

Quantitative assessment of drivers of recent global temperature variability: an information theoretic approach

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Abstract Identification and quantification of possible drivers of recent global temperature variability remains 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: CO₂, CH₄ and N₂O; 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 signals of global temperature variability. Estimates of their relative contributions reveal that CO₂ (~24%), CH₄ (~19%) and volcanic aerosols (~23%) are the primary contributors to the observed variations in *GMTA*. While, *UV* (~9%) and *ENSO* (~12%) act as secondary drivers of variations in the *GMTA*, the remaining play a marginal role in the observed recent global temperature variability. Interestingly, *ENSO* and *GMTA* mutually drive each other at varied time lags. This study assists future modeling efforts in climate science.

Keywords Aerosols · Global temperature variability · ENSO · Greenhouse gases · Transfer entropy · Climate · Information theory

1 Introduction

Global temperature 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 global temperature 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. (Herschel 1801; Dickinson 1975; Eddy 1976; Timmermann et al. 1999; Haigh 1996; Beer et al. 2000; Shindell et al. 2001; Le Mouél et al. 2005; Usoskin and Kovaltsov 2008; Kerton 2009; Laken et al. 2012; Robock 2000; Solomon et al. 2010; Hansen et al. 2000; Montzka et al. 2011; Dergachev et al. 2012). These studies recognize four major drivers of the recent global temperature variability. One stems from the natural climate variables essentially connected to solar activity whereas the others are directly linked to greenhouse gases, 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

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still remain largely elusive and uncertain. It is important to realise that the cause-effect relationship inferred between the variables and global temperature 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 (Verdes 2005). Hence, it becomes rather difficult to decipher the true causal relationship between any two physical processes using these techniques. Therefore, many aspects related to global temperature variability and/or change still remain contentious and unresolved in the absence of reliable quantitative assessments of causality.

The information theory based techniques are widely being used in many disciplines to infer cause-effect relationship between different variables (for example Kleeman 2011; Kakad et al. 2015; Johnson and Wing 2014; Li et al. 2013; Kleeman 2007). There are number of attempts to address the causality between global temperature and the natural and anthropogenic drivers using information theory approach (Kodra et al. 2011; Attanasio et al. 2012; Attanasio 2012; Das Sharma et al. 2012; Stern and Kaufmann 2014; Runge et al. 2014). Kodra et al. (2011) showed that radiative forcing mainly due to CO_2 affects global temperature. The Granger causality is applied to global climate data by Stern and Kaufmann (2014). They observed that both anthropogenic and natural forcing cause temperature change, and as a feedback, temperature changes affect greenhouse gas concentration. Whereas, Attanasio (2012) showed that there is no signature of Granger causality from natural forcing to global temperature but is observed in anthropogenic forcing. 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/or anthropogenic origin adopting time series analyses applying information theory-based stochastic methods which revolve around the concept of entropy or ensemble information content (Shannon 1948). In essence, the relationship between 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 (Schreiber 2000; De Michelis et al. 2011), we show that all the proxies representing natural and/or anthropogenic sources 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*) (Wang et al. 2011). 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 ($\sim 25\%$) of its variability. Among the remaining variables studied here, *ENSO* and *UV* radiation together contribute $\sim 20\%$ to the observed *GMTA* with similar share, while the rest are marginal.

