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Complementary explanation of temperature response in the lower atmosphere

Igor Esau1,2,3, Richard Davy1 and Stephen Outten1,2

1 Nansen Environmental and Remote Sensing Centre, Bergen, Norway
2 Center for Climate Dynamics (SKD), Bergen, Norway

E-mail: igor.esau@nersc.no

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Abstract
There are a number of asymmetries in the surface air temperature response to forcing, including polar amplification and changes to the diurnal and seasonal temperature ranges. We propose that such spatial–temporal signatures of climate change can, in part, be explained by differences in the effective heat capacity of the atmosphere. We have demonstrated that predictions arising from this hypothesis are simultaneously satisfied through the analysis of temperature records from daily to inter-decadal timescales using observational and reanalysis datasets. This mechanism can help to explain why we see the largest temperature trends in the winter months (0.42 K/decade in winter compared to 0.18 K/decade in summer) and why the diurnal temperature range decreases in a warming world, having decreased by ∼0.4 K since 1950.

Keywords: boundary layer, surface air temperature, climate, climate change

Online supplementary data available from stacks.iop.org/ERL/7/044026/mmedia

1. Introduction
The global temperature record, established from observations and reanalysis datasets, displays variability on timescales from days to millennia (Petit et al 1999, Hansen et al 2010). There are many asymmetries in the observed global climate records both geographically and temporally. For instance, there is the phenomenon of arctic amplification i.e. the faster warming of the arctic than other regions (Johannessen et al 2004); night-time temperatures have increased more rapidly than day-time temperatures (Karl et al 1993, New et al 2000, Dai and Trenberth 2003, Vose et al 2005, Braganza et al 2004); and winter months have seen more pronounced warming than summer months (ACIA 2005, Knutti et al 2006). There has been some indication that such asymmetries are partially contained within the lowest region of the atmosphere, the planetary boundary layer (PBL). It has been shown (Weber et al 1994) that at low altitudes the diurnal minimum temperature, $T_{\text{min}}$, has increased more rapidly than the maximum, $T_{\text{max}}$, but that this was not the case for high-altitude stations. Such features of climate change have been treated as separate issues and attributed to strong, geographically-based phenomena or specific physical conditions. For instance, the attribution of arctic warming to ice-albedo feedback (Curry et al 1995, Serreze et al 2009) or the reduction in the diurnal temperature range (DTR) due to cloud effects (Dai et al 1999, Stone and Weaver 2003). In order to determine the changes to SAT in response to a given forcing or feedback one has to account for the effective heat capacity of the system as well as such mechanisms.
Figure 1. (a) The percentage of days governed entirely by conditions of an SBL and (b) the corresponding mean depth of these SBLs. Data source: ERA-Interim.

The surface air temperature trends and variability at a given timescale are determined by three factors: the forcing, the feedbacks and the effective heat capacity of the system (Hasselmann 1976). The effective heat capacity of the atmosphere is determined by the volume of air through which the heat is mixed. This heat is determined by a surface heat flux and is distributed through a column of the atmosphere defined by the PBL depth. The shallower the PBL, the lower the effective heat capacity and the more sensitive the SAT is to forcing. Here we propose that the heterogeneity of the atmospheric effective heat capacity can explain a significant component of the spatial–temporal signatures of climate change—PBL-response. In this short letter, we focus more on causality than on signal-to-noise ratio and statistical correlations and therefore we do not follow the formal detection–attribution framework (Hasselmann 1997). Indeed, a physical mechanism may be at work and will induce a unique, coherent pattern of effects even if data quality is not sufficient for formal statistical attribution of each of those effects. Hence we have chosen to focus on hypothesis falsification through the utilization of the predictive capacity of PBL-response hypothesis. These predictions arise from consideration of the relationship between PBL depth and temperature changes. We can define the change in potential temperature due to a divergence of heat flux as:

$$\frac{\partial \theta}{\partial t} = \frac{Q}{\rho c_p h}$$  \hspace{1cm} (1)

where $Q$ is the divergence of heat flux (W m$^{-2}$), $\rho$ is the air density (kg m$^{-3}$), $c_p$ is the heat capacity at constant pressure (J kg$^{-1}$ K$^{-1}$), $\theta$ is the potential temperature (K) and $h$ is the PBL depth (m). $Q$ can be described by:

$$Q = F_{Lat} + F_{SW} + F_{LW} + F_{Latent} + F_{Heat} + F_{Ground}.$$  \hspace{1cm} (2)

where $F_{Lat}$ is the lateral heat flux, $F_{SW}$ and $F_{LW}$ are the shortwave and longwave radiative fluxes, $F_{Latent}$ is the latent heat flux, $F_{Heat}$ is the sensible heat flux and $F_{Ground}$ is the heat flux into the ground. At the top of the boundary layer $Q$ is determined solely by the radiative fluxes, $F_{SW}$, $F_{LW}$ and $F_{Lat}$, by definition. The latent, sensible heat and ground flux terms are zero, which defines the PBL depth as a non-linear function of these fluxes with parametric dependence on a broad range of variables including the temperature and wind profiles and radiative and heat fluxes. Here we do not concern ourselves with how the PBL depth is obtained, how it may change in time or the precise nature of $Q$. Instead we focus on how the climatology of the PBL depth determines the magnitude of the temperature response to perturbations in $Q$.

Several independent types of evidence exist that support the hypothesis that temperature anomalies of the PBL depend on the mixing within the layer: (a) the temperature sensitivity of deep and shallow layers to radiative forcing (Kurklu et al 2003); (b) temperature sensitivity to artificial enhancement of turbulence (by installation of a wind farm) in natural atmospheric conditions (Zhou et al 2012); (c) numerical experiments using climate models with different effective heat capacity (of the ocean mixed layer) show this reciprocal dependence of temperature trends upon effective heat capacity (Frame et al 2005, Meehl et al 2003).

The PBL depth is known to vary by approximately two orders of magnitude on diurnal, seasonal and geographical scales. We can expect to find the smallest value of $h$ under conditions of a stable boundary layer (SBL) (Zilitinkevich et al 2007): these occur when the surface sensible heat flux is negative and buoyancy forces act to suppress turbulence. SBLs are prevalent across much of the Northern Hemisphere, especially over snow and ice-covered areas in the high latitudes (figure 1). The transition between stable and convective conditions is—in the majority of cases—very
Figure 2. Mean boundary-layer depth as a function of mean SAT for the years 1979–2010 from the ERA-Interim dataset. The correlation is $r = 0.83$, $p < 0.01$. The boundary-layer depth data were binned into forty equally spaced bins of mean temperature with the black line representing the mean of each bin and the grey shaded area representing one standard deviation within each bin.

Figure 3. (a) The standard deviation (SD) and trend of SAT as a function of the mean boundary-layer depth. Shaded areas are one SD of the binned data. The correlation between PBL depth and SAT trend is $r = -0.54$, $p < 0.01$ and between PBL depth and SAT SD is $r = -0.70$, $p < 0.01$. (b) The standard deviation (SD) and trend as a function of the annual mean air temperature at 2 m. Shaded areas are one SD of the binned data. (c) The temperature SD as a function of mean temperature with associated percentage of northern hemisphere land-area. Shaded areas are one SD of the binned data. Data source: ERA-Interim reanalysis, CRU CRUTEM3 gridded data and CMIP3 models from the northern hemisphere over the period 1979–1999.

We are presented with a number of practical challenges in the following analysis of the characteristic effects anticipated from the PBL-response. Earth’s climate necessarily includes a geographical aspect, which often obscures the background physical relationships. To distinguish geographical factors from the physical mechanism proposed here, we show that the basic relationship holds true across different regions. There are significant difficulties in determining the PBL depth from observations (Seibert et al. 2000), with large uncertainties in even the most direct methods. PBL depth data from models are also unreliable as the parameter is inferred from atmospheric properties. Surface air temperature is assimilated in reanalysis but the PBL depth is a derived property of the model scheme used and is rather uncertain (Cuxart et al. 2006). In ERA-Interim the PBL depth is estimated using a threshold value of the flux Richardson number. For further discussion of the challenges involved in establishing the climatology of the PBL see Seidel et al. (2010). We have chosen to use mean SAT as a proxy for the PBL depth given the strong correlation ($r = 0.83$, $p < 0.01$) found in reanalysis data (figure 2). We confirm the validity of this proxy by testing our hypothesis using the PBL depth data from the ERA-Interim reanalysis dataset (figure 3(a)). This relation can be understood in terms of the surface sensible heat flux (SSHF): with a persistent negative heat flux the SAT reduces and the atmosphere becomes increasingly stable, leading to a shallower boundary layer and vice versa. Mean SAT is a robust proxy since it is an observed variable—enabling us to falsify our hypothesis against station observations—and a widely used climate metric available in aggregated climate datasets e.g. the Climate Model Intercomparison Project (CMIP).
2. Hypotheses

