ISIMIP
Inter-Sectoral Impact Model
Intercomparison Project

# ATTRICI v1.1 – counterfactual climate for impact attribution

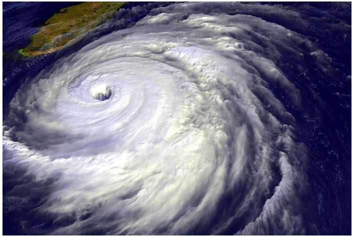
**Matthias Mengel, Simon Treu, Stefan Lange, Katja Frieler**

PIK

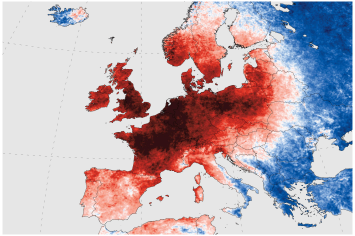
# Outline

| | |
|---|---|
| Motivation: | impact attribution |
| Method: | ATTRICI v1.1 |
| Results: | counterfactual climate data |
| Discussion: | caveats and opportunities |

# Changes in extreme climate impact events

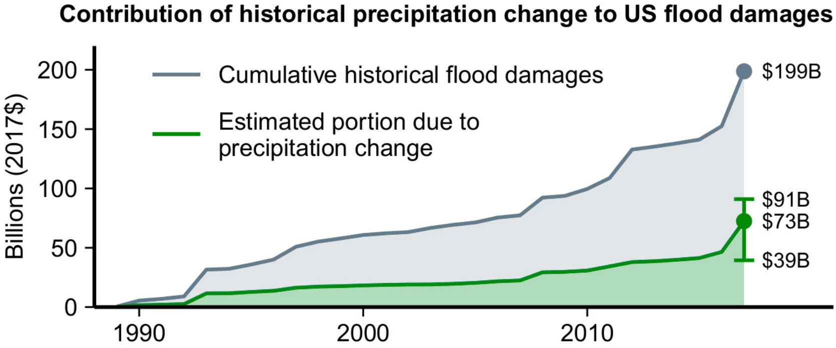







# Different drivers of change

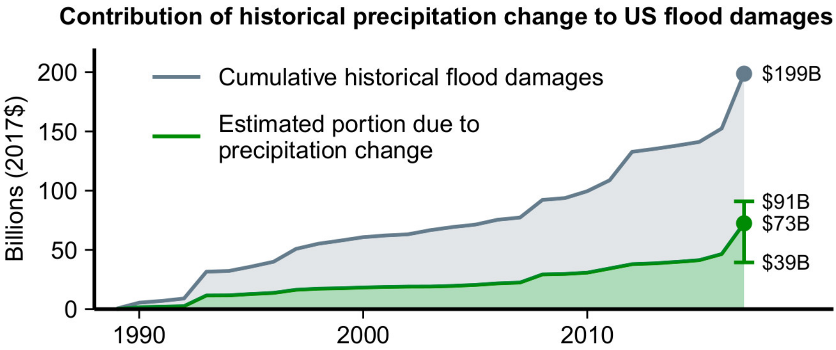
Davenport, Burke, Diffenbaugh (2021) PNAS



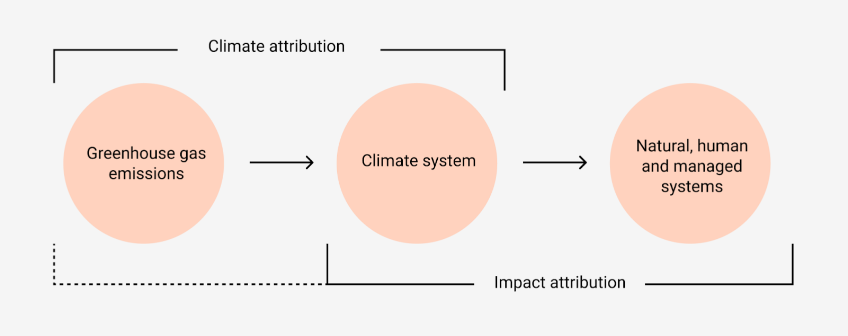
# Different drivers of change

- climate change
- land-use change
- management change
- infrastructure change
- population change

