Earth Syst. Dynam. Discuss., 3, 561–596, 2012
www.earth-syst-dynam-discuss.net/3/561/2012/
doi:10.5194/esdd-3-561-2012

Earth System Dynamics Discussions

Polynomial cointegration tests of anthropogenic impact on global warming

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Received: 6 May 2012 – Accepted: 25 June 2012 – Published: 16 July 2012

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Published by Copernicus Publications on behalf of the European Geosciences Union.

Abstract

We use statistical methods for nonstationary time series to test the anthropogenic interpretation of global warming (AGW), according to which an increase in atmospheric greenhouse gas concentrations raised global temperature in the 20th century. Specifically, the methodology of polynomial cointegration is used to test AGW since during the observation period (1880–2007) global temperature and solar irradiance are stationary in 1st differences whereas greenhouse gases and aerosol forcings are stationary in 2nd differences. We show that although these anthropogenic forcings share a common stochastic trend, this trend is empirically independent of the stochastic trend in temperature and solar irradiance. Therefore, greenhouse gas forcing, aerosols, solar irradiance and global temperature are not polynomially cointegrated. This implies that recent global warming is not statistically significantly related to anthropogenic forcing. On the other hand, we find that greenhouse gas forcing might have had a temporary effect on global temperature.

1 Introduction

Considering the complexity and variety of the processes that affect Earth's climate, it is not surprising that a completely satisfactory and accepted account of all the changes that occurred in the last century (e.g. temperature changes in the vast area of the Tropics, the balance of CO_2 input into the atmosphere, changes in aerosol concentration and size and changes in solar radiation) has yet to be reached (IPCC, AR4, 2007). Of particular interest to the present study are those processes involved in the greenhouse effect, whereby some of the longwave radiation emitted by Earth is re-absorbed by some of the molecules that make up the atmosphere, such as (in decreasing order of importance): water vapor, Carbon Dioxide, Methane and nitrous oxide (IPCC, AR4, 2007). Even though the most important greenhouse gas is water vapor, the dynamics

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of its flux in/out of the atmosphere by evaporation, condensation and subsequent precipitation are not understood well enough to be explicitly and exactly quantified.

While much of the scientific research into the causes of global warming has been carried out using calibrated general circulation models (GCMs), since 1997 a new branch of scientific inquiry has developed in which observations of climate change are tested statistically by the method of cointegration (Kaufmann and Stern, 1997, 2002; Stern and Kaufmann, 1999, 2000; Kaufmann et al., 2006a,b; Liu and Rodriguez, 2005; Mills, 2009). The method of cointegration, developed in the closing decades of the 20th century, is intended to distinguish between genuine and spurious regression phenomena in nonstationary time series (Phillips, 1986; Granger and Engle, 1987). Nonstationary arises when the sample moments of a time series (mean, variance, covariance) depend on time. Spurious regression occurs when unrelated nonstationary time series appear to be significantly correlated because they happen to have time trends.

The method of cointegration has been successful in detecting spurious correlation in economic time series data[1]. Indeed, cointegration has become the standard econometric tool for testing hypotheses with nonstationary data (Maddala, 2001; Greene, 2012). As noted, climatologists too have used cointegration to analyse nonstationary climate data (Kaufmann and Stern, 1997). Cointegration theory is based on the simple notion that time series might be highly correlated even though there is no causal relation between them. For the correlation to be genuine, the residuals from a regression between these time series must be stationary, in which case the time series are "cointegrated". Since stationary residuals mean-revert to zero, there must be a genuine long-term relationship between the series, which move together over time because they share a common trend. If on the other hand, the residuals are nonstationary, the residuals do not mean-revert to zero, the time series do not share a common trend, and the relationship between them is "spurious" because the time series are not cointegrated.

[1]For example, Enders (1988) in the case of Purchasing Power Parity theory, Johansen and Juselius (1994) in the case of the influential Keynesian IS-LM model, and Hendry and Ericsson (1991) on the demand for money.

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Indeed, the R^2 from a regression between nonstationary time series may be as high as 0.99, yet the correlation may nonetheless be spurious.

The method of cointegration originally developed by Engle and Granger (1987) assumes that the nonstationary data are stationary in changes, or first differences. For example, temperature might be increasing over time, and is therefore nonstationary, but the change in temperature is stationary. In the 1990s cointegration theory was extended to the case in which some of the variables have to be differenced twice (i.e. the time series of the change in the change) before they become stationary. This extension is commonly known as polynomial cointegration. Previous analyses of the nonstionarity of climatic time-series (e.g. Kaufmann and Stern, 2002; Kaufmann et al., 2006a; Stern and Kaufmann, 1999) have demonstrated that global temperature and solar irradiance are stationary in first differences whereas changes in greenhouse gases (GHG, hereafter) are stationary in second differences. In the present study we apply the method of polynomial cointegration to test the hypothesis that global warming since 1850 was caused by various anthropogenic phenomena. Our results show that GHG forcings and other anthropogenic phenomena do not polynomially cointegrate with global temperature and solar irradiance. Therefore, despite the high correlation between anthropogenic forcings, solar irradiance and global temperature, AGW is not statistically significant.

2 Data and methods

We use annual data (1850–2007) on greenhouse gas (CO_2, CH_4 and N_2O) concentrations and forcings, as well as on forcings for aerosols (black carbon, reflective tropospheric aerosols). We also use annual data (1880–2007) on solar irradiance, water vapor (1900–2000) and global mean temperature (sea and land combined 1880–2007). These widely used secondary data are obtained from NASA-GISS (Hansen et al., 1999, 2001). Details of these data may be found in Table A1.

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We carry out robustness checks using new reconstructions for solar irradiance from Lean and Rind (2009), for globally averaged temperature from Mann et al. (2008) and for global land surface temperature (1850–2007) from the Berkeley Earth Surface Temperature Study.

Key time series are shown in Fig. 1 where panels a and b show the radiative forcings for three major GHGs, while panel c shows solar irradiance and global temperature. All these variables display positive time trends. However, the time trends in panels a and b appear more nonlinear than their counterparts in panel c. Indeed, statistical tests reported below reveal that the trends in panel c are linear whereas the trends in panels a and b are quadratic. The trend in solar irradiance weakened since 1970 while the trend in temperature weakened temporarily in the 1950s and 1960s.

The statistical analysis of nonstationary time series, such as those in Fig. 1, has two natural stages. The first consists of unit root tests in which the data are classified by their order and type of nonstationarity. If the data are nonstationary, sample moments such as means, variances and covariances depend upon when the data are sampled, in which event least squares and maximum likelihood estimates of parameters may be spurious. In the second stage, these nonstationary data are used to test hypotheses using the method of cointegration, which is designed to distinguish between genuine and spurious regression. Since these methods may be unfamiliar to readers of Earth System Dynamics, we provide an overview of key concepts and tests.

2.1 Unit root tests

A time series is (weakly) stationary if its sample moments (means, variances and covariances) do not depend on when they are measured. By definition, a time series is nonstationary or integrated to order d, I(d) for short, if its d-th difference is stationary but its $d-1$-th difference is not. We quantify the order of the data's nonstationarity using a variety of unit root tests. The most well-known is the Dickey–Fuller (DF) test statistic (Dickey and Fuller, 1981), which is based on the null hypothesis that the variable is nonstationary. The KPSS test statistic is based on the null hypothesis that the

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variable is stationary (Kwiatkowski et al., 1992). Given the low power of these tests there is a case for using both types of test (Maddala and Kim, 1998). If DF rejects its null of nonstationarity and KPSS does not reject its null of stationarity, both test statistics are compatible, and the variable is likely to be stationary. The same applies when DF does not reject its null and KPSS rejects its null, i.e. the variable is not stationary. It is, however, logically possible for KPSS to reject its null hypothesis (the variable is nonstationary) and for DF not to reject its null hypothesis (the variable is not nonstationary) since the two types of test are conceptually different. In this event, a dilemma arises since DF and KPSS happen to be incompatible.

Nonstationary I(1) variables are either "trend stationary" or "difference stationary". In the former case the deviation from a deterministic linear trend is stationary, random shocks to the variable are expected to dissipate over time as the trend is re-established. In the latter case, the first difference of the variable is stationary, random shocks are expected to persist over time and the trend is therefore stochastic. Critical values for the DF and KPSS statistics are more stringent in the former case because the trend stationary model involves an additional parameter (time trend). In the event that both models appear to be consistent with the data, Dickey and Fuller (1981) have proposed a test that distinguishes between them.

The DF and KPSS statistics assume that the residuals in the data generating process are serially independent. If they are not, these statistics have to be corrected. The augmented DF statistic (ADF, see Said and Dickey, 1984) assumes that the serial correlation is induced by dynamics in the data generating process (DGP). Another correction for the DF statistic is the DF-GLS statistic (i.e. DF statistic estimated by Generalized Least Squares see Elliott, Rothenberg and Stock, 1996), which assumes that serial correlation in the DGP is inherent and is estimated by generalized least squares (GLS). The Phillips-Perron (PP) statistic (Phillips and Perron, 1988) is a robust estimate of the DF statistic, which corrects its standard deviation for serial correlation in the DGP. This correction method is also used by KPSS.

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Stationary time series which contain structural breaks may appear nonstationary because their mean varies over time. The same applies to trend stationary time series which contain structural breaks. For example, Kaufmann et al. (2010) show that global temperature is not trend stationary in the presence of structural breaks, and that it is difference stationary. See Clemente et al. (1988) regarding DF tests in the presence of structural breaks and Lee and Strazicich (2001) for KPSS tests in the presence of structural breaks.

2.2 Cointegration tests

Cointegration tests typically refer to hypothesized steady-state relationships in the data. This feature is particularly useful because it means that it is unnecessary to specify auxiliary hypotheses regarding dynamic convergence processes towards steady states. Although this methodological simplification applies asymptotically, it has a number of important advantages. First, steady states may be inherently more interesting than adjustment paths. In the case of AGW the main interest is the long-term anthropogenic impact on climate rather than how it diffuses over time. Secondly, tests of the steady state are robust asymptotically with respect to unknown paths of adjustment. Often, steady state theory is more developed than its ancillary theory of adjustment. These adjustment theories may be nonlinear, as they commonly are in GCMs, but cointegration does not require the specification of these details. Third, estimates of long-term cointegrated relationship are "super-consistent"; the causal effect of forcing on global temperature is asymptotically identified even if there happens to be reverse causality from temperature to forcing.

If the steady state is linear (i.e. the assumed relationship between the variables in the regression model is linear) then linear cointegration theory is sufficient to test restrictions regarding the steady state. If the steady state is nonlinear then nonlinear cointegration theory may be used to test relevant restrictions about the steady state (Choi and Siakkonen, 2010). Nonlinear cointegration theory is naturally more complex than its linear counterpart. GCMs are nonlinear because they embody nonlinear terms

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and adjustment processes rather than nonlinear steady states. Therefore, for the most part we focus on linear cointegration tests. However, we also use nonlinear cointegration theory to test AGW in nonlinear contexts.

Several different cointegration methodologies are available. The original methodology proposed by Engle and Granger (1987), based on ordinary least squares, is designed for "asymptotic samples" in which the steady state is repeatedly observable. Typically, this requires long time series in terms of calendar time. In our case we use annual data from 1850 or 1880. If the adjustment process of temperature with respect to forcings is very protracted this sample may be too short to test hypotheses about steady states. Engle and Yoo (1987) have suggested a test to determine whether estimates based on the Engle–Granger methodology are subject to finite sample bias. We use this test to show that the sample is sufficiently long.

Other cointegration methodologies have been proposed for non-asymptotic samples in which the steady state may be concealed by short-term adjustment processes in the data. These include the methodology of Johansen (1988), the dynamic ordinary least squares (DOLS) methodology of Stock and Watson (1989) and the error correction (ECM) methodology (Ericsson and MacKinnon, 2002). All these methodologies filter out (in different ways) short-term dynamics in the data that may conceal the hypothesized steady states. In all of these methodologies the null hypothesis is "no cointegration, or spurious regression". Shin (1994) has extended the KPSS methodology (see above) to test the null hypothesis of "cointegration or genuine regression."

2.3 Polynomial cointegration

In standard cointegration tests the variables must be difference stationary or trend stationary, in which case all the variables are I(1). If some of the variables happen to be I(2) the null hypothesis may be tested using polynomial cointegration. Normally variables such as greenhouse gas forcings that are I(2) cannot be cointegrated with I(1) variables such as global temperature, and the empirical relationship between them is generally spurious. An exception, however, arises when the I(2) variables cointegrate into an I(1) variable, which happens to be cointegrated with other I(1) variables, i.e. they are polynomially cointegrated. There are also different methodologies for polynomial cointegration, which have been reviewed by Maddala and Kim (1998). Haldrup (1994) extended the Engle–Granger methodology to polynomial cointegration, as did Johansen (1995) for his methodology, and Stock and Watson (1993) for theirs'. There are conceptual differences between these methodologies. Haldrup's methodology hypothesizes that the I(2) variables may "cointegrate down" to an I (1) variable, i.e. they share a common stochastic trend. Johansen's methodology hypotheses the existence of a deterministic trend among the I(2) variables[2]. In the context of greenhouse gas forcing this means that there is an autonomous time trend causing forcing to diverge over time.

We prefer Haldrup's methodology over Johansen's for several reasons. First, there is no physical justification for an autonomous time trends in greenhouse gas forcing. For example, the anthropogenic component of CO_2 forcing depends on world consumption of hydrocarbons, which has a stochastic trend rather than a deterministic trend. Therefore CO_2 forcing should not have a deterministic trend (as confirmed by our unit root tests). Second, Johansen's method is less robust than least squares methods (Maddala and Kim, 1998, p. 173) due to its greater parametricity[3]. On the other hand, Johansen's method takes account of feedback between the covariates. However, this advantage does not apply in our case since for physical reasons there is no feedback

[2]In reference to Johansen's I(2) estimator Juselius (2007) notes (p. 315) that, "In particular, this means that we need to allow for trend-stationary relations as a starting hypothesis.".

[3] Juselius (2007) writes (p. 55) in relation to the assumption that the residuals in Johansen's method must be multivariate normal, "If they do not pass these tests, for example, because they are autocorrelated or heteroscedastic, or because the distribution is skewed or leptokurtic, then the estimates may no longer have optimal properties and cannot be considered full-information maximum likelihood (FIML) estimates. The obtained parameter estimates may not have any meaning, and since we do not know their "true" properties, inference is likely to be hazardous." We might add that the Johansen method is based on concentrated ML, which assumes that short run dynamics in the data may be concentrated out independently of their long-run behavior. In short, the robustness of Johansen's method is weakened by its numerous assumptions.

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between solar irradiance and greenhouse gas forcing, nor does temperature feedback onto solar irradiance and greenhouse gas forcing. Fourth, as noted by Davidson and MacKinnon (2008, p. 617), Johansen's methodology is more prone to finite sample bias than its least squares alternatives. Therefore, if we suspect that our sample is insufficiently long, it is preferable to use least squares methods. Fifth, as noted by Maddala and Kim (1998, p. 203), the Engle-Granger procedure upon which Haldrup's method is based is statistically under-powered, i.e. it tends to accept false positive results by more than it should. In the present context this means that our polynomial cointegration methodology is too "soft" with respect to AGW. Since a positive result might have been incorrect, rejection of AGW is in some sense against the odds, and therefore more convincing. A final reason is that previous researchers have used least squares methods. Therefore, Haldrup's method enables us to reconstruct incorrect inferences in previous least squares studies which ignored the important fact that greenhouse gas forcing is I(2).

Parameters estimated from stationary time series (in which the data are I(0)) are $T^{1/2}$-consistent, where T denotes the number of observations. If the data are I(1) and are cointegrated the parameter estimates are $T^{1\,1/2}$-consistent, or "super-consistent". If the data are I(2) and are polynomially cointegrated the parameter estimates are $T^{2\,1/2}$-consistent, or "super-super consistent". The higher the order of consistency, the faster the parameter estimates converge in probability on their true values. The super-super consistency property of polynomial cointegration means in theory that one learns from 150 yr of climate data what would have required at least a millenium of stationary data.

We do not report t-statistics for the parameter estimates in the cointegrating vector because it is well-known that when the data are nonstationary the parameter estimates based on OLS have non-standard distributions. This is particularly the case when variables such as temperature and greenhouse gas forcing may be dynamically dependent. Since t-tests and chi-squared tests are invalid, we test rival hypotheses by carrying out nested cointegration tests. For example, suppose that temperature, solar irradiance and greenhouse gas forcings seem to be cointegrated. To test whether

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cointegration arises because of the specification of greenhouse gas forcings, we omit these forcings from the model (jointly or severally) and test whether temperature and solar irradiance are still cointegrated. If they are not cointegrated, we confirm that greenhouse gas forcings should be specified and AGW is confirmed. In the opposite case the model is cointegrated without greenhouse forcings, AGW is rejected and temperature in the steady state depends entirely on solar irradiance.

2.4 Stochastic energy balance models (SEBM)

We use the stochastic energy balance model (SEBM) to motivate our cointegration tests. SEBM is written as:

$$C\frac{\Delta T_t}{\Delta t} = -\lambda T_{t-1} + F_t + e_t \tag{1}$$

where T denotes temperature, F denotes forcing, e denotes a stochastic iid (identically and independently distributed) component, subscript t denotes discrete time, and λ/C is the rate at which temperature converges to its steady state. Normalizing Δt to unity, the general solution to Eq. (1) for T is:

$$T_t = \frac{1}{C}\sum_{i=1}^{\infty}\rho^i(F_{t-i} + e_{t-i}) + \kappa\rho^t \tag{2}$$

where $0 < \rho = 1 - \lambda/C < 1$ and κ is an arbitrary constant reflecting initial conditions. Since $\rho < 1$ the final term in Eq. (2) tends zero. Suppose forcing is a random walk with drift:

$$\Delta F_t = \varphi + f_t, \tag{3}$$

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where f is iid. Substituting Eq. (3) into Eq. (2) for F_{t-i} gives:

$$\begin{aligned} T_t &= \alpha + \beta F_t + u_t, \\ \alpha &= -\frac{\rho\varphi}{C(1-\rho)^2}, \\ u_t &= \frac{1}{C}\sum_{i=0}^{\infty}\rho^i e_{t-i} - \frac{1}{\lambda}\sum_{i=0}^{\infty}\rho^{1+i} f_{t-i}. \end{aligned} \tag{4}$$

Equation (4) decomposes temperature into a stationary, serially correlated component (u) and a nonstationary component, F. Finally, we disaggregate forcing (F) into its component parts:

$$T_t = \alpha + \beta_s S_t + \beta_g G_t - \beta_a A_t + u_t, \tag{5}$$

where S denotes solar irradiance, G denotes greenhouse gas forcing, A denotes aerosols and the β coefficients are parameters to be estimated. SEBM predicts that the steady-state parameters in Eq. (5) are positive. The model is cointegrated if the residual error, u, is stationary I(0). If the residuals are nonstationary the estimated model is spurious. Equation (5) is assumed to be linear, but it may also be specified to be nonlinear.

2.5 Dependent and independent forcings

We distinguish between dependent and independent forcing, denoted by F_A and F_B, respectively, where $F = F_A + F_B$. Dependent forcing depends on global temperature and perhaps other forcing, while independent forcing is also driven by factors other than those considered here. For example, greenhouse gas and aerosol forcings are independent because they do not depend on temperature. Solar irradiance is obviously independent because what happens to the sun is independent of what happens on

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earth. Water vapor forcing on the other hand is dependent because it depends on temperature. Suppose that dependent forcings are linearly related in the long run to their independent counterparts and global temperature as follows:

$$F_{Bt} = \pi F_{At} + \mu T_t + \varpi_t \tag{6}$$

where ϖ denotes a stationary error. Equation (6) states that dependent forcings are cointegrated with independent forcings and temperature. Substituting Eq. (6) into Eq. (4) gives:

$$T_t = \psi_0 + \psi_1 F_{At} + v_t \tag{7}$$

where:

$$\psi_0 = \frac{\alpha}{1-\beta\mu}, \quad \psi_1 = \beta\frac{1+\pi}{1-\beta\mu}, \quad v_t = \frac{\beta\varpi_t + u_t}{1-\beta\mu}. \tag{8}$$

Equation (7) states that global temperature varies directly with independent forcing. However, the coefficient ψ_1 reflects the direct effect of forcing (β) and the indirect effect of F_A and temperature through F_B. Typically, $\psi_1 > \beta$ because $\pi > 0$ and $\beta\mu < 1$, i.e. the total long-run effect of independent forcing is greater than its direct effect. Since ϖ and u are stationary so must v be stationary.

What is important for our purposes is that cointegration tests do not require data on dependent forcing since $\psi_1 = 0$ when $\beta = 0$. Therefore, dependent variables, such as water vapor and ocean heat content, do not in principle affect cointegration tests. This conclusion is consistent with Stern (2006) who shows that cointegration tests of the relationship between temperature and forcing do not depend on the relationship between temperature and ocean heat content. If Eq. (6) is cointegrated or not, so must Eq. (4) be cointegrated or not. Finally, F_A may be decomposed into I(1) and I(2) components. F_A must be I(2) if at least one of its components is I(2). In the next section we show that although solar irradiance is I(1), anthropogenic forcings are I(2).

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3 Results

3.1 Time series properties of the data

We begin by classifying the variables in terms of their order of stationarity (d) using various tests. In Table 1 we provide details of the classification procedure for the radiative forcing of CO_2 ($rfCO_2$). Test 1 shows that according to all three test statistics $rfCO_2$ is not trend stationary (the deviation from a deterministic time trend is not stationary). Test 2 shows that according to the PP statistic $rfCO_2$ is marginally difference stationary, but the KPSS and ADF statistics clearly reject this hypothesis. Test 3 establishes that the 2nd difference of $rfCO_2$ is stationary according to all three test statistics. Therefore, $rfCO_2$ is clearly I(2).

We also check whether $rfCO_2$ is I(1) subject to a structural break. A break in the stochastic trend of $rfCO_2$ might create the impression that $d = 2$ when in fact $d = 1$. We apply the test suggested by Clemente et al. (1998) (CMR). The CMR statistic (which is the ADF statistic allowing for a break) for the first difference of $rfCO_2$ is −3.877. The break occurs in 1964, but since the critical value of the CMR statistic is −4.27 we can safely reject the hypothesis that $rfCO_2$ is I(1) with a break in its stochastic trend.

We have applied these test procedures to the variables in Table 2. The results of these tests show that the radiative forcings of CO_2, CH_4 and N_2O are all I(2), but the radiative forcing of water vapour and ocean heat content are I(1). In addition, the radiative forcings of reflective tropospheric aerosols and black carbon are also I(2). However, the radiative forcing of stratospheric aerosols (mainly volcanic in origin) is I(0). Global temperature and solar irradiance are I(1). The radiative forcing of stratospheric H_2O is I(1) which turns out to be cointegrated with global temperature. In summary, anthropogenic forcings are I(2), whereas all other forcings are I(1), like global temperature.

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3.2 An anthropogenic trend?

Normally, I(1) and I(2) variables cannot be cointegrated in which case observed relationships between them are spurious. Since the radiative forcings of greenhouse gases, tropospheric aerosols and black carbon are I(2) they cannot be cointegrated with global temperature and solar irradiance, which are I(1). An exception arises if the I(2) variables happen to be cointegrated between themselves and they cointegrate into an I(1) variable. If this I(1) variable is cointegrated with other I(1) variables, the relationship between the I(2) and I(1) variables is not spurious. In this case the variables are polynomially cointegrated[4].

We therefore test the hypothesis that the anthropogenic I(2) forcings are cointegrated, and if so, whether they cointegrate into an I(1) variable, which we refer to as the "anthropogenic trend". We carry out this test with and without tropospheric aerosols and black carbon (Eqs. 9 and 10, respectively). The least squares estimate of the cointegrating vector for the three greenhouses gases ($rfCO_2$, $rfCH_4$ and rfN_20) using data from 1850–2007 is:

$$rfCO_2 = 10.972 + 0.046 rfCH_4 + 10.134 rfN_2O + g_1 \tag{9}$$

where g_1 denotes the residual and $\bar{R}^2$ of this regression is 0.994. When tropospheric aerosols and black carbon are included, the OLS estimate using data from 1880 to 2003 is:

$$rfCO_2 = 12.554 + 0.345 rfCH_4 + 9.137 rfN_2O + 1.029 BC + 0.441 Reflaer + g_2 \tag{10}$$

where BC denotes radiative forcing of black carbon concentration, Reflaer is the radiative forcing of all reflective aerosols and g_2 denotes the residual. The $\bar{R}^2$ of this regression is 0.996. We use a variety of cointegration test statistics to estimate the order of integration of g_1 and g_2 (d_g) in Eqs. (9) and (10). Haldrup (1994) reports critical values (for ADF) when there are mixtures of I(1) and I(2) variables. According to

[4] Enders (2010) refers to this phenomenon by "multicointegration".

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Haldrup the critical value for the cointegration test statistic at $p = 0.05$ is -3.85 for g_1 and -4.1 for g_2. If $d_g = 2$ the GHG are not cointegrated. The test statistics are shown in Fig. 2 where panels a, c and e test whether g_1 and g_2 are stationary and panels b, d and f test whether the first difference of g_1 and g_2 are stationary. Since all the tests statistics in panels a, c and e are clearly greater than their critical values (shown by the horizontal lines), we may reject the hypothesis that g_1 and g_2 are stationary. Since in panels b, d and f all test statistics for g_1 (left columns in panels b, d and f) are smaller than their critical values, we cannot reject the hypothesis that g_1 is difference stationary. However, in the case of g_2 (right columns in panels b, d and f) matters are less clear-cut. Although according to the KPSS test (using the cointegration test statistic from Shin, 1994) and PP test statistics g_2 is difference stationary, the ADF statistic is slightly submarginal.

We therefore confidently conclude in the case of g_1 that $d_g = 1$. The same almost certainly applies also to g_2. The fact that $d_g = 1$ means that greenhouse gas forcings, tropospheric aerosols and black carbon share a common stochastic trend, which we represent by g_1 or g_2. This "anthropogenic trend" is difference stationary and is named as such because the variables concerned share a common anthropogenic factor. We therefore have two candidates, g_1 and g_2, for the anthropogenic trend, which we use in our polynomial cointegration tests. If g_1 or g_2 cointegrate with temperature and solar irradiance then AGW is corroborated because the I(2) variables are polynomially cointegrated with the I(1) variables.

3.3 Polynomial cointegration test

We now test whether greenhouse gas forcings are polynomially cointegrated with global temperature and solar irradiance. Using data for 1880–2007 the OLS estimate of the relationship between global temperature (T), solar irradiance (S) and g_1 is:

$$T = 13.800 + 1.763S - 0.019g_1 \tag{11}$$

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where $\bar{R}^2$ is 0.447. There is a positive relationship between temperature and solar irradiance, but there is a small negative relationship between temperature and the anthropogenic trend represented by g_1. Using the broader definition of the anthropogenic trend (g_2) the OLS estimate is:

$$T = 13.795 + 1.806S - 1.822g_2 \qquad (12)$$

where $\bar{R}^2$ is 0.468. The coefficients of solar irradiance are similar in Eqs. (11) and (12), but the anthropogenic trend has a positive coefficient in Eq. (12), which has a slightly better goodness-of-fit. Only I(1) variables are specified in Eqs. (11) and (12) since I(0) variables, such as stratospheric aerosols (volcanic emissions) have no asymptotic effect on the coefficients of the cointegrating vector.

According to Haldrup (1994) the critical value ($p = 0.05$) of the test statistic to test for polynomial cointegration is −4.56 in the case of Eq. (11) and about −4.8 in the case of Eq. (12). Unfortunately, there is no KPSS test statistic for polynomial cointegration. According to Shin (1994) the critical value of the KPSS cointegration test statistics are 0.121 and about 0.08 respectively under the assumption that the variables are I(1). Since polynomial cointegration test statistics are more stringent than ordinary cointegration test statistics, Shin's critical values serve as upper limits for polynomial cointegration tests. The results for these polynomial cointegration tests are presented in the two left columns on the three panels of Fig. 3. From panels a and c it is clear that the ADF and KPSS tests agree that both models (Eqs. 11. and 12) are not cointegrated (test results higher than their critical values) while the panel b implies that the PP test is marginal for these two models. We may, therefore, reject the hypothesis that temperature is polynomially cointegrated with solar irradiance and the anthropogenic trend. This means that although global temperature and greenhouse gas forcings are highly correlated (e.g. the Pearson correlation coefficient of $rfCO_2$ and T is 0.87), the correlation between them might in fact be spurious. Indeed, this result applies to other anthropogenic phenomena such as tropospheric aerosols and black carbon (middle columns in panels a, b and c).

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3.4 Reconstructing invalid cointegration tests

As noted, a number of studies (Kaufmann and Stern, 2002; Kaufmann et al., 2006b, 2010; Mills, 2009) recognize that greenhouse gas forcings are I(2) variables, but their cointegration tests treat the I(2) variables as if they were I(1) variables. To explore the implications of this oversight we use the model specification used in these studies[5] estimated with data for 1880–2000:

$$T = -18.05 + 1.06\mathrm{rfCO_2}0.66S - 1.89\mathrm{rfCH_4} + 0.71\mathrm{rfN_2O} \quad (13)$$

where $\bar{R}^2$ is 0.6829. According to Eq. (13) temperature varies directly with solar irradiance and CO_2 forcing, implying that a doubling of atmospheric $\mathrm{rfCO_2}$ raises global temperature by almost 4°. The cointegration test statistics are $\mathrm{ADF}_4 = -4.76$, $\mathrm{PP} = -7.73$, $\mathrm{KPSS} = 0.11$. Since the critical values of ADF and PP are −4.18 (MacKinnon, 1991) and the critical value for KPSS is 0.121 (Shin, 1994), it would appear that Eq. (13) is cointegrated. But this result ignores the fact that greenhouse gas forcings are I(2).

The correct cointegration test involves specifying an I(2) variable as a regressand (Haldrup, 1994). Using $\mathrm{rfCO_2}$ for such purposes we estimate:

$$\mathrm{rfCO_2} = 11.92 + 0.03T - 0.12S + 0.15\mathrm{rfCH_4} + 9.36\mathrm{rfN_2O} \quad (14)$$

where $\bar{R}^2 = 0.996$. According to Eq. (14) temperature is more sensitive to forcings than in Eq. (13), however, despite the high goodness-of-fit the regression is spurious. The critical value of the ADF for polynomial cointegration is −4.56 (Haldrup, 1994) when their test values are −2.22. The KPSS statistic is 0.277. Although there is no KPSS statistic for polynomial cointegration, its critical value must be smaller than 0.121, which is its critical value for I(1) variables from Shin (1994). The ADF and KPSS statistics strongly suggest that Eq. (14) is spurious. Therefore treating the I(2) variables, which

[5] Since tropospheric aerosols and black carbon did not feature in their model, we do not include these variables. However, this omission does not affect the results.

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are exclusively anthropogenic, as if they were I(1) variables, predisposes the results into falsely accepting the anthropogenic interpretation of global warming.

In summary, ignoring the fact that greenhouse gas forcings are I(2) and treating them as if they were I(1) variables creates the false impression that global temperature is cointegrated with solar irradiance and greenhouse gas forcings. This "spurious" regression suggests (spuriously) that a doubling of carbon forcing will raise global temperature by about 4 degrees. Once the I(2) status of anthopogenic forcings is taken into consideration, there is no significant effect of anthropogenic forcing on global temperature.

3.5 Water vapor and ocean heat content

It has been suggested by Stern (2006) that cointegration tests should take into account the transfer of heat that occurs between the atmosphere and the oceans. The heating of earth by the sun is absorbed mostly by the oceans, and part of this energy is transformed into evaporated water (i.e. latent heat) that heats the atmosphere and cools the ocean. The top ten meters of the water column stores as much heat as the entire atmosphere. There are two issues here that are relevant to the statistical tests performed here. First, as discussed above, because water vapor and ocean heat content are entirely dependent on temperature, they cannot affect cointegration tests asymptotically. Therefore, omitting these variables does not affect the tests that we have reported because their effect is intermediated by other variables in the model.

Secondly, because water vapor is dependent on I(1) variables, it is an I(1) variable (see Table 2) as expected. Indeed, water vapor and global temperature turn out to be cointegrated (results not shown) with global temperature. Water vapor is I(1) because global temperature is I(1), not the other way around. Since water vapor and ocean heat are not I(2) variables their omission cannot affect our main result that the anthropogenic I(2) variables in Eqs. (11), (12) and (15) do not polynomially cointegrate with global temperature and solar irradiance.

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3.6 Nonlinear cointegration

Thus far our results reject a linear representation of AGW. Suppose instead that AGW is nonlinear. Naturally, a test of this hypothesis requires an explicit nonlinear specification of AGW. Two types of nonlinearity might be involved. First, although anthropogenic forcings are I(2), there might be some nonlinear transformation of them that is I(1). An example of such a nonlinear transformation of a linear I(2) series is the gross domestic product (GDP), which is typically I(2) but the logarithm of GDP is I(1) (Banerjee et al., 1993). Nonlinear cointegration testing would include nonlinear transformations of the I(2) variables in the cointegrating vector. If these nonlinear transformations turn out to be cointegrated with temperature and solar irradiance, nonlinear AGW would be corroborated. We have experimented with numerous nonlinear transformations[6] of GHG forcings (*n*th roots, reciprocals, logarithms etc), but none of them was found to be I(1).

A second type of nonlinearity might be induced by interactions between variables. However, these interactions would have to be I(1) since global temperature is I(1). It would therefore be necessary to interact anthropogenic forcings with some other variable such that their product is I(1). Normally, the product of an I(1) variable and an I(2) variable is not I(1). Perhaps there is some product of an I(0) variables and an I(2) variable that is I(1). If so, we have been unable to find it. Therefore, we have been unable to find some nonlinear specification of AGW even after extensive data-mining. Based on many tests, we conclude that anthropogenic forcings are not nonlinearly cointegrated with temperature and solar irradiance. Nor, of course are they linearly cointegrated.

[6] Choi and Saikkonen (2010) limit their tests to cases in which the covariates are I(1) and their nonlinear transformations are I(1). The nonlinear transformations must be I(1), but there is no reason why the covariates should be I(1). If $x \sim \mathrm{I}(0)$ nonlinear cointegration requires that $f(x) \sim \mathrm{I}(1)$. If $x \sim \mathrm{I}(2)$, it requires $f(x) \sim \mathrm{I}(1)$.

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3.7 A model of short-run AGW

The first differences of I(2) variables are necessarily I(1) variables. Although AGW is rejected by polynomial cointegration tests, we investigate a modified version of AGW in which the first differences of anthropogenic forcings are hypothesized to be cointegrated with temperature and solar irradiance. Although there is no physical theory for this modified theory of AGW, we report it out of curiosity and simply because it turns out to be cointegrated. Indeed, it is the only model for which we can find a statistically significant role for anthropogenics.

In this test all the variables are I(1) in which case standard cointegration tests apply. In this modified AGW the null hypothesis is that anthrpogenic forcings have a temporary rather than a permanent effect on global temperature. Using data for 1880 to 2007 we find that the statistically significant variables include solar irradiance and the first differences (denoted by Δ) in the forcings of three greenhouse gases:

$$T = 13.821 + 1.508S + 10.765\Delta \mathrm{rfCO_2} - 46.256\Delta \mathrm{rfCH_2} + 36.199\Delta \mathrm{rfN_2O} \tag{15}$$

where $\bar{R}^2$ is 0.6539. According to Eq. (15) temperature varies with solar irradiance and it varies directly with the change in $\mathrm{rfCO_2}$ and $\mathrm{rfN_2O}$ and inversely with the change in $\mathrm{rfCH_4}$. This difference between methane and other greenhouse gases has been noted by Liu and Rodriguez (2005) and others. Cointegration tests for this model are presented in the third column of Fig. 3. The test statistics for ADF and PP are clearly smaller than their critical values (MacKinnon, 1991) but the KPSS statistic exceeds its critical value (Shin, 1994). Therefore Eq. (15) is not unambiguously cointegrated. The ADF and PP test statistics suggest that there is a causal effect of the change in CO_2 forcing on global temperature.

3.8 Error correction

Cointegration implies error correction, which is the dynamic process through which temperature converges to its long-term equilibrium level (Engle and Granger, 1987).

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We report the error correction model (ECM) for global temperature since this is the main variable of interest here. This model uses the residuals (u) from Eq. (15), which measure the deviation of temperature from its long-term equilibrium level. Its dynamic specification is estimated using the general-to-specific methodology, which nests-down to a restricted dynamic specification (see e.g. Hendry, 1995 for details of this methodology) which in the present case yields:

$$\begin{aligned}\Delta T_t = \underset{(0.05)}{0.005} - \underset{(1.71)}{0.14\Delta T_{t-2}} - \underset{(2.51)}{0.20\Delta T_{t-3}} + \underset{(2.09)}{0.71\Delta_2^2 S_t} + \underset{(4.08)}{4.72\Delta^3 \mathrm{rfCO}_{2t}} \\ + \underset{(2.41)}{29.74\Delta^2 \mathrm{rfN_2O}_{t-2}} - \underset{(6.38)}{0.50u_{t-1}}\end{aligned} \tag{16}$$

R^2 adj = 0.379 se = 0.12 DW = 1.98 LM = 4.36.

Since the variables in Eq. (16) are stationary and their coefficient estimates have standard distributions, we report absolute t-statistics in parentheses. Since the critical value for the t-statistic ($p = 0.05$) is 1.98, all the parameter estimates in Eq. (16) are statistically significant with the possible exception of the first. In Eq. (16) the change in temperature varies directly with the 3rd difference in $\mathrm{rfCO_2}$ and the twice lagged 2nd difference in $\mathrm{rfN_2O}$. It also varies directly with the 2nd ("seasonal") difference of solar irradiance ($\Delta_2^2 S_t = \Delta S_t - \Delta S_{t-2}$). It does not depend at all on methane. There is evidence of 2nd and 3rd order negative autoregression in the change in temperature. Finally, the error correction coefficient is very significant and is equal to a half. This means that when the temperature deviates from its steady state equilibrium as determined in Eq. (15) about half of the deviation is corrected within a year. These estimated speeds of adjustment are similar to those obtained from time series models (Liu and Rodriguez, 2005; Kaufmann et al., 2006). The Durbin Watson (DW) and Lagrange Multiplier (LM) statistics for serial correlation in the residuals indicate that the dynamic specification of Eq. (16) is appropriate. The t-statistic on the error correction term is large and negative (−6.38). This constitutes further evidence that Eq. (15) is cointegrated.

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3.9 Robustness checks

We carry out a variety of robustness checks regarding the rejection of AGW by polynomial cointegration tests, and the non-rejection of modified AGW. These checks are additional to those that we have already reported, such as nonlinear cointegration tests. The robustness checks fall into three distinct groups. First, we check for the presence of finite sample bias. Second, we check whether our results are robust with respect to different estimation methods. Finally, we check whether they are robust with respect to different data measurements.

We use the 3-stage procedure suggested by Engle and Yoo (1987) to test for finite sample bias. Since the p-value of the F-statistic for the 3rd stage (for which Eq. 16 is the 2nd stage and Eq. 15 is the 1st) is 0.48, we may reject the hypothesis of finite sample bias in Eq. (15). We can only apply this test to cointegrated results. We therefore cannot apply it to Eqs. (11) and (12) since they are not polynomially cointegrated. Nevertheless, the fact that finite sample bias cannot be detected in Eq. (15) suggests that finite sample bias does not explain why AGW is not polynomially cointegrated. If there is no finite sample bias in Eq. (15) where the parameter estimates are super consistent, there is all the more reason to believe that finite sample bias is not present in our polynomial cointegration tests where the estimates are super-super consistent. Therefore, our failure to corroborate AGW according to which global temperature and solar irradiance are polynomially cointegrated with anthopogenic forcings is not attributable to lack of data and associated finite sample bias.

Next, we use DOLS (Stock and Watson, 1993) rather than OLS to estimate Eqs. (11), (12) and (15). In the cases of Eqs. (11) and (12) the DOLS estimate of the coefficient on the anthropogenic trend is negative, and is not polynomially cointegrated. In the case of Eq. (15) the cointegration test statistics slightly improve, e.g. $\mathrm{ADF}_4 = -6.43$ instead of -5.17 and the parameter estimates are slightly different. Therefore, changing the estimation method does not alter the conclusion that anthropogenics are not polynomially cointegrated with global temperature and solar irradiance.

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We have estimated Eq. (15) using revised and extended (to 2006) data for solar irradiance (Lean and Rind, 2009). Prior to 1980 these data were based on various proxy measures. Data since 1980 are based on instrumental measurements taken from satellites. Whereas the data in NASA GISS used 15 yr of satellite data, the revised data we used, employs 26 yr. We note that the revised data behave differently from the original in that the ratio between the revised data and the original decreases during 1850 to 1950 but increases subsequently. We have focused on the original data since these were used by others who claimed that global temperature is cointegrated with solar irradiance and greenhouse gas forcings.

When we use these revised data, Eqs. (11) and (12) remain polynomially uncointegrated. However, Eq. (15) ceases to be cointegrated. This happens because, as noted, the revised data are quite different to the original. Therefore these revised data reject both AGW and its modified version. Finally, we re-estimated all the models using temperature as measured by the Berkeley Earth Surface Temperature Study (BEST) instead of NASA-GISS. Data for BEST are available from 1850 rather than 1880, which adds 30 yr more data for our cointegration tests. However, BEST unlike NASA-GISS refers to land temperature only. BEST, like temperature in NASA-GISS, is difference stationary. Estimates of Eqs. (11), (12) and (15) using BEST are almost identical to their NASA-GISS counterparts. AGW continues to be polynomially uncointegrated, while modified AGW continues to be cointegrated.

Our results are therefore robust with respect to a variety of misspecification tests and alternative estimators and data.

4 Discussion

We have shown that anthropogenic forcings do not polynomially cointegrate with global temperature and solar irradiance. Therefore, data for 1880–2007 do not support the anthropogenic interpretation of global warming during this period. This key result is shown graphically in Fig. 4 where the vertical axis measures the component of global

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temperature that is unexplained by solar irradiance according to our estimates. In panel a the horizontal axis measures the anomaly in the anthropogenic trend when the latter is derived from forcings of carbon dioxide, methane and nitrous oxide. In panel b the horizontal axis measures this anthropogenic anomaly when apart from these greenhouse gas forcings, it includes tropospheric aerosols and black carbon. Panels a and b both show that there is no relationship between temperature and the anthropogenic anomaly, once the warming effect of solar irradiance is taken into consideration.

However, we find that greenhouse gas forcings might have a temporary causal effect on global temperature. This result is illustrated in panel c of Fig. 4 in which the horizontal axis measures the change in the estimated anthropogenic trend. Panel c clearly shows that there is a positive relationship between temperature and the change in the anthropogenic anomaly once the warming effect of solar irradiance is taken into consideration.

Currently, most of the empirical evidence supporting AGW theory is derived by calibration methods and the simulation of GCMs. Calibration shows, e.g. Crowley (2000), that to explain the increase in temperature in the 20th century, and especially since 1970, it is necessary to specify a sufficiently strong anthropogenic effect. However, calibrators do not report tests for the statistical significance of this effect, nor do they check whether the effect is spurious. The implication of our calculations is that the permanent effect is not statistically significant. Nevertheless, there seems to be a temporary anthropogenic effect.

The fact that since the mid 19th century global temperature is unrelated to anthropogenic forcings does not contravene the laws of thermodynamics, greenhouse theory, or any other physical theory. Given the complexity of earth's climate, and our incomplete understanding of it, it is difficult to attribute to carbon emissions and other anthropogenic phenomena the main cause for global warming in the 20th century. This is not an argument about physics, but an argument about data interpretation. Do climate developments during the relatively recent past justify the interpretation that global warming was induced by anthropogenics during this period? Had global temperature not increased in the 20th century despite the increase in anthropogenic forcings (as was the case during the second half of the 19th century), this would not have constituted evidence against greenhouse theory. Nor do our results constitute evidence against greenhouse theory, or any other physical theory. However, our results challenge the data interpretation that since 1880 global warming was caused by anthropogenic phenomena.

Nor does the fact that during this period anthropogenic forcings are I(2), i.e. stationary in second differences, whereas global temperature and solar irradiance are I(1), i.e. stationary in first differences, contravene any physical theory. For physical reasons it might be expected that over the millennia these variables should share the same order of integration; they should all be I(1) or all I(2), otherwise there would be persistent energy imbalance. However, during 150 yr there is no physical reason why these variables should share the same order of integration. However, the fact that they do not share the same order of integration over this period means that scientists who make strong interpretations about the anthropogenic causes of recent global warming should be cautious. Our polynomial cointegration tests challenge their interpretation of the data.

Finally, all statistical tests are probabilistic and depend on the specification of the model. Type 1 error refers to the probability of rejecting a hypothesis when it is true (false negative) and type 2 error refers to the probability of not rejecting a hypothesis when it is false (false positive). In our case the type 1 error is very small because anthropogenic forcing is I(1) with very low probability, and temperature is polynomially cointegrated with very low probability. Also we have experimented with a variety of model specifications and estimation methodologies. This means that our rejection of AGW is not absolute; it might be a false negative, and we cannot rule out the possibility that recent global warming has an anthropogenic footprint. However, this possibility is highly improbable, and is not statistically significant at conventional levels.

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Table 1. The Order of Integration of $rfCO_2$: 1850–2006. The table presents results of the level of nonstationarity of the radiative forcing of CO_2 ($rfCO_2$). Test 1 checks for stationarity ($d = 0$), test 2 tests for linear non-stationarity ($d = 1$) and test 3 tests for non-linear non-stationarity ($d = 2$). The null hypothesis in the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) test is that there is a unit root in the variable. The null hypothesis in the KPSS test due to Kwiatkowski et al. (1992) is that there is no unit root in the variable. PP uses the Newey-West bandwidth default of 4 lags and KPSS uses a bandwidth of 3 lags.

Test	d	Root	Trend	ADF	DW	PP	KPSS
1	0	1.02	Yes	7.37	1.04	4.41	0.81
2	1	0.93	No	−1.38*	1.99	−3.25	2.66
3	2	−0.35	No	−17.88	2.21	−20.86	0.03

*ADF statistics include 4 augmentations. In tests 2 and 3 the critical values for ADF and PP at $p = 0.05$ are −2.886 and for KPSS 0.463. In test 1 these critical values are −3.442 and 0.146, respectively.

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Table 2. Orders of integration for the various time-series analyzed. The table presents results of stationarity tests similar to those presented in Table 1. $rfCH_4$ is the radiative forcing of methane. rfN_2O is the radiative forcing of nitrous oxide.

Series	*d*	Years
$rfCO_2$	2	1850–2006
Temperature	1	1880–2006
Solar irradiance	1	1850–2000
$rfCH_4$	2	1850–2006
rfN_2O	2	1850–2006
Reflective tropospheric aerosols	2	1880–2003
Black carbon	2	1880–2003
Stratospheric aerosols	0	1880–2003
Stratospheric H_2O	1	1880–2003
Ocean heat content	1	1952–1996

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Table A1. Data Appendix.

Variable name	unit	Data source	Link
Temperature	anomalies	NASA-GISS surface temperature analysis	http://data.giss.nasa.gov/gistemp/
Temperature (Mann, 2008, reconstruction)	anomalies	Mann et al. (2008)	
Temperature (Berkeley Earth Surface Temperature)	anomalies	Berkeley Earth Surface Temperature study	http://berkeleyearth.org/analysis.php
Solar irradiance	$W m^{-2}$	Lean et al. (1995)	
Solar irradiance – updated	$W m^{-2}$	Lean and Rind (2009)	
CO_2 concentrations	ppm	NASA-GISS	http://data.giss.nasa.gov
N_2O concentrations	ppm	NASA-GISS	http://data.giss.nasa.gov
CH_4 concentrations	ppm	NASA-GISS	http://data.giss.nasa.gov
Ocean heat content	1022 jouls	Levitus et al. (2005)	
black carbon (forcing)	$W m^{-2}$	NASA-GISS	http://data.giss.nasa.gov/modelforce/RadF.txt
reflective tropospheric aerosols (forcing)	$W m^{-2}$	NASA-GISS	http://data.giss.nasa.gov/modelforce/RadF.txt
stratospheric aerosols (forcing)	$W m^{-2}$	NASA-GISS	http://data.giss.nasa.gov/modelforce/RadF.txt
water vapour (forcing)	$W m^{-2}$	NASA-GISS	http://data.giss.nasa.gov/modelforce/RadF.txt

Note: Concentrations of CO_2, N_2O and CH_4 are converted into radiative forcings using the formula provided by Myhre et al. (1998).

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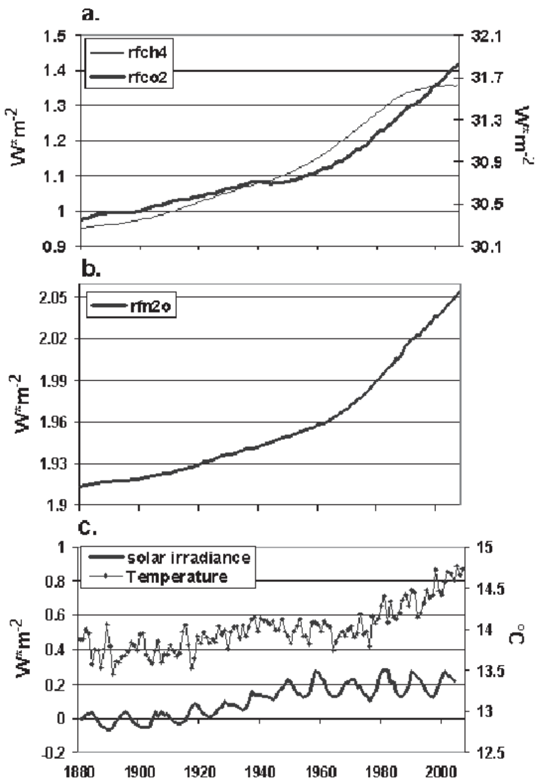

Fig. 1. Time series of the changes that occurred in several variables that affect or represent climate changes during the 20th century. **(a)** Radiative forcings (rf, in units of $W m^{-2}$) in the period 1880 to 2007 of CH_4 (Methane) and CO_2 (Carbon dioxide); **(b)** same period as in panel **(a)** but for Nitrous-Oxide (N_2O); **(c)** solar irradiance (left axis, units of $W m^{-2}$) and annual global temperature (right axis, units of °C) in the period 1880–2003.

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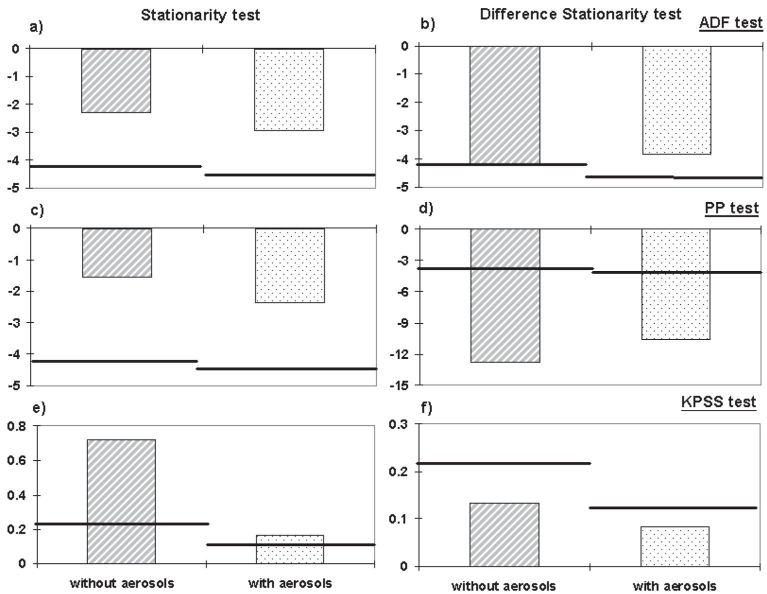

Fig. 2. The statistics of stationarity tests and their level of significance for the residuals from Eqs. (9) (without aerosols columns in the panels) and (10) (with aerosols columns in the panels). (**a** and **b**) present results of the Augmented Dickey-Fuller (ADF) test, (**c** and **d**) present results of the Phillips-Perron (PP) test. Both these tests share the same null hypothesis of non-stationarity of the time-series and test statistics lower than the critical values (shown here by the solid horizontal lines) indicate a rejection of the null hypothesis (i.e. stationarity as in **b** and **d**). (**e** and **f**) present results of the KPSS test where the null hypothesis is that the variable is stationary. Accordingly, test statistics lower than the critical values (solid horizontal line) indicate that the null hypothesis can not be rejected, i.e. the variable is stationary. (**a**, **c** and **e**) test the residuals themselves for non-stationarity, whereas (**b**, **d** and **f**) test the difference of the residuals for non-stationarity. All three tests agree that the original time-series (**a**, **c** and **e**) are not stationary while the differences (**b**, **d** and **f**) are.

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Polynomial cointegration tests of anthropogenic impact

M. Beenstock et al.

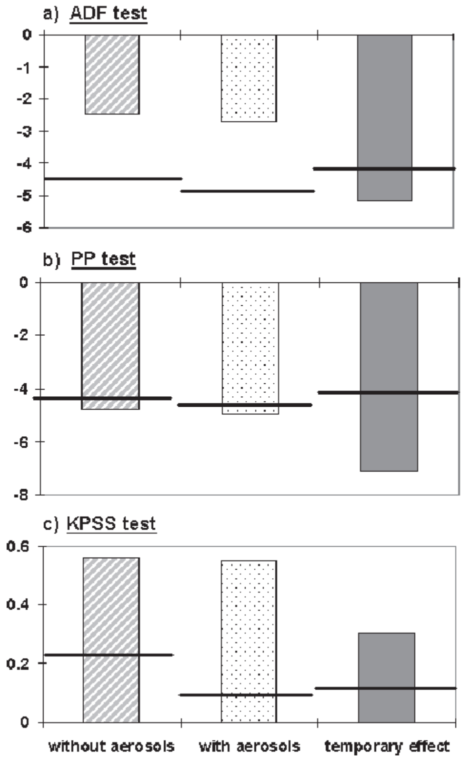

Fig. 3. Cointegration test statistics and their level of significance for the three statistical tests: ADF, PP and KPSS (see Fig. 2 for the designation of these tests and the null hypotheses associated with them). The columns titled without aerosols refer to the model presented in Eq. (11); the columns titled with aerosols refer to the model presented in Eq. (12); the columns titled temporary effect refer to the model presented in Eq. (15). **(a)** ADF test results; **(b)** PP test results; **(c)** KPSS test results. Solid horizontal lines indicate the critical value for each test. All three tests agree that the temporary effect is the only one that can be confidently classified as cointegrated.

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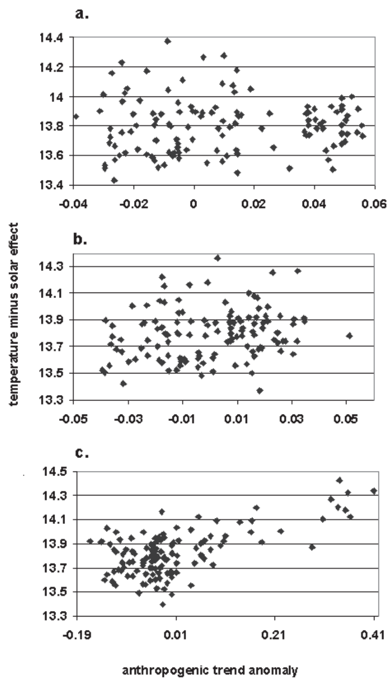

Fig. 4. Statistical association between (scatter plot of) anthropogenic trend anomaly (x-axes), and net temperature effect (i.e. temperature time-series from which the solar irradiance effect is subtracted; y-axes). (**a**, **b** and **c**) display the results of the models presented in Eqs. (11), (12) and (15), respectively. The anthopogenic trend anomaly sums the weighted radiative forcings of the greenhouse gases (CO_2, CH_4 and N_2O). The calculation of the net temperature effect (as defined above) change is calculated by subtracting from the observed temperature in a specific year the product of the solar irradiance in that year times the coefficient obtained from the regression of the particular model equation: 1.763 in the case of Eq. (11) **(a)**; 1.806 in the case of Eq. (12) **(b)** and 1.508 in the case of Eq. (15) **(c)**.

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