

1 **Global Human Fingerprints on Daily Temperatures in 2022**

2 Daniel M. Gilford*, Andrew J. Pershing, and Joseph Giguere

3 *Climate Central, Princeton, NJ, USA*

4 Friederike E. L. Otto

5 *Grantham Institute of Climate Change, Imperial College London, UK*

6 *Corresponding author: D. M. Gilford, dgilford@climatecentral.org

7 *Capsule summary.* Extreme temperatures in the UK (July 2022) and India/Pakistan (Spring 2022)
8 are confidently attributed to climate change using an automated system. Similarly attributable
9 extremes occurred frequently worldwide in 2022.

10 **1. Introduction**

11 2022 was an exceptional year for heat around the globe. Heat-related disasters worldwide
12 worsened droughts and forest fires, and threatened millions of people's health (EM-DAT 2008;
13 Ballester et al. 2023). While human-induced climate change is no doubt responsible for the
14 globally-increasing rate and intensity of extreme heat (Masson-Delmotte et al. 2021), there is
15 an ongoing need to continually investigate and communicate the extent of this human influence
16 depending on time of year, region, and event persistence (Swain et al. 2020).

17 The rapid advancement of climate attribution science is enabling quantitative and confident
18 attribution of human influences on the likelihood of individual heat events within days of occurrence
19 (National Academies of Sciences 2016; Masson-Delmotte et al. 2021; Clarke et al. 2022). The
20 World Weather Attribution Initiative (WWA) has pioneered rapid attribution approaches, and
21 regularly publishes detailed attribution reports of specific events using peer-reviewed methods
22 (e.g. Philip et al. 2020). These self-consistent reports reliably inform which 2022 heat events were
23 potentially most noteworthy and attributable (World Weather Attribution Initiative 2023; Otto and
24 Raju 2023). But WWA's in-depth studies require limited resources and days-to-weeks to produce,
25 which restricts the number of heat events that can be assessed and attributed over a given year.

26 A new automated attribution system has been developed to enable real-time climate attribution of
27 heat events every day, everywhere (G22; Gilford et al. 2022). We implement this system to expand
28 on WWA's capacity, producing a hindcast of daily attribution estimates for globally-resolved air
29 temperatures in 2022. We also evaluate the system by comparing with WWA reports for two events:

30 a 2-day event over the UK (July 2022) and a 2-month-long event over India/Pakistan (Mar/Apr
31 2022). Using these as a benchmark, we demonstrate the attributable scale and spacial-temporal
32 scope of similarly-defined events around the world in 2022.

33 2. Approach and Data

34 We quantify the attributable climate influence on observed daily and multi-day temperatures with
35 a metric called the “Change in Information due to Perspective” (ChIP) based on the definition of
36 Shannon information content from information theory (MacKay 2003; Pershing et al. 2023). ChIP
37 compares the occurrence probability of daily temperature, T , in the observed present day climate
38 (P_{mod} ; +1.27 K global mean temperature; GMT) with that from a counterfactual climate without
39 greenhouse gas emissions (P_{cf} ; +0 K),

$$\text{ChIP}(T) \equiv \log_2(P_{mod}(T)/P_{cf}(T)) \quad (1)$$

40 Evaluating attribution with ChIP has several advantages. The occurrence ratio in Eqn. 1 considers
41 changes in the probability of *observing* T , rather than commonly-employed “probability ratios”
42 (PRs; e.g. Philip et al. 2020) that consider changes in the probability of *exceeding* T . This approach
43 enables attribution assessments for not only extremely hot days, but all days, which allows negative
44 ChIP values to be assigned to conditions made less likely by climate change.

45 As part of their standard analysis, WWA estimates the PR of the multi-day mean temperature.
46 ChIP’s logarithmic form allows its daily values to be averaged or summed, providing a meaningful
47 attribution estimates for multi-day events. We use this feature to derive a variance-scaled ChIP
48 that can be directly compared with WWA’s multi-day PRs.

