Evaluating the Time-Invariance Hypothesis of Climate Model Bias Correction: Implications for Hydrological Impact Studies

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ABSTRACT

The bias correction of climate model outputs is based on the main assumption of the time invariance of the bias, in which the statistical relationship between observations and climate model outputs in the historical period stays constant in the future period. The present study aims to assess statistical bias correction under nonstationary bias conditions and its implications on the simulated streamflow over two snowmelt-driven Canadian catchments. A pseudoreality approach is employed in order to derive a proxy of future observations. In this approach, CRCM–ECHAM5 ensemble simulations are used as pseudoreality observations to correct for bias in the CRCM–CGCM3 ensemble simulations in the reference (1971–2000) period. The climate model simulations are then bias corrected in the future (2041–70) period and compared with the future pseudoreality observations. This process demonstrates that biases (precipitation and temperature) remain after the bias correction. In a second step, the uncorrected and bias-corrected CRCM–CGCM3 simulations are used to drive the Soil and Water Assessment Tool (SWAT) hydrological model in both periods. The bias correction decreases the error on mean monthly streamflow over the reference period; such findings are more mixed over the future period. The results of various hydrological indicators show that the climate change signal on streamflow obtained with uncorrected and bias-corrected simulations is similar in both its magnitude and its direction for the mean monthly streamflow only. Regarding the indicators of extreme hydrological events, more mixed results are found with site dependence. All in all, bias correction under nonstationary bias is an additional source of uncertainty that cannot be neglected in hydrological climate change impact studies.

1. Introduction

The assessment of climate change impacts on water resources is generally based on a hydroclimate model chain that consists of a combination of projections of global climate models (GCMs), which are often dynamically downscaled by regional climate models (RCMs). The variables of climate models are then used as inputs to hydrological models to project potential future changes on water resources (Muerth et al. 2013).

However, it is desired to apply postprocessing methods (such as bias correction) to adjust the variables to correct for climate model biases rather than using raw climate model outputs to drive hydrological models (Ho et al. 2012).

Model biases (or systematic model errors) are defined as systematic differences between model simulations and observations (Jung 2005; Teutschbein and Seibert 2013). Therefore, the bias correction (BC) of climate model outputs adjusts the climate model meteorological variables with respect to station observations with a correction function, so that the main characteristics of the climate model variables match the observed characteristics. This function is then applied to future climate model outputs under the assumption that the statistical

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relationship between the model outputs and the observations in the current period stays constant in the future, that is, under the assumption of the time invariance of the climate model bias (Chen et al. 2013b; Teutschbein and Seibert 2013; Ho et al. 2012; Ehret et al. 2012; Maraun 2012; Haerter et al. 2011; Vannitsem 2011). However, the validity of this assumption has been questioned (Ehret et al. 2012). Christensen et al. (2008) explored the bias in the simulated monthly mean temperature and precipitation from an ensemble of 13 RCMs forced with ERA-40 for a historical 40-yr period over Europe. They revealed the nonlinear behavior of model biases as a function of increasing temperatures or precipitation amounts, suggesting that model biases may not be invariant in a changing climate. Maurer et al. (2013) showed that, for a 50-yr historical period over the United States, the bias in GCM outputs, on average, is statistically the same between two sets of years; however, some GCM biases are variable in time, depending on the meteorological variable and the geographical location. Chen et al. (2013a) evaluated the precipitation biases in a 20-yr time series by dividing the dataset into two periods (odd and even years) for two North American catchments. They found relatively large differences in biases between odd and even years and suggested that differences in biases between the periods of calibration and validation are a possible cause of the lack of coherence between modeled and corrected precipitation time series.

The validity of the time-invariance assumption of the climate model bias has important implications for impact studies and needs to be verified to properly address uncertainty in future climate projections. However, this assumption cannot be directly validated since the future observations are, by definition, unknown. To fill this gap, the pseudoreality approach (i.e., the use of climate model outputs as pseudo-observations or proxies of future conditions; Vrac et al. 2007) can be considered as an alternative to provide some insights into the stationarity of climate model bias. For instance, Maraun (2012) used this approach to assess the stationarity of the climate model bias with an ensemble of four RCMs (driven by one GCM run) over Europe. The differences of bias between the present and future periods was assessed by considering one RCM as pseudoreality observations and the other three as climate model simulations. The results showed that biases are relatively stable, stable enough that bias correction improves scenarios for impact studies. However, some nonstationary biases were identified for regions where the future physical processes are expected to have important changes. Maraun (2012) pointed out that nonstationary biases would probably be caused by

changes in future physical processes that are expected to change significantly, such as snow cover, ice albedo, or clouds.

Räisänen and Räty (2013) used intermodel cross validation to assess the performance of various postprocessing methods in projecting future climate. From a set of six RCMs, each model at its time is selected as a pseudotruth (i.e., verifying model), against which the projections constructed using the rest of the models (i.e., predicting models) are verified. The procedure is cycled over all model combinations and the results averaged over the verifying models to obtain overall verification statistics for the methods. The authors showed that no single method performs best under all circumstances, and the performance of the methods depends on season and location.

Velázquez et al. (2014, unpublished manuscript) assessed the use of GCM simulations as pseudoreality observations in order to evaluate the time-invariance assumption of climate model biases (for temperature and precipitation) over the North American territory. They showed that the bias between two GCMs is comparable to the bias between observed data and one GCM in terms of magnitude and spatial and temporal structures. By considering one GCM ensemble simulation as pseudoreality observations and the other GCM ensemble simulations as climate simulations, they estimated the biases in the reference and future periods. They found that the differences between model simulations and observations vary between periods. In addition, the authors showed that such differences were not entirely caused by the internal variability of the climate model and suggested that this methodology will make it possible to evaluate the effect of nonstationary bias in hydrological climate change impact studies.

Bias-correction methods were evaluated and compared for their use in hydrological impact studies under the assumption of the time invariance of the climate model bias (e.g., Mpelasoka and Chiew 2009; Themeßl et al. 2011; Teutschbein and Seibert 2012; Chen at al. 2013b; Troin et al. 2015). Only the study of Teutschbein and Seibert (2013) has evaluated the performance of several bias-correction methods under varying climate conditions by performing a differential split-sample test on outputs from different RCMs over a 40-yr (1961–2000) period. They showed that more advanced correction methods (e.g., quantile–quantile mapping) perform better than simpler methods (e.g., local intensity scaling) when tested under contrasting climatic conditions.

The present study aims to evaluate the performance of one statistical bias-correction method when the climate

model bias is not time invariant and to determine its implications on hydrological climate change impact studies. In particular, this study focuses on

1) the error of the bias correction (for precipitation and temperature) in the future period when it is based on the hypothesis of the time invariance of the bias and
2) the effect of such error on the projected changes for hydrological indicators.

The pseudoreality approach is used in this study. The Soil and Water Assessment Tool (SWAT) hydrological model is fed by uncorrected and bias-corrected climate model outputs, which constitutes the hydroclimate model chain. A set of hydrological indicators is then estimated based on the hydrological simulations obtained for two Canadian catchments for the present and future periods.

The study is organized as follows: section 2 introduces the climate data and methodology, section 3 presents results, and a discussion and concluding remarks appear in section 4.

