Diurnal asymmetry to the observed global warming

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ABSTRACT: The observed warming of the surface air temperature (SAT) over the last 50 years has not been homogenous. There are strong differences in the temperature changes both geographically and on different time frames. Here, we review the observed diurnal asymmetry in the global warming trend: the night-time temperatures have increased more rapidly than day-time temperatures. Several explanations for this asymmetric warming have been offered in the literature. These generally relate differences in the temperature trends to regionalized feedback effects, such as changes to cloud cover, precipitation or soil moisture. Here, we discuss a complementary mechanism through which the planetary boundary layer (PBL) modulates the SAT response to changes in the surface energy balance. This reciprocal relationship between boundary-layer depth and temperature response can explain a part of why the night-time has warmed more rapidly than the daytime. We used a multi-linear regression model to explore the effect of the PBL, cloud cover, precipitation and soil moisture on the SAT. From this, we demonstrate that it is the boundary-layer depth which is the strongest predictor of the strength of temperature trends in the boreal annual cycle, and in all seasons except the summer.

KEY WORDS climate change; surface air temperature; climate feedback; energy-budget model

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1. Introduction
The global mean surface air temperature (SAT) is one of the most common measures of global climate variability and change. However, changes to the diurnal cycle, as defined by the diurnal minimum, T min, and maximum, T max, temperatures can be just as important as they regulate many physical processes in Earth’s climate system. There has been a reduction in the diurnal temperature range (DTR = T max − T min) during the 20th century due to the more rapid warming of the T min than the T max (Karl et al., 1993; Braganza et al., 2003; Vose et al., 2005; Alexander et al., 2006). However, the observed asymmetry in the trends of the diurnal temperature extremes have not been correctly reproduced in the climate models (e.g. Lewis and Karoly, 2013). There is evidence that this reduction in DTR has had a significant effect on vegetation (Alward et al., 1999; Peng et al., 2004, 2013; Zhou et al., 2015) and has led to temperature-related fatalities (Yang et al., 2013). Differences in the warming of T min and T max during the 20th century have previously been attributed to clouds (Dai et al., 1999; Sun et al., 2000), precipitation (Dai et al., 1997; Zhou et al., 2009), soil moisture (Dai et al., 1999) or other feedback processes. While strong relationships can be found between the DTR and a given feedback process for a specific geographical region or season (Makowski et al., 2009; Lewis and Karoly, 2013; Sun and Prinker, 2014), none of these works have provided a conclusive attribution of the global DTR reduction. Moreover, the use of climate models with incorrect responses in the diurnal temperature extremes may lead to inconsistencies with the observed temperature trends as, e.g. the attribution of the decreasing mid-latitude DTR to the impact of the changing land use – land cover on the diurnal maximum temperature (Hua and Chen, 2013). As Stone and Weaver (2003) emphasized, variations in the DTR are much more sensitive to variations in the model feedbacks than in the applied direct forcings. Their study with the Canadian Centre for Climate Modelling and Analysis-coupled model, along with the majority of other climate model studies, attributed the summertime DTR decrease to the effect of cloud cover changes on T max whereas the wintertime DTR decrease was considered as a model artefact. However, the data analysis in this study, as well as in Esau et al. (2012); Davy and Esau (2014) and in Wang et al. (2014) reveal the significance of the larger DTR changes due to increasing T min in the winter season.

It has been established since the early work of Hasselmann (1976) that the strength of changes to the SAT is determined not only by the strength of the forcing and feedback effects, but also by the effective heat capacity of the system. Kim and North (1991) used this conceptual, energy-balance model, and realistic atmospheric boundary-layer parameters, to demonstrate how a small effective heat capacity leads to a large temperature response over the continents and cold areas. Surprisingly,
these semi-analytical results predicting the greater night-
and winter-time anthropogenic warming in the continental
extra-tropics have been largely ignored in the discussion of
the observed DTR changes after Karl et al. (1993). So in
this article, we address the importance of the atmospheric
heat capacity in explaining the variations in SAT trends.

Section 2 presents and discusses the datasets and meth-
ods used in the article. In Section 3, we present an assess-
ment of the climatology and trends of the $T_{\text{max}}$, $T_{\text{max}}$, and
DTR in the most recent high-resolution, gridded observa-
tions published by the Climate Research Unit (CRU). In
Section 4, we go on to discuss the various mechanisms
proposed in the literature to explain the asymmetric warm-
ing in the diurnal cycle, and the degree to which they have
been successful. This includes consideration of how the
effective heat capacity of the atmosphere, as defined by
the depth of the planetary boundary layer (PBL), deter-
mines the strength of the SAT response to perturbations in
the energy budget (Hasselmann, 1976; Esau and Zilitin-
kevich, 2010). In this framework, we need to consider the
covariation of feedback processes with the PBL depth in
order to understand the trends in the SAT. In Section 5,
we demonstrate how a multi-linear regression model can
be used to compare the relative importance of the differ-
ent feedback processes discussed in Section 3, along with
the PBL depth, as predictors of the strength of SAT trends.
The results of this model demonstrate that it is the cli-
matology of the PBL depth which is the strongest predictor
of the pattern of SAT trends. Finally, in Section 6, we go on
to assess the effects of the PBL depth on the SAT in sta-
ton observations. Contrary to the, perhaps intuitive, notion
that a warmer world has greater SAT variability (Hansen
et al., 2012), the modulating effect of the PBL depth on
SAT implies that SAT variability is actually expected to
decrease in the future. This has been confirmed in stud-
ies by Kim, (2013) and Huntingford et al., (2013), and
is supported by earlier work based on gridded observa-
tions which indicated that there had been a decrease in
the intra-annual and intra-monthly SAT variability during
the 20th century (Michaels et al., 1998). Furthermore, we
can predict that the diurnal minimum temperatures should
see the greater reduction in variability, compared with the
diurnal maximum, and this was confirmed using station
observations.

2. Datasets and methods

2.1. CRU-gridded observations

To investigate the changes to the SAT mean, range and
diurnal extremes on multi-decadal timescales, we used the
observation dataset ‘CRU TS 3.10.01’, produced by the
CRU (Harris et al., 2014) and published online. The
dataset is available at: http://badc.nerc.ac.uk/view/badc.
nerc.ac.uk_ATOM_dataaent_125622377332328276. This
data set includes monthly means of the daily temperature
minimum, mean, maximum and range. These were cal-
culated on a high-resolution (0.5 x 0.5 degree) grid from
historical records from over 4000 weather stations world-
wide, covering the period 1901–2009 (see Mitchel and
Jones (2005) for the methodology used in constructing
these gridded datasets). The last 50 years (1960–2009)
of the time series of each variable was extracted from the
dataset.

