



HAL
open science

Searching for the most extreme temperature events in recent history

Julien Cattiaux, Aurélien Ribes, Vikki Thompson

► **To cite this version:**

Julien Cattiaux, Aurélien Ribes, Vikki Thompson. Searching for the most extreme temperature events in recent history. *Bulletin of the American Meteorological Society*, In press, 10.1175/BAMS-D-23-0095.1 . hal-04331905

HAL Id: hal-04331905

<https://hal.science/hal-04331905v1>

Submitted on 8 Dec 2023

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

1 **Searching for the most extreme temperature events in recent history**

2 Julien Cattiaux^a Aurélien Ribes,^a Vikki Thompson,^b

3 ^a *Centre National de Recherches Météorologiques (CNRM), Université de Toulouse, CNRS,*

4 *Météo-France, Toulouse, France*

5 ^b *Royal Netherlands Meteorological Institute (KNMI), De Bilt, the Netherlands*

6 *Corresponding author: Julien Cattiaux, julien.cattiaux@meteo.fr*

7 ABSTRACT: Because they are rare, extreme weather events have critical impacts on societies
8 and ecosystems and attract public and scientific attention. The most unusual events are regularly
9 documented as part of routine climate monitoring by meteorological services. A growing number
10 of attribution studies also aim at quantifying how their probability has evolved under human
11 induced climate change. However, it is often recognized that (i) the selection of studied events
12 is geographically uneven, and (ii) the definition of a given event, in particular its spatio-temporal
13 scale, is subjective, which may impact attribution statements. Here we present an original method
14 that objectively selects, defines, and compares extreme events that have occurred worldwide in the
15 recent years. Building on previous work, the event definition consists of automatically selecting
16 the spatio-temporal scale that maximizes the event rarity, accounting for the non-stationary context
17 of climate change. We then explore all years, seasons, and regions and search for the most extreme
18 events. We demonstrate how our searching procedure can be both useful for climate monitoring
19 over a given territory, and resolve the geographical selection bias of attribution studies. Ultimately,
20 we provide a selection of the most exceptional hot and cold events in the recent past, among which
21 are iconic heatwaves such as those seen in 2021 in Canada or 2003 in Europe.

22 SIGNIFICANCE STATEMENT: The purpose of the article is to objectively select and rank the
23 most exceptional heatwaves and cold spells that have occurred worldwide in the recent years. As
24 these events often have the greatest socio-economic impacts, better knowledge and characterization
25 of historical events in a changing climate can inform adaptation strategies. We exhaustively scan
26 temperature data over all years and regions to identify extreme events using the event probability
27 as a universal metric. Applied over a specific location, such as on a national level, our method
28 provides useful information for the climate monitoring of weather events. Applied globally, it can
29 help attribution studies to pick events without the selection bias related to authors origin or media
30 coverage.

31 CAPSULE: The most extreme historical heatwaves and cold spells across the globe are objectively
32 selected from their occurrence probability by an exhaustive scan of temperature events.

33 1. Introduction

34 Extreme weather events are rare, and so they inevitably attract attention and cause socio-
35 environmental impacts when they occur. Explaining events that have occurred and putting them in
36 a climate perspective constitutes a key challenge for both national weather services and the "event
37 attribution" community.

38 The former have the responsibility to document historical weather events and maintain long-
39 term statistics over their territory. This includes describing events from a synoptic perspective,
40 quantifying their rarity (e.g. return period), and comparing with inventories of past events of the
41 same type. The selection of documented events is generally made on the basis of fixed thresholds,
42 so that events can be characterized by a level and duration of exceedance. As the climate warms,
43 the thresholds for defining heatwaves (cold spells) are exceeded more (less) easily: for instance, 37
44 (16) of the 46 heatwaves (46 cold spells) officially reported in France by Météo-France over 1947–
45 2022 have occurred after 1985, in the second half of the record period¹. This raises new questions
46 for climate monitoring. Are recent episodes of threshold exceedance really extreme events in
47 today's climate? How rare were past events relative to their respective climate? Besides, due to
48 possible adaptation, the impacts associated with a given temperature event are not necessarily the

¹ClimatHD by Météo-France [<http://www.meteofrance.fr/climat-passe-et-futur/climathd>], online, accessed 2023-10-15.

49 same today as in the past. Taking non-stationarity into account in regular climate monitoring has
50 therefore become a necessity for weather services.

51 Placing extreme weather events in the perspective of climate change is precisely the aim of "event
52 attribution" studies. This field seeks to assess how climate change has altered event probability or
53 intensity, through quantities such as the probability ratio or the fraction of attributable risk. It has
54 emerged since the pioneering analysis of the European heatwave of summer 2003 by Stott et al.
55 (2004). It has become a regular activity as illustrated by the series of supplements to the annual State
56 of the Climate report since Peterson et al. (2012)² or the creation of the World Weather Attribution
57 (WWA) group³, and there is a growing interest from weather services in making it operational.
58 Many events have been scrutinized over the past two decades, but it is often expressed that studies
59 suffer from a "selection bias", as in the IPCC AR6 Chapter 11: "studies in the developing world
60 are [...] lacking (Otto et al. 2020)" and "events that have been studied are not representative of
61 all extreme events that occurred [...]" (Seneviratne et al. 2021). There are a variety of reasons for
62 this bias (origin of the authors, quality of the data, media coverage, etc.), but so far little has been
63 proposed to limit it and objectify event selection.

64 A common issue to climate monitoring and event attribution analyses is that their statements are
65 dependent on the event definition, in particular the spatio-temporal extent considered. Weather
66 services need to identify the duration and extent where the event was extreme to analyze it
67 appropriately and provide relevant information to local decision-makers. In attribution studies,
68 using large scales generally yields a higher detection of the signal (climate change) due to the
69 smoothing out of the noise (internal variability), and therefore larger probability ratios (Angélic
70 et al. 2014, 2018; Cattiaux and Ribes 2018; Kirchmeier-Young et al. 2019). Event definition is often
71 subjective in the literature, which is referred to as another type of "selection bias" (Seneviratne et al.
72 2021). In a previous paper (Cattiaux and Ribes 2018, hereafter CR18), we proposed an objective
73 definition procedure consisting in automatically selecting the spatio-temporal scale that maximizes
74 the event rarity. This was motivated by the fact that the meteorological extremeness of an event is
75 generally what makes it of interest and generates the greatest socio-economic impacts. Importantly,
76 we showed that our procedure does not artificially bias attribution statements: maximizing the rarity
77 does not systematically maximize (or minimize) the attributable signal.

²BAMS explaining extreme events from a climate perspective [<https://www.ametsoc.org/ams/index.cfm/publications/bulletin-of-the-american-meteorological-society-bams/explaining-extreme-events-from-a-climate-perspective>], online, accessed 2023-10-15.

³WWA webpage [<https://www.worldweatherattribution.org>], online, accessed 2023-10-15.

78 Here we show that this method can also be used to compare the rarity of different events,
 79 for example, two heatwaves of different spatio-temporal scales occurring in different years and
 80 at different locations. It can therefore serve both meteorological services to create inventories
 81 of historical events, and the event attribution community to address the issue of selection bias.
 82 Ultimately, we provide objective selections of historical heatwaves and cold waves at a national
 83 level (France) and at the global level, which constitute new information on observed extremes and
 84 can serve as databases for the validation of climate models or statistical methods.

85 **2. The event probability as the ranking metric**

86 Our study complements products of national weather services and rankings of extreme temper-
 87 ature events that have already been recently proposed in the literature. Russo et al. (2015) have
 88 proposed a ranking of European heatwaves on the basis of an index combining the fraction of
 89 area over which daily temperatures exceed reference (fixed) thresholds and the magnitude of the
 90 exceedances. Röthlisberger et al. (2021) and Boettcher et al. (2023) have developed a methodology
 91 to identify extreme seasonal temperatures at the grid point scale, also from fixed thresholds, and
 92 then form spatially coherent objects. Thompson et al. (2022) have compared the spectacular Pacific
 93 Northwest heatwave of June 2021 to the most extreme 1-day hot events ever recorded globally,
 94 defined at each region of the world as the largest daily temperature anomaly normalized with re-
 95 spect to local mean and variance. In a follow-up paper, Thompson et al. (2023) have also provided
 96 estimates of the return period of current records of daily maximum temperatures worldwide.

97 Here, as in CR18, we wish to introduce flexibility in the definition of the spatio-temporal scale
 98 of the events. We thus need a metric enabling the comparison of the temperature events not only
 99 over all dates and locations, but also over several temporal durations and spatial domain sizes.
 100 The probability of occurrence of the event in its factual climate — which will be denoted as
 101 p_1 throughout this paper — perfectly meets this requirement. Mathematically, it writes as the
 102 probability that an equally or more intense event occurs at the same place and time:

$$p_1 = \Pr \left\{ X^{(t_1)} \geq x_{t_1} \right\}, \quad (1)$$

103 where $X^{(t_1)}$ is the random variable describing all possible realizations of the climate at time t_1 ,
 104 and x_{t_1} is the value effectively observed at that time. As discussed in CR18, p_1 has the intrinsic

105 property of being uniformly distributed within the interval $[0,1]$: by definition, a randomly selected
106 (weather) event can indeed be anywhere in the (climate) distribution of all possible events. Provided
107 that p_1 is well estimated, this property thus enables to confront all dates, locations and scales on
108 the basis of a fair and universal metric.

