

The background of the entire page is a dramatic, apocalyptic landscape. A massive, intense fire burns across the horizon, sending thick, dark smoke billowing into a sky filled with orange and yellow light. In the foreground, a herd of cattle and sheep stands on a dry, brown field, looking towards the viewer. The scene conveys a sense of environmental crisis and extreme weather events.

EXPLAINING EXTREME EVENTS OF 2017

From A Climate Perspective

Special Supplement to the
Bulletin of the American Meteorological Society
Vol. 100, No. 1, January 2019

EXPLAINING EXTREME EVENTS OF 2017 FROM A CLIMATE PERSPECTIVE

Editors

Stephanie C. Herring, Nikolaos Christidis, Andrew Hoell,
Martin P. Hoerling, and Peter A. Stott

Special Supplement to the

Bulletin of the American Meteorological Society

Vol. 100, No. 1, January 2019

AMERICAN METEOROLOGICAL SOCIETY

CORRESPONDING EDITOR:

Stephanie C. Herring, PhD
NOAA National Centers for Environmental Information
325 Broadway, E/CC23, Rm 1B-131
Boulder, CO, 80305-3328
E-mail: stephanie.herring@noaa.gov

COVER CREDIT:

©Dean Sewell/Fairfax Syndication—Sir Ivan Bushfire, February 2017. A bushfire that started near Leadvill, east of Duneedoo in the New South Wales (NSW) Central tablelands, ripped through bush and grasslands in a day that NSW fire authorities classified as catastrophic. Sheep and cattle maneuver around a dam to avoid a fast running bushfire as the fire front moved east. Photograph by Dean Sewell/Oculi.

HOW TO CITE THIS DOCUMENT

Citing the complete report:

Herring, S. C., N. Christidis, A. Hoell, M. P. Hoerling, and P. A. Stott, Eds., 2019: Explaining Extreme Events of 2017 from a Climate Perspective. *Bull. Amer. Meteor. Soc.*, **100** (1), S1–S117, <https://doi.org/10.1175/BAMS-ExplainingExtremeEvents2017.1>.

Citing a section (example):

Hope, P., M. T. Black, E.-P. Lim, A. Dowdy, G. Wang, A. S. Pepler, and R. J. B. Fawcett, 2019: On determining the impact of increasing atmospheric CO₂ on the record fire weather in eastern Australia in February 2017 [in “Explaining Extremes of 2017 from a Climate Perspective”]. *Bull. Amer. Meteor. Soc.*, **100** (1), S111–S117, <https://doi.org/10.1175/BAMS-D-18-0135.1>.

TABLE OF CONTENTS

1. Introduction to Explaining Extreme Events of 2017 from a Climate Perspective.....	S1
2. Actuaries are Paying Attention to Climate Data	S5
3. Hydroclimatic Extremes as Challenges for the Water Management Community: Lessons from Oroville Dam and Hurricane Harvey	S9
4. Observations of the Rate and Acceleration of Global Mean Sea Level Change	S15
5. Anthropogenic Contributions to the Intensity of the 2017 United States Northern Great Plains Drought.....	S19
6. Attribution of the 2017 Northern High Plains Drought	S25
7. The Extremely Wet March of 2017 in Peru.....	S31
8. Contribution of Anthropogenic Climate Change to April–May 2017 Heavy Precipitation over the Uruguay River Basin.....	S37
9. December 2016: Linking the Lowest Arctic Sea-Ice Extent on Record with the Lowest European Precipitation Event on Record	S43
10. The Exceptional Summer Heat Wave in Southern Europe 2017	S49
11. Examining the Potential Contributions of Extreme “Western V” Sea Surface Temperatures to the 2017 March–June East African Drought	S55
12. Risks of Pre-Monsoon Extreme Rainfall Events of Bangladesh: Is Anthropogenic Climate Change Playing a Role?	S61
13. The Effects of Natural Variability and Climate Change on the Record Low Sunshine over Japan during August 2017	S67
14. Anthropogenic Contribution to 2017 Earliest Summer Onset in South Korea	S73
15. Anthropogenic Influence on the Heaviest June Precipitation in Southeastern China since 1961	S79
16. Attribution of the Persistent Spring–Summer Hot and Dry Extremes over Northeast China in 2017.....	S85
17. Anthropogenic Warming has Substantially Increased the Likelihood of July 2017–Like Heat Waves over Central Eastern China	S91
18. Attribution of a Record-Breaking Heatwave Event in Summer 2017 over the Yangtze River Delta.....	S97
19. The Role of Natural Variability and Anthropogenic Climate Change in the 2017/18 Tasman Sea Marine Heatwave.....	S105
20. On Determining the Impact of Increasing Atmospheric CO ₂ on the Record Fire Weather in Eastern Australia in February 2017	S111

