THE RELATIONSHIP BETWEEN RADIATIVE FORCING AND TEMPERATURE: WHAT DO STATISTICAL ANALYSES OF THE INSTRUMENTAL TEMPERATURE RECORD MEASURE?

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Abstract. Comparing statistical estimates for the long-run temperature effect of doubled CO_2 with those generated by climate models begs the question, is the long-run temperature effect of doubled CO_2 that is estimated from the instrumental temperature record using statistical techniques consistent with the transient climate response, the equilibrium climate sensitivity, or the effective climate sensitivity. Here, we attempt to answer the question, what do statistical analyses of the observational record measure, by using these same statistical techniques to estimate the temperature effect of a doubling in the atmospheric concentration of carbon dioxide from seventeen simulations run for the Coupled Model Intercomparison Project 2 (CMIP2). The results indicate that the temperature effect estimated by the statistical methodology is consistent with the transient climate response and that this consistency is relatively unaffected by sample size or the increase in radiative forcing in the sample.

1. Introduction

Analysts use the notion of cointegration to analyze the relationship between observed surface temperature and radiative forcing (Kaufmann and Stern, 2002; Kaufmann et al., 2006). The results show that the variables cointegrate. Cointegration indicates that there is a statistically meaningful long-run relationship between radiative forcing and surface temperature. This result is consistent with those of climate models, which indicate that human activity is partially responsible for the increase in surface temperature over the last 150 years (Cubasch and Meehl, 2001; Mitchell and Karoly, 2001).

The finding of cointegration implies that the statistical results can be used to estimate the long-run temperature effect of a doubling in the atmospheric concentration of carbon dioxide. These estimates indicate that doubling atmospheric carbon dioxide would raise surface temperature by 1.7–3.5 °C (Kaufmann and Stern, 2002; Kaufmann et al., 2006). This range is consistent with estimates for ΔT_{2x} of 3.5 ± 0.9 °C reported by Cubasch and Meehl (2001), but are considerably smaller than the range reported by Forest et al. (2002) who argue that the 5 to 95% confidence interval for ΔT_{2x} lies between 1.4° and 7.7°K and Andronova and

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Schlesinger (2001) who argue that the 90 percent confidence interval for ΔT_{2x} is 1 to 9.3 °C.

Comparing statistical estimates for the temperature effect of doubled CO_2 with those generated by climate models is complicated by the fact that modeled temperature adjusts to radiative forcing over many time scales. These adjustments are summarized by three definitions of temperature sensitivity; the transient climate response, equilibrium climate sensitivity, and effective climate sensitivity (Cubash and Meehl, 2001). These definitions beg the question, which if any of these climate sensitivities is consistent with the long run temperature effect of doubled CO_2 that is estimated from the instrumental temperature record using statistical techniques?

Here, we attempt to answer the question, what do statistical analyses of the observational record measure, by using these same statistical techniques to estimate the temperature effect of a doubling in the atmospheric concentration of carbon dioxide from seventeen simulations run for the Coupled Model Intercomparison Project 2 (CMIP2). The results indicate that the temperature effect estimated by the statistical methodology is consistent with the transient climate response and that this consistency is unaffected by the length of the sample or the increase in radiative forcing during the sample.

These results and the methods used to obtain them are described in four sections. In Section 2, we describe the data and the statistical methodology used to analyze them. Section 3 reports statistical estimates for the temperature effect of a doubling in the atmospheric concentration of CO_2 and their relation to the transient climate response that is implicit in the model output. The implications of these results for arguments about attribution and the magnitude of the anthropogenic temperature effect are discussed in Section 4.

2. Methodology

We analyze simulations of global surface temperature generated by seventeen of the models that participated in CMIP2 (Covey et al., 2003). As part of this comparison, the models simulate the same experiment – the so-called one percent experiment. In the one percent experiment, the atmospheric concentration of CO_2 is increased 1% per annum compounded for seventy years. At this point, the atmospheric concentration is doubled. Once doubled, the atmospheric concentration of CO_2 is held constant at its elevated (2×) level. Most modelers report results for another ten years, which generates eighty years of data. We also analyze the GFDL_R15_a experiment (run by the GFDL model) which continues the simulation for another 430 years after the atmospheric concentration of CO_2 doubles, which generates 500 years of data (Stouffer, personal communication).