49 To derive this expression, we assume temperatures (T) are normally distributed, and the likelihood
50 of T is given by $P \sim \mathcal{N}(T, \mu, \sigma)$, with a mean, μ , and standard deviation, σ . The attributable change

51 in likelihood between historical and counterfactual periods can then be described by a change in
 52 the mean, $\mu + \delta$, where δ is linearly related to attributable GMT changes in the framework's median
 53 method (see below). Rewriting Eqn. 1:

$$\text{ChIP}(T) \simeq \log_2(\mathcal{N}_{hist}(T, \mu + \delta, \sigma) / \mathcal{N}_{cf}(T, \mu, \sigma)) \quad (2)$$

$$\simeq -\delta \frac{1}{2\sigma^2} (\delta - 2T + \mu). \quad (3)$$

54 Assuming μ , δ , and daily σ are representative over the n -day period, then the ChIP of n -day average
 55 temperatures ($\bar{T} = (1/n) \sum_{j=1}^n T_j$) is,

$$\text{ChIP}_n(\bar{T}) = \left(\frac{\sigma^2}{\sigma_n^2} \right) \overline{\text{ChIP}(T_j)} \quad (4)$$

56 where σ_n is the standard deviation of the n -day means. The resulting variance-scaled ChIP,
 57 $\text{ChIP}_n(\bar{T})$, quantifies the influence of climate change on multi-day average temperatures.

58 We implement G22's multi-method attribution framework (Gilford et al. 2022; Pershing et al.
 59 2023) following established attribution protocols (Philip et al. 2020) to create a 2022 daily hindcast
 60 of ChIP and $\text{ChIP}_n(\bar{T})$ around the world. The multi-method approach uses observed trends from
 61 ERA5 (Hersbach et al. 2020) and climate simulations from CMIP6 (CMIP6; Eyring et al. 2016) to
 62 generate an ensemble of modern and counterfactual distributions (Supplementary Materials). For
 63 each observed daily 2m maximum (T_{max}), average (T_{avg}), and minimum air temperature (T_{min}) we
 64 calculate empirical- and model-derived P_{mod} and P_{cf} , which are synthesized to produce a ChIP
 65 for each daily temperature observation in 2022.

66 3. Results

67 Figure 1 summarizes analyses of United Kingdom’s 2-day extreme heat event during 17-18
68 July 2022. WWA analyzed two extreme event definitions averaged over the region (black box):
69 the 2-day mean T_{avg} and the annual maximum of T_{max} . Both metrics were observed above their
70 climatological 99th percentiles.

71 Mean ChIP values during the UK event were 3.0 (T_{avg}) and 2.8 (T_{max}), indicating the extreme
72 temperatures were made $\sim 8\times$ more likely because of climate change. This equivalent ratio is
73 smaller than WWA’s final PR estimate (10 \times), but under near-record temperatures the underesti-
74 mate is consistent with G22’s conservative system design. Because ChIP values are constructed
75 occurrence probabilities, their ratio will always be lower than the PR. Secondly, to enable au-
76 tonomous real-time attribution, G22’s framework evaluates a continuous skew-normal fit across
77 each probability distribution rather than using extreme value theory in the tails (e.g., van Olden-
78 borgh et al. 2021). This effectively bounds reliable ChIP calculations, because tail probabilities
79 will be undersampled and thus uncertain. Pershing et al. (2023) codifies this limitation by fixing
80 an absolute upper bound of $|\text{ChIP}| \leq 4$ on each method’s output, so the maximum equivalent PR
81 is 16 (if the empirical- and model-based methods both reach this maximum). Altogether, while
82 ChIP values are often a conservative underestimate, results agree with WWA that human-caused
83 climate change made the UK event much more likely.

84 To screen for comparable events in 2022, we regrid temperature and ChIP to a resolution
85 comparable to the UK event ($2^\circ \times 2^\circ$, black box Fig. 1a) and then search for when/where 2-
86 day rolling-mean T_{avg} values exceeded their climatological 99th percentile. Without a climate
87 shifted distribution we would expect 3.7 exceedances per year, but globally we find these events
88 were much more common in 2022. Hotspots with 20+ events include central/west N. America,

89 Argentina/Paraguay, central Africa, western Europe, China, and Papua New Guinea. These events
90 were robustly attributable ($\text{ChIP} > 0.5$, shading Fig. 1c) with some reaching the maximum ($\text{ChIP} =$
91 4.0). Zonal-mean ChIP over these hotspots was typically between 1 and 2.5.

