

# Mapping climate change in European temperature distributions

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## Abstract

Climate change poses challenges for decision makers across society, not just in preparing for the climate of the future but even when planning for the climate of the present day. When making climate sensitive decisions, policy makers and adaptation planners would benefit from information on local scales and for user-specific quantiles (e.g. the hottest/coldest 5% of days) and thresholds (e.g. days above 28 °C), not just mean changes. Here, we translate observations of weather into observations of climate change, providing maps of the changing shape of climatic temperature distributions across Europe since 1950. The provision of such information from observations is valuable to support decisions designed to be robust in today's climate, while also providing data against which climate forecasting methods can be judged and interpreted. The general statement that the hottest summer days are warming faster than the coolest is made decision relevant by exposing how the regions of greatest warming are quantile and threshold dependent. In a band from Northern France to Denmark, where the response is greatest, the hottest days in the temperature distribution have seen changes of at least 2 °C, over four times the global mean change over the same period. In winter the coldest nights are warming fastest, particularly in Scandinavia.

**Keywords:** climate, thresholds, distributions, quantiles, climate change, regional climate change, observations, climate adaptation, climate impacts

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## 1. Introduction

Global warming consists of complex changes in local climate which have implications for sectors as diverse as water management (Milly *et al* 2008, DEFRA 2012, Carpenter

*et al* 1999), building design (DEFRA 2012, CIBSE 2005), agriculture (Challinor and Wheeler 2008, Lobell and Burke 2008, IPCC 2007b, Porter and Semenov 2005) and insurance (Mills 2005). Providing guidance at these local scales is a key element of efforts to supply 'climate services' (WMO 2011). This is intrinsically challenging because organizations are vulnerable to different aspects of climate: different thresholds, variables and spatial patterns in the distribution of weather variables which constitutes climate (IPCC 2007a, Stainforth



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*et al* 2007). Assessments of where and which societal vulnerabilities are changing fastest require information on how all these aspects are co-varying. Here we use a gridded dataset of observations (Haylock *et al* 2008) to provide such information by mapping the changing shape of local climate (Chapman *et al* 2013) across Europe. The implications are highlighted for some societally relevant thresholds including freezing point and temperatures related to labour productivity (Hsiang 2010, Zivin and Neidell 2010) and building overheating (DEFRA 2012, CIBSE 2006). The approach provides information at scales relevant for both local decisions and national planning, while also being of significance for the evaluation of climate models (van Oldenborgh *et al* 2009) and the study of processes which influence local climate change. Our aim is to process observations of weather variables into observations of climate change. Some choices are inevitable in this process and the implications of these are tested, but the incorporation of methodological assumptions is minimized to the greatest extent possible so that the results can be interpreted as representing the robustly identifiable changes in climate experienced over the last 60 years as closely as possible.

Section 2 provides a description of the dataset used, along with the interpretational approach adopted and the rationale for such an approach. Section 3 illustrates the application of the method at three locations. Given the large natural variability in climatic datasets, a key element of the analysis is the process for identifying robust messages. Examples are presented of illustrative situations in which robust messages can and cannot be extracted. In section 4 maps of observed changes in European climate are generated for summer and winter, for a selection of quantiles representing the changing shape of the temperature distributions, and for two application-relevant thresholds. The implications of these results are reviewed in the conclusions.

## 2. From weather to climate

Observations of weather variables are taken on at least a daily basis at thousands of weather stations around the world. Many of these datasets stretch back to the mid-20th century with some going back hundreds of years (Parker *et al* 1992). Several recent initiatives have taken these data and constructed high-resolution gridded datasets of daily weather information across large regions (Haylock *et al* 2008, Yatagai *et al* 2012). Some of these processed datasets, and even some of the underlying station data, are openly available for use by researchers and policy makers. For many purposes, however, they are of limited direct value because they don't provide information about the aspects of changing climate which impact policy/business decisions and climate impacts research. By acknowledging that climate is inherently a distribution, and changing climate a changing distribution (Stainforth *et al* 2007, IPCC 2012, Hansen *et al* 2012), these data can be analysed in a model independent manner to provide a more valuable picture of how local climate is changing; one which more closely reflects perceptions of climate change.

A description of climate change on a regional basis requires an exploration of correlated variations across multiple dimensions: space (geographical variations), likelihood (rare versus common events in the climatic distribution), variable (the aspect of climate under consideration), and time (the period over which a change is considered). Using the state-of-the-art E-OBS dataset (Haylock *et al* 2008), which runs from 1950 to 2011, we present climate change variations in space and quantile for four variables: maximum and minimum daily temperatures in summer and winter.

The E-OBS dataset is constructed using data from 2316 stations but the station density varies considerably across Europe (see Haylock *et al* 2008) with the highest density of stations in the UK, the Netherlands and Switzerland, and relatively low densities in the Balkans, Scandinavia, Iberia and Northern Africa. The E-OBS data at  $0.5^\circ \times 0.5^\circ$  resolution is used in this analysis; higher resolution gridded data is available but the use of such data for this purpose is not considered justified given the density of the underlying observational network.

At  $0.5^\circ \times 0.5^\circ$  the data has a resolution of roughly 40–50 km. The term 'local climatic distributions' is used to refer to results on this scale. 'Regional' behaviour refers to the results across clusters of several such grid boxes. The grid box resolution is somewhat higher than the typical resolution of global circulation models (GCMs,  $\sim 100$  km) but a little lower than is typical in regional climate models ( $\sim 25$  km). To the extent that the E-OBS dataset reflects the underlying observations it is appropriate to examine grid box results individually. This is not the case for GCMs where the numerical solution is not expected to necessarily be representative of the solutions of the continuous equations at the smallest scale of the model. The method described herein could be applied to, and interpreted for, individual grid boxes and even individual station data, thus providing higher resolution information than is available from models. However, gridded observational datasets are also subject to limitations, due to in-homogeneities in the data and inaccuracies arising from the interpolation procedures (Hofstra *et al* 2009, 2010). These limitations are more significant in regions with fewer stations. As a consequence the results below are more reliable in some regions than others; in North Africa they are not considered at all reliable because there are so few stations. Spatial correlation patterns are however outputs of the approach. Here we focus on regionally consistent behaviour because this is unlikely to be the result of inaccuracies in the dataset. The application of the approach to individual grid boxes or individual station data would require careful analysis of the reliability of the data at that location.

