ON STATISTICAL SCALING METHODS FOR EVENT ATTRIBUTION. Global climate change can be factored into our parametric statistical analysis for event attribution by enabling the Gaussian or GPD fit to be a function of the global mean surface temperature (GMST; typically low-pass filtered), or even global CO₂ concentration (but that neglects the influence of anthropogenic aerosols and

Fig. ESI. (a)–(c) February 2018 total precipitation in the southern Africa (using grayscale) from UCSB CHIRPS v2 (Funk et al. 2015; starting in 1981), UR TAMSAT v3 (Maidment et al. 2014; starting in 1987), and NASA TRMM 3B43 (Huffman et al. 2010; starting 1998), respectively. The closed red contour marks the MZZ region. (d)–(f) Time series of February total precipitation averaged over the MZZ region from CHIRPS2 (February 2018 has the highest February value of 333 mm), TAMSAT3 (February 2018 has the highest February value of 284 mm), and NASA 3B43 (February 2018 has the third highest February value of 287 mm), respectively.
Fig. ES2. February total precipitation climatology in the southern Africa from (a) UCSB CHIRPS v2 (Funk et al. 2015; using 1998–2018), (b) UR TAMSAT v3 (Maidment et al. 2014; using 1998–2018), and (c) NASA TRMM 3B43 (Huffman et al. 2010; using 1998–2018), (d) CRU TS v4.03 (Harris et al. 2014; using 1951–2010), (e) GPCC v2018 (Schneider et al. 2018; using 1951–2010), and (f) NOAA PREC/L (Chen et al. 2002; using 1951–2010). The main tropical climatology rainband (region of strong climatology precipitation roughly above 200 m) in southeast Africa in February is broadly located from 20° to 40°E and from 15° to 10°S in all of these gridded observational products.

Fig. ES3. February total precipitation climatology in the southern Africa (using grayscale) from (a) UCSB CHIRPS v2 (Funk et al. 2015; using 1998–2018), (b) UR TAMSAT v3 (Maidment et al. 2014; using 1998–2018), (c) NASA TRMM 3B43 (Huffman et al. 2010; using 1998–2018), (d) CRU TS v4.03 (Harris et al. 2014; using 1951–2010), (e) GPCC v2018 (Schneider et al. 2018; using 1951–2010), and (f) NOAA PREC/L (Chen et al. 2002; using 1951–2010). The main tropical climatology rainband (region of strong climatology precipitation roughly above 200 m) in southeast Africa in February is broadly located from 20° to 40°E and from 15° to 10°S, which is just north of the MZZ region (marked by the red closed contour).
historical volcanic events). In the case of Gaussian scale fit

\[ P(x) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left( -\frac{(x - \mu')^2}{2\sigma'^2} \right) \]

we postulate that the standard deviation \( \sigma' \) (or scale parameter) scales with the mean \( \mu' \) (or position parameter) of the Gaussian fit, and the probability distribution function is scaled up or down with the GMST using an exponential dependency resembling Clausius–Clapeyron phase transition scaling (e.g., Wallace and Hobbs 2006): \( \mu' = \mu \exp(\alpha T/\mu) \) and \( \sigma' = \sigma \exp(\alpha T/\mu) \), where \( T \) is GMST and \( \alpha \) is the trend fitted together with \( \mu \) and \( \sigma \) (e.g., Philip et al. 2018). Equivalently, in the case of GPD fit (for \( \xi \neq 0 \), as in the used observations and climate models)

\[ H\left( x + \mu' \right) = 1 - \left( 1 + \frac{x}{\sigma'} \right)^{-\frac{1}{\xi}} \]
we again set $\mu' = \mu \exp(\alpha T/\mu)$ and $\sigma' = \sigma \exp(\alpha T/\mu)$, where $\mu'$ is the location parameter, $\sigma'$ is the scale parameter, and $\xi$ represents the shape parameter of the curve. The scale fit is estimated using a maximum likelihood method where $\sigma'$, $\mu$, $\sigma$, and $\xi$ are varied, and a Gaussian penalty on $\xi$ of width 0.2 is applied (e.g., Otto et al. 2018b). Performing such Gaussian and GPD scaling fits with different covariate series (e.g., GMST, CO$_2$ concentration, etc.) is possible on the KNMI Climate Explorer (https://climexp.knmi.nl) under Trends in return times of extremes after one selects or uploads data of interest.

The used fully coupled CMIP5 and CMIP6 climate models are the following:

1) EC-Earth2.3 (Hazeleger et al. 2010) is a coupled climate model (CMIP5 generation, Taylor et al. 2012) with an atmospheric resolution of T159 (1.125°). We analyze 16 available ensemble members of 1901–2018 simulations (historical + RCP8.5 scenario from 2006).

2) CSIRO-Mk3.6 (Jeffrey et al. 2013) is a CMIP5-generation coupled climate model with an atmospheric resolution of T63 (1.875°). We use a 30-member ensemble of 1901–2018 simulations (historical + RCP8.5 scenario from 2006).

3) MIROC6 (Tatebe and Watanabe 2018) is a coupled climate model (CMIP6 generation; Eyring et al. 2016) with an atmospheric resolution of T85 (nominal resolution of 250 km). We use 10 ensemble members of 1901–2014 historical simulations.

4) NCAR–DOE CESM1-CAM5 (Kay et al. 2015) is a coupled climate model of CMIP5 generation with the nominal atmospheric resolution of 1°. We use a 40-member large ensemble of 1920–2018 simulations (historical + RCP8.5 scenario from 2006).

5) GFDL-CM3 (Donner at al. 2011) is a CMIP5-generation climate model with $\sim$2.0° $\times$ 2.5° atmospheric resolution. We use 20 ensemble members of 1920–2018 simulations (historical + RCP8.5 scenario from 2006).

6) CNRM-CM6.1 (Voldoire et al. 2019) is a CMIP6-generation climate model with an atmospheric resolution of T127 (1.4° nominal resolution). We use 10 ensemble members of 1901–2014 historical simulations.

**REFERENCES**


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