

Probabilistic attribution using the rwwa package

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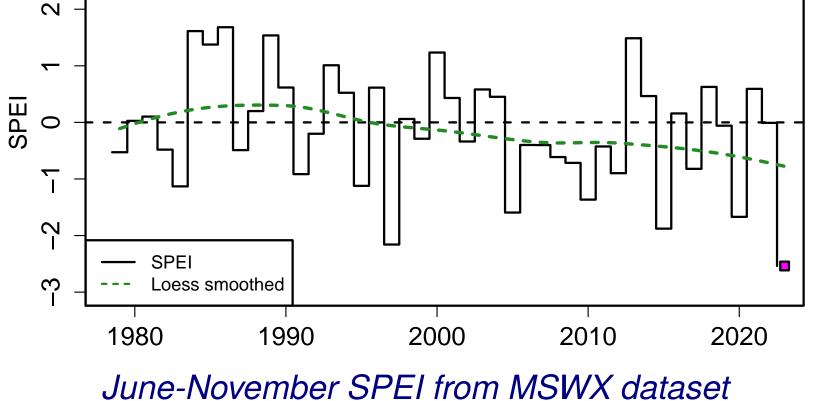
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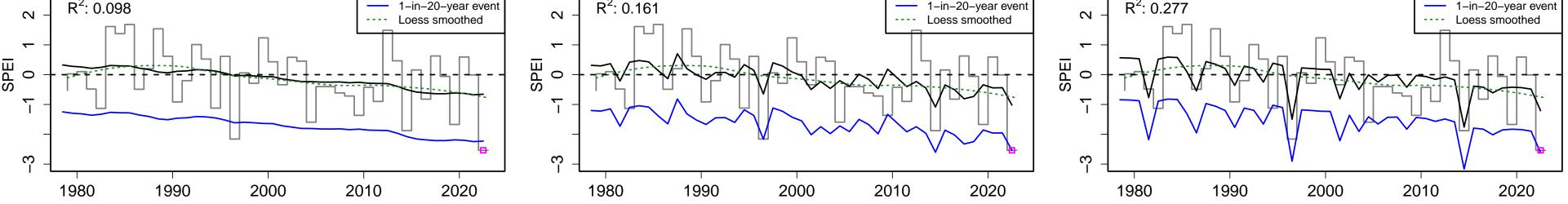
World Weather Attribution (WWA) use probabilistic attribution to evaluate the role of climate change in extreme weather events (Philip et al., 2020). An R package is now available (https://github.com/WorldWeatherAttribution/rwwa) to allow users to quickly carry out WWA-style analyses and synthesise the results from observations and climate models. The main package functions are illustrated below using an example adapted from Clarke et al. (2024), which can be downloaded from https://github.com/WorldWeatherAttribution/rwwa_mwe.

- Data: June-November standardised precipitation-evapotranspiration (SPEI) over the Amazon basin
- Statistical model: SPEI is normally distributed and is expected to depend linearly on GMST and Niño3.4 index, but perhaps only when Niño3.4 is positive (set Niño3.4 < 0 to 0)

CHOOSING THE STATISTICAL MODEL

ω –	SPEI	I~GMSI SPEI	SDEL CMST + Nino3 /		SPEI ~ GMST + positive Nino3.4	
	ო – AIC: 130	Fitted value ··· AIC: 128	Fitted value	ო – AIC: 122	Fitted value	