Davenport, Burke, Diffenbaugh (2021) PNAS



# Impact attribution



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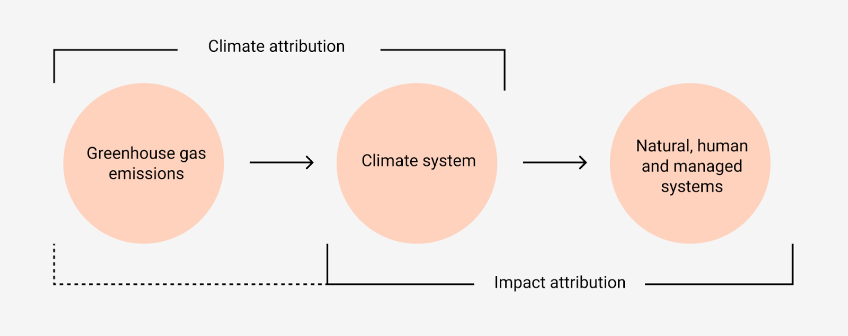


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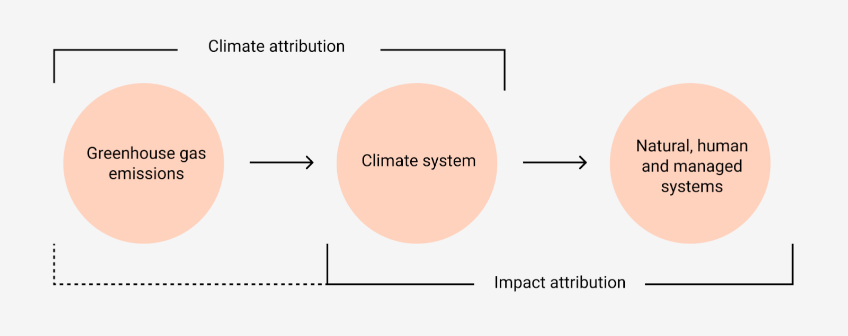


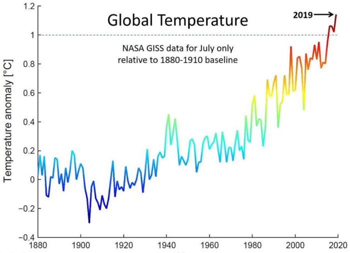

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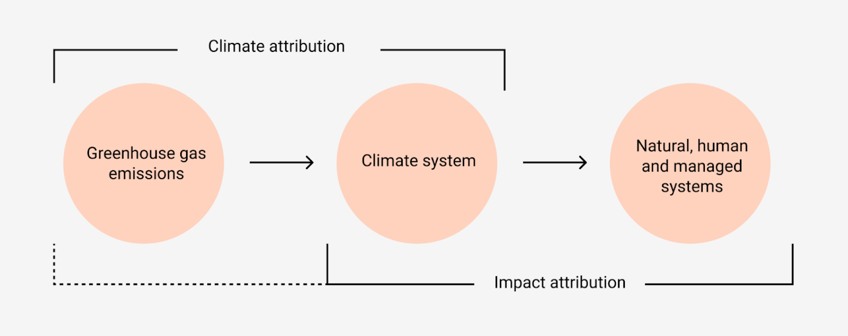


