Qin, D., Manning, M., Chen, Z., Marquis, M., Avery, K.B., Tignor, M. and Miller, H.L. (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 2007.

IPCC, 2014: 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.

Kaufmann R.K., Kauppi H., and Stock J.H.: Emissions, concentrations, and temperature: a time series analysis, Clim. Change, 77, 249–278, 2006.

Keeling R-F, Piper S-C, Bollenbacher A-F, Walker S-J (2009) Carbon Dioxide Research Group, Scripps Institution of Oceanography (SIO), University of California, La Jolla, California USA 92093-0444, Feb 2009., http://cdiac.ornl.gov/ftp/trends/co2/maunaloa.co2, last access: 14 July 2014.

Kiviet, J.F.: On the rigour of some misspecification tests for modelling dynamic relationships, Review of Economic Studies*, 53*, 241-261, 1986.

Kodra, E., Chatterjee, S., and Ganguly, A.R.: Exploring Granger causality between global average observed time series of carbon dioxide and temperature, Theoretical and Applied Climatology, 104, 3-4, 325-335, 2011.

Kopp, G. and Lean, J. L.: A new, lower value of total solar irradiance: evidence and climate significance. Geophys. Res. Lett., 38, 2011.

Kosaka, Y. and Shang-Ping, X.: Recent global-warming hiatus tied to equatorial Pacific surface cooling, Nature, doi:10.1038/nature12534, 2013.

Kuo C., Lindberg C., and Thomson D.J.: Coherence established between atmospheric carbon dioxide and global temperature, Nature, 343, 709–714, 1990.
Kwiatkowski, D.; Phillips, P. C. B.; Schmidt, P. and Shin, Y.: Testing the null hypothesis of stationarity against the alternative of a unit root, Journal of Econometrics 54, 159–178, 1992.

Le Quéré, C., Peters, G. P., Andres, R. J., Andrew, R. M., Boden, T., Ciais, P., Friedlingstein, P., Houghton, R. A., Marland, G., Moriarty, R., Sitch, S., Tans, P., Arneth, A., Arvanitis, A., Bakker, D. C. E., Bopp, L., Canadell, J. G., Chini, L. P., Doney, S. C.,Harper, A., Harris, I., House, J. I., Jain, A. K., Jones, S. D., Kato, E., Keeling, R. F., Klein Goldewijk, K., Körtzinger, A., Koven,C., Lefèvre, N., Omar, A., Ono, T., Park, G.-H., Pfeil, B., Poulter, B., Raupach, M. R., Regnier, P., Rödenbeck, C., Saito, S.,Schwinger, J., Segschneider, J., Stocker, B. D., Tilbrook, B., vanHeuven, S., Viovy, N., Wanninkhof, R., Wiltshire, A., Zaehle, S.,and Yue, C.: Global carbon budget 2013, Earth Syst. Sci. Data, 6, 235–263, 2014

Lean, J.L. and Rind, D.H.: How natural and anthropogenic influences alter global and regional surface temperatures: 1889 to 2006, Geophys. Res. Lett., 35, 2008.

Lean, J. L. and Rind , D.H.: How will Earth's surface temperature change in future decades? Geophys. Res. Lett. 36, L15708, 2009.

Lean, J.L. and Rind, D.H.: How natural and anthropogenic influences alter global and regional surface temperatures: 1889 to 2006, Geophys. Res. Lett., 35, 2008.

Lockwood M.: Recent changes in solar outputs and the global mean surface temperature. III. Analysis of contributions to global mean air surface temperature rise. Proceedings of the Royal Society, Mathematical Physical and Engineering Sciences, 464, 1387–1404, 2008.

Marcellino, M.: Some consequences of temporal aggregation in empirical analysis. Journal of Business and Economic Statistics, 17, 129-136, 1999.

Meehl, G. A. Arblaster, J.M. Fasullo, J.T.1, Hu, A, and Trenberth, K.E.: Model-based evidence of deep-ocean heat uptake during surface-temperature hiatus periods, Nature Climate Change, DOI: 10.1038/NCLIMATE1229, 2011.

Meehl, G. A., C. Covey, T. Delworth, M. Latif, B. McAvaney, J. F. B. Mitchell, R. J. Stouffer, and K. E. Taylor: The WCRP CMIP3 multi-model dataset: A new era in climate change research,Bulletin of the American Meteorological Society, **88**, 1383-1394. 2007. (CMIP3) Multi-Model Mean20c3m/sresa1, http://climexp.knmi.nl/selectfield_CO2, last access 10 June 2014

Moberg, A., D.M. Sonechkin, K. Holmgren, N.M. Datsenko and W. Karlén.: Highly variable Northern Hemisphere temperatures reconstructed from low- and high-resolution proxy data, Nature, 433, 7026, 613-617, 2005.

Morice, C.P., Kennedy, J.J., Rayner, N.A. and Jones, P.D.: Quantifying uncertainties in global and regional temperature change using an ensemble of observational estimates: the HadCRUT4 dataset. Journal of Geophysical Research, **117**, 2012. D08101, doi:10.1029/2011JD017187 http://www.metoffice.gov.uk/hadobs/hadcrut4/data/download.html, last access 25 August 2014.

Mudelsee, M.: Climate Time Series Analysis. Springer, 2010.

Ng, S. and Perron, P.: Lag length selection and the construction of unit root tests with good size and power, Econometrica, 69, 1519-1554, 2001.

Olekalns, N.: Testing for unit roots in seasonally adjusted data. Economics Letters, 45, 273-279, 1994.

Pankratz, A.: Forecasting with Dynamic Regression Models. Wiley, 1991. ~~New York, 386 pp. 1991.~~

Pierrehumbert, R.: Infrared radiation and planetary temperature. Physics Today, 64, 33–38, 2011.

Pretis, F. and Hendry, D. F.: Comment on “Polynomial cointegration tests of anthropogenic impact on global warming” by Beenstock et al. (2012) - some hazards in econometric modelling of climate change. Earth System Dynamics 4, 375–384, 2013.

Phillips, P.C.B. and Perron, P.: Testing for a unit root in time series regression, Biometrika, 75, 335–346, 1988.

Robertson, A. Overpeck, J. Rind, D. Mosley-Thompson, D. E. Zielinski, G. Lean, J. Koch, D. Penner, J. Tegen, I. & Healy, R.: Hypothesized climate forcing time series for the last 500 years, Journal of Geophysical Research,106, D14, 2001.

Running, S. W., Nemani, R. R., Heinsch, F. A., Zhao, M., Reeves, M. C., and Hashimoto, H.: A continuous satellite-derived measure of global terrestrial primary production, BioScience, 54, 547–560, 2004

Sato, M., Hansen, J. E., McCormick, M. P. & Pollack, J. B. Stratospheric aerosol optical depths, 1850–1990. J. Geophys. Res., 98, 22987–22994, 1993. http://data.giss.nasa.gov/modelforce/strataer/tau.line_2012.12.txt, last access 10 August 2014.

Stahle, D.W., R.D. D'Arrigo, P.J. Krusic, M.K. Cleaveland, E.R. Cook, R.J. Allan, J.E. Cole, R.B. Dunbar, M.D. Therrell, D.A. Gay, M.D. Moore, M.A. Stokes, B.T. Burns, J. Villanueva-Diaz and L.G. Thompson: Experimental dendroclimatic reconstruction of the Southern Oscillation. Bull. American Meteorological Society 79: 2137-2152, 1998.

Stern, D.I. and Kander, A.: The role of energy in the industrial revolution and modern economic growth, CAMA Working Paper Series, Australian National University, 2011.

Stern, D.I and Kaufmann, R.K.: Anthropogenic and natural causes of climate change, Climatic Change, 122, 257-269, DOI 10.1007/s10584-013-1007-x, 2014.

Sun, L. and Wang, M.: Global warming and global dioxide emission: an empirical study, Journal of Environmental Management, 46, 327–343, 1996.

Thornton, D. L. and Batten, D. S.: Lag-length selection and tests of Granger causality between money and income. Journal of Money, Credit and Banking, 17, 164-178, 1985.

Toda, H. Y. and Yamamoto, T.: Statistical inferences in vector autoregressions with possibly integrated processes, Journal of Econometrics, 66, 225-250. 1995.

Triacca, U.: Is Granger causality analysis appropriate to investigate the relationship between atmospheric concentration of carbon dioxide and global surface air temperature?, Theoretical and Applied Climatology, 81, 133–135, 2005.

Troup, A.J.: The Southern Oscillation, Quarterly Journal of Royal Meteorological Society, 91, 490-506, 1965. https://www.longpaddock.qld.gov.au/seasonalclimateoutlook/southernoscillationindex/soidatafiles/MonthlySOI1887-1989Base.txt, last access 25 August 2014.

Tucker, C.J., J. E. Pinzon, M. E. Brown, D. Slayback, E. W. Pak, R. Mahoney, E. Vermote and N. El Saleous, An extended AVHRR 8-km NDVI data set compatible with MODIS and SPOT vegetation NDVI data, International Journal of Remote Sensing, 26, 4485-5598, 2005. http://climexp.knmi.nl/select.cgi?id=someone@somewhere&field=ndvi, last access 30 July 2014.

Tung, K.-K. and Zhou, J.: Using data to attribute episodes of warming and cooling in instrumental records, PNAS, 110, 2058-2063, 2013.

