THE EXTREMELY WET MARCH OF 2017 IN PERU

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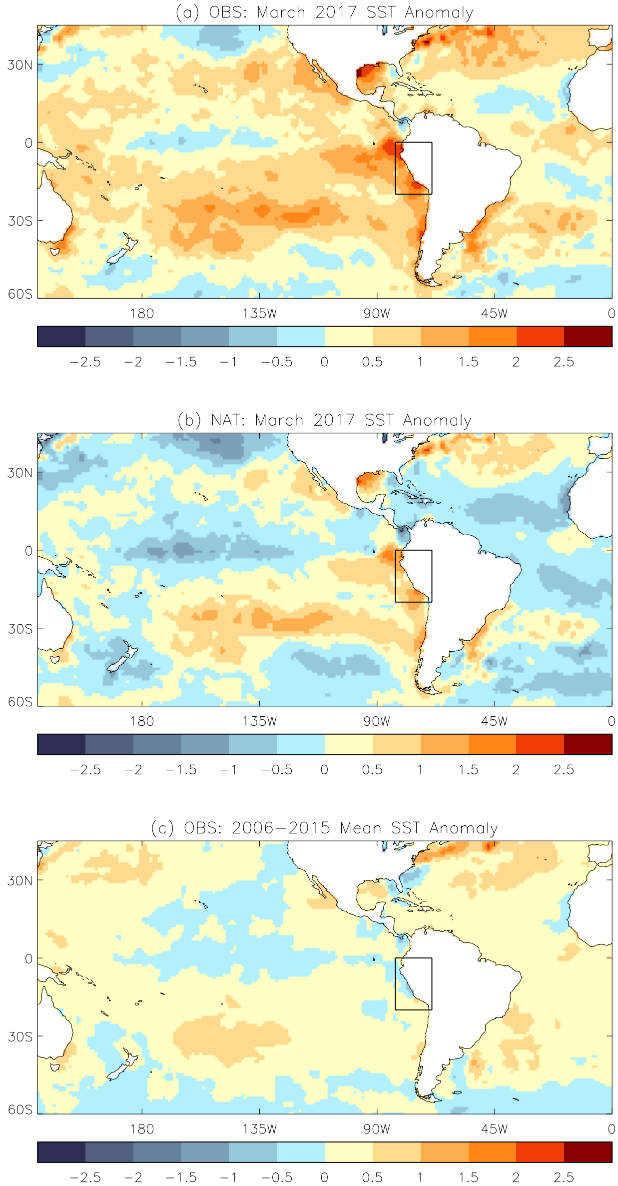
BOUNDARY CONDITIONS. Figure ES1 shows the SST anomaly patterns in HadGEM3-A simulations. The observed regional mean anomaly in March 2017 is 1.6°C. The anomaly is reduced in the NAT simulations to about 1°C. While attribution results can be sensitive to the estimate of the anthropogenic warming of the ocean (ΔSST) used in the construction of the NAT boundary conditions (Christidis et al. 2018), the coastal El Niño of 2017 is still present in the NAT SST pattern and its effect would probably take precedence over the ΔSST uncertainty. The observed anomaly during 2006–15 (Fig. ES1c) is near zero (0.05°C).