2.2. ERA-interim

For the multi-linear regression analysis, we required a
dataset which included boundary-layer depth, cloud cover,
2 m air temperature, precipitation and soil-moisture data,
and so we chose the ERA Interim reanalysis product.
The monthly time series of boundary-layer depth, cloud
cover, and the 2 m minimum and maximum temperatures
over the period 1979–2010 for the ERA-Interim reanal-
ysis dataset were obtained from the ECMWF website.
The diurnal minimum and maximum temperatures were
used to create datasets of the diurnal temperature range
(DTR = $T_{\text{max}} - T_{\text{min}}$) and mean ($T_{\text{mean}} = (T_{\text{max}} + T_{\text{min}})/2$).
We assessed the consistency in the DTR and $T_{\text{mean}}$ between
the ERA Interim and CRU datasets in the overlapping
period, 1979–2009. We found a strong consistency in the
area-weighted-mean timeseries of these datasets with $R = 0.97$, $p < 0.01$ for $T_{\text{mean}}$ and $R = 0.77$, $p < 0.01$
for the DTR. However, there are some strong geographical
variations to the correlation between the datasets (Figure
S1, Supporting Information). The DTR in the two datasets
are strongly correlated over much of Europe and North
America, but relatively weakly over North-Eastern Russia
and the high-Arctic of Canada. We also compare the
pattern of trends in the two datasets, although, given the
short period of overlap, there are relatively few locations
with statistically significant trends in the DTR during the
overlap period. There is a good consistency in the DTR
trends over Europe and Asia, but there is a big discrepancy
over the continental US. The ERA Interim data shows a
general increase in DTR over this period, whereas CRU
has some increasing, but mostly decreasing trends in the
DTR over the US, which is consistent with recent analysis
of the DTR trends using an alternative observation dataset
(Qu et al., 2014). However, the two datasets show a much
greater agreement in the diurnal-mean temperature. There
is a very strong correlation in the monthly anomalies
across the northern-hemisphere, and a reasonable agree-
ment in the pattern of trends in $T_{\text{mean}}$ (a spatial-correlation
of $R = 0.59$, $p < 0.01$).

2.3. Weather station data

To demonstrate the anticipated relationships between the
mean SAT and the SAT trends and variability, we used
observations from weather stations which are available
from the National Oceanic and Atmospheric Adminis-
tration (NOAA) at http://www.ncdc.noaa.gov/data-access/
land-based-station-data/land-based-datasets. The stations
in question were selected for their location within the
region of Siberia where the role of the PBL was antic-
ipated to be important due to the persistent stable strat-
ification found in this region, and for the availability of
temperature data of sufficiently high temporal resolution
that we could assess the diurnal cycle over the period
under consideration, 1960–2009. The station names are Tura, Vorogovo, Verheimbatsk, Vereshchagino, Vel’no, Vanavara, Ust’-Kano, Ust-Ilmsk, Ucamy, Tsembenshi, Syu, Sukhaya Tunguska and Strelka Chunya, and they are all located within the area defined by 60–65°N, 85–105°E. Firstly, the two coldest and warmest periods in the diurnal cycle were selected to represent the diurnal minimum and maximum temperature: these were at 0000 and 1200 UTC. These daily minimum and maximum temperatures were then averaged to monthly values.

In order to compare the differences in the behaviour of the diurnal minimum and maximum temperature between different stations, the values of the trends and variability at each station were normalized to the trend and variability of the annual-mean, diurnal-mean temperature at each station respectively.

2.4. Methods
Monthly anomalies were calculated by removing the climatological mean (average of the full-period of the time series) of each month from the time series of each variable. The trend in each variable was calculated from the time series of monthly anomalies using a least-squares linear regression, with the trends filtered for significance using a requirement that \( p < 0.05 \). A land-sea mask for the ERA-Interim dataset was obtained from the ECMWF website. This was applied to remove data for grid points which lay over ocean. The northern hemisphere and global means of the anomaly time series were created by taking the area-weighted-mean of over-land grid points for each variable in a band from 30°–90°N (northern hemisphere) and the whole globe, respectively. The northern hemisphere and global trends and variability were then calculated from these time series. This method was repeated for each season by using only 3 months of data: winter (DJF), spring (MAM), summer (JJA) and autumn (SON). When the trends or variability are calculated for a given season, we use the monthly anomalies appropriate to that season, e.g. for winter, we use the anomalies for December, January and February.

One limitation of the application of the multi-linear regression technique was the implicit assumption that the predictor variables are independent, a condition we may expect not to be met, given the physically inter-related nature of the chosen variables. We might naturally expect the cloud cover, precipitation and soil moisture to be linked as they are all measures of the hydrological cycle, but also the boundary-layer depth can be strongly coupled to the hydrological cycle through partitioning of surface fluxes between sensible and latent heat (Betts et al., 1996; Dirmeyer et al., 2014). In order to explore this issue, we assessed the correlation of the predictor variables with each other for each season, and in the annual-average (Figure S2). Overall, there is a moderate \( (R \sim 0.3, p < 0.05) \) correlation between the three predictor variables associated with the hydrological cycle: precipitation, cloud cover and soil moisture; but no strong correlation among the other variables at any time. There can be a strong seasonality to the correlation of the predictor variables, e.g. cloud cover and precipitation are strongly correlated in summer, but very weakly so in winter. The strong correlations between the hydrological-cycle predictor variables in summer indicates that at this time of the year we cannot distinguish the contributions from these variables to the temperature trends using this method. However, on the annual-average these processes are only weakly correlated, and it is the inverse PBL depth which is a stronger predictor of the temperature response than the other processes combined.

3. Observations of diurnal temperature extremes and range
Variations in solar heating drive a strong diurnal oscillation in the temperature at the surface, and in the lower atmosphere. This diurnal cycle affects the surface and atmospheric fluxes of momentum, energy and water vapour. The magnitude of this diurnal cycle is important in determining the interactions between the atmosphere and the surface as there is an asymmetrical response to a given forcing, depending on the timing of the forcing in the diurnal cycle. And even a given physical change can induce an asymmetrical response, e.g. increased cloud cover during the day can reduce surface temperatures by decreasing the incoming shortwave radiation, whereas increased nocturnal cloud cover at the same location can increase surface temperatures by trapping long-wave radiation in the near-surface layer. Therefore, the accurate depiction of the diurnal cycle in global climate models is important in capturing these non-linear interactions.

There has been a more rapid increase in the globally averaged diurnal minimum temperature \( (T_{\text{min}}) \) than the diurnal maximum temperature \( (T_{\text{max}}) \) in the last 50 years leading to a decrease in the DTR (Figure 1). The global decrease in the DTR during the latter half of the 20th century has been documented in the literature (Karl et al., 1984). Later, this distinct pattern was discovered in both global and regional temperature records (Karl et al., 1993). However, there has been some degree of temporal variation in the rate of change of the DTR, with some evidence of a slowing or even reversal of the negative trend in recent decades (Hartmann et al., 2013).

Karl et al. (1993) concluded that forcing due to greenhouse gases (GHGs) is unlikely to be the direct cause of the observed asymmetry of the temperature trends. These differences in the trends in the diurnal extreme temperatures can be seen on different geographical scales (global, hemispheric) and at all times of year (Table 1 and Figure 1). However, the magnitude of these trends strongly varies across these spatial and temporal scales. The northern-hemisphere trends are much stronger than the global trends for both the \( T_{\text{min}} \) and \( T_{\text{max}} \); and the trend in \( T_{\text{min}} \) is significantly greater than the trend in \( T_{\text{max}} \) in both cases (Figure 1). There is also a strong seasonal variation in the magnitude of temperature trends. There are stronger trends in both diurnal extremes in the boreal winter (DJF) than in the boreal summer (JJA), and at the same time
Figure 1. The trends in the area-weighted average of the (a) diurnal minimum and maximum temperature and (b) diurnal mean temperature and temperature range from a least-squares best-fit, with the associated 95% confidence interval, for global and northern hemisphere annual data, and for Winter (DJF) and Summer (JJA) means over the northern hemisphere for the period 1960–2009. Data are from the CRU high-resolution gridded observations.

we see a more rapid decrease in the diurnal temperature range in the winter, which is the season when the diurnal mean temperature has increased most rapidly (Figure 1). We can also see that there is a much greater variability in the wintertime temperatures, which has led to a larger confidence interval in the trends in this season. Indeed, it is the regions and seasons which have the strongest trends which also have the greatest variability – as seen in the larger range for the confidence interval. This suggests there will be an inherently low signal-to-noise ratio for climate forcing signals on the temperature trends, regardless of the magnitude of these trends (Esau et al., 2012).

