

Empirical evidence for a global atmospheric temperature control system: physical structure

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ABSTRACT

There is evidence that a natural control system influences global atmospheric surface temperature (Leggett and Ball 2020). The present paper sets up and tests a hypothesis concerning the physical makeup of the sequential elements of the control system and its outcomes. The final outcome that the control system influences is defined as global atmospheric surface temperature. The terms used for the control system element types in the hypothesis are, in sequence: leading element, controller and actuator. Actuators are hypothesised to affect, in turn, the final outcome – either directly, or via penultimate outcomes. The existence of the control system is evidenced by demonstration of statistically significant one-way Granger causality across each step of the hypothesised control system sequence. Evidence is presented that the leading element of the control system, represented by the Normalized Difference Vegetation Index, is the global biosphere. The biosphere as a control system has previously been referred to as Gaia (Lovelock and Margulis 1974). A fourth, second-derivative, term is found to enhance the Proportional, Integral and Derivative process terms of the control system shown in Leggett and Ball (2020). The main actuators of the control system found are shown to be wind speed and cloud cover. Cloud cover is shown to influence the final outcome, global surface temperature, directly. It and wind speed also influence the penultimate outcomes found, those of enhanced ocean heat uptake and enhanced outgoing longwave radiation. These together lead to control system output to the final outcome, global atmospheric temperature. Overall, evidence for the activity of the control system is shown to be present across many major physical dimensions of the Earth's atmosphere.

Keywords: global surface temperature, control system, Granger causality time series analysis, empirical

1. Introduction

In Leggett and Ball (2020), we provided statistically significant observational evidence that a feedback control system moderating atmospheric temperature is presently operating coherently at global scale. Further, this control system was shown to be of a sophisticated type, displaying controller process terms with proportional-integral-derivative characteristics. The controller process terms correlated with the level of the atmospheric CO₂ time series, and its integral and derivative.

This paper seeks further evidence about the controller process terms of the control system, and also about its physical components.

1.1. Expected nature of physical control system

In Leggett and Ball (2020), evidence for a physical control system came from one aspect of a control system. In seeking evidence that physical components of the atmosphere might have control system roles, the fuller range of control system possibilities should be considered.

These possibilities include one whereby an overall control system is made up of a group of individual control systems which operate in parallel (side by side) (Wade 2017); and within that, one or more individual control systems might contain elements which operate in series (Wade 2017).

Using this framework, and on the basis of the evidence for a control system with proportional-integral-derivative characteristics shown in Leggett and Ball (2020), the existence of a parallel-type control system with three channels (one for each of the proportional, integral and derivative controllers) is implied.

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When we turn to physical components of the atmosphere that might be part of any control system, it is noted that there are many drivers of atmospheric trends (IPCC 2013; Stern and Kaufmann 2014). Hence we may expect that control system channels may consist of chains of elements in series.

1.2. Detection of control system

Noting that physical systems with time-varying internal couplings between components are abundant in nature, BozorgMagham et al. (2015) observe that the definitive approach to detecting causal relationships between such elements of a system is to fully identify the underlying mechanisms. They note, however, that in the absence of complete knowledge of internal components, observed data is required to establish causal relationships between candidate elements.

In this paper, we use observed data to seek causal relationships between candidate elements of the control system. Time series analysis is used for this purpose.

Two major methods for seeking causal relationships are Granger causality (Granger 1969) and Convergent Cross Mapping (CCM) (Sugihara et al. 2012; BozorgMagham et al. 2015). Each provides a framework that uses predictability, as opposed to correlation, to identify causation between time-series variables (Sugihara et al. 2012).

Use of Granger causality or CCM in connectivity studies also enables identification of the *directionality* of causal interaction or information flow between the putative components of a control system (for Granger causality, see Granger 1969; for CCM, see Sugihara et al. 2012). CCM is relevant when there is major phase shifting between variables over time, such that Granger causality testing would not show a relationship (Sugihara et al. 2012).

Granger causality was used in initial data analysis for this study to determine whether or not CCM would be required. This was found not to be the case, and therefore Granger causality was used for this study.

We note that the evidence for directional Granger causality between X and Y is in the domain of information, implying information flow between X and Y . In this paper we sometimes use the term ‘information flow’ instead of ‘causality’. If X is Granger-causal of Y we sometimes describe this as Granger-causal connectivity.

In this study, Granger causality in its form as an output of Vector Autoregression (VAR) analysis (Sims 1980; Stock and Watson 2001) was used to assess relationships between candidate control system elements. A relationship is said to be Granger-causal if the probability of it being due to chance is less than a specified value. The

probability level used in this study is the standard 0.05 statistical significance level.

As well as its probability, the *strength* of Granger causality is also of interest, and a method of estimation has been developed (Geweke 1982; Hesse et al. 2003). The method estimates the strength of Granger causality, for example of Y to X , as a measure of linear feedback between two signals. This estimate is made for each time period or lag assessed. The maximum value found from this series of Y to X estimates represents a simple measure for the strength of feedback in the Y to X direction.

In this paper, the strength of Granger-causal interaction in both the Y to X and the X to Y directions is calculated according to Geweke’s equations 4.1 to 4.4 (Geweke 1982, p.209); and Hesse’s equations 5 to 7 (Hesse et al. 2003). The strength of causality is termed F_{YX} and F_{XY} respectively here. The calculations were conducted using code (available on request) written for the statistical analysis package used for this study (IHS EViews 2017).

Where climate studies are concerned, Hlinka et al. (2017) note that the majority of climate network studies have been limited to the use of symmetric dependence measures such as correlation, and recommend an approach to climate network studies based on prediction rather than correlation, and which enables the capture of the directionality of causal interaction.

Some relationships were assessed using multiple regression of the autoregressive distributed lag (ARDL) form (Pesaran et al. 2001). Section 2 (Methods) provides further information on the approach to VAR and ARDL analysis used in this study.

A time series X is said to be Granger-causal of Y if it can be shown that values of X provide statistically significant information about future values of Y that is not contained in past values of Y and other relevant information (Kaufmann and Stern 1997; Terrell 2019). If Granger causality is directional, information from Y is not present in future values of X . We use the term ‘one-way Granger causality’ to describe such directional causality.

A key and powerful benefit for the study is that, if many one-way Granger-causal results are found, they can only fit together in one way. For example, if Granger causality tests show that control system element A causes B but not the reverse, and the same is true for B to C, C to D, and so on, we have determined that the elements unambiguously make up the causal chain as hypothesised. This we term ‘end-to-end one-way Granger-causal connectivity’ for the control system channel.

1.3. Terminology

With the above background, we hypothesise a control system consisting of multiple channels acting in parallel,

Table 1. Hypothesised flow of causality by control system element across the hypothesised causal channel.

Control system step	From	Flow of Causality	To
1	Candidate leading element	→ and not ←	Candidate controller terms
2	Candidate controller terms	→ and not ←	Candidate actuators
3	Candidate actuators	→ and not ←	Outcome

each channel potentially made up of elements in series – element A, B, C, D, etc. – so as to make up a chain of sequential linked elements.

For the element at the start of the control system sequence, we use the term ‘leading element’ (BozorgMagham et al. 2015).

With respect to terminology used for concepts at further stages of a control system channel, Åström and Murray (2008) write:

A modern controller senses the operation of a system, compares it against the desired behavior, computes corrective actions based on a model of the system’s response to external inputs and actuates the system to effect the desired change. This basic feedback loop of sensing, computation and actuation is the central concept in control.

Accordingly, for each chain of elements, we will group candidate controller process terms and candidate physical components for the control system under the headings ‘controller’ and ‘actuator’ respectively. These make up ‘elements’ of the control system. After Sahib (2015), we use the expression ‘n-term control type’ to describe controller process terms. Hence, the Proportional-Integral-Derivative (PID) control type as derived in Leggett and Ball (2020) is classed as a ‘three-term control type’.

Based on Åström and Murray (2008) as quoted above, we term the next type of element in each channel an ‘actuator’ element. An actuator may then directly affect the ‘outcome’ of the control system (global surface temperature) or affect what we term ‘penultimate outcomes’ (ocean heat uptake and outgoing longwave radiation – see Section 3.1.1), which then affect the final outcome (in this case global surface temperature).

1.4. Hypothesis

We hypothesise the existence of a global atmospheric control system consisting of multiple control system channels operating in parallel. Each channel is hypothesised to display end-to-end one-way connectivity in a sequence from control system element to subsequent control system element, starting from the leading element and concluding with the outcome. The hypothesis is depicted diagrammatically for a control system channel in Table 1.

1.5. Link-to-link and longer-range analyses

The study aim is to search for evidence of causal chains of physical control system stages by seeking one-way causality from each stage of such putative causal chains to the next, using Granger causality analysis.

The hypothesised chain in Table 1 has three stages. Let us term the stages A, B, and C.

An issue may potentially arise in the link-to-link analysis of this chain, in that it may provide strong evidence for connectivity from A to B but the evidence for connectivity between B and C may exist, but may be less strong.

In this situation one can turn from link-to-link studies of connectivity to the presence of information at longer range. Demonstrating strong connectivity from A to C would indicate that the B to C issue represents either a possible data issue with the B to C connection, or that an additional connection exists other than the one being tested in this study.

This method of investigation has much in common with the use of electronic signal tracer test equipment used to troubleshoot radio and other electronic circuitry (Bishop 2007). Here, a test signal is injected into the device under test. Then, by using the signal tracer,

the signal can be followed through the various circuits of the device. So long as the signal can be detected, the circuitry up to that point is (at least minimally) connected. If the signal is not detected, there is no evidence of a connection between those circuit elements.

Such longer-range causality analyses are used from time to time in this study.

1.6. Protocol for each Granger causality analysis

The study investigates the existence of multiple control system channels, each with multiple chains of elements and associated causal steps. This is done by carrying out a separate Granger causality analysis for each pair of elements or steps.

As a result, many Granger causality studies are reported in this paper. The *probability* of Granger causality is the measure reported in the majority of Granger causality studies, and for reasons of space is the main measure used here.

That said, the *strength* of Granger causality is also assessed in some situations. The reason for this is as follows.