109 We perform an exhaustive "scan" of all possible warm and cold events and identify the highest
110 rarity (or lowest p_1) events. As p_1 is the probability of the event occurring the year it actually
111 did, our procedure provides a non-stationary view of the monitoring of extremes — in a warming
112 climate, a heatwave of a given intensity will become increasingly likely (less extreme) —, which
113 can meet the needs of weather services. In attribution studies, p_1 is a key quantity, denoted
114 "factual probability", which reinforces its relevance for our purpose. It is often compared to a
115 "counterfactual probability" p_0 measuring the rarity of the event x_{t_1} in a different climate X , e.g.
116 without human influence or at a other (distant) time t_0 :

$$p_0 = \Pr \left\{ X^{(t_0)} \geq x_{t_1} \right\} . \quad (2)$$

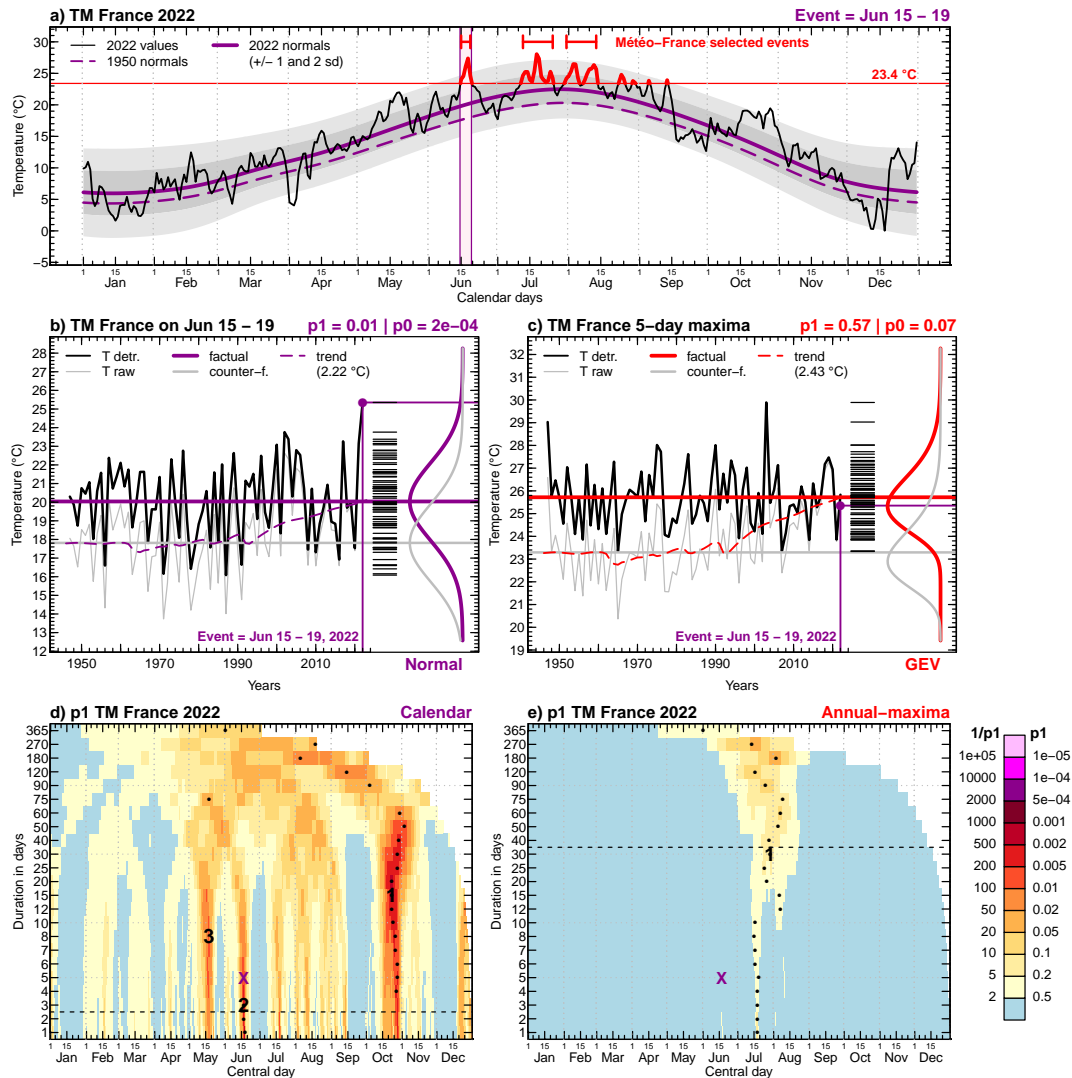
117 3. Scanning a given region: France

118 We first illustrate our scanning procedure at a fixed location: metropolitan France. We use the
119 national daily thermal index provided by Météo-France over the 1947–2022 period (Ribes et al.
120 2022). We search for the most extreme warm and cold events in this time series (i.e. the lowest
121 p_1), exploring all years, all days of a year, and several temporal durations of n days. To keep the
122 computation time reasonable, we restrict n to 1–8, 10, 12, 15, 20, 25, 30, 40, 50, 60, 75, 90, 120,
123 180, 270, and 365 days (23 values). The methodology for estimating p_1 and p_0 is depicted in
124 Figure 1 using the example of the 5-day heatwave of June 15–19, 2022. This episode is one of the
125 three heatwaves reported by Météo-France in 2022 and the earliest one in records⁴ based on the
126 reference threshold⁵ of 23.4 °C (Figure 1a).

136 As in CR18, the event rarity is assessed through an empirical estimation method consisting of
137 (i) detrending the sample of observations x_t to make all values representative of the climate at
138 $t_1 = 2022$ (factual) or $t_0 = 1950$ (counterfactual) and (ii) fitting stationary parametric distributions

⁴Weather extremes of summer 2022 by Météo-France [<https://meteofrance.com/actualites-et-dossiers/actualites/changement-climatique-lete-2022-et-ses-extremes-meteorologiques>], online, accessed 2023-10-15.

⁵Definition of heatwaves by Météo-France [<https://meteofrance.com/actualites-et-dossiers/comprendre-la-meteo/temperature/comment-les-climatologues-evaluent-vagues-chaaleur-canicules>], online, accessed 2023-10-15.



127 FIG. 1. (a) Daily-mean temperatures of 2022 (black). 2022 normals (solid violet), associated ± 1 and ± 2
 128 s.d. (gray shading), and 1950 normals (dashed violet). Heatwaves reported by Météo-France (i.e. with 3
 129 days above 23.4 °C) in red, with June 15–19 highlighted. (b) Computing calendar p_1 : raw (thin gray) and
 130 detrended (wrt. 2022, thick black) time series of June 15–19 temperatures. Long-term trend (dashed colored)
 131 and its levels in 2022 (horizontal colored, factual climate) and 1950 (horizontal gray, counterfactual climate).
 132 Barcode: detrended (factual) sample, with the fitted normal distribution (violet). Counterfactual distribution
 133 in gray. (c) Computing annual-maxima p_1 : same as (b) except that the time series is Tx5day and the fits are
 134 GEV distributions. (d) Calendar and (e) annual-maxima p_1 as function of the time of the year (x-axis) and the
 135 temporal averaging (y-axis), with our selections of events indicated and ranked.

139 on the detrended samples to derive p_1 and p_0 . Our detrending procedure is described in detail in
140 Appendix A; in short, the shape of the trend is estimated from a multi-model ensemble of historical
141 simulations and the amplitude from observations alone, with a dependency on the time of year
142 and the temporal duration n . Two different options are then taken for the sample x_t and the fitted
143 distribution to describe the event conditionally to its calendar context or not.

144 The first — calendar conditioning — consists of comparing the n -day mean temperature of the
145 event with the multi-year sample of temperatures observed on the exact same dates, and using a
146 Gaussian distribution fit after detrending (Figure 1b). In this case minimizing p_1 is equivalent
147 to searching for the largest normalized anomalies, i.e. departures from the mean in numbers of
148 standard deviations (s.d.)⁶. For the June 2022 event we find a 5-day anomaly of 5.2 K, (2.6 s.d),
149 which gives a calendar p_1 of 0.005; the interpretation is that an equally or hotter heatwave had a
150 0.5 % chance to occur *at these exact dates* in 2022.

151 However a 5-day average temperature of 25.4 K is not that exceptional in France in the climate
152 of 2022: it is actually close to the expectance of the annual maxima of 5-day mean temperatures
153 (hereafter Tx5day) for that year (estimate of 25.8 K, Figure 1c). Thus the second option —
154 no conditioning — consists of comparing the n -day event with the sample of Tx n day and using a
155 Generalized Extreme Value (GEV) distribution fit after detrending. In this case $1/p_1$ is interpretable
156 as a formal return period. For the June 2022 event, the annual-maxima p_1 is found to be 0.57,
157 which means that a heatwave at least as hot had more than 50 % chance to occur *in any dates* in
158 2022, and translates into an estimated return period of $1/p_1 \sim 1.8$ years.

159 For both calendar and annual-maxima approaches, p_0 is estimated by detrending the respective
160 x_t sample relative to $t_0 = 1950$ instead of $t_1 = 2022$ (gray distributions in Figure 1b,c). As climate
161 has warmed — estimates of 2.22 °C for June 15–19 and 2.43 °C for Tx5day — p_0 is unsurprisingly
162 smaller than p_1 . Finally, it must be noted that:

- 163 • the formalism of Equations 1 and 2 and the use of annual "maxima" is well suited for hot
164 events; to apply it to cold events one has to consider that X is the temperature multiplied by
165 -1 and to consider annual "minima";
- 166 • there is a debate in the community as to whether the value of the event should be included in
167 or excluded from the sample when estimating its probability of occurrence (Philip et al. 2020;

