## 22. CLIMATE CHANGE AND EL NIÑO INCREASE LIKELIHOOD OF INDONESIAN HEAT AND DROUGHT

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El Niño and human-induced climate change have substantially increased the likelihood of rainfall deficits and high temperatures, respectively, in Indonesia such as those experienced in the drought conditions of July–October 2015.

*Introduction.* Indonesia experienced severe heat and drought throughout the dry season of 2015. The period July–October saw extreme precipitation deficits and record-breaking hot temperatures (Figs. 22.1a,b). The combination of heat and drought contributed to fires across much of the country, which were associated with fatalities and were likely the worst since 1997 (Huijnen et al. 2016). The fires had broader health impacts through increased prevalence of respiratory problems (Koplitz et al. 2016).

El Niño conditions in the central Pacific are strongly linked with seasonal precipitation deficits south of the equator in the dry season (Hendon 2003; Fig. 22.1c) and, to a lesser extent, warmer land temperatures (Harger 1995; Fig. 22.1d). Previous strong El Niño events, such as 1997, were associated with severe drought conditions in Indonesia. Anthropogenic influences may also have played a role in this event. The relative influences of El Niño–Southern Oscillation (ENSO) and human-induced climate change are investigated here.

Data and methods. To assess this current extreme event in the long-term context of a changing climate, it is desirable to have high-quality longterm observational time series. It is also preferable to have gridded observations, when comparing with climate model output, at a moderate resolution, especially over Indonesia where larger grid boxes contain both land and ocean. Unfortunately, in many regions of the developing world such data do not exist. The use of temperature and precipitation

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A supplement to this article is available online (10.1175 /BAMS-D-16-0164.2) data from a range of observation-based datasets were investigated, and ERA-Interim (1979-2015; Dee et al. 2011) was selected for use in this analysis. Other longer-running reanalyses and analyses, such as ERA-20C (Poli et al. 2016) and CRU-TS3.23 (Harris et al. 2014), were found to include inhomogeneities prior to the satellite era (1979 onwards). A long, relatively homogenous, precipitation series was obtained from the GPCC 1° V7 analysis (1901-2015) extended by the V5 monitoring analysis (Schneider et al. 2015). Temperature and precipitation data were regridded onto a regular 2° grid and averaged over land boxes within the region 0°-11°S, 95°-141°E for July-October (time series shown in Supplemental Fig. S22.1). There is agreement in temperature trends between ERA-Interim and limited observational data from the public Global Historical Climatology Network-Monthly database (Lawrimore et al. 2011) available since 1979 (Supplemental Fig. S22.2). The trends and connection to El Niño were also investigated in observational data. It was impossible to find a temperature series longer than the ERA-Interim series, as the station density is low, variability is small, and coastal effects make interpolation to the interiors of large islands doubtful. For further details on our observational analysis, see the online Supplemental Material.

The Niño-3.4 index was calculated from HadISST (Rayner et al. 2003) for July–December. Values of the Niño-3.4 index more than  $+0.83^{\circ}C(1\sigma)$  above zero in the observations were deemed to be El Niño seasons. Applying this threshold to the climate models results in selecting 10% of the seasons due to a tendency toward lower Niño-3.4 variability in most models.

Model data were extracted from the CMIP5 archive (Taylor et al. 2012) and evaluated for their performance in capturing observed temperature and precipitation variability. The model data processing followed the same regridding and subsequent masking as the reanalysis (the raw resolution of most



FIG. 22.1. (a) Precipitation and (b) temperature anomaly in Jul-Oct 2015 relative to a 1979–2005 climatological average in ERA-Interim. The box in (a) denotes the region of study. Detrended area-average (c) precipitation and (d) temperature anomalies for the boxed region from 1979–2015 in ERA-Interim plotted with average Jul-Dec Niño-3.4 index. Spearman rank correlation coefficients are shown and 2016 is marked (red crosses).

models used here is finer than 2°). July–October temperature and precipitation averages over Indonesia and July–December Niño-3.4 index values were extracted. Simulations from the "historical" experiment (including natural and anthropogenic forcings for 1861–2005) were compared with observation-based data over the common 1979–2005 period. To account for the shorter period over which the evaluation takes place, additional evaluation steps were included that test model ability to capture Indonesian climate variability and ENSO relationships (described in the Supplemental Material). Models with at least three historical simulations (listed in Supplemental Table S22.1) were tested for similarity to observational data.

The ten models that passed the evaluation were further analyzed. Equivalent Indonesian temperature and precipitation averages and Niño-3.4 index values were calculated from the historicalNat (natural forcings only for 1861–2005) and RCP8.5 (projected climate under a high greenhouse gas emissions scenario for 2006–30) simulations.

The historical and equivalent RCP8.5 simulations were joined to form simulations included in an all-forcings ensemble (2000–30), which were compared

with a natural-forcings ensemble (1861–2005) using the historicalNat runs. These ensembles were then used to investigate the change in likelihood of extreme heat (above +0.7°C anomaly) and drought (below 60% of average precipitation) in Indonesia due to anthropogenic climate change and El Niño–Southern Oscillation.

In addition, we estimated the change in magnitude of hot and dry July–October periods in Indonesia due to climate change and the El Niño conditions. See the online Supplemental Material for more details and the results.

Uncertainty in results was measured through bootstrapping model simulations (see the Supplemental Material). Results reported here are conservative 10th percentile estimates with best estimates in parentheses.