However, the question as to whether it is the trends in $T_{\text{min}}$ which are being amplified or the trend in $T_{\text{max}}$ which is being damped is not easily resolved.

The trends in the diurnal mean temperature from the last 50 years of gridded observations are almost entirely positive (i.e. warming) trends, across the northern hemisphere (Figure 2). Geographically, we see relatively stronger positive trends over continental Eurasia and the high latitudes of North America. These are also the regions where we see a general negative trend (reduction) in the diurnal temperature range, with only a few locations showing a positive trend (Figure 2). There is a consistent pattern such that, as the world warms, it is the diurnal minimum temperature which increases more rapidly than the maximum temperature, leading to a decrease in the diurnal temperature range. It is generally the regions (Figure 2) and the seasons (Figure 1) which warm the most rapidly that have seen the biggest decrease in the $DTR$: there is a $R = -0.25, p < 0.05$ spatial correlation and $R = -0.45, p < 0.05$ intra-annual correlation between the trends in $T_{\text{mean}}$ and $DTR$.

4. Causes of diurnal asymmetry in warming

4.1. PBL effects

In this study, our understanding of the complementarity of the PBL effects is central to the analysis of the diurnal asymmetry in the observed warming. These effects are...
different from the effects of the diverse climate forcings in the sense that the PBL effect does not induce a forcing as such, but rather it creates and modulates the asymmetry of the temperature response. The structure of forcing is important here only in a statistical sense, i.e. in the sense of correlations between the spatial-temporal variability in temperature and forcing. In an asymptotic limit of a constant climate forcing, the asymmetric trends in the diurnal (seasonal, geographical) temperature extremes could be explained by the forcing efficacy modulation by the difference in the effective heat capacity of the PBL, which can be simply expressed through the thickness of the layer. It is convenient to discuss this proposition using a simple energy-budget model, which facilitates reference to numerous results of past studies, such as Budyko (1969) and North et al. (1981). This energy-budget model takes the form:

\[
\frac{dT}{dt} = C^{-1}dQ
\]  

(1)

Here, \( T \) (K) is a characteristic temperature of the mixed layer, which in climatological studies can be represented by the SAT. The SAT change in time, i.e. \( dT/dt \), should be understood as the change of the temperature averaged on timescales sufficiently large, at least a few hours, such that we remove the influence of turbulent fluctuations. In principal, we should also account for the trend in the boundary layer-depth in Equation 1, but the trends are generally very small, and so may be neglected (Figure 3). In a limit which is of interest here, the \( T \) can be described by two quantities on the diurnal time scale, namely, \( T_{\text{max}} \) and \( T_{\text{min}} \). In this sense, \( dT/dt \) will be the temperature change, on timescales longer than the diurnal time scale, in response to an anomalous heat forcing \( dQ \) (W m\(^{-2}\)). We note that the normal heat forcing, \( Q \), which corresponds to the unperturbed climate of the lower atmospheric column, also varies in time. The daytime \( Q \) is of order of 100–500 (W m\(^{-2}\)) but the nocturnal values of \( Q \) are \(-5 \) to \(-40\) (W m\(^{-2}\)). This varying forcing creates the SAT diurnal cycle: a non-linear, time-dependent function of the point of view of idealized PBL dynamics forced by a constant value, which can play an important role in determining how the surface temperature responds to changes in the forcing. We cannot necessarily expect the inverse relationship with boundary-layer depth across a range of stably stratified conditions. However, here we restrict our focus to the extremes in the diurnal cycle when there are large differences between the boundary-layer

**Table 1. Assessment of changes in the temperature extremes and range for the diurnal cycle: \( T_{\text{min}}, T_{\text{max}} \) and DTR, as published in the literature.**

| Reference          | Period and geographical area | Changes in degrees per 10 years | Conclusions                                                                 |
|--------------------|------------------------------|---------------------------------|-----------------------------------------------------------------------------|
| Karl et al. (1993) | 1951–1990; USSR              | \(-0.14\) \(0.14\) \(0.28\)    | \(DTR\) is significantly decreased largely because of strong increase in \(T_{\text{min}}\) in wintertime (December through May) and in high latitudes |
|                    | 1951–1990; USA               | \(-0.15\) \(-0.06\) \(0.10\)   |                                                                             |
|                    | 1951–1990; Alaska            | \(-0.24\) \(0.21\) \(0.45\)    |                                                                             |
|                    | 1951–1990; Canada            | \(-0.06\) \(0.09\) \(0.15\)    |                                                                             |
|                    | 1951–1990; China             | \(-0.20\) \(-0.07\) \(0.13\)   |                                                                             |
|                    | 1950–1990; Northern Hemisphere | \(-0.14\) \(0.05\) \(0.20\)     |                                                                             |
|                    | 1951–2000; Globe             | \(-0.14\) \(0.07\) \(0.21\)    | The trends in \(T_{\text{min}}\) are the largest in March through May       |
| Bradzil et al.     | 1951–1990; Europe            | \(-0.08\) \(0.52\) \(0.60\)    |                                                                             |
| (1996)             |                              |                                 |                                                                             |
| Easterling et al.  | 1950–1993; Northern Hemisphere | \(-0.09\) \((-0.14)^a\) \(0.08\) \((0.13)^a\) \(0.17\) \((0.27)^a\) | The same as in Karl et al. (1993)                                           |
| (1997)             |                              |                                 | Practically all warming must be attributed to \(T_{\text{min}}\) increase     |
| Tuomenvirta et al. | 1910–1995; Greenland, Nordic Seas, Scandinavia | \(-0.17\) \((-0.32\) \(0.09\) \((-0.57\) \(0.17\) \((-0.24)^2\) |                                                                             |
| (2000)             |                              |                                 |                                                                             |
| Braganza et al.    | 1951–2000; Globe             | \(-0.07\) \(0.12\) \(0.19\)    |                                                                             |
| (2003)             |                              |                                 |                                                                             |
| Vose et al. (2005) | 1950–2004; Globe             | \(-0.07\) \((-0.09)^a\) \(0.14\) \((0.18)^a\) \(0.20\) \((0.27)^a\) | \(DTR\) change is smaller after 1979 but strong increase in \(T_{\text{min}}\) in wintertime continues |
|                    | Northern hemisphere          | \(-0.08\) \((-0.10)^a\) \(0.16\) \((0.21)^a\) \(0.22\) \((0.31)^a\) |                                                                             |
|                    | 1979–2004; Globe             | \(-0.00\) \((-0.04)^a\) \(0.29\) \((0.34)^a\) \(0.30\) \((0.39)^a\) |                                                                             |
|                    | Northern hemisphere          | \(-0.03\) \((-0.05)^a\) \(0.34\) \((0.44)^a\) \(0.36\) \((0.49)^a\) |                                                                             |

\(a\) The maximum change in December through February.
Figure 2. Trends in the diurnal mean and temperature range over the period 1960–2009 from the CRU-gridded observations. Trends are filtered for significance using a threshold requirement that \( p < 0.05 \).