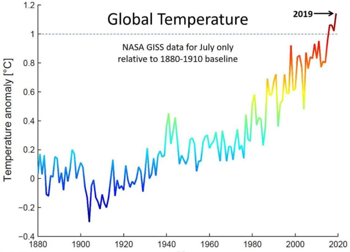


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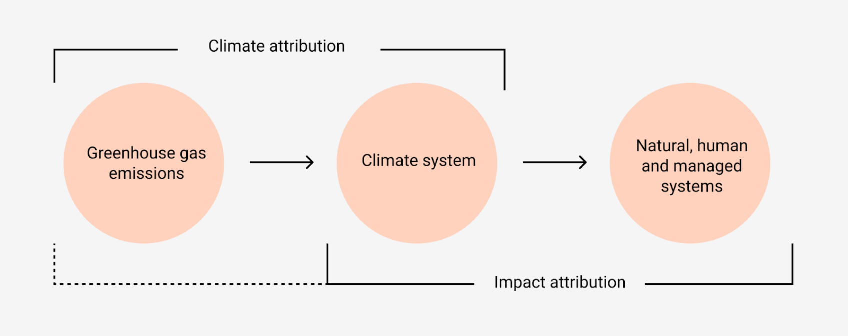
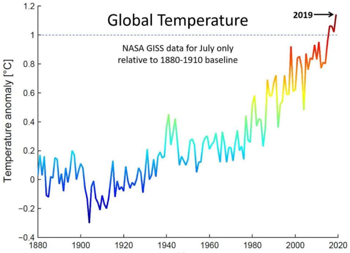
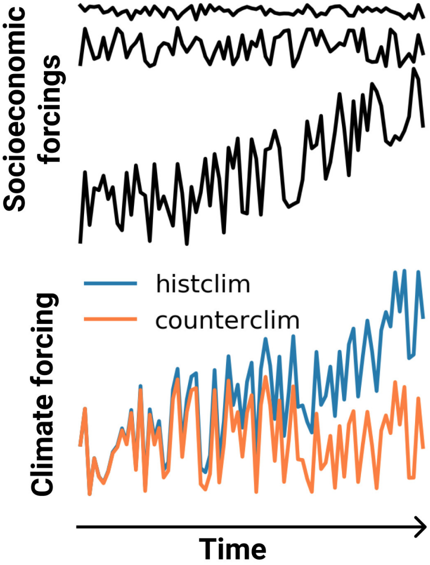



# Counterfactual climate forcing for counterfactual impact modeling



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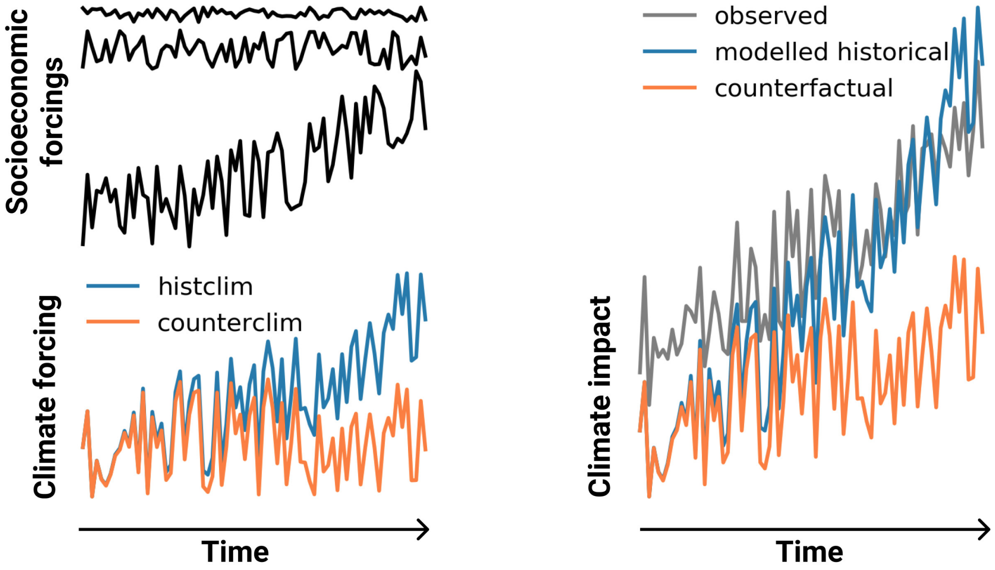
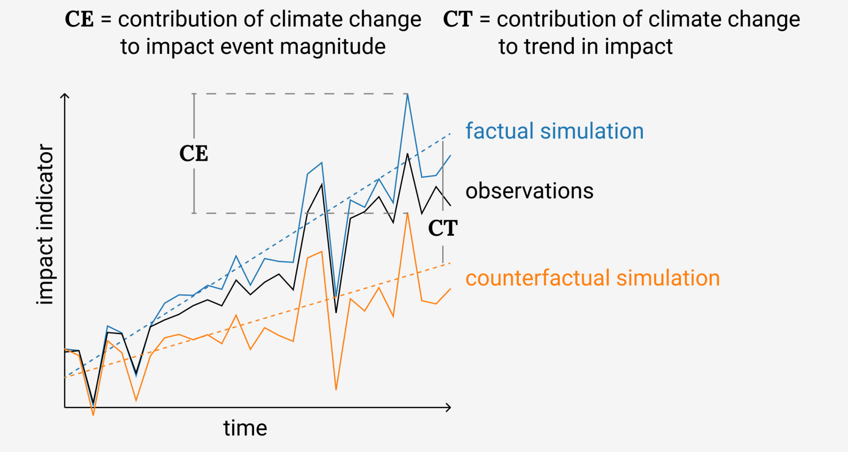


