Detection and attribution of human influence on the global diurnal temperature range decline

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Key Points

1. The global decrease in diurnal temperature range is attributed to an anthropogenic signal, primarily driven by greenhouse gas forcing.

2. Aerosol forcing has had a detectable positive (negative) impact on the diurnal temperature range in Europe (East Asia).

3. The global diurnal temperature range is projected to increase (stabilize) under a high (low) emissions scenario.

Abstract A decline in the global diurnal temperature range (DTR) and its implications for human and natural systems have been widely reported, yet it remains unclear whether humans have a detectable influence on the DTR and to what extent anthropogenic greenhouse gases (GHG) may be driving such changes. Results indicate that the effect of anthropogenic forcing (ANT) on the DTR is detectable separately from natural forcing (NAT) across the globe and in many regions. GHG is the dominant contributor to DTR changes and caused the global DTR to decrease by -0.32℃ during 1951–2018, close to the observed change of -0.41℃. Decreased anthropogenic aerosols (AER) increased the DTR in Europe, while increased AER decreased the DTR in Asia. If greenhouse gas emissions continue to rise, further decreases in the DTR are likely to be observed in the future.

Plain Language Summary Contrary to rising temperatures, the diurnal temperature range has been decreasing over the past several decades. Although the impacts of humans on global warming have been widely demonstrated, formal detection and attribution of the impacts of human-made greenhouse gases and aerosols on the DTR are still lacking. Our results suggest that human impacts on the DTR are clearly detectable, separately from natural changes. Human-made greenhouse gases (GHG) are the dominant factor controlling decreases in the DTR worldwide. In contrast, anthropogenic aerosols are the dominant contributor for Europe and have led to an abnormal increase in the DTR in this region. If human emissions continue, we expect to see further decreases in the DTR in most regions. Our first quantification of human impacts on the global and regional DTR has significant implications for climate change assessments and future climate projections.

1. Introduction

Despite the rising global temperature, the diurnal temperature range (DTR; the difference between daily maximum and minimum temperature) has declined in recent decades. The DTR is an effective proxy to assess changes in radiative forcing (Thorne et al., 2016; Wang and Clow, 2020), a critical index for climate change assessment in the World Climate Research Program (Braganza et al., 2004). In addition, DTR changes have important implications for many aspects of both human and natural systems, such as human health (e.g., mortality (Paaijmans et al., 2010; Yang et al., 2013)), agricultural production (e.g., crop yields (Battisti and Naylor, 2009; Tatsumi and Yamashiki, 2012)), ecological systems (e.g., vegetation growth (Buntgen et al., 2013; Peng et al., 2013)), and earth systems (e.g., land-atmosphere carbon exchange (Xia et al., 2014)). These impacts of changes in the DTR highlight the fundamental importance of understanding why the observed DTR is decreasing and whether it is likely to continue decreasing in the future.

Recent detection and attribution studies have identified an anthropogenic influence on a series of meteorological and hydrological variables, such as extreme precipitation (Dong et al., 2021; Kirchmeier-Young and Zhang, 2020; Madakumbura et al., 2021; Paik et al., 2020), temperature (Blackport et al., 2021; Gillett et al., 2021; Wang et al., 2021), drought (Chiang et al., 2021; Williams et al., 2020; Zhang et al., 2021), evapotranspiration (Liu et al., 2021a), and streamflow (Gudmundsson et al., 2021). However, there are relatively few studies devoted to investigating human influence on the DTR, despite the important implications of changes in the DTR for humans and nature. Although several studies have shown that historical global climate model (GCM) simulations can largely capture the observed DTR changes (Lindvall and Svensson, 2015; Liu et al., 2016; Wang and Clow, 2020), quantitative detection of the effect of greenhouse gases and aerosols remains to be attempted at both global and regional scales. For example, by comparing the observed DTR with simulated DTRs under natural forcings (NAT) and historical forcing (ALL) from the Coupled Model Intercomparison Project Phase 5 (CMIP5), Zhou et al., (2010) found that observed changes in the DTR could not be explained by NAT forcing during 1951–1999. In a comparison between observations and simulations, Liu et al. (2016) indicated that anthropogenic greenhouse gas (GHG) forcing reproduced the spatiotemporal distribution of the DTR and suggested that GHG forcing has a dominant role in driving changes in the DTR over Asia during 1961–2005. These studies highlighted the important influence of anthropogenic forcings on the global decrease in the DTR. However, the anthropogenic signals driving observed changes in the DTR have never been detected separately from NAT forcing using a formal detection and attribution framework. Moreover, the contribution of ANT, GHG, and AER forcings remains to be quantified at both global and regional scales. The AER forcing has been found to decrease temperature over most regions globally (Jones et al., 2013), which may neutralize GHG effects, but the models with an AER-only experiment are few in CMIP5 (Paik et al., 2020). New CMIP6 simulations now provide individual (e.g., GHG-only, AER-only, and NAT-only) forcing simulations, which allow us to quantify the contribution of ANT, GHG, and AA separately from NAT forcings (Seong et al., 2021).