For each simulation, we use the methodology used by Kaufmann et al. (2006) to analyze the relationship between modeled global surface temperature and radiative forcing. In the first step, we determine whether the global temperature data that are simulated by the model cointegrate with radiative forcing that are used to simulate the model. In the second step, we estimate the cointegrating relation between modeled temperature and radiative forcing. In the third step, the statistical estimate for this relationship is used to calculate the temperature effect of a doubling in CO_2 and this effect is compared to the model's transient climate response.

Both Kaufmann et al. (2006) and Kaufmann and Stern (2002) conclude that observed values for surface temperature and radiative forcing cointegrate. By definition, cointegration occurs if there is at least one linear combination of the nonstationary temperature and radiative forcing variables that is stationary. To determine whether the radiative forcing series used to simulate the climate model cointegrates with its temperature output, we follow the two-step procedure described by Engle and Granger (1987). In the first step, ordinary least squares (OLS) is used to estimate the following equation:

$$T_t = \lambda + \theta \mathrm{RFCO}_{2t} + \mu_t \tag{1}$$

in which T is the global surface temperature simulated by the model for year t, RFCO_2 is the radiative forcing associated with the atmospheric concentration of carbon dioxide that is used to simulate the model, and μ_t is the regression error.

In the second step, we test whether the error (μ_t) in Equation (1) is stationary. If it is stationary, then modeled temperature and radiative forcing cointegrate. We test this hypothesis using the augmented Dickey Fuller statistic (Dickey and Fuller, 1979), which is given by Equation (2):

$$\Delta\hat{\mu}_t = \eta + \gamma\hat{\mu}_{t-1} + \sum_{i=1}^{s} \delta_i \Delta\hat{\mu}_{t-i} + \varepsilon_t \tag{2}$$

in which $\hat{\mu}_t$ is the OLS residual from Equation (1), Δ is the first difference operator (e.g. $\Delta\hat{\mu}_t = \hat{\mu}_t - \hat{\mu}_{t-1}$), and ε_t is a random error term. The number of augmenting lags used to estimate Equation (2) is chosen using the Akaike information criterion (Akaike, 1973).

The null hypothesis of the augmented Dickey Fuller (ADF) test is that the series contains a stochastic trend. The ADF test evaluates this null, $\gamma = 0$ by comparing the t-statistic for γ against a non-standard distribution that depends on the number of regressors in the first-stage equation, here one (MacKinnon, 1994). Rejecting the null hypothesis indicates that the series is stationary. If the ADF test for μ rejects the null hypothesis, T and RFCO_2 are said to cointegrate.

We estimate the long-run relationship between these variables with the methodology used by Kaufmann et al. (2006). This methodology uses the dynamic ordinary least squares (DOLS) estimator developed by Stock and Watson (1993). DOLS generates asymptotically efficient estimates of the regression coefficients for variables that cointegrate using the following specification:

$$T_t = \alpha + \beta \mathrm{RFCO}_{2t} + \sum_{i=-q}^{q} \phi_i \Delta \mathrm{RFCO}_{2t-i} + \zeta_i \tag{3}$$

in which β represents the cointegrating relation between radiative forcing and modeled temperature and ζ is the regression error. The number of lags and leads used by the DOLS estimator is chosen with the Bayesian information criterion (Schwartz, 1978). The maximum number of lags examined is given by $N^{1/3}$.

The DOLS estimate for β is used to calculate the temperature effect of a doubling in CO_2 with the same formula used by Kaufmann and Stern (2002) and Kaufmann et al. (2006), $\beta \times 6.3 \times \ln(2)$. The transient climate response implied by the climate model is calculated by averaging temperature between years 61 and 80 (Cubasch and Meehl, 2001). For the GFDL_R15_a experiment, the transient climate response is calculated by subtracting the average from years 61 through 80 of the control simulation from the average of the GFDL_R15_a experiment for years 61 through 80 (Stouffer, personal communication).

To determine whether the statistical estimates for the temperature effect of a doubling in CO_2 are consistent with the transient climate response, we examine the results across experiments and the results for individual experiments. To examine the results across experiments, we estimate the following regression:

$$\mathrm{TCRGCM}_i = \pi + \varphi \mathrm{TCRDOLS}_i + \nu_i \tag{4}$$

in which TCRGCM is the transient climate response simulated by climate model i (eighteen models including the GFDL_R15_a simulation), TCRDOLS is the transient climate response estimated from the temperature data from climate model i using the statistical methodology, and ν is the regression error. If the statistical methodology generates an unbiased estimate for the climate model's TCR, the data will lie along a 45° line that passes through the origin. To evaluate this notion, we use t and F tests to test the null hypothesis that $\pi = 0$ and/or $\varphi = 1$.

