Recent United Kingdom and global temperature variations

Timothy J. Osborn,[1,2] **Phil D. Jones**[1,3] **and Manoj Joshi**[1,2]

[1]*Climatic Research Unit, School of Environmental Sciences, University of East Anglia, Norwich*
[2]*National Centre for Atmospheric Science (NCAS), University of East Anglia, Norwich*
[3]*Department of Meteorology, Center of Excellence for Climate Change Research, King Abdulaziz University, Jeddah, Saudi Arabia*

Introduction

Recent temperature changes have been notable at both global and UK scales, such as the rate of global warming in the early 2000s followed by record warmth in 2015 and 2016, and the relative warmth in the UK during the last two decades that was interrupted by a spell of mostly cooler years from 2008 to 2013 (though 2011 was warm and all but 2010 remained above the long-term mean). The aim of this paper is threefold: to provide a brief review of the key issues in observing the Earth's surface temperature, to present an update of these temperature time series to show the latest changes, and to discuss some of the mechanisms that have contributed to the observed changes.

Temperature datasets

A number of groups makes estimates of global surface temperature change that

RMetS
Royal Meteorological Society

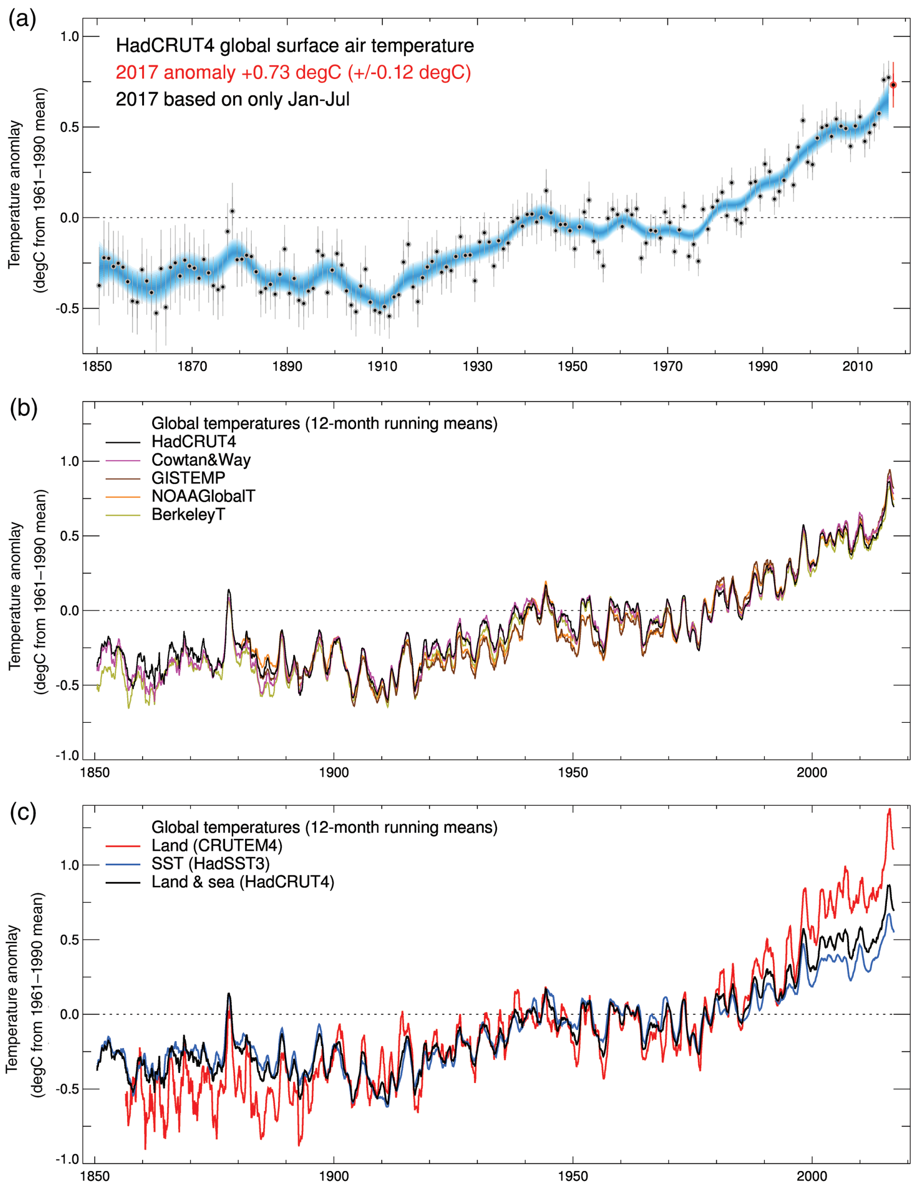

Figure 1. Estimates of global surface temperature anomalies (degC with respect to the 1961–1990 mean) during the instrumental period. (a) Individal annual averages (dots: median estimates; vertical bars: 95% uncertainty ranges) and decadally-smoothed values (graded shading from dark to light blue for values from the median to the outer 95% uncertainty) from HadCRUT4. (b) 12-month running means from HadCRUT4 (black), HadCRUT4 infilled by Cowtan and Way (2014; magenta), GISTEMP (brown), NOAA (orange) and Berkeley Earth (mustard). (c) 12-month running means from HadCRUT4 combining land and sea (black) and its separate land surface air temperature (red: CRUTEM4) and sea surface temperature (blue: HadSST3) components.

are routinely updated (see Jones, 2016). Until the mid-1980s, such series were principally derived from surface air temperature (SAT) data from the terrestrial regions of the world. From the mid-1980s, land-based series were combined with sea surface temperature (SST) series from marine regions to produce a more complete estimate of the global-mean temperature. The different global temperature change estimates are in close agreement with each other (Figure 1(b)), which is not surprising because it has been shown (e.g. Jones *et al*., 1997) that a limited number of evenly-spaced sites is all that is necessary to obtain a good estimate of global-mean temperature change. A simple example to show that the underlying course of global temperature change has been known for a long time was illustrated by Hawkins and Jones (2013). They showed that the painstaking work in the pre-computer age of Guy Stewart Callendar in 1938 and 1963 produced a global SAT series from as few as 147 weather stations that is very similar to a modern compilation for land areas (CRUTEM4; Jones *et al*., 2012).