2. Data and methods

a. The climate ensemble simulations

The GCM ensemble simulations used in this work are the five members of the CCCma Coupled Global Climate Model, version 3 (CGCM3; Scinocca et al. 2008), and the three members of the Max Planck Institute for Meteorology ECHAM5 model (Jungclaus et al. 2006) under IPCC SRES A2 greenhouse gas emissions. The Canadian Regional Climate Model (CRCM), version 4.2.3, derived as an evolution of its previous versions (Caya and Laprise 1999; Laprise et al. 2003; Plummer et al. 2006), is the regional model used for the present investigation. The CRCM uses the Bechtold–Kain–Fritsch convective scheme (Bechtold et al. 2001). The simulated region covers the large North American domain (AMNO; 200×192 grid points) with a horizontal gridpoint spacing of 45 km (true at 60°N; Troin et al. 2015).

b. The pseudoreality approach

The pseudoreality approach includes an ensemble of CRCM simulations and a hydrological model. The pseudoreality approach considers one climate model simulation as pseudoreality observations (in present and future periods) in order to evaluate the effect of nonstationary bias on hydrological indicators. Climate model simulations are interchangeable as pseudoreality observations. The CRCM–CGCM3 simulations are used as the ensemble simulations to be corrected. Each

CRCM–ECHAM5 simulation is considered as a pseudoreality and is used to correct the bias in the CRCM–CGCM3 simulations. Considering each pseudoreality observation for correcting the bias in the climate model simulations makes it possible to assess the effect resulting from the availability of various observations on the bias-correction procedure.

The uncorrected and corrected CRCM–CGCM3 simulations are then used to drive the hydrological model for the study catchments over the reference (1971–2000) and future (2041–70) periods.

For the climate variables of interest, the monthly m bias over the reference (ref) period is computed as

$$b_{T_{(m)}^{\mathrm{ref}}} = T_{\mathrm{sim}(m)}^{\mathrm{ref}} - T_{\mathrm{obs}(m)}^{\mathrm{ref}} \qquad (1)$$

and

$$b_{P_{(m)}^{\mathrm{ref}}} = \frac{P_{\mathrm{sim}(m)}^{\mathrm{ref}}}{P_{\mathrm{obs}(m)}^{\mathrm{ref}}} - 1, \qquad (2)$$

where $b_{T_{(m)}^{\mathrm{ref}}}$ and $b_{P_{(m)}^{\mathrm{ref}}}$ are the biases in temperature and precipitation, respectively; $T_{\mathrm{obs}(m)}^{\mathrm{ref}}$ and $P_{\mathrm{obs}(m)}^{\mathrm{ref}}$ are the pseudoreality observed variable values; and $T_{\mathrm{sim}(m)}^{\mathrm{ref}}$ and $P_{\mathrm{sim}(m)}^{\mathrm{ref}}$ are the simulated variable values. The temperature is expressed in degrees Celsius and the precipitation is expressed in percentage (or mm day^{-1} when no relative bias is considered).

The biases in the future (fut) period $b_{T^{\mathrm{fut}}}$ and $b_{P^{\mathrm{fut}}}$ are computed in a similar manner, based on the differences between the future pseudoreality observations and the simulated variable values.

c. The bias-correction method

A comprehensive assessment of BC methods was conducted in many recent studies. Chen et al. (2013a) assessed the performance of six BC methods over 10 North American catchments. They classified the BC methods into mean- [e.g., linear scaling (Lenderink et al. 2007) and local intensity scaling (Schmidli et al. 2006)] and distribution-based methods [e.g., daily translation (DT; Mpelasoka and Chiew 2009) and quantile mapping (Themeßl et al. 2011)]. They showed that distribution-based methods are consistently better than mean-based methods. Mpelasoka and Chiew (2009) compared several postprocessing methods in the construction of runoff projection across Australia by using a lumped hydrological model. They showed that distribution-based methods are better at representing extreme runoff than the mean-based method because they take into account the increase in extreme daily rainfall.
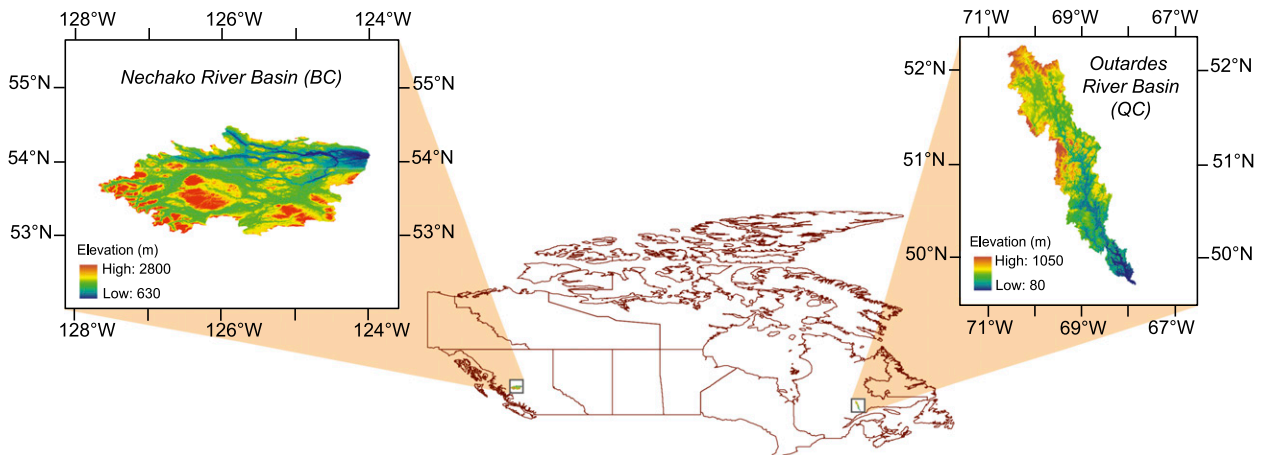
FIG. 1. Location of the Nechako and Outardes River basins.

The present study is conducted with the DT method, which has proven to be one of the best-performing methods in adjusting for model bias over the study catchments (Troin et al. 2015). This method was also used in many studies to correct bias in climate model simulations in order to evaluate the climate change impacts on water resources (e.g., Levison 2013; Mehdi et al. 2013; CEHQ 2013; Kurylyk and MacQuarrie 2013; Sulis et al. 2012). Despite the wide use of the DT method for climate change impact studies, the efficacy of the method is questioned. Maraun et al. (2010) pointed out that the DT approach does explicitly not consider the tail of the distribution, and extreme events might be misrepresented. Maraun (2013) showed that the spatial and temporal structures of the corrected time series are misrepresented with the DT approach, the drizzle effect for area means is overcorrected, and seasonal trends are affected. To overcome these problems, the use of stochastic bias correction is suggested (Wong et al. 2014).