*Results.* 1) Attribution to anthropogenic influences: low rainfall extremes

Based on our model analysis, precipitation deficits like those experienced during July–October 2015 in Indonesia were made at least 37% (best estimate: 100%) more likely due to anthropogenic climate change. This result is based on the models that passed our evaluation tests and adequately capture Indonesian climate variability and ENSO relationships. The significant increase in frequency of low rainfall totals in the all-forcings ensemble compared with the natural-forcings ensemble is consistent with the simulated reduction in July– October mean precipitation. These results contrast previous attribution analyses of precipitation deficits in other parts of the world, such as Australia (King et al. 2014), Brazil (Otto et al. 2015), and Texas (Rupp et al. 2015) that found limited evidence of a strong anthropogenic influence.

The observational precipitation time series (for 1901–2014) shows a downward trend in low extremes, albeit a nonsignificant trend (Fig. 22.2a), and no trend

in mean July–October precipitation. The dry tail of the observations and the El Niño tail in the models agree well (Fig. 22.2a).

2) Attribution to anthropogenic influences: high temperature extremes

High temperatures like those observed in 2015 do not occur in our natural-forcings ensemble (as indicated by all green crosses being below the 2015 mark in Fig. 22.2c), but do exist in our all-forcings ensemble. Therefore, in our model-based analysis, the high temperatures are entirely attributable to anthropogenic influence. The probability is also vanishingly small in the observations (Fig. 22.2c), even though we can only go back to 1979, which misses about 1/3 of the warming signal. We also did not separate out El Niño years in the observations due to the small num-



Fig. 22.2. (a),(b) The change in likelihood of dry Jul-Oct periods like 2015 in modeled and observed precipitation due to (a) anthropogenic influence and (b) ENSO. (c),(d) The same but for hot Jul-Oct periods like 2015. (a) Scaled observed precipitation in the current climate fitted to a Generalized Pareto Distribution (GPD) function that scales with the smoothed global mean temperature for 1901 (blue lines and symbols) and 2015 (red lines and symbols), including 95% confidence intervals. The crosses denote the observations shifted with fitted trend. The purple symbols denote El Niño seasons in the model-simulated current climate, green simulated El Niño seasons without anthropogenic forcings. (b) The same for El Niño (red observations, purple models) against neutral, using 2005 as an example neutral year (blue observations), and neutral plus La Niña (green models). (c) As in (a) but for temperature, fitted to a Gaussian distribution that shifts with the smoothed global mean temperature. The reanalysis only starts in 1979, which misses 1/3 of the heating. (d) As in (b) but for temperature.

ber of samples. The warming trend in ERA-Interim can also be seen in longer observational time series, such as Jakarta (Siswanto et al. 2015).

3) Attribution to El Niño: low rainfall extremes Given the strong ENSO relationship with Indonesian dry-season precipitation (Fig. 22.1c) and the strong El Niño of 2015-16, it is expected that the El Niño also influenced the likelihood of a rainfall deficit occurring. Comparing precipitation deficits in the all-forcings ensemble between El Niño seasons with neutral and La Niña seasons, we found at least a 300% increase (best-estimate: 500% increase) in likelihood of having dry July-October periods in El Niño years. An analysis of the detrended long observed rainfall series shows that the probability of a dry season like July-October 2015 increases by at least a factor 20 over neutral years (Fig. 22.2b). The models have a somewhat broader distribution toward dry seasons than the observations.

4) Attribution to El Niño: high temperature extremes

In comparison, ENSO has a weaker (but statistically significant relationship) with Indonesian land temperatures. In the models, the likelihood of hot July–October periods in Indonesia is raised by at least 22% (best estimate: 51%) in El Niño seasons relative to neutral and La Niña events combined (Fig. 22.2d). The reanalysis shows a stronger effect, with the probability increased by at least 300% compared to a neutral year like 2005 (after detrending). This is again caused by the broader modeled distribution than the observed one (Fig. 22.2d).

Conclusions. Indonesia endured severe heat and drought during the dry season of 2015. By investigating the July-October high temperatures and low rainfall totals in ensembles of coupled climate models with and without anthropogenic forcings, an attribution of these extreme conditions to humaninduced climate change and the concurrent El Niño was conducted. The model-based and observational analyses show that El Niño conditions strongly increased the probability of a drier-than-normal dry season, and that the background warming trend due to anthropogenic climate change increased the likelihood of high temperatures. El Niño also caused somewhat higher land temperatures. The models also show a trend toward less rain and more extreme dry events, which is smaller than can be significantly detected in the observations to now.

Dry-season precipitation variability in Indonesia is strongly related to ENSO, while a very clear warm-

ing trend is detectable there. Our results are in line with time of emergence studies in that regard (e.g. King et al. 2015; Mahlstein et al. 2011), which find an earlier warming signal in tropical regions such as Indonesia due to a high signal-to-noise ratio. A difficulty with performing this study was the lack of high-quality long-running observational climate data representative of our study area. The use of ERA-Interim reanalyses to evaluate the models and provide thresholds for the CMIP5-based analysis is not ideal. This difficulty is a problem across much of the developing world, where extreme weather and climate events also tend to have the strongest impacts. Further analysis on how to best conduct attribution studies where observations are sparse or have suspected inhomogeneities is required.

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