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Aglaé Jézéquel, Pascal Yiou, Sabine Radanovics

Climate Dynamics manuscript No.
(will be inserted by the editor)

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Received: September 22, 2016/ Accepted:

Abstract The intensity of European heatwaves is connected to specific synoptic atmospheric circulation. Given the relatively small number of observations, estimates of the connection between the circulation and temperature require ad hoc statistical methods. This can be achieved through the use of analogue methods, which allow to determine a distribution of temperature conditioned to the circulation.
The computation of analogues depends on a few parameters. In this article, we evaluate the influence of the variable representing the circulation, the size of the domain of computation, the length of the dataset, and the number of analogues on the reconstituted temperature anomalies. We tested the sensitivity of the reconstitution of temperature to these parameters for four emblematic recent heat waves : June 2003, August 2003, July 2006 and July 2015. The paper provides general guidelines for the use of flow analogues to investigate European summer heat waves. We found that Z500 is better suited than SLP to simulate temperature anomalies, and that rather small domains lead to better reconstitutions. The dataset length has an important influence on the uncertainty. We conclude by a set of recommendations for an optimal use of analogues to probe European heatwaves.

Keywords Heatwaves, Europe, Atmospheric circulation

1 Introduction

There have been many studies showing that heatwaves are bound to become more intense and more frequent under climate change (Field and Intergovernmental Panel on Climate Change 2012). The evolution of the probabilities of those events and of their properties, such as intensity, duration and extent,

Aglaé Jézéquel
LSCE, CEA Saclay l'Orme des Merisiers, UMR 8212 CEA-CNRS-UVSQ, U Paris-Saclay, IPSL, Gif-sur-Yvette, France
Tel.: +33-169081142
Fax: +33-169087716
E-mail: aglae.jezequel@lsce.ipsl.fr

Pascal Yiou
LSCE, CEA Saclay l'Orme des Merisiers, UMR 8212 CEA-CNRS-UVSQ, U Paris-Saclay, IPSL, Gif-sur-Yvette, Franc

Sabine Radanovics
LSCE, CEA Saclay l'Orme des Merisiers, UMR 8212 CEA-CNRS-UVSQ, U Paris-Saclay, IPSL, Gif-sur-Yvette, Franc

is a key question for adaptation due to their impacts, including on crop yields (Ciais et al 2005) and human health (Peng et al 2011; Fouillet et al 2006). A first step is to understand the physical processes at play during heat waves, such as the influence of soil moisture (Seneviratne et al 2010), or SST (Feudale and Shukla 2007). Yiou and Nogaj (2004) studied the relation between the atmospheric circulation and extreme events over the North Atlantic and Horton et al (2015) linked the increase of heatwaves to the increase of the frequency of mainly anticyclonic weather types. In this paper, we aim at quantifying the role of the atmospheric circulation during spells of high temperatures, that occurred in major European heat waves. In particular, we want to understand which proportion of the heat wave intensities can be explained solely based on the associated atmospheric circulation, in an effort to disentangle its contribution compared to other factors (Shepherd 2015).

Our methodology is based on flow analogues (e.g. Yiou et al 2014). Historically, analogues were used in weather forecasting ((e.g. Lorenz 1969; Duband 1981; Toth 1991a; Chardon et al 2016; Ben Daoud et al 2016). They have been used in empirical downscaling (e.g. Chardon et al 2014; Zorita and von Storch 1999), circulation dependent bias correction (e.g. Turco et al 2011; Hamill and Whitaker 2006; Hamill et al 2015; Djalalova et al 2015), in combination with ensemble data assimilation (Tandeo et al 2015), in probabilistic wind energy potential estimation (Vanvyve et al 2015), and paleo climate reconstruction (Schenk and Zorita 2012; Gómez-Navarro et al 2014).

Here, they are defined as days with an atmospheric circulation similar to the day of interest, with the assumption that circulation is connected to a climate variable such as temperature. They allow us to isolate certain types of circulation and to measure their influence on the temperature. We then compare the probability density functions of temperature anomalies reconstructed for both randomly picked days and days picked among analogues. The analogues depend on many parameters, including the size of the domain of computation, or the length of the dataset. The goal of this paper is to provide general guidelines to choose those parameters to get flow analogues adapted to the study of European summer heatwaves. Those guidelines are obtained from four emblematic cases of heatwaves. A former study of Toth (1991b) focused on the distance to minimize for obtaining analogues. Van Den Dool (2007) provided tests of predictability based on analogues. Our paper includes physical parameters on which the analogues are computed, and focuses on temperature reconstructions.

Section 2 details the methodology used in this study. Section 3 tests the sensitivity of several physical and statistical parameters on which the methodology is based. A part of this section is devoted to a qualitative evalutation of the uncertainty related to the limited size of the datasets. Section 4 focuses on the role played by the circulation in each of the chosen case studies. The results are discussed in Section 5 and conclusions appear in Section 6.

2 Methodology

2.1 Heat wave selection

We focus on summer heat waves, knowing that the processes involved in the development of a heat wave vary from one season to the other. We focus on warm months (June–July–August: JJA). We chose heatwaves that stroke Europe since 2000: June and August 2003 (e.g. Beniston and Diaz 2004; Fischer

et al 2007; Cassou et al 2005; Stéfanon et al 2012) in Western Europe (WE), July 2006 (Rebetez et al 2009) in Northern Europe (NE), and July 2015 (Russo et al 2015) in Southern Europe (SE). We use the NCEP reanalysis I dataset (Kalnay et al 1996), which provides us with 68 years of data from 1948 to 2016. The advantage of this dataset is that it is updated near real time (with a three days delay), so that the methodology could give results already a few days after a given event. Longer datasets like ERA20C (Poli et al 2016) or the NCEP 20th Century Reanalysis (Compo et al 2011) are less frequently updated or do not include 2015, and were therefore not retained.

The peak temperatures occurred in different regions for each heatwave. These regions correspond to the black boxes in figure 1. They are centered on the region of highest temperature anomaly. The size of the boxes was defined such that the monthly temperature anomalies averaged over them are records (see figure 2). Hence we identify two heatwaves in 2003, in June and August, which is consistent with (Stéfanon et al 2012). Choosing a slightly larger box does not alter the results or the methodology.

