Quantitative assessment of drivers of recent climate variability: An information theoretic approach

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Abstract Identification and quantification of possible drivers of recent climate variability remain a challenging task. This important issue is addressed adopting a non-parametric information theory technique, the Transfer Entropy and its normalized variant. It distinctly quantifies actual information exchanged along with the directional flow of information between any two variables with no bearing on their common history or inputs, unlike correlation, mutual information etc. Measurements of greenhouse gases, $CO_2$, $CH_4$ and $N_2O$; volcanic aerosols; solar activity: $UV$ radiation, total solar irradiance ($TSI$) and cosmic ray flux ($CR$); El Niño Southern Oscillation ($ENSO$) and Global Mean Temperature Anomaly ($GMTA$) made during 1984-2005 are utilized to distinguish driving and responding climate signals. Estimates of their relative contributions reveal that $CO_2$ ($\sim 24\%$), $CH_4$ ($\sim 19\%$) and volcanic aerosols ($\sim 23\%$) are the primary contributors to the observed variations in GMTA. While, $UV$ ($\sim 9\%$) and $ENSO$ ($\sim 12\%$) act as secondary drivers of variations in the GMTA, the remaining play a marginal role in the observed recent climate variability. Interestingly, $ENSO$ and GMTA mutually drive each other at varied time lags. This study assists future modelling efforts in climate science.

Keywords Aerosols · Climate variability · ENSO · Greenhouse gases · Transfer Entropy · Solar activity
1 Introduction

Global climate variability is of paramount importance to mankind and society as well. It is therefore widely discussed in public domain and is extensively studied by researchers. Several significant scientific investigations carried out during the past few decades attribute climate variability mainly to atmospheric greenhouse gases, solar activity and aerosols from both natural and anthropogenic sources besides internal variability of the ocean-atmosphere system. Most of these studies report good correlation between variations in global mean temperature and climate variables such as greenhouse gases, cosmic rays, solar radiation, El Niño Southern Oscillation (ENSO), global cloud cover, geomagnetic pole position, geomagnetic field, etc. [18,14,15,16,14,37,24,44,20,23,31,38,17,30,13]. These studies recognise four major drivers of the recent climate variability. One stems from the natural climate variables essentially connected to solar activity whereas the others are directly linked to anthropogenic sources such as the greenhouse gases and to volcanic aerosols and internal variability of the Ocean-Atmosphere system manifested as ENSO, etc. Though the causal links between several of the above cited climate variables and variability in global mean temperature have been well studied, precise estimates of their quantitative influence still remain largely elusive and uncertain. It is important to realise that the cause-effect relationship inferred between the variables and climate variability are essentially based either on observed correlations or parametric modeling approaches. Techniques like linear correlation and mutual information which are symmetric in nature suffer from lack of information on the sense of directionality, while model-based methods are limited by model idealization [45]. Hence, it becomes rather difficult to decipher the true causal relationship between any two physical processes using these techniques. Therefore, many aspects related to climate variability and/or change still remain contentious and unresolved in the absence of reliable quantitative assessments of causality.

There are number of attempts to address the causality between natural and anthropogenic drivers using information theory approach [22,11,39,33]. [22] showed that radiative forcing mainly due to $CO_2$ affects global temperature. The granger causality is applied to global climate data by [39]. They observed that both anthropogenic and natural forcing cause temperature change and as a feedback temperature changes affect greenhouse gas concentration. Whereas, [11] showed that there is no signature of Granger causality from natural forcing to global temperature but Granger causality is observed from anthropogenic forcing to global temperature. So there is still ambiguity in understanding the role of the natural drivers in global temperature changes.

With this background, we investigate the relationship between various climate proxy records of both natural and anthropogenic origin adopting climatic time series analyses applying information theory-based stochastic methods which revolve around the concept of entropy or ensemble information content [33]. In essence, the relationship between climate forcing variables related to solar activity, greenhouse gases and volcanic aerosols and the response signal
i.e. Global Mean Temperature Anomaly (GMTA) is explored and quantified in terms of the transfer of information with direction. Firstly, using transfer entropy (TE) with a directionality index \[34,12\], we show that all the natural and anthropogenic proxies considered in this study indeed drive variations in the GMTA. Further, their relative contributions in inducing the GMTA are evaluated using normalized transfer entropy (NTE) \[48\]. An important finding which emerges from this study is that volcanic aerosols (a natural source, henceforth referred as aerosols) indeed compete with the well known greenhouse gases CO\(_2\) and CH\(_4\) in contributing to the GMTA by accounting for a quarter (\(~ 25\%\)) of its variability. Among the remaining climate proxies studied here, ENSO and UV radiation together contribute \(~ 20\%\) to the observed GMTA with a similar share, while the rest are marginal.