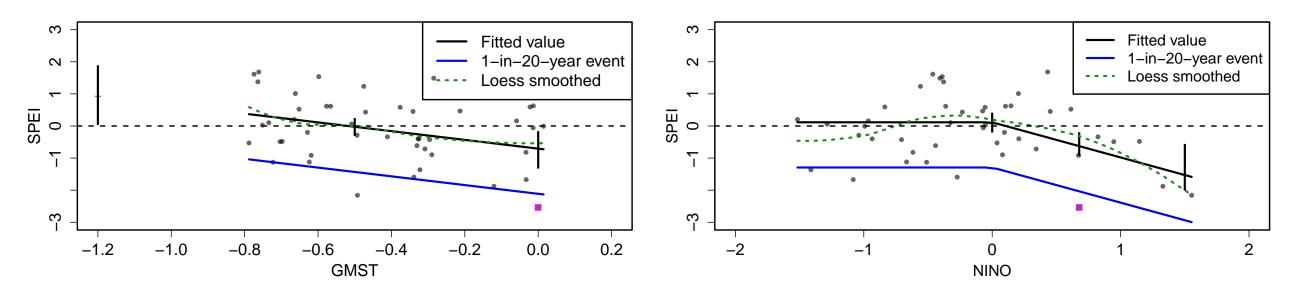




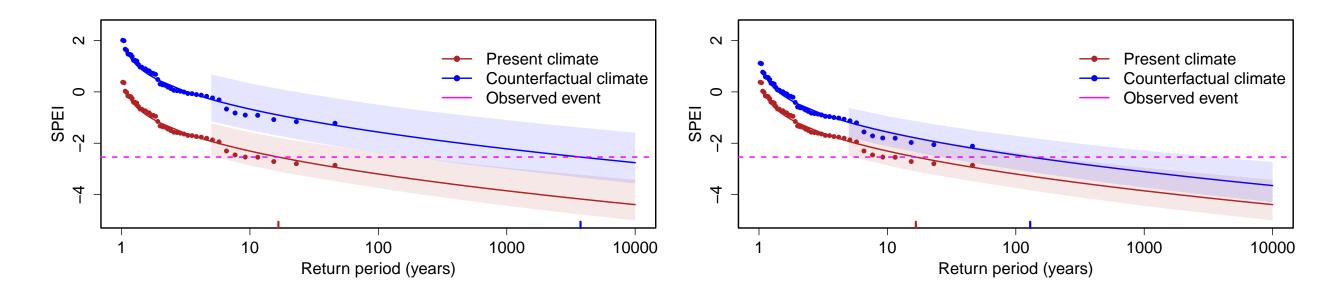
Of the three models tested, the best fit is obtained by including both GMST and the positive phase of the Nino3.4 index as covariates

EVALUATING THE OBSERVED TREND

We use the fitted model to estimate changes in the frequency and intensity of similar droughts due to climate change and different ENSO phases; confidence intervals are obtained by bootstrapping.



SPEI and fitted trend against a single covariate, with all other covariates held at their mean level: (left) GMST and (right) 6-month SPEI



Expected return levels of 6-month SPEI in the 2023 climate (red lines) and a counterfactual climate (blue lines); (left) counterfactual is 1.2C cooler; (right) counterfactual has neutral Niño3.4 index.

- Return period of 2023 drought in 2023 climate: 17 years (95% confidence interval: 5 152 years)
- Similar droughts are estimated to be 225 times more likely (3-400,000) in the current climate than in a 1.2°C cooler world, with 1.6sd lower SPEI (-3.1 to -0.3)

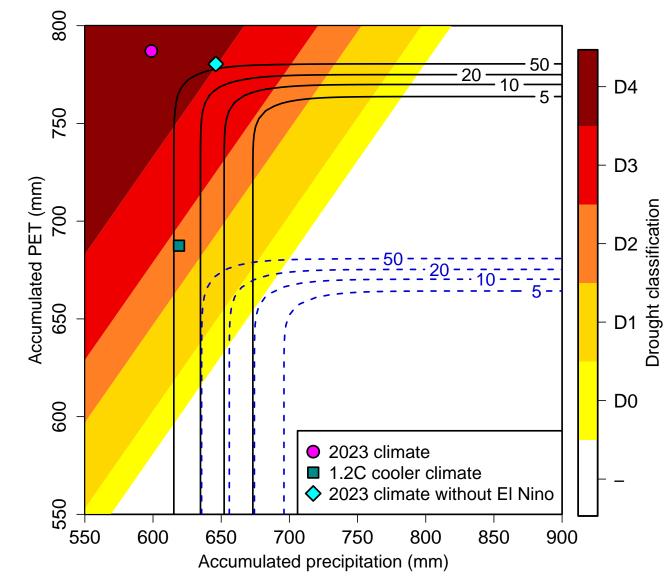
Similar droughts are estimated to be 8 times more likely (2-33) in the 2023 positive Niño phase than in neutral conditions, with 0.7sd lower SPEI (-1 to -0.1)

SYNTHESIS WITH CLIMATE MODELS

To confidently attribute the observed trends, we also look at changes in climate models, where the large-scale forcings are known and where longer time series are typically available. The same statistical model is fitted to the climate model outputs, and the results are combined using the synthesis function to produce an overall attribution statement (details soon to be published in Otto et al., in review)