In assessing the existence of putative control system steps in line with the hypothesis for one-way Granger causality between any two candidate elements, the following types of results may occur:

1. No statistically significant Granger causality is found between the two elements. In this case the result is reported and no further assessment carried out.
2. Statistically significant Granger causality is found for a control system step, but it applies in both directions. This result it is not treated as evidence for the control system.
3. One-way Granger causality in the proposed control system direction is found based on the 0.05 significance level, and the evidence for causality in the other direction is well in excess of the 0.05 level (greater than 0.1). Results of this type are considered sufficient to meet the control system hypothesis.
4. Evidence is as for category 3 except that the evidence for reverse causality is greater than, but close to, the 0.05 level (between 0.05 and 0.1). Here two-way causality is not being strongly rejected. In this situation a second line of evidence is sought, using strength of Granger causality.

In this last instance, if the result of the analysis of the strength of Granger causality for the putative control system step is stronger in the direction of the control system hypothesis than in the other direction, then these two pieces of evidence are considered to provide strong

evidence overall that the putative control system step is likely to exist.

1.7. Note on the scope of the study

The scope of this paper is limited to seeking evidence that supports the hypothesis. As such, potential connections between many pairs of climate series are assessed. Some connections may not support the hypothesis, but are still reported. While further investigation of these may be of some interest, they are generally not discussed further in this paper in order to maintain the focus on the hypothesis.

2. Methods

Statistical methods used are standard (Greene 2012) and generally as used in Leggett and Ball (2015; 2019). Categories of methods used are: normalisation; differentiation (approximated by differencing); integration (approximated by the cumulative sum); and time-series analysis.

Within time-series analysis, methods used are: Z-scoring; smoothing; testing for the order of integration of each series (a prerequisite for using data series in time-series analysis); autoregressive distributed lag (ARDL) dynamic regression modelling to include autocorrelation in models; and Vector Autoregression (VAR) modelling to enable Granger causality testing. These methods will now be described in turn.

2.1. Normalisation of data series

To make it easier to visually assess the relationship between the variables and to estimate the relative scale of regression coefficients in multiple regression analysis, each data series was normalised using statistical Z scores (also known as standardised deviation scores). In a Z-scored data series, each data point is part of an overall data series that sums to a zero mean and variance of 1, enabling comparison of data having different native units. Hence, when several Z-scored time series are depicted in a graph, all the time series will closely superimpose, enabling visual inspection to clearly discern the degree of similarity or dissimilarity between them. Individual figure legends contain details on the series lengths used as base periods for the Z-scoring.

A regression using Z-scored variables provides standardised regression coefficients. These coefficients report how much change a one-standard-deviation change in the independent variable produces in the dependent variable. Although comparisons between these coefficients must be interpreted with care, a standardised coefficient for

independent variable a of 2, for example, indicates that independent variable a is twice as influential upon the dependent variable as another independent variable that has a standardised coefficient of 1 (Allen 1997).

2.2. Smoothing of data

Smoothing was used on some data series to the extent required to reveal whether significant relationships were present. Smoothing using moving averages removes large month-to-month variations to reveal the underlying pattern or trend. Smoothing was carried out by means of a 13-month moving average, which also minimises seasonal effects.

2.3. Labelling data series

A key explaining the labels used for each series in the paper, including its smoothing and Z-scoring status, is provided in Table S3 in the [Supplementary Information](#).

2.4. Notation for candidate control elements

Given that the present disturbance to global temperature is leading to an increase, and this disturbance is resisted by the control system, any candidate control element or penultimate outcome would be expected to show a decreasing trend (Leggett and Ball 2020).

As these candidate series of themselves are often increasing (see the trend for each series depicted in [Section 3.4](#), [Figs. 2](#) and [3](#)), each candidate control element series is converted to control system form by reversing its sign. Each candidate control series converted in this way is identified as such by the suffix ‘_CONTR’. Each penultimate outcome series converted in this way is given the suffix ‘_REVERSE’.

A regression model supporting the hypothesis that the temperature series correlates with one or more control or penultimate outcome elements will display a minus sign for each element.

2.5. Time series analysis

Time series models differ from ordinary regression models in that the results are in a sequence. Hence, the dependent variable is influenced not only by the independent variables, but also by prior values of the dependent variable itself. This is termed ‘autocorrelation’ between measured values. The serial nature of the measurements must be addressed by careful examination of the lag structure of the model. This type of ordinary least squares regression is termed ‘time series analysis’ (Greene 2012).

A further issue in time series analysis concerns what is termed the ‘order of integration’ of each of the series used. Greene (2012) states: “The series yt is said to be integrated of order one, denoted $I(1)$, because taking a first difference produces a stationary process. A non-stationary series is integrated of order d , denoted $I(d)$, if it becomes stationary after being first-differenced d times. An $I(1)$ series in its raw (undifferenced) form will typically be constantly growing, or wandering about with no tendency to revert to a fixed mean.”

In this paper, from time to time we deal with combinations of series with different orders of integration. Methods used to address this are outlined in the following sections.

2.5.1. Regression. For regression, the ARDL method (Pesaran et al. 2001) can be used whether variables are purely of order of integration $I(0)$ (a stationary series), purely $I(1)$ or a mixture of both $I(0)$ and $I(1)$ (Greene 2012; Janjua et al. 2014; Ahmad and Du 2017).

For ARDL, the stationarity or otherwise of each series must still be assessed to ensure that there are no $I(2)$ or higher series present. ARDL does not work for such series (Pesaran et al. 2001). A range of tests exists to assess stationarity. In this study, the augmented Dickey-Fuller (ADF) test is used.

The usual tests for stationarity (for example, the ADF test) can allow for the presence of a *linear* deterministic trend in the time-series in question, but they cannot allow for the possibility of a *polynomial* trend. It will be shown that this possibility needs to be tested for in this study.

There is evidence that if a unit root test that allows for only a linear trend is applied mistakenly to a series with a polynomial trend, then the test may have extremely low power. For example, see the results of Harvey et al. (2008) in the context of the de-trended ADF-type tests of Elliott et al. (1996).

This problem may be resolved by using the Lagrange multiplier (LM) unit root test(s) proposed by Schmidt and Phillips (1992). These tests make explicit allowance for the possibility of a polynomial deterministic trend of order up to 4 in the series under test. As with the ADF test, the null hypothesis is that the series has a unit root, and the alternative hypothesis is that it is stationary. A value for the LM test statistic that is more negative than the tabulated critical value leads to a *rejection* of the null hypothesis, and suggests that the series is stationary.

The Schmidt-Phillips test is available in the ‘urca’ package in the R statistical software (R Development Core Team 2009) and is described in the documentation by Pfaff et al. (2016). Specifically, the `ur.sp-class` allows us to apply the Schmidt-Phillips tests. Although there are two such tests, the so-called τ test and the ρ test, the

results of only the former test are reported (the results of the ρ test in our models led to exactly the same conclusions). Testing is reported at the 0.01 significance level, but the results are not sensitive to this choice.

The order of integration of each series used has been determined and is presented in Tables S1 and S2 in the [Supplementary Information](#). The tables show that each series displays an order of integration suitable for use in the ARDL multiple regressions and VAR models reported.

The ARDL method uses special significance tests called ‘bounds tests’ (Pesaran et al. 2001). These test the significance of results against both an $I(0)$ realm and an $I(1)$ realm. If the result passes the test for each realm, a defensible model is obtained.

If the outcome of the bounds testing is positive, a long-run ‘levels model’ is estimated. These results are then used to measure short-run dynamic effects.

The above is carried out for models in which any autocorrelation present in the short-run relationship is fully accounted for by use of an optimal lag structure. In this study, this is done within the modelling process by reference to the adjusted coefficient of determination, R^2 , and to the Akaike Information Criterion.

The adjusted R^2 is used because there is a problem that the unadjusted R^2 cannot fall when independent variables are added to a model in multiple regression (Greene 2012). To address this issue, the adjusted R^2 is a fit measure that penalises the loss of degrees of freedom that result from adding variables to the model. There is, however, some question about whether the penalty is sufficiently large to ensure that the criterion will necessarily lead the analyst to the correct model as the sample size increases (Greene 2012). Several alternative fit measures termed ‘information criteria’ have been developed. Several criteria are available for selection within the Eviews ARDL method. We use the ARDL default criterion, the Akaike Information Criterion.

Pesaran et al. (2001) point out that ARDL modelling is “also based on the assumption that the disturbances ... are serially uncorrelated. It is therefore important that the lag order p of the underlying VAR is selected appropriately. There is a delicate balance between choosing p sufficiently large to mitigate the residual serial correlation problem and, at the same time, sufficiently small so that the conditional ECM is not unduly over-parameterized, particularly (when) limited time series data ... are available.”

To avoid over-parameterisation, we seek the model with the fewest lags that produces a model with no autocorrelation affecting results.

The specific information sought from each well-specified ARDL model is the effect of each of the potential

control variables on the dependent variable, and the degree of statistical significance of each effect.

We note that, to avoid duplication of results, in the ARDL analyses we focus on the long-run model results; shorter dynamics, which are at the heart of VAR Granger causality analysis, are dealt with there.

The ARDL econometric model used here was that implemented in the Eviews 10 package (IHS EViews 2017). The time series statistical software package Gnu Regression, Econometrics and Time-series Library (GRETL) was also used (accessed 17 June, 2019).

2.5.2. Granger causality. We have previously noted (Leggett and Ball 2015), that Granger causality (Granger 1969) more closely approaches the quality of information derived from random placement into experimental and control categories, although using correlational data.

According to Stern and Kaufmann (2014), a time-series variable Bx (e.g. atmospheric CO_2) is said to be Granger-causal of variable By (e.g. surface temperature) if past values of x help to predict the current level of y better than just the past values of y do, given all other relevant information. Granger causality has been noted as being quite close to information theory (Amblard and Michel, 2012). The case where information is being transmitted against a background containing a noise – or stochastic – element is central to information theory. Bearing the noise element in mind, if some of the signature (‘signal’) of series a is seen at a later point in the makeup of the signal of series b (and the opposite is not true), this becomes the focus.

