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Sensitivity of bias adjustment methods to low-frequency internal climate variability over the reference period: an ideal model study

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LETTER

Sensitivity of bias adjustment methods to low-frequency internal climate variability over the reference period: an ideal model study


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Abstract

Climate simulations often need to be adjusted before carrying out impact studies at a regional scale. Technically, bias adjustment methods are generally calibrated over the last few decades, in order to benefit from a more comprehensive and accurate observational network. At these timescales, however, the climate state may be influenced by the low-frequency internal climate variability. There is therefore a risk of introducing a bias to the climate projections by bias-adjusting simulations with low-frequency variability in a different phase to that of the observations. In this study, we developed a new pseudo-reality framework using an ensemble of simulations from the IPSL-CM6A-LR climate model in order to assess the impact of the low-frequency internal climate variability of the North Atlantic sea surface temperatures on bias-adjusted projections of mean and extreme surface temperature over Europe. We show that using simulations in a similar phase of the Atlantic Multidecadal Variability reduces the pseudo-biases in temperature projections. Therefore, for models and regions where low frequency internal variability matters, it is recommended to sample relevant climate simulations to be bias adjusted in a model ensemble or alternatively to use a very long reference period when possible.

1. Introduction

Global climate model (GCM) or regional climate model (RCM) simulations are usually used as input for models in order to assess the impacts of climate change on the environment and available resources. However, biases are often present in climate models, leading to a misrepresentation of the statistical distribution of simulated variables [1]. To overcome this issue, bias adjustment methods are usually applied to the output of climate models before their use in climate impact models in order to avoid meaningless results (e.g. [2]). Maraun and Widmann [3] provide a review of the strength and limitations of the various methods that can be used depending on the region and variable of interest.

Over a timescale of a few decades, internal climate variability is one of the main sources of uncertainties, especially at regional scales [4]. These climate variations affect the results of bias adjustment methods and the related uncertainty is difficult to assess in a changing climate due to their possible non-stationarity (e.g. [5–7]). Switanek *et al* [8] have shown that internal climate variability and therefore the choice of the calibration period strongly affect the simulated climate change signal using a quantile mapping adjustment method. Internal variability can also affect the evaluation of a bias adjustment method. Maraun and Widmann [3] have found that at multidecadal timescales, the internal climate variability can affect the results of a cross-validation analysis and therefore may lead to misleading assessment.

When applying a bias adjustment method, a reference period on which the adjustment is calibrated is chosen. This period ideally includes good observational coverage and is often defined as the 2 or 3 more recent decades (e.g. [9–11]). However, on these time scales, the observed mean state of climate variables can

be strongly influenced by the low-frequency internal climate variability. For example, the Atlantic Multidecadal Variability (AMV), which is the leading mode of low-frequency internal climate variability in the North Atlantic ocean [12–14], is known to influence the climate over Europe on multidecadal timescale [15], with knock-on effects on the statistics of extreme temperature over the Mediterranean region [16, 17] and floods and drought, for example in France [18, 19]. Therefore, calibrating a bias adjustment on a simulation that is in the opposite phase of the AMV to the observed one could induce a misleading adjustment compared to a simulation in a phase close to the observed one. This can have major repercussions on the results from impact models that may underestimate or overestimate future changes.

To account for the uncertainty related to the internal climate variability over future periods, Vaittinada Ayar *et al* [20] developed a new univariate adjustment method to adjust an ensemble of climate simulations while conserving the uncertainties related to the internal variability as well as preserving the climate change signal. Pseudo-reality approach, which consists of successively choosing a simulation as a reference to estimate the biases with respect to the other simulations, can be also useful to investigate the impact of the internal climate variability in bias adjustment results. This approach was first used to verify the bias stationary assumption in RCMs for European seasonal mean temperature and precipitation totals [21]. The strength of this method is that it allows to evaluate the evolution of biases in climate projections, as well as to disentangle the role of internal climate variability from that of climate sensitivity (i.e. the difference in the model responses to the external forcings). Using a pseudo-reality approach, a recent study by Hui *et al* [22] investigated the impact of bias non-stationarity from precipitation and temperature over China on future climate projections of GCMs. Hui *et al* found that the biases in mean annual and seasonal temperature and precipitation vary with time and have an important role on future projections for precipitation with a large contribution from internal climate variability over the next decades. However, the authors did not look at the impact of these bias nonstationarities on the results of the bias adjustment method itself. Another recent study [23] used a similar approach but applied a quantile mapping bias adjustment method to precipitation and temperature over the Quebec region. Their results show that large biases remain in far future periods and that climate sensitivity is the main contributor to these biases. The role of internal climate variability is similar over near and far future but can dominate for near future periods, especially for precipitation.

