Diurnal Temperature Variability: An Observations-Climate Model Intercomparison

Jamin K. Rader

Academic Affiliation, Fall 2018: Senior, University of Washington

SOARS® Summer 2018

Science Research Mentor: Kristopher B. Karnauskas
Writing and Communication Mentor: Jessica Y. Luo

ABSTRACT

Surface temperature measurements since the mid-20th century have revealed a diurnally asymmetric global warming trend, with nighttime minimum temperatures increasing faster than daily maxima. The result is an overall decrease in the diurnal temperature range (DTR), which has implications for agriculture, streamflow, winter sports, as well as the overall magnitude of global warming. We begin with an assessment of the fidelity of global climate model (GCM)-simulated DTR baseline estimates between 2007 and 2016 through comparison with similar calculations using modern atmospheric reanalysis data. Significant deviations between observed and GCM-simulated baseline DTR, largely characterized by an overestimate of DTR by GCMs, are proposed to be associated with inaccuracies in GCM-simulated water vapor concentrations, as DTR is known to be closely related to atmospheric water vapor concentration. Further, through linear regression, we built an empirical model for predicting DTR variability with respect to changes in specific humidity. This was used to derive an alternative approach to projecting how the diurnally asymmetric warming trend may continue and interact with global warming. Such projections indicate that DTR will decline by 1-2°C over global land regions and by ~0.5°C over the global oceans. Model biases in DTR may be symptomatic of other limitations such as the physical parameterizations of cloud and precipitation processes, warranting further investigation to increase the reliability of global warming projections.
1. Introduction

It is certain that global surface temperatures will increase through the end of the 21st century. The extent of this warming, however, remains relatively uncertain. As summarized by the Intergovernmental Panel on Climate Change (IPCC), for all Representative Concentration Pathway (RCP) scenarios 2.6-8.5, which represent various emissions scenarios, global climate models project that surface temperatures will warm between 1°C and 6°C by 2100. Regionally, this warming varies significantly: under high-emission scenarios, the Arctic Ocean may see as much as 11°C of warming, while the north Atlantic, under a low emission scenario, may not see any appreciable warming at all (IPCC 2014). Such uncertainty is an obstacle to forecasting future changes in sea-level, snowpack, agricultural yield and other environmental factors are closely coupled with surface temperature. While much of the uncertainty comes from the differences in anthropogenic emissions used in each RCP scenario, within each RCP scenario there is still considerable inter-model variability. RCP 8.5 for example, which represents a high emissions scenario, projects that globally averaged surface temperatures will rise by $4 \pm 1$ °C by 2100 (IPCC 2014).

Observations over the past century have shown significant warming in both daily maximum and minimum temperatures as well as a diurnally asymmetric warming trend where diurnal minimum temperatures are rising more rapidly than diurnal maxima (Dai et al. 1999; Karl et al. 1984, 1991; Lauritsen and Rogers 2012). The result is a decrease in diurnal temperature range (DTR), the difference between daily maxima and minima. Karl et al. (1984) was among the first to identify this trend and proposed that increases in cloudiness, aerosols, carbon dioxide and water vapor were factors contributing to such diurnal asymmetry. DTR is reduced by cloud cover as sunlight is reflected reducing the daytime maximum temperature and the emissivity of the atmosphere is increased amplifying returned downward longwave radiation (the “greenhouse effect”) which increases the nighttime minimum temperature. Greater soil moisture or a shift from sea ice to open ocean reduces DTR as the thermal inertia of surface is greater and hinders temperature shifts in the lowest few meters of the atmosphere. Other factors, such as vegetation (Collatz et al. 2000), play less significant, but quantifiable, roles in altering DTR. Dai et al. (1999) confirmed that clouds, precipitation and soil moisture all worked to reduce DTR (accounting for 80% of DTR variability), while water vapor did little to impact DTR given its warming affect during both daytime and nighttime. Further investigation by Lauritsen and Rogers (2012) found that across the United States, 34% of the DTR trends could be explained by changes in cloud cover, however regionally this varied between 10% (in the southwest) and 63% (in the northeast). These DTR trends, however, were not consistently negative across the United States. Instead, statistically significant decreases in DTR were only seen the northern Plains and northeast, while slight, statistically insignificant increases were seen in the southwest. Some global climate model (GCM)-based studies such as Braganza et al. (2004), Cao et al. (1992) and Mitchell et al. (1995) have confirmed that cloud cover, soil moisture, and snow/ice feedbacks play an important role in diurnally asymmetric warming. As Cao et al. (1992) warns, however, that the asymmetric warming trend may be a result of natural climate variability rather than anthropogenic impacts.