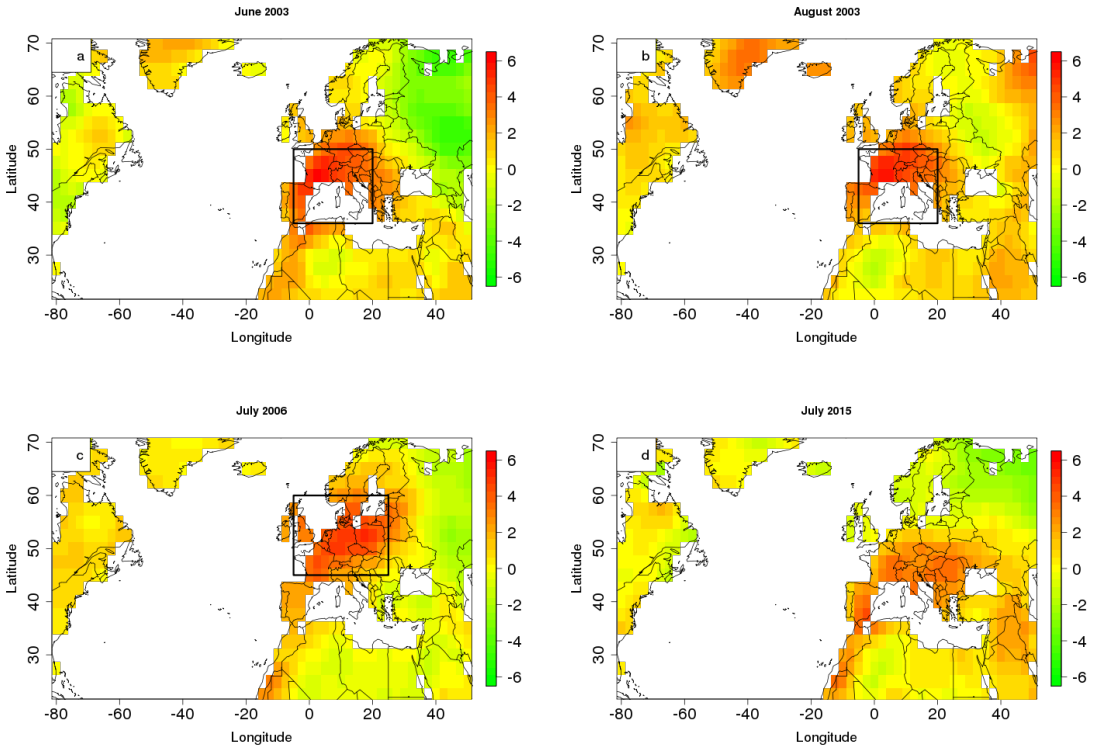

Fig. 1: Monthly mean land temperature anomalies (NCEP dataset with reference to the 1948-2015 mean) for the four case studies (in C). The black rectangles indicate the regions of interest for the rest of the study.

We observe a significant linear trend ($p - value < 0.05$), related to climate change, for each month and region studied (red lines in figure 2): 0.23 C per decade for June (WE), 0.24 C for July (NE and SE) and 0.25 C for August(WE). For the rest of the study we calculate detrended temperatures using a non-linear trend, calculated with a cubic smoothing spline (green lines in figure 2). The reason is to extract the role of circulation in high temperature extremes, regardless of the state of the background climate, the evolution of which is non-linear.

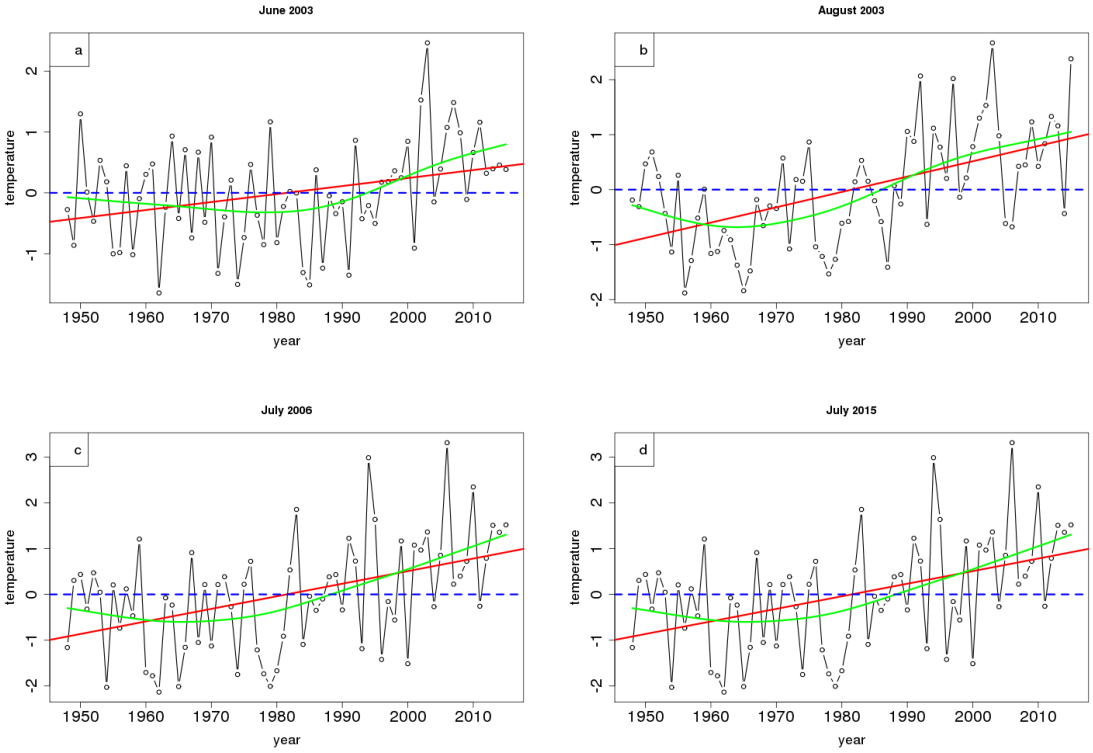

Fig. 2: Evolution of the monthly temperature anomalies averaged over the regions defined in figure 1. The red line corresponds to the linear trend, which is significant ($p - value < 0.05$). The green line corresponds to a non linear trend calculated with a cubic smoothing spline.

2.2 Flow analogues

We used flow analogues to extract the contribution of circulation dynamics to the chosen heat wave events comparing their temperature anomalies to those of analogues. Analogues were defined as the N days with the most similar sea level pressure (SLP) or geopotential height at 500 hPa (Z500) fields. The

similarity was measured with the Euclidean distance between two maps (Yiou 2014). We only considered the days within a 61 calendar days (30 days before and 30 days after) window centered on the day of interest because of the seasonal cycle of both circulation and temperature (Yiou et al 2012). We further exclude the days coming from the same year as the event from the 1948–2015 data set, because of the persistence of the circulation. The program used to compute analogues CASTf90 is available online (`https://a2c2.lsce.ipsl.fr/index.php/licences/file/castf90?id=3`). Once the analogues were selected, we took the observable of interest (the detrended temperature) on those selected days. The whole process is summarized in figure 3.

