

LETTER • OPEN ACCESS

A novel statistical decomposition of the historical change in global mean surface temperature

To cite this article: Gangzhen Qian *et al* 2021 *Environ. Res. Lett.* **16** 054057

View the [article online](#) for updates and enhancements.

ENVIRONMENTAL RESEARCH
LETTERS

LETTER

A novel statistical decomposition of the historical change in global mean surface temperature

OPEN ACCESS

RECEIVED

5 November 2020

REVISED

12 February 2021

ACCEPTED FOR PUBLICATION

26 February 2021

PUBLISHED

7 May 2021

Original content from this work may be used under the terms of the [Creative Commons Attribution 4.0 licence](#).

Any further distribution of this work must maintain attribution to the author(s) and the title of the work, journal citation and DOI.

Gangzhen Qian¹, Qingxiang Li^{1,5,*} , Chao Li², Haiyan Li^{1,5}, Xiaolan L Wang³, Wenjie Dong^{1,5} and Phil Jones⁴¹ School of Atmospheric Sciences and Key Laboratory of Tropical Atmosphere–Ocean System, Ministry of Education, Zhuhai, People's Republic of China² School of Geosciences, East China Normal University, Shanghai, People's Republic of China³ Climate Research Division, Environment and Climate Change Canada, Toronto, Canada⁴ Climatic Research Unit, School of Environmental Sciences, University of East Anglia, Norwich, United Kingdom⁵ Southern Marine Science and Engineering Guangdong Laboratory (Zhuhai) and China Association for Science and Technology Working Group for UN Environment Consultation, Zhuhai, People's Republic of China

* Author to whom any correspondence should be addressed.

E-mail: liqingx5@mail.sysu.edu.cn**Keywords:** external forcing, internal variability, GMST, statistical modelsSupplementary material for this article is available [online](#)**Abstract**

According to the characteristics of forced and unforced components to climate change, sophisticated statistical models were used to fit and separate multiple scale variations in the global mean surface temperature (GMST) series. These include a combined model of the multiple linear regression and autoregressive integrated moving average models to separate the contribution of both the anthropogenic forcing (including anthropogenic factors (GHGs, aerosol, land use, Ozone, etc) and the natural forcing (volcanic eruption and solar activities)) from internal variability in the GMST change series since the last part of the 19th century (which explains about 91.6% of the total variances). The multiple scale changes (inter-annual variation, inter-decadal variation, and multi-decadal variation) are then assessed for their periodic features in the remaining residuals of the combined model (internal variability explains the rest 8.4% of the total variances) using the ensemble empirical mode decomposition method. Finally, the individual contributions of the anthropogenic factors are attributed using a partial least squares regression model.

1. Introduction

It is generally believed that long-term climate changes can be divided into two parts: the external forcing 'signals' (including both the anthropogenic and the natural forcing) and the internal variability (also called 'noise') of the climate system (Santer *et al* 2001, Hegerl *et al* 2007, Bindoff *et al* 2013). Of these, the longest-term and largest-scale climate changes are dominated by external forcing, with internal variability playing an essential role at the shorter term, smaller spatial scales. A good example is the recently heated discussion of global warming slowdown (Frankcombe *et al* 2015). Since the latter part of the last century, climate change attribution research has been based on the comparison of models and observations (Hasselmann 1993, Hegerl *et al* 1996, Tett *et al* 1999, Stott and Kettleborough 2002, Zhang *et al* 2006). An optimal fingerprint (OFP) is used

to estimate the response coefficient of the climate change to external forcing. It can be implemented by generalized multiple regression (GMR), that is, observational climate changes are always regarded as the result of linear superposition of the climate change signals caused by external forcing, plus the internal variabilities of the climate system. Statistically, if effective radiative forcing and other impact factors are precisely quantified, their signals/responses can be near linearly reflected in the observational data. Thus there are a few studies on the causes of historical climate change based solely on using statistical methods to decompose climate change series into contributions of external forcing and internal variability (Haigh 2003, Staeger *et al* 2003, Lean and Rind 2008, Zhou and Tung 2013, Ribes *et al* 2017, Folland *et al* 2018).

The separation of the major components of climate change has always been one of the difficulties

and is a core topic in modern climate change research. The simplest one is the linear detrending approach, where a linear trend is removed from the climate change series (Zhang and Wang 2013). The method is extremely simple and can be useful without any better estimates of forcing data (Frankcombe *et al* 2015), but has been shown to introduce biases in both amplitude and phase of the estimated internal variability (Mann and Emanuel 2006, Mann *et al* 2014). Another popular component extraction method is principal component analysis (PCA), or the similar statistical method termed empirical orthogonal functions in climatology (Preisendorfer 1988, von Storch and Zwiers 1999, Li *et al* 2020). The maximum remaining variance criterion used in PCA makes it a useful tool for information compression but also limits its ability for decomposing climate change into individual modes (Ilin and Valpola 2005). It can lead to problems like mixing different patterns in one extracted component (Kim and Wu 1999). The modified PCA method, which adopts orthogonal or oblique rotation of the PCs has proved to improve the interpretability of the extracted PCs (Richman 1986). An alternative rotational approach called independent component analysis (ICA), has also been applied to climate research since it was first proposed in about 2000 (Aires *et al* 2000, Hyvärinen *et al* 2001, Lotsch 2003). It is a statistical method for component extraction which can also be used for the rotation of PCs, and its basic assumption of the statistical independence of the extracted components can lead to more meaningful data representation (Richman 1986). More recently, Ilin *et al* (2006) developed a novel extension of ICA called denoising source separation framework, which does not necessarily exploit the independence assumption but uses means of temporal filtering or denoising procedure to look for interesting hidden components. MultiTaper method-singular value decomposition, a frequency-based SVD method, can be used to isolate and construct quasiperiodic or unstable oscillations that are spatially coherent but may exhibit phase-lags from site to site, which can be used to identify the most significant oscillations (Mann and Park 1999, Ribera *et al* 2020). Component extraction techniques also aid in identifying and interpreting the significant modes in climate change, such as Pacific decadal oscillation (PDO) and Atlantic multi-decadal oscillation (AMO) (Hurrell 1995, Mantua *et al* 1997). For example, Folland *et al* (2018) successfully reconstructed the GMST series since 1891 from known natural and anthropogenic forcing factors, including internal climate variability, using a multiple regression technique. Additionally, Wu *et al* (2019) directly decomposed the contribution of long-term changes in global observed temperature into greenhouse gases (about 70%) and AMO and PDO (about 30%). Also Wei *et al* (2019) divided the de-trended global surface temperature sequence

during the period 1850–2013 into three components: IAV, IDV and MDV showing that ENSO, PDO, and AMO each dominate the changes in these three components.