Wang, C., Deser, C., Yu, J.-Y., DiNezio, P., and Clement, A.: El Niño–Southern Oscillation (ENSO): a review, in: Coral Reefs of the Eastern Pacific, Glynn, P. Manzello, D., and Enochs, I., Springer Science, 2012.

Wang, W., Ciais, P., Nemani, R. R., Canadell, J. G., Piao, S., Sitch, S., White, M. A., Hashimoto, H., Milesi, C., and Myneni, R. B.: Variations in atmospheric CO_2 growth rates coupled with tropical temperature, Proc. Natl. Acad. Sci. USA, 110, 13061–13066, 2013.

Wei, W. W. S.: The effect of systematic sampling and temporal aggregation on causality – a cautionary note. Journal of the American Statistical Association, 77, 316-319, 1982.

Wilks, D.S.: Statistical methods in the atmospheric sciences: an introduction. Academic Press; 2011.

Zhang, Y., Guanter, L., Berry J.A., Joiner, J., van der Tol, C., Huete, A., Gitelson, A.,Voigt. M., and Köhler P.: Estimation of vegetation photosynthetic capacity from space-based measurements of chlorophyll fluorescence for terrestrial biosphere models, Global Change Biology, doi: 10.1111/gcb.12664, 2014.

Zhou, J. and Tung, K.: Deducing multidecadal anthropogenic global warming trends using multiple regression analysis, Journal of the Atmospheric Sciences, 70, 1-8, 2013.

Table 1. Lag of first-difference CO_2 relative to surface temperature series for global, tropical, northern hemisphere and southern hemisphere categories

	Lag in months of first-difference CO_2 relative to global surface temperature category
H~~h~~adcrut4SH	-1
H~~h~~adcrut4Trop	-1
~~H~~H~~h~~ad~~CRUT~~crut4_nh	-3
H~~h~~adcrut4Glob	-2

Table 2. Lag of FIRST-DIFFERENCE CO_2 relative to surface temperature series for global, tropical, northern hemisphere and southern hemisphere categories, each for three time-series sub-periods

Temperature category	**Time period**	**Lag of first-difference CO_2 relative to global surface temperature series**
NH	1959.87 to 1976.46	-6
NH	1976.54 to 1993.21	-6
Global	1959.87 to 1976.46	-4
SH	1959.87 to 1976.46	-3
Global	1976.54 to 1993.21	-2
Tropical	1959.87 to 1976.46	0
Tropical	1976.54 to 1993.21	0
Tropical	1993.29 - 2012.37	0
Global	1993.29 - 2012.37	0
NH	1993.29 - 2012.37	0
SH	1976.54 to 1993.21	0
SH	1993.29 - 2012.37	0

Table 3. Augmented Dickey–Fuller (ADF) test for tests for unit roots stationarity in both monthly and annual data 1969 to 2012 for, level of atmospheric CO_2, first-difference CO_2 and global surface temperature

	Monthly data				Annual data			
	ADF statistic*	**p-value**	**Order of integration**	**Test interpret-ation**	**ADF statistic***	**p-value**	**Order of integration**	**Test interpret-ation**
Level of CO_2	-0.956	0.9481	I(1)	Non-stationary	-0.309	0.991	I(1)	Non-stationary
First-Difference CO_2	-17.103	5.72 E-54	I(0)	Stationary	-4.319	0.003	I(0)	Stationary
Temp	-5.115	0.00011	I(0)	Stationary	-3.748	0.019	I(0)	Stationary

* The Dickey-Fuller regressions allowed for both drift and trend; the augmentation level was chosen by minimizing the Schwarz Information Criterion.

Table 4. OLS dynamic regression between first-difference atmospheric CO_2 and global surface temperature for monthly data for the period 1959 - 2012, with autocorrelation taken into account

Independent variable/s [1]	Dep-endent variable [1]	Independent variable regression coefficients	Indep-endent variable P-value	Whole model adjusted R-squared	Whole model P-value	LM test for autocorr-elation [2]
Led2mx13mma 1stderiv CO_2	TEMP	0.097	<0.00001	0.861	6.70E-273	0.144
Led1mTEMP		0.565	<0.00001			
Led2mTEMP		0.306	<0.00001			

[1] Z-scored
[2] Whole model: LM test for autocorrelation up to order 12 - Null hypothesis: no autocorrelation

Table 5. Pairwise correlations (correlation coefficients (R)) between selected climate variables

	2x13mmafirstderiv CO_2	**Hadcrut4Global**	**3x13mma2ndderivCO_2**
Hadcrut4Global	**0.7**	1	
3x13mma2ndderivCO_2	0.06	-0.05	1
13mmaReverseSOI	0.25	0.14	**0.37**

Table 6. Pairwise correlations (correlation coefficients (R)) between selected climate variables, phase-shifted as shown in the table

	Led2m2x13mmafirstderivCO_2	**Hadcrut4Global**	**Led4m3x13mma2ndderivCO_2**
Hadcrut4Global	**0.71**	1	
Led4m3x13mma2nddiff~~eriv~~ CO_2	0.23	0.09	1
13mmaReverseSOI	0.16	0.14	**0.49**

Table 7. Pairwise correlations (correlation coefficients (R)) between selected climate variables, phase-shifted as shown in the table

	ZLed2m2x13mma2ndderivCO_2	**ZReverse~~LongPaddock~~SOI**
ZReverse~~LongPaddock~~SOI	0.28	1.00
ZLed3m13mmafirstdiff~~deriv~~hadcrut4 global	0.35	0.41

Table 8. OLS dynamic regression between second-difference atmospheric CO_2 and reversed Southern Oscillation Index for monthly data for the period 1959 - 2012, with autocorrelation taken into account

Independent variable/s [1]	**Dep-endent variable [1]**	**Independent variable regression coefficients**	**Indep-endent variable P-value**	**Whole model adjusted R-squared**	**Whole model P-value**	**LM test for autocorr-elation [2]**
Led3m2x13mma 1stderivCO_2	ReverseSOI	0.07699	<0.011	0.478	1.80E-89	0.214
Led1mReverseSOI		0.456	<0.00001			
Led2mreverseSOI		0.272	<0.00001			

[1] Z-scored
[2] Whole model: LM test for autocorrelation up to order 12 - Null hypothesis: no autocorrelation

Table 9. OLS dynamic regression between first-difference global surface temperature and reversed Southern Oscillation Index for monthly data for the period 1877-2012, with autocorrelation taken into account

Indep-endent variable/s [1]	**Dep-endent variable [1]**	**Independent variable regression coefficients**	**Indep-endent variable P-value**	**Whole model adjusted R-squared**	**Whole model P-value**	**LM test for autocorr-elation [2]**
Led3m12mma1stdiff~~eriv~~TEMP	ReverseSOI	0.140	<0.00001	0.466	3.80E-221	0.202
Led1mReverseSOI		0.465	<0.00001			
Led2mReverseSOI		0.210	<0.00001			

[1] Z-scored
[2] Whole model: LM test for autocorrelation up to order 3 - Null hypothesis: no autocorrelation

Table 10: Augmented Dickey–Fuller (ADF) test for stationarity for monthly data 1959 to 2012 for second-difference CO_2 and sign-reversed SOI

	ADF statistic	p-value	Test interpretation
Second-difference CO_2	-10.077	0.000	Stationary
Sign-reversed SOI	-6.681	0.000	Stationary

Table 11. VAR Residual Serial Correlation LM Tests component of Granger causality testing of relationship between second-difference CO_2 ~~CO2~~ and SOI. Initial 2-lag model

Lag order	LM-Stat	P-value*
1	10.62829	0.0311
2	9.71675	0.0455
3	2.948737	0.5664
4	9.711391	0.0456
5	10.67019	0.0305
6	37.13915	0
7	1.268093	0.8668

*P-values from chi-square with 4 df.

Table 12. VAR Residual Serial Correlation LM Tests component of Granger causality testing of relationship between second-difference CO_2 ~~CO2~~ and SOI. Preferred 3-lag model

Lag order	LM-Stat	P-value*
1	1.474929	0.8311
2	4.244414	0.3739
3	2.803332	0.5913
4	13.0369	0.0111
5	8.365221	0.0791
6	40.15417	0
7	1.698265	0.791

*P-values from chi-square with 4 df.

Table 13. Correlations (R) between paleoclimate CO_2 and temperature estimates 1500-1940

	Temperature (speliothem)	Temperature (tree ring)
Level of ~~CO_2 CO2~~ CO_2 (ice core)	0.369	0.623

1st differiv. CO_2 (ice core)	0.558	0.721

~~**Table 14:** ADF test results for time series based on automatic Schwarz Information Criterion (SIC) lag length selection~~

~~-~~	~~**ADF**~~	
~~-~~		~~Prob.~~
~~1stderivCO_2~~	~~Lag Length: 15 (Automatic - based on SIC, maxlag=16)~~	~~0.0895~~
~~Temp~~	~~Lag Length: 1 (Automatic - based on SIC, maxlag=16)~~	~~0.0000~~
~~NDVI~~	~~Lag Length: 1 (Automatic - based on SIC, maxlag=16~~	~~0.0000~~
~~Climate model/temperature difference~~	~~Lag Length: 1 (Automatic - based on SIC, maxlag=16)~~	~~0.0000~~

~~**Table 15.** Order of integration test results for first-derivative CO_2 for monthly data from 1981-2012. The Akaike iInformation Ceriterion (AIC) was used to select an optimal maximum lag length (k) for the variables in the test. The null hypothesis for the tests is non-stationarity, except for the KPSS test for which the null hypothesis is stationarity.~~

~~-~~	~~**Test critical values**~~	~~**ADF**~~	~~**DF-GLS**~~	~~**Elliott-Rothenberg-Stock Point Optimal**~~	~~**Ng-Perron - Modified ERS Point Optimal statistic**~~
~~**Test statistic**~~	~~-~~	~~-2.75~~	~~-2.73~~	~~5.77~~	~~6.11~~
~~-~~	~~1% level~~	~~-3.98~~	~~-3.48~~	~~3.97~~	~~4.03~~
~~-~~	~~5% level~~	~~-3.42~~	~~-2.90~~	~~5.63~~	~~5.48~~
~~-~~	~~10% level~~	~~-3.13~~	~~-2.58*~~	~~6.89*~~	~~6.67*~~

~~(1) Significant at <1% level~~

Table 14. Order of integration test results for NDVI series for monthly data from 1981-2012. The Schwartz Information Criterion (SIC) was used to select an optimal maximum lag length in the tests.

