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Response to Referee Reports of 16 July and 28 August 2015

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Abstract

Response to Referee Report of 7 May 2015 on amended manuscript of 18 June 2015
“First and second derivative atmospheric CO₂, global surface temperature and ENSO”.

1. Overall Response

The comments of both referees are very much valued.

In our response we first provide the referees' reports in their entirety (pages 1 to 5).

We then (from page 5 onward) provide our responses to the individual comments of the first referee (pages 5 - 6) and the second referee (pages 5 - 15). Finally we provide the marked-up difference between the original and revised manuscripts (pages 16 - end).

2. Report dated 16 July 2015 of Referee 1

This is, yet again, virtually a new paper, but much the best of the three. It is generally clearly written and presents what seems to me to be some very interesting evidence. I think that their findings are likely to be robust to any reasonable changes of technique and, as such, deserve consideration.

In particular, in the matter of series smoothing which I raised previously, they claim (in the supplement) to show that their results are not affected by this. I am still not entirely convinced that the difference between seasonal adjustment (which removes specifically seasonal frequencies) and moving average smoothing (which attenuates all higher frequencies) is fully appreciated. But never mind, I think that they have made their point on this, that their transformations do not materially affect their findings. They correctly point out that transformations of stationary series cannot induce spurious correlations between unrelated series, even if they could mask existing correlations.

Evidence of a significant relation between temperature and growth in CO₂ concentration would appear to be of considerable importance to the AGW debate. If long-term global warming really does require continuously accelerating growth in CO₂, that fact immediately throws light on the current "pause", and also dramatically changes the prospects for the next 50-100 years. Of course, at the moment this is just a data regularity, and the lack of any established geophysical theory to explain it is a problem. One could suggest that there are regulatory mechanisms in play that respond as a negative feedback, but it would help to know what these are. These authors are aware of the issue and they suggest a role for the biosphere, the known fact of faster photosynthesis in the presence of higher CO₂ concentrations. They claim some statistical support for a role for NDVI. Section 4.4 still seems to me a bit weak and speculative (and could be deleted from the paper without loss) but this evidence, such as it is, maybe is worth mentioning.

While by no means perfect, the paper could help to stimulate further research on these important questions. If I have one comment they might be asked act on, it relates to their third paragraph on page 21. Comment 9 of my last report pointed out that this test result is a logical implication of their findings on integration order, not a new

1 finding. They have ignored this comment; they should point out clearly that
2 correlations between stationary and nonstationary series are not well defined.

3 4 5 6 7 8 3. Report dated 28 August 2015 of Referee 2 9

10
11 The paper is interesting and quite well written. However, after a deep analysis, I have
12 a few major concerns and some minor comments. I consider this paper acceptable if
13 some revisions (which you may consider major or minor, as you like) will be
14 performed. In any case, I would like to reconsider the paper after these revisions.
15

16 Major concerns

17 While the technical part of the paper is satisfying inside the statistical framework
18 chosen (see, however, the a following major concern), the framework of the paper
19 (abstract, introduction and objectives of the study) is poorly written and mixes several
20 different statements which may create confusion to the reader. It is quite clear that the
21 authors are not regulars of the scientific literature concerning climate change.

22 In fact, the first result that should be cited is that the increase of CO₂ concentration in
23 the atmosphere is mainly due to the anthropogenic emissions, as shown by the
24 isotopic signature of the CO₂ itself. Only after this recognition we can speak about the
25 causes of the variations of CO₂ concentrations due to natural variability. It is clear, in
26 fact, that the recognition of this forcing leads to think that the CO₂ concentration must
27 obviously have a causal role on temperature. In this framework also ENSO can have a
28 role just in the interannual variations of the temperature. Please, insert these pieces of
29 information at the beginning of the section on the objectives of this study.

30 In this framework, the authors speak about a “standard model” of linear increase.
31 They should refer to the GCM outputs (very complex dynamical models) which show
32 how the global temperature is linked to CO₂ and other greenhouse gases
33 concentrations and radiative forcings.

34 Even the continuous reference to the hiatus seems too much emphasized, because it
35 has been completely addressed just in the last section, by means of the consideration
36 of NDVI. On the other hand, this part is not cited in the title... Please, address this
37 problem.

38 Finally, a major concern is about the way in which the Granger causality has been
39 applied. In particular, the authors used in-sample investigations and tests. In order to
40 do so, they had to establish the stochastic properties of the time series involved, by
41 analyzing whether these series are stationary, non-stationary or co-integrated,
42 because, for instance, the use of non-stationary time series can lead to spurious
43 causality results. Of course, the weakness of this approach is that incorrect
44 conclusions drawn by this preliminary analysis may affect the results of causality tests
45 and their reliability: for instance, is the temperature time series I(0) or I(1)? This is
46 why the studies of the global warming problem addressed through Granger in-sample
47 analyses draw sometimes to contrasting results. Instead, an out-of-sample approach is
48 less dependent on the preliminary assumptions, and more properly predictive, and
49 more in the spirit of the original concept of Granger causality, so that it is suggested
50 for obtaining reliable results. See a review in Attanasio et al. (2013), Atmospheric and

1 Climate Sciences, 3, 515-522, and two specific papers in Attanasio et al (2012),
2 Atmospheric Science Letters, 13, 67-72, and Pasini et al. (2012), Environmental
3 Research Letters, 7, 034020.
4 Now, it is not sure that this invalidates the results of the authors, but it is necessary to
5 present these drawbacks to the reader, explicitly citing the out-of-sample approach
6 and its advantages. Incidentally, the fact that the authors address also the problem of
7 the hiatus in the last 15 years could give them the possibility to test an out-of-sample
8 approach considering just this period as test set.
9 Another word of caution must be spoken about the possibility of spurious causality
10 due to omission of variables. It is very useful to perform multivariate analyses which
11 can corroborate or falsify bivariate ones. See, for instance, Triacca et al. (2013),
12 Environmetrics, 24, 260-268. Please, refer also to this drawback of your treatment in
13 your revised paper.

14
15 Minor comments

16 P. 1, row 18. "... and this gap is presently continuing to increase". This is not true.
17 2014 and 2015 have been very hot years, at the top of the record, and a new large
18 increasing trend seems to start now. Please, delete this sentence.

19 P. 1, rows 23-31. The abstract is too long and full of not clear and not discussed
20 sentences: the standard model, causality of the temperature to rate of change of CO₂ ,
21 without any mention of the causality role of anthropogenic CO₂ on temperature. This
22 certainly causes confusion in the reader. Please, delete these rows.

23 P. 2, row 5. You use the verb "to demonstrate" here. This verb can be applied to a
24 mathematical theorem but not to what you are doing in this paper: it is a too strong
25 statement! Please, substitute demonstrated → shown.

26 P. 2, row 9. As before. Substitute demonstrates → shows.

27 P. 3, row 7. You introduce the hiatus here. However you have to cite also that recent
28 studies have reconsidered the correct quantification of this hiatus: they show that the
29 pause in the increase of temperature was in effect less evident. Please, cite Cowtan &
30 Way (2014), Q. J. Roy. Met. Soc., 140, 1935-1944, and Karl et al. (2015), Science,
31 348, 1469-1472. Then you may assert that you consider, however, a standard times
32 series of temperature (HADCrut4).

33 P. 3, rows 19-.... When you introduce ENSO, you have to briefly discuss its accepted
34 role in the scientific literature, that is its influence on interannual variability of
35 temperature. Refer to Hoerling et al. (2008), Geophys. Res. Lett., 35, L23712;
36 DelSole et al. (2011), J. Climate, 24, 909-926; Triacca et al. (2014), J. Climate, 27,
37 7903-7910.

38 P. 5, rows 12-13. The difference is not between climate models and temperature but
39 between climate model outputs and temperature. Please, change the sentence
40 accordingly.

41 P. 6, row 15. Insert here the presentation of the role of anthropogenic CO₂ on
42 temperature, as required in the major concerns.

43 P. 8, rows 23-.... First of all, the review indicated as Attanasio 2012 is not a review.
44 The review is Attanasio et al. (2013), Atmospheric and Climate Sciences, 3, 515-522.
45 Please, substitute the reference. Then, here you have to insert the discussion about in-
46 sample and out-of-sample Granger causality tests, as indicated in the major concerns.
47 Finally, insert consideration about the limits of bivariate analyses vs. multivariate
48 ones.

49 P. 9, row 26. A citation of the peculiar role of ENSO discovered in Triacca et al.
50 (2014), J. Climate, 27, 7903-7910, could be useful for the reader.

1 P. 31, rows 20-21. Once again, you refer to a linear AGW hypothesis. In the more
2 complex reality of the research on dynamical climate models, even in these models
3 when increased sinks are considered we could arrive to results similar to your own. I
4 suggest to delete this sentence.

8 **4. Response to specific comments of Referee 1**

10 **Referee 1 Comment, paragraph 4 of 4.** ... *If I have one comment they might be*
11 *asked act on, it relates to their third paragraph on page 21. Comment 9 of my last*
12 *report pointed out that this test result is a logical implication of their findings on*
13 *integration order, not a new finding. They have ignored this comment; they should*
14 *point out clearly that correlations between stationary and nonstationary series are*
15 *not well defined.*

16
17 *(Comment 9 of previous report of Referee 1. The application of the Toda-*
18 *Yamamoto result is most interesting, but it needs to be seen in context. These*
19 *authors propose tests for a VAR in levels with an unknown number of unit*
20 *roots. However, please note that in such a model, Granger causality of an*
21 *I(1) series by an I(2) series is ruled out by construction. A model generating*
22 *variables with different orders of integration can only embody long-run*
23 *relations between variables transformed to have the same orders of*
24 *integration: in particular, between the level of an I(1) and the differences of*
25 *an I(2), or between the level of an I(0) and the differences of an I(1)). (To*
26 *verify this statement, consider the VAR () $A L x u$ and verify the properties*
27 *that $A L ()$ must satisfy to ensure that $A L ()$ contains different powers of*
28 *the factor $1 L$ appearing in different rows.) The outcome of the reported test is*
29 *inevitable, given the other reported results. I guess it does not harm to report*
30 *it, but with suitable caveats.)*

31 Response: This comment is closely related to one made by Referee 2. That comment
32 will be listed here and a joint response then given to both.

33 **Referee 2 Comment** *Finally, a major concern is about the way in which the*
34 *Granger causality has been applied. In particular, the authors used in-sample*
35 *investigations and tests. In order to do so, they had to establish the stochastic*
36 *properties of the time series involved, by analyzing whether these series are*
37 *stationary, non-stationary or co-integrated, because, for instance, the use of non-*
38 *stationary time series can lead to spurious causality results. Of course, the weakness*
39 *of this approach is that incorrect conclusions drawn by this preliminary analysis may*
40 *affect the results of causality tests and their reliability: for instance, is the*
41 *temperature time series I(0) or I(1)? This is why the studies of the global warming*
42 *problem addressed through Granger in-sample analyses draw sometimes to*
43 *contrasting results. Instead, an out-of-sample approach is less dependent on the*
44 *preliminary assumptions, and more properly predictive, and more in the spirit of the*
45 *original concept of Granger causality, so that it is suggested for obtaining reliable*
46 *results. See a review in Attanasio et al. (2013), Atmospheric and Climate Sciences, 3,*
47 *515-522, and two specific papers in Attanasio et al (2012), Atmospheric Science*

1 *Letters, 13, 67-72, and Pasini et al. (2012), Environmental Research Letters, 7,*
2 *034020.*

3 *Now, it is not sure that this invalidates the results of the authors, but it is necessary to*
4 *present these drawbacks to the reader, explicitly citing the out-of-sample approach*
5 *and its advantages. Incidentally, the fact that the authors address also the problem of*
6 *the hiatus in the last 15 years could give them the possibility to test an out-of-sample*
7 *approach considering just this period as test set.)*

8 **Response:** The purpose of the testing for order of integration of the time-series is
9 simply so that the Toda-Yamamoto method of testing for G-causality can be applied
10 properly. This methodology is NOT affected adversely by the prior tests. The reason
11 why studies differ in their results when doing within-sample G-causality testing in this
12 field is because they don't use the T-Y procedure (or the equivalent Lutkepohl
13 procedure).

14 With this background we stress that the point of the T-Y procedure is to enable us to
15 test properly for non-causality when in fact we have a mixture of I(0) and I(1)
16 variables.

17 We recognise that *correlations* between I(0) and I(1) variables will be spurious. We
18 suggest keeping the existing causality result re levels, with a statement that this
19 *supports the finding about causality when differenced CO₂ is considered.* We also
20 suggest use of "confirmation", rather than "evidence".

21
22 We propose to replace lines 11 to 16 on Page 21 with the following:

23
24 We recognise that as temperature is stationary, while CO₂ is not, these two
25 variables cannot correlate in the usual sense. However, given that Granger
26 non-causality tests can have low power due to the presence of lagged
27 dependent variables, it is sensible to seek support, or confirmation, for the
28 result just discussed. This can be done by testing for Granger non-causality
29 between the levels of CO₂ and TEMP. In this case, the testing procedure must
30 be modified to allow for the differences in the orders of integration of the data
31 series.

32
33
34 Despite the lack of stationarity in the level of CO₂ time series (meaning it
35 cannot be used to model temperature), one can still assess the answer to the
36 question: "Is there evidence of Granger causality between level of CO₂ and
37 TEMP?" In answering this question, because the TEMP series is stationary,
38 but the CO₂ series is non-stationary (it is integrated of order one, *I(1)*), the
39 testing procedure is modified.