As in Leggett and Ball (2015; 2019), Granger causality analysis is implemented in this study by using a standard VAR model. As discussed, the Akaike Information Criterion (AIC) is used to select an optimal maximum lag length (k) for the variables in the VAR. This lag length is then lengthened, if necessary, to ensure that firstly the estimated model is dynamically stable (i.e. all of the inverted roots of the characteristic equation lie inside the unit circle), and secondly, the errors of the equations are serially independent.

Granger causality results in this study are reported only if the VAR models meet the criteria in the preceding paragraph.

This study requires testing for Granger causality between the levels of some of the data series. In this case, the Granger causality testing procedure must be modified to allow for the differences in the orders of integration of the data series. Here, for each VAR model, the maximum lag length (k) is determined, but then one additional lagged value of each of the two variables is included in each equation of the VAR.

However, the Wald test for Granger non-causality is applied only to the coefficients of the original k lags. Toda and Yamamoto (1995) show that this modified Wald test statistic will still have an asymptotic distribution that is chi-square, even though the series is non-stationary, and the Granger causality test will be reliable.

2.5.2.1. Lag-length selection for Granger causality testing. In this paper, over the several dozen VARs run, the AIC sometimes suggests a large number of lags (numbering 40 and more) for a particular VAR (see Tables 3–6).

The following points are made in this connection.

Firstly, Clarke and Mirza (2006) note that the choice of lag length in the VAR is important in order to avoid spurious causality or spurious absence of causality. They identify that the AIC has a positive probability of overestimating the true lag order, but suggest that overestimation of the lag order may be preferable, due to the problems that can occur with incorrect inferences in an underspecified model. Clarke and Mirza (2006) considered up to 10 lags of quarterly data, (a time span of 40 lags for monthly data) when choosing the systems lag order for a VAR model. In their selected models, the AIC criterion led to six and eight quarterly lags, respectively, equivalent to 24 and 32 monthly lags.

Turning to climate series, according to Mudelsee (2010) and Wilks (2011) autocorrelation in the atmospheric sciences (also called dependence, persistence or ‘memory’) is characteristic of many types of climatic fluctuations.

Further, what is termed long-range dependence can be seen in climate series, including atmospheric temperature series. For example, Franzke (2012) investigating trends in four temperature time series – Central England Temperature (CET), Stockholm, Faraday-Vernadsky, and Alert – found evidence of long-range dependence. Having established this, Franzke states that “Predictions of a long-range-dependent process need the knowledge of the whole past to predict the next state.”

Further on climate series, using annual data, Triacca (2005) chose a maximum lag order of 10 (equivalent to 60 months), stating that it was important for the maximum order for the VAR to be high enough that high-order VAR specifications are given a reasonable chance of getting selected, if they happen to be appropriate.

Finally, the statistical package used in this study, the widely used EViews (IHS EViews 2017) contains extensive error detection to prevent inappropriate model set-up in the statistical sense. The relevant error message reads: “Insufficient number of observations for specified maximum lag length.” When this message appears the VAR cannot be run. All VARs reported were run and therefore

by definition contained sufficient observations for the specified maximum lag length.

In conclusion, while some of our analyses led to lowest AIC results with large lag orders, with the above background, we consider these lag lengths to be legitimate for this study.

2.5.2.2. Reporting of Granger causality results. In the Granger causality results reported in each case, the relevant EViews output from the VAR model entitled ‘VAR Granger causality/block Exogeneity’ is used and the Wald Statistic (p -value) is reported. The extended EViews output for each Granger causality analysis is available in the [Supplementary Information](#) that accompanies this paper.

2.6. Data

For global surface temperature, we use the Hadley Centre–Climate Research Unit combined Landsat and SST monthly surface temperature series (HadCRUT) version 4.6.0.0 (Morice et al. 2012). In the paper, this series is abbreviated to ‘At_temp’.

For atmospheric CO₂ data from 1958 to the present, we use monthly data from the CO₂ series produced by the US Department of Commerce National Oceanic and Atmospheric Administration Earth System Research Laboratory Global Monitoring Division Mauna Loa, Hawaii (Keeling et al. 2009). In the paper, this series is termed ‘CO₂’.

To represent global surface temperature models, a monthly data series projected from a business-as-usual global climate model (GCM) for global surface temperature was used. We used the CMIP5, RCP4.5 scenario model (Taylor et al. 2012) run for the IPCC fifth assessment report (IPCC 2013).

Normalized Difference Vegetation Index (NDVI) monthly data from 1980 to 2006 come from the Global Inventory Modeling and Mapping Studies (GIMMS) dataset (Tucker et al. 2005); NDVI monthly data from 2006 to 2013 were provided by the Institute of Surveying, Remote Sensing and Land Information, University of Natural Resources and Life Sciences, Vienna. Being from the same disaggregated data set, the two series are readily merged for use (for method, see Leggett and Ball 2015) and the merged series is termed ‘NDVI’.

The highest frequency data available for ocean heat content is reported quarterly. Quarterly data for ocean heat content from the surface to 700 metres is from the NOAA National Oceanographic Data Center (NODC) (Levitus et al. 2012) for the period 1955 to the present. According to Climate Change Synthesis Report AR4 (IPCC 2007), two-thirds of energy stored in the ocean is absorbed between the surface and a depth of 700 metres.

The ocean heat from surface to 700 metres series as used in the paper is termed ‘ocean heat uptake’.

Volcanic aerosol data is from the Stratospheric Aerosol Optical Thickness monthly series produced by the National Aeronautic and Space Administration Goddard Institute for Space Studies (Sato et al. 1993). It has previously been shown that increasing volcanic aerosols correlate with reduced temperature (Yan et al. 2016). In radiative forcing terms, the forcing from volcanic aerosols is approximately 27 times the optical thickness (Stern and Kaufmann 2014; Pasini et al. 2017). Hence, the volcanic aerosol series used in the paper is sign-reversed and is termed ‘reverse volcanic aerosols’.

Two cloud cover data sets are used – ocean and land. The monthly cloud cover data set used for ocean cloud is the Cloudiness Monthly Mean at Surface ICOADS v2.5 cloud cover (Freeman et al. 2017). The monthly land cover data set used is the CRUTS 4.03 (land) series (Harris et al. 2014).

Wind speed data comes from the monthly global ICOADS v2.5 wind speed (Variable wind speed – Scalar Wind Monthly Mean at Surface – in m/s) (Freeman et al. 2017).

Southern Oscillation Index (SOI) monthly data (Troup 1965) are from the Science Delivery Division of the Department of Science, Information Technology, Innovation and the Arts (DSITIA), Queensland, Australia.

Outgoing longwave radiation (OLR) monthly data was accessed from Climate Explorer (Lee et al. 2007).

3. Results

This section is structured as follows. Firstly, we scan for candidates for roles in the control system as considered from a number of perspectives: either as physical elements, as outcomes, or as control terms. We then reassess the number of control terms in the control system model. Following this, we conduct Granger causality analysis on the selected time series under the terms of the control system hypothesis.

Finally, we scan the results to select chains of elements that pass the tests, which therefore suggest that they comprise the physical control system.

3.1. Candidate elements of the control system

In this section, as set out in the hypothesis (Section 1.4), we develop a list of putative candidate elements for a global atmospheric surface temperature control system.

The state of the atmosphere involves the major phenomena of temperature, humidity, precipitation, air pressure, wind speed, and cloud cover (Schneider et al. 2011).

These constitute potential candidates for the entities of the hypothesis: leading element, controller term, candidate actuator and outcome.

3.1.1. Outcomes of the control system. We address two terms under this heading: final outcome and penultimate outcome.

3.1.1.1. Final outcome of the control system. The final outcome of the global atmospheric temperature control system is, by definition, global atmospheric temperature.

3.1.1.2. Candidate penultimate outcomes of the control system. An overall scan of atmospheric series leads us to nominate a further outcome class: the penultimate outcome. Penultimate outcomes of the control system are temperature-related and contribute to the final temperature outcome of the control system.

One candidate penultimate outcome of the control system selected for assessment is outgoing longwave radiation (OLR). This creates a cooling control by emitting infrared radiation from the surface of the earth (IPCC 2013). It is part of terrestrial radiation, which is radiation emitted by the Earth’s surface, the atmosphere and the clouds. As it may be affected by the degree of global cloud cover, it is considered a penultimate outcome contributing to the final outcome.

A second candidate penultimate outcome would arise if the control system enhanced heat uptake from the atmosphere by the ocean, thereby cooling the atmosphere (IPCC 2013).

3.1.2. Candidate actuators of the control system. As this is a permutational study, we seek to minimise the number of permutations generated, by reducing the number of variables involved in the study wherever possible and reasonable.

We look for candidate actuators from major atmospheric phenomena previously outlined (that is, temperature, humidity, precipitation, air pressure, wind speed, and cloud cover (Schneider et al. 2011)).

Of these phenomena, it can be shown that there are close correlations between humidity, cloud cover and precipitation (for example, Richards and Arkin 1981; Walcek 1994). For this study, we choose cloud cover to represent these phenomena.

We therefore selected atmospheric pressure, wind speed and cloud cover as candidate actuators for this study.

We note that cloud cover is assessed not only for a relationship from actuator to penultimate outcome but also directly from actuator to final outcome.

3.1.2.1. Atmospheric pressure. The trend in atmospheric pressure is commonly indicated by the Southern Oscillation Index (SOI) (IPCC 2013), which is used in this study. The SOI is one of the two components of the El Niño–Southern Oscillation (ENSO).

3.1.2.2. Wind Speed. A large body of literature supports the inference that wind stress (force per unit area exerted by the wind on the ocean) directly controls the mass fluxes in the top several hundred meters of the ocean (Wunsch 2002). Wunsch notes that the ocean is both heated and cooled within about 100 m of the surface.

Sarmiento and Gruber (2006) also state that winds are the main source of energy for ocean circulation, producing wind-driven ocean currents. A theory exists that biosphere-enhanced evaporation and condensation plays a general and dominant role in atmospheric dynamics (for overview see Sheil 2018).

We thus have a potential pathway for the control system from the biosphere to the ocean.

