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.

19. RECORD-BREAKING HEAT IN NORTHWEST CHINA IN JULY 2015: ANALYSIS OF THE SEVERITY AND UNDERLYING CAUSES

CHIYUAN MIAO, QIAOHONG SUN, DONGXIAN KONG, AND QINGYUN DUAN

The record-breaking heat over northwest China in July 2015 was linked directly to atmospheric general circulation indices and anthropogenic forcing. The latter increased the risk of extreme heat by three-fold.

Introduction. In July 2015, northwest China experienced an unusually long and intense heat wave, especially in Xinjiang Autonomous Region (Fig. 19.1a). Maximum daily temperatures (TMX) exceeded 40°C on a record-breaking number of July days in 50 out of 88 counties in Xinjiang, and historical TMX records were broken in 28 counties. The highest TMX was 47.7°C in Turpan. This year also smashed the historical records of heat wave duration in 51 counties.

Our paper poses three questions: How extreme was the heat in Northwest China in July 2015 in a historical context? What factors led to the record-breaking heat? Did human-induced climate change increase the odds of abnormally high July heat in Xinjiang?

Data and methods. We collected the July TMX from National Meteorological Information Center (NMIC; <http://data.cma.cn>). The NMIC has conducted data quality control, including extreme value control, consistency check, and spatial consistency test (Liu and Li 2003). We used the data at the 53 stations with continuous July TMX records throughout the period of 1961–2015. We defined the extreme threshold as the 90th percentile of area-averaged July TMX between 1961 and 1990 (Mazdiyasni and AghaKouchak 2015). Heat wave duration was defined as the total number of days within July that TMX exceeded the threshold (Meehl and Tebaldi 2004).

Simulations from 10 global climate models (GCMs) from the Coupled Model Intercomparison

Project Phase 5 of (CMIP5; Taylor et al. 2012) were used to assess the contribution of human influences on the observed July TMX (Supplemental Table S19.1 for the model list). The simulations driven by preindustrial control setting, natural forcing, all forcings, and anthropogenic greenhouse gases (GHG) forcing were assessed. As compared to the usual 2005, these 10 models extend the historical and natural simulations to 2012. However, we focused the GCM simulation analysis on the period 1961–2015 to enable comparison with observations. We used the TMX projection from the Representative Concentration Pathways 4.5 (RCP4.5) scenario to extend the time series of all forcings simulations through 2015, similar to Zhou et al. (2014) and Sun et al. (2014). For each GCM, only one member (r1i1p1) run was employed in this study. We used several statistical techniques to assess the severity and causes of the extreme heat:

1) To estimate the univariate return period, we selected the generalized extreme value (GEV) distribution for parametric fitting. This allows more stable estimates of return periods for extreme events occurring in the upper tail of the distribution (Fig. 19.1b). We used the Kolmogorov–Smirnov (K–S) goodness-of-fit test to verify the distribution (Wilks 2006).

2) We focused on the concurrence of July mean TMX anomaly and the duration of the heatwave (Fig. 19.1c). To estimate the concurrent extreme return period, we used the concept of copulas designed to model the dependence between multiple variables (Nelsen 2007). We used the Akaike information criterion (AIC; Akaike 1974) to identify the Gumbel copula as the most appropriate: smaller AIC values indicate a more reliable joint distribution (Supplemental Table S19.2).

3) To evaluate the impact of external forcing, we estimated scaling factors using the regularized optimal fingerprinting (ROF) method (Ribes et al.

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FIG. 19.1. (a) Time series of observed area-averaged Jul TMX over Xinjiang Autonomous Region, China, from 1961–2015. (b) Return period for Jul mean TMX. The univariate distribution was fit with a GEV function. Maximum likelihood estimates (MLEs) were used to obtain the location parameter μ , scale parameter σ , and shape parameter k . (c) Return period for concurrent Jul mean TMXs and heat wave durations. The bivariate joint distribution was fit with the Gumbel copula function. The numbers on the contour lines indicate the compound return period. (d) Spatial distribution of changes in July mean TMX anomaly (°C) and heat wave duration (%), relative to the average for each individual station during the baseline of 1961–90.

2013). Two categories were assessed: anthropogenic variations in GHG and natural forcing (Fig. 19.2b). Uncertainty ranges (5–95%) for the scaling factors were evaluated via Monte Carlo simulations. If the scaling factor for a forcing simulation was significantly greater than zero, then the influence of that forcing on the variable (i.e., July TMX) is detected (Zhang et al. 2013).

4) To analyze the attributable risk, we employed the conventional fraction of attributable risk ($FAR = 1 - P_{nat}/P_{all}$) method (Stone and Allen 2005; Stott et al. 2015). We compared the probability of the observed 2015 July mean TMX anomaly occurring in the all forcing (P_{all}) and natural forcing (P_{nat}) simulations to ascertain the contribution of anthropogenic climate change. Bootstrapping (with replacement) was performed 1000 times per period to estimate the FAR uncertainty (Fig. 19.2c).