Figure 3. The PBL depth climatology (left) and normalized trend (right), taken over the period 1979–2010 from ERA-interim reanalysis. Arguably, the largest impact on the SAT will be the co-variability between heat forcing and the PBL heat capacity over the northern continents, which is where the PBL thickness, \( h \) (m), is the shallowest. For this reason, we choose to focus on the northern hemisphere in our analysis. When \( C \) is small, the PBL does not integrate the stochastic forcing perturbations, as is done in the ocean mixed layer. Instead, being in quasi-equilibrium with the local state of the system at the diurnal and longer time scales, it selectively and asymmetrically modulates the SAT response to the given forcing perturbations. The following simple example demonstrates this feature. Let \( dQ \) be a constant and \( C = c_{\text{atm}} h \) where \( c_{\text{atm}} \) is some dimensional atmospheric

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proportionality constant. This type of perturbation corresponds to the radiative forcing from the increasing concentration of greenhouse gases. It has been demonstrated statistically in Esau et al. (2012) that the minimum $h$, of the order of 100 m, corresponds to the stably stratified PBL when $T_{\text{min}}$ is reached. And vice versa: the maximum $h$, of the order of 1000 m, corresponds to the convective daytime PBL when $T_{\text{max}}$ is reached. Thus,

$$\frac{dT_{\text{min}}}{dT_{\text{max}}} = \frac{h_{\text{SBL}}^{-1}dQ}{h_{\text{CBL}}^{-1}dQ} \approx \frac{10}{1}$$

This means that $T_{\text{max}}$ should be about an order of magnitude more sensitive to the perturbation in the heat forcing than $T_{\text{min}}$.

In this example, the forcing perturbation was time-independent. But many known feedbacks and forcing perturbations are time dependent. A perturbation, which is small but well correlated with the occurrence of $h_{\text{CBL}}$, could have a larger impact on the SAT than a perturbation which is large, but more strongly correlated with $h_{\text{CBL}}$. This selection effect which governs the asymmetric SAT sensitivity has not yet been properly studied. We are not attempting a general study of this problem, but rather we look at the emergence of the inverse PBL thickness dependence as the strongest term in linear multi-variant regression analysis. It is worth noting that the previous attempts of regression analysis, e.g. Tuomenvirta et al. (2000) did not include this complementary mechanism affecting the SAT response. In this sense, they were biased towards the analysis of feedbacks which are well correlated with $h_{\text{CBL}}$. The overwhelming majority of previous studies have paid little if any attention to this selective amplification effect of the PBL. Such studies were focused on specific perturbations in the heat forcing induced by external effects, with respect to the PBL physical processes. A typical study only considers the statistical links between the SAT change and the applied forcing perturbation.

The heat balance of the PBL can be written as:

$$Q = Q_b + Q_t + Q_{\text{lat}} + P_{\text{bulk}}$$

where $Q_b$, $Q_t$, and $Q_{\text{lat}}$ are the partial heat balances at the surface (bottom), top and lateral boundaries of a column of thickness $h$. As the horizontal atmospheric circulation at different time scales definitely plays a significant role in shaping the regional climate, the term $Q_{\text{lat}}$ is generally non-zero. Here, we neglected its contribution, accepting that it will reduce the correlations and regression significance with the considered effects. The heat/cooling due to precipitation/evaporation in the bulk of the PBL is given by $P_{\text{bulk}}$. The surface (with index b) and top (with index t) heat balances are composed as

$$Q_{b,t} = R_{b,t} + H_{b,t} + G_{b,t}$$

where the radiation balance is composed of the downward shortwave $SW_1$ flux ($A$ is the integral atmospheric and surface albedo) and the downward and upward long-wave fluxes $LW_1$ and $LW_t$ correspondingly:

$$R_t = (1 - A)SW_{1t} + (LW_1 + LW_t)$$

$$R_t = (LW_1 + LW_t)$$

It is worth noting that the daytime convective PBL with typically thick $h_{\text{SBL}} \sim O(1000m)$ are statistically associated with $T_{\text{max}}$ (Esau et al., 2012). Thus, the variability of $T_{\text{max}}$ can be strongly modulated by variations in $(1 - A)SW_{1t}$ (e.g. by clouds). This factor is absent in the nocturnal, shallow PBL of $h_{\text{SBL}} \sim O(100m)$ associated with $T_{\text{min}}$.

The turbulent flux is composed of sensible $H_t$ and latent $H_L$ fluxes:

$$H_t = \beta H_b$$

The fraction of the turbulent heat flux in the form of latent and sensible heat is strongly altered by hydrological conditions, e.g. soil-moisture content. The turbulent entrainment coefficient $0 < \beta < 1$ describes the heat flux due to the growth of the boundary layer. It should be noted that the PBL thickness is only determined by the sensible heat flux while the rest of the heat goes to the warming of the PBL. The heat flux into the ground is given by $G_b$ with $G_t = 0$.

The description of the climate effects below refer to the details of the PBL heat balance given here. Thus, in our data analysis, the correlations between the temperature extremes and effects, which have been presented in earlier studies rather for reference and were not used for the attribution (Dai et al., 1999), now become central elements of the analysis. The correlations now link the specific effect with the asymmetry in the temperature extremes it could potentially induce.

The following physical effects will be considered in the linear regression analysis in this study. The cloud effect is the effect on the PBL radiation heat balance, $R$, induced by changes in the cloud cover. The soil-moisture effect is a combined effect of changes in the soil heat capacity, which affects $G$, induced by soil moisture and the effect of changing latent heat flux contribution to the PBL heat budget, $H_L$. The precipitation effect combines the mechanisms of the cloud cover and the soil-moisture effects. Thus, as one can see, these effects are not independent in the physical sense but as they are acting on different time scales, they are distinct from the point of view of the PBL response. The cloud and precipitation effects are considered to have no time lag with respect to variations in $h$. Whereas, the soil moisture is an integral effect, which may better correlate with $h$ at some time lag. For instance, the increase of snow water equivalent in winter months may increase soil moisture in spring and summer months with resulting decrease of the diurnal temperature range. The effect of changing land cover – land use, while being recognized as
an important factor (Feddema et al., 2005; Hua and Chen, 2013), is not included in our analysis, nor are effects linked to atmospheric aerosols, the effect of which on the DTR in all-sky conditions over Europe was found to be weak, with a somewhat larger effect on the DTR decrease only during clear-sky conditions (Auchmann et al., 2013).

