# Global climate change: Analyzing anthropogenic warming and causality

**Conference Paper** · May 2015

DOI: 10.1109/OCEANS-Genova.2015.7271393



**4 authors:**

Adolf Stips
European Commission


Diego Macías
European Commission


Clare Eayrs
New York University Abu Dhabi


Elisa Garcia-Gorriz
European Commission- Joint Research Centre, Ispra, Italy

# Global Climate Change: Analyzing Anthropogenic Warming and Causality

A. K. Stips, D. Macias, C. Coughlan, E. Garcia-Gorriz
Joint Research Centre, Water Resources Unit
European Commission
I-21027 Ispra, TP270, Italy
Adolf.stips@jrc.ec.europa.eu

***Abstract*— Here, we analyze recent measured data on global mean surface air temperature anomalies (GMTA) and various external forcing's covering the last 160 years using newly developed techniques that allow discrimination between correlation and causality. This evaluation is based on a new concept for calculating the information flow between time series. Our result demonstrates one-way causality in the sense that the recent $CO_2$ increase is causing the temperature increase and not the other way around. The positive value of the information flow indicates further that $CO_2$ has a positive feedback and therefore a destabilizing effect on GMTA; more $CO_2$ would lead to a stronger increase in GMTA. The results of investigating the information flow between the major radiative forcing's and the GMTA time series clearly show that total Green House Gases (GHG), dominated in particular by $CO_2$ forcing, is the main driver of changing global surface air temperature. Radiative forcing caused by aerosols and clouds is still important, but significantly smaller. Neither forcing by solar irradiance nor volcanic forcing contributes in a significant manner to the GMTA development. Finally, we applied the same causality analysis to the globally-gridded GMTA product in order to assess regional "sensitivity" to anthropogenic forcing's versus natural modes of variability. This analysis reveals a surprising causal pattern: the increasing anthropogenic forcing mainly originated in the northern hemisphere has especially strong warming effects in the southern hemisphere.**

***Keywords*— *Earth climate; anthropogenic forcing; correlation; causality;***

## I. INTRODUCTION

During the past five decades, global air temperatures have been warming at a rather high rate (*Intergovernmental Panel on Climate Change,* IPCC [1]) resulting in scientific and social concern. This warming trend is observed in field [2] and model data [3] and affects air temperatures both over land and over the ocean. IPCC attributes this temperature increase to the total increase in radiative forcing and maintains that this is primarily caused by the increase in the atmospheric concentration of $CO_2$ during the last 200 years. However, the warming rate changes with time and this has led to discussion on the causes underlying the observed trends [4]. Another major problem is related to the relatively large uncertainty in the different external forcing components [5] used for global climate simulations that might have overestimated global warming [6].

'Detection' and 'attribution' are therefore regarded as key priorities in climate change research. IPCC defines 'detection' as the process of demonstrating that climate has changed in some statistical sense, where the likelihood of occurrence by chance due to internal variability alone is small. This is typically done by using climate models to predict the expected responses to external forcing and the consistency of this response pattern with respect to different components of the climate system is evaluated. The more challenging problem is then to 'attribute' this detected climate change to the most likely external causes within some defined level of confidence, which we will address in this contribution. As noted already in the Third Assessment Report [7], unequivocal attribution would require controlled experimentation with the climate system. Since that is not possible, in practice attribution of anthropogenic climate change is understood to mean demonstration that a detected change is 'consistent with the estimated responses to the given combination of anthropogenic and natural forcing' and 'not consistent with alternative, physically plausible explanations of recent climate change that exclude important elements of the given combination of forcing's [7]. Even when plausibility is achieved in this way this leaves room for alternative explanations and leads to disputes about possible alternative reasons. As a common practice the above consistency assessment is usually through correlation analysis. A fundamental problem here, however, is that correlation between different variables does not necessarily imply causation [8]. As stated by Barnard [9]: "That correlation is not causation is perhaps the first thing that must be said." Therefore the high correlation between rising $CO_2$ levels and increasing surface temperatures alone is insufficient to prove that the increased radiative forcing resulting from the increasing GHG atmospheric concentrations is indeed causing the warming of the earth.

Very recently, a new approach has been rigorously developed to evaluate quantitatively the causal relation between two time series [10]. The resulting formula is tight in form, allowing an explicit discrimination between correlation and causality. It is based on the recently rigorized fundamental physical notion namely information flow, which, for two events, provides not only the magnitude but also the direction of the cause-effect relation lying in between; in this sense, it is an appropriate measure of causality [11].

