25. THE HOT AND DRY APRIL OF 2016 IN THAILAND

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The record temperature of April 2016 in Thailand would not have occurred without the influence of both anthropogenic forcings and El Niño, which also increased the likelihood of low rainfall.

Introduction. April is typically one of the hottest months in Thailand, marking the end of the dry season and the onset of monsoon rains. April heat reached unprecedented levels in 2016 (NASA 2016) and exacerbated the adverse socio-economic impacts from a prolonged drought that started in early 2015 and persisted until mid-2016, evidently favored by the presence of a strong El Niño (Singhrattna et al. 2005). The severe drought affected 41 Thai provinces, had devastating effects on major crops, such as rice and sugar cane, and incurred a total loss in the agricultural production of about half a billion U.S. dollars (Ministry of Agriculture and Cooperatives; MOAC 2016). Moreover, the extreme heat culminating in the April heat wave resulted in an estimated six-fold increase in heatstroke cases relative to 2014 (Ministry of Public Health; MOHP 2017), while record-breaking peak electricity demand was also reported (Electricity Generating Authority of Thailand; EGAT 2016), and extensive forest fires ravaged the country (Forest Fire Control Division; FFCD 2017).

This work considers possible drivers of the exceptionally high temperature and low rainfall over land in the region of Thailand (5°–20°N, 95°–110°E) in April 2016. We concentrate on the effect of anthropogenic forcings and the El Niño Southern Oscillation (ENSO), investigating how they influence the occurrence of extremes similar to 2016. The study focuses on the month of April when the heat peaked. In that month, temperatures in excess of 44°C set new records in some regions, and the severe weather and its impacts were extensively reported in the national press. Although our study does not consider the drought in which the event was embedded, or its hydrological impacts, we examine streamflow data from the Royal Irrigation Department of Thailand for the country's two main river basins (see online-supplemental material), as this provides a context for the April event. For each month since 1950, normalized streamflow values are computed from the station data as the mean flow during the year ending at that month. The resulting streamflows reveal that in both basins the drought was greatly intensified after mid-2015. At least 7 months leading up to April 2015 ranked in the top ten since the 1950s in terms of severity (Figs. 25.1a,b; only recent years plotted for clarity).

Methods. We define extreme events using thresholds (Stott et al. 2016) and identify hot and dry events as those instances when the temperature rises above and the rainfall falls below the 2016 observed values. Our analysis sets out to answer three attribution questions: 1) How does anthropogenic climate change modify the likelihood of hot and dry events under the 2016 El Niño conditions?; 2) What would the anthropogenic effect on the likelihood be under any ENSO conditions?; and 3) How does ENSO affect the likelihood of extreme events in the current climate, already influenced by anthropogenic forcings? Local surface processes which may drive or amplify heat waves are better studied with regional and hydrological models, and their effect is not explicitly addressed here. Regional temperature and rainfall time series constructed with the CRUTEM4 (Jones et al. 2012) and GPCC (Schneider et al. 2014) datasets show that April 2016 was the hottest (Fig. 25.1c) and fourth driest (Fig. 25.1d) since 1900. Using these observations, we demonstrate the clear influence of ENSO on temperature and rainfall by grouping the data in consecutive bins and computing the mean Southern Oscillation Index in the years corresponding to each bin (Figs. 25.1e,f). El Niño favors warmer and drier conditions, so the markedly strong El Niño in 2015–16 (L'Heureux et al. 2017) is expected to have made a considerable contribution to the extreme conditions in April 2016.

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DOI:10.1175/BAMS-D-17-0071.1

A supplement to this article is available online (10.1175/BAMS-D-17-0071.2)

