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Summary

Bias correction (BC) methods are mostly evaluated in a split sample test, where a part of the period is left out for validating the correction methods. Often used cross-validation approaches do not allow targeted analysis of the performance of the BC-method when exposed to data outside the range of the calibration period, since the calibration and validation periods are not normally chosen for distinct climate regimes.

In this milestone we present the basis of a protocol designed in AQUACLEW expalining the differential split sample test for calibration, validation and transferability of bias correction methods in a climate change context.

Here, we design a set of experiments for selected focus areas across Europe from the AQUACLEW case studies to address this issue. Each focus area/ case study has defined a metric to evaluate the Differential Split Sample Test (DSST) used here; e.g. wet years, or convectively active summers. Each participating institute is providing one or more bias adjustment methods, from the individual case studies (WP3).

The experimental design for exploring the potential for analyzing each bias correction method's applicability across climate regimes is evaluated with the pseudo-reference method based on an ensemble of 12 km grid scale EURO-CORDEX models. A set of six bias correction methods are then applied for each case study, and we examine the performance of the different methods in historical and future climates. The main task is to examine the DSST approach as a means to identify robust bias correction methods that can be applied outside their calibration period.

1. Introduction

Bias correction (BC) methods are mostly evaluated in a split sample test, where a part of the period is left out for validating the correction methods. A more robust approach is to apply a cross-validation approach (Maraun et al., 2015). However, such methods do not allow targeted analysis of the performance of the BC-method when exposed to data outside the range of the calibration period.

Teutschbein and Seibert (2013; TS13) applied a differential split sample test (DSST, see also Klemes, 1986) to a set of BC-methods where calibration was performed on the driest and validated on the wettest years. The analysis showed quite large differences in the methods' performance outside the calibrated data range. Also Wang et al. (2018) explored different stationarity tests based on annual average temperature, precipitation, sea surface temperature and the NAO circulation index.

Here, we want to extend the work of TS13 and Wang et al. (2018) with a set of experiments for selected focus areas across Europe from the AQUACLEW case studies. Each focus area has a defined metric for basing the DSST on, e.g. wet years, or convectively active summers. Each participating institute is providing one or more bias adjustment methods, which will be applied to each case study.

An emerging method for evaluating BC-methods is based on pseudo-reference data; see e.g. (Maraun, 2012). The core idea is that instead of using observations as reference data set for the bias correction, one makes use of model data. In an ensemble of climate model projections, one model is defined as the reference, and the others are bias corrected towards that. Then, the reference model is shifted to another model, and the procedure is repeated. This provides a large statistical sample to evaluate the potential of different bias corrections methods. Further, the use of models as reference data also means that one can evaluate the performance of the bias correction method in a future climate.

2. Methods

DSST

We follow the normal DSST approach (Klemeš, 1986). The methodology applied in each site satisfies two key principles:

a) Identify periods in the present with contrasting conditions for climate variable of interest (here precipitation and temperature)

b) Application of the DSST. The two periods with contrasting conditions from step a) are used in a split sample approach, i.e. calibrate on one period, validate on the other, then vice versa.

TS13 ranked the years of the reference data sets (PTHBV gridded station obs) and split each data set (reference and model downscaled ERA-Interim reanalysis) into two sets with 20-years each. The implicit assumptions are:

1. The reanalysis reproduces wet/dry (or warm/cold) years similar to observations
2. The regional model must not significantly change assumption 1.

A more generic method would be to sort reference and model time series independently. The assumption is then that similar extreme years are present in both time series. With sufficiently long time series, this should be fulfilled. The method allows comparison of non-reanalysis driven regional model simulations, or direct application to GCMs. This approach would also solve the issue with non-synchronized data in a cross-validation approach as raised by Maraun and Widmann (2018).

This generalization relaxes the connection between the two data sets, and the statistically powerful (large samples) method of using pseudo-reference data within a model ensemble becomes applicable. In general, the pseudo-reference approach consists of in turn using one GCM-RCM combination as pseudo-reference, and testing all other models against that reference. This also includes a pseudo-observed future in the validation of the GCM-RCM combination and the bias correction method. Even if the “pseudo world” does not properly reflects the real world, it is still a good test of the applicability of the BC method to other climate regimes.

Further, with the pseudo-reference method, the number of years in each simulation is generally greater, which further allows the use of a buffer in-between the two samples, e.g. consisting of the intermediate years of average conditions which appear in both samples.

Data

Here, we apply the pseudo-reference method to an ensemble of 12 km grid scale EURO-CORDEX models for daily mean precipitation and temperature. We restrict the study to the historical time period, as well as the future scenario RCP8.5.

A set of six bias correction methods are then applied for each case study, and we examine the performance of the different methods in historical and future climates. The main task is to examine the DSST approach as a means to identify robust bias correction methods that can be applied outside their calibration period.

The complete time period is 1951-2100, and we will use the first 60 years for DSST analysis, where 25 are used for calibration, 25 for validation and 10 are left out in between the samples. This leaves also the remaining 90 years for validation of future climates.

Regional climate models:

CNRM-CERFACS-CNRM-CM5_r1i1p1_ALADIN53

CNRM-CERFACS-CNRM-CM5_r1i1p1_ALARO-0

ICHEC-EC-EARTH_r12i1p1_CCLM4-8-17

ICHEC-EC-EARTH_r12i1p1_RACMO22E

ICHEC-EC-EARTH_r3i1p1_HIRHAM5

MPI-M-MPI-ESM-LR_r1i1p1_REMO2009

How we share data:

SMHI provides single time series of climate model data based on a nine grid point average for a representative point of each participating case study. The data are supplied to each participating group as single ASCII files with columns for date, temperature, and precipitation. The data will already be arranged such that the first 25 years are to be calibrated on, and the complete time series is then bias corrected. This means that the dates of the first 60 years are not reflecting the actual dates of the model since the data has been reshuffled. However, the procedure reduces the risk of errors when several people are handling the data for the different BC methods.