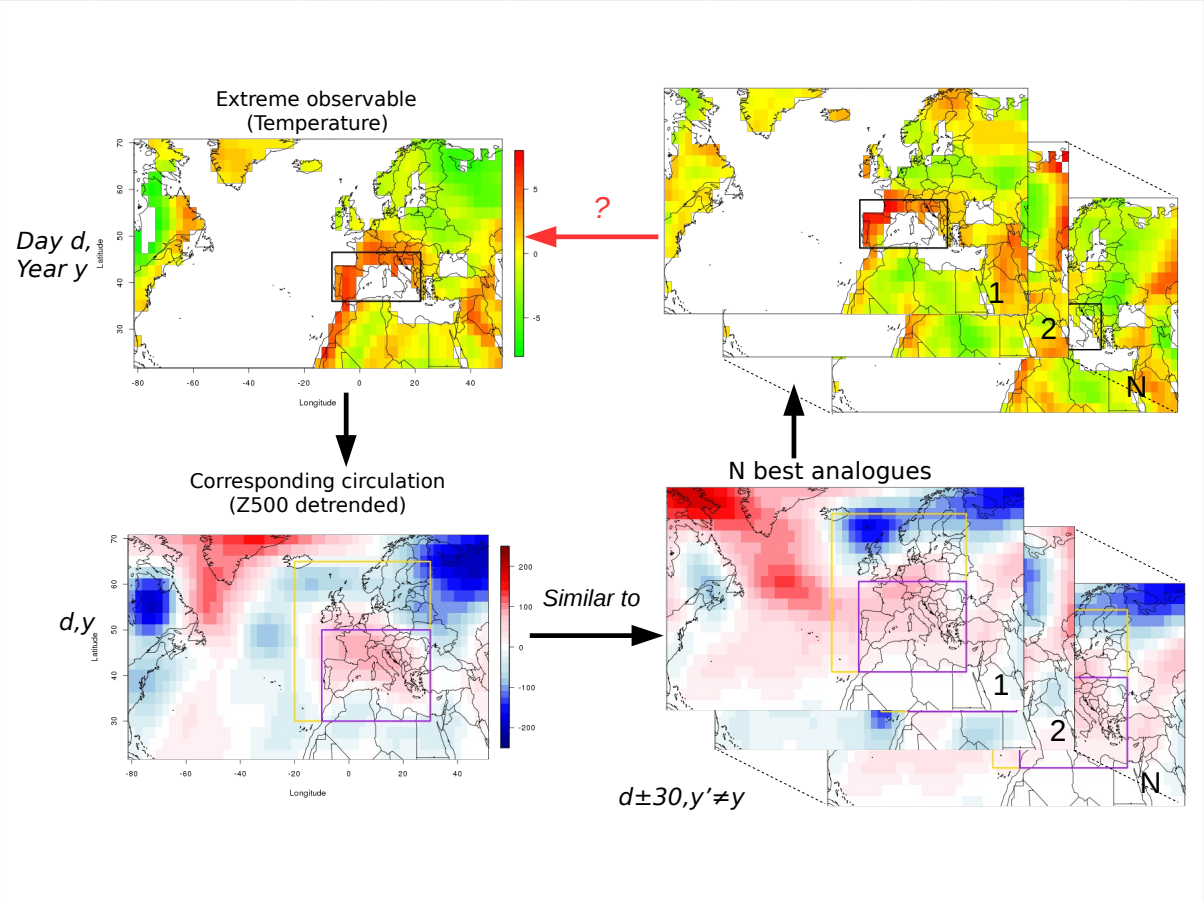

Fig. 3: A day with an extreme temperature (map on the top left) has a corresponding circulation, represented by the geopotential at 500 hPa (map on the bottom left). Flow analogues are days within the database which have a similar circulation to the day of interest (maps on the bottom right). The temperatures of the analogues (maps on the top right) are then compared to the temperature of the day of interest (map on the top left).

Days of the event	Corresponding analogues	Randomly picked analogue
01/07/2015	ana_1^1,ana_1^2,...,ana_1^N	ana_1^i
02/07/2015	ana_2^1,ana_2^2,...,ana_2^N	ana_2^i
⋮	⋮	⋮
31/07/2015	ana_{31}^1,ana_{31}^2,...,ana_{31}^N	ana_{31}^i

Table 1: Simulation of uchronic months using randomly picked analogues for July 2015.

2.3 Reconstruction of temperature distributions

The goal is to reconstruct the probability distribution of temperature conditional to the atmospheric circulation. For this, we consider a day i, with a temperature T_i and a circulation C_i with N analogues $C_i^1 \ldots, C_i^N$. The circulation analogues $\text{ana}_i^1 \ldots \text{ana}_i^N$ provide N copies of the temperature. Hence, for each day, we can randomly pick one of the N best analogues, in order to recreate a sequence of temperatures over a month. Its resulting mean temperature will be called *uchronic*, because it is a temperature that might have been for a given circulation pattern sequence. By reiterating this process, we recreate probability distributions of uchronic monthly detrended temperature conditional to the atmospheric circulation. We then compare this distribution to a distribution built from random days instead of analogues. In the rest of the article, we set the number of random iterations to 1000. This procedure is a simplified version of the stochastic weather generator of Yiou (2014), who also used weights based on the distances of the analogues. Table 1 illustrates this process for the July 2015 case.

In order to measure the contribution of the circulation we compared the distribution of uchronic temperature anomalies with a control distribution built using random days. However, the variability of random summers built that way is not realistic because the dependence between consecutive days is not accounted for. Analogues are by construction dependent from one another, because they are calculated using maps from following (hence correlated) days. Randomly picked days are independent.

In order to create a more realistic distribution of temperature using random days, we also calculated means by using only one out of M days. M is an assessment of the persistence of the circulation. We computed the autocorrelation of the detrended Z500 NCEP dataset for summer months (JJA) on each of the four small domains, for each grid points, with lags from 1 to 20 days (similar to Yiou et al (2014)). For more than 10 days, the autocorrelations median tends to an asymptotic value of approximately 0.1. For three days, the median of the autocorrelation distribution is of approximately 0.65. For four days, it decreases to 0.45. Since the regions are small, the number of degrees of freedom is small too, which means that an autocorrelation of 0.45 is negligible. We hence arbitrarily decided to set M=3. This is probably an underestimation for events alike the ones studied here with a long-lasting blocking situation.