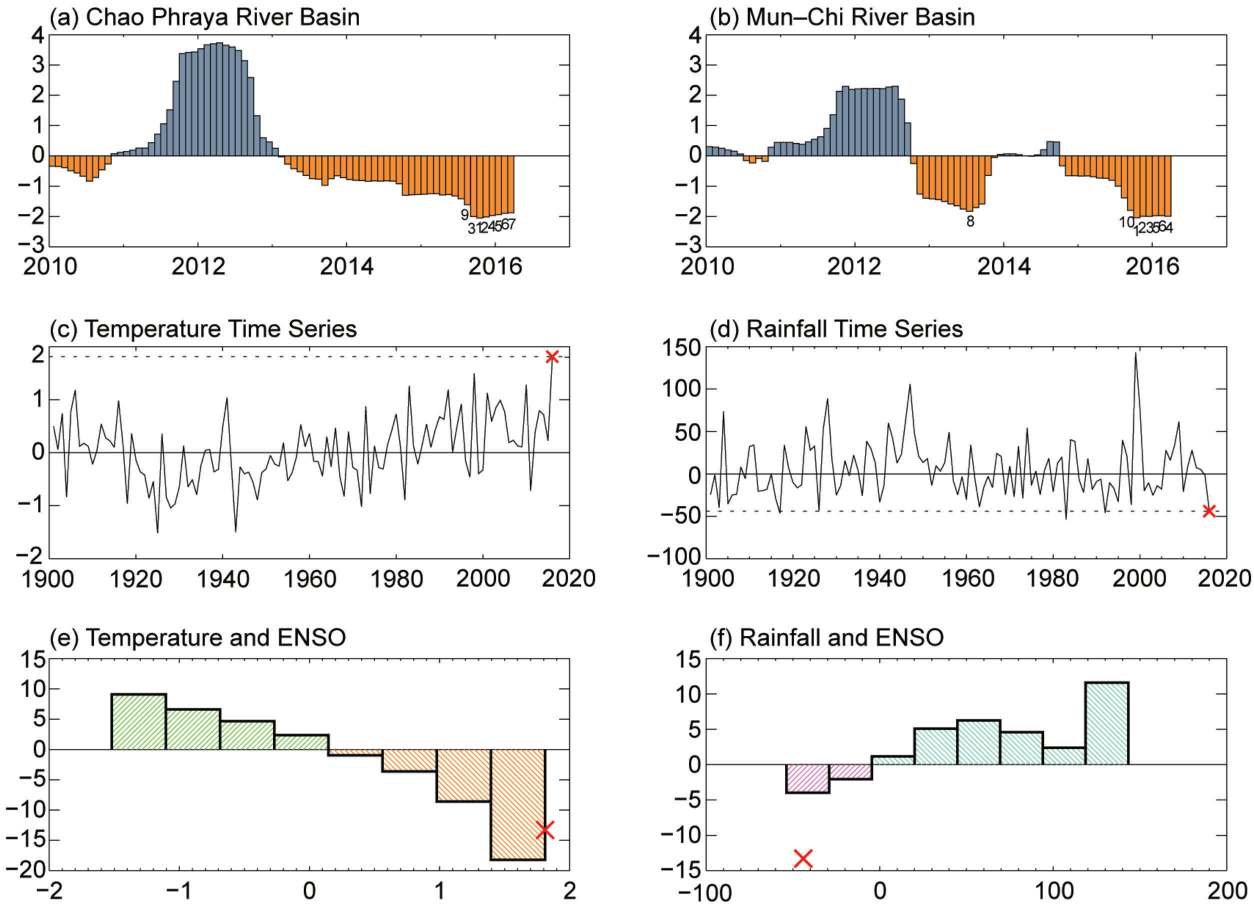

Fig. 25.1. Normalized monthly running sums (12-months back-totaled) of streamflow constructed with data from stations located in two major Thai river basins: (a) Chao Phraya and (b) Mun-Chi. Only recent years are plotted for clarity; last record is Mar 2016. Months with streamflows among the ten lowest are marked. (c),(d) Time series of the Apr mean temperature (°C) and rainfall (mm) in the region of Thailand from observations. (e),(f) Histograms showing the mean Southern Oscillation index (SOI) in years corresponding to different temperature and rainfall data bins. (c)–(f) Red asterisk marks year 2016 and all anomalies are relative to 1961–90.