Given this background, wind is considered to be a candidate actuator for moving heat from the atmosphere to the ocean.

3.1.2.3. Cloud cover. According to IPCC (2013), clouds can act on global temperature in two ways. The first is to warm the Earth by trapping outgoing longwave infrared radiative flux at the top of the atmosphere. Secondly, lower level clouds can also cool the Earth by reflecting shortwave solar radiative flux (the albedo effect) back to space. The cloud radiative effect on the Earth’s radiation budget can be inferred from satellite data by comparing upwelling radiation in cloudy and non-cloudy regions. This comparison shows that cloud conditions exert a global and annual shortwave cloud radiative effect of approximately -50 W/m^2 and a mean longwave cloud radiative effect of approximately 30 W/m^2 . Thus the net global mean cloud radiative effect is approximately -20 W/m^2 , implying a strong net cooling effect of clouds on the current climate.

In light of the above, one-way Granger causality from clouds is sought both on longwave radiation and on the final outcome, atmospheric temperature.

Both land and ocean cloud cover time series are used in the analysis.

3.1.2.4. Candidate control terms. The control terms initially used in this analysis were the PID terms from Leggett and Ball (2020), termed here P_CONTR, I_CONTR and D_CONTR.

3.1.2.4.1. Number of control terms in the control system. In Leggett and Ball (2020) we provided evidence

that the atmospheric surface temperature control system had Proportional-Integral-Derivative (PID), that is, 3-term, control system characteristics.

It is well known that SOI (ENSO) and CO_2 variability are linked (Bacastow 1976; for overview see Imbers et al. 2013.) In particular, Leggett and Ball (2015) showed that SOI correlated with second-difference CO_2 , and this is the relationship that we explore further here. The relationship is shown in Fig. 1, and the relevant ARDL analysis is provided in Tables A1 and A2 of the Appendix.

Tables A1 and A2 show that SOI is statistically significantly correlated with second-difference CO_2 (DD_ CO_2). This would suggest that the control system may not be simply a PID system, but may include an extra control term reflecting second difference (that is, a PID + DD system). In man-made engineering, such systems exist and can perform better than PID systems alone (Sahib 2015; Raju et al. 2016).

We investigate this possibility for the atmospheric temperature control system as follows. ARDL analysis is carried out for both PID and PID + DD combinations. If the PID + DD combination displays a higher adjusted R^2 value and an improved Information Criterion, then this provides evidence for the control system being of PID + DD type.

The results of this analysis are presented in Tables A3 to A6 of the Appendix.

Tables A3 to A6 show that the DD term is significant in the four-term control type model, and that this model displays an improved adjusted R^2 value and Akaike Information Criterion value. The I term also displays a higher R^2 value (that is, displays a better fit) in the four-term model than in the three-term model.

We conclude that the above is statistically significant evidence that the atmospheric temperature control system is of four-term PID + DD type.

This presents a practical consequence for the remainder of this study – in the connectivity analysis, we assess the DD term alongside the P, I and D terms.

3.2. Candidate leading element

The most prominent global-level control system hypothesis proposes that the control system is biotic in origin (Lovelock and Margulis 1974). Here, Lovelock and Margulis referred to “...the notion of the biosphere as an active adaptive control system able to maintain the Earth in homeostasis...” They referred to this as the ‘Gaia’ hypothesis.

In Leggett and Ball (2020), we noted that the control system for which we provided evidence carries out a task similar to that which Gaia is hypothesised to perform.

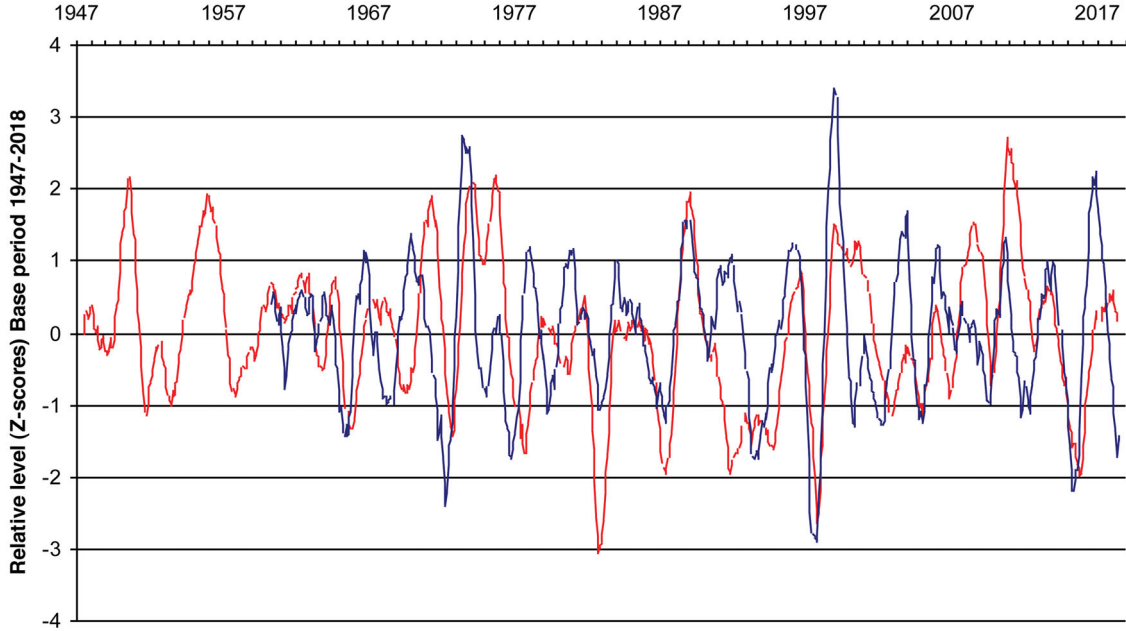


Fig. 1. Second-difference CO_2 (blue curve) and Reverse Southern Oscillation Index (red curve); monthly data.

However that study did not go so far as to identify a physical mechanism.

The biosphere is hence a candidate in this study for being the lead element of the control system. It can be considered to be the physical entity in which the controller resides – the controller outputs would clearly not constitute all of the outputs of the biosphere.

An indicator of the action of the biosphere is through measurement of its extent, and the amount of its photosynthesis. There is no single time series available for global photosynthesis. Photosynthesis takes place on land and in the oceans.

In considering the separate land and ocean domains, on the one hand the extent of photosynthesising *biomass* is dominated by land with 450 Gt C compared with the oceans at 2 Gt C (Bar-On et al. 2018). On the other hand, the relative contributions of land and oceans in *photosynthesis* are much closer together, with terrestrial sources representing 53.8% and oceanic sources 46.2% (Field et al. 1998).

Given the overall dominant position of terrestrial photosynthesis in both of these two measures, any biosphere control system effects are likely to be seen from the terrestrial photosynthesis trend. The global terrestrial photosynthesis trend is therefore considered suitably representative of the biosphere for use in this study.

An accepted measure of global terrestrial photosynthesis is through satellite measurements of vegetation reflectance, such as the Normalized Difference Vegetation Index (NDVI) (Tucker et al. 2005). We use the trend in NDVI to indicate that of the global biosphere in this study.

We now address the manner in which the biosphere might specifically affect climate, and in particular from the perspective of the candidate control system actuators of wind speed and cloud cover.

With respect to wind speed, Sheil (2018) reviews evidence that biosphere-enhanced evaporation and condensation play a general and dominant role in the generation of atmospheric motion – global circulation patterns, including winds.

Hence we have a potential causality pathway from the NDVI candidate leading element to the wind speed candidate actuator.

Turning to cloud cover, according to Gordon et al. (2016) most cloud droplets need tiny airborne particles to act as ‘seeds’ for their formation and growth. More particles in the atmosphere lead to more reflective clouds and a cooler climate. Trees produce a large fraction of cloud ‘seeds’ over the cleanest forested parts of the world. Such cloud seeds are particles generated by trees as a result of their emission of terpene gases (Gordon et al. 2016).

Hence we have a further potential causality pathway from the NDVI candidate leading element, via production of terpenes, to the cloud cover candidate actuator.

3.3. Developing a possible structure for the control system

After identifying candidate elements and then sorting them by type, we arrive at a hypothesised four-step control sequence: leading element to each controller term;

Table 2. Candidate control system elements in the combinations to be assessed for connectivity by Granger causality analysis.

Control system step 1			Control system step 2		Control system step 3		Control system step 4	
Leading element to	Controller term	Controller term to	Actuator	Actuator to	Penultimate outcome	Penultimate outcome to	Final outcome	
NDVI_CONTR	P_CO2_CONTR	P_CO2_CONTR	Wind_speed_CONTR	Wind_speed_FROM_2002_CONTR	Ocean_heat_uptake_REVERSE	Ocean_cloud_CONTR	At_temp	
NDVI_CONTR	I_CO2_CONTR	P_CO2_CONTR	Ocean_cloud_CONTR	Wind_speed_CONTR	OLR_REVERSE	Land_cloud_CONTR	At_temp	
NDVI_CONTR	D_CO2_CONTR	P_CO2_CONTR	Land_cloud_CONTR	Ocean_cloud_CONTR	Ocean_heat_uptake_REVERSE	Ocean_heat_uptake_REVERSE	At_temp	
NDVI_CONTR	DD_CO2_CONTR	P_CO2_CONTR	SOI_CONTR	Ocean_cloud_CONTR	OLR_REVERSE	OLR_REVERSE	At_temp	
		I_CO2_CONTR	Wind_speed_CONTR	Land_cloud_CONTR	Ocean_heat_uptake_REVERSE			
		I_CO2_CONTR	Ocean_cloud_CONTR	Land_cloud_CONTR	OLR_REVERSE			
		I_CO2_CONTR	Land_cloud_CONTR	SOI_CONTR	Ocean_heat_uptake_REVERSE			
		I_CO2_CONTR	SOI_CONTR	SOI_CONTR	OLR_REVERSE			
		D_CO2_CONTR	Wind_speed_CONTR					
		D_CO2_CONTR	Ocean_cloud_CONTR					
		D_CO2_CONTR	Land_cloud_CONTR					
		D_CO2_CONTR	SOI_CONTR					
		DD_CO2_CONTR	Wind_speed_CONTR					
		DD_CO2_CONTR	Ocean_cloud_CONTR					
		DD_CO2_CONTR	Land_cloud_CONTR					
		DD_CO2_CONTR	SOI_CONTR					

each controller term to each actuator; each actuator to each penultimate outcome; and each penultimate outcome to final outcome. With five candidate actuators, two penultimate outcomes and one final outcome, the permutations of the foregoing provide the hypothesised control system shown in Table 2.