In the present study, different correction factors (differences in percentiles between pseudo-observed and simulated data at the reference period) are applied to the frequency distribution of projected data for the future period. The DT method is applied on a monthly basis, and 100 percentiles are calculated for each month. Each model member is adjusted separately based on the transfer function established on the ensemble mean. The corrected temperature and precipitation in the reference period are computed with the following equations:

$$
\begin{aligned}
T(\text{corr})_d^{\text{ref}} &= T_{\text{sim}(d)}^{\text{ref}} + [T_{\text{obs}(m,q)}^{\text{ref}} - T_{\text{sim}(m,q)}^{\text{ref}}] \\
&= T_{\text{sim}(d)}^{\text{ref}} - b_{T_{(m,q)}^{\text{ref}}}
\end{aligned}
\tag{3}
$$

and

$$
P(\text{corr})_d^{\text{ref}} = P_d^{\text{ref}} \left[\frac{P_{\text{obs}(m,q)}^{\text{ref}}}{P_{\text{sim}(m,q)}^{\text{ref}}} \right] = P_d^{\text{ref}} \left[\frac{1}{b_{P_{(m,q)}^{\text{ref}}} + 1} \right],
\tag{4}
$$

where $T(\text{corr})$ and $P(\text{corr})$ are the bias-corrected variables and the indexes correspond to the percentile q, monthly m time step, and daily d time step. For the future period, the corrected precipitation and temperature are obtained as

$$
T(\text{corr})_d^{\text{fut}} = T_{\text{sim}(d)}^{\text{fut}} - b_{T_{(m,q)}^{\text{ref}}}
\tag{5}
$$

and

$$
P(\text{corr})_d^{\text{fut}} = P_d^{\text{fut}} \left[\frac{1}{b_{P_{(m,q)}^{\text{ref}}} + 1} \right].
\tag{6}
$$

d. Description of the study catchments

Two Canadian catchments were selected to conduct this analysis: the Outardes River basin ($15\,267\,\text{km}^2$) located in the province of Quebec and the Nechako River basin ($25\,105\,\text{km}^2$) located in the province of British Columbia. The surface hydrology of these basins is dominated by snowmelt processes. The catchments' locations and topography are presented in Fig. 1, and the general characteristics of the study basins are displayed in Table 1.

The Outardes River basin presents an elevation range from 80 to 1050 m and the Nechako River basin has an elevation range varying from 630 to 2800 m. Both catchments are mainly covered by forest. The two catchments are selected for this study because of their geographical locations in different regions in terms of

TABLE 1. General characteristics of the study basins. The type of climate is based on the Köppen–Geiger classification (Peel et al. 2007).

Type of climate	Nechako warm summer continental	Outardes continental subarctic
Annual average precipitation total (mm)	824	931
Snow ratio	41	36
Annual daily temperature (°C)		
Min	−40.2	−45.9
Max	+33.1	+32.4
Mean	+2.5	−1.5

topography and climate patterns. In addition, both basins are located in latitudes where the effects of projected warming are expected to be greatest (IPCC 2014). For example, the projected changes in mean annual temperature in central Quebec by the year 2050 (based on the baseline period 1961–90) is likely to range from 2.3° to 4.9°C, and the projected changes for mean annual precipitation should vary between 6% and 14% (DesJarlais et al. 2010). Regarding the Bulkley–Nechako region of British Columbia, the projected changes at year 2050 (from the baseline of the historical 1961–90 period) on mean annual temperature are expected to vary from 1.2° to 2.6°C, while the change of annual precipitation is projected to range between −2% and 14% (Pacific Climate Impacts Consortium 2012).

e. The hydrological model

The SWAT hydrological catchment model was chosen for this study (Arnold et al. 1998). SWAT is a physically based semidistributed model that operates at the daily time step (Neitsch et al. 2002). The hydrological model takes into account the spatial variability of the topography, land use, and soil type in order to represent the catchment in multiple hydrologic response units (HRUs). The input variables required to run SWAT are the daily precipitation and the daily maximum and minimum air temperatures. The watershed hydrology in SWAT is simulated in two steps. The first step is the land phase of the hydrologic cycle that calculates the water balance of each HRU in order to provide the amount of water available for each subbasin main channel at a given time step. The second step is the channel routing, which determines the progress of water through the river network toward the basin outlet (Neitsch et al. 2002). A detailed description of the model components is presented in Neitsch et al. (2005).

Technical details on model implementation and calibration as well as the statistical analysis of SWAT's performance at simulating streamflow over both catchments are presented in Troin et al. (2014, manuscript submitted to *J. Hydrol.*).

f. Hydrological indicators

Four hydrological indicators were selected to evaluate the impact of the statistical bias correction under nonstationary conditions on the catchment's hydrology. The hydrological indicators I are the following:

- The mean monthly streamflow Q_m, which is the mean of all of the daily values ($m^3 s^{-1}$) over a given monthly period.
- The 2-yr return period high flow (HF2), which is the flow exceeded on average every 2 years, or, in other words, that has a 50% chance of being exceeded in any given year.
- The 10-yr return period high flow (HF10), which is the flow that has a 10% chance of being exceeded in any given year. HF10 is an indicator of less common flows. Both high-flow indicators are evaluated from the time series of each year's maximum daily runoff.
- The 2-yr return period 7-day low flow (L7F2), which is calculated from a 7-day moving average applied on daily runoff data. The lowest value over a year is kept as the yearly low flow. A statistical distribution is fitted to the series of yearly low flows to compute the low flow that occurs statistically every 2 years.

To calculate L7F2 and HF2, it is assumed that the time series follow the log Pearson III probability density function (e.g., Muerth et al. 2013; Velázquez et al. 2013). These indicators are typically used to evaluate the climate change impacts on water resources over Quebec catchments (e.g., CEHQ 2013; Velázquez et al. 2013).

The relative error E between indicators is estimated as

$$E = \frac{I_{sim}^{ref} - I_{obs}^{ref}}{I_{obs}^{ref}}, \tag{7}$$

where E is the error computed in the reference period, I_{obs}^{ref} is the value of the indicator as computed from the pseudo-observed flows, and I_{sim}^{ref} is the indicator calculated from the simulated flows with the climate model simulations.

The impact of climate change on hydrological indicators ΔI_{sim} is expressed as the differences of simulated hydrological indicators from the reference I_{sim}^{ref} to the future period I_{sim}^{fut}:

$$\Delta I_{sim} = \frac{I_{sim}^{fut} - I_{sim}^{ref}}{I_{sim}^{ref}}. \tag{8}$$
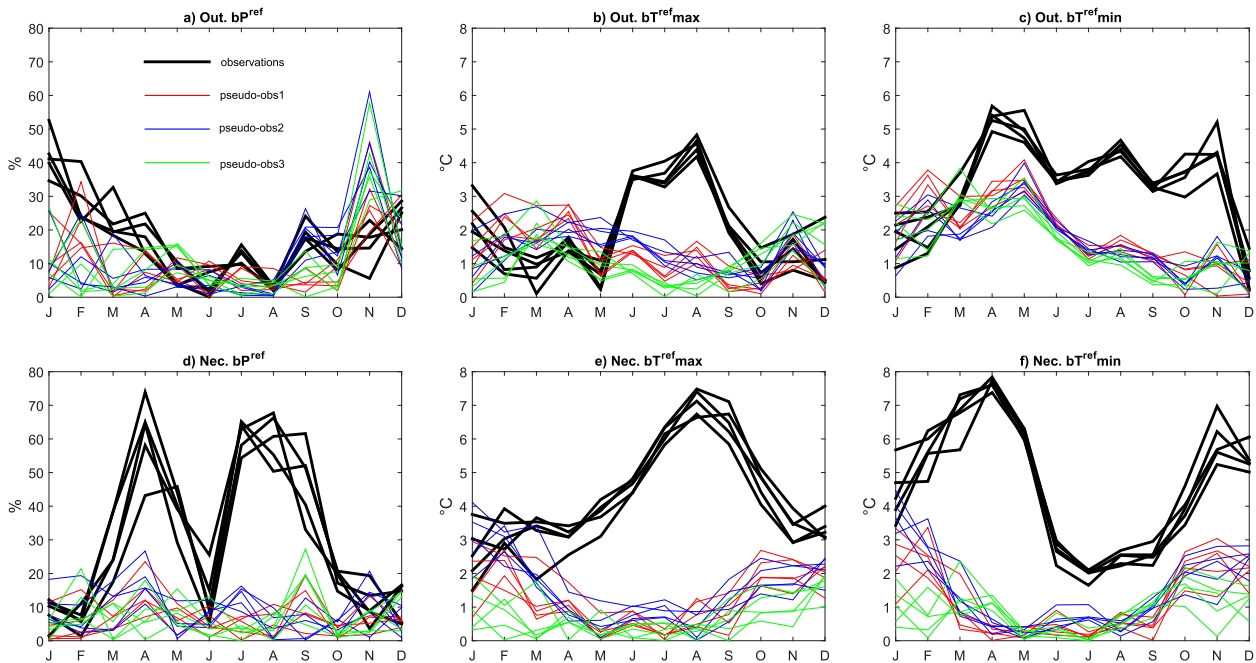
FIG. 2. The 30-yr mean monthly bias in reality and pseudoreality (absolute value) for precipitation, max temperature, and min temperature, as computed with Eqs. (1) and (2), for the (a)–(c) Outardes and (d)–(f) Nechako River basins over the 1971–2000 period.

3. Results and discussion

a. Climate model bias in reality and bias in pseudoreality

The CRCM's ability at reproducing observed climate patterns with respect to station observations over both catchments was evaluated in Troin et al. (2015). The CRCM provides considerable biases in precipitation and mean temperature over the two basins when comparing the simulated climate at the reference period with the observations. The CRCM shows a cold bias, particularly pronounced over the Nechako River basin. The model overestimates precipitation over the Nechako River basin while underestimating precipitation of the Outardes River basin by a smaller amount.

Figure 2 shows the 30-yr mean monthly bias for temperature and precipitation computed with Eqs. (1) and (2). The bias in reality is calculated as the difference between the climate simulations (CRCM–CGCM3 simulations) and the observations, while the bias in pseudoreality is computed as the difference between the climate simulations and each of the three pseudoreality observations (from the CRCM–ECHAM5 ensemble).

For the Outardes River basin, $b_{T_{\max}^{\mathrm{ref}}}$ is comparable in reality and in pseudoreality between October and May. For $b_{T_{\min}^{\mathrm{ref}}}$, the bias in reality and pseudoreality has similar values in winter (December–February), but shows

smaller values in pseudoreality than in reality the rest of the year. The $b_{P\mathrm{ref}}$ values in reality are somewhat covered in the envelope of $b_{P\mathrm{ref}}$ in pseudoreality. For the Nechako River basin, $b_{T_{\max}^{\mathrm{ref}}}$ and $b_{T_{\min}^{\mathrm{ref}}}$ have smaller values in pseudoreality than in reality. The envelope of $b_{P\mathrm{ref}}$ in pseudoreality covers the $b_{P\mathrm{ref}}$ values in reality only for the period extending from November to February.

The comparison of the biases in reality and in pseudoreality shows that, while they do share several features, they are not exactly the same. As this study focuses on the change in bias between two periods and not on the bias itself, the proposed pseudoreality approach can be used with confidence to evaluate the effect of nonstationary bias on hydrological indicators.

b. Evaluation of the BC performance under nonstationary conditions

The DT method is applied to the CRCM outputs in order to fit the distribution of temperature and precipitation (with a transfer function) with that of the pseudo-observations in the reference period. The transfer function is then applied to the meteorological variables' series in the future period.

Figures 3 and 4 show the scatterplots (for the Outardes and Nechako River basins, respectively) of the monthly precipitation bias b_P and monthly minimum
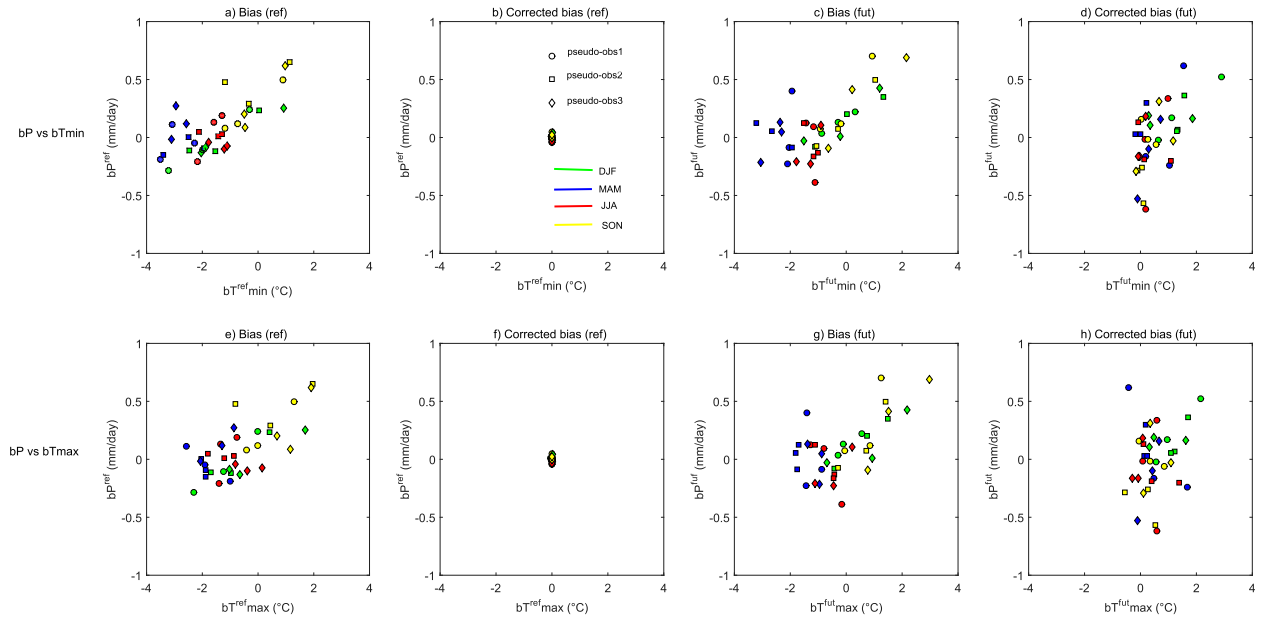
FIG. 3. Structure of monthly bias for the Outardes River basin (top) $b_{T_{min}}$ vs b_P and (bottom) $b_{T_{max}}$ vs b_P in the (a),(b),(e),(f) reference and (c),(d),(g),(h) future periods (a),(c),(e),(g) before and (b),(d),(f),(h) after bias correction.