In this study, we go one step further by quantifying the impact of the internal climate variability over the next decades on bias-adjusted climate simulations of mean and extreme temperature over Europe, which are of particular interest for impact studies. As an illustration a commonly used bias adjustment method, the cumulative distribution function transform (CDF-t) [24] is used here. In order to isolate the influence of internal variability, we used the historical simulations and their extensions into the future performed with the IPSL-CM6A-LR climate model (CM stands for climate model and LR for low resolution) [19]. These simulations have the same external forcing and only differ by their initial conditions and therefore their internal climatic variability. From these simulations, we have developed a new pseudo-reality framework for assessing the impact of internal climate variability on the results of bias adjustment methods. We focus on surface temperature over Europe as an example but our framework can be easily applied to other regions and climate variables such as precipitation or wind. The idea of this new framework is to use two simulations with opposite AMV phases over the reference period as pseudo-realities and to use them to calibrate a bias adjustment for two simulations also characterised by opposite AMV phases. In order to remain consistent with studies using bias adjustment methods, we will use the period 1990–2020 as reference. New indices are developed in order to separate the part of the bias due to an error in the method from that aimed at preserving the evolution of the model. The interest of this new framework is that it allows us to evaluate the uncertainties related to a specific mode of variability using only few simulations and therefore little computing time. However, the total uncertainty related to the internal climate variability cannot be evaluated.

Based on this new framework, the objectives of this study are: (a) to assess the impact of the North Atlantic low-frequency internal climate variability on the results of a bias adjustment method and (b) to quantify this impact in terms of bias non-stationarity.

The data, model, bias adjustment method and pseudo-bias indices are presented in section 2. Then, the results are presented in section 3, with an evaluation of the bias adjustment method in section 3.1 and the investigation of the impact of the internal climate variability in the pseudo-bias in section 3.2. The results are then discussed in section 4 and the main conclusions are presented in section 5.

2. Method

2.1. Data and variables of interest

The IPSL ensemble of extended historical simulations (IPSL-EHS) is composed of 32 simulations available over the 1850–2059 period [19]. These simulations were performed with the IPSL-CM6A-LR model [25] using the CMIP6 protocol for the historical period (1850–2014) and then extended with the SSP2-4.5

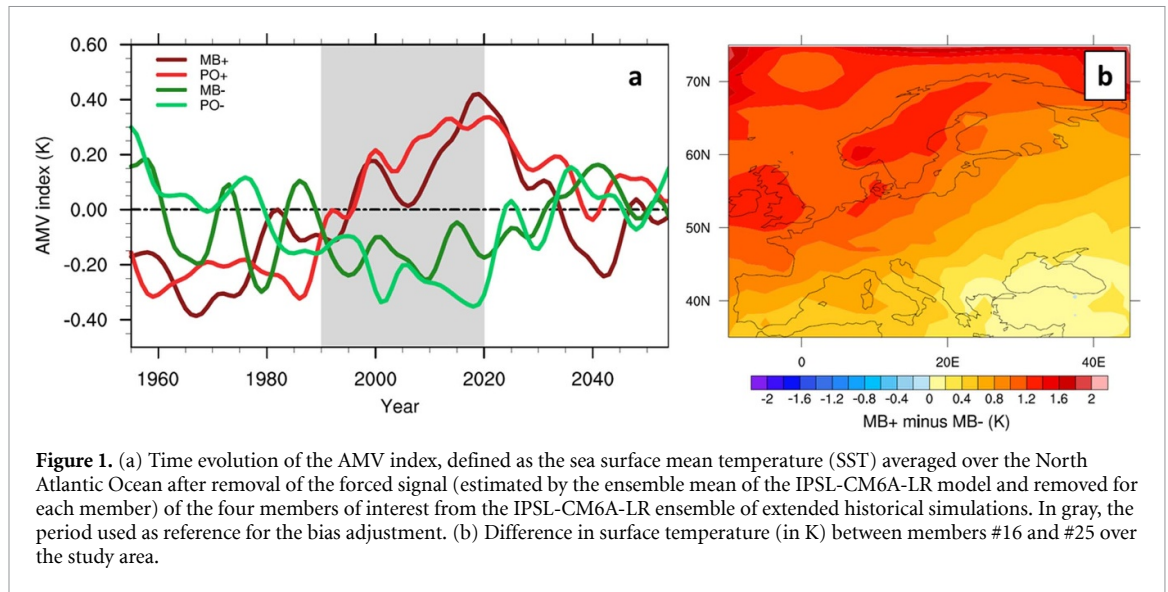


Figure 1. (a) Time evolution of the AMV index, defined as the sea surface mean temperature (SST) averaged over the North Atlantic Ocean after removal of the forced signal (estimated by the ensemble mean of the IPSL-CM6A-LR model and removed for each member) of the four members of interest from the IPSL-CM6A-LR ensemble of extended historical simulations. In gray, the period used as reference for the bias adjustment. (b) Difference in surface temperature (in K) between members #16 and #25 over the study area.