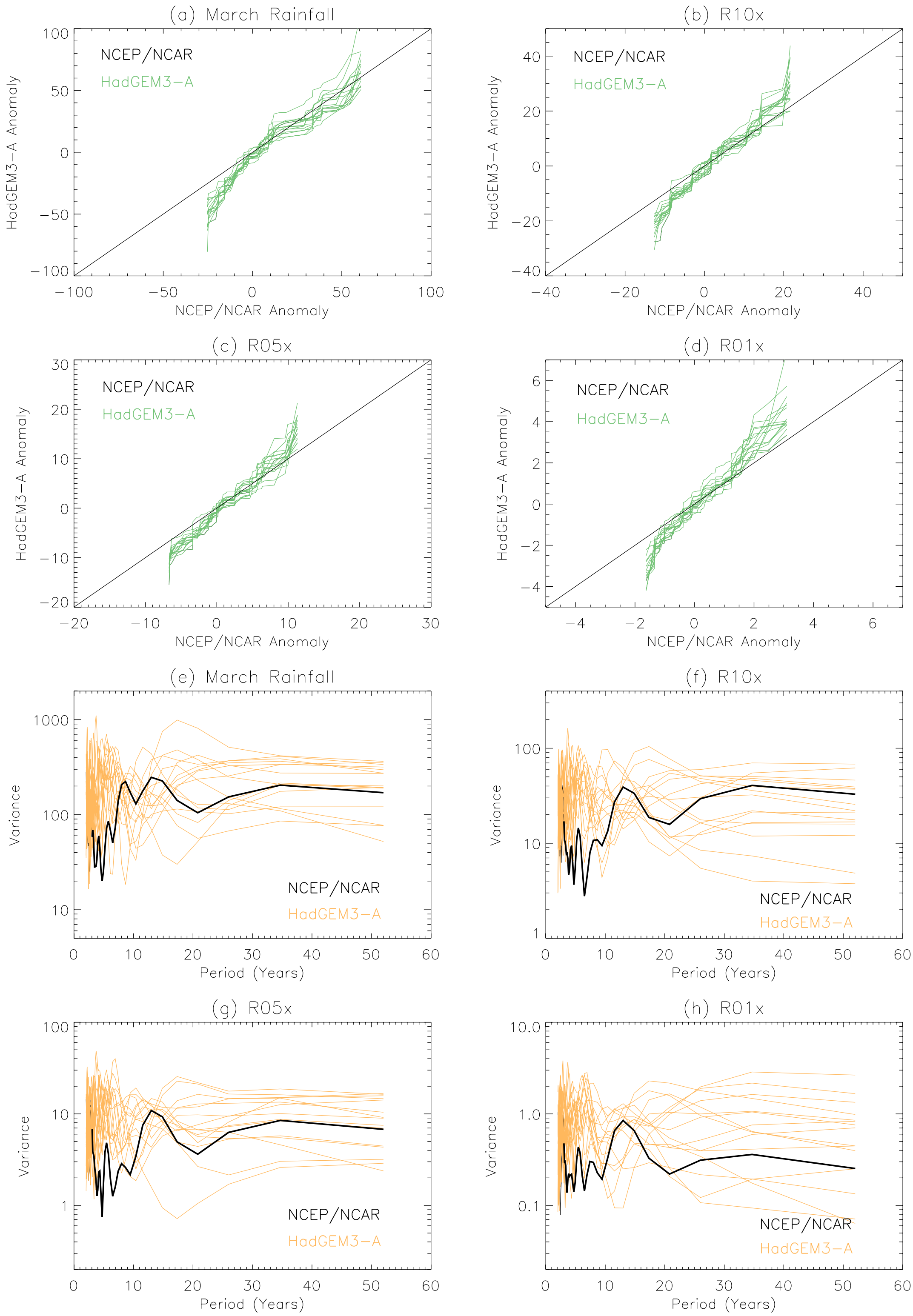


◄ **Fig. ES1. SST anomalies (°C) relative to 1961–90. (a) Observed anomalies used in the ALL simulations of March 2017. (b) Adjusted anomalies used in simulations of the natural climate in March 2017. (c) Observed anomalies in March averaged over years 2006–15 used in the multidecadal ALL simulations. The study area is marked by the black box.**

Evaluation. Two-sided Kolmogorov–Smirnov tests applied to HadGEM3-A and NCEP–NCAR reanalysis data reveal no significant differences (at the 10% level) across all time scales considered in this study. Quantile–quantile (Q-Q) plots (Figs. 2a–d) show that simulated heavy rainfall is generally consistent with the reanalysis, although somewhat overestimated at shorter time scales (R01x). This, however, may not indicate model error, as similar Q-Q plots produced with the 20CR dataset (www.esrl.noaa.gov/psd/data/20thC_Rean/) indicate good agreement at short time scales and some discrepancy at larger ones instead. This inconsistency underlines the need for long, reliable observational rainfall records in the region. Regional rainfall in the GPCC record does not capture the extreme event of 2017 and also displays different variability to other datasets. While it is uncertain which dataset would be most suitable for model evaluation, it can be concluded on the basis of the simple assessments shown here that HadGEM3-A provides a reasonable representation of the regional rainfall and its extremes. Power spectra (Figs. 2e–h) also indicate that the modeled variability is in good agreement with the reanalysis.

► **Fig. ES2. HadGEM3-A evaluation against the NCEP-NCAR reanalysis. An ensemble of 15 ALL simulations of the historical climate was employed. Different panels show results for different periods of rainfall (March mean to R01x). (a)–(d) Q-Q plots of regional rainfall anomalies during 1960–2015. Each green line on the panels corresponds to a different model simulation. (e),(f) Power spectra for the rainfall anomaly in Peru during 1960–2015 [for details, see Christidis et al. (2013)]. Reanalysis spectra are plotted in black and the modeled spectra in orange.**

The effect of the complex terrain. The change in the likelihood of extreme events with a monthly mean rainfall above the 1-in-10-yr threshold due to the warm SSTs in March 2017 is estimated in three subregions with different topographic characteristics (Fig. ES3a): one over the sea (region 1), one over the Andes (region 2), and one to the east of the mountains (region 3). In all three regions March 2017 stands out as a record in time series constructed with NCEP–NCAR reanalysis data (Fig. ES3b), rising about 5 standard deviations above the climatological mean over land (regions 2 and 3) and 7 standard deviations over sea (where both variability and the long-term trend appear to be less pronounced). A risk ratio of about 1.5–4 is computed over land (best estimates in regions 3 and 2) and of about 45 over the sea (Fig. ES3c). The risk ratio for the original region, which includes topographic features of all the three subregions, is about 5 (Fig. 2d). This simple sensitivity assessment does not indicate any peculiar orographic effect on the attribution findings.


