ATTRICI - counterfactual climate for impact attribution

Short fact sheet for the methods discussed in Mengel et al. (submitted).

Summary

Climate has changed over the past century due to anthropogenic greenhouse gas emissions. In parallel, societies and their environment have evolved rapidly. To identify the impacts of historical climate change on human or natural systems, it is therefore necessary to separate the effect of different drivers. By definition this is done by comparing the observed situation to a counterfactual one in which climate change is absent and other drivers change according to observations. As such a counterfactual baseline cannot be observed, it has to be estimated by process-based or empirical models. We here present ATTRICI (ATTRIbuting Climate Impacts), an approach to remove the signal of global warming from observational climate data to generate forcing data for the simulation of a counterfactual baseline of impact indicators. Our method identifies the interannual and annual cycle shifts that are correlated to global mean temperature change. We use quantile mapping to a baseline distribution that removes the global mean temperature related shifts to find counterfactual values for the observed daily climate data. Applied to each variable of two climate datasets, we produce two counterfactual datasets that are made available through the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP) along with the original datasets. Our method preserves the internal variability of the observed data in the sense that observed (factual) and counterfactual data for a given day remain in the same quantile in their respective statistical distribution. That makes it possible to compare observed impact

events and counterfactual impact events. Our approach adjusts for the long-term trends associated with global warming but does not address the attribution of climate change to anthropogenic greenhouse gas emissions.

Approach

Assuming that "climate change refers to any long-term trend in climate, irrespective of its cause" (IPCC 2014, chap. 18) we here present a method to develop time series of stationary “no climate change” climate data from observational daily data by removing the long-term trend while preserving the internal day-to-day variability.

We use a functional form (finite number of periodic Fourier modes) to model the annual cycle of each climate variable. We set up probability models with explicit representations of the statistical distribution of the climate variables, which allows for non-normal distributions to represent our data. This is particularly important for a probability model of precipitation that can account for positivity constraints and separate trends in the number of wet days and the intensity of precipitation on wet days. We use global mean temperature instead of time as a predictor of the long-term changes in the different climate variables.

We aim to capture the statistics of a climate variable in the historical record with a parametric distribution A. This distribution evolves in time through the time dependence of its parameters. We model the parameters as linear functions of both the global mean temperature T and the annual cycle. We produce a counterfactual distribution B from the factual distribution A by restricting T to the early period in which it does not deviate significantly from zero. The probabilistic model is illustrated for daily temperatures at an exemplary grid cell in panel A of Figure 1.

We utilize the distributions A and B to quantile-map each value from the observed dataset to a counterfactual value. Quantile mapping is different for each day of the time series because our approach accounts for the annual cycle and a change in the annual cycle. In Figure 1 the quantile mapping step is shown for an exemplary day. We obtain the percentile of the factual (i.e. observed) temperature (blue dot in panel A) at that day from the factual cumulative distribution function (CDF) (blue line in panel B). We then obtain the counterfactual temperature (orange dot in panel A) from the counterfactual CDF (orange line in panel B) at the same percentile.