All of the variable pairs in Table 2 are tested for Granger causality. This process will provide empirical evidence about the relationship between each pair of elements in the hypothesis.

We point out that the above table is a framework for the assessment of potential causal links, not a model of a proposed control system – we do not propose that causal links should necessarily be found between each variable pair.

We also point out that when all of the above assessments have been carried out, and if any causal links and chains are found, we are not claiming that the result depicts the entirety of the control system. Issues with data quality or inadequacy of time series length may prevent a true linkage being shown, and additional climate variables which have not been assessed in this paper may be part of any control system.

A flow of one-way Granger causality across each of the four control system stages in at least one of the four P, I, D, or DD control type ‘channels’ would provide evidence of at least some of the elements of a physical control system.

It is noted that a thorough search for Granger causality is carried out. If it exists over only a portion of the time span of the series for a pair of elements, then it is included.

The next step of the analysis is to assess the information flow pattern found, and identify (i) any A to B relationships that are non Granger-causal, and (ii) any B to A Granger-causal relationships. Any such relationship even in a single step in a given candidate control system channel suggests on the face of it that the channel does not exist.

3.4. Potential scale of influence of each candidate actuator

To enable consideration of the nature of their potential influence, we now visually depict the trend of each of the candidate control system elements in the context of the trend being controlled – global surface temperature.

In the depiction, please note that as stated in Section 2.4 above, a control system in the “real world” can be expected to display an increasing trend, combating the rising trend in temperature. In the control system, this will therefore display as a decreasing trend – the reverse of the real world trend.

A real world trend, expressed in terms of its control system effect, has the suffix ‘_CONTR’ appended.

Hence the real world net rising trends for wind speed and ocean cloud cover, for example, become decreasing trends when expressed as control system components, and as such are labelled in control system terms Wind_speed_CONTR and Cloud_ocean_CONTR.

Candidate process (controller) elements are plotted in Fig. 2 and candidate physical (actuator) elements are plotted in Fig. 3. The data series used are from 1901 to 2018 and are Z-scored from 1901 to 1987 in order to show any points of departure from prior trends in the later period (1988 to 2018). Figs. 2 and 3 show the candidate control system elements compared against (i) the expected temperature from the output of a mid-range scenario model (CMIP5, RCP4.5 scenario) (Taylor et al. 2012) run for the IPCC fifth assessment report (IPCC 2013) and with (ii) observed temperature.

Figs. 2 and 3 show that the trends of the potential control system elements fall into three main classes in terms of degree of potential temperature reduction, based on their deviation from the level in the base period (1901 to 1987). These are: from slight or none – DD_CO₂_CONTR, SOI and Land_cloud; to moderate – D_CO₂_CONTR, OLR_REVERSE, NDVI_CONTR, Wind_speed_CONTR and Ocean_cloud_CONTR; to largest – P_CO₂_CONTR, I_CO₂_CONTR, and Ocean_heat_uptake_CONTR. These trends will be further referred to after the results of causality analysis are presented in Section 3.5.2.

3.5. Results of assessments of Granger causality for candidate control elements

Results of Granger causality testing between candidate control elements are presented first for link-by-link causal relationships, and then for long-range causal relationships.

Tables 3–6 present the results of the Granger causality assessments at link-by-link level.

3.5.1. Basis of Granger causality testing for link-by-link causal relationships between candidate control elements. In general, the results in Tables 3–6 are from bivariate Granger causality assessments, with an exception in four cases (noted in Table S7 of the Supplementary Information) involving trivariate analysis. These four cases will be addressed before discussing the overall results.

3.5.1.1. Trivariate Granger causality analysis: NDVI and control system process terms. In bivariate Granger causality analyses for NDVI and the control system process terms (P_CO₂_CONTR, I_CO₂_CONTR, D_CO₂_CONTR and

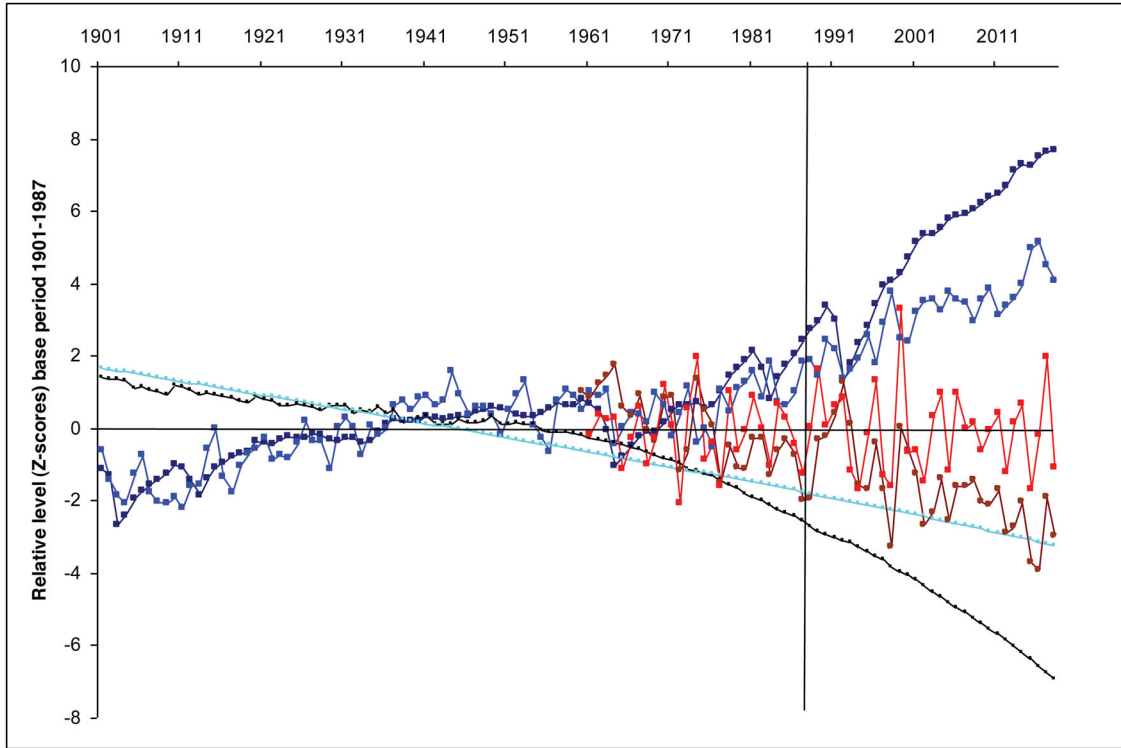


Fig. 2 Trends in expected temperature from the output of a mid-range IPCC scenario model (CMIP5, RCP4.5 scenario) (dark blue curve), observed temperature (blue curve), and control system candidate process elements: P_CO₂_CONTR (black curve); I_CO₂_CONTR (turquoise curve); D_CO₂_CONTR (brown curve); and DD_CO₂_CONTR (red curve); annual data, 1901 to 2018; all data Z-scored, base period 1901-1987.

DD_CO₂_CONTR), we explored the lag space extensively but could not find causality.

This situation was explored further by conducting Granger causality analysis using a third, auxiliary, variable in the causality analyses (for example, see Triacca et al. 2013).

A possible candidate for the auxiliary variable was volcanic aerosols (abbreviated here to ‘Volc’). The relationship between NDVI and Volc is shown in Fig. 4.

Fig. 4 shows that, while displaying an essentially neutral long-term trend, short-term variability in the volcanic aerosol series correlates with NDVI. As a result, volcanic aerosols might be appropriate as an auxiliary variable.

Therefore, trivariate Granger causality analyses were conducted for NDVI with Volc and each of the control system process terms P_CO₂_CONTR, I_CO₂_CONTR, D_CO₂_CONTR and DD_CO₂_CONTR. This approach found causality for the CO₂ variables, with the results being reported in Table 3.

For clarity, following Triacca et al. (2013), only results for NDVI and the CO₂ terms are reported in Table 3. Full results for the trivariate analysis including Volc are provided in the Supplementary Information.

3.5.2. Results of assessments of Granger causality for candidate control elements at link-by-link level.

3.5.2.1. Overview of presentation of results. Tables 3–6 present the results of all Granger causality testing for each control system step as outlined in Table 2. These tables provide the numerical Granger causality results for each candidate A-B relationship.

Table 7 combines the results of all of the steps in Tables 3–6 without the numerical information present in those tables. Instead, each pair of cells displaying one-way Granger causality at the 0.05 level in accordance with the hypothesis is shown by means of a grey background to the pair of cells.

If a continuous pathway of these grey causal steps can be traced all the way from the biosphere/NDVI leading element to the final outcome, then this indicates statistically significant evidence for an end-to-end control system causal chain.

