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An atmosphere–ocean time series model of global climate change

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Abstract

Time series models of global climate change tend to estimate a low climate-sensitivity (equilibrium effect on global temperature of doubling carbon dioxide concentrations) and a fast adjustment rate to equilibrium. These results may be biased by omission of a key variable—heat stored in the ocean. A time series model of the atmosphere–ocean climate system is developed, in which surface temperature (atmospheric temperature over land and sea surface temperature) moves towards a long-run equilibrium with both radiative forcing and ocean heat content, while ocean heat content accumulates the deviations from atmospheric equilibrium. This model is closely related to Granger and Lee's multicointegration model. As there are only 55 years of observations on ocean heat content, the Kalman filter is used to estimate heat content as a latent state variable, which is constrained by the available observations. This method could be applied to other climate change problems where there are only limited observations on key variables. The final model adopted relates surface temperature to the heat content of the upper 300 m of the ocean. The resulting parameter estimates are closer to theoretically expected values than those of previous time series models and the estimated climate sensitivity to a doubling of carbon dioxide is 4.4 K.

Keywords: Global climate change; Time series analysis; Multicointegration; Kalman filter

1. Introduction

Most research on the historical effects of anthropogenic greenhouse gases on the global climate compares the output of simulation models such as general circulation models (GCMs) and energy balance models (EBMs) with observed temperatures. Relatively few studies take the alternative approach of estimating the parameters of a statistical model of the climate system from the observed data, and even fewer use time series methods. Among the time series studies, work by myself and colleagues (Stern and Kaufmann, 2000; Kaufmann and Stern, 2002; Kaufmann et al., 2003) has used recent time series econometric methods to estimate the climate sensitivity (equilibrium effect on global temperature of doubling carbon dioxide concentrations) and the adjustment path of global temperature to long-run equilibrium. Our time series models have yielded relatively low estimates of the global temperature sensitivity to doubling carbon dioxide concentrations, ranging from 1.4 (Stern and Kaufmann, 2000) to 2.1 K (Kaufmann et al., 2003). This range is lower than the range of sensitivities estimated by empirical studies such as Andronova and Schlesinger (2001) or surveys of GCM results (Cubasch et al., 2001; Sokolov et al., 2003) though it spans Harvey and Kaufmann's (2002) preferred estimate of 2K derived using an energy balance model.

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However, most of those time series models that estimate the rate of adjustment to equilibrium, estimate a rate that is much higher than physics-based deterministic models would suggest is possible. Typical estimates indicate that around 50% of the disequilibrium between radiative forcing and surface temperature (a series that combines atmospheric temperature measurements on land and sea surface temperatures) is eliminated per year (e.g. Kaufmann and Stern, 2002; Kaufmann et al., 2003). It is generally believed that temperature may adjust to increased forcings for a century or more due to the high thermal inertia of the oceans. It takes a long time to heat up the oceans. In the meantime, they have a cooling effect on the atmosphere. It is possible that previous estimates are biased due to the omission of an ocean heat content variable.

In this paper, I address these issues and propose an alternative approach based on a more sophisticated but related class of time series models, known as multicointegration models, which was first introduced by Granger and Lee (1989) but have been used very little so far in economics. These models are designed to handle the relations between flow and stock variables allowing for long-run relationships between both the flows themselves and between the flows and stocks. Changes in the stock—for example inventory in manufacturing industry—are a linear function of the disequilibrium between the flows, for example production and sales. Sales depend on both production and inventory levels, while production depends on sales and inventory. Optimization models suggest that producers will want to maintain the proportions between these three variables in the long-run. Thus there is a direct path from production to sales and an indirect slower one via inventory. It turns out that a simple energy balance model has a very similar structure.

In the climate system, the temperature of the atmosphere and surface depends on both radiative forcing and the temperature or heat content of the ocean. In the long-run, surface temperature will move to be in equilibrium with each of these two variables. If surface temperature is below its long-run or steady state equilibrium as determined by the level of radiative forcing, then heat must be accumulating in the system either in the atmosphere and surface or in the oceans and vice versa. The deviations from long-run equilibrium that do not result in warming of the atmosphere are accumulated in the ocean. In the long-run there is also a thermal equilibrium between the ocean and atmosphere. Thus there are two channels of influence of radiative forcing on temperature, one direct, and the other indirect via the heat stored in the ocean. Introduction of this stock variable—ocean heat content—buffers the system and should reduce the adjustment rate of atmospheric temperatures to radiative forcing (Granger and Lee, 1989).

Compared to the length of the surface temperature time series there are only limited observations on many other climate time series including ocean heat content. Detection and attribution of climate change are enhanced if we can use these partial series together with the much longer series for surface temperature and radiative forcing. If we replace the shorter or partially observed time series by latent variables estimated using the Kalman filter and constrained by the observed data when it is available, we can exploit both the full length of the longer time series and the information in the more fragmentary series. In this paper, I constrain the estimates of the build-up of ocean heat using observations for a 50–55-year period, estimated by Levitus et al. (2000, 2005), while the Kalman filter extracts conditional estimates of this state variable for all years for which surface temperature data is available (almost 150 years). The technique could be extended to other series such as radiatively active trace gases for which only sporadic ice core measurements exist prior to modern atmospheric sampling. Though I use this state space approach to estimate the latent variables, my approach is otherwise the traditional econometric regression approach.

The results from the very simple pilot model presented in this paper are very promising, resulting in a higher climate sensitivity and lower adjustment rate than a comparable time series model that does not include the multicointegration mechanism. The climate sensitivity is close to the mean found in some surveys of GCMs (Cubasch et al., 2001; Sokolov et al., 2003).

The paper is structured as follows. The next section discusses previous results in more detail. The third section discusses the methodology, including the rationale behind the choice of the multicointegration approach, an explanation of the econometrics of the model, and its implementation. The fourth section of the paper presents the results. The final section provides some conclusions.

2. Previous results

Using a structural time series model (see Harvey (1989)) Stern and Kaufmann (2000) found that there is a common stochastic trend shared by temperature in the two hemispheres and that this trend is close to a second order integrated process (such as an integrated random walk and designated I(2)) as are some radiative forcing variables such as carbon dioxide and methane concentrations. There is, however, a difference between the two hemispheres which is a simple random walk or I(1) trend, which is mostly explained by changes in anthropogenic sulfur emissions. On theoretical grounds we know that the climate system is not really second order integrated, but the first differences of variables such as carbon dioxide concentrations are so highly autocorrelated that standard regression based tests may be unable to distinguish them from random walks. The stochastic trends extracted in the first stage of the analysis were then explained in an auxiliary regression model that related them to the radiative forcing variables and took into account the I(2) nature of the data. The reason for using this methodology is that the temperature series are noisy—presumably due to the internal variability of the climate system—and hence detecting the global warming signal directly is difficult. The two stage analysis is rather inelegant and the model does not allow the relation of emissions variables to temperature and hence policy analysis. This is because the primary model decomposes temperature into separate long run trends and short-run dynamics. This makes it impossible to compute an impulse response function or the rate of adjustment to equilibrium. The estimated global average climate sensitivity from the second stage analysis is 1.44 K.

On the other hand, Kaufmann and Stern (2002) proceed on the basis that all the relevant time series are integrated at most of order one and use the Johansen cointegration method to obtain maximum likelihood estimates of a vector autoregression model of the climate system in the two hemispheres. Variables lagged more than one period (year) were found to be statistically insignificant. The results show that temperature and radiative forcing cointegrate—i.e. they share a common stochastic trend—however, the I(1) assumption and first order autoregressive model cause some problems. Specifically, the rate of adjustment of temperature to changes in radiative forcing is very fast at around 50% per annum. The average global climate sensitivity is 2.03 K.

