

Response to Anonymous Referee #1

Comment: This paper presents a method to detect causality in climate time series. This method is based on principles of recurrences in dynamical systems. While interesting a priori, many points need to be improved and/or discussed.

Answer: Dear Anonymous Referee #1, Thank you for your insightful review. We appreciate that you consider our approach to be interesting. The following is our response to your comments:

Major points

Comment: The literature review does not seem complete and misses crucial contributions. The paper is about attribution (of climate change), through the identification of causal links. There is an ample published literature on the subject, including in climate sciences. For instance, google scholar shows:

Hannart, A., Pearl, J., Otto, F. E. L., Naveau, P., & Ghil, M. (2016). Causal counterfactual theory for the attribution of weather and climate-related events. *Bulletin of the American Meteorological Society*, 97(1), 99-110. (J. Pearl, who made the theory of causality, is a co-author of that paper); Runge, J., Petoukhov, V., Donges, J. F., Hlinka, J., Jajcay, N., Vejmelka, M., ... & Kurths, J. (2015). Identifying causal gateways and mediators in complex spatio-temporal systems. *Nature communications*, 6, 8502; A report of the US Academies of Science (National Academies of Sciences Engineering and Medicine 2016) also mention causality.

Answer: Though we have never aspired that our contribution may serve our readers as a review paper, we concede that you are correct and the reference list must be extended.

Action: In addition to a few items you advised us about, we will discuss and reference additional sources such as,

Abarbanel, H. D., Brown, R., Sidorowich, J. J., and Tsimring, L. S.: The analysis of observed chaotic data in physical systems. *Reviews of modern physics*, 65(4), 1331, 1993

Attanasio, A., Pasini, A., and Triacca, U.: A contribution to attribution of recent global warming by out-of-sample Granger causality analysis. *Atmospheric Science Letters*, 13(1), 67-72, 2012

Egorova, T., Schmutz, W., Rozanov, E., Shapiro, A.I., Usoskin, I., Beer, J., Tagirov, R., and Peter, T.: Revised historical solar irradiance forcing, *Astron. Astrophys.*, 615, id A85. doi 10.1051/0004-6361/201731199, 2018

McCracken, J. M.: Exploratory Causal Analysis with Time Series Data. *Synthesis Lectures on Data Mining and Knowledge Discovery*, 8(1), 1-147, 2016

Meehl, G. A., Arblaster, J. M., Matthes, K., Sassi, F., and van Loon, H.: Amplifying the Pacific climate system response to a small 11-year solar cycle forcing. *Science*, 325(5944), 1114-1118, 2009

O'Brien, J. P., O'Brien, T. A., Patricola, C. M., and Wang, S. Y. S.: Metrics for understanding large-scale controls of multivariate temperature and precipitation variability. *Climate Dynamics*, 1-19, 2019

Sauer, T., Yorke, J. A., and Casdagli, M.: Embedology. Journal of statistical Physics, 65(3-4), 579-616, 1991

Vejmelka, M. et al.: Non-random correlation structures and dimensionality reduction in multivariate climate data. Climate Dyn. 44, 2663–2682, 2015

DONE: See References section pp. 11-13 and corresponding references throughout the text

Comment: Although I do like dynamical systems, the transition from a 2-D discrete Hénon attractor to a “real world” problem sounds like a leap of faith. There are many numerical problems with the application of embedding methods (“à la” Takens). The main one is that there is no bound to the necessary embedding dimension, so that the low dimensional example that is treated is not sufficient to be convincing. The authors never mention questions linked to the so called “curse of dimensionality” to treat causality. When they treat the Hénon attractor, they use variables of the dynamical system, and do not need to evaluate embedding to make reconstructions. The climate application uses observables of the climate system (northern hemisphere temperature and CO₂), which might not give a straightforward connection to variables of the underlying system. Therefore all interpretations might be misleading.

Answer: We use Hénon attractor just as an illustration of the MCD concept because we want our readers to be well equipped before they review and interpret the sigma(epsilon) curves that are presented in the following chapters. Nevertheless, your concern regarding the “curse of dimensionality” is legitimate. Yes, we treat the climate variables the same way as Hénon attractor variables (with evaluation “à la” Takens embedding, dimension 7). Fortunately, though, as it has been shown by Čenys et al. (1991), the MCD method is not very sensitive to the embedding dimension and the slope of sigma(epsilon) curves increases only slightly with the increase of the dimension. Indeed, despite the fact that numerous methods have been developed to better determine an embedding dimension (e.g., Abarbanel et al. 1993), it is still a challenge to determine embedding from a *measured* variable (such as temperature) because time series always have limited length and are corrupted with the noise which can be misinterpreted as a higher dimension. We use a hypothesis that NH temperature is an observable of the global climate system and CO₂ concentration is an observable of the system of external forcing. An observable may not necessary have straightforward connection to (“hidden”) physical variables of the underlying system. The embedding theorem (e.g. Sauer et al., 1991) states that reconstructed space is topologically equivalent to the underlying system in a sense that there exists a continuous differentiable transform from a reconstructed to the hidden space.