4.2. Cloud effects

The cloud cover, CC, has a strong effect on the SAT, which can be characterized through the sensitivity $dT/dCC$ (Sun et al., 2000). Clouds change the energy budget by reducing the $SW_1$ and increasing the $LW_1$ terms in $Q$. Thus, clouds may act to either increase or decrease the SAT, depending on local conditions (Sun et al., 2000) reported that $dT/dCC$ is about 0.7 to 1.0 K tenth$^{-1}$ (one tenth deviation of cloud cover from the average value) in mid-latitudes during winter months, thus inducing an overall warming effect under these conditions. But there is a cooling effect of $-0.05$ to $-0.4$ K tenth$^{-1}$ in the tropics. The strength of the cloud effect decreases in a more cloudy and humid atmosphere. Eastman and Warren (2013) showed there was an overall reduction of cloud cover for the period 1971–2009 with the linear trend of $-0.41\%$ per decade. Norris (2005) reported that the global cloud cover radiative forcing anomalies have been decreasing between 1985–1997, i.e. over the period when the strongest warming of the SAT has been observed.

The overall-negative trend observed in the CC is in conflict with the observed reduction in the DTR, since less cloud should lead to an enhanced DTR (Dai et al., 1999). However, this conclusion cannot be supported without analysis of correlations, because the cloud cover may predominantly change during daytime. Indeed, Warren et al. (2007) and Eastman and Warren (2013) concluded that the amount of convective (generally daytime) types of clouds has increased (with a linear trend of 0.10% per decade for the globe over the last 40 years), whereas the stratiform cloud types (generally occurring in nighttime) have decreased (with the trend $-0.15\%$ per decade). Additionally, Eastman and Warren (2014) found that cloud types appear to show a greater trend during the half of the day with the highest cloud cover. This asymmetric change in cloud cover is compatible with the observed SAT asymmetries, as has been found by Dai et al. (1997, 1999). Furthermore, the strongest increase in the convective cloud types was found in the Eurasian mid-latitudes in summertime (Chernokulsky et al., 2011; Eastman and Warren, 2013) with the correlations between the CC and the SAT of $-0.72$ (Europe) and $-0.56$ (Northern Asia and China) as obtained by Tang and Leng (2012) from the analysis of satellite cloud cover data over 1982–2009.

Thus, despite no significant overall change in the cloud cover over the northern hemisphere during the considered periods, the asymmetric changes of the different cloud types, with their non-negligible tendency to correlate with one of the diurnal temperature extremes, can result in a large contribution to the regression model presented here.

4.3. Soil-moisture effects

Differences in soil moisture can significantly modulate: (1) the Bowen ratio, i.e. the ratio of sensible heat flux, $H_s$, to latent heat flux, $H_l$; and (2) the soil heat capacity, an increase of which dampens changes to the surface temperature by altering the groundflux, $G$. The former effect is more significant in the daytime convective PBL where the surface heat balance is positive, while the latter effect is more pronounced in the nocturnal, stably stratified PBL when this balance is negative. Furthermore, $T_{max}$ is more sensitive to the soil moisture than $T_{min}$, as cooling due to evaporation increases exponentially with temperature, as described by the Clausius–Clayperon relationship.

In a regional study, Wu and Zhang (2013) used statistical analysis to investigate the effects of soil moisture on $T_{max}$, $T_{min}$ and DTR over eastern China using the Global Land Data Assimilation System soil moisture and observed temperatures. They concluded that soil-moisture exerts asymmetric effects on diurnal temperatures leading to substantial changes in the DTR. However, the sign of the effect varied across the seasons and ecosystem types. Hence, their results could be re-interpreted in terms of the amplification of the asymmetrical temperature response on the different sign on the heat balance anomaly induced by soil-moisture fluctuations. The extreme case of the soil-moisture change is exemplified by irrigation. Puma and Cook (2010) investigated the impacts of observed irrigation changes over the 20th century with two ensemble simulations using an atmospheric general circulation model: ModelE of the Goddard Institute for Space Studies. The effect of irrigation is mostly localized over the irrigated regions, primarily in South-East Asia, where it causes strong cooling of up to $-3$ K when compared with the model runs without irrigation. Over the continents the average temperature change due to irrigation is about $-0.03$ K in winter (DJF) and $-0.16$ K in summer (JJA). This effect is due to a decrease in the Bowen ratio which reduces the heat available for warming the PBL.

4.4. Precipitation effects

It has been shown that for specific regions there is a strong correlation between DTR and precipitation (Dai et al., 1997; Zhou et al., 2009, 2015). This is primarily the result of the association of precipitation with cloud cover and soil-moisture content. Clouds associated with strong precipitation have a high albedo and reflect shortwave radiation back into space before it can be absorbed at the surface, thus reducing daytime temperatures. But precipitation also increases the soil-moisture content. This acts to dampen the changes to the surface temperature, as described in the previous section.

5. Regression model

A multiple-linear-regression (MLR) model was used to assess the relative role of the PBL-response mechanism in determining SAT trends. This MLR model allows us to assess the relative importance of cloud cover, precipitation,
soil-moisture content and the PBL depth in determining the trend in SAT, and the model takes the form:

$$\frac{dT}{dt} = b_1 \left( \frac{1}{h} \right) + b_2 \frac{dq}{dt} + b_3 \frac{dCC}{dt} + b_4 \frac{dPr}{dt} + b_5$$  (7)

where $q$ is the monthly mean soil-moisture content (m$^3$ m$^{-3}$), $h$ is the boundary-layer depth (m), $CC$ is the fraction of cloud cover and $Pr$ is the monthly total precipitation (m). The predictor variables were standardized (mean removed and normalized by their standard deviation) in order to make a direct comparison between the regression coefficients. The extreme values, defined as outside the 5-sigma range, were removed.

Firstly, we performed linear regressions of the monthly anomalies in cloud cover, precipitation, soil-moisture, and inverse boundary-layer depth against the SAT anomaly for each season, and for the full-annual cycle for the period 1960–2009. This allowed us to assess the importance of each process on short timescales, and to assess the geographical regions and seasons in which each process is strongest. Secondly, we applied this model using the inter-annual trends in cloud cover, precipitation, SAT and soil moisture, and the climatology of reciprocal boundary-layer depth. This was used to determine the aggregated climatological effect of each process on longer timescales, as well as the importance of each within different seasons.

As the PBL depth modulates the magnitude of the temperature response to forcing, regardless of whether the forcing leads to a warming or a cooling effect, we performed a linear regression of the anomalies of reciprocal PBL depth against the magnitude of the SAT anomalies. Whereas for the other predictor variables – which could be related to the sign of the SAT anomaly – we performed a linear regression of the predictor variable against the SAT anomalies. However, this was not an answer for the analysis of the inter-annual temperature trends (Equation 7) as SAT trends over the period of analysis were positive everywhere (Figure 2).

5.1. Monthly anomalies

Figure 4 shows the linear regression of the monthly anomalies in each predictor variable: reciprocal boundary-layer depth, cloud cover, precipitation and soil-moisture content, against the anomalies in monthly mean temperature. While these maps do not indicate the relative importance of each predictor variable in relation to the temperature anomaly, they do indicate the regions and seasons in which each predictor is found to strongly correlate with the temperature anomaly.

In the annual cycle as a whole there is a strong positive regression between the anomalies in reciprocal PBL depth and the magnitude of SAT anomalies over the ocean, over mid-latitude arid regions and over high latitude (>50°N), continental Eurasia. The latter is a region dominated by shallow boundary-layers and so a relatively small change in the PBL depth is expected to have a significant effect on the SAT, under a given forcing. The strong regression over the ocean, and over high latitudes is governed by the winter signal. During the summer, we only see a strong regression over mid-latitude, arid regions. This is to be expected as in the boreal summer northern latitudes are dominated by convective conditions with relatively deep boundary-layers, but in the arid regions very shallow boundary layers can form over night and so the SAT can be strongly modulated by variations in the PBL depth.