ANTHROPOGENIC WARMING HAS SUBSTANTIALLY INCREASED THE LIKELIHOOD OF JULY 2017–LIKE HEAT WAVES OVER CENTRAL EASTERN CHINA

YANG CHEN, WEI CHEN, QIN SU, FEIFEI LUO, SARAH SPARROW, FANGXING TIAN, BUWEN DONG, SIMON F. B. TETT, FRASER C. LOTT, AND DAVID WALLOM

Heat waves in central eastern China like the record-breaking July 2017 event were rare in natural worlds but have now become approximately 1-in-5-yr events due to anthropogenic forcings.

INTRODUCTION. During July 2017, an unprecedentedly intense heat wave struck central eastern China, resulting in drastically increased human morbidity/mortality, steeply reduced agriculture productivity, and serious shortage of electricity and water supply (CMA 2017). Many meteorological stations registered 15–25 hot days (daily maximum temperature over 35°C), and some even had record-high July temperatures, such as a new record of 40.9°C among historical observations since 1873 at Xu-Jia-Hui station in Shanghai (CMA 2017). The China

Meteorological Administration issued 10 high-level warnings against hot weather during 21–25 July. Such unprecedentedly frequent alarms within only 5 days attracted intense scrutiny from policy-makers, media, and the public on the relationship between this heat wave and global warming.

Previous studies usually conducted attribution analyses on seasonal warmth in central eastern China (e.g., the 2013 record-breaking summer; Sun et al. 2014), leaving attribution statements for short-term (synoptic) hot extremes sparsely reported. This study therefore attempts to answer whether and to what extent anthropogenic warming has increased the likelihood of 5-day heat waves as hot as or hotter than the 21–25 July 2017 case over central eastern China.

DATA AND METHODS. Homogenized observations of daily maximum temperatures (Tmax) during 1960–2017 from 760 meteorological stations are used [Li et al. 2015; for homogenization methods see Szentimrey (1999)]. Daily observations is interpolated onto the $0.56^\circ \times 0.83^\circ$ grid of the model via a “natural neighbor” scheme (Sibson 1981), following the model’s resolution and geography.

The upgraded HadGEM3-GA6-N216 model is employed (Christidis et al. 2013; Ciavarella et al. 2018). Model outputs include all-forced simulations conditioned on the observed 2017 sea surface temperature (SST) and sea ice from the HadISST dataset (Rayner et al. 2003) and naturalized simulations with anthropogenic signals removed from observed SSTs and with preindustrial forcings. Accordingly, occurrence probabilities and resultant attribution conclusions reported in this study are also conditioned on the 2017 SST patterns. The ensemble is generated through physics perturbations of multiple initial conditions with identical external forcings.

AFFILIATIONS: Y. CHEN—State Key Laboratory of Severe Weather, Chinese Academy of Meteorological Sciences, Beijing, China; W. CHEN—State Key Laboratory of Numerical Modeling for Atmospheric Sciences and Geophysical Fluid Dynamics, Institute of Atmospheric Physics, Chinese Academy of Sciences, Beijing, China; SU—Department of Atmospheric Sciences, Yunnan University, Kunming, China; LUO—Nansen-Zhu International Research Centre and Climate Change Research Center, Institute of Atmospheric Physics, Chinese Academy of Sciences, Beijing, China; SPARROW AND WALLOM—University of Oxford, Oxford e-Research Centre, Oxford, United Kingdom; TIAN AND DONG—National Centre for Atmospheric Science, Department of Meteorology, University of Reading, Reading, United Kingdom; TETT—School of Geosciences, University of Edinburgh, Edinburgh, United Kingdom; LOTT—Met Office Hadley Centre, Exeter, United Kingdom

CORRESPONDING AUTHOR: Dr. Wei Chen, chenwei@mail.iap.ac.cn

DOI:10.1175/BAMS-D-18-0087.1

A supplement to this article is available online (10.1175/BAMS-D-18-0087.2)

© 2019 American Meteorological Society

For information regarding reuse of this content and general copyright information, consult the [AMS Copyright Policy](#).