3.5.2.2. Results of assessments. In each of Tables 3–6, information is provided on: the degree of smoothing (when used) of each series; lag length selected; extent of

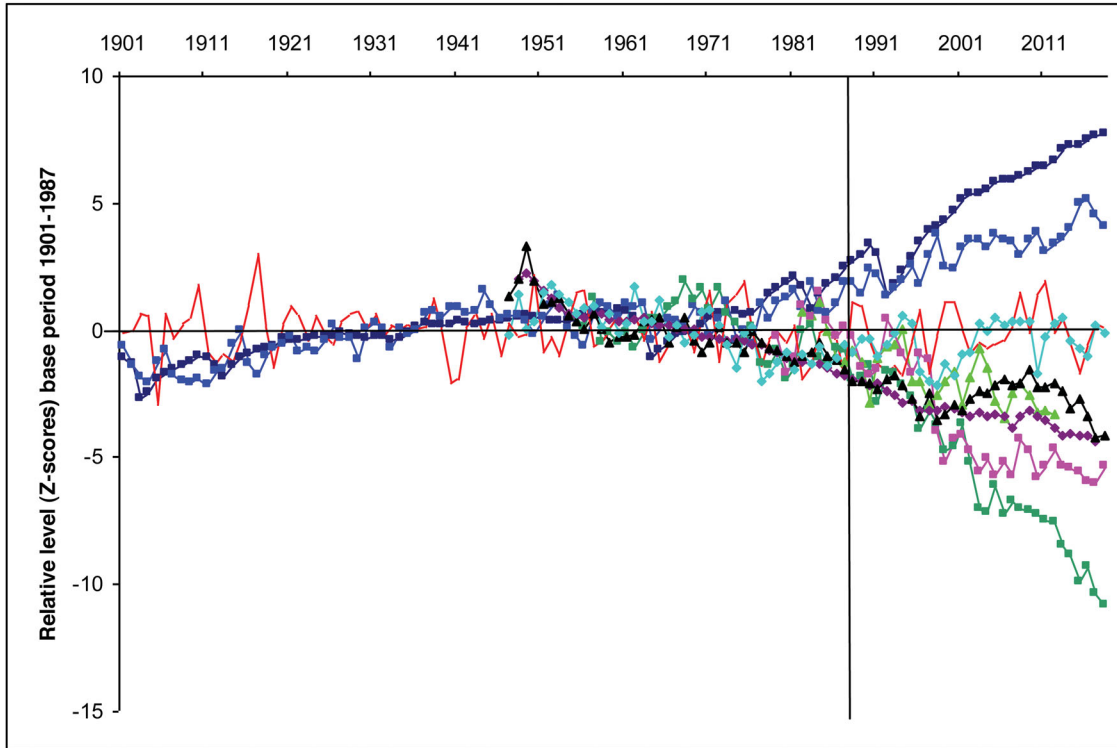


Fig. 3. Trends in expected temperature from the output of a mid-range IPCC scenario model (CMIP5, RCP4.5 scenario) (dark blue curve), observed temperature (blue curve), and control system candidate physical elements: Ocean_heat_uptake_REVERSE (sea green curve); NDVI_CONTR (bright green curve); Wind_speed_CONTR (violet curve); OLR_REVERSE (purple curve); Ocean_cloud_CONTR (black curve); Land_cloud_CONTR (aqua curve); and SOI_CONTR (red curve); annual data, 1901 to 2018; all data Z-scored, base period 1901-1987.

Table 3. Results of assessments of Granger causality for candidate control elements over Step 1 of the control system. Abbreviations not otherwise explained in text: T-Y – Toda-Yamamoto; AIC – Akaike information criterion. Data series used are monthly.

Control system step 1							
Biosphere leading element		Controller term					
Row	Variable A	Variable B	Lags (AIC)	T-Y test used	No autocorrelation out to n lags	Probability that relationship not Granger causal	
						Causality A to B	Causality B to A
1	NDVI_CONTR	P_CO ₂ _CONTR	74	N	24	1.58E-05	<i>0.4123</i>
2	NDVI_CONTR	I_CO ₂ _CONTR	74	N	9	0.0069	<i>0.2394</i>
3	NDVI_CONTR	D_CO ₂ _CONTR	49	N	13	0.0124	<i>0.3303</i>
4	NDVI_CONTR	DD_CO ₂ _CONTR	46	N	12	0.023	<i>0.355</i>

autocorrelation taken into account; and whether the Toda-Yamamoto procedure was used. More extensive information on Granger causality attributes for each assessment is provided in the [Supplementary Information](#).

In [Tables 3–6](#), the single best evidence for causality from a particular Granger causality assessment is shown. Hence the assessment in the tables may be from either monthly or

quarterly data. The type of data used for each assessment is specified in the [Supplementary Information](#).

Bold figures in [Tables 3–6](#) represent a statistically significant relationship (that is, a Granger-causal relationship with a probability of 0.05 or less of being due to chance). A non-significant relationship is presented in italics. Therefore, a relationship in line with the hypothesis (showing one-way

Table 4. Results of assessments of Granger causality for candidate control elements over Step 2 of the control system. Abbreviations not otherwise explained in text: T-Y – Toda-Yamamoto; AIC – Akaike information criterion. Data series used are monthly.

Control system step 2							
Controller term		Actuator					
Row	Variable A	Variable B	Lags (AIC)	T-Y test used	No autocorrelation out to n lags	Probability that relationship not Granger causal	
						Causality A to B	Causality B to A
1	P_CO ₂ _CONTR	Wind_speed_CONTR	41	Y	12	0.0268	0.1847
2	P_CO ₂ _CONTR	Ocean_cloud_CONTR	61	Y	7	0.0766	0.6547
3	P_CO ₂ _CONTR	Land_cloud_CONTR	54	Y	12	0.0143	0.1987
4	P_CO ₂ _CONTR	SOI_CONTR	67	N	20	0.0009	0.0537
5	I_CO ₂ _CONTR	Wind_speed_CONTR	27	Y	15	0.0141	0.2104
6	I_CO ₂ _CONTR	Ocean_cloud_CONTR	15	N	7	0.0222	0.0148
7	I_CO ₂ _CONTR	Land_cloud_CONTR	27	N	11	0.0881	0.01
8	I_CO ₂ _CONTR	SOI_CONTR	41	N	16	0.0196	0.0076
9	D_CO ₂ _CONTR	Wind_speed_CONTR	41	Y	9	0.054	0.1164
10	D_CO ₂ _CONTR	Ocean_cloud_CONTR	80	N	12	0.0343	0.4853
11	D_CO ₂ _CONTR	Land_cloud_CONTR	68	N	12	0.0474	0.8088
12	D_CO ₂ _CONTR	SOI_CONTR	29	N	10	0.004	0.0008
13	DD_CO ₂ _CONTR	Wind_speed_CONTR	18	Y	4	0.0249	0.0079
14	DD_CO ₂ _CONTR	Ocean_cloud_CONTR	67	N	9	0.0809	0.3354
15	DD_CO ₂ _CONTR	Land_cloud_CONTR	81	N	12	0.0209	0.6945
16	DD_CO ₂ _CONTR	SOI_CONTR	80	N	5	0.001	0.07

Table 5. Results of assessments of Granger causality for candidate control elements over Step 3 of the control system. Abbreviations not otherwise explained in text: T-Y – Toda-Yamamoto; AIC – Akaike information criterion. Data series used are monthly except where marked with the suffix ‘quar’, which are quarterly. The Granger causality assessment for Wind speed to Ocean_heat_uptake is based on data from 2002 onwards (see text).

Control system step 3							
Actuator		Penultimate outcome					
Row	Variable A	Variable B	Lags (AIC)	T-Y test used	No autocorrelation out to n lags	Probability that relationship not Granger causal	
						Causality A to B	Causality B to A
1	Wind_speed_FROM_2002_CONTR_Quar	Ocean_heat_uptake_REVERSE_quar	8	Y	8	0.0029	0.1377
2	Wind_speed_CONTR	OLR_REVERSE	40	Y	12	0.0055	0.1077
3	Ocean_cloud_CONTR_quar	Ocean_heat_uptake_REVERSE_quar	27	Y	12	0.7044	0.626
4	Ocean_cloud_CONTR	OLR_REVERSE	55	Y	20	0.0157	0.1029
5	Land_cloud_CONTR_quar	Ocean_heat_uptake_REVERSE_quar	40	Y	20	0.4002	0.5482
6	Land_cloud_CONTR	OLR_REVERSE	27	Y	12	0.0006	0.1338
7	SOI_CONTR_quar	Ocean_heat_uptake_REVERSE_quar	41	Y	20	0.1283	0.4654
8	SOI_CONTR	OLR_REVERSE	30	Y	20	0.1713	0.0503

Table 6. Results of assessments of Granger causality for candidate control elements over Step 4 of the control system. Abbreviations not otherwise explained in text: T-Y – Toda-Yamamoto; AIC – Akaike information criterion. Data series used are monthly except where marked with the suffix ‘quar’, which are quarterly.

Control system step 4							
Actuator or Penultimate outcome		Final outcome					
Row	Variable A	Variable B	Lags (AIC)	T-Y test used	No autocorrelation out to n lags	Probability that relationship not Granger causal	
						Causality A to B	Causality B to A
1	Ocean_cloud_CONTR	At_temp	14	Y	11	0.0145	<i>0.3109</i>
2	Land_cloud_CONTR_quar	At_temp	12	N	13	0.0034	<i>0.2047</i>
3	Ocean_heat_uptake_REVERSE_quar	At_temp_quar	5	Y	6	0.0017	<i>0.0702</i>
4	OLR_REVERSE	At_temp	28	Y	6	0.0045	<i>0.2533</i>

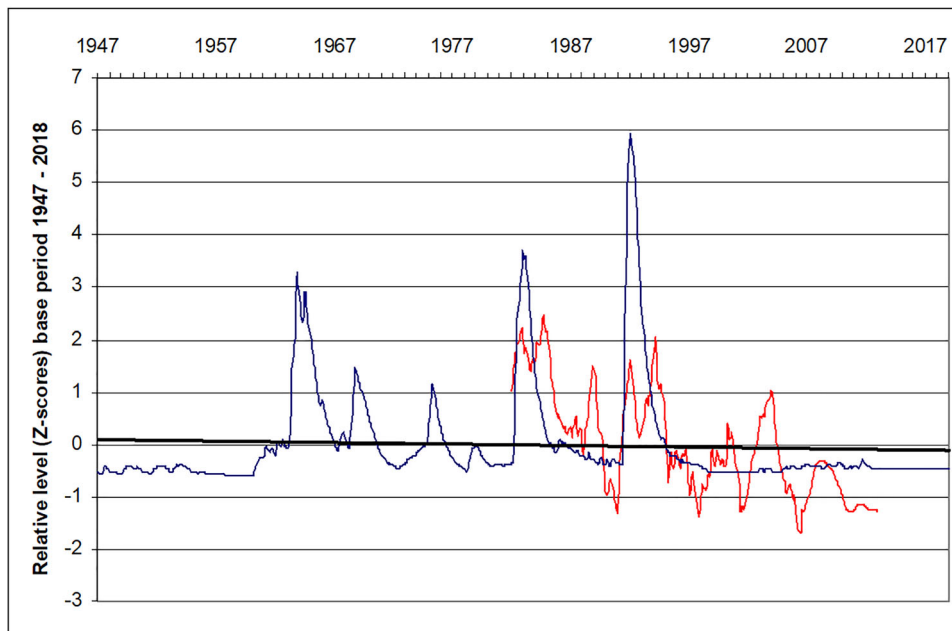


Fig. 4. Trends in NDVI (red line) and volcanic aerosols (sign reversed – blue line). Also shown is the linear trend for volcanic aerosols (black line); annual data, 1947 to 2018; all data Z-scored.