92 Figure 2 summarizes analyses of India and Pakistan’s 2-month-long extreme heat during
93 March/April 2022. Two-month-average T_{max} peaked during the second warmest March/April
94 since 1991. Anomalies ranged from +1 to +6 across the averaging region (black polygon Fig.
95 2a), while variance-scaled ChIP estimates reached 16.0 along India’s northwest coastal region and
96 $\text{ChIP}_n(\bar{T}) \sim 5$ stretched into the interior during the event. $\text{ChIP} = 16$ implies that the 2-month
97 average temperature was made $65,536\times$ more likely because of climate change.

98 Region-average equivalent PRs show these event anomalies were $\sim 2^{3.1} = 8.6\times$ more likely
99 because of human-caused climate change, lower than the average but falling within the range of
100 WWA PR estimates ($30\times [2-140]$). Despite cooler anomalies through the rest of 2022, 2-month-
101 average T_{max} was robustly attributable throughout the year; this result implies that the signal of
102 climate change in India/Pakistan 2-month-mean temperatures has effectively emerged from the
103 baseline climate.

104 To find events similar to the WWA event definition, we search for places and periods around
105 the world where the rolling 2-monthly-average temperatures in 2022 were ranked in the top two
106 since 1991. The mapped number of monthly-pair events that met this criteria (out of 12) shows
107 many places globally where persistent heat stretched across multiple months. The most prominent
108 hotspots include south-central US, western Europe, Mediterranean coasts, central and eastern
109 Africa, most of China, northern Australia, and Papua New Guinea. Variance-scaled ChIP estimates
110 indicate these events are strongly attributable, consistently averaging ≥ 4.0 .

111 We also examined attributable T_{min} estimates over India/Pakistan. Despite cooler anomalies
112 overall, regionally-averaged variance-scaled ChIP estimates of 2-monthly T_{min} are consistently

113 larger than those of T_{max} (except in Jan/Feb), with a regional average of 7.0 in March/April (i.e.
114 made 128× more likely by climate change). In September/October, cooler overall T_{min} values
115 had attribution estimates of equivalent PR > 18,000×, consistent with climate change’s strong
116 overnight influence (Karl et al. 1993; Doan et al. 2022).

117 **4. Discussion**

118 A hindcast attributing daily 2022 temperatures to human-caused climate change shows that the
119 WWA definitions of short- (2-day) and long-lived (2-month) extreme temperature events were both
120 relatively common across the globe and highly attributable. Using WWA event definitions, this
121 study demonstrates good agreement between WWA attribution estimates and the G22 automated
122 attribution system over two distinct extreme heat events: a 2-day event over the UK (July 2022) and
123 a 2-month-long event over India/Pakistan (Mar/Apr 2022). While the framework’s conservative
124 design often underestimates the climate influence compared with WWA’s numbers, we find the
125 approach is capable of rapidly identifying and confidently attributing these events. It has also been
126 extended to evaluate similar events on a daily, global basis, and can serve as an early-warning
127 system to support immediate climate change communications.

128 There are clear and robust human fingerprints on 2022’s daily weather. For instance, our results
129 expose the powerful emergence of human influence on overnight temperatures, a well-known (but
130 often under-communicated and under-studied) result of climate change with potentially critical
131 impacts on global health and economics (Royé et al. 2021; Wang et al. 2022; Kim et al. 2023;
132 He et al. 2022). While a thorough examination of the negative impacts associated with these
133 events is beyond our scope here, multiple lines of early evidence indicate that the widespread
134 2022 attributable heat had human consequences (e.g. Ballester et al. 2023; Tobías et al. 2023).

135 Our analyses reveal that there are still many outstanding opportunities to study and communicate
136 attributable temperature events throughout the world each year.

137 **Figures**

138 *Acknowledgments.* Funding provided by the Bezos Earth Fund, Eric and Wendy Schmidt Fund for
139 Strategic Innovation/The Schmidt Family Foundation, High Meadows Foundation, and the William
140 and Flora Hewlett Foundation.