(a) March Rainfall
NCEP/NCAR
HadGEM3−A
HadGEM3−A Anomaly
NCEP/NCAR Anomaly
(b) R10x
NCEP/NCAR
HadGEM3−A
HadGEM3−A Anomaly
NCEP/NCAR Anomaly
(c) R05x
NCEP/NCAR
HadGEM3−A
HadGEM3−A Anomaly
NCEP/NCAR Anomaly
(d) R01x
NCEP/NCAR
HadGEM3−A
HadGEM3−A Anomaly
NCEP/NCAR Anomaly
(e) March Rainfall
Variance
NCEP/NCAR
HadGEM3−A
Period (Years)
(f) R10x
Variance
NCEP/NCAR
HadGEM3−A
Period (Years)
(g) R05x
Variance
NCEP/NCAR
HadGEM3−A
Period (Years)
(h) R01x
Variance
NCEP/NCAR
HadGEM3−A
Period (Years)

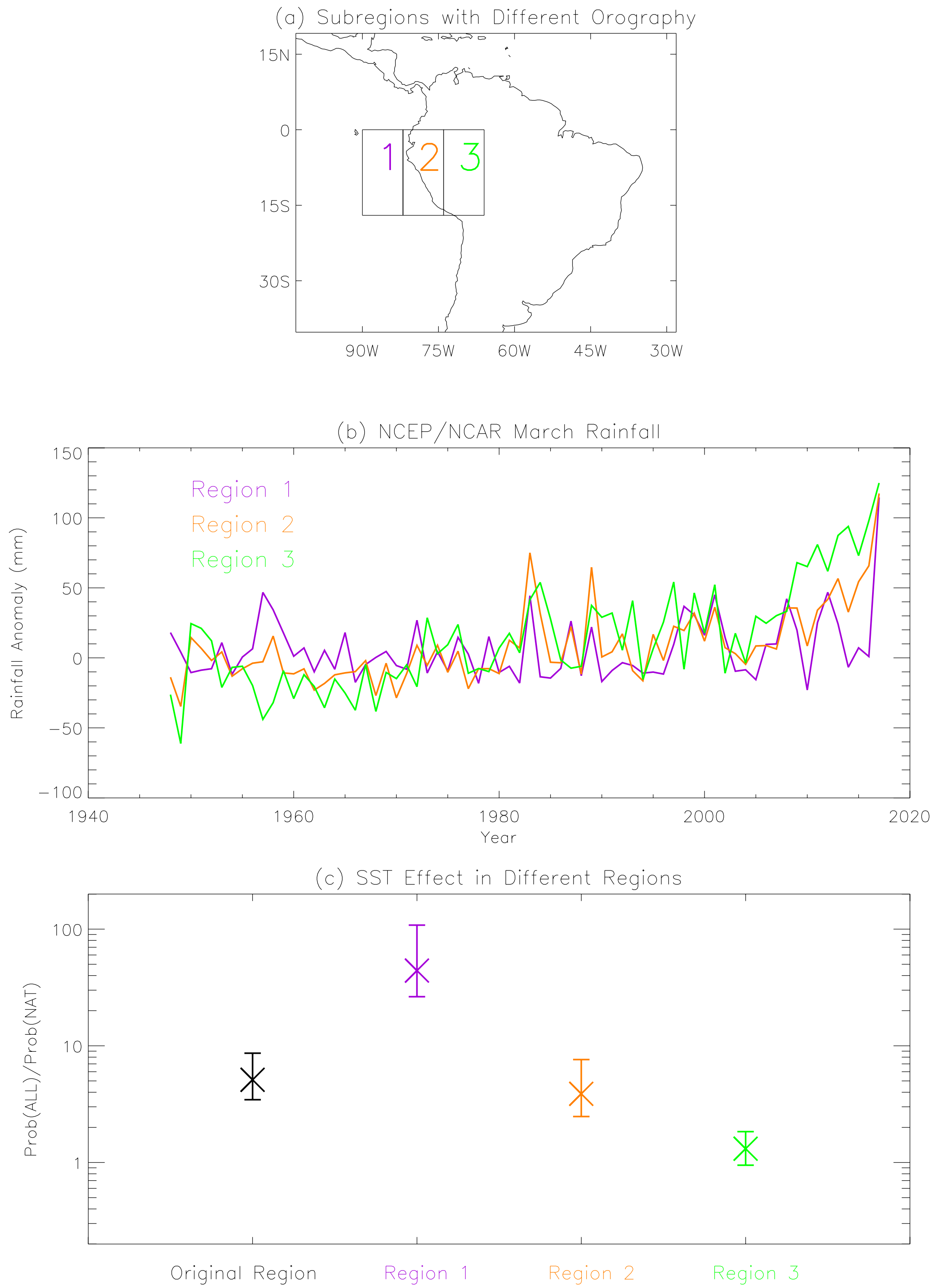


Fig. ES3. (a) Three subregions with different topographic features. (b) March rainfall time series estimated with NCEP–NCAR reanalysis data. (c) Estimates of the risk ratio measuring the effect of the 2017 warm SSTs on the likelihood of extreme (1-in-10 yr) events in different regions.