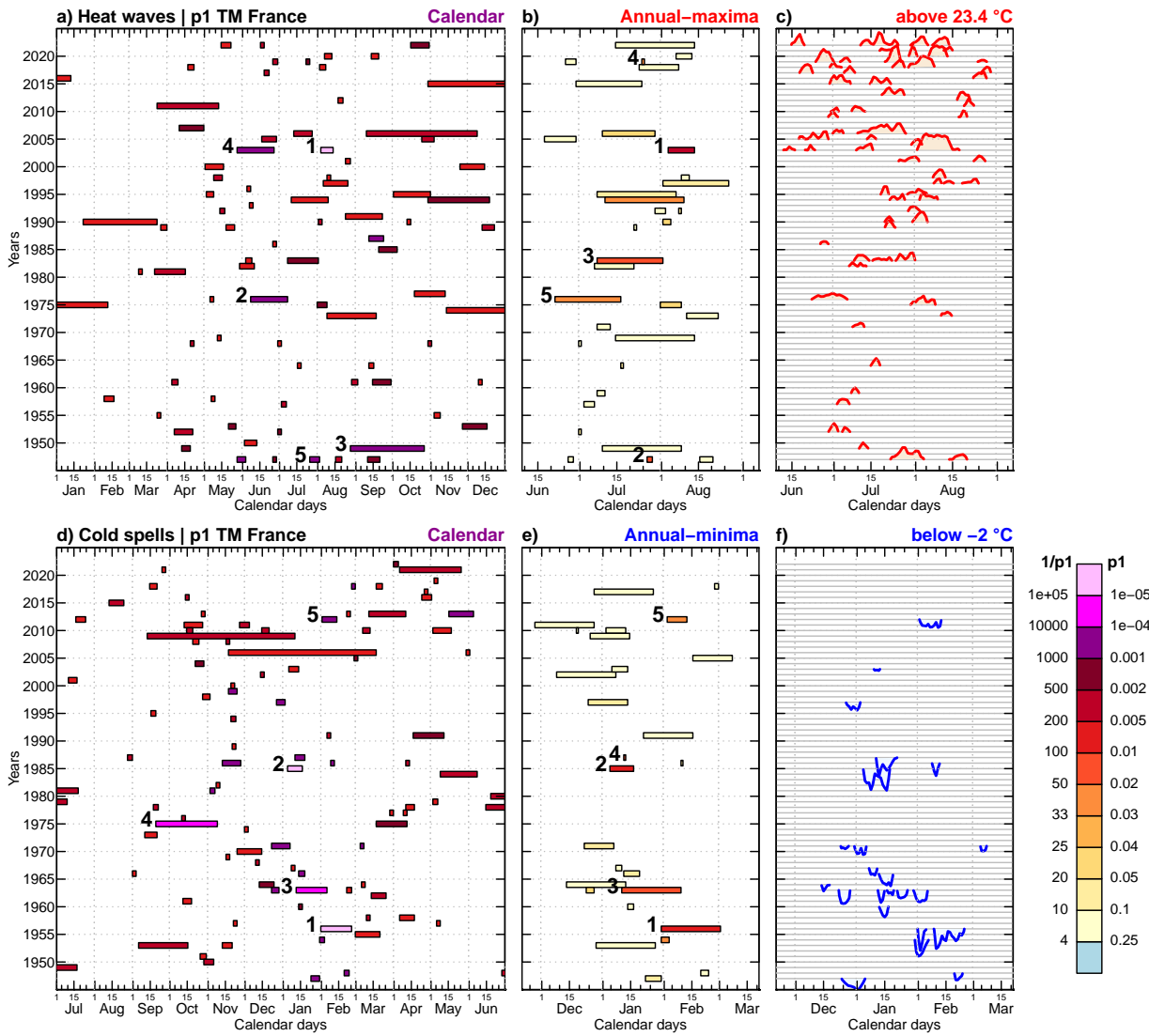
⁶For $X \sim N(\mu, \sigma)$, p_1 is a monotonic function of $(X - \mu)/\sigma$.

168 van Oldenborgh et al. 2021b). The question especially arises when the time series is stopped
169 because the last event is particularly extreme and we want to study it. Solutions to properly
170 formulate stopping rules have been proposed (e.g., Barlow et al. 2020). Here we decide to
171 systematically include the value of the event in the sample, because (i) we scan all the events of
172 the whole period so we have no particular stopping rule and (ii) GEV distributions for annual
173 maxima of temperature are often right-bounded (negative shape parameters) and in case of a
174 very rare event, excluding its value for the fit can lead to an estimated upper bound lower than
175 the event effectively observed (as in Philip et al. 2022). In such a case, it would be nonsense
176 to conclude that the event has $p_1 = 0$ while we *know* that it has occurred.

177 The scanning procedure then consists of computing calendar and annual-maxima (-minima) p_1
178 for all 27740 days of 1947–2022 (February 29s are omitted) and 23 n -day temporal extents, and
179 search for the local minima of p_1 — the most extreme events — within these 27740×23 matrices.
180 To do so, we select the absolute minimum of p_1 , then mask all overlapping calendar windows
181 (we consider that they correspond to the same event) and iterate while there remains p_1 smaller
182 than a given threshold: we choose 0.01 for the calendar method and 0.25 for annual-maxima and
183 -minima methods. In addition, we impose a minimal duration of 3 days for the calendar approach
184 for readability and a maximal duration of 30 days for annual-maxima (-minima) approaches for the
185 quality of GEV fits.

186 This procedure is first illustrated on the complete year 2022 (Figure 1d,e). Three hot events are
187 selected in the calendar approach; the June event mentioned above ranks 2nd and is found to be
188 the most extreme at the 3-day scale. In the annual-maxima approach, a unique 30-day event is
189 selected that overlaps the two episodes reported by Météo-France in July and August. Its estimated
190 return period is small ($1/p_1 = 10$ years), reflecting the fact that exceeding the reference threshold
191 of 23.4 °C has become likely in the climate of 2022 (see also Figure 1a). (The 180-day event from
192 May to October has a lower p_1 but the use of annual blocks and GEV is questionable for such long
193 durations).

208 Now expanding to the entire period, the calendar approach enables quick identification of ab-
209 normally hot events throughout the whole year, which is useful for routine climate monitoring
210 and can be relevant for impacts studies (Figure 2a). Only the heatwaves occurring near the peak
211 of the annual cycle are retained by the annual-maxima approach (Figure 2b). Both approaches



194 FIG. 2. (a–c) Selection of the hottest events with the (a) calendar and (b) annual-maxima approaches, compared
 195 with (c) Météo-France threshold-based selection (3 days above 23.4 °C, source of graphics: Les Décodéurs, Le
 196 Monde). (d–f) Same for cold events, with annual-minima in (e) and exceedances below -2 °C in (f). Rectangles
 197 and pieces of time series indicate the dates (x-axis) and years (y-axis) of the events, with a restricted x-axis
 198 on middle and right columns. Rectangle colors indicate p_1 with the five most extreme events highlighted. A
 199 minimal duration of 3 days and a maximal p_1 of 0.01 are imposed to calendar events. A maximal duration of 30
 200 days and a maximal p_1 of 0.25 are imposed to annual-maxima and -minima events. p_1 values are lower in the
 201 calendar method due to the condition that the event occurs at these exact dates.

202 TABLE 1. The five hottest and coldest events selected by the annual-maxima and -minima approaches in
 203 France, ordered by increasing p_1 (see also Figure 2). Associated p_0 and p_1/p_0 are indicated, as well as
 204 average temperature and normalized anomaly. Brackets indicate 90%-level confidence intervals computed by
 205 bootstrapping years in the T_{xnday} or T_{nnday} samples; as random resampling removes the value of the year of
 206 interest from the N -year sample with a probability $(1 - \frac{1}{N})^N \xrightarrow{N \gg 1} e^{-1} \sim 0.37$, the upper bound of the confidence
 207 interval of $1/p_1$ can be found to be infinite whereas the event actually occurred.

#	Year	Dates	T (°C)	s.d.	$1/p_1$	$1/p_0$	p_1/p_0
Heatwaves							
1.	2003	Aug 4 - 13	28.6	4.4	410 [93 to Inf]	3200 [250 to Inf]	7.6 [2.6 to Inf]
2.	1947	Jul 27 - 28	27.7	3.3	97 [37 to 3200]	95 [37 to 3000]	0.98 [0.94 to 0.99]
3.	1983	Jul 8 - Aug 1	24.3	3	64 [31 to 350]	62 [30 to 320]	0.96 [0.92 to 0.97]
4.	2019	Jul 25	29.4	3	35 [20 to 130]	1100 [160 to Inf]	32 [7.1 to Inf]
5.	1976	Jun 22 - Jul 16	23.7	3.3	34 [20 to 100]	28 [17 to 77]	0.84 [0.75 to 0.89]
Cold spells							
1.	1956	Jan 31 - Mar 1	-3.2	-4.3	170 [56 to 8700]	180 [58 to 9700]	1 [1 to 1.1]
2.	1985	Jan 5 - 16	-6.9	-4.4	110 [44 to 880]	110 [43 to 850]	0.99 [0.97 to 0.99]
3.	1963	Jan 11 - Feb 9	-2.8	-3.7	96 [36 to 4100]	120 [42 to 11000]	1.2 [1.1 to 1.9]
4.	1987	Jan 12	-9	-3.8	50 [25 to 220]	45 [23 to 180]	0.89 [0.8 to 0.92]
5.	2012	Feb 3 - 12	-4.3	-3.7	46 [25 to 150]	18 [12 to 35]	0.38 [0.21 to 0.49]

212 agree that the greatest hot event for France is the heatwave of early August 2003, considered as
 213 a 10-day event (August 4–13, consistent with CR18). It corresponds to a normalized anomaly of
 214 4.4 s.d. and an estimated return period of 410 [95 to Inf] years (Table 1, see caption for details
 215 on the confidence interval). Other major heatwaves are found in summers 1947, 1976, 1983 and
 216 2019, with durations of respectively 2, 25, 25 and 1 days. This is overall consistent with the events
 217 selected by Météo-France on the basis of fixed thresholds (Figure 2c). As for cold spells, the most
 218 extreme events are found in winters 1956, 1963, 1985, 1987 and 2012 (Figure 2d,e and Table 1),
 219 which is also consistent with Météo-France reporting (Figure 2f). The events of February 1956
 220 and January 1985 have normalized anomalies of -4.4 s.d. (Table 1), i.e. are equally unusual as the
 221 August 2003 heatwave from a calendar perspective; however, their formal return periods estimated
 222 from the annual-minima approach are shorter (respectively 170 and 110 years).

