Detection of changes in temperature extremes during the second half of the 20th century

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Received 22 June 2005; revised 19 August 2005; accepted 26 August 2005; published 26 October 2005.

[1] Since 1950, the warmest and coldest days and nights of the year have become warmer. Comparing these observations with climate model simulations in an optimal detection analysis shows a significant human influence on patterns of change in extremely warm nights. Human influence on cold nights and days is also detected, although less robustly, but there is no detection of a significant human influence on extremely warm days. In the future, extreme temperatures are expected to intensify considerably, with adverse consequences for human health.
Citation: Christidis, N., P. A. Stott, S. Brown, G. C. Hegerl, and J. Caesar (2005), Detection of changes in temperature extremes during the second half of the 20th century, *Geophys. Res. Lett.*, *32*, L20716, doi:10.1029/2005GL023885.

1. Introduction

[2] There is growing evidence that human activity has contributed to the observed warming near the surface of the earth over the last 50 years [*Hegerl et al.*, 1997; *Tett et al.*, 1999, 2002; *Stott et al.*, 2000]. The Intergovernmental Panel on Climate Change (IPCC) Third Assessment Report (TAR [*Intergovernmental Panel on Climate Change*, 2001]) concluded that changes in greenhouse gas concentrations were likely to have been the dominant contributor. Since the TAR, additional evidence has supported and strengthened this conclusion [*International ad hoc Detection and Attribution Group* (*IDAG*), 2005]. Human influence has been detected on a wide range of climate variables and detection and attribution analyses have been extended to show significant anthropogenic effects at regional scales [*Zwiers and Zhang*, 2003; *Karoly et al.*, 2003; *Stott*, 2003]. The analysis of regional changes and extremes is potentially of great importance for assessing societal impacts of climate change.

[3] While many detection and attribution studies have analysed the control exerted on mean temperatures by external forcings [*IDAG*, 2005] and the importance of human influence on extremes has been shown [*Kiktev et al.*, 2003], the formal attribution of changes in extremes has yet to be made. The lack of high quality observational data sets of daily temperature with good coverage has posed a major hindrance. Moreover, the definition of indices suitable for detection is not straightforward. An alternative approach would be to infer changes in extremes implicitly from changes in longer term means, by assuming that the tail of the distribution changes in accordance with the mean. However this assumption was found not valid, with changes in extreme near surface temperature being significantly different than seasonal mean changes [*Klein Tank and Können*, 2003; *Hegerl et al.*, 2004] over a large fraction of the globe. Our aim here is to apply for the first time a standard optimal detection approach to patterns of change in temperature extremes, in order to investigate the anthropogenic influence in the observed warming, using a formal methodology.

2. Detection Indices for Temperature Extremes

[4] A great variety of indices has been developed for the study of climatic extremes, as a result of an international effort to provide a common benchmark to the analysis of such events [*Folland et al.*, 1999; *Nicholls and Murray*, 1999]. Comparisons between temperature index values from observations and models in early analyses showed reasonable consistency [*Kiktev et al.*, 2003]. The indices used here describe changes in the N warmest days and nights of the year (N = 30, 10, 5 and 1), sampling the shift from moderate to more pronounced extreme events. We focus especially on warm nights because of their impact on human health. Sustained night time high temperatures are characteristic of the most severe heat waves, which contribute to increased discomfort and mortality rates [*Karl and Knight*, 1997; *Meehl and Tebaldi*, 2004; *Trigo et al.*, 2005].

[5] The same set of indices was employed previously in a perfect model study [*Hegerl et al.*, 2004], which showed that changes in extremes are detected in synthetic model observations at the time when CO_2 is expected to double or triple relative to pre-industrial times. That work also suggested that changes over global land may already be detectable in 20-year trends. We now aim to establish whether we can detect changes as early as in the second half of the 20th century, when the signal may not have sufficiently intensified, and for signal comparison against real observations, which cover only 48% of the global land masses.

3. Observations and Model Data

[6] The observations are gridded daily data of maximum and minimum temperature from a newly compiled dataset (J. Caesar et al., Large-scale changes in observed daily maximum and minimum temperatures, 1946–2000, submitted to *Journal of Geophysical Research*, 2005), covering land areas, mainly over the N. Hemisphere and Australia.

