Fact Sheet: Bias correction in the ISI-MIP

Bias correction methods are often applied within Climate impact studies to correct the climate input data provided by General Circulation Models (AOGCMs) or regional climate models for systematic statistical deviations from observational data. They generally adjust the long-term mean by adding the average difference between the simulated and observed data over the historical period to the simulated data, or by applying an associated multiplicative correction factor. In addition, differences between the variance of the simulated and observed data are often corrected.

Bias correction is advantageous for the following reasons:

- It allows for comparison of observed and simulated impacts during the historical reference period, and for a smooth transition into the future.
- The bias corrected data for the future period account for *changes* in the climate variables in comparison to the current status. Accurate description of impacts that are triggered when certain critical thresholds (in temperature or precipitation, for example) are exceeded, require such an adjustment to the reference starting level. Simply describing the change in impacts starting from an uncalibrated climate-model-based reference level, cannot capture this threshold-activated behaviour.
- Adjustment of the variance of the simulated data may help to get a more realistic understanding of the impacts that depend on changes in both the mean and variability of the data. As the AOGCM data are provided on a coarser grid (approximately 2 x 2 degree) than the observational data, correction of the variance ensures that a realistic (higher) variance is attributed to the downscaled data (on the 0.5 x 0.5 degree ISI-MIP grid). Such a variability change is not captured by a simple interpolation of the GCM data.
- Bias correction also incorporates the more detailed height information associated with the observational data.

On the other hand, there are serious disadvantages:

- Even the most basic bias correction method (adding the mean deviation from the observed data to the simulated data) destroys the physical consistency of the data.

- Some bias correction methods (such as the one described by Piani et al., 2010) have the potential to change the trend in the simulated climate data. While adequately representing the mean state of the observed period and the associated variability, these methods may change the climate signal (absolute changes in temperature and relative changes in precipitation) projected by the AOGCMs. This corresponds to introducing a new level of uncertainty, comparable in magnitude to the inter-AOGCM spread of the climate projections (Hagemann et al., 2011).

Within ISI-MIP we decided to apply a bias correction method, fully aware of these disadvantages, since the described advantages are essential to the description of changes in impacts. However, given the lively debate related to this issue, we are committed to describing transparently what climate change information is actually retained from the AOGCMs and what is lost.

We modified the Piani et al. (2010) approach to preserve the absolute temperature changes and the relative changes in precipitation and other variables as fundamental elements of the AOGCM projections. Here we describe the algorithm.

1. Adjustment of the monthly mean values

1.1 Temperature

The bias correction algorithm for temperature preserves the monthly mean values provided by the AOGCM, by adding a grid-point and month specific (one for January, one for February etc.) constant offset. In this way the absolute changes in temperature are not modified by the bias correction but the reference starting level is adjusted to the observational level provided by a 40-year average of the Watch data.

It is essential for ISI-MIP that the absolute temperature changes projected by the AOGCMs are not changed, since the project is dedicated to the description of impacts at different levels of global warming. As the global warming information provided will be based on the non-bias-corrected monthly AOGCM data (the observational data needed for the bias correction are not available over the ocean) we must ensure that it stays consistent with the climate change signal used within the impact simulations.

The minimum and maximum daily temperatures (*Tmin* and *Tmax* respectively) are also corrected for systematic bias. The algorithm ensures that in the historical period, the mean distance between the maximum (minimum) daily temperature value and the daily average temperature *(T) is* preserved. This is achieved by calculating the following factor over the historical period:

$$k = \mathrm{mean}[Tmin(max)_{,Watch}-T_{Watch}]/\mathrm{mean}[Tmin(max)_{GCM}-T_{GCM}],$$

and the resulting bias-corrected maximum (minimum) temperature is then given by:

$$Tmin(max)_{BC}=k[Tmin(max)_{GCM}-T_{GCM]}+T_{GCM}\,.$$

1.2 Precipitation

For precipitation data we use a multiplicative correction to adjust the monthly mean values in the historical period to the observed climatological monthly mean values. This ensures that the monthly mean precipitation values are preserved up to a constant multiplicative factor. The monthly means are multiplied by a grid-point and month specific (one for January, one for February etc.) constant correction factor (hereafter μ). We thereby ensure that the relative change in precipitation as described by the original AOGCM data is preserved.

In combination with the applied temperature correction, we preserve the hydrological sensitivity of the AOGCM (relative change of precipitation per degree of warming). In comparison to the additive approach used for the temperature correction, a multiplicative approach was chosen for the precipitation data to ensure non-negative precipitation values.

Snowfall is not directly bias corrected, but rather the ratio of snowfall to rainfall in the original AOGCM data is preserved, based on the bias-corrected rainfall data.