Table 1. Summary of the simulations used: the pseudo-observations (PO), the members to be bias-adjusted (MB) and the bias-adjusted simulations (BA).

	Pseudo-observations (PO) (1990–2020)		
Member (MB)	PO– (#25)	PO+ (#16)	
MB+ (#31)	BA+–	BA++	Bias-adjusted simulations (BA)
MB– (#29)	BA–	BA–+	

scenario onwards [26]. Note that because the ozone field was not available at the time of performing the extensions, it has been kept constant to its 2014 climatology. The ozone hole recovery and changes in the tropospheric ozone are therefore not ‘seen’ in these simulations. However, this is of minor importance to our topic of study. The initialisation of these simulations is done by taking the initial conditions from different years in a long preindustrial simulation after it has reached a quasi-stationary state. The IPSL-CM6A-LR resolution is of $1.26^\circ \times 1.25^\circ$ with 79 levels (model top at 1 Pa) for the atmosphere and of 1° resolution and 75 levels for the ocean.

We focus the analysis on two quantities, the mean surface temperature and an extreme temperature index, defined as the 99th percentile of the summer (June–July–August) surface temperature.

2.2. Model framework

We now describe the perfect model framework used in this study with pseudo-observations (POs) selected in opposite phases of the AMV.

Specifically the evolution of the AMV index is calculated for each simulation of the IPSL-EHS. This index is based on the average sea surface temperature over the North Atlantic Ocean ($0\text{--}60^\circ\text{N}$) after the removal of the forced signal, estimated as the ensemble mean.

From the AMV index, we select two members in the IPSL-EHS with opposite variations over the 1990–2020 period that we consider as two PO datasets. Member #16 (PO+) is in a positive phase of the AMV whereas member #25 (PO–) is in a negative phase (figure 1(a)). As a result, PO+ is warmer than PO– over the domain of interest and period of reference (figure 1(b)). Then, we select two other members, #31 (MB+, in a positive AMV phase) and #29 (MB–, in a negative AMV phase), each being in a similar phase of the AMV to the previously selected members (figure 1(a)). Finally, we adjust these members (MB+ and MB–) with a classic bias adjustment method using the two members considered as POs (PO+ and PO–). Therefore, we have four bias-adjusted simulations: BA++ (MB+ adjusted using PO+ as reference), BA–+ (MB– adjusted using PO+), BA–– (MB– adjusted using PO–), BA+– (MB+ adjusted using PO–). The bias adjustment is applied to the surface temperature. The experimental setup is summarized in table 1.

As a result of this framework, the only difference between the model and the POs arises from the internal climate variability. Note that, usually, a bias represents the systematic deviations between a climate model and observations, due to the model physics or the uncertainties related to the forcings. However, in impact studies using a single bias-adjusted simulation, a fraction of the total bias is due to the internal variability of

the climate system. In the present study, as there are no systematic errors but only deviations due to internal variability, the statistical difference between the model and the POs is only apparent. Therefore, this deviation is referred to as pseudo-bias in the following.

2.3. Bias adjustment method

We used the CDF-t bias adjustment method [24] to adjust the MB simulations to the POs. The idea of this method is to match the CDF of a climate variable simulated by a model to the observed CDF using a mathematical function. It can be considered as a variant of the non-parametric quantile-quantile (QQ) method [27]. The added value of the CDF-t method, in comparison to the QQ method, is that it takes into account the CDF change from the historic to the future time period of the model simulation.

This non-parametric method has been widely used for example for temperature and precipitation (e.g. [9, 28, 29]) but also for other diverse climate, atmospheric or environmental parameters, like the monthly river flows and temperature percentiles used as hydroclimatic descriptors of fish habitats [30] or to assess the climate impact on agriculture in West Africa [31]. More details on the CDF-t method can be found in Vrac *et al* [9].

In this study, the CDF-t method is applied for adjusting daily temperature over the 1990–2060 period, with 1990–2020 serving as the calibration period. CDF-t is run month by month to take into account the seasonality and for each grid point over Europe (30° N–75° N, 20° W–45° E). A 20 year moving window is used as ‘target’ for the CDF and the GCM data are adjusted over a central 10 year moving window, in order to smooth discontinuities.