More specifically, historical simulations (histCLIM) consisting of 15 members over 1961–2013 are compared with interpolated observations to evaluate the model's fidelity in simulating climatological statistics (mean and variability) of the strongest 5-day heat waves. Two ensembles of 525-member simulations for the 2017 July with (hereafter histALL, as an extension of previous histCLIM runs) and without (hereafter histNAT) anthropogenic forcings are used to estimate the probability of the 21–25 July heat wave in each scenario. Denoting P_{ALL} and P_{NAT} as the occurrence probability of events equivalent to or stronger than the targeted case in 525-member histALL and histNAT ensembles, the risk ratio (RR) is expressed as P_{ALL}/P_{NAT} . The fraction of attributable risks (FAR) is expressed as $1 - P_{NAT}/P_{ALL}$.

Reference climatologies over 1961–90 are formed for both simulations (ensemble mean of 15-member

histCLIM) and observations from the hottest 5-day running mean Tmax in July. These pentad climatologies are approximately 2°–3°C warmer than July monthly-mean Tmax climatologies in both simulations and observations, and serve to distinguish especially intense 5-day heat waves from more typical 5-day cases (Figs. 1c,d). Respective climatologies are then removed from observations and simulations to create overlapping pentad Tmax anomalies (hereafter PTmax; see Fig. 1c). Based on these PTmax anomalies, both the historical distribution of the hottest 5-day heat waves and warm anomalies for the 2017 case could be well reproduced by this model (see Fig. ES1 in the online supplemental information), indicating the suitability of using this model and PTmax anomalies for attributing this 5-day heat wave. Freychet et al. (2018) also reported good performance of this model in simulating characteristics of 5-day heat waves in