NDVI Series	Null Hypothesis: the series has a unit root	Probability of unit root
NDVIV	Lag Length: 16 (Automatic - based on SIC, maxlag=16)	0.0122
NDVIG	Lag Length: 1 (Automatic - based on SIC, maxlag=15)	7.23e-14
NDVIGV	Lag Length: 1 (Automatic - based on SIC, maxlag=16)	4.18E-16

~~**Table 16.** Order of integration test results for first-derivative CO_2 for monthly data from 1981-2012. The Schwartz iInformation cCriterion (SIC) was used to select an optimal maximum lag length (k) for the variables in the test. The null hypothesis for the tests is non-stationarity, except for the KPSS test for which the null hypothesis is stationarity.~~

~~-~~	~~**Test critical values**~~	~~**ADF**~~	~~**DF-GLS**~~	~~**Elliott-Rothenberg-Stock Point Optimal**~~	~~**Ng-Perron - Modified ERS Point Optimal statistic**~~
~~**Test statistic**~~	~~-~~	~~-3.183~~	~~-2.73~~	~~3.193~~	~~6.105~~
~~-~~	~~1% level~~	~~-3.984~~	~~-3.476~~	~~3.971*~~	~~4.03~~
~~-~~	~~5% level~~	~~-3.422~~	~~-2.898~~	~~5.625~~	~~5.48~~
~~-~~	~~10% level~~	~~-3.134*~~	~~-2.585*~~	~~6.886~~	~~6.670*~~

~~**Table 17.** Order of integration test results for first-derivative CO_2 for monthly data from 1981-2012. Tests use bandwidth criteria for lag selection. The null hypothesis for the tests is non-stationarity, except for the KPSS test for which the null hypothesis is stationarity.~~

~~-~~	~~**Test critical values**~~	~~**KPSS does not use AIC or SIC**~~	~~**Phillips-Perron does not use AIC or SIC**~~
~~**Test statistic**~~	~~-~~	~~0.07~~	~~-3.60~~

~~-~~	~~1% level~~	~~0.22*~~	~~-3.98~~
~~-~~	~~5% level~~	~~0.15~~	~~-3.42*~~
~~-~~	~~10% level~~	~~0.12~~	~~-3.13~~

~~**Table 18.** Order of integration test results for NDVI series for monthly data from 1981-2012. The Schwartz Information Criterion (SIC) was used to select an optimal maximum lag length in the tests.~~

~~**NDVI Series**~~	~~**Null Hypothesis: the series has a unit root**~~	~~**Probability of unit root**~~
~~NDVIV~~	~~Lag Length: 16 (Automatic - based on SIC, maxlag=16)~~	~~0.0122~~
~~NDVIG~~	~~Lag Length: 1 (Automatic - based on SIC, maxlag=15)~~	~~7.23e-14~~
~~NDVIGV~~	~~Lag Length: 1 (Automatic - based on SIC, maxlag=16)~~	~~4.18E-16~~

~~**Table 19**. Pairwise Granger causality tests for first-derivative CO_2 and temperature~~

~~**Null Hypothesis:**~~	~~**Lags suggest-ed by AIC**~~	~~**Number of lags imple-mented**~~	~~**Total observ-ations**~~	~~**Included observ-ations**~~	~~**Chi-sq**~~	~~**df**~~	~~**Prob.**~~	~~**Interpret-ation**~~
~~TEMP does not GC 1stderivCO_2~~	~~8~~	~~Add one more lag to allow for fact that 1stderiv CO_2 CO2 is characterised I(1), but don't include extra lag in GC test (Toda and Yamamoto ,1995)~~	~~378~~	~~369~~	~~7.39~~	~~8~~	~~p=0.4962~~	~~TEMP does not GC 1stderivCO_2~~
~~1stderivCO_2 does not GC TEMP~~	~~8~~		~~378~~	~~369~~	~~32.79~~	~~8~~	~~p=0.0001~~	~~1stderivCO_2 does GC TEMP~~

~~**Table 20**. Pairwise Granger causality tests for first-derivative CO_2 characterised as *I(1)* and NDVI~~

~~**Null Hypothesis:**~~	~~**Lags suggest-ed by AIC**~~	~~**Number of lags imple-mented**~~	~~**Total observ-ations**~~	~~**Included observ-ations**~~	~~**Chi-sq**~~	~~**df**~~	~~**Prob.**~~	~~**Interpret-ation**~~
~~NDVI does not GC 1stderivCO_2 -~~	~~8~~	~~Add one more lag to allow for fact that 1stderiv~~	~~378~~	~~369~~	~~3.184~~	~~8~~	~~p=0.9223~~	~~NDVI does not GC 1stderivCO_2 -~~

~~1stderivCO_2 does not GC NDVI~~	~~8~~	~~CO_2 is characterised I(1), but don't include extra lag in GC test (Toda and Yamamoto ,1995)~~	~~378~~	~~369~~	~~12.312~~	~~8~~	~~p=0.1378~~	~~-1stderivCO_2 does not GC NDVI~~

~~**Table 21.** OLS dynamic regression between first-derivative atmospheric CO_2 and global surface temperature for monthly data for the period 1981-2012, with autocorrelation taken into account~~

~~**Independent variable/s [1]**~~	~~**Dependent variable [1]**~~	~~**Independent variable regression coefficients**~~	~~**Independent variable P-value**~~	~~**Whole model adjusted R-squared**~~	~~**Whole model P-value**~~	~~**LM test for autocorrelation [2]**~~
~~Twox13mma1stderivCO_2~~	~~**TEMP**~~	~~0.107~~	~~0.00077~~	~~0.770~~	~~4.00E-118~~	~~0.445~~
~~Led1mTEMP~~	-	~~0.545~~	~~<0.00001~~	-	-	-
~~Led2mTEMP~~	-	~~0.293~~	~~<0.00001~~	-	-	-

~~[1] Z-scored~~

~~[2] Whole model: LM test for autocorrelation up to order 20 - Null hypothesis: no autocorrelation~~

~~**Table 22.** Pairwise Granger causality tests for first-derivative atmospheric CO_2 and global surface temperature~~

~~**Null Hypothesis:**~~	~~**Criterion for number of lags selected**~~	~~**Number of lags implemented**~~	~~**Observations**~~	~~**F-Statistic**~~	~~**Probability**~~	~~**Interpretation of statistically significant probabilities**~~
~~TEMP does not Granger Cause 1stderivCO_2~~	~~AIC~~	~~2~~	~~373~~	~~2.88~~	~~0.06~~	-
~~1stderivCO_2 does not Granger Cause TEMP~~		-	-	~~5.02~~	~~0.01~~	~~1stderivCO_2 Granger Causes TEMP~~

~~**Table 23.** OLS dynamic regression between first-derivative atmospheric CO_2 and NDVI for monthly data for the period 1981 - 2012, with autocorrelation taken into account~~

~~**Independent variable/s [1]**~~	~~**Dependent variable [1]**~~	~~**Independent variable regression coefficients**~~	~~**Independent variable P-value**~~	~~**Whole model adjusted R-squared**~~	~~**Whole model P-value**~~	~~**LM test for autocorrelation [2]**~~
~~Twox13mma 1stderivCO_2~~	~~NDVI~~	~~0.094~~	~~0.01103~~	~~0.549~~	~~3.74E-64~~	~~0.092~~

Led1mNDVI	-	0.765	<0.00001	-	-	-
Led2mNDVI	-	−0.075	0.15231	-	-	-

[1] Z-scored
[2] Whole model: LM test for autocorrelation up to order 20 - Null hypothesis: no autocorrelation

Table 24. Pairwise Granger causality tests for first-derivative CO_2 and NDVI: lag selection by AIC

Null Hypothesis:	Criterion for number of lags selected	Number of lags imple-mented	Observations	F-Statistic	Probability	Interpretation of statistically significant probabilities
NDVI does not Granger Cause 1stderivCO_2	AIC	2	373	1.25	0.29	Not significant
1stderivCO_2 does not Granger Cause NDVI		-	-	3.01	0.0504	Not significant

Table 25. First-derivative CO_2 displays Granger causality of NDVI: lag selection by extensive search

Null Hypothesis:	Criterion for number of lags selected	Number of lags imple-mented	Observations	F-Statistic	Probability	Interpretation of statistically significant probabilities
NDVI does not Granger Cause 1stderivCO_2	Result of extensive search of lag space	1	374	0.87	0.352	-
1stderivCO_2 does not Granger Cause NDVI		-	-	5.11	0.024	1stderivCO_2 Granger Causes NDVI