978-1-4799-8736-8/15/$31.00 

## II. Methods and Data

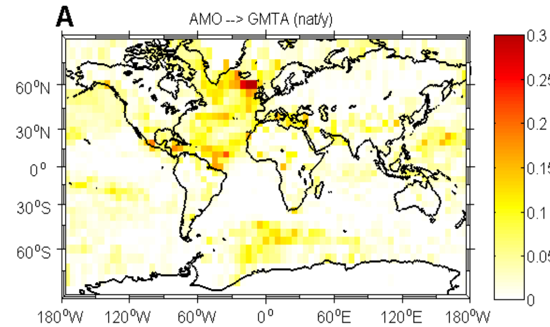
### A. Methods

We follow [10] to evaluate the cause-effect relation between time series. Causality is measured as the time rate of information flowing from one time series to another. In Liang's formalism, a fundamental property, or property of causality as called, is that if the evolution of one system X1 does not depend on some other system X2, the information flow from X2 to X1 then vanishes. The derived tight formula is explicitly expressed in terms of the sample covariances of the involved time series and their derivatives. In a strict sense, it is precise only for linear systems but the validations have shown that it is a good approximation for nonlinear time series, and has seen remarkable success with highly touchstone nonlinear systems. The formula also confirms in a quantitative way that causation implies correlation, whereas correlation does not imply causation.

The confidence interval estimation also follows Liang [10]; it is based on the observation that, for a large ensemble, the maximum likelihood estimate of a parameter approximately obeys a normal distribution around its true value.

### B. Data

Mean surface air temperature anomalies were obtained from the HadCRUT4 dataset [12] available at http://www.cru.uea.ac.uk/cru/data/temperature/ (data downloaded on 01/2015). Datasets spanning the period 1850–2013 were obtained for the global mean temperature, temperatures of the Southern and Northern Hemispheres; the gridded data have a 5°x5° resolution. The Meinshausen forcing data [13], which cover the period from 1765 to 2005, were downloaded (11/2014) from http://www.pik-potsdam.de/~mmalte/rcps. The overlap period of the two datasets, 1850 - 2005 (156 years), is hence chosen for our analysis.



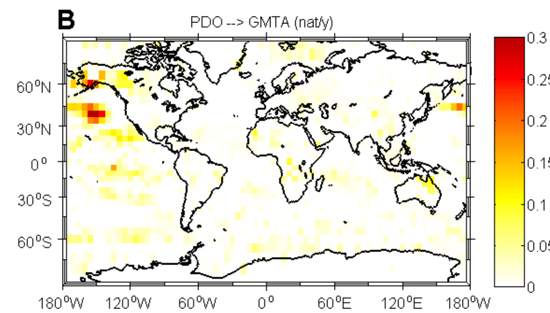




Fig. 1. Global causality flow from natural variability to GMTA. Spatial distribution of the information flow between the Atlantic Multidecadal Oscillation (AMO) and the gridded global mean temperature anomalies (GMTA) 1A. Spatial distribution of the information flow between the Pacific Decadal Oscillation (PDO) and the gridded global mean temperature anomalies (GMTA) 1B.

## III. Results and Discussion

We use this technique to analyze the recently measured global mean surface air temperature anomalies [12] and various reconstructed external forcing's covering the period from 1850 to 2005 (156 years) from [13]. Calculating for example the information flow in *nat* (natural unit of information) per unit time from the time series of global $CO_2$ concentration to GMTA we get 0.348±0.112 [nat/y] and -0.006±0.003 [nat/y] in the reverse direction. Obviously, the former is significantly different from zero, while the latter, in comparison to the former, is negligible. Our result hence unambiguously shows a one-way causality in the sense that the $CO_2$ increase is causing the temperature increase, but not the other way around. The positive value of the information flow indicates further that $CO_2$ has a positive feedback and therefore a destabilizing effect on GMTA, i.e., more $CO_2$ would lead to a stronger increase in GMTA. The correlation and the information flow between the major reconstructed radiative forcing's [13] and the GMTA time series are given in Tab. 1, correlations and causations significant at the 95% level are in bold. This result clearly confirms that the total Green House Gases (GHG), especially the $CO_2$, are the main drivers of the changing global surface air temperature. The radiative forcing caused by aerosols and clouds is also important, but significantly smaller (0.2 vs. 0.3 [nat/y]). Neither solar irradiance nor volcanic forcing contributes in a significant manner to the GMTA evolution. For the volcanic forcing it is quite likely that the number of relevant events covered in the time series might be insufficient for establishing a significant correlation or causality relation. For the known major natural modes, the information flows between the Pacific Decadal Oscillation (PDO) and Atlantic Multidecadal oscillation (AMO) from and to the global surface temperatures are close to 0.0, so essentially no causality relations could be identified here, in contrast to the significant correlation between AMO and GMTA time series (Tab. 1).