There are several testable predictions we can make from PBL-response theory, but they all stem from the same principle: that locations with shallower boundary layers have lower effective heat capacity and therefore the SAT at these locations is more sensitive to forcing. We can generally associate $T_{\text{min}}$ with shallow, SBL conditions (where the SSHF is negative) and $T_{\text{max}}$ with deeper CBLs (with positive SSHF) (supplementary figure 1 available at stacks.iop.org/ERL/7/044026/mmedia). Hence we expect that $T_{\text{min}}$ should have a stronger trend than $T_{\text{max}}$, so in a warming climate we expect the PBL-response to cause the DTR to decrease and vice versa.

With regard to seasonal variation we expect the colder seasons to show the strongest trends in mean temperature. Geographically we predict that the regions with the lowest annual mean temperature to have the strongest inter-annual temperature trends. We can make similar predictions with regards to temperature variability. Since a shallower boundary layer is more sensitive to radiative forcing we can expect the locations with the strongest temperature trends to also have the greatest variability and that temperature variability will decrease in a warming world. This result is supported by historical instrumental records: it has been shown that intra-annual and intra-monthly temperature variability declined during the 20th century (Michaels et al 1998). The timescale of interest informs the conditions under which the PBL-response is most pronounced. Considering the effect of this mechanism on the DTR, we can expect that $T_{\text{min}}$ will be more strongly affected than $T_{\text{max}}$ and therefore we anticipate changes to the DTR to be driven by changes to $T_{\text{min}}$. However, we can expect that changes in cloud cover, which primarily affects $T_{\text{max}}$, will be the more dominant mechanism during summer time when changes in cloud cover can significantly alter the radiation balance (Chernokulsky et al 2011, Tang and Leng 2012). Thus we anticipate finding the greatest effects of this PBL-response mechanism at mid-latitudes during the winter and at high latitudes during the spring and autumn months. Similarly, we can expect the greatest effect on annual mean temperature to be found at the coldest locations, regardless of latitude. On the diurnal timescale we anticipate that the PBL-response will be most apparent when there is a large difference between the night-time and day-time boundary-layer depths e.g. in deserts during the summer months.

3. Results

In observations and reanalysis data, we see strong links between the mean, the trend and the variability of the SAT (figure 3(b)). The SAT trend and variability have a strong negative correlation with the mean temperature such that the strongest trends and greatest variability are found at the lowest temperatures. Overall there is a high correlation ($r = 0.8, p < 0.01$) between the temperature variability and the magnitude of the temperature trend. The regions with these strong temperature trends correspond to a relatively small fraction of the landmass and as such may be poorly represented in climate models without a significant effect on simulated global mean temperatures (figure 3(c)). The linear relationship between the mean and variability of the SAT appears to change at low temperatures ($T < 260$ K). The locations corresponding to these low mean temperatures are to be found over elevated Greenland locations where the local PBL is more exposed to free atmosphere. This is in agreement with previous work that has indicated the relations predicted from PBL-response theory are not found in surface locations within the free atmosphere (Weber et al 1994, Davy and Esau 2012).

The regions with the lowest temperatures, where we anticipate seeing the greatest effects of the PBL-response, are also the regions that have the greatest inter-model spread in SAT trends and variability (figure 4). However, because they represent a relatively small fraction of the surface, this poor fit may not significantly affect the simulated global mean temperature trend. Figure 3(b) shows the temperature standard deviation (SD) as a function of mean temperature from ERA-Interim reanalysis and climate models for the period 1979–1999. We have chosen this period because it is the overlap in temporal coverage between the ERA-Interim reanalysis and the CMIP3 20th century climate model runs.