2.4. Definition of the pseudo-bias indices

In order to assess the impact of the low-frequency internal variability on the results of the bias adjustment method, we decomposed the pseudo-bias in temperature projections calculated between the bias-adjusted simulations and the POs (named Future pseudo-bias, equation (1)) into three quantities

$$\text{Future pseudo-bias} = T_{\text{future}}(\text{BA}) - T_{\text{future}}(\text{PO}). \quad (1)$$

First, we define the evolution difference (equation (2)) as the difference between the change in temperature (ΔT) from one of the members (MB) to be bias adjusted minus the change in temperature from one of the POs. The change in temperature (ΔT) is calculated as the difference between a future period of interest minus the reference period, here 2029–2059 and 1990–2020, respectively. This evolution difference is due to the disagreement between the evolution of the member and of the POs. The CDF-t method aims at preserving this difference in the evolution between the model and the observations while adjusting the distribution over the projection time period

$$\text{Evolution difference} = \Delta T(\text{MB}) - \Delta T(\text{PO}). \quad (2)$$

Then, we define the error related to the bias adjustment method (Total error in equation (3)), which is based on the addition of two different quantities, (a) the initial pseudo-bias in temperature over the reference period between one of the bias-adjusted (BA) simulations and its corresponding PO (equation (4)) and (b) the difference in temperature evolution between one of the BA simulations and the corresponding member before bias adjustment (MB) (equation (5))

$$\text{Total error} = \text{Initial pseudo-bias} + \text{Evolution error} \quad (3)$$

$$\text{Initial pseudo-bias} = T_{\text{ref}}(\text{BA}) - T_{\text{ref}}(\text{PO}) \quad (4)$$

$$\text{Evolution error} = \Delta T(\text{BA}) - \Delta T(\text{MB}). \quad (5)$$

In contrast to the evolution difference, the initial pseudo-bias and the evolution error corresponds to the errors induced by the adjustment method. The first is what the method fails to adjust over the reference period and the second is what the method fails to preserve in the model evolution. The pseudo-bias in future temperature (equation (6), which is equal to equation (1), see the supplementary for the details available online at stacks.iop.org/ERCL/1/011001/mmedia) between one bias-adjusted simulation and the corresponding PO is equal to the sum of the equations (2) and (3)

$$\text{Future pseudo-bias} = \text{Evolution difference} + \text{Total error}. \quad (6)$$

A schematic of this bias decomposition is given in figure S1 and the decomposition from equations (6) to (1) is provided in the supplementary. From these indices, it is therefore possible to quantify the part of the pseudo-bias in future temperature that is due to an error in the bias adjustment method and the part that is induced by the difference in evolution between the member to be adjusted and the PO. As a reminder, the term pseudo-bias used in equations (1) and (4) are only influenced by the internal climate variability and not by the forcing uncertainties or model errors.

As a reminder, in the present study, the term pseudo-bias used in equations (1) and (4) is only influenced by the internal climate variability and not by the forcing uncertainties or model errors.

3. Results

3.1. Evaluation of the bias adjustment method over the reference period

In this section, we evaluate whether the bias-adjusted temperature simulations are well-adjusted to the POs over the reference period.

As expected, the mean surface temperature evolution in simulations MB+ and PO+ are warmer than in MB- and PO- over the reference period, due to their opposite phase of the AMV (figure 2(a)). Therefore, for the reference period, there is a negative pseudo-bias in mean surface temperature over the whole domain between the MB- and the PO+ simulations, and conversely for the MB+ and PO- simulations (figures S2(c) and (g)). On the other hand, considering the members to be bias adjusted and the POs in the same phase (figures S2(a) and (e)), the pseudo-bias in surface temperature is smaller and more heterogeneous regionally. The differences over the reference period are found by design, as the members with similar or opposite phases of the AMV are selected, whereas this is not the case for the future period. From the 2030s onwards, however, the mean surface temperature evolution is quite close between these four simulations (figure 2(a)). This could be due to the decrease of the low-frequency internal climate variability in the North Atlantic induced by the external forcing [32].