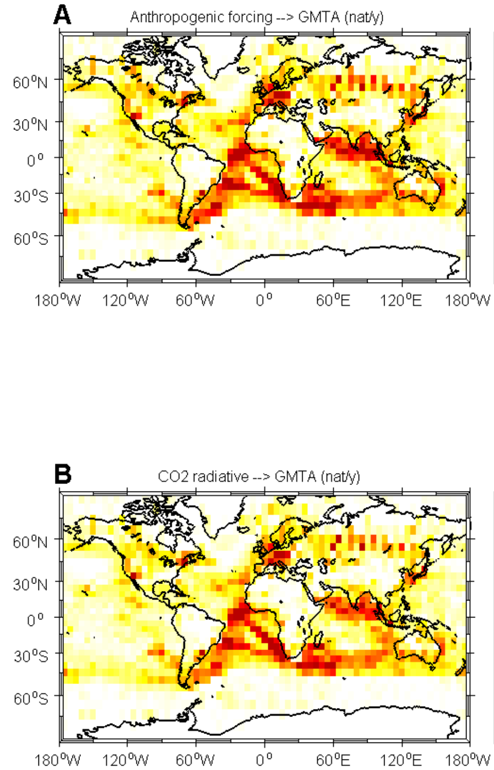



Fig. 2. Global causality flow from anthropogenic forcing to GMTA. Spatial distribution of the information flow between the total anthropogenic forcing and the gridded global mean temperature anomalies (GMTA) 2A. Spatial distribution of the information flow between the radiative forcing caused by CO2 and the gridded global mean temperature anomalies (GMTA) 2B.

This is a good real world example that illustrates the basic fact: correlation does not mean causation.

Another crucial research question that we can address with this method is "where has the increasing anthropogenic forcing caused the most pronounced consequences?". In order to assess which regions of the earth are more 'sensitive' to anthropogenic forcings and where natural modes of variability contribute more to the temperature series, we applied the same causality analysis to the globally-gridded GMTA product. Looking first at the natural modes we find that the PDO is the main driving force for temperature changes in the North Pacific, whereas the AMO influences mainly the North Atlantic (Fig. 1). This kind of expected results also provides a first order validation of the method when applied to climate data. For the information flow from the global anthropogenic forcing to the GMTA (Fig. 2), in the Northern Hemisphere, the distribution is also just as expected. For example, it takes largest values in Europe, United States, and Japan. Particularly, in North America, we see only a scattering of two small centers of high values, i.e., the Mid-Atlantic region and California, a remarkable result that again serves to validate the method. In the Southern Hemisphere, however, this distribution displays a most unexpected pattern, with high values in a large swath of the southern Atlantic and Indian Oceans. This is true for both the total anthropogenic forcing (Fig. 2a) and the radiative forcing caused by $CO_2$ alone (Fig. 2b). The analysis of the spatial distributions of the information flows between solar forcing and GMTA and volcanic forcing and GMTA (not shown) confirms that these flows are basically insignificant, in agreement with the previous analysis with the global mean values.

## IV. Conclusions

Assuming that the available time series are long enough to contain sufficient statistics we were able to demonstrate the inherent one-way causality between the main anthropogenic radiative forcing and the GMTA time series, a result that cannot be inferred from traditional time delayed correlation analysis. The spatial explicit analysis gives the surprising result that the increasing northern hemisphere anthropogenic forcing is causing especially strong warming effects in the southern hemisphere. This could support the assumption that warming in the southern hemisphere has been previously underestimated [14] because of sparse data sampling.