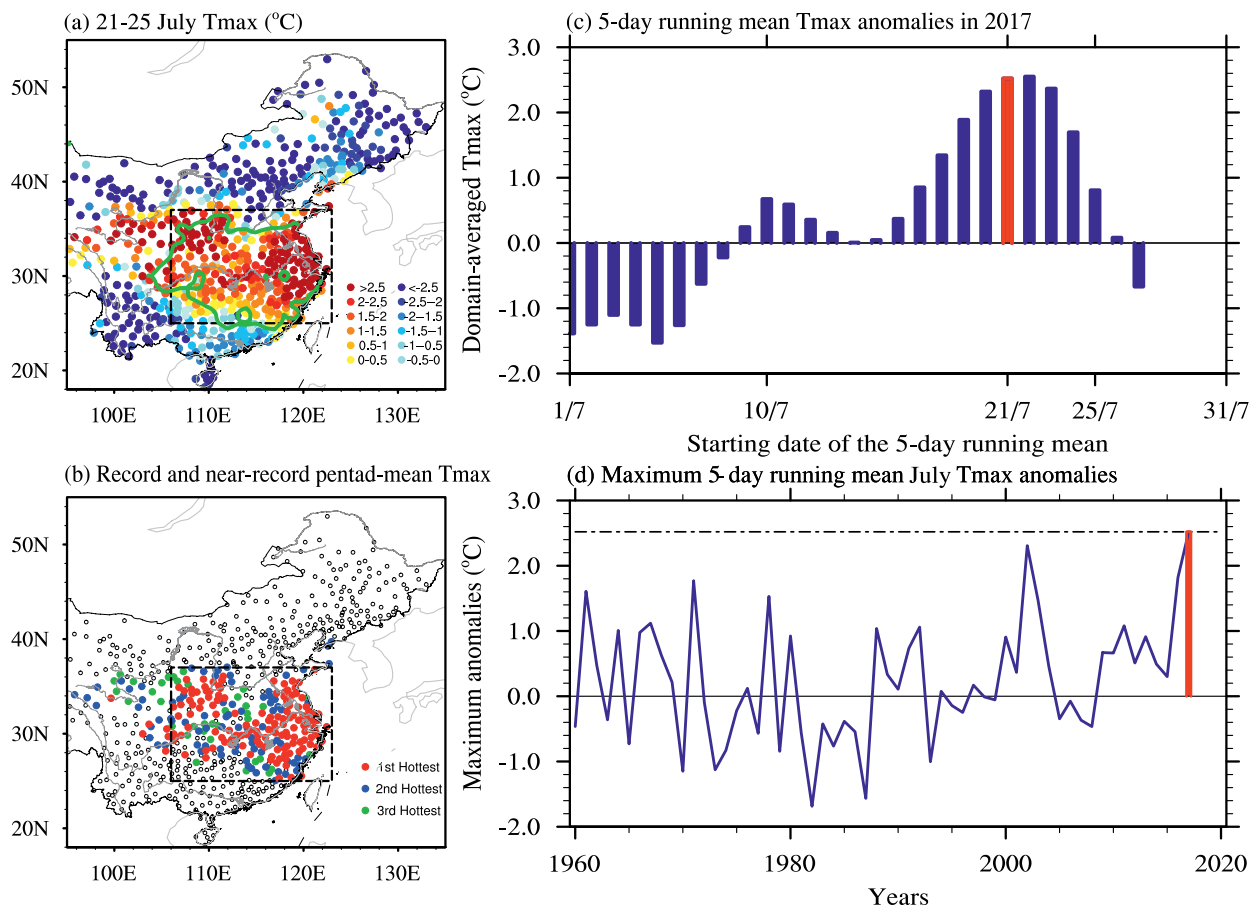


FIG. 1. (a) Observed pentad-mean (21–25 Jul 2017) Tmax anomalies (°C) relative to the 1961–90 climatology for the maximum 5-day mean Tmax. The green contour indicates the 35°C-isoline of mean Tmax during this pentad. Central eastern China is shown by the dashed rectangle. (b) Spatial distribution of stations that registered record- and near-record (since 1960) pentad-mean July Tmax during 21–25 Jul 2017. (c) Observed overlapping pentad-mean Tmax anomaly averaged over central eastern China during July 2017. Each value is indexed by the first day of the pentad. (d) Observed maximum 5-day mean Tmax anomaly averaged over central eastern China in each July over 1960–2017. The red vertical line labels the 2017 event, and the dashed line indicates its anomaly.

central eastern China, as it is capable of capturing critical mechanisms generating heat waves there. In the remainder of this paper, we used the PTmax anomaly to define the threshold.

RESULTS. During 21–25 July, almost the entirety of central eastern China had temperatures over 35°C, equivalent to 2°–6°C PTmax anomalies (Fig. 1a). Anomalies of these magnitudes produced numerous record- or near-record July PTmax (Fig. 1b). In terms of domain-averaged values, the PTmax in this pentad not only peaked during July 2017, but also set a new record among all historical July counterparts (any 5-day mean Tmax during July) since 1960 (Figs. 1c,d; note that we consider this pentad instead of 22–26 July because of its extensive social and economic repercussions). It is well known that heat waves in this area result dynamically from the persistence of anticyclonic circulations that facilitate increased surface solar radiation and adiabatic heating (Freychet et al. 2017; Chen and Lu 2015). Specific to this case, an unprecedentedly (all Julys since 1960) strong anomalous anticyclonic cell was centered above central eastern China, dynamically explaining the origin of the “record-breaking” Tmax (Fig. ES2) and its exclusive occurrence in this domain (Fig. 1a).

The PTmax anomaly from the interpolated observation (2.52°C) was used as a threshold to characterize the July 2017–like heat wave. Events of this magnitude are fairly rare ($P_{\text{NAT}} = 2.1\%$) in natural-forcing simulations (Fig. 2a, green). Without anthropogenic warming, similar heat waves should have been seen one to three times per century [mean return period: 47.7 yr; 95% confidence interval (CI): 30.8–75.0 yr; Fig. 2b, green]. By contrast, the distribution of simulated PTmax anomaly is markedly positive-displaced in all-forcing worlds, signifying substantially increased odds ($P_{\text{ALL}} = 20.1\%$) of events this hot. In the current climate, anthropogenic warming has exposed central eastern China to 2017-like heat waves about twice per decade (mean return period: 4.9 yr; 95% CI: 4.3–5.8 yr; Fig. 2b, red).