Action: We will add this discussion to the appropriate parts of the paper. **DONE: See p.8 lines 5-17.**

Comment: In Eqs (1-5), the systems have dimensionless variables, so that the choice of the range for epsilon is easy. The normalization of CO₂ and temperature for figure 2, to compute Eq. (1) is not explained. The authors do not explain how they embed the climate time series. Their results are not reproducible from the text and figures.

Answer: CO₂ and temperature time series have been normalized by subtracting their mean values and by dividing over standard deviation.

Action: This will be added to the text. **DONE: See p.8 lines 21-22.**

Comment: I do not quite agree with the interpretation of Fig. 2b. The slopes of $\sigma(\epsilon)$ are significantly positive for both ways (T and CO₂). Therefore both observable interact with each other, in rather well physically understood way. The discussion on the slope to define the strength of the unidirectional interaction is irrelevant because it depends on the units of the variables and the shape of their probability distribution (from eye-balling Eq. (1)). The authors should compare how curves depart from a horizontal line when dealing with heterogeneous variables. If this type of analysis was done between a proxy for solar activity and temperature, I would expect a horizontal line. Is it the case?

Answer: It is not the case. We have relatively short time series with a strong linear trend. We show in Fig. 5 that the $\sigma(\epsilon)$ slope can deviate significantly from the horizontal line because of linear correlation introduced by a trend, even in the case of completely independent time series. Solar activity does have a trend and the corresponding $\sigma(\epsilon)$ curve will deviate from the horizontal line. Therefore, in our paper, we are focusing not on the slope by itself but on the difference between two slopes, both in instrumental measurements and in model simulations.

Action: We will articulate this notion more clearly in the text. **DONE: See p.8 lines 36-38, p.9 lines 1-2.**

Comment: What is the added value of the MCD analysis over the CMIP5 simulations and all the literature on attribution? The trend in observations cannot be obtained with control simulations and simulations with natural forcings. Only simulations with increasing CO₂ can reproduce the recent trend. The analysis of this manuscript “just” reflects this known result. Such diagnostics (either visual, as reported by the IPCC or statistical in this manuscript) are relevant to measure causality. They do not state by which mechanism this causality operates: only first principles of physics can do that!

Answer: We can't agree more that only laws of physics may identify the mechanism of causality. In this sense the causality is encoded in the differential equations of the mathematical models. With our calculations, we are not challenging the consensus whether CO₂ is the cause of the temperature increase, but rather calibrate MCD against existing measurements and simulations. Unfortunately, despite the fact that multiple methods exist to detect causality in the data, none is perfect for analysis of complex systems such as the Earth climate (McCracken, 2016). High uncertainty in natural forcing (e.g., Egorova et al., 2018) may be amplified by model uncertainties (e.g. Meehl et al., 2009). Therefore, a properly calibrated causality detection method like MCD may help to reduce these uncertainties in quantifying the climate response to different forcings by providing new data driven constraints. As long as MCD is recognized as a trusted approach, it can be used for express testing of new models and, may be more importantly, can serve as a first test for any new candidate external forcing that may be considered as an alternative or supplement to CO₂.

Action: We will add this discussion to the test. **DONE: See p.11 lines 18-27.**

Comment: Specific points

Fig. 1 caption: $\alpha=0$ and $\beta=0.3$ is when x is the cause of u . The legend says the opposite (x depends on u). Please clarify or correct.

Answer: We agree that it may be confusing

Action: We will make a more clear legend. **DONE: See Fig.1. It is now “x dependence on u”**

Response to Anonymous Referee #2

Comment: This paper argues that by using method of conditional dispersion (MCD) it is possible to detect causal relationship between surface temperature anomalies and CO₂ concentrations in climatological time series (observed and simulated). The method was initially developed to estimate interrelation in low-dimensional dynamical systems and applying it to climatological time series is indeed a novel approach within the scope of this journal.

Answer: Dear Anonymous Referee #2, Thank you for your review and suggestions. We appreciate that you consider our approach to be novel and appropriate for Geoscientific Model Development. The following is our response to your comments:

Comment:

Two points need to be clarified to better understand results presented in the paper

The transition from analyzing chaotic time series produced by two coupled Henon maps (briefly discussed in paragraph 2) to studying climatological time series is not as straightforward as it is made in the paper. In particular, it requires some underlying assumptions about the nature of climatological system and interdependences between its variables which are not clearly mentioned in the paper.

Answer: We use a hypothesis that NH temperature is an observable of the global climate system and CO₂ concentration is an observable of the system of external forcing. An observable may not necessary have straightforward connection to (“hidden”) physical variables of the underlying system. The embedding theorem (e.g. Sauer et al., 1991) states that reconstructed space is topologically equivalent to the underlying system in a sense that there exists a continuous differentiable transform from a reconstructed to the hidden space.