Kaufmann et al. (2003) also assume that the variables are integrated of order one but they also estimate equations for the concentrations of the two chief greenhouse gases—carbon dioxide and methane. The estimated climate sensitivity is 2.1 K. The model seems plausible but they find that the equations for concentrations do not cointegrate and hence cannot be estimated in the levels form. These equations are estimated in first differences. The autoregressive coefficient in the carbon dioxide equation of 0.832 implies an unreasonably high rate of removal of CO_2 from the atmosphere. The methane rate of removal is also very high. Additionally, the impulse response of temperature to a pulse of carbon dioxide shows a decline in temperature towards long-run equilibrium after an initial spike instead of the expected increase. Kaufmann and Stern's (2002) model behaves similarly. The initial increase in temperature from doubling CO_2 is around 10 °C with the response declining to a minimum after 4 years and then rising slightly to the long-run equilibrium.

Simple AR(1) I(1) autoregressive models of this type assume that temperature adjusts in an exponential fashion towards the long run equilibrium. The estimate of that adjustment rate tends to go towards that of the fastest adjusting process in the system, if, as is the case, that is the most obvious in the data. Schlesinger et al. (no date) illustrate these points with a very simple first order autoregressive model of global temperature and radiative forcing. They show that such a model approximates a model with a simple mixed layer ocean. Parameter estimates can be used to infer the depth of such an ocean. The models that they estimate have inferred ocean depths of 38.7–185.7 m. Clearly, an improved time series model needs to simulate a deeper and possibly more complex ocean component. Autoregressive models with more than one lag of the variables can incorporate more than one adjustment rate, which can represent more than one physical process (e.g. warming of atmosphere and oceans). But, as the number of parameters increases, estimation efficiency declines. The proposed multicointegrating model uses more prior theory and observed data (on the ocean) to constrain the estimates, has fewer parameters than high order autoregressive models, and is easier to interpret in terms of physical mechanisms.

I briefly review some other recent estimates of the climate sensitivity for the purpose of comparison. Harvey and Kaufmann (2002) use an EBM with a variety of forcings and conclude that a sensitivity of 2K (with a likely range of 1–3 K) is most compatible with the observed climate record. Schlesinger et al. (no date), using another EBM, estimate a mean sensitivity of 3.2 K. Using a method combining observations on surface temperature and ocean heat content and GCM results, Forest et al. (2002) estimate a 90% confidence interval of 1.4 to 7.7 K. Andronova and Schlesinger (2001) use a similar approach, but use only surface temperature and EBM results, estimating that the 90% confidence interval extends from 1 to 9.3 K. Knutti et al. (2002) run many simulations of a simplified ocean–atmosphere model with different climate sensitivities and ocean diffusivities and plot the resulting surface temperature and ocean heat changes for the present day against the distribution of observations. Using the ocean heat variable, they find a mean climate sensitivity of 5.7 K, and based on the surface temperature variable, 4.6 K with large uncertainty bands. However, the results are very sensitive to assumptions about forcing due to anthropogenic sulfates. Gregory et al. (2002) carry out an empirical analysis of the observed surface and oceanic data to determine the climate sensitivity. They conclude that there is far more uncertainty than even that suggested by Andronova and Schlesinger (2001). The mode of their distribution is 2.1, the median 6.1 K, and the mean is undefined as the 90% confidence interval includes infinity! The eight GCMs discussed by Sokolov et al. (2003) have sensitivities ranging from 2.1 to 4.8 K with a mean of 3.54 K. Cubasch et al. (2001) report the mean from seventeen mixed layer coupled GCMs as 3.8 K with a standard deviation of 0.8 K. Stainforth et al. (2005) ran more than 2000 simulations of a single GCM with a range of values for some key parameters. The sensitivity of the unperturbed GCM was 3.4 K but some model runs had sensitivities as low as 1.9 K or as high as 11.5 K.

3. Methodology

3.1. Model requirements

Given the above, an appropriate model of the climate system needs to meet the following criteria *inter alia*:

1. The model must be able to model nonstationary time series data using the notion of cointegration to model and test for a long-run equilibrium relation.
2. The model needs to incorporate a model of the ocean.
3. The model must allow for the computation of impulse response functions of the effect of gas concentrations (and eventually emissions) on temperature so that we can assess the actual adjustment path to long-run equilibrium. Vector autoregressive models such as those estimated by Kaufmann and Stern (1997, 2002) are suitable for this purpose while structural time series models (as in Stern and Kaufmann, 2000) are not.
4. Preferably the model should have a readily interpretable physical explanation rather than be a "black-box".
5. The model must relate observable variables that have reasonably long time series. For example radiation and reflection from Earth back to space are critical variables in the planetary energy balance, but we do not have time series observations on such variables.
6. The model must be able to deal with time series of non-uniform length as only around fifty years of observations are available on ocean heat content.

The model I develop in the following sections meets all these criteria. The basic approach is to embed a simple physical model of the energy balance of the atmosphere and ocean in a vector autoregressive model, which is constrained by multicointegrating restrictions. A latent variable constrained by the partial observations on ocean heat content is used to model the ocean.

3.2. Physical model

Based on Nordhaus (1992) and Schneider and Thompson (1981) we can model the temperature, T, of the atmosphere–surface box of the climate system as a function of radiative forcing, F, and ocean heat content, Q. using the following time-series equation:

$$\Delta T_t = \alpha_1 \left(T_{t-1} + \beta_{12} F_{t-1} + \beta_{14}\right) + \alpha_2 \left(T_{t-1} + \beta_{23} Q_{t-1} + \beta_{24}\right) + \pi \Delta F_t + \varepsilon_{1t} \tag{1}$$

which is a single equation of a vector autoregression model in error correction form. The first two terms on the RHS of (1) are known as error correction mechanisms. The first term in parentheses is equal to the imbalance between radiative forcing and temperature and reflects the net energy transfer to space. Due to a lack of time series observations on energy entering and leaving the planetary system we cannot explicitly model those flows, which are modeled explicitly by Schneider and Thompson (1981) but not by Nordhaus (1992). The second term is the heat transfer function between the atmosphere–surface box and the ocean. The third term (the first difference of radiative forcing) in (1) accounts for the correlation between the current innovations in this exogenous variable and the dependent variable in (1)—it would be omitted if we specified an equation for the evolution of F (Hamilton, 1994). ε_{1t} is an independently normally distributed random error with mean zero.

Eq. (1) embeds two long-run or steady state relations:

$$T_t + \beta_{12} F_t + \beta_{14} = u_{1t}, \tag{2}$$

$$T_t + \beta_{23} Q_t + \beta_{24} = u_{2t}. \tag{3}$$

Both β_{12} and β_{23} are negative. Eq. (2) expresses the relationship between the endogenous variable, surface temperature (T), and the exogenous variable, radiative forcing (F). u_{1t} is a stationary disturbance with mean zero and probably a high level of serial correlation. If u_{1t} is stationary then temperature gradually adjusts to changes in radiative forcing or other shocks and approaches a long-run equilibrium. The coefficient, $-\beta_{12}$ is the long-run multiplier of radiative forcing on temperature. The radiative forcing generated by a change in carbon dioxide is $5.35\Delta \ln(CO_2)$ where CO_2 is the atmospheric concentration of carbon dioxide and radiative forcing is measured in $W\,m^{-2}$ (Kattenberg et al., 1996). Therefore, the climate sensitivity to doubling carbon dioxide is given by $-5.35\beta_{12} \ln(2)$ where carbon dioxide is measured relative to a base year. This is the basic long-term model in Kaufmann and Stern (2002) and other time series studies. The constant term, β_{14}, in the equation allows for the arbitrary constants in the two time series.