Table 26. OLS dynamic regression between global surface temperature and NDVI for monthly data for the period 1981 – 2012, with autocorrelation taken into account

Indep-endent variable/s [1]	Dependent variable [1]	Independent variable regression coefficients	Independent variable P-value	Whole model adjusted R-squared	Whole model P-value	LM test for autocorrelation [2]
TEMP	NDVI	0.215	<0.00001	0.574	1.18E-68	0.536
Led1mNDVI	-	0.720	<0.00001	-	-	-

Led2mNDVI	-	-0.122	0.01874	-	-	-

~~[1] Z-scored~~

~~[2] Whole model: LM test for autocorrelation up to order 20 - Null hypothesis: no autocorrelation~~

~~**Table 27.** Pairwise Granger causality tests for temperature and NDVI~~

Null Hypothesis:	Criterion for number of lags selected	Number of lags imple-mented	Observations	F-Statistic	Probability	Interpretation of statistically significant probabilities
NDVI does not Granger Cause TEMP	AIC	2	373	3.18	0.043	NDVI Granger Causes TEMP
TEMP does not Granger Cause NDVI		-	-	11.59	1.00E-05	TEMP Granger Causes NDVI

~~**Table 28.** OLS dynamic regression between NDVI and the difference between the observed level of atmospheric CO_2 and global surface temperature for monthly data for the period 1981 - 2012, with autocorrelation taken into account~~

Indep-endent variable/s [1]	Depen-dent variable [1]	Independent variable regression coefficients	Independent variable P-value	Whole model adjusted R-squared	Whole model P-value	LM test for autocorrelation [2]
Led17mNDVI	Climate model/temperature difference	0.069	0.00795	0.557	1.36E-62	0.874
Led1mClimate model/temperature difference	-	0.490	<0.00001	-	-	-
Led2mClimate model/temperature difference	-	0.265	<0.00001	-	-	-

~~[1] Z-scored~~

~~[2] Whole model: LM test for autocorrelation up to order 20 - Null hypothesis: no autocorrelation~~

~~**Table 29.** Pairwise Granger causality tests for NDVI and the difference between the observed level of atmospheric CO_2 and global surface temperature: Akaike Iinformation cCriterion used to select lag~~

Null Hypothesis:	Criterion for number of lags selected	Number of lags imple-mented	Observations	F-Statistic	Probability	Interpretation of statistically significant probabilities
Climate model/temperature difference does not Granger Cause Led17mNDVI	AIC	2	356	2.35	0.10	Not significant

~~Led17mNDVI does not Granger Cause climate model/temperature difference~~		~~-~~	~~-~~	~~1.03~~	~~0.36~~	~~Not significant~~

~~**Table 30.** Pairwise Granger causality tests for NDVI and the difference between the observed level of atmospheric CO_2 and global surface temperature: extensive search of the lag space~~

~~**Null Hypothesis:**~~	~~**Criterion for number of lags selected**~~	~~**Number of lags imple-mented**~~	~~**Observations**~~	~~**F-Statistic**~~	~~**Probability**~~	~~**Interpretation of statistically significant probabilities**~~
~~Climate model/temperature difference does not Granger Cause Led17mNDVI~~	~~Result of extensive search of lag space~~	~~15~~	~~343~~	~~0.83~~	~~0.65~~	~~-~~
~~Led17mNDVI does not Granger Cause climate model/temperature difference~~		~~-~~	~~-~~	~~1.81~~	~~0.03~~	~~Led17mNDVI Granger Causes climate model/temperature difference~~

Figure 1. Monthly data: global surface temperature (Had~~AD~~CRUT4 dataset) (red dotted curve) and an IPCC mid-range scenario model (CMIP3, SRESA1B scenario) run for the IPPC fourth assessment report (IPCC~~,~~ 2007) (blue curve), each expressed in terms of Z scores to aid visual comparison (see Sect. 1).

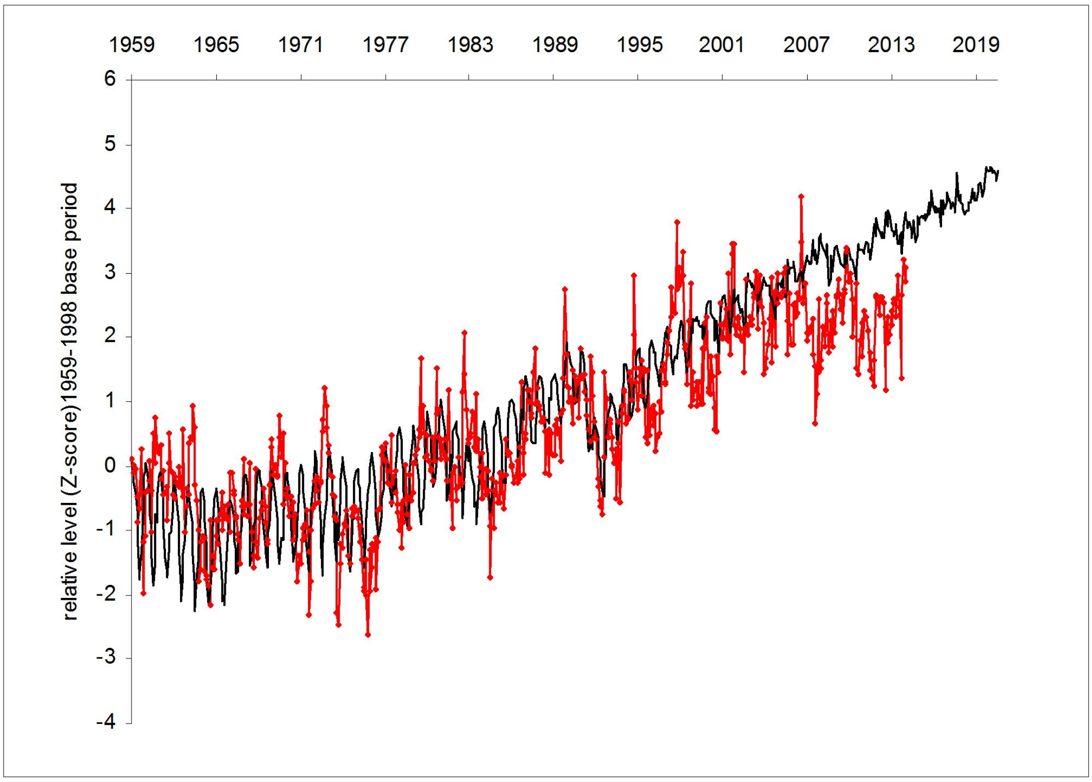

1959
1965
1971
1977
1983
1989
1995
2001
2007
2013
2019
6
5
4
3
2
1
0
-1
-2
-3
-4
relative level (Z-score)1959-1998 base period

Figure 2. Z scored monthly data: global surface temperature (green dashed curve) compared to an IPCC mid-range scenario global climate model (GCM) – the CMIP3, SRESA1B scenario run for the IPCC fourth assessment report (IPCC~~,~~ 2007) (blue curve) and also showing the trend in first-difference atmospheric CO_2 (smoothed by two 13 month moving averages) (red dotted curve). To show their core trends for illustrative purposes the three series are fitted with 5th order polynomials.

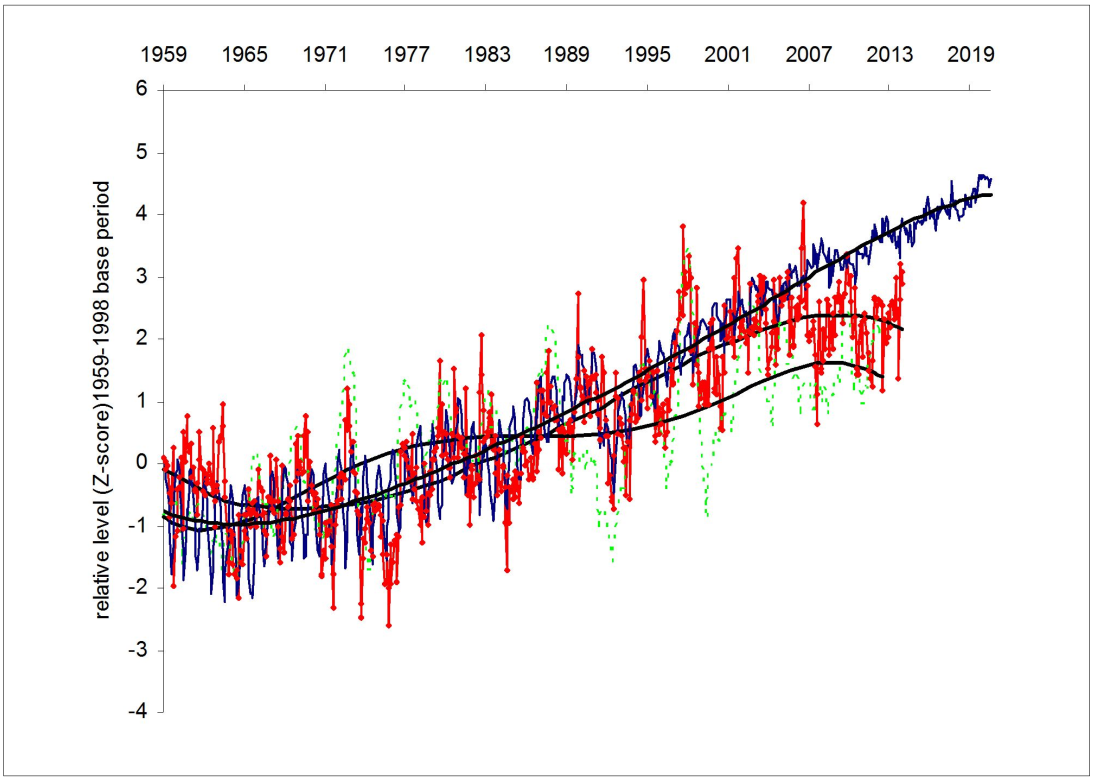


Figure 3. Z scored monthly data: global surface temperature (red curve) compared to first-difference atmospheric CO_2 smoothed by two 13 month moving averages (black dotted curve).

