Diurnal temperature range as an index of global climate change during the twentieth century

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[1] The usefulness of global-average diurnal temperature range (DTR) as an index of climate change and variability is evaluated using observations and climate model simulations representing unforced climate variability and anthropogenic climate change. On decadal timescales, modelled and observed intrinsic variability of DTR compare well and are independent of variations in global mean temperature. Observed reductions in DTR over the last century are large and unlikely to be due to natural variability alone. Comparison of observed and anthropogenic-forced model changes in DTR over the last 50 years show much less reduction in DTR in the model simulations due to greater warming of maximum temperatures in the models than observed. This difference is likely attributed to increases in cloud cover that are observed over the same period and are absent in model simulations. *INDEX TERMS:* 1610 Global Change: Atmosphere (0315, 0325); 1620 Global Change: Climate dynamics (3309); 3309 Meteorology and Atmospheric Dynamics: Climatology (1620). **Citation:** Braganza, K., D. J. Karoly, and J. M. Arblaster (2004), Diurnal temperature range as an index of global climate change during the twentieth century, *Geophys. Res. Lett.*, *31*, L13217, doi:10.1029/2004GL019998.

1. Introduction

[2] While changes in global mean surface temperature are a useful indicator of climate change and variability, changes in daily maximum and minimum temperatures provide more information than the mean alone. This is because trends in mean surface temperature can be due to changes in either maximum or minimum temperature, or relative changes in both. Over the last 50 years, observed surface warming over land has been associated with relatively larger increases in daily minimum temperatures (T_{min}) than in maximum temperatures (T_{max}) [*Karl et al.*, 1993; *Easterling et al.*, 1997; *New et al.*, 2000], though both show significant increases. Hence, there have been decreases in observed area-average diurnal temperature range (DTR) over land during the last 50 years. This decrease is not spatially uniform in observations [*Easterling et al.*, 1997] or in general circulation models (GCMs) [*Stone and Weaver*, 2003].

[3] *Dai et al.* [2001] and *Stone and Weaver* [2002, 2003] showed that anthropogenic forcing by greenhouse gases and sulphate aerosols in GCMs caused small ($\sim$0.2°C) decreases in global DTR over the 20th century. In this paper, we assess global diurnal temperature range (DTR) over land as a possible index of radiative forced climate change that provides information that is independent from global mean temperature. Recent studies [*Karoly et al.*, 2003; *Braganza et al.*, 2003] have shown that a set of multiple climate indices, that are independent in internal climate variations and show a coherent response to greenhouse forcing, provide additional information for the detection and attribution of climate change in much the same manner as spatial fingerprints of climate change. The definition of additional indices such as DTR may be useful in defining a signature of observed climate change that is less likely to show a common response to different radiative forcing mechanisms.

[4] Global-mean DTR is also a useful diagnostic index for the evaluation of GCM-simulated climate variability. Whereas previous studies have been limited to analysis from one or two models, here we show a comparison of observed variability and trends in T_{max}, T_{min} and DTR with simulations of unforced climate variability and anthropogenic forced climate change from five GCMs. These represent a range of differences in model resolution, the parameterization of radiative effects and climate sensitivity. The method we follow is similar to *Braganza et al.* [2003], who used multiple indices of area-average surface temperature to describe observed and simulated climate change.

2. Data Sets

[5] In this study, we use the University of East Anglia's Climatic Research Unit data set CRU TS 2.0 (T. D. Mitchell et al., A comprehensive set of high-resolution grids of monthly climate for Europe and the globe: The observed record (1901–2000) and 16 scenarios (2001–2100), submitted to *Journal of Climate*, 2003) for observed maximum and minimum temperatures over land and for observed total cloud amounts. It must be noted that CRU TS 2.0 has not had the effects of urbanisation and land use changes removed. While the effect of urbanisation on trends in maximum and minimum temperatures has been estimated to be very small on the global scale [*Easterling et al.*, 1997],

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the potential effect on DTR due to the differential impact of urbanisation on T_{max} and T_{min} remains unclear.

[6] Here, we transformed the 0.5° monthly grid of the original data set into a 5° latitude and longitude grid using area averaging. We then removed monthly grid boxes that did not contain any station data. Finally, the data was masked to exclude grid boxes with less than 40 years of data since 1901. The effect of missing data within any individual year for individual grid boxes had very little impact on the annual mean. We used a fixed data mask rather than a temporally-varying mask as changes in global-mean DTR were found to be relatively insensitive to time variations in the data coverage since 1910. The station-based region of coverage for maximum and minimum temperatures (shown in Figure 1) and the region of coverage for total cloud cover in CRU TS 2.0 is essentially the same.

