EXPLAINING EXTREME EVENTS OF 2015

From A Climate Perspective

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EXPLAINING EXTREME EVENTS OF 2015 FROM A CLIMATE PERSPECTIVE

Editors

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COVER CREDIT:

©Photo by Joe Raedle/Getty Images—A vehicle drives through flooded streets caused by a combination of the lunar orbit which caused seasonal high tides and what many believe is the rising sea levels due to climate change on September 30, 2015, in Fort Lauderdale, Florida. South Florida is projected to continue to feel the effects of climate change, and many of the cities have begun programs such as installing pumps or building up sea walls to try and combat the rising oceans.

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This fifth edition of explaining extreme events of the previous year (2015) from a climate perspective continues to provide evidence that climate change is altering some extreme event risk. Without exception, all the heat-related events studied in this year's report were found to have been made more intense or likely due to human-induced climate change, and this was discernible even for those events strongly influenced by the 2015 El Niño. Furthermore, many papers in this year's report demonstrate that attribution science is capable of separating the effects of natural drivers including the strong 2015 El Niño from the influences of long-term human-induced climate change.

Other event types investigated include cold winters, tropical cyclone activity, extreme sunshine in the United Kingdom, tidal flooding, precipitation, drought, reduced snowpack in the U.S. mountain west, arctic sea ice extent, and wildfires in Alaska. Two studies investigated extreme cold waves and monthly-mean cold conditions over eastern North America during 2015, and find these not to have been symptomatic of human-induced climate change. Instead, they find the cold conditions were caused primarily by internally generated natural variability. One of these studies shows winters are becoming warmer, less variable, with no increase in daily temperature extremes over the eastern United States. Tropical cyclone activity was extreme in 2015 in the western North Pacific (WNP) as measured by accumulated cyclone energy (ACE). In this

report, a study finds that human-caused climate change largely increased the odds of this extreme cyclone activity season. The 2015 Alaska fire season burned the second largest number of acres since records began in 1940. Investigators find that human-induced climate change has increased the likelihood of a fire season of this severity.

Confidence in results and ability to quickly do an attribution analysis depend on the “three pillars” of event attribution: the quality of the observational record, the ability of models to simulate the event, and our understanding of the physical processes that drive the event and how they are being impacted by climate change. A result that does not find a role for climate change may be because one or more of these three elements is insufficient to draw a clear conclusion. As these pillars are strengthened for different event types, confidence in the presence and absence of a climate change influence will increase.

This year researchers also link how changes in extreme event risk impact human health and discomfort during heat waves, specifically by looking at the role of climate change on the wet bulb globe temperature during a deadly heat wave in Egypt. This report reflects a growing interest within the attribution community to connect attribution science to societal impacts to inform risk management through “impact attribution.” Many will watch with great interest as this area of research evolves in the coming years.

20. HUMAN INFLUENCE ON THE 2015 EXTREME HIGH TEMPERATURE EVENTS IN WESTERN CHINA

YING SUN, LIANCHUN SONG, HONG YIN, XUEBIN ZHANG, PETER STOTT, BOTAO ZHOU, AND TING HU

Human influence has very likely increased the probability of occurrence of the 2015 western China extreme summer temperature events by at least 3-fold and 42-fold for the highest daily maximum and minimum temperatures, respectively.

Introduction. The 2015 summer (June–August) was historically the hottest in western China (west of 105°E), setting new records for the regionally averaged seasonal mean temperature, annual maxima of daily maximum (TXx), and daily minimum (TNx) temperatures. Many stations set new record high temperatures as well. During the period of 12 June–10 August, the daily high temperature above 38°C covered an area of about 753 000 km², with the highest temperature of 47.7°C recorded in Dongkan station (42.83°N, 89.25°E) of Turpan. The long-lasting extreme high temperature events exerted serious impacts on agriculture and other sectors, resulting in severe heat damage for different crops such as corn, wheat, and fruit trees (CMA 2016).