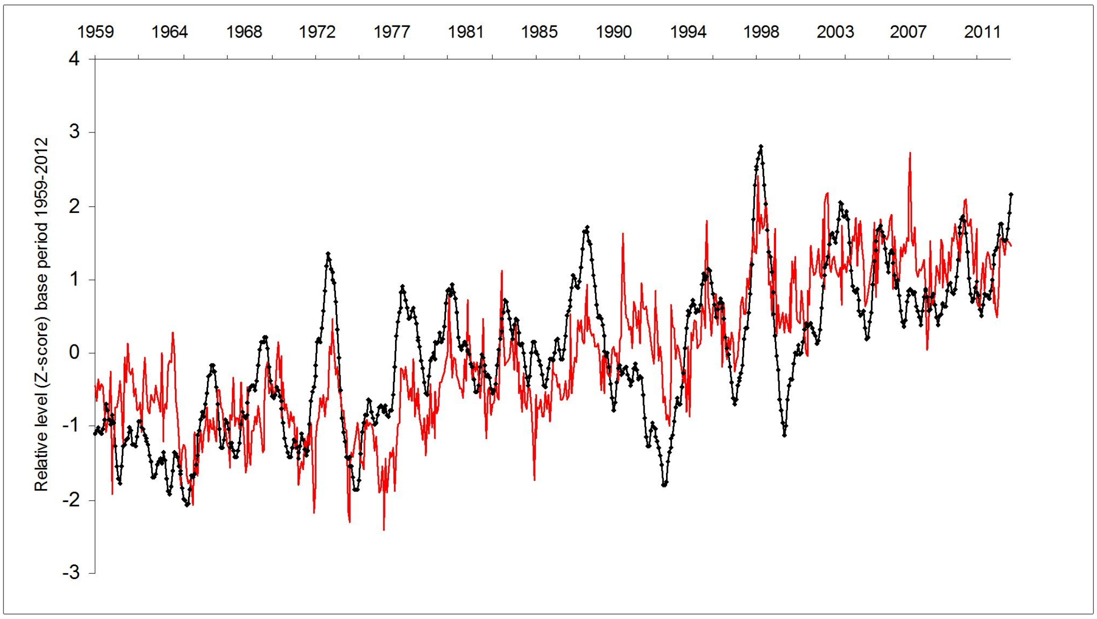


Figure 4. Correlograms of first-difference CO_2 with surface temperature for global (turquoise curve with crosses), tropical (blue curve with triangles), Northern Hemisphere (purple curve with boxes) and Southern Hemisphere (black curve with diamonds) categories

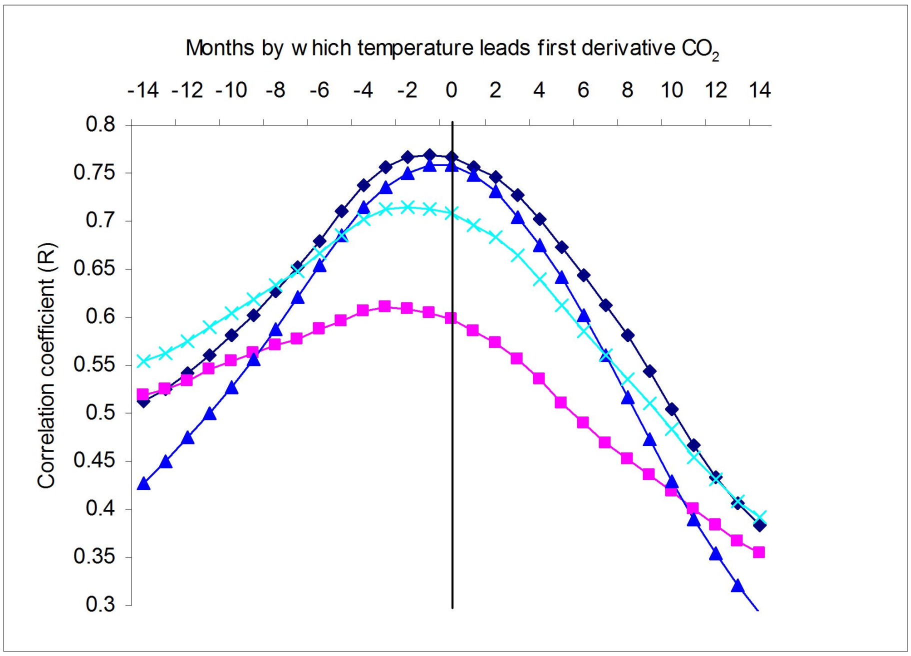


Figure 5. Correlograms of first-difference CO_2 with surface temperature for global, tropical, Northern Hemisphere and Southern Hemisphere categories, each for three time-series sub-periods.

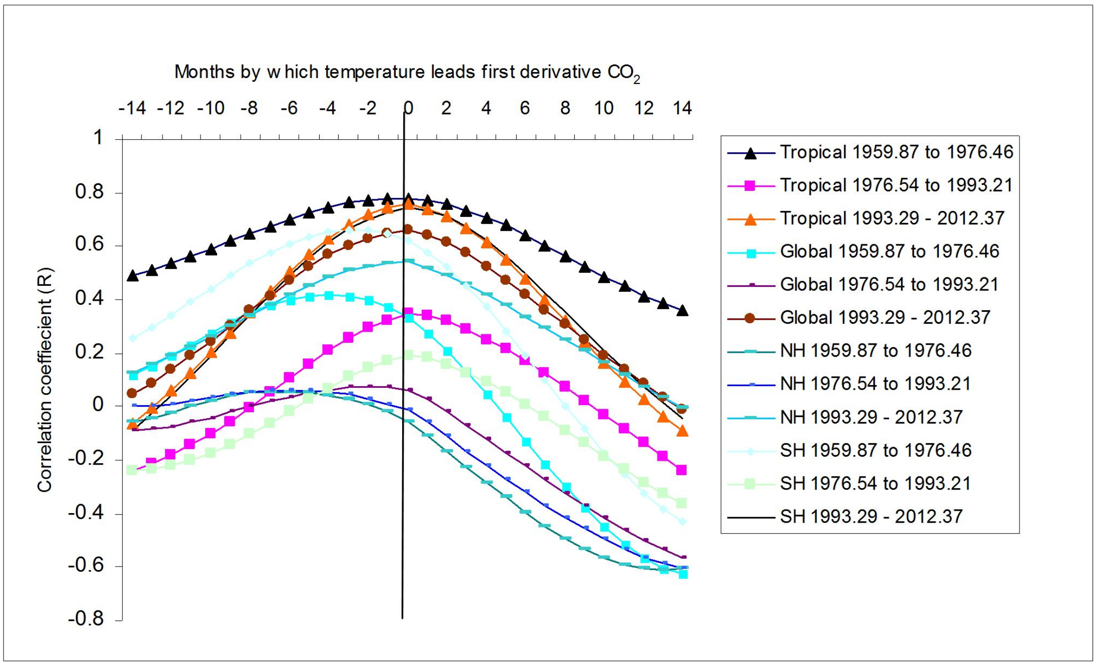


Figure 6. Z scored monthly data: global surface temperature (red curve) and first-difference atmospheric CO_2 smoothed by two 13 month moving averages (black dotted curve) (left-hand scale); sign-reversed SOI smoothed by a 13 month moving average (blue dashed curve) and second-difference atmospheric CO_2 smoothed by three 13 month moving averages (green barred curve) (right-hand scale)

