Rebuttal to review comments on:
"Hen-or-egg causality: Atmospheric CO_2 and temperature"

by D. Koutsoyiannis, and Z. W. Kundzewicz

As a rebuttal to the review comments of the manuscript with the above title, rejected by the *Science of the Total Environment*, which we made available on ResearchGate, here we post parts of our final published paper whose beginning is shown below.

Specifically, the rebuttals are contained in the following sections of the final paper:

4.2. Complications in Seeking Causality
4.3. Additional Clarifications of Our Approach
Appendix A.4. Some Notes on the Alternative Procedures on Causality
Appendix A.5. Additional Graphical Depictions

These are contained in the following pages (along with the References). Comments are welcome.

Links of related material:

Rejected manuscript: https://www.researchgate.net/publication/343878781
Review comments: https://www.researchgate.net/publication/343879018
Final published paper: http://dx.doi.org/10.3390/sci2040083

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Atmospheric Temperature and CO_2: Hen-Or-Egg Causality?

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Abstract: It is common knowledge that increasing CO_2 concentration plays a major role in enhancement of the greenhouse effect and contributes to global warming. The purpose of this study is to complement the conventional and established theory, that increased CO_2 concentration due to human emissions causes an increase in temperature, by considering the reverse causality. Since increased temperature causes an increase in CO_2 concentration, the relationship of atmospheric CO_2 and temperature may qualify as belonging to the category of "hen-or-egg" problems, where it is not always clear which of two interrelated events is the cause and which the effect. We examine the relationship of global temperature and atmospheric carbon dioxide concentration in monthly time steps, covering the time interval 1980–2019 during which reliable instrumental measurements are available. While both causality directions exist, the results of our study support the hypothesis that the dominant direction is $T \rightarrow CO_2$. Changes in CO_2 follow changes in T by about six months on a monthly scale, or about one year on an annual scale. We attempt to interpret this mechanism by involving biochemical reactions as at higher temperatures, soil respiration and, hence, CO_2 emissions, are increasing.

Keywords: temperature; global warming; greenhouse gases; atmospheric CO_2 concentration

- ~~If $\eta_1 > 0$, then the dominant direction is $\underline{x}_\tau \to \underline{y}_\tau$.~~
- ~~If $\eta_1 < 0$, then the dominant direction is $\underline{y}_\tau \to \underline{x}_\tau$.~~

~~Justification and further explanations of these conditions are provided in Appendix A.3.~~

4.2. Complications in Seeking Causality

It must be stressed that the above conditions are considered as necessary and not sufficient conditions for a causative relationship between the processes $\underline{x}_\tau$ and $\underline{y}_\tau$. Following Koutsoyiannis [30] (where additional necessary conditions are discussed), we avoid seeking sufficient conditions, a task that would be too difficult or impossible due to its deep philosophical complications as well as the logical and technical ones.

Specifically, it is widely known that correlation is not causation. As Granger [62] puts it,

> *when discussing the interpretation of a correlation coefficient or a regression, most textbooks warn that an observed relationship does not allow one to say anything about causation between the variables.*

Perhaps that is the reason why Suppes [61] uses the term "prima facie cause" in his definition given above which, however, he does not explain, apart for attributing "prima facie" to Jaakko Hintikka. Furthermore, Suppes discusses *spurious causes* and eventually defines the *genuine cause* as a "prima facie cause that is not spurious"; he also discusses the very existence of genuine causes which under certain conditions (e.g., in a Laplacean universe) seems doubtful.

Granger himself also uses the term "prima facie cause", while Granger and Newbold [63] note that a cause satisfying a causality test still remains prima facie because it is always possible that, if a different information set were used, it would fail the new test. Despite the caution issued by its pioneers, including Granger, through the years, the term "Granger causality" has become popular (particularly in the so-called "Granger causality test", e.g., [64]). Probably because of that misleading term, the technique is sometimes thought of as one that establishes causality, thus resolving or overcoming the "correlation is not causation" problem. In general, it has rarely been understood that identifying genuine causality is not a problem of choosing the best algorithm to establish a statistical relationship (including its directionality) between two variables. As an example of misrepresentation of the actual problems, see [65], which contains the statement:

> *Determining true causality requires not only the establishment of a relationship between two variables, but also the far more difficult task of determining a direction of causality.*