Given that cloud cover, soil moisture and ice/snow cover are closely coupled with water vapor concentrations in the bottom few meters of the atmosphere, this study focuses on the relationship between DTR and 2-meter specific humidity. Section 2 describes the reanalysis and GCM data used in the study and how we designed an empirical model for predicting DTR variability with respect to
changes in future water vapor concentrations. Section 3 investigates the relationship between DTR and water vapor variability, reveals our model’s projections of end-of-century DTR and compares this from GCM-derived, end-of-century DTR calculations. Section 4 summarizes our main findings and identifies the future work of this project.

2. Data and Methods

2.1 Observational Data

While many observational studies on DTR used annual and monthly data to identify long-term trends (Dai et al. 1999; Karl et al. 1993), in this study we use daily maxima and minima to compute DTR. Daily maximum and minimum temperature and daily averaged specific humidity were produced by NCEP-DOE Reanalysis 2 with a resolution of 2.0° latitude by 1.75° longitude, in which observations every six hours force a weather model to give us a best estimate of the state of our atmosphere in areas where observations are not available. This can cause inaccuracies in areas like the poles or open ocean where direct observations are infrequent at best. However, our study uses maximum and minimum temperature at 2 meters, as well as 2-meter specific humidity, which are well sampled over the majority of the globe, have large spatial decorrelation scales, and thus reanalysis deviations from the true state of the atmosphere should be minimal. This dataset can be found at https://www.esrl.noaa.gov/psd/data/gridded/data.ncep.reanalysis2.gaussian.html.

2.2 GCM-derived Data

GCM-derived daily maximum and minimum temperature and daily averaged specific humidity were produced by four GCMs using RCP 8.5: Centre National de Recherches Météorologiques Climate Model 5 (CNRM-CM5), Geophysical Fluid Dynamics Laboratory Climate Model 3 (GFDL-CM3), Russian Institute for Numerical Mathematics Climate Model 4 (INM-CM4), and the Model for Interdisciplinary Research on Climate 5 (MIROC5). These four models were part of the IPCC’s fifth Climate Model Intercomparison Project (CMIP5) and were incorporated into their Fifth Assessment Report. The horizontal atmospheric resolution of these models range between 1.4° latitude by 1.4° longitude and 2.0° latitude by 2.5° longitude. All four model simulations span at least 1 Jan. 2006 through 31 Dec. 2100. Due to time constraints, the selection of the models used in this study was purely random. Given that DTR and specific humidity trends for all four models are generally similar, we use the multi-model ensemble mean interpolated to match the reanalysis grid when presenting results throughout the remainder of this study. Results for individual models are provided in supplemental materials.

![Figure 1: Annual mean DTR (a) and specific humidity (b) over 2007-2016 from NCEP-DOE Reanalysis 2.](image-url)
2.3 Calculation of DTR

We adopt a similar method as most studies that calculate DTR by differencing the maximum and minimum temperature over a 24-hour period of time, except that we define DTR for a given day by differencing the minimum temperature on that day with the average of the maximum temperature of that day and the adjacent days. Using a three day average of maximum temperature accounts for uncertainty regarding which 24-hour period in which the maximum DTR occurs. Present day annual means of DTR and specific humidity for each period were computed by taking the rolling mean of 31 days around the given date through all 10 years of the period.