Sauer, T., Yorke, J. A., and Casdagli, M.: Embedology. Journal of statistical Physics, 65(3-4), 579-616, 1991

Action: We plan to add this discussion to the paper. **DONE: See p.8 lines 5-17.**

Comment:

In paragraphs 3.2 and 3.3, MCD is applied to a set of model simulations. It is unclear from the paper, if these models include parametrization of the effect of surface temperature on CO₂ emissions. If not, it would make the connection one-directional (see discussion in paragraph 2) which by itself explains the results presented in Figures 3 and 4.

Answer: We agree with your comment that clarification about the origin of CO₂ time series used to produce Figures 3 and 4 is needed. In fact, in all experiments we used the same atmospheric carbon dioxide concentration measurements (CO₂ NASA GISS Data, 2016). We assume therefore that the effect of the surface temperature on CO₂ concentration has been naturally included in the CO₂ time series.

Action: We will clarify this in the text. **DONE: See p.9 lines 11-14.**

Detecting causality signal in instrumental measurements and climate model simulations: global warming case study

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Abstract. Detecting the direction and strength of the causality signal in observed time series is becoming a popular tool for exploration of distributed systems such as Earth’s climate system. Here we suggest that in addition to reproducing observed time series of climate variables within required accuracy a model should also exhibit the causality relationship between variables found in nature. Specifically, we propose a novel framework for a comprehensive analysis of climate model responses to external natural and anthropogenic forcing based on the method of conditional dispersion. As an illustration, we assess the causal relationship between anthropogenic forcing (i.e., atmospheric carbon dioxide concentration) and surface temperature anomalies. We demonstrate a strong directional causality between global temperatures and carbon dioxide concentrations (meaning that carbon dioxide affects temperature stronger than temperature affects carbon dioxide) in both the observations and in (CMIP5) climate model simulated temperatures.

1. Introduction

The standard approach to attribution of observed global warming employs experiments with climate models. Such “detection and attribution” approaches (e.g., Stocker, 2014) attempt to reproduce observed trends under different external forcing conditions and demonstrate a consistency (or its absence) of simulated climate changes with instrumental observations. A substantial body of detection and attribution studies (e.g., Santer, *et al.*, 2009, 2012; Jones, *et al.*, 2013) spanning the past two decades demonstrates that anthropogenic increases in atmospheric carbon dioxide are very likely the cause of the observed global temperature increase since the mid-19th century. Semi-empirical approaches that combine information from model simulations and observations have also proven useful for investigations of modern climate change attribution. Previous work (e.g., Mann *et al.*, 2017) has employed estimates of natural variability derived from a combination of historical simulations and observations to attribute the sequence of record-breaking global temperatures in 2014, 2015, and 2016 to anthropogenic warming. Direct investigations of the causal relationship between climate system variables using statistical tools have become recently more common. The most simplistic approach, the Pearson’s correlation between two time series, which is often mentioned in the context of causality, does not really measure the causality. While statistically significant correlation quantifies similarity between time series, it does not imply a causality resulting from physical relationships between the natural processes that are expressed by the time series and that can be modeled using differential equations. Instead, it provides a statistical test of a hypothesis that describes a physical link between the two variables (i.e., expressed as times series) without actually testing **neither the direction of causality nor** the plausibility of the physics underlying the hypothesis. The breakthrough Granger developments (Granger, 1969) provided a foundation for several causality measuring techniques based on different hypotheses of data origin. The requirement of the cause leading the effect (but not *vice-versa*) defines the direction of a causal link if a more general hypothesis of lagged linear connection between noisy autoregressive processes is assumed. Though this hypothesis leads to statistically significant estimates of climate response to the forcing input (e.g., Kaufmann *et al.*, 2006, 2011, Attanasio, 2012, **Attanasio *et al.*, 2012**, Mokhov *et al.*, 2012, Triacca *et al.*, 2013), it may not be able to reliably detect the direction of causality in the climate system because the potential for non-linearities in the climate system (leading to extreme sensitivity to initial conditions, i.e., deterministic chaos) is not taken into account. For example, Palus *et al.* (2018) demonstrated that coupled chaotic dynamical systems can “violate the first principle of Granger causality that the cause precedes the effect.” The Shannon information flow approach expands Granger causality to non-linear systems, using transfer entropy as a causality measure. Barnett *et al.* (2009) have shown that transfer entropy is equivalent to Granger causality for Gaussian processes. The transfer entropy between two probability distributions is typically considered the most general approach for causality detection, and numerous