2 Data, Method and Analysis

2.1 Databases used

In the present study, a total of nine proxies representing the recent climate variations for the epoch 1984-2005 are extracted from several databases and used. This time window was selected for two reasons. One, prominent climate changes are observed during this window and secondly, accurate simultaneous measurements of all these climate variables are available during this time period. The proxies used in this study are: ENSO index; global mean concentration of greenhouse gases, namely, CO\(_2\), CH\(_4\) and N\(_2\)O; global mean aerosol optical depth at 550 nm; total solar irradiance (TSI) along with solar ultraviolet flux (UV) for wavelength window 120-400 nm; cosmic ray flux/neutron flux (CR) and GMTA. The global monthly mean data of greenhouse gases were obtained from the World Data Center for Greenhouse Gases [http://ds.data.jma.go.jp/gmd/wdegg/wdegg.html] whereas ENSO index was collected from http://ncar.ucar.edu/. Global mean aerosol optical depth data were taken from http://data.giss.nasa.gov/modelforce/strataer/. TSI and UV fluxes were retrieved from the World Radiation Center (http://www.pmodwrc.ch/). The neutron flux is measured at Oulu Cosmic Ray Station (http://cosmicrays.oulu.fi/). The global mean temperature anomaly of the Earth was drawn from Met Office Hadley Center (http://www.metoffice.gov.uk/). All the proxies used are monthly mean values and are shown in Figure 1

These data show certain interesting features such as steady increasing trend in the GMTA mimicking the greenhouse gases increase. The sudden increase in aerosol optical depth seen in the figure is due to the atmospheric impact of the volcano eruptions (El Chichon, 1982, and Pinatubo, 1991) resulting in enhanced atmospheric opacity. The TSI, UV and cosmic rays clearly reflect the solar activity cycle. The TSI and UV peaks coincide with solar maxima while cosmic ray flux peaks correlate with the solar minimum. The ENSO index shows occurrence of warm (positive) and cold (negative) phases across the Pacific associated with ocean currents during the studied epoch.
2.2 Transfer Entropy and Directionality Index

[36] realized that the concepts of information and uncertainty are related to each other. He demonstrated that the occurrence of an event of lower probability ($P$) indicates more information. This information can be characterized by the Information Entropy or Shannon Entropy and it is defined for a random variable $x$ as:

$$H_x = \sum_{i=1}^{N} P_i(x) \log_2 \left( \frac{1}{P_i(x)} \right) \tag{1}$$

where $P_i(x)$ is the probability of observing $x$ independently. Similarly, Shannon entropy, $H_y$ can be defined for the other variable $y$. To quantify actual information explicitly exchanged between these two variables $x$ and $y$, an information measure known as Transfer Entropy was introduced by [34]. This overcomes the limitations posed by measures of correlation and other entropy metrics by enabling us to distinctly quantify actual information exchanged along with the directional flow of information between any two variables with no bearing on their common history or inputs [34,12,11,3,47]. The TE from a process $x$ to another process $y$ after a time lag $\tau$ is the quantity of information that the state of $y$ has at a time $t + \tau$ based exclusively on the state of $x$ at time $t$. This can be represented by the following expression [28]:

$$\text{Transfer Entropy (} \tau \text{)} = \left[ \text{information about future observation of } y(t + \tau) \text{ gained from past joint observations of } x \text{ and } y \right] - \left[ \text{information about future observation } y(t + \tau) \text{ gained from past observations of } y \text{ only} \right] = \text{information flow from } x \text{ to } y.$$  