We see a general negative relationship between cloud cover and SAT anomalies which is strongest over continental regions. In the summer, there is a strong negative relationship between cloud cover and temperature anomalies across the northern hemisphere. This may be anticipated given the surface energy budget at this time of year is dominated by down-welling shortwave radiation, which is strongly affected by the presence of clouds. However, in the winter an increase in cloud cover is expected to be associated with warmer temperatures as long-wave radiation emitted from the surface becomes trapped and is absorbed in the near-surface layer, increasing temperatures. This is seen in the positive relationship between cloud cover and SAT anomalies over coastal land, and is especially strong at high latitudes.

The annual relationship between precipitation and SAT anomalies is dominated by the summer signal of a weak, negative relation over land and a negligible regression over ocean. The positive regression is related to the passage of warm, moist air being associated with periods of precipitation. The relationship becomes more complicated in the winter as precipitation can either be associated with rain or snow, both of which can have a strong effect on the monthly temperature anomaly. For example, we see a strong positive relationship between precipitation and SAT anomaly over regions covered by sea-ice, with a sharp change at the boundary, i.e. at the marginal ice zone. During the winter in these regions, precipitation is always snowfall, which is associated with warmer conditions. As precipitation is strongly correlated with cloud cover, we can expect the same positive relation between precipitation and SAT at high latitudes during the winter.

Annually, we see a negative relationship between soil-moisture content and SAT in all locations except permafrost regions. This is consistent with the expectation that an increase in soil moisture dampens air temperatures by decreasing the Bowen ratio and by increasing the soil heat capacity – which dampens temperature trends. This hypothesis is further supported when we look at the seasonal pattern: in the summer we see a stronger negative regression across all land areas as the damping of daytime temperatures by increased moisture content is more pronounced. And in the winter, we see the region of positive regression is further extended to mid-latitudes – regions which typically have snow-cover in winter. Under such conditions, it is warmer temperatures which may be expected to be associated with wetter conditions, i.e. higher soil-water content.

For the annual cycle as a whole, the strongest regression against the SAT anomaly is with the reciprocal boundary-layer depth. This is consistent with our expectation that perturbations to the boundary-layer depth
Figure 4. Maps of the coefficient of regression for the linear regressions of monthly SAT anomaly against anomalies in (a) reciprocal boundary-layer depth (1/BLH), (b) cloud cover (CC), (c) precipitation (Precip) and (d) soil-moisture content (qSoil) for the full-annual cycle, the summer (JJA) and the winter (DJF) months. Note that the reciprocal boundary-layer depth was regressed against the magnitude of the temperature anomaly, and that all anomalies were normalized by their standard deviation.
Figure 5. (a) The regression coefficients, $b_i$, for each of the four components of the multi-linear regression model for each season and for the full-annual cycle. The error bars represent the 95% confidence interval on the coefficients. (b) The regression coefficients, $b_i$, for each of the four components of the multi-linear regression model, filtered for positive SAT trends, for each season and for the full-annual cycle. The error bars represent the 95% confidence interval on the coefficients.

modulate the magnitude of the temperature response to forcing, and that this will be most apparent in shallow boundary layers, e.g. in winter and at high latitudes. In the summer other factors may dominate the SAT response, such as cloud cover and soil-moisture content, which both show strong negative regressions against the summer SAT anomaly. However, such regressions of monthly anomalies do not allow us to determine the aggregated climatological effect, nor the relative importance of each process in determining the magnitude of temperature trends. In order to assess the relative importance of these processes, we applied the multi-linear regression model of Equation 7.

5.2. Inter-annual regression

Figure 5(a) shows the regression coefficients for each of the predictor variables for the annual cycle, and for each season. In all seasons, we see a strong positive relationship between the reciprocal PBL depth and the temperature trends. Indeed, this is the strongest relationship seen in any of the predictor variables in all seasons except the summer. This is to be expected from PBL-response theory as it is the colder seasons which are more dominated by shallow boundary-layers – and so this is when the reciprocal relationship between PBL depth and the magnitude of temperature response will be most apparent. This becomes weaker in the summer since most land areas are dominated
by convective conditions with deep boundary layers. So processes which strongly alter the surface energy budget (such as changes to cloud cover) dominate the pattern of temperature response at this time. Note that the relatively weak regression coefficient between reciprocal PBL depth and SAT trend in the winter is due to the presence of negative SAT trends in this season. When we perform a multi-linear regression against the positive SAT trends, we find the strength of the regression in winter is comparable with that obtained for the spring and autumn (Figure 5(b)).

In the summer, we see a strong negative relationship between the cloud cover trend and SAT trend, with only a weakly positive relationship in the autumn or winter. Any trend in the cloud cover in the summer months, when the solar heating is strongest, will greatly alter the amount of SW radiation reaching the surface, and thus the amount of direct solar heating. Indeed, Tang and Leng (2012) demonstrated that a recent increase in summer cloud cover over Eurasia has been accompanied by a damped summer warming trend. However, this is not a dominant process for the rest of the year.

In all seasons except the winter, we see a weak negative relationship between the soil-moisture content and the SAT. This is to be anticipated given that an increase in soil moisture is expected to dampen temperature trends by increasing the soil heat capacity and by increasing the Bowen ratio; both of which may be expected to reduce SAT trends. However, in the winter much of the northern-hemisphere land is frozen, and so changes to the soil-moisture content at this time will not have the same effect on SAT trends. There is a weak, positive regression between precipitation trends and SAT trends at all times of year, with a peak in the spring.

So in all seasons except summer it is the PBL depth which plays the largest role in determining the strength of the temperature trends. The change in forcing due to the trends in the other predictor variables is not as strong as the modulation of forcing by the effective heat capacity of the atmosphere. As our analysis covers a period of relatively weak changes to the DTR, as compared with the second half of the 20th century as a whole (Hartmann et al., 2013), we might reasonably expect a clearer signal from an MLR analysis covering this longer time period.

6. PBL response in observations

From the maps of the linear regression of reciprocal PBL depth against SAT anomaly, we expect the boundary-layer depth to be of most importance in determining the temperature response in cold, continental regions, such as Siberia, which are dominated by shallow boundary-layers. We have used station data from this region to test the prediction that the PBL will play a dominant role in determining the nature of temperature trends/variability such that: the night-time temperatures exhibit more variability and stronger trends than the day-time temperatures and that this effect will be more pronounced in winter as compared with summer. In both cases, the colder conditions can be related to shallower boundary-layers (there is a shallower boundary-layer at night than during the day, and in winter as compared with summer) and so these times are expected to have the stronger SAT response to forcing.

Figure 6(a) shows the average inter-annual trends in the monthly mean diurnal minimum and maximum temperatures across all stations, normalized to the trend in the diurnal mean temperature at each station. These are given for the full-annual data as well as for the winter (DJF) and summer (JJA) seasons. We can see that in all conditions there is a stronger trend in the nighttime temperatures than the daytime. We also see that the night-time temperatures show a greater variability than the day-time temperatures at all stations (Figure 6(b)). The temperature variability is much greater in the winter compared with the summer, when there is also a significantly stronger variability in the nighttime temperatures than the daytime. This is consistent with our expectation from PBL-response theory and indicates that the planetary boundary-layer plays a significant role in determining the magnitude of the temperature changes at these locations.