There will be in total one time series per model, case study and calibration period. The pseudo reality experiment will combine the different models such that a total of around 280 experiments are carried out.

Each participant will apply their bias correction method(s) to each file, and write the results to a file with the same layout, but followed with a leading tag in the filename to identify the method used. The partners have identified metrics relevant to each case study in order to evaluate the performance of the DSST approach.The files are sent back to SMHI for analysis with a common analysis script. The complete analysis will be presented in a joint publication.

3. Results

Case studies and experiment setup

Danish case (GEUS):

The main goal of the Danish site is to assess changes in drainage and irrigation needs for agriculture. Therefore, precipitation influencing the soil wetness is the main focus of the analysis. Changes in the soil wetness can impact on the sowing and crop growth. A waterlogged field can be inaccessible and affect the production, requiring to be drained. In contrast, dry soil conditions increase the irrigation needs. In addition, low temperature is an important factor to analyze as freezing conditions impact on the agricultural productivity. Both climate variables will be analyzed per month to assess seasonal variations.

Metric: total precipitation from October to March based on the hydrological (water) year. Ranking of the time series based on this approach, going from driest to wettest.

Swedish case (SMHI):

Biodiversity in the lakes and streams (aquatic) is affected negatively by dry and wet summers which lead to elevated lake temperature and reduced living space for some species in smaller lakes. Moths react oppositely. Therefore, we will here try to split the sample into hot-dry and wet-cold summer onsets.

Metric: jointly ranks the mean AMJ precipitation (wet to dry) and AMJ temperature (cold to warm).

French case (IRSTEA):

The impacts of climate change on the hydrological cycle raises a growing concern among the water manager community, especially in the hydropower sector which may face a strong evolution of water resources. In France, where 12 % (in 2018) of the electricity production comes from hydropower plants, the sector is constrained by the multi-purpose nature of most hydropower reservoirs: a high energetic demand in winter competes with a high irrigation demand in summer, as well as with minimum water level requirements of the touristic sector. It must therefore prepare to face future conditions that might potentially be marked by higher seasonal contrasts, drastic rain events and a reduced snowpack.

Metric: Annual mean precipitation.

Spanish case (UCO):

Water allocation (tourism, agriculture and energy) in semiarid mountainous areas is highly dependent on snow. Wet and cold snow seasons normally produce deeper snowpacks and consequently higher snow water equivalents. The opposite effect occurs in dry and warmer years. Hence, we will split the sample into wet-cold and dry-warm snow seasons. For that we define two variable: annual snowfall (precipitation within the hydrological year that falls at temperatures lower than 0ºC) and days with snow (number of days when precipitation occurs as snowfall).

Metric: jointly rank of the annual snowfall and days with snow. The joint probability function of both variables is calculated. The years will be ranked according to percentiles in the joint probability space giving priority to the snowfall over days with snow.

Austrian Case (UIBK, BOKU):

The Austrian case study aims to a) reconstruct past pluvial-flash floods and b) investigate the effect of climate change on possible future events. The study area are three communities in Upper Austria, which were affected by pluvial flash-floods. Therefore reliable, spatially and temporally highly resolved time-series of precipitation for the period of the events and possible future events under climate change conditions are required. Also key is the soilmoisture during the events, which is governed by antecedent precipitation, temperature, radiation and wind-speed.

Metric: Convectively active summers.

Bias correction methods

- ***DBS_GEUS (Distribution Based Scaling)****:* Fits a distribution to a theoretical PDF. For precipitation, a double Gamma distribution (90th percentile) is used. For temperature, a normal distribution is used for the correction.

- ***MIdAS (Multi-scale bias AdjuStment)*****:** Separately corrects 30-day averages and daily data using combinations of different methods such as multiplicative/additive scaling, empirical quantile mapping, or multivariate regression. Reference: Not yet available.

- ***DBS_SMHI (Distribution Based Scaling)*****:** Fits a distribution to the PDF, which gives a transfer function similar to quantile mapping. Precipitation uses a double gamma distribution (95^{th} percentile) and temperature a double Gaussian distribution. Reference: Yang et al. (2010).

- ***CDF-t (Cumulative Distribution Function method)***: we use temperature and precipitation data already corrected by this method available on the Drias portal (http://www.drias-climat.fr/). The CDFt statistical method is to generate cumulative distribution function (CDF) locally based upon data on a large scale. Instead of applying the quantile-quantile correction between future data from model and actual station data a cumulative function distribution (CDF) is used for future station data. The mathematical transformation function is applied to the cumulative distribution function on a large scale. Reference: Michelangeli et al. (2009).

- ***LS (Linear Scaling)*****:** constant correct factor derived from the comparison between both observation and model samples. Precipitation is corrected with a factor based on the ratio of long-term monthly mean and temperature with an additive term based on the difference of long-term monthly mean (Lenderik et al., 2007).

- ***DBS_UCO (Distribution Based Scaling)*****:** Fits a distribution to the PDF. Precipitation uses a double gamma distribution (95^{th} percentile) and temperature a normal distribution.

- ***Scaled Distribution Mapping (SDM)*****:** scales observed distributions by raw model projected changes in magnitude, rain-day frequency and likelihood of events (return period). For SDM no assumption of stationarity is made during bias correction since the scaling between model and observations changes as a function of the bias correction period. Reference: Switanek et al. (2017).

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