3 Parameter sensitivity tests

The presented method depends on a few parameters. Their choice has an influence on both the results and their robustness. The following section explores the role of those parameters and how tuning them may give us further information on the relationship between circulation patterns and extreme temperature. We also want to know whether those parameters should depend on the specific event or not. This

133 determines how general the approach can be and therefore its potential application to future events and
134 other extra-tropical regions. In particular, we studied the role played by physical parameters: the variable
135 on which we compute analogues (SLP vs. Z500), the choice of the size of the domain on which we compute
136 analogues, and the length of the dataset, and a statistical parameter: the number N of analogues we kept.
137

138 ## 3.1 Variable representing the circulation

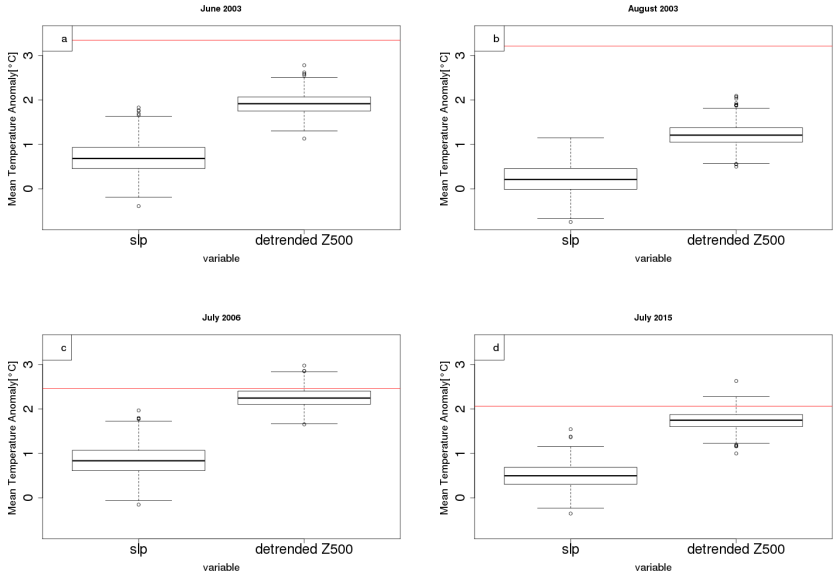

Fig. 4: Dependence of the probability density on the variable representing circulation. Difference between analogues generated distributions calculated using SLP (left boxplot of each subfigure) or detrended geopotential height at 500 hPa (right boxplot of each subfigure) for each case study: June 2003 (a), August 2003 (b), July 2007 (c), July 2015 (d). The red line represents the observed detrended temperature anomaly of the event.

139 SLP (e.g. Cassou and Cattiaux 2016; Sutton and Hodson 2005; Della-Marta et al 2007) and Z500 (e.g.
140 Horton et al 2015; Quesada et al 2012; Dole et al 2011) are the most commonly used variables to study
141 the atmospheric circulation. We calculated analogues using either the SLP or the detrended Z500. The
142 detrending was needed due to the dependence of Z500 on lower tropospheric temperatures, which are
143 increasing due to anthropogenic climate change. The detrending was done for the mean field using a
144 nonlinear trend. The resulting uchronic temperature anomalies for each event are shown in figure 4.
145 The analogues computed using Z500 give results closer to the actual anomaly of the event than those
146 computed using SLP. This is probably related to the heat low process (e.g. Portela and Castro 1996).
147 Warm anomalies of surface temperature lead to convection. The elevation of warm air masses creates a

local depression, which adds on top of an anticyclonic anomaly a cyclonic anomaly. This flattens the SLP patterns and blurs the signal, which does not happen with Z500. By using Z500 we also avoid any influence of the relief. Hence, we keep the detrended Z500 to compute the analogues for the rest of the study.

3.2 Size of the domain

The scale on which we compare circulation patterns plays a key role in the computation of the analogues. If the domain is too large, the system becomes too complicated, with too many degrees of freedom. The analogues could consequently only extract a low frequency signal, like the seasonal cycle. Van den Dool (1994) evaluates that it would take 10^{30} years of data to find two matching observed flows for analogues computed over the Northern Hemisphere. If we choose too small a domain, then we cannot study the role of the synoptic circulation. So, on the one hand, it is no use to calculate analogues on whole hemispheres, and on the other hand, we do not want to select domains which are smaller than the typical scale of extra-tropical cyclones (1000 km approximately). Radanovics et al (2013) investigated automatic algorithms to adjust the domain size of the analogues for precipitation. Here, we prefer to select a domain that yields an a priori physical relevance to account for the most important features of the flow that affects high temperatures in Europe.

The ideal size of the domain reveals the scale at which the processes are relevant and may very well vary from one event to the other. This especially applies for studies on other types of events such as heavy precipitation, droughts or storms. We compared three different domains shown in figure 5 (right hand side):

- a large domain (the whole maps in figure 5), including the North Atlantic region, which corresponds to the domain usually used to calculate weather regimes (Vautard 1990; Michelangeli et al 1995),
- a medium domain (the golden rectangles in figure 5), centered on Europe, which is much smaller than the North Atlantic domain while being common to all events, and
- a small domain tailored for each event (the purple rectangles in figure 5), depending on the circulation pattern of the specific summer .

The results are displayed on the left hand side of figure 5. The event of interest, shown by the red lines, is better reproduced for the smaller domains. This is because there are circulation patterns included in the North Atlantic domain which probably play no role in the establishment of a heat wave over Europe. For example in July 2015 we observe an important anticyclonic anomaly over Greenland. It adds a constraint on the analogues while supposedly playing no role on the lesser anticyclonic anomaly over the Northern Mediterranean region. The standard deviation also decreases with the size of the domain.

It is relevant to rely on standard domains for a first estimation of the role played by the circulation in the occurrence of a heat wave, for example by using the regions defined in Field and Intergovernmental Panel on Climate Change (2012). However, for a finer analysis focused on one specific heatwave, or a few given events, the choice of a tailored small domain will give better results. In the rest of the study, we hence kept the smaller domains.

3.3 Length of the dataset

The NCEP dataset contains 68 years. Although the recombination of analogues allows to recreate new events, the dataset is finite and hence does not cover the whole range of possible events. For example, if the circulation leading to a heat wave has a return period of more than the dataset length, there might not be the like of it in the dataset. Furthermore, even if there are close daily analogues to the daily circulation of the event, it might not account for other thermodynamical processes that may or may not happen simultaneously and lead to extreme temperatures. This shortcoming is called sampling uncertainty (Committee on Extreme Weather Events and Climate Change Attribution 2016, Chap. 3), related to the fact that the past is one occurrence of many realizations which could have happened for a given state of the climate.

In order to get an order of magnitude of that uncertainty in the reconstruction of probability densities of temperature we used a 500 years long pre-industrial run from CMIP5 (Taylor et al 2012). The model used is GFDL-ESM2M (Dunne et al 2012, 2013). We chose this model because it was the model available on the IPSL data center with the longest run for both the temperature and the Z500. We selected one heat wave similar to July 2015, both in terms of temperature anomaly (compared to the detrended anomaly of July 2015) and circulation patterns (see figure 6). We assume that the internal variability of the model is similar to the internal variability of the reanalysis.