In essence, the "Granger causality test" studies the improvement of prediction of a process $\underline{y}_\tau$ by considering the influence of a "causing" process $\underline{x}_\tau$ through the Granger regression model:

$$\underline{y}_\tau = \sum_{j=1}^{\eta} a_j \underline{y}_{\tau-j} + \sum_{j=1}^{\eta} b_j \underline{x}_{\tau-j} + \varepsilon_\tau \tag{14}$$

where a_j and b_j are the regression coefficients and ε_τ is an error term. The test is based on the null hypothesis that the process $\underline{x}_\tau$ is not actually causing $\underline{y}_\tau$, formally expressed as

$$H_0 : b_1 = b_2 = \ldots = b_\eta = 0 \tag{15}$$

Algorithmic details of the test are given in [64], among others. The rejection of the null hypothesis is commonly interpreted in the literature with a statement that $\underline{x}_\tau$ "Granger-causes" $\underline{y}_\tau$.

This is clearly a misstatement and, in fact, the entire test is based on correlation matrices. Thus, it again reflects correlation rather than causation. The rejection of the null hypothesis signifies improvement of prediction and this does not mean causation. To make this clearer, let us consider the following example: people sweat when the atmospheric temperature is high and also wear light clothes. Thus, it is reasonably expected that in the prediction of sweat quantity, temperature matters. In the absence of temperature measurements (e.g., when we have only visual information, like when watching a video), the weight of the clothes algorithmically improves the prediction of sweat quantity. However, we could not say that the decrease in clothes weight causes an increase in sweat (the opposite is more reasonable and becomes evident in a three-variable regression, temperature–clothes weight–sweat, as further detailed in Appendix A.4).

Cohen [66] suggested replacing the term "Granger causality" with "Granger prediction" after correctly pointing out this:

> *Results from Granger causality analyses neither establish nor require causality. Granger causality results do not reveal causal interactions, although they can provide evidence in support of a hypothesis about causal interactions.*

To avoid such philosophical and logical complications, here, we replace the "prima facie" or "Granger" characterization of a cause and, as we already explained, we abandon seeking for genuine causes by using the notion of *necessary conditions* for causality. One could say that if two processes satisfy the necessary conditions, then they define a prima facie causality, but we avoid stressing that as we deem it unnecessary. Furthermore, we drop "causality" from "Granger causality test", thus hereinafter calling it "Granger test".

Some have thought they can approach genuine causes and get rid of the caution "correlation is not causation" by replacing the correlation with other statistics in the mathematical description of causality. For example, Liang [44] uses the concept of information (or entropy) flow (or transfer) between two processes; this method has been called "Liang causality" in the already cited work he co-authors [43]. The usefulness of such endeavours is not questioned, yet their vanity to determine genuine causality is easy to infer: It suffices to consider the case where the two processes, for which causality is studied, are jointly Gaussian. It is well known that in any multivariate Gaussian process, the covariance matrix (or the correlation matrix along with the variances) fully determines all properties of the multivariate distribution of any order. For example, the mutual information in a bivariate Gaussian process is (Papoulis, [67])

$$H[\underline{y}|x] = \ln \sigma_y \sqrt{2\pi e(1 - r^2)} \tag{16}$$

where σ and r denote standard deviation and correlation, respectively. Thus, using any quantity related to entropy (equivalently, information), is virtually identical to using correlation. Furthermore, in Gaussian processes, whatever statistic is used in describing causality, it is readily reduced to correlation. This is evident even in Liang [44], where, e.g., in his Equation (102), the information flow turns out to be the correlation coefficient multiplied by a constant. In other words, the big philosophical problem of causality cannot be resolved by technical tricks.

From what was exposed above (Section 4.1), the time irreversibility (or directionality) is most important in seeking causality. In this respect, we certainly embrace Suppes's condition (i) and Granger's first axiom, as stated above. Furthermore, we believe there is no meaning in refusing that axiom and continuing to speak about causality. We note though that there have been recent attempts to show that

> *coupled chaotic dynamical systems violate the first principle of Granger causality that the cause precedes the effect*. [68]

Apparently, however, the particular simulation experiment performed in the latter work which, notably, is not even accompanied by any attempt for deduction based on stochastics, cannot show any violation. In our view, such a violation, if it indeed happened, would be violation of logic and perhaps of common sense.