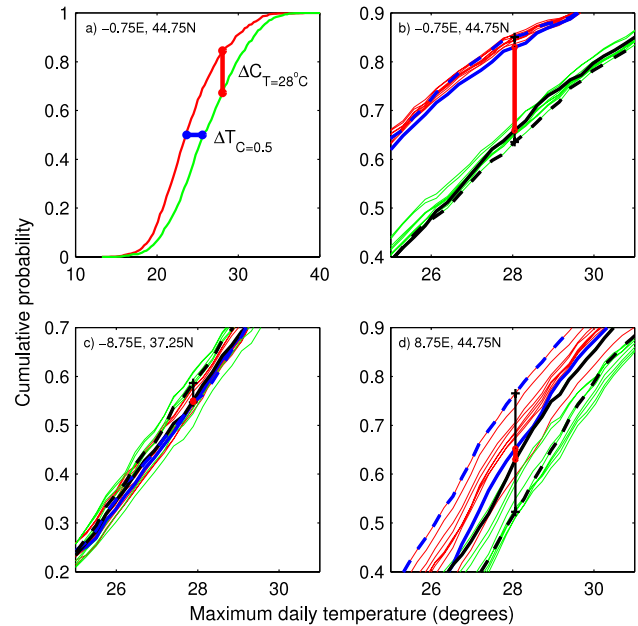
Our aim is to maintain as close a link as possible to the underlying observed quantities while representing them in terms of climate, a set of distributions. It is commonly accepted that climate change could lead to changes in the mean, changes in the mean and variance, or to more complicated variations in the shape of climatic distributions (IPCC 2012), but there have been very few studies on what observations tell us about such changes at the local scale

(see Vinnikov *et al* 2002 for one such). This information would be valuable not only for decision makers but also as a guide for research into how local geographic factors affect the consequences of synoptic scale changes. Previous studies which have considered regional distributions or extremes, have made assumptions including: (i) the presence of a continuous linear trend over time (Reich 2012, Simolo *et al* 2010, Min *et al* 2013, Alexander *et al* 2006), (ii) spatial dependences (Simolo *et al* 2010, Reich 2012, Alexander *et al* 2006), and (iii) that the changing shape can be captured by changes in only low order moments (e.g. mean and variance) (Jones *et al* 2009). Such assumptions are debatable given the complexity of the drivers of local climate. The possibility of multi-decadal climatic oscillations (Schlesinger and Ramankutty 1994, Chambers *et al* 2012) suggests that the first is an oversimplification while the last is questionable in such a complex nonlinear system. Regarding the second, the presence of spatial dependences is of course clear, but applying assumptions regarding their character at any given quantile, and their consistency across any given region, risks providing misleading information unless it can be founded on well understood physical mechanisms. We therefore propose a method which remains as close as possible to simply representing the data. Any spatial, variable or likelihood relationships which arise can thus be interpreted with greater confidence, simplifying their use in societal planning. If, in the future, their physical basis can be understood then this can provide a foundation for better local information regarding plausible future climate change.

### 3. The identification of robust changes in climate

The local climate for a variable at some time in the past can conceptually be represented by a distribution, D1. In the present day the same variable has distribution D2. Our interest is in how, or whether, D1 and D2 differ. Consider daily maximum (hereafter ‘daytime’) summer (June/July/August) temperatures in the gridbox around Bordeaux. A distribution of this variable is constructed using 9 years of data centred on 1954 and compared with another using 9 years of data centred on 1997 (see figure 1(a) and appendix A). From this can be extracted the change in the probability of remaining below a certain threshold,  $\Delta C$  (figure 1(a)). The thresholds of relevance vary according to the natural or human system of interest. Two aspects of economic interest are labour productivity, which has been shown to decrease when daytime temperatures exceed about 28 °C (Hsiang 2010, Zivin and Neidell 2010) and overheating in buildings, which has been related to temperatures exceeding 28 and 26 °C (DEFRA 2012, CIBSE 2006). For these, as for many thresholds it is most intuitive to consider the change in the exceedance probability ( $-\Delta C$ ) which has increased by 0.17 at 28 °C for summer days in Bordeaux over this period.