During the last 30 years or so, significant effort has been directed towards locating and digitising many more of the measurements that have been made since the eighteenth century, improving the availability of historic data from more parts of the world. This improvement, which is particularly apparent for marine regions, has hardly altered the underlying character of the global series (in terms of warm/cold years/decades and the warming trend), but it has improved the spatial coverage and details of the long-term change at a regional scale. This has facilitated more detailed analyses of the spatial and seasonal details of observed temperature changes (e.g. in this paper we look at zonal-mean changes for each latitude). Further improvement would help, but effort is best focused on regions/periods with sparse coverage and not just illustrated by greater observational counts (see the discussion regarding marine areas by Kent *et al*., 2017).

Instrumental temperature recording began in Western Europe, and Manley's Central England Temperature (CET, Manley, 1974) series is the longest local temperature series in the world. The network around the world was not originally designed for the long-term measurement of temperature. Instead, we have inherited a network designed for multiple purposes, the dominant one being weather forecasting. Improvements and changes to the way temperature has been measured (thermometer design, exposure/screen design, observation times, location changes and changes to land-use in the vicinity of a weather station) over the centuries have made it necessary to determine the quality of the data (Trewin, 2010). Manley was fully aware of this, and his papers reveal the efforts he made to produce a series that was homogeneous (i.e. climatically consistent) and not influenced by these changes. Groups monitoring global temperature assess the quality of all the available land station temperatures, and quantify and remove the largest non-climatic influences in a process referred to as 'homogeneity adjustment' or 'homogenisation' (Jones, 2016). Of particular importance in this regard are the introduction of Stevenson screens between the mid-nineteenth and early twentieth centuries, the more recent changes to automated recording, widespread changes in observation times and the way the daily and monthly average temperatures are calculated (e.g. from the average of observations at fixed times or from the average of observations from a minimum/maximum thermometer). Different issues affect the marine data (Kent *et al*., 2017), especially those related to widespread changes from sampling via buckets to engine-room intake measurements, and more recently a huge expansion in measurements from drifting buoys. Due to the greater area of oceans and more pervasive changes in observing systems, changes in marine recording practices since the 1850s are more important than issues over land.

The value in continuing to update and improve multiple global temperature datasets is that independent approaches applied to different (though clearly related) compilations of observations help to assess structural uncertainty and robustness or sensitivity to different methodological choices and data selection criteria. Next we highlight some example differences between approaches, though the purpose of the present paper is not to provide a comprehensive evaluation of them.

The Met Office Hadley Centre–Climatic Research Unit series (HadCRUT; Morice *et al*., 2012) uses a relatively simple gridding of temperature anomalies (relative to a fixed baseline period, such as 1961–1990), whereas Berkeley Earth (Rohde *et al*., 2013) combines Kriging interpolation with an iterative approach to estimate the appropriate baseline for each station segment, thereby allowing the use of additional stations (with shorter, earlier or later periods of record) that do not have data during a specified baseline period. Although most use land station SAT data that are included in the Global Historical Climatology Network (GHCN; Peterson and Vose, 1997), HadCRUT compile many of their stations from National Meteorological Service (NMS) sources and prefer to use NMS homogeneity adjustments than rely on homogenisation algorithms that are applied globally for the other datasets. Although all main groups use the International Comprehensive Ocean–Atmosphere Data Set (ICOADS; Freeman *et al*., 2017) marine database, there are different approaches for creating homogeneous gridded SST fields and, as noted earlier, getting SST adjustments correct is key for the global mean (e.g. figure 12 of Huang *et al*., 2017, shows the effect of recent updates). There are varying levels of interpolation with which to infill data gaps, with Berkeley Earth, Cowtan and Way (2014) and GISTEMP (Hansen *et al*., 2010) obtaining more globally complete temperature fields, NOAA (Karl *et al*., 2015) providing an intermediate level of infilling, and HadCRUT limiting its coverage to those 5° latitude by 5° longitude grid cells that contain at least one observation point. The HadCRUT approach is not dependent on a particular interpolation scheme but can give a biased estimate of the true global mean when the poorly sampled areas (e.g. the Arctic) are warming (or cooling) at a different rate to the sampled areas (Cowtan and Way, 2014). Globally complete temperature series have recently begun to be developed from reanalyses (ERA-Interim; Simmons *et al*., 2017), where the physical processes represented by the Numerical Weather Prediction models provide estimates of SAT where there are no observations to assimilate, rather than statistical interpolation.