temperature bias $b_{T_{min}}$, and also the scatterplots of b_P and monthly maximum temperature bias $b_{T_{max}}$. They allow us to compare the structure of the bias before and after bias correction in both the reference and future periods. We can see that the bias is well corrected in the reference period (Figs. 3b,f and 4b,f). However, the bias correction changes the temporal structure of the bias (Figs. 3d,h and 4d,h) in the future period. For instance, $b_{T_{min}}$ is mostly negative before correction over the Outardes River basin (Figs. 3a,c), while $b_{T_{min}}$ remaining bias changes to positive values in the future period after bias correction (Fig. 3d). Over the Nechako River basin, $b_{T_{min}}$ is mostly positive before bias correction (Figs. 4a,c) and moves to negative values in the future period after bias correction (Fig. 4d). Similar findings can be observed for $b_{T_{max}}$ (Figs. 4e,g,h).

The results reveal that, when the bias is not time invariant, the bias correction modifies the structure of the bias in the future period. In other words, when an expected future cold bias in temperature is corrected, it could lead, in the end, to a hot bias, as illustrated by the Outardes River basin.

c. Annual hydrological cycle

Figure 5 shows the mean monthly streamflows simulated by SWAT when forced by the uncorrected CRCM–CGCM3 simulations and the three pseudoreality observations over both basins in the reference period.

Over the Outardes River basin (Fig. 5a), the ensemble mean of the CRCM–CGCM3 simulations captures the

spring peak flow. The mean monthly discharge is underestimated in April by 60%, while it is overestimated for the summer and autumn seasons by 15%–30%. The Nechako River basin (Fig. 5b) shows a summer peak flow that is quite well represented by the ensemble mean of the CRCM–CGCM3 simulations. The differences in mean monthly discharges between CRCM–CGCM3 and the pseudoreality observations are smaller over that catchment; however, some discrepancies do exist. For example, the CRCM–CGCM3 ensemble mean overestimates the summer peak flow by 12% and the autumn streamflows by 25% when compared with pseudo-observation 3. The differences are expected to be reduced after the bias correction of the CRCM–CGCM3 ensemble simulations.

d. Impact of the nonstationary climate model bias on streamflow

SWAT was fed by each member of the CRCM–CGCM3 ensemble corrected using each member of the CRCM–ECHAM5 ensemble as pseudo-observation alternately. Thirty hydrological simulations were obtained for each basin, which served to estimate the hydrological indicators.

Figures 6 and 7 show the boxplots of the relative error [as computed with Eq. (7)] on monthly streamflow for the Outardes River basin and the Nechako River basin, respectively. The bias correction generally reduces the error on monthly streamflow in the reference period. Over the Outardes River basin, the median in the Q_m
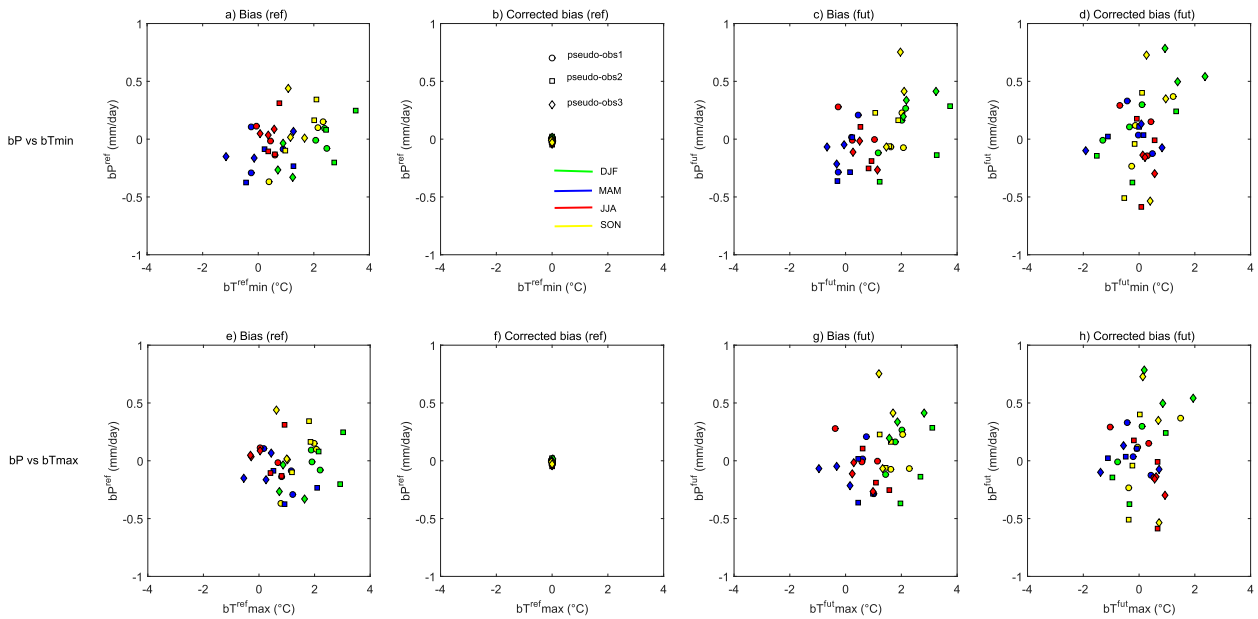
FIG. 4. As in Fig. 3, but for the Nechako River basin.

values is close to 0% after bias correction for the various pseudoreality observations. The error dispersion is also considerably reduced after bias correction. Similarly to the reference period, the direction of the change of the median values shifts from positive to (almost) negative values after bias correction in the future period. The bias correction can lead to improvement of the median error (e.g., from 22% to 3%, from 9% to −7%, and from 18% to 1% for pseudoreality observations 1, 2, and 3, respectively). The error dispersion is slightly reduced in the future period, depending on the pseudoreality observations used for evaluation.

The results for the Nechako River basin are rather similar to the results for the Outardes River basin: the bias correction in the reference period reduces both the median error and the dispersion of the error on monthly streamflow. In contrast, the median error slightly increases in the future period (for pseudo-observations 2 and 3), despite a reduction of the dispersion in the monthly streamflow. Of these results for both catchments, we can conclude that in the future period, the median error and dispersion are somewhat reduced by the bias correction.