Therefore, transfer entropy between two random variables or processes represented by $x$ and $y$ is mathematically depicted as [11]:

$$TE_{x \rightarrow y}(\tau) = \sum P(y(t+\tau), y(t), x(t)) \log_2 \left( \frac{P(y(t+\tau), y(t), x(t)) \ast P(y(t))}{P(x(t), y(t)) \ast P(y(t+\tau), y(t))} \right) \tag{2}$$

Similarly, transfer entropy from $y$ to $x$, $TE_{y \rightarrow x}(\tau)$ can be estimated for different time lags/delays ($\tau$). Few interesting properties of TE emerge from the above equation. These are listed as follows: Transfer entropy, $TE$ (a) is an asymmetric measure, (b) is based on transition probabilities (i.e. in a Markov process the probability of going from a given state to the next state.), hence incorporates the directionality of information flow, (c) is a measure of information transfer (exchange) rather than information shared, (d) enables quantifying information flow separately in both directions, and (e) is a model independent measure. Therefore, asymmetric nature of $TE$ can be used to detect the directed net flow of information between two physical processes represented as two time series. Depending on the magnitudes of $TE_{x \rightarrow y}(\tau)$ and $TE_{y \rightarrow x}(\tau)$ the driver and response signals/processes can thus be identified. The statistical significance of the obtained $TE$ is evaluated following the
surrogate data test [40,12]. The null hypothesis to be tested is that there is no cause-effect relationship between the two variables (time series). This hypothesis is evaluated adopting a significance level of 5% utilizing 100 randomized surrogate data-sets.

In the presence of multiple drivers, estimation of relative contribution of each variable/proxy to the observed response signal assumes importance. To enable this, [48] have introduced a measure known as normalized transfer entropy (NTE) by accounting for the amount of information stored in \( x(t) \) and \( y(t+\tau) \) which is given as [11]:

\[
NTE_{x\rightarrow y}(\tau) = \frac{TE_{x\rightarrow y}(\tau)}{\sqrt{H_x + H_{y+\tau}}}
\]

Similarly, \( NTE_{y\rightarrow x}(\tau) \) can also be estimated. This NTE enables comparison of contributions by several driver-response pairs. In the present research, the relative contribution to the global mean temperature anomaly (variable \( y \)) from climate proxies (variable \( x \)) are estimated using \( TE \) and \( NTE \). Further, the directionality index defined by the following equation is used to compute the net flow of information, which is a convenient way to visualize the direction of net information flow between any two time series.

\[
D_{x\rightarrow y}(\tau) = NTE_{x\rightarrow y}(\tau) - NTE_{y\rightarrow x}(\tau)
\]

The positive values of \( D_{x\rightarrow y} \) indicate that the flow of information is in the direction of \( x \rightarrow y \), suggestive of \( x \) being a driver and \( y \) being the response. Whereas, negative values of \( D_{x\rightarrow y} \) would indicate \( y \) as the driver and \( x \) as the response signal.

2.3 Analysis

Prior to estimation of \( TE \) and \( NTE \), the recorded non-stationary time series are interpolated for uniformity of data using cubic Hermite polynomial to yield data with 10 samples per month. In order to minimize edge effects, 20 data points from both ends of the interpolated time series are discarded from the analysis. Following [7,6,8], these time series are transformed into stationary sequences. This is accomplished by subtracting the estimated moving averages from the original time series. The moving average is estimated using the formula:

\[
\bar{x}_n(t) = \frac{1}{n} \sum_{k=0}^{n} x(t-k)
\]

Several trial moving average window sizes (\( n \)) were adopted for the analysis and a window size \( n=20 \) was found optimal to impart stationarity to the recorded time series used in this study. Since, moving average is low pass filter, the subtracted stationary time series now contains high frequency, the monthly stochastic variations of the variables. To estimate \( TE \), we need to arrive at the true probability distribution of a variable under consideration. We adopted the
non-parametric histogram technique for this purpose. However, determination of an optimum bin-width becomes crucial in order to avoid over-smoothing arising from a large bin-width choice or empty bins because of too small a bin size.

An optimum bin-width is arrived using expression \( w = 3.49 \sigma N^{-1/3} \), where \( N \) is the number of data points and \( \sigma \) is the standard deviation. Based on values of \( w \) determined for each time series, the corresponding probability distributions are estimated. These are further used in the calculation of \( TE \).