modifications of transfer-entropy-based causality measuring techniques have been developed for different applications (Pearl, 2009), including causality measurements of global warming (e.g., Stips *et al.*, 2016). It should be noted though that all **probability based causality measures require long time series to calculate statistical distributions and may lack applicability to local climate due to high inhomogeneity and non-stationarity of the data** (e.g., O'Brien *et al.*, 2019). The prediction improvement approach is often considered as a generalization of Granger causality for non-linear systems (e.g., Krakovska and Hanzely, 2016). It is highly practical and, besides causality calculations, it may help to improve the prediction accuracy. For pure causality purposes, however, it adds an additional uncertainty because the causality may depend on the chosen prediction method. The convergent cross-mapping approach (Sugihara *et al.*, 2012, Van Nes *et al.*, 2015) has been recently designed to work with relatively short data series, thus addressing the major constraint of transfer-entropy approach. The background hypotheses of the method is more narrow and includes only nonlinear *dynamical* systems, though convergent cross-mapping remains applicable to most natural systems in ecology and geosciences (Sugihara *et al.*, 2012). The approach considers conditional evolution of nearest neighbors in the reconstructed Takens' space so it is sensitive to the noise and may not be applicable to a wide range of time scales. Moreover, Palus *et al.* (2018) have shown that convergent cross-mapping is not capable of determining the directionality of a causal link. **Therefore identification of specific causal effect measures for climate observables is still a challenge. When causal effect measures are identified, the graph theory could be employed for further analysis of multiple causality chains** (Hannart *et al.*, 2016, Runge, *et al.*, 2015). **Along with dimensionality reduction formalism (e.g., Vejmelka *et al.*, 2015) it may lead to a general and promising approach.**

For our case study, we advocate the method of conditional dispersion (MCD) developed by Čenys *et al.* (1991) **as a causal effect measure**. It has also been designed for non-linear systems and exploits the asymmetry of the conditional dispersion of two variables in Takens' space along all available scales. Therefore, it remains more general and noise resistant than convergent cross-mapping techniques and more general than prediction improvement approaches because it is insensitive to the choice of the prediction method. We propose here to employ the MCD-based causality measurements for a comprehensive analysis of climate model responses to external natural and anthropogenic forcing. While climate models have been tuned in a rough sense to reproduce the observational record, their predictions differ from the observations due to various types of errors and uncertainties. These include: (a) measurement errors in external forcing (e.g., greenhouse gas concentrations, land use, solar variability) used to drive the models; (b) errors in the representation of physical processes in the models (e.g., ocean circulation, cryosphere and biosphere processes, various feedback mechanisms, *etc.*) and incomplete representation of the Earth system (i.e., in many cases lack of representations of dynamic vegetation responses, or oceanic carbon cycle dynamics); (c) errors associated with internal variability in the climate system – for example, models may accurately represent ENSO, The El Niño-Southern Oscillation, but ENSO is an inherently random process and models therefore do not, and should not, reproduce the actual real-world realization of that random process; (d) errors and uncertainties in observational data - for example, surface temperature measurements contain sampling uncertainty due to the irregular sampling in space and time (e.g., lack of data at higher latitudes increasingly back in time). Such sampling uncertainties might lead to model – observational data mismatch that is unrelated to model performance. In addition, there is the potential for biases due, for example, to changes in oceanic and terrestrial measurement platforms over time (e.g., bucket measurements *vs.* intake valves for ocean seawater measurements, or residual urban heat island biases in land-based temperature measurements). The challenge, then, is to determine the best-performing models when all reproduce the observations similarly well. We believe that in addition to reproducing observed time series of climate variables, a model should exhibit the causality relationship between variables found in nature. Since the MCD approach is based on the assumption that each time series is produced by a hypothetical low-dimensional system of dynamical equations, *similarity of causal relationships in both model and observations speaks to the similarities of their parent systems*.

Accordingly, our paper is structured as follows. First, we will briefly describe the method of conditional dispersion. We will illustrate it with several numerical experiments that investigate the causal relationship between surface temperature anomalies for the Northern Hemisphere and atmospheric carbon dioxide concentration measurements. We will show that the causality between carbon dioxide and temperature anomalies is a directional causality, meaning that carbon dioxide affects temperature stronger than temperature affects carbon dioxide. We will then demonstrate that this directional connection cannot be replicated with an independent trend and red noise.

2. A glimpse into the method of conditional dispersion.

The MCD approach has been designed for measuring causality between two time series. It is assumed that each time series is a variable produced by its hypothetical low-dimensional system of dynamical equations. The variables contain information about the dynamics of hypothetical parent systems which can be reconstructed using Takens

(1981) procedure. Since each of the variables can be used to reconstruct the original parent system manifold, there is one-to-one correspondence between them. Specifically, if points of one time series are close, the synchronous points of another variable are close as well. Therefore, if two variables (u and x) do not belong to the same or coupled dynamical systems, or in other words, they are independent, then the distance from a reference point to its neighbors of one variable (u) does not depend on the distance (ε) between synchronous points of another variable (x). In the case of dependency, though, the distance between neighboring points of the controllable variable will be smaller when the distance between points of the driving variable is reduced. Therefore, the dependence of the conditional dispersion $\sigma(\varepsilon)$ of the variable u upon the distance ε between points of the variable x becomes a signature of causal relationship between u and x (Čenys *et al.*, 1991):

$$\sigma_{xu}^M(\varepsilon) = \left(\frac{\sum_{i \neq j} \|u_i^M - u_j^M\|^2 \Theta(\varepsilon - \|x_i^M - x_j^M\|)}{\sum_{i \neq j} \Theta(\varepsilon - \|x_i^M - x_j^M\|)} \right)^{1/2} \quad (1)$$