5) To test causality, we applied Granger causality analysis (GCA; Granger 1969). We examined the impact of the El Niño–Southern Oscillation (ENSO) on

the monthly mean TMX during the period of 1961–2015 (Supplemental Fig. S19.1). The fundamental concept in GCA is that if the prediction of X (monthly mean TMX) is improved by including Y (here, the monthly ENSO index) as a predictor, then Y is said to be Granger causal for X (significance determined by F -test; $p < 0.05$; Sun et al. 2016). In addition, a contour map for the South Asia high (SAH) was generated to explore its coincidence with the heat events.

Results. A. Observed 2015 July TMX in historical context.

Figure 19.1a shows that the July mean TMX in 2015 (32.76°C) was the highest during the past 55 years and was 2.87°C higher than the mean TMX during the baseline period (1961–90). The gray and red lines in the embedded figure in Fig. 19.1b correspond to July mean TMX anomaly during 1961–2014 and in 2015, respectively, relative to the baseline period. The K–S test shows that the GEV distribution was not rejected at $p < 0.05$ level. The 2015 July heat was close to a 1-in-166-year event. Because only 55 years of observed

FIG. 19.2. (a) PDFs for Jul mean TMX anomaly (relative to 1961–90) for the all forcing (red) and natural forcing (blue) simulations; (b) Attribution analysis based on the TMX time series under different forcing conditions, (c) PDFs for estimated FAR focused on all forcing (1961–2015) and natural forcing (1961–2012). The blue histogram was generated by bootstrap resampling; the red line is the median. The embedded figure shows estimated FAR results (median and 25th–75th percentiles) from the all forcing simulation for different 30-year periods against the natural forcing simulation for 1961–2012. The x-axis indicates the starting year of the 30-year moving window. (d) The geopotential height anomaly field (m) for Jul 2015 at 100 hPa (baseline period: 1980–2009) estimated with the NCEP–DOE Reanalysis 2 datasets.

data were used, the 166-year return period can be considered as a lower bound. The blue and red dots in Fig. 19.1c indicate the return periods for concurrent July mean TMX and heat wave duration during the period 1961–2014 and in 2015. The July 2015 concurrency was a 1-in-200-year event. We also found that the most severe changes from baseline in 2015 July mean TMX and heatwave duration were mainly in the middle and northeastern areas of Xinjiang. The heat wave duration was approximately double that of the baseline period (Fig. 19.1d).

Results. B. Analysis of the attributable risk. We compared the likelihood of the July mean TMX anomaly occurring in different CMIP5 experiments (Fig. 19.2a). When anthropogenic forcing was included, the probability density function (PDF) shifted to the right, indicating an increased likelihood of high temperatures. The scaling factor for the GHG-forcing

simulation, estimated by the regularized optimal fingerprinting method, was 0.41 [90% confidence interval (CI): 0.09–0.76; Fig. 19.2b], suggesting that the changes in area-averaged July mean TMX were responsive to the anthropogenic greenhouse-gases forcing. It was estimated that all PDFs assumed a GEV distribution. When the 2015 July mean TMX anomaly (2.87°C) was marked as the threshold, the equivalent FAR value was 0.68 (90% CI: 0.51–0.81; Fig. 19.2c), indicating that 68% of the risk of such event is attributed to anthropogenic climate change. This translates to about three-fold (90% CI: 2.04–5.32) increase in the probability of 2015 July mean TMX anomaly occurring due to anthropogenic influence. The RCP4.5 experiments indicated that the risk from human-induced climate change increases with time, while uncertainty reduces with time (Fig. 19.2c, embedded figure). We also attempted to find other factors that contributed to the extremely high TMX

in July 2015. The 2015 ENSO was one of the strongest since 1960. GCA showed that there was no significant ($p = 0.35$) causal relationship between area-averaged mean TMX and ENSO index (Supplemental Fig. S19.1a). However, for 10 stations in central Xinjiang, significant causal relationship ($p < 0.05$) was detected between TMX changes and ENSO (Supplemental Fig. S19.1b). The extreme heat events in July 2015 might be also related to the movement of the South Asia high (SAH), which is the most intense and persistent anticyclone system in the upper troposphere and lower stratosphere over southern Asia during boreal summer (Mason and Anderson 1963). Less precipitation and heat events usually occur in the region where the SAH moves in (Chen et al. 2011). According to the geopotential height anomaly field in July 2015 at 100 hPa, the SAH center moved northward (Fig. 19.2d) and dominated the weather of the entire Xinjiang region, coinciding with the extreme heat events in northwest China.

Conclusions. Our analysis of July TMX records over the last 55 years indicates that the record-breaking heat observed over Northwest China in 2015 was at least a 1-in-166-year event. The return period increased to ~200 years if heat wave duration was also taken into account. CMIP5-based FAR analyses suggest that anthropogenic climate change increased the likelihood of such an extreme event by three-fold. The extreme heat event is related to the ENSO and SAH. This study is an important step toward a comprehensive understanding of the record-breaking 2015 heat in Xinjiang.

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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