Eq. (3) relates surface temperature, T, to the ocean heat content Q. u_{2t} is another stationary disturbance. In the long-run there must be a thermal equilibrium between the atmosphere and ocean. The constant term, β_{24}, in the equation allows for the arbitrary constants in the two time series and the fact that, due to meridonial overturning or downwelling/upwelling, even in the long-run the temperature of the surface and ocean boxes may not be equal.

Eqs. (2) and (3) are called cointegrating relations in the econometrics literature. This is because, though T, F, and Q are likely to be integrated variables or random walks (Stern and Kaufmann, 2000), their linear combination may be stationary and would, then represent a valid regression-type relationship. This is because if radiative forcing is integrated and drives the change in temperature then temperature too will be integrated and share the same common stochastic trend with radiative forcing. Ocean heat content, too, will share the same trend. In the absence of forcing, however, both surface temperature and ocean heat content are stationary variables. Stationarity of u_{1t} and u_{2t} can be tested using cointegration tests as described below.

Both α_1 and α_2 in (1) are negative. When (2) is negative, surface temperature is below its long-run equilibrium value with radiative forcing and, as α_1 is negative, T increases to restore long-run equilibrium and vice versa. Hence the term "error correction mechanism". Similarly, when (3) is negative (positive), surface temperature is below (above) its long-run equilibrium with oceanic temperature and will increase (decrease) to restore equilibrium.

In (2) and (3), T and Q are endogenous variables that in the long-run are determined by the radiative forcing F. The steady state solution for T is given by setting the error term in (2) to zero and solving for T. The steady state solution for Q can be found by setting the error terms to zero in both equations, solving both equations for T, and then equating the RHS of (2) and (3) and solving for Q:

$$Q = (1/\beta_{23}) \left[\beta_{12} F + \beta_{14} - \beta_{24}\right].$$

The sensitivity of ocean heat content to radiative forcing is then equal to the climate sensitivity divided by the relative heat capacity of the surface box to the ocean box.

During the climate change process, the imbalance between the imposed radiative forcing, F, and the temperature response, λT, where $\lambda = -1/\beta_{12}$ is the climate feedback, is absorbed by the heat capacity of the system, which resides overwhelmingly in the ocean (Levitus et al., 2001) but also partly resides in the surface system including atmosphere, land, and ice. Hence:

$$\Delta H_t = F_t - \lambda T_t - \lambda \beta_{14} = u_{1t}, \tag{4}$$

where ΔH is the change in heat stored in the planetary system as a whole (Gregory et al., 2002). The change in heat content is distributed between the two boxes:

$$\Delta H_t = \Delta Q_t + \mu \Delta T_t. \tag{5}$$

$\Delta Q(t)$ is the heat flux into the ocean or change in the heat stored in the ocean Q, $\Delta T(t)$ is the change in temperature of the surface system, and μ is the heat capacity of the surface system. As there is some uncertainty about μ (how much ice is melted for example by a given atmospheric temperature increase) we choose to estimate it. Levitus et al. (2001) find that the heat content of the atmosphere increased by 6.6E21 J between 1955 and 1996 while the melting of ice absorbed a further 12.5E21 J in the same period. Atmospheric temperature increased during this period by approximately 0.4 K. Therefore, μ is expected to be about 5. Eq. (5) states that if surface temperature is out of steady state then heat must be accumulating either in the surface or ocean components of the system. Equating the RHS of (4) and (5) and solving for ΔQ_t we have

$$\Delta Q_t = 1.609\left(\left(1/\beta_{12}\right) T_t + F_t + \beta_{14}/\beta_{12}\right) - \mu \Delta T_t, \tag{6}$$

where the constant 1.609 converts W m^{-2} to annual global energy flows in terms of 10^{22} J (Hansen et al., 1997).

Eq. (1) is underidentified as it has more parameters than RHS variables. Identification is achieved by jointly estimating (1) with (6), which has only one additional parameter.

Eqs. (1) and (6) bear a close resemblance to a first order autoregressive multicointegration model between two flow variables and one stock variable as represented by Granger and Lee (1989). Multicointegration occurs where there is a long-run equilibrium relation between two flow variables, such as production and sales in manufacturing industry, as well as a long-run relation between a stock such as inventory and the flow variables. The stock variable accumulates the deviations from long-run equilibrium in the relation between the flow variables (Granger and Lee, 1989). When sales exceed production, inventory is run down and vice versa. The level of sales depends on production, but both production and sales will respond to the level of inventory. Engsted and Haldrup (1999) present more general results for systems with more variables and more autoregressive lags.

Here the underlying multicointegration model would be between the incoming and outgoing flows of energy between the Earth and space and the stock of heat in the Earth system. But we do not have time series measurements on these variables. The model instead is formulated in terms of equilibrium between surface temperature and radiative forcing. When temperature is below its equilibrium level, heat accumulates in the system and vice versa. If heat only accumulated in the oceanic stock, so that the term $\mu\Delta T(t)$ was omitted from (4), we would have a standard multicointegration model where T reacted to the flow F and stock Q which accumulated the deviations from long-run equilibrium between T and F. But here T is in a sense both a stock and a flow in that T controls the outflow of radiation to space but also is a measure of the stock of heat in the surface system. Still the basic structure of the system is the same—there are two long-run equilibria between T and F, one direct (2) and one indirect via Q (3).

Additionally, in conventional multicointegration models all variables are observed in all periods and regression methods are used to estimate the model. Here, Q is only observed in some periods. This necessitates using the Kalman filter to estimate it as a latent state variable constrained by the available observations. This state variable must then be related to the available observation on heat content. Levitus et al. (2000, 2005) have estimated time series of ocean heat content for various depths and regions of the world's oceans. The global series for the top 300 m are available as yearly anomalies for the period 1948 to 2003. Eq. (7) equates observed heat content L_t to the latent state variable Q when observations are available. The equation is dropped when L is not observed

$$L_t = Q_t + \varepsilon_{2t}. \tag{7}$$

The global series for the top 3000 m of the ocean is available as a five year moving average for the period from 1952 to 1998, where the observation for 1998 covers the period from 1994 to 1998. In these cases, Eq. (7) takes the form:

$$L_t = 0.2\sum_{i=0}^{4} Q_{t-i} + \varepsilon_{2t}. \tag{8}$$

3.3. State space representation and estimation of the multicointegration model

The Kalman filter is used to estimate models in state-space format. A state-space model of the form used here is given by (De Jong, 1991):

$$y_t = ZA_t + g(x_t) + G\upsilon_t, \tag{9}$$

$$A_{t+1} = RA_t + h(x_t) + H\upsilon_t, \tag{10}$$

where (9) are the measurement equations and (10) are the state transition equations. y is the vector of observed variables and A is the vector of the unobserved state variables. Z is the design matrix, relating the observed variables to the unobserved state, and R is the transition matrix explaining the evolution of the state vector. g and h are possibly nonlinear functions of a vector, x, of other observed variables. G and H are fixed matrices modeling the covariance structure of the perturbations. The vector υ_t is normally and independently distributed with zero mean and variance of unity. The classic seemingly unrelated regression model includes only Eqs. (9) with $Z = 0$.

I translate the model (1), (6), (7) into state–space form by setting $A_t = Q_{t-1}$ and treating (1) and (7) as the measurement equations and (6) as the state transition equation. For the 300 m model the matrices in (9) and (10) take the following form when ocean heat is observed:

$$G = \begin{bmatrix} \sigma_1 & 0 \\ 0 & \sigma_2 \end{bmatrix}, \tag{11}$$

$$H = [0 \quad 0], \tag{12}$$

$$R = 1, \tag{13}$$

$$Z = \begin{bmatrix} \alpha_2 \beta_{23} \\ 1 \end{bmatrix}, \tag{14}$$

$$g(x_t) = \alpha_1 \left(T_{t-1} + \beta_{12} F_{t-1} + \beta_{14}\right) + \alpha_2 \left(T_{t-1} + \beta_{24}\right) + \pi \Delta F_t, \tag{15}$$

$$h(x_t) = 1.609 \left(\left(1/\beta_{12}\right) T_t + F_t + \beta_{14}/\beta_{12}\right) - \mu \Delta T_t. \tag{16}$$

The adjustments needed when the second measurement equation is dropped should be obvious. The 3000 m ocean model requires additional state variables as the observed ocean heat content is a five period moving average.

