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Climate change uncertainty for daily minimum and maximum temperatures: A model inter-comparison

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[1] Several impacts of climate change may depend more on changes in mean daily minimum (T_{min}) or maximum (T_{max}) temperatures than daily averages. To evaluate uncertainties in these variables, we compared projections of T_{min} and T_{max} changes by 2046–2065 for 12 climate models under an A2 emission scenario. Average modeled changes in T_{min} were similar to those for T_{max}, with slightly greater increases in T_{min} consistent with historical trends exhibiting a reduction in diurnal temperature ranges. In contrast, the inter-model variability of T_{min} and T_{max} projections exhibited substantial differences. For example, inter-model standard deviations of June–August T_{max} changes were more than 50% greater than for T_{min} throughout much of North America, Europe, and Asia. Model differences in cloud changes, which exert relatively greater influence on T_{max} during summer and T_{min} during winter, were identified as the main source of uncertainty disparities. These results highlight the importance of considering separately projections for T_{max} and T_{min} when assessing climate change impacts, even in cases where average projected changes are similar. In addition, impacts that are most sensitive to summertime T_{min} or wintertime T_{max} may be more predictable than suggested by analyses using only projections of daily average temperatures. **Citation:** Lobell, D. B., C. Bonfils, and P. B. Duffy (2007), Climate change uncertainty for daily minimum and maximum temperatures: A model inter-comparison, *Geophys. Res. Lett.*, *34*, L05715, doi:10.1029/2006GL028726.

1. Introduction

[2] Climate models are often characterized by their climate sensitivity, defined as the equilibrium change in globally averaged surface temperature that results from a doubling of atmospheric carbon dioxide (CO_2) levels [*Cubasch et al.*, 2001]. The range or standard deviation of climate sensitivity among different models provides a common measure of uncertainty in the response of the climate system to atmospheric CO_2 increases. For example, a range of 1.5–4.5°C is commonly cited based on evaluation of 15+ models [*Cubasch et al.*, 2001], with recent studies suggesting this range should be slightly higher [*Murphy et al.*, 2004; *Stainforth et al.*, 2005].

[3] In addition to studies of average temperature responses, recent model inter-comparisons have focused on changes in extreme temperature events, such as frost days or heat waves [*Hegerl et al.*, 2004; *Tebaldi et al.*, 2006]. This focus reflects the importance of both average daily temperatures and extreme events in determining climate change impacts [*Easterling et al.*, 2000]. However, several societal and ecosystem impacts are more directly related to changes in mean daily minimum (T_{min}; i.e., nighttime) or maximum (T_{max}, i.e., daytime) temperatures than to average temperatures or extreme events. For example, quantities such as growing degree days and accumulated chill hours, which are widely used in models to predict crop and pest development, are influenced differently by T_{min} and T_{max} [*McMaster and Wilhelm*, 1997; *Wilkens and Singh*, 2001]. In addition, changes in evapotranspiration and photosynthetic rates are likely to be more affected by T_{max} than T_{min} [*Dhakhwa and Campbell*, 1998].

[4] Much of the uncertainty in climate sensitivity has been attributed to model differences in cloud behavior [*Soden and Held*, 2006; *Webb et al.*, 2006]. Increased cloud cover, particularly of low clouds, leads to a greater fraction of reflected solar radiation and therefore cooling of T_{max} [*Groisman et al.*, 2000; *Sun et al.*, 2000]. In comparison, clouds have a relatively small net effect on T_{min} [*Dai et al.*, 1999].

[5] Given the important role of clouds in climate change uncertainty and the differential effect of clouds on day and night temperatures, a reasonable hypothesis is that inter-model differences in T_{min} changes would be smaller than associated T_{max} changes. Here we evaluate this hypothesis with daily T_{min} and T_{max} output for simulations from 12 general circulation models (GCMs) archived by the Program in Climate Model Diagnosis and Intercomparison (PCMDI; http://www-pcmdi.llnl.gov) and used in the Fourth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC AR4.).

2. Models and Methods

[6] Daily output of T_{min} and T_{max} used in this analysis were available for 12 models (Table 1). For each model, we computed average monthly and seasonal T_{min}, T_{max}, and average temperature (T_{avg}) for two available time slices: the 1961–1999 period in a simulation of 20th century climate (20c3m in the IPCC AR4 nomenclature), and the 2046–2065 period in a simulation of 21st century climate using an A2 emission scenario (SRES A2 in the IPCC nomenclature). An ensemble average was computed for models that provided output from multiple realizations (Table 1). Differences between the two time slices were computed and then regridded for all models to a common 2° × 2° grid. For

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Table 1. Climate Models Whose Output Was Used in This Study[a]