# Specific goal in ISIMIP3a

day-to-day correspondence between factual and counterfactual climate data

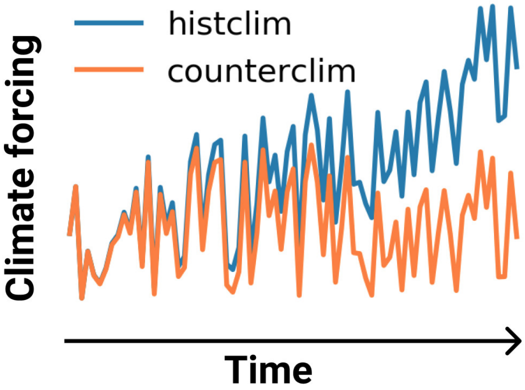
→ easy to integrate in ISIMIP framework

→ facilitates both event attribution and trend attribution



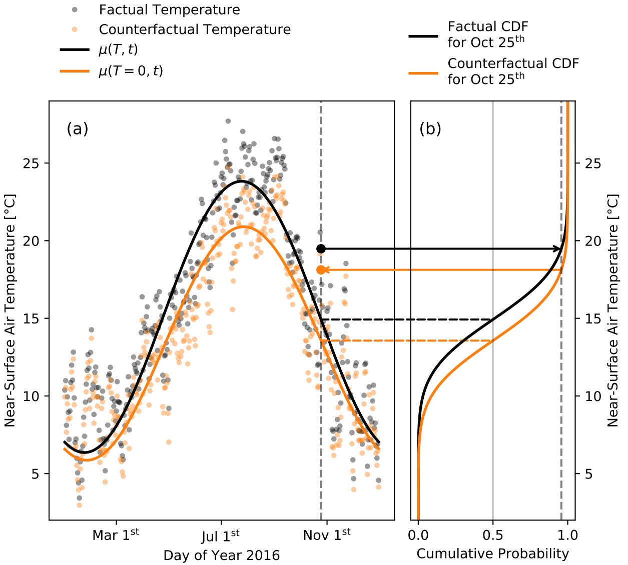
# ATTRICI = ATTRIbuting Climate Impacts

ATTRICI is a detrending method for daily climate data

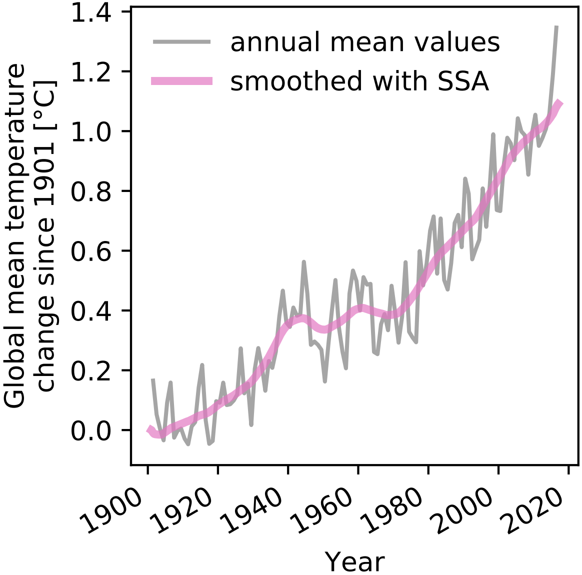


# Approach for daily mean temperature

- goal: remove trend in mean value, account for different trends in different seasons
- model data with parametric distribution $A(T, t)$, use parameters that vary with global mean temperature change $(T)$ and day of the year $(t)$
- for temperature: Gaussian with $\mu(T, t)$ and $\sigma(t)$
- detrend with quantile mapping from $A(T, t)$ to $A(0, t)$