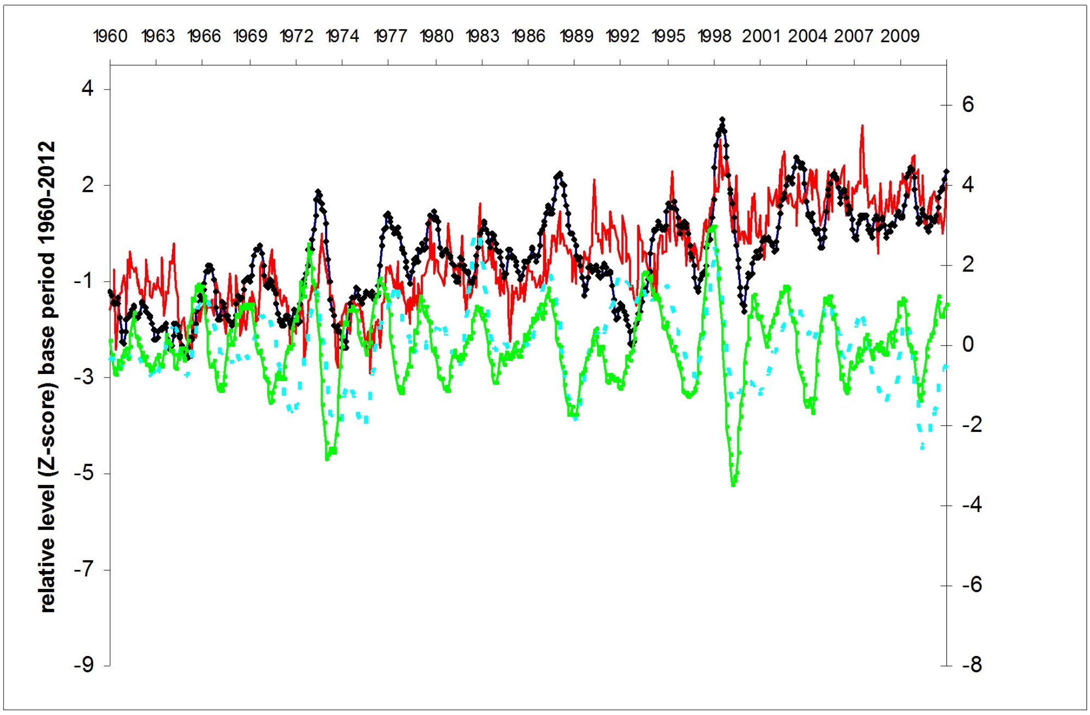


Figure 7. Z scored monthly data from 1960 to 2012: sign-reversed SOI (unsmoothed and neither led nor lagged) (dotted black curve); second-difference CO_2 smoothed by a 13 month × 13 month moving average and led relative to SOI by 2 months (green dashed curve); and first-difference global surface temperature smoothed by a 13 month moving average and led by 3 months (red curve).

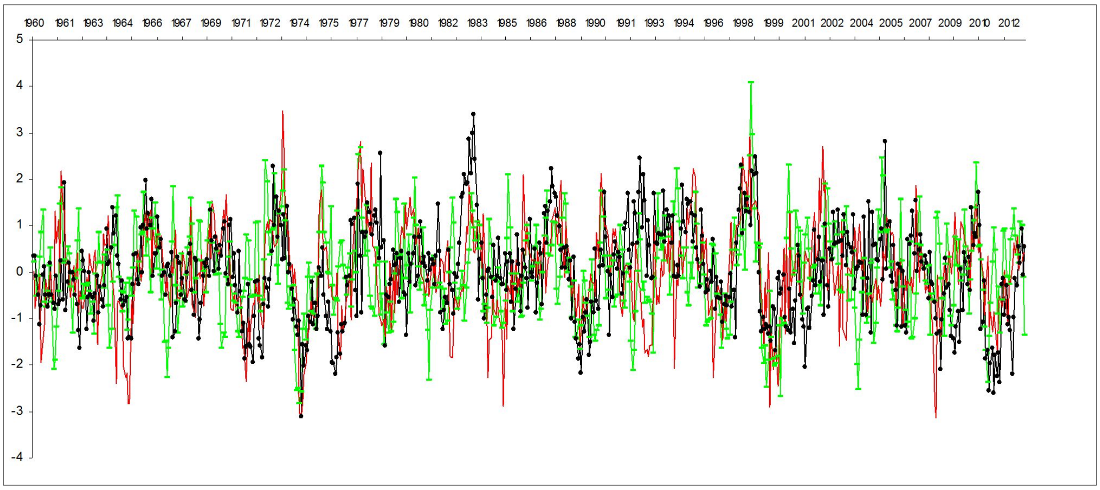


Figure 8. Z scored monthly data from 1877 to 2012: sign-reversed SOI (unsmoothed and neither led nor lagged) (red curve); and first-difference global surface temperature smoothed by a 13 month moving average and led relative to SOI by 3 months (black dotted curve)

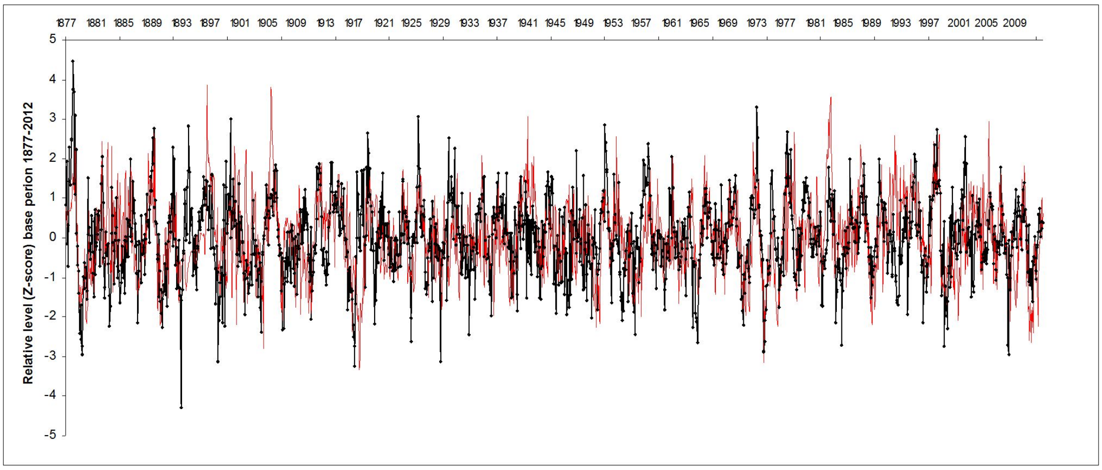


Figure 9. *Z* scored annual data: paleoclimate time series from 1500: ice core level of CO_2 (blue curve), level of CO_2 transformed into first-difference form (green barred curve); and temperature from speliothem (red dashed curve) and tree ring data (black boxed curve).

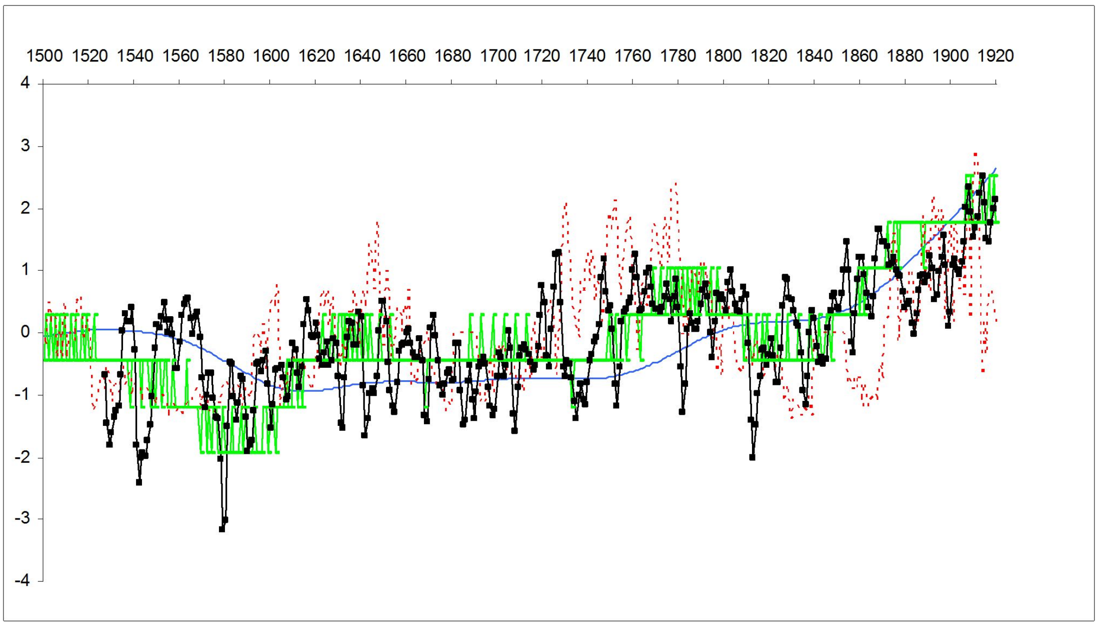
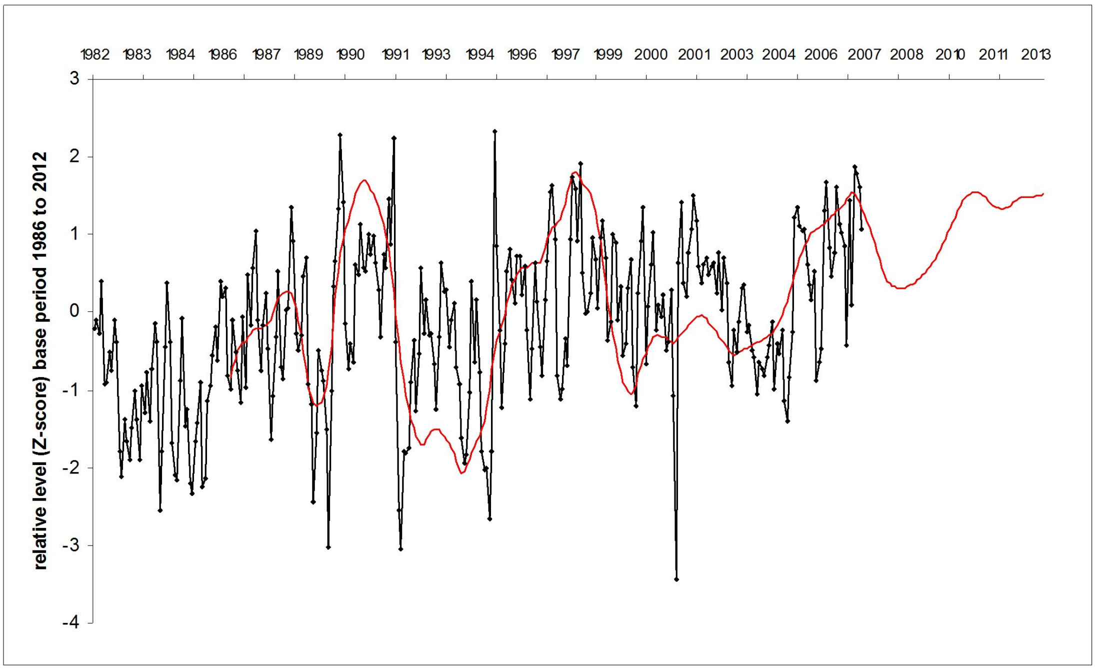
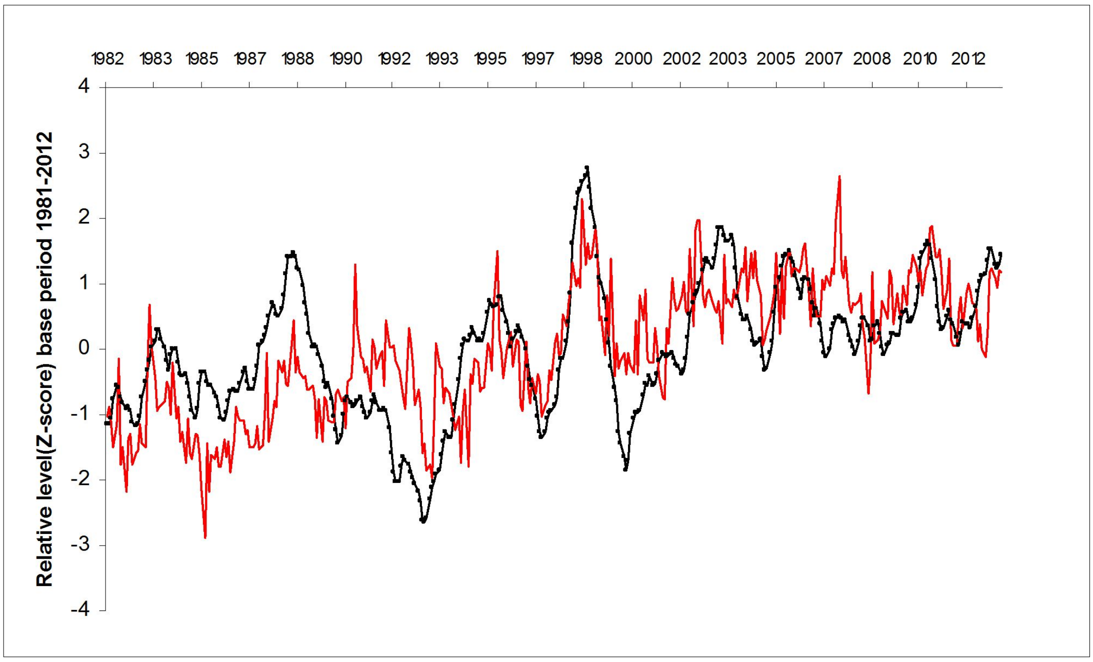