[7] For the GCM simulations, we have data available from five global coupled ocean-atmosphere climate models. They are CSIRO Australia's CSIRO Mk2 [*Gordon and O'Farrell*, 1997; *Hirst et al.*, 2000], the UK Met Office Hadley Centre HadCM2 [*Johns*, 1996; *Johns et al.*, 1997], the Max-Planck-Institute fur Meteorologie ECHAM4 [*Roeckner et al.*, 1996], the National Center for Atmospheric Research (NCAR) Parallel Climate Model (PCM) [*Washington et al.*, 2000] and the Canadian Centre for Climate Modelling and Analysis (CCCMA) second version global climate model (CGCM2) [*Flato and Boer*, 2001]. PCM is the only model that does not use surface flux adjustments in maintaining a stable control climate simulation.

[8] The model simulations include two long control simulations, where external forcing factors have been left unchanged, 1000 years from CSIRO Mk2 and 530 years from PCM. For HadCM2 and ECHAM4 we have 240 years of control simulation data and 201 years of data for CGCM2. The forced experiments simulate observed anthropogenic changes to radiative forcing over the 20th century through changes to greenhouse gases and sulphate aerosols (GS). HadCM2, CSIRO Mk2 and CGCM2 express greenhouse gases as equivalent CO_2, while ECHAM4 and PCM explicitly represent the effects of major and minor greenhouse gases. ECHAM4 and PCM also include explicit treatment for the direct radiative effects of aerosols. For GS simulations, we have a 2-member ensemble from ECHAM4, a 3-member ensemble from CGCM2, a 4-member ensemble from HadCM2, a 5-member ensemble from CSIRO Mk2 and a 7-member ensemble from PCM. Aerosol changes in CSIRO Mk2, HadCM2 and CGCM2 have been parameterised using relative changes to surface albedo in the northern hemisphere, while ECHAM4 and PCM include the direct radiative effect of historic aerosol concentrations. The PCM GS runs also include historic changes to tropospheric and stratospheric ozone. None of the models used here represent the indirect radiative effects of aerosols on clouds.

3. Simulated and Observed Changes in Diurnal Temperature Range

[9] DTR is defined here as the difference between the mean daily maximum temperature (T_{max}) and minimum temperature (T_{min}), at each grid point in the data mask region for each season, and then averaged annually and

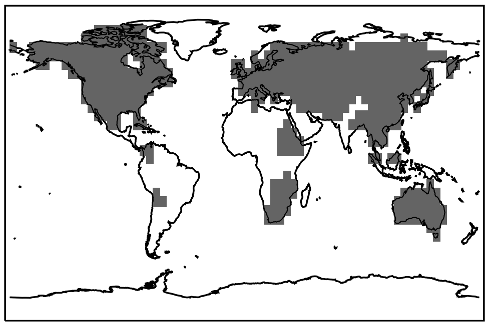

Figure 1. Data mask used for observed and GCM DTR data. Shaded regions represent areas that were included in the mask with more than 40 years of data during the period 1901–2000.

globally. Following *Braganza et al.* [2003], we first look at the variability and correlation structure of DTR, to determine how closely global DTR is associated with global mean temperature (T_{mean}) for unforced climate.

[10] We use the decadal standard deviation as a measure of variability in DTR. Interannual changes were smoothed using a 21-point binomial filter (half power at periods of 10 years). For observations and transient model experiments, standard deviations are calculated for the period 1901–2000. For the control runs, we use 100-year samples, taken at 50-year intervals, to estimate the mean standard deviation. Error estimates are taken from the 5–95% confidence interval from the range of 100 year samples. Uncertainty for decadal scale variability in the control is also used to estimate uncertainty in the decadal smoothed GS forced response for each of the models. For ECHAM4, HadCM2 and CGCM2, the relative shortness of the control time series is a limitation, although results are generally similar to those for CSIRO Mk2 and PCM.

[11] Correlation of T_{max}, T_{min} and DTR with T_{mean} is calculated using the same sampling method. Global-mean temperature has been calculated after applying the observed DTR coverage mask to the data, hence T_{mean} will differ (with expected greater variability) from the mean calculated with unrestricted coverage, and is more similar to the mean temperature over land.

[12] Table 1 shows the decadal standard deviations of T_{max}, T_{min}, DTR and T_{mean}. Estimates of observed unforced variability are calculated by removing a 4th order polynomial trend from the observed time series. This method of detrending has been evaluated by *Braganza et al.* [2003] and was shown to provide a reasonable estimate for comparison with intrinsic climate variability in the models. For T_{max}, T_{min} and T_{mean}, the magnitude of the observed decadal, detrended standard deviation is similar to or smaller than that from each of the control runs, with control variability larger in the 240 year data sets. For DTR, the variability of the detrended observations is not significantly different from model estimates of climate noise.