However, most of the above-mentioned statistical methods or models do not strictly distinguish the climate response of external forcing from internal variability. In addition, these models are also much less useful for detecting the individual contribution of each external forcing to climate change (especially for some highly related external forcings such as carbon dioxide and other greenhouse gases, etc). Due to the uncertainties in climate change observation, external forcing factor estimation and model simulation, it is very difficult to accurately quantify the contribution of external forcing to climate change. In addition, the traditional OFP analysis needs to carry out coupled model simulation experiments for attempts at distinguishing the contribution of different external forcings. At present, the latest Detection and Attribution Model Intercomparison Project (DAMIP) has only carried out relevant simulation experiments on fully-mixed greenhouse gases, CO₂, anthropogenic aerosols, stratospheric-ozone, and natural forcings, but has not carried out systematic tests on other individual external forcing factors (Gillett *et al* 2016). The cost of carrying out such experiments is huge and cannot be borne by individuals or an independent research group alone. Therefore, there is still a wide space for further research on the methodology of the separation and relative contribution of climate change.

In this paper, based on statistical modeling experiments, we found that reasonable statistical models can be built to quantify the individual and total contributions of natural forcing, anthropogenic forcing (consisted of all components representing different human activities) and internal variabilities and successfully getting the contribution of these forecasting factors with known climate change time series and effective radiative forcing. Taking GMST series as the dependent variable, we set up a set of statistical models to separate the contributions of different forecasting factors and derive some interesting conclusions.

Thus the structure of this paper is arranged as follows: section 2 introduces the newly released China merged global surface temperature (CMST) dataset together with the radiative forcing data for anthropogenic and natural components used in this paper. In section 3 we set up a set of combined statistical models to model and separate the GMST changes into external forcing ('signals') and internal variabilities ('noise'), and also detect the individual contributions of human activities with a partial least squares regression (PLSR) model. Section 4 presents a brief summary and discussion of the paper.

2. Data and methods

2.1. GMST and radiation data

The station surface air temperature series have been quality controlled and homogenized (Xu *et al* 2018, Li *et al* 2021), and then converted to a $5^\circ \times 5^\circ$ latitude and longitude grid dataset using the climate anomaly method (CAM) (Jones *et al* 1997), based on the 1961–1990 period. Then this China global land surface air temperature dataset (C-LSAT) was merged with NOAA's ERSSTv5 (Huang *et al* 2017), to develop a new CMST dataset and new GMST series, with 5%–95% uncertainty ranges evaluated (Yun *et al* 2019, Li *et al* 2020). The CMST dataset/series covers the monthly *in situ* data from January 1880 to December 2019. Comparative studies (Li *et al* 2020, 2021) showed that CMST has similar trends of global surface temperature and have similar uncertainties compared to other existing datasets. While the significant trends during the so called 'hiatus' period are identified by CMST, HadCRUTem4-Hybrid (infilled by the polar surface air temperature) (Cowtan and Way 2014) and ERA-5 (Simons *et al* 2017), etc.

Anthropogenic forcing data includes carbon dioxide (CO₂), other greenhouse gases, atmospheric aerosols, snow albedo changes and land use (Hansen *et al* 2007, Myhre *et al* 2013, Shindell *et al* 2013), as well as the natural forcing data including volcanic eruptions and solar irradiation (Hegerl *et al* 2007, Bindoff *et al* 2013, Myhre *et al* 2013, Shindell *et al* 2013). Data for all these (best evaluation) were downloaded from PANGAEA database and KNMI's Climate Explorer website (<https://doi.pangaea.de/10.1594/PANGAEA.919662>) (CMST), (C-LSAT2.0) and <http://climexp.knmi.nl/selectindex.cgi?Id=someone@somewhere> (radiative forcing), all downloaded in Jan 2020). The time range of these forcing data are from 1850 to 2017 as shown in figure S1 (supplement information (SI) (available online at stacks.iop.org/ERL/16/054057/mmedia)).

2.2. Models for separating the forced and unforced variations

Previous IPCC assessment reports stated that climate change signals can be decomposed into externally forced responses and internal climate (unforced) variability. Anthropogenic activities are becoming much clearer as the main contributors to surface air temperature warming, natural external forcing (such as volcanic eruptions, changes in solar output, represented by corresponding radiative forcing) also contribute to the climate change (Hegerl *et al* 2007, Bindoff *et al* 2013), and these contributions have also generally used a linear relationship expressed from at least one General Circulation Model through OPF method (Haywood *et al* 1997, Ramaswamy and Chen 1997). Therefore, a multiple linear regression (MLR) model is first used in this study, trying to separate the

contribution of climate changes due to external forcing and internal variability.

Taking the GMST as the dependent variable, two variables (total anthropogenic forcing, natural forcing) are selected as the independent variables in the MLR model. We established the following MLR models of GMST change for the period 1880–2017:

$$y = a_0 + a_1x_1 + a_2x_2 + \varepsilon \quad (1)$$

where, x_1 , x_2 are the total natural and anthropogenic forcing, respectively, ε is the residual series of the MLR model. a_0 , a_1 and a_2 are the regression coefficients evaluated by the ordinary least square (OLS) method. It should be noted that the recent OPF uses the total least square (TLS) method, which can be interpreted as the OLS with noise elimination (Bindoff *et al* 2013). However, in terms of linear regression in this paper, the OLS method will provide the best linear unbiased estimator (BLUE) of the regression coefficient according to the Gauss–Markov Theorem (Theil 1971), while the TLS needs more assumptions.

Normally, if equation (1) is strictly a BLUE, its physical meaning is very clear, the MLR represents the part of the dependent variable (GMST) affected (caused) by the independent variables (the total natural and anthropogenic forcings), and ε also represents internal variability in annual GMST. Since the residual analysis shows that there is no collinearity between natural forcing and artificial forcing, we only need to investigate if the residual has obvious negative or positive autocorrelation, which leads to the linear model no longer being BLUE, and the statistical significance of the variables is meaningless, that is, the simulation (fitting) of the model is invalid. In this case, equation (1) will need to be combined with ARIMA models (including the autoregressive (AR), moving average (MA), ARMA and ARIMA models, see Li (2020), and the supplemental information (SI)).