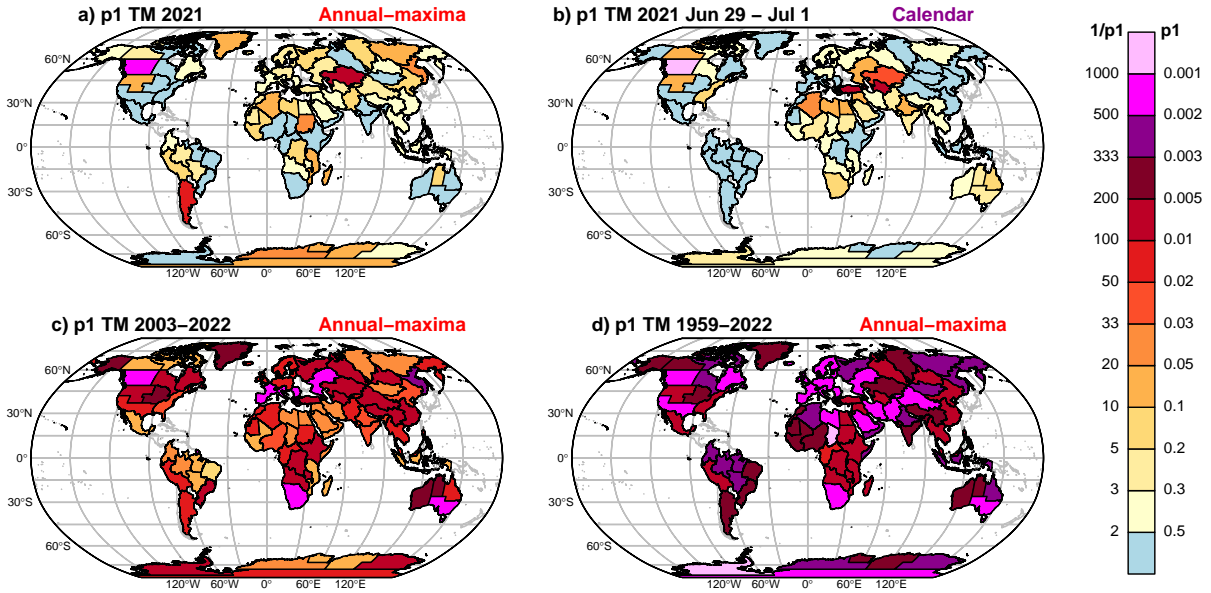
223 The right panels in Figure 2 illustrate the limitations of climate monitoring of extremes using
 224 fixed threshold approaches. On the one hand, using the same threshold for the whole year makes it
 225 impossible to describe certain events conditionally to their calendar context, e.g. late cold snaps in

226 early spring, which have an impact on vegetation (Vautard et al. 2022). On the other hand, global
227 warming leads to heatwave thresholds being exceeded almost every summer (we can no longer
228 speak of "extreme" events), while cold spell thresholds are almost never reached (we can no longer
229 speak of events at all). Our method provides complementary and useful information for national
230 weather services on both these calendar and non-stationary aspects. Lastly, note that an interactive
231 application associated to this paper enables to reproduce the analyses carried out in this section
232 and retrace Figure 1 for various choices of years and dates and Figure 2 for different thresholds of
233 p_1 and duration (details in Appendix C).

234 **4. Scanning worldwide**

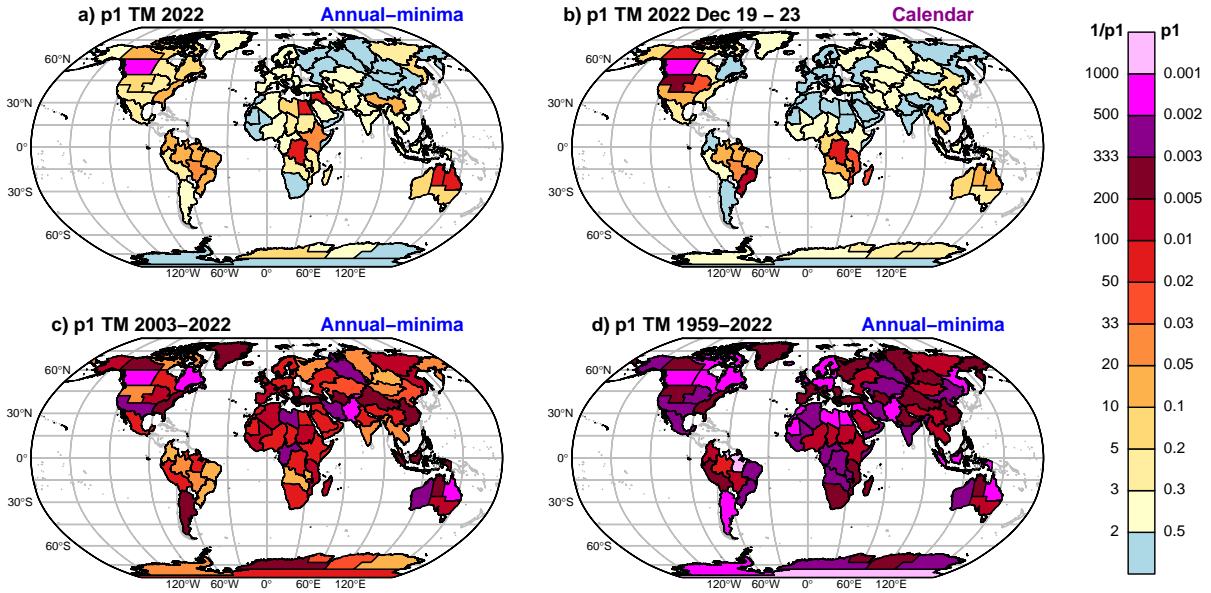
235 To extend the scanning procedure to the global scale, we use daily-mean 2-meter temperatures
236 provided by the ERA5 reanalysis over the 1959–2022 period (Hersbach et al. 2020). The advantage
237 of ERA5 is that it is a physically consistent dataset globally (model simulation) with a sufficiently
238 fine resolution for our purpose and without missing values, which is particularly convenient for
239 the calculation of annual maxima or minima. The main disadvantage is that it is not temporally
240 homogenized (assimilated observations evolve in time), which can cause problems for both our
241 detrending and p_1 calculations. Nevertheless, we have verified that the main results of this
242 section, i.e. the selections of extremes, do not suffer from obvious heterogeneity problems. To our
243 knowledge, there exists no observational dataset of global daily temperature with time homogeneity,
244 long history, and no missing values.

245 The exploration of spatial domains is performed with the hierarchical collection of economic and
246 political regions defined by Stone (2019) within the "Weather Risk Attribution Forecast" (WRAF)
247 framework. This collection provides successive divisions of land areas into regions of 10, 5, 2, and
248 0.5 million km^2 (hereafter Mkm^2), each division being nested in the previous one, with only a few
249 gaps in the global coverage (for instance Europe appears only from 5 Mkm^2). The set of 0.5 Mkm^2
250 regions was also used by Thompson et al. (2022, 2023). The full range of spatial sizes covers
251 the vast majority of event definitions in recent attribution studies, with the exception of studies at
252 global scale or at the local scale (in this case we could refine within a 0.5 Mkm^2 region). Scanning
253 the full period at global scale thus involves considering 64 years \times 365 days \times 347 WRAF regions
254 \times 23 time durations \sim 186 million temperature events.



255 FIG. 3. Scanning heatwaves worldwide. (a) For each 2 Mkm² region, the minimum p_1 of all 2021 events in
 256 the annual-maxima approach is shown. (b) Calendar p_1 of a warm event occurring on June 29 – July 1, 2021,
 257 i.e. coinciding with the absolute minimum of p_1 in (a). (c–d) Same as (a) for (c) 2003–2022 and (d) 1959–2022.

266 Firstly, we scan a single year to identify the most extreme events of that year, as this can be
 267 useful for annual reports of climate monitoring and event attribution. Figures 3a and 4a provide the
 268 minima of p_1 at each 2 Mkm² region for respectively the annual-maxima approach (heatwaves) in
 269 2021 and the annual-minima approach (cold spells) in 2022. We have chosen these two examples
 270 because outstandingly, west Canada holds the strongest event in both cases, i.e. the 3-day heatwave
 271 of June 29 – July 1, 2021 — the famous "heat dome" analyzed in numerous studies (e.g., Bercos-
 272 Hickey et al. 2022; Philip et al. 2022; Schumacher et al. 2022; Thompson et al. 2022; Terray 2023;
 273 White et al. 2023) — and the 5-day cold spell of December 19–23, 2022, related to winter storm
 274 "Elliott". We estimate that these two events have remarkably low values of p_1 , corresponding to
 275 estimated return periods of 810 years for the heatwave and 550 years for the cold spell (Table 2).
 276 There is certainly no meteorological relationship between these two events, suggesting that this
 277 region has, by chance, experienced particularly extreme temperatures over the past two years. For
 278 a closer look, the equivalent of Figure 1 for these two events has been plotted in Figures S1 and
 279 S2. The top 3 heatwaves in 2021 then include a 7-day July event in Kazakhstan and a 30-day
 280 event in December 2021 – January 2022 in Argentina, while a 30-day November event in Congo



258 FIG. 4. Scanning cold spells worldwide. (a) For each 2 Mkm² region, the minimum p_1 of all 2022 events in
 259 the annual-minima approach is shown. (b) Calendar p_1 of a cold event occurring on 2022, December 19–23,
 260 2022, i.e. coinciding with the absolute minimum of p_1 in (a). (c–d) Same as (a) for (c) 2003–2022 and (d)
 261 1959–2022.

281 and a 12-day July event in Queensland complete the podium of cold spells 2022. By construction,
 282 about half of the regions have a minimum p_1 above 0.5 in Figures 3a and 4a; for a given temporal
 283 duration, the distribution of yearly minimum p_1 across regions is indeed uniform (Appendix B).