2 Data, method and analysis

2.1 Datasets

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 global temperature changes are observed during this window and secondly, accurate simultaneous measurements of all these 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_2O ; 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/wdcgg/pub/global/globalmean.html#content2>) (Tsutsumi et al. 2009). Whereas *ENSO* (NINO 3.4) index was collected from http://www.cgd.ucar.edu/cas/catalog/climind/TNI_N34/index.html#Sec5 (Trenberth 1997). Global mean aerosol optical depth data were taken from https://data.giss.nasa.gov/modelforce/strataer/tau.line_2012.12.txt (Sato et al. 1993; Vernier et al. 2011). *TSI* and *UV* fluxes were retrieved from the World Radiation Center (<http://www.pmodwrc.ch/pmod.php?topic=tsi/composite/SolarConstant> and <http://lasp.colorado.edu/lisird/cssi/> respectively) (Fröhlich 2006; DeLand and Cebula 2008). The neutron flux is measured at Oulu Cosmic Ray Station (<http://cosmicrays oulu.fi/>) (Bhaskar et al. 2016). The global mean temperature anomaly of the Earth was drawn from Met Office Hadley Center, http://www.metoffice.gov.uk/hadobs/hadcrut4/data/current/time_series/HadCRUT.4.5.0.0.monthly_ns_avg.txt (Morice et al. 2012). All the proxies used are monthly mean values and are shown in Fig. 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 two volcano eruptions (El Chichon in 1982, and Pinatubo during 1991) resulting in enhanced atmospheric opacity. The *TSI*, *UV* and cosmic rays clearly reflect the solar activity

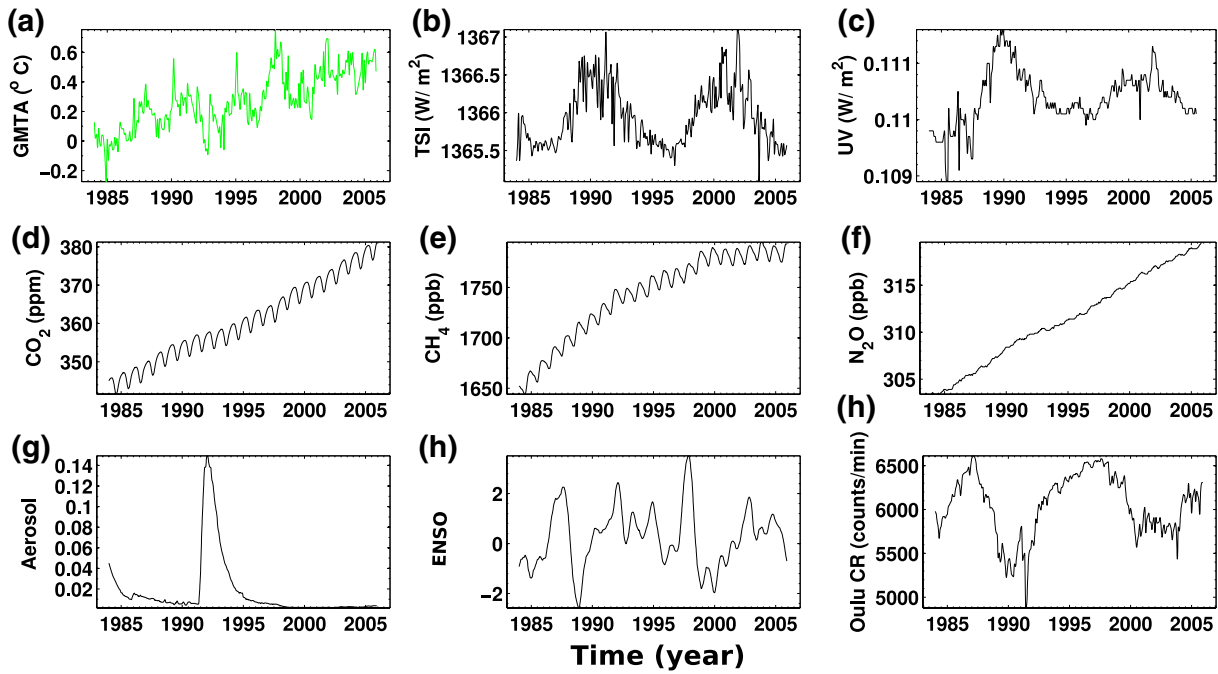


Fig. 1 Time-series of various climate proxies employed in this study for the years 1984–2005: **a** global mean temperature anomaly (GMTA), **b** total solar irradiance (TSI), **c** ultraviolet irradiance (UV), concentration of **d** carbon dioxide (CO₂), **e** methane (CH₄) and **f**