2.3. Multiple scales variations of internal climate (unforced) variability

Generally, the residual of a successful MLR model should have the following characteristics: (a) the residual obeys the normal distribution with zero mean; (b) the residual is a normal distribution with equal variances; (c) the residual sequence is independently distributed. That is, the residuals cannot be linearly fitted with new independent variables, leaving only periodic and random components. According to the MLR model, the residual represents the random error term of the model, which is the error between the fitted value and the actual value excluding the constant term in the independent variable interpretation space. In the sense of climate change, when the fitted external forced 'signal' is subtracted from the GMST anomaly series, the remaining series (i.e. the residual) can be considered to be mainly composed of the internal variability component ('noise')

of climate change). We can know from the section 3 that the residual of MLR ('noise' or internal climate variability) still explains about 8.4% of the total variance of the GMST series. Due to the relatively more important contribution of internal climate variability has been claimed in the shorter term GMST variations in recent studies (Dai *et al* 2015, Frankcombe *et al* 2015, Folland *et al* 2018, Li *et al* 2020), we further decomposed the periodic signals in the residual series by an ensemble empirical mode decomposition (EEMD) method.

EMD model is a method of decomposing complex signals into a finite number of intrinsic mode functions (IMFs) through empirical mode decomposition:

$$x(t) = \sum_{i=1}^n imf_i(t) + r_n(t) \quad (2)$$

where, $imf_i(t)$ is the i th IMF obtained by EMD; $r_n(t)$ is the signal residual component after n IMFs are decomposed and screened.

Each IMF component contains local characteristic signals of different time scales of the original signal. Compared with Fourier transform, wavelet decomposition and its basis function are derived from the data itself. Therefore, this method is intuitive, direct, posterior, and adaptive. EEMD is a noise-aided data analysis method based on the shortcomings of EMD method in modal aliasing (Huang and Wu 2008). The principle is that when a signal is added with a uniformly distributed white noise background, signal regions of different scales are automatically mapped to the appropriate scale related to the background white noise. Since the noise is different in each independent test, when the overall average of enough tests is used, the noise will be eliminated, and the only lasting and stable part is the signal itself (Huang *et al* 1998, Huang and Wu 2008, Wu *et al* 2011).

2.4. Separation of the individual external forcing's contribution

PLSR is an approach that is relatively new multivariate statistical data analysis tool. Because it can solve some problems that conventional ordinary multiple regression methods cannot, it has attracted the attention of researchers. PLSR provides a method for regression modeling of multiple dependent variables to multiple independent variables especially when there is a high degree of correlation among the variables tool, the analysis model is more reliable and the overall conclusion is most robust. It can also perform regression analysis, data structure simplification (PCA), and correlation analysis between two groups of variables (canonical correlation analysis) comprehensively. It is suitable for establishing regression models when there is a high degree of multiple correlation among the variables, which improves the deficiencies of traditional multiple regression analysis, making

the analysis conclusions more reliable and robust. It is also suitable for regression modeling when the sample size is less than the number of variables (see the detailed introduction in text S2 in SI). In the past four decades, PLSR has been developed rapidly in both theory and practice, and its application field has also rapidly expanded to more social and natural science fields (Wang 1999, Li *et al* 2008). A PLSR model has also been used here to investigate the individual external forcings responses to the global and regional land precipitation variations like Li (2020).

3. The forced and unforced variations of GMST

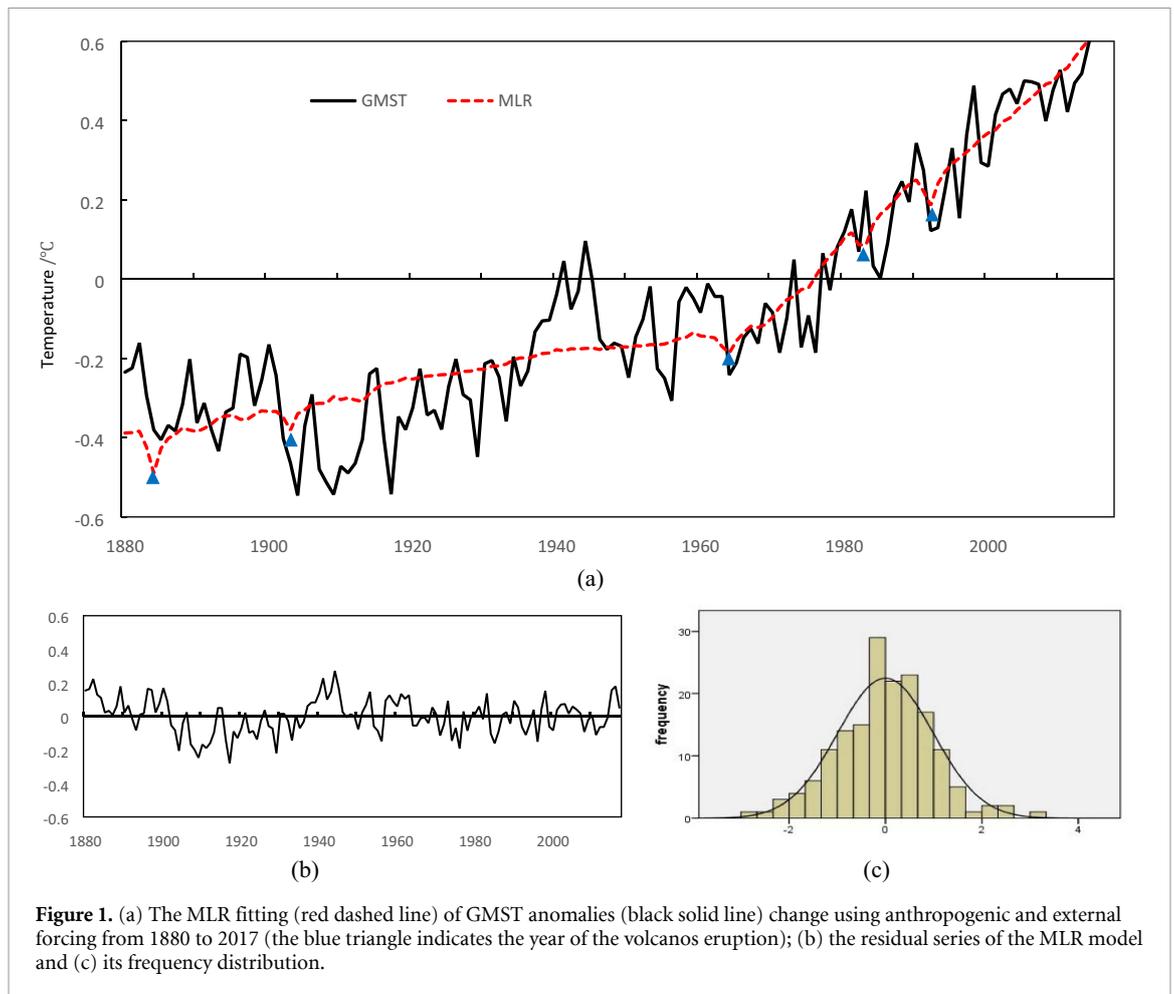
3.1. The combined modeling of the external forcing responses