Here, M is dimension of the reconstructed manifold, and Θ is the Heaviside function. If variable u is independent of variable x , its conditional dispersion $\sigma_{xu}^M(\varepsilon)$ does not depend upon ε . If variable x is the cause of u -variability, then conditional dispersion of the variable u will decline for diminishing ε . As an illustration, we show on Fig.1 the conditional dispersion of two variables x and u of coupled Henon (1976) maps:

$$\begin{cases} x_{n+1} = 1 + y_n - 1.4x_n x_n \\ y_{n+1} = 0.3x_n + \alpha(v_n - y_n) \end{cases} \quad (2)$$

$$\quad (3)$$

$$\begin{cases} u_{n+1} = 1 + v_n - 1.4u_n u_n \\ v_{n+1} = 0.3u_n + \beta(y_n - v_n) \end{cases} \quad (4)$$

$$\quad (5)$$

Here variables u and x belong to two dynamical subsystems, (2) - (3) and (4) - (5). The interdependence of these subsystems is defined by coefficients α and β . When connection is one-directional (for example, $\alpha=0, \beta=0.3$), i.e., x is the cause of u but is independent of u , the conditional dispersion of x -variable does not depend on ε (where ε is the distance between synchronous points of u) but conditional dispersion of u -variable declines for diminishing ε (where ε is the distance between synchronous points of x). When the connection is two-directional (for example, $\alpha=0.1, \beta=0.3$), the conditional dispersion of both variables declines for smaller ε , but a variable which provides a stronger causal force (i.e., x) has a dispersion with a less articulated slope. When variables are equally interdependent (i.e., synchronized), the conditional dispersions of both variables may have the same slope.

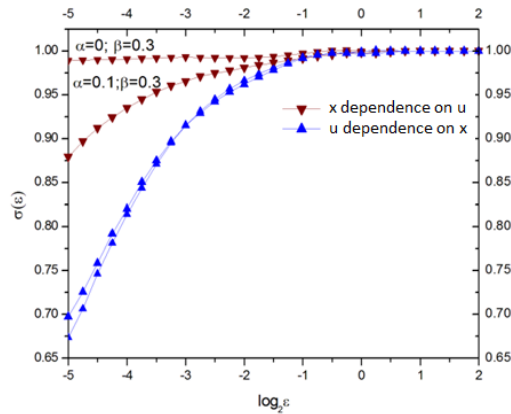


Fig. 1. The conditional dispersion of coupled dynamical variables u and x as described by equations (2) - (5). When connection is one-directional ($\alpha=0, \beta=0.3$), i.e., x is the cause of u but is independent of u , the conditional dispersion of x -variable does not depend on ε , but conditional dispersion of u -variable declines for diminishing ε . When the connection is two-directional ($\alpha=0.1, \beta=0.3$), the conditional dispersion of both variables declines for smaller ε , but x -variable which provides a stronger causal force has a dispersion with weaker slope.

3. The case study of global warming causality

We will now employ the MCD approach in three numerical experiments for time series of atmospheric carbon dioxide concentration and surface temperature obtained from both direct instrumental measurements and model simulations. Since we now advance from a discrete attractor to measured and simulated time series, some assumptions need to be articulated. Indeed, despite the fact that numerous methods have been developed to better determine an embedding dimension (e.g., Abarbanel et al., 1993), it is still a challenge to determine embedding from a measured variable (such as temperature) because time series always have limited length and are corrupted with the noise which can be misinterpreted as a higher dimension. We will treat the climate variables the same way as Hénon attractor variables (with evaluation “à la” Takens embedding, dimension 7). Fortunately, as it has been shown by Čenys et al. (1991), the MCD method is not very sensitive to the embedding dimension and the slope of $\sigma(\varepsilon)$ curves increases only slightly with the increase of the dimension. We will use a hypothesis that Northern Hemisphere temperature is an observable of the global climate system and CO₂ concentration is an observable of the system of external forcing. An observable may not necessary have straightforward connection to (“hidden”) physical variables of the underlying system. The embedding theorem (e.g. Sauer et al., 1991) states that reconstructed space is topologically equivalent to the underlying system in a sense that there exists a continuous differentiable transform from a reconstructed to the hidden space.

3.1 Detecting causality in instrumental measurements.

First, we investigate the causal relationship between GISTEMP (Hansen et al., 2006) surface temperature assessments for the Northern Hemisphere and atmospheric carbon dioxide concentration measurements (CO₂ NASA GISS Data, 2016) spanning 1880 through 2016. For this purpose, we normalize CO₂ and temperature time series by subtracting their mean values and by dividing over standard deviation and calculate conditional dispersion of Northern Hemisphere temperature variability (as a function of distance ε between synchronous points of the carbon dioxide time series) and conditional dispersion of carbon dioxide (as a function of distance ε between synchronous points of the temperature time series). The results are shown in Fig. 2.