Analogues were computed for 60 different subsets of the 500 year dataset. The lengths of the subsets are 33, 68, 100 and 200 years (e.g. subsets of 68 consecutive years each, starting every 5 years of the data set). We then compared the means of reconstructed distributions to one another for a given subset length. The difference between the maximum and minimun means calculated this way gives an estimation of the uncertainty related to the limited length of the dataset.

Figure 7 displays the results for subsets of 33, 68, 100 and 200 years. When the number of years of the subset decreases, the variability increases, going up to approximately 0.71 C for the 33 years subsets, 0.62 C for 68 years, 0.36 C for 100 years, and 0.14 C for 200 years. This information is precious to determine in which measure smaller datasets are relevant for this methodology. It also proves that dividing the NCEP dataset in two smaller periods of 33 years is not enough to attribute the difference between the two to climate change, rather than to natural variability. Indeed, the internal variability between the two periods would be of the same order of magnitude than the difference caused by climate change.

The ability to find analogues close to the circulation of interest is related to both the size of the dataset and the size of the domain on which the analogues are computed (Van den Dool 1994). It means that the analogues method will get more and more accurate as the reanalysis dataset extends in the years to come.

3.4 Number of analogues

For the reconstruction of events by recombination of analogues, we kept the N best analogues. The choice of N has an influence on both the reconstructed anomalies of temperature and the statistical robustness of the study. The best analogues temperature anomalies are closer to the temperature anomalies of the actual events for all case studies (see figure 8). We need to find a trade-off between having the best ana-

Event	Observed detrended temperature	Mean detrended uchronic temperature
06/2003	3.3 C	1.9 C
08/2003	3.2 C	1.2 C
07/2006	2.5 C	2.3 C
07/2015	2.1 C	1.7 C

Table 2: Observed detrended temperature compared to the mean detrended uchronic temperature for each case study.

logues which give results closer to both the observed circulation and temperature anomaly, and having enough analogues to create a robust distribution. The difference of temperature mean between keeping 5 and 30 analogues is of less than 0.2 C, so the sensitivity on this parameter is rather low. We kept 20 analogues for the rest of the study.

4 The role of circulation in heat waves

With the parameters kept (Z500, small domains, 68 years reanalysis data, and 20 analogues) we simulated 1000 uchronic monthly mean temperature anomalies for each of the four selected heatwave events (see the analogues boxplots in figure 9). The circulation contribution corresponds to the mean of the uchronic temperature distribution. The spread of the boxplots is due to the range of other processes which can, for a given circulation, lead to different temperatures. The control boxplots correspond to randomly picked days. The control with dependence boxplots correspond to randomly picked days using only one out of three days. The circulation during heat waves corresponds to a long-lasting blocking situation, hence the persistence is probably more than three days. This underestimation, combined with the limited length of the dataset explains why the studied events are all outside of the distribution calculated using random days.

For every events, the circulation plays a significant role in the occurrence of the extreme. It only explains a part of it, more or less significant depending on the event. Indeed, it explains 38% of the anomaly for August 2003, 57% for June 2003, 81% for July 2015 and 92% for July 2006 (see table 2). The standard deviation of the analogues distribution is also systematically lower than both the random ones, and approximately a third of the one taking into account the persistence of the circulation. Using this approach is equivalent to zooming on a specific part of the distribution conditioned to the flow.

In order to contextualize the four case studies, we reproduced the same kind of probability density function experiments for the same regions from 1948 to 2015 (figure 10). This type of recontextualisation can be interpreted as an estimation of how extreme an event really is, as regards to its atmospheric circulation.

The observed month falls between the tenth and ninetieth percentiles of the analogues distribution for more than half of the years and between the first and ninety-ninth percentiles for more than two thirds of the years, even though the analogue distribution has a small spread compared to the total distribution. The years out of the 98% interval correspond mostly to important anomalies of temperature (absolute value > 0.5 C). Less than a quarter of the years have different signs of anomaly between the real event and the mean of the analogue distribution. Those years correspond to small anomalies of temperature

(absolute value $< 0.5\,\mathrm{C}$).

5 Discussion

The median of the uchronic distribution is generally different from the observed temperature. In some cases, the observed anomaly (red line on figure 9) is not even in the uchronic distribution. On figure 9 for June and August 2003, and for some of the years on figure 10, this is the case (indeed, the monthly detrended anomaly for both months are of more than $3\,\mathrm{C}$). This difference shows caveats in the methodology, and that heatwave events cannot be explained only by its circulation.

Flow analogues are unable to take into account the role played by the soil-moisture feedback. Indeed, the analogues do not take into account the history of the heat wave. Extreme heat waves happen when the circulation causing the initial anomaly of temperature lasts more than a few days. As soil moisture becomes limited, the cooling of the atmosphere through evapotranspiration gets weaker, which exercises a positive feedback on the temperature. Seneviratne et al (2010) isolates a dry and a wet regime, with a transition phase between both. The three regions used here are prone to different evaporative regimes. In particular, the Northern Europe region is wetter than the other two. The role of soil moisture is thus less important (Seneviratne et al 2006). On the other hand, several articles (Stéfanon et al 2012; Fischer et al 2007) showed the role of soil moisture in the exceptional temperature anomalies of summer 2003, especially for August. The analogues are picked without any condition on the previous days, and consequently they fail to reach the observed anomaly.

The main caveat of this methodology is the limited size of the dataset, which introduces an important sampling uncertainty, as seen in section 3.3, and also affects the quality of the analogues. As a result, the analogues might not be good enough to accurately reproduce the dynamical contribution. Indeed, an extreme temperature can be related to a rare circulation, which might not be found in a short dataset. The distances between the analogues and the event, as well as their correlations, are indices to evaluate the relevance of the analogues in each case. A better definition of what is a good analogue will require further studies. Depending on the magnitude of the studied event, it might not be possible to reconstruct a comparable month by resampling the days in the dataset. This is the case for both June and August 2003, which have temperature anomalies about one degree Celsius above all the other years, despite the detrending. If the event is too rare, it will not be possible to reconstitute uchronic temperature close to the observed one.

Another limitation relates to the coherence of the uchronic summers computed using analogues. Due to the persistence of the circulation, the analogues we picked for each day might be correlated to one another. In fact, when we compare the analogues sample of 20 times the number of days of the month we want to study, only half of the analogues are unique. However, the persistence is still underestimated compared to real summers. Consequently, the spread of the computed distributions is underestimated.