# Global mean temperature change ($T$)



# Generalized linear model for expectation value

$$g(\mu(T,t)) = a_0(T) + \sum_{k=1}^{n} a_k(T)\cos(k\omega t) + b_k(T)\sin(k\omega t)$$

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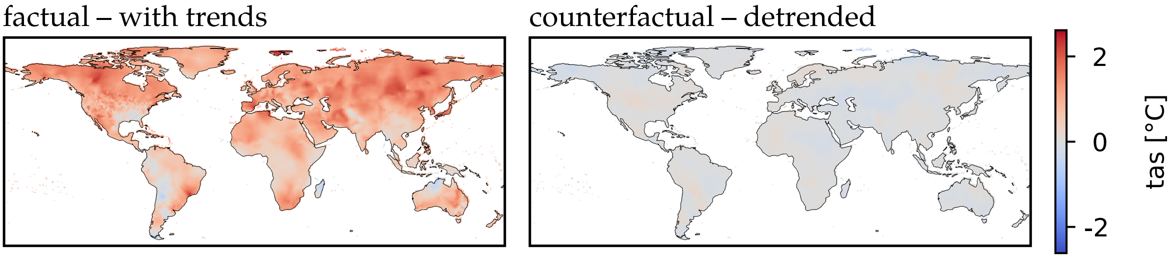
$$a_k(T) = a_k^{(\text{slope})}\, T + a_k^{(\text{intercept})} \qquad (\text{Baysian estimation})$$

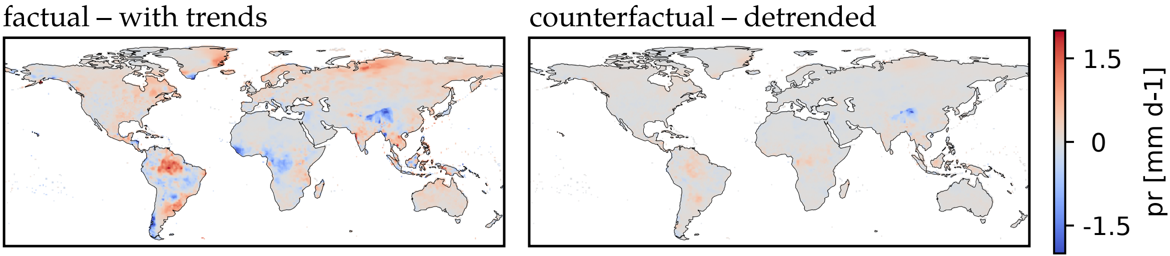
# Approach for precipitation

- mixed Bernoulli–Gamma distribution
- Bernoulli for precipitation occurrence with dry-day probability $p(T, t)$
- Gamma for wet-day precipitation intensity with expectation value $\mu(T, t)$ and shape $k(t)$
- link functions $g(p) = \ln(p/(1-p))$ and $g(\mu) = \ln(\mu)$
- detrending of dry-day probability and mean wet-day precipitation intensity