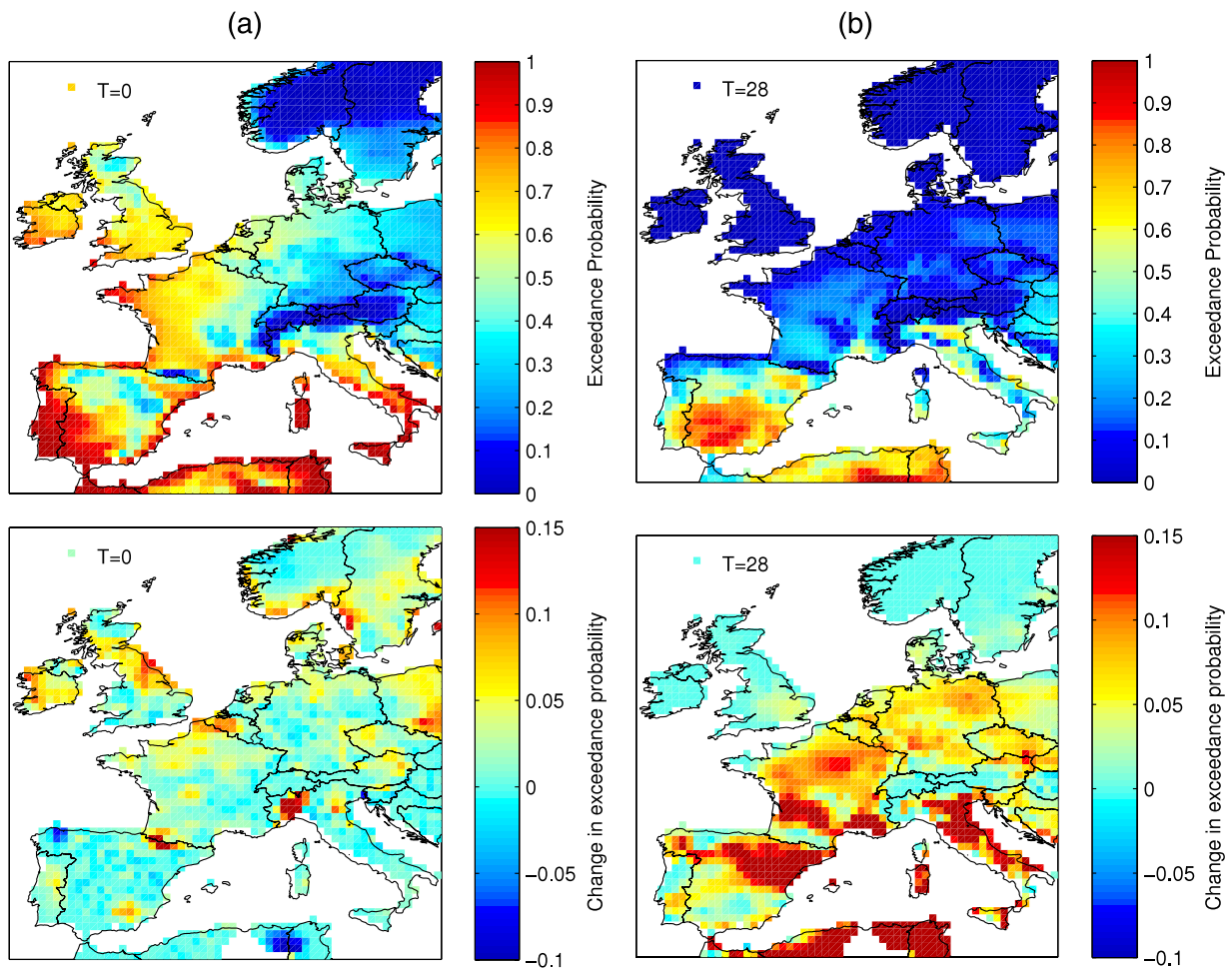
For such information to be useful its robustness must be assessed. Repeating the analysis using ten different period pairs with equal length separations in time (i.e. 1954–1997, 1955–1998, ..., 1963–2006, see appendix A), produces ten pairs of distributions and ten assessments of



**Figure 1.** Changing cumulative distribution functions for maximum daily (daytime) summer temperatures for three E-OBS grid boxes. Red cdfs are centred on each year from 1954 to 1963 (1954 only in (a)). Green cdfs are centred on each year from 1997 to 2006 (1997 only in (a)). In (a) the blue horizontal line shows  $\Delta T_q$  for the median quantile ( $q = 0.5$ ), the vertical red line  $\Delta C_T$  at  $T = 28^\circ\text{C}$ . In (b)–(d) the vertical red line (thin black line) is the smallest (largest)  $\Delta C_T$  at  $T = 28^\circ\text{C}$ ; the corresponding cdfs are shown as solid (dashed) blue and black lines representing the earlier and later period respectively. Locations are: (a) and (b) Bordeaux, France, (c) western Algarve, Portugal, (d) eastern Piedmont, Italy.

the change in exceedance probability over a 43 year period (figures 1(b)–(d)). This represents an estimate of the range of behaviour due to short timescale variability (see Chapman *et al* 2013) while also capturing the diversity of longer timescale variability in the data. They are not, however, independent samples. We therefore take a conservative approach to the evaluation of these ten values by considering only the smallest and largest change (see appendix B). A large value for the smallest change suggests a robust, large signal over the last 60 years at the given threshold e.g. 0.17 at 28 °C around Bordeaux (figure 1(b)). A small value for the largest change implies a robust signal of little change, e.g.  $-0.04$  at 28 °C in the Algarve, Portugal (figure 1(c)). A large range (maximum minus minimum values for  $-\Delta C$ ) implies no clear signal e.g.  $-0.04$  minimum with 0.24 maximum at 28 °C in Piedmont, Italy (figure 1(d)).

This approach quantifies changes between two periods in time; it cannot attribute (Stott 2003) these changes to, for instance, the enhanced greenhouse effect or multi-decadal internal climatic oscillations (Schlesinger and Ramankutty 1994, Chambers *et al* 2012). This is not a detriment when optimizing plans for the climate of the present day. Information on where and how vulnerabilities are changing is useful irrespective of the physical drivers, particularly when planning requirements, or conventional approaches, are based on illustrative past years (Hitchin *et al* 1983) or probability distributions constructed over historic periods (Milly *et al*



**Figure 2.** Maps of the exceedance probability (upper plots) and the smallest evaluated change in exceedance probability, smallest  $-\Delta C_T$ , (lower plots) over the 1950–2011 period for (a)  $T = 0^\circ\text{C}$  for nighttime winter temperatures (left plots), and (b)  $T = 28^\circ\text{C}$  for daytime summer temperatures (right plots).

2008). In the context of either human-induced climate change or multi-decadal oscillations, the method can be interpreted as quantifying how global, or large scale, variations in the system, manifest themselves on the smaller scales of human society (at least in locales where land-use change is not considered a significant factor).