40
41
42 Once again, the levels of both series are used. For each VAR model, the
43 maximum lag length (k) is determined, but then one additional lagged value of
44 both TEMP and CO₂ is included in each equation of the VAR. However, the
45 Wald test for Granger non-causality is applied only to the coefficients of the

1 original k lags of CO₂. Toda and Yamamoto (1995) show that this modified
2 Wald test statistic will still have an asymptotic distribution that is chi-square,
3 even though the level of CO₂ is non-stationary. Here the relevant Wald
4 Statistic (p-value): Null is there is No Granger Causality from level of CO₂ to
5 TEMP; Number of lags K= 4; Chi-Square 2.531 (p-value = 0.470). The lack of
6 statistical significance indicated by the p-value is strong confirmation
7 that level of CO₂ does not Granger-cause TEMP.
8
9

10 **5. Response to further specific comments of Referee 2**

11
12 For reply, the remaining comments of Referee 2 are excerpted and grouped, and listed
13 as 16 items. Our response to each of the 16 items is given after the item in question.
14

15 **Referee 2, Item 1 of 16.** ... *the first result that should be cited is that the increase of*
16 *CO₂ concentration in the atmosphere is mainly due to the anthropogenic emissions,*
17 *as shown by the isotopic signature of the CO₂ itself. Only after this recognition we*
18 *can speak about the causes of the variations of CO₂ concentrations due to natural*
19 *variability. It is clear, in fact, that the recognition of this forcing leads to think that*
20 *the CO₂ concentration must obviously have a causal role on temperature. In this*
21 *framework also ENSO can have a role just in the interannual variations of the*
22 *temperature. Please, insert these pieces of information at the beginning of the section*
23 *on the objectives of this study.*
24
25

26 With, for example, Fyfe (2014) we have followed a method of providing the materials
27 needed for our account by starting with from the particular issue in question and
28 adding in the context step by step.
29

30 The referee recommends in essence that we restructure and outline the context much
31 earlier in the narrative.
32

33 We have attempted this but found that trying to change the narrative order was
34 arduous and ran the risk of introducing new sequencing and numbering errors at this
35 stage.
36

37 We note that the way we have done it has not been an issue until now.
38

39 Concerning the specifics of the above Comment, we underline that in the existing ms.
40 we have referred to anthropogenic CO₂ and stated that ENSO has been the variable
41 considered to embody interannual change. This is on Page 9, lines 16-24, where we
42 list the range of major forcings in the context of each other:
43

44 From such studies, a common set of main influencing factors (also called
45 explanatory or predictor variables) has emerged. These are (Lockwood (2008);
46 Folland (2013); Zhou and Tung (2013)): El Nino–Southern Oscillation
47 (ENSO), or Southern Oscillation Index (SOI) alone; volcano aerosol optical
48 depth; total solar irradiance; and the trend in anthropogenic greenhouse gas
49 (the predominant anthropogenic greenhouse gas being CO₂). In these models,
50 ENSO/SOI is the factor embodying interannual variation.

1
2 We propose to incorporate the further point the referee makes concerning “the
3 isotopic signature of the CO₂ itself” in the Discussion where AGW is already
4 discussed, in new text , as follows (at Page 31 after line 12):

5
6 The anthropogenic global warming (AGW) hypothesis has two main
7 dimensions (IPCC 2007; Pierrehumbert 2011): (i) that increasing CO₂ causes
8 increasing atmospheric temperature (via a radiative forcing mechanism) and
9 (ii) that most of the increase in atmospheric CO₂ in the last hundred years has
10 been due to human causes - *a result of accelerated release of CO₂ from the*
11 *burning of fossil fuels. The evidence for this (Levin and Heisshamer, 2000)*
12 *comes from the analysis of changes in the proportion of carbon isotopes in*
13 *tree rings from the past two centuries.*

14
15
16 **2 of 16.** *P. 3, rows 19-.... When you introduce ENSO, you have to briefly discuss its*
17 *accepted role in the scientific literature, that is its influence on interannual variability*
18 *of temperature. Refer to Hoerling et al. (2008), Geophys. Res. Lett., 35, L23712;*
19 *DelSole et al. (2011), J. Climate, 24, 909-926; Triacca et al. (2014), J. Climate, 27,*
20 *7903-7910.*

21
22 As mentioned above for Item 1 of 20, we note that on Page 9, lines 16-24, we list the
23 full range of accepted major forcings in the context of each other. This section stresses
24 that ENSO has been seen as the factor embodying interannual variation, and provides
25 peer-reviewed references for this:

26
27 From such studies, a common set of main influencing factors (also called
28 explanatory or predictor variables) has emerged. These are (Lockwood (2008);
29 Folland (2013); Zhou and Tung (2013)): El Nino–Southern Oscillation
30 (ENSO), or Southern Oscillation Index (SOI) alone; volcano aerosol optical
31 depth; total solar irradiance; and the trend in anthropogenic greenhouse gas
32 (the predominant anthropogenic greenhouse gas being). In these models,
33 ENSO/SOI is the factor embodying interannual variation.

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37 **3 of 16.** *In this framework, the authors speak about a “standard model” of linear*
38 *increase. They should refer to the GCM outputs (very complex dynamical models)*
39 *which show how the global temperature is linked to CO₂ and other greenhouse gases*
40 *concentrations and radiative forcings.*

41
42 Response: firstly, references to a “standard model” have been removed, where
43 appropriate being replaced with “the majority of GCM simulations”.

44
45 Secondly, concerning the GCM-related point, we note that two main sorts of peer-
46 reviewed quantitative analysis of the relationships between climate variables have
47 been carried out. One type of analysis has utilised General Circulation Models, also
48 known as General Climate Models (GCMs). These (IPCC, 2014) “are numerical
49 representations of the climate system based on the physical, chemical and biological

1 properties of its components, their interactions and feedback processes, and
2 accounting for some of its known properties.”
3

4 The other type of quantitative analysis involves using empirical regression analysis to
5 seek correlations between empirical climate-data time series (for a survey see Imbers
6 et al., 2013). Our study is within this regression tradition of climate research which
7 includes studies such as those of Lean and Rind (2008, 2009); Foster and Rahmstorf
8 (2011); Kopp and Lean (2011); and Zhou and Tung (2013). Unfortunately being from
9 this tradition we are not qualified to interpret GCM modelling and so have attempted
10 to deal with the suggestion of Referee 2 to *show how the global temperature is linked*
11 *to CO₂ and other greenhouse gases concentrations and radiative forcings* using peer-
12 reviewed climate literature from the empirical regression field. We trust this will
13 adequately achieve the result sought.
14

15 The relevant text is again that on Page 9, lines 16-24, where we list the full range of
16 accepted major forcings in the context of each other:
17

18 From such studies, a common set of main influencing factors (also called
19 explanatory or predictor variables) has emerged. These are (Lockwood (2008);
20 Folland (2013); Zhou and Tung (2013)): El Nino–Southern Oscillation
21 (ENSO), or Southern Oscillation Index (SOI) alone; volcano aerosol optical
22 depth; total solar irradiance; and the trend in anthropogenic greenhouse gas
23 (the predominant anthropogenic greenhouse gas being CO₂). In these models,
24 ENSO/SOI is the factor embodying interannual variation.
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29 **4 of 16.** *Even the continuous reference to the hiatus seems too much emphasized,*
30 *because it has been completely addressed just in the last section by means of the*
31 *consideration of NDVI.*
32

33 Response: Various terminology has been used by authors to describe this situation
34 (again, for example Fyfe et al., 2013) – including pause, hiatus and slow-down. In this
35 paper we use the term “model-observation difference” with synonyms for difference:
36 gap; disparity; and mismatch.
37
38

39 The concept of the model-observation difference is core to the premise of the paper.
40 The premise is then productive of other results, which are duly described. We then
41 return, in discussion of potential mechanisms, to evoke the concept of the model-
42 observation difference again. We use it in our opinion only as much as is needed to
43 establish the premise.
44
45
46

47 **5 of 16.** *... NDVI. On the other hand, this part is not cited in the title... Please,*
48 *address this problem.*
49

1 Response. In seeking to incorporate the photosynthesis-related content of the paper in
2 the title, we also sought to manage length and increase clarity. As a result we propose
3 to remove the technical terms “first and second difference” from the title and replace
4 them with their precise plain English equivalent – “change in level”.

5
6 Hence we propose to replace the existing title:

7
8
9 Granger causality from the first and second differences of atmospheric CO₂ to
10 global surface temperature and the El Niño–Southern Oscillation respectively

11
12
13 ...with the proposed new title:

14
15 Granger causality from change in level of atmospheric CO₂ to global surface
16 temperature and the El Niño–Southern Oscillation, and a candidate mechanism
17 in global photosynthesis

18
19
20
21 **6 of 16.** *P. 1, row 18. “... and this gap is presently continuing to increase”. This is*
22 *not true. 2014 and 2015 have been very hot years, at the top of the record, and a new*
23 *large increasing trend seems to start now. Please, delete this sentence.*

24
25 Response: “... and this gap is presently continuing to increase” will be deleted.

26
27 **7 of 16.** *P. 3, row 7. You introduce the hiatus here. However you have to cite also*
28 *that recent studies have reconsidered the correct quantification of this hiatus: they*
29 *show that the pause in the increase of temperature was in effect less evident. Please,*
30 *cite Cowtan & Way (2014), Q. J. Roy. Met. Soc., 140, 1935-1944, and Karl et al.*
31 *(2015), Science, 348, 1469-1472. Then you may assert that you consider, however, a*
32 *standard times series of temperature (HADCrut4).*

33
34
35 Response: We propose to incorporate the Cowtan & Way (2014) and Karl et al.
36 (2015) material alongside the existing content of Figure 1 in a new figure. As well, to
37 provide a longer time perspective of the situation, in the proposed new figure we have
38 taken the opportunity to replace the existing figure start year of 1959 with a start year
39 of 1880.

40
41
42
43 We also propose to delete the following paragraph on Page 3, starting at line 9:

44
45 The situation is illustrated visually in Figure 1 which shows the increasing
46 departure over recent years of the global surface temperature trend from that
47 projected by a representative mid-range global climate model (GCM) for
48 global surface temperature - the CMIP3, SRESA1B scenario model (Meehl et
49 al. 2007).

1 We propose to replace the above paragraph with the following:

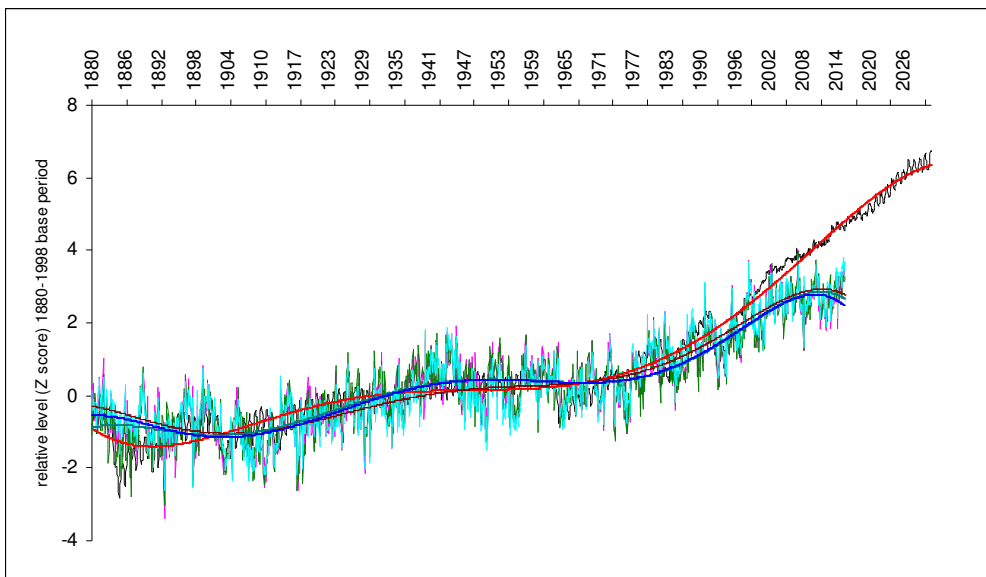
2
3 It is noted that recent studies have reconsidered the correct quantification of
4 this model-observation difference: they report analysis suggesting that it is in
5 effect less evident (Cowtan & Way (2014), Q. J. Roy. Met. Soc., 140, 1935-
6 1944, and Karl et al. (2015), Science, 348, 1469-1472).

7
8 We illustrate the effect of both the initial observations and these alternative
9 quantifications on the model-observation difference in Figure 1.

10
11 Figure 1 shows the departure over recent years of a standard time series of
12 temperature (HadCRUT4) from that projected by a representative mid-range
13 global climate model (GCM) for global surface temperature – the CMIP3,
14 SRESA1B scenario model (Meehl et al. 2007). The figure also shows the
15 alternative temperature series (Cowtan & Way (2014), and Karl et al. (2015)).

16
17 The figure shows the general similarity between all curves from 1880 to the
18 late 1990s, followed by the three empirical temperature curves departing from
19 the RCP4.5 curve together. It is noted that while there is some increase in the
20 three empirical curves in 2014 and 2015 they remain below that expected from
21 the RCP4.5 model output.

22
23
24 Figure 1. Monthly data, Z scored to aid visual comparison (see Sect. 1). To show
25 their core trends for illustrative purposes the four series are fitted with 6th order
26 polynomials. Shown are: the output of an IPCC mid-range scenario model (CMIP5,
27 RCP4.5 scenario) run for the IPCC fifth assessment report (IPCC 2014) (black
28 curve)(polynomial fit (pn): red curve). Global surface temperature datasets:
29 HadCRUT4 (purple curve) (pn: blue curve); Cowtan and Way (2014) (green curve)
30 (pn: light green curve); Karl et al. (2015) (aquamarine curve) (pn: brown curve).



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8 of 16. From Referee 2 Minor comments. P. 8, rows 23-.... *First of all, the review indicated as Attanasio 2012 is not a review. The review is Attanasio et al. (2013), Atmospheric and Climate Sciences, 3, 515-522. Please, substitute the reference. Then, here you have to insert the discussion about in-sample and out-of-sample Granger causality tests, as indicated in the major concerns.)*

Response: 1. The reference has been substituted. 2. Concerning in-sample and out-of-sample Granger causality tests, we would note that the purpose of the testing for order of integration of the time-series is simply so that the Toda-Yamamoto method of testing for G-causality can be applied properly. This methodology is NOT affected adversely by the prior tests. The reason why studies differ in their results when doing within-sample G-causality testing in this field is because they don't use the T-Y procedure (or the equivalent Lutkepohl procedure).

We propose to replace lines 15 to 20 on page 21:

Despite the lack of stationarity in the level of CO₂ 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 CO₂ and TEMP?”

In answering this question, because the TEMP series is stationary, but the CO₂ series is non-stationary (it is integrated of order one, $I(1)$), the testing procedure is modified slightly

...with the following:

We recognise that as temperature is stationary, while CO₂ is not, these two variables cannot correlate in the usual sense. However, given that Granger non-causality tests can have low power due to the presence of lagged dependent variables, it is sensible to seek support, or confirmation, for the result just discussed. This can be done by testing for Granger non-causality between the levels of CO₂ and TEMP. In this case, the testing procedure must be modified to allow for the differences in the orders of integration of the data series.

