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Nonstationarities of regional climate model biases in European seasonal mean temperature and precipitation sums

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[1] Bias correcting climate models implicitly assumes stationarity of the correction function. This assumption is assessed for regional climate models in a pseudo reality for seasonal mean temperature and precipitation sums. An ensemble of regional climate models for Europe is used, all driven with the same transient boundary conditions. Although this model-dependent approach does not assess all possible bias non-stationarities, conclusions can be drawn for the real world. Generally, biases are relatively stable, and bias correction on average improves climate scenarios. For winter temperature, bias changes occur in the Alps and ice covered oceans caused by a biased forcing sensitivity of surface albedo; for summer temperature, bias changes occur due to a biased sensitivity of cloud cover and soil moisture. Precipitation correction is generally successful, but affected by internal variability in arid climates. As model sensitivities vary considerably in some regions, multi model ensembles are needed even after bias correction. **Citation:** Maraun, D. (2012), Nonstationarities of regional climate model biases in European seasonal mean temperature and precipitation sums, *Geophys. Res. Lett.*, *39*, L06706, doi:10.1029/2012GL051210.

1. Introduction

[2] Regional climate models (RCMs) provide added value to global climate simulations [*Feser et al.*, 2011], but the actually simulated fields of climate variables are often considerably biased compared to gridded observational data [*Christensen et al.*, 2008]. End users of RCM simulations therefore often apply bias correction methods. Most of these methods derive a correction function that maps the empirical distribution of a simulated present day climate time series to the corresponding observed distribution. This function is then applied to correct a future climate simulation (for a review, see *Maraun et al.* [2010]). Approaches range from simple additive corrections of the mean or variance [e.g., *Déqué*, 2007; *Lenderink et al.*, 2007], scaling of precipitation [*Widmann and Bretherton*, 2000] to more advanced quantile mapping methods [e.g., *Piani et al.*, 2010; *Li et al.*, 2010].

[3] A crucial assumption of bias correction is stationarity of the bias, which is calculated for present climate, under future climate change. This assumption is, however, questionable [*Christensen et al.*, 2008]. Just as model biases themselves are caused by an imperfect model representation of the atmospheric physics, also the local modelled response to external forcing, i.e., the local climate sensitivity is biased in general. Corresponding bias changes might be called sensitivity related bias changes (SBC). In addition to such real bias changes, apparent changes might occur. First, biases are estimated from finite time series and afflicted with sampling uncertainty. Corresponding bias changes merely caused by internal variability may be called variability related apparent bias changes (VABC). Second, most bias correction methods are applied to unconditional climatological distributions and disregard that the derived overall bias may actually be a mixture of different underlying biases depending on weather types. For instance, biases for convective and stratiform precipitation might be different. If the relative occurrence of such weather types changes, also the overall bias might change. Such bias changes might be called mixture related apparent bias changes (MABC).

[4] It is difficult to assess non-stationarities of biases because the period with a dense observational network shows a relatively small climate change signal and is hardly long enough for robust calibration and validation. Therefore, I use a pseudo reality [*Frías et al.*, 2006; *Vrac et al.*, 2007; *van der Linden and Mitchell*, 2009] to assess the extent and type of RCM bias changes under future climate change. For the strongest changes, I also analyse potential mechanisms causing the identified changes. To isolate RCM biases I employ a perfect boundary setting, biases from global climate models are explicitly not considered. As an example I investigate the correction of winter and summer mean temperature and precipitation sums over Europe.

2. Concept and Data

[5] As pseudo reality, I choose one global climate model / RCM combination, where the global climate model represents pseudo observed large scale boundary conditions for present and future climate, the reference RCM itself represents regional pseudo observations. An ensemble of other RCMs is treated as models to be corrected. Using an ensemble and employing each of the RCMs in turns as pseudo reality reduces the RCM dependence of the results. The RCMs are forced with the same pseudo observed boundary conditions as the reference RCM, i.e., the same global climate model. For present day climate simulations, this corresponds to a perfect boundary condition setting, i.e., RCMs driven with reanalysis data. Under the assumption that GCM and RCM biases do not interact, this setting isolates RCM biases. Forcing with equal boundary conditions also synchronises variability on scales beyond a few days and allows for relatively short calibration periods. I select the subset of RCMs from the ENSEMBLES project [*van der Linden and Mitchell*, 2009] which are all driven by the same boundary conditions of ECHAM5 run three for the SRES A1B scenario and operate on the same grid: HIRHAM5 (Danish Meteorological Institute), RACMO2 (Royal Dutch Meteorological Institute), REMO (Max Planck

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Institute for Meteorology) and RCA (Swedish Meteorological and Hydrological Institute). The RCMs have a horizontal resolution of 25 km and cover the European domain of the ENSEMBLES project. As calibration period, I choose 1970–1999, as future period 2070–2099.