Other authors have analysed SAT variability on intra-annual and intra-monthly timescales using gridded observations and model results. Kim (2013) and Lewis and Karoly (2013) examined the day-to-day variability of the diurnal minimum and maximum temperatures in current climate conditions and in projected future conditions, simulated by global climate models as part of the coupled model intercomparison project (CMIP5). They found a reduction in the variability for both the minimum and maximum temperature, with a more pronounced reduction for the diurnal minimum temperature. A similar relationship between global temperature anomaly and intra-annual variance – such that the colder years have the greater intra-annual variance – has been demonstrated in observations (Michaels et al., 1998). These results are in-line with our expectation from PBL-response theory: as the world warms, the effective heat capacity of the atmosphere increases, and so the SAT variability decreases. Due to the reciprocal relationship between heat capacity and temperature response, we may expect this effect to be more pronounced in colder conditions, e.g. we expect there to be a more pronounced effect for the diurnal minimum temperature than the diurnal maximum. This is apparent if we compare two climatologies, from the middle and from the end of the 20th century: we can predict there will have been an overall reduction in the variability of both $T_{\text{min}}$ and $T_{\text{max}}$ and for this to be most pronounced in $T_{\text{max}}$. Naturally, there has been an increase in the number of warm extremes and decrease in the cold extremes as the world warms (Rahmstorf and Coumou, 2011), but we would expect both the decrease in cold extremes and increase in warm extremes to be more pronounced in the $T_{\text{min}}$ than the $T_{\text{max}}$. This can readily be demonstrated from available SAT observations: the Hadley centre’s CRU TS 3.10.01 gridded observations (Harris et al., 2014). We defined a reference climatology...
over the period 1950–1979 and a current climatology covering the period 1980–2009. There was a 0.58 K warming in the area-averaged mean temperature between these periods. A common spatial mask was applied to both climatologies in order to control for differences in the extent of the observational network between these periods and we included a requirement for a temporally complete dataset at each location. The variability was defined as the standard deviation of the monthly anomalies for each period. An extreme event was defined as being a temperature anomaly greater than two standard deviations from the climatological mean. The significance of the difference between the two distributions was tested using a two-sample F-test and the null hypothesis that they were drawn from the same distribution rejected with \( p < 0.05 \). The difference in the variability and the temperature extremes between these two climatologies is summarized in Table 2. Here, we can see that the variability of both \( T_{\text{min}} \) and \( T_{\text{max}} \) have decreased with a more pronounced decrease in the variability of \( T_{\text{min}} \). There has been both a greater decrease in the number of cold extremes, and a greater increase in the number of hot extremes, in \( T_{\text{min}} \) than \( T_{\text{max}} \). This illustrates the greater sensitivity of the \( T_{\text{min}} \) than the \( T_{\text{max}} \) to the increased forcing during this period, consistent with our expectations.

7. Conclusions

The PBL-response mechanism discussed here should not be perceived as yet another mechanism to introduce climate forcing perturbations, such as those previously proposed and considered in this work, e.g. changes in cloud cover, soil moisture, precipitation and land use/land cover. Rather we say that, while established mechanisms related to differences in the forcing clearly affect surface temperatures, their effect on SAT climatology is modulated by the state of the PBL. In this sense, the PBL response is a complementary climate control mechanism, the effect of which is significant when (1) the imposed forcing (changes in the sensible heat flux divergence across the PBL) is not small; and (2) the PBL is sufficiently shallow.

While there are many factors which may asymmetrically affect the radiative forcing on the diurnal extreme temperatures, here, we demonstrate that the night-time temperatures are inherently more sensitive to perturbations to the radiation balance and will warm more rapidly on a uniform forcing (such as that from the build-up of greenhouse-gases). This effect is most pronounced in regions where there is a strong diurnal cycle in the boundary-layer depth, with shallow boundary-layers forming at night. This presents a challenge for the use of global climate models in assessing changes to the diurnal temperature range. Lewis and Karoly (2013) noted that the largest discrepancies between the modelled and observed DTR occurred due to an under-estimation of the \( T_{\text{min}} \) trends in the boreal winter. Furthermore, it has been shown that a large part of this is due to the fact that global climate models have a bias towards over-estimating boundary-layer depth under stable stratification, and
therefore under-estimating temperature trends (Seidel et al., 2012; Davy and Esau, 2014). This is consistent with McNider et al. (2012) who suggested models over-estimate mixing in the stable boundary layer, likely due to the form of the stability functions used in large scale models. Such over-mixing leads to larger boundary-layer heights and makes the models less sensitive to the redistribution of heat due to radiative forcing or land use changes.

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Supporting information

The following supporting information is available as part of the online article: Figure S1. The trends in the diurnal temperature range (upper-left) and diurnal mean temperature (lower-left) and the correlation in the monthly mean anomalies of the diurnal temperature range (upper-right) and mean (lower-right) over the period 1979–2009. Data are from the Hadley-gridded observations (CRU) and the ERA-Interim reanalysis (ERAI). Figure S2. The area-weighted correlation coefficients between each pair of the predictor variables used in the multi-linear regression model for each season and for the full-annual cycle.

References

Alexander LV, Zhang X, Peterson TC, Caesar J, Gleason B, Klein Tank AMG, Haylock M, Collins D, Trewin B, Rahimzadeh F, Tagipour A, Rupa Kumar K, Revadekar J, Griffiths G, Vincent L, Stephenson DB, Burn J, Aguilar E, Brunet M, Taylor M, New M, Zhai P, Rusticucci M, Vazquez-Aguirre JL. 2006. Global observed changes in daily climate extremes of temperature and precipitation. J. Geophys. Res. 111: D05109.

Alward RD, Deting JK, Milchunas DG. 1999. Grassland vegetation changes and nocturnal warming. Science 283: 229–231.

Auchmann R, Arteille F, Wegmann M, Franke J, Barriendos M, Prohom M, Sanchez-Lorenzo A, Bhend J, Wild M, Folini D, Stepanek P, Bronnimann S. 2013. Impact of volcanic stratospheric aerosols on diurnal temperature range in Europe over the past 200 years: Observations versus model simulations. J. Geophys. Res. 118: 9064–9077.

Betts AK, Ball JH, Beljaars ACM, Miller MJ, Viterbo PA. 1996. The land surface-atmosphere interaction: a review based on observational and global modeling perspectives. J. Geophys. Res. 101:7209–7225.

Bradzil R, Budikova M, Auer I, Bohm R, Cegnar T, Fasko P, Lapin M, Gajic-Capka M, Zaninovic K, Koleva E, Niedzwiedz T, Ustrnul Z, Szalai S, Weber RO. 1996. Trends of maximum and minimum daily temperatures in central and southeastern Europe. Int. J. Climatol. 16: 765–782.

Braganza K, Karoly D, Hirst AC, Mann ME, Stott PA, Stouffer RJ, Tett SB. 2003. Simple indices of global climate variability and change: part I, variability and correlation structure. Clim. Dyn. 20: 491–502.