### 3 Salient Results

The transfer entropy in both the directions corresponding to the global mean temperature anomaly and eight other proxies which represent natural and anthropogenic processes are computed. Figure 2 shows the estimated \( TE \) values for different time lags (\( \tau \)) related to various pairs along with their corresponding threshold of 5% statistical significance level. The calculated \( TE \) values are observed unambiguously above the threshold significance. This suggests that the information flow is statistically significant. Therefore, we reject the null hypothesis and suggest that there exists a statistically significant cause-effect relationship between the pairs of proxies investigated in this study with GMTA being always one of the time series. Further, note that the red curves representing the significative \( TE \) from climate variable to GMTA are generally higher than the blue lines which represent the transfer in the reverse flow direction. Clearly, for proxies \( CO_2, CH_4, UV \) and \( aerosols \) the red curves \( (TE \text{ from proxy to GMTA}) \) are prominently above the blue curves \( (TE \text{ from GMTA to proxy}) \). This distinct segregation of \( TE \) curves is not observed in the case of TSI, cosmic rays and \( N_2O \). Interestingly, for ENSO, the \( TE \) in the direction GMTA \( \rightarrow \) ENSO is higher after a time lag of \( \sim 3 \) months compared to that in the reverse direction. This suggests that both GMTA and ENSO perhaps interact variably at different time delays \( \tau \). One common feature in all the plots is that \( TE \) drastically increases between delay times 0 and 1 month with steady values thereafter, indicating that the two variables affect almost instantaneously.

In summary, an important inference from above is that the flow of information related to the proxies; \( CO_2, CH_4, aerosols \) and \( UV \); is significant and generally higher towards the GMTA compared with the corresponding flow in the reverse directions. Thus, these four variables qualify to be the prominent drivers of the observed climate variability manifested as variations in GMTA. In order to estimate the strength of net information flow for each driver, using Equation 4, the directionality index \( (D_{x \rightarrow y}) \) is computed. The directionality index for each climate proxy as a function of time lag presented in Figure 3 confirms that among climate variables \( CO_2, CH_4, aerosols \) and \( UV \), the first three are indeed the primary drivers with competing strength while \( UV \) is a relatively weak driver. It is surprising to note that \( aerosols \) which were lighth-
To estimate percent contribution of each climate proxy to the observed variability in the global mean temperature anomaly, we computed the integrated net information flow (directionality index using Equation 4) employing time lags of 3 months and 10 months which yielded consistent results. Here, 100% sum is calculated by considering the information flow of studied drivers alone. Moreover, we do not rule out the possibility of other variables which could influence the present climate variability. Therefore, the estimated percentage of each driver is relative in nature. Note that 100% sum does not mean that the complete variance of GMTA is explained by studied drivers, it is the total normalized information flow to GMTA. The pie chart shown in Figure 4 corresponds to percent contributions calculated for a lag of 3 months and clearly demonstrates the hierarchy of contribution by each variable to the observed global climate variability. It can be clearly seen that greenhouse gases (\(CO_2\) and \(CH_4\)) and aerosols are the chief contributors to the observed recent climate variability with near similar (\(\sim 19-24\%\)) percent contributions. While, \(UV\) and \(ENSO\) which together explain nearly \(\sim 21\%\) variations in GMTA qualify as secondary contributors. The remaining candidate climate variables \(CR\), \(N_2O\) and \(TSI\) are marginal players in the observed climate variability. These interesting results are discussed in the following section in the context of our current understanding of climate variability.

4 Discussion and Conclusions

The two principal issues addressed here are: (1) identification of primary drivers of recent (1984-2005) climate variability (GMTA) among the eight climate variables considered in this study and (2) quantification of their influence on the climate variability. Transfer entropy and its variant are used to address these issues. Use of this technique in climate studies is a recent trend [45,21,11,32]. Its application to study the recent climate variability in particular is in its infancy. For example, [45] limiting their study to greenhouse gases and \(TSI\) conclude that the former are the significant contributors to the present climate change, while [11] showed that during cooler climate epochs of the interglacial Marine Isotope Stages (MIS), the sea surface temperature was more similar to the atmospheric \(CO_2\) forcing. Recently, [33] proposed the method based on the graphical model to identify the causal connection, strength of interaction and the time delays. In the present work, the recent climate variability is investigated in a more inclusive manner by incorporating aerosols, inter-variability of the atmosphere-ocean system and several manifestations of solar activity as proxies and estimating their relative contributions.

