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Systematic temperature and precipitation biases in the CLARIS-LPB ensemble simulations over South America and possible implications for climate projections

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ABSTRACT: Within the framework of the CLARIS-LPB EU Project, a suite of 7 coordinated Regional Climate Model (RCM) simulations over South America driven by both the ERA-Interim reanalysis and a set of Global Climate Models (GCMs) were evaluated. The systematic biases in simulating monthly mean temperature and precipitation from the 2 sets of RCM simulations were identified. The Climate Research Unit dataset was used as a reference. The systematic model errors were more dependent on the RCMs than on the driving GCMs. Most RCMs showed a systematic temperature overestimation and precipitation underestimation over the La Plata Basin region. Model biases were not invariant, but a temperature-dependent temperature bias and a precipitation-dependent precipitation bias were apparent for the region, with the warm bias amplified for warm months and the dry bias amplified for wet months. In a climate change scenario, the relationship between model bias behaviour and the projected climate change for each individual model revealed that the models with the largest temperature bias amplification projected the largest warming and the models with the largest dry bias amplification projected the smallest precipitation increase, suggesting that models' bias behaviour may affect the future climate projections. After correcting model biases by means of a quantile-based mapping bias correction method, projected temperature changes were systematically reduced, and projected precipitation changes were systematically increased. Though applying bias correction methodologies to projected climate conditions is controversial, this study demonstrates that bias correction methodologies should be considered in order to better interpret climate change signals.

KEY WORDS: Regional Climate Models · Regional climate change · South America · Systematic bias · La Plata Basin

1. INTRODUCTION

The demand for high-resolution regional climate projections from the impact-assessment community has increased during recent years, in response to the need to develop adaptation measures and strategies to future climate conditions. Driven by ongoing evidence of the impact of the increase of greenhouse gas (GHG) concentrations on the recent climate, the scientific community has undergone an unprecedented development to provide valuable climate scenario information to the impact community. Though during recent years there has been enormous progress on the development of comprehensive Global Climate Models (GCMs), GCMs generally operate on a spatial resolution that is insufficient to account for regional scale forcings that modulate the regional climate (Giorgi et al. 2009). In response to this limita-

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tion, Regional Climate Models (RCMs) have been largely developed as one of the more promising tools to spatially refine the GCM climate information and provide high-resolution products for climate change assessment studies (IPCC 2014). This approach has been increasingly employed in a number of collaborative research projects devoted to produce coordinated RCM experiments over the major continental areas of the world, such as CORDEX (Giorgi et al. 2009), ENSEMBLES for Europe (Christensen & Christensen 2007) and NARCAPP for North America (Mearns et al. 2013), among others. For South America (SA), the first collaborative effort in producing a coordinated RCM experiment has been developed within the framework of the CLARIS-LPB EU Project (http://eolo.cima.fcen.uba.ar/~sweb). The CLARIS-LPB RCM ensemble, described by Sánchez et al. (2015), allowed both the provision of high-resolution climate change information over SA and evaluation of uncertainties in regional climate change projections.

It has already been discussed in the literature that regional climate projections are affected by several sources of uncertainty associated with internal variability, the GHGs emission scenario and the model's imperfections, with the last factor the most relevant at the regional scales for longer lead times (Hawkins & Sutton 2011). The uncertainty due to model imperfections comes from the model's deficiencies in reproducing observed climate conditions, and one of the key concerns is whether the biases in the simulated present climate conditions will remain invariant under changing climate conditions. As discussed by Christensen et al. (2008) and Boberg & Christensen (2012), the assumption of invariability of model's biases may not be appropriate, with serious implications for the interpretation of the projected climate change. In these studies, the authors identified a temperature-dependent temperature bias, suggesting that models may amplify the warming signal under future climate conditions. Hence, one of the necessary steps before exploring and interpreting future climate provided by RCMs is the evaluation of model performance to identify systematic biases in reproducing present climate conditions and to explore the bias behaviour.

