EXPLAINING EXTREME EVENTS OF 2018

From a Climate Perspective

Special Supplement to the
Bulletin of the American Meteorological Society
Vol. 101, No. 1, January 2020

EXPLAINING EXTREME EVENTS OF 2018 FROM A CLIMATE PERSPECTIVE

Editors

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

BAMS Special Editors for Climate

Andrew King, Thomas Knutson,
John Nielsen-Gammon, and Friederike Otto

Special Supplement to the

Bulletin of the American Meteorological Society

Vol. 101, No. 1, January 2020

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: iStock.com/Alena Kravchenko—River Thames receded during a heatwave in summer 2018 in London, United Kingdom.

HOW TO CITE THIS DOCUMENT

Citing the complete report:

Herring, S. C., N. Christidis, A. Hoell, M. P. Hoerling, and P. A. Stott, Eds., 2020: Explaining Extreme Events of 2018 from a Climate Perspective. *Bull. Amer. Meteor. Soc.*, **101** (1), S1–S128, doi:10.1175/BAMS-ExplainingExtremeEvents2018.1.

Citing a section (example):

Mahoney, K., 2020: Extreme Hail Storms and Climate Change: Foretelling the Future in Tiny, Turbulent Crystal Balls? [in “Explaining Extremes of 2018 from a Climate Perspective”]. *Bull. Amer. Meteor. Soc.*, **101** (1), S17–S22, doi:10.1175/BAMS-D-19-0233.1.

TABLE OF CONTENTS

1. The Extreme 2018 Northern California Fire Season	1
2. Anthropogenic Impacts on the Exceptional Precipitation of 2018 in the Mid-Atlantic United States	5
3. Quantifying Human-Induced Temperature Impacts on the 2018 United States Four Corners Hydrologic and Agro-Pastoral Drought	11
4. Extreme Hail Storms and Climate Change: Foretelling the Future in Tiny, Turbulent Crystal Balls?	17
5. The Extremely Cold Start of the Spring of 2018 in the United Kingdom.....	23
6. The Exceptional Iberian Heatwave of Summer 2018	29
7. Analyses of the Northern European Summer Heatwave of 2018.....	35
8. Anthropogenic Influence on the 2018 Summer Warm Spell in Europe: The Impact of Different Spatio-Temporal Scales	41
9. On High Precipitation in Mozambique, Zimbabwe and Zambia in February 2018.....	47
10. The Record Low Bering Sea Ice Extent in 2018: Context, Impacts, and an Assessment of the Role of Anthropogenic Climate Change	53
11. The Late Spring Drought of 2018 in South China.	59
12. Anthropogenic Influence on 2018 Summer Persistent Heavy Rainfall in Central Western China	65
13. Conditional Attribution of the 2018 Summer Extreme Heat over Northeast China: Roles of Urbanization, Global Warming, and Warming-Induced Circulation Changes	71
14. Effects of Anthropogenic Forcing and Natural Variability on the 2018 Heatwave in Northeast Asia.	77
15. Anthropogenic Influences on the Persistent Night-Time Heat Wave in Summer 2018 over Northeast China	83
16. Anthropogenic Contributions to the 2018 Extreme Flooding over the Upper Yellow River Basin in China	89
17. Attribution of the Record-Breaking Consecutive Dry Days in Winter 2017/18 in Beijing	95
18. Quantifying Human Impact on the 2018 Summer Longest Heat Wave in South Korea	103
19. The Heavy Rain Event of July 2018 in Japan Enhanced by Historical Warming.	109
20. Deconstructing Factors Contributing to the 2018 Fire Weather in Queensland, Australia	115
21. A 1-Day Extreme Rainfall Event in Tasmania: Process Evaluation and Long Tail Attribution	123
22. Attribution of the Warmest Spring of 2018 in Northeastern Asia Using Simulations of a Coupled and an Atmospheric Model.	129

ATTRIBUTION OF THE WARMEST SPRING OF 2018 IN NORTHEASTERN ASIA USING SIMULATIONS OF A COUPLED AND AN ATMOSPHERIC MODEL

YING SUN, SIYAN DONG, TING HU, XUEBIN ZHANG, PETER STOTT

Anthropogenic forcing has increased the occurrence probability of the warmest spring in northeastern Asia. Similar increases in probability are obtained from two different model setups.