Each global-mean temperature time series represents a combination of the response to external climate forcings (natural and anthropogenic), the influence of internal climate variability and contributions from random errors and systematic biases (including incomplete coverage) in the datasets. The latter have been quantified by various groups; arguably, HadCRUT has a more complete, sophisticated model of its errors on multiple spatial scales and timescales (from grid cells to the global mean and from months to decades; Figure 1(a)), which is presented using an ensemble approach that allows a wider range of applications to take account of the uncertainties (Morice *et al*., 2012). These applications include comparison of observed temperatures with those simulated by climate model simulations, when it is also necessary to take into account that the observational datasets combine land SAT with SST, not ocean SAT (Cowtan *et al*., 2015). This matters because of differential rates of warming between the sea surface and the overlying air, especially in sea-ice covered regions.

Global and zonal temperature variations

Overall global warming is clearly much greater than the uncertainties in the record, whether the quantified errors in the HadCRUT4 record (Figure 1(a)) or the structural uncertainties between datasets (Figure 1(b)) are considered. This is, of course, well established and is one of the lines of evidence assessed by the Intergovernmental Panel on Climate Change to determine that 'warming of the climate system is unequivocal' (IPCC, 2013, p. 4). The rate of warming has varied considerably on multi-decadal timescales, with phases of no warming or slight cooling (1850–1910, 1940–1975) and faster warming (1910–1940, 1975–present). Within these phases there are also shorter-term fluctuations in the rate of warming, including the 15 years from 1998 to 2012 where the rate of surface warming was apparently less than it was in the final decades of the twentieth century (but note that this is a period of slightly greater spread between global temperature series, with HadCRUT4 warming less than the others due to differences in Arctic interpolation and adjustments for changes in SST measurement from ships to buoys; Figure 1(b)).

This apparent slowdown (termed the 'hiatus in surface warming' by some) has received much scientific and public attention in recent years. In general, the warming slowdown and its implications for understanding and predicting the climate have been poorly communicated. For simply describing what the data show, it is seemingly straightforward to just state the actual changes. The complexity arises when inferring something about climate change from the rate of surface warming in these data, since that requires the attribution of observed changes to external forcings and knowledge (or assumptions) about the amplitude and temporal structure of internal climate variability. Medhaug *et al*. (2017) highlight that some apparently contradictory findings can be resolved by understanding the different assumptions and definitions used. They show that a combination of internal variability, recent changes in natural solar and volcanic forcings and limitations of observational datasets can together explain differences between observations and climate model simulations over this period.

Considering changes in global-mean temperature alone provides limited understanding of both the drivers that force observed trends and of the processes that determine the climate response to forcing. Accordingly, it is informative to consider the spatial structure of recent changes in surface temperature. Here, we consider land and sea temperatures separately (Figure 1(c)), along with the variation of zonal-mean temperature anomalies at each latitude (Figure 2). We visualise the zonal-mean values using a latitude scale (*y*-axis of Figure 2 panels) that is proportional to the Earth's surface area in each latitudinal zone, to avoid giving undue prominence to the small surface area at high latitudes. Land and sea temperatures are strongly correlated, but the amplitudes of their variability and the long-term trend are clearly greater over land (Figure 1(c)), a difference that grows stronger with increasing latitude in the Northern Hemisphere (Figure 2(c)). Record warmth associated with the 2015/2016 El Niño event is apparent in both land and sea temperatures.

Zonal-mean temperature anomalies have much greater variability at high latitudes in both hemispheres (Figure 2(a)). The irregular warming associated with El Niño events is clear (e.g. 1877/1878), and in many of these events it shows first as a warming in the low latitudes, with a warm response appearing in the subtropics and mid-latitudes a few months later (e.g. 1982/1983, 1986/1987, 1997/1998). The temporary cooling following explosive volcanic eruptions (e.g. Agung in 1963, Pinatubo in 1991) is most evident at those latitudes with the greatest land areas (northern mid-latitudes), reflecting the capacity of land to respond more rapidly to such transitory forcing events.

At the longer timescales, the global-mean warming during 1910–1945 is apparent, especially in the subtropics and high latitudes of the Northern Hemisphere (Figure 2). The slight global cooling that followed (1945–1975, Figure 1) was most conspicuous northwards of 20°S, associated in part with the cooling effects of increased anthropogenic