9 of 16. P. 1, rows 23-31. *The abstract is too long and full of not clear and not discussed sentences: the standard model, causality of the temperature to rate of change of CO₂, without any mention of the causality role of anthropogenic CO₂ on temperature. This certainly causes confusion in the reader. Please, delete these rows.*

Response: remove rows 23-31, P. 1.

1 **10 of 16.** *P. 2, row 5. You use the verb “to demonstrate” here. This verb can be*
2 *applied to a mathematical theorem but not to what you are doing in this paper: it is a*
3 *too strong statement! Please, substitute demonstrated → shown*

4
5 Response: Substitution made.

6
7
8 **11 of 16.** *P. 2, row 9. As before. Substitute demonstrates → shows.*

9
10 Response: Substitution made.

11
12
13 **12 of 16.** *P. 5, rows 12-13. The difference is not between climate models and*
14 *temperature but between climate model outputs and temperature. Please, change the*
15 *sentence accordingly.*

16
17 Response: “outputs” added.

18
19 **13 of 16.** *Another word of caution must be spoken about the possibility of spurious*
20 *causality due to omission of variables. It is very useful to perform multivariate*
21 *analyses which can corroborate or falsify bivariate ones. See, for instance, Triacca et*
22 *al. (2013), Environmetrics, 24, 260-268. Please, refer also to this drawback of your*
23 *treatment in your revised paper.*

24 Our testing for Granger non-causality is performed in a bivariate setting, as is
25 commonly the case. This has both advantages and disadvantages. On the one
26 hand, testing in a multivariate setting can avoid the spurious results that may arise if
27 relevant variables are unwittingly omitted from the analysis (e.g., Triacca *et al.*,
28 2013). However, testing for Granger non-causality with three or more variables is
29 problematic. While a pairwise analysis can be undertaken, this can lead to ambiguous
30 results (e.g., Geweke, 1984; Ding *et al.*, 2006). Indeed the very concept of Granger
31 causality is ambiguous in such cases (Lutkepohl, 1993; Dufour and Renault, 1998),
32 and researchers sometimes resort to so-called "conditional causality". For these
33 reasons we have retained a bivariate analysis, subject to the caveat above.

34
35 References:

36
37 Ding, M, Chen, Y. and Bressler, S. L.: Granger causality: Basic theory and
38 applications to neuroscience. In: Handbook of Time Series Analysis (eds. B. Schelter,
39 M. Winterhalder, and J. Timmer), Wiley-VCH Verlag, Weinheim, 437–460, 2006.

40
41 Dufour, J.-M. and Renault, E.: Short run and long run causality in time series: theory,
42 *Econometrica*, 66, 1099-1125. 1998.

43
44 Geweke, J.: Measures of conditional linear dependence and feedback between time
45 series, *Journal of the American Statistical Association*, 79, 907–915, 1984.

46
47 Lutkepohl, H.: Testing for causation between two variables in higher dimensional

1 VAR models. In: Studies in Applied Econometrics (eds. H. Schneeweiss and K.
2 F. Zimmerman), Physica-Verlag, Heidelberg, 75-91, 1993.

3
4 Triacca, U., Attanasio A. and Pasini, A.: Anthropogenic global warming hypothesis:
5 testing its robustness by Granger causality analysis. *Environmetrics*, 24, 260-268,
6 2013.

7
8
9 **14 of 17.** P. 8, rows 23-.... *First of all, the review indicated as Attanasio 2012 is not*
10 *a review. The review is Attanasio et al. (2013), Atmospheric and Climate Sciences, 3,*
11 *515-522. Please, substitute the reference.*

12
13 Response: Reference substituted

14
15
16 **15 of 16.** P. 9, row 26. *A citation of the peculiar role of ENSO discovered in Triacca*
17 *et al. (2014), J. Climate, 27, 7903-7910, could be useful for the reader.*

18
19 Response: Despite reviewing Triacca et al. (2014), we are unable to identify the
20 precise point or points from the paper which add to the thrust of this section of our
21 study.

22
23
24 **16 of 16.** P. 31, rows 20-21. *Once again, you refer to a linear AGW hypothesis. In the*
25 *more complex reality of the research on dynamical climate models, even in these*
26 *models when increased sinks are considered we could arrive to results similar to your*
27 *own. I suggest to delete this sentence.*

28
29 Response: Concerning “linear AGW” we note we have ever only cited the IPCC: We
30 here provide the reference verbatim (IPCC, 2014: Climate Change 2013: The Physical
31 Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the
32 Intergovernmental Panel on Climate Change [Stocker, T.F., D. Qin, G.-K. Plattner, M.
33 Tignor, S.K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex and P.M. Midgley
34 (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York,
35 NY, USA, 1535 pp.), page 62:

36
37 ...on decadal to interdecadal time scales and under continually increasing
38 effective radiative forcing, the forced component of the global surface
39 temperature trend responds to the forcing trend relatively rapidly and almost
40 linearly.

41
42 This said, instead of the paragraph commencing at Page 31, line 19:

43
44 The difference between this evidence for the effect of CO₂ on climate and that
45 of the standard AGW hypothesis is that the standard model proposes that
46 temperature will rise roughly linearly with atmospheric CO₂, whereas the
47 present results show that the climate effects result from persistence of previous
48 effects and from rates of change of CO₂.

49
50 We propose the following new text:

1
2 The difference between this evidence for the effect of CO₂ on climate and that
3 from the majority of GCM simulations is that in the simulations the
4 temperature rises roughly linearly with the level of atmospheric CO₂, whereas
5 the present results show that the climate effects result from persistence of
6 previous effects and from change in the level of CO₂.
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14 **Granger causality from changes in level of**
15 **atmospheric CO₂ to global surface temperature**
16 **and the El Niño–Southern Oscillation, and a**
17 **candidate mechanism in global photosynthesis**

18
19 **L.M.W. Leggett¹ and D.A. Ball¹**

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

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23
24

25 **Abstract**

26
27 A significant **difference**, now of some 16 years in length has been shown to exist
28 between the observed global surface temperature trend and that expected from the
29 majority of climate simulations. For its own sake, and to enable better climate
30 prediction for policy use, the reasons behind this mismatch need to be better
31 understood. While an increasing number of possible causes have been proposed, the
32 candidate causes have not yet converged.
33

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1 | ~~With this background, this paper reinvestigates the relationship between change in~~
2 | ~~level of CO₂ and two of the major climate variables, atmospheric temperature and the~~
3 | ~~El Niño–Southern Oscillation (ENSO).~~

4 |
5 | Using time series analysis in the form of dynamic regression modelling with
6 | autocorrelation correction, it is ~~shown~~ that first-difference CO₂ leads temperature and
7 | that there is a highly statistically significant correlation between first-difference CO₂
8 | and temperature. Further, a correlation is found for second-difference CO₂ with the
9 | Southern Oscillation Index, the atmospheric-pressure component of ENSO. This
10 | paper also ~~shows~~ that both these correlations display Granger causality.

11 |
12 | It is shown that the first-difference CO₂ and temperature model shows no trend
13 | mismatch in recent years.

14 |
15 | These results may contribute to the prediction of future trends for global temperature
16 | and ENSO.

17 |
18 | Interannual variability in the growth rate of atmospheric CO₂ is standardly attributed
19 | to variability in the carbon sink capacity of the terrestrial biosphere. The terrestrial
20 | biosphere carbon sink is created by the difference between photosynthesis and
21 | respiration (net primary productivity): a major way of measuring global terrestrial
22 | photosynthesis is by means of satellite measurements of vegetation reflectance, such
23 | as the Normalized Difference Vegetation Index (NDVI). In a preliminary analysis,
24 | this study finds a close correlation between an increasing NDVI and the increasing
25 | climate model/temperature mismatch (as quantified by the difference between the
26 | trend in the level of CO₂ and the trend in temperature).

31 | 1 Introduction

32 |
33 | Understanding current global climate requires an understanding of trends both in
34 | Earth's atmospheric temperature and the El Niño–Southern Oscillation (ENSO), a

Deleted: The standard model which is now displaying the disparity has it that temperature will rise roughly linearly with atmospheric CO₂. However research also exists showing correlation between the interannual variability in the growth rate of atmospheric CO₂ and temperature. Rate of change of CO₂ had not been considered a causative mechanism for temperature because it was concluded that causality ran from temperature to rate of change of CO₂. ¶
¶ However more recent studies have found little or no evidence for temperature leading rate of change of CO₂ but instead evidence for simultaneity.

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1 characteristic large-scale distribution of warm water in the tropical Pacific Ocean and
2 the dominant global mode of year-to-year climate variability (Holbrook et al. 2009).
3 However, despite much effort, the average projection of current climate models has
4 become statistically significantly different from the 21st century global surface
5 temperature trend (Fyfe et al. 2013; Fyfe and Gillett 2014) and has failed to reflect the
6 statistically significant evidence that annual-mean global temperature has not risen in
7 the 21st century (Fyfe et al. 2013; Kosaka and Shang-Ping 2013).

8
9 The situation is illustrated visually in Figure 1 which shows the increasing departure
10 over recent years of the global surface temperature trend from that projected by a
11 representative mid-range global climate model (GCM) for global surface temperature
12 - the CMIP3, SRESA1B scenario model (Meehl et al. 2007).

13 It is noted that recent studies have reconsidered the correct quantification of this
14 model-observation difference: they report analysis suggesting that it is in effect less
15 evident (Cowtan & Way (2014), Q. J. Roy. Met. Soc., 140, 1935-1944, and Karl et al.
16 (2015), Science, 348, 1469-1472).

17
18 We illustrate the effect of both the initial observations and these alternative
19 quantifications on the model-observation difference in Figure 1.

20
21 Figure 1 shows the departure over recent years of a standard time series of
22 temperature (HadCRUT4) from that projected by a representative mid-range global
23 climate model (GCM) for global surface temperature – the CMIP3, SRESA1B
24 scenario model (Meehl et al. 2007). The figure also shows the alternative temperature
25 series (Cowtan & Way (2014), and Karl et al. (2015)).

26
27 Figure 1 shows that the alternative quantifications reduce the scale of the difference
28 seen using HadCRUT4 but do not eradicate it.

29
30 It is noted that the level of atmospheric CO₂ is a good proxy for the International
31 Panel on Climate Change (IPCC) models predicting the global surface temperature
32 trend: according to IPCC (2014), on decadal to interdecadal time scales and under
33 continually increasing effective radiative forcing, the forced component of the global

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1 surface temperature trend responds to the forcing trend relatively rapidly and almost
2 linearly.

3

4 ~~The extremes of this ENSO variability cause extreme weather events (such as floods
5 and droughts) in many regions of the world. Modelling provides a wide range of
6 predictions for future ENSO variability, some showing an increase, others a decrease,
7 and some no change (Guilyardi et al. 2012; Bellenger 2013).~~

Deleted: 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).

8

9 A wide range of physical explanations has now been proposed for the global warming
10 slowdown. These involve proposals either for changes in the way the radiative
11 mechanism itself is working or for the increased influence of other physical
12 mechanisms. Chen and Tung (2014) place these proposed explanations into two
13 categories. The first involves a reduction in radiative forcing: by a decrease in
14 stratospheric water vapour, an increase in background stratospheric volcanic aerosols,
15 by 17 small volcano eruptions since 1999, increasing coal-burning in China, the
16 indirect effect of time-varying anthropogenic aerosols, a low solar minimum, or a
17 combination of these. The second category of candidate explanation involves
18 planetary sinks for the excess heat. The major focus for the source of this sink has
19 been physical and has involved ocean heat sequestration. However, evidence for the
20 precise nature of the ocean sinks is not yet converging: according to Chen and Tung
21 (2014) their study followed the original proposal of Meehl et al. (2011) that global
22 deep-ocean heat sequestration is centred on the Pacific. However, their observational
23 results were that such deep-ocean heat sequestration is mainly occurring in the
24 Atlantic and the Southern oceans.

25

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

31

32 It is widely considered that the interannual variability in the growth rate of
33 atmospheric CO₂ is a sign of the operation of the influence of the planetary biota.

1 Again, IPCC (2007) states: “The atmospheric CO₂ growth rate exhibits large
2 interannual variations. The change in fossil fuel emissions and the estimated
3 variability in net CO₂ uptake of the oceans are too small to account for this signal,
4 which must be caused by year-to-year fluctuations in land-atmosphere fluxes.”
5 In the IPCC Fourth Assessment Report, Denman et al. (2007) state (italics denote
6 present author emphasis): “Interannual and inter-decadal variability in the growth rate
7 of atmospheric CO₂ is dominated by the *response of the land biosphere to climate*
8 *variations*. The terrestrial biosphere *interacts strongly with the climate*, providing
9 both positive and negative feedbacks due to biogeophysical and biogeochemical
10 processes. ... Surface climate is determined by the balance of fluxes, which can be
11 changed by radiative (e.g., albedo) or non-radiative (e.g., water cycle related
12 processes) terms. Both radiative and non-radiative terms *are controlled by details of*
13 *vegetation*.”

14
15 Denman et al. (2007) also note that many studies have confirmed that the variability
16 of CO₂ fluxes is mostly due to land fluxes, and that tropical lands contribute strongly
17 to this signal. A predominantly terrestrial origin of the growth rate variability can be
18 inferred from (1) atmospheric inversions assimilating time series of CO₂
19 concentrations from different stations, (2) consistent relationships between δ¹³C and
20 CO₂, (3) ocean model simulations, and (4) terrestrial carbon cycle and coupled model
21 simulations. For one prominent estimate carried out by the Global Carbon Project, the
22 land sink is calculated as the residual of the sum of all sources minus the sum of the
23 atmosphere and ocean sinks (Le Quere et al. 2014).

24
25 The activity of the land sink can also be estimated directly. The terrestrial biosphere
26 carbon sink is created by photosynthesis: a major way of measuring global land
27 photosynthesis is by means of satellite measurements of potential photosynthesis from
28 greenness estimates. The measure predominantly used is the Normalized Difference
29 Vegetation Index (NDVI) (Running et al. 2004; Zhang et al. 2014). NDVI data are
30 available from the start of satellite observations in 1980 to the present. For this period
31 the trend signature in NDVI has been shown to correlate closely with that for
32 atmospheric CO₂ (Barichivich et al. 2013). This noted, we have not been able to find
33 studies which have compared NDVI data with the difference between climate model
34 outputs, and temperature.

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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)). 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.