Quantitatively speaking, the risk of an event as hot or hotter increased at least tenfold ($\text{RR} = 9.8$; 95% CI: 5.9–18.9) due to anthropogenic warming. Translating into FAR, human influence accounted for at least 90% (95% CI: 83.0%–94.7%) for the presence of 2017-like heat waves. To avoid selection bias potentially introduced by using the critical threshold at the very end tail (Stott et al. 2004), we also adopted the second hottest July record (2.09°C in July 2002) as an alternative threshold. Simulated anomalies

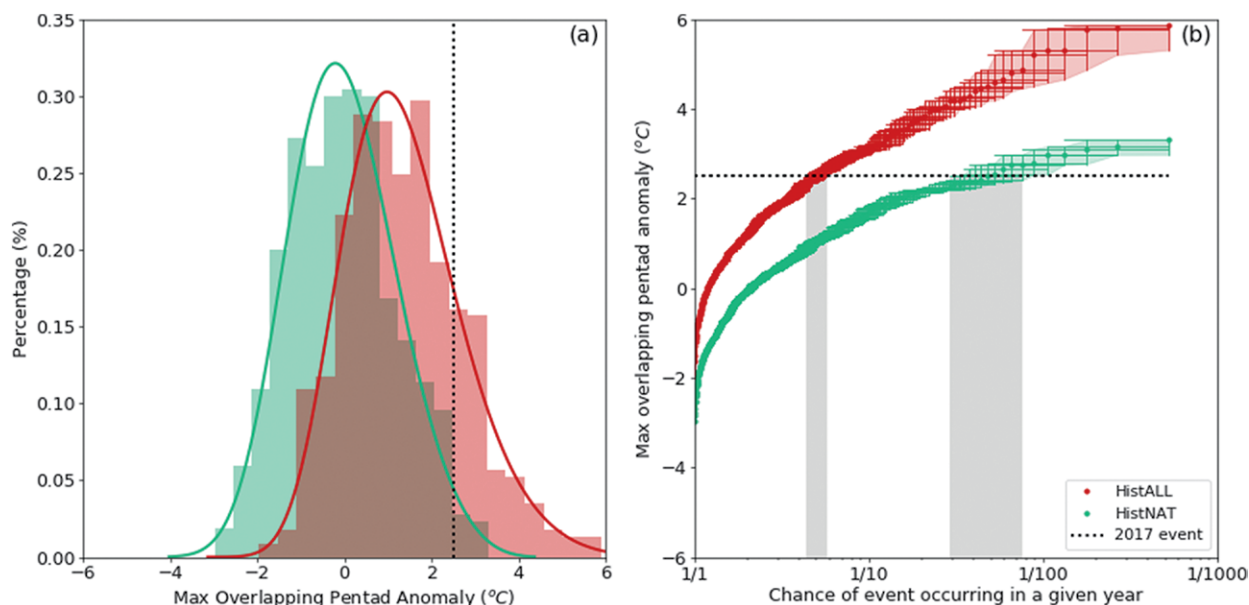


FIG. 2. (a) Distribution of domain-averaged hottest 5-day mean Tmax anomalies during July 2017 (histogram), based on 525-member histALL (red) and histNAT (green) ensembles, and their generalized extreme value (GEV)-fitted curves shown by respective colors. (b) Return periods of domain-averaged hottest 5-day mean Tmax anomalies in histALL (red) and histNAT (green) ensembles. The threshold value of 2.52°C is indicated by dashed lines in (a) and (b). In (b), vertical and horizontal bars represent the 5%–95% uncertainty interval of temperature anomalies and return periods, derived via the bootstrapping method ($N = 1000$). Gray shadings specify the uncertainty interval of return period of the threshold exceedance in histNAT and histALL runs.

exceeding this threshold are recorded 5 times more frequently ($RR = 4.5$; 95% CI: 3.4–6.5) in the all-forcing world ($P_{ALL} = 26.8\%$) than in the natural-forcing world ($P_{NAT} = 5.9\%$). These results also indicate that anthropogenic forcings contributed more to increases in the risks of rarer, more extreme heat waves. So, we reiterate that anthropogenic warming played an overarching role ($FAR = 77.8\%$; 95% CI: 70.4%–84.6%) in elevating the risk of heat waves stronger than this second-hottest threshold (e.g., the July 2017 case).

CONCLUSIONS AND DISCUSSION. In central eastern China, heat waves hotter than the July 2017 event should have had a very slim chance to occur in natural-forcing worlds. But now, forced by anthropogenic warming and conditioned on the 2017 SST pattern, a 5-day heat wave like this case has become 10 times more likely, as a 1-in-5-yr or more common event.