[6] I consider seasonal mean temperature and precipitation sums, separately for each season. Pseudo temperature observations of season i are denoted as $T_{o,i}$, model simulations as $T_{m,i}$, precipitation observations as $P_{o,i}$ and model simulations as $P_{m,i}$; temperature means over the calibration and scenario period are denoted as $\bar{T}_o^{cal}$ and $\bar{T}_o^{fut}$, precipitation sums as $\bar{P}_o^{cal}$ and $\bar{P}_o^{fut}$, respectively. The temperature and precipitation biases over the calibration period are defined as

$$\begin{aligned} BT^{cal} &= \bar{T}_m^{cal} - \bar{T}_o^{cal}, \\ BP^{cal} &= \frac{\bar{P}_m^{cal}}{\bar{P}_o^{cal}}. \end{aligned} \tag{1}$$

For precipitation relative changes are considered, i.e., a value of 1 indicates no bias. Biases for the future, BT^{fut} and BP^{fut}, are defined accordingly. Model output corrected relative to the calibration period is calculated as $T_{m,i}^{corr} = T_{m,i} - BT^{cal}$ and $P_{m,i}^{corr} = \frac{P_{m,i}}{BP^{cal}}$ with corresponding temporal means and sums. The change in temperature and precipitation bias from calibration to future period is given as

$$\begin{aligned} DBT &= BT^{fut} - BT^{cal}, \\ DBP &= \frac{BP^{fut}}{BP^{cal}}, \end{aligned} \tag{2}$$

The change in bias is equivalent to the future bias remaining after a correction based on the calibration period. When the uncorrected future bias is larger than the present day bias, bias correction improves the results. Even when the uncorrected future temperature bias is smaller than the calibration bias, the absolute remaining bias might still be smaller than without correction, although the remaining bias changes sign. Only when the uncorrected future bias reduces to less than half the calibration bias, bias correction deteriorates the original future simulation. A similar argument holds in case of precipitation, but positive (negative) values have to be replaced by values larger (smaller) one. To highlight the actual reduction in bias, I consider the improvement in absolute bias as the difference (ratio for precipitation) between the absolute future bias without correction and with correction:

$$\begin{aligned} IBT &= \left|BT^{fut}\right| - |DBT|, \\ IBP &= \frac{R\left(BP^{fut}\right)}{R(DBP)}. \end{aligned} \tag{3}$$

Here $R(x)$ is x for $x >= 1$ and $1/x$ for $0 < x < 1$. The function $R(x)$ applied to ratios is the equivalent of taking absolute values of differences. In the following, I will refer to both operations as taking absolute values.

3. Results

[7] Of the four selected RCMs, all six permutations of one model being the pseudo observation and the other three simulations are considered. As pseudo observations and models are interchangeable, only absolute biases and absolute changes in biases are considered (the absolute values of definitions (1) and (2)).

[8] Columns one and two of Figure 1 present the bias for the calibration period (equation (1)) and the remaining bias in the future (equation (2)), averaged over all permutations. In general, the temperature bias (Figure 1, top two rows) as well as the precipitation bias (Figure 1, bottom two rows) are on average strongly reduced by the bias correction. The change in temperature bias is lowest over the open Atlantic and the Mediterranean (Figures 1b and 1f), where temperature is controlled by the prescribed SST boundary conditions, and highest in the Barents Sea, White Sea and the Gulf of Bottnia during winter (Figure 1b) and spring (not shown). Over land, the change in winter temperature bias is strongest in the Alps (Figure 1b). In general a stronger temperature bias remains in summer, in particular in southwestern Europe (Figure 1f). The change in precipitation bias is in general low. It is highest during summer around the Mediterranean (Figure 1n).