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

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

Shannon (1948) 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:

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

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 Schreiber (2000). 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 (Schreiber 2000; De Michelis et al. 2011; Das Sharma et al. 2012; Balasis et al. 2013; Vichare et al. 2016). The TE from a process *x* to another process *y* after a time lag τ 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 (Marschinski and Kantz 2002):

Transfer Entropy (τ) = [information about future observation of $y(t + \tau)$ gained from past joint observations of *x* and *y*] – [information about future observation $y(t + \tau)$ gained from past observations of *y* only] = information flow from *x* to *y*.

Therefore, transfer entropy between two random variables or processes represented by *x* and *y* is mathematically depicted as (Das Sharma et al. 2012):

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

Similarly, transfer entropy from *y* to *x*, $TE_{y \rightarrow x}(\tau)$ can be estimated for different time lags/delays (τ). 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 (Theiler et al. 1992; De Michelis et al. 2011). 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. Any cross-correlation between two time series is destroyed by randomly shuffling one of the time series. After shuffling the time series, transfer entropy is estimated. This estimated non-zero transfer entropy is not due to actual cause and effect between two time series, as any relationship between two time series is destroyed. This non-zero transfer entropy is just due to the finite sample length effect (Marschinski and Kantz 2002). Also, note that, the 5% significance level itself indicates that the estimated transfer entropy values have only 5% chance that they are due to just by chance and not due to cause and effect relationship between two time series.

In the presence of multiple drivers, estimation of relative contribution of each variable/proxy to the observed response signal assumes importance. To enable this, Wang et al. (2011) 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:

$$NTE_{x \rightarrow y}(\tau) = \frac{TE_{x \rightarrow y}(\tau)}{\sqrt{H_x * H_{y+\tau}}} \quad (3)$$

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 the remaining 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.

$$D_{x \rightarrow y}(\tau) = NTE_{x \rightarrow y}(\tau) - NTE_{y \rightarrow x}(\tau) \quad (4)$$

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 and more number of data points 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. The application of transfer entropy requires the time series to be stationary (Das Sharma et al. 2012; Marschinski and Kantz 2002). Therefore, following (Carbone et al. 2004; Carbone 2013; Carbone and Stanley 2007), these time series are transformed into stationary sequences. As a contrast to non-stationary series, stationary time series shows constant mean and variance over time. The removal of deterministic trends transforms the time series into stationary one. This can be achieved by removing the moving average from the original series, which acts like a high pass filter (Carbone et al. 2004). Thus, by subtracting the moving average, we remove longer wavelengths/trends from the data. This method of imparting stationarity is effectively used in many studies (for example, Das Sharma et al. 2012; Kakad et al. 2015; Vichare et al. 2016). The moving average is estimated using the formula:

$$\bar{x}_n(t) = \frac{1}{n} \sum_{k=0}^n x(t-k) \quad (5)$$

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. Note that the stationary time series contains information of short time scale variations. The study aims to know how stochastic variations in GMTA are affected by considered variables, thus, subtracting moving average should not affect the conclusions drawn from the analysis. 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 (Scott 1979) expression $w = 3.49\sigma N^{-1/3}$, where N is the number of data points and σ is the standard deviation. Based on values of w determined for each time series, the corresponding