1.3 Other variables

Monthly values of the other variables that are also subject to positivity constraints are corrected in a multiplicative way as described above for precipitation. The only exception is wind.

In the case of wind, the magnitude of wind is corrected using the multiplicative algorithm. The individual wind components are then derived by preserving the direction of the original AOGCM data.

2. Adjustment of the daily variability

As described above, we adjust neither the monthly variability of the temperature information in absolute terms, nor the monthly variability of the other variables in relative terms. However, we do adjust the daily variability around the monthly mean values as described below. The method is similar to the correction of the daily variability in Haerter et al. (2011).

2.1 Temperature

The daily variability of the temperature data is simply adjusted to reproduce the variability of the observed data. The data is processed as follows:

1. Subtract the monthly means from both data sets.

2. Multiply the residual daily variations by a constant month and grid-point specific factor, thereby matching the variance of the simulations to the variance of the observations.

3. This bias corrected daily variations are afterwards added to the bias corrected monthly means provided by the AOGCM.

2.2 Precipitation

For precipitation we again adopt a multiplicative approach, which adjusts the relative variability. The data is processed as follows:

1. Normalize the daily precipitation data from the AOGCM and the Watch data set by dividing by their monthly mean values. The daily variability of dry months, specified by a certain threshold, is not modified.

2. After normalization of the wet months, map the distribution of the simulated data to the distribution of the observed daily data using a transfer function [as introduced by Piani et al. (2010) and applied to the non-normalized data within Water-MIP]. The transfer function corrects both the frequency of dry days as well as the distribution of the precipitation intensity to the observed statistics.

3. For the future projections, apply the generated transfer functions to the normalized daily precipitation of wet months.

4. Multiply the transfered data by the bias corrected monthly mean values. By ensuring the mean value of the transferred normalized daily data is equal to one (by simply dividing by the associated mean value) we ensure that the corrected monthly mean values are preserved when factoring in the daily variability.

2.3 Other variables

For the other variables we also use the same multiplicative approach as for precipitation. However, in these cases the situation is simplified as it usually does not require a treatment of months or days with mean values of zero.

3. Known Problems

3.1 Extremely high precipitation values

At grid points and within months where the monthly mean precipitation of the AOGCM is very low, while the observational data are significantly higher, the correction factor can get extremely high. As we apply a multiplicative correction based on the ratio between the monthly mean precipitation from the Watch data and the simulated data, this can mean that we multiply singular high daily precipitation values by a very high correction factor, leading to unphysically high values of daily precipitation.

To fix that problem we decided to limit the correction factor μ to 10. In addition, the remaining extremely high precipitation values are truncated at 400 mm/day. An example map of the number of days effected by this truncation over the period 2000-2099 for the HadGEM2-ES model and RCP 8.5 is shown in Figure 1.

The map of μ in Figure 2 gives a clear indication where differences between simulated data and observational data are very high and results should be interpreted with caution. We archive these plots for each AOGCM and provide them to you alongside the bias corrected data (in the same directory).

3.2 Inconsistencies in specific humidity

Saturation specific humidity (*SSH*) can be calculated from temperature (Tas) and pressure (ps). In combination with specific humidity (*SH), SSH* can be used to calculate relative humidity (*RH*), which takes values between 0 and

1. The applied bias correction does not guarantee that this basic property is preserved. Based on feedback from modeling groups, we have ascertained that our bias correction algorithm produces *RH* values outside the [0,1] range.

We are currently devising a fix for that problem and would greatly appreciate your feedback on this issue. Two possible options are:

1. Calculate *RH* based on bias corrected *Tas*, *ps* and *SSH*, and simply truncate all values of *RH* greater than 1.

2. Use *Tas* and *ps* to calculate the *SSH*. Then use the original uncorrected *RH* data to calculate *SH*. In this case the current version 1 *SH* data should not be used. In this case, we provide the uncorrected GCM interpolated (0.5x0.5 degree) *RH*. *SH* would then to be calculated by the modeling groups that need it.

Thus, if *RH*, *ps* and specific vapour pressure (*SVP)* are given the specific humidity can be calculated by:

$$SH = RH*SVP*100*0.622/(ps-RH*SVP*100) .$$

SVP is a polynomial function of *T* (Flatau, 1992):

$$SVP = \sum_i w_i T^i ,$$

where

w_i = [6.11176750, 0.443986062, 0.143053301E-01,0.265027242E-03, 0.302246994E-05, 0.203886313E-07, 0.638780966E-10].

We invite your comments on the best way to proceed.