In the spring of 2018, anomalously high temperatures were observed in northeastern Asia (including Northern China, Mongolia, and southern Russia; the box bounded by 90°–120°E, 35°–55°N in Fig. 1). The mean, maximum, and minimum temperatures were the highest on record since 1961 when China started to have reliable observations. Accompanied by these high temperatures were precipitation deficits, resulting in severe drought in the northern and northeastern parts of China. Some crops, such as corn, could not be sown as scheduled. More than 50 million hectares of crops were affected (CMA 2019; NCC 2019). This high temperature event also influenced surrounding regions including Mongolia and southern Russia. For example, spring temperature in Mongolia was the highest on record (NOAA NCEI 2019).

Previous studies have investigated human influence on high summer and spring temperature events in Asia and some parts of China (Takahashi et al. 2016; Min et al. 2015; Sun et al. 2014, 2016; Song et al.

2015). They consistently show that anthropogenic forcing has increased the occurrence probability of these events. Some studies (e.g., Min et al. 2015; Sun et al. 2014) examine changes in event probability conditional on the observed external forcing using coupled model (CMIP-type) simulations. Other studies (e.g., Takahashi et al. 2016) analyze changes in event probability conditional on both the observed external forcing as well as state of atmospheric–oceanic circulation based on simulations of atmospheric models (AMIP-type). Here, we examine event probabilities based on both types of conditioning, involving simulations by a coupled model and an atmospheric model.

DATA AND METHODS. The observational data used in this study are monthly mean temperature anomalies of HadCRUT4, which is a gridded data product with resolution of 5° × 5° (available at <https://www.metoffice.gov.uk/hadobs/hadcrut4/>). The temperature anomalies (relative to 1961–90 average) for the grid boxes within the northeastern Asia during spring [March–May (MAM)] are averaged to obtain the regional mean temperature anomalies.

We use ensemble simulations from a coupled model and an atmospheric model. The coupled model is the Canadian Earth System Model version 2 (CanESM2; Arora et al. 2011). The CanESM2 simulations are 50-member ensemble runs on a T63 triangular truncation (about 2.81° resolution), driven by combined historical anthropogenic and natural forcings (ALL) and by historical natural forcing (NAT) for the period 1950–2004. From 2005 until 2020, the ALL simulations are forced with the RCP8.5 while the NAT simulations are forced with natural forcing by repeating the solar forcing during the last period cycle alone, without any volcano eruptions (Fyfe et al. 2017). The atmospheric model is HadGEM3-A-N216

AFFILIATIONS: SUN—National Climate Center, China Meteorological Administration, Beijing, China, and Collaborative Innovation Center on Forecast and Evaluation of Meteorological Disasters, Nanjing University of Information Science & Technology, Nanjing, China; DONG AND HU—National Climate Center, China Meteorological Administration, Beijing, China; ZHANG—Climate Research Division, Environment and Climate Change Canada, Toronto, Canada; STOTT—Met Office Hadley Centre, Exeter, United Kingdom

CORRESPONDING AUTHOR: Ying Sun, sunying@cma.gov.cn

DOI:10.1175/BAMS-D-19-0264.1

© 2020 American Meteorological Society

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

FIG. 1. Top panel: A map of spring mean temperature anomalies in 2018 (relative to 1961–90 average) based on HadCRUT4 data. The box shows the area under investigation for observation, CanESM2 and HadGEM3. Lower panel: Time series of spring temperature anomalies (relative to 1961–90 average) based on HadCRUT4.

with a horizontal resolution of $0.56^\circ \times 0.83^\circ$ (Christidis et al. 2013; Ciavarella et al. 2018). The simulations conducted with this model consist of two sets of experiments: 1) The historical simulation is forced with ALL and the observed sea surface temperatures (SST) and sea ice concentrations (SIC) from HadISST (Rayner et al. 2003). 2) Historical NAT simulations forced by preindustrial forcing and the observed SST and SIC with anthropogenic contribution removed (Christidis et al. 2013). For the period of 1961–2013, there are 15 simulations for ALL and NAT experiments. While for 2018, a 525-member ensemble for

ALL and NAT experiments is used to investigate anthropogenic influence as simulated by HadGEM3.