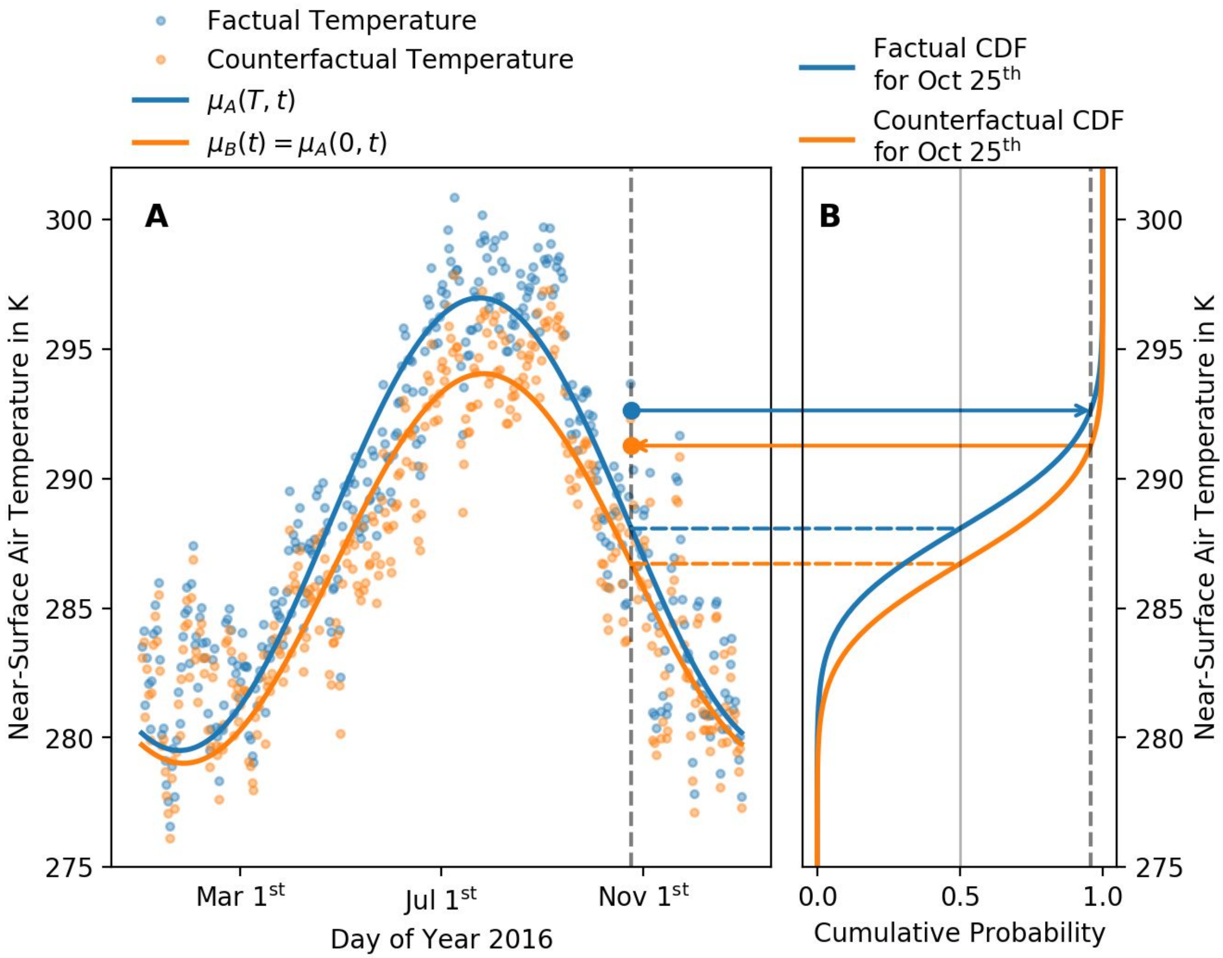

Figure 1: Illustration of quantile mapping sensitive to the annual cycle. Panel A shows factual (blue points) and counterfactual (orange points) daily mean near-surface air temperature for the year 2016 of the GSWP3-W5E5 for a single grid cell in the Mediterranean region at 43.25°N, 5.25°E. In panel A, the blue and orange lines show the temporal evolution of the expected value μ (50th percentile) of the factual and the counterfactual distribution. In panel B, the blue and orange lines show the factual and counterfactual cumulative distribution function (CDF) for a single day (October 25th, 2016). The large blue and orange points in panel A show the factual and counterfactual daily mean temperature on October 25th. They correspond to the 95th percentile in their respective distributions.

Variables

We model the different climatic variables using the statistical distributions listed below.

Variable	Short name	Unit	Statistical distributions
Daily Mean Near-Surface Air Temperature	tas	K	Gaussian
Daily Near-Surface Temperature Range	tasrange	K	Gaussian
Daily Near-Surface Temperature Skewness	tasskew	1	Gaussian
Daily Minimum Near-Surface Air Temperature	tasmin	K	Derived from tas, tasrange and tasskew
Daily Maximum Near-Surface Air Temperature	tasmax	K	Derived from tas, tasrange and tasskew
Precipitation	pr	$kg\ m^{-2}\ s^{-1}$	Bernoulli-Gamma
Surface Downwelling Shortwave Radiation	rsds	$W\ m^{-2}$	Gaussian
Surface Downwelling Longwave Radiation	rlds	$W\ m^{-2}$	Gaussian
Surface Air Pressure	ps	Pa	Gaussian
Near-Surface Wind Speed	sfcWind	$m\ s^{-1}$	Weibull

Near-Surface Relative Humidity	hurs	%	Gaussian
Near-Surface Specific Humidity	huss	kg kg^{-1}	Derived from hurs ps and tas

Table 1: Specs of climate variables for the ISIMIP3b counterfactual climate datasets. The variables tasrange and tasskew are auxiliary variables to calculate tasmin and tasmax

For tasmin and tasmax, we do not estimate counterfactual time series individually to avoid large relative errors in the daily temperature range as pointed out by (Piani et al. 2010). Following (Piani et al. 2010), we estimate counterfactuals of the daily temperature range tasrange = tasmax - tasmin and the skewness of the daily temperature tasskew = (tas - tasmin) / tasrange. A counterfactual huss is derived from the counterfacual tas, ps and hurs using the equations of Buck (1981) as described in Weedon et al. (2010).

References

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