284 Figures 3b and 4b show the calendar p_1 associated with the 2021 and 2022 west Canadian events.
 285 We find normalized calendar anomalies of respectively 5.0 and 3.0 s.d. over this region, which
 286 highlights the extremeness of these two events (this gives a lower p_1 than in the annual-maxima
 287 approach since here it is conditioned by the time of the year). The global picture of calendar p_1
 288 can be useful for routine climate monitoring: for example here we see that the 2021 heatwave was
 289 restricted to west Canada while the 2022 cold spell also spreads over the northwest USA region
 290 (2.7 s.d.), and to a lesser extent over NWT & Yukon (2.2 s.d.) and midwest USA (1.9 s.d.). This
 291 is consistent with the characteristic spatial size of atmospheric patterns responsible for summer
 292 vs. winter extremes in mid-latitudes. Figures 3a also shows that the 2021 Kazakhstan heatwave
 293 occurred concurrently with the west Canadian one, which could be a coincidence or result from
 294 an amplified circumglobal wave pattern. Note that for given dates, the distribution of calendar p_1

262 TABLE 2. The ten hottest and coldest worldwide events selected by the annual-maxima and -minima approaches
 263 for 2 Mkm² regions, ordered by increasing p_1 (see also Figure 3 and 4). Brackets indicate 90%-level confidence
 264 intervals computed as in Table 1 with the same remark about the possibly infinite upper bound of $1/p_1$. Region
 265 ID and names from Stone (2019).

#	Reg ID	Region name	Year	Dates	$1/p_1$	$1/p_0$	p_1/p_0
Heatwaves							
1.	1.2.1	west Canada	2021	Jun 29 - Jul 1	810 [120 to Inf]	39000 [630 to Inf]	48 [4.4 to 540]
2.	7.1.2	southwest Russia	2010	Jul 21 - Aug 14	780 [110 to Inf]	46000 [520 to Inf]	59 [3.9 to 1700]
3.	X.2.2	south EEA	2003	Aug 3 - 14	740 [120 to Inf]	Inf [1800 to Inf]	Inf [11 to Inf]
4.	11.1.2	southeast Australia	2019	Jan 14 - 17	670 [110 to Inf]	Inf [44000 to Inf]	Inf [72 to Inf]
5.	6.2.2	south SADC	2016	Jan 1 - 7	630 [100 to Inf]	1700 [160 to Inf]	2.7 [1.5 to 3.9]
6.	8.2.2	south Pacific Russia	2011	Jul 17 - 28	390 [83 to Inf]	99000 [610 to Inf]	250 [6 to Inf]
7.	2.1.3	Midwest USA	2012	Jun 27 - Jul 26	320 [75 to Inf]	7500 [240 to Inf]	24 [2.8 to Inf]
8.	11.1.1	Western Australia	2019	Dec 22 - 29	320 [77 to Inf]	37000 [330 to Inf]	120 [3.4 to Inf]
9.	2.1.1	Alaska (USA)	2019	Jul 6 - 10	310 [71 to Inf]	33000 [360 to Inf]	110 [4.3 to Inf]
10.	11.2.1	Northern Territory (Australia)	2019	Dec 17 - 26	270 [70 to Inf]	560 [110 to Inf]	2.1 [1.5 to 380]
Cold spells							
1.	1.2.3	east Canada	2014	Jan 2 - 3	760 [120 to Inf]	12 [8.3 to Inf]	0.016 [0 to 0.085]
2.	11.2.2	Queensland (Australia)	2007	Jun 20 - Jul 19	620 [110 to Inf]	84 [35 to Inf]	0.14 [0 to 0.37]
3.	9.2.2	southeast ECO	2008	Jan 18 - 27	560 [97 to Inf]	100 [38 to Inf]	0.19 [0 to 0.42]
4.	1.2.1	west Canada	2022	Dec 19 - 23	550 [110 to Inf]	6.2 [4.7 to 13]	0.011 [0 to 0.051]
5.	5.2.2	central and south CEMAC	2015	Jan 11 - 12	420 [94 to Inf]	5.1 [4 to 8.1]	0.012 [0 to 0.047]
6.	11.1.1	Western Australia	2006	Jul 12 - 17	400 [87 to Inf]	47 [24 to Inf]	0.12 [0.071 to 0.35]
7.	4.2.1	Libya	2017	Dec 31 - Jan 11	360 [82 to Inf]	20 [12 to Inf]	0.054 [0 to 0.19]
8.	7.2.1	West Siberia (Russia)	2006	Jan 11	340 [75 to Inf]	240 [63 to Inf]	0.7 [0.58 to 0.87]
9.	2.2.1	southwest USA	2013	Dec 25 - Jan 18	340 [74 to Inf]	5.8 [4.2 to 9.7]	0.017 [0 to 0.077]
10.	9.1.2	Iran	2008	Jan 8 - 17	330 [78 to Inf]	44 [21 to 7000]	0.13 [0 to 0.29]

CEMAC = Economic and Monetary Community of Central Africa, ECO = Economic Cooperation Organization, EEA = European Economic Area, SADC = Southern Africa Development Community, USA = United States of America.

295 across regions is expected to be uniform in our procedure, so that about half of the regions are
 296 expected to have p_1 above 0.5 in such maps (Appendix B).

297 We now extend the scan to two time periods: the last 20 years (2003–2022, Figures 3c and 4c and
 298 Table 2) over which event attribution has developed, and the whole period of study (1959–2022,
 299 Figures 3d and 4d) — the interactive application enables to further visualize the results of any year
 300 or period (Appendix C). The podium of heatwaves of the last 20 years is occupied by events well
 301 known in the scientific community (Figure 3c): west Canada 2021, southwest Russia 2010, and
 302 south Europe 2003 (the same as in France in Figure 2). This first one is consistent with Thompson

303 et al. (2022) while the last two are in Russo et al. (2015). Other major events include heatwaves
304 that have been well documented in the scientific literature (e.g. January and December 2019 in
305 Australia and associated bushfires, e.g. van Oldenborgh et al. (2021a)), and others for which no
306 attribution study exist (e.g. South Africa 2016, south Pacific Russia 2011, see Table 2), illustrating
307 the geographic selection bias. Over the whole period, only two events of size 2 Mkm² (May 1998
308 in Chad and January 1993 in west Antarctica, Figure 3d) appear to exceed the 2021 west Canadian
309 heatwave, with estimated return periods of 2200 and 1100 years respectively.

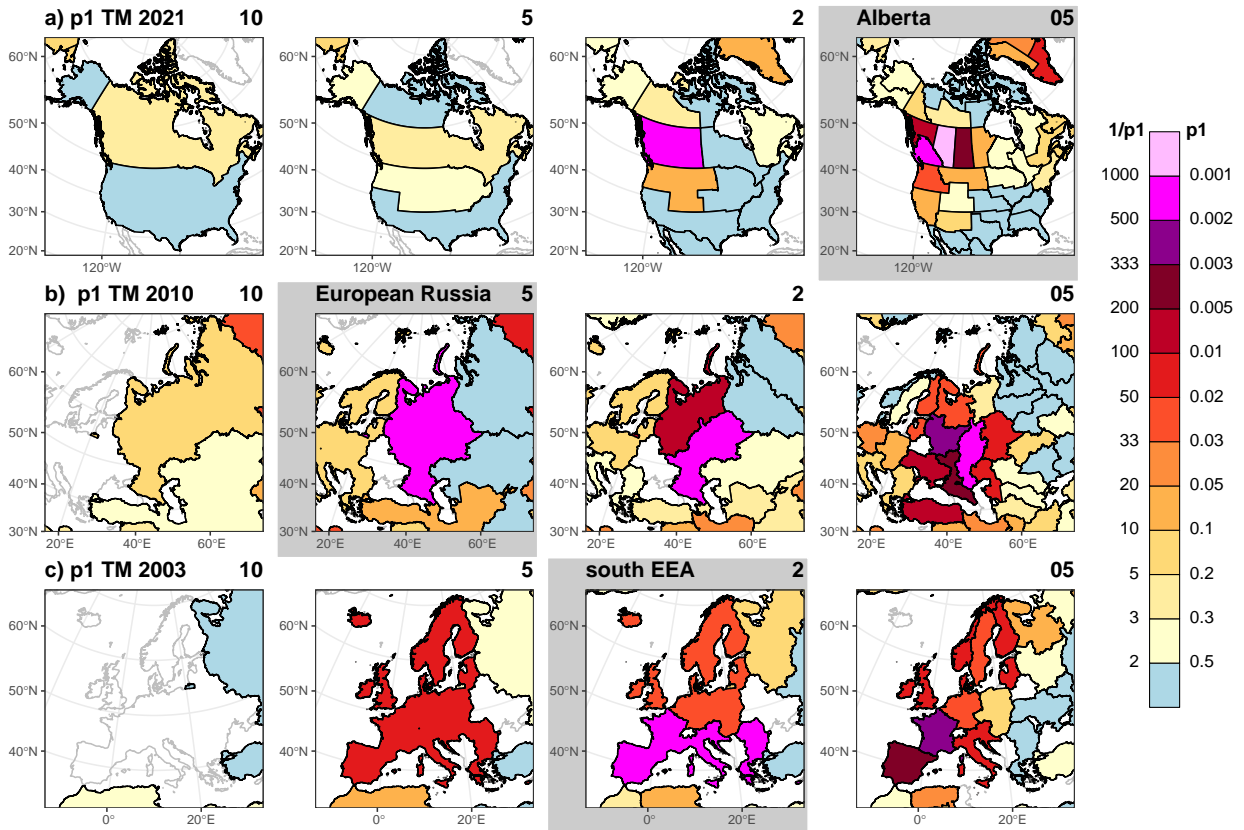
310 On the cold spell side, a 4-day event in July 1975 in central North Brazil wins the contest in the
311 2 Mkm² category, with January 2014 in east Canada being the most extreme event of the last 20
312 years (Figure 4c,d and Table 2). The December 2022 "Elliott" storm in west Canada ranks 4th over
313 2003–2022 and 12th over the whole period, which again highlights its extremeness in the climate
314 of 2022.

320 Lastly, the hierarchical character of the collection of WRAF regions is used to refine the selection
321 of events among spatial scales. Figure 5 shows the minimum p_1 associated with the three major
322 heatwaves identified in Figure 3 and Table 2 on the geographical division of the 10, 5, 2 and
323 0.5 Mkm² regions. The 2021 Canadian event is found to be the most extreme for a 0.5 Mkm²
324 region (Alberta), the 2010 Russian event for a 5 Mkm² region (European Russia), and the 2003
325 European event for the 2 Mkm² region as in Figure 3.