To test whether the statistical methodology generates an accurate estimate of the TCR for individual models, we calculate a Z statistic as follows:

$$Z = \frac{\beta 6.3 \ln(2) - \mathrm{TCRGCM}}{\sqrt{\sigma_\beta^2 (6.3 \ln(2))^2 + \frac{\sigma^2_{\mathrm{TCRGCM}}}{20}}} \tag{5}$$

in which σ_β^2 is the variance of the DOLS estimate for β in Equation (3) generated by a procedure developed by Newey and West (1987), σ^2_{TCR} is the variance of the estimate for the climate model's transient climate response, and 20 is the number of data points used to calculate the climate model's transient climate response.

The null hypothesis of the Z statistic is that the statistical estimate for the temperature effect of a doubling in CO_2 is equal to the transient climate response simulated by the climate model. This Z statistic can be evaluated against the standard normal distribution. Failure to reject the null hypothesis would indicate that the temperature effect estimated by the statistical methodology can not be distinguished from the transient climate response in a statistically significant fashion. Conversely, the statistical estimate for temperature effect is not consistent with the climate model's transient climate response if the Z statistic rejects the null hypothesis.

The one percent experiment includes data in which the radiative forcing of carbon dioxide has doubled. These data may facilitate the ability of the statistical methodology to estimate the transient climate response relative to its ability to estimate the same effect from the instrumental temperature record, where radiative forcing has achieved only about 35% of the increase associated with a doubling of CO_2. To investigate this effect on the statistical estimate for β, we repeat the analysis of model simulations with subsamples that end before the atmospheric concentration of carbon dioxide doubles. One sub-sample starts in year 1 and ends in year 40, another ends in year 50, year 60, and year 70. If the results are robust, this would indicate that the small change in radiative forcing during the instrumental temperature record (relative to the doubling in the one percent experiment) does not affect the statistical estimate for the temperature effect of a doubling in CO_2.

It is also possible that data beyond a doubling of CO_2 would allow the statistical methodology to estimate the temperature effects that occur over time scales longer than the transient climate response (i.e. the effective climate sensitivity or the equilibrium climate sensitivity). To evaluate this possibility, we analyze the results of the GFDL_R15_a experiment for which five hundred years of data are available. If the statistical estimate for the temperature effect of a doubling in CO_2 does not change as the regression sample is extended beyond 70 years, this too would indicate that the limited change in radiative forcing in the observational record does not affect the temperature affect of a doubling in CO_2 estimated by the statistical methodology.

3. Results

The ADF statistics indicate that the temperature data generated by the model generally cointegrate with the radiative forcing data used to simulate the model (Table I). The presence of a cointegrating relation is confirmed by the analysis of the GFDL_R15_a simulation (Table II). The findings of cointegration are not surprising. The ADF statistic should be able to detect a relationship between temperature and radiative forcing if the relation is fairly linear. Consistent with this interpretation, the literature suggests that nonlinearities are not important during the instrumental temperature record (Allen et al., 2000).

The importance of linearity to the finding of cointegration is highlighted by the two models for which the ADF tests consistently fail to reject the null hypothesis, the NRL and MRI models. In these models, temperature responds to radiative forcing in a nonlinear fashion. In the NRL model, temperature rises sharply in the first ten years of the simulation and then rises slowly in a nearly linear fashion thereafter (Figure 1). The change in the rate of temperature increase prevents the ADF statistic from rejecting the null hypothesis for short samples in which the sharp rise in temperature during the first decade predominates. Conversely, temperature rises slowly during the first forty years of the MRI simulation and rises sharply thereafter (Figure 1).

TABLE I
ADF statisics (Equation (2)) for models with 80 observations

Experiment	Sample period				
	Years 1–40	Years 1–50	Years 1–60	Years 1–70	Years 1–80
GFDL	−2.31	−2.20	−2.92	−3.22+	−3.24+
GISS	−2.43	−2.09	−3.49*	−4.00**	−3.00
BMRC	−3.59*	−4.25**	−4.44**	−4.52**	−3.86**
CCC	−2.68	−3.95**	−4.86**	−5.21**	−3.84*
CCSR	−5.11**	−4.82**	−5.58**	−5.57**	−5.70**
CERF	−3.71*	−3.00	−3.42*	−3.99**	−3.91**
CSIR	−3.44*	−4.18**	−4.41**	−4.54**	−3.25+
ECH3	−3.51*	−2.11	−2.15	−3.84*	−3.18+
IAP	−2.81	−3.63*	−3.74*	−4.13**	−2.67
LMD	−4.84**	−3.25+	−4.02**	−3.66*	−3.59*
MRI	−3.04	−2.67	−2.45	−1.50	−0.33
NCAR_CSM	−4.09**	−4.65**	−4.41**	−3.67*	−3.29+
NCAR_WM	−3.68*	−3.54*	−3.55*	−2.69	−1.68
NRL	−1.87	−1.49	−1.93	−2.40	−2.84
PCM	−2.68	−3.77*	−4.19**	−4.64**	−4.60**
UKMO	−3.07+	−3.83*	−4.04**	−4.12**	−4.29**
UKMO3	−5.91**	−3.87*	−4.12**	−3.78*	−3.97**