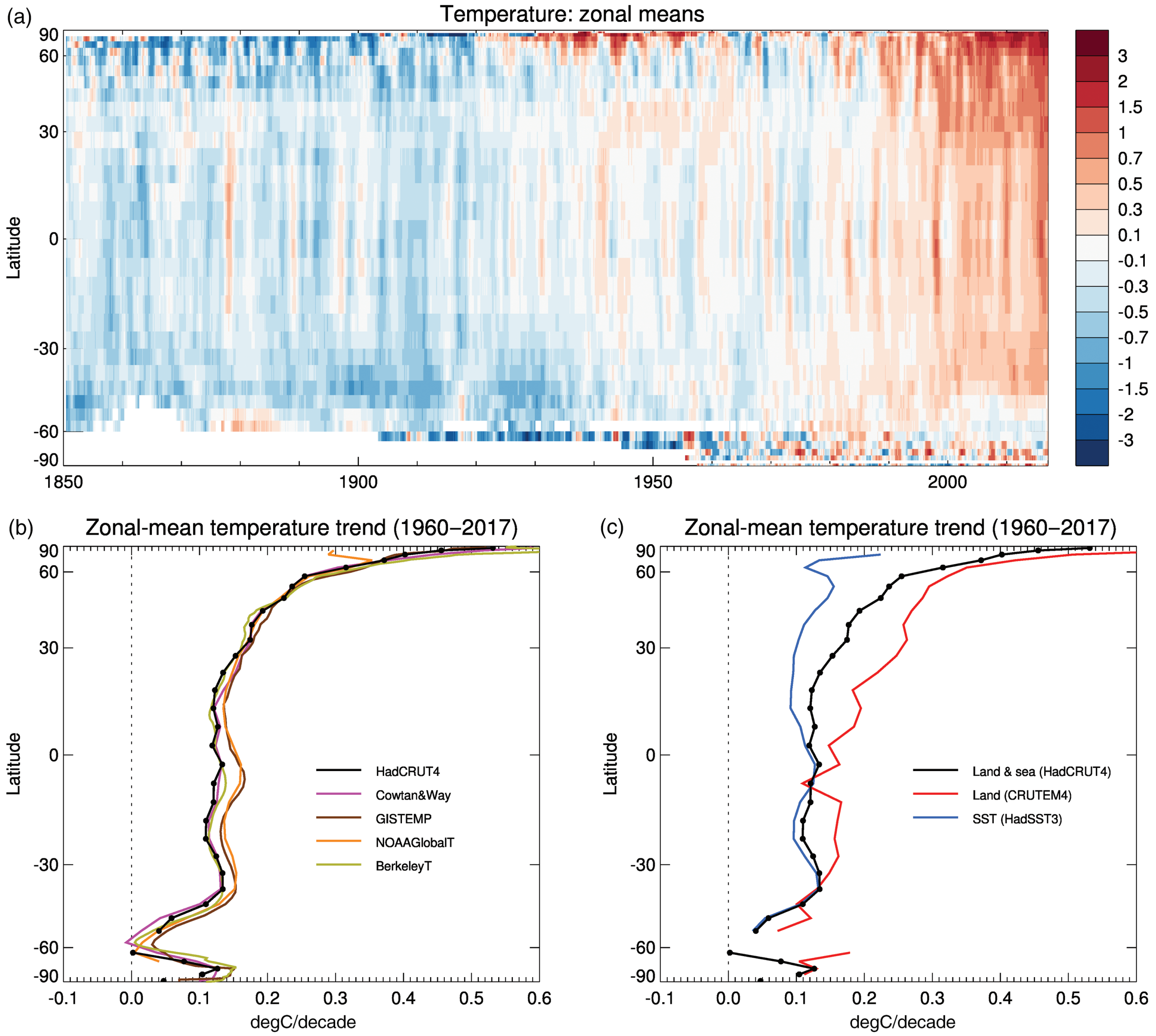

Figure 2. (a) Zonal means of 12-month running mean HadCRUT4 surface temperature anomalies (degC relative to the 1961–1990 mean). Linear trends (degC/decade) in zonal-mean temperature anomalies over the period since 1960 for (b) HadCRUT4 (black), HadCRUT4 infilled by Cowtan and Way (2014, magenta), GISTEMP (brown), NOAA (orange) and Berkeley Earth (mustard); and (c) for HadCRUT4 combining land and sea (black) and its separate land surface air temperature (red: CRUTEM4) and sea surface temperature (blue: HadSST3) components. All latitude scales are shown proportionally to the Earth's surface area in each latitudinal zone. Trends are only computed if at least 90% of the zonal-mean values are available during the period since 1960 (a zonal mean is calculated provided at least one grid cell at that latitude has data). HadCRUT4 trends are also shown by black dots so that values at isolated latitudes (e.g. South Pole) are visible.

tropospheric sulphate aerosols during this period (Wilcox *et al.*, 2013) and to internal variability in the Atlantic basin.

The warming of the last 60 or so years has spanned almost all latitudes (Figure 2(b)), with the exception of parts of the Southern Ocean around 60°S, though this is sensitive to the period used to calculate the trend. There is close agreement between datasets in the amplification of warming towards the mid and high latitudes of the Northern Hemisphere (though the NOAA temperature dataset shows less warming than the others at the most northern latitudes). In the tropics, the NOAA and GISTEMP datasets show a warming trend that is consistently around 10% higher than the trend in the other datasets. This is likely to be due to differences in bias adjustments applied to SST because SST is the main distinction between the two groups of datasets (e.g. figure 4 of Kent *et al.*, 2017).

The patterns in Figures 1(c) and 2 display three broad characteristics, which are well-understood and robustly simulated by climate models: (i) Arctic amplification, (ii) sub-polar suppression, and (iii) the land–ocean warming contrast.

Arctic amplification is usually associated with the positive feedback between albedo and surface temperature. Ice and snow have high albedos and reflect more sunlight to space than bare ground or ocean. A warming climate typically has less Arctic snow and ice cover, which absorbs more sunlight overall, causing more warming. Lesser known effects, which can be just as important, also contribute to Arctic amplification, such as increases in high latitude moisture and latent heating ultimately caused by increases in evaporation from warmer subtropical oceans (e.g. Cai, 2005), and changes to the radiative balance of the Arctic itself (e.g. Pithan and Mauritsen, 2014).

Sub-polar suppression is a transient and spatially variable effect caused by the large effective heat capacity of sub-polar oceans. Oceans are weakly stratified in these regions, allowing a much greater mixing of heat into the ocean depths (Manabe *et al.*, 1991) and slowing the surface warming. The effect is more pronounced in the Southern Ocean than in the sub-polar Atlantic, although historic observations of such suppression (e.g. at 60°S in Figure 2(c)) must be interpreted carefully because of the confounding effects of stratospheric ozone depletion on the surface (Ferreira *et al.*, 2015).