The results for the other indicators are mixed. The median error (from the three pseudo-observations) of the HF10 varies from −4% to −13.7% for the Outardes River basin and from −12.6% to +0.5% for the Nechako River basin after bias correction in the reference period (Table 2). This suggests that the performance of the bias-correction method is site dependent. For instance, Chen et al. (2013a) show that the bias-correction methods are sounder for certain basins than for others, so that the performance of the bias-correction method varies according to the hydrological regime of the basin. In addition, Muerth et al. (2013) claim that the bias correction may affect different hydrological processes in different ways; those processes are intertwined in the hydrological model, and runoff is sometimes affected in unpredictable ways. Regarding the future period, Table 2 shows that the bias correction does not reduce the error on hydrological indicators when the bias is nonstationary for the Outardes River basin; however, for the Nechako River basin the error is somewhat corrected.

e. Impact of climate change signals on hydrological indicators

The expected impact of climate change on streamflow is analyzed with the quantification of the climate change signal (CCS) on hydrological indicators—the relative differences in the indicators between the reference and future periods. Figure 8 shows the relative change [as computed with Eq. (8)] on monthly streamflow calculated with both uncorrected and bias-corrected CRCM–CGCM3 simulations. For the Outardes River basin, the relative change on monthly streamflow is in the same direction in both the uncorrected and bias-corrected CRCM–CGCM3 simulations, with a positive CCS from November to May and a negative or close to zero CCS for the rest of the year. The CCS signal over the
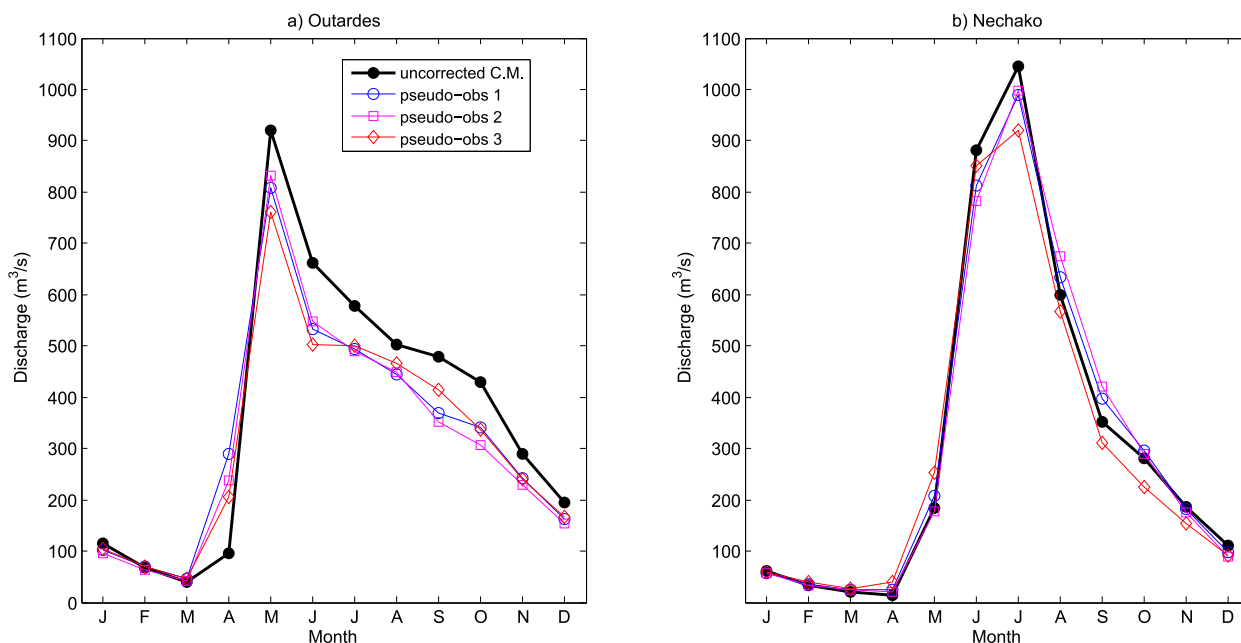
FIG. 5. Hydrographs for the (a) Outardes and (b) Nechako River basins over the reference period (1971–2000) forced by the uncorrected climate model and the pseudo-observations.

Nechako River basin indicates a similar direction in both the uncorrected and bias-corrected CRCM–CGCM3 simulations (positive from October to June and negative in summer).

Regarding the magnitude of the CCS, it can be seen that, for both catchments, the relative changes in monthly streamflow obtained with bias-corrected CRCM–CGCM3 simulations are very close to the changes obtained with uncorrected CRCM–CGCM3 simulations. The only exception is the beginning of the flood (in April), where differences are higher.

The larger positive changes of monthly streamflow for winter and spring could result from increase in temperature, which would lead to less snow and more liquid precipitation (Troin et al. 2015). The small negative change in summer monthly discharge could be explained by the increase in evapotranspiration due to the increase in temperature, thus reducing streamflow (DesJarlais et al. 2010).

The impact of the CCS on high- and low-flow indicators is summarized in Table 3. Over the Outardes River basin, the direction and the magnitude of the relative changes derived from the uncorrected and bias-corrected CRCM–CGCM3 simulations are comparable. The CCS on HF2 ranges from 22.5% to 43.1% with bias-corrected CRCM–CGCM3 simulations that encompasses the value of the CCS on HF2 (25%) from uncorrected CRCM–CGCM3 simulations. However, some discrepancies between uncorrected and bias-corrected

CRCM–CGCM3 simulations can be noticed for HF10, with a CCS value of 77.7% for the uncorrected CRCM–CGCM3 simulations compared to the 33.7%–58.4% range for the bias-corrected CRCM–CGCM3 simulations. Similar findings are noticeable for L7F2 over that catchment.

Regarding the Nechako River basin, the CCS on HF2 and HF10 are positive with bias-corrected CRCM–CGCM3 simulations and negative with uncorrected CRCM–CGCM3 climate simulations. The CCS on L7F2 is of smaller magnitude in the bias-corrected CRCM–CGCM3 simulations than in the CRCM–CGCM3 uncorrected simulations.

For the investigated catchments, the direction of the relative changes on the hydrological indicators obtained with bias correction is generally the same as for the changes obtained with uncorrected climate simulations. The magnitude of the CCS is also comparable for most hydrological indicators. The only exception is the CCS on high flows over the Nechako River basin, which shifts from negative to positive values after bias correction. The shift of direction on climate change signal was observed in the catchment with the smaller biases (see Fig. 2), so the nonstationarity of bias can have more influence on the performance of bias correction when biases are small.