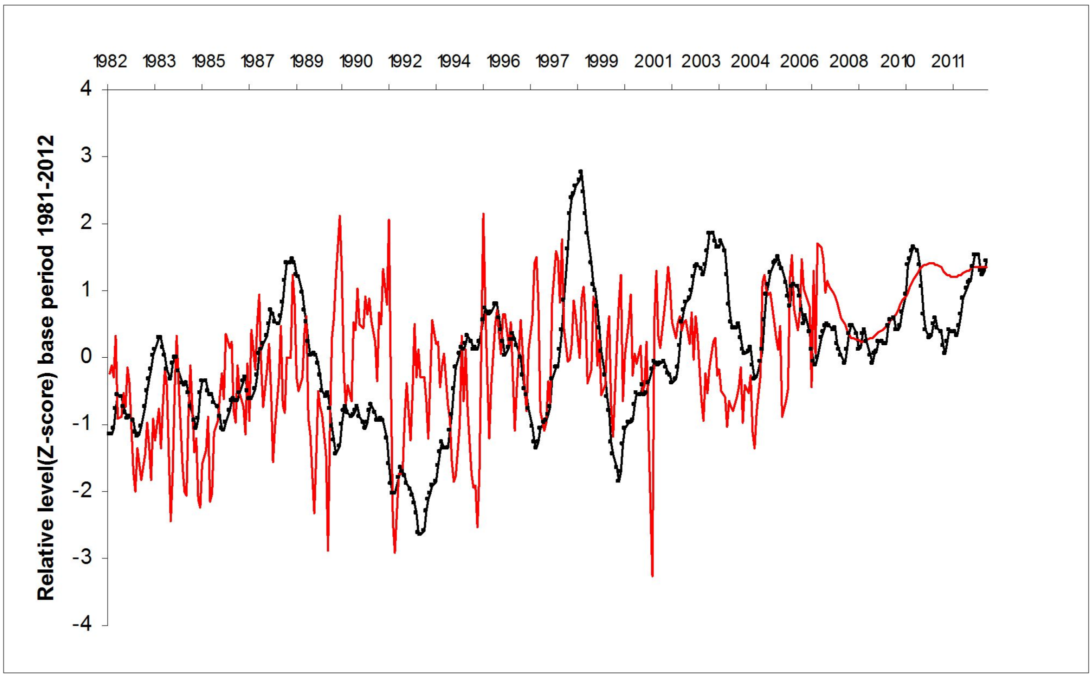
Figure 10: *Z* scored monthly data: NDVIG (black dotted curve) compared to NDVIV (red curve).



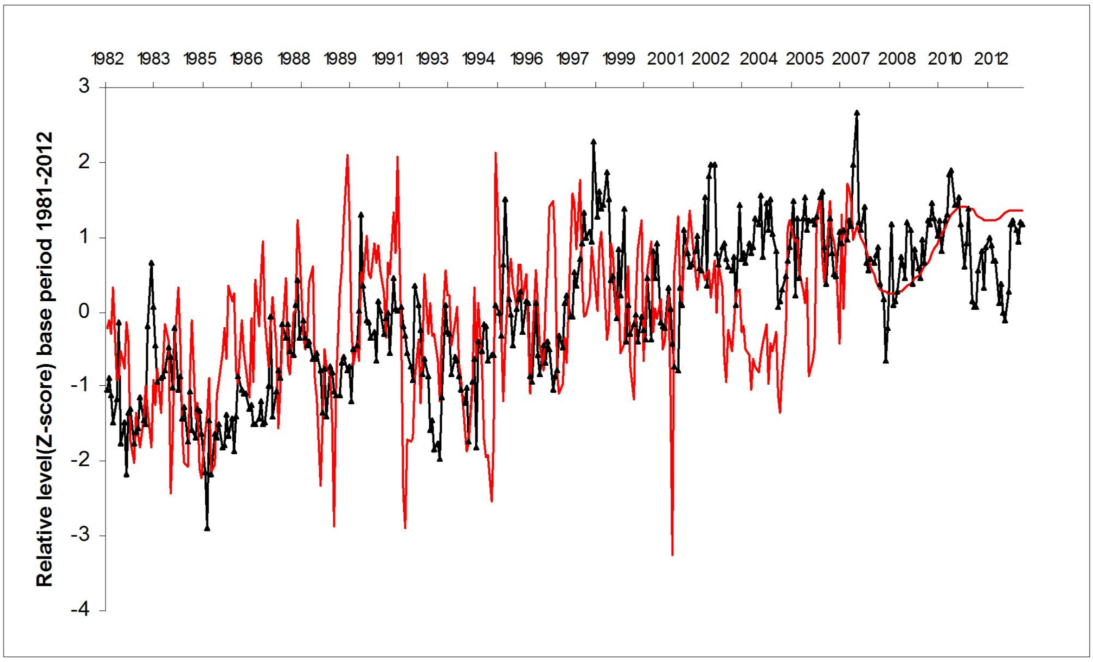
~~**Figure 11.** *Z* scored monthly data: global surface temperature (red curve) compared to first-derivative atmospheric CO_2 smoothed by two 13-month moving averages (black dotted curve).~~