Budyko MI. 1969. The effect of solar radiation variations on the climate of the Earth. Tellus 21: 611–619.

Chemoukisky AV, Bulygina ON, Mokhov II. 2011. Recent variations of cloudiness over Russia from surface daytime observations. Environ. Res. Lett. 6: 035202.

Dai A, Del Genio AD, Fung IY. 1997. Clouds, precipitation and temperature range. Science 286: 665–666.

Dai A, Trenberth KE, Karl TR. 1999. Effects of clouds, soil moisture, precipitation, and water vapor on diurnal temperature range. J. Clim. 12: 2451–2473.

Davy R, Esau I. 2014. Global climate models’ bias in surface temperature trends and variability. Environ. Res. Lett. 9: 114024.

Dirmeyer PA, Wang Z, Mbuhi MJ, Norton HE. 2014. Intensified land surface control on boundary layer growth in a changing climate. Geophys. Res. Lett. 41: 1290–1294, doi:10.1002/2013GL058826.

Easterling DR, Horton B, Jones PD, Peterson TC, Karl TR, Parker DE, Salinger MJ, Razuvaev V, Plummer N, Jamason P, Folland CK. 1997. Maximum and minimum temperature trends for the globe. Science 277: 364–367.

Eastman R, Warren SG. 2013. A 39-yr survey of cloud changes from land stations worldwide 1971–2009: long-term trends, relation to aerosols, and expansion of the tropical belt. J. Clin. 26: 1286–1303.

Eastman R, Warren SG. 2014. Diurnal cycles of cumulus, cumulonimbus, stratus, stratoscumulus, and fog from surface observations over land and ocean. J. Clim. 27: 2386–2404.

Esau I, Zilitinkevich S. 2010. On the role of the planetary boundary layer depth in the climate system. Adv. Sci. Res. 4: 63–69.

Esau I, Davy R, Outten S. 2012. Complementary explanation of temperature response in the lower atmosphere. Environ. Res. Lett. 7: 044026.

Feddeema JJ, Oleson KW, Bonan GB, Mearns LO, Buja LE, Meehl GA, Washington WM. 2005. The importance of land-cover change in simulating future climates. Science 310(5754): 1674–1678.

Hansen J, Sato M, Ruedy R. 2012. Perception of climate change. Proc. Natl. Acad. Sci. USA 109: E2415–E2423.

Harris I, Jones PD, Osborn TJ, Lister DH. 2014. Updated high-resolution grids of monthly climatic observations – the CRU TS3.10 Dataset. Int. J. Climatol. 34: 623–642, doi: 10.1002/joc.3711.

Hartmann DL, Klein Tank AMG, Rusticucci M, Alexander LV, Brönnimann S, Charabi Y, Dentener FJ, Dlugokencky EJ, Easterling DR, Kaplan A, Soden BJ, Thorne PW, Wild M, Zhai PM. 2013. Observations: atmosphere and surface. In Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change, Stocker TF, Qin D, Plattner G-K, Tignor M, Allen MK, Boschung J, Nauels A, Xia Y, Yeh Yu H, Chen Z, Midgley PM (eds). Cambridge University Press: London and New York, NY, 159–254, doi:10.107/CBO9781107453114.008.

Hasselmann K. 1976. Stochastic climate models part I. Theory. Tellus 28: 473–85.

Hua W-J, Chen H-S. 2013. Impacts of regional-scale land use/land cover change on diurnal temperature range. Adv. Clim. Chang. Res. 4: 166–172.

Huntingford C, Jones PD, Livina VN, Lenton TM, Cox PM. 2013. No increase in global temperature variability despite changing regional patterns. Nature 500: 327–330.

Karl TR, Kukla G. 1984. Decreasing diurnal temperature range in Europe over the past 200 years: Observations versus model simulations. J. Geophys. Res. 91: 1007–1023.

Kim K-Y, North GR. 1991. Surface temperature fluctuations in the United States and Canada from 1941 through 1980. J. Clim. Appl. Meteorol. 23: 1499–1504.

Karl TR, Jones PD, Knight RW, Kukla G, Plummer N, Razuvaev V, Gallo KP, Lindsey J, Charlson RJ, Peterson TC. 1993. A new perspective on recent global warming: asymmetric trends of daily maximum and minimum temperature. Bull. Am. Meteorol. Soc. 74: 1027–1035.

Kim O-Y, Wang B, Shin S-H. 2013. How do weather characteristics change in a warming climate? Clim. Dyn. 41: 3261–3281, doi:10.1007/s00382-013-1795-8.

Kim K-Y, North GR. 1991. Surface temperature fluctuations in a stochastic climate model. J. Geophys. Res. 96(D10): 18,573–580.

Lewis SC, Karoly DJ. 2013. Evaluation of historical diurnal temperature range trends in CMIP5 models. J. Clin. 26: 9077–9089.

Makowski K, Jaeger EB, Chiacchio M, Wild M, Ewen T, Ohmura A. 2009. On the relationship between diurnal temperature range and surface solar radiation in Europe. J. Geophys. Res. 114: D00D07.

McNider R, Steeneveld GJ, Holtslag AAM, Pielke Sr RA, Mackaro S, Pour-Biazar A, Walters J, Nair U, Christy J.
DIURNAL ASYMMETRYR IN THE OBSERVED GLOBAL WARMING

2012. Response and sensitivity of the nocturnal boundary layer over land to added longwave radiative forcing. *J. Geophys. Res.* 117: D14106.

Michaels PJ, Balling RC Jr, Vose RS, Knappenberger PC. 1998. Analysis of trends in the variability of daily and monthly historical temperature measurements. *Clim. Res.* 10: 27–33.

Mitchel TD, Jones PD. 2005. An improved method of constructing a database of monthly climate observations and associated high-resolution grids. *Int. J. Climatol.* 25: 693–712, doi: 10.1002/joc.1181.

Norris JR. 2005. Multidecadal changes in near-global cloud cover and estimated cloud cover radiative forcing. *J. Geophys. Res.* 110: D14106.

North GR, Cahalan RF, Coakley JA. 1981. Energy balance climate models. *Rev. Geophys.* 19(1): 91–121, doi: 10.1029/RG019i001p00091.

Stone D, Weaver A. 2003. Factors contributing to diurnal temperature range trends in twentieth and twenty-first century simulations of the CCCma coupled model. *Clim. Dyn.* 20: 435–445.

Sun D, Pinker R. 2014. Factors contributing to the spatial variability of Satellite estimates of diurnal temperature range in the United States. *IEEE Geosci. Remote Sens. Lett.* 11(9): 1524–1528.

Sun B, Groisman PY, Bradley R, Keimig F. 2000. Temporal changes in the observed relationship between cloud cover and surface air temperature. *J. Clim.* 13(12): 4341–4357.

Walters JT, McNider RT, Shi X, Norris WB. 2007. Positive surface temperature feedback in the stable nocturnal boundary layer. *Geophys. Res. Lett.* 34: L12709, doi: 10.1029/2007GL029505.

Yang J, Liu H-Z, Ou C-Q, Lin G-Z, Zhou Q, Shen G-C, Chen P-Y, Guo Y. 2013. Global climate change: impact of diurnal temperature range on mortality in Guangzhou. *China. Environ. Pollut.* 175: 131–136.