Note. ADF tests reject the null hypothesis at the: **1%, *5%, +10% level.

During the initial rise, there is a near linear relationship between temperature and radiative forcing which is weakened as the sample lengthens and the slow initial rise is supplemented with data in which temperature rises sharply. Because of this change, the ADF test suggests cointegration for samples to year fifty, but fails to reject the null hypothesis that the residual is stationary for longer samples.

The results indicate that the statistical methodology is able to generate an unbiased estimate for the TCR in the climate model. The estimates for the TCR seem to lie along a 45° line that passes through the origin (Figure 2). The OLS 95% confidence interval for π and φ are 0.016 ± 0.11 and 0.948 ± 0.053 (adjusted $R^2 = 0.95$). Consistent with the point estimates, we fail to reject $\pi = 0$ ($t = 0.15$, $p > 0.88$) or $\varphi = 1$ ($t = -0.98$, $p > 0.34$). We reject the null hypothesis $\pi = 0$ and $\varphi = 1.0$, in Equation (4) ($F(2, 16) = 4.18$, $p < 0.04$), although the underlying deviation from the null hypothesis is very small from a substantive perspective.

The Z statistics for individual models generally do not reject the null hypothesis that the statistical estimate for the temperature effect of a doubling in the atmospheric concentration of carbon dioxide is equal to the transient climate response (Tables II and III). This effect does not seem to vary by the size of the

TABLE II
Results for the GFDL_R15_a simulation

Sample period	ADF statistics	Z test
Years 1–40	−3.94*	−1.01
Years 1–60	−3.67*	−0.25
Years 1–80	−3.85*	0.42
Years 1–100	−4.37**	0.43
Years 1–120	−2.89	0.31
Years 1–140	−2.75	0.31
Years 1–160	−2.94	0.31
Years 1–180	−3.18+	0.27
Years 1–200	−4.61**	0.27
Years 1–220	−4.84**	0.27
Years 1–240	−5.18**	0.27
Years 1–260	−5.37**	0.27
Years 1–280	−5.59**	0.19
Years 1–300	−5.90**	0.19
Years 1–320	−6.13**	0.19
Years 1–340	−6.36**	0.19
Years 1–360	−6.51**	0.19
Years 1–380	−6.77**	0.19
Years 1–400	−6.81**	0.19
Years 1–420	−7.00**	0.19
Years 1–440	−7.10**	0.17
Years 1–460	−7.14**	0.17
Years 1–480	−7.35**	0.17
Years 1–500	−7.51**	0.17

Note. Test statistics rejects the null hypothesis at the: **1%, *5%, +10% level.

sample. The sole exception is the simulation generated by the MRI model for years 1–50. This failure is not surprising based on the lack of cointegration between radiative forcing and modeled temperature, as indicated by the ADF tests reported in Table I.

4. Discussion

Cubasch and Meehl (2001) define three measures of temperature sensitivity; the transient climate response, the equilibrium climate sensitivity, and the effective climate sensitivity. Differences among these measures are defined by the time scales