Our study quantifies the effect of greenhouse gases \((CO_2 + CH_4)\) on recent climate variability with \(\sim 43\%\) contribution. Interestingly, aerosols which alone contribute \(\sim 23\%\) to the observed climate signal qualify as the other primary driver in addition to \(CO_2\) and \(CH_4\). The internal climate forcing by
ENSO with \( \sim 12\% \) contribution and UV share of \( \sim 9\% \) owing to solar variability constitute the minor components of climate variability that deserve attention. These relative contributions are consistent with earlier reports by [29,19,46]. Evidently, the other components of solar variability, TSI and CR together with the greenhouse gas \( \mathrm{N}_2\mathrm{O} \) with contributions \( \sim 5\% \) are the marginal components. It is pertinent to note, though the greenhouse gas \( \mathrm{N}_2\mathrm{O} \) has stronger radiative forcing per molecule and long residence time (\( \sim 120 \) years), its atmospheric concentration is less (see Figure 1). This could be the reason for \( \mathrm{N}_2\mathrm{O} \) being among the weakest contributors. In the following, we briefly discuss possible mechanisms by which aerosols, ENSO, and UV influence the climate variability represented by GMTA.

Atmospheric aerosols as one of the competing prime drivers of GMTA is brought out by the data used in this study, since the data had contributions from at least two volcanic episodes. Atmospheric aerosols originate from volcanic eruptions and have relatively less concentration compared to anthropogenic aerosols. However, as they are released at higher altitudes resulting in their longer residence time in the atmosphere [31], they can affect the climate variability on different time scales. The initial effect of aerosols is net cooling near the surface, as they stay in the atmosphere for few years having e-folding time of \( \sim 1 - 2 \) years. These aerosols also enhance the destruction of ozone, and cause stratospheric warming which could contribute to possible global climate variability. It is therefore generally difficult to comprehend their exact atmospheric impact and feedback mechanisms owing to several complexities [31] through model based studies. Hence we are content with quantifying the percent contribution of aerosols to recent climate variability, which forms an important input to future modeling studies.

Among the secondary drivers of GMTA, ENSO is more prominent than UV. Identification of ENSO as a driver or response signal remained contentious with conflicting results [10,41]. The occurrences of ENSO during the last millennium are explained invoking natural variability of the ocean-atmosphere system [10], while frequent occurrences of ENSO in last few decades and in a climate model are attributed to the greenhouse warming [43,41,5]. One may say that the effect on global climate due to ENSO is positive at some places and negative in another places. However, it has been reported that ENSO and super ENSO periods cause increase in global temperature [27,26]. Interestingly, our transfer entropy estimates shown in Figure 2, indicate the cross-talk between ENSO and GMTA at different time lags is mixed in nature. That said, at lags till 3 months ENSO drives GMTA, while, at later time lags GMTA assumes the role of a driver. Thus, ENSO and GMTA mutually affect each other differently at varied time lags by exchanging their roles. While the mechanism of ENSO driving GMTA is better understood, it is unclear how GMTA drives occurrence of ENSO. We speculate that variations in GMTA perturb the energy (heat) budget of the ocean-atmosphere system that would affect the occurrence of ENSO.

Based on percent contributions derived from our analysis, the solar UV flux influences GMTA more than TSI. This is in consonance with simulation studies
reported by [16]. During a solar cycle, the amplitude of variation in total solar irradiance ($TSI$) is on the order $< 0.1\%$, while it attains the highest amplitude in the ultraviolet ($UV$) radiation band reaching $32\%$ [25,16]. Therefore, solar radiation in the $UV$ band can affect the Earth’s climate distinctly more than TSI. It is well established that the solar $UV$ radiation affects the atmosphere through changes in the photochemical dissociation rate and ozone heating. This is clearly brought out in the simulation studies by [16] adopting a general circulation model. However, the nature of coupling between the stratosphere and the troposphere remains a topic of investigation. In this context, it is important to note that the current phase of decreasing solar cycle amplitude should give rise to a global cooling effect. However, as observed in this study and by others (e.g. [29,19,46]), the solar radiative forcing is small compared to that of greenhouse gases resulting in the dominance of the effects of greenhouse gases on climate variability. Moreover, greenhouse gases like $CO_2$, $N_2O$ etc have large residual life times in the atmosphere. In particular, $CO_2$ can reside in the atmosphere for 100-1000 years [30]. This would lead to warming as greenhouse gases accumulate in the atmosphere and counter the cooling effect due to the low solar flux. Even, the initial short duration cooling effects due to aerosols, which are short lived, may not be adequate to mask the warming induced by enhancement in greenhouse gases of longer life.