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 CO₂) 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

1
2 What has been considered to influence the biota's creation of the pattern observed in
3 the trend in the growth rate of atmospheric CO₂? The candidates for the influences on
4 the biota have mainly been considered in prior research to be atmospheric variations,
5 primarily temperature and/or ENSO (e.g., Kuo et al. 1990; Wang W. et al. 2013).
6 Despite its proposed role in global warming overall, CO₂ (in terms of the initial state
7 of atmospheric CO₂ exploited by plants at time *A*) has not generally been isolated and
8 studied in detail through time series analysis as an influence in the way the biosphere
9 influences the CO₂ left in the atmosphere at succeeding time *B*.

10

11 This lack of attention to the influence of the biosphere on climate variables seems to
12 have come about for two reasons, one concerning ENSO, the other, temperature. For
13 ENSO, the reason is that the statistical studies are unambiguous that ENSO leads rate
14 of change of CO₂ (e.g., Lean and Rind 2008). On the face of it, therefore, this ruled
15 out CO₂ as the first mover of the ecosystem processes. For temperature, the reason
16 was that the question of whether atmospheric temperature leads rate of change of CO₂
17 or vice versa is less settled.

18 In the first published study on this question, Kuo et al. (1990) provided evidence that
19 the signature of interannual atmospheric CO₂ (measured as its first difference) fitted
20 temperature (passing therefore one of the four tests for causality, of close
21 conjunction).

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22 The relative fits of both level of and change in level of atmospheric CO₂ (measured as
23 its first difference) with global surface temperature up to the present are depicted in
24 Figure 2. Attention is drawn to both signature (fine grained data structure) and, by
25 means of polynomial smoothing, core trend for each data series.

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26 Concerning signature, while clearly first-difference CO₂ and temperature are not
27 identical, each is more alike than either is to the temperature model based on level of
28 CO₂. As well, the polynomial fits show that the same likeness groupings exist for core
29 trend.

1 Kuo et al. (1990) also provided evidence concerning another of the causality
2 prerequisites – priority. This was that the signature of first-difference CO₂ *lagged*
3 temperature (by 5 months). This idea has been influential. More recently, Adams and
4 Piovesan (2005) noted that climate variations acting on ecosystems are believed to be
5 responsible for variation in CO₂ increment, but there are major uncertainties in
6 identifying processes, including uncertainty concerning *instantaneous* (present
7 authors’ emphasis) versus lagged responses. Wang et al. (2013) observed that the
8 strongest coupling is found between the CO₂ growth rate and the *concurrent* (present
9 authors’ emphasis) tropical land temperature. Wang et al. (2013) nonetheless state in
10 their conclusion that the strong temperature–CO₂ coupling they observed is best
11 explained by the additive responses of tropical terrestrial respiration and primary
12 production to temperature variations, which reinforce each other in enhancing
13 *temperature’s control* (present author emphasis) on tropical net ecosystem exchange.

14 Another perspective on the relative effects of rising atmospheric CO₂ concentrations
15 on the one hand and temperature on the other has been provided by extensive direct
16 experimentation on plants. In a large scale meta-analysis of such experiments,
17 Dieleman et al. (2012) drew together results on how ecosystem productivity and soil
18 processes responded to combined warming and CO₂ manipulation, and compared it
19 with those obtained from single factor CO₂ and temperature manipulation. While the
20 meta-analysis found that responses to combined CO₂ and temperature treatment
21 showed the greatest effect, this was only slightly larger than for the CO₂-only
22 treatment. By contrast, the effect of the CO₂-only treatment was markedly larger than
23 for the warming-only treatment.

24
25 In looking at leading and lagging climate series more generally, the first finding of
26 correlations between the rate of change (in the form of the first-difference) of
27 atmospheric CO₂ and a climate variable was with the foregoing and the Southern
28 Oscillation Index (SOI) component of ENSO (Bacastow 1976). Here evidence was
29 presented that the SOI led first-difference atmospheric CO₂. There have been further
30 such studies (see Imbers et al. (2013) for overview) which, taken together,
31 consistently show that the highest correlations are achieved with SOI leading
32 temperature by some months (3-4 months).

33

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1 In light of the foregoing, this paper reanalyses by means of time series regression
2 analysis which of first-difference CO₂ and temperature lead. The joint temporal
3 relationship between interannual atmospheric CO₂, global surface temperature and
4 ENSO (indicated by the SOI) is also investigated.

5
6 The foregoing also shows that a strong case can be made for further investigating the
7 planetary biota influenced by atmospheric CO₂ as a candidate influence on (cause of)
8 climate outcomes. This question is also explored in this paper.

9
10 A number of Granger causality studies have been carried out on climate time series
11 (see review in Attanasio 2012). We found six papers which assessed atmospheric CO₂
12 and global surface temperature (Sun and Wang 1996; Triacca 2005; Kodra et al. 2011;
13 Attanasio and Triacca 2011; Attanasio 2012; Stern and Kaufmann 2014). Of these,
14 while all but one (Triacca 2005) found Granger causality, it was not with CO₂
15 concentration as studied in this paper but with CO₂ radiative forcing (lnCO₂
16 (Attanasio and Triacca 2011)).

17
18 As well, all studies used annual not monthly data. Such annual data for each of
19 atmospheric CO₂ and temperature is not stationary of itself but must be transformed
20 into a new, stationary, series by differencing (Sun and Wang 1996). Further, data at
21 this level of aggregation can "mask" correlational effects that only become apparent
22 when higher frequency (e.g., monthly) data are used.

23
24 Rather than using a formal Granger causality analysis, a number of authors have
25 instead used conventional multiple regression models in attempts to quantify the
26 relative importance of natural and anthropogenic influencing factors on climate
27 outcomes such as global surface temperature. These regression models use
28 contemporaneous explanatory variables. For example, see Lean and Rind (2008,
29 2009); Foster and Rahmstorf (2011); Kopp and Lean (2011); Zhou and Tung (2013).
30 This type of analysis effectively assumes a causal direction between the variables
31 being modelled. It is incapable of providing a proper basis for testing for the presence
32 or absence of causality. In some cases account has been taken of autocorrelation in the
33 model's errors, but this does not overcome the fundamental weakness of standard
34 multiple regression in this context. In contrast, Granger causality analysis that we

1 adopt in this paper provides a formal testing of both the presence and direction
2 of this causality (Granger 1969).

3
4 From such studies, a common set of main influencing factors (also called explanatory
5 or predictor variables) has emerged. These are (Lockwood (2008); Folland (2013);
6 Zhou and Tung (2013)): El Nino–Southern Oscillation (ENSO), or Southern
7 Oscillation Index (SOI) alone; volcano aerosol optical depth; total solar irradiance;
8 and the trend in anthropogenic greenhouse gas (the predominant anthropogenic
9 greenhouse gas being CO₂). In these models, ENSO/SOI is the factor embodying
10 interannual variation. Imbers et al. (2013) show that a range of different studies using
11 these variables have all produced similar and close fits with the global surface
12 temperature.

13
14 With this background, this paper first presents an analysis concerning whether the
15 first-difference of atmospheric CO₂ leads or lags global surface temperature. After
16 assessing this, questions of autocorrelation, strength of correlation, and of causality
17 are then explored. Given this exploration of correlations involving first-difference
18 atmospheric CO₂, the possibility of the correlation of second-difference CO₂ with
19 climate variables is also explored.

20
21
22 Correlations are assessed at a range of time scales to seek the time extent over which
23 relationships are held, and thus whether they are a special case or possibly longer term
24 in nature. The time scales involved are, using instrumental data, over two periods
25 starting respectively from 1959 and 1877; and, using paleoclimate data, over a period
26 commencing from 1515. The correlations are assessed by means of regression models
27 explicitly incorporating autocorrelation using dynamic modelling methods. Granger
28 causality between CO₂ and, respectively, temperature and SOI is also explored.
29 Atmospheric CO₂ rather than emissions data is used, and where possible at monthly
30 rather than annual aggregation. Finally, as noted, we have not been able to find studies
31 which have compared the gap between climate models and temperature with NDVI
32 data, so an assessment of this question is carried out. All assessments were carried out
33 using the time series statistical software packages Gnu Regression, Econometrics and

1 Time-series Library (GRETl) (Available from: <http://gretl.sourceforge.net/> (Accessed
2 January 23, 2014)) and IHS EViews (IHS EViews 2011).

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6 **3. Data and methods**

7
8

9 We present results of time series analyses of climate data. The data assessed are
10 global surface temperature, atmospheric carbon dioxide (CO₂) and the Southern
11 Oscillation Index (SOI). The regressions are presented in several batches based on the
12 length of data series for which the highest temporal resolution is available. The first
13 batch of studies involves the data series for which the available high resolution series
14 is shortest: this is for atmospheric carbon dioxide (CO₂) and commences in 1958.
15 These studies are set at monthly resolution.

16

17 The second batch of studies is for data able to be set at monthly resolution not
18 involving CO₂. These studies begin with the time point at which the earliest available
19 monthly SOI data commences, 1877.

20

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

23

24 Data from 1877 and more recently are from instrumental sources; earlier data are from
25 paleoclimate sources.

26

27 For instrumental data sources for global surface temperature, we used the Hadley
28 Centre–Climate Research Unit combined land SAT and SST (HadCRUT) version
29 4.2.0.0 (Morice et al. 2012), for atmospheric CO₂, the U.S. Department of Commerce
30 National Oceanic ~~and~~ Atmospheric Administration Earth System Research Laboratory
31 Global Monitoring Division Mauna Loa, Hawaii, monthly CO₂ series (Keeling et al.
32 2009), and for volcanic aerosols the National Aeronautic and Space Administration
33 Goddard Institute for Space Studies Stratospheric Aerosol Optical Thickness series
34 (Sato et al. 1993). Southern Oscillation Index data (Troup 1965) is from the Science
35 Delivery Division of the Department of Science, Information Technology, Innovation

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1 and the Arts (DSITIA) Queensland, Australia. Solar irradiance data is from Lean, J.
2 (personal communication 2012).

3
4 With regard to the El Niño-Southern Oscillation, according to IPCC (2014) the term
5 El Niño was initially used to describe a warm-water current that periodically flows
6 along the coast of Ecuador and Peru, disrupting the local fishery. It has since become
7 identified with a basin-wide warming of the tropical Pacific Ocean east of the
8 dateline. This oceanic event is associated with a fluctuation of a global-scale tropical
9 and subtropical surface atmospheric pressure pattern called the Southern Oscillation.
10 This atmosphere–ocean phenomenon is coupled, with typical time scales of two to
11 about seven years, and known as the El Niño-Southern Oscillation (ENSO).

12
13 The El Niño (temperature) component of ENSO is measured by changes in the sea
14 surface temperature of the central and eastern equatorial Pacific relative to the average
15 temperature. The Southern Oscillation (atmospheric pressure) ENSO component is
16 often measured by the surface pressure anomaly difference between Tahiti and
17 Darwin.

18
19 For the present study we choose the SOI atmospheric pressure component rather than
20 the temperature component of ENSO to stand for ENSO as a whole. This is because it
21 is considered to be more valid to conduct an analysis in which temperature is an
22 outcome (dependent variable) without also having temperature as an input
23 (independent variable). The correlation between SOI and the other ENSO indices is
24 high, so we believe this assumption is robust.

25
26
27
28 Paleoclimate data sources are: Atmospheric CO₂, from 1500 – ice cores (Robertson et
29 al. (2001)); (NH) temperature, from 1527 – tree ring data (Moberg, A. et al. 2005);
30 SOI, from 1706 – tree ring data (Stahle et al. (1998)).

31
32 Normalized Difference Vegetation Index (NDVI) monthly data from 1980 to 2006 is
33 from the GIMMS (Global Inventory Modeling and Mapping Studies) data set (Tucker
34 et al. 2005) . NDVI data from 2006 to 2013 was provided by the Institute of

1 Surveying, Remote Sensing and Land Information, University of Natural Resources
2 and Life Sciences, Vienna.

3
4 Statistical methods used are standard (Greene 2012). Categories of methods used are:
5 normalisation; differentiation (approximated by differencing); and time series
6 analysis. Within time series analysis, methods used are: smoothing; leading or lagging
7 of data series relative to one another to achieve best fit; assessing a prerequisite for
8 using data series in time series analysis, that of stationarity; including autocorrelation
9 in models by use of dynamic regression models; and investigating causality by means
10 of a multivariate time series model, known as a vector autoregression (VAR) and its
11 associated Granger causality test. These methods will now be described in turn.

12

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

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

22

23 In the time series analyses, SOI and global atmospheric surface temperature are the
24 dependent variables. We tested the relationship between each of these variables and
25 (1) the change in atmospheric CO₂ and (2) the variability in its rate of change. We
26 express these CO₂-related variables as finite differences. The finite differences used
27 here are of both the first- and second-order types (we label these “first” and “second”
28 differences in the text). Variability is explored using both intra-annual (monthly) data
29 and interannual (yearly) data. The period covered in the figures is shorter than that
30 used in the data preparation because of the loss of some data points due to calculations
31 of differences and of moving averages (in monthly terms of up to 13 x 13), which
32 commenced in January 1960.

1
2 Smoothing methods are used to the degree needed to produce similar amounts of
3 smoothing for each data series in any given comparison. Notably, to achieve this
4 outcome, series resulting from higher levels of differences require more smoothing.
5 Smoothing is carried out initially by means of a 13-month moving average – this also
6 minimises any remaining seasonal effects. If further smoothing is required, then this is
7 achieved by taking a second moving average of the initial moving average (to
8 produce a double moving average) (Hyndman 2010). Often, this is performed by
9 means of a further 13 month moving average to produce a 13 x 13 moving average.
10 For descriptive statistics to describe the long-term variation of a time series trend,
11 polynomial smoothing is sometimes used.

12 It is important to consider what effects this filtering of our data may have on the
13 ensuing statistical analysis. In these analyses, only the CO₂ series was smoothed and
14 therefore requires assessment. To do this, we tested if the smoothed (2 x 13 month
15 moving average) first-difference CO₂ series used here has different key dynamics to
16 that of the original raw (unsmoothed) data from which the smoothed series was
17 derived. Lagged correlogram analysis showed that the maximum, and statistically
18 significant, correlation of the smoothed series with the unsmoothed series occurs
19 when there is no phase shift. This suggests that the particular smoothing used should
20 provide no problems in the assessment of which of first-difference CO₂ and
21 temperature has priority.

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

1 Eichenbaum (1987), Marcellino (1999), Breitung and Swanson (2002), and
2 Gulasekaran and Abeysinghe (2002).

3 Finally, seasonally adjusting the data by a range of alternative approaches did not
4 qualitatively change the results discussed in the paper. The results of these
5 assessments are given in the Supplement.