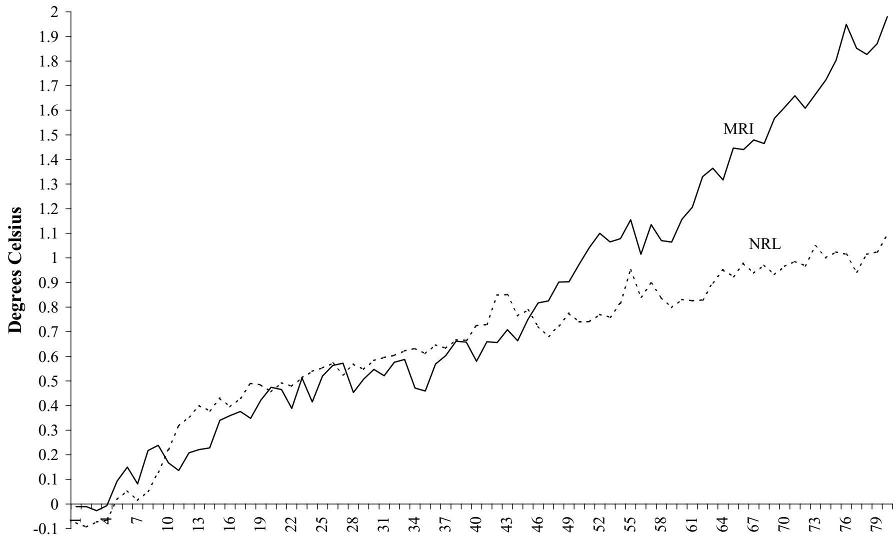

Figure 1. Simulations for the one percent experiment run by the MRI and NRL models.

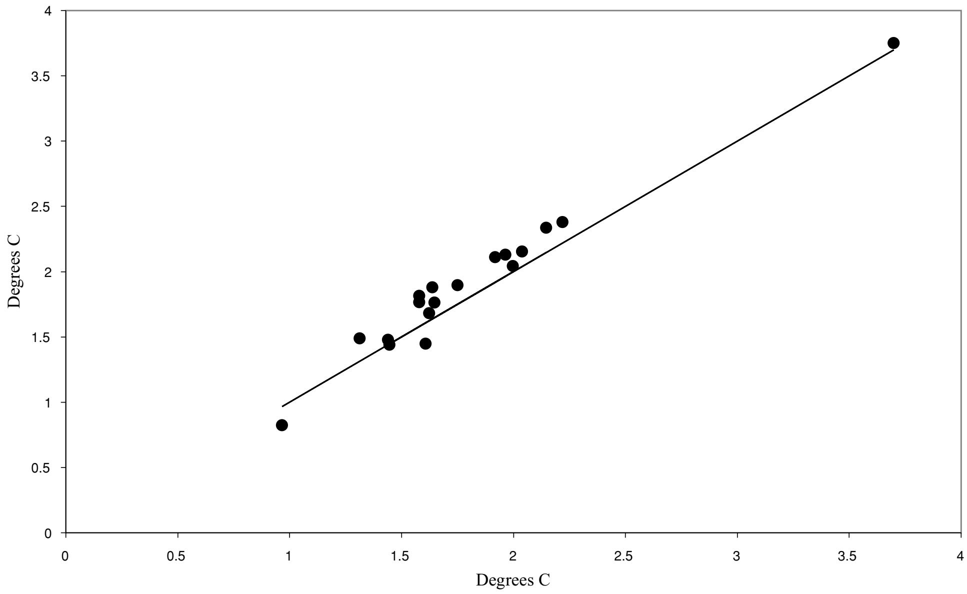

Figure 2. Values of the transient climate response calculated from model temperature data (*X* axis) versus the transient climate response estimated from the model temperature data using the statistical methodology (*Y* axis).

and feedbacks by which radiative forcing affects temperature. Transient climate sensitivity is the temperature change observed at the time that the atmospheric concentration of carbon dioxide doubles. Although this effect "integrates all processes operating in the system, including the strength of the feedbacks and the

TABLE III
Z statistics (Equation (5)) for comparison of statistical estimate and transient climate response

				Sample size				
Experiment	$\bar{T}_{1-10}$	TCR	TCR[a]	Years 1–40	Years 1–50	Years 1–60	Years 1–70	Years 1–80
GFDL	0.00	2.15	2.33	−0.02	−0.19	0.42	0.6	0.66
GISS	0.17	1.45	1.44	−0.51	−0.05	−0.32	−0.09	−0.02
BMRC	−0.11	1.58	1.82	0.52	0.91	0.96	0.84	0.93
CCC	−0.01	1.92	2.11	0.47	0.39	0.32	0.56	0.78
CCSR	0.06	1.62	1.68	−0.03	−0.26	−0.05	−0.14	0.16
CERF	0.12	1.64	1.88	−0.79	0.09	0.46	0.77	0.80
CSIR	0.14	2.00	2.04	−0.55	−0.10	−0.02	−0.01	0.17
ECH3	0.02	1.58	1.76	−0.65	−0.20	0.39	0.61	0.78
IAP	0.09	1.65	1.76	0.15	0.16	0.18	0.59	0.58
LMD	0.06	1.96	2.13	−0.20	−0.25	0.17	0.42	0.66
MRI	0.09	1.61	1.45	−0.98	−2.22*	−1.20	−1.12	−0.64
NCAR_CSM	0.08	1.44	1.48	−0.53	−0.34	−0.62	0.07	0.14
NCAR_WM	0.28	3.70	3.75	−0.63	−0.82	−0.66	−0.25	0.07
NRL	0.02	0.97	0.82	0.52	0.37	−0.07	−0.36	−0.52
PCM	0.09	1.31	0.49	−0.28	−0.13	0.05	0.39	0.56
UKMO	0.07	1.75	1.90	0.22	0.16	0.01	0.41	0.30
UKMO3	0.01	2.04	2.15	0.36	0.23	0.40	0.36	0.28