Granger causality in the A to B direction) will be displayed in each of Tables 3–6 with bold numbering in the A to B column and italics in the B to A column.

Table 3 provides results of assessments of Granger causality for candidate control elements over the first step of the proposed four steps of the control system.

As introduced in Section 3.5.1.1, Table 3 shows that from trivariate analyses with volcanic aerosols as an auxiliary variable, the links from NDVI to the four CO₂ control forms all show Granger causality in line with the control system hypothesis. This raises the question of

whether or not volcanic aerosols must be considered as part of the control system.

Volcanic aerosols act to decrease global surface temperature (IPCC 2013). This would assist any control system to reach a set point that requires a cooling action. However we consider that volcanic aerosols are a factor external to the control system influencing the initial temperature to which it responds, similar to the effect of clouds on the air conditioning system of a building, and therefore not constituting a part of the control system itself.

Table 7. Summary of the results of the scan of Tables 3 to 6 for causal steps connecting to make end-to-end causal chains in line with the control system hypothesis. Results are assembled without the numerical information presented in those tables. Instead, each pair of cells displaying one-way Granger causality at the 0.05 level in accordance with the hypothesis is shown by means of a grey background to the pair of cells.

Row	Control system step 1			Control system step 2		Control system step 3		Control system step 4	
	Biosphere leading element to		Controller term	Controller term to	Actuator	Actuator to	Penultimate outcome	Actuator or Penultimate outcome to	Final outcome
	Variable A	Variable B	Variable A	Variable B	Variable A	Variable B	Variable A	Variable B	Variable B
1	NDVI_CONTR	P_CO ₂ _CONTR	P_CO ₂ _CONTR	Wind_speed_CONTR	WSPEED_FROM_2002_CONTR_Quar	Ocean heat uptake_REVERSE_quar	Ocean_cloud_CONTR	At_temp	
2	NDVI_CONTR	I_CO ₂ _CONTR	P_CO ₂ _CONTR	Ocean_cloud_CONTR	Wind_speed_CONTR	OLR_REVERSE	Land_cloud_CONTR_quar	At_temp	
3	NDVI_CONTR	D_CO ₂ _CONTR	P_CO ₂ _CONTR	Land_cloud_CONTR	Ocean_cloud_CONTR_quar	Ocean heat uptake_REVERSE_quar	Ocean heat uptake_REVERSE_quar	At_temp_quar	
4	NDVI_CONTR	DD_CO ₂ _CONTR	P_CO ₂ _CONTR	SOI_CONTR	Ocean_cloud_CONTR	OLR_REVERSE	OLR_REVERSE	At_temp	
5			I_CO ₂ _CONTR	Wind_speed_CONTR	Land_cloud_CONTR	Ocean heat uptake_REVERSE_quar			
6			I_CO ₂ _CONTR	Ocean_cloud_CONTR	Land_cloud_CONTR	OLR_REVERSE			
7			I_CO ₂ _CONTR	Land_cloud_CONTR	SOI_CONTR_quar	Ocean heat uptake_REVERSE			
8			I_CO ₂ _CONTR	SOI_CONTR	SOI_CONTR				
9			D_CO ₂ _CONTR	Wind_speed_CONTR					
10			D_CO ₂ _CONTR	Ocean_cloud_CONTR					
11			D_CO ₂ _CONTR	Land_cloud_CONTR					
12			D_CO ₂ _CONTR	SOI_CONTR					
13			DD_CO ₂ _CONTR	Wind_speed_CONTR					
14			DD_CO ₂ _CONTR	Ocean_cloud_CONTR					
15			DD_CO ₂ _CONTR	Land_cloud_CONTR					
16			DD_CO ₂ _CONTR	SOI_CONTR					

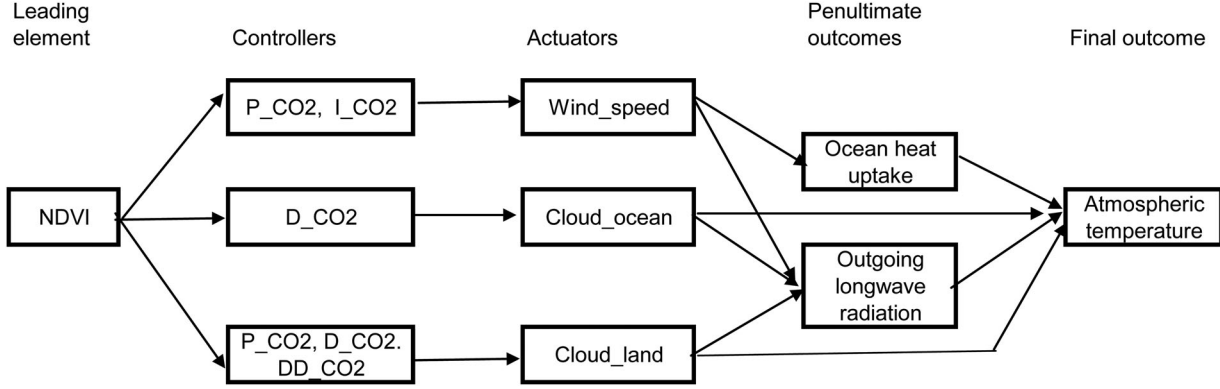


Fig. 5. Evidence for the existence of a physical control system: end-to-end sequences of candidate control system elements that display one-way Granger causality at 0.05 probability level across each step of the sequence (derived from Table 7). Note that for clarity in this Figure all terms are expressed without their _CONTR or _REVERSE suffixes.

Table 4 provides results of assessments of Granger causality for candidate control elements over the second step of the proposed four steps of the control system.

It can be seen that results are more varied for the controller term to actuator control system step than in the first step. Specific results will be discussed after Table 7.

Table 5 provides results of assessments of Granger causality for candidate control elements over the third step of the proposed four steps of the control system.

Once again, some variability can be seen in the results of the Granger causality testing.

Table 6 shows results for the final control system step from penultimate outcome (ocean heat uptake and outgoing longwave radiation) to final outcome.

All elements in Table 6 display one-way Granger causality to the final outcome, atmospheric temperature.

However, it can be seen that the control system step from ocean heat uptake to atmospheric temperature also displays a degree of causality in the other direction ($p=0.07$), which would be significant if the 0.1 level of statistical significance was chosen.

For this reason (and as outlined in Section 1.2), the strength of causality F_{XY} and F_{YX} is calculated for each direction in this relationship. The results are $F_{Ocean\ heat\ to\ At.\ temp} = 0.1406$, and $F_{At.\ temp\ to\ Ocean\ heat} = 0.0565$. This result shows that causality is close to 2.5 times stronger in the direction of ocean heat uptake to atmospheric temperature than the reverse. We consider this as further evidence for effective one-way causality in line with the control system hypothesis. These results would appear to increase the likelihood that the relationship from wind speed to ocean heat uptake may exist for the full time span of data available, and that the lack of a clear Granger-causal result for the full time span may be due to as-yet undetermined statistical or other factors.

3.5.3. *End-to-end control system causal chains.* The results of the scan of Tables 3–6 for causal steps connecting to make end-to-end causal chains in line with the control system hypothesis are assembled in Table 7, without the numerical information presented in those tables. Instead, each pair of cells displaying one-way Granger causality at the 0.05 level in accordance with the hypothesis is shown by means of a grey background to the pair of cells.

If a continuous pathway of these grey causal steps can be traced all the way from the biosphere/NDVI leading element to the final outcome, then this comprises statistically significant evidence for an end-to-end control system causal chain.

The end-to-end control system causal chains revealed in Table 7 are depicted in Fig. 5. Fig. 5 shows the chains that display one-way causality across each of the four sequential control system stages from leading element to final outcome (note that for clarity, the ‘Controllers’ column displays the relevant controllers for each Actuator).

Fig. 5 shows complete end-to-end one-way Granger causality pathways sufficient to meet the control system hypothesis.

3.5.4. Action of the leading element of the control system

Turning to the question of the leading element of the control system, the patterns of one-way Granger causality shown in Table 7 and summarised in Fig. 5 show that the leading element is NDVI. Noting that, in this paper, NDVI represents the biosphere (Section 3.2), as previously outlined the most prominent global-level atmospheric control system that has been hypothesised also

Table 8. Results of Granger causality tests from leading element to control system final outcome.

Variable A	Variable B	Lags	T-Y test used	No autocorrelation out to n lags	Probability that relationship not Granger causal	
					Causality A to B	Causality B to A
NDVI_CONTR	At_temp	40	N	9	0.0113	0.1593

proposes that the control system is biotic in origin (Lovelock and Margulis 1974). Here, Lovelock and Margulis referred to “... [t]he notion of the biosphere as an active adaptive control system able to maintain the Earth in homeostasis ...”

They went on to write “...we are calling [this] the ‘Gaia’ hypothesis ...”

In Table 2, then, NDVI stands for the Gaia candidate. The biosphere can be considered to be the physical entity in which the controller resides (the controller outputs being some of the outputs of the biosphere).

The pattern of results in Tables 3–6, then, can be read to provide strong evidence of the existence of Gaia as proposed in the Gaia hypothesis.

The evidence of control system connectivity is from the leading element to each of the four control-type terms, through to three actuators and then via one actuator to the ocean heat uptake penultimate outcome and via all three actuators to the outgoing longwave radiation penultimate outcome. Both penultimate outcomes display one-way Granger causality to the final outcome. Hence there are multiple lines of evidence for the existence of the physical control system.