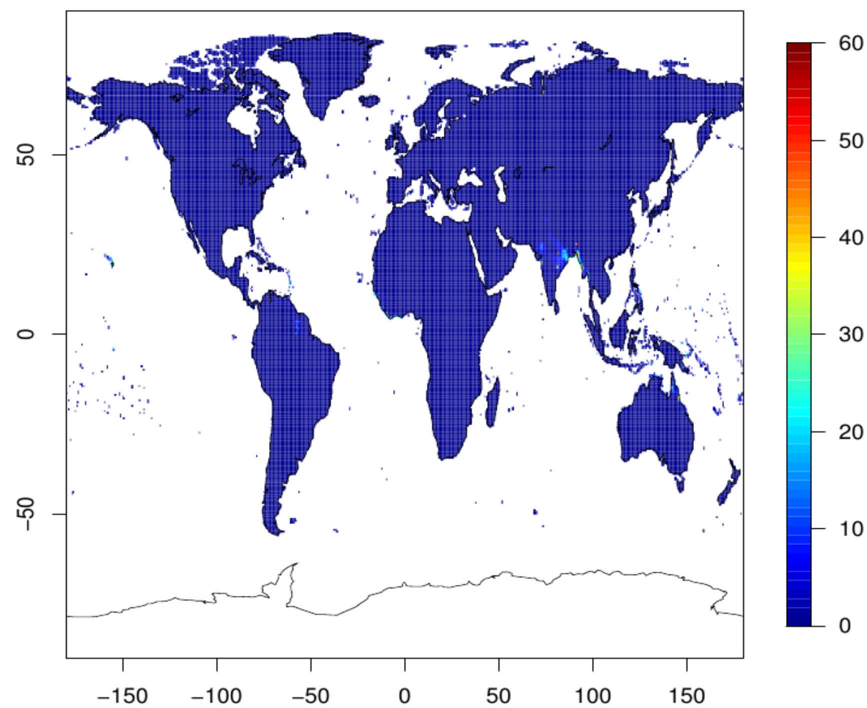

Figure 1. Number of days for which precipitation has been truncated at 400 mm/day in the period 2000-2099 for the HadGEM2-ES model and the RCP 8.5.

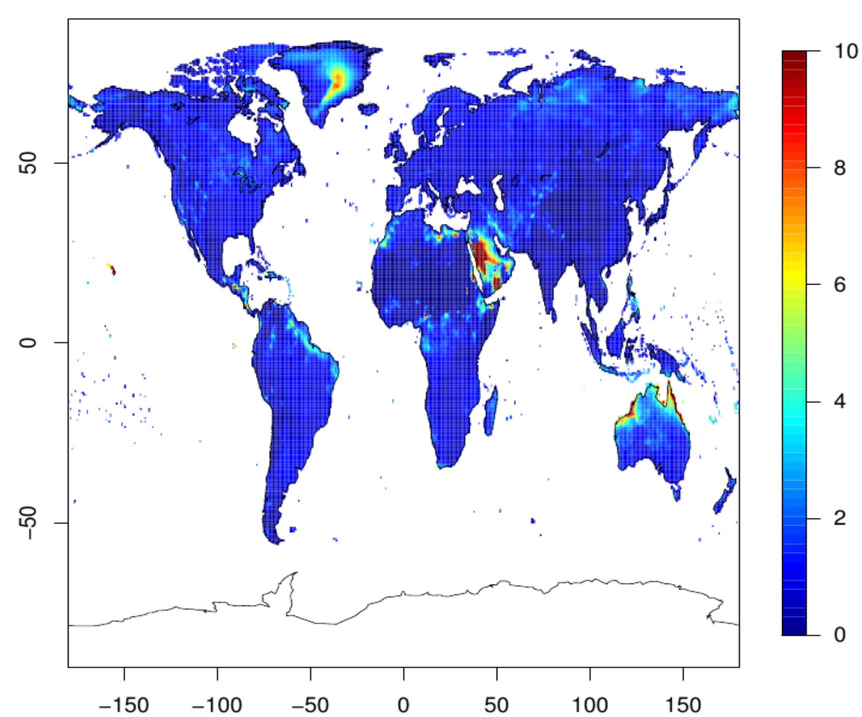

Figure 2. meanratio for January in the HadGEM2-ES model, truncated to a maximum value of 10, as per the bias-correction algorithm. The red regions indicate where the bias correction algorithm is less effective due to very low precipitation values from the AOGCM.

4. References

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Flatau P., L. W. Robert, W. R. Cotton, *Polynomial Fits to Saturation Vapor Pressure*, J. Appl. Meterology 31: 1507-1513, 1992.