Additional notes for other procedures detecting causality, which are not included in the focus of our study, are given in Appendix A.4.

4.3. Additional Clarifications of Our Approach

After the above theoretical and methodological discourse, we can clarify our methodological approach by emphasizing the following points.

1. To make our assertions and, in particular, to use the "hen-or-egg" metaphor, we do not rely on merely statistical arguments. If we did that, based on our results presented in the next section, we would conclude that only the causality direction $T \rightarrow [CO_2]$ exists. However, one may perform a thought experiment of instantly adding a big quantity of CO_2 to the atmosphere. Would the temperature not increase? We believe it would, as CO_2 is known to be a greenhouse gas. The causation in the opposite direction is also valid, as will be discussed in Section 6, "Physical Interpretation". Therefore, we assert that both causality directions exist, and we are looking for the dominant one under the current climate conditions (those manifest in the datasets we use) instead of trying to make assertions of an exclusive causality direction.
2. While we occasionally use statistical tests (namely, the Granger test, Equations (14) and (15)), we opt to use, as the central point of our analyses, Equation (13) (and the conditions below it) because it is more intuitive and robust, fully reflects the basic causality axiom of time precedence, and is more straightforward, transparent (free of algorithmic manipulations), and easily reproducible (without the need for specialized software).
3. For simplicity, we do not use any statistic other than correlation here. We stress that the system we are examining is indeed classified as Gaussian and, thus, it is totally unnecessary to examine any statistic in addition to correlation. The evidence of Gaussianity is provided by Figures A1 and A2 in Appendix A.5, in terms of marginal distributions of the processes examined and in terms of their relationship. In particular, Figure A2 suggests a typical linear relationship for the bivariate process. We note that the linearity here is not a simplifying assumption or a coincidence as there are theoretical reasons implying it, which are related to the principle of maximum entropy [67,69].
4. All in all, we adhere to simplicity and transparency and, in this respect, we illustrate our results graphically, so they are easily understandable, intuitive, and persuasive. Indeed, our findings are easily verifiable even from simple synchronous plots of time series, yet we also include plots of autocorrelations and lagged cross-correlation, which are also most informative in terms of time directionality.

~~5. Results~~

~~*5.1. Original Time Series*~~

~~Here, we examine the relationship of atmospheric temperature and carbon dioxide concentration using the available modern data (observations rather than proxies) in monthly time steps, as described in Section 3. To apply our stochastic framework, we must first make the two time series linearly compatible. Specifically, based on Arrhenius's rule (Equation (1)), we take the logarithms of~~ $\cancel{CO_2}$ ~~concentration while we keep~~ $\cancel{T}$ ~~untransformed. Such a transformation has also been performed in previous studies, which consider the logarithm of~~ $\cancel{CO_2}$ ~~concentration as a proxy of total radiative forcing (e.g., [41]). However, by calling this quantity "forcing", we indirectly give it, a priori (i.e., before investigating causation), the role of being the cause. Therefore, here, we avoid such interpretations; we simply call this variable the logarithm of carbon dioxide concentration and denote it as~~ $\cancel{\ln[CO_2]}$.

~~A synchronous plot of the two processes (specifically, UAH temperature and~~ $\cancel{\ln[CO_2]}$ ~~at Mauna Loa) is depicted in Figure 8. Very little can be inferred from this figure alone. Both processes show increasing trends and thus appear as positively correlated. On the other hand, the two processes appear to have different behaviours. Temperature shows an erratic behaviour while~~ $\cancel{\ln[CO_2]}$ ~~has a smooth evolution marked by the annual periodicity. It looks impossible to infer causality from that graph alone.~~

~~For $\eta > 0$, using the property that $c_x[\eta]$ is an even function ($c_x[\eta] = c_x[-\eta]$), we get~~

$$c_{xy}[\eta] = \sum_{j=0}^{\infty} \alpha_j c_x[j-\eta] = \sum_{j=0}^{\eta-1} \alpha_j c_x[\eta-j] + \sum_{j=\eta}^{\infty} \alpha_j c_x[j-\eta], \tag{A9}$$