The analyses include the following steps: 1) For observations and model simulations, all the regional mean temperatures are calculated as anomalies relative to the 1961–90 average in north-eastern Asia. We compare the observed spring mean temperature anomaly in 2018 (denoted as TA_{OBS}) with model simulations. 2) CanESM2 has a high climate sensitivity (with a transient climate response 3°C ; IPCC 2013) and its simulated global mean near-surface temperature (GMST) warms rapidly since mid-twentieth century. The CanESM2 simulated GMST for 2007–16 has increased by 1.45°C above preindustrial level, which is much warmer than the observed $\sim 1^\circ\text{C}$ increase of GMST in the climate of 2018. This too rapid increase in GMST could affect the attribution results and needs to be adjusted. As global temperature response scale well with external forcing and as regional temperature increase also scales well with the global value, we consider a 10-year period (1995–2004) in model simulations whose multi-run ensemble mean

temperature is about 1°C warmer than the pre-industrial level, which is consistent with the human-induced warming in the climate around 2018 (Allen et al. 2018). This GMST-based adjustment is reasonable but there is also a caveat that the aerosols effects in different period could be different. The occurrence probability of the 2018-like temperature simulated by CanESM2 $P_{ALL-CanESM}$ is determined by computing the probability for temperature anomalies above TA_{OBS} during 1995–2004. The occurrence probability in the natural world ($P_{NAT-CanESM}$) is determined similarly based on the NAT 50-run simulations. 3) For

HadGEM3 simulations, we used the 525 runs for the year 2018 under the world with or without human influence. This is because the transient simulation has only 15 runs. The occurrence probabilities, denoted as $P_{\text{ALL-HadGEM}}$ and $P_{\text{NAT-HadGEM}}$ for 2018-like spring, are estimated by computing the probability for temperature anomalies above TA_{OBS} in the ALL and NAT simulations, respectively. 4) In all cases, the normal distribution is used when estimating the probability because regional mean temperature should follow a normal distribution according to the central limit theorem, although the histogram does show some degree of skewness (Fig. 2e). The risk ratio RR for the event probability in ALL and NAT worlds is calculated by $P_{\text{ALL}}/P_{\text{NAT}}$. The confidence interval in the risk ratio is estimated using 1000 bootstrap samples with replacement. For example, when estimating the confidence interval for the case of CanESM2 simulation, we draw 50 samples of 10-yr data from 50 ALL runs and 50 NAT runs, separately, with replacement. We then estimate P_{ALL} and P_{NAT} and compute an RR based on these samples. This procedure is repeated for 1,000 times. The 5th and the 95th percentiles are used to represent the 90% confidence interval.

RESULTS. Figure 1 shows spring temperature anomalies in 2018 in Asia and time series for 1961–2018 in the studied region. There were positive temperature anomalies centered in northern China and Mongolia, with the largest anomaly value around 4.8°C. The regional mean temperature anomaly in 2018 is the highest on record at 2.9°C above the 1961–90 average and exceeds 2.7 times the observed standard deviation computed from 1961–2017. The 500-hPa geopotential height (not shown) illustrate that an anomalous high pressure ridge was controlling northeastern Asia during the spring. The subsidence airflow related to this sets important circulation background for the high temperature event.

It is difficult to evaluate the fitness of climate model simulations for the purpose of this study because of the relatively small scale at which it is difficult to quantify natural variability and climate response from the observations. The limited availability of observational data adds more complexity to this problem. Nevertheless, we compared some statistics in the observations and simulations to provide some sense about model's performance. Figure 2 shows observed and simulated time series along with their histograms. In general, both models broadly reproduce the observed changes and the model spreads also cover the range of the observations (Figs. 2a,b). Over 1961–2013, the observed spring mean tempera-