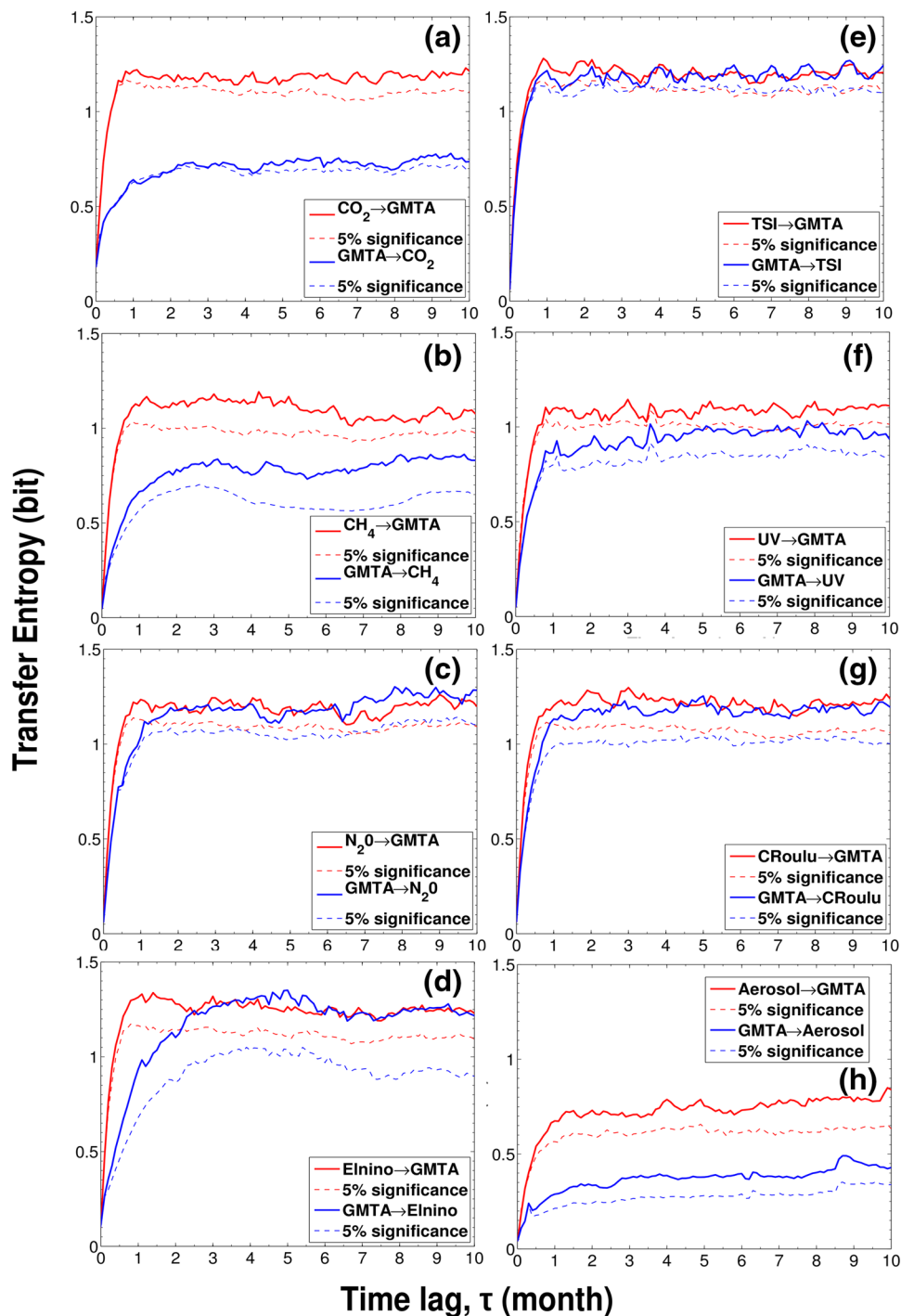
probability distributions are estimated. These are further used in the calculation of *TE*.

3 Salient results

The *transfer entropy* in both the directions which correspond to the global mean temperature anomaly and eight other proxies representing natural and/or anthropogenic

processes are computed. Figure 2 shows the estimated *TE* values for different time lags (τ) 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 proxies investigated in this study

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*, blue line corresponds to 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



and *GMTA*. Further, note that the red curves representing the significant *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* from proxy to *GMTA*) are prominently above the blue curves (*TE* 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 ~ 3 months compared to that in the reverse direction. This suggests that both *GMTA* and *ENSO* perhaps interact variably at different time delays τ . 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.