141 **References**

- 142 Ballester, J., and Coauthors, 2023: Heat-related mortality in europe during the summer of 2022.
143 *Nature Medicine*, **29** (7), 1857–1866, doi:10.1038/s41591-023-02419-z, URL [https://doi.org/](https://doi.org/10.1038/s41591-023-02419-z)
144 [10.1038/s41591-023-02419-z](https://doi.org/10.1038/s41591-023-02419-z).
- 145 Clarke, B., F. Otto, R. Stuart-Smith, and L. Harrington, 2022: Extreme weather impacts of
146 climate change: an attribution perspective. *Environmental Research: Climate*, **1** (1), 012 001,
147 doi:10.1088/2752-5295/ac6e7d.
- 148 Doan, Q. V., F. Chen, Y. Asano, Y. Gu, A. Nishi, H. Kusaka, and D. Niyogi, 2022: Causes for
149 Asymmetric Warming of Sub-Diurnal Temperature Responding to Global Warming. *Geophysi-*
150 *cal Research Letters*, **49** (20), 1–11, doi:10.1029/2022GL100029.
- 151 EM-DAT, 2008: Em-dat: The international disaster database. Available at: <http://www.emdat.be/>
152 [Database/Trends/trends.html](http://www.emdat.be/Database/Trends/trends.html).
- 153 Eyring, V., S. Bony, G. A. Meehl, C. A. Senior, B. Stevens, R. J. Stouffer, and K. E. Taylor,
154 2016: Overview of the coupled model intercomparison project phase 6 (cmip6) experimental

155 design and organization. *Geoscientific Model Development*, **9** (5), 1937–1958, doi:10.5194/
156 gmd-9-1937-2016, URL <https://gmd.copernicus.org/articles/9/1937/2016/>.

157 Gilford, D. M., A. Pershing, B. H. Strauss, K. Haustein, and F. E. L. Otto, 2022: A multi-
158 method framework for global real-time climate attribution. *Advances in Statistical Climatology,*
159 *Meteorology and Oceanography*, **8** (1), 135–154, doi:10.5194/ascmo-8-135-2022, URL <https://ascmo.copernicus.org/articles/8/135/2022/>.

161 He, C., and Coauthors, 2022: The effects of night-time warming on mortality burden under
162 future climate change scenarios: a modelling study. *The Lancet Planetary Health*, **6** (8), e648–
163 e657, doi:10.1016/S2542-5196(22)00139-5, URL [http://dx.doi.org/10.1016/S2542-5196\(22\)](http://dx.doi.org/10.1016/S2542-5196(22)00139-5)
164 [00139-5](http://dx.doi.org/10.1016/S2542-5196(22)00139-5).

165 Hersbach, H., and Coauthors, 2020: The era5 global reanalysis. *Quarterly Journal of the Royal*
166 *Meteorological Society*, **146** (730), 1999–2049, doi:<https://doi.org/10.1002/qj.3803>, URL <https://rmets.onlinelibrary.wiley.com/doi/abs/10.1002/qj.3803>.

168 Karl, T. R., and Coauthors, 1993: Asymmetric Trends of Daily Maximum and Minimum
169 Temperature. *Bulletin of the American Meteorological Society*, **74** (6), 1007–1023, doi:
170 [10.1175/1520-0477\(1993\)074<1007:ANPORG>2.0.CO;2](https://doi.org/10.1175/1520-0477(1993)074<1007:ANPORG>2.0.CO;2).

171 Kim, S. E., M. Hashizume, B. Armstrong, A. Gasparrini, K. Oka, Y. Hijioka, A. M. Vicedo-
172 Cabrera, and Y. Honda, 2023: Mortality risk of hot nights: A nationwide population-based
173 retrospective study in japan. *Environmental Health Perspectives*, **131** (5), 057005, doi:10.
174 [1289/EHP11444](https://doi.org/10.1289/EHP11444), URL <https://ehp.niehs.nih.gov/doi/abs/10.1289/EHP11444>, <https://ehp.niehs.nih.gov/doi/pdf/10.1289/EHP11444>.

176 MacKay, D. J. C., 2003: *Information Theory, Inference, and Learning Algorithms*. Copyright
177 Cambridge University Press.