The solar activity modulates the incident flux of cosmic rays on the Earth’s atmosphere through changes in the interplanetary magnetic field. Cosmic rays could affect the global cloud cover through ionization resulting in changes in global temperature [9,12]. Present study reveals that cosmic rays contribute $\sim 5\%$ to GMTA variability. Albeit small, these quantitative estimates obtained for the period of 1984-2005 point that cosmic rays do contribute to GMTA. Also, it supports the earlier studies [14,9,42] which report influence of cosmic rays on the global temperature.

In summary, the present study unambiguously establishes that greenhouse gases and aerosols contribute dominantly to the global mean temperature anomaly. The greenhouse gases alone account for $\sim 50\%$ of the recent observed climate variability. The forcing due to the Sun in $UV$ band and inter variability of the atmosphere-ocean system ($ENSO$) plays a secondary role in climate variability. As an interesting sidelight, all the constituents of natural forcings together seem to make contributions equal to the anthropogenic sources (greenhouse gases) in the context of recent climate variability. In spite of the present low solar activity, our results imply that global warming would continue mainly due to increase in greenhouse gases forcing and decline in volcanic aerosols. Due to the well documented increase in greenhouse gases in the atmosphere and mutual driving ability of GMTA and $ENSO$ as revealed in this study, frequent future occurrence of $ENSO$ remains a distinct possibility independent of its internal variability. The application of transfer entropy to climate proxies can be further used to identify other drivers of climate variability and understand their relative importance.
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Fig. 1 Time-series of various climate proxies employed in this study for year 1984-2005: (a) Global mean temperature anomaly (GMTA), (b) Total solar irradiance (TSI), (c) Ultraviolet irradiance (UV), concentration of (d) Carbon dioxide (CO₂), (e) Methane (CH₄) and (f) Nitrous oxide (N₂O) (g) Stratospheric aerosol optical depth, (h) ENSO index and (i) Cosmic ray flux (CR) at Oulu neutron monitor station. The cause-effect relationships between GMTA (shown in green) and the remaining climate variables (shown in black) are investigated.
Fig. 2  Transfer entropy (TE) between various climate proxies and GMTA. The red lines represent the information flow from the studied climate variables to GMTA whereas blue line is representation of information flow from GMTA to the climate variables. The dashed line is the 5% significance level, constructed from 100 surrogate datasets. Note that the net flow of information from remaining proxies to GMTA is generally higher than that in the reverse direction.
Fig. 3. Directionality Index \( (D_{x \rightarrow y}) \) of information transfer from the climate proxies to the GMTA as a function of time lag, \( \tau \). The magnitude and sign of the index indicate the strength of information transfer and its direction respectively. Note that at different time lags the net information flow from \( CO_2, CH_4 \) and aerosol to GMTA is dominant.
Fig. 4 Percent contribution of various drivers estimated using integrated directionality index for 0-3 month time lag. The dominance of greenhouse gases ($CO_2$ and $CH_4$) and volcanic aerosols is evident.
References