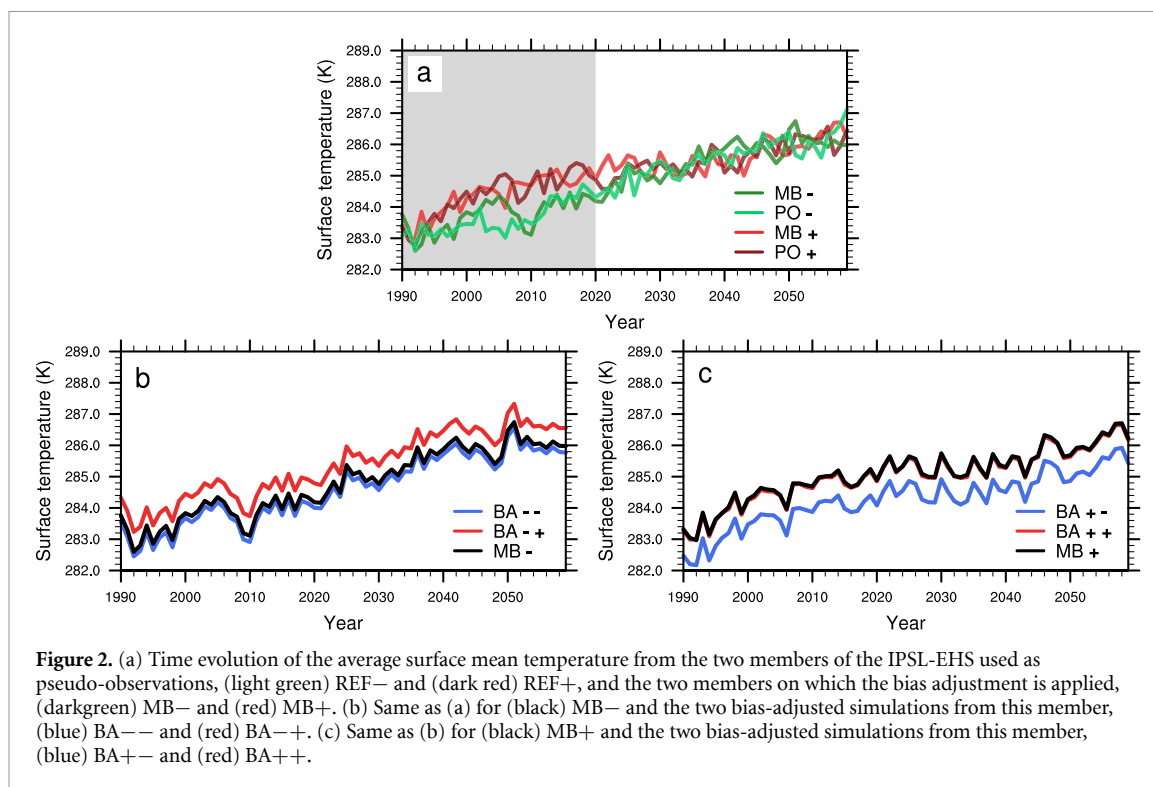
Due to this difference in the mean state surface temperature, the BA-+ simulation has warmer surface temperature than MB-, whereas the BA-- simulation has surface temperature very close to that of MB- (figure 2(b)). Conversely, the BA+- simulation has colder surface temperature than MB+, whereas the BA++ simulation has surface temperature very close to that of MB+ (figure 2(c)). The bias-adjusted simulations of surface temperature show almost no differences with the POs (figures S2(b), (d), (f) and (h)), indicating that, as expected, the bias adjustment method is efficient over the reference period. The initial pseudo-bias (equation (4)) is therefore negligible for mean surface temperature.

Relatively similar results are obtained for extreme temperature, defined as the 99th percentile of the summer (June–July–August) surface temperature. There is overall a negative pseudo-bias over the domain between MB- and PO+, except over the eastern and Northern Europe less influenced by the Atlantic, and a positive pseudo-bias over the domain between MB+ and PO- (figures S3(c) and (g)). Smaller pseudo-biases in extreme temperature are found when considering the MB and PO simulations in the same phase, except for the eastern part of Europe with the PO+ simulation (figures S3(a) and (e)). These pseudo-biases are nevertheless larger than for mean temperature (figures S2(a) and (e)). The extreme temperatures from the BA simulations have very small pseudo-biases with their respective PO in comparison to the biases before applying the bias adjustment (figures S3 (b), (d), (f) and (h)). The bias adjustment method is therefore also efficient for extreme temperature over the reference period. The initial pseudo-bias is therefore also small for extreme surface temperature, although it is slightly larger than for the average surface temperature.

3.2. Impact of the low-frequency internal variability on future pseudo-bias

This section investigates how adjusting bias from a simulation with a similar or an opposite phase of the AMV than the POs over the reference period influences the future pseudo-bias results (i.e. over the 2029–2059 period) in mean and extreme surface temperatures.

Because of their close mean state over the reference period, future pseudo-biases in mean surface temperature between the MB and the PO simulations in the same AMV phase (figures S4(a) and (i)) are overall smaller and more spatially heterogeneous than when considering PO simulations in an opposite AMV phase (figures S4(e) and (m)). Indeed, there is a negative bias in mean surface temperature over the whole domain between MB- and PO+ (figure S4(e)) over the 2029–2059 period and conversely, there is a positive bias over the whole domain between MB+ and PO- (figure S4(m)). Very similar results are found for the future pseudo-bias, defined as the difference between the BA and PO simulations (figures S4(b), (f), (j) and (n)). Therefore, a large part of the future pseudo-biases in the BA simulations comes from the original pseudo-bias between the members to be bias adjusted and the POs. As a result, the evolution difference is very similar to the future pseudo-bias (figures S4(c), (g), (k) and (o)). The total error is very