6 Conclusion

This paper proposes to quantify the role of the atmospheric circulation in the occurrence of an extreme monthly anomaly of temperature. The strength of our methodology is that it is easily adaptable to other regions, and to other events. The parameter sensitivity tests of section three provide general guidelines to choose flow analogues to investigate European summer heatwaves. It is best to use detrended Z500 as a proxy of circulation, and to compile the analogues on a small domain centered on the Z500 anomaly concomitant to the event. We also advise to use as long a dataset as possible.

The results on parameter sensitivities have potential implications for applications of the analogue method in a downscaling or reconstruction context as well. The questions of the predictor variable (or variables), that is the circulation proxy, is relevant in the downscaling context but may vary depending on the predictand variable. The question of domain size has been treated by several authors (e.g. Chardon et al 2014; Radanovics et al 2013; Beck et al 2015) and the results are systematically in favor of relatively small domains, in line with our findings. Tests on archive lengths larger than typical reanalysis record lengths are rarely performed. The results are relevant since split-sample validation of downscaling methods is common practice and our results show that splitting the limited length reanalysis record leads to large uncertainties in the uchronic temperatures due to the limited sample size even using a relatively small domain.

The reconstitution of an ensemble of uchronic temperatures for a given circulation is a first step in refining Cattiaux et al (2010)'s approach to extreme event attribution. Indeed, looking at changes for a given circulation should reduce the signal to noise ratio of climate change versus natural variability (Trenberth et al 2015) in what Shepherd (2016) calls a storyline approach to extreme events attribution. Since among the tested parameters only the regions of the temperature anomaly and the geopotential height field depend on the event, a diagnosis on heat waves can be automatized and computed in less than a day once the data set is available. This should allow to use the presented method in an operational way for example for conditional fast-track attribution of extreme events (Haustein et al 2016).

7 Acknowledgment

NCEP Reanalysis data provided by the NOAA/OAR/ESRL PSD, Boulder, Colorado, USA, from their Web site at `http://www.esrl.noaa.gov/psd/`.
Program to compute analogues available online `https://a2c2.lsce.ipsl.fr/index.php/licences/file/castf90?id=3`. PY and SR are supported by the ERC Grant A2C2 (No. 338965).

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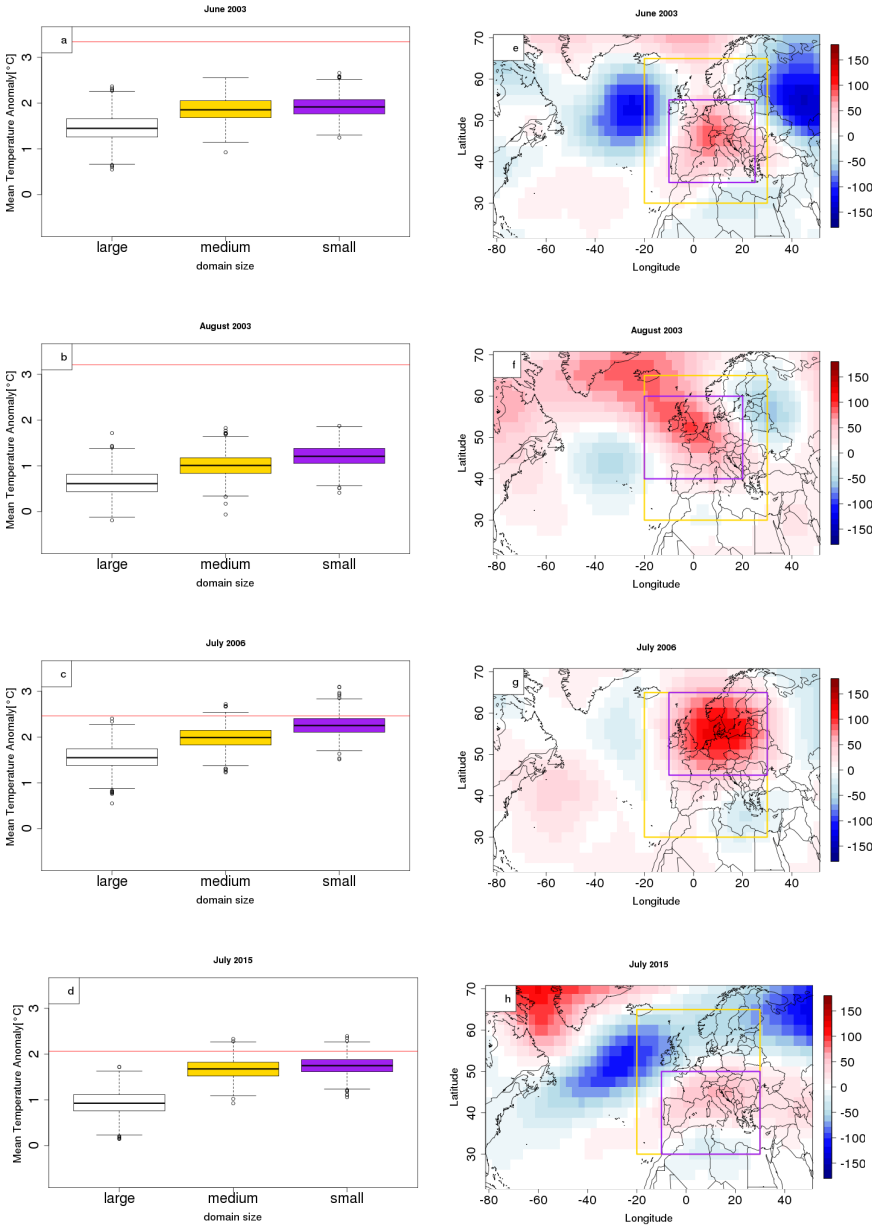

Fig. 5: Dependence of the probability density of uchronic temperature anomalies on the size of the domain. The maps on the right column represent the detrended Z500 monthly anomaly (m). The purple rectangles indicate the smallest zones of computation of flow analogues. The golden rectangles indicate the medium zone of computation of flow analogues. The large zone is the whole map. The boxplots of the left column display the distribution of the 1000 uchronic monthly detrented temperature constituted from randomly picked analogues. The color of the boxplot corresponds to the color of the rectangle delineating the region on which the analogues are computed. The red lines on the left hand side of the figure represent the observed detrended temperature of the case studies, from top to bottom : June 2003, August 2003, July 2006, July 2015.