~~and for the negative part~~

$$c_{xy}[-\eta] = \sum_{j=0}^{\infty} \alpha_j c_x[j+\eta]. \tag{A10}$$

~~With intuitive reasoning, assuming that the autocovariance function is decreasing ($c_x[j'] < c_x[j]$ for $j' > j$), as usually happens in natural processes, we may see that the rightmost term of Equations (A9) and (A10) should be decreasing functions of η (as for $j' > j$ it will be $c_x[j'-\eta] < c_x[j-\eta]$ and $c_x[j'+\eta] < c_x[j+\eta]$). However, the term $\sum_{j=0}^{\eta-1} \alpha_j c_x[\eta-j]$ of Equation (A9) is not decreasing. Therefore, it should attain a maximum value at some positive lag $\eta = \eta_1$. Thus, a positive maximizing lag, $\eta = \eta_1 > 0$, is a necessary condition for causality direction from $\underline{x}_\tau$ to $\underline{y}_\tau$. Conversely, the condition that the maximizing lag is negative is a sufficient condition to exclude the causality direction exclusively from $\underline{x}_\tau$ to $\underline{y}_\tau$.~~

~~All above arguments remain valid if we standardize (divide) by the product of standard deviations of the processes $\underline{x}_\tau$ and $\underline{y}_\tau$ and, thus, we can replace cross-covariances $c_{xy}[\eta]$ with cross-correlations $r_{xy}[\eta]$ (or, in the case of differenced processes, $r_{xy}[\nu, \eta]$).~~

Appendix A.4. Some Notes on the Alternative Procedures on Causality

Reviewer Yog Aryal [85] opined that we missed referring to the recent relevant works by Hannart et al. [92] and Verbitsky et al. [93]. In response to this comment, we include this Appendix (not contained in Version 1 of our paper) explaining, in brief, why we do not compare our results with the ones of those studies, also noting that only the latter study contains material that is prima facie comparable to ours. The former study, focusing on the so-called causal counterfactual theory, is more theoretical and also much more interesting. While we, too, are preparing a theoretical study, in which we will discuss some theories in detail, in this Appendix, we give some key elements of our theoretical disagreements and a counterexample that illustrates the disagreements.

We first note that in order to define causality, Hannart et al. [92] refer to the work on the 18th century philosopher David Hume and, in particular, his famous book *Enquiry concerning Human Understanding* [94] first published in 1748. From this book, we wish to quote the following important passage, which emphasizes the difficulties even in defining causality:

> *Our thoughts and enquiries are, therefore, every moment, employed about this relation: Yet so imperfect are the ideas which we form concerning it, that it is impossible to give any just definition of cause, except what is drawn from something extraneous and foreign to it.*

Hannart et al. [92], while studying the probability of occurrence of an event Y, introduced the two-valued variable X_f to indicate whether or not a forcing f is present, and continue as follows:

> *The probability $p_1 = P(Y = 1 | X_f = 1)$ of the event occurring in the real world, with f present, is referred to as factual, while $p_0 = P(Y = 1 | X_f = 0)$ is referred to as counterfactual. Both terms will become clear in the light of what immediately follows. The so-called fraction of attributable risk (FAR) is then defined as*
>
> $$\mathrm{FAR} = 1 - \frac{p_0}{p_1} \tag{A11}$$
>
> *The FAR is interpreted as the fraction of the likelihood of an event that is attributable to the external forcing.*

They also show that under some conditions, FAR is a probability which they denote PN and call probability of necessary causality. They stress that it "is important to distinguish between necessary and sufficient causality" and they associate PN (or FAR) "with the first facet of causality, that of necessity". They claim to have "introduced its second facet, that of sufficiency, which is associated with the symmetric quantity $1-(1-p_1)/(1-p_0)$"; they denote it as PS, standing for probability of sufficient causality.

Central to the logical framework of Hannart et al. [92] is the notion of *intervention* of an experimenter, which is equivalent to experimentation with the ability to set the value of the assumed cause to a desired value. Clearly, this is feasible in laboratory experiments and infeasible in natural processes. The authors resort to the "so-called *in silico experimentation*" which, despite the impressive name chosen, is intervention in a mathematical model that represents the process. Hence, objectively, they examine the "causality" that is embedded in the model rather than the natural causality. One may argue that this it totally unnecessary. It would be better to inspect the model's equations or code to investigate what causality has been embedded in the model instead of running simulations and calculating probabilities. In particular, if the models used are climate models as in [92], their inability to effectively describe (perform in "prime time") the real-world processes [50,95–100] makes the entire endeavour futile. Another notion these authors use is *exogeneity*, which is related to the so-called *causal graph*, reflecting the assumed dependencies among the studied variables. Specifically, they state "a sufficient condition for X to be exogenous wrt any variable is to be a top node of a causal graph".