Figure 2 shows significant information flow from *GMTA* to various studied parameters. This is a normally observed feature in the Transfer entropy technique (for example Das Sharma et al. 2012; De Michelis et al. 2011; Vichare et al. 2016). A very well known possibility of its origin is finite sample effect due to small sample size (example: Grassberger 1988; Kantz and Schürmann 1996; Marschinski and Kantz 2002). Due to less number of samples the information contained in past observations of both series may be misinterpreted as information flow from *GMTA* to other proxies. However, the estimated significance level using surrogate data should take care of this effect upto certain extent (Marschinski and Kantz 2002). Note that after estimating finite sample effect using surrogate data, there still exists some significant flow of information from *GMTA* to other studied variables. However, it is possible to have the flow of information from *GMTA* to CO_2 , CH_4 , N_2O , *ENSO*, as it is known that *GMTA* can influence the greenhouse gas content in the atmosphere through feedback mechanism. It is well known that the atmospheric concentration of CO_2 can vary with global temperature i.e warm temperature can increase the atmospheric CO_2 (see for example Jenkinson et al. 1991; Nemanill 1997). This could be true for even CH_4 or N_2O (Shindell et al. 2004). Natural and cultivated wetlands (rice paddies) are important sources of CH_4 , and the extent and strength of these sources may increase as a result of global warming and extension of rice production (See for example Cao et al. 1998; Bartlett and Harriss 1993). The information flow from *GMTA* to aerosol, solar irradiance and cosmic ray flux is slightly intriguing. The cosmic ray flux proxy is flux of secondary particles generated in the Earth's atmosphere, mainly neutrons. The measured flux is generally corrected for pressure variations at the station. However, some pressure effect may still exist and could be related to the global temperature changes. The measurements of *TSI*, *UV* and *aerosols* also might have some instrumental temperature drift due

to solar heating which might give rise to some information flow from *GMTA* to *TSI*, *UV* and *aerosols*. For information flow from *GMTA* to volcanic aerosols there could be one more possibility. The concentration of suspended volcanic aerosol in the air gets affected by global temperature changes and this might result in information flow from *GMTA* to volcanic aerosols. However, it is difficult to understand how exactly *GMTA* affects the particulate matter in the air and other atmospheric constituents.

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 to the corresponding flow in the reverse directions. Thus, these four variables qualify to be the prominent drivers of the observed global temperature variability manifested as variations in *GMTA*. In order to estimate the strength of net information flow for each driver, using Eq. (4), the directionality index ($D_{x \rightarrow y}$) is computed. The directionality index for each climate proxy as a function of time lag is presented in Fig. 3. It can be seen that among the 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 hitherto not so well studied do contribute to *GMTA* as much as the greenhouse gases, CO_2 and CH_4 .

To estimate percent contribution of each proxy to the observed variability in the global mean temperature anomaly, we computed the integrated net information flow (directionality index using Eq. 4) employing time lags of 3 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 global temperature 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 the studied drivers, but, it is the total normalized information flow to *GMTA*. The pie chart shown in Fig. 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 temperature variability. It can be clearly seen that greenhouse gases (CO_2 and CH_4) and *aerosols* are the chief contributors to the observed recent global temperature variability with near similar (~ 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 global temperature variability. These interesting results are discussed in the following section in the context of our current understanding of global temperature variability.

Fig. 3 Directionality Index ($D_{x \rightarrow y}$) of information transfer from the climate proxies to the *GMTA* as a function of time lag, τ . 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