[9] The changes in bias are reflected in patterns of improvement due to the bias correction (equation (3)). Columns three and four of Figure 1 show the mean (Figures 1c, 1g, 1k, and 1o) and worst case improvement (Figures 1d, 1h, 1l, and 1p) after a bias correction for the future based on the calibration period bias. The top two rows show winter and summer temperature, the bottom two rows the corresponding results for precipitation. On average the temperature bias correction improves the future simulation despite changes in bias. Yet over central Europe the improvement is negligible and for some regions even deteriorates the simulation. The strongest deterioration occurs for the Barents Sea, White Sea and the Gulf of Bottnia during winter (Figure 1c) and spring (not shown). The worst case panels show the lowest improvement of all permutations for each grid box. For winter (Figure 1d), biases in the Alps, the Barents Sea, White Sea and Gulf of Bottnia, and for summer (Figure 1h), biases over central Europe, Northern Italy and the Balkans stand out. Only over some regions, temperature bias correction improves the simulations even in the worst case. Precipitation bias correction on average leads to an improvement over most regions (Figures 1k and 1o). Even for the worst case the deterioration is weak, apart from the Mediterranean and Northern Africa during summer (Figure 1p).

4. Discussion

[10] To further investigate the causes leading to the described bias changes, I consider future changes in potentially relevant climatic variables. Figure 2 shows the standard deviation of changes between 1970–1999 and 2070–2099 for winter surface albedo (Figure 2a), summer cloud cover (Figure 2b), summer soil moisture (Figure 2c) and summer sea level pressure (Figure 2d). A strong model spread in winter albedo can be observed in the Alps (Figure 2a), whereas the spread in winter snow cover changes is negligible (not shown). This finding indicates a spread in temperature response due to different changes in the perennial snow fraction. Furthermore a strong model spread in winter albedo is apparent in the Gulf of Bottnia, White Sea and Barents Sea (Figure 2a), which exceeds changes in sea ice cover (not shown). In these regions, the spread in temperature response might thus be explained by different sea ice/albedo parameterisations. Changes in cloud