- All of the observations (blue bars) and models (red bars) indicate an increased likelihood of similar droughts due to climate change (left) and due to the positive Niño3.4 phase (right)
- Overall (purple bars), the probability of a similar drought is estimated to have increased by a factor of about 33 (7-200) due to climate change, and a factor of about 10 (4-25) due to the positive ENSO phase
- These results must be interpreted in the context of physical understanding and previous literature

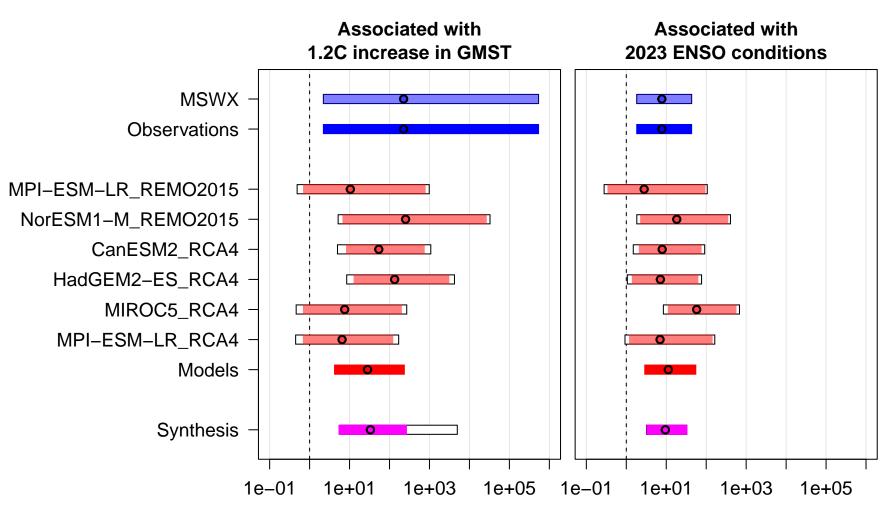
DECOMPOSITION OF TRENDS IN A COMPOSITE INDEX



The SPEI measures climatic water balance (precipitation - potential evapotranspiration) in standard deviations from the 1990-2020 climatology. We can jointly model the precipitation and PET to understand which is driving the change in SPEI. For precipitation (X), find the parameters of a distribution $f_X(X)$ that scales exponentially with GMST and positive Niño3.4

- For PET (Y), find the parameters of a distribution $f_Y(Y)$ that shifts linearly with GMST and positive Niño3.4
- Use the cumulative distribution functions (CDFs) of these two distributions to compute the probabilities u and v of exceeding the values observed at each time t, so that $u_t = P(X \le x_t)$ and $v_t = 1 - P(Y \le y_t)$





Example of synthesised probability ratios using a subset of the models from Clarke et al., 2024

Joint distribution of 6-month accumulated precipitation and PET with corresponding SPEI drought class

- REFERENCES
- Clarke, Ben et al. (2024). Climate change, not El Niño, main driver of extreme drought in highly vulnerable Amazon River Basin. Tech. rep. World Weather Attribution. DOI: 10.25561/108761.
- Otto, F et al. (in review). "Formally combining different lines of evidence in extreme event attribution". In: Advances in Statistical Climatology, Meteorology and Oceanography.
- Philip, S. et al. (2020). "A protocol for probabilistic extreme event attribution analyses". In: Advances in Statistical Climatology, Meteorology and Oceanography 6.2, pp. 177–203. DOI: 10.5194/ascmo-6-177-2020.

- The joint cumulative distribution function C is estimated from the marginal exceedance probabilities u and v by fitting a stationary Student's-t copula such that $C(u, v) = P(U \le u, V \le v)$ for all (u, v) pairs
- The contours and points show pairs of P and PET with the same joint exceedance probability/return period according to this model, in the 2023 climate (solid lines) and a 1.2°C cooler climate (dashed lines)
- Climate change has resulted in much more PET and slightly less precipitation in 2023 (round marker) than in an event of the same rarity in a 1.2°C cooler climate (square marker)
- The 2023 El Niño conditions are associated with less rainfall than would be expected in a neutral or La Niña year (diamond marker); PET was only slightly higher than in a neutral year.
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