[13] Also shown in Table 1 are the unforced decadal correlations of T_{max}, T_{min} and DTR with T_{mean}. As expected, all model estimates of intrinsic variability show a large association between T_{max}, T_{min} and T_{mean} temperature. For DTR, the unforced association with global mean temperature is much smaller and much more variable. The

Table 1. Decadal Variability and Correlation With T_{mean} From Observations 1901–2000 (Detrended) and GCM Control Integrations

Model	Decadal Standard Deviation				Correlation With T_{mean}		
	T_{mean}	T_{min}	T_{max}	DTR	T_{min}	T_{max}	DTR
Observed	0.07	0.07	0.07	0.04	0.97	0.96	−0.24
CSIRO Mk2	0.09 ± 0.02	0.10 ± 0.03	0.10 ± 0.02	0.04 ± 0.01	0.98 ± 0.01	0.98 ± 0.01	0.03 ± 0.24
HadCM2	0.13 ± 0.02	0.14 ± 0.01	0.14 ± 0.01	0.04 ± 0.02	0.97 ± 0.05	0.98 ± 0.04	0.20 ± 0.28
ECHAM4	0.12 ± 0.03	0.12 ± 0.03	0.11 ± 0.03	0.03 ± 0.01	0.99 ± 0.01	0.94 ± 0.05	−0.53 ± 0.18
PCM	0.09 ± 0.01	0.09 ± 0.01	0.09 ± 0.01	0.04 ± 0.01	0.98 ± 0.01	0.97 ± 0.01	0.02 ± 0.22
CGCM2	0.13 ± 0.01	0.13 ± 0.01	0.14 ± 0.01	0.04 ± 0.01	0.99 ± 0.01	0.99 ± 0.01	0.22 ± 0.11

correlation between DTR and T_{mean} in the control simulations from all of the models has relatively large variability for 100 year samples. Hence the strength of the relationship is sensitive to the size of the control run and reduces the significance of results for the smaller control time series. For the long control integrations of CSIRO Mk2 and PCM, the correlation of DTR with T_{mean} is not significantly different from that observed, with essentially zero mean correlation. It therefore seems reasonable to conclude that DTR is independent of T_{mean} for internal climate variability and therefore should contain additional information for the attribution of global climate change.

[14] Next, we compare observed and simulated trends in DTR over the latter part of the 20th century. Figure 2 shows the magnitude of 50-year linear trends in the indices, including T_{mean}, for the period 1951–2000. This period has the largest and most consistent data coverage. Trends from each model represent the ensemble mean trend. Uncertainties in trends were estimated by taking the 5–95% confidence interval from the distribution of 50-year trends from each of the control runs. The mean trend for each of the indices from the control runs was zero. Uncertainty for the observed trend was taken from the broadest distribution from the controls (CSIRO Mk2). For the GS forced simulations, the trends in T_{mean} and T_{min} from the models compare well with the observations. For T_{max}, we find that the response of global maximum temperature in four of the five models used here is too large compared to that observed. This result is similar to *Stone and Weaver* [2002], who compare observed and modelled DTR changes using CGCM1 and CGCM2. While observed T_{max} changes are ~0.4°C less than T_{min} changes for this period, the models show similar magnitude trends in both T_{max} and T_{min}. This difference is reflected in the magnitude of the simulated 50-year DTR trends, which are much smaller than observed. While the differences between the observed and simulated T_{max} response are not statistically significant in analysis presented here, the effect on the DTR response highlights the sensitivity of this index to small relative changes in maximum and minimum temperatures. While this is useful in amplifying the signal of T_{max} and T_{min} in the observations, DTR will be similarly sensitive to model error in the simulation of its controlling parameters and to the way forcing changes are applied in the models. In addition, similar changes to DTR can be caused by quite different mechanisms. For PCM, a low sensitivity model, DTR trends are roughly equivalent to those of the other GCMs but due to lower than observed T_{min} rather than larger maximum temperature trends.

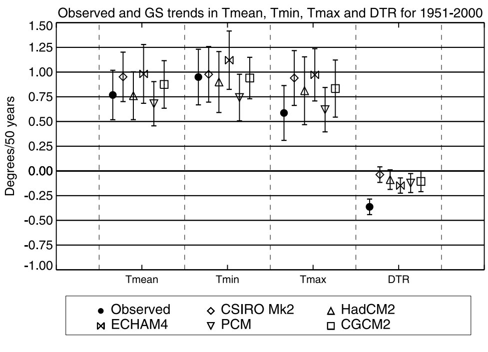

Figure 2. 50-year linear trends in T_{mean}, T_{min}, T_{max} and DTR from 1951–2000 from the decadal observations and GS simulations.

[15] Studies that have sought to determine the controlling factors of DTR [*Stenchikov and Robock*, 1995; *Dai et al.*, 1999, 2001; *Stone and Weaver*, 2002, 2003] have shown that DTR responds strongly to forcing from clouds and soil moisture. *Dai et al.* [1999] show a strong correlation between annual DTR and annual cloud cover, while changes in soil moisture are important to DTR through the effect of evaporative cooling [*Dai et al.*, 1999; *Stone and Weaver*, 2003]. As a preliminary step in understanding the causes of the differences between GCM and observed DTR, we investigate the relationship between T_{max} and cloud cover. We calculate correlations of interannual variations in area averaged total cloud (percentage cloud) with T_{max} from detrended observations and from unforced simulations from CSIRO Mk2 and HadCM2, using the same sampling method previously outlined. Table 2 shows a strong negative correlation between unforced cloud cover and T_{max} in the models. This simulated relationship is consistent with *Dai et al.* [1999], who calculated seasonal cross correlation coefficients of observed T_{max} with various components of the surface heat balance over the United States, China and Australia. Conversely, the relationship between observed cloud and T_{max} shows zero correlation in the decadal, detrended time series used here. However this

Table 2. Correlation (*R*) of Unforced and Observed (Detrended) Decadal Changes in Total Cloud (%) With T_{max} (Column 1) and Observed and Ensemble Mean GS Forced 50-Year Linear Trends (1951–2000) in Total Cloud (%) (Column 2)[a]

Model	*R* Unforced	GS Trends
Observed	−0.02	0.3814
CSIRO MK2	−0.58	−0.007
HadCM2	−0.55	−0.004

[a]Note HadCM2 has a relatively short control period of 100 years for total cloud.

result was found to be extremely sensitive to the sampling period and detrending method which casts some doubt on the usefulness of this statistic.

[16] Also shown in Table 2 are 50 year linear trends in cloud cover for 1951–2000. Both models show no significant changes in cloudiness over land under GS forcing while observed cloud cover has increased over this period. It therefore seems likely that the absence of trends in cloudiness in the model simulations, and the associated damping of T_{max}, contributes to the much smaller trends in DTR than observed. Surprisingly, the correlation between cloud cover and minimum temperatures is weak in the control simulations on interannual and decadal timescales. This result is supported by *Dai et al.* [1999] and *Stone and Weaver* [2003] who find the net effect of cloud on nighttime minima to be small. Nevertheless changes in cloud are likely to have some effect on T_{min}, particularly on seasonal and regional scales.

4. Summary

[17] Diurnal temperature range appears to be a suitable index of climate variability and change, in the context of similar simple global indices outlined by *Braganza et al.* [2003]. While changes in maximum and minimum temperature are strongly associated with changes in global mean temperature, DTR provides additional information for the attribution of recent observed climate change. Natural variability of T_{min}, T_{max} and DTR is reasonably well simulated in long, unforced GCM simulations. Observed DTR over land shows a large negative trend of ~0.4°C over the last 50 years that is very unlikely to have occurred due to internal variability. This trend is due to larger increases in minimum temperatures (~0.9°C) than maximum temperatures (~0.6°C) over the same period. Analysis of trends in DTR over the last century from five coupled climate models shows that simulated trends in DTR due to anthropogenic forcing are much smaller than observed. This difference is attributable to larger than observed changes in maximum temperatures in four of the five models analysed here, a result consistent with previous modelling studies.

[18] The overestimation of T_{max} warming in anthropogenic forced simulations may be due to poor representation of cloud changes over land. Observed increases in cloud cover since 1951 are not simulated by models forced with increasing greenhouse gases. This is supported by *Stone and Weaver* [2002, 2003] and *Dai et al.* [1999] who have described the association between the observed reducing trend in DTR and increases in cloudiness. Changes to water vapour, soil moisture and precipitation, not considered here, are also likely to have lesser but important impacts on simulated trends in T_{max} and T_{min}.

[19] Since DTR is highly sensitive to small changes in maximum and minimum temperatures it is important that we fully understand the causes of model inconsistencies with observations. This study does not consider simulated changes in DTR due to changes in solar irradiance or volcanic aerosols or forcing due to other aerosols such as black carbon, the indirect radiative effect of aerosols or land use changes, all of which may be expected to impact on DTR.

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