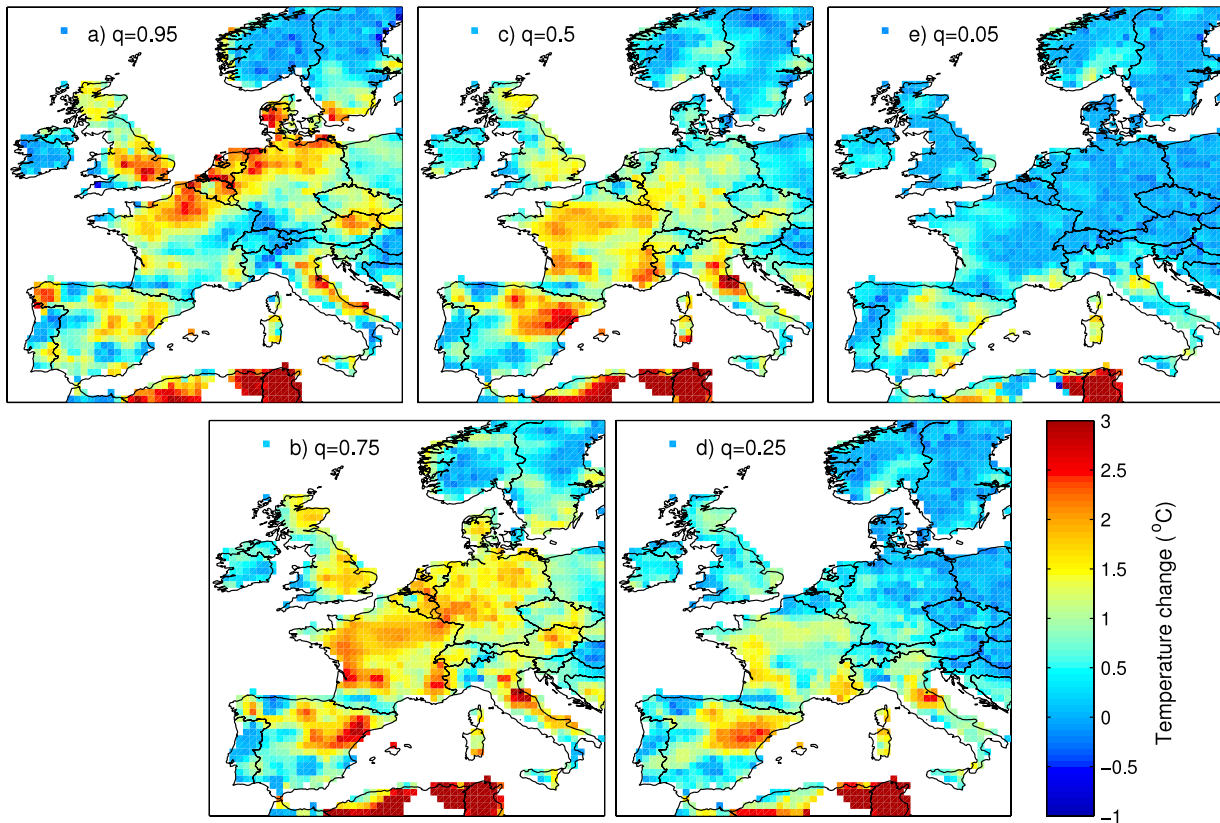
The ability to separate long timescale variations (which the analysis captures) from shorter ones (which are incorporated within the individual cdfs) is limited by the timeseries of observations available (see appendix A). However, the approach makes no assumptions of spatial relationships so when coherent spatial patterns of change emerge it provides confidence that such patterns represent a signal which is robust in that region.

#### 4. Maps of climate change

Mapping the smallest changes in the threshold exceedance probability produces some clear patterns for both a zero degree threshold in daily minimum (hereafter ‘nighttime’) temperatures in winter and a  $28^\circ\text{C}$  threshold in daytime temperatures in summer—see figure 2. In many parts of Ireland, northern England, southern Scotland and southern

Sweden, the fraction of winter nights which fall below zero degrees has decreased by at least 0.05–0.1. North west Italy and the western Pyrenees show even greater changes in this threshold. Most of southern Sweden and coastal Norway have in addition seen a substantial decrease ( $\sim 0.05$ –0.15) in the fraction of winter daytime temperatures which fall below zero (figure S3 available at [stacks.iop.org/ERL/8/034031/mmedia](http://stacks.iop.org/ERL/8/034031/mmedia)). These changes presumably relate to observed changes in snow reliability in Scandinavian skiing resorts (Moen and Fredman 2007). In summer, the  $28^\circ\text{C}$  threshold in daytime temperatures is changing fastest in western France, eastern Spain and central Italy; changes in the fraction of days above this threshold are often greater than 0.15 in these regions. Smaller but nevertheless substantial changes ( $>0.06$ , sometimes  $>0.1$ ) with implications for labour productivity and building design/management are seen across northern France, Germany and Eastern Europe; even across southern England changes greater than 0.04 are found.

Although changes in frequency are important for impact-specific thresholds, for research objectives such as understanding the processes which link climate at different spatial scales, and for climate model evaluation, it is more useful to have information on the changing local distributions.



**Figure 3.** Maps of the smallest evaluated change in temperature (smallest  $\Delta T_q$ ) over the 1950–2011 period for daytime summer temperatures at the following quantiles of the cumulative distribution function: (a)  $q = 0.95$ , (b)  $q = 0.75$ , (c)  $q = 0.50$ , (d)  $q = 0.25$ , and (e)  $q = 0.05$ .

Are they simply shifting or are they changing shape (IPCC 2012) and in either case are the changes consistent across regions? To answer these questions quantile-specific changes are evaluated (Chapman *et al* 2013) ( $\Delta T$  in figure 1(a)). Again a large (small) value for the smallest (largest) change over ten samples is interpreted as providing an indication of robust large (small) changes.