In this study, we performed a quantitative detection and attribution of DTR changes. This is achieved by using an optimal fingerprinting technique combined with the newly available observations from HadEX3 and simulations from CMIP6 for 1951–2018. Given the considerable regional impacts of anthropogenic forcing (Dong et al., 2017) and the differential response of the DTR (Liu et al., 2016), the detection and attribution are conducted at both global and regional scales. Thus, this quantitative detection and attribution of changes in DTR will advance our understanding of anthropogenic impacts on the climate system and how it may evolve when considering external forcings.

2. Data

The HadEX3 dataset provides the DTR index over the global land surface (1.875°×1.25°) during 1901–2018 (https://www.metoffice.gov.uk/hadobs/hadex3). The DTR is obtained using the daily maximum temperature minus the daily minimum temperature based on 7056 meteorological stations (Dunne et al., 2020). The DTR was calculated only when the missing observations were less than 3 days for a specific month and less than 15 days for a specific year, otherwise, the DTR value in that month or year was set to a missing value. Further details about the data processing are provided in Text S1.

3. Optimal fingerprinting technique

The optimal fingerprinting technique is applied to detect and quantify the impacts of external forcing on the changes in DTR. The observations (DTR time series; Y) are regressed onto the external forcing (g) using total least squares estimates (Allen and Stott, 2003):

$$Y = \sum_i^n \beta_i g_i + \varepsilon \quad (1)$$

where β_i is the scaling factor that presents the responses of DTR to external forcing (g_i). The fingerprint of g_i is obtained based on the multimodel ensemble averages of external forcing simulations from CMIP6. The ε represents the internal variability and can be estimated from CTL experiments (Liu et al., 2021). The 200 chunks of 68-year length from CTL are divided into two independent sets: one is applied to estimate the optimized scaling factor β_i; the other is applied to obtain the 95% confidence interval of the corresponding scaling factor (Gu et al., 2019a). If the confidence interval of β_i lies above zero, this indicates the corresponding signal is detectable in the observed changes, and if it larger than one this means that the simulated trends underestimate the observed trends (Allen and Stott, 2003; Wang and Clow, 2020). Further details about the use of optimal fingerprinting techniques are provided in Text S2 in the Supporting Information.

4. Results

4.1 Observed and simulated changes in DTR

The newly released HadEX3 data show a declining DTR in most (76.1%) areas covered by observations, with 50.7% of the grid cells showing significant decreasing trends (Figure 1). The observed global area-weighted average DTR decreased by -0.43℃ during 1951–2018. The observed regional area-weighted average DTR decreased in all regions except for Europe (Figure S3). Trend analysis using other observation-based DTR datasets also shows a wide decline in DTR across the globe. Specifically, 52.6% and 52.7% of grid cells show significant decreasing trends in DTR based on the CRU TS and Princeton Global Forcings datasets, respectively (Text S3 and Figure S2 in Supporting Information). These results generally agree with previous observations (Wang and Clow, 2020; Zhou et al., 2010).