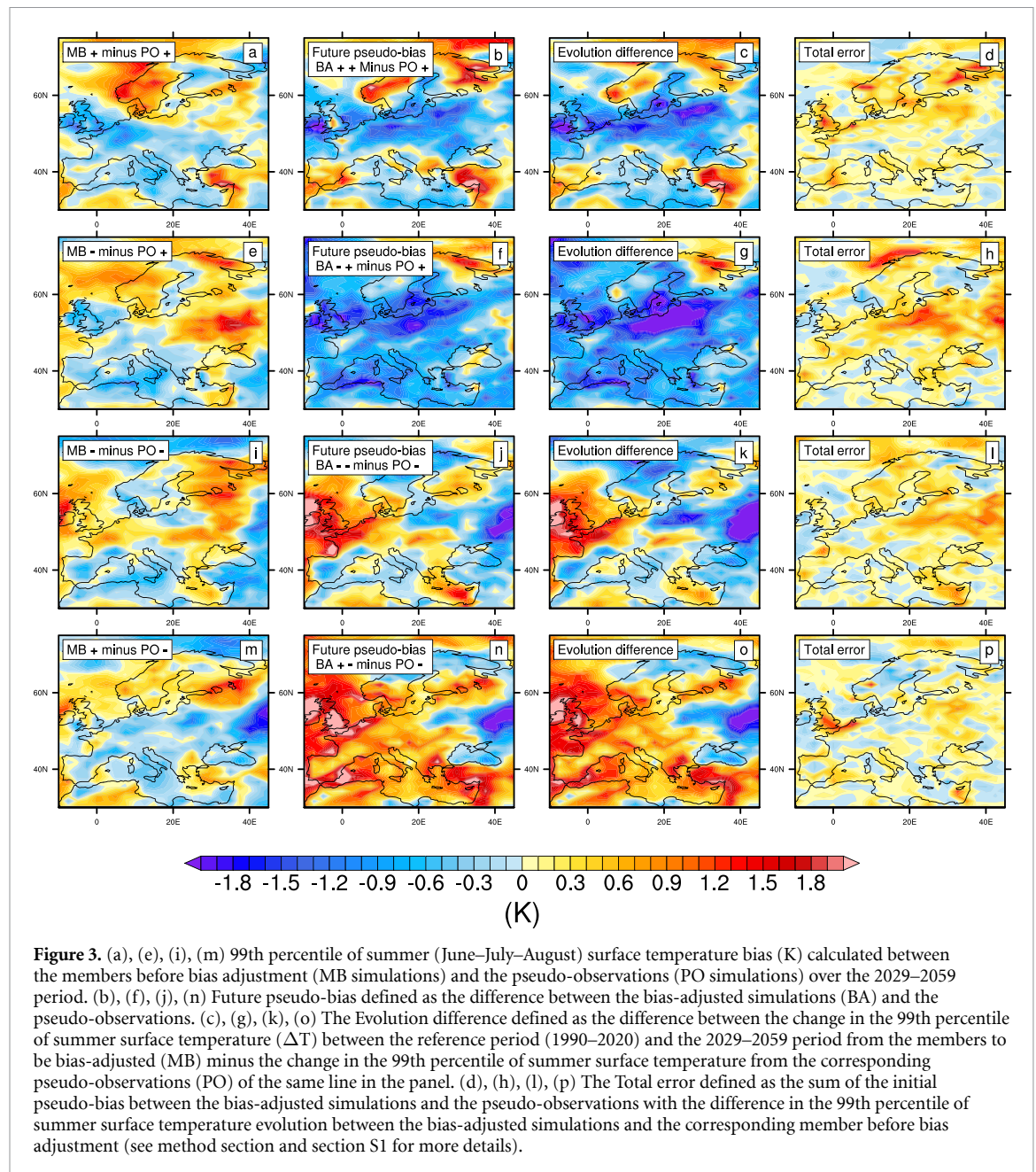


small for all the bias-adjusted simulations (figures S4(d), (h), (l) and (p)). This is due to the small initial pseudo-bias (equation (3)), as shown in section 3.1, and because the evolution error (equation (4)) is also small (not shown). It therefore has very little impact on the future pseudo-bias.