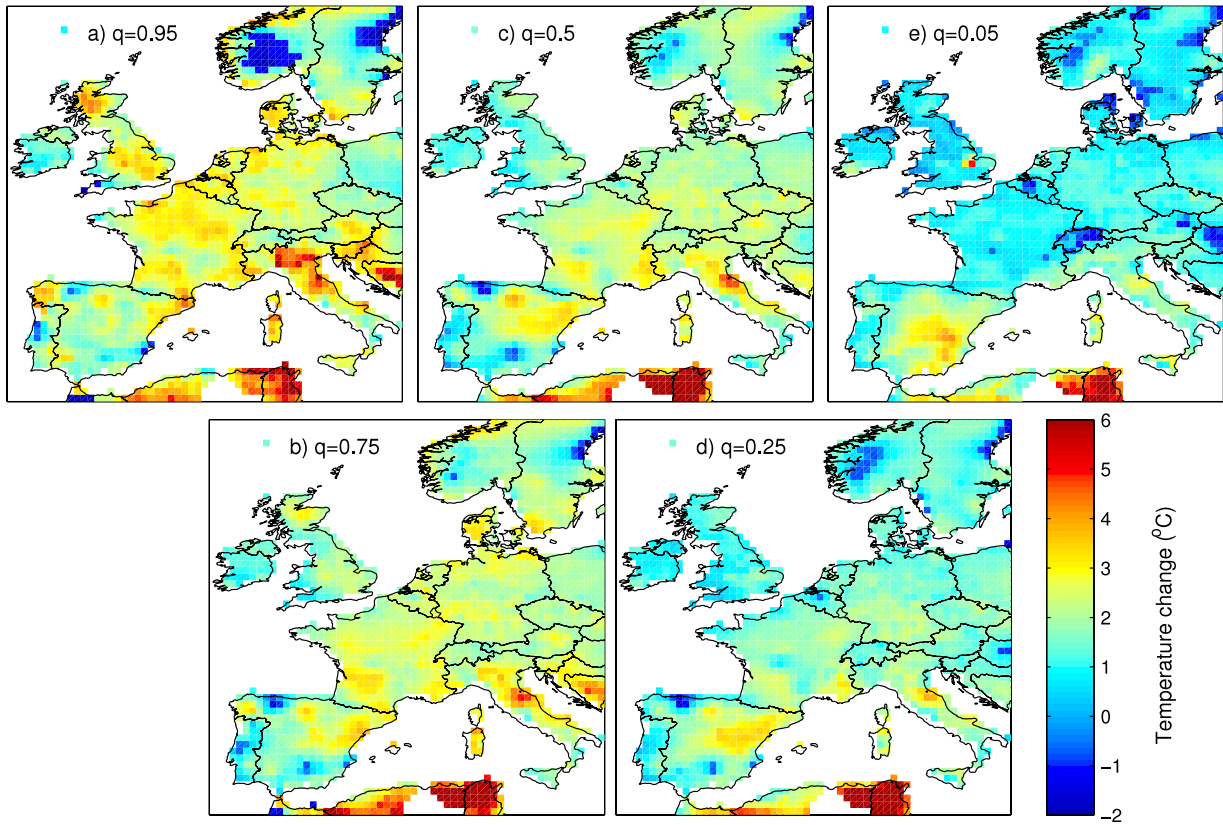
The smallest (largest) change in five quantiles across the distributions of summer daytime and winter nighttime temperatures are presented in figures 3 and 5 (figures 4 and 6). Daytime summer temperatures tend to increase most in the upper quantiles in many regions (figure 3). At the 0.95 quantile a band across northern Europe from northern France to Denmark and southern Sweden show substantial changes of at least 2 °C (figure 3(a)). At the 0.75 and 0.5 quantiles the greatest changes are further south in central France and Germany (figure 3(b)). Eastern Spain and central Italy show very substantial changes, in some places at least 2.5 °C, across the whole distribution, but for most regions the low, 0.25 and 0.05 quantiles, show smaller changes. Much of southern and western Iberia along with Norway and Sweden reveal either robustly small changes or no clear signal at all quantiles (figures 4 and 3). By contrast it is the lowest quantiles which show large change in nighttime winter temperatures (figures 5 and 6) for large parts of Europe. This is evident in only the most extreme, 0.05 quantile, for central western Europe but for Norway and Sweden it is seen in

all quantiles below the median, where the smallest changes can be over 3 °C. Changes in Spain are close to zero and sometimes negative even in the lowest quantiles but in central and southern Portugal they are positive across all quantiles. The relatively small size of the region with a positive signal and the substantial difference with that seen in the surrounding region suggests that this result should be treated cautiously without further understanding of the underlying datasets or the processes responsible.