Moreover, when dealing with RCMs, it is also well known that biases in the simulated climate may be due to errors in the driving model and errors in the RCM itself (Giorgi et al. 2009). Though it is difficult to identify the source of model's biases, a standard procedure in the RCM community has been to carry out an evaluation of the simulated climate under the 'perfect boundary setting', which means driving the RCMs by reanalysis. Though reanalyses are not perfect, and RCMs nested into different reanalysis datasets can produce different biases (de Elía et al. 2008), this approach allows identification of biases due to RCM imperfections, rather than biases due to errors in the boundary forcing data. However, for the scenario projection analysis, RCMs are driven by GCMs; therefore, errors in the large-scale forcing, inherited through the boundary conditions, are combined with the errors in the RCM itself. Consequently, exploring both reanalysis-driven and GCM-driven RCM simulations is necessary in order to quantify RCM performance under current climate conditions and to identify the source of RCM errors.

Following this common approach, under the CLARIS-LPB coordinated experiment, 2 sets of RCM simulations were performed. For evaluation purposes, a set of 7 RCMs was driven by the ERA-Interim reanalysis dataset. This reanalysis-driven RCM ensemble allowed the identification of model deficiencies in reproducing the current climate over SA (Solman et al. 2013, hereafter So13). Particularly over the La Plata Basin (LPB) region, almost every RCM depicts a systematic underestimation of rainfall and overestimation of temperature, suggesting common shortcomings in every RCM. For the climate projection framework, the RCMs were nested into a set of 3 CMIP3 GCMs under the SRES A1B emission scenario, hereafter the CLARIS-LPB ensemble. Sánchez et al. (2015) (hereafter Sa15) summarized the main features of the CLARIS-LPB ensemble, identifying the main biases in the present climate simulated by the GCM-driven RCMs, the climate change signal and their associated uncertainties over the SA continent.

The analyses performed in So13 and Sa15 suggested that the set of RCM simulations, driven either by reanalysis or GCMs, share common biases in simulating the observed temperature and precipitation patterns over SA. However, it is still not clear if the intrinsic RCM imperfections are the main source of model biases when models are driven by GCMs. Moreover, exploring the behaviour of model biases is also necessary to assess the validity of the assumption that model biases are invariant, which may contribute to better interpret the climate change signal, as suggested by Christensen et al. (2008). The climate change signal identified in Sa15 suggested a warming and wetting trend projected at the end of the 21st century over the LPB region. Therefore, it is worth exploring the extent to which the behaviour of model biases may affect the projected changes. Moreover, identifying the behaviour of model biases

is also useful for developing bias correction methodologies, widely used by the impact community.

In this context, the focus of this study is twofold: (1) to characterize the biases in simulating the mean temperature and precipitation in the CLARIS-LPB ensemble to identify whether the model biases are GCM- or RCM-dependent, which would help identify possible paths for model improvements; (2) to evaluate the bias behaviour to determine how the bias may affect the future climate change signal.

The analysis is focused on both the ERA-Interim and GCM-driven RCM simulations from the CLARIS-LPB ensemble described in So13 and Sa15. To explore the source of model biases, the analysis covers also the driving GCMs and ERA-Interim datasets.

2. DATASETS AND METHODOLOGY

2.1. Datasets: the evaluation and projection frameworks of the CLARIS-LPB ensemble

Two sets of simulations from the CLARIS-LPB ensemble are used in this study: a set of 7 RCM simulations driven by the ERA-Interim reanalysis dataset (Dee et al. 2011) for the period 1990–2008 and a set of 11 RCM simulations driven by 3 CMIP3 GCMs for the SRES A1B emission scenario, covering the periods 1961–1990, 2011–2040 and 2071–2100. Details of the 2 sets of RCM simulations can be found in So13 and Sa15, respectively. All simulations have been performed for the SA domain at 50 km horizontal resolution, following the CORDEX protocol. Table 1 summarizes the simulations evaluated in this study.