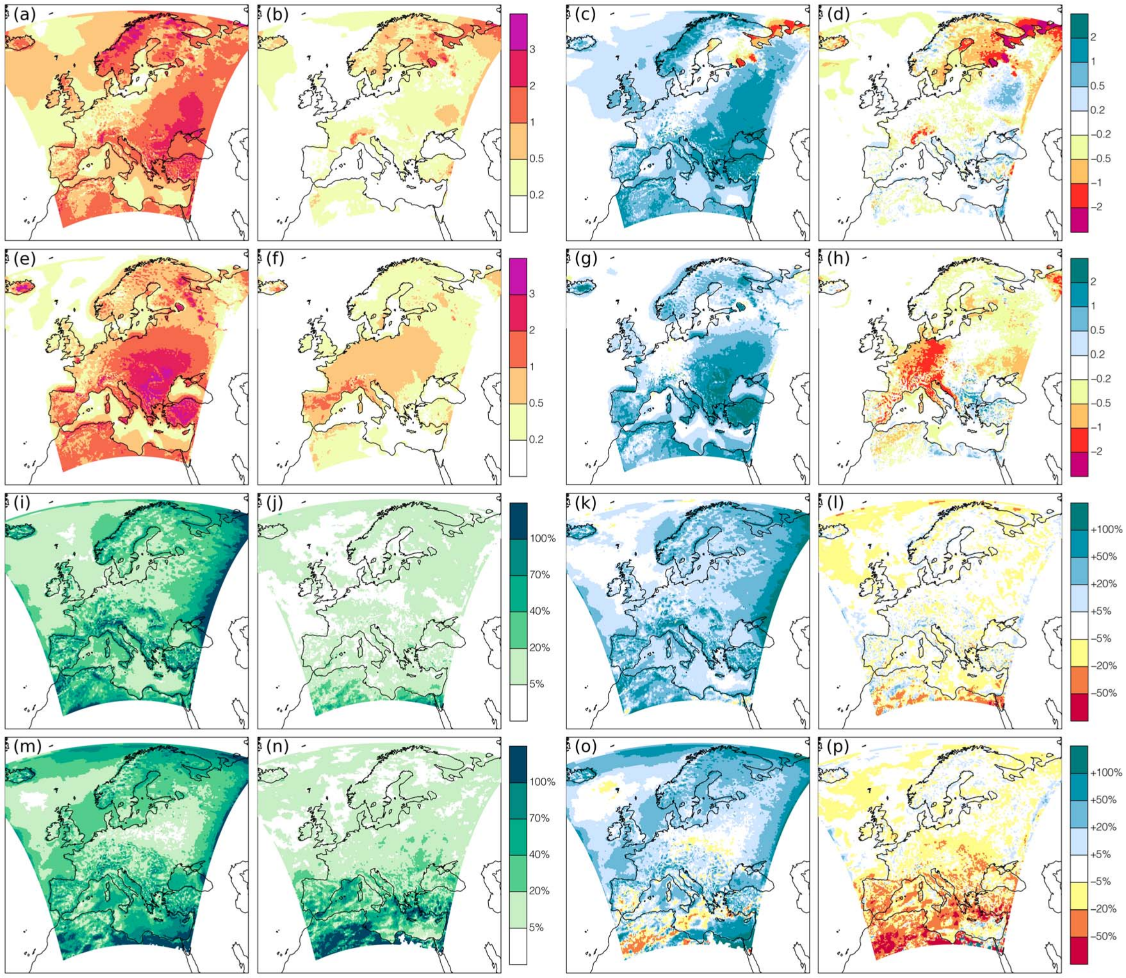

Figure 1. Biases and bias correction. (a–d) DJF temperature [K], (e–h) JJA temperature [K], (i–l) DJF precipitation [%], and (m–p) JJA precipitation [%]. Shown are (left to right) 1970–1999 bias, mean across all permutations; change in bias 2070–2099 vs. 1970–1999; mean improvement across all permutations; and minimum improvement across all permutations.

cover exhibit the most apparent spread in summer, in particular in central Europe (Figure 2b). The corresponding responses in radiative surface heating may partly explain changes in temperature biases. These might have been amplified in some regions by soil moisture feedbacks (Figure 2c). Figure 2d shows the spread in summer sea level pressure changes. The pattern is likely a response to the spread in diabatic heating of the atmosphere (Figure 1e). Yet the initial presence of such a response pattern causes a meridional wind anomaly that might also contribute to the bias change patterns. To conclude, the described changes in temperature biases can be related to different responses of the climate system to the prescribed greenhouse forcing and thus constitute SBC.

[11] Figure 3 shows regional mean changes in precipitation biases for precipitation averaged to different space scales. Results for central Europe (48N, 5E to 53N, 17E, the regions are aligned parallel to the rotated grid) are depicted in dark blue (circles), for the Iberian peninsula (36N, 9W to 44N, 0E) in light blue (triangles) and for the western Maghreb (30N, 5W to 35N, 10E) in orange (crosses). Solid lines indicate winter changes, dashed lines summer changes. The fact that averaging precipitation, in particular for summer arid regions, strongly reduces the bias, indicates a key role of VABC: where precipitation occurs as rather rare and localised convective events, internal variability may dominate the estimated seasonal biases on a local scale even when averaging over 30 years.

5. Conclusions

[12] Non-stationarities in RCM biases of European seasonal mean temperature and total precipitation, and their potential causes have been assessed in a pseudo reality. To this end a multi RCM ensemble has been employed, driven by the same global climate model simulation to isolate RCM biases. Each RCM has in turns been taken as pseudo reality, the others as models to be corrected. I investigated the change in bias between a present day calibration period and future simulations, as well as the improvement of the future simulations by a bias correction based on the calibration period.

[13] Biases between the models are in general relatively stable, such that bias correction on average considerably improves future scenarios for many regions and all seasons (results for spring and autumn not shown). Biases, however, remain and for some regions and seasons bias correction may even deteriorate future simulations. Temperature bias correction on average improves future simulations, but some SBC