6 This means that our results relating to the existence of Granger causality should not be
7 affected adversely by the smoothing of the data that has been undertaken.

8
9 Variables are led or lagged relative to one another to achieve best fit. These leads or
10 lags were determined by means of time-lagged correlations (correlograms). The
11 correlograms were calculated by shifting the series back and forth relative to each
12 other, 1 month at a time.

13

14 With this background, the convention used in this paper for unambiguously labelling
15 data series and their treatment after smoothing or leading or lagging is depicted in the
16 following example. The atmospheric CO₂ series is transformed into its second
17 difference and smoothed twice with a 13 month moving average. The resultant series
18 is then Z-scored. This is expressed as $Z2x13mma2ndDerivCO_2$.

19

20 Note that, to assist readability in text involving repeated references, atmospheric CO₂
21 is sometimes referred to simply as CO₂ and global surface temperature as temperature.

22

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

31

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

4
5 After Greene (2012): the results of standard ordinary least squares (OLS) regression
6 analysis assume that the errors in the model are uncorrelated. Autocorrelation of the
7 errors violates this assumption. This means that the OLS estimators are no longer the
8 Best Linear Unbiased Estimators (BLUE). Notably and importantly this does not bias
9 the OLS coefficient estimates. However statistical significance can be overestimated,
10 and possibly greatly so, when the autocorrelations of the errors at low lags are
11 positive.

12
13 Addressing autocorrelation can take either of two alternative forms: *correcting for it*
14 (for example, for first order autocorrelation by the Cochrane-Orcutt procedure), or
15 *taking it into account*.

16
17 In the latter approach, the autocorrelation is taken to be a consequence of an
18 inadequate specification of the temporal dynamics of the relationship being
19 estimated. The method of dynamic modelling (Pankratz 1991) addresses this by
20 seeking to explain the current behavior of the dependent variable in terms of both
21 contemporaneous and past values of variables. In this paper the dynamic modelling
22 approach is taken.

23
24 To assess the extent of autocorrelation in the residuals of the initial non-dynamic OLS
25 models run, the Breusch-Godfrey procedure is used. Dynamic models are then used to
26 take account of such autocorrelation. To assess the extent to which the dynamic
27 models achieve this, Kiviet's Lagrange multiplier F-test (LMF) statistic for
28 autocorrelation (Kiviet 1986) is used.

29
30 Hypotheses related to Granger causality (see Introduction) are tested by estimating a
31 multivariate time series model, known as a vector autoregression (VAR), for level of
32 and first-difference CO₂ and other relevant variables. The VAR models the current
33 values of each variable as a linear function of their own past values and those of the

1 other variables. Then we test the hypothesis that x does not cause y by evaluating
2 restrictions that exclude the past values of x from the equation for y and vice versa.

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

10

11 **4 Results**

12

13 **4.1. Relationship between first-difference CO₂ and temperature**

14

15 **4.1.1. Priority**

16

17 Figure 2 showed that, while clearly first-difference CO₂ and temperature are not
18 identical in signature, each is more alike than either is to the temperature model based
19 on level of CO₂. As well the figure shows that the same likeness relationships exist for
20 the core trend. The purpose of the forthcoming sections is to see the extent to which
21 these impressions are statistically significant.

22

23 The first question assessed is that of priority: which of first-difference atmospheric
24 CO₂ and global surface temperature leads the other. The two series are shown for the
25 period 1959 to 2012 in Figure 3.

26

27 To quantify the degree of difference in phasing between the variables, time-lagged
28 correlations (correlograms) were calculated by shifting the series back and forth
29 relative to each other, one month at a time. These correlograms are given in Figure 4
30 for global and regional data. For all four relationships shown, first-difference CO₂
31 always leads temperature. The leads differ as quantified in Table 1.

32

33 It is possible for a lead to exist overall on average but for a lag to occur for one or
34 other specific subsets of the data. This question is explored in Figure 5 and Table 2.

35 Here the full 1959-2012 period of monthly data – some 640 months – for each of the

1 temperature categories is divided into three approximately equal sub-periods, to
2 provide 12 correlograms. It can be seen that in all 12 cases, first-difference CO₂ leads
3 temperature. It is also noted that earlier sub-periods tend to display longer first-
4 difference CO₂ leads. For the most recent sub-period the highest correlation is when
5 the series are neither led nor lagged.

6 7 8 9 **4.1.2 Correspondence between first-difference CO₂ and global surface** 10 **temperature curves**

11
12
13 Next, the second prerequisite for causality, close correspondence, is also seen between
14 first-difference CO₂ and global surface temperature in Figure 3.

15 16 **4.1.3 Time series analysis**

17
18 Both first-difference CO₂ being shown to lead temperature, and the two series
19 displaying close correspondence, are considered a firm basis for the time series
20 analysis of the statistical relationship between first-difference CO₂ and temperature
21 which follows. For this further analysis, we choose global surface temperature as the
22 temperature series because, while its maximum correlation is not the highest (Figure
23 5), its global coverage by definition is greatest. (In this section, TEMP stands for
24 global surface temperature ((HadCRUT4), and other block capital terms are variable
25 names used in the modelling).

26
27 The order of integration, denoted $I(d)$, is an important characteristic of a time series. It
28 reports the minimum number of differences required to obtain a covariance stationary
29 series. As stated above, all series used in a time series regression must be series which
30 are stationary without further differencing (Greene 2012); that is, display an order of
31 integration of $I(0)$. If a series has an order of integration greater than zero, it can be
32 transformed by appropriate differencing into a new series which is stationary.

33
34 By means of the Augmented Dickey–Fuller (ADF) test for unit roots, Table 3
35 provides the information concerning stationarity for the level of, and first-difference
36 of, CO₂, as well as for global surface temperature. Test results are provided for both

1 monthly and annual data. The test was applied with an allowance for both a drift and
2 deterministic trend in the data, and the degree of augmentation in the Dickey-Fuller
3 regressions was determined by minimizing the Schwarz Information Criterion.

4
5 The results show that for both the monthly and annual series used, the variables
6 TEMP and FIRST-DIFFERENCE CO₂ are stationary (I(0)); but level of CO₂ is not.
7 Level of CO₂ is shown to be I(1) because (Table 3) its first-difference is stationary .
8 In contrast, Beenstock et al. (2012), using annual data, report that their series for the
9 level of atmospheric CO₂ forcing is an I(2) variable and therefore is stationary in
10 *second* differences. To reconcile these two results, we refer to Pretis and Hendry
11 (2013), who reviewed Beenstock et al. (2012). Pretis and Hendry (2013) take issue
12 with the finding of I(2) for the anthropogenic forcings studied – including CO₂ – and
13 find evidence that this finding results from the combination of two different data sets
14 measured in different ways which make up the 1850-2011 data set which Beenstock
15 et al. test. Regarding this composite series Pretis and Hendry (2013) write:

16
17 In the presence of these different measurements exhibiting structural changes,
18 a unit-root test on the entire sample could easily not reject the null hypothesis
19 of I(2) even when the data are in fact I(1). Indeed, once we control for these
20 changes, our results contradict the findings in Beenstock et al. (2012).

21
22 Pretis and Hendry (2013) give their results for CO₂ in their Table 1. Note that, in the
23 table, level of CO₂ data is transformed into first-difference data (Beenstock et al claim
24 the *level* of CO₂ is I(2); if that is the case, the first-difference of the level of CO₂ Pretis
25 and Hendry (2013) should find would be I(1)).

26
27 Pretis and Hendry (2013) state:

28
29 Unit-root tests are used to determine the level of integration of time series.
30 Rejection of the null hypothesis provides evidence against the presence of a
31 unit-root and suggests that the series is I(0) (stationary) rather than I(1)
32 (integrated).

33 ...based on augmented Dickey–Fuller (ADF) tests (see Dickey and Fuller,
34 1981), the first-difference of annual radiative forcing of CO₂ is stationary

1 initially around a constant (over 1850–1957), then around a linear trend (over
2 1958–2011). Although these tests are based on sub-samples corresponding to
3 the shift in the measurement system, there is sufficient power to reject the null
4 hypothesis of a unit root.

5
6 Hence for annual data Pretis and Hendry (2013) find first-difference CO₂ to be
7 stationary – I(0), not I(1) – as is found in this study (Table 3).

8
9 With this question of the order of integration of the time series considered, we now
10 turn to the next step of the time series analysis. As Table 3, above, and Pretis and
11 Hendry (2013) show, the variable of the level of CO₂ is non-stationary (specifically,
12 integrated of order one, i.e., I(1)). Attempting to assess TEMP in terms of the level of
13 CO₂ would result in an “unbalanced regression”, as the dependent variable (TEMP)
14 and the explanatory variable (CO₂) have different orders of integration. It is well
15 known (e.g., Banerjee et al. 1993, pp. 190-191, and the references therein) that in
16 unbalanced regressions the t-statistics are biased away from zero. That is, one can
17 appear to find statistically significant results when in fact they are not present. In fact,
18 this occurrence of spurious significance is found when we regress TEMP on CO₂.
19 This is strong evidence that any analysis should involve the variables TEMP and
20 FIRST-DIFFERENCE CO₂, and not TEMP and CO₂.

21
22 For TEMP and FIRST-DIFFERENCE CO₂, one must next assess the extent to which
23 autocorrelation affects the time series model. This is done by obtaining diagnostic
24 statistics from an OLS regression. This regression shows, by means of the Breusch-
25 Godfrey test for autocorrelation (up to order 12 – that is, including all monthly lags up
26 to 12 months), that there is statistically significant autocorrelation at lags of one and
27 two months, leading to an overall Breusch-Godfrey Test statistic (LMF) = 126.901,
28 with p-value = $P(F(12,626) > 126.901) = 1.06 \times 10^{-158}$.

29
30 Autocorrelation is a consequence of an inadequate specification of the temporal
31 dynamics of the relationship being estimated. With this in mind, a dynamic model
32 (Greene 2012) with two lagged values of the dependent variable as additional
33 independent variables has been estimated. Results are shown in Table 4. The LMF
34 test shows that there is now no statistically significant unaccounted-for

1 autocorrelation, thus supporting the use of this dynamic model specification. Table 4
2 shows that a highly statistically significant model has been established. First it shows
3 that the temperature in a given period is strongly influenced by the temperature of
4 closely preceding periods (see Discussion for a possible mechanism for this). Further,
5 it provides evidence that there is also a clear, highly statistically significant role in the
6 model for first-difference CO₂.

9 **4.1.4 Granger causality analysis**

11 We now can turn to assessing if first-difference atmospheric CO₂ may not only
12 correlate with, but also contribute causatively to, global surface temperature. This is
13 done by means of Granger causality analysis.

15 Recalling that both TEMP and FIRST-DIFFERENCE CO₂ are stationary, it is
16 appropriate to test the null hypothesis of no Granger causality from FIRST-
17 DIFFERENCE CO₂ to TEMP by using a standard Vector Autoregressive (VAR)
18 model without any transformations to the data. The Akaike Information Criterion
19 (AIC) and the Schwartz Information Criterion (SIC) were used to select an optimal
20 maximum lag length (k) for the variables in the VAR. This lag length was then
21 lengthened, if necessary, to ensure that:

- 22 (i) The estimated model was dynamically stable (i.e., all of the inverted roots
23 of the characteristic equation lie inside the unit circle);
- 24 (ii) The errors of the equations were serially independent.

26
27
28 The relevant EViews output from the VAR model is entitled VAR Granger
29 Causality/Block Exogeneity Wald Tests and documents the following summary
30 results – Wald Statistic (p-value): Null is there is No Granger Causality from FIRST-
31 DIFFERENCE CO₂ to TEMP; Number of lags K=4; Chi-Square 26.684 (p-value =
32 0.000). A p-value of this level is highly statistically significant and means the null
33 hypothesis of No Granger Causality is very strongly rejected. That is, over the period
34 studied there is strong evidence that FIRST-DIFFERENCE CO₂ Granger-causes
35 TEMP.

1
2 We recognise that as temperature is stationary, while CO₂ is not, these two variables
3 cannot correlate in the usual sense. However, given that Granger non-causality tests
4 can have low power due to the presence of lagged dependent variables, it is sensible
5 to seek support, or confirmation, for the result just discussed. This can be done by
6 testing for Granger non-causality between the levels of CO₂ and TEMP. In this case,
7 the testing procedure must be modified to allow for the differences in the orders of
8 integration of the data series.

Deleted: Despite the lack of stationarity in the level of CO₂ 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 CO₂ and TEMP?"¶
¶
In answering this question, because the TEMP series is stationary, but the CO₂ series is non-stationary (it is integrated of order one, $I(1)$), the testing procedure is modified slightly

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10 Once again, the levels of both series are used. For each VAR model, the maximum lag
11 length (k) is determined, but then one additional lagged value of both TEMP and CO₂
12 is included in each equation of the VAR. However, the Wald test for Granger non-
13 causality is applied only to the coefficients of the original k lags of CO₂. Toda and
14 Yamamoto (1995) show that this modified Wald test statistic will still have an
15 asymptotic distribution that is chi-square, even though the level of CO₂ is non-
16 stationary. Here the relevant Wald Statistic (p-value): Null is there is No Granger
17 Causality from level of CO₂ to TEMP; Number of lags K= 4; Chi-Square 2.531 (p-
18 value = 0.470) . The lack of statistical significance indicated by, the p-value is strong
19 confirmation, that level of CO₂ does not Granger-cause TEMP.

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21 With the above two assessments done, it is significant that with regard to global
22 surface temperature we are able to discount causality involving the level of CO₂, but
23 establish causality involving first-difference CO₂.

26 4.2 Relationship between second-difference CO₂ and temperature and 27 Southern Oscillation Index

29 4.2.1 Priority and correspondence

31 Given the results of this exploration of correlations involving first-difference
32 atmospheric CO₂, the possibility of the correlation of second-difference CO₂ with
33 climate variables is also explored. The climate variables assessed are global surface
34 temperature and the Southern Oscillation Index (SOI). In this section, data is from the
35 full period for which monthly instrumental CO₂ data is available, 1958 to the present.
36 For this period, the series neither led nor lagged appear as follows (Figure 6). For the

1 purpose of this figure, to facilitate depiction of trajectory, second-difference CO₂ (left
2 axis) and SOI (right axis) are offset so that all four curves display a similar origin in
3 1960.