ture has increased by 0.034°C yr⁻¹ (90% confidence interval: 0.020 to 0.049). The median trend of the CanESM2 simulation is 0.031°C yr⁻¹ (model spread: 0.018 to 0.044; Fig. 2a). The corresponding values of the HadGEM3 simulations are 0.017°C yr⁻¹ (model spread 0.002 to 0.026; Fig. 2b). The HadGEM3 ensemble shows less warming than the observations. It warms less than that simulated by CanESM2 as expected, since CanESM2 has high climate sensitivity. The standard deviations for observation and simulations are also roughly comparable though variability in HadGEM3 simulation seems to be high (Figs. 2c,d). When a linear trend is not removed from the series, the standard deviation in the observation is 0.98°C, and the median value of standard deviation is 1.11°C (spread: 0.93 to 1.25) in CanESM2 simulation and 1.23°C (spread: 1.04 to 1.37) in the HadGEM3 simulations, respectively. It seems that variability in HadGEM3 simulation is larger than that in the observation, which can result in larger risk ratio estimate for the same amount of warming. When the trend is removed from the series, the above values become 0.83°C for observations, 0.98°C (spread: 0.79 to 1.17) for the CanESM2 simulation and 1.18°C (spread: 1.03 to 1.34) for the HadGEM3 simulation. Overall, the model simulations may not be perfect but should be reliable enough for the purpose of this study.

The histograms of the model simulations under ALL forcing clearly shift to warmer temperatures when compared with that under NAT forcing, suggesting an increase of probability of extreme high temperatures due to human influence (Figs. 2e,f). In CanESM2 simulations, the probability of 2018-like temperature is 2.02% (90% CI: 1.44% to 2.65%) under ALL forcing and it is 0.11% (90% CI: 0.09% to 0.14%) under NAT forcing. This gives a risk ratio of 18.4 (90% CI: 11.9 to 25.7). In the HadGEM3 simulations for 2018, the probability of 2018-like temperature is 6.67% (90% CI: 5.55% to 8.12%) under ALL forcing and it is 0.38% (90% CI: 0.25% to 0.58%) under NAT forcing, resulting in a risk ratio of 17.5 (90% CI: 11.2 to 28.5).

CONCLUSIONS AND DISCUSSION. We have examined human influence on the probability of occurrence of 2018-like spring temperature in northeastern Asia. We used simulations from a coupled model and an atmospheric model. Taking into account caveats in the observations and simulations, including problems in observational data and differences in model simulated trends and variability when compared with those in the observations, the balance of evidence clearly indicates that human influence has increased the probability of temperature

(a) CanESM2

(b) HadGEM3-A-N216

(c) PDFs

(d) PDFs(detrend)

(e) CanESM2

(f) HadGEM3-A-N216

extremes substantially, with the probability of 2018-like extreme temperatures increasing by as much as 18 times.

The risk ratio that is conditional on the historical forcing as simulated by CanESM2 is of similar magnitude to that conditional on the anthropogenic

FIG. 2. (a) Observed (black) and CanESM2 simulated spring mean temperature anomalies (relative to 1961–90 average) in the region during 1960–2020. The multi-run averages under ALL and NAT forcing are illustrated by red and blue lines and the model spread is represented by red and blue shadings, respectively. (b) As in (a), but for HadGEM3-A-N216. The mean and spread of 2018 temperature anomalies (relative to 1961–90 average) under ALL (red) and NAT (blue) forcing are marked by cross and vertical bars, respectively. (c) Probability density functions (PDFs) of spring temperature anomalies during 1961–2013 for observation (black) and model simulations under ALL forcing based on CanESM2 (red) and HadGEM3-A-N216 (orange). (d) As in (c), but for the results with linear trends in 1961–2013 removed. (e) PDFs of spring mean temperature anomalies under 1°C warming period (red) and NAT (blue) forcing for CanESM2. (f) PDFs of spring temperature anomalies in 2018 under ALL (red) and NAT (blue) forcing for HadGEM3-A-N216.

forcing and the historical SST pattern as simulated by HadGEM3-A; this similarity is not necessarily a proof that the two are the same in the real world because there are uncertainties from multiple sources. We note that the CanESM2 has a high climate sensitivity but the effect on the estimation of risk ratio has already been accounted for. HadGEM3-A has a smaller long-term trend than the observations but this is not necessarily an indication of underestimation by the model. The external forcing and natural variability may have both contributed to the trend since the observed trend is more comparable to simulations by a high sensitivity model. More careful analyses are required to better quantify the role of human influence and natural variability in the occurrence of event like 2018 spring temperature anomalies. Nevertheless, to first-order approximation, human influence has clearly increased the occurrence probability by 10–30 times of temperature extremes such as the 2018 event.