2.4 Quantification of DTR

Sensitivity to Global Warming

Preliminary analysis of DTR and specific humidity over 2007-2016 (Figure 1) reveals an apparent negative correlation between the two, where regions with high DTR correlate with low specific humidity, and vice versa. Through a linear regression model of DTR on specific humidity, we derive \( \Delta DTR/\Delta Q \), which represents how we expect DTR to change (°C) relative to climatology per specific humidity departure (g/kg) from climatology. We make the assumption that relative humidity will stay constant with global warming (Held and Soden 2006) and use the Clausius-Clapeyron relation to calculate \( \Delta Q1C \), the change in specific humidity, for 1°C uniform warming across the globe. Multiplying \( \Delta Q1C \) by \( \Delta DTR/\Delta Q \) leaves us with \( \Delta DTR1C \), the projected change in DTR for 1°C uniform warming. This value, derived from a simple linear regression model, then allows us to investigate regions in which DTR is less sensitive, compared to regions where DTR is projected to change more significantly with a degree warming.

2.5 Empirical Model for DTR based on Water Vapor Concentrations

We use a similar process for creating an empirical model for DTR based on water vapor concentrations as we used for quantifying the sensitivity of DTR to warming (Section 2.4). Using \( \Delta DTR/\Delta Q \) and the specific humidity projections of the four GCM models, we then derive regression-based projections of DTR change. However, it should be noted that this empirical model only projects DTR change based on its linear relationship with specific humidity. While cloud cover, soil moisture, and snow/ice cover are accounted for as they are closely related to specific humidity, other elements and interactions are not considered. The changing terrain of the Arctic, for example, is not accounted for in the model beyond the impacts it has on specific humidity. As a result, our projections of DTR change likely do not fully reflect how DTR will change in regions where snow/ice cover will change dramatically between now and the end of the century.

3. Results

3.1 Comparison of Model-derived and Reanalysis-derived DTR Calculations

Comparing reanalysis- and GCM-derived DTR for 2007-2016 (Figure 2a) reveals that GCMs overestimated DTR values over most land areas by 1°C to 5°C, and underestimated DTR in the Arctic and Antarctic. As expected, given the negative correlation found between DTR and specific humidity (Section 3.2), a comparison of reanalysis- and GCM-derived specific humidity over the same period of time (Figure 2b) revealed that overestimates
of DTR often correlate with underestimates of specific humidity and vice versa. This may explain some of the disagreement between our regression-based and multi-model ensemble mean projections of DTR.

### 3.2 Linear Regression of DTR on 2-m Specific Humidity

A linear regression of DTR on 2-m specific humidity shows that DTR and specific humidity are negatively correlated over all areas of the globe, excluding some parts of the Sahara and over the oceans along the equator (Figure 3a). Over land, specific humidity values that are one standard deviation above (below) normal tend to correlate with DTR values that are one to three degrees less (more) than climatology. Over oceans, where variations in DTR and specific humidity are minimal due to the high thermal capacity of water, changes in specific humidity correlate with very minor amplitude changes in DTR. Exceptions to this are the Arctic and Southern Oceans where

![Figure 2: Multi-model ensemble minus reanalysis annual mean DTR (a) and specific humidity (b) over 2007-2016.](image)

![Figure 3: Regression coefficients (a) and correlation coefficients (b) of the linear regression of DTR on specific humidity from reanalysis data for 2007-2016.](image)

![Figure 4: Projected change in DTR (a) and specific humidity (b) from the empirical model for 1°C uniform warming.](image)
there are seasonal fluctuations in sea ice cover. The higher regression coefficients in these regions reflect the dramatically lower values of 2-meter specific humidity and thermal inertia over ice than over the ocean, and the corresponding increase in DTR.

Excluding some parts of the Sahara and the equatorial oceans, the majority of correlation coefficient values indicate a strong negative correlation (-0.3 to -0.7) between DTR and specific humidity, suggesting that the two variables are closely coupled (Figure 3b). Causes for the weak (< 0.1) positive correlation seen in the Sahara and equatorial oceans are undetermined, but may relate to cloud and precipitation processes. One hypothesis is that nighttime thunderstorms, which may cause overnight temperatures to drop (i.e. DTR to increase) and specific humidity values to increase, are promoting this positive correlation.