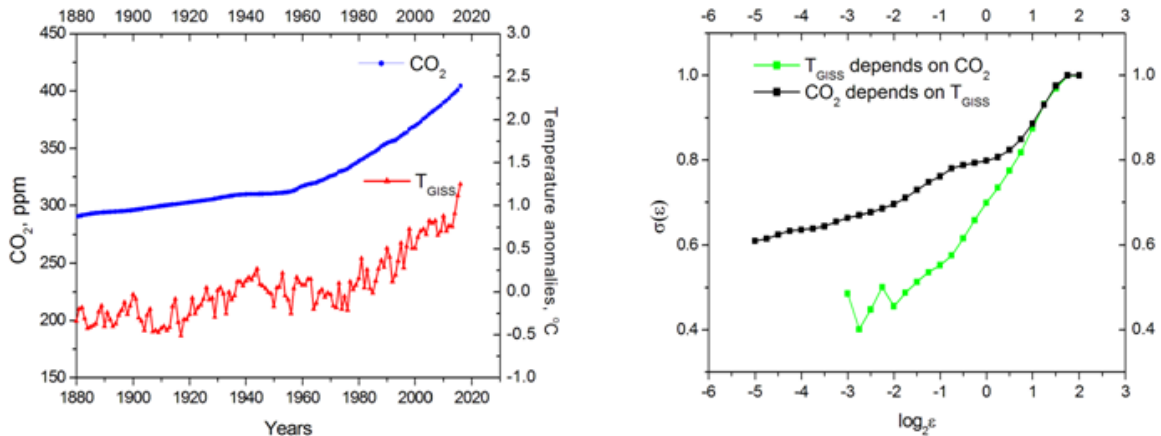


Fig. 2. Left: GISTEMP (Hansen et al., 2006) surface temperature anomalies and atmospheric carbon dioxide concentration measurements (CO₂ NASA GISS Data, 2016); **Right:** Conditional dispersion of instrumental measurements. Black curve is conditional dispersion of the carbon dioxide concentration. Green curve represents conditional dispersion of the Northern Hemisphere temperature anomalies; its dependence on ε is much stronger than that of black curve indicating that carbon dioxide is the cause of temperature changes.

It can be seen that surface temperature and carbon dioxide are interdependent systems (the conditional dispersions of both variables depend upon ε). Nevertheless, *carbon dioxide is the causal force of global warming* because the dependence of the temperature conditional dispersion upon ε is much stronger than the same dependence of carbon dioxide conditional dispersion. It is important for the interpretation of MCD produced results to remember that we deal with relatively short time series that contain a strong linear trend. We will show in Section 4 that the $\sigma(\varepsilon)$ slope can deviate significantly from the horizontal line because of linear correlation introduced by a trend, even in the case

of completely independent time series. Therefore, it is not the absolute value of a slope but, instead, the difference (the “distance”) between two slopes that speaks about the direction of causality.

3.2 Detecting causality in model simulations. Anthropogenic and natural (volcanic and solar) forcing.

We now apply MCD to the model simulations adopted from the Coupled Model Intercomparison Project Phase 5 (CMIP5) historical simulation experiments (Stocker, 2014). Estimates of the total forced component of Northern Hemisphere mean temperature have been derived by averaging over the full ensemble of CMIP5 multimodel all-forcing historical experiments (Mann *et al.*, 2014, Steinman *et al.*, 2015, Mann *et al.*, 2017). We generated 50 temperature series surrogates using a Monte Carlo resampling approach of Mann *et al.* (2017) and calculated conditional dispersion of Northern Hemisphere temperature variability for each of the 50 surrogates (as a function of distance ε between synchronous points of carbon dioxide time series) and conditional dispersion of carbon dioxide (as a function of distance ε between synchronous points of every surrogate time series). In all experiments we used the same atmospheric carbon dioxide concentration measurements (CO2 NASA GISS Data, 2016). We assume therefore that the effect of the surface temperature on CO2 concentration has been naturally included in the CO2 time series.

The results are presented in Fig.3. It can be seen that the behavior of dispersions derived from multiple simulations’ surrogates is quantitatively close to the dispersions obtained from the direct measurements, and therefore that carbon dioxide is the driver of temperature changes in the model simulations. Though in this experiment we applied MCD-testing network to the full ensemble of CMIP5 models, the same procedure can be applied to any sub-ensemble or to individual models if the task is to identify the models that are more consistent with the instrumental data in terms of causality.