1. Attanasio, A.: Testing for linear granger causality from natural/anthropogenic forcings to global temperature anomalies. Theoretical and Applied Climatology 110(1-2), 281–289 (2012)
2. Attanasio, A., Pasini, A., 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)
3. Balasis, G., Donner, R.V., Potirakis, S.M., Runge, J., Papadimitriou, C., Daglis, I.A., Eftaxias, K., Kurths, J.: Statistical mechanics and information-theoretic perspectives on complexity in the earth system. Entropy 15(11), 4844–4888 (2013)
4. Beer, J., Mende, W., Steinhacher, B.: The role of the sun in climate forcing. Quaternary Science Reviews 19(1), 403–415 (2000)
5. Cai, W., Borlace, S., Lengaigne, M., Van Rensch, P., Collins, M., Vecchi, G., Timmermann, A., Santoso, A., McPhaden, M.J., Wu, L., et al.: Increasing frequency of extreme el niño events due to greenhouse warming. Nature Climate Change 4(2), 111–116 (2014)
6. Carbone, A.: Information measure for long-range correlated sequences: the case of the 24 human chromosomes. Scientific reports 3 (2013)
7. Carbone, A., Castelli, G., Stanley, H.: Analysis of clusters formed by the moving average of a long-range correlated time series. Physical Review E 69(2), 026,105 (2004)
8. Carbone, A., Stanley, H.E.: Scaling properties and entropy of long-range correlated time series. Physica A: Statistical Mechanics and its Applications 384(1), 21–24 (2007)
9. Carslaw, K., Harrison, R., Kirkby, J.: Cosmic rays, clouds, and climate. Science 298(5599), 1732–1737 (2002)
10. Cobb, K.M., Charles, C.D., Cheng, H., Edwards, R.L.: El nino/southern oscillation and tropical pacific climate during the last millennium. Nature 424(6946), 271–276 (2003)
11. Das Sharma, S., Ramesh, D., Bapanayya, C., Raju, P.: Sea surface temperatures in cooler climate stages bear more similarity with atmospheric co2 forcing. Journal of Geophysical Research: Atmospheres (1984–2012) 117(D13) (2012)
12. De Michelis, P., Consolini, G., Materassi, M., Tozzi, R.: An information theory approach to the storm-substorm relationship. Journal of Geophysical Research: Space Physics 116(A8) (2011)
13. Dergachev, V., Vasiliev, S., Raspopov, O., Jungner, H.: Impact of the geomagnetic field and solar radiation on climate change. Geomagnetism and Aeronomy 52(8), 959–976 (2012)
14. Dickinson, R.E.: Solar variability and the lower atmosphere. Bulletin of the American Meteorological Society 56(12), 1240–1248 (1975)
15. Eddy, J.A.: The maunder minimum. Science 192(4245), 1189–1202 (1976)
16. Haigh, J.D.: The impact of solar variability on climate. Science 272(5264), 981–984 (1996)
17. Hansen, J., Sato, M., Ruedy, R., Lacis, A., Oinas, V.: Global warming in the twenty-first century: An alternative scenario. Proceedings of the National Academy of Sciences 97(18), 9875–9880 (2000)
18. Herschel, W.: Observations tending to investigate the nature of the sun, in order to find the causes or symptoms of its variable emission of light and heat; with remarks on the use that may possibly be drawn from solar observations. Philosophical Transactions of the Royal Society of London pp. 265–318 (1801)
19. Hofmann, D., Butler, J., Dlugokenczyk, E., Elkins, J., Masarie, K., Montzka, S., Tans, P.: The role of carbon dioxide in climate forcing from 1979 to 2004: introduction of the annual greenhouse gas index. Tellus B 58(5), 614–619 (2006)
20. Kerton, A.K.: Climate change and the earth’s magnetic poles, a possible connection. Energy & environment 20(1), 75–83 (2009)
21. Knuth, K.H., Gotera, A., Curry, C.T., Huyser, K.A., Wheeler, K.R., Rossow, W.B.: Revealing relationships among relevant climate variables with information theory. arXiv preprint arXiv:1311.4632 (2013)
22. Kodra, E., Chatterjee, S., Ganguly, A.R.: Exploring granger causality between global average observed time series of carbon dioxide and temperature. Theoretical and applied climatology 104(3-4), 325–335 (2011)
23. Laken, B.A., Pallé, E., Čalogović, J., Dunne, E.M.: A cosmic ray-climate link and cloud observations. Journal of Space Weather and Space Climate 2, A18 (2012)