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0094-8276/05/2005GL023885$05.00

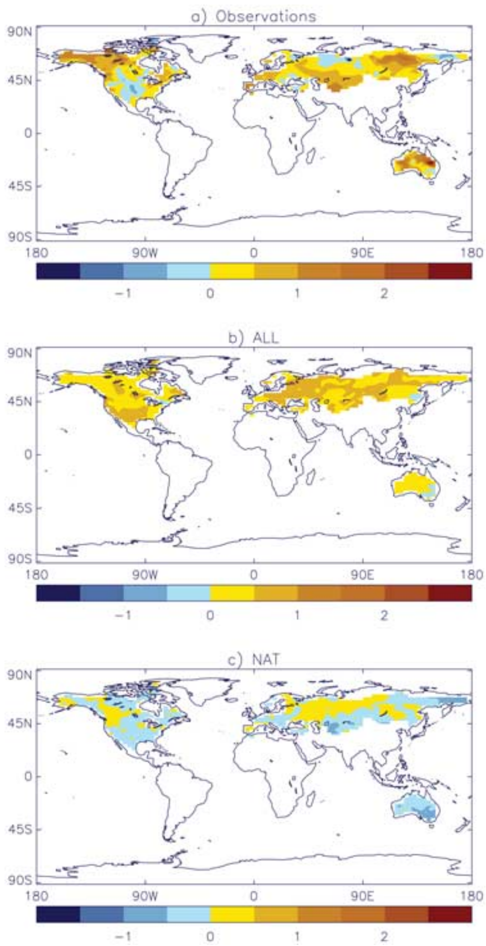

Figure 1. Patterns of change in the warmest night of the year for a late period (1980–1999) relative to an early period (1950–1969) of the second half of the 20th century from a) observations and model experiments with b) anthropogenic and natural forcings and c) natural forcings only. The model patterns are the average of four ensemble members.

Station data have not been homogenised, so that genuine climatic shifts will not inadvertently be adjusted, while erroneous extremes have been checked and filtered. This new dataset provides the first opportunity to analyse quasi-global daily data. Model data came from runs with HadCM3, the 3rd generation Hadley Centre Atmosphere Ocean General Circulation Model [*Gordon et al.*, 2000; *Pope et al.*, 2000; *Stott et al.*, 2000]. Four model experiments were considered [*Johns et al.*, 2002], forced with: a) changes in well-mixed greenhouse gases (GHG), b) changes in well-mixed greenhouse gases, tropospheric and stratospheric ozone and sulphate aerosols with their indirect effect taken into account (ANTHRO), c) changes in volcanic aerosols and in the solar output (NAT), and d) the combined effect of ANTHRO and NAT (ALL). A control simulation was also used to provide estimates of natural climate variability.

[7] The detection signals comprise spatial (2-D) response patterns, constructed as the change in the period mean index between periods 1950–1969 and 1980–1999. To minimise the impact of internal climate variability on the model response, we used the ensemble mean of the model signals to form the model patterns. A comparison between observation and model patterns of change for the warmest night of the year is shown in Figure 1. The observations (Figure 1a) show a global mean increase in the warmest night, with large regional variations, while the model response to all forcings (Figure 1b) shows a more uniform warming pattern. This discrepancy is expected, since the observations show a strong imprint of internal climate variability that is reduced by ensemble averaging of the model simulations. The model response to natural forcings only (Figure 1c) is negative in the global mean, with large regional variations. Like the warmest night of the year, all the other indices under investigation also indicated a warming during the last 50 years of the 20th century, in both observations and experiments which include the greenhouse gas forcing and a cooling in experiments with natural forcings only.

4. Analysis

[8] Our analysis used a formal optimal detection technique to assess in an objective way how well the model response patterns match the observations. Optimal detection is a generalised multivariate regression, extensively used in the detection of climate change and its attribution to external forcings [*Hasselmann*, 1979; *Allen and Tett*, 1999]. The aim is to estimate scaling factors that are applied to the model fingerprints in order to best match the observations, given a model estimate of the internal climate variability. We used 39 control segments (20 non-overlapping) to construct the covariance matrix of the internal climate variability and 19 additional segments (10 non-overlapping) to estimate the uncertainty in the scaling factors. A power spectra analysis of detrended global indices timeseries for observations and 30 non-overlapping control segments indicates HadCM3 provides an adequate representation of internal climate variability. Most discrepancy appears at interdecadal timescales for indices of cold extremes, suggesting that the model may underestimate variability in these cases. We restricted the analysis to the sub-space of the noise covariance defined by the 20 leading eigenvectors, as this truncation was found to satisfy prescribed criteria for the majority of the indices [*Allen and Tett*, 1999]. The results are insensitive to the exact level of truncation. Scaling factors consistent with zero imply no detection, whereas values consistent with unity and with a small uncertainty range imply a good match between model and observations. Our detection algorithm has been previously used in numerous investigations [*Tett et al.*, 1999, 2002; *Stott*, 2003; *Stott et al.*, 2004] and its details are discussed elsewhere [*Allen and Stott*, 2003]. *Gillett et al.* [2000] found that changes in the N. Hemisphere circulation had no adverse impact on the detection of changes in temperature and it is assumed that this also holds true for analyses of temperature extremes.