The state variable Q_t is given a diffuse prior as the starting value is unknown. I use De Jong's (1991) diffuse Kalman filter algorithm to estimate the initial value of the state variable. The Kalman filter estimates the state variables given the values of the ten unknown parameters $\left(\alpha_1, \alpha_2, \beta_{12}, \beta_{14}, \beta_{23}, \beta_{24}, \pi, \mu, \sigma_1, \sigma_2\right)$, which are known collectively as hyperparameters. The filter is also used to compute the prediction error decomposition of the likelihood function in parallel with the state vector. This likelihood function in maximized using the BFGS nonlinear optimization algorithm to find the maximum likelihood values of the hyperparameters. Given maximum likelihood estimates of the hyperparameters, the Kalman filter produces maximum likelihood estimates of the state variables using only data for previous periods. Given these estimates, a fixed interval smoother algorithm is used to calculate values for the unobserved state variables utilizing the entire data set.

3.4. Simple autoregressive model

I also estimate a simple autoregressive model that excludes the multicointegration mechanism and the ocean heat content variable from (1):

$$\Delta T_t = \alpha_1 \left(T_{t-1} + \beta_{12} F_{t-1} + \beta_{14}\right) + \pi \Delta F_t + \varepsilon_t. \tag{17}$$

The results from this model are compared with the multicointegration results to show the effect of including the ocean model. The point of this model is to examine the effect of excluding the multicointegration mechanism and compare the results to previous research. Eq. (17) is a single equation of a vector autoregressive model and, as such, is a more aggregated version of the model used by Kaufmann and Stern (2002). It is also very similar to the AR(1) model in Schlesinger et al. (no date).

3.5. Data

The data are described in the appendix. I use two versions of the radiative forcing aggregate F. Both series include radiative forcing due to greenhouse gases (carbon dioxide, methane, nitrous oxide, and the two main CFCs), solar irradiance, and anthropogenic sulfate emissions. One series also includes volcanic forcing. Previous results found that the parameters relating temperature to volcanic forcing were statistically insignificant. Furthermore, volcanic forcing is stationary while the other forcings have stochastic trends (Stern and Kaufmann, 2000). Therefore, it is worthwhile to

Table 1
Summary econometric results for the four versions of the model

Forcing	No volcanic forcing		Volcanic forcing	
Ocean depth	300 m	3000 m	300 m	3000 m
R^2 Atmospheric equation	0.8314	0.8311	0.8291	0.8406
R^2 Ocean equation	0.5066	0.4806	0.1163	0.4234
Impact climate sensitivity	1.24 K	1.33 K	0.23 K	0.21 K
Equilibrium climate sensitivity	1.87 K	1.59 K	4.39 K	14.65 K
α_1	−0.5321	−0.5316	−0.0452	−0.0141
α_2	−0.0105	−0.0024	−0.3870	−0.5108
β_{23}	−0.1818	−0.5132	−0.0168	−0.0111
μ	−3.2677	4.6656	4.9200	9.3124
ADF CR1	−4.41	−3.81	−5.11	−4.42
ADF CR2	−4.65	−4.62	−3.85	−3.17
p $Q(24)$	0.1873	0.1784	0.07	0.1064
Standard deviation first dif state variable (observed value in parentheses)	3.773 (2.089)	3.411 (1.622)	2.317 (2.089)	1.496 (1.622)
R^2 First dif ocean	−0.0187	0.0207	0.0191	−0.0206
β First dif ocean	−0.0547	−1.385	0.2869	0.1455

See text for definitions of statistics.

investigate how the models differ when the volcanic forcing is included or excluded. I also experimented with different forcing coefficients for the direct and indirect anthropogenic sulfur forcing (not reported). In line with Harvey and Kaufmann's (2002) conclusion that the fossil fuel aerosol cooling was around 1 W m^{-2} in the later 20th century, larger coefficients gave poor results.

3.6. Research design and diagnostic statistics

I estimate four models using the two measures of radiative forcing and two different indicators of ocean heat content—the top 300 m and the top 3000 m of the ocean. Though the latter is logically the relevant variable for measuring total heat storage, surface temperature will perhaps reflect more closely the heat stored in the upper 300 and the 300 m series is more informative than the 3000 m series which is a five year moving average. I use a variety of indicators to select the best model—several are based directly on the econometric estimates and several on a simulation. The simulation takes the observed forcing variable and the initial values for temperature and ocean heat content from the econometric estimates but calculates ocean heat content and surface temperature endogenously thereafter. In Table 1 the first eight rows give measures of goodness of fit and the values of model parameters. The augmented Dickey Fuller (ADF) statistic is a test for cointegration—i.e. a stationary residual—in the long-run relationships (Dickey and Fuller, 1979; Engle and Granger, 1987). The ADF is a t-test on ρ_i in the following auxiliary regression:

$$\Delta u_{it} = \alpha_i + \rho_i u_{it-1} + \sum_j \delta_{ij} \Delta u_{it-j} + e_{it}, \quad i = 1, 2, \tag{18}$$

which is evaluated against a special non-standard distribution. Large negative values of the statistic reject the null hypothesis that the long-run relation does not cointegrate. The Q statistic is a general test of serial correlation in the residuals with a null of no serial correlation (Box and Pierce, 1970). The remaining statistics in Table 1 will be explained in the results section. The additional statistics for the simulation results in Table 2 are defined as follows. Theil's inequality coefficient (Theil, 1961; Pindyck and Rubinfeld, 1981):

$$U = \frac{\sqrt{1/T \sum_t \left(y_t^s - y_t\right)^2}}{\sqrt{1/T \sum_t y_t^{s2}} + \sqrt{1/T \sum_t y_t^2}}, \tag{19}$$

Table 2
Simulation results

	Forcing	No volcanic forcing		Volcanic forcing	
	Ocean depth	300 m	3000 m	300 m	3000 m
Atmosphere	R^2	0.848	0.847	0.835	0.508
	Theil's U	0.203	0.205	0.214	0.414
	U^B	0.000	0.002	0.001	0.702
	U^V	0.068	0.088	0.107	0.050
	U^C	0.932	0.911	0.892	0.248
Ocean	R^2	−0.026	0.647	−0.286	−2.315
	Theil's U	0.422	0.281	0.469	0.668
	U^B	0.085	0.031	0.289	0.838
	U^V	0.168	0.025	0.105	0.008
	U^C	0.747	0.944	0.606	0.153

See text for definitions of statistics.

which is zero if the simulated series, y_t^s, is equal to the actual series, y_t, and unity if there is no fit at all. U can be decomposed into three further statistics, which are normalized to sum to unity:

$$U^B = \frac{(\bar{y}^s - \bar{y})^2}{1/T\sum_t \left(y_t^s - y_t\right)^2}, \quad U^V = \frac{\left(\sigma_y^s - \sigma_y\right)^2}{1/T\sum_t \left(y_t^s - y_t\right)^2}, \quad U^C = \frac{2\,(1-r)\,\sigma_y^s\sigma_y}{1/T\sum_t \left(y_t^s - y_t\right)^2}, \tag{20}$$

where bars above variables indicate means, σ indicates the standard deviation and r the correlation coefficient between the simulated and actual variables. The first statistic, the bias proportion, U^B, indicates the degree to which the simulation error is due to incorrectly simulating the mean of the series. The variance proportion, U^V, shows to what extent the simulation error is due to the inability of the model to replicate the degree of variability in the data. Finally, the covariance proportion, indicates unsystematic error. Ideally, $U^C = 1$ (Pindyck and Rubinfeld, 1981).