Although influences of anthropogenic warming could be detected and were largely attributable, attribution conclusions for a single high-impact case may be subject to some uncertainties. First, the estimated RR and FAR may be quantitatively sensitive to the selection of baseline periods (here 1961–90), as reported by Knutson et al. (2013). Still, sensitivity tests adopting varying baselines for this case indicate that the qualitative statement “increase in the likelihood of a July 2017–like heat wave could be largely attributable to anthropogenic warming” robustly holds. Second, the estimated RR and FAR only apply to the current climate. As the planet keeps warming, a higher RR of a July 2017-like case would be expected (Perkins and Gibson 2015). Future reductions in aerosols due to increasingly stricter air quality control in this area may also give a greater RR of a July 2017-like case (van Oldenborgh et al. 2018; Wang et al. 2018). This study is based only on factual and counterfactual runs in a single atmosphere-only model, with the intention of exploiting its large ensembles for calculating the statistics of rare events (Otto 2017). Estimated RRs should still be compared with those derived via other methods/models, such as observation-constrained estimates (van Oldenborgh et al. 2015), alternative atmosphere-only model-based estimates (e.g., weather@home; Massey et al. 2015), and fully coupled model-based estimates (CMIP5; Sun et al. 2014) to further clarify uncertainties.

Comparing temperatures alone in factual and counterfactual simulations, the estimated RR only delivers a general attribution message, leaving physical interpretations about how anthropogenic forcings influenced the likelihood of the heat wave and its preferential occurrence in central eastern China to

be addressed. To this end, follow-up efforts will be made to disentangle this general attribution effort into a dynamic (e.g., large-scale circulations) and a thermodynamic part (Vautard et al. 2016; Schaller et al. 2016). A critical step toward dynamic attribution is to quantify the extent to which anthropogenic warming affected the presence, location, maintenance, and amplitude of anticyclonic circulations akin to the 2017 case (Fig. ES2). Such a separation could also facilitate tracking down and communicating the source of attribution uncertainties from both dynamic and thermodynamic perspectives (Vautard et al. 2016; Wehrli et al. 2018).

ACKNOWLEDGMENTS. This study was conducted during the Operational Attribution Workshop at the University of Oxford. The study, SFBT, SS, BD, FL, and DW were supported by the U.K.–China Research and Innovation Partnership Fund through the Met Office Climate Science for Service Partnership (CSSP) China as part of the Newton Fund. Chinese authors were jointly supported by the National Key Research and Development Program (2016YFA0601504), the NSF of China (41675078, U1502233, 41320104007 and 41505037), the Youth Innovation Promotion Association of CAS (2018102), and the MOST Key Project (2016YFA0601802).

REFERENCES

- Chen, R., and R. Lu, 2015: Comparisons of the circulation anomalies associated with extreme heat weather in different regions in eastern China. *J. Climate*, **28**, 5830–5844, <https://doi.org/10.1175/JCLI-D-14-00818.1>.
- Christidis, N., P. A. Stott, A. A. Scaife, A. Arribas, G. S. Jones, D. Copsey, J. R. Knight, and W. J. Tennant, 2013: A new HadGEM3-A-based system for attribution of weather- and climate-related extreme events. *J. Climate*, **26**, 2756–2783, <https://doi.org/10.1175/JCLI-D-12-00169.1>.
- Ciavarella, A., and Coauthors, 2018: Upgrade of the HadGEM3-A based attribution system to high resolution and a new validation framework for probabilistic event attribution. *Wea. Climate Extremes*, **20**, 9–32, <https://doi.org/10.1016/j.wace.2018.03.003>.
- CMA, 2017: China Climate Bulletin 2017 (in Chinese with English abstract). China Meteorological Administration, 54 pp., www.cma.gov.cn/root7/auto13139/201801/t20180117_460484.html.
- Freychet, N., S. F. B. Tett, J. Wang, and G. C. Hegerl, 2017: Summer heat waves over eastern China: Dynamical processes and trend attribution. *Environ.*