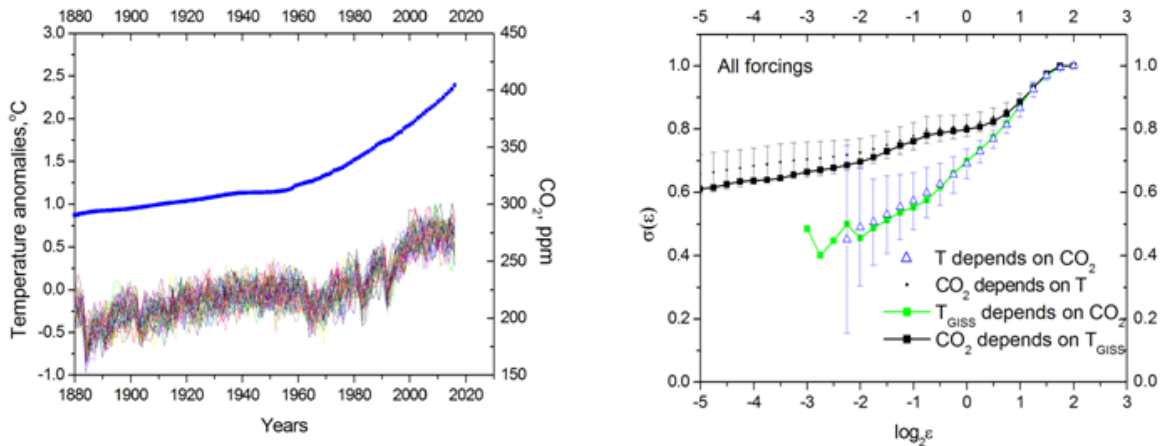


Fig. 3. Detecting causality in model simulations. Anthropogenic and natural (volcanic and solar) forcing.

Left: Surrogates of model temperature deviations induced by both natural and anthropogenic forcing together with carbon dioxide concentration measurements (CO2 NASA GISS Data, 2016). **Right:** Conditional dispersion of the Northern Hemisphere temperature and carbon dioxide concentration. Black curve is conditional dispersion of the carbon dioxide concentration instrumental measurements; green curve represents conditional dispersion of the Northern Hemisphere temperature measurements (same as in the right panel of Fig.2). Blue triangles are mean of 50 multimodel surrogates’ conditional dispersions of the Northern Hemisphere temperature; small black dots are mean of 50 multimodel surrogates conditional dispersions of carbon dioxide. Bars represent doubled standard deviation.

3.3 Detecting causality in model simulations. Anthropogenic forcing only.

We repeat the analysis described in paragraph 3.2 but for a separate ensemble of anthropogenic-only forcing experiments (Stocker, 2014, Mann *et al.*, 2016 a, 2016 b, 2017). The results are presented in Fig.4.

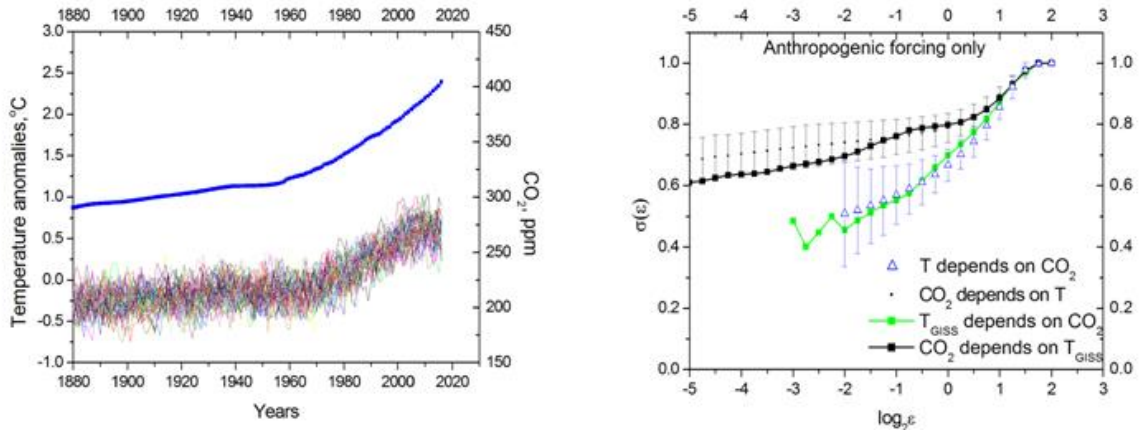


Fig. 4. Same as in Fig.3 but for anthropogenic CO₂ forcing only.

Interestingly, the results of the analysis change minimally when natural forcing (volcanic and solar) are excluded, which implies the dominant causality role of carbon dioxide.

4. Testing boundaries of MCD applicability.

Initially, the MCD approach was applied to causality measurements between deterministic chaotic time series (Čenys *et al.*, 1991). In this study, we expand its applicability to a situation where one of the time series (CO₂) is essentially a regular trend and the history of observations for both CO₂ and temperature is relatively short. In the next experiment we will test boundaries of MCD applicability and investigate if the MCD approach can distinguish between *interdependent* processes, like CO₂ and temperature, and *independent* but highly autocorrelated processes. For this purpose, we calculate conditional dispersion for two independent but highly autocorrelated time series resembling properties of carbon dioxide series and temperature surrogates. For the carbon dioxide “role” we selected a linear trend. GISS temperature surrogates were replaced by 50 red noise surrogates. Results of the conditional dispersion calculations are shown in Fig.5.