As the GCM simulations have considerable systematic biases relative to observations, bias correction methods are commonly recommended to correct these biases (Cannon, 2015; Ficklin et al., 2016; Liu et al., 2017). Here, we used a quantile delta mapping (QDM) algorithm to correct biases in GCMs simulations and projections to reduce the error in subsequent analysis (Text S4 in Supporting Information). We found that QDM can, to some extent, improve the trend simulations (Figure S4), and can significantly improve the performance of GCM simulations and projections of mean DTR (Figure S5) and DTR variability (Figure S6).

The spatial patterns of simulated trends under ALL forcing are largely consistent with the observed trends, similarly showing significant decreases in DTR over most areas (Figure 1b). Nevertheless, ALL simulations also show increasing trends in some regions of southern Europe, southern Africa, southern Argentina, and southern Australia (Figure 1b), where observed DTR also primarily shows significant increasing trends (Figure 1a). Interestingly, these increases have mainly occurred in regions with strong soil moisture drying (Figure 8 in Gu et al., 2019b). Previous studies have suggested that GHG leads to soil moisture drying (Gu et al., 2019a), which may further increase the DTR (Dai et al., 1999; Durre et al., 2000). Over southern Europe, the DTR increase is largely caused by the significant impacts of AER forcing (Figure 1f). Owing to the “clear air” laws, aerosol emissions have significantly decreased over Europe since the 1980s, which caused a reversal from solar “dimming” to “brightening” and led to increases in the DTR (Norris and Wild, 2007). The major features of observed trends in the DTR are generally captured by simulations of ANT and GHG, but cannot be explained by NAT (Text S5 in Supporting Information for details), which is in line with previous studies (Liu and Sun, 2016; Wang and Clow, 2020; Zhou et al., 2010). Nevertheless, whether the human fingerprint is detectable in the DTR changes remains largely unknown.

4.2 Detection and Attribution

Figure 2 shows the best estimates of the scaling factors and their 95% confidence interval based on one-way, two-way, and four-way detection during 1951–2018. One-way detection shows that the scaling factors of ALL are larger than zero over the globe and in most subcontinents of the Northern Hemisphere, indicating the ALL signal is detectable in the global and regional DTR changes. Over the globe, the scaling factors of ALL are generally larger than unity and thus suggest that the simulated trends from CMIP6 tend to underestimate the observed trends. Similar results are found during 1951–2014, when the ALL simulations are not extended to 2018 by using the simulations from SSP2-4.5 (Figure S9), implying the underestimation is not caused by the extension of the record. The smaller trend in simulated DTR, relative to observations, could be caused by the underestimation of the trend in minimum temperature primarily due to the inadequate consideration of increased cloudiness in the simulations (Padrón et al., 2020; Zhou et al., 2010). Besides, model deficiencies exist in the simulation of hydrological variables (e.g., precipitation and soil moisture), land use/cover changes, and terrain, all of which would go against the ability of GCMs to reproduce the observed DTR trends (Wang and Clow, 2020; Zhao et al., 2014). For example, the inadequate consideration of urbanization effects is an important reason for the underestimation of trends in the DTR over eastern China (Liu et al., 2016). Underestimations of changes in the DTR were also found in previous papers using the CMIP5 models (Thorne et al., 2016; Zhou et al., 2010).

Two-way detection shows that the ANT signal is clearly detectable from the NAT signal over the globe, and is detectable over most subcontinents in the Northern Hemisphere. Over the Middle East, North America, Western Africa, Russia, and Southeast Asia, the scaling factors are very close to one, implying that ANT simulations agree well with the observed trends in these regions. In contrast, over the globe and in

East Asia, the scaling factors of ANT are larger than one and thus suggest ANT simulations underestimate the DTR trend relative to the observations. The ANT signal cannot be detected in regions of the Southern Hemisphere, which is similar to the findings from Dong et al. (2021), although they aimed to detect observed changes in extreme precipitation. The spatial coverage of meteorological gauging stations in the Southern Hemisphere is relatively limited, and insufficient for the detection of an ANT signal (Dong et al., 2021).