The land–ocean warming contrast is a phenomenon whereby land at most latitudes warms more than the ocean by a

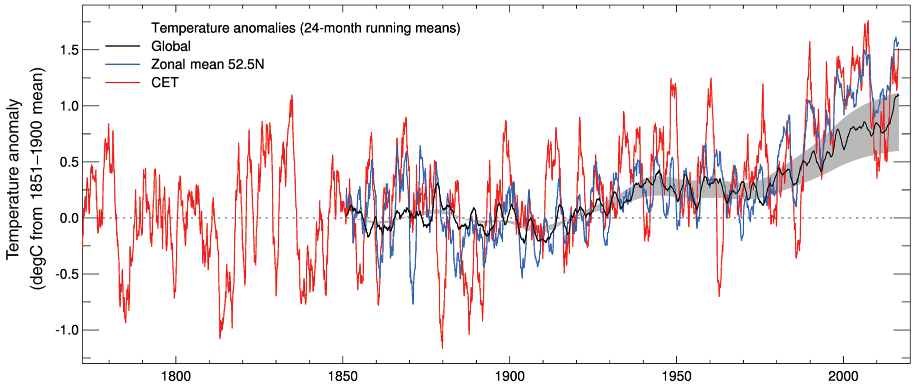

Figure 3. Temperature anomalies (degC relative to the 1851–1900 mean) for the global mean (black: HadCRUT4), the zonal mean closest to central England (blue: HadCRUT4 at 52.5°N) and Central England Temperature (red). All series are 24-month running means. The long-term changes in observed global-mean temperature (30-year smoothed) are also shown scaled by the ratios of central-England-to-global temperature change simulated by CMIP5 climate models under historical and future forcing (grey: multi-model ensemble spread of scaling factors).

factor of approximately 1.5. Somewhat counter-intuitively, on timescales of decades and longer, the difference between land and ocean thermal inertias plays a relatively small role in this effect (Manabe *et al*., 1991; Lambert and Chiang, 2007); rather it is land–ocean contrasts in surface moisture and boundary layer humidity, with consequent effects on lapse rates and low cloud feedbacks, that cause the amplification of warming over land (Joshi *et al*., 2008; Doutriaux-Boucher *et al*., 2009; Fasullo, 2010). This effect has been somewhat mitigated in the past by aerosol forcing over the Northern Hemisphere (Allen and Sherwood, 2010; Joshi *et al*., 2013).

Recent temperature variations over the UK

Here, we use CET as representative of the UK, noting that the correlation with CET is above 0.8 for temperatures from all of mainland UK except the far northwest of Scotland (figure 9.5 of Jones and Hulme, 1997).

Internal variability and regional external forcings (e.g. aerosols) become increasingly important factors at smaller spatial scales: compare the 24-month running means of CET and global-mean temperature in Figure 3. Some of this enhanced variability is still quite 'large-scale'; for example, it is present in the zonal-mean temperature at the latitude of the UK. For the series shown in Figure 3, the correlation between the global mean and CET is 0.65, while that between the zonal mean at 52.5°N and CET is higher at 0.72. At short timescales (e.g. applying a 10-year high-pass filter to the data) there is almost zero correlation between CET and the global mean, but CET still has a correlation of 0.40 with its zonal temperature. An example of this type of interannual feature is the spell from 2008 to 2013 during which CET was much cooler (for 24-month running means) than the preceding decade, a feature also present in its zonal temperature, but not in the global-mean series (Figure 3). Note that, in contrast to Figures 1 and 2, Figure 3 uses an earlier baseline (1851–1900) to more clearly illustrate the overall warming observed since the nineteenth century in each of the timeseries.

Sutton *et al*. (2015) have shown that much of this enhanced local variability principally influences interannual timescales and that there is similarity between even a small region like CET and the global mean at multi-decadal timescales. Applying a 10-year low-pass filter to the series shown in Figure 3 increases the correlations to 0.82 (global vs CET), 0.86 (zonal vs CET) and 0.96 (zonal vs global). Even though the series in Figure 3 are highly correlated at these longer timescales, the magnitudes of the changes are not necessarily the same. We might expect CET to warm *more* than the global mean because of the land–ocean warming contrast mechanisms, but this is not apparent from current climate model simulations. Osborn *et al*. (2016) diagnosed the warming simulated over central England per degC of global warming from a set of CMIP5 climate models and found ratios between 0.7 and 1.3, with a multi-model mean close to 1.0. With the caveat that the CMIP5 models are generally too coarse to simulate features such as land–sea breezes that would affect CET, this suggests that CET warming from external forcings should be close to the global-mean warming, plus or minus 30% (this is depicted in Figure 3 by the grey shading, which has scaled the multi-decadal global-mean warming by the range of CMIP5 CET/global ratios). Strictly, these ratios apply to periods where the dominant forcing is from increasing greenhouse gases since they were diagnosed from CMIP5 simulations from the mid-twentieth to the end of the twenty-first century. In fact, CET appears to have warmed more than the global mean, with most of the period since 1990 showing a higher positive anomaly than the global mean (indeed, higher than the global change scaled by 1.3, the top of the grey shading). The high levels of variability inherent in the series mean that further investigation is needed to determine whether CET is warming more rapidly than the global mean in response to external forcings.