Here, we will use the simple example of Section 4.2, temperature–clothes weight–sweat, to show that using the quantities FAR (or PN) and PS may give spurious results that do not correspond to necessary or sufficient conditions for causality, at least with their meaning in our paper.

We use the two-valued random variables $\underline{x}, \underline{y}, \underline{z}$ to model the states of temperature, clothes weight, and sweat, respectively. We designate the following states:

$x = 1$: being hot *above* a threshold;
$y = 1$: wearing clothes with weight *below* a threshold;
$z = 1$: sweat quantity *above* a threshold;

and the opposite states with $x = 0, y = 0, z = 0$, respectively. We choose the threshold of temperature so that $P\{\underline{x} = 0\} = P\{\underline{x} = 1\} = 0.5$ and that of clothes weight so that $P\{\underline{y} = 0\} = P\{\underline{y} = 1\} = 0.5$. We choose a small probability, 0.05, of wearing light clothes when cold, or heavy clothes when hot, i.e., $P\{\underline{y} = 1 | \underline{x} = 0\} = P\{\underline{y} = 0 | \underline{x} = 1\} = 0.05$ (generally, we avoid choosing zero probabilities; rather the minimum value we choose is 0.05).

Using the definition of conditional probability,

$$P\{\underline{y} = y | \underline{x} = x\} = \frac{P\{\underline{y} = y, \underline{x} = x\}}{P\{\underline{x} = x\}}, \tag{A12}$$

we find the probability matrix A with elements $a_{ij} = P\{\underline{x} = i, \underline{y} = j\}$ as follows:

$$A = \begin{array}{cc} \begin{bmatrix} 0.475 & 0.025 \\ 0.025 & 0.475 \end{bmatrix} & \begin{array}{c} x = 0 \\ x = 1 \end{array} \\ \begin{array}{cc} y = 0 & y = 1 \end{array} & \end{array}. \tag{A13}$$

Now, we assign plausible values to the conditional probabilities of high sweat, $P\{\underline{z} = 1 | \underline{x} = x, \underline{y} = y\}$, as follows:

Cold, heavy clothes: $P\{\underline{z} = 1 | \underline{x} = 0, \underline{y} = 0\} = 0.2$
Cold, light clothes: $P\{\underline{z} = 1 | \underline{x} = 0, \underline{y} = 1\} = 0.1$
Hot, heavy clothes: $P\{\underline{z} = 1 | \underline{x} = 1, \underline{y} = 0\} = 0.95$
Hot, light clothes: $P\{\underline{z} = 1 | \underline{x} = 1, \underline{y} = 1\} = 0.80$

Again, we have avoided setting any of the conditional probabilities to 0 (or 1), and we have used multiples of 0.05 for all of them.

Using the definition of conditional probability in the form

$$P\left\{\underline{z}=z \middle| \underline{x}=x, \underline{y}=y\right\}=\frac{P\left\{\underline{z}=z, \underline{y}=y, \underline{x}=x\right\}}{P\left\{\underline{y}=y, \underline{x}=x\right\}}, \tag{A14}$$

we find the joint probabilities for each of the triplets $\{x, y, z\}$ that are shown in Table A1.

Table A1. Joint probabilities $P\left\{\underline{x}=x, \underline{y}=y, \underline{z}=z\right\}$ for all triplets $\{x, y, z\}$

x	y	$z = 0$	$z = 1$
0	0	0.38	0.095
0	1	0.0225	0.0025
1	0	0.00125	0.02375
1	1	0.095	0.38
	$P\left\{\underline{z}=z\right\}=$	0.49875	0.50125