178 Masson-Delmotte, V., and Coauthors, 2021: Cambridge University Press, Cambridge,
179 United Kingdom and New York, NY, USA, 1–3949 pp., URL [https://www.ipcc.ch/report/
180 sixth-assessment-report-working-group-i/](https://www.ipcc.ch/report/sixth-assessment-report-working-group-i/).

181 National Academies of Sciences, 2016: *Attribution of Extreme Weather Events in the Context of
182 Climate Change*. 186 pp. pp., doi:10.17226/21852, URL <http://nap.edu/21852>.

183 Otto, F. E. L., and E. Raju, 2023: Harbingers of decades of unnatural disasters. *Communications
184 Earth & Environment*, **4** (1), 280, doi:10.1038/s43247-023-00943-x, URL [https://doi.org/10.
185 1038/s43247-023-00943-x](https://doi.org/10.1038/s43247-023-00943-x).

186 Pershing, A. J., K. L. Ebi, D. M. Gilford, J. Giguere, B. W. Placky, and B. H. Strauss, 2023: Beyond
187 extremes: quantifying the exposure of people and ecosystems to climate-driven heat every day,
188 everywhere. *PNAS*, under review.

189 Philip, S., and Coauthors, 2020: A protocol for probabilistic extreme event attribution analyses.
190 *Advances in Statistical Climatology, Meteorology and Oceanography*, **6** (2), 177–203, doi:
191 10.5194/ascmo-6-177-2020.

192 Royé, D., and Coauthors, 2021: Effects of hot nights on mortality in southern europe. *Epidemi-
193 ology*, **32** (4), URL [https://journals.lww.com/epidem/fulltext/2021/07000/effects_of_hot_nights_
194 on_mortality_in_southern.5.aspx](https://journals.lww.com/epidem/fulltext/2021/07000/effects_of_hot_nights_on_mortality_in_southern.5.aspx).

195 Swain, D. L., D. Singh, D. Touma, and N. S. Diffenbaugh, 2020: Attributing Extreme Events
196 to Climate Change: A New Frontier in a Warming World. *One Earth*, **2** (6), 522–527, doi:
197 10.1016/j.oneear.2020.05.011, URL <https://doi.org/10.1016/j.oneear.2020.05.011>.

198 Tobías, A., D. Royé, and C. Iñiguez, 2023: Heat-attributable mortality in the summer of 2022 in
199 Spain. *Epidemiology*, **34** (2), URL [https://journals.lww.com/epidem/fulltext/2023/03000/heat_](https://journals.lww.com/epidem/fulltext/2023/03000/heat_attributable_mortality_in_the_summer_of_2022.19.aspx)
200 [attributable_mortality_in_the_summer_of_2022.19.aspx](https://journals.lww.com/epidem/fulltext/2023/03000/heat_attributable_mortality_in_the_summer_of_2022.19.aspx).

201 van Oldenborgh, G. J., and Coauthors, 2021: Pathways and pitfalls in extreme event attribution.
202 *Climatic Change*, **166** (1), 13, doi:10.1007/s10584-021-03071-7, URL [https://doi.org/10.1007/](https://doi.org/10.1007/s10584-021-03071-7)
203 [s10584-021-03071-7](https://doi.org/10.1007/s10584-021-03071-7).