It was recently stated that the bias correction is safe to use in order to produce coherent present and future hydroclimatic scenarios for adaptation strategies, since
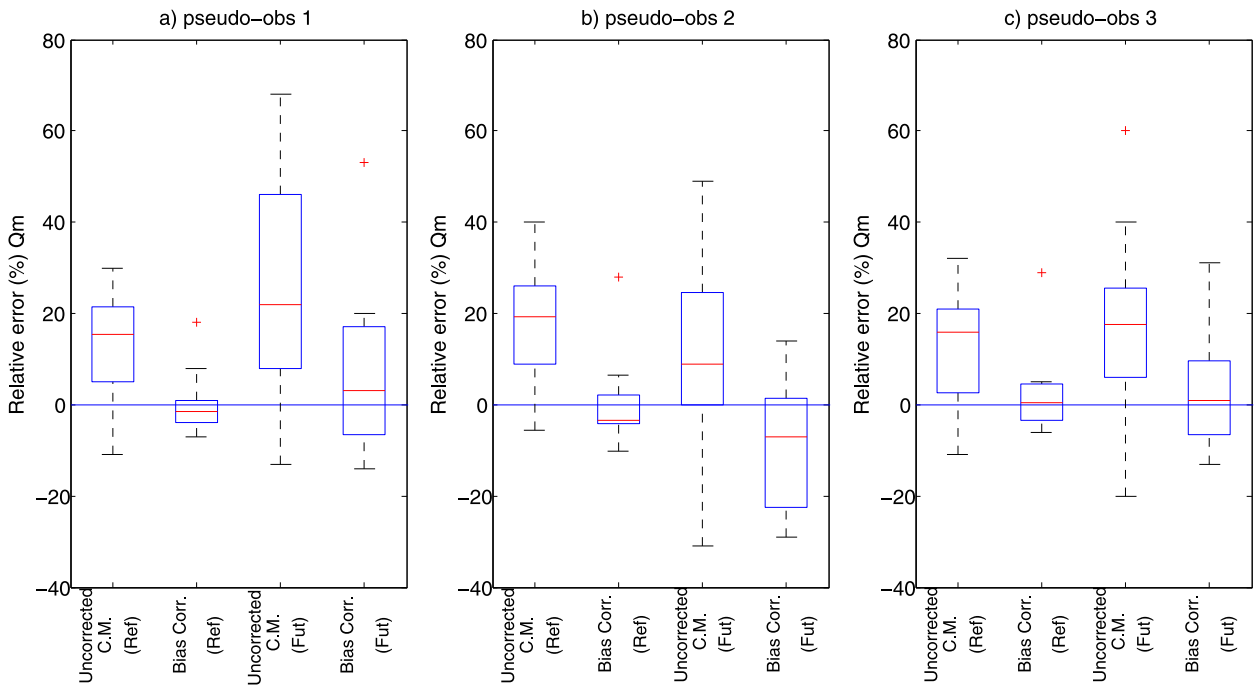
FIG. 6. Boxplots of the relative errors on Q_m for the Outardes River basin, between the indicator obtained from climate model (labeled "C.M.") simulations and from the pseudo-observations [as computed with Eq. (7)] with and without bias correction, for the reference (1971–2000) and future (2041–70) periods. On each box, the central mark is the median, the edges of the box are the 25th and 75th percentiles, and the whiskers extend to the 99th percentile.

it does not significantly alter the CCS of hydrological indicators (Muerth et al. 2013). However, our results demonstrate that the CCS on extreme hydrological indicators are less stable than that on mean monthly streamflow, and that the CCS can change when the bias correction is made under nonstationary conditions.

4. Conclusions

Climate change impact studies on water resources have a large source of uncertainties. The uncertainties arise from the climate scenarios, the climate model, the statistical postprocessing and the hydrological model. These uncertainties have a different weight on the projected future change in streamflow. Graham et al. (2007) found that GCM forcing has a larger impact on the projected hydrological changes than the selected emission scenario or RCM. The choice of hydrological model also has an important impact on the climate change response in terms of hydrological indicators (e.g., Ludwig et al. 2009). Regarding the uncertainty related to bias correction, Chen et al. (2013a) showed that the use of only one bias-correction method could give misleading results in climate change impact studies.

Bias correction is applied under the main assumption that bias is time invariant; however, this assumption is

being challenged. To the authors' knowledge, the uncertainty related to the time invariance of the bias on hydrological climate change impact studies has not been explored. This study therefore assesses the impact of one statistical bias-correction method under nonstationary conditions on hydrological indicators with the pseudoreality approach. Comparison with other sources of uncertainty is out of the scope of the present study.

The pseudoreality approach used in the present study considers each simulation in the CRCM–ECHAM5 ensemble as one pseudoreality observation; the pseudoreality observations are then used to correct the climate model (i.e., the CRCM–CGCM3) ensemble simulations in the reference period. The pseudoreality approach also includes the SWAT hydrological model.

First, the statistical relationship established in the reference period between the climate model simulation and the pseudoreality observations is used to correct the future climate model simulation. The selected bias-correction method is the distribution-based DT method. Second, the uncorrected and bias-corrected CRCM–CGCM3 simulations are used to drive SWAT. Finally, four hydrological indicators in the reference and future periods are estimated from the hydrological simulations. The main findings of this study are as follows:
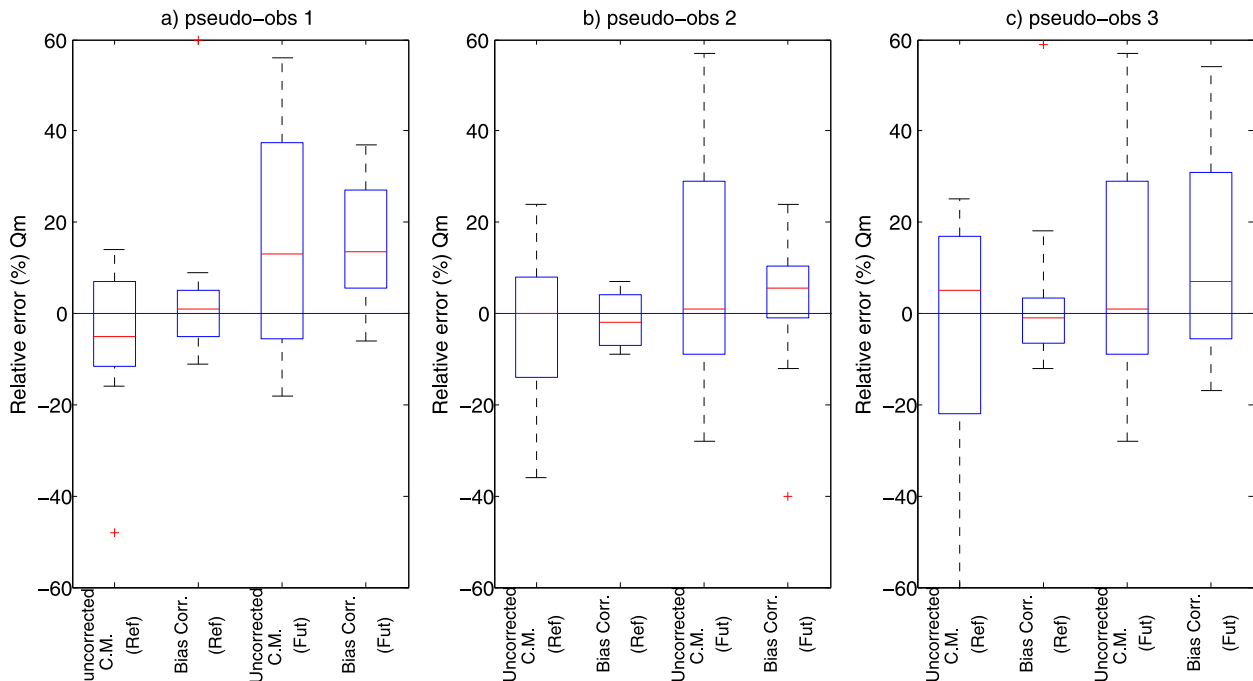
FIG. 7. As in Fig. 6, but for the Nechako River basin.

1) Under nonstationary conditions, biases remain (in precipitation and temperature) after bias correction in the future period, which are comparable to the biases of uncorrected climate simulations. Furthermore, the bias correction could change the structure (i.e., precipitation vs temperature) of the biases in the future period.

2) Bias correction decreases the error on monthly streamflow for the reference period. In the future period, the median error and dispersion are somewhat reduced.