The matrix of RCM simulations available includes different RCM/GCM combinations. All RCMs are driven by the ERA-Interim reanalysis dataset and at least 1 GCM, allowing for evaluation of the extent to which the biases in the present climate simulations are dominated by RCM imperfections or by the driving model errors. Moreover, some RCMs are driven by more than 1 GCM, which allows for identification of the extent to which the bias in the RCM simulation is amplified or reduced by superimposing the intrinsic bias of the RCM to the bias in the driving model. Finally, several RCMs are driven by the same GCM, making it possible to explore the impact of the bias in the driving model on the RCM results.

For evaluation purposes, all present-climate simulations have been compared against the Climate Research Unit (CRU) observational dataset version 3.1 (Mitchell & Jones 2005) for the corresponding present climate conditions. Monthly mean temperature and precipitation data from all RCM simulations have been interpolated onto a common regular 0.5° × 0.5° latitude–longitude grid. Details of the interpolation procedure can be found in So13.

2.2. Methodology and metrics

First, the mean biases for both the seasonal mean temperature and precipitation are identified from the set of simulations described above. To explore the spatial structure of the mean biases, differences between each model and the reference dataset are evaluated for austral summer (December-January-February, DJF) and austral winter (June-July-August, JJA) seasons for the whole SA domain. As mentioned above, one of the regions in the SA continent where all models seem to share similar biases is the LPB region, defined as between 65° and 55°W and between 40° and 25°S (see the red box in the upper left panel of Fig. 1). For this reason, the analysis of model bias behaviour is focused in the LPB region.

For the reanalysis-driven simulations, both temperature and precipitation biases are analysed by means of scatter plots of area-averaged monthly mean bias against observations, as in Christensen et al. (2008). This analysis can be used to reveal the validity of the assumption of model bias invariability, and also the range of the biases.

For the GCM-driven simulations, this comparison is not possible because the model's calendar does not necessarily correspond to the real world. Instead, monthly mean values averaged within the LPB region from both the model and observations were ranked independently in ascending order to produce

Table 1. Matrix of RCM simulations from the CLARIS-LPB ensemble for both the ERAI-Interim driven and GCM-driven frameworks

Driving model	RCM						
	ETA	LMDZ	MM5	PROMES	RCA	REGCM3	REMO
ERA-Interim	×	×	×	×	×	×	×
HadCM3-Q0	×		×	×		×	
EC5OM-R1					×	×	
EC5OM-R2					×		
EC5OM-R3		×			×		×
IPSL		×					

a q–q plot which spans the range of simulated versus observed values and the correspondence among them, following the methodology employed by Boberg & Christensen (2012).

Finally, a bias correction method based on the quantile-quantile approach, as used by Saurral et al. (2013), was applied to the modelled monthly mean temperature and precipitation for both present and future periods from a subset of RCMs to highlight the possible implications of varying biases for the interpretation of the climate change signal. Details of the bias correction methodology are given in Section 3.3.

3. RESULTS

3.1. Characterizing the mean biases of the RCM simulated temperature and precipitation

Figs. 1 & 2 display the seasonal mean temperature bias for DJF and JJA, respectively, as depicted by the driving models and the RCMs for the ERA-Interim driven and the GCM-driven RCMs listed in Table 1. Because not every RCM has been driven by every GCM, and in order to organize the panels to explore the RCM/GCM combinations, the figure is organized by putting the RCMs in columns and GCMs in rows, so that gaps indicate that the intersection of the given RCM/GCM is not available. Note that the order of the panels in Figs. 1 to 4 is the same as in Table 1.