- Res. Lett.*, **12**, 024015, <https://doi.org/10.1088/1748-9326/aa5ba3>.
- , —, G. C. Hegerl, and J. Wang, 2018: Central-eastern China persistent heat waves: Evaluation of the AMIP models. *J. Climate*, **31**, 3609–3624, <https://doi.org/10.1175/JCLI-D-17-0480.1>.
- Knutson, T. R., F. Zeng, and A. T. Wittenberg, 2013: The extreme March–May 2012 warm anomaly over the eastern United States: Global context and multimodel trend analysis [in “Explaining Extreme Events of 2012 from a Climate Perspective”]. *Bull. Amer. Meteor. Soc.*, **96**, S13–S17, <https://journals.ametsoc.org/doi/10.1175/BAMS-D-13-00085.1>.
- Li, Z., Z.-W. Yan, and H. Y. Wu, 2015: Updated homogenized Chinese temperature series with physical consistency. *Atmos. Ocean. Sci. Lett.*, **8**, 17–22, <https://doi.org/10.3878/AOSL20140062>.
- Massey, N., and Coauthors, 2015: weather@home—Development and validation of a very large ensemble modelling system for probabilistic event attribution. *Quart. J. Roy. Meteor. Soc.*, **141**, 1528–1545, <https://doi.org/10.1002/qj.2455>.
- Otto, F. E. L., 2017: Attribution of weather and climate events. *Annu. Rev. Environ. Resour.*, **42**, 627–646, <https://doi.org/10.1146/annurev-environ-102016-060847>.
- Perkins, S. E., and P. B. Gibson, 2015: Increased risk of the 2014 Australian May heatwave due to anthropogenic activity [in “Explaining Extremes of 2014 from a Climate Perspective”]. *Bull. Amer. Meteor. Soc.*, **96**, S154–S157, <https://doi.org/10.1175/BAMS-D-15-00074.1>.
- Rayner, N. A., D. E. Parker, E. B. Horton, C. K. Folland, L. V. Alexander, D. P. Rowell, E. C. Kent, and A. Kaplan, 2003: Global analyses of sea surface temperature, sea ice, and night marine air temperature since the late nineteenth century. *J. Geophys. Res.*, **108**, 4407, <https://doi.org/10.1029/2002JD002670>.
- Schaller, N., and Coauthors, 2016: Human influence on climate in the 2014 southern England winter floods and their impacts. *Nat. Climate Change*, **6**, 627–634, <https://doi.org/10.1038/nclimate2927>.
- Sibson, R., 1981: A brief description of natural neighbor interpolation. *Interpreting Multivariate Data*, V. Barnett, Ed., Wiley, 21–36.
- Stott, P. A., D. A. Stone, and M. R. Allen, 2004: Human contribution to the European heatwave of 2003. *Nature*, **432**, 610–614, <https://doi.org/10.1038/nature03089>.
- Sun, Y., X. Zhang, F. W. Zwiers, L. C. Song, H. Wan, T. Hu, H. Yin, and G. Y. Ren, 2014: Rapid increase in the risk of extreme summer heat in eastern China. *Nat. Climate Change*, **4**, 1082–1085, <https://doi.org/10.1038/nclimate2410>.
- Szentimrey, T., 1999: Multiple analysis of series for homogenization (MASH). *Proc. Second Seminar for Homogenization of Surface Climatological Data*. Budapest, Hungary, WMO, 27–46.
- van Oldenborgh, G. J., R. Haarsma, H. de Vries, and M. R. Allen, 2015: Cold extremes in North America vs. mild weather in Europe: The winter 2013–14 in the context of a warming world. *Bull. Amer. Meteor. Soc.*, **96**, 707–714, <https://doi.org/10.1175/BAMS-D-14-00036.1>.
- , and Coauthors, 2018: Extreme heat in India and anthropogenic climate change. *Nat. Hazards Earth Syst. Sci.*, **18**, 365–381, <https://doi.org/10.5194/nhess-18-365-2018>.
- Vautard, R., P. Yiou, F. Otto, P. Stott, N. Christidis, G. J. van Oldenborgh, and N. Schaller, 2016: Attribution of human-induced dynamical and thermodynamical contributions in extreme weather events. *Environ. Res. Lett.*, **11**, 114009, <https://doi.org/10.1088/1748-9326/11/11/114009>.
- Wang, J., S. F. B. Tett, Z. Yan, and J. Feng, 2018: Have human activities changed the frequencies of absolute extreme temperatures in eastern China? *Environ. Res. Lett.*, **13**, 014012, <https://doi.org/10.1088/1748-9326/aa9404>.
- Wehrli, K., B. P. Guillod, M. Hauser, M. Leclair, and S. I. Seneviratne, 2018: Assessing the dynamic vs. thermodynamic origin of climate model biases. *Geophys. Res. Lett.*, **45**, 8471–8479, <https://doi.org/10.1029/2018GL079220>.