Our analysis uses the Hadley Centre event attribution system (Christidis et al. 2013), which provides ensembles of simulations with the HadGEM3-A model for the actual climate with all external forcings included ("factual" experiment) and a hypothetical natural climate without the effect of human influence ("counterfactual" experiment). The system was recently upgraded to high resolution (N216 and 85 vertical levels; Ciavarella et al. 2017, *manuscript submitted to Wea. Climate Extremes*). Observed oceanic conditions were prescribed in the factual simulations using the HadISST dataset (Rayner et al. 2003). A model-based estimate of the ocean's warming calculated as the average across 51 simulations from 19 coupled models that provided data to the CMIP5 archive (http://portal.nersc.gov/c20c/experiment.html) was subtracted from the observations in the counterfactual simulations and the sea–ice was adjusted accordingly (Christidis et al. 2013). The system provides ensembles of 525 simulations of March–May 2016 for each experiment, which include strong El Niño conditions through the prescribed boundary conditions. We also use shorter, 15-member ensembles of factual and counterfactual simulations over the period 1960–2015 and extract the last 15 years to approximate the near present-day climate. For each experiment, we extract the month of April and compute the monthly and regional mean temperature and rainfall. This yields samples of 525 months per variable and experiment for year 2016 and 225 months for the recent past (years 2001–15). With these we subsequently construct temperature and rainfall distributions and estimate the probability of a hot or dry April using our pre-specified thresholds and the return period, calculated as the reverse of the probability. Extreme probabilities are derived with the generalized Pareto distribution and their uncertainties with a Monte Carlo bootstrap procedure (Christidis et al. 2013). Model evaluation assessments were also carried out (see online supplemental material), which suggest that HadGEM3-A represents well the climatological distribution of April temperature and rainfall in the region and also provides realistic probability estimates for extreme events.

Results. First, the effect of anthropogenic forcings under the observed El Niño conditions is examined. Temperature and rainfall distributions are constructed from the model simulations of April 2016 (Figs. 25.2a,b). The thresholds used to define extreme events are also marked on the distribution plots. The modeled rainfall data were bias corrected to have the same mean as the observations in the period 1961–90. The temperature threshold is set to be 3.3 standard deviations above the modeled climatological mean, as estimated from observations for April 2016. Human influence (i.e., the overall effect of anthropogenic emissions of well-mixed greenhouse gases, aerosols and ozone, as well as land-use changes) is shown to increase the chances of both dry and hot events. The associated reduction in the return time of extremes is shown in Fig. 25.2c. The likelihood of extremely low rainfall is estimated to increase by a factor of 2 (best estimate). However, the anthropogenic effect on temperature is far more pronounced, and we find that April temperatures as high as in 2016 cannot occur in the natural climate, even under the influence of a strong El Niño. The joint probability of hot and dry