Now, assume that we let an "artificial intelligence entity" (AIE) decide on causality based on the probability rules of the Hannart et al. [92] framework. Our AIE has access to numerous videos of people and is "trained" to assign accurate values of y and z, referring to clothes and sweat, based on the images in videos. In the video images, no thermometers are shown and, thus, our AIE cannot assign values of x, nor can it be aware of the notion of temperature. Our AIE tries to construct a causal graph putting, say, $\underline{y}$ as a top node and $\underline{z}$ as an end node; hence, it assumes that $\underline{y}$ is exogenous. Based on the huge information it can access, our AIE can (a) claim that it has constructed a prediction model based on one part of the data (e.g., using the so-called deep-learning technique) and, hence, is able to perform "in silico experimentation" (even though this is not absolutely necessary) and (b) accurately estimate the joint and conditional probabilities related to $\{y, z\}$ using either the model, the data, or both. Provided that the dataset is large enough, it will come up with the true values for the conditional probabilities, which are $b_{ij}=P\left\{\underline{y}=i, \underline{z}=j\right\}$ and $c_{ij}=P\left\{\underline{z}=j \middle| \underline{y}=i\right\}$, and form the matrices B and C, respectively, with values as follows:

$$B=\begin{array}{cc} \begin{bmatrix} 0.38125 & 0.11875 \\ 0.1175 & 0.3825 \end{bmatrix} & \begin{array}{c} y=0 \\ y=1 \end{array} \\ \begin{array}{cc} z=0 & z=1 \end{array} & \end{array}, \quad C=\begin{array}{cc} \begin{bmatrix} 0.7625 & 0.2375 \\ 0.235 & 0.765 \end{bmatrix} & \begin{array}{c} y=0 \\ y=1 \end{array} \\ \begin{array}{cc} z=0 & z=1 \end{array} & \end{array}. \tag{A15}$$

Here, the true values b_{ij} have been determined from the values of Table A1 noting that

$$b_{ij}=P\left\{\underline{y}=i, \underline{z}=j\right\}=P\left\{\underline{z}=j, \underline{y}=i, \underline{x}=0\right\}+P\left\{\underline{z}=j, \underline{y}=i, \underline{x}=1\right\} \tag{A16}$$

and the true values c_{ij} have been determined from the definition of conditional probability:

$$P\left\{\underline{z}=z \middle| \underline{y}=y\right\}=\frac{P\left\{\underline{z}=z, \underline{y}=y\right\}}{P\left\{\underline{y}=y\right\}}. \tag{A17}$$

Our AIE will then implement the causality conditions of sweat on clothes weight, assigning $p_0=P\left\{\underline{z}=1 \middle| \underline{y}=0\right\}=0.2375$ and $p_1=P\left\{\underline{z}=1 \middle| \underline{y}=1\right\}=0.765$. It will further calculate the probability of necessary causality as PN = 0.690, and the probability of sufficient causality even higher, PS = 0.692. Hence, our AIE will inform us that there is all necessary and sufficient evidence that light clothes cause high sweat.

Now, coming to the study by Verbitsky et al. [93], we notice that it assumes that "each time series is a variable produced by its hypothetical low dimensional system of dynamical equations" and uses the technique of distances of multivariate vectors for reconstructing the system dynamics. As demonstrated in Koutsoyiannis [101], such assumptions and techniques are good for simple toy models but, when real-world systems are examined, low dimensionality appears as a statistical artifact because the reconstruction actually needs an incredibly high number of observations to work, which are hardly available. The fact that the sums of multivariate vectors of distances is a statistical estimator with huge uncertainty is often missed in studies of this type, which treat data as deterministic quantities to obtain unreliable results. We do not believe that the Earth system and Earth processes (including global temperature and CO_2) are of low dimensionality, and we deem it unnecessary to discuss the issue further. We only note the fact that global temperature and CO_2 virtually behave as Gaussian, which enables reliable estimation of standard correlations and dismiss the need to use the overly complex and uncertain correlation sums.