We now focus on the extreme temperature, which is of particular interest regarding the climate impact studies. The pseudo-biases calculated over the 2029–2059 period between the MB and the PO simulations for the extreme temperature are more heterogeneous spatially in comparison to the mean temperature (figures 3(a), (e), (i) and (m)). Interestingly, the pseudo-biases are overall larger for the bias-adjusted simulations than the original member (figures 3(b), (f), (j) and (n)). The future pseudo-bias between the BA–+ and the PO+ simulations is overall negative over the majority of the domain, whereas it is more heterogeneous between the BA++ and the PO+. Considering the PO– simulation, the future pseudo-bias is overall positive for the BA+– simulation, with values greater than 1.5 K over the western part of the domain and around the mediterranean sea, whereas it is lower and more heterogeneous between the BA–– and the PO–. In order to synthesise the results, we calculate the absolute pseudo-bias over each grid point and then average these absolute pseudo-biases over the whole domain. Consistent with the previous results, the future mean absolute pseudo-bias over the whole area is much smaller for the bias-adjusted simulations based on the member and the POs in the same AMV phase (about 0.6 K) than with the POs in the opposite AMV phase (0.8 K for BA–+ and 0.9 K for BA+–) (figure 4).

A large part of the future pseudo-biases in extreme surface temperature are due to the evolution difference, as the maps are very close (compare panels c, g, k, o) with panels b, f, j, n). Therefore, the mean absolute future pseudo-bias and evolution difference are smaller for the bias-adjusted simulations based on a PO in the same AMV phase than in an opposite AMV phase (figure 4). In the case of the BA–+ simulation related to the PO+, the evolution difference is larger than the future pseudo-bias (figures 3(f) and (g)), with absolute values of 0.93 K and 0.83 K, respectively (figure 4). For the other simulations, the evolution difference and the future pseudo-bias are close.

The total error is larger for the extreme surface temperature than for the mean surface temperature, with values larger than 1 K for some regions. The average absolute total error values are the same for the BA+– and BA–– simulations (about 0.19 K), but are slightly larger for the BA–+ in comparison to the BA++ simulation (0.25 and 0.22 K respectively). The total error can be decomposed in two terms (see section 2), the initial pseudo-bias between the BA and the PO simulations and the evolution error between the BA and the MB simulations. Regarding the absolute values for these two terms, the evolution error is twice as large as the initial pseudo-bias in a fairly similar way for the four simulations, meaning that a large part of the total error is due to a bias non-stationarity, clearly induced by disagreements between the evolution in the reference (PO) and the evolution of the member to adjust (MB).