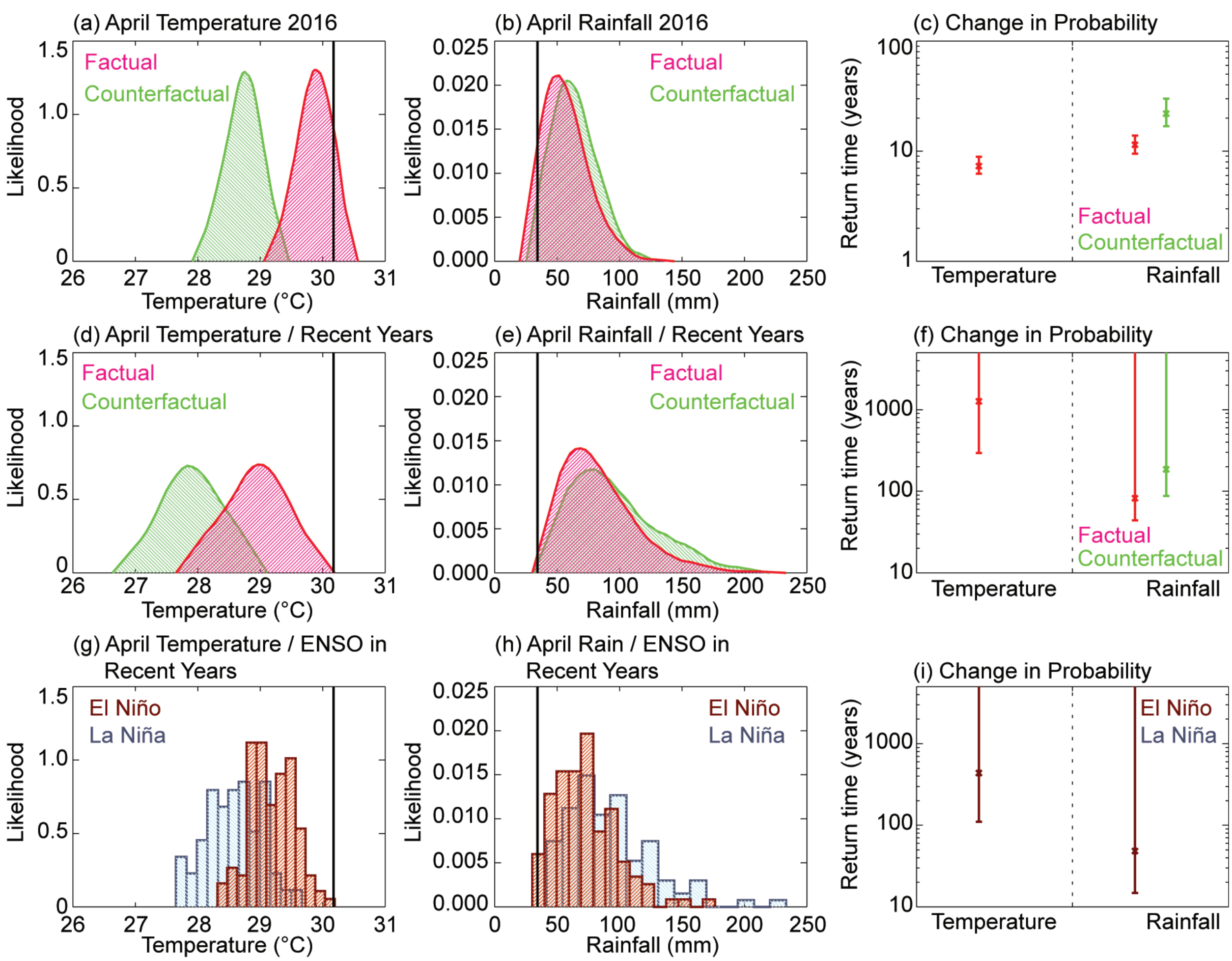

FIG. 25.2. Normalized distributions of the April mean temperature (°C) and rainfall (mm) in the region of Thailand with (red) and without (green) anthropogenic climate change constructed with HadGEM3-A data for (a),(b) 2016 and (d),(e) 2001–15. Distributions are also shown for El Niño (dark red) and La Niña (blue) conditions in (g),(h) recent years. Year 2016 is marked by the vertical line. (c), (f), and (i) illustrate estimates of the return times of extreme events corresponding to different model experiments or ENSO phases. The best estimate (50th percentile) is marked by a cross and the 5%–95% uncertainty range by whiskers.

events occurring simultaneously is also computed, and it is estimated that in the factual climate the return time is 105 years (5%–95% range: 53–263 years), while in the counterfactual world the likelihood is too small to be accurately estimated. Our results are to some extent affected by a known caveat arising from the uncertainty in the counterfactual boundary conditions (Christidis and Stott 2014; Solomon and Newman 2012), sometimes sampled by using several estimates of the oceanic warming from individual models. A computationally cheaper approach would be using improved boundary conditions derived from observations (Christidis and Stott 2014; Seager and Hoerling 2014). In this work, we use boundary conditions from a multimodel ensemble instead, which should (to some extent) alleviate errors from individual models.

The anthropogenic effect on extreme events irrespective of the ENSO phase is investigated next, based on the temperature and rainfall distributions for the recent past (Figs. 25.2d,e). Although human influence increases the likelihood of extremes, their probabilities are much smaller (Fig. 25.2f). We again find that the NAT experiment cannot reproduce the extreme April heat of 2016, which is also rare in the actual climate (Fig. 25.2d), but becomes more likely in years with a strong El Niño (Fig. 25.2a).

Finally, the influence of the ENSO phase on the likelihood of extremes in the current climate is also examined. We partition the simulated, near present-day data between positive and negative ENSO phases and construct the distributions for the two phases (Figs. 25.2g,h). As expected, El Niño conditions increase the chances of extreme events, which are not found to occur in La Niña years. The chance of extreme temperature events is small even under El Niño conditions (Fig. 25.2i), but apparently increases during stronger episodes (Fig. 25.2a).