Appendix A.5. Additional Graphical Depictions

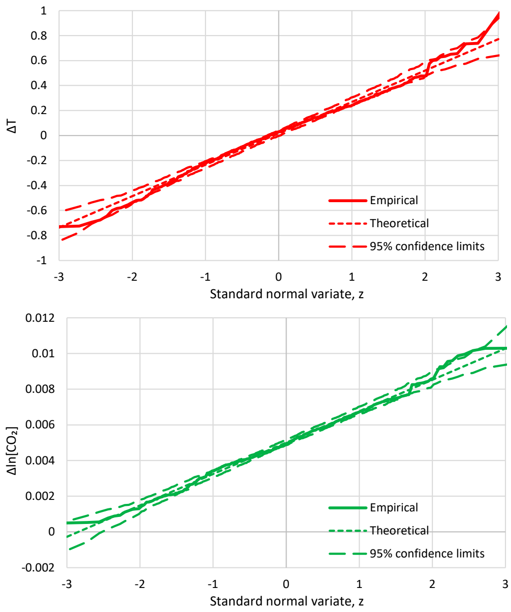

Figure A1. Normal probability plots of ΔT and $\Delta\ln[CO_2]$ where T is the UAH temperature and $[CO_2]$ is the CO_2 concentration at Mauna Loa at monthly scale.

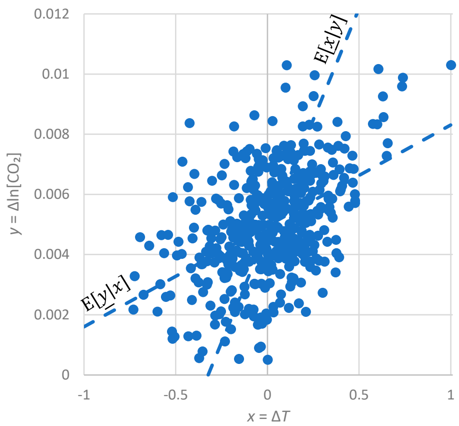

Figure A2. Scatter plot of ΔT and $\Delta\ln[CO_2]$ where T is the UAH temperature and $[CO_2]$ is the CO_2 concentration at Mauna Loa at monthly scale; the two quantities are lagged in time using the optimal lag of 5 months (Table 1). The two linear regression lines are also shown in the figure.

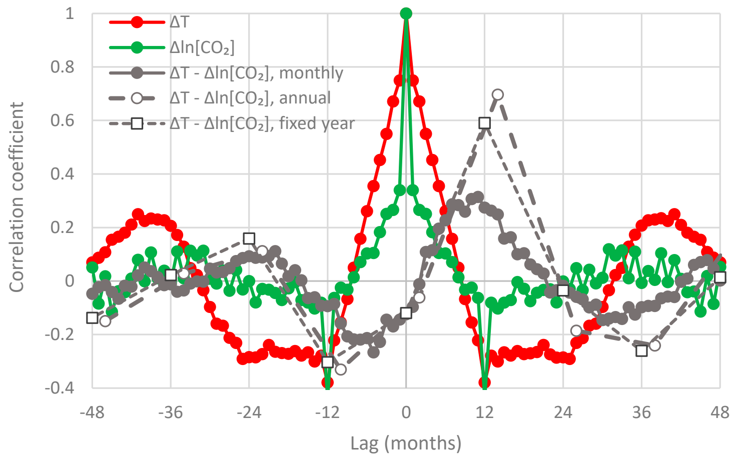

Figure A3. Auto- and cross-correlograms of the differenced time series of UAH temperature and Barrow CO_2 concentration.

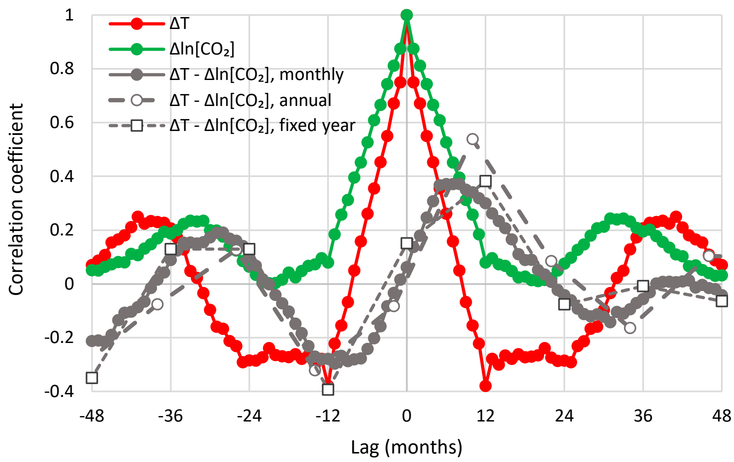

Figure A4. Auto- and cross-correlograms of the differenced time series of UAH temperature and South Pole CO_2 concentration.