Data and Methods. The observational data were extracted from the national dataset of homogenized daily temperatures for 1958–2015 with 492 stations in western China (see Fig. 20.1a for a map of station locations) available for the analyses. Even though the station density is poor in some areas, the available station observations represent the region reasonably well because extreme warm events are of fairly large spatial scale. These data were quality controlled and homogenized with RHtest (Xu et al. 2013) by the China National Meteorological Information Center. Two indices representing the hottest day and night temperatures in the summer season, TXx and TNx, were first calculated for individual stations. Regional mean values of TXx and TNx are then computed, with

consideration of uneven spatial distribution of the stations, by first averaging available station data within each 5° × 5° grid box and then taking the averages of the available gridbox values within the region. Based on daily data from climate models participating in the Coupled Model Intercomparison Project Phase 5 (CMIP5; Taylor et al. 2012), the simulated TXx and TNx were used to estimate extreme temperature responses to external anthropogenic and natural forcing (ALL), natural forcing only (NAT), and the internal variability of the climate system. Model data are interpolated onto the same 5° × 5° grids. Detailed information about observations, model data, and calculations are provided in the online supplemental material.

To estimate the influence of anthropogenic forcing (ANT) on the extreme events, our method involves three steps. 1) We first conduct a formal detection and attribution analysis for regional mean TXx and TNx values for 1958–2012 using an optimal fingerprinting method (Hegerl et al. 1997; Allen and Stott 2003) as implemented in Ribes et al. (2013). This is done by regressing the observations onto one or more model-simulated responses to external forcings (ALL, ANT, and NAT). We obtain the scaling factors that scale the model-simulated responses to best match the observations. 2) We then multiply the model simulated responses to ALL and NAT with the relevant scaling factors to obtain the ALL and NAT reconstructions. 3) We finally estimate the probability of occurrence for an event as hot as the 2015 summer in the worlds with or without human influence, using a method described in Sun et al. (2014). The world without human influence is represented by adding preindustrial control simulations to the reconstructed 5-year average model responses to NAT forcing in 2007–12. The world with human influence is represented by adding preindustrial control simulations to the reconstructed 5-year average model response to ALL forcing in 2013–17 that was estimated from simulations from

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FIG. 20.1. (a) A map of China showing the locations of the observing stations (blue dots) used in the study. The colors show elevation (in meters). (b) Time series of summer mean temperature (black), the maximum daily maximum temperature TXx (red), and the maximum daily minimum temperature TNx (blue) anomalies over western China. (c) Spatial distribution of 2015 summer TXx, and (d) TNx anomalies relative to 1961–90 average (°C).

RCP 4.5 experiments. The percentage of years with temperatures at or above the 2015 summer temperature in the reconstructed series is considered as the probability for that event to occur in the worlds with or without human influence.

The fraction of attributable risk (FAR; Allen 2003; Stott et al. 2004) and its uncertainty range are estimated using a method described in Song et al. (2015). Because the effect of urbanization is not particularly strong in western China, it is not considered in this study.

Results. The regional averages of the 2015 summer (June–August) mean and the TXx and TNx in western China (west of 105°E) were the highest on record beginning in 1958, with 1.54°C, 2.14°C, and 2.06°C above their respective 1961–90 averages (Fig. 20.1b). The long-term changes in the mean and the extreme temperatures are very similar, with the linear trends of 0.28°C (10 yr)^{−1} for mean temperature, 0.22°C (10 yr)^{−1} for TXx, and 0.30°C (10 yr)^{−1} for TNx during 1958–2012, respectively. Warming continued during

the so-called global warming hiatus, consistent with the findings of Seneviratne et al. (2014).

Figures 20.1c,d show the maps of 2015 summer TXx and TNx anomalies in China, respectively. Both the maxima of daily maximum and daily minimum temperatures were very high in western China with positive anomalies almost everywhere in the region. In particular, the anomalies are generally larger than 3°C with the maximum above 5°C in the region north of 35°N.

The 5-year mean time series shows that the evolutions of observed TXx and TNx are consistent with the model-simulated responses to ALL forcing but not with that to NAT forcing (Figs. 20.2a,b). Additionally, the 90% ranges of model-simulated TNx responses to ALL and NAT forcings do not overlap beyond the year 2000. The model-simulated response to NAT forcing shows small positive values near the end of the period, especially for TXx. This might be a reflection of underestimation of volcanic aerosols used in the CMIP5 simulations for the early twenty-first century as suggested by Santer et al. (2014). An implication is

FIG. 20.2. Five-year mean nonoverlapping (a) TXx and (b) TNx anomalies (°C) from observations (black) and simulations of multimodel ensembles. The model ensemble averages are represented by red (ALL) and blue (NAT) lines. The blue and pink shadings show the 5%–95% ranges of the ALL and NAT simulations. (c) Probability histograms for the mean summer TXx and (d) TNx anomalies from the best estimates of NAT (blue) and ALL (red) forcing simulations in comparison with the observed values (OBS, vertical black line) in 2015.

that we might have underestimated human influence on the 2015 summer heat.