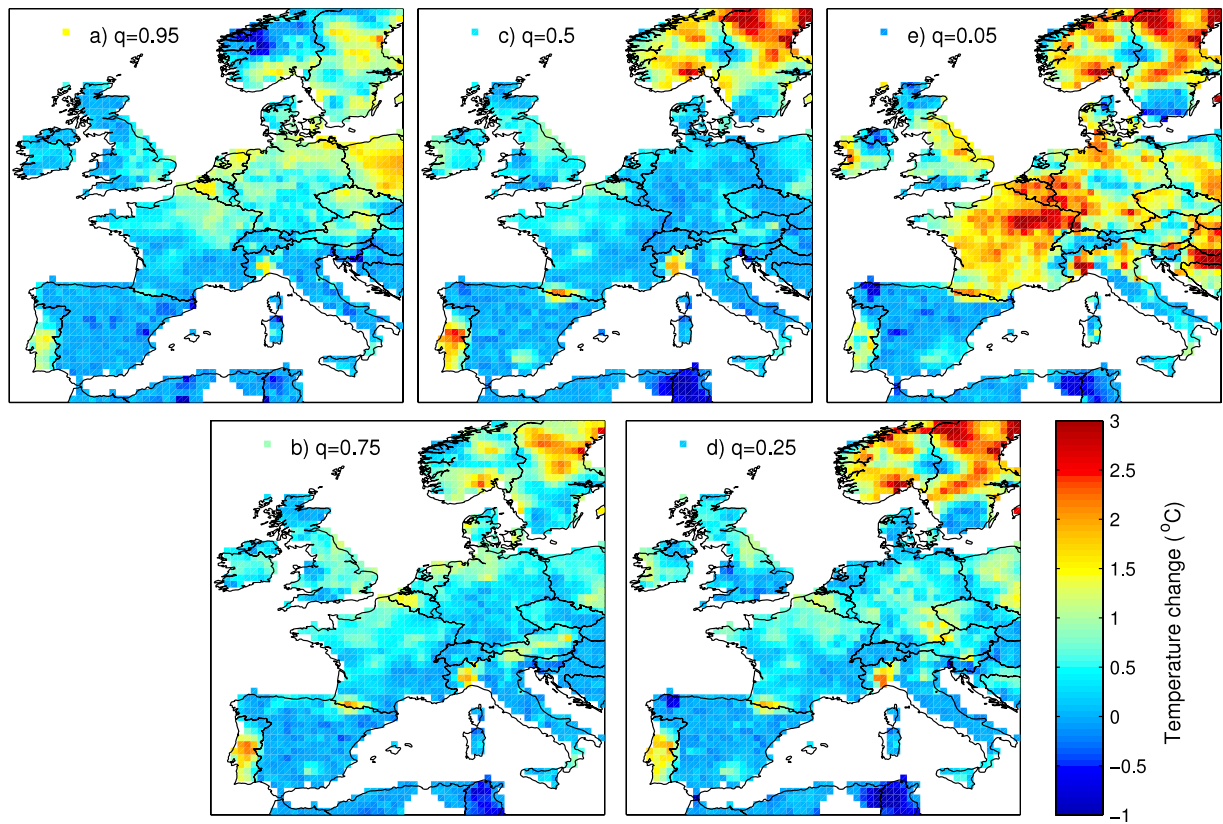
Changes in summer nighttime temperatures are smaller than in daytime temperatures; smallest values less than 1.5 °C across most of Europe (figures S5 and S6 available at [stacks.iop.org/ERL/8/034031/mmedia](http://stacks.iop.org/ERL/8/034031/mmedia)). Few large scale regional patterns are evident although northern Portugal is a hot spot for mid- to-upper quantiles. The strong signal in nighttime temperatures in winter in central western Europe is not apparent in daytime winter temperatures but large changes are found in this variable in the lowest quantiles in central Italy and the northern Balkans (figure S7 available at [stacks.iop.org/ERL/8/034031/mmedia](http://stacks.iop.org/ERL/8/034031/mmedia)). The signal in daytime winter temperatures in Scandinavia is clear but less strong than in the nighttime values.

### 5. Concluding remarks

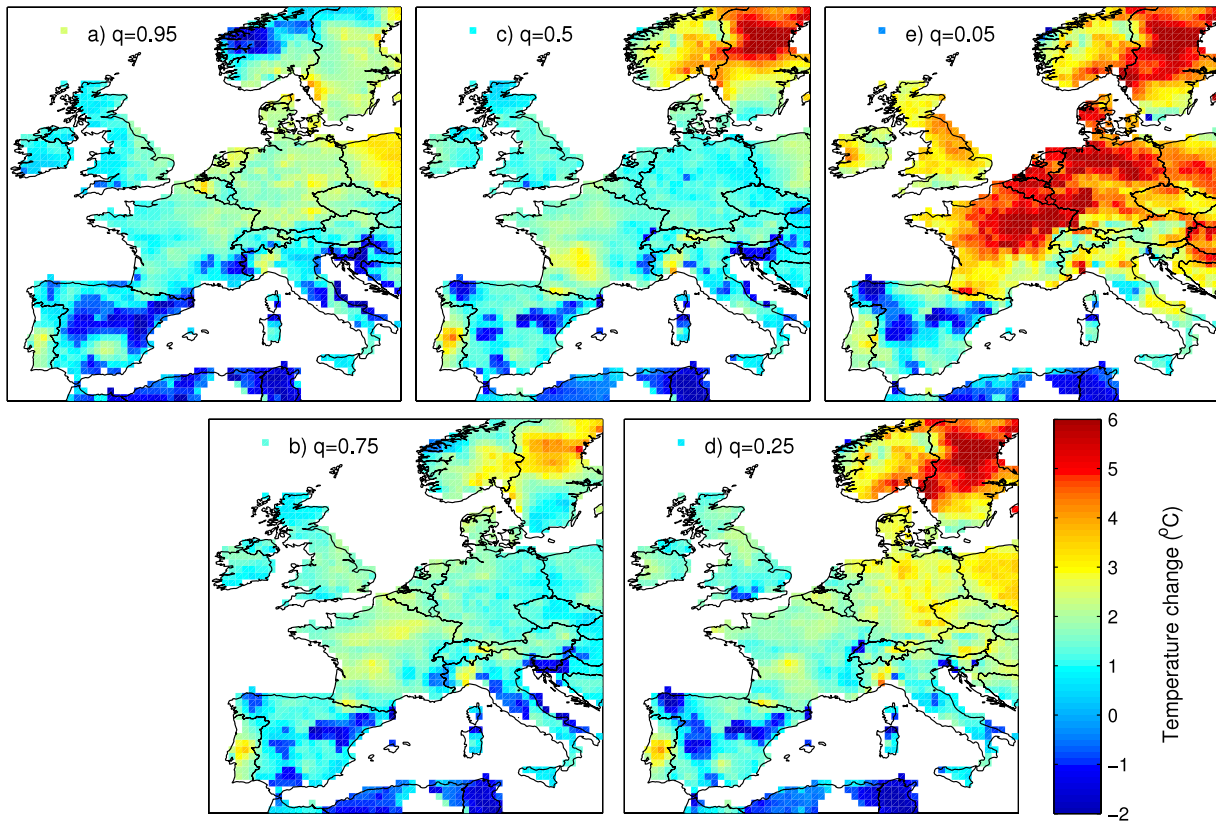
Previous work has demonstrated that timeseries of local temperatures are sufficiently long to identify a warming



**Figure 4.** As figure 3 but for largest change in temperature (largest  $\Delta T_q$ ). Note the different colour scale.