The final preferred model is used to derive the impulse (or step) response functions of surface temperature and ocean heat content with respect to changes in the forcing variables by perturbing the forcing variable and seeing how the endogenous variables—surface temperature and ocean heat content—evolve over time. The impulse response functions and the simulations, discussed below, were carried out using a *Microsoft Excel* spreadsheet. The econometric model was estimated using the *RATS* econometrics package. As the model is linear, the starting point for the simulation (in terms of any given W m^{-2} perturbations) is not important as long as the system is in equilibrium before the perturbation is introduced. This can be achieved by adjusting the starting values for the endogenous variables.

4. Results

4.1. Selecting the error correction model

Table 1 presents some summary econometric results for the four versions of the model, while Table 2 presents simulation results. The R^2 for both equations is in terms of the level of the dependent variable rather than its first difference. The atmospheric or surface R^2 is very similar across all models giving little basis for a choice between models but is slightly higher for the volcanic 3000 m model than for the 300 m volcanic model. The R^2 for the ocean equation varies significantly. It is higher for the non-volcanic models and particularly low for the volcanic 300 m model. However, other indicators of the ability of the model to reproduce the ocean heat observations favor the 300 m volcanic model. Comparing the variance of the first differences of the state variable to the variance of the first differences of the observed ocean heat content, we see that the volcanic models reproduce the variability in this series much better than the non-volcanic models. I also regressed the first differences of observed ocean heat content on the first differences of the smoothed state variable. The correlation between the first difference series was negative for both non-volcanic models suggesting a spurious correlation in these cases. The fit of the 300 m volcanic model is superior to that of the 3000 m model for this first differences regression.

Looking at the simulation results in Table 2, the oceanic R^2 is again better for the non-volcanic models than for the volcanic models. But for the volcanic models it is best for the 300 m model and for the non-volcanics best for the 3000 m model. The simulation fit of the atmospheric equation is much poorer for the 3000 m volcanic model than for the other three models. The decomposition of Theil's inequality coefficient shows that the 3000 m volcanic model suffers very significantly from the failure of the simulation to reproduce the mean behavior of both series. The non-volcanic models have the edge over the volcanic models in this regard.

The impact (one year) climate sensitivity for doubling carbon dioxide is much greater when volcanics are omitted (Table 1). The equilibrium climate sensitivity is greater with the volcanic forcing. The sensitivity ranges from 1.59 K for the 3000 m non-volcanic model to 14.65 K for the 3000 m volcanic model. The estimate for the 300 m volcanic model is close to the mean for the GCMs reported by Cubasch et al. (2001). α_1 and α_2 are the adjustment parameters in (1). The response to disequilibrium between atmospheric temperature and radiative forcing for the non-volcanic models is fast. The models with volcanic forcing have much slower adjustment, with the 3000 m model, having the slowest adjustment of all. By contrast, the values for the adjustment to ocean heat content are small for the non-volcanic models and large for the models with volcanic forcing. The higher value makes sense—surface temperature adjusts faster to the temperature of the ocean than to radiative forcing. As the ocean warms slowly over time, the atmosphere gradually comes into equilibrium with its forcing. Again, the volcanic model does seem more realistic. The estimate of the heat capacity of the surface box ranges from −3.26 to 9.31. The 3000 m non-volcanic model and 300 m volcanic model have estimates close to the expected value of 5. β_{23} is the sensitivity of the atmosphere to changes in ocean heat content. The values for the volcanic models are close to expected values.

The ADF statistics test for cointegration in the two long-run relations. The critical value at the 5% significance level is −3.37. All models pass this test for the long-run relation between surface temperature and radiative forcing and all but the fourth model pass this test for the long-run relation between T and Q. p $Q(24)$ is the significance level for the $Q(24)$ test for serial correlation, which shows that all models have insignificant residual serial correlation in the atmospheric equation.

Summarizing all these results, I believe the weight of the evidence shows that the volcanic model performs more realistically and that the 300 m volcanic model is superior to the 3000 m model especially as measured by the simulation results. The fact that the shallow ocean model fits better than the deep ocean model points to the need to model a more complex ocean in future research. The 3000 m data is a five-year moving average and has, therefore, less information. This might partly explain the poor performance of this model.

4.2. Detailed results for the preferred model

Table 3 presents detailed results for the preferred model with a 300 m ocean and volcanic forcing included. The coefficients of radiative forcing, π_1 and β_{12} imply that the immediate impact from increasing radiative forcing is 0.23 K for the equivalent of doubling CO_2, while the long-run equilibrium climate sensitivity is 4.39 K, which is much higher than previous time series estimates and higher than Schlesinger et al.'s estimate for an EBM model with volcanic aerosols of 3.20 K. The sensitivity of surface temperature to ocean heat content is 0.0168. This parameter is somewhat smaller than the expected value for the top 300 m of the ocean of 0.04–0.05 based on the relative changes in heat content and temperature over the period examined by Levitus et al. (2000, 2001). The atmosphere warmed by around 0.4 K for a 6.6E21 J increase in heat content while the upper 300 m of the ocean warmed by 0.31 K for a 8E22 to 10E22 J increase in heat content [(6.6E21/0.4 K)/(9E22/0.31 K) = 0.045]. However, based on a 3000 m ocean depth and the heat absorbed by both the warming of the atmosphere and the decrease in ice volume the parameter is expected to be 0.016. The atmosphere and cryosphere together absorbed 1.9E22 J and the top 3000 m of the ocean warmed by 0.06 K while absorbing 18E22 J [(1.9E22/0.4 K)/(18E22/0.06 K) = 0.016].

The adjustment rate to long-run equilibrium between temperature and radiative forcing implies that 4.5% of the disequilibrium between the two variables is eliminated each year. This is much slower than other time series model estimates but still relatively fast as it implies an e-folding time of 30 years. The adjustment rate to ocean heat content is much faster at 38.7% per annum—an implied e-folding time of two years. Surface temperature mostly reflects oceanic temperature rather than the current level of radiative forcing. Because of the interaction of the two feedback mechanisms

Table 3
Multicointegration model—300 m ocean and volcanic forcing

Parameter	Value of parameter	Standard error	t Statistic
α_1	−0.0452	0.0117	−3.8708
α_2	−0.3870	0.0559	−6.9289
β_{12}	−1.1826	0.0637	−18.5779
β_{23}	−0.1668	0.0177	−9.4267
β_{14}	−0.0168	1.7797e − 03	−9.4616
β_{24}	−0.0599	0.0361	−1.6596
π	0.0628	0.0166	3.7913
μ	4.92	1.9904	2.4724
σ_1	0.0968	4.7755e − 03	20.2694
σ_2	2.2519	0.2114	10.6529
Impact climate sensitivity	0.2329		
Equilibrium climate sensitivity	4.3857		
p $Q(1)$	0.3000		
p $Q(24)$	0.0663		
R^2 Atmosphere	0.8291		
R^2 Ocean	0.1163		
ADF CR1	−5.1054		
ADF CR2	−3.8460		

See text for definitions of statistics.