The recent cooler period in CET (2008–2013) is also apparent in the zonal-mean temperatures at this latitude and might therefore be indicative of regional variability over the North Atlantic basin. Additional local-scale variability (in CET) is driven mostly by synoptic-scale weather processes. Osborn and Jones (2000) developed a method to quantify and remove this influence, based on empirical relationships between CET observations and three metrics of the synoptic-scale atmospheric circulation, namely the direction, strength and vorticity of the geostrophic airflow over the UK. These relationships were defined at the daily timescale, and here we have used them to predict the expected daily sequence of CET anomalies up to spring 2017 using airflow indices derived from reanalysis data (Jones *et al*., 2013), and these daily predictions are then aggregated to form seasonal and annual means (Figure 4, see Osborn and Jones, 2000, for details). The correlations between the observed seasonal-mean CET and the variations predicted from the airflow range from 0.48 (summer) to 0.77 (winter).

Significant warming is observed on timescales of 50 years or more for the annual-mean CET and for all individual seasons except winter (Figure 4). The lack of significant winter warming is not because an externally-forced signal is being masked by a cooling trend driven by weather variability, since the changes in synoptic circulation over this period would have generated a slight warming trend in winter. Subtracting this circulation-based prediction from the observed winter CET leaves a very flat winter residual. Changes in summer atmospheric circulation over the UK would likely have led to a small long-term cooling; subtracting this effect leaves a residual with a slightly stronger overall summer trend that also stands out more clearly against the interannual variability, which is reduced in the residual series because some of it is explained by circulation variability.

The recent cooler period in the 24-month running mean CET, remarked on earlier, arises from cooler intervals in both winter and summer, along with a flattening of the warming trend in the other seasons since the early 2000s (Figure 4). This feature is not explained by synoptic circulation anomalies, except for a small contribution in summer. Nevertheless, some individual cold

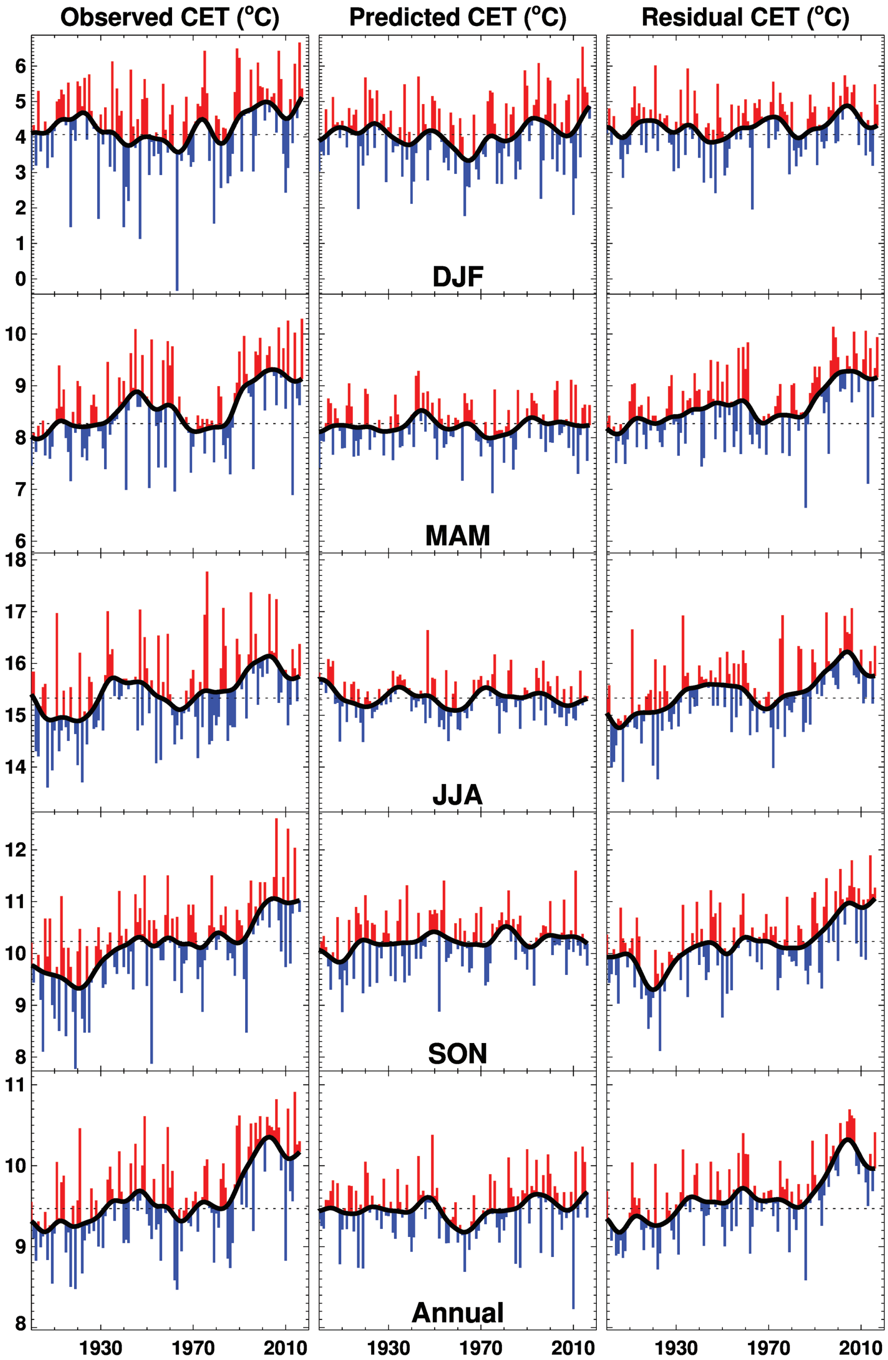

Figure 4. Time series of Central England Temperature (CET, °C) as observed (left), predicted from variations in daily atmospheric circulation (middle), and the residual (observed minus predicted). Seasonal (labelled with the initials of each month included) and annual averages are shown in rows. Each time series is shown as individual bars above (red) or below (blue) its 20-year smoothed variations (black). The horizontal dashed line marks the observed 1961–1990 mean for each season. The analysis period is from 1871 to spring 2017, though only values from 1901 onwards are shown here, for clarity.