**Figure 5.** Maps of the smallest evaluated change in temperature (smallest  $\Delta T_q$ ) over the 1950–2011 period for nighttime winter temperatures at the following quantiles of the cumulative distribution function: (a)  $q = 0.95$ , (b)  $q = 0.75$ , (c)  $q = 0.50$ , (d)  $q = 0.25$ , and (e)  $q = 0.05$ .



**Figure 6.** As figure 5 but for largest change in temperature (largest  $\Delta T_q$ ). Note the different colour scale.

trend (van Oldenborgh *et al* 2009); this work uses them to provide a picture of changing local climate distributions of value to both policy makers and researchers. Given the relatively short timeseries and the large natural variations it is important to focus on aspects which are robust in the record. Thus changes are highlighted only when they are consistently large, or small, when analysed over different periods, and only when a consistent message is seen across a region. In identifying locations/quantiles/variables with substantial changes, a conservative approach has been taken by presenting the smallest change found over the multiple periods analysed.

The analysis presented herein has used gridded observations. The approach could be applied to reanalysis datasets or directly to the underlying station data, both of which come with different underlying limitations. One might expect the large scale patterns to be similar to those presented herein but the sensitivity of the results to different ways of processing the observational data would be informative in the identification of robust local changes.

These results illustrate that at specific quantiles, local changes can be substantially more than four times greater than the global mean annual mean change. They are not well represented by the local mean change because the local distributions change shape in a manner which does not allow for a simple relationship between the mean and other quantiles. These are important points for policy negotiations based on the two degrees guardrail (Richardson *et al* 2009). The results demonstrate the complex pattern of changes

seen in recent European climate. They represent a key input to climate services and provide a yard stick against which scientists and users can evaluate model-derived data. For regional climate research they represent observations of climate change against which theories of global/local relationships can be assessed; a key step towards the provision of decision-relevant climate predictions on sub-continental scales.

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### Appendix A. Data processing

The E-OBS dataset (Haylock *et al* 2008) provides a timeseries of daily maximum and minimum temperatures ( $T_{\max}$ ,  $T_{\min}$ ) on a  $0.5^\circ \times 0.5^\circ$  grid over Europe from 1950 to 2011. E-OBS version 6.0 is used in this analysis. Taking data

only for the season under consideration (June/July/August for summer, December/January/February for winter), the cumulative distribution function (cdf),  $C$ , is constructed using  $\tau$  years of data centred on year  $t_1$ . A second cdf is constructed for some later period centred on  $t_2$  and changes evaluated in terms of both the changing quantile function for specific temperatures,  $\Delta C_T$  (figures 1(a) and 2), and changing quantiles ( $\Delta T_q$ ) for specific values of cumulative probability,  $q$  (figures 1(a) and 3–6).

In a stationary climate,  $C$  would be independent of  $t$ ; variations between time periods would be a consequence only of the finite sample size specified by  $\tau$ . Both  $\Delta C_T$  and  $\Delta T_q$  must be interpreted in the context of such natural variability. The impact of high frequency variations (inter- and intra-year) is explored by varying  $\tau$  (see the supplementary materials available at [stacks.iop.org/ERL/8/034031/mmedia](http://stacks.iop.org/ERL/8/034031/mmedia)). (See Chapman *et al* 2013 for an illustration using synthetic data built from mathematically defined distributions.) The impact of low frequency variations (decadal timescales) is evaluated by repeating the analysis  $n$  times while maintaining the same value of  $\Delta t (= t_2 - t_1)$  i.e. multiple evaluations of the change over time windows of equal length but with different start and end dates.

Given the limited length timeseries available a balance must be struck between  $n$ ,  $\tau$  and  $\Delta t$ . Each should be as large as possible in order to (respectively): (i) evaluate the impact of low frequency natural variability, (ii) maximize the resolution of the cdfs and thus minimize the uncertainty resulting from high frequency variability, and (iii) maximize the signal/noise of any long term changes. We use  $n = 10$ ,  $\tau = 9$  and  $\Delta t = 43$ . With  $\tau = 9$ , the cdfs consist of  $>800$  values. The results are robust to higher and lower values of  $\tau$ —see supplementary figures S9–S16 (available at [stacks.iop.org/ERL/8/034031/mmedia](http://stacks.iop.org/ERL/8/034031/mmedia)).

$\Delta C_T$  is extracted directly from the cdfs.  $\Delta T_q$  is calculated using the method of Chapman *et al* (2013).

## Appendix B. Smallest/largest changes

The exceedance probability for temperature  $T$  is  $(1 - C_T)$  and thus a change in exceedance probability is simply  $-\Delta C_T$ . In figure 2 (figures 3 and 5) each grid box is calculated independently and shows the value of  $-\Delta C_T$  ( $\Delta T_q$ ) for the cdf pair where  $|\Delta C_T|$  ( $|\Delta T_q|$ ) is a minimum i.e. the ‘signed equivalent’ of the minimum absolute value of the change in exceedance probability across all ten sample pairs. This is termed the ‘smallest change’. Figures 4 and 6 contain maps of the signed equivalent of the maximum absolute change—termed ‘the largest change’.