Note. Z statistic is statistically significantly different from zero at the: **1%, *5%, +10% level.
$\bar{T}_{1-10}$ Average temperature for the first decade of observations.
[a]TCR estimated by DOLS from observations years 1 through 80.

rate of heat storage in the ocean" the short time frame over which the atmospheric concentration doubles in the one percent experiment (seventy years) means that the transient climate response does not include the full effect of deep ocean mixing and feedbacks.

The full effects of deep ocean mixing and feedbacks are measured by the equilibrium climate sensitivity and the effective climate sensitivity. Equilibrium climate sensitivity is defined as "the change in global mean temperature, ΔT_{2x}, that results when the climate system, or climate model, attains a new equilibrium with the forcing changes F_{2x}, resulting from a doubling of the atmospheric CO_2 concentration (Cubasch and Meehl, 2001)." Consistent with this definition, the equilibrium temperature sensitivity includes feedback processes that offset the change in radiative forcing. Because the strength of these feedbacks may change over time, quantifying the equilibrium climate sensitivity dictates that the climate model be run to equilibrium, which can require thousands of years.

The demand for computer time that is associated with these long simulations can be alleviated by holding the feedback effect constant. The value is set according to the feedback effect estimated from output generated by the model during the evolution of nonequilibrium conditions (Cubash and Meehl, 2001). The resultant estimate for the temperature effect of a doubled CO_2 is termed the effective climate sensitivity.

Of these three definitions for the temperature effect of a doubling in CO_2, the results reported in the previous section indicate that the long-run temperature effect that is estimated by the statistical methodology represents the transient climate response. This interpretation does not change with the length of the sample period of the changes in radiative forcing during that sample. This implies that the statistical methodology used by Kaufmann et al. (2006) can be applied reliably to the instrumental temperature record. The instrumental temperature record runs for slightly more than a century. As such, it is unlikely that statistical analyses of these observations can capture effects that occur over hundreds to thousands of years.

The notion that the statistical methodology used by Kaufmann et al. (2006) recovers the transient climate response from the instrumental temperature record is supported by a comparison of estimates for the transient climate response estimated by climate models and statistical analyses. The transient climate response estimated by the models analyzed here range between 0.97 and 3.70 °C. This range brackets the temperature effect a doubling of CO_2 that is estimated statistically from the observational record 1.7 to 3.5 °C (Kaufmann and Stern, 2002; Kaufmann et al., 2006).

The consistency in the range of estimates for the transient climate response generated by climate models and statistical analyses of the observational record can be used to clarify the affect of human activity on temperature, narrow uncertainty about the size of its effect, and help decision makers formulate economically efficient policy. The finding of cointegration between radiative forcing and temperature in both climate models and the observational record provides direct evidence for the effect of human activity on surface temperature. That climate models generate estimates for the transient climate response that are consistent with values implied by the instrumental temperature record undercuts arguments made by skeptics about the importance of model uncertainty.

5. Conclusions

Statistical models of the relationship between surface temperature and radiative forcing that are estimated from the observational temperature record often are viewed skeptically by climate modelers. One reason is uncertainty about what statistical models measure. Because statistical models do not represent physical linkages directly, it is difficult to assess the time scale associated with statistical estimates for the effect of a doubling in CO_2 on surface temperature. The results of this analysis indicate that the statistical methodology used by Kaufmann et al. (2006) to analyze the instrumental temperature record is able to provide an accurate and unbiased estimate for the true (model specific) estimate for the TCR. This accuracy gives us added confidence in the statistical estimates for the TCR that are estimated from the instrumental temperature record. Although the transient climate response does not include the full effects of deep ocean mixing and feedbacks, it does represent the challenge for the twenty-first century and therefore is important for attributing climate change to human activity and efforts to formulate economically efficient policy.

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