4
5 Figure 6 shows that, alongside the close similarity between first-difference CO₂ and
6 temperature already demonstrated, there is a second apparent distinctive pairing
7 between second-difference CO₂ and SOI. The figure shows that the overall trend,
8 amplitude and phase – the signature – of each pair of curves is both matched within
9 each pair and different from the other pair. The remarkable sorting of the four curves
10 into two groups is readily apparent. Each pair of results provides context for the other
11 – and highlights the different nature of the other pair of results.

12
13
14 Recalling that (even uncorrected for any autocorrelation) correlational data still holds
15 information concerning regression coefficients, we initially use OLS correlations
16 without assessing autocorrelation to provide descriptive statistics. Table 5 includes,
17 without any phase-shifting to maximise fit, the six pairwise correlations arising from
18 all possible combinations of the four variables other than with themselves. Here it can
19 be seen that the two highest correlation coefficients (in bold in the table) are firstly
20 between first-difference CO₂ and temperature, and secondly between second-
21 difference CO₂ and SOI.

22
23 In Table 6, phase shifting has been carried out to maximise fit (shifts shown in
24 variable titles in the table). This results in an even higher correlation coefficient for
25 second-difference CO₂ and SOI.

26
27
28 The link between all three variable realms – CO₂, SOI and temperature – can be
29 further observed in Figure 7 and Table 7. Figure 7 shows SOI, second-difference
30 atmospheric CO₂ and first-difference temperature, each of the latter two series phase-
31 shifted for maximum correlation with SOI (as in Table 5). Looking at priority, Table 6
32 shows that maximum correlation occurs when second-difference CO₂ leads SOI. It is
33 also noted that the correlation coefficients for the correlations between the curves
34 shown in Table 6 have all converged in value compared to those shown in Table 5.

35

1 Looking at the differences between the curves shown in Figure 7, two of the major
2 departures between the curves coincide with volcanic aerosols – from the El Chichon
3 volcanic eruption in 1982 and the Pinatubo eruption in 1992 (Lean and Rind 2009).
4 With these volcanism-related factors taken into account, it is notable (when expressed
5 in the form of the transformations in Figure 7) that the signatures of all three curves
6 are so essentially similar that it is almost as if all three curves are different versions of
7 – or responses to – the same initial signal.
8 So, a case can be made that first- and second-difference CO₂ and temperature and SOI
9 respectively are all different aspects of the same process.

13 **4.2.2 Time series analysis**

15 We now assess more formally the relationship between second-difference CO₂ and
16 SOI. As for first-difference CO₂ and temperature above, stationarity has been
17 established. Again, there is statistically significant autocorrelation at lags of one and
18 two months, leading to an overall Breusch-Godfrey Test statistic (LMF) of 126.9,
19 with p-value = $P(F(12,626) > 126.901) = 1.06 \times 10^{-158}$.

20 Table 8 shows the results of a dynamic model with the dependent variable used at
21 each of the two lags as further independent variables; there is now no statistically
22 significant autocorrelation which has not been accounted for.

24 As Table 8 shows, a highly statistically significant model has been established. As for
25 temperature, it shows that the SOI in a given period is strongly influenced by the SOI
26 of closely preceding periods. Again as for temperature, it provides evidence that there
27 is a clear role in the model for second-difference CO₂.

28 With this established, it is noted that while the length of series in the foregoing
29 analysis was limited by the start date of the atmospheric CO₂ series (January 1958),
30 high temporal resolution (monthly) SOI goes back considerably further, to 1877. This
31 long period SOI series (for background see Troup (1965)) is that provided by the
32 Australian Bureau of Meteorology, sourced here from the Science Delivery Division
33 of the Department of Science, Information Technology, Innovation and the Arts,
34 Queensland, Australia. As equivalent temperature data is also available (the global
35 surface temperature series already used above (HadCRUT4) goes back as far as

1 1850), these two longer series are now plotted in Figure 8. Notable is the continuation
2 of the striking similarity between the two signatures already shown in Figure 7 over
3 this longer period.

4
5 Turning to regression analysis, as previously the Breusch-Godfrey procedure shows
6 that, for lags up to lag 12, the majority of autocorrelation is again restricted to the first
7 two lags. Table 9 shows the results of a dynamic model with the dependent variable
8 used at each of the two lags as further independent variables.

9
10 In comparison with Table 8, the extended time series modelled in Table 9 shows a
11 remarkably similar R-squared statistic: 0.466 compared with 0.477. By contrast, the
12 partial regression coefficient for second-difference CO₂ has increased, to 0.14
13 compared with 0.077. It is beyond the scope of this study, but the relationship of SOI
14 and second-difference CO₂ means it is now possible to produce a proxy for monthly
15 atmospheric CO₂ from 1877 – a date approximately 75 years prior to the start of the
16 CO₂ monthly instrumental record in January 1958.

19 **4.2.3 Granger causality analysis**

20
21 This section assesses whether second-difference CO₂ can be considered to Granger-
22 cause SOI. This assessment is carried out using data for the period 1959 to 2012.

23
24 Results of stationarity tests for each series are given in Table 10. Each series is shown
25 to be stationary. These results imply that we can approach the issue of possible
26 Granger causality by using a conventional VAR model, in the levels of the data, with
27 no need to use a "modified" Wald test (as used in the Toda and Yamamoto (1995)
28 methodology).

29
30 Simple OLS regressions of SOI against separate lagged values of second-difference
31 CO₂ (including an intercept) confirm the finding that the highest correlation is when a
32 two-period lag is used.

1

2 A 2-equation VAR model is needed for reverse-sign SOI and second-difference CO₂.
3 Using SIC, the optimal maximum lag length is found to be 2 lags. When the VAR
4 model is estimated with this lag structure (Table 11), testing the null hypothesis that
5 there is no serial correlation at lag order h, shows that there is evidence of
6 autocorrelation in the residuals.

7

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

13

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

17

18 The relevant EViews output from the VAR model is entitled VAR Granger
19 Causality/Block Exogeneity Wald Tests and documents the following summary
20 results – Wald Statistic (p-value): Null is there is No Granger Causality from second-
21 difference CO₂ to sign-reversed SOI; Chi-Square 22.554 (p-value = 0.0001).

22 The forgoing Wald statistic shows that the null hypothesis is strongly rejected – in
23 other words, there is very strong evidence of Granger Causality from second-
24 difference CO₂ to sign-reversed SOI.

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28 **4.3 Paleoclimate data**

29

30 So far, the time period considered in this study has been pushed back in the
31 instrumental data realm to 1877. If non-instrumental paleoclimate proxy sources are
32 used, CO₂ data now at annual frequency can be taken further back. The following
33 example uses CO₂ and temperature data. The temperature reconstruction used here
34 commences in 1500 and is that of Frisia et al. (2003), derived from annually

1 laminated speleothem (stalagmite) records. A second temperature record (Moberg et
2 al. 2005) is from tree ring data. The atmospheric CO₂ record (Robertson et al. 2001) is
3 from fossil air trapped in ice cores and from instrumental measurements. The trends
4 for these series are shown in Figure 9.

5
6 Visual inspection of the figure shows that there is a strong overall likeness in
7 signature between the two temperature series, and between them and first-difference
8 CO₂. The similarity of signature is notably less with level of CO₂. It can be shown
9 that level of CO₂ is not stationary and, even with the two other series which are
10 stationary, the strongly smoothed nature of the temperature data makes removal of the
11 autocorrelation impossible. Nonetheless, noting that data uncorrected for
12 autocorrelation still provides valid correlations (Greene 2012) – only the statistical
13 significance is uncertain – it is simply noted that first-difference CO₂ displays a better
14 correlation with temperature than level of CO₂ for each temperature series (Table 13).

17 18 **4.4 Normalized Difference Vegetation Index (NDVI)**

19
20 Using the Normalized Difference Vegetation Index (NDVI) time series as a measure
21 of the activity of the land biosphere, this section now investigates the land biosphere
22 as a candidate mechanism for the issue, identified in the Introduction, of the
23 increasing difference between the observed global surface temperature trend and that
24 suggested by general circulation climate models.

25
26 The trend in the terrestrial CO₂ sink is estimated annually as part of the assessment of
27 the well-known global carbon budget (Le Quere et al. 2014). It is noted that there is a
28 risk of circular argument concerning correlations between the terrestrial CO₂ sink and
29 interannual (first-difference) CO₂ because the terrestrial CO₂ sink is defined as the
30 residual of the global carbon budget (Le Quere et al. 2014). By contrast, the
31 Normalized Difference Vegetation Index (NDVI) involves direct (satellite-derived)
32 measurement of terrestrial plant activity. For this reason and because, of the two
33 series, only NDVI is provided in monthly form, we will use only NDVI in what
34 follows.

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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

1 series. Pooling was done by appending the Z-scored NDVIV data to the Z-scored
2 NDVIG data at the point where the Z-scored NDVIG data ended (in the last month of
3 2006).

4
5 As discussed in the Introduction, Figure 1 shows that since around the year 2000 there
6 is an increasing difference between the temperature projected by a mid-level IPCC
7 model and that observed. Any cause for this increasing difference must itself show an
8 increase in activity over this period.

9
10 The purpose of this section is, therefore: (i) to derive an initial simple indicative
11 quantification of the increasing difference between the temperature model and
12 observation; and (ii) to assess whether global NDVI is increasing. If NDVI is
13 increasing, this is support for NDVI being a candidate for the cause of the temperature
14 model-observation difference. If there is a statistically significant relationship
15 between the two increases, this is further support for NDVI being a candidate for the
16 cause of the model-observation difference, and hence worthy of further detailed
17 research. A full analysis of this question is beyond the scope of the present paper.

18 19 20 **4.4.2 Preparation of the indicative series for the difference between the** 21 **temperature projected from a mid-level IPCC model and that observed**

22
23 A simple quantification of the difference between the temperature projected from a
24 mid-level IPCC model and that observed can be derived by subtracting the (Z-scored)
25 temperature projected from the IPCC mid-range scenario model (CMIP3, SRESA1B
26 scenario run for the IPCC fourth assessment report (IPCC 2007)) shown in Figure 1,
27 from the observed global surface temperature also shown in Figure 1. This
28 quantification is depicted in Figure 13 for monthly data and, to reduce the influence of
29 noise and seasonality, in Figure 14 for the same data pooled into three-year bins.

30 31 **4.4.3. Comparison of the pooled NDVI series with the difference between** 32 **projected and observed global surface temperature**

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

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

19 **5 Discussion**

20
21
22 The results in this paper show that there are clear links – at the highest standard of
23 non-experimental causality — that of Granger causality — between first- and second-
24 difference CO_2 and the major climate variables of global surface temperature and the
25 Southern Oscillation Index, respectively.

26
27 Relationships between first- and second-difference CO_2 and climate variables are
28 present for all the time scales studied, including temporal start points situated as long
29 ago as 1500. In the instances where time series analysis accounting for autocorrelation
30 could be successfully conducted, the results were always statistically significant. For
31 the further instances (for those studies using data series commencing before 1877) the
32 data was not amenable to time series analysis – and therefore also not amenable to
33 testing for Granger causality – due to the strongly smoothed nature of the temperature
34 data available which made removal of the autocorrelation impossible (see Section
35 4.3). Nonetheless, the scale of the non-corrected correlations observed was of the

1 same order of magnitude as those of the instances that were able to be corrected for
2 autocorrelation.

3
4 Given the time scales over which these effects are observed, the results taken as a
5 whole clearly suggest that the mechanism observed is long term, and not, for example,
6 a creation of the period of the steepest increase in anthropogenic CO₂ emissions, a
7 period which commenced in the 1950s (IPCC 2014).

8 Taking autocorrelation fully into account in the time series analyses demonstrates the
9 major role of immediate past instances of the dependent variable (temperature, and
10 SOI) in influencing its own present state. This was found in all cases where time
11 series models could be prepared. This was not to detract from the role of first- and
12 second-difference CO₂ – in all relevant cases, they were significant in the models as
13 well.

14
15 According to Wilks (1995) and Mudelsee (2010), such autocorrelation in the
16 atmospheric sciences also called persistence or “memory” is characteristic for many
17 types of climatic fluctuations.

18
19 In the specific case of the temperature and first-difference CO₂ relationship, the
20 significant autocorrelation for temperature occurred with present temperature being
21 affected by the immediately prior month and the month before that. As mentioned
22 above, for atmospheric CO₂ and global surface temperature, others (Sun and Wang
23 1996; Triacca 2005; Kodra et al. 2011; Attanasio and Triacca 2011; Attanasio 2012;
24 Stern and Kaufmann 2014) have conducted Granger causality analyses involving the
25 use of lags of both dependent and independent variables. These studies, however, are
26 not directly comparable with the present study. Firstly, while reporting the presence or
27 absence of Granger causality, the studies did not report lead or lag information.
28 Secondly, the studies used annual data, so could not investigate the dynamics of the
29 relationships at the interannual (monthly) level where our findings were greatest.

30
31 The anthropogenic global warming (AGW) hypothesis has two main dimensions
32 (IPCC 2007; Pierrehumbert 2011): (i) that increasing CO₂ causes increasing
33 atmospheric temperature (via a radiative forcing mechanism) and (ii) that most of the
34 increase in atmospheric CO₂ in the last hundred years has been due to human causes -

1 causes - a result of accelerated release of CO₂ from the burning of fossil fuels. The
2 evidence for this (Levin and Heisshamer, 2000) comes from the analysis of changes in
3 the proportion of carbon isotopes in tree rings from the past two centuries.

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6 The results presented in this paper are supportive of the AGW hypothesis for two
7 reasons: firstly, increasing atmospheric CO₂ is shown to drive increasing temperature;
8 and secondly, the results deepen the evidence for a CO₂ influence on climate in that
9 second-difference CO₂ is shown to drive the SOI.

10
11 The difference between this evidence for the effect of CO₂ on climate and that of the
12 standard AGW hypothesis is that from the majority of GCM simulations, is that in the
13 simulations the temperature rises roughly linearly with atmospheric CO₂, whereas the
14 present results show that the climate effects result from persistence of previous effects
15 and from change in the level of CO₂.

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16
17 On the face of it, then, this model seems to leave little room for the linear radiative
18 forcing aspect of the AGW hypothesis.

19
20 However more research is needed in this area.

21
22 Reflection on Figure 1 shows that the radiative mechanism would be supported if a
23 second mechanism existed to cause the difference between the temperature projected
24 for the radiative mechanism and the temperature observed. The observed temperature
25 would then be seen to result from the addition of the effects of these two mechanisms.