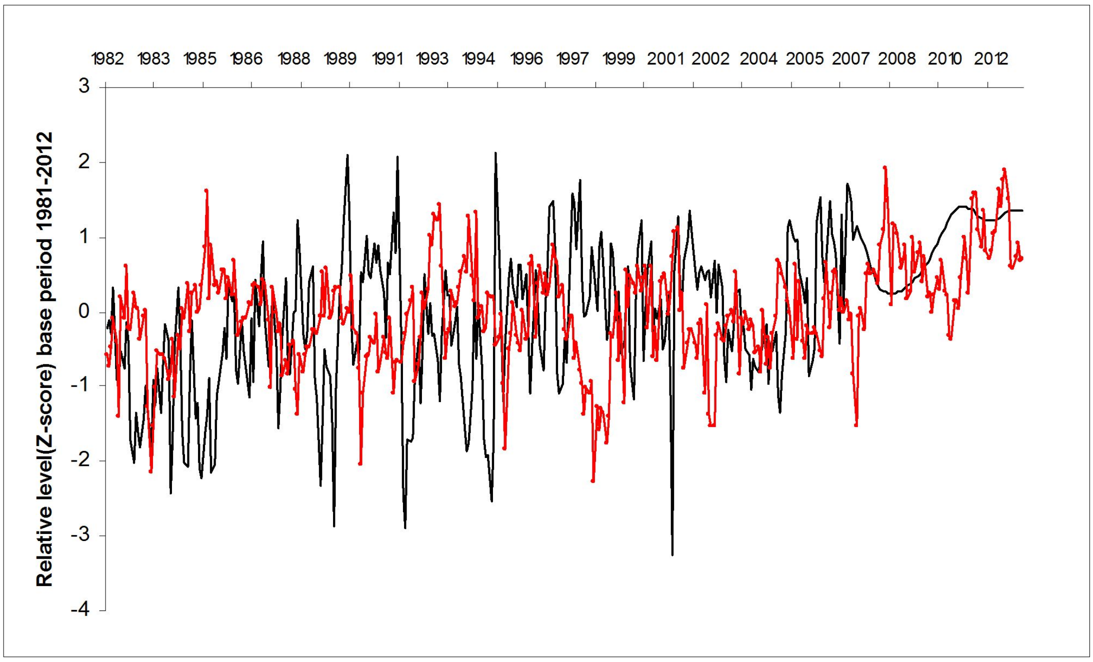
~~**Figure 12.** *Z* scored monthly data: NDVI (red curve) compared to first-derivative atmospheric CO_2 smoothed by two 13-month moving averages (black dotted curve).~~



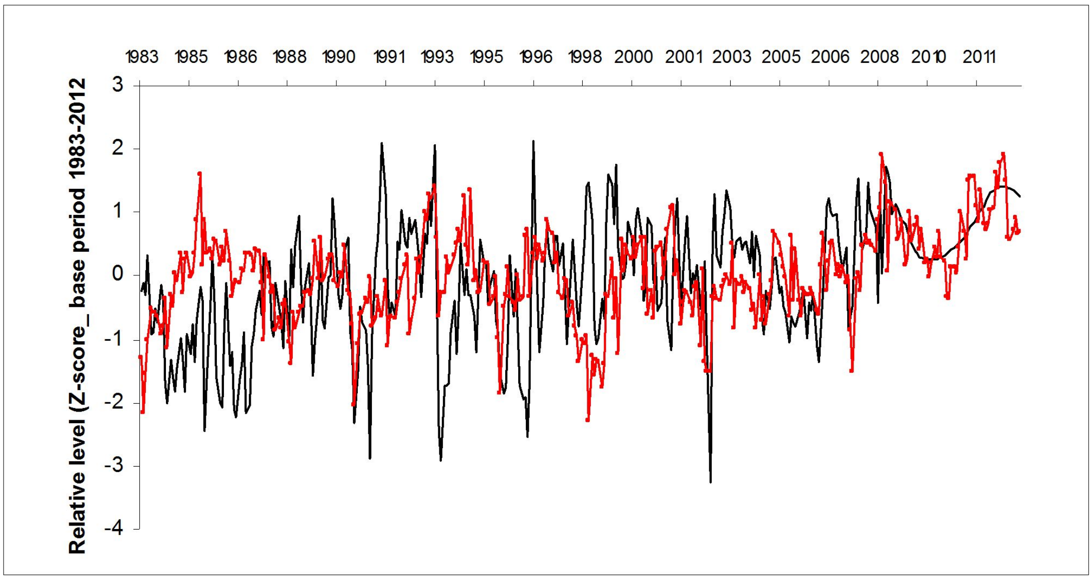
~~**Figure 13.** *Z* scored monthly data: NDVI (red curve) compared to first-derivative atmospheric CO_2 smoothed by two 13 month moving averages (black dotted curve).~~



~~**Figure 14.** *Z* scored monthly data: NDVI (black curve) compared to the difference between the observed level of atmospheric CO_2 and global surface temperature (red dotted curve).~~



~~**Figure 15.** Z scored monthly data: NDVI (black curve) led by 17 months compared to the difference between the observed level of atmospheric CO_2 and global surface temperature (red dotted curve). Months of lead of the NDVI series indicated by OLS dynamic regression modelling~~



~~**Figure 16.** Reverse log probability values (red dotted curve) for lags generated by extensive search of the lag space from lag 2 to lag 40 for the null hypothesis that NDVI does not Granger-cause the difference between the observed level of~~

~~atmospheric CO_2 and global surface temperature. Green dashed line represents 0.05 level of statistical significance.~~

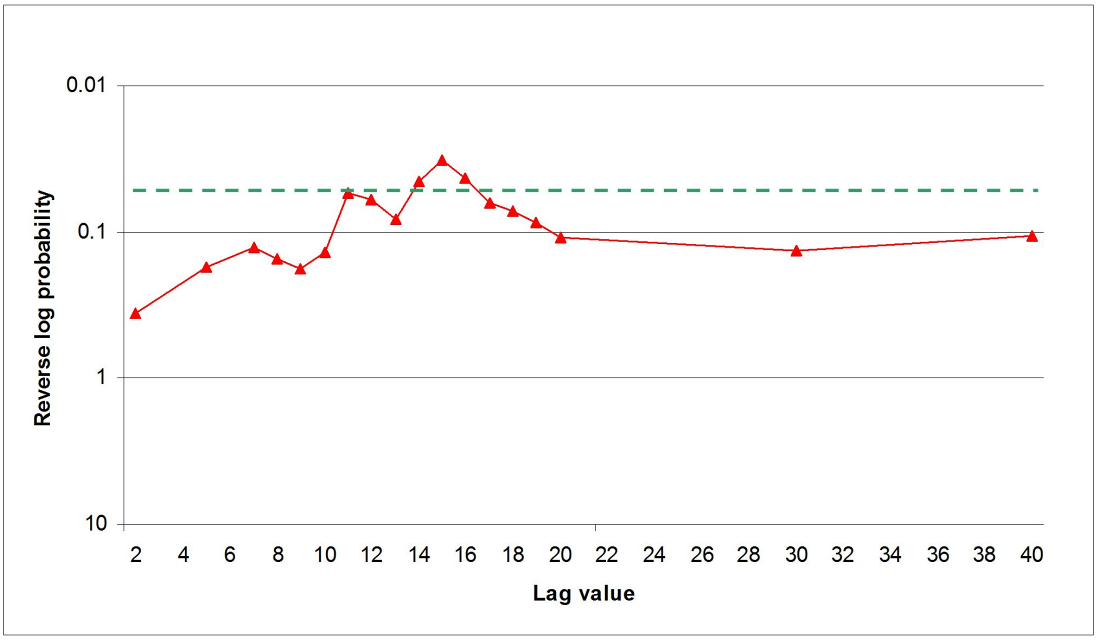


Figure 13. *Z* scored monthly data: NDVI (black curve) compared to the difference between the temperature projected from an IPCC mid-range scenario model (CMIP3, SRESA1B scenario) run for the IPPC fourth assessment report (IPCC 2007) and global surface temperature (red dotted curve).

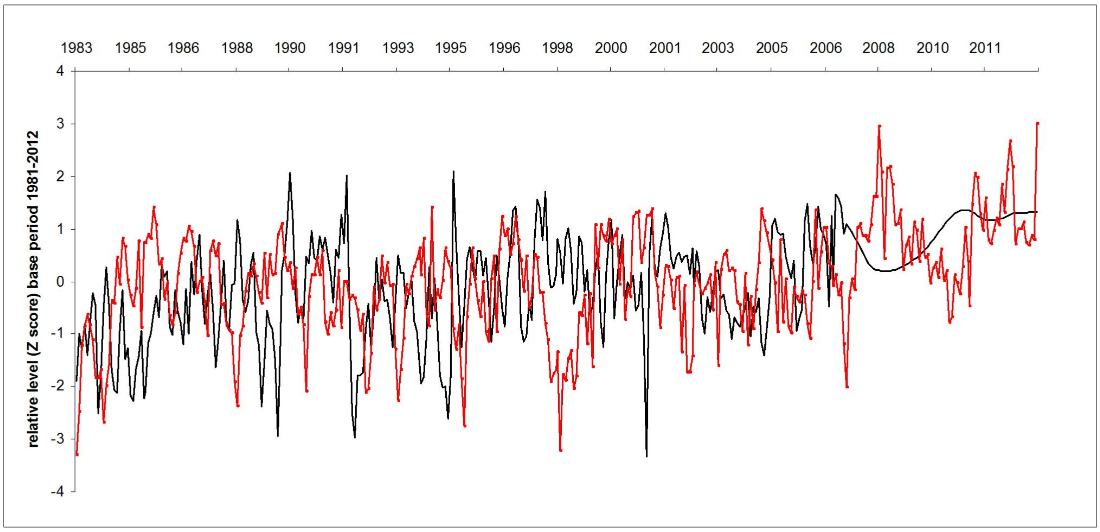


Figure 14. *Z* scored data for periods each of 36 months, averaged: NDVI (black curve) compared to the difference between the temperature projected from an IPCC mid-range scenario model (CMIP3, SRESA1B scenario) run for the IPPC fourth assessment report (IPCC 2007) and global surface temperature (red dotted curve).


1983-1985
1986-1998
1989-1991
1992-1994
1995-1997
1998-2000
2001-2003
2004-2006
2007-2009
2010-2012
2.5
2.0
1.5
1.0
0.5
0.0
-0.5
-1.0
-1.5
-2.0
Relative level (Z score) base period 1981-2012