Taking the GMST as the dependent variable, two other variables (the total anthropogenic forcing and the natural forcing) are selected as the independent variables to construct the MLR model. We established the following combined model of MLR and ARIMA models of GMST variations for the periods of 1880–2017:

$$y = -0.438 + 0.048 * x_1 + 0.410 * x_2 + 1.014 * AR(4) + \varepsilon \quad (3)$$

The analysis of the MLR model shows that neither of the above two variables (natural forcing x_1 ; anthropogenic forcing x_2) can be eliminated (both are important). The adjusted square of the multiple correlation coefficient (total variance explained by the model) of the combined model is 91.6%; the analysis of variance shows that at the 5% level, the dependent variable and the two independent variables have a clear linear relationship, which proves the combined 'MLR and ARIMA' model is statistically meaningful (note that only the AR model is needed here); and both of the coefficients of the two independent variables (the anthropogenic and external natural forcing) have significant meaning. The variance inflation factors are 1.000, which also indicates that there is no collinear relationship between the two independent variables; the Durbin–Watson (DW) test of the residuals also shows there is no first order autocorrelation in equation (3) (DW = 2.026, also see the table S1 of SI). From the above analysis and statistics, the combined model (3) are successful (BLUE) of GMST with the two independent variables, which also shows that the contribution of these two independent variables to the GMST variation is quite clear.

Figure 1(a) shows that the above regression fits well the GMST long term trend signals due to the response of the anthropogenic and natural forcing in the 138 years from 1880 to 2017. Figure 1(b) shows the residual of the combined model, and figure 1(c) shows the residual is a normal distribution with equal variances and the model is meaningful



(BLUE) according to the three criteria mentioned in section 2.3. Of the two kinds of the external factors, the anthropogenic forcing has caused most of the GMST warming during the last 138 years. Before the second half of the 20th century, greenhouse gas emissions increased slowly, so the GMST also increased slowly, and it entered a period of rapid warming since the 1970s. However, we also notice that a certain contribution of the ‘noise’ (or internal variability), which explains about the rest 8.4% of the total variance contribution also agrees well with the previous studies (Li *et al* 2020). In addition, the fitted series was obviously affected by external forcing influences from five large volcanic eruptions: 1884 (Krakatau volcano, Indonesia, eruption in 1883), 1903 (Mt Pelee, Martinique, eruption in 1902), 1964 (Agung volcano, Indonesia, eruption in 1963), 1983 (Kilauea volcano, Hawaii USA, eruption in 1983), 1992 (Pinatubo volcano, Philippines, eruption in 1991) (Zhang and Zhang 1985, Hou and Li 2000).

3.2. The multi-scales variations of internal climate (unforced) variability

Based on the EEMD model, the residual series of the above regression (figure 1(b)) is decomposed into six IMFs (the fluctuations at different timescales) and the remainder (figure 2),

there are obvious periodic signals in the internal variability of 2.9 years, 6.0 years, 13.8 years, 33.4 years, 69.8 years and 136.1 years. Among these, the first five IMF1–IMF5 (the variance contribution explained are 25.8%, 19.0%, 17.9%, 23.5% and 13.7%, respectively) passed the significant test at the 5% level, IMF6 explains only about 0.21% of the variance, and its periodicity was not significant. In other words, all these former five periodic changes are significantly reflected in the long-term variations of GMST. The further comparison also shows that the deposition of the multi-scale periodic signals is not sensitive to whether the external forcing effect is extracted in advance.

Figures 2(a)–(f) also show that the internal climate variability term in the residual can be well decomposed into these several periodic signals. It can be seen that the inter-annual changes and the high and low phase of the GMST anomalies are well explained. IMF1, IMF2 explain the inter-annual variations (IAV) of the GMST, IMF3, IMF4 explain the IDV of the GMST, and IMF5 well explains the MDV warmer or colder fluctuation, and these five IMFs are exactly the eigenmodes with the largest contribution of variance, explaining a total of about 99% of the total variance of the combined model’s residual, which in total accounts for about 8.4% of the