years within this period are well explained by anomalous circulation. For example, the cold annual mean of 2010 (0.6 degC below the 1961–1990 mean, which was only the 21st coldest since our analysis starts in 1871, yet was very notable as the coldest year for almost 25 years) is entirely explained by anomalous circulation that year: the airflow-based prediction is 1.2 degC below the 1961–1990 mean, so the observed CET was 0.6 degC *warmer* than expected given the airflow of that year. Similar results are found for individual seasons: winter 2009/2010 CET was 13th coldest (anomaly −1.6 degC) but −2.3 degC was expected given the airflow conditions, and the cool summer of 2011 (anomaly −0.5 degC) could be mostly explained by the airflow conditions (predicted anomaly −0.4 degC). The cold spring of 2013, however, is not very well explained by anomalous synoptic airflow (at least, not by our simple approach): it was the 5th coldest spring in the CET since 1871 (the four colder springs are all before 1900, not shown in Figure 4) with an anomaly 1.4 degC below the 1961–1990 mean, but the residual after subtracting our estimate of the airflow effect is still an anomaly of −1.2 degC, making it the 4th coldest in the residual series (1871–present).

Turning briefly to some recent years with warm CET anomalies, the mildest observed winter (2015/2016) was partly due to anomalous circulation that winter and falls to only 9th mildest in the residual series. The warmest spring in the CET record (2017, anomaly 2.0 degC) is only 5th warmest after factoring out the circulation effect using our method (1.7 degC anomaly). Although 1976 is the warmest summer in the CET record, this warmth was partly explained by the anomalous circulation that year, and when this is factored out it falls to 3rd warmest in the residual series, with 2006 taking the top spot. Of the three recent very mild autumns (2006, 2011 and 2014), anomalous circulation played a significant role in the earlier two, but less so for 2014, leaving 2014 as the warmest autumn in the residual series.

These estimates of the role of synoptic circulation are useful because they can help distinguish the response to external forcings from the internal variability. While some parts of the forced signal may be a dynamical response (i.e. arising from circulation changes), it is nevertheless the case that most of the forced *temperature* signal is expected to arise from the thermodynamic processes of the enhanced greenhouse effect and the feedbacks that ensue. So removing an estimate of the dynamical variations will not alter the forced signal very much but will significantly reduce the superimposed internal variability. It is interesting to note that the prominent peak in annual CET in the first decade of the current century followed by some cooler years is not captured by our airflow-based approach. This may be because the Osborn and Jones (2000) method is unable to capture all aspects of the circulation influence (e.g. Parker, 2009, captured more temperature variability by using a two-day trajectory approach), or perhaps because these decadal-scale fluctuations are part of broader modes of internal variability also involving ocean circulation and SST (support for this is provided by the presence of these features in the zonal-mean temperature at this latitude too; Figure 3).

Conclusions

We conclude by highlighting three key findings. First, the most important single issue that affects our estimates of global temperature is the adjustment for biases in SST measurements. Nevertheless, there is consistency between the global temperature datasets regarding overall warming and its latitudinal structure across land and oceans. Second, we understand the mechanisms that determine the warming patterns at the largest scales, including Arctic amplification, land–ocean warming contrast and suppression of warming in the sub-polar oceans. Third, temperature at local scales (e.g. central England) is greatly influenced by internal variability (from synoptic weather to regional climate variability). Long-term warming is observed in spring, summer and autumn over central England and is even more apparent after accounting for synoptic weather variability, whereas warming in winter is weaker and becomes less apparent after the effect of synoptic weather variability is factored out.

Acknowledgements

This work was supported by NERC (grant number NE/N006348/1, SMURPHS) and the National Centre for Atmospheric Science (NCAS).

References

Allen RJ, Sherwood SC. 2010. Aerosol-cloud semi-direct effect and land-sea temperature contrast in a GCM. *Geophys. Res. Lett.* **37**: L07702.

Cai M. 2005. Dynamical amplification of polar warming. *Geophys. Res. Lett.* **32**: L22710.

Cowtan K, Way RG. 2014. Coverage bias in the HadCRUT4 temperature series and its impact on recent temperature trends. *Q. J. R. Meteorol. Soc.* **140**: 1935–1944.

Cowtan K, Hausfather Z, Hawkins E *et al.* 2015. Robust comparison of climate models with observations using blended land air and ocean sea surface temperatures. *Geophys. Res. Lett.* **42**: 6526–6534.

Doutriaux-Boucher M, Webb MJ, Gregory JM *et al.* 2009. Carbon dioxide induced stomatal closure increases radiative forcing via a rapid reduction in low cloud. *Geophys. Res. Lett.* **36**: L02703.

Fasullo JT. 2010. Robust land–ocean contrasts in energy and water cycle feedbacks. *J. Clim.* **23**: 4677–4693.

Ferreira D, Marshall J, Bitz C *et al.* 2015. Antarctic ocean and sea ice response to ozone depletion: a two-time-scale problem. *J. Clim.* **28**: 1206–1226.