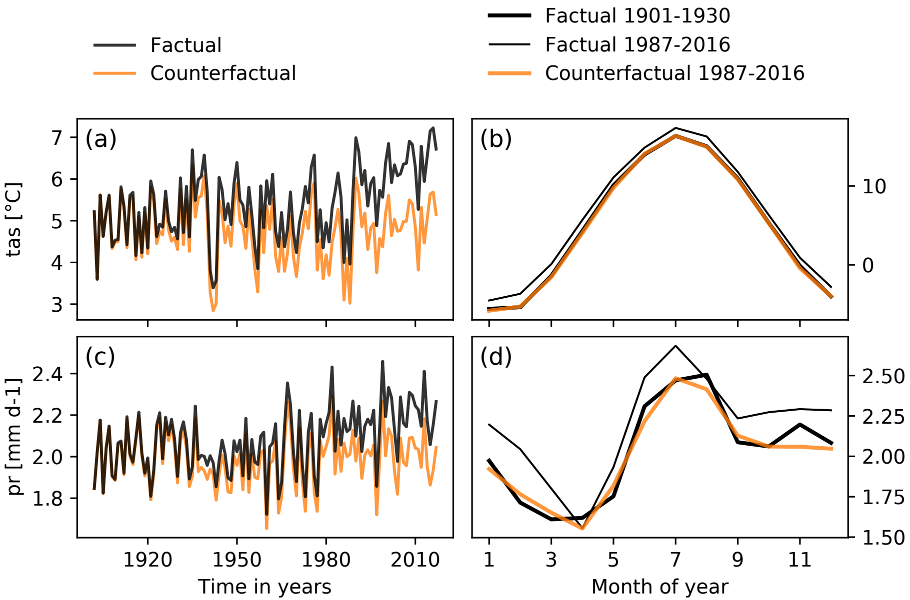
# Temperature: 1987–2016 mean minus 1901–1930 mean



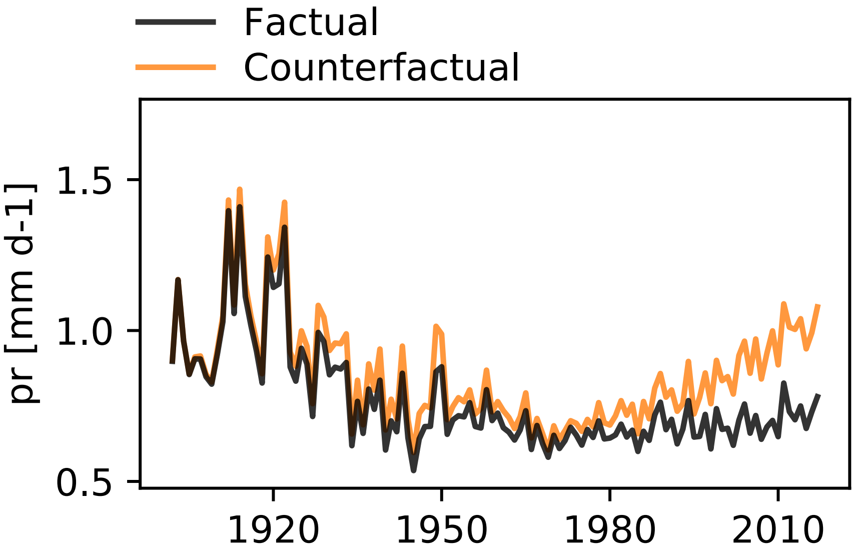
# Precipitation: 1987–2016 mean minus 1901–1930 mean