Over the latter half of the 20th century $T_{\text{min}}$ increased more rapidly than $T_{\text{max}}$, causing a reduction in the DTR (Alexander et al 2006). This has previously been attributed to increased cloud cover (CC) causing a reduction in the shortwave radiation reaching the surface and thus damping the increase in $T_{\text{max}}$ (Dai et al 1999, Stone and Weaver 2003, Tang and Leng 2012). While this is readily demonstrated on the diurnal scale the aggregated effects on climatological scales are uncertain. Indeed, it remains unclear if the observed trends in CC correlate with the trends in $T_{\text{max}}$ and DTR (Dai et al 2006, King’uyu et al 2000, Kaiser 1998). Warren et al (2007) showed that the total cloud cover over land was decreasing in 1971–1996, which following the CC causality should result in amplification (not damping) of DTR. We have used the ERA-Interim reanalysis dataset over the period 1979–2010 to assess the trends in the temperature indices and the CC for consistency with each hypothesis. This period was chosen to maximize the number of locations with statistically significant trends but the result is not sensitive to the period selected: the analysis was repeated for the first and last 20 yr of the dataset and the same pattern of correlations was found. The ERA-Interim reanalysis project used International Satellite Cloud Climatology Project (ISCCP) observations as a reference for validation of cloud cover (Dee et al 2011). Furthermore, the relationships between temperature metrics demonstrated here are not dependent on our choice of reanalysis (Davy and Esau 2012).

The trend in cloud cover is not significantly correlated with the trend in either temperature extremes and is only weakly correlated to the DTR (table 1). The trend in DTR has a strong negative correlation ($r = -0.63$) with the trend in $T_{\text{min}}$ but only a small correlation with the trend in $T_{\text{max}}$ (table 1). Analysis of the trends in annual means showed the same pattern. The data was also partitioned
Figure 4. Temperature SD as a function of latitude from various CMIP3 models and the ERA-Interim reanalysis from the period 1979–1999. In the regions highlighted by the black boxes we see the greatest SAT SD and inter-model spread is found in the coldest locations with only a small inter-model spread found in tropical locations despite large model differences in the representation of synoptic processes at these latitudes.

Table 1. Correlation of trends. Correlation of trends in daily values of \( T_{\text{min}}, T_{\text{max}}, \text{DTR} \) and \( \text{CC} \). Trends in bold are statistically significant with \( p \)-values < 0.05. Trends are indicated using the Newtonian notation.

<table>
<thead>
<tr>
<th>( \dot{T}_{\text{max}} )</th>
<th>DTR</th>
<th>CC</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \dot{T}_{\text{min}} )</td>
<td>0.91</td>
<td>-0.63</td>
</tr>
<tr>
<td>( \dot{T}_{\text{max}} )</td>
<td>-0.25</td>
<td>0.01</td>
</tr>
<tr>
<td>DTR</td>
<td>-0.23</td>
<td></td>
</tr>
</tbody>
</table>

into boundary-layer type: under CBL conditions there is a negligible \( r = 0.04 \) correlation between \( \dot{T}_{\text{min}} \) and DTR and a very high \( r \approx 1 \) correlation between \( \dot{T}_{\text{max}} \) and DTR. The trends in the SBL showed the inverse with an \( r = -0.98 \) correlation between \( \dot{T}_{\text{min}} \) and DTR and a much weaker \( r = -0.37 \) correlation between \( \dot{T}_{\text{max}} \) and DTR. In neither case was there any strong correlation with the trend in cloud cover.

When we partition the annual data by season, we see that in the cooler months (September–May) DTR has a much stronger negative correlation with \( \dot{T}_{\text{min}} \) than with \( \dot{T}_{\text{max}} \) (table 2, green). This is reversed in the summer months (June–August) where we see a strong positive correlation between DTR and \( \dot{T}_{\text{max}} \). There is good evidence that this summer-time correlation is due to changes in the cloud cover as there are strong negative correlations between CC and both DTR and \( \dot{T}_{\text{max}} \) at this time (table 2, yellow). A result supported by analysis of observations over Eurasia (Tang and Leng 2012). While we see significant correlations between DTR and CC during the spring and autumn months there is no corresponding correlation between CC and \( \dot{T}_{\text{max}} \) at this time (table 2, blue). This is inconsistent with the cloud-feedback hypothesis. The strongest indication of the PBL-response is, as anticipated, seen in the spring and autumn months.