Model Designation	Resolution	Originating Group(s)	Number of Runs[b]	Volcanic and Solar Forcings in 20th Century Runs?
GFDL-CM2.0	2.0 × 2.5°	GFDL, USA	1, 1	Yes
GFDL-CM2.1	2.0 × 2.5°	GFDL, USA	1, 1	Yes
GISS-ER	4.0 × 5.0°	GISS, USA	1, 1	Yes
MIROC3.2(medres)	T42	CCSR/NIES/FRCGC, Japan	3, 3	Yes
MIUB/ECHO-G	T30	MIUB/METRI/MD Germ./Korea	3, 3	Yes
MRI-CGCM2.3.2	T42	MRI, Japan	5, 5	Yes
BCCR-BCM2.0	T63	BCCR, Norway	1, 1	No
CCCma-CGCM3.1(T47)	T47	CCCma, Canada	5, 3	No
CNRM-CM3	T63	CNRM, France	1, 1	No
CSIRO-Mk3.0	T63	CSIRO, Australia	3, 1	No
ECHAM5/MPI-OM	T63	MPI, Germany	2, 1	No
IPSL-CM4	2.5 × 3.75°	IPSL, France	2, 1	No

[a]See PCMDI web site (http://www-pcmdi.llnl.gov) for more details on individual models.
[b]The number of realizations used for the 20th century (before comma) and A2 scenario (after comma) simulations.

comparison with T_{min} and T_{max}, monthly output for total cloud cover (clt) were processed in a similar manner. Below we focus on results for the June–August (JJA) and December–February (DJF) seasons.

3. Results and Discussion

[7] For most locations, average changes in T_{min} across all models were larger than associated changes in T_{max} for both JJA and DJF (Figures 1a and 1d). Exceptions included the United States and Western Europe in JJA, and Mexico in DJF. These trends toward a reduction in the diurnal temperature range (DTR = $T_{max} - T_{min}$) are consistent with previous modeling results [*Dai et al.*, 2001; *Stone and Weaver*, 2003], as well as observed 20th century trends [*Easterling et al.*, 1997; *Vose et al.*, 2005]. However, in most locations, with the exception of Europe where DTR increased, the average simulated changes in JJA DTR were small and not consistent across models (Figure 1b). DTR trends for DJF were consistently negative across models for high latitudes and parts of Africa and India, but were insignificant elsewhere (Figure 1e).

[8] The inter-model standard deviations of T_{min} changes, used here to quantify climate change uncertainty for a prescribed emission scenario, were significantly smaller than the standard deviation of T_{max} in many locations For example, throughout much of North America and Eurasia, T_{max} changes for JJA were 50% or more variable among models than changes in T_{min} (Figure 1c; Ratios above 1.68 or below 0.60 are significant at p = 0.05 for an F-test with 11 degrees of freedom.) The large variability of projected T_{max} changes relative to T_{min} is similar to the observation by *Alfaro et al.* [2006] that the inter-annual standard deviation for JJA T_{max} over central and western United States was 30% larger than for T_{min}.

[9] Consistent with the hypothesis that projected T_{max} changes are sensitive to cloud cover and downwelling radiation, the greatest disparity between T_{max} and T_{min} uncertainty was mainly observed during the local summer season (JJA in northern latitudes and DJF in southern latitudes) when the diurnal amplitude of downwelling solar radiation is greatest. To further evaluate the mechanism behind increased T_{max} uncertainty, we computed the correlation across models between projected changes in T_{min} or

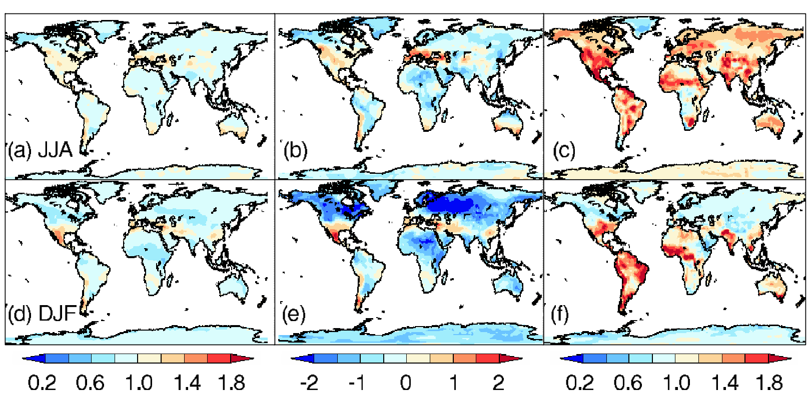

Figure 1. (a) Ratio of average projected changes in T_{max} for 12 climate models to projected changes in T_{min} for June–August season. (b) Mean projected change in JJA DTR divided by inter-model standard deviation. Values below −2.2 or above +2.2 are statistically significant (t-test, p = 0.05). (c) Ratio of inter-model standard deviation of T_{max} changes to standard deviation of T_{min} changes for June–August season. Values outside the intervals (0.67, 1.49) and (0.60, 1.68) are significant at p = 0.10 and p = 0.05, respectively (F-test). (d–f) Same as Figures 1a–1c except for December–February season. All changes correspond to the difference between 2046–2065 averages in a SRES A2 simulation and 1961–1999 averages in a 20th century simulation.