ACKNOWLEDGMENTS. We thank three anonymous reviewers for their helpful suggestions. Y. S., S. D., and T. H. are supported by China funding agencies through multiple grants: China 2018YFC1507702, NSFC 41675074, 2018YFA0605604, CCSF 201805 and CCSF201906. PAS was 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, the EUCLEIA project funded by the European Union’s Seventh Framework Programme [FP7/2007–13] under Grant Agreement 607085 and by the Joint U.K. DECCBEIS/Defra Met Office Hadley Centre Climate Programme (GA01101).

REFERENCES

- Allen, M. R., and Coauthors, 2018: Framing and context. Global Warming of 1.5°C. An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty, V. Masson-Delmotte et al., Eds., https://www.ipcc.ch/site/assets/uploads/sites/2/2019/05/SR15_Chapter1_Low_Res.pdf.
- Arora, V. K., and Coauthors, 2011: Carbon emission limits required to satisfy future representative concentration pathways of greenhouse gases. *Geophys. Res. Lett.*, **38**, L05805, <https://doi.org/10.1029/2010GL046270>.
- 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, 2019: China Climate Bulletin 2018 (in Chinese with English abstract). China Meteorological Administration, 50 pp., http://www.cma.gov.cn/root/7/auto13139/201903/t20190319_517664.html.
- Fyfe, J. C., and Coauthors, 2017: Large near-term projected snowpack loss over the western United States. *Nat. Commun.*, **8**, 14996, <https://doi.org/10.1038/ncomms14996>.
- IPCC, 2013: *Climate Change 2013: The Physical Science Basis*. T. F. Stocker et al., Eds., Cambridge University Press, 1535 pp.
- Min, S. K., Y. Kim, S. Paik, M. Kim, and K. Boo, 2015: Anthropogenic influence on the 2014 record-hot spring in Korea [in “Explaining Extreme Events of 2014 from a Climate Perspective”]. *Bull. Amer. Meteor. Soc.*, **96** (12), S95–S99, <https://doi.org/10.1175/BAMS-D-15-00079.1>.
- NCC, 2019: China Monthly Climate Bulletin 2018. National Climate Center of China Meteorological Administration, 10 pp., https://cmdp.ncc-cma.net/influ/moni_china.php.

- NOAA National Centers for Environmental Information, 2018: State of the Climate: Global Climate Report for May 2018, accessed 5 April 2019, <https://www.ncdc.noaa.gov/sotc/global/201805>.
- 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>.
- Song, L. C., Y. Sun, S. Y. Dong, B. T. Zhou, P. A. Stott, and G. Y. Ren, 2015: Role of anthropogenic forcing in 2014 hot spring in Northern China [in “Explaining Extreme Events of 2014 from a Climate Perspective”]. *Bull. Amer. Meteor. Soc.*, **96** (12), S111–S115, <https://doi.org/10.1175/BAMS-D-15-00111.1>.
- Sun, Y., X. B. 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>.
- , L. C. Song, H. Yin, X. B. Zhang, P. Stott, B. T. Zhou, and T. Hu, 2016: Human influence on the 2015 extreme high temperature events in Western China [in “Explaining Extreme Events of 2015 from a Climate Perspective”]. *Bull. Amer. Meteor. Soc.*, **97** (12), S102–S106, <https://doi.org/10.1175/BAMS-D-16-0158.1>.
- Takahashi, C., M. Watanabe, H. Shiogama, Y. Imada, and M. Mori, 2016: A persistent Japanese heat wave in early August 2015: Roles of natural variability and human-induced warming [in “Explaining Extreme Events of 2015 from a Climate Perspective”]. *Bull. Amer. Meteor. Soc.*, **97** (12), S107–S112, <https://doi.org/10.1175/BAMS-D-16-0157.1>.