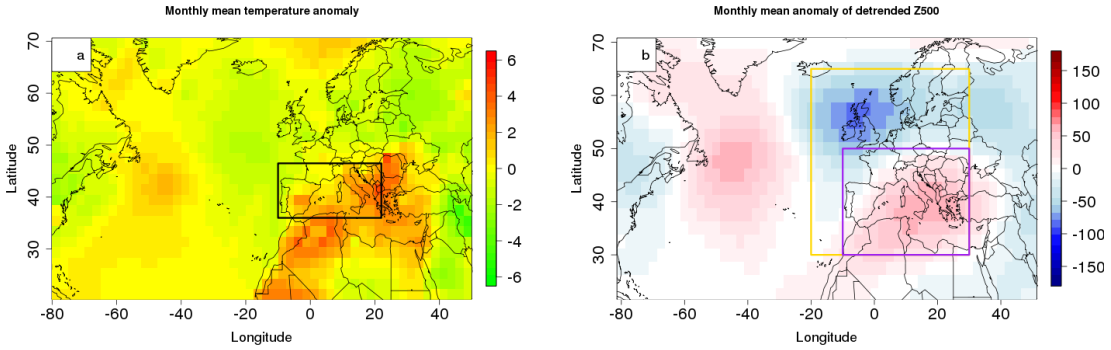

Fig. 6: Temperature anomaly (a) and Z500 anomaly (m) (b) of a July month from GFDL-ESM2M CMIP5 pre-industrial control run similar to July 2015.

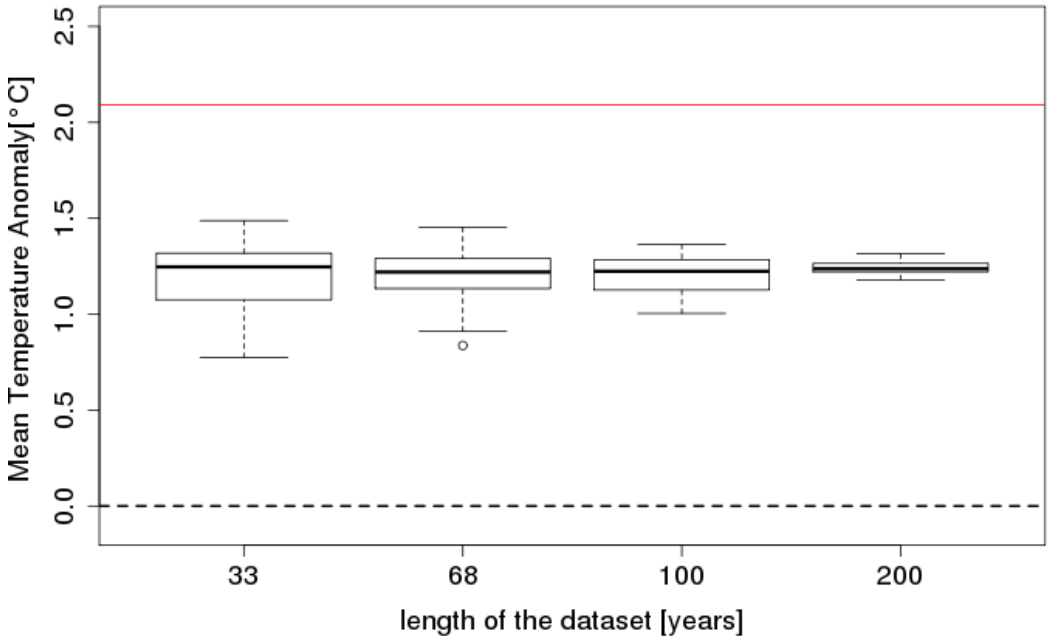

Fig. 7: Sensitivity to interdecadal variability depending on the length of the dataset. Distributions of the mean temperature of analogues generated distributions of temperature for 60 different subsets of varying sizes (33, 68, 100, or 200 years) from a 500 years long pre-industrial control run (model GFDL-ESM2M) for the small domain of analogues computation.

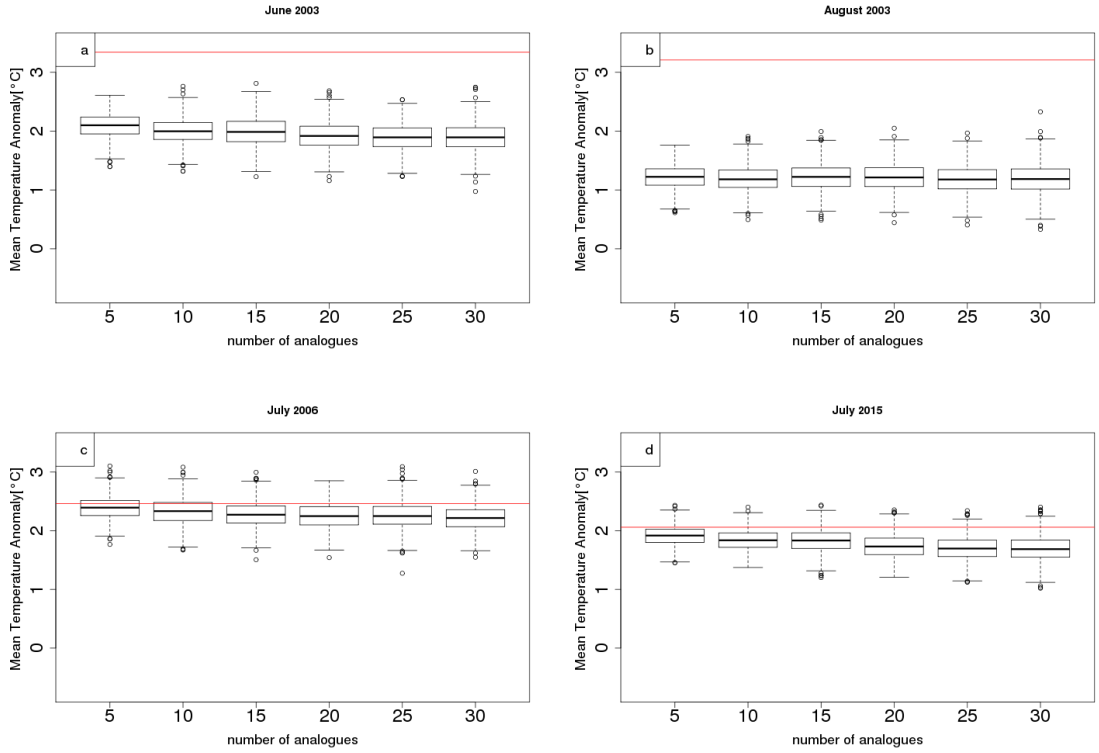

Fig. 8: Dependence of the probability density to the number of analogues. Difference between analogues generated distributions calculated using different numbers of analogues for each case study: June 2003 (a), August 2003 (b), July 2007 (c), July 2015 (d). The red line represents the observed detrended anomaly of the event.