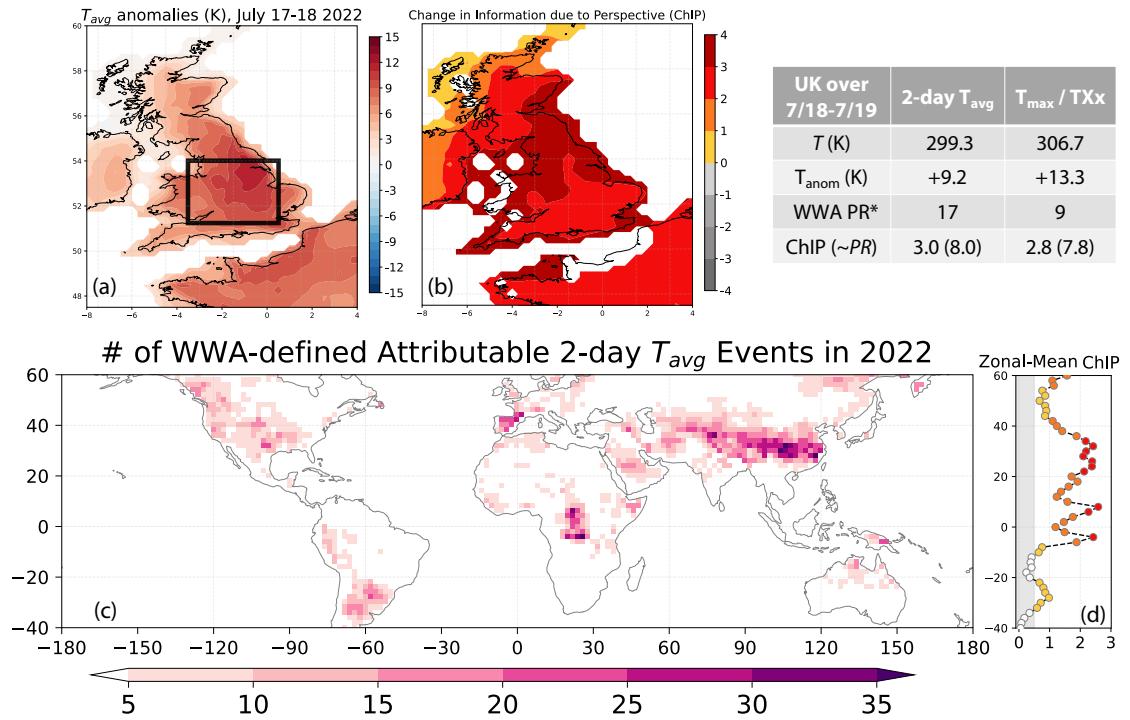
204 Wang, Y., X. Shen, M. Jiang, S. Tong, and X. Lu, 2022: Daytime and nighttime temperatures
205 exert different effects on vegetation net primary productivity of marshes in the western songnen
206 plain. *Ecological Indicators*, **137**, 108 789, doi:<https://doi.org/10.1016/j.ecolind.2022.108789>,
207 URL <https://www.sciencedirect.com/science/article/pii/S1470160X22002606>.

208 World Weather Attribution Initiative, 2023: Heatwave Reports. [Accessed 17-08-2023], [https:](https://www.worldweatherattribution.org/analysis/heatwave/)
209 [//www.worldweatherattribution.org/analysis/heatwave/](https://www.worldweatherattribution.org/analysis/heatwave/).