Our detection and attribution analyses were conducted on nonoverlapping 5-year mean series. We first regress the observations onto ALL and ALL-NAT (ANT) signals separately (one-signal analyses) and then onto ALL and NAT jointly (two-signal analyses). The one-signal analyses show that the ALL and ANT signals can be detected in the extreme temperatures, and there is no evidence to indicate, from residual consistency tests, that the model may have underestimated natural internal variability. The best estimates of scaling factors for ALL are 0.80 (90% confidence level 0.46–1.14) and 1.20 (90% confidence level 1.00–1.41) for TXx and TNx, consistent with earlier findings (e.g., Zwiers et al. 2011; Kim et al. 2015) for that general region yet over a much larger area.

The two-signal detection results indicate that the ANT signal can be separately detected from the NAT signal for both TXx and TNx, and that the NAT signal can be detected in TNx. The scaling factors for ANT and NAT are 0.78 (90% confidence level 0.38–1.18)

and 0.89 (90% confidence level –0.16–1.95) for TXx and 1.21 (90% confidence level 0.96–1.47) and 1.17 (90% confidence level 0.48–1.87) for TNx, indicating the robustness of detectable human influence on the extreme temperatures. The residual consistency test shows that the model-simulated variability for TXx is consistent with the observed internal variability; however, the model-simulated TNx variability is larger than that of observations. These all suggest that the observed warming in the extreme temperatures are mainly attributable to anthropogenic external forcing rather than natural external forcing.

The 2015 summer TXx was 2.14°C higher than the 1961–90 average. The best estimate of temperature response to ALL forcing at the 2015 climate is 0.88°C (with a 90% range of 0.51°C–1.26°C) above the 1961–90 climatology. This suggests that 1.26°C of the TXx anomaly was due to natural internal variability. By calculating the percentage of years with TXx temperature anomalies at or above 2.14°C in the reconstructions with ALL forcing and with the NAT forcing, the hot 2015 TXx would be roughly a

once-in-272-year event (with a 90% range of 143–572 years) in the natural world, and that it became a once-in-28-year event (with a 90% range of 12–94 years) under the climate appropriate for the anthropogenic-forcing-induced world of 2015. The probability of the event occurring has increased by almost 10-fold due to human influence; there is more than a 90% chance for this increase to be at least 3-fold. The FAR (Stott et al. 2004) can thus be estimated as 0.90 (with a 90% range of 0.66–0.96).

The 2015 summer TN_x was 2.06°C above its 1961–90 average. The best estimate of temperature response to ALL forcing at the 2015 climate is 1.40°C (with a 90% range 1.17°C – 1.65°C) above the 1961–90 climatology. This suggests that 0.66°C of the TN_x anomaly was due to natural internal variability. We estimate that the observed extreme warm temperature for 2015 would be a once-in-1430-year event (with a 90% range of 715–2860 years) in the NAT world, and that it became a once-in-16-year event (with a 90% range of 6–41 years) under the climate appropriate for the anthropogenic-forcing-induced world of 2015. The probability of the event occurring has increased by almost 89-fold due to human influence; there is more than 90% chance for this increase to be at least 42-fold. The FAR can thus be estimated as 0.99 (with a 90% range of 0.97–1.00).

Conclusions. We have detected anthropogenic influence on the highest maximum (TX_x) and minimum (TN_x) temperatures in western China. We found that the record-breaking 2015 summer temperatures are the result of the combination of natural internal variability of the climate system and human emission of greenhouse gases. The natural internal variability may be associated with anomalous anticyclones on a range of time scales, the possible circulation features causing anomalously high temperatures in northwestern China and dryness in the Tibetan Plateau (Chen et al. 2011; Zhu et al. 2011).

We noted a much larger FAR for TN_x than for TX_x . This may come about for the following reason: the smaller variance in TN_x would mean a larger change in the probability for a similar magnitude of temperature increase when compared with TX_x . We also noted that the models may have slightly overestimated natural variability in the region. An implication of this is that our calculated changes in probability (and consequently the FAR) may be underestimated.