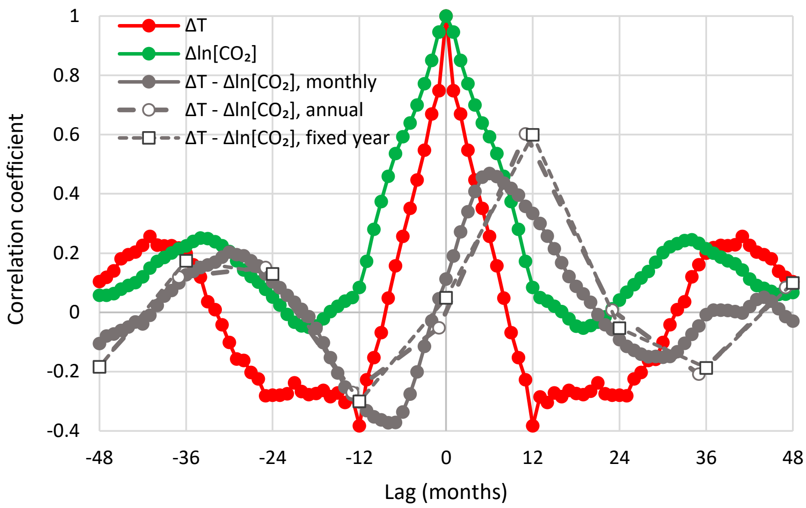

Figure A5. Auto- and cross-correlograms of the differenced time series of UAH temperature and global CO_2 concentration.

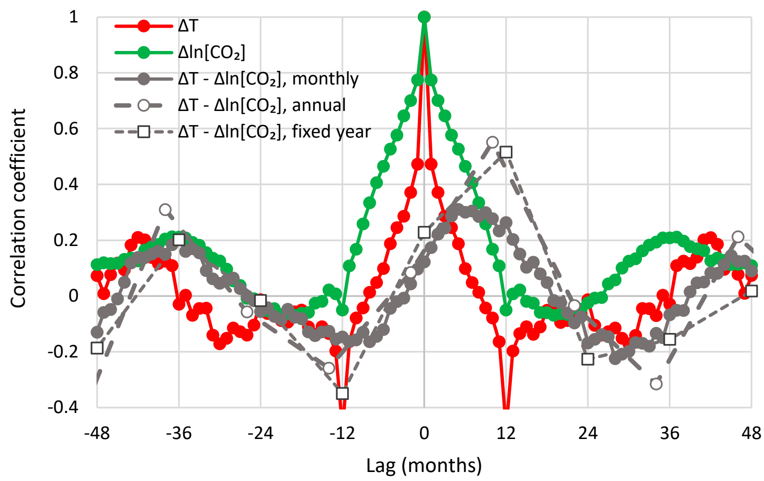

Figure A6. Auto- and cross-correlograms of the differenced time series of CRUTEM4 temperature and Mauna Loa CO_2 concentration.

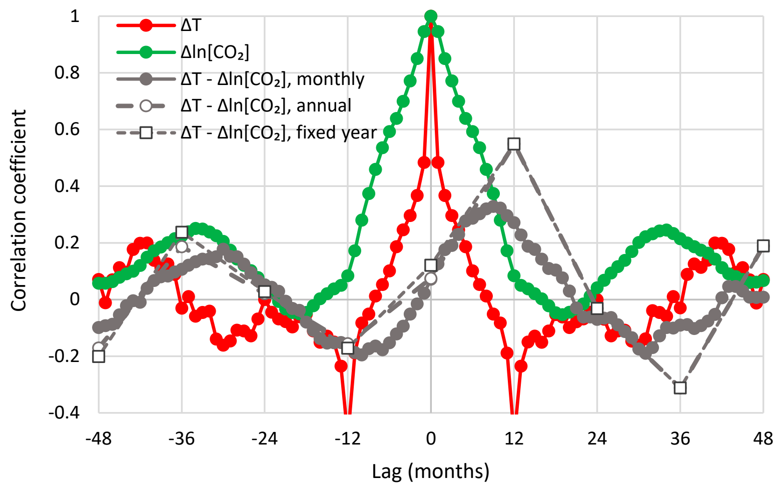

Figure A7. Auto- and cross-correlograms of the differenced time series of CRUTEM4 temperature and global CO_2 concentration.

References

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