24. Le Mouël, J.L., Kossobokov, V., Courtillot, V.: On long-term variations of simple geomagnetic indices and slow changes in magnetospheric currents: The emergence of anthropogenic global warming after 1990? Earth and Planetary Science Letters 232(3), 273–286 (2005)
25. Lean, J.: Contribution of ultraviolet irradiance variations to changes in the sun’s total irradiance. Science 244(4901), 197–200 (1989)
26. Lean, J.L., Kossobokov, V., Courtillot, V.: On long-term variations of simple geomagnetic indices and slow changes in magnetospheric currents: The emergence of anthropogenic global warming after 1990? Earth and Planetary Science Letters 232(3), 273–286 (2005)
27. Lean, J.L., Rind, D.H.: How will earth’s surface temperature change in future decades? Geophysical Research Letters 36(15) (2009)
28. Marschinski, R., Kantz, H.: Analysing the information flow between financial time series. The European Physical Journal B-Condensed Matter and Complex Systems 30(2), 275–281 (2002)
29. Mende, W., Stellmacher, R.: Solar radiative forcing und klimaentwicklung. Potsdam Institute for Climate Impact Research (1994)
30. Montzka, S., Dlugokencky, E., Butler, J.: Non-co2 greenhouse gases and climate change. Nature 476(7358), 43–50 (2011)
31. Robock, A.: Volcanic eruptions and climate. Reviews of Geophysics 38(2), 191–219 (2000)
32. Runge, J., Kurths, J.: Quantifying causal coupling strength: A lag-specific measure for multivariate time series related to transfer entropy. Physical Review E 86(6), 061,121 (2012)
33. Runge, J., Petoukhov, V., Kurths, J.: Quantifying the strength and delay of climatic interactions: the ambiguities of cross correlation and a novel measure based on graphical models. Journal of Climate 27(2), 720–739 (2014)
34. Schreiber, T.: Measuring information transfer. Physical review letters 85(2), 461 (2000)
35. Scott, D.W.: On optimal and data-based histograms. Biometrika 66(3), 605–610 (1979)
36. Shannon, C.E.: A mathematical theory of communication. Bell Syst Tech. J. 27, 623–656 (1948)
37. Shindell, D.T., Schmidt, G.A., Mann, M.E., Rind, D., Waple, A.: Solar forcing of regional climate change during the maunder minimum. Science 294(5549), 2149–2152 (2001)
38. Söllner, S., Daniel, J.S., Sanford, T.J., Murphy, D.M., Plattner, G.K., Knutti, R., Friedlingstein, P.: Persistence of climate changes due to a range of greenhouse gases. Proceedings of the National Academy of Sciences 107(43), 18,354–18,359 (2010)
39. Stern, D.I., Kaufmann, R.K.: Anthropogenic and natural causes of climate change. Climatic change 122(1-2), 257–269 (2014)
40. Theiler, J., Eubank, S., Longtin, A., Galdrikian, B., Doyne Farmer, J.: Testing for non-linearity in time series: the method of surrogate data. Physica D: Nonlinear Phenomena 58(1), 77–94 (1992)
41. Timmermann, A., Oberhuber, J., Bacher, A., Esch, M., Latif, M., Roeckner, E.: Increased el niño frequency in a climate model forced by future greenhouse warming. Nature 398(6729), 694–697 (1999)
42. Tinsley, B.: The global atmospheric electric circuit and its effects on cloud microphysics. Reports on Progress in Physics 71(6), 066,801 (2008)
43. Trenberth, K.E., Hoar, T.J.: El niño and climate change. Geophysical Research Letters 24(23), 3057–3060 (1997)
44. Usoskin, I.G., Kovaltsov, G.A.: Cosmic rays and climate of the earth: Possible connection. Comptes Rendus Geoscience 340(7), 441–450 (2008)
45. Verdes, P.: Assessing causality from multivariate time series. Physical Review E 72(2), 026,222 (2005)
46. Verdes, P.F.: Global warming is driven by anthropogenic emissions: a time series analysis approach. Physical review letters 99(4), 048,501 (2007)
47. Vichare, G., Bhaskar, A., Ramesh, D.S.: Are the equatorial electrojet and the sq coupled systems? transfer entropy approach. Advances in Space Research 57(9), 1859–1870 (2016)
48. Wang, C., Yu, H., Grout, R.W., Ma, K.L., Chen, J.H.: Analyzing information transfer in time-varying multivariate data. In: Pacific Visualization Symposium (PacificVis), 2011 IEEE, pp. 99–106. IEEE (2011)