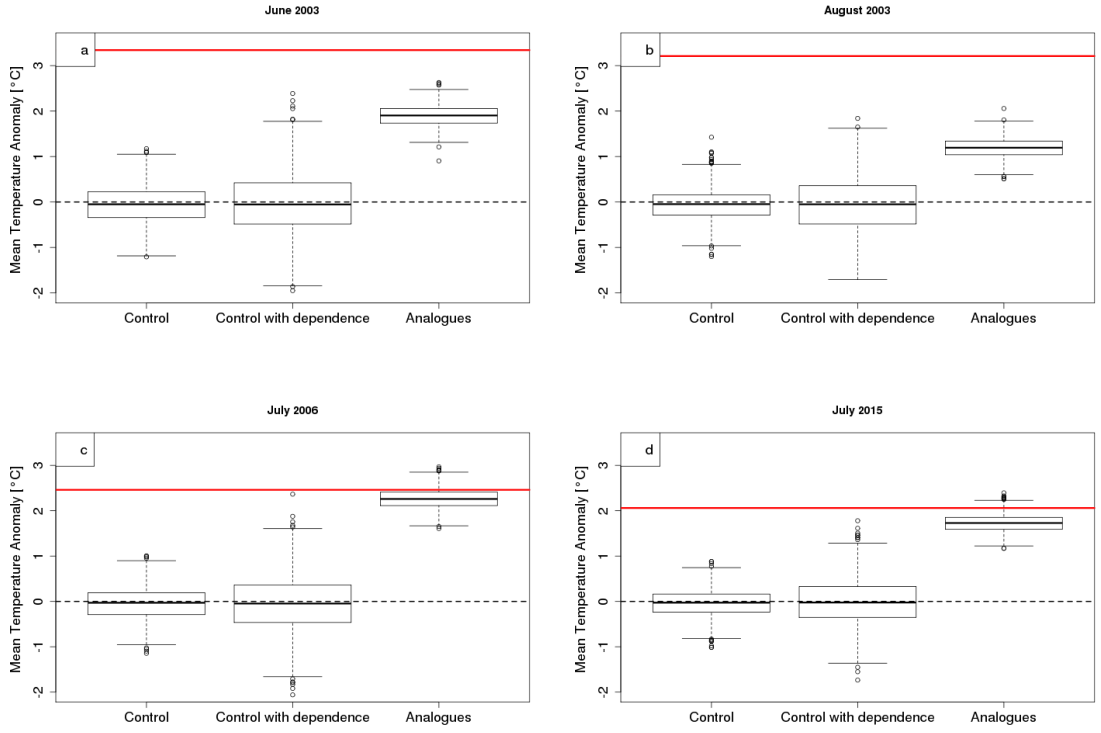

Fig. 9: Probability distributions of detrended monthly temperatures reconstructed using random days (left boxplot of each subfigure), random days picked every three days (middle boxplot of each subfigure) and analogues (right boxplot of each subfigure) for each case study: June 2003 (a), August 2003 (b), July 2007 (c), July 2015 (d). The red line represents the observed detrended anomaly of the event.

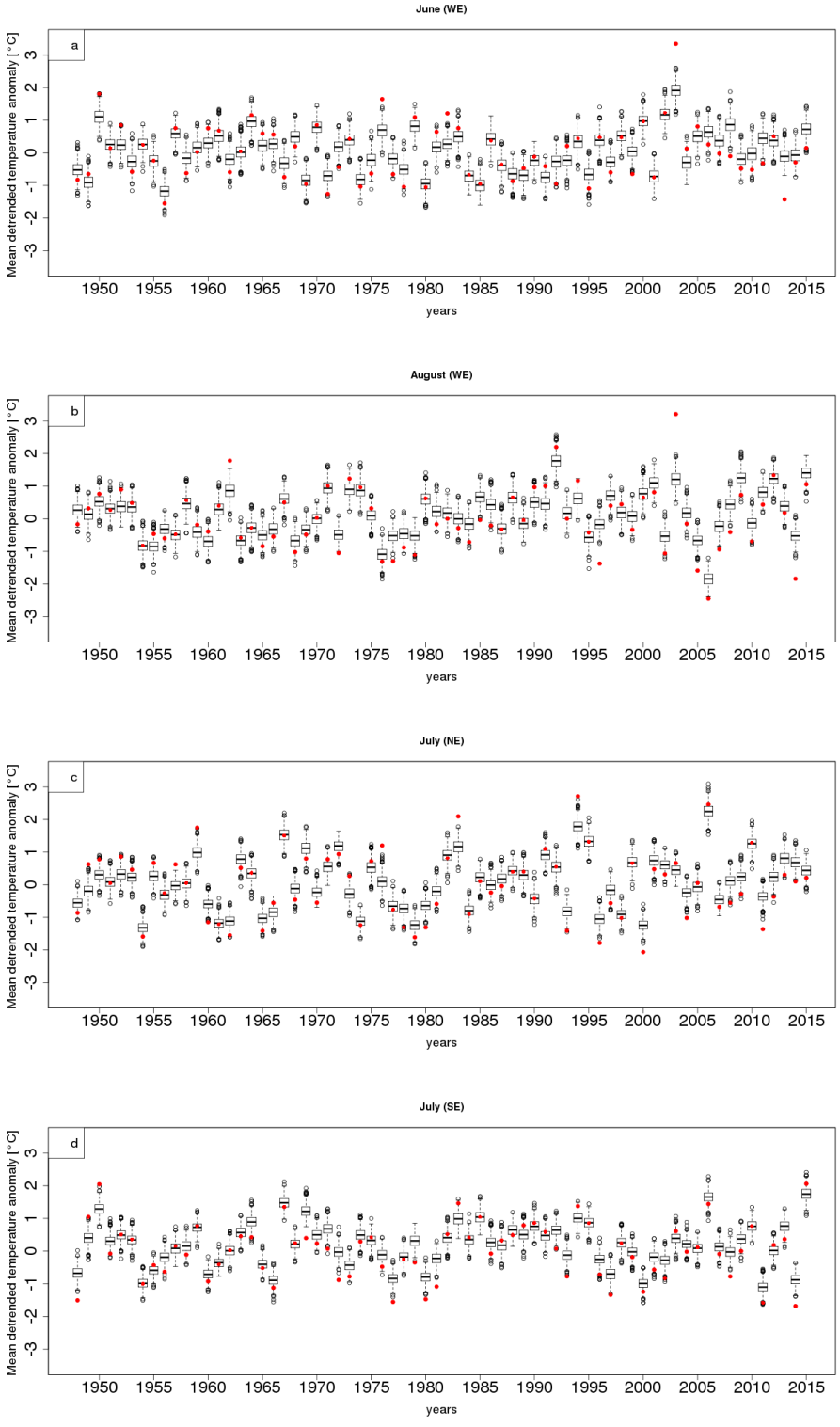

Fig. 10: Evolution of the detrended temperature distributions for all the months of June in Western Europe (a), August in Western Europe (b), July in Northern Europe (c) and July in Southern Europe (d). The regions are displayed in figure 1. The red dots correspond to the observed detrended temperature anomaly for each year.