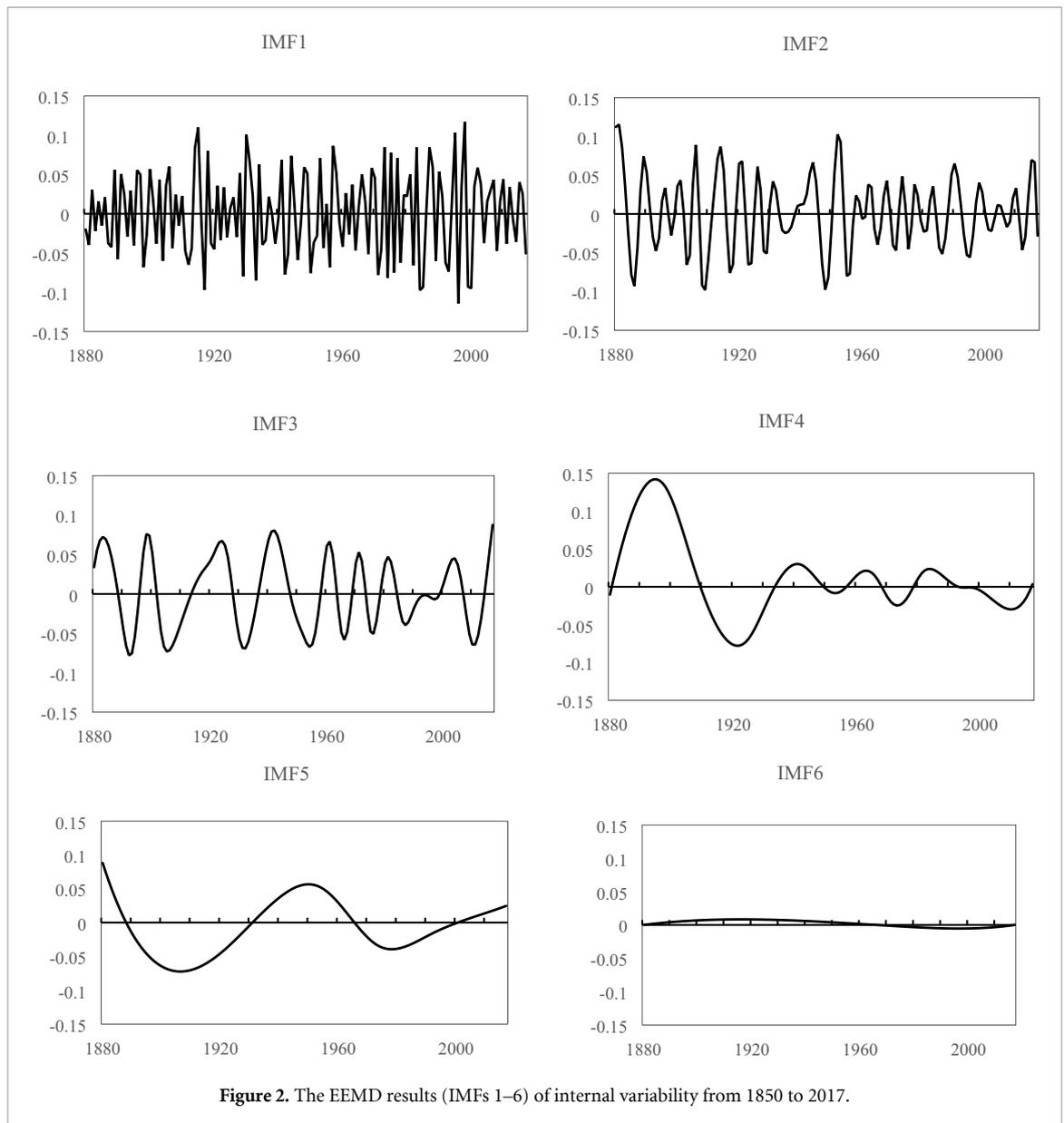


Figure 2. The EEMD results (IMFs 1–6) of internal variability from 1850 to 2017.

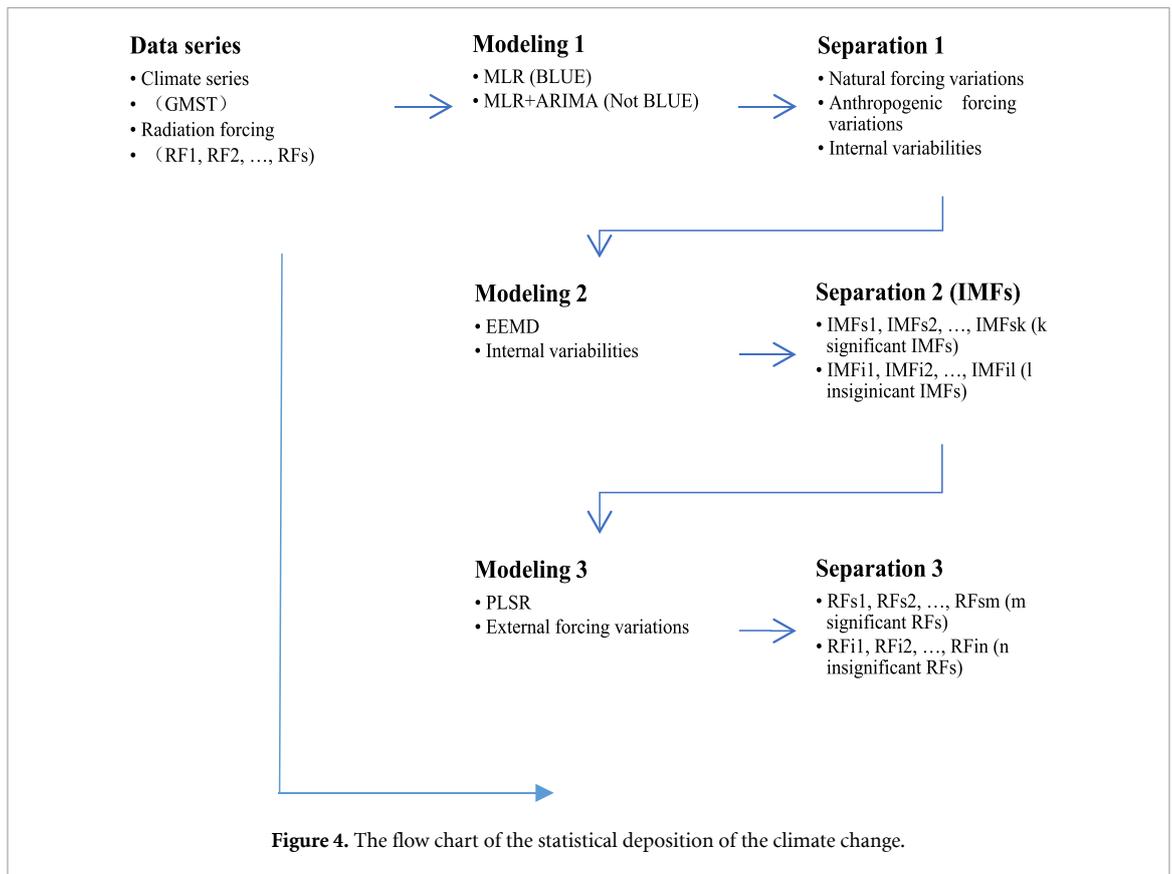
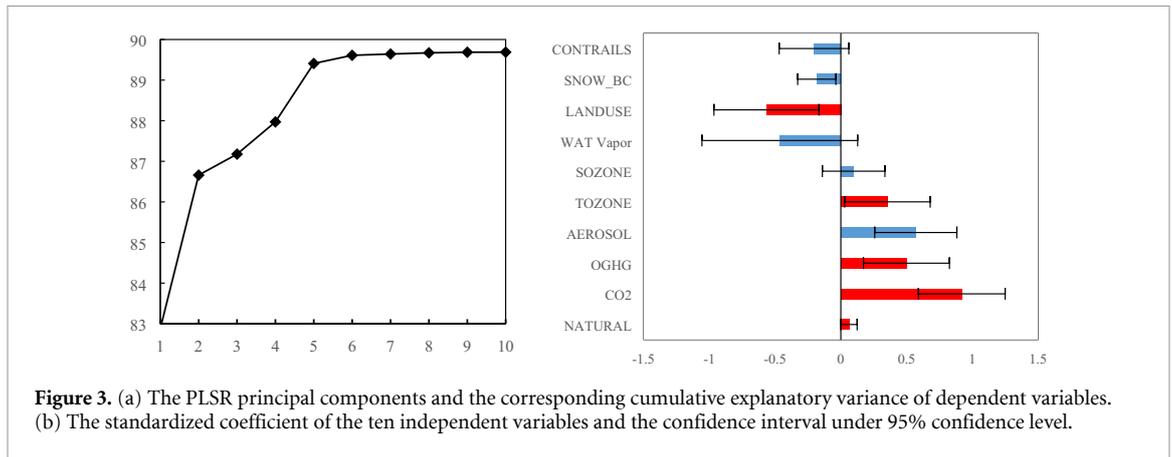
total variance of GMST variations. Further, numerous previous studies indicated that the ENSO (2–7 year cycle), AMO (65–80 year cycle) and PDO/IPO (inter-decadal variation) are the dominant modulation signals of these three components (Dai *et al* 2015, Folland *et al* 2018, Wei *et al* 2019, Wu *et al* 2019). This agrees well with the multi-scales variations of internal climate (unforced) variability separated by EEMD in this paper.