## References

- Alexander L V *et al* 2006 Global observed changes in daily climate extremes of temperature and precipitation *J. Geophys. Res.—Atmos.* **111** D05109
- Carpenter T M, Sperflage J A, Georgakakos K P, Sweeney T and Fread DL 1999 National threshold runoff estimation utilizing GIS in support of operational flash flood warning systems *J. Hydrol.* **224** 21–44
- Challinor A J and Wheeler T R 2008 Crop yield reduction in the tropics under climate change: processes and uncertainties *Agric. Forest Meteorol.* **148** 343–56
- Chambers D P, Merrifield M A and Nerem R S 2012 Is there a 60-year oscillation in global mean sea level? *Geophys. Res. Lett.* **39** L18607
- Chapman S C, Stainforth D A and Watkins N W 2013 On estimating local long term climate trends *Phil. Trans. R. Soc. A* **371** 20120287
- CIBSE 2005 *TM36 Climate Change and the Indoor Environment: Impacts and Adaptation* (London: CIBSE)
- CIBSE 2006 *Guide A: Environmental Design* (London: CIBSE)
- DEFRA 2012 *The UK Climate Change Risk Assessment 2012 Evidence Report* (London: DEFRA)
- Hansen J, Sato M and Ruedy R 2012 Perception of climate change *Proc. Natl Acad. Sci. USA* **109** E2415–23
- Haylock M R, Hofstra N, Tank A, Klok E J, Jones P D and New M 2008 A European daily high-resolution gridded data set of surface temperature and precipitation for 1950–2006 *J. Geophys. Res.—Atmos.* **113** D20119
- Hitchin E R, Holmes M J, Hutt B C, Irving S and Nevrala D 1983 The CIBS example weather year *Build. Serv. Eng. Res. Technol.* **4** 119–24
- Hofstra N, Haylock M, New M and Jones P D 2009 Testing E-OBS European high-resolution gridded data set of daily precipitation and surface temperature *J. Geophys. Res.—Atmos.* **114** D21101
- Hofstra N, New M and McSweeney C 2010 The influence of interpolation and station network density on the distributions and trends of climate variables in gridded daily data *Clim. Dyn.* **35** 841–58
- Hsiang S M 2010 Temperatures and cyclones strongly associated with economic production in the Caribbean and Central America *Proc. Natl Acad. Sci. USA* **107** 15367–72
- IPCC 2007a *Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change* (Cambridge: Cambridge University Press)
- IPCC 2007b *Climate Change 2007: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change* (Cambridge: Cambridge University Press)
- IPCC 2012 *Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation. A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change* (Cambridge: Cambridge University Press)
- Jones P D, Kilsby C G, Harpham C, Glenis V and Burton A 2009 *UK Climate Projections Science Report: Projections of Future Daily Climate for the UK from the Weather Generator* (Newcastle upon Tyne: University of Newcastle)
- Lobell D B and Burke M B 2008 Why are agricultural impacts of climate change so uncertain? The importance of temperature relative to precipitation *Environ. Res. Lett.* **3** 034007
- Mills E 2005 Insurance in a climate of change *Science* **309** 1040–4
- Milly P C D, Betancourt J, Falkenmark M, Hirsch R M, Kundzewicz Z W, Lettenmaier D P and Stouffer R J 2008 Stationarity is dead: whither water management? *Science* **319** 573–4
- Min E, Hazeleger W, van Oldenborgh G J and Sterl A 2013 Evaluation of trends in high temperature extremes in north-western Europe in regional climate models *Environ. Res. Lett.* **8** 014011
- Moen J and Fredman P 2007 Effects of climate change on Alpine skiing in Sweden *J. Sustain. Tourism* **15** 418–37
- Parker D E, Legg T P and Folland C K 1992 A new daily central England temperature series, 1772–1991 *Int. J. Climatol.* **12** 317–42
- Porter J R and Semenov M A 2005 Crop responses to climatic variation *Phil. Trans. R. Soc. B* **360** 2021–35



- Reich B J 2012 Spatiotemporal quantile regression for detecting distributional changes in environmental processes *J. R. Stat. Soc. C* **61** 535–53
- Richardson K *et al* 2009 *Climate Change: Global Risks, Challenges and Decisions—Synthesis Report* (Cambridge: Cambridge University Press)
- Schlesinger M E and Ramankutty N 1994 An oscillation in the global climate system of period 65–70 years *Nature* **367** 723–6
- Simolo C, Brunetti M, Maugeri M, Nanni T and Speranza A 2010 Understanding climate change-induced variations in daily temperature distributions over Italy *J. Geophys. Res.—Atmos.* **115** D22110
- Stainforth D A, Allen M R, Tredger E R and Smith L A 2007 Confidence, uncertainty and decision-support relevance in climate predictions *Phil. Trans. R. Soc. A* **365** 2145–61
- Stott P A 2003 Attribution of regional-scale temperature changes to anthropogenic and natural causes *Geophys. Res. Lett.* **30** 1728
- van Oldenborgh G J, Drijfhout S, van Ulden A, Haarsma R, Sterl A, Severijns C, Hazeleger W and Dijkstra H 2009 Western Europe is warming much faster than expected *Clim. Past* **5** 1–12
- Vinnikov K Y, Robock A and Basist A 2002 Diurnal and seasonal cycles of trends of surface air temperature *J. Geophys. Res.—Atmos.* **107** 4641
- WMO 2011 *Climate Knowledge for Action: A Global Framework for Climate Services—Empowering the Most Vulnerable* (Geneva: World Meteorological Organisation)
- Yatagai A, Kamiguchi K, Arakawa O, Hamada A, Yasutomi N and Kito A 2012 APHRODITE constructing a long-term daily gridded precipitation dataset for Asia based on a dense network of rain gauges *Bull. Am. Meteorol. Soc.* **93** 1401–15
- Zivin J G and Neidell M J 2010 *Temperature and the Allocation of Time: Implications for Climate Change* (Cambridge, MA: National Bureau of Economic Research)