329 More generally, when minimizing p_1 both over time and the entire collection of WRAF regions
330 for the period 2003–2022, most of the events of Table 2 stand out, sometimes on parent or child
331 domains (Table 3). Notably, two Chinese heatwaves slip into the trio of heatwaves described above:
332 a 3-day event in 2003 and a 25-day event in 2022, with estimated return periods similar to the
333 2021 Canadian heatwave. These two events were reported in the media⁷ but seem to have received
334 less scientific attention. Extending the scan to the entire period 1959–2022 can be done in the
335 interactive application (Appendix C): other events join the top 10, but sometimes with obvious
336 data problems (Appendix B). The top events remain the heatwave of May 1998 in Chad (at size
337 2 Mkm²) and the cold spell of July 1975 in Brazil (at size 0.5 Mkm², south Para).

338 Using the collection of WRAF regions can thus be helpful to both (i) identify the most extreme
339 events of a given period worldwide, and (ii) give a rough idea of their spatial size. However extreme

⁷eg. https://www.lemonde.fr/en/asia-and-pacific/article/2022/08/24/china-s-record-heatwave-causes-severe-threat-to-crop-production_5994568_153.html



315 FIG. 5. Zooming over a region. (a) For each 10, 5, 2 and 0.5 Mkm² region (from left to right), the minimum p_1
 316 of all 2021 events in the annual-maxima approach is shown, which coincides with the 2021 Canadian heatwave
 317 listed as 1st in Table 2 and 2nd in Table 3. (b) Same as (a) for the 2010 Russian heatwave (2nd and 4th). (c) Same
 318 as (a) for the 2003 European heatwave (3rd and 5th). For each event, the region with the lowest p_1 is explicitly
 319 named and its panel (i.e. region size) is highlighted in gray.

340 events do not stop at administrative borders, and once an event has been selected for a study, its
 341 precise definition may be decided through a more systematic exploration of various spatial domains
 342 and sizes (e.g., CR18), and possibly on a more suitable dataset than ERA5 for the area of interest.

343 5. Discussion and conclusions

344 We have objectively identified and ranked the most extreme temperature events over a large
 345 spatio-temporal range, using the probability of event occurrence in the factual climate (p_1) as
 346 a universal metric. We produce a list of the greatest hot and cold extremes over the recent
 347 past, together with their spatio-temporal scale. Applied locally, such as on a national level, this

326 TABLE 3. Same as Table 2 but for the entire collection of WRAF regions. The number of characters in the
 327 region ID indicates its size: X for 10 Mkm², X.X for 5 Mkm², X.X.X for 2 Mkm² and X.X.X.X for 0.5 Mkm².
 328 Region ID and names from Stone (2019).

#	Reg ID	Region name	Year	Dates	$1/p_1$	$1/p_0$	p_1/p_0
Heatwaves							
1.	10.2.2.3	Fujian, Hunan, and Jiangxi (China)	2003	Jul 30 - Aug 1	1100 [130 to Inf]	50000 [410 to Inf]	47 [2.7 to 2200]
2.	1.2.1.3	Alberta (Canada)	2021	Jun 29 - Jul 1	1000 [120 to Inf]	5900 [240 to Inf]	5.7 [1.9 to 12]
3.	10.2.1.3	Chongqing and Sichuan (China)	2022	Aug 3 - 27	1000 [130 to Inf]	Inf [2200 to Inf]	Inf [11 to Inf]
4.	7.1	European Russia	2010	Jul 23 - Aug 11	790 [120 to Inf]	31000 [450 to Inf]	40 [3.4 to Inf]
5.	X.2.2	south EEA	2003	Aug 3 - 14	740 [120 to Inf]	Inf [2000 to Inf]	Inf [11 to Inf]
6.	3.2.3.2	southern Brazil	2014	Jan 19 - Feb 12	730 [98 to Inf]	110000 [560 to Inf]	150 [5 to Inf]
7.	6.2.2.4	east South Africa	2016	Jan 6 - 7	690 [110 to Inf]	4700 [250 to Inf]	6.8 [2.2 to 140]
8.	11.1.2	southeast Australia	2019	Jan 14 - 17	670 [120 to Inf]	Inf [31000 to Inf]	Inf [77 to Inf]
9.	X.X.1.2	Northeast Greenland National Park	2012	Jul 10 - Aug 8	640 [110 to Inf]	Inf [150000 to Inf]	Inf [260 to Inf]
10.	2.1.1.2	south Alaska (USA)	2019	Jul 5 - 9	640 [90 to Inf]	34000 [350 to Inf]	53 [3.3 to 2000]
Cold spells							
1.	1.2.3.2	south Québec (Canada)	2014	Jan 2 - 3	870 [130 to Inf]	59 [28 to Inf]	0.068 [0 to 0.23]
2.	6.2.2.3	west South Africa	2014	Jul 6 - 10	740 [120 to Inf]	42 [22 to Inf]	0.057 [0.038 to 0.23]
3.	1.2.3.1	Nord-du-Québec (Canada)	2015	Jan 31 - Feb 19	730 [100 to Inf]	14 [9.1 to 70]	0.019 [0 to 0.12]
4.	10.2	south China	2008	Jan 22 - Feb 5	700 [110 to Inf]	43 [21 to Inf]	0.061 [0.039 to 0.23]
5.	4.1.2.2	west Algeria	2005	Jan 28 - Feb 1	690 [110 to Inf]	18 [11 to Inf]	0.026 [0 to 0.12]
6.	11.2.2.2	central Queensland (Australia)	2007	Jun 7 - Jul 1	690 [110 to Inf]	130 [44 to Inf]	0.18 [0.14 to 0.44]
7.	7.2.1.1	Yamalo-Nenets (Russia)	2006	Jan 11	680 [120 to Inf]	37 [20 to Inf]	0.055 [0.037 to 0.2]
8.	8.1.2.2	northeast Sakha (Russia)	2013	Jan 29 - Feb 27	650 [94 to Inf]	17 [10 to 130]	0.027 [0 to 0.12]
9.	11.2.2.3	south Queensland (Australia)	2007	Jul 13 - 20	650 [120 to Inf]	120 [49 to Inf]	0.19 [0.14 to 0.44]
10.	6.1.1.3	west DR Congo	2022	Nov 25 - Dec 24	630 [110 to Inf]	1 [1 to 1]	0.0016 [0 to 0.0094]

DR Congo = Democratic Republic of Congo, EEA = European Economic Area, USA = United States of America.

348 procedure can provide additional method for the climate monitoring of weather events in a warming
 349 world. Applied globally, it ensures extreme events are identified objectively, independently of the
 350 populations concerned or the media coverage. This can help the event attribution community both
 351 by providing objective lists of events to be studied in dedicated annual reports, without selection
 352 bias, and by building reference databases of extreme events on which climate models and statistical
 353 attribution methods can be confronted.

354 Our procedure is not without limitations, particularly because applying it in such a generalized
 355 and exhaustive way requires use of simple and fast methods. A first remark concerns the long-term
 356 trend, which is crucial when comparing extreme events of various years. As its amplitude is

357 here estimated solely from the observations (Appendix A and Figure S3), it may contain traces
358 of decadal internal variability, and this can locally affect p_1 estimates. In regions where internal
359 variability causes recent years to be persistently warmer than the forced response — as suspected
360 e.g. in France (Ribes et al. 2022) —, our procedure could overestimate the trend and underestimate
361 the rarity of recent hot events. Using a long-term trend estimated from a combination of observed
362 and modeled data would be more reliable but for future work. Importantly, the histogram of years
363 of selected events or the time series of yearly minimum p_1 do not suggest any collective bias related
364 to trend estimates (Appendix B and Figure S4.).

365 A second remark concerns the estimation procedure for p_1 , more precisely the fit of parametric
366 laws onto observed samples. To compare various temporal durations and spatial domains, it is
367 assumed here that the same, simple, distributions apply to all seasons, regions, and a wide range
368 of time and space scales (with different parameters). For the calendar approach, we use the normal
369 distribution, which is classical for temperature, but does not account for potential asymmetric
370 behaviors (e.g., McKinnon and Simpson 2022). For the annual-maxima or -minima approaches,
371 we use GEV distributions to fit T_{xnday} or T_{nnday} samples, which is well suitable for small n (here
372 we have limited to $n = 30$) but less for large n (typically $n=365$, ie. full year). In both cases, we
373 find pretty uniform histograms of the p_1 of all events in all regions, suggesting that the estimation
374 procedure is "collectively" correct (Appendix B and Figure S3.). Ideally, one would need a family
375 of distributions that allows a slow transition from skewed or GEV distributions for small scales to
376 normal distributions when the law of large numbers starts to apply. This would affect the values
377 of p_1 , but without changing the philosophy of our work (the idea of focusing on p_1) nor even the
378 ranking of events in a dramatic way.

379 Lastly, exploring extreme events in a generalized way over so many years and regions requires
380 a high quality data set of temperature observations with temporal homogenization. Here we use
381 ERA5 which performs well over many regions where the data assimilation and the numerical model
382 are efficient. For France we have verified that ERA5 and the Météo-France thermal index are very
383 close. However there are some regions where one may question the data quality (Appendix B and
384 Figure S4) as previously noted by Thompson et al. (2022) in their ranking of heatwaves. Repeating
385 the scanning exercise with other datasets could allow to quantify how observational uncertainties
386 reverberate in our results.