3.3. Contribution of the individual external forcing response

Although the components of the natural and anthropogenic forcing responses have been separated through the above combined model of MLR and ARIMA, it is obviously not enough. More in-depth studies often need to clarify the contributions of individual forcing (such as CO₂, aerosol, and even ozone in tropospheric and stratospheric layers), then the above models are no longer applicable. It has always

been a difficult problem to separate the impacts of various anthropogenic forcings on climate change, that is, the ‘confusion’ between multiple independent variables. For example, the effects of urbanization and greenhouse gases on surface temperature variations are very similar (The average temperature increases, but the daily temperature range decreases). In terms of statistical language, these two variables may have a very clear correlation (Chong and Jun 2005) (this is very common in the case of multiple variables, namely multiple correlations or collinearity between factors, see table S2 in SI).

Figure 3 shows that the first six principal components (PCs) explained nearly 90% of the variance GMST, and it will not increase much with the introduction of more PCs. This shows the PLSR fits the GMST change well during the period of 1880–2017 with the first six PCs. Figure 3 presents the standardized PLSR coefficients of the independent variables. From figure 3 (and table S3 in SI), the coefficients



for CO₂, black carbon on snow (snow_BC), other GHGs, Aerosol and Natural forcing are significant at the 5% level, the land use's coefficient is marginally significant at 10% level, and the rest are insignificant. The independent variables including CO₂, other GHG, land use and natural forcing, contribute to the GMST warming, while the rest (including aerosol, snow_BC, Ozone, water vapor and contrails (the last three variables' coefficients are insignificant)) contribute to cooling of the GMST. The slight difference with Myhre *et al* (2013) occurs in the warming (cooling) effect caused by the surface albedo change related to the land use and the black carbon on the snow surface. This shows there is still a large uncertainty about the correlation between surface albedo and global climate change

currently (Schwaiger and Bird 2010, Sieber *et al* 2019).

4. Summary and discussion

Based on the current scientific understanding of the GMST change and its causes, this study developed a set of new statistical methods to quantify the contribution of external forcing to large-scale GMST change without relying on climate model simulations. This simplified model (figure 4) is based on the following assumptions: (a) it is assumed that the main external forcing factors affecting the process of climate change have been fully understood; (b) the impact of external forcing factors on climate change is linear and the contribution

of different external forcing factors is additive. The following conclusions are achieved with the above approach:

- (a) When using the MLR to model the observed GMST change, the regression equation cannot satisfy the BLUE rules due to the autocorrelation and variance heterogeneity of the observed series, while the new model introduces an ARIMA model combined with MLR to solve this problem. Based on this, the human activities and natural forcing explain the main signals of GMST long term changes, which explain about 91.6% of the variance contribution;
- (b) The internal variability components of the GMST series can be further separated into obvious multi-scale periodic variation characteristics, which can be decomposed into three change components for IAV (3.9%), IDV (3.6%) and MDV (1.2%); showing that the contribution of the inner variability would be limited over the long term period, but it would be more significant during the shorter periods;
- (c) Taking into account the possible multicollinearity (correlation) between different external forcing factors, a PLSR is introduced to solve the problem of 'factor confusion' in this attribution study. PLSR model shows that the independent variables including CO₂, other GHGs, land use and natural forcing, contribute to the GMST warming, while the rest including aerosol, snow_BC, water vapor, contrails and Ozone in stratosphere (the last four variables' coefficients are insignificant at 5% significance level) contribute to cooling of GMST. These conclusions are broadly consistent with the relatively complex detection and attribution results based on the comparisons between the observations and simulations (Hegerl *et al* 2007, Bindoff *et al* 2013), which also shows the 'robustness' of the above statistical methods.

In addition, the whole process of the modeling is used to decompose and model the historical observation data. So in theory, it should also help to decompose the contribution of regional climate change caused by fully mixed radiative forcing factors, especially in the comparison of contributions to different regional climate changes; It is also helpful to separate the forced and unforced components of climate change of different lengths, and has the potential to provide a powerful and convenient supplement and reference for global and regional climate change attribution analysis.

However, at the same time, our study implies strict requirements on the 'purity' of the baseline observational dataset and the radiation forcing data. The uncertainties of both datasets will lead a certain uncertainties on the deposition results, which will be evaluated in depth with ensemble datasets (Sun *et al* 2021) in the future. The results described in this paper should be considered as preliminary since how to combine the simulation results of the climate system model to further conduct in-depth mechanism analysis of the statistical results is an important area for further research.

Data availability statement

The data that support the findings of this study are openly available at the following URL/DOI: <https://doi.pangaea.de/10.1594/PANGAEA.919662>.