26
27 As discussed in the Introduction, Hansen et al. (2013) have suggested that the
28 mechanism for the pause in the global temperature increase since 1998 may be the
29 planetary biota, in particular the terrestrial biosphere. As an initial indicative
30 quantified characterisation of this possibility, Section 4.4 derived a simple measure of
31 the increasing difference between the global surface temperature trend projected from
32 a mid-range scenario climate model and the observed trend. This depiction of the
33 difference displayed a rising trend. The time series trend for the globally aggregated
34 Normalized Difference Vegetation Index – which represents the changing levels of

1 activity of the terrestrial biosphere was also presented. This was shown also to
2 display a rising trend.

3
4 If by further research, for example by Granger causality analysis, the global
5 vegetation can be shown to embody the second mechanism, this would be evidence
6 that the observed global temperature does result from the effects of two mechanisms
7 in operation together – the radiative, level-of-CO₂ mechanism, with the biological
8 first-difference of CO₂ mechanism.

9
10 Hence the biosphere mechanism would supplement, rather than replace, the radiative
11 mechanism.

12
13 Further comprehensive time series analysis of the NDVI data and relevant climate
14 data, beyond the scope of the present paper, could throw light on these questions.

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1

2 **Table 1.** Lag of first-difference CO₂ relative to surface temperature series for global,
3 tropical, northern hemisphere and southern hemisphere categories

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	Lag in months of first-difference CO₂ relative to global surface temperature category
Hadcrut4SH	-1
Hadcrut4Trop	-1
Hadcrut4_nh	-3
Hadcrut4Glob	-2

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1 **Table 2.** Lag of FIRST-DIFFERENCE CO₂ relative to surface temperature series for
 2 global, tropical, northern hemisphere and southern hemisphere categories, each for
 3 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

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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 CO₂, first-difference CO₂ and global surface temperature

	Monthly data				Annual data			
	ADF statistic*	p-value	Order of integration	Test interpretation	ADF statistic*	p-value	Order of integration	Test interpretation
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.

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Table 4. OLS dynamic regression between first-difference atmospheric CO₂ and global surface temperature for monthly data for the period 1959 - 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]
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

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1 **Table 5.** Pairwise correlations (correlation coefficients (R)) between selected climate
 2 variables
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	2x13mmafirstderiv CO₂	Hadcrut4Global	3x13mma2ndderivCO₂
Hadcrut4Global	0.7	1	
3x13mma2ndderivCO ₂	0.06	-0.05	1
13mmaReverseSOI	0.25	0.14	0.37

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7 **Table 6.** Pairwise correlations (correlation coefficients (R)) between selected climate
 8 variables, phase-shifted as shown in the table
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	Led2m2x13mmafirstderivCO₂	Hadcrut4Global	Led4m3x13mma2ndderivCO₂
Hadcrut4Global	0.71	1	
Led4m3x13mma2nddiffCO ₂	0.23	0.09	1
13mmaReverseSOI	0.16	0.14	0.49

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12 **Table 7.** Pairwise correlations (correlation coefficients (R)) between selected climate
 13 variables, phase-shifted as shown in the table
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	ZLed2m2x13mma2ndderivCO₂	ZReverseSOI
ZReverseSOI	0.28	1.00
ZLed3m13mmafirstdiffhadcrut4global	0.35	0.41

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17 Table 8. OLS dynamic regression between second-difference atmospheric CO₂ and
 18 reversed Southern Oscillation Index for monthly data for the period 1959 - 2012, with
 19 autocorrelation taken into account
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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]
Led3m2x13mma1stderivCO ₂	ReverseSOI	0.07699	<0.011	0.478	1.80E-89	0.214
Led1mReverseSOI		0.456	<0.00001			
Led2mreverseSOI		0.272	<0.00001			

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

1 Table 9. OLS dynamic regression between first-difference global surface temperature
 2 and reversed Southern Oscillation Index for monthly data for the period 1877-2012,
 3 with autocorrelation taken into account
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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]
Led3m12mma1stdiffTEMP	ReverseSOI	0.140	<0.00001	0.466	3.80E-221	0.202
Led1mReverseSOI		0.465	<0.00001			
Led2mReverseSOI		0.210	<0.00001			

5 [1] Z-scored

6 [2] Whole model: LM test for autocorrelation up to order 3 - Null hypothesis: no autocorrelation
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11 **Table 10:** Augmented Dickey–Fuller (ADF) test for stationarity for monthly data
 12 1959 to 2012 for second-difference CO₂ and sign-reversed SOI
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	ADF statistic	p-value	Test interpretation
Second-difference CO ₂	-10.077	0.000	Stationary
Sign-reversed SOI	-6.681	0.000	Stationary

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

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

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 7 **Table 13.** Correlations (R) between paleoclimate CO₂ and temperature estimates
 8 1500-1940

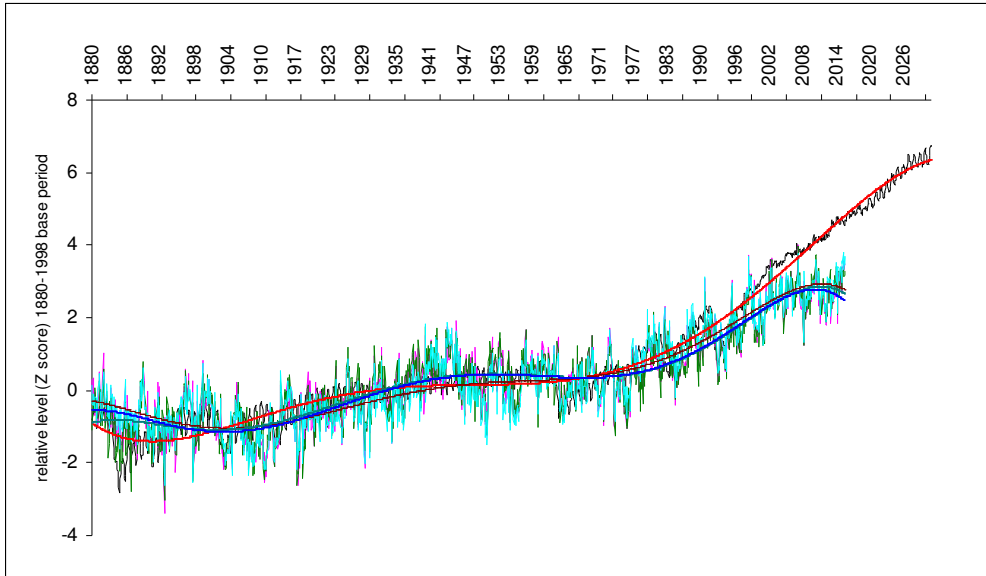
	Temperature (speliotherm)	Temperature (tree ring)
Level of CO ₂ (ice core)	0.369	0.623
1st diff. CO ₂ (ice core)	0.558	0.721

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 12 **Table 14.** Order of integration test results for NDVI series for monthly data from
 13 1981-2012. The Schwartz Information Criterion (SIC) was used to select an optimal
 14 maximum lag length in the tests.
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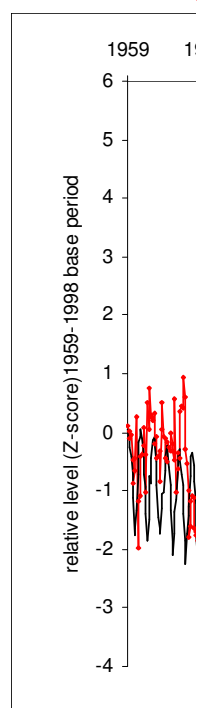
NDVI Series	Null Hypothesis: the series has a unit root	Probability of unit root
NDVIV	Lag Length: 16 (Automatic - based on SIC, maxlag=16)	0.0122
NDVIG	Lag Length: 1 (Automatic - based on SIC, maxlag=15)	7.23e-14
NDVIGV	Lag Length: 1 (Automatic - based on SIC, maxlag=16)	4.18E-16

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3 Figure 1. Monthly data, Z scored to aid visual comparison (see Sect. 1). To show their
4 core trends for illustrative purposes the four series are fitted with 6th order
5 polynomials. Shown are: the output of an IPCC mid-range scenario model (CMIP5,
6 RCP4.5 scenario) run for the IPCC fifth assessment report (IPCC 2014) (black
7 curve)(polynomial fit (pn): red curve). Global surface temperature datasets:
8 HadCRUT4 (purple curve) (pn: blue curve); Cowtan and Way (2014) (green curve)
9 (pn: light green curve); Karl et al. (2015) (aquamarine curve) (pn: brown curve).
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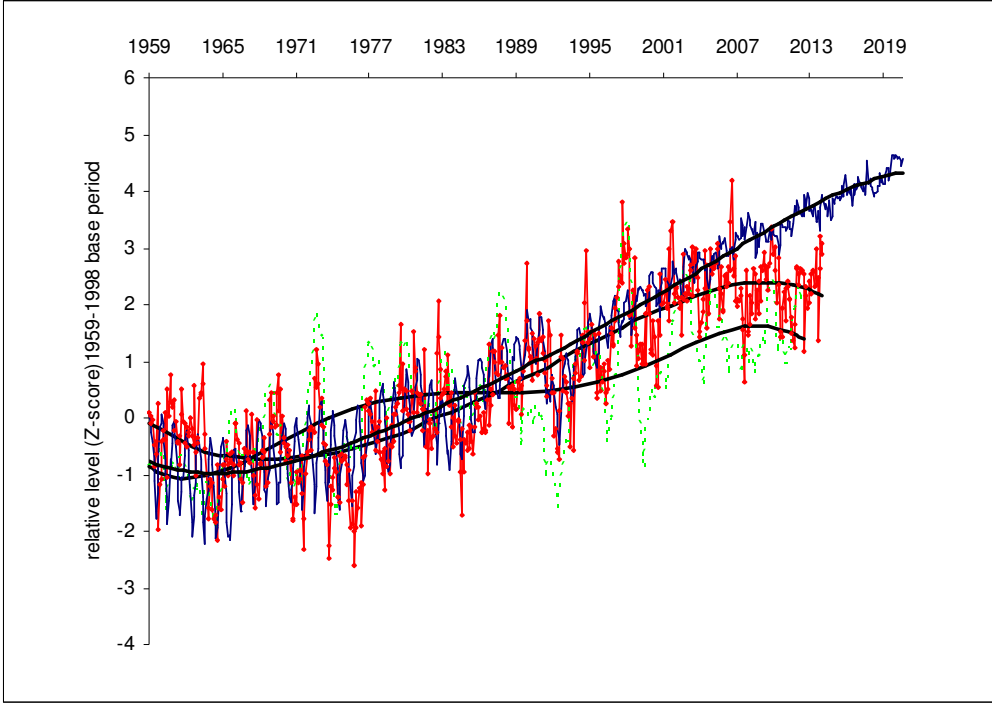
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Deleted: Figure 1. Monthly data: global surface temperature (HadCRUT4 dataset) (red dotted curve) and an IPCC mid-range scenario model (CMIP3, SRESA1B scenario) run for the IPCC fourth assessment report (IPCC 2007) (blue curve), each expressed in terms of Z scores to aid visual comparison (see Sect. 1).



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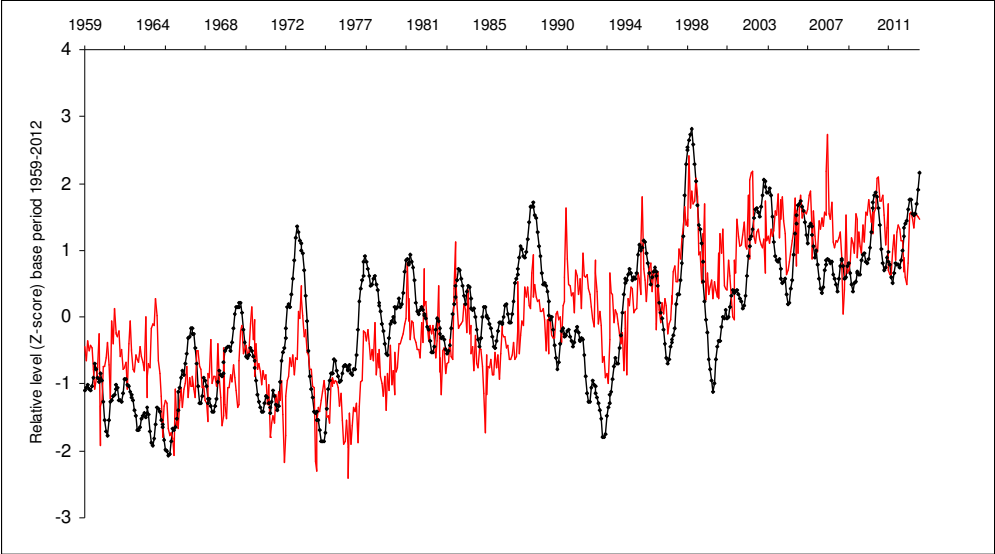
Figure 2. Z scored monthly data: global surface temperature (green dashed curve) compared to an IPCC mid-range scenario global climate model (GCM) – the CMIP3, SRESA1B scenario run for the IPCC fourth assessment report (IPCC 2007) (blue curve) and also showing the trend in first-difference atmospheric CO₂ (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.



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Figure 3. Z scored monthly data: global surface temperature (red curve) compared to first-difference atmospheric CO₂ smoothed by two 13 month moving averages (black dotted curve).