Four-way detection indicates that the GHG, and OANT (other ANT, e.g., ozone and land use change) signals can be robustly detected over the globe. At the regional scale, the GHG signal is detectable over most subcontinents (except for Northern Africa) with detectable ANT, which implies that GHG plays a crucial role in the impacts of ANT. An AER signal is detectable over East Asia, the Middle East, and Southeast Asia; while OANT can be detected in South America, South Asia, Southeast Asia, and western Africa. The changes in land use, land cover, and land management (LULC) can influence DTR through non-radiative processes (Bright et al., 2017). However, its contribution is relatively smaller and the signals cannot be detected in observed DRT changes in all regions except for South America (Figure S11).

To investigate the robustness of this detection and attribution, we also used three observation-based datasets, i.e., Princeton Global Forcing, Berkeley Earth Surface Temperature, and CRU TS (Text S3 in Supplementary Information). Here, the mean values of the DTR from these three datasets are regarded as observations. We find that although some differences exist in specific values of scaling factors, the key results describing whether a signal is detectable are similar when using only HadEX3 or multiple datasets (Figure 2 and Figure S12). These three datasets have valid values for all land-surface grids, which allows us to further detect and attribute the DTR changes in Eastern and Western Africa. Although significant trends were observed in these two regions (Figure S2), no signals can be detected (Figure S12). Considering that the observation-based DTR datasets employ spatial and temporal interpolations, we use the HadEX3 dataset alone for the remaining analysis.

To quantify the sources of observed changes in DTR, we attributed the observed trends to individual external forcings using the annual trends multiplied by the corresponding scaling factors (Figure 3). The resulting values indicate that the global decrease in DTR attributed to ALL is -0.40℃, which matches the trend in the observations (-0.43℃). ANT makes the largest contribution to the decrease in DTR by -0.38℃ (95% confidence intervals: from -0.26℃ to -0.49℃). Among the ANT signals, GHG is the major contributor to DTR change, and causes it to decrease by -0.32℃ (from -0.21℃ to -0.44℃), contributing 88.4% of the global decline in DTR; while the AER signal has limited contribution to global changes in the DTR. OANT is the second contributor following GHG, and results in a decrease in DTR by -0.12 ℃ (from -0.03℃ to -0.20℃). The negative effect of OANT could be explained by the differential response of daytime and nighttime temperature to land use change (Mohan and Kandya, 2015; Ren and Zhou, 2014). Land use change, such as urbanization, can alter the regional climate by re-adjusting the surface energy balance (Sarangi et al., 2021). The urban heat island effect on rising temperature is much stronger during nighttime than daytime (Sarangi et al., 2021; Yang et al., 2017). NAT has weak impacts on global DTR changes, leading it to increase by 0℃ and 0.02℃ according to the two-way and four-way analyses, respectively. This is largely supported by the fact that the impacts of NAT forcing triggered by volcanoes are generally confined to a few years following an eruption (Iles et al., 2015) and their effect is limited in long-term trends (Gudmundsson et al., 2021). Internal climate variability such as ENSO has limited influences on DTR trends (Text S6 in Supplementary Information). The effects of ALL, ANT, GHG, AER, and OANT are reliable based on the optimal fingerprint analysis, while the contribution of NAT to global DTR change should be understood with caution since a NAT signal cannot be detected. Similar results can be found during 1951–2014, when the ALL simulations are not extended with the simulations from SSP2-4.5 (Figure S13). Further, attribution analysis using the mean of the four observed DTR datasets also show similar results, i.e., GHG is the dominant forcing controlling changes in DTR, followed by the OANT, and the impacts of AER and NAT are relatively weak (Figure S14), highlighting the robustness and strength of the anthropogenic impacts.