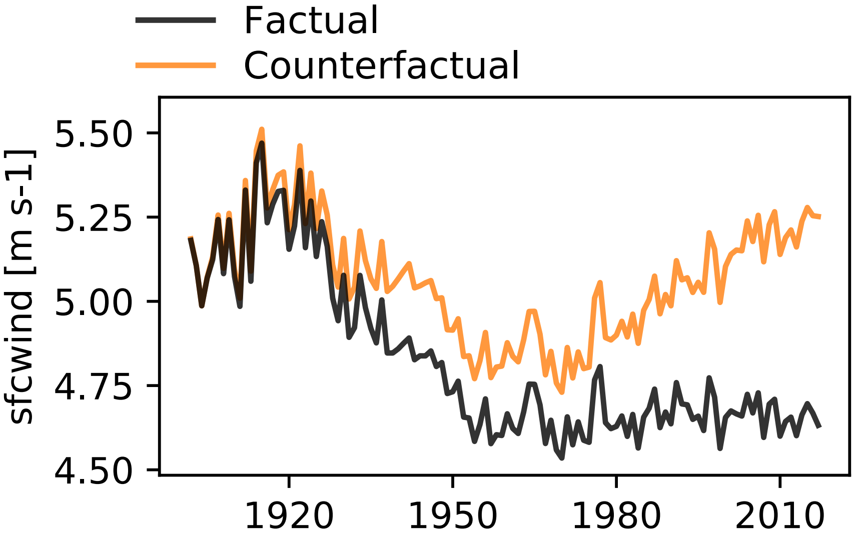
# Temperature & precipitation: Northern Europe