[9] Scaling factors for various applications of the optimal detection technique together with the associated 5–95% uncertainty range are depicted in Figure 2. We first concentrate on changes in the warm nights (Figure 2a). The leftmost panel of Figure 2a shows the scaling factors from a single fingerprint detection analysis with spatial response

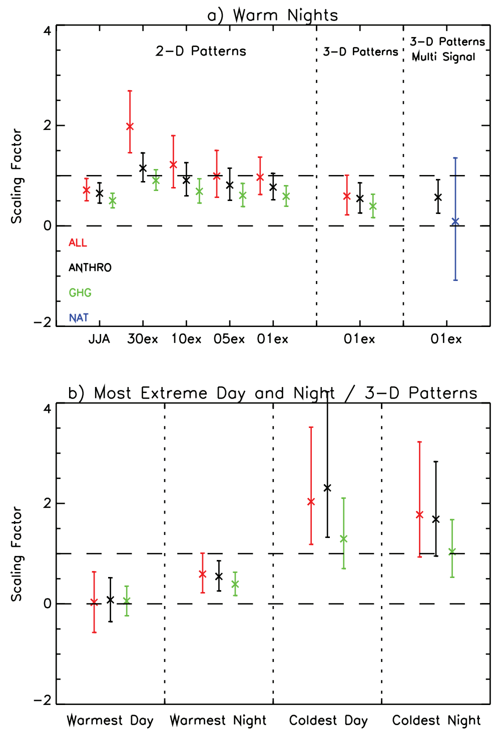

Figure 2. Scaling factors and their 5–95% uncertainty range from the optimal detection analysis. a) Changes in the N warmest nights (N = 30, 10, 5 and 1) and in the boreal summer (JJA) mean of the daily minimum temperature from a single fingerprint analysis with 2-D patterns (left panel) and 3-D patterns (middle panel, warmest night only). Results from a two-fingerprint (ANTHRO and NAT) analysis with 3-D patterns are also shown (right panel, warmest night only). b) Changes in the most extreme day and night of the year from a single fingerprint analysis with 3-D patterns. Single fingerprint analyses used patterns from 3 different HadCM3 experiments (ALL, ANTHRO and GHG).

patterns from different experiments and for indices of different extremity. Apart from changes in the N warmest days of the year, changes in the seasonal mean were also considered. In all cases, the warming trend is detected in the observations when greenhouse gas emissions are taken into account. GHG generates more warming than the observations, due to the absence of the negative sulphate aerosol and volcanic forcings and is assigned a scaling factor less than one, to account for the excess warming. ANTHRO and ALL experiments have scaling factors that are consistent with unity for the more pronounced extreme indices. Warming in the seasonal mean is overestimated by the model, whereas extreme changes seem to be modelled better than seasonal changes. NAT experiments, not shown here, have negative scaling factors and large uncertainties, indicating an opposite response (cooling) to the observations. As the results are similar for different extreme indices, as expected from [*Hegerl et al.*, 2004], we will henceforth focus solely on changes in the most extreme annual record.

[10] We have applied our detection analysis also to spatio-temporal (3-D) response patterns, as an alternative signal definition that allows us to represent its evolution in more detail. The patterns in this case are constructed as the five decadal mean index anomaly values for the five decades in the segment 1950–1999, and the anomalies are relative to the segment mean. The middle panel of Figure 2a shows that 3-D patterns are also detected in the observations, even though they are assigned smaller scaling factors. When all forcings are included, the scaling factor is consistent with unity. The rightmost panel of Figure 2a gives an example of a multi-fingerprint analysis, where the model response is represented by the linear combination of the ANTHRO and NAT 3-D patterns. Such an analysis attempts to partition the response between the two components and is therefore useful for attribution purposes. As in the single-fingerprint case, the ANTHRO patterns are detected in the observations, whereas the NAT scaling factor is associated with a large uncertainty range. The high uncertainty could imply that the signal is dominated by the ANTHRO response, which makes it difficult to separate the smaller NAT contribution from the internal climate variability.

[11] Scaling factors for all types of indices are plotted in Figure 2b. Results are shown for 3-D response patterns and again only for the change in the most extreme annual value. Apart from warm days, the response patterns for all other types of indices are detected in the observations, for model runs that include the greenhouse gas forcing. Daily minimum temperatures are known to have risen faster than daily maximum temperatures [*Braganza et al.*, 2004; *Stone and Weaver*, 2002], which may in part explain why changes in warm day extremes are not detected, without, however, explaining the difference between cold days and warm days. The scaling factors for cold days and nights are close to unity for GHG and increase significantly when anthropogenic aerosol forcing is included, suggesting that aerosols cause too much cooling in the model, although it is also possible that there are confounding errors with the model's greenhouse gas response. An analysis of 2-D patterns for cold days gives large scaling factor increases between ANTHRO and ALL. This discrepancy suggests that when taking the difference between period means some of the cooling in ANT is lost, while the cooling in ALL from natural forcing is exacerbated. As all the forcings are variable with time, the use of 3-D patterns is deemed the most appropriate.

5. Warm Night Trends

[12] The change in the annual mean and area averaged temperature anomaly for the warmest night of the year, relative to the 1950–1959 mean, is illustrated in Figure 3. The warming trend in the observations during the second half of the 20th century is also captured in the ALL runs, while simulations with natural forcings only give an opposite trend. The warming of about 1 K in the end of the 20th century shows a manifold increase over the 21st century under the SRES A2 scenario and grows to about 7 K by 2100. Such a scale of change would not only increase the intensity of heat waves in areas that already experience them, but also their frequency in areas where such events are currently uncommon.

6. Conclusions

[13] Our analysis demonstrates the early detection of a significant anthropogenic influence in temperature extremes

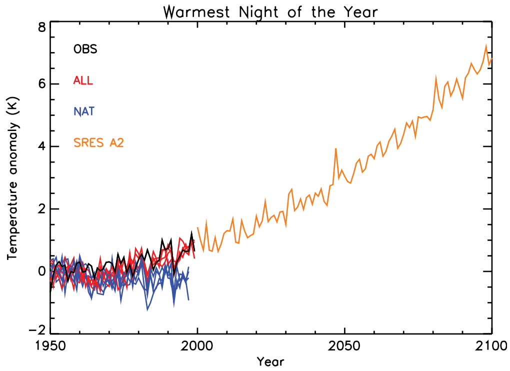

Figure 3. Temperature anomalies (relative to the 1950–1959 mean) of the warmest night of the year over the area covered by the observations. Shown are observed temperatures (black thick line), modelled temperatures from four HadCM3 simulations with both anthropogenic and natural forcings (red lines) and natural forcings only (blue lines). Temperatures after 2000 (orange line) come from a HadCM3 run with greenhouse gas and sulphur emissions that follow the SRES A2 scenario [*Nakicenovic and Swart*, 2000].

with the exception of changes in warm days. The model appears to overestimate the warming in the warm nights and underestimate the warming in cold days and nights (3-D patterns of change). Although the model changes do not exactly match the observations, they are in both cases significantly different than the model estimate of variability generated internally within the climate system.

[14] For the number of indices considered here, it is for the ones that describe the warm nights that we can make the most robust attribution statement. Response patterns for warm nights are always detectable and yield scaling factors which have a relatively small uncertainty range and are not as strongly dependent on the way the pattern was defined, as in cold extremes. Previous work [*Meehl and Tebaldi*, 2004] has shown that both models and observations agree that heat waves have intensified, while model projections warn that they will continue to do so. Our findings are complementary, indicating that changes in the warm nights are fortuitously the easiest to detect, at least among the indices we examined. The 21st century model projection shows a manifold increase in the warming of the warmest night of the year.

[15] **Acknowledgments.** NC, SB, PAS and JC were funded by the Department of Environment, Food and Rural Affairs under contract PECD 7/12/37. GCH was supported by NSF grant ATM-0296007, by NOAA grant NA16GP2683 and NOAA's Office of Global programs, DOE in conjunction with the Climate Change Data and Detection element.

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