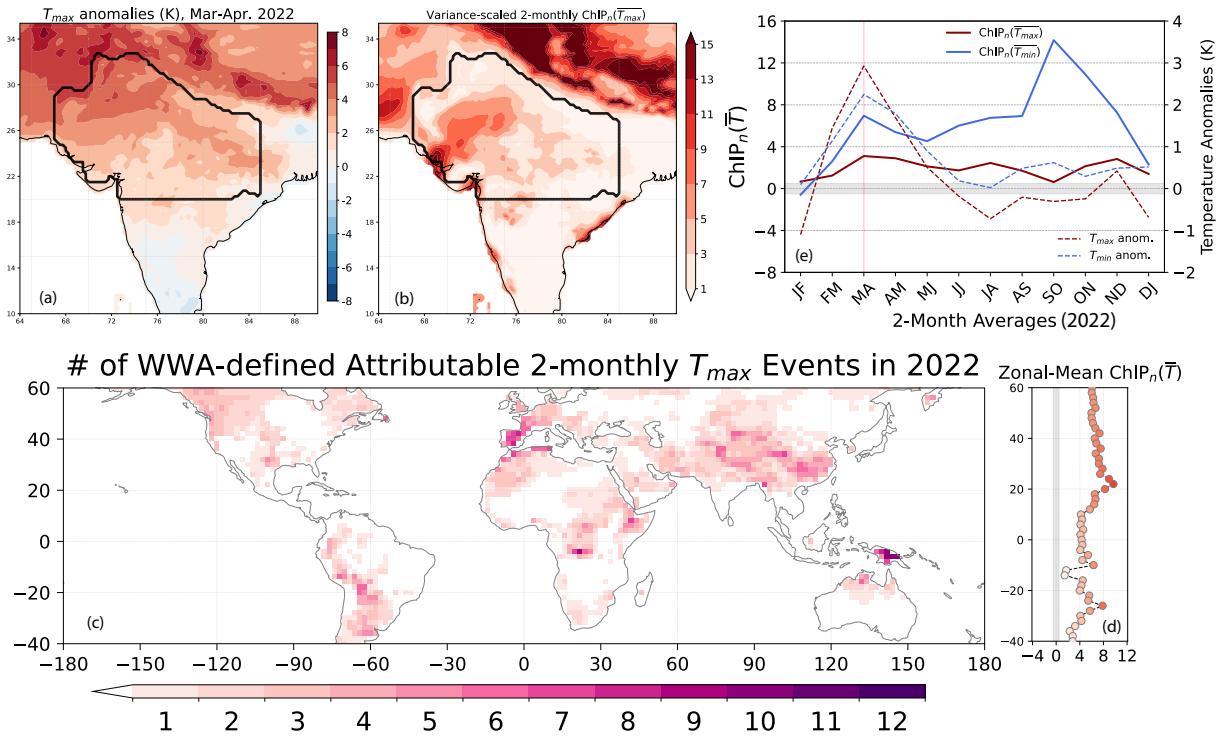
210 **LIST OF FIGURES**

211 **Fig. 1.** 17-18 July 2022 (a) average temperature anomalies and (b) the associated Change in Informa-
212 tion due to Perspective (ChIP; i.e. this study’s daily attribution estimate). The accompanying
213 table includes temperatures (the defining basis for similar extreme events, see text) and compares
214 World Weather Attribution range of *lower bound probability ratios against this study’s
215 ChIP estimates and the equivalent PR. (c) Number of 2-day average temperatures in 2022 consi-
216 stent with the WWA UK event definition in each $2^\circ \times 2^\circ$ land pixel, and (d) the zonal-mean
217 ChIP associated with these events. 13

218 **Fig. 2.** March/April-mean 2022 (a) maximum temperature anomalies and (b) the associated
219 variance-scaled ChIP. (c) Number of 2-monthly-mean maximum temperatures in 2022 (of
220 twelve 2-monthly periods, Jan-Feb. through Dec-Jan.) consistent with the WWA In-
221 dia/Pakistan event definition (see text) in each $2^\circ \times 2^\circ$ land pixel, and (d) the zonal-mean
222 variance-scaled ChIP associated with these events. (e) The 2022 seasonal cycle of 2-monthly-
223 mean maximum (red lines) and minimum (blue lines) temperature anomalies (dashed lines)
224 and their associated variance-scaled ChIP levels (solid lines). 14



225 FIG. 1. 17-18 July 2022 (a) average temperature anomalies and (b) the associated Change in Information due
 226 to Perspective (ChIP; i.e. this study’s daily attribution estimate). The accompanying table includes temperatures
 227 (the defining basis for similar extreme events, see text) and compares World Weather Attribution range of *lower
 228 bound probability ratios against this study’s ChIP estimates and the equivalent PR. (c) Number of 2-day average
 229 temperatures in 2022 consistent with the WWA UK event definition in each $2^\circ \times 2^\circ$ land pixel, and (d) the
 230 zonal-mean ChIP associated with these events.



231 FIG. 2. March/April-mean 2022 (a) maximum temperature anomalies and (b) the associated variance-scaled
 232 ChIP. (c) Number of 2-monthly-mean maximum temperatures in 2022 (of twelve 2-monthly periods, Jan-Feb.
 233 through Dec-Jan.) consistent with the WWA India/Pakistan event definition (see text) in each $2^\circ \times 2^\circ$ land pixel,
 234 and (d) the zonal-mean variance-scaled ChIP associated with these events. (e) The 2022 seasonal cycle of
 235 2-monthly-mean maximum (red lines) and minimum (blue lines) temperature anomalies (dashed lines) and their
 236 associated variance-scaled ChIP levels (solid lines).