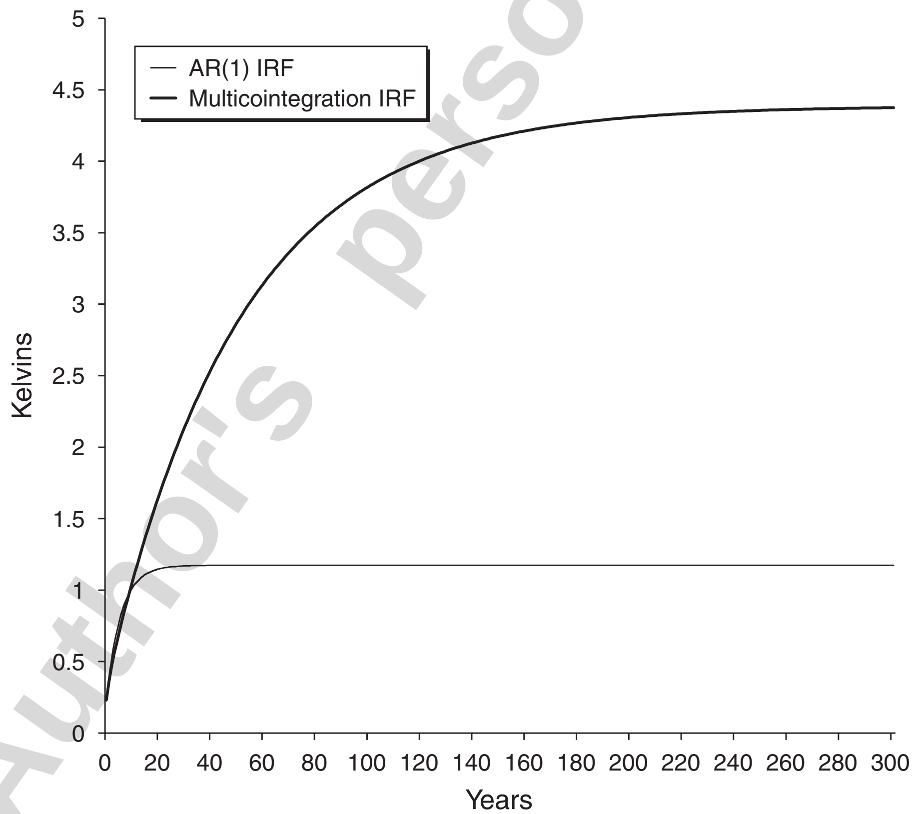

Fig. 1. Impulse response functions: response of atmospheric temperature to doubling carbon dioxide.

the actual rate of adjustment to the long-run equilibrium is slower than either number. After the first few years it settles down to 1.95% per annum.

Fig. 1 illustrates the impulse (step) response function to a sudden permanent doubling of CO_2. The response in the initial year is only 5.3% of the final response. After that, the annual increments of temperature decline. After 33 years

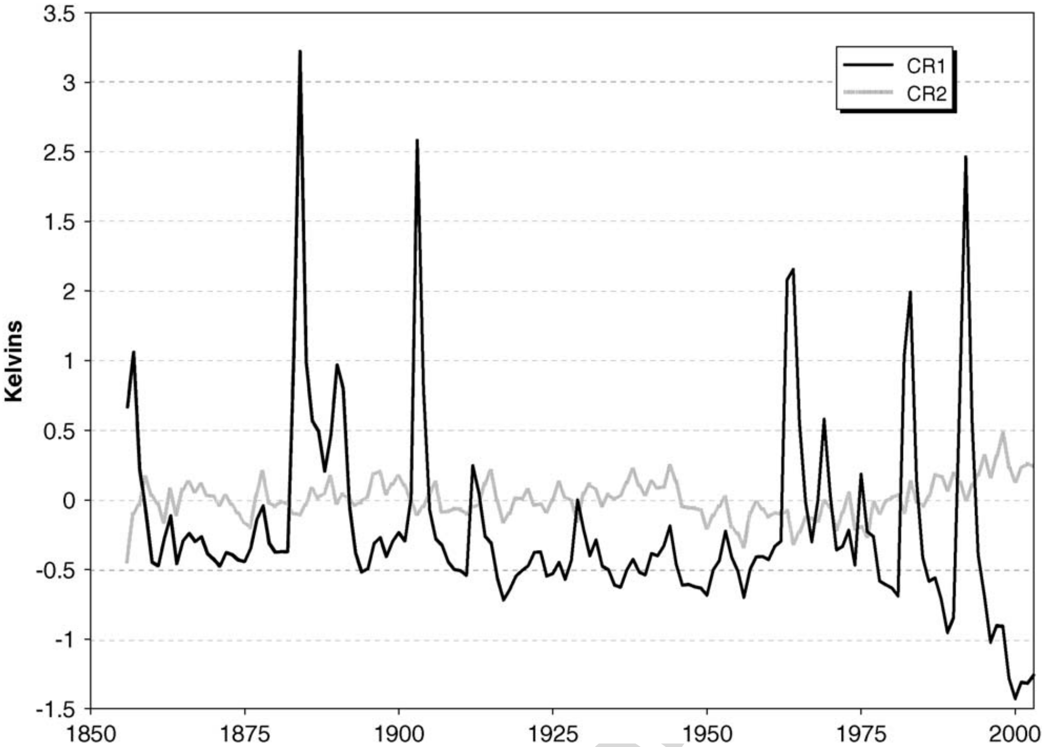

Fig. 2. Cointegrating residuals.

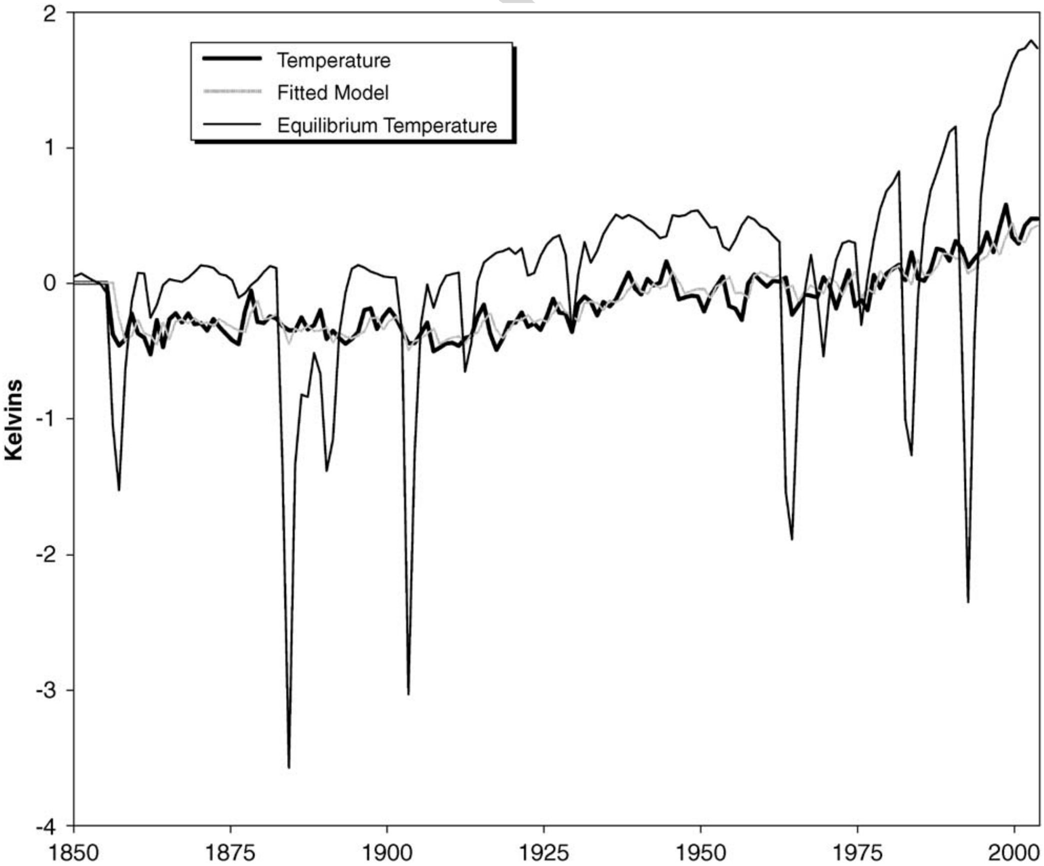

Fig. 3. Global temperature and long-run equilibrium.

half the response is complete. The e-folding time is 48 years and after 195 years, 98% of the response is complete while 99% is complete after 230 years. The impulse response function of ocean heat content (not shown) has a very similar profile to the surface temperature impulse response function. The figure also shows the impulse response function for the simple AR(1) autoregressive model discussed below.