For DJF, the ERA-Interim driven simulations, displayed in the first row of Fig. 1, show that the bias in simulating the austral summer temperatures over the SA continent has a spatial distribution that differs from the bias in the driving reanalysis, suggesting that the biases are more dependent on the RCM itself that on the driving model. The ERA-Interim reanalysis depicts a negative bias over the tropics, but individual RCMs display both positive and negative biases depending on the RCM. Note also a systematic positive and negative bias over the western and eastern subtropical Andes, respectively. Over LPB, though the bias in the ERA-Interim reanalysis is very small, a systematic warm bias can be identified from every RCM, as already pointed out in So13, with the magnitude of this warm bias varying from model to model (the PROMES and ETA RCMs depict the largest biases; the RCA and LMDZ RCMs depict the smallest biases). The spatial structure of the bias from the set of GCMs varies from model to model, although, again, every driving GCM depicts a similar behaviour over LPB. Note that the spatial structure of the bias in the GCM-driven RCMs is largely dominated by the RCM itself rather than by the model providing the driving forcing. For the GCM-driven RCMs, the warm bias over LPB is the common feature, except for the LMDZ RCM. This analysis suggests that the errors in the RCMs dominate when combined with the errors inherited through the boundary conditions.

For JJA (Fig. 2), the impact of the biases in the driving models on the biases in the RCMs seems to have a similar behaviour as for DJF, with the bias more dependent on the RCM than on the driving model. Model biases over tropical SA spread over a wide range of values, with no systematic errors shared by the set of RCMs evaluated here. Over the subtropical Andes region, a systematic bias is apparent, as for DJF.

Focusing on LPB, from both the ERA-Interim and GCM-driven simulations, it is apparent that the biases are smaller compared with those in the warm season, with some RCMs depicting negative biases (such as LMDZ and REGCM3). Note also that the combined effect of GCM and RCM biases can be highly non-linear; for some RCMs, the bias can either be stronger or be of opposite sign compared with the driving GCM (as for PROMES/HadCM3 and ETA/HadCM3), but for other RCMs, the bias can be additive (as for REMO/EC5OM3). Overall, every RCM seems to share a similar bias over the LPB region, with a strong warm bias during DJF and weak warm bias or even cold bias during JJA.

Seasonal mean precipitation biases for the austral summer and winter seasons are displayed in Figs. 3 & 4, respectively. Note that the bias is displayed as a percentage, so that areas with rainfall <1 mm mo^{-1} are masked out. SA rainfall is characterized by a monsoon regime, with rainfall over most of the continent (particularly from the Amazon basin to the LPB areas) predominantly during the summertime (Marengo et al. 2012). From Fig. 3, a common shortcoming of every model, both global and regional, is the strong underestimation of the monsoonal precipitation, particularly over the western Amazon basin and over the LPB region. From the ERA-Interim-driven simulations, it is evident that the pattern of the seasonal bias is highly RCM-dependent. Moreover, there is a large discrepancy among RCMs on the sign of the bias mainly over tropical SA. Over LPB, though most RCMs systematically underestimate summer rainfall, there are some exceptions. In particular, the MM5, RCA and REMO RCMs depict a positive precipitation bias. When the models are driven by GCMs, the spatial pattern of the rainfall bias generally agrees with that of the ERA-Interim driven simulations, suggesting that, as for temperature, the bias is more dependent on the RCMs