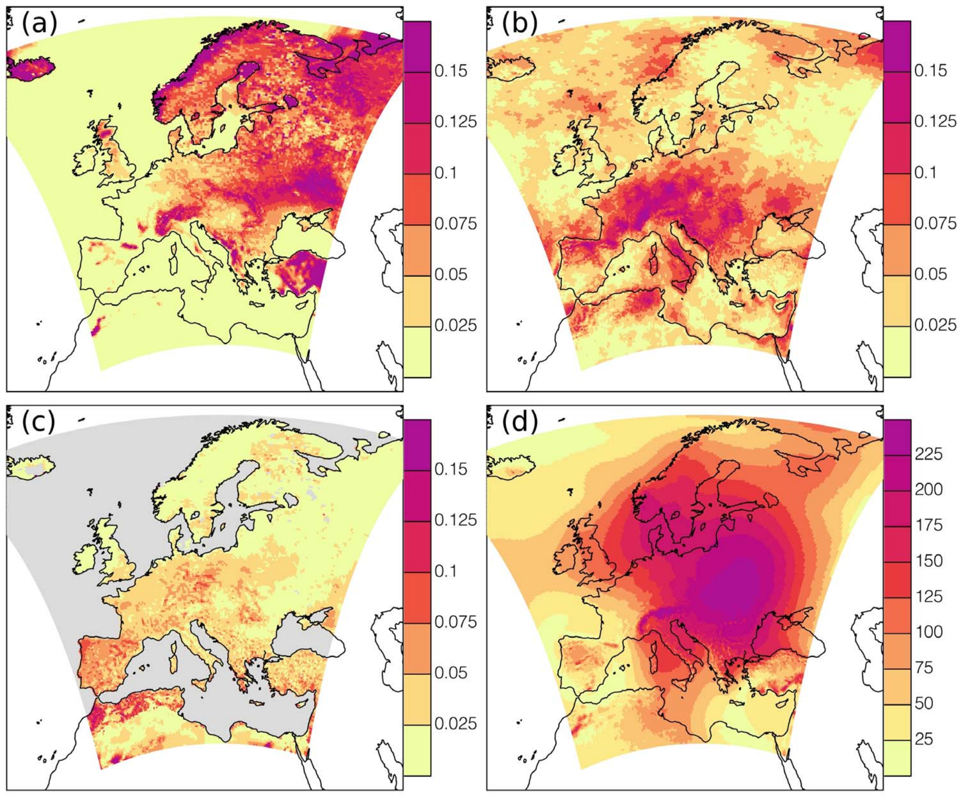

Figure 2. Standard deviation of changes in different variables, 2070–2099 vs. 1970–1999, across all permutations. (a) DJF surface albedo, (b) JJA fractional cloud cover, (c) JJA soil moisture (relative to the 1970–1999 mean), and (d) JJA sea level pressure [hPa].

have been identified. During winter, for the Alps as well as the Barents Sea, White Sea and Gulf of Bottnia large biases remain; in these regions bias correction may even increase the future bias. These changes are likely linked to changes in surface albedo, with biased responses of perennial snow cover in the Alps and sea ice albedo in the Northern seas (the latter is also relevant in spring). During summer, in Southern France and the Iberian Peninsula large biases remain, and in Central Europe bias correction may even deteriorate future simulations. These changes can be explained by biased responses of cloud cover and soil moisture. Precipitation bias correction appears to be successful for most of Europe, but is affected by VABC in arid regions. Here, especially during the dry season (summer, and in the Maghreb also spring) precipitation events are so rare that bias estimates even of seasonal sums are dominated by internal variability. For these regions it is advisable not to derive precipitation biases on a grid box scale, but rather to consider larger regions or smoothly varying bias models. As biases have not been conditoned on weather types, this study could not identify MABCs. The fact that the strongest bias changes have been identified as SBC and VABC, however, indicates that in practice MABCs play only a minor role.

[14] Although the results have been obtained in a pseudo reality, they also demonstrate the likely problems one might face using bias correction in real world applications; where different RCMs disagree, at least some of them will also differ from reality. As an agreement among RCMs does not prove an agreement with reality, a pseudo reality approach does not unambiguously identify where bias correction will be successful. Nevertheless, the results indicate potential problems as well as regions less prone to non-stationary biases. As extreme events are governed by different mechanisms than the mean climate, also biases for high quantiles tend to be different from biases in the mean [*Christensen et al.*, 2008]. Therefore, this analysis should be carried out separately for extreme events. The fact that the minimum improvement shows strong non-stationarities in biases between at least some models highlights that even after bias correction multi model ensembles are still required to assess the range of uncertainties in local climate sensitivities.

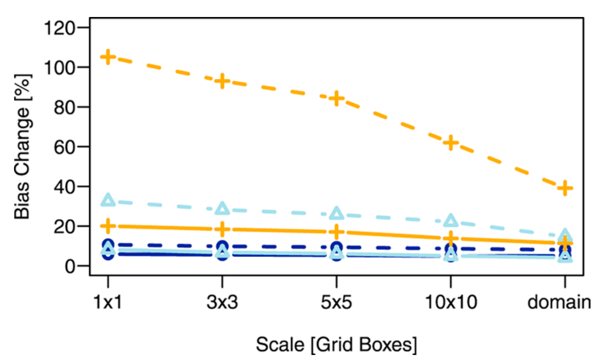

Figure 3. Precipitation bias change as function of spatial scale, average across all model permutations. Orange crosses: northern Africa, light blue triangles: Iberian Peninsula, dark blue circles: central Europe. Solid lines: DJF, dashed lines: JJA.

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