387 Overall, we show that p_1 is an appropriate metric to identify the most extreme weather events
388 in recent history. We have opted for a non-stationary view of climate monitoring — p_1 is the
389 probability of occurrence in the factual, evolving, climate — but minimizing p_0 instead of p_1 can
390 provide a stationary view. The method can be extended to other meteorological variables, such as
391 precipitation or surface winds; yet the estimation of p_1 over various space and time scales is more
392 delicate than for temperature. Following van der Wiel et al. (2020), it can also be adapted to select
393 extreme events in terms of impacts, not weather, by replacing the meteorological variable (e.g.
394 temperature) with an impact-oriented variable (e.g. heat stress). Writing p_1 as a joint probability
395 would also allow to consider compound events. Ultimately, the range of applications for such an
396 exhaustive spatio-temporal scan goes beyond the area of extreme events: for example, replacing p_1
397 with an appropriate evaluation metric could enable the identification of regions and periods where
398 discrepancies between observations and climate models are the strongest, which could make this
399 approach useful for a much wider community.

400 *Acknowledgments.* The authors are grateful to M. Wehner (LBNL) and two anonymous reviewers
401 for their careful proofreading. They thank Y. Robin and M. Schneider (Météo-France) for providing
402 the France thermal index and the associated selections of events and D. Stone (National Institute of
403 Water & Atmospheric Research) for the WRAF regions files. They acknowledge the ERA5 dataset
404 provided by the ECMWF and climate modeling groups involved in CMIP6 for producing and
405 making available their simulations. J.C. particularly thanks S. Qasmi and R. Samacoïts (Météo-
406 France) for their great support on spatial and interactive visualization with R and the shiny package
407 (<https://cran.r-project.org>) and M. Goar (Le Monde).

408 *Data availability statement.* Input data and scanning results are available on a Zenodo archive:
409 <https://doi.org/10.5281/zenodo.7966559>. This includes Météo-France thermal index, ERA5 data
410 averaged over WRAF regions, CMIP data used for the detrending, WRAF data used for the
411 analysis, and date vs. duration matrices of estimated p_1 and p_0 for the three methods (calendar,
412 annual-maxima and -minima) and all regions. R scripts for computing the scanning procedure and
413 visualizing the results are available on GitHub: <https://github.com/jlncttx/CRT23/>. Figures and
414 Tables can also be reproduced on the interactive application: [https://jlncttx.shinyapps.io/CRT23-](https://jlncttx.shinyapps.io/CRT23-app/)
415 [app/](https://jlncttx.shinyapps.io/CRT23-app/).

416 APPENDIX A

417 **Details on the detrending procedure**

418 The statistical procedure used to estimate p_1 involves (i) detrending the time series (making
419 it stationary) and (ii) using standard statistical methods for stationary data. It is equivalent to
420 empirical methods using non-stationary fits on observations (Philip et al. 2020) but we prefer to
421 do a two-step process to ensure consistency of trends between consecutive calendar dates or n -day
422 durations. Here we detail how we correct a (non-stationary) yearly temperature time series with
423 respect to a reference year to make all values representative of the (stationary) climate of that year.
424 We do that by fitting observations onto a multi-model estimate of climate change (forced response
425 F); this is illustrated with the example of France in Figure S3.

426 First, following Ribes et al. (2020), we estimate the pattern of long-term warming at the location
427 of interest by isolating natural and anthropogenic forced responses in a multi-model average of
428 annual mean temperatures. We use an ensemble of 227 historical + SSP5-8.5 members from 46

429 models⁸ of the Phase 6 of the Coupled Model Intercomparison Project and write the multi-model
 430 multi-member mean of yearly temperatures $\mu(y)$ as:

$$\mu(y) = \underbrace{\mu_{nat}(y) + \mu_{ant}(y)}_{F(y)} + \varepsilon(y) , \quad (\text{A1})$$

431 where μ_{nat} the natural forced response, μ_{ant} the anthropogenic forced response, $F = \mu_{nat} + \mu_{ant}$
 432 the total forced response and ε the residual internal variability. This separation is done through a
 433 Generalized Additive Model fit, considering that μ_{nat} is proportional to the response of an Energy
 434 Budget Model to natural forcings (Geoffroy et al. 2013) and μ_{ant} is a smooth spline with 10 degrees
 435 of freedom (Ribes et al. 2020; Robin and Ribes 2020).

436 Second, we subtract from the sample of observations its linear fit onto $F(y)$. For the calendar
 437 approach, the detrending is done on a daily basis, prior to the computation of n -day averages,
 438 to account for potential changes in the annual cycle (e.g. a greater warming in summer than in
 439 winter). Following Rigal et al. (2019), we decompose the daily temperature T of day d and year y :

$$T(d, y) = T_{cyc}(d) + \beta_T(d) \times F(y) + T'(d, y) , \quad (\text{A2})$$

440 with T_{cyc} the average annual cycle (equals to $\frac{1}{n_y} \sum_y T(d, y)$), β_T the scaling factor of each calendar
 441 day onto the forced response F (centered so that $\sum_y F(y) = 0$) and T' the residual or daily anomaly
 442 (verifies $\sum_y T'(d, y) = 0$). Note that T_{cyc} and β_T are smoothed using periodic splines of respectively
 443 12 and 6 degrees of freedom, and that $T_{cyc} + \beta_T \times F$ provides an estimate of the daily non-stationary
 444 normals (i.e. the average annual cycle plus a deformation associated with the long-term trend).
 445 Then the detrending of $T(d, y)$ with respect to the year y_1 writes:

$$T^{(y_1)}(d, y) = T(d, y) - \beta_T(d) \times (F(y) - F(y_1)) . \quad (\text{A3})$$

⁸ACCESS-CM2 (3 members), ACCESS-ESM1-5 (10), AWI-CM-1-1-MR (1), BCC-CSM2-MR (1), CAMS-CSM1-0 (2), CanESM5-CanOE (3), CanESM5 (50), CAS-ESM2-0 (2), CESM2 (3), CESM2-WACCM (3), CIESM (1), CMCC-CM2-SR5 (1), CMCC-ESM2 (1), CNRM-CM6-1-HR (1), CNRM-CM6-1 (6), CNRM-ESM2-1 (5), E3SM-1-1 (1), EC-Earth3-CC (1), EC-Earth3 (3), EC-Earth3-Veg-LR (3), EC-Earth3-Veg (4), FGOALS-f3-L (1), FGOALS-g3 (4), FIO-ESM-2-0 (3), GFDL-CM4 (1), GFDL-ESM4 (1), GISS-E2-1-G (7), HadGEM3-GC31-LL (4), HadGEM3-GC31-MM (4), IITM-ESM (1), INM-CM4-8 (1), INM-CM5-0 (1), IPSL-CM6A-LR (7), KACE-1-0-G (3), KIOST-ESM (1), MCM-UA-1-0 (1), MIROC6 (49), MIROC-ES2L (9), MPI-ESM1-2-HR (2), MPI-ESM1-2-LR (10), MRI-ESM2-0 (2), NESM3 (2), NorESM2-LM (1), NorESM2-MM (1), TaiESM1 (1), UKESM1-0-LL (5).

446 For the annual-maxima and -minima approaches, the detrending is done on a yearly basis, but
 447 separately for all n -day averages, to account for different warming rates in n -day temperature
 448 extremes (e.g. a greater warming in Tx1day than in Tx90day):

$$\begin{aligned} \text{Txnday}^{(y_1)}(y) &= \text{Txnday}(y) - \beta_{\text{Tx}n} \times (F(y) - F(y_1)) \\ \text{Tnnday}^{(y_1)}(y) &= \text{Tnnday}(y) - \beta_{\text{Tn}n} \times (F(y) - F(y_1)) \end{aligned} \quad (\text{A4})$$

449 with $\beta_{\text{Tx}n}$ and $\beta_{\text{Tn}n}$ scaling factors of Txnday and Tnnday onto the forced response.

450 Two important remarks on this simple detrending procedure must be made. First, it only corrects
 451 for potential changes in the mean, not in the variance or higher moments; this is not a major problem
 452 for temperature because changes in the mean dominate the total signal, but a more sophisticated
 453 correction could be used, especially to extend the method to other variables. Second, as we
 454 allow the scaling factors β_T to be different from 1, we correct for possible mismatches between
 455 observations and models on the magnitude of long-term trends; in other words, our correction
 456 $\beta_T \times F$ has the shape of the multi-model mean forced response but the amplitude of the observed
 457 trend.

458 APPENDIX B

459 **Validation of the p_1 estimation procedure**

460 Here we provide further elements of validation of the p_1 estimation procedure. First, we verify
 461 that the selected events are evenly distributed throughout the scanning period, and that no clear
 462 long-term trend is visible in the yearly minimum p_1 (Figure S4). This suggests that the long-term
 463 trend is reasonably accounted for in all regions. Note that El Nino (La Nina) years coincide with
 464 peaks in the number of regions having a record heat-wave (cold spell), as expected since a large
 465 number of regions are dominated by this mode of variability.

466 Second, we verify that the distributions of our p_1 estimates are close to uniform. Figure S5
 467 shows the histograms of p_1 estimates for all events of all 2 Mkm² regions, for various temporal
 468 durations and the three (calendar, annual-maxima, annual-minima) methods. In all cases p_1 is
 469 rather uniformly distributed, suggesting that fitting normal distributions to calendar temperatures
 470 and GEV to annual-maxima and -minima is reasonable. In the calendar approach, slight departures
 471 from the uniform arise at the edges of the [0,1] interval, which could result for asymmetric behaviors.

472 Finally, we show examples of problems encountered in a few cases when scanning the full period
473 and all the regions. Importantly, there is no obvious evidence that the events listed in the main text
474 or tables are concerned by such issues.

475 Figure S6a shows a time series of Tx20day in the 5 Mkm² region of east and south Brazil. The
476 first 5 years of the series (1959–1963) appear well above the rest of the detrended series, which
477 clearly points to a homogeneity problem. This event of October 1963 is selected by our procedure
478 in this region and several child regions with pretty high rankings, but it is at least partly for wrong
479 reasons.

480 Figure S6b illustrates another type of problem: the time series is Tn3day in Pacific Russia, for
481 which the GEV fit gives a very negative shape parameter ($\xi = -0.7$). This very sharp "upper" tail
482 — right side of the distribution since the GEV is reversed for annual minima — results in a very
483 low p_1 associated with this January 1960 event, although its value does not look that extreme. This
484 is partly because several years have "not so low" values, and encourages to increase block size (i.e.
485 more than one year) to help estimating ξ and ensure a better GEV fit.