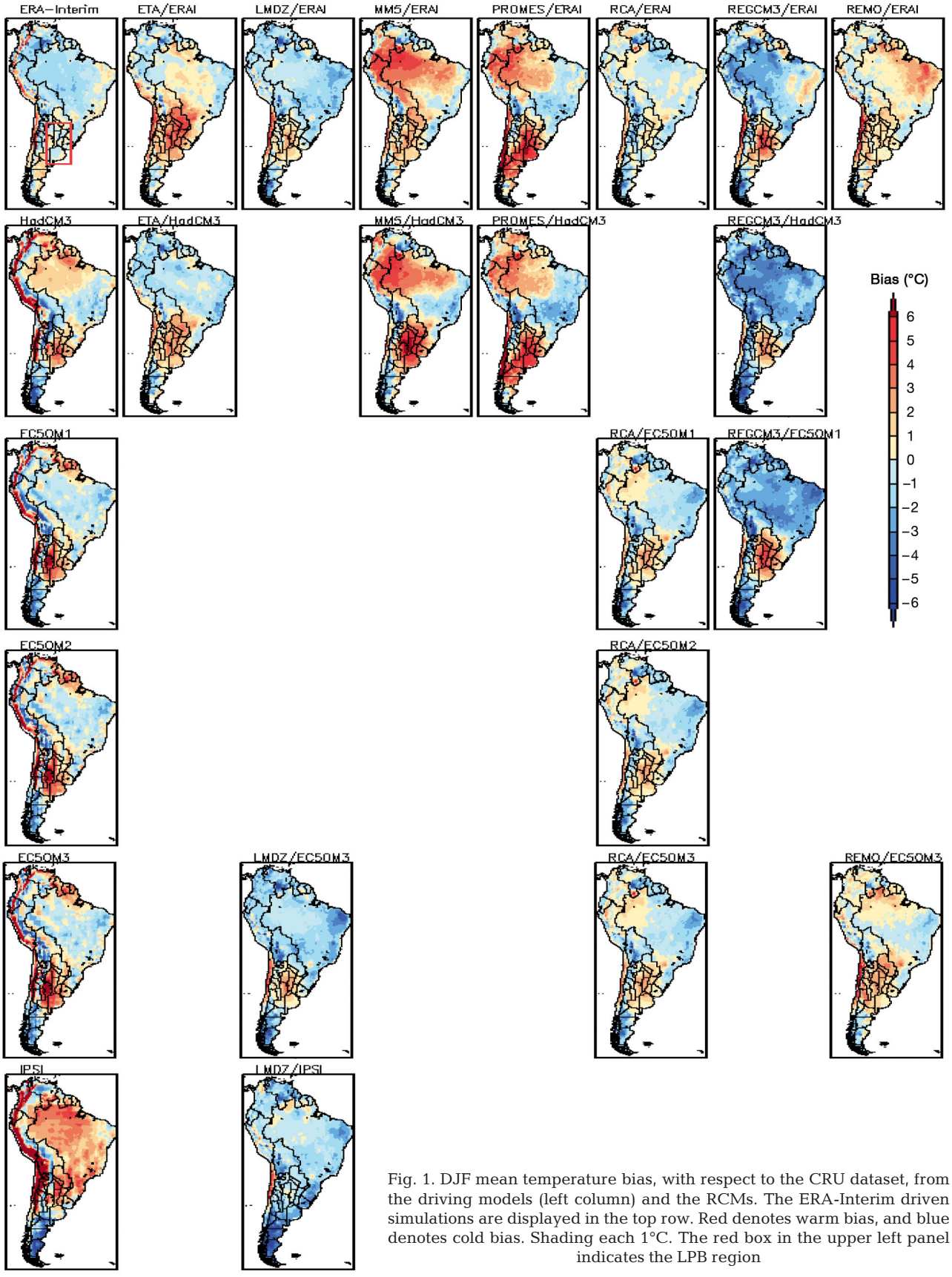

Fig. 1. DJF mean temperature bias, with respect to the CRU dataset, from the driving models (left column) and the RCMs. The ERA-Interim driven simulations are displayed in the top row. Red denotes warm bias, and blue denotes cold bias. Shading each 1°C. The red box in the upper left panel indicates the LPB region