Table 2. Correlation of seasonal trends. Correlation of trends in seasonal means of \( T_{\text{min}}, T_{\text{max}}, \text{DTR} \) and \( \text{CC} \). The changes to DTR in the colder months are dominated by changes in \( T_{\text{min}} \) (green). In spring and autumn there are moderate, negative correlations between DTR and CC, but changes to CC do not correlate with changes in \( T_{\text{max}} \) (blue). In summer there is good support for the hypothesis that changes to CC affect \( T_{\text{max}} \), and that changes to \( T_{\text{max}} \) are the primary cause of changes to the DTR (yellow). Source: ERA-Interim daily data.

<table>
<thead>
<tr>
<th>Seasonal correlations</th>
<th>DJF</th>
<th>MAM</th>
<th>JJA</th>
<th>SON</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \dot{T}_{\text{min}} ), DTR</td>
<td>-0.42</td>
<td>-0.71</td>
<td>-0.31</td>
<td>-0.72</td>
</tr>
<tr>
<td>( \dot{T}_{\text{max}} ), DTR</td>
<td>-0.18</td>
<td>-0.25</td>
<td>0.65</td>
<td>-0.41</td>
</tr>
<tr>
<td>( \dot{T}_{\text{min}} ), CC</td>
<td>0.17</td>
<td>0.27</td>
<td>-0.15</td>
<td>0.40</td>
</tr>
<tr>
<td>( \dot{T}_{\text{max}} ), CC</td>
<td>0.11</td>
<td>0.08</td>
<td>-0.66</td>
<td>0.09</td>
</tr>
<tr>
<td>DTR, CC</td>
<td>0.05</td>
<td>-0.45</td>
<td>-0.71</td>
<td>-0.60</td>
</tr>
</tbody>
</table>

Arid regions tend to have very shallow night-time boundary layers so we expect that these regions should also have strong temperature trends and variability (figure 5). In sub-tropical desert regions there is an especially large difference in depth between the day-time CBL, which can be several km, and the night-time SBL, of order 10 m during some months. Therefore we can predict from PBL-response theory that there should be an especially large difference between the variability of \( T_{\text{min}} \) and \( T_{\text{max}} \) in these regions.

This difference in the variability of \( T_{\text{min}} \) and \( T_{\text{max}} \) can be clearly seen in the map (supplementary figure 2 available at stacks.iop.org/ERL/7/044026/mmedia) of the sensitivity ratio—ratio of SD of \( T_{\text{min}} \) to SD of \( T_{\text{max}} \)—in July. This is
consistent with our expectations from PBL-response theory. In the polar regions there is generally a very small DTR so we expect there to be little difference in the variability of $T_{\text{min}}$ and $T_{\text{max}}$. As mean temperature increases towards lower latitudes the DTR is increasingly driven by $T_{\text{max}}$ as solar radiative forcing, with greater variability due to variable CC, plays a larger role. So in this range the variability of $T_{\text{max}}$ increases more rapidly than that of $T_{\text{min}}$ and the sensitivity ratio decreases. In the warmest regions, the Asian continental and north African desert, the cold and dry nights lead to very shallow boundary layers which enhance the variability of $T_{\text{min}}$, hence the sensitivity ratio increases.

Climate models all have different treatments of the atmospheric effective heat capacity but they vary in similar ways owing to the diurnal and seasonal cycles. However, even models with the same mean effective heat capacity can produce very different results depending on the degree of asymmetry in the variance of effective heat capacity. Since subtle differences in the description of shallow boundary layers can have a large effect on the predicted temperature we expect the model descriptions of the coldest regions to have the greatest variability and inter-model differences. Indeed, this is exactly what we find when we compare different models used to simulate the climate of the 20th century (figure 4).

4. Conclusions

We have proposed that a thermo-dynamical relationship—PBL-response—can help explain many of the asymmetries of SAT response to forcing and falsified this hypothesis against predicted signatures of SAT trends and variability. We have demonstrated the possibility to extend application of this theory over a wide range of timescales and across different regions. For example, rather than focusing on the ‘polar’ aspect of polar amplification, we propose that it is, in part, a consequence of the wider-reaching PBL-response theory that contribute to understanding why colder regions have the greatest temperature trends and variability. This has been demonstrated here by the analysis of non-polar (sub-tropical desert) regions with similarly shallow boundary layers and thus low atmospheric effective heat capacity. It is such regions which are characterized by shallow boundary layers where the PBL-response will have the strongest influence on SAT variability. In summer months over land where there are deep boundary layers, other factors, such as changes in cloud cover, may be expected to be the dominant influence on SAT.

Acknowledgments

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