From a regional perspective, the contribution of external forcings to the DTR varies in both magnitude and direction over different regions. Compared with NAT, ANT is the dominant contributor to changes in DTR for 11 of the 12 subcontinental regions. AER has distinct impacts (both positive and negative) on regional changes in DTR. In East Asia, the Middle East, and South Asia, the impacts of rising aerosol emissions are associated with a strong decreasing trend in the observed DTR. In contrast, the DTR in Europe shows an increasing trend owing to decreasing aerosol emissions. Using the idealized experiments from the Precipitation Driver and Response Multimodel Intercomparison Project (PDRMIP), Stjern et al. (2020) found that the aerosols (in particular black carbon) significantly reduced the DTR over India and China, which is consistent with our results in terms of AER effects. Aerosols can weaken shortwave radiation through scattering and absorbing, and enhance longwave radiation by re-emission of the absorbed energy (Chakraborty and Lee, 2019; Chakraborty et al., 2021). Zhou et al., (2010) explained the changes in GCMs simulated DTR through shortwave and longwave radiation, and found that decreased shortwave radiation and increased longwave induced by rising aerosol have important impacts on the decrease of DTR. Nevertheless, it is worth noting that aerosol effects have large uncertainties in the model simulations (Chakraborty et al. 2021) and the simulations of direct and indirect impacts of aerosols remain problematic (Lewis and Karoly, 2013).

4.3 Projected changes

If the impacts of anthropogenic greenhouse gas emissions on the DTR are robust, decreases in the DTR may continue in the future. Hence, we investigated future changes in the DTR from the multimodel ensemble under different scenarios. The projected trends are calculated by using the time series of QDM-corrected simulations multiplied by the scaling factor of ALL forcing during the historical period. The global assessment suggests that the DTR is projected to decline in most regions in the future (Figure 4a-c). The magnitude of the decrease is predicted to strengthen with the emissions levels of the scenarios, with a negative trend of -0.04, -0.26, -0.44°C/century under SSP1-2.6, SSP2-4.5, and SSP5-8.5, respectively (Figure 4p-r).

During the late century (2071–2100), the global DTR is projected to decrease by -0.51℃ under SSP5-8.5 compared to the period of 1951–1980 (Figure 4d). At the regional scale, the DTR is projected to decrease in all regions but South Africa. A Gaussian probability density function is used to describe the distribution of mean changes in DTR for all considered grid cells during late 2071–2100 compared with 1951–1980. The probability density curves of mean DTR changes tend to become increasingly negative during the late century, especially under SSP5-8.5, implying that more extensive decreases in DTR may appear in more regions under future higher emissions scenarios (Figure 4d-o). Under SSP1-2.6, the projected changes in the global mean DTR during 2071–2100 are smaller than the observed changes during 1989–2018 compared to 1951–1980 (Figure 4d). Besides, the decreasing trends in DTR tend to stagnate or even increase in the future period (Figure 4p). These projections imply that the decrease in DTR may be halted if carbon emissions are controlled, as is the assumption in SSP1-2.6. Furthermore, the future DTR is projected to change only weakly under the CTL simulations, suggesting that changes in the DTR are likely to be negligible if there are no human effects (Figure 4d-o). These results indicate that the strengthening decrease in the future DTR is primarily controlled by human-induced climate change.

Projected results suggest that the effects of anthropogenic activities are intensifying with the rise of greenhouse gases. Our findings highlight the necessity of reducing carbon emissions to control the decline in DTR, to minimize its adverse effects on health (Cheng et al., 2014), agriculture (Battisti and Naylor, 2009; Tatsumi and Yamashiki, 2012), and ecological environments (Buntgen et al., 2013; Peng et al., 2013).

5. Summary and Conclusions

In this study, we perform a formal quantification of human impacts on the observed changes in the diurnal temperature range (DTR) based on newly released observations and CMIP6 simulations. We find that the anthropogenic forcing signal (ANT) is detectable separately from natural forcing (NAT) across the globe and in most regions. ANT forcing can largely explain the observed decrease in the global DTR, with negligible impacts from NAT forcing. Furthermore, greenhouse gases (GHG) are a primary forcing in the ANT signal, which dominates the decreasing trend in the DTR. GHG caused the global DTR to decrease by -0.32 ℃ during 1951–2018, and accounts for 74.4% of the observed trend (-0.43℃).

AER has substantial regional impacts on the DTR, although its signal is not detectable at the global scale. Specifically, aerosols (AER) have a detectable positive impact in Europe and have led to an unusual increase in DTR (0.31℃) in this region. This is consistent with the decline in aerosol emissions in Europe after the 1980s (Norris & Wild, 2007). As suggested by Philipona et al. (2009), the increase in shortwave radiation induced by the decrease in AER is 2-3 times higher than the increase in longwave radiation driven by the rise in greenhouse gases over Europe. In contrast, a negative effect of AER is found in East Asia and is also detectable from the NAT forcing, supported by the rapid socio-economic development and increasing aerosol emissions over this region since the 1980s. Projections suggest that the DTR will continue to decrease in the future under the high emission scenarios, whereas the decrease will stabilize if greenhouse gas emissions are limited following SSP1-2.6.