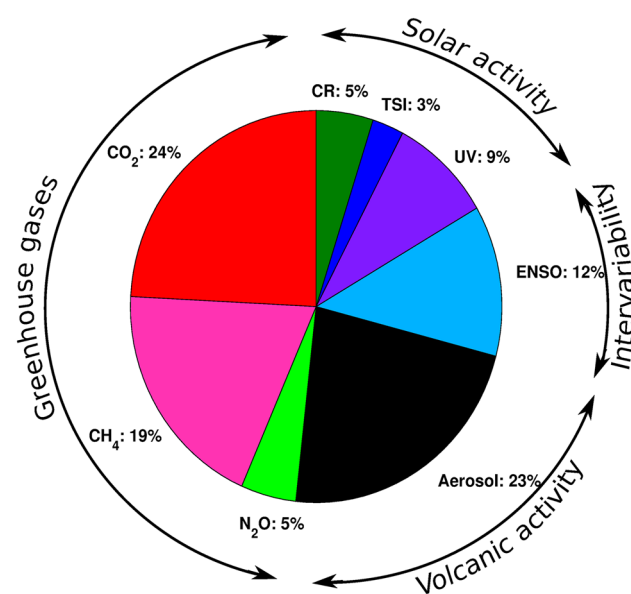
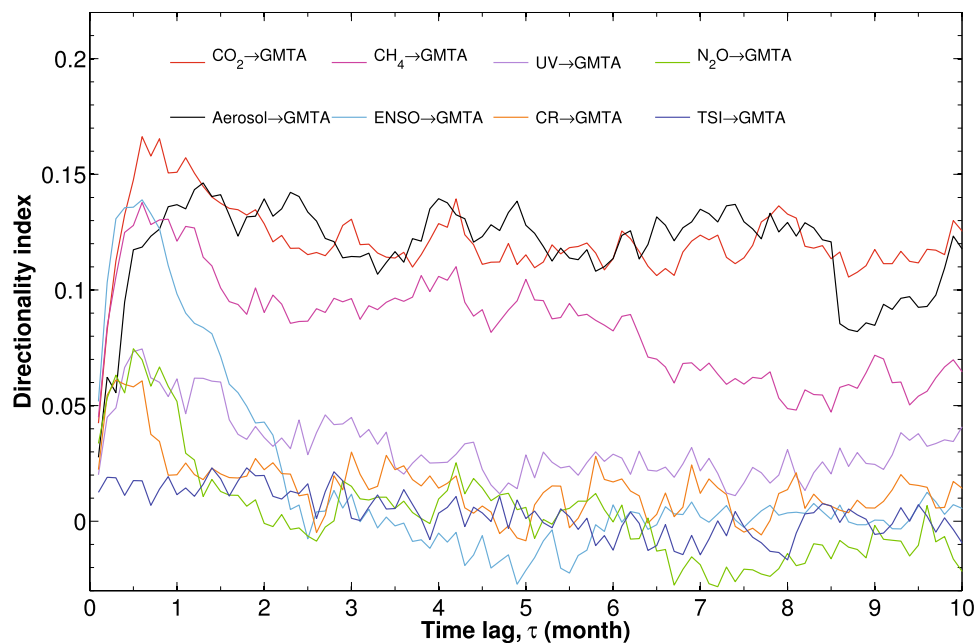


Fig. 4 Percent contribution of various drivers estimated using integrated directionality index for 0–3 month time lag. The dominance of greenhouse gases (CO_2 and CH_4) and volcanic aerosols is evident

4 Discussion and conclusions

The two principal issues addressed here are: (1) identification of primary drivers of recent (1984–2005) global temperature variability (*GMTA*) among the eight climate variables considered in this study and (2) quantification of their influence on the global temperature variability. Transfer entropy and its variant are used to address these issues. Use of this technique in climate studies is a recent trend (Verdes

2005; Knuth et al. 2013; Das Sharma et al. 2012; Runge et al. 2012). Its application to study the recent climate variability in particular is in its infancy. For example, Verdes (2005), limiting their study to greenhouse gases and *TSI* conclude that the former are the significant contributors to the present climate change, while Das Sharma et al. (2012) 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, Runge et al. (2014) proposed a method based on the graphical model to identify the causal connection, strength of interaction and the time delays involved in climatic interactions. In the present work, the recent global temperature 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 ($\text{CO}_2 + \text{CH}_4$) on recent global temperature variability with $\sim 43\%$ contribution. Note that the time series of greenhouse gases represent variations not only of anthropogenic sources but also those of natural origin (Watson et al. 1992). Interestingly, *aerosols* which alone contribute $\sim 23\%$ to the observed global temperature variability qualify as the other primary driver in addition to CO_2 and CH_4 . The internal forcing by *ENSO* with $\sim 12\%$ contribution and *UV* share of $\sim 9\%$ owing to solar variability constitute the minor components of global temperature variability that deserve attention. These relative contributions are consistent with earlier reports by Mende and Stellmacher (1994), Hofmann et al. (2006), and Verdes (2007). Intergovernmental Panel on Climate Change (IPCC) AR5 report (figure 10.6)