Possible physical actions to produce these control system results are described in the following.

Evidence was provided in Section 3.1.2.2 of wind activity induced by evaporation and condensation from the biosphere (Sheil 2018) and in Section 3.2 of cloud cover being influenced by terpene production from the biosphere (Gordon et al. 2016).

The CO₂ controller terms (P_CO₂_CONTR, I_CO₂_CONTR, D_CO₂_CONTR and DD_CO₂_CONTR) represent the various ways that the biosphere may manages its control system output of evaporation, condensation and terpenes in response to the disturbance of rising atmospheric CO₂. In addition to a direct linear increased output of evaporation, condensation and terpenes in response to the disturbance (P_CO₂_CONTR), it also demonstrates an increased output proportional to change of the disturbance (D_CO₂_CONTR), to the total disturbance (I_CO₂_CONTR), and also to the rate of change of the disturbance (DD_CO₂_CONTR).

Turning to actuators, it appears that global wind speed and global cloud cover (both land- and ocean-based) are likely the main actuators, with wind speed moving heat

from the atmosphere to the ocean and cloud cover reflecting incoming solar radiation and allowing upwelling of terrestrial radiation to space.

These results, then, are evidence for the physical nature of the control system affecting global surface temperature.

3.6. Long-range causality from candidate leading element to control system final outcome

We now test for Granger causality from NDVI, shown in Table 2 to be the leading element of the control system, to atmospheric temperature, the final outcome of the control system.

By analogy with the electronic signal tracer test equipment used to troubleshoot radio and other electronic circuitry described in Section 1.4 (Bishop 2007), this tests to confirm that the influence of the leading element appears in the outcome, confirming that the intervening elements are therefore connected as an unbroken chain.

Results are presented in Table 8.

Table 8 shows that NDVI demonstrates clear statistically significant one-way Granger causality to the final outcome of the system, global surface temperature.

We suggest that this overall result serves to underline the detailed results shown in Tables 3 to 7.

4. Discussion

By applying Granger causality analysis, this paper has provided empirical evidence relevant to a number of the aspects of the functioning of the control system affecting global atmospheric temperature: the physical nature of control system elements; the existence of full step-by-step one-way Granger-causal control between the elements from leading element to outcome; the identification of four controller terms for the control system; a possible means for the physical connection of the biosphere, represented by NDVI, to the CO₂-related controller process terms; the actuators of the control system found and their relationship to the final outcome, global surface temperature, either directly or indirectly via penultimate outcomes; and evidence for the leading element of the control system being the global biosphere, and therefore Gaia.

The hypothesis put forward in this paper for the nature of the physical control system affecting global atmospheric temperature proposed a sequence of candidate element types making up the control system – the leading element, controllers, actuators, penultimate outcomes and final outcome. This paper provides evidence that one-way Granger causality is observed across each step of this proposed sequence of candidate element types. Hence these results are evidence for the physical existence of the control system, and of its nature.

We provide evidence that the control system shown by Leggett and Ball (2020) to contain three controller terms – proportional, integral and derivative (PID) – demonstrates an improvement in statistical fit when a fourth, second-derivative (approximated by second difference) or DD, controller term is included.

Clear, directional Granger-causal or information flow connectivity is shown from NDVI to the four CO₂ controller terms and then to the actuators.

To support physical mechanisms, evidence was provided in Section 3.1.2.2 of wind activity induced by evaporation and condensation from the biosphere (Sheil 2018), and in Section 3.2 of cloud cover being influenced by terpene production from the biosphere (Gordon et al. 2016).

In Section 3.5.4, we noted that the CO₂ controller terms (P_CO₂, I_CO₂, D_CO₂ and DD_CO₂) represent evidence for the various ways that the biosphere manages its control system output of evaporation, condensation and terpenes in response to the disturbance of rising atmospheric CO₂. In addition to a direct linear increased output of evaporation, condensation and terpenes in response to the disturbance (P_CO₂_CONTR), the evidence from this paper is for an increased output proportional to change of the disturbance (D_CO₂_CONTR), to the total disturbance (I_CO₂_CONTR), and also to the rate of change of the disturbance (DD_CO₂_CONTR).

Turning to actuators, we present evidence that global wind and global cloud cover (both land- and ocean-based) are actuators. Cloud cover is shown to influence the final outcome, global surface temperature, directly by reflecting incoming solar radiation. Cloud cover and wind speed also influence the penultimate outcomes found, those of enhanced ocean heat uptake and enhanced outgoing longwave radiation, with wind speed moving heat from the atmosphere to the ocean and cloud cover showing causality to outgoing longwave radiation. These processes together lead to control system output to the final outcome, global atmospheric temperature.

We provide evidence that the leading element of the control system is the global biosphere, and show, by way

of outlining the mechanisms of its action to control global atmospheric temperature, that this is evidence for the existence of Gaia as postulated by Lovelock and Margulis in 1974.

A notable feature of these results is that evidence for the activity of the control system is present across an extensive range of the major atmospheric series assessed in this paper.

Future research might be warranted into the possible existence of further processes of the control system involving, for example, feedforward (Åström and Murray 2008) and seasonal timers. These might be further aspects enabling the precise application of coordinated control outputs worldwide into the global atmosphere.

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No potential conflict of interest was reported by the authors.

Author contribution statement

LMWL conducted the statistical analysis. Both authors collaborated on interpreting the results and contributed to the final manuscript.

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Appendix

Table A1. Eviews ARDL estimation output for period May 1960 to July 2018 for SOI as a function of second-difference CO₂: overall statistics for short-run model dynamic relationship.

Model dependent variable	Number of models evaluated	Selected model	Autocorrelation out to 12 lags	Adjusted R-squared	F-statistic	p-value
SOI_CONTR	156	ARDL (4,2)	Nil	0.987121	7610.544	0.00E+100

Table A2. Eviews ARDL estimation output for period May 1960 to July 2018 for SOI as a function of second-difference CO₂: statistics for each dependent variable in short-run model dynamic relationship.

Model independent variables	Coefficient	Std. Error	t-Statistic	Prob.*
SOI_CONTR(-1)	1.337157	0.037865	35.31336	0.00E+00
SOI_CONTR(-2)	-0.1111	0.06333	-1.75436	7.98E-02
SOI_CONTR(-3)	-0.16888	0.062944	-2.683005	7.50E-03
SOI_CONTR(-4)	-0.08494	0.037848	-2.244243	0.0251
DD_CO2_CONTR	0.082316	0.027114	3.035941	0.0025
DD_CO2_CONTR(-1)	-0.01275	0.047181	-0.270272	0.787
DD_CO2_CONTR(-2)	-0.05543	0.02721	-2.037153	0.042
C	-0.00136	0.004421	-0.308568	0.7577

Tables A1 and A2 show that SOI is statistically significantly correlated with second difference CO₂ (DD_CO2). This would suggest that the control system may not be simply a PID system, but may include an extra control term reflecting second difference (that is, a PID+DD system). In man-made engineering, such systems exist and can perform better than PID systems alone (Sahib, 2015; Raju et al., 2016).

We investigate this possibility for the atmospheric temperature control system as follows. ARDL analysis is carried out for both PID and PID+DD combinations. If the PID+DD combination displays a higher adjusted R-squared value and an improved Information Criterion, then this provides evidence for the control system being of PID+DD type.

The results of this analysis are presented in Tables A3 to A6.

Table A3. Eviews ARDL estimation output for period May 1960 to July 2018 for atmospheric surface temperature as a function of putative control system P_CONTR, I_CONTR and D_CONTR terms: overall statistics for short-run model dynamic relationship.

Model dependent variable	Number of models evaluated	Selected model (SIC)	Autocorrelation out to 36 lags	Adjusted R-squared	F-statistic	p-value	Akaike Information Criterion
At_temp	3,584	ARDL(4, 0, 0, 5)	Nil	0.902242	539.3778	0.00E + 00	0.525009

Table A4. Eviews ARDL estimation output for period May 1960 to July 2018 for temperature as a function of putative control system P_CONTR, I_CONTR and D_CONTR terms: statistics for long-run model independent variables.

Model independent variables	Coefficient	Std. Error	t-Statistic	Prob.*
P_CO2_CONTR	-1.687791	0.596673	-2.828668	0.0048
I_CO2_CONTR	1.013032	0.598024	1.693965	0.0907
D_CO2_CONTR	-0.290399	0.087033	-3.336661	0.0009
C	0.181349	0.051687	3.508626	0.0005

Table A5. Eviews ARDL estimation output for period May 1960 to July 2018 for atmospheric surface temperature as a function of putative control system P_CONTR, I_CONTR, D_CONTR and DD_CONTR terms: overall statistics for short-run model dynamic relationship.

Model dependent variable	Number of models evaluated	Selected model	Autocorrelation out to 36 lags	Adjusted R-squared	F-statistic	p-value	Akaike Information Criterion
At_temp	28,672	ARDL(4, 1, 0, 2, 0)	Nil	0.903408	594.4807	0.00E + 00	0.507034

Table A6. Eviews ARDL estimation output for period May 1960 to July 2018 for temperature as a function of putative control system P_CONTR, I_CONTR, D_CONTR and DD_CONTR terms: statistics for long-run model independent variables.

Model independent variables	Coefficient	Std. Error	t-Statistic	Prob.*
P_CO2_CONTR	-1.9408	0.6487	-2.99183	0.0029
I_CO2_CONTR	1.4016	0.654659	2.140961	0.0326
D_CO2_CONTR	-0.519331	0.104663	-4.961912	8.81E-07
DD_CO2_CONTR	-0.25982	0.098192	-2.646033	0.0083
C	0.370506	0.103063	3.594928	0.0003

Tables A3 to A6 show that the DD term is significant in the four-term control type model and that this model displays an improved adjusted R-squared value and Akaike Information Criterion value. Note that the I term also displays a higher R-squared value (that is, displays a

better fit) in the four-term model than in the three-term model.

We conclude that the above is statistically significant evidence that the atmospheric temperature control system is of four-term PID+DD type.