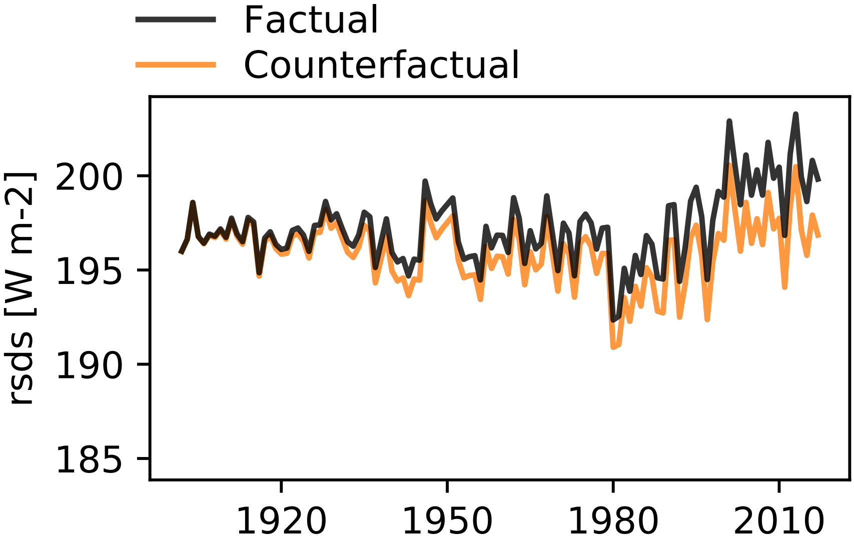
## Precipitation: Tibetean Plateau



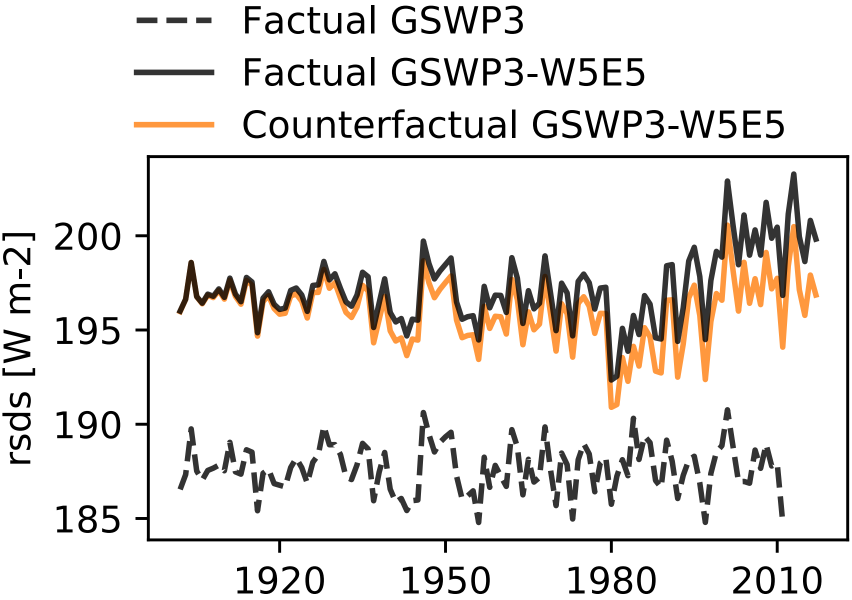
## Wind speed: Greenland



## Shortwave radiation: Mediterranean Basin



**Shortwave radiation: Mediterranean Basin**



# Caveat: counterfactual not fully stationary because

- of spurious trends in factual data due to quality and homogeneity issues
- only trends correlated to global mean temperature change were removed, trends related to aerosols and land-use change may still be there
- only trends in mean values were removed, trends in variability and extremes may still be there

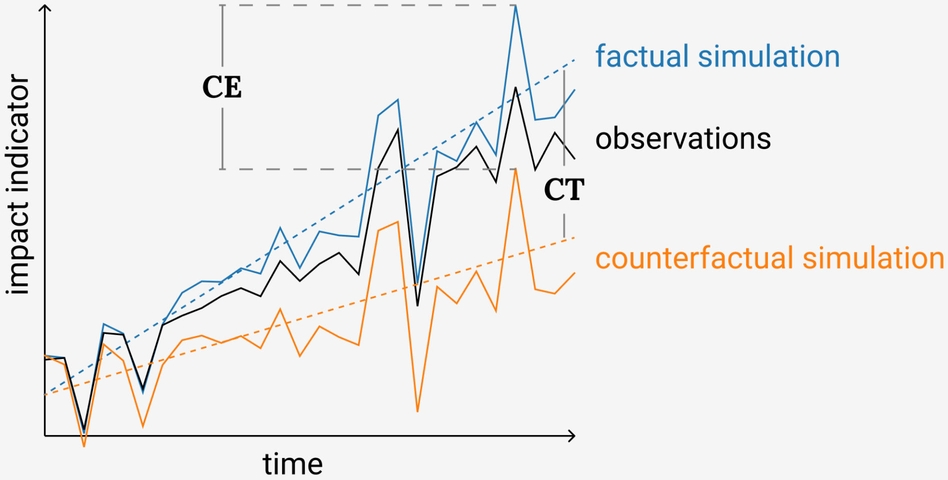
$\Rightarrow$ scan climate data for artifact before doing simulations

$\Rightarrow$ use several pairs of factual–counterfactual datasets to quantify uncertainty

# Opportunities

**CE** = contribution of climate change to impact event magnitude

**CT** = contribution of climate change to trend in impact



# New in v1.1 (compared to v1.0)

- precipitation dry-day probability bug fixed (detrending overwritten)
- precipitation now modelled with seasonal cycle in both dry-day probability and wet-day precipitation intensity (no seasonal cycle)
- more suitable distributions for relative humidity (Beta instead of Gaussian) and the diurnal temperature range (Gamma instead of Gaussian)
- annual cycle now modelled with $n = 4$ Fourier modes ($n = 1$) thanks to numerically more stable parameter estimation (better priors and solver)
- revised paper submitted, new counterfactual data coming soon