Conclusions. Our analysis demonstrates that anthropogenic climate change results in a clear shift of the April temperature distribution toward warmer conditions and a more moderate, albeit distinct, shift of the rainfall distribution toward drier Aprils in Thailand. The synergy between anthropogenic forcings and a strong El Niño was crucial to the breaking of the temperature record in 2016, which our results suggest would not have occurred if one of these factors were absent. Rainfall as low as in 2016 is found to be extremely rare in La Niña years. The joint probability for hot and dry events similar to April 2016 is found to be relatively small (best estimate of about 1%), which implies that in addition to the drivers examined here, other possible causes could have also played a role, like moisture availability and transport (especially in the context of the prolonged drought), atmospheric circulation patterns, and the effect of other non-ENSO modes of unforced variability.

ACKNOWLEDGMENTS. NC, AC, and PAS were supported by the Joint DECC/Defra Met Office Hadley Centre Climate Programme (GA01101). We thank the Royal Irrigation Department of Thailand for providing the streamflow data.

REFERENCES

Christidis, N., P. A. Stott, 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, doi:10.1175/JCLI-D-12-00169.1.

——, and ——, 2014: Change in the odds of warm years and seasons due to anthropogenic influence on the climate. *J. Climate*, **27**, 2607-2621, doi: 10.1175/JCLI-D-13-00563.1.

EGAT, 2016: Record breaking of peak electricity load for seventh time in 2016 by accumulated heat (in Thai). Electricity Generating Authority of Thailand. [Available online at www.egat.co.th/index.php?option=com_content&view=article&id=1491:press-20160511-01&catid=31&Itemid=208.]

FFCD, 2017: Forest fire occurrence statistics (in Thai). Forest Fire Control Division, Department of National Park, Wildlife and Plant Conservation, Thailand. [Available online at www.dnp.go.th/forestfire/2546/firestatistic%20Th.htm.]

Jones, P. D., D. H. Lister, T. J. Osborn, C. Harpham, M. Salmon, and C. P. Morice, 2012: Hemispheric and large-scale land surface air temperature variations: An extensive revision and an update to 2010. *J. Geophys. Res.*, **117**, D05127, doi:10.1029/2011JD017139.

L'Heureux, M., and Coauthors, 2017: Observing and predicting the 2015-16 El Niño. *Bull. Amer. Meteor. Soc.*, **98**, 1363–1382, doi:10.1175/BAMS-D-16-0009.1.

MOAC, 2016: Daily reports of drought situations and mitigation (in Thai). National Operation Center of Drought Response and Mitigation for 2015/2016, Ministry of Agriculture and Cooperatives, Thailand. [Available online at www.moac.go.th/drought.]

MOPH, 2017: Health Data Center Services (in Thai). Ministry of Public Health, Thailand. [Available online at http://hdcservice.moph.go.th.]

NASA, 2016: Heat wave hits Thailand, India: Natural Hazards. [Available online at http://earthobservatory.nasa.gov/NaturalHazards/view.php?id=87981.]

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, doi:10.1029/2002JD002670.

Schneider, U, A. Becker, P. Finger, A. Meyer-Christoffer, M. Ziese, and B. Rufolf, 2014: GPCC's new land surface precipitation climatology based on quality-controlled in situ data and its role in quantifying the global water cycle. *Theor. Appl. Climatol.*, **115**, 15–40, doi:10.1007/s00704-013-0860-x.

Seager, R., and M. Hoerling, 2014: Atmosphere and ocean origins of North American droughts. *J. Climate*, **27**, 4581–4606, doi: 10.1175/JCLI-D-13-00329.1.

Singhrattna, N., B. Rajagopalan, K. Krishna Kumar, and M. Clark, 2005: Interannual and interdecadal variability of Thailand summer monsoon season. *J. Climate*, **18**, 1697–1708, doi:10.1175/JCLI3364.1.

Solomon, A., and M. Newman, 2012: Reconciling disparate twentieth-century Indo-Pacific ocean temperature trends in the instrumental record. *Nat. Climate Change*, **2**, 691–699, doi:10.1038/nclimate1591.

Stott, P. A., and Coauthors, 2016: Attribution of extreme weather and climate-related events. *Wiley Interdiscip. Rev: Climate Change*, **7**, 23–41,doi: 10.1002/wcc.380.