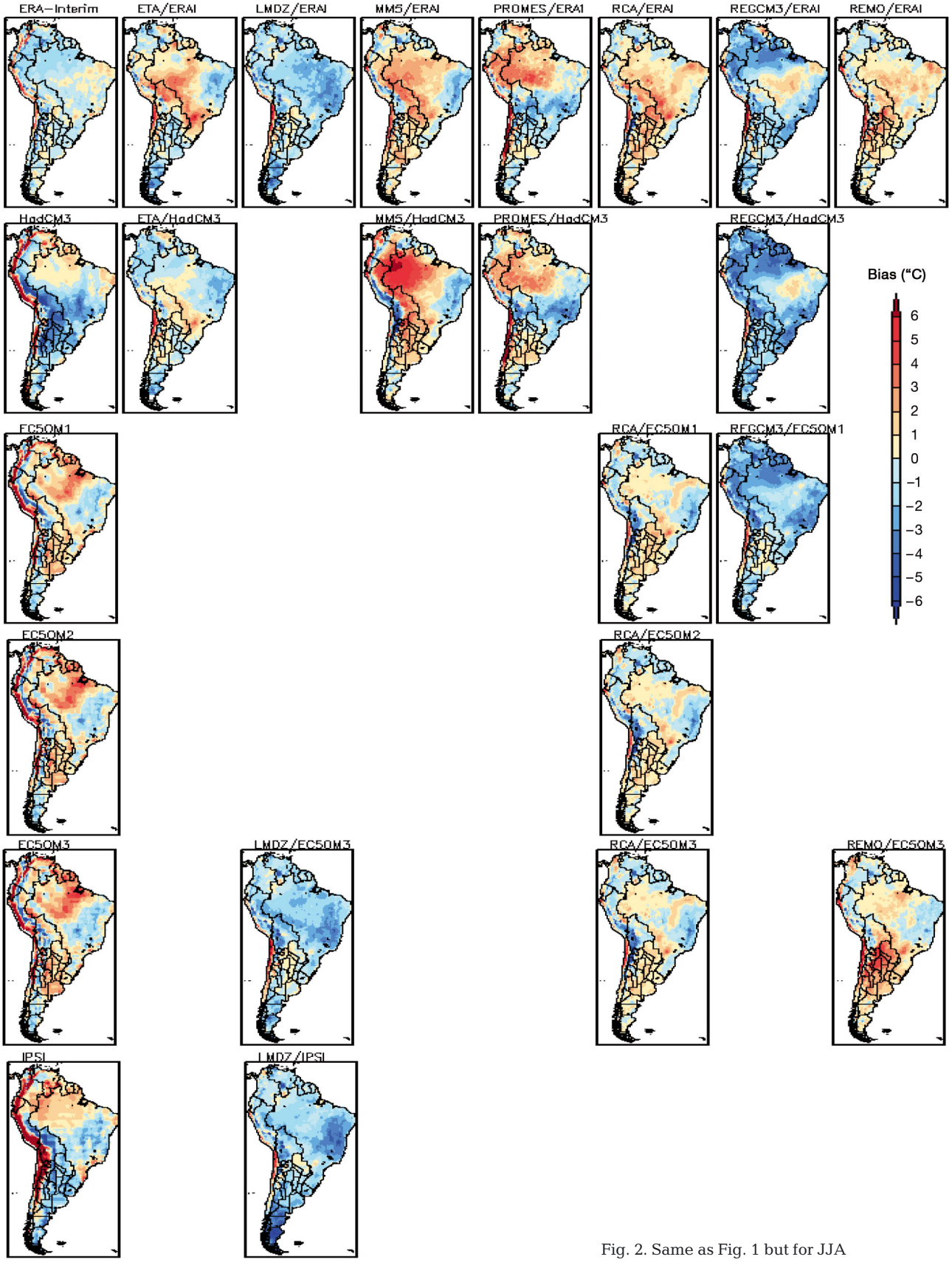

Fig. 2. Same as Fig. 1 but for JJA

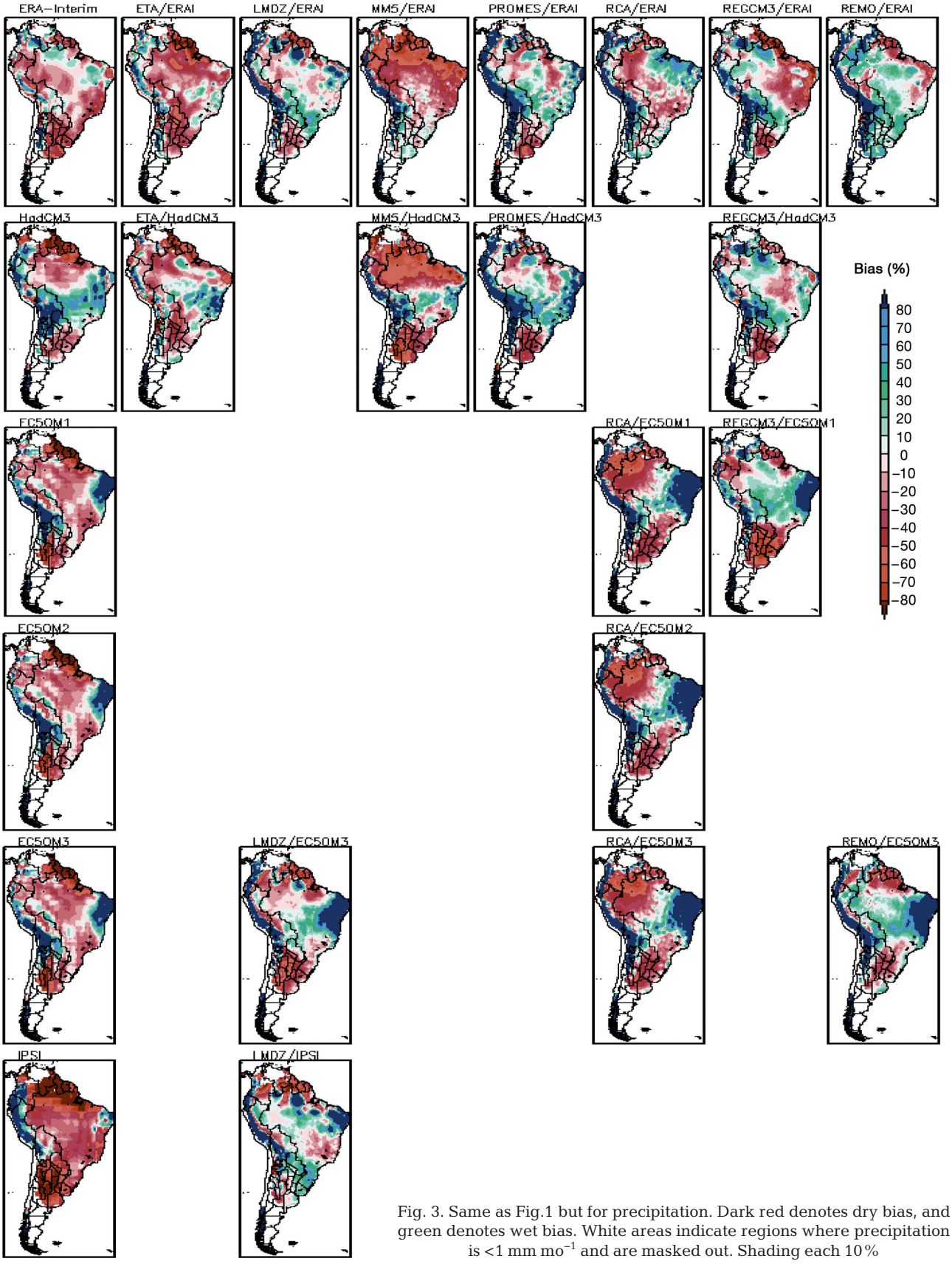

Fig. 3. Same as Fig.1 but for precipitation. Dark red denotes dry bias, and green denotes wet bias. White areas indicate regions where precipitation is <1 mm mo^{-1} and are masked out. Shading each 10 %