Acknowledgments

This study is supported by the National Key R&D Program of China (Grant Nos. 2018YFC1507705; 2017YFC1502301) and the Natural Science Foundation of China (Grant No. 41975105). The authors thank the editor and the anonymous reviewers for their constructive suggestions/comments in the initial reviews.

Appendix

Table A1. List of acronyms (technical jargon).

Acronym	Full name
MLR	Multiple linear regression
GMR	Generalized multiple regression
OLS/TLS	Ordinary/Total least square
BLUE	Best linear unbiased estimator
ANOVA	Analysis of variance
VIF	Variance inflation factors
DW test	Durbin–Watson test
ARIMA (AR, MA, ARMA)	Autoregressive integrated moving average (autoregressive, moving average, autoregressive moving average)
EEMD (EMD)	Ensemble empirical mode decomposition (empirical mode decomposition)
IMF	Intrinsic mode functions
PLSR	Partial least squares regression
PCA (PC)	Principal component analysis (principal component)
EOF	Empirical orthogonal functions
CCA	Canonical correlation analysis
IAV	Inter-annual variation
IDV	Inter-decadal variation
MDV	Multi-decadal variation
ICA	Independent component analysis
DSS	Denoising source separation
MTM-SVD (SVD)	MultiTaper method-singular value decomposition (singular value decomposition)
OFP	Optimal fingerprint

Table A2. List of acronyms (climate).

Acronym	Full name
C-LSAT	China-land surface air temperature
ERSST	Extended reconstruction sea surface temperature
CMST	China merged surface temperature
GMST	Global mean surface temperature
CAM	Climate anomaly method
PDO	Pacific decadal oscillation
AMO	Atlantic multi-decadal oscillation
ENSO	Elnino and southern oscillation
DAMIP	Detection and attribution model intercomparison project
DTR	Daily temperature range
OGHG (GHG)	Other greenhouse gases (greenhouse gases)

ORCID iD

Qingxiang Li  <https://orcid.org/0000-0002-1424-4108>

References

- Aires F, Chédin A and Nadal J-P 2000 Independent component analysis of multivariate time series: application to the tropical SST variability *J. Geophys. Res. Atmos.* **105** 17437–55
- Bindoff N et al 2013 Detection and attribution of climate change: from global to regional *Climate Change 2013 the Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* ed T F Stocker, D Qin, G-K Plattner, M Tignor, S K Allen, J Boschung, A Nauels, Y Xia, V Bex and P M Midgley (Cambridge: Cambridge University Press)
- Chong I-G and Jun C-H 2005 Performance of some variable selection methods when multicollinearity is present *Chemometr. Intell. Lab. Syst.* **78** 103–12
- Dai A, Fyfe J C, Xie S P and Dai X 2015 Decadal modulation of global surface temperature by internal climate variability *Nat. Clim. Change* **5** 555–9
- Folland C K, Boucher O, Colman A and Parker D E 2018 Causes of irregularities in trends of global mean surface temperature since the late 19th century *Sci. Adv.* **4** eaao5297
- Frankcombe L M, England M H, Mann M E and Steinman B A 2015 Separating internal variability from the externally forced climate response *J. Clim.* **28** 1814–202
- Gillett N P, Shiogama H, Funke B, Hegerl G, Knutti R, Matthes K, Santer B D, Stone D and Tebaldi C 2016 The detection and attribution model intercomparison project (DAMIP v1.0) contribution to CMIP6 *Geosci. Model Dev.* **9** 3685–97
- Haigh J D 2003 The effects of solar variability on the Earth's climate *Phil. Trans. R. Soc. A* **361** 95–111
- Hansen J et al 2007 Climate simulations for 1880–2003 with GISS model E *Clim. Dyn.* **29** 661–96