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Table 28.1. Summary of Results

ANTHROPOGENIC INFLUENCE ON EVENT			
	INCREASE	DECREASE	NOT FOUND OR UNCERTAIN
Heat	Global Temperature (Ch. 2) South India & Sri Lanka (Ch. 2) Central Europe (Ch. 11) Europe (Ch. 12) Ethiopia and Southern Africa (Ch. 15) N.W. China (Ch. 19) W. China (Ch. 20) Japan (Ch. 21) Indonesia (Ch. 22) S. Australia (Ch. 23) Australia (Ch. 24)		Central Equatorial Pacific (Ch. 2)
Cold		Northeastern U.S. (Ch. 7)	Mid-South Atlantic U.S. (Ch. 7) N. America (Ch. 8)
Heat & Humidity	Egypt (Ch. 14) India & Pakistan (Ch. 16)		
Dryness	Indonesia (Ch. 22) Tasmania (Ch. 25)		
Heavy Precipitation	China (Ch. 18)		Nigeria (Ch. 13) India (Ch. 17)
Sunshine	United Kingdom (Ch. 10)		
Drought	Canada (Ch. 9) Ethiopia and Southern Africa (Ch. 15)		
Tropical Cyclones	Western North Pacific (Ch. 26)		
Wildfires	Alaska (Ch. 4)		
Sea Ice Extent		Arctic (Ch. 27)	
HIGH TIDE FLOODS	SOUTHEASTERN U.S. (Ch. 6)		
SNOWPACK DROUGHT	WASHINGTON U.S. (Ch. 5)		
TOTAL	23	2	5

	METHOD USED	Total Events
Heat	Ch. 2: CMIP5 modeling Ch. 11: Observations; weather@home modeling Ch. 12: HadGEM3-A modeling Ch. 15: CMIP5 modeling Ch. 19: CMIP5 modeling with ROF; FAR Ch. 20: CMIP5 modeling with ROF; FAR Ch. 21: MIROC5-AGCM modeling Ch. 22: Observations; CMIP5 modeling Ch. 23: weather@home modeling; FAR Ch. 24: BoM seasonal forecast attribution system and seasonal forecasts	12
Cold	Ch. 7: Observations; CMIP5 modeling Ch. 8: AMIP (IFS model) modeling	3
Heat & Humidity	Ch. 14: weather@home modeling Ch. 16: Non-stationary EV theory; C20C+ Attribution Subproject	2
Dryness	Ch. 22: Observations; CMIP5 modeling Ch. 25: Observations; Modeling with CMIP5 and weather@home	2
Heavy Precipitation	Ch. 13: Observations; Modeling with CAM5.1 and MIROC5 Ch. 17: Observations; Modeling with weather@home, EC-Earth and CMIP5 Ch. 18: HadGEM3-A-N216 modeling; FAR	3
Sunshine	Ch. 10: Hadley Centre event attribution system built on the high-resolution version of HadGEM3-A	1
Drought	Ch. 9: Observations; CMIP5 modeling; Trend and FAR analyses Ch. 15: CMIP5 modeling, land surface model simulations, and statistical analyses	2
Tropical Cyclones	Ch. 26: GFDL FLOR modeling; FAR	1
Wildfires	Ch. 4: WRF-ARW optimized for Alaska with metric of fire risk (BUI) to calculate FAR	1
Sea Ice Extent	Ch. 27: OGCM modeling	1
HIGH TIDE FLOODS	Ch. 6: TIDE-GAUGE DATA; TIME-DEPENDENT EV STATISTICAL MODEL	1
SNOWPACK DROUGHT	Ch. 5: OBSERVATIONS; CESM1 MODELING	1
		30

ACRONYMS:

AMIP: Atmospheric Model Intercomparison Project

BoM: Bureau of Meteorology, Australia

BUI: Buildup Index

CAM: Community Atmosphere Model, <http://www.cesm.ucar.edu>

CESM: Community Earth System Model

CMIP: Coupled Model Intercomparison Project

FAR: Fraction of Attributable Risk

EC-EARTH: <https://verc.enes.org/>

EV: Extreme Value

GFDL FLOR: Geophysical Fluid Dynamics Laboratory Forecast version Low Ocean Resolution

GHCN: Global Historical Climatology Network

IFS: Integrated Forecast System

MIROC5-AGCM: Model for Interdisciplinary Research on Climate-Atmospheric General Circulation Model

OGCM: Ocean General Circulation Model

ROF: Regularized Optimal Fingerprinting

weather@home: <http://www.climateprediction.net/weatherathome>

WRF-ARW: Advanced Research (ARW) version of the Weather Research and Forecasting (WRF) model