3) The climate change signals on hydrological indicators, obtained with uncorrected and bias-corrected simulations, are similar in magnitude and direction for most of the hydrological indicators. Regarding the high-flow indicators, the findings are mixed and more site dependent.

Our results show that the temporal structure of the bias changes after the application of bias correction. The change of structure in bias with time results from both the non-stationary of bias and the natural variability of the climate. In our pseudoreality approach, both features partly explain the "poor" performance of the bias-correction method. The influence of the natural variability on bias correction has been recently explored by Chen et al. (2015).

The efficacy of the bias correction has been also recently debated. Eden et al. (2012) argue that model errors caused by parameterization and orography can reasonably be corrected by bias correction, but not for systematic bias in large-scale atmospheric states. Our study shows that bias correction under a nonstationary bias is an additional source of uncertainty for impact studies. An adjustment of the climate variables to correct for model biases is often necessary for a meaningful translation of climate projections to the hydrological scale. However, as the future bias is unknown, both bias-corrected and uncorrected climate variables should be considered in order to evaluate the effect of bias correction on the climate change signal on hydrological indicators (e.g., Muerth et al. 2013; Troin et al. 2015). Furthermore, a bias reduction could be achieved on the basis of a better understanding of the cause of biases in climate models (Addor and Seibert 2014).

Our pseudoreality approach rests on a physically based, semidistributed hydrological model. Recent studies showed that the choice of the hydrological model strongly affects the estimation of climate change response of impacts on hydrological indicators, especially those related to low flows (Maurer et al. 2010; Najafi et al. 2011; Velázquez et al. 2013). Further investigations will be dedicated to an ensemble of hydrological models with different degrees of complexity in order to take into account the uncertainty related to the hydrological model.

TABLE 2. Median relative error (%) in hydrological indicators obtained from the climate model simulations and the pseudo-observations [as computed with Eq. (7)] with and without bias correction, for the reference (1971–2000) and future (2041–70) periods over the Outardes and Nechako River basins.

	Error (%) uncorrected climate model (ref)	Error (%) bias-corrected climate model (ref)	Error (%) uncorrected climate model (fut)	Error (%) bias-corrected climate model (fut)
Outardes				
HF2	1.8	−6.7	17.2	−3.5
HF10	−4.0	−13.7	18.6	−26.9
L7F2	−31.4	−15.8	29.5	36.6
Nechako				
HF2	−3.8	−3.4	−10.8	−6.0
HF10	−12.6	0.5	−30.2	−7.5
L7F2	−26.5	7.8	56.8	31.0

The study of Teutschbein and Seibert (2013) assessed several bias-correction methods under contrasting conditions. Their findings were that simpler methods (e.g., the linear transformation) result in large deviations and are the least reliable under changed conditions; they recommended the use of a more complex method, such as the distribution mapping. Our results show that even a complex method, such as DT, leads to important deviations in future biases. Further investigations based on the pseudoreality approach with a range of bias-correction methods are therefore necessary in order to generalize our findings. In addition, the experiment should be repeated in basins where the biases (in reality and pseudoreality) have a comparable magnitude in order to extend our conclusions.

Finally, the pseudoreality approach used in this study is based on two CRCM–GCM combinations; additional RCMs should be included to reinforce the results, in particular, to fill the gap of the bias magnitude between reality and pseudoreality. This study focuses on two northern-latitude catchments where the hydrological cycle is dominated by snow accumulation and melting. The results could differ for rainfall-driven catchments where the hydrological response will be more sensitive to biases in precipitation.
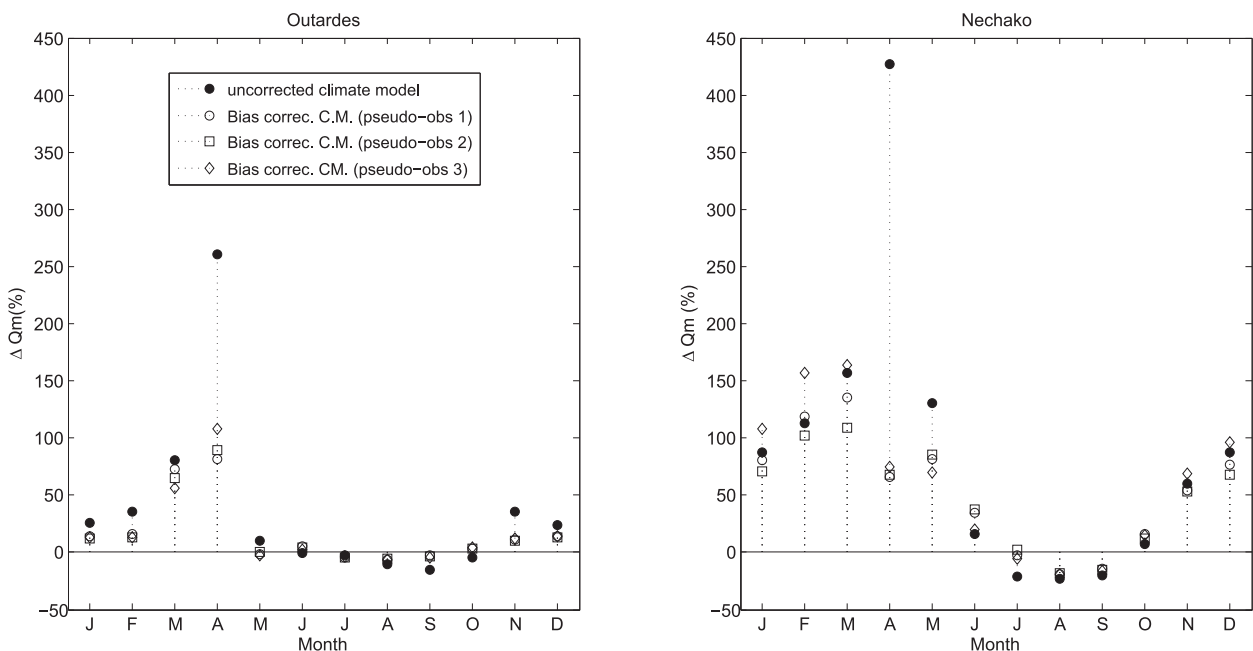

FIG. 8. Relative changes in Q_m between the reference and future periods [as calculated with Eq. (8)], with the indicator obtained with the uncorrected and bias-corrected climate model simulations (labeled "Bias correc. C.M.") for the (left) Outardes and (right) Nechako River basins.

TABLE 3. Relative changes in hydrological indicators between the reference and future periods [as computed with Eq. (8)] for the Outardes and Nechako River basins.

	ΔI (%) uncorrected climate model	ΔI (%) bias-corrected climate model (pseudo-observation 1)	ΔI (%) bias-corrected climate model (pseudo-observation 2)	ΔI (%) bias-corrected climate model (pseudo-observation 3)
Outardes				
HF2	25	23.9	22.5	43.1
HF10	77.7	39.8	33.7	58.4
L7F2	82.6	54.4	36.8	68.3
Nechako				
HF2	−5.7	13.6	15.5	7.9
HF10	−6.2	23.0	23.1	26.4
L7F2	272	130	111	218

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