- Hasselmann K 1993 Optimal fingerprints for the detection of time-dependent climate change *J. Clim.* **6** 1957–71
- Haywood J, Stouffer R, Wetherald R, Manabe S and Ramaswamy V 1997 Transient response of a coupled model to estimated changes in greenhouse gas and sulfate concentrations *Geophys. Res. Lett.* **24** 1335–8
- Hegerl G C, Von Storch H, Hasselmann K, Santer B D, Cubasch U and Jones P D 1996 Detecting greenhouse-gas-induced climate change with an optimal fingerprint method *J. Clim.* **9** 2281–306
- Hegerl G, Zwiers F, Braconnot P, Gillet N, Luo Y, Marengo Orsini J, Nicholls N, Penner J and Stott P 2007 Understanding and attributing climate change *Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change* ed S Solomon, D Qin, M Manning, Z Chen, M Marquis, K B Averyt, M Tignor and H L Miller (Cambridge: Cambridge University Press)
- Hou Z S and Li X D 2000 Signal detection of climate changes and external forcing factors *Acta Sci. Nat. Univ. Pekin.* **36** 641–50
- Huang B et al 2017 Extended reconstructed sea surface temperatures version 5 (ERSSTv5): upgrades, validations, and intercomparisons *J. Clim.* **30** 8179–205
- Huang N E, Shen Z, Long S R, Wu M C, Shih H H, Zheng Q, Yen N-C, Tung C C and Liu H H 1998 The empirical mode decomposition and the Hilbert spectrum for nonlinear and nonstationary time series analysis *Proc. R. Soc. A* **454** 903–95
- Huang N E and Wu Z 2008 A review on Hilbert–Huang transform: method and its applications to geophysical studies *Rev. Geophys.* **46** RG2006
- Huiwen W 1999 *Partial Least Squares Regression Method and Its Application* (Beijing: National Defense Industry Publisher) (in Chinese)
- Hurrell J W 1995 Decadal trends in the North Atlantic oscillation: regional temperature and precipitation *Science* **269** 676–9
- Hyvärinen A, Karhunen J and Oja E 2001 *Independent Component Analysis* (New York: Wiley)
- Ilin A and Valpola H 2005 Frequency-based separation of climate signals *Proc. Ninth European Conf. on Principles and Practice of Knowledge Discovery in Databases (PKDD'2005) (Porto, Portugal)* pp 519–26
- Ilin A, Valpola H and Oja E 2006 Exploratory analysis of climate data using source separation methods *Neural Netw.* **19** 155–67
- Jones P D, Osborn T J and Briffa K R 1997 Estimating sampling errors in large scale temperature averages *J. Clim.* **10** 2548–68
- Kim K-Y and Wu Q 1999 A comparison study of EOF techniques: analysis of nonstationary data with periodic statistics *J. Clim.* **12** 185–99
- Lean J L and Rind D H 2008 How natural and anthropogenic influences alter global and regional surface temperatures: 1889–2006 *Geophys. Res. Lett.* **35** L18701
- Li Q 2020 Statistical modeling experiment of land precipitation variations since the start of the 20th century with external forcing factors *Chin. Sci. Bull.* **65** 2266–78
- Li Q, Huang J and Ju X 2008 Experimental study on reconstruction of maximum temperature data in Shanghai *J. Trop. Meteorol.* **24** 349–53
- Li Q, Sun W, Huang B, Dong W, Wang X, Zhai P and Jones P 2020 Consistency of global warming trends strengthened since 1880s *Sci. Bull.* **65** 1709–12
- Li Q, Sun W, Yun X, Huang B, Dong W, Wang X, Zhai P and Jones P 2021 An updated evaluation of the global mean land surface air temperature and surface temperature trends based on CLSAT and CMST *Clim. Dyn.* **56** 535–50
- Lotsch A, Friedl M A and Pinzón J 2003 Spatio-temporal deconvolution of NDVI image sequences using independent component analysis *IEEE Trans. Geosci. Remote Sens.* **41** 2938–42
- Mann M E and Emanuel K A 2006 Atlantic hurricane trends linked to climate change *EOS Trans. Am. Geophys. Union* **87** 233–41
- Mann M E, Steinman B A and Miller S K 2014 On forced temperature changes, internal variability, and the AMO *Geophys. Res. Lett.* **41** 3211–9
- Mantua N J, Hare S R, Zhang Y, Wallace J M and Francis R C 1997 A Pacific interdecadal climate oscillation with impacts on salmon production *BAMS* **78** 1069–79
- Myhre G et al 2013 Anthropogenic and natural radiative forcing *Climate Change (2013) the Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* ed T F Stocker, D Qin, G-K Plattner, M Tignor, S K Allen, J Boschung, A Nauels, Y Xia, V Bex and P M Midgley (Cambridge: Cambridge University Press)
- Preisendorfer R W 1988 *Principal Component Analysis in Meteorology and Oceanography* (Amsterdam: Elsevier)
- Ramaswamy V and Chen C-T 1997 Linear additivity of climate response for combined albedo and greenhouse perturbations *Geophys. Res. Lett.* **24** 567–70
- Ribera P et al 2020 Internal variability and external forcings in the ocean atmosphere multidecadal oscillator over the North Atlantic *Clim. Dyn.* **55** 909–23
- Ribes A, Zwiers F W, Azais J-M and Naveau P 2017 A new statistical approach to climate change detection and attribution *Clim. Dyn.* **48** 367–86
- Richman M B 1986 Rotation of principal components *J. Climatol.* **6** 293–335
- Santer B D, Wigley T M L, Doutriaux C, Boyle J S, Hansen J E, Jones P D, Meehl G A, Roeckner E, Sengupta S and Taylor K E 2001 Accounting for the effects of volcanoes and ENSO in comparisons of modeled and observed temperature trends *J. Geophys. Res.* **106** 28033–59
- Schwaiger H P and Bird D N 2010 Integration of albedo effects caused by land use change into the climate balance: should we still account in greenhouse gas units? *For. Ecol. Manage.* **260** 278–86
- Shindell D T et al 2013 Radiative forcing in the ACCMIP historical and future climate simulations *Atmos. Chem. Phys.* **13** 2939–74
- Sieber P, Ericsson N and Hansson P A 2019 Climate impact of surface albedo change in life cycle assessment: implications of site and time dependence *Environ. Impact Assess. Rev.* **77** 191–200
- Staeger T, Grieser J and Schönwiese C D 2003 Statistical separation of observed global and European climate data into natural and anthropogenic signals *Clim. Res.* **24** 3–13
- Stott P A and Kettleborough J A 2002 Origins and estimates of uncertainty in predictions of twenty-first century temperature rise *Nature* **416** 723–6
- Sun W, Li Q, Huang B, Cheng J, Song Z, Li H, Dong W, Zhai P and Jones P 2021 The assessment of global surface temperature change from 1850s: the CLSAT2.0 ensemble and the CMST-Interim datasets *Adv. Atmos. Sci.* (<https://doi.org/10.1007/s00376-021-1012-3>)
- Tett S F B, Stott P A, Allen M R, Ingram W J and Mitchell J F B 1999 Causes of twentieth century temperature change near the Earth's surface *Nature* **399** 569–72
- Theil H 1971 Least squares and the standard linear model *Principles of Econometrics* (New York: Wiley) pp 101–62
- von Storch H and Zwiers W 1999 *Statistical Analysis in Climate Research* (Cambridge: Cambridge University Press)
- Wei M, Qiao F, Guo Y, Deng J, Song Z, Shu Q and Yang X 2019 Quantifying the importance of interannual, interdecadal and multidecadal climate natural variabilities in the modulation of global warming rates *Clim. Dyn.* **53** 6715–27
- Wu T, Hu A, Gao F, Zhang J and Meehl G A 2019 New insights into natural variability and anthropogenic forcing of global/regional climate evolution *npj Clim. Atmos. Sci.* **2** 18

- Wu Z, Huang N E, Wallace J M, Smoliak B V and Chen X 2011 On the time-varying trend in global-mean surface temperature *Clim. Dyn.* **37** 759–73
- Xu W *et al* 2018 A new integrated and homogenized global monthly land surface air temperature dataset for the period since 1900 *Clim. Dyn.* **50** 2513–36
- Yun X, Huang B, Cheng J, Xu W, Qiao S and Li Q 2019 A new merge of global surface temperature datasets since the start of the 20th Century *Earth Syst. Sci. Data* **11** 1629–43
- Zhang L and Wang C 2013 Multidecadal North Atlantic sea surface temperature and Atlantic meridional overturning circulation variability in CMIP5 historical simulations *J. Geophys. Res. Oceans* **118** 5772–91
- Zhang X and Zhang F 1985 The relationship between large volcanic eruptions and the dryness/wetness and cold/warm in China *Acta Meteorol. Sin.* **43** 196–207
- Zhang X, Zwiers F W and Stott P A 2006 Multi-model multi-signal climate change detection at regional scale *J. Clim.* **19** 4294–307
- Zhou J and Tung K K 2013 Deducing the multi-decadal anthropogenic global warming trend using multiple regression analysis *J. Atmos. Sci.* **70** 3–8