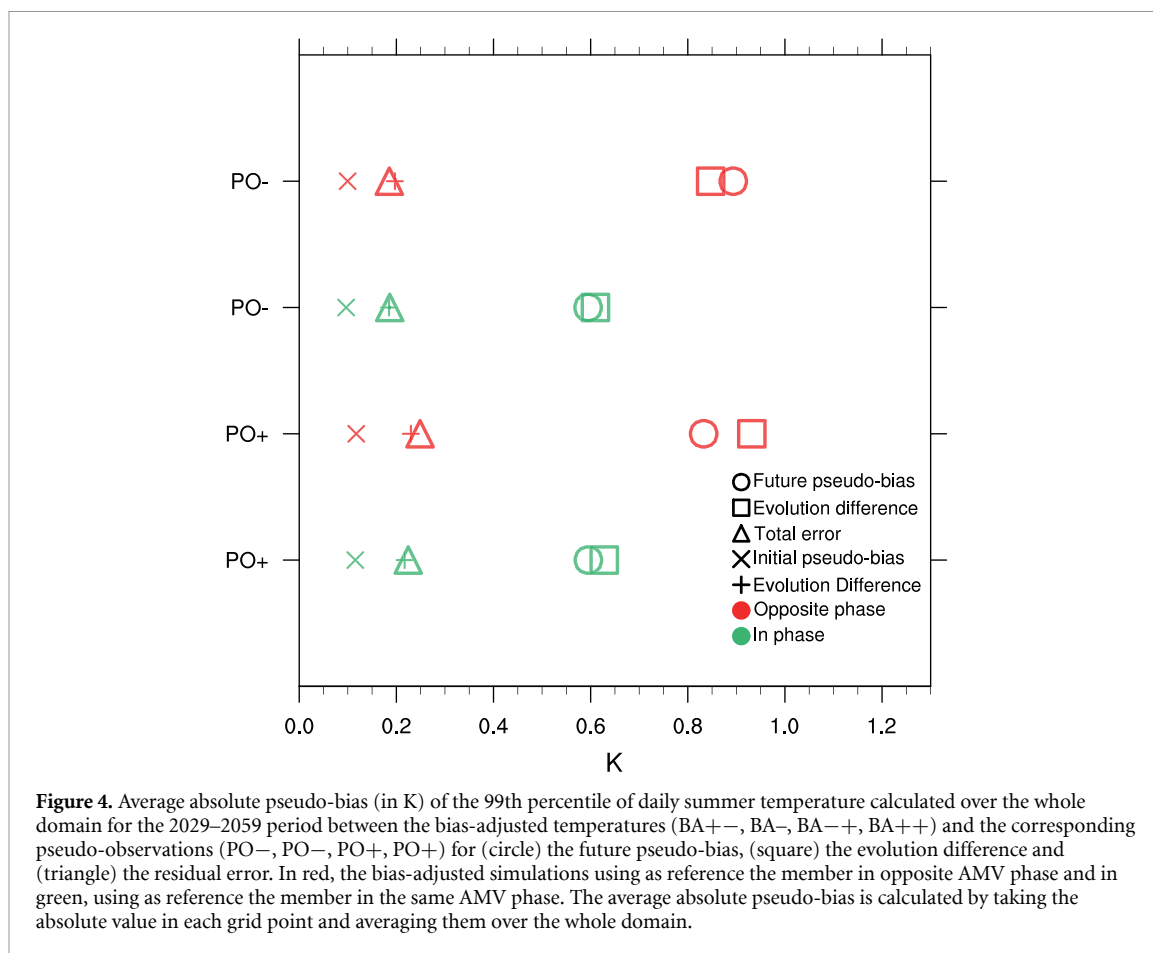


4. Discussion

In this study, we developed a new pseudo-reality framework to assess the impact of the low-frequency internal climate variability on the results of a bias adjustment method, as well as indices in order to decompose and quantify the origins of the pseudo-biases. This method is easily reusable over another region or with another bias adjustment method. In particular, this could allow a quick comparison of the influence of internal variability on the outcome of different adjustment methods without having to apply it to an entire simulation ensemble.

The influence of a particular mode of variability, the AMV, on the results of the bias adjustment has been evaluated. However, other modes of decadal variability, like the North Atlantic Oscillation [33] affect the climate over Europe, especially at seasonal timescale (e.g. [34]). Nevertheless, they seem related to the AMV [35], so we assume that by focusing on the AMV, a large part of the low-frequency internal climate variability over Europe is taken into account. Another way to use this framework could be to select directly the opposite phases of low-frequency internal variability of the detrended variable of interest itself. This could be useful in areas without a known or dominant mode of low frequency variability.

As discussed in the introduction, recent studies used pseudo-reality approaches to investigate the role of the internal variability versus climate sensitivity [22, 23]. In this study, we have adopted a different strategy in



order to go further in estimating the impact of internal variability over the coming decades in Europe. The CDF-t bias adjustment method used in this study works well over the reference period, even for extreme temperature, consistently with previous studies [9, 36]. For the bias-adjusted surface temperature projections, however, we found that the low-frequency internal climate variability of the North Atlantic impacts the future pseudo-biases, especially for the extremes. As previously suggested [23], one way to limit this impact is to take a longer reference period when it is possible. Another way is to make a selection of climate simulations close to the observation in order to limit this impact.

The decomposition of the pseudo-bias in temperature projections allows us to evaluate the performance of the method and to investigate the origin of the future pseudo-bias. Here, there is a part of this pseudo-bias that is due to errors of the method itself. However, a large part of the future pseudo-bias comes from a disagreement between the model evolution and the evolution of the POs. Indeed, the bias adjustment method is not designed to modify the climate change signal provided by the model to be adjusted. Therefore, the bias adjustment method preserves the evolution difference.

5. Conclusion

Based on a new pseudo-reality framework, we show that low-frequency internal climate variability, here in the North Atlantic, can impact the result of the CDF-t bias adjustment method in a worst-case scenario. Indeed, the bias-adjusted mean and extreme surface temperature simulations are characterized by larger future pseudo-bias when the simulations to be bias-adjusted are in an opposite AMV phase of the POs than when they are in the same AMV phase.

A large part of the pseudo-bias in mean and extreme surface temperature projections from the bias-adjusted simulations is due to the evolution difference between the simulations and the pseudo observations. The CDF-t method is not designed to correct this evolution difference, in order to preserve the evolution of the simulation to be bias adjusted. For the extreme surface temperature, a non-negligible part of the future pseudo-bias in the bias-adjusted simulations are errors induced by adjustment method (around 0.2 K).

The results highlight that bias adjusting climate model simulations to observations with modes of variability that are out of phase in the reference period may lead to undesired biases in future projections. This brings out the importance of generating a large ensemble of climate simulations and selecting simulations with modes of climate variability in phase with observations before conducting a bias-adjustment method when the bias adjustment of a whole ensemble is not possible. Such a selection has to be targeted to the mode(s) of variability that are relevant to the region of interest and may depend on the climate impacts being considered. Alternatively the bias adjustment method could be performed by using a longer (i.e. >30 years) reference period so as to minimize the impact of low-frequency internal climate variability.

Future works using other climate variables, such as the precipitation or the wind would be interesting, as well as the application of this framework over other regions strongly influenced by other modes of low-frequency internal climate variability such as the Pacific Decadal Oscillation.

Data availability statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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