It should be noted that as in any other climate detection study (e.g., Gudmundsson et al, 2021), there are considerable uncertainties in the results of detection and attribution, due to the uncertainties in the fingerprint technique, model simulations and observations (Wang and Clow, 2020). Li et al. (2021) indicated that the two-sample method in the optimal fingerprint technique may provide a lower coverage of the confidence intervals, further leading to narrow confidence intervals of the detectable changes. They suggested that using a large sample to estimate the natural variability is helpful to improve the validity of confidence intervals. Hence, this study used the CTL from all available models to structure the noise covariance of internal variability. The underestimation in DTR simulation and attribution may be caused by the insufficient consideration of aerosol-cloud interactions and increased cloudiness (Wild, 2009) and their impacts on downward longwave radiation, which leads to an underestimation of nighttime temperature (Zhou et al., 2010). There are equally uncertainties in the observations due to measurement biases, sparse station distributions, and the treatment of missing data (e.g., Wang and Clow, 2020). The uncertainties existing in both the simulations and observations are likely to lead to uncertainties in the detection and attribution results. Hence, we applied a QDM algorithm to correct the biases in the simulations and employed several observed datasets to investigate the uncertainties in the observations. Our results indicate that bias correction effectively improves the performance of GCMs simulations, but that using different datasets has limited impacts on the detection and attribution results.

This work provides a detectable evidence of anthropogenic influence on observed changes in the global DTR. Notably, the decrease in the DTR is reliably attributed to GHG, highlighting new and robust evidence of human impacts on climate change. Understanding the causes of decreases in the DTR and future changes has significant implications for climate change impact assessments.

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Figure Captions

Figure 1. Spatial distribution of trends (℃/decade) in DTR during 1951–2018. Trends in (a) observed DTR (Obs); and trends in CMIP6 multimodel ensemble mean simulations with: (b) anthropogenic and natural forcing (ALL), (c) natural forcing only (NAT), (d) anthropogenic forcing (ANT), (e) greenhouse gas forcing only (GHG), and (f) anthropogenic aerosol forcing only (AER). Black points indicate that the trends are significant at the 95% confidence level. The inset histograms summarize the percentage of the land surface showing a significant decrease (SD), decrease (D), increase (I), and significant increase (SI) in DTR, respectively.

Figure 2. Optimized scaling factors and their 95% confidence intervals during 1951–2018. The observations are regressed onto ALL simulations by one-way detection, onto ANT and NAT by two-way detection, and onto GHG, AER, OANT, and NAT by four-way detection. The horizontal black and red dashed lines indicate zero and unity, respectively. When the 95% confidence interval of the scaling factor lies above zero this indicates the corresponding signal can be detected in the observed DTR, and a scaling factor larger than one suggests that the simulated trend underestimates the observed one.

Figure 3. Observed annual DTR trends and their drivers during 1951–2018. Attributable change is calculated by multiplying the annual trends by the corresponding scaling factors. Error bars are the corresponding 95% confidence intervals.

Figure 4. Projected changes in DTR under different scenarios. (a-c) Spatial distribution of trends during 1951–2100 (℃/century) for SSP1-2.6, SSP2-4.5, and SSP5-8.5,

respectively. (d-o) Probability density function (PDF) of mean DTR changes (℃) for the late twenty-first century (2071–2100) compared with the period of 1951–1980. (p-r) Anomalies of annual time series of global DTR during 1951–2100. The data for the period of 1951–2014 is derived from the ALL experiments, and the data for 2015–2100 are derived from (p) SSP1-2.6, (q) SSP2-4.5, and (r) SSP5-8.5 scenarios. The trend values are calculated as the linear trend of the projections multiplied by the corresponding scaling factor of ALL experiments shown in Figure 2.