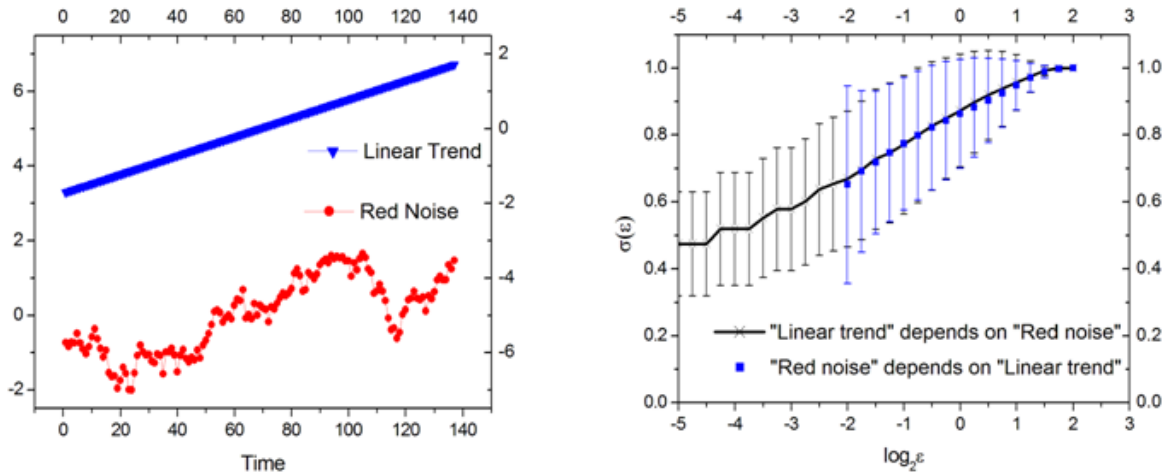


Fig. 5. Conditional dispersion of two independent processes having high autocorrelations. **Left:** Example of one-lag autocorrelated (0.92) red noise series simulating statistical properties of GISS temperature record and a linear trend; **Right:** Average conditional dispersion of 50 red noise surrogates. Error bars mark doubled standard deviation.

This example shows that, for relatively short time series, MCD is unable to discriminate cases of independence and very strong interdependence (i.e., synchronization) because spontaneous local correlations may be induced with autocorrelated red noise leading to the same slope of conditional dispersions for both time series. Nevertheless, unlike natural (CO₂ and temperature) time series, these correlations are not able to induce any directional causality. In other words, were temperature and CO₂ equally interdependent, MCD would not be able to distinguish this

situation from independent trends and red noise. In reality though, carbon dioxide affects temperature stronger than temperature affects CO₂, and this situation cannot be replicated by a trend and red noise.

5. Conclusions.

In this study we propose an additional climate model validation procedure that assesses whether causality signals between model drivers and responses are consistent with those observed in nature. Specifically, we suggest the method of conditional dispersion (MCD) as the best approach to directly measure the causality between model forcing and response. As an illustration of MCD applicability, we detect the causality signal between atmospheric carbon dioxide concentration and variations of global temperature. Our results suggest that there is a strong causal signal from the carbon dioxide series to the global temperature series or, in other words, that carbon dioxide is the principal *cause* of global warming. This conclusion is applicable to both direct instrumental measurements and multimodel temperature series surrogates. The strength of the causality signal does not significantly change when the additional contribution from natural factors (such as solar and volcanic) are accounted for, implying that increases in carbon dioxide are the main driver of observed warming. It is noteworthy that the causality between carbon dioxide and temperature anomalies is a directional causality: carbon dioxide affects temperature stronger than temperature affects carbon dioxide. This directional connection cannot be replicated using simplistic statistical models for the observed temperature increase (an independent trend and red noise).

Indeed, only laws of physics may identify the mechanism of causality and therefore the causality is encoded in the differential equations of the mathematical models. Unfortunately, high uncertainty in natural forcing (e.g., Egorova et al., 2018) may be amplified by model uncertainties (e.g., Meehl et al., 2009) and despite the fact that multiple methods exist to detect causality in the data, none is perfect for the analysis of complex systems such as the Earth climate (McCracken, 2016). Therefore, a properly calibrated causality detection method like MCD may help to reduce these uncertainties in quantifying the climate response to different forcings by providing new data driven constraints. With our calculations, we calibrate MCD against existing measurements and simulations. As long as MCD is recognized as a trusted approach, it can be used for express testing of new models and, may be even more importantly, can serve as a first test for any new candidate external forcing that may be considered as an alternative or supplement to CO₂.

Code and data availability. The MatLab source code and data (Verbitsky et al., 2019) are available at <https://zenodo.org/record/2605142#.XJirxyIzbcS> (<http://doi.org/10.5281/zenodo.2605142>). Scripts were tested under MatLab version R2015b (last access: 25 March 2019).

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Competing interests. The authors declare that they have no conflict of interest.

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