TABLE I. GLOBAL CORRELATION AND INFORMATION FLOW

| **Radiative Forcing** | **Correlation and Causality** | | |
|---|---|---|---|
| | ***Correlation*** | ***Forcing-GMTA [nat/year]*** | ***GMTA->Forcing [nat/year]*** |
| Total forcing | **0.804**±0 | **0.244**±0.091 | 0.036±0.080 |
| Anthropogenic | **0.863**±0 | **0.355**±0.112 | -0.008±0.005 |
| ALL GHG | **0.852**±0 | **0.318**±0.108 | -0.005±0.003 |
| CO2 | **0.852**±0 | **0.316**±0.108 | -0.003±0.003 |
| Aerosol | **-0.810**±0 | **0.232**±0.095 | -0.002±0.006 |
| Cloud | **-0.796**±0 | **0.208**±0.092 | -0.001±0.004 |
| Solar | **0.616**±0 | **0.082**±0.059 | 0.035±0.051 |
| Volcanic | 0.089±0.267 | 0.003±0.006 | -0.004±0.009 |
| AMO (1900-2008) | **0.477**±0 | 0.018±0.043 | 0.021±0.014 |
| PDO (1900-2008) | 0.123±0.204 | -0.002±0.013 | -0.011±0.025 |

## Acknowledgment

The authors thank the Climatic Research Unit of the University of East Anglia for providing the surface temperature data and the Potsdam Institute for Climate Impact Research for the forcing data.

## REFERENCES


[1] T. Stocker, Q. Dahe and G.K. Plattner, (coordinating lead authors), "Intergovernmental Panel on Climate Change. Approved Summary for Policymakers of full draft report of Climate Change 2013: Physical Science Basis," (http://www.ipcc.ch/report/ar5/wg1/#.U1CweRCvHMM), 2013.

[2] P.D. Jones, D.H. Lister, T.J. Osborn, C. Harpham, M. Salmon and C.P. Morice, "Hemispheric and large-scale land surface air temperature variations: an extensive revision and an update to 2010," *J. Geophys. Res.*, 7, D05127, doi:10.1029/2011JD017139, 2012.

[3] G.A. Meehl, A. Hu, J.M. Arblaster, J. Fasullo and K.E. Trenberth, "Externally forced and internally generated decadal climate variability associated with the interdecadal pacific oscillation," *J. Climate*, 26, 2013, pp. 7298-7310.

[4] G.A. Florides, P. Christodoulides, Global warming and carbon dioxide through sciences, *Environment International* **35** 390–401, doi:10.1016/j.envint.2008.07.007, 2009.

[5] G.L. Stephens, et al., An update on earth's energy balance in light of the latest global observations. *Nature Geoscience*, doi:10.1038/NGEO1580 2012.

[6] J.C. Fyfe, N.P. Gillet and F.W Zwiers, "Overestimated global warming over the past 20 years," *Nature Climate Change* 3, 2013, pp. 767-769.

[7] IPCC, 2001: Climate Change 2001: The Scientific Basis. Contribution of Working Group I to the Third Assessment Report of the Intergovernmental Panel on Climate Change [Houghton, J. T., et al. (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 881pp (2001).

[8] H. Sies, A new parameter for sex education. *Nature* **332** 495, doi:10.1038/332495a0 (1988).

[9] G.A. Barnard, "Causation," in *Encyclopedia of Statistical Sciences* **1**, [Kotz, S., Jansen, N., Read, C. Eds.]. New York, John Wiley, 387-389 (1982).

[10] X.S. Liang, Unraveling the cause-effect relation between time series. *Phys. Rev. E* **90**, doi:10.1103/PhysRevE.90.052150, 2014.

[11] N. Ay, D. Polani, Information flows in causal networks, *Advs. Complex Syst.* 11, doi:10.1142/S0219525908001465 (2008).

[12] C.P. Morice, J.J. Kennedy, N.A. Rayner and P.D. Jones, "Quantifying uncertainties in global and regional temperature change using an ensemble of observational estimates: the HadCRUT4 dataset," *J. Geophys. Res.*, 117, D08101, doi:10.1029/2011JD017187, 2012.

[13] M. Meinshausen, et al., The RCP GHG concentrations and their extension from 1765 to 2300. *Climatic Change* DOI 10.1007/s10584-011-0156-z, 2011.

[14] P.J. Durack, P.J. Gleckler, F.W. Landerer, K.E. Taylor, Quantifying underestimates of long-term upper-ocean warming. *Nature Climate Change* **4**, 999-1005, 2014.