486 APPENDIX C

487 **An interactive webpage to further explore the results**

488 We have deployed a R shiny application to reproduce the Figures and Tables of the pa-
489 per for all methods, years, and other variables (daily-maximum and -minimum temperatures):
490 <https://jlncttx.shinyapps.io/CRT23-app/>.

491 The "Local scan" tab enables the user to explore the France data and redo Figures 1, 2 and Table 1
492 for any selection of variable, method and year.

493 The "Global scan" tab enables the user to explore results of the ERA5 scan and redo Figures 3
494 and 4 and Tables 2 for any selection of variable, method, year(s) and size of WRAF regions.

495 **References**

- 496 Angéilil, O., D. A. Stone, M. Tadross, F. Tummon, M. Wehner, and R. Knutti, 2014: Attribution of
497 extreme weather to anthropogenic greenhouse gas emissions: sensitivity to spatial and temporal
498 scales. *Geophys. Res. Lett.*, **41** (6), 2150–2155, <https://doi.org/10.1002/2014GL059234>.
- 499 Angéilil, O., and Coauthors, 2018: On the nonlinearity of spatial scales in extreme weather attri-
500 bution statements. *Clim. Dyn.*, **50** (7), 2739–2752, <https://doi.org/10.1007/s00382-017-3768-9>.
- 501 Barlow, A. M., C. Sherlock, and J. Tawn, 2020: Inference for extreme values under threshold-
502 based stopping rules. *Journal of the Royal Statistical Society Series C: Applied Statistics*, **69** (4),
503 765–789, <https://doi.org/10.1111/rssc.12420>.
- 504 Bercos-Hickey, E., T. A. O’Brien, M. F. Wehner, L. Zhang, C. M. Patricola, H. Huang, and M. D.
505 Risser, 2022: Anthropogenic contributions to the 2021 Pacific Northwest heatwave. *Geophys.*
506 *Res. Lett.*, e2022GL099396, <https://doi.org/10.1029/2022GL099396>.
- 507 Boettcher, M., M. Röthlisberger, R. Attinger, J. Rieder, and H. Wernli, 2023: The ERA5 extreme
508 seasons explorer as a basis for research at the weather and climate interface. *Bull. Am. Meterol.*
509 *Soc.*, **104** (3), E631–E644, <https://doi.org/10.1175/BAMS-D-21-0348.1>.
- 510 Cattiaux, J., and A. Ribes, 2018: Defining single extreme weather events in a climate perspective.
511 *Bull. Am. Meterol. Soc.*, **99** (8), 1557–1568, <https://doi.org/10.1175/BAMS-D-17-0281.1>.
- 512 Geoffroy, O., D. Saint-Martin, D. J. L. Olivié, A. Voltaire, G. Bellon, and S. Tytéca, 2013:
513 Transient climate response in a two-layer energy-balance model. Part I: Analytical solution
514 and parameter calibration using CMIP5 AOGCM experiments. *J. Clim.*, **26** (6), 1841–1857,
515 <https://doi.org/10.1175/JCLI-D-12-00195.1>.
- 516 Hersbach, H., and Coauthors, 2020: The ERA5 global reanalysis. *Q. J. R. Meteorol. Soc.*, **146** (730),
517 1999–2049, <https://doi.org/10.1002/qj.3803>.
- 518 Kirchmeier-Young, M. C., H. Wan, X. Zhang, and S. I. Seneviratne, 2019: Importance of framing
519 for extreme event attribution: The role of spatial and temporal scales. *Earth’s Future*, **7** (10),
520 1192–1204, <https://doi.org/10.1029/2019EF001253>.

- 521 McKinnon, K. A., and I. Simpson, 2022: How Unexpected Was the 2021 Pacific Northwest
522 Heatwave? *Geophys. Res. Lett.*, **49**, <https://doi.org/10.1029/2022GL100380>.
- 523 Otto, F. E. L., and Coauthors, 2020: Challenges to understanding extreme weather changes
524 in lower income countries. *Bull. Am. Meteorol. Soc.*, **101** (10), E1851–E1860, <https://doi.org/10.1175/BAMS-D-19-0317.1>.
525
- 526 Peterson, T. C., P. A. Stott, and S. Herring, 2012: Explaining extreme events of 2011 from
527 a climate perspective. *Bull. Am. Meteorol. Soc.*, **93** (7), 1041–1067, <https://doi.org/10.1175/BAMS-D-12-00021.1>.
528
- 529 Philip, S., and Coauthors, 2020: A protocol for probabilistic extreme event attribution analyses. *Adv.
530 Stat. Clim. Meteorol. Oceanogr.*, **6** (2), 177–203, <https://doi.org/10.5194/ascmo-6-177-2020>.
- 531 Philip, S. Y., and Coauthors, 2022: Rapid attribution analysis of the extraordinary heat wave on
532 the Pacific coast of the US and Canada in June 2021. *Earth Syst. Dynam.*, **13** (4), 1689–1713,
533 <https://doi.org/10.5194/esd-13-1689-2022>.
- 534 Ribes, A., J. Boé, S. Qasmi, B. Dubuisson, H. Douville, and L. Terray, 2022: An updated
535 assessment of past and future warming over France based on a regional observational constraint.
536 *Earth Syst. Dynam.*, **13** (4), 1397–1415, <https://doi.org/10.5194/esd-13-1397-2022>.
- 537 Ribes, A., S. Thao, and J. Cattiaux, 2020: Describing the relationship between a weather event
538 and climate change: a new statistical approach. *J. Clim.*, **33** (15), 6297–6314, <https://doi.org/10.1175/JCLI-D-19-0217.1>.
539
- 540 Rigal, A., J.-M. Azais, and A. Ribes, 2019: Estimating daily climatological normals in a changing
541 climate. *Clim. Dyn.*, **53** (1), 275–286, <https://doi.org/10.1007/s00382-018-4584-6>.
- 542 Robin, Y., and A. Ribes, 2020: Nonstationary extreme value analysis for event attribution com-
543 bining climate models and observations. *Adv. Stat. Clim. Meteorol. Oceanogr.*, **6** (2), 205–221,
544 <https://doi.org/10.5194/ascmo-6-205-2020>.
- 545 Russo, S., J. Sillmann, and E. M. Fischer, 2015: Top ten European heatwaves since 1950 and
546 their occurrence in the coming decades. *Environ. Res. Lett.*, **10** (12), 124 003, <https://doi.org/10.1088/1748-9326/10/12/124003>.
547

548 Röthlisberger, M., M. Hermann, C. Frei, F. Lehner, E. M. Fischer, R. Knutti, and H. Wernli, 2021:
549 A new framework for identifying and investigating seasonal climate extremes. *J. Clim.*, **34** (19),
550 7761–7782, <https://doi.org/10.1175/JCLI-D-20-0953.1>.

551 Schumacher, D. L., M. Hauser, and S. I. Seneviratne, 2022: Drivers and mechanisms of the
552 2021 Pacific Northwest heatwave. *Earth's Future*, **10** (12), e2022EF002967, <https://doi.org/10.1029/2022EF002967>.
553

554 Seneviratne, S., and Coauthors, 2021: Weather and Climate Extreme Events in a Changing Climate.
555 In *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the*
556 *Sixth Assessment Report of the Intergovernmental Panel on Climate Change*, journal=Cambridge
557 University Press pages=1513--1766, doi=10.1017/9781009157896.013.

558 Stone, D. A., 2019: A hierarchical collection of political/economic regions for analysis of climate
559 extremes. *Climatic Change*, **155** (4), 639–656, <https://doi.org/10.1007/s10584-019-02479-6>.

560 Stott, P. A., D. A. Stone, and M. R. Allen, 2004: Human contribution to the European heatwave of
561 2003. *Nature*, **432** (7017), 559–60, <https://doi.org/10.1038/nature03089>.

562 Terray, L., 2023: A storyline approach to the June 2021 northwestern North American heatwave.
563 *Geophys. Res. Lett.*, **50** (5), e2022GL101640, <https://doi.org/10.1029/2022GL101640>.

564 Thompson, V., D. Mitchell, G. C. Hegerl, M. Collins, N. J. Leach, and J. M. Slingo, 2023: The
565 most at-risk regions in the world for high-impact heatwaves. *Nat. Commun.*, **14** (1), 2152,
566 <https://doi.org/10.1038/s41467-023-37554-1n>.

567 Thompson, V., and Coauthors, 2022: The 2021 western North America heat wave among the most
568 extreme events ever recorded globally. *Sci. Adv.*, **8** (18), eabm6860, <https://doi.org/10.1126/sciadv.abm6860>.
569

570 van der Wiel, K., F. M. Selten, R. Bintanja, R. Blackport, and J. Screen, 2020: Ensemble climate-
571 impact modelling: extreme impacts from moderate meteorological conditions. *Environ. Res.*
572 *Lett.*, **15**, 034050, <https://doi.org/10.1088/1748-9326/ab7668>.

573 van Oldenborgh, G. J., and Coauthors, 2021a: Attribution of the Australian bushfire risk to
574 anthropogenic climate change. *Natural Hazards and Earth System Sciences*, **21** (3), 941–960,
575 <https://doi.org/10.5194/nhess-21-941-2021>.

- 576 van Oldenborgh, G. J., and Coauthors, 2021b: Pathways and pitfalls in extreme event attribution.
577 *Climatic Change*, **166 (1-2)**, 13, <https://doi.org/10.1007/s10584-021-03071-7>.
- 578 Vautard, R., and Coauthors, 2022: Human influence on growing-period frosts like the early April
579 2021 in Central France. *Nat. Hazards Earth Syst. Sci.*, **2022**, 1–25, <https://doi.org/10.5194/nhess-23-1045-2023>.
580
- 581 White, R. H., and Coauthors, 2023: The unprecedented Pacific Northwest heatwave of June 2021.
582 *Nat. Commun.*, **14 (1)**, 727, <https://doi.org/10.1038/s41467-023-36289-3>.