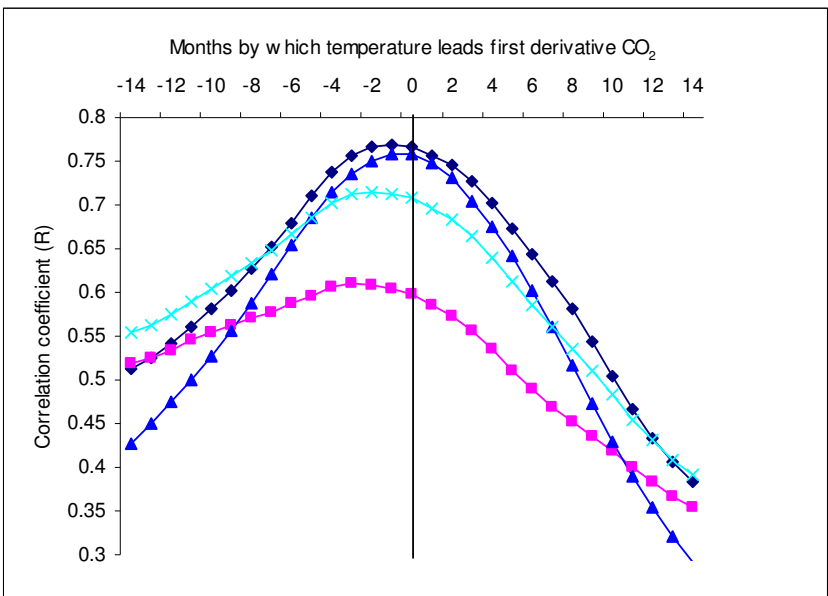


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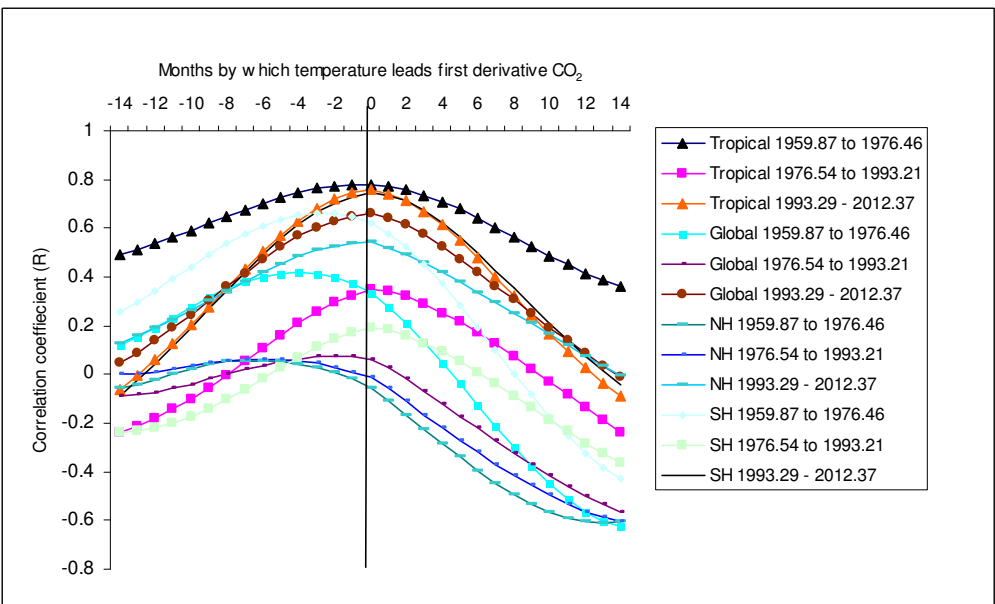
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Figure 4. Correlograms of first-difference CO₂ with surface temperature for global (turquoise curve with crosses), tropical (blue curve with triangles), Northern Hemisphere (purple curve with boxes) and Southern Hemisphere (black curve with diamonds) categories



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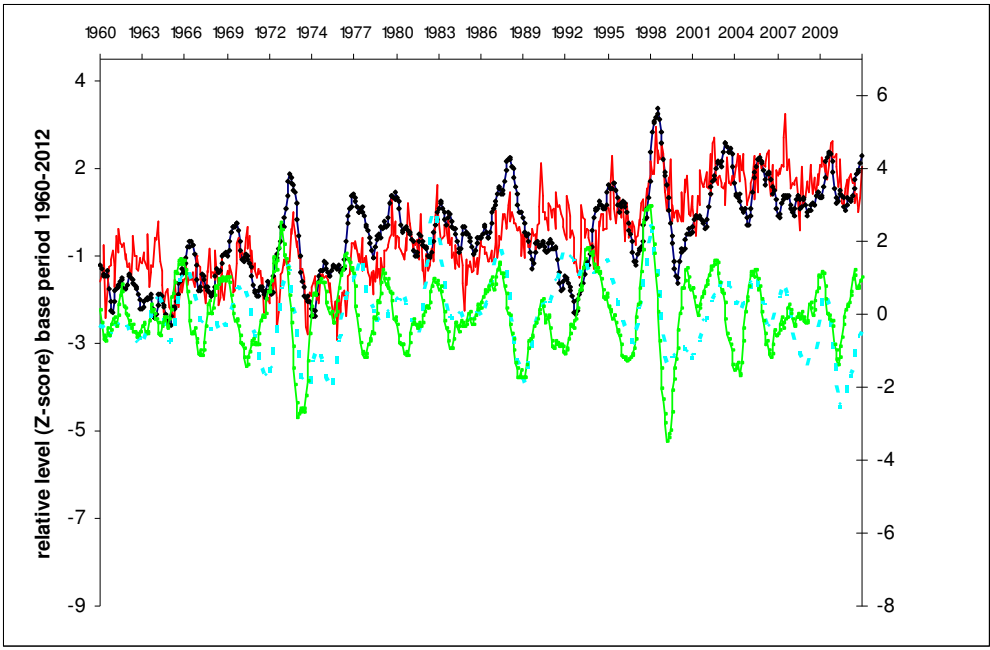
Figure 5. Correlograms of first-difference CO₂ with surface temperature for global, tropical, Northern Hemisphere and Southern Hemisphere categories, each for three time-series sub-periods.



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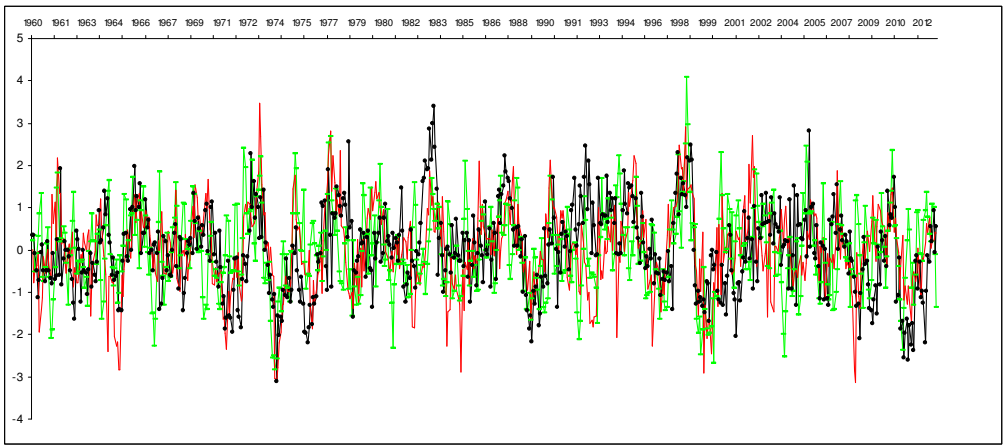
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Figure 6. Z scored monthly data: global surface temperature (red curve) and first-difference atmospheric CO₂ smoothed by two 13 month moving averages (black dotted curve) (left-hand scale); sign-reversed SOI smoothed by a 13 month moving average (blue dashed curve) and second-difference atmospheric CO₂ smoothed by three 13 month moving averages (green barred curve) (right-hand scale)



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Figure 7. Z scored monthly data from 1960 to 2012: sign-reversed SOI (unsmoothed and neither led nor lagged) (dotted black curve); second-difference CO₂ 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).

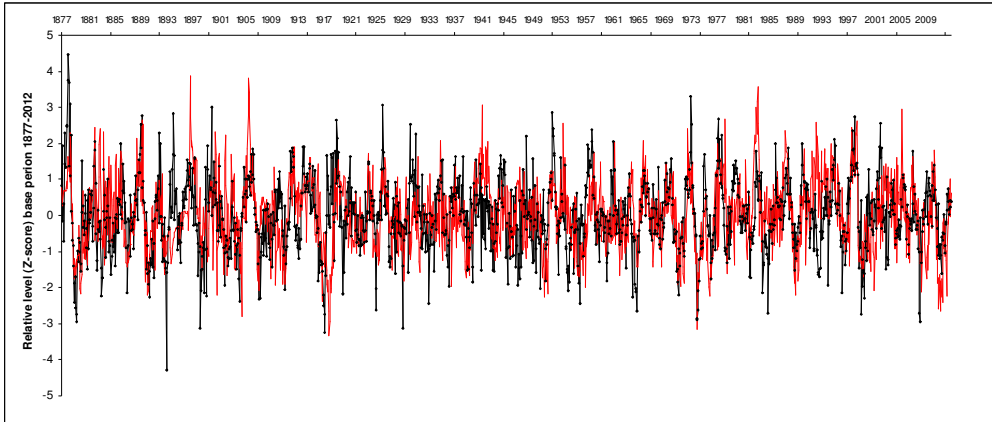


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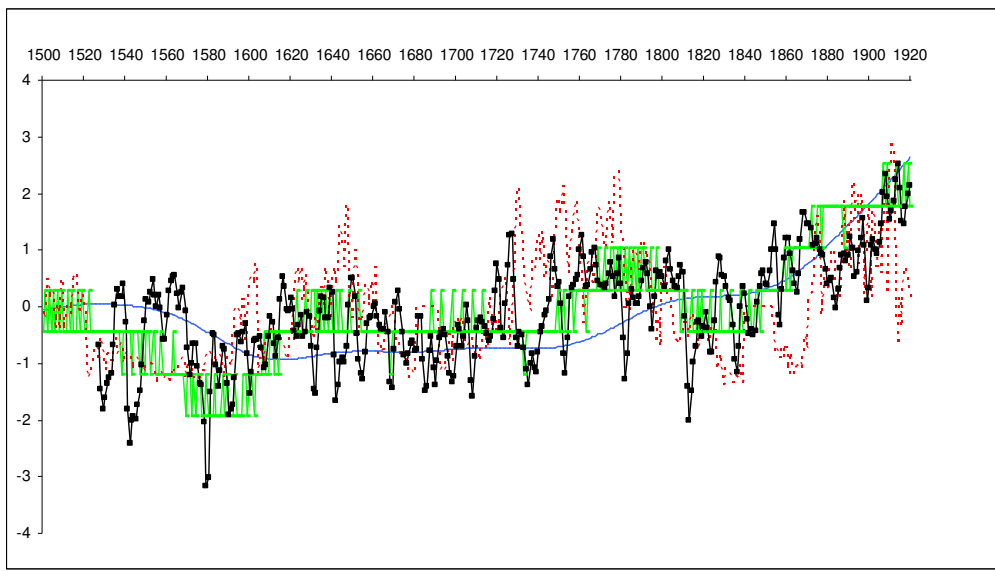
Figure 8. Z scored monthly data from 1877 to 2012: sign-reversed SOI (unsmoothed and neither led nor lagged) (red curve); and first-difference global surface temperature smoothed by a 13 month moving average and led relative to SOI by 3 months (black dotted curve)



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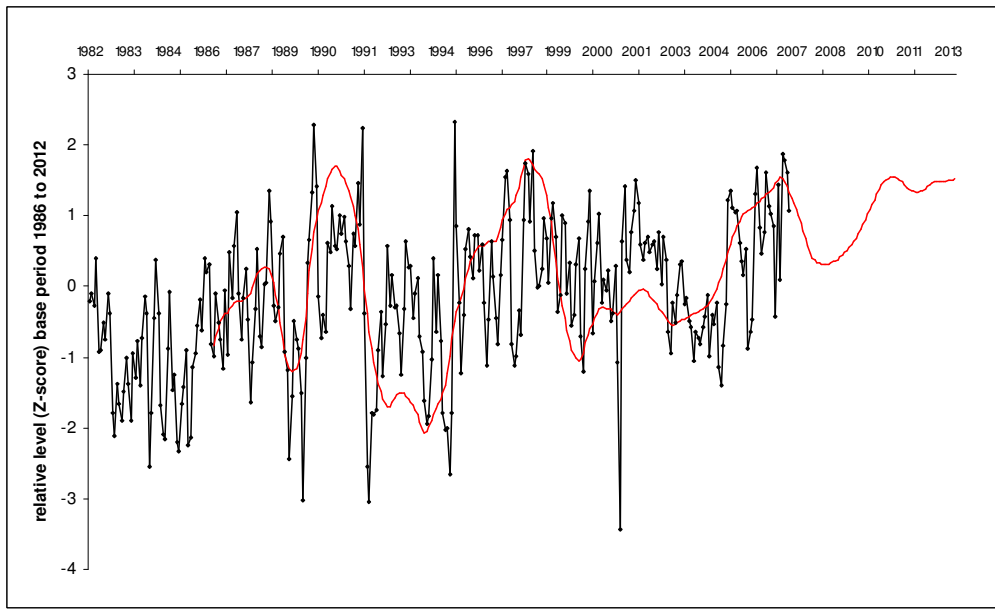
Figure 9. Z scored annual data: paleoclimate time series from 1500: ice core level of CO₂ (blue curve), level of CO₂ transformed into first-difference form (green barred curve); and temperature from speliotem (red dashed curve) and tree ring data (black boxed curve).



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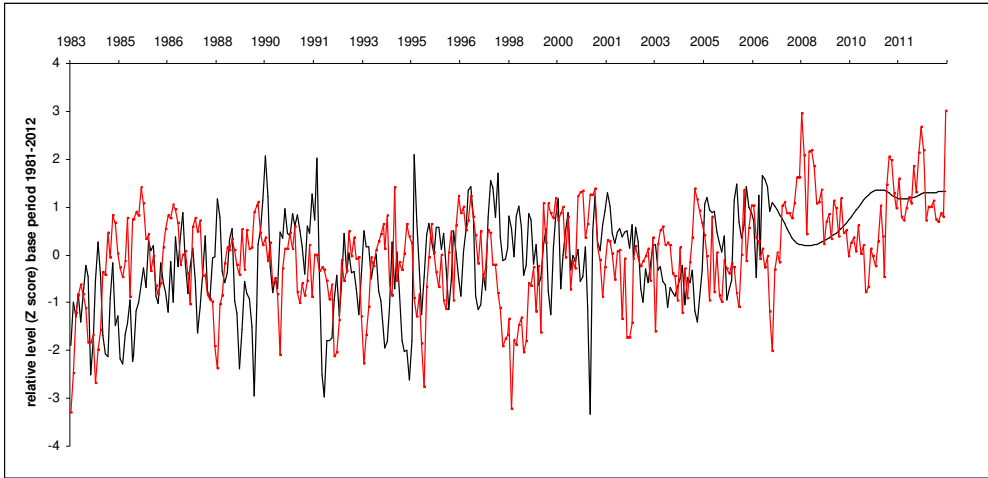
Figure 10: Z scored monthly data: NDVIG (black dotted curve) compared to NDVIV (red curve).



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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 IPCC fourth assessment report (IPCC 2007) and global surface temperature (red dotted curve).



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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 IPCC fourth assessment report (IPCC 2007) and global surface temperature (red dotted curve).



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