Freeman E, Woodruff SD, Worley SJ *et al.* 2017. ICOADS release 3.0: a major update to the historical marine climate record. *Int. J. Climatol.* **37**: 2211–2232.

Hansen J, Ruedy R, Sato M *et al.* 2010. Global surface temperature change. *Rev. Geophys.* **48**: RG4004.

Hawkins E, Jones PD. 2013. On increasing global temperatures: 75 years after Callendar. *Q. J. R. Meteorol. Soc.* **139**: 1961–1963.

Huang B, Thorne PW, Banzon VF *et al.* 2017. Extended Reconstructed Sea Surface Temperature version 5 (ERSSTv5): upgrades, validations, and intercomparisons. *J. Clim.* **30**: 8179–8205.

IPCC. 2013. Summary for policymakers, 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 *et al* (ed.). Cambridge University Press: Cambridge, UK, pp 3–29.

Jones P. 2016. The reliability of global and hemispheric surface temperature records. *Adv. Atmos. Sci.* **33**: 269.

Jones PD, Harpham C, Briffa KR. 2013. Lamb weather types derived from reanalysis products. *Int. J. Climatol.* **33**: 1129–1139.

Jones P, Hulme M. 1997. The changing temperature of 'Central England', in *Climates of the British Isles: Present, Past and Future*. Hulme M, Barrow E (eds). Routledge: London. pp 173–196.

Jones PD, Lister DH, Osborn TJ *et al.* 2012. Hemispheric and large-scale land-surface air temperature variations: an extensive revision and an update to 2010. *J. Geophys. Res*. 117: D05127.

Jones PD, Osborn TJ, Briffa KR. 1997. Estimating sampling errors in large-scale temperature averages. *J. Clim.* **10**: 2548–2568.

Joshi MM, Gregory JM, Webb MJ *et al.* 2008. Mechanisms for the land/sea warming contrast exhibited by simulations of climate change. *Clim. Dyn.* **30**: 455–465.

Joshi MM, Lambert FH, Webb MJ. 2013. An explanation for the difference between twentieth and twenty-first century land–sea warming ratio in climate models. *Clim. Dyn.* **41**: 1853–1869.

Karl TR , Arguez A, Huang B *et al.* 2015. Possible artifacts of data biases in the recent global surface warming hiatus. *Science* **348**: 1469–1472.

Kent EC, Kennedy JJ, Smith TM *et al.* 2017. A call for new approaches to quantifying biases in observations of sea-surface temperature. *Bull. Am. Meteorol. Soc.* **98**: 1601–1616.

Lambert FH, Chiang JCH. 2007. Control of land-ocean temperature contrast by ocean heat uptake. *Geophys. Res. Lett.* **34**: L13704.

Manabe S, Stouffer RJ, Spelman MJ *et al.* 1991. Transient responses of a coupled ocean–atmosphere model to gradual changes in atmospheric CO_2. Part I: annual mean response. *J. Clim.* **4**: 785–817.

Manley G. 1974. Central England temperatures: monthly means 1659 to 1973. *Q. J. R. Meteorol. Soc.* **100**: 389–405.

Medhaug I, Stolpe MB, Fischer EM *et al.* 2017. Reconciling controversies about the 'global warming hiatus'. *Nature* **545**: 41–47.

Morice CP, Kennedy JJ, Rayner NA *et al.* 2012. Quantifying uncertainties in global and regional temperature change using an ensemble of observational estimates: the HadCRUT4 dataset. *J. Geophys. Res.* **117**: D08101.

Osborn TJ, Jones PD. 2000. Air flow influences on local climate: observed United Kingdom climate variations. *Atmos. Sci. Lett.* **1**: 62–74.

Osborn TJ, Wallace CJ, Harris IC *et al.* 2016. Pattern scaling using ClimGen: monthly-resolution future climate scenarios including changes in the variability of precipitation. *Clim. Change* **134**: 353–369.

Parker DE. 2009. Anomalies of Central England temperature classified by air source. *J. Clim.* **22**: 1069–1081.

Peterson TC, Vose RS. 1997. An overview of the global historical climatology network temperature database. *Bull. Am. Meteorol. Soc.* **78**: 2837–2849.

Pithan F, Mauritsen T. 2014. Arctic amplification dominated by temperature feedbacks in contemporary climate models. *Nat. Geosci.* **7**: 181–184.

Rohde R, Muller R, Jacobsen R *et al.* 2013. Berkeley Earth temperature averaging process. *Geoinfor. Geostat.: An Overview* **1**(2): 1–13.

Simmons AJ, Berrisford P, Dee DP *et al.* 2017. A reassessment of temperature variations and trends from global reanalyses and monthly surface climatological datasets. *Q. J. R. Meteorol. Soc.* **143**: 101–119.

Sutton R, Suckling E, Hawkins E. 2015. What does global mean temperature tell us about local climate? *Philos. Trans. R. Soc. A* **373**: 20140426.

Trewin B. 2010. Exposure, instrumentation, and observing practice effects on land temperature measurements. *Wiley Interdiscip. Rev. Clim. Change* **1**: 490–506.

Wilcox LJ, Highwood EJ, Dunstone NJ. 2013. The influence of anthropogenic aerosol on multi-decadal variations of historical global climate. *Environ. Res. Lett.* **8**: 024033.

Correspondence to: T. J. Osborn

t.osborn@uea.ac.uk

doi:10.1002/wea.3174