3.3 Sensitivity of DTR with Near-Surface Warming

Using the regression relationship between DTR and specific humidity and projected changes in specific humidity with 1°C uniform warming (Figure 4a), we calculated the sensitivity of DTR to 1°C uniform warming (Figure 4b). DTR is most sensitive in tropical land areas where it is projected to decrease by 0.5-1.0 degrees from present-day values, and least sensitive over the equatorial oceans and parts of the Sahara where no change is seen. Given that DTR change is dominated by rising minimum temperatures relative to maximum temperatures, which generally results in overall warming, this suggests that the asymmetrical warming in tropical land areas will contribute more significantly to global surface warming.

3.4 End-of-Century DTR Projections

Our regression-based, empirical model for DTR projects that by the end of the century, the Arctic, land areas and Antarctic will see the largest decreases in DTR, while tropical and midlatitude areas of the oceans will see virtually no change (Figure 5a). However, as discussed in Section 2.5, the changing terrain
of the Arctic and Antarctic may compromise the integrity of this empirical model over these regions. Globally, our model projects DTR to decrease by -0.82°C by the end of the century, suggesting that continued asymmetrical warming could contribute as much as 0.41°C to overall global warming in that same period of time.

The multi-model ensemble mean projects a more modest global DTR change of -0.15 °C by the end of the century, which is dominated by decreasing DTR in the upper latitudes, Africa and southern Asia, with slight increases in DTR projected in southern North America, southern Europe and most of South America (Figure 5b). Given these projections, asymmetrical warming could at most contribute to 0.08°C degrees of global warming.

A comparison of DTR projections from the GCMs and our empirical model (Figure 5c) reveals significant differences in both the sign and magnitude of end-of-century DTR change. While the empirical model projects that DTR will decrease by approximately 1°C over Europe, the multi-model ensemble mean suggests a 1°C increase in DTR. The empirical model also projects DTR decreases over land will be about 2°C greater than projections from the multi-model ensemble mean.

4. Summary and Discussion

Surface temperature measurements since the mid-20th century have revealed a diurnally asymmetric global warming trend, with nighttime minimum temperatures increasing faster than daily maxima, resulting in an overall decrease in DTR. This study found that the models used in the IPCC’s Fifth Assessment Report overestimated DTR for 2007-2016, which corresponded with underestimates of specific humidity. Our empirical model based on the linear relationship between DTR and specific humidity projects that DTR will decrease by 0.82°C by the end of the century, while the multi-model ensemble mean projects a more modest global DTR decrease of 0.15 °C. This discrepancy may come from model misestimates of DTR or other influencers of DTR that aren’t captured by the empirical model.

If our climate models aren’t accurately capturing the continuation of the asymmetrical warming trend into the latter half of the century, they may be missing as much of a third of a degree of warming that can be attributed to changes in DTR. The implications of continued asymmetrical warming span beyond the overall magnitude of global warming to include agriculture, streamflow, winter sports, and human health. The growing season will likely lengthen as warming minimum temperatures cause first and last freezes of the winter to occur closer and closer together. Similarly, watersheds will likely become less reliant on snowpack and more dominated by rainfall. With warming surface temperatures, ski resorts and the winter sports industry are becoming more reliant on snowmaking, the artificial production of snow, to supplement the natural snow cover (Burakowski and Magnusson 2012). And in extreme heat events, where nighttime offers a much-needed respite from potentially deadly temperatures, higher overnight minimums may have adverse effects on human health.

Acknowledgements

This work was performed under the auspices of the Significant Opportunities in Atmospheric Research and Science Program. SOARS is managed by the University Corporation for Atmospheric Research and is funded by the National Science Foundation, the National Center for Atmospheric Research, the National Oceanic and Atmospheric Administration, the Woods Hole Oceanographic Institute, the Constellation Observing System for Meteorology, Ionosphere, and Climate and
the University of Colorado at Boulder. The authors would like to extend an additional thanks to Dr. Elizabeth Maroon for her contributions to this research.

REFERENCES