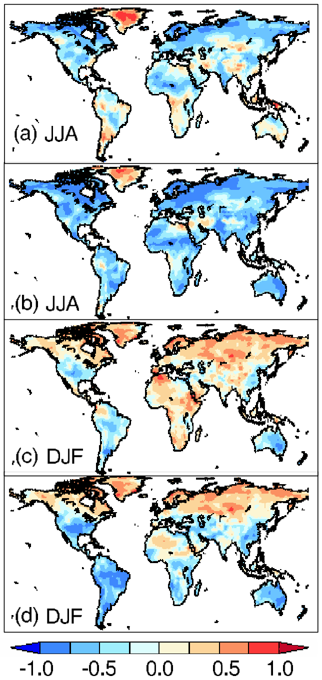

Figure 2. Inter-model correlation of projected changes in total cloud cover and changes in (a) minimum temperatures and (b) maximum temperatures for June–August season. (c and d) Same as Figures 2a and 2b except for December–February season.

T_{max} and total cloud cover (Figure 2). Modeled changes in T_{max} were strongly and negatively correlated with changes in clt for most locations in northern latitudes in JJA and southern latitudes in DJF, reflecting the cooling influence of increased clouds and reduced surface downwelling solar radiation on daytime temperature. Correlations between clt and T_{min} were comparatively smaller, illustrating that uncertainty in cloud cover changes generally have less of an impact on T_{min} than T_{max}.

[10] However, in Northern Hemisphere boreal latitudes in DJF, T_{min} and T_{max} changes were positively correlated with cloud changes, and T_{min} projections were more variable across models than T_{max}. Downwelling solar fluxes at high latitudes in DJF are relatively small, as reflected in low average values of DTR; the absolute sensitivity of these fluxes to cloud cover is therefore small as well. The insulating effect of clouds, which tends to warm surface temperatures by trapping infrared radiation, therefore becomes more important and gives rise to a positive relationship between cloud cover and temperature changes.

[11] Inter-model standard deviations of T_{min} and T_{max} were also compared with those of T_{avg} (Figure 3), because projected changes in T_{avg} are often more readily available than T_{min} and T_{max} [e.g., *Cubasch et al.*, 2001]. Standard deviations of T_{max} averaged ~20% higher than standard deviations for T_{avg} in summer months (JJA in Northern Hemisphere and DJF in Southern Hemisphere), while uncertainty for T_{min} was roughly 10% lower than for T_{avg}.

[12] In DJF, T_{min} uncertainty above 40°N was ~10% higher than T_{avg} uncertainty, while T_{max} uncertainty was slightly lower than T_{avg}. Interestingly, in some situations uncertainties for T_{min} and T_{max} were both larger than for

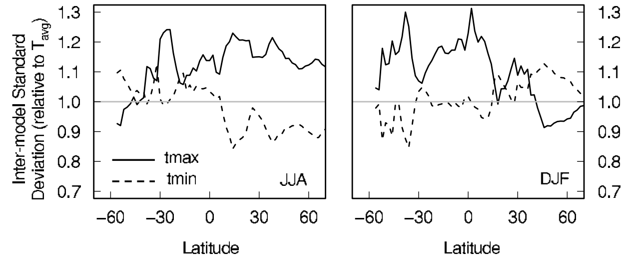

Figure 3. Zonal means of standard deviation for minimum and maximum temperature changes, expressed as a fraction of the standard deviation for average temperature changes, for (a) June–August and (b) December–February.

T_{avg} (0–20°S in JJA and 20–40°N in DJF). This result reflects the fact that modeled changes in T_{max} and T_{min} exhibited negative correlations in these regions, with the largest projected increases in T_{max} tending to come from the same models with the smallest projected increases in T_{min}.

[13] While cloud cover changes represent a principal control on downwelling radiation, variability in solar irradiance and volcanic aerosols can also affect incident surface radiation. Of the 12 models considered in this study, six included representations of forcings from solar variability and volcanic activity for the 20th century, while the other six considered only greenhouse gas and sulfate aerosol forcings (Table 1; other forcings differences also exist [e.g., *Santer et al.*, 2006].) Analysis of these two separate subsets revealed a tendency for models with volcano and solar forcing to exhibit slightly larger average changes in T_{max} and T_{min} (not shown), as well as a larger contrasts between intermodel standard deviations in T_{max} and T_{min} (Figure 4). The disparities between the two model groups were generally not statistically significant (F-test, $p > 0.1$) owing to the small sample size ($n = 6$). However, this result suggests that part of the difference between model uncertainty in T_{max} and T_{min} may be related to inclusion of volcanic or solar forcings and their effects on radiation fluxes, a topic worthy of further study.

[14] As mentioned in the Introduction, agricultural impacts are one case where differences between T_{min} and T_{max} changes may be important, because many biological processes are differentially sensitive to daytime and night-

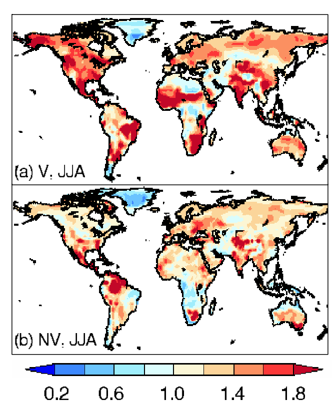

Figure 4. Same as Figure 1c for models (a) with and (b) without volcanic forcings and solar variability in the 20th century simulations.

Table 2. Statistics of Projected Changes in June–August Average Daily Minimum, Maximum, and Average Temperatures Over Selected Agricultural Regions[a]

Region			ΔT_{min}					ΔT_{max}					ΔT_{avg}				
Description	Latitude, deg N	Longitude, deg E	Mean	S.D.	Min	Max	Range	Mean	S.D.	Min	Max	Range	Mean	S.D.	Min	Max	Range
U.S. Corn Belt	38–48	−100– −80	3.0	0.7	2.1	4.5	2.4	3.2	1.0	2.1	5.6	3.5	3.1	0.8	2.2	5.1	2.9
Europe	45–55	−5–25	2.0	0.4	1.5	2.9	1.4	2.3	0.5	1.4	3.0	1.6	2.2	0.5	1.4	2.9	1.5
India	22–32	68–88	2.4	0.5	1.3	3.3	2.0	1.9	0.7	0.7	3.1	2.4	2.1	0.6	1.2	3.2	2.0
Eastern China	20–50	108–128	2.1	0.4	1.4	2.8	1.3	2.0	0.4	1.3	2.6	1.3	2.0	0.4	1.4	2.7	1.3
California	35–40	−123– −119	2.5	0.4	1.5	2.9	1.4	2.4	0.7	0.8	3.3	2.5	2.4	0.6	1.2	3.0	1.9

[a]Values are for 2046–2065 under an A2 emission scenario compared to 1961–1999. Statistics refer to mean, standard deviation, minimum, and maximum values, and range across the 12 climate models in Table 1.

time conditions. Spatial averages for T_{min}, T_{max}, and T_{avg} changes in major agricultural regions for JJA were computed to more directly assess uncertainties relevant to agriculture (Table 2). In contrast to the predominant global pattern, average changes in DTR were positive for several regions and significantly negative only in India, where all 12 models projected a DTR decrease with an average change of −0.5°C.

[15] Consistent with global patterns, uncertainty in T_{max} was larger than for T_{min} for most regions. For example, the inter-model range for T_{max} changes was 1.1°C larger than T_{min} in the U.S. Corn Belt and California, despite the fact that average changes in T_{max} and T_{min} were similar. Previous work has demonstrated that T_{max} changes are more important than T_{min} for U.S. maize yields, as water stress and development rates are both more sensitive to T_{max} [*Dhakhwa et al.*, 1997; *Dhakhwa and Campbell*, 1998; *Schlenker and Roberts*, 2006]. Studies of climate change impacts on U.S. agriculture may therefore underestimate uncertainties if using only projected changes in average temperatures. Uncertainties for T_{min} and T_{max} were more similar in regions such as Europe and China, and therefore use of T_{avg} in these regions may be less problematic.

4. Conclusions

[16] Analysis of simulated responses to increased greenhouse gases in 12 global climate models reveals that projected changes in T_{min} are generally more consistent across models than changes in T_{max}. This finding was attributed, in part, to the fact that T_{min} responses are less strongly influenced by cloud changes (Figure 2), which represent a major source of climate sensitivity uncertainty. The 12 models considered in this study provided an inconsistent view of future changes in DTR for most regions. Only for northern high latitudes during winter months did models agree in projecting a negative DTR trend.

[17] The results of this study indicate that changes in summertime daytime temperatures and associated impacts are currently less predictable than corresponding changes at nighttime. Studies that assess impacts of climate change using only projections of average temperatures therefore risk over- or under-estimation of uncertainties when considering processes that respond differently to day and night temperatures. Future work to evaluate the performance of each model in simulating past changes of T_{min}, T_{max}, and DTR would be useful for further constraining uncertainty in future projections, for example by enabling probabilistic regional forecasts using performance-based model weightings [e.g., *Tebaldi et al.*, 2004].

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