<http://www.ipcc.ch/> clearly showed the impacts of different components to temperature variability. It shows greenhouse gases as dominant contributors, whereas, volcano and ENSO are secondary contributors. It also shows that solar radiance has very small contribution to global temperature change. Interestingly, our observations are more or less consistent with the results presented in IPCC AR5 report (figure 10.5 and 10.6) even though a new approach is adopted.

Evidently, the other components of solar variability, *TSI* and *CR* together with the greenhouse gas N_2O with contributions $\sim 5\%$ are the marginal components. It is pertinent to note that, though the greenhouse gas N_2O has stronger radiative forcing per molecule and long residence time (~ 120 years), its atmospheric concentration is less (see Fig. 1). This could be the reason for N_2O being among the weakest contributors. In the following, we briefly discuss possible mechanisms by which *aerosols*, *ENSO*, and *UV* influence the global temperature 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 (Robock 2000), they can affect the global temperature 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 an 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 temperature variability. It is therefore generally difficult to comprehend their exact atmospheric impact and feedback mechanisms through model based studies owing to several complexities (Robock 2000). Hence we are content with quantifying the percent contribution of *aerosols* to recent global temperature 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 (Cobb et al. 2003; Timmermann et al. 1999). The occurrences of *ENSO* during the last millennium are explained invoking natural variability of the ocean-atmosphere system (Cobb et al. 2003). While frequent occurrences of *ENSO* in last few decades and also validated by a climate model are attributed to the greenhouse warming (Trenberth and Hoar 1997; Timmermann et al. 1999; Cai et al. 2014). One may say that the effect on global temperature due to *ENSO* is positive at some places and negative

in another. However, it has been reported that *ENSO* and super *ENSO* periods cause rise in global temperature (Lean and Rind 2009; Lean 2010). Interestingly, our *transfer entropy* estimates shown in Fig. 2d indicate the crosstalk between *ENSO* and *GMTA* at different time lags to be of mixed 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 Haigh (1996). 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% (Lean 1989; Haigh 1996; Beer et al. 2000). Therefore, solar radiation in the *UV* band can affect the Earth's global temperature 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 Haigh (1996) 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. Mende and Stelmacher 1994; Hofmann et al. 2006; Verdes 2007), the solar radiative forcing is small compared to that of greenhouse gases resulting in the dominance of the effects of greenhouse gases on global temperature 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 (Montzka et al. 2011). 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 (Carslaw et al. 2002; Tinsley 2008). 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 (Dickinson 1975; Carslaw et al. 2002; Tinsley 2008) which report influence of cosmic rays on the global temperature.

The global climate change is average scenario of all the regional climate variability. The regional and global trends might not always correlate. Therefore, it is possible that the similar study performed for regional or different time scales may give different results. Though we have not examined for regional scales, we have tried to validate the results for longer time window between (1870–2007) by using dataset of ENSO and *GMTA* (not shown here). Interestingly, the conclusions are unchanged even for longer datasets.

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 ~50% of the recent observed global temperature variability. The forcing due to the Sun in *UV* band and inter variability of the atmosphere-ocean system (*ENSO*) plays a secondary role in global temperature variability. As an interesting sidelight, all the constituents of natural forcings together seem to make contributions equal to the greenhouse gases in the context of recent global temperature 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 global temperature variability and understand their relative importance.

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