Fig. 2. presents the deviations from long-run equilibrium in the two cointegrating relations. CR1 is the deviation from long-run equilibrium between surface temperature and radiative forcing. It fluctuates a lot due to the impact of volcanic eruptions. In years without significant volcanic eruptions temperature is below equilibrium indicating accumulation of heat in the ocean. The minima also trend downward indicating an increasing rate of heating. The difference of this residual from zero reflects committed warming—warming that will happen but has not happened yet—which is around 1.3 K in 2003. This is more than the warming from the mid-19th century till today. CR2 shows the deviation of surface temperature from equilibrium with ocean heat content. The results show that the atmosphere has mostly been close to equilibrium with the ocean due to the fast rate of adjustment of the atmosphere to oceanic temperature. As discussed above these residuals are stationary, though highly autocorrelated.

Another way of looking at these relations is shown in Fig. 3, which plots global temperature, the fitted model, and the long-run equilibrium value due to radiative forcing. The gap between actual and potential temperature indicates the committed warming. In the early twentieth century there was a long period with few volcanic eruptions. According to the model, the atmosphere remained below equilibrium temperature and heat was added consistently to the ocean. This could represent the end of the catch-up period after the Little Ice Age and the large volcanic eruptions in the 19th century. Hansen et al. (1997) find evidence of a 0.5 W m^{-2} disequilibrium in 1979, which corresponds to 0.59 K in our model. The actual disequilibrium in 1979 in my model is 0.61 K.

In Fig. 4, I compare the ocean heat content state variable to the upper ocean heat content observations from Levitus et al. (2000, 2005). In the observational period, the two series show similar cyclical behavior. In the last couple of decades, the phase of the cycles aligns more and the state variable reproduces well the recent steep rise in heat content. The cycles I estimate appear to fit the cycles in the data somewhat better than those estimated by Harvey and Kaufmann (2002) though they worked with older 3000 m data. In the first half of the 20th century, ocean heat content rises steeply and monotonically due to the absence of volcanic eruptions as explained in the previous paragraph. This may be

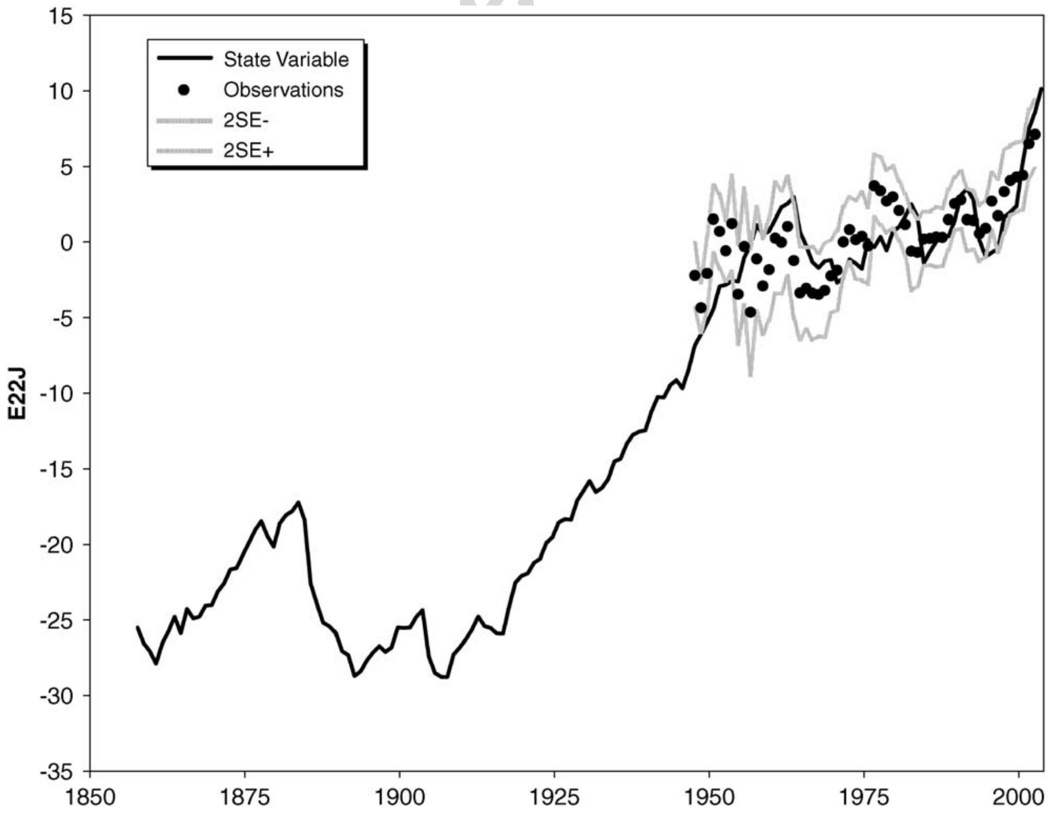

Fig. 4. Estimated state variable and observations of ocean heat content.

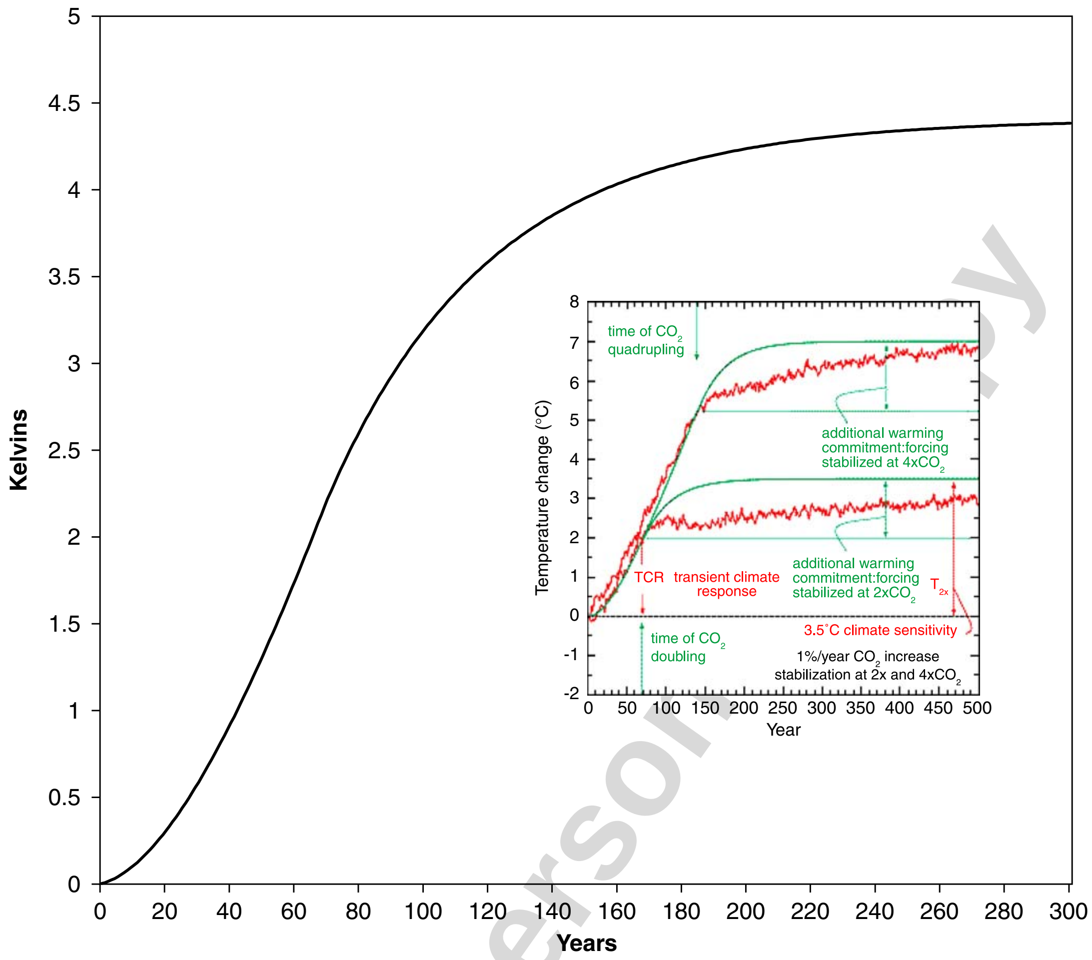

Fig. 5. Transient response.

an overestimate of the actual increase. However, due to renewed volcanic eruptions and a high anthropogenic sulfur loading, the period from 1963 to 1993 had lower average radiative forcing than the previous four decades. Only in the late 1990s does radiative forcing reach unprecedented levels.

I also carried out the standard transient response experiment where carbon dioxide is increased by 1% per annum until doubling occurs after seventy years and is then held constant (Cubasch et al., 2001). At the time of doubling, 49% of the final response had occurred—a 2.17 K warming. 98% of the final response was complete 160 years later. The response is shown in Fig. 5 together with Fig. 9.1 from Cubasch et al. (2001). The typical transient response from the GFDL GCM shown in that figure results in about 57% of total warming at the time of doubling—a 2 K warming. My results quite closely match the pattern shown by the smooth lines in the inset figure, which represents a model without transport of heat to the deep ocean.

4.3. Simple autoregressive model

As (17) involves the products of regression parameters, I estimate the model using nonlinear least squares in order to get direct estimates of the parameters of interest and their standard deviations. The results presented in Table 4 include volcanic forcing. Excluding the latter forcing increased the climate sensitivity to 2.3 K and the adjustment rate to 0.48. These latter are close to existing time series estimates, which have usually omitted volcanic forcing. The R-squared of the model with volcanic forcing is 0.7930, which is lower than that of the atmospheric equation in the multicointegration model. The adjustment rate to disequilibrium between radiative forcing and surface temperature is 0.16, which is between the two adjustment rates in the multicointegration model. The climate sensitivity is only 1.17 K. This result is much lower than that for any GCMs. Fig. 1 also presents the impulse response function for this AR(1)

Table 4
Simple AR(1) autoregressive model (including volcanic forcing)

Parameter	Value of parameter	Standard error	t statistic
α_1	−0.1644	0.0452	−3.64
β_{12}	−0.3165	0.0959	−3.30
β_{14}	0.0887	0.0559	1.58
π	0.0610	0.0194	3.14
$\sigma(\varepsilon)$	0.1076	n.a.	n.a.
R^2	0.7930		

model. The profile ramps up very fast. The e-folding time is 5 years and 98% of the entire adjustment is complete in 20 years. The multicointegration model has more plausible behavior.

5. Discussion and conclusions

The multicointegration model presented in this paper clearly represents an advance on previous time series models of the global climate system. The model is validated by matching important features of the system derived from the observations and GCM simulations. A high climate sensitivity and a slow adjustment rate to forcing particularly distinguish the model. I believe that this confirmation of results derived from deterministic simulation models is strong evidence of anthropogenic warming.

These new results were obtained by adding both the ocean component and volcanic forcing to previous time series models. Previous time series models found little effect due to volcanic forcing. In this study too, the volcanic series reduces the goodness of fit as measured by R^2 but clearly improves several features of the model, in particular the behavior of the ocean, that make the model more realistic.

The model also demonstrates the potential for using partial time series observations for constraining models via the Kalman filter. This approach could be extended to the use of other incomplete and irregular time series. However, I found that using observations on heat storage in the upper 300 m of the ocean alone provided a better model fit than the 3000 m series. The results suggest that a multilayer ocean model is needed with the atmosphere in equilibrium with the upper ocean and the upper ocean transmitting heat to a deep ocean layer.

This basic model is only intended to demonstrate the approach. It can be easily generalized in several ways to allow: spatial and vertical disaggregation (e.g. northern and southern hemispheres, upper ocean and deep ocean); more general error processes such as moving average errors and higher order autoregressive processes; the addition of other submodels such as the carbon cycle; and disaggregation of the radiative forcing variable.

Though the model presented here clearly needs various improvements and extensions, discussed above, this pilot study has shown that a time series model based on the multicointegration approach can yield interesting insights and more realistic behavior than traditional time series models.

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Appendix: Data sources

I assembled an annual time series data set for the period 1856 to 2003 for the variables described below.

Ocean heat content. Data for 1955–2003 are from Levitus et al. (2005). We added data for 1948–1954 for the top 300 m of the World Ocean from Levitus et al. (2000) with an adjustment for the difference in means of the two series. For the top 3000 m data for 1955–1959 through 1994–1998 are from Levitus et al. (2005) with data for 1948–1952 through 1954–1958 added from Levitus et al. (2000) with an adjustment for the difference in means of the two series.

Atmospheric temperature. We use global mean annual temperature. These data have not been adjusted for ENSO. These data are described by Jones and Moberg (2003). The temperature series were downloaded from the University of East Anglia website. The uncertainties in the data described on the website are used for the standard error of measurement in the temperature equation. Jones et al. (1997) discuss the background to those uncertainty estimates.

Carbon dioxide, *methane*, *nitrous oxide*, *CFCs*. Data on trace gas concentrations based on atmospheric measurement and interpolation of ice core data is taken from Hansen et al. (1998) with updated data downloaded from the Goddard Institute for Space Sciences website. For carbon dioxide, methane, and nitrous oxide, formulae for converting concentrations to radiative forcing are from Ramaswamy et al. (2001) using the first line in Table 6.2. For CFCs we include the radiative forcing due to ozone depletion. Kattenberg et al. (1996) give the following formulae:

$$\text{CFC-11,} \quad 0.22y - 0.0552(3y)^{1.7},$$

$$\text{CFC-12,} \quad 0.28z - 0.0552(2z)^{1.7},$$

where y and z are in parts per billion.

Anthropogenic sulfate aerosols. We use estimates of anthropogenic emissions of SO_x, which are described in Stern (2005) and updated to 2003. Data is available for most countries through 2000. Data is available for many countries for 2001, for China, US, and Mexico for 2002, and for China only for 2003. Emissions for countries without data are projected at their mean growth rate over the previous ten years. Radiative forcing is assumed to be $-0.3(S_t/S_{1990}) - 0.8\ln(1+S_t/28)/\ln(1+S_{1990}/28)$ where S is in megatonnes (Kattenberg et al., 1996; Wigley and Raper, 1992). The emissions are modified to account for the increase in stack heights over time (Wigley and Raper, 1992).

Volcanic forcing. We use the series downloaded from the Goddard Institute for Space Sciences website described by Hansen et al. (1996) and Sato et al. (1993) for years through 1889. For 1890–1999 we used the optical depth data from Ammann et al. (2003) multiplied by -20 and averaged globally weighted by the area of each latitudinal zone. In 2000–2003 it is assumed that the optical depth was zero, which seems congruent with the available data from the SAGE experiments.

Solar irradiance. We use the index of solar irradiance assembled by Lean (2000) and obtained from the Goddard Institute for Space Studies website updated with the mean of daily observations from satellites provided by Fröhlich and Lean (1998) from the PMODWRC website. The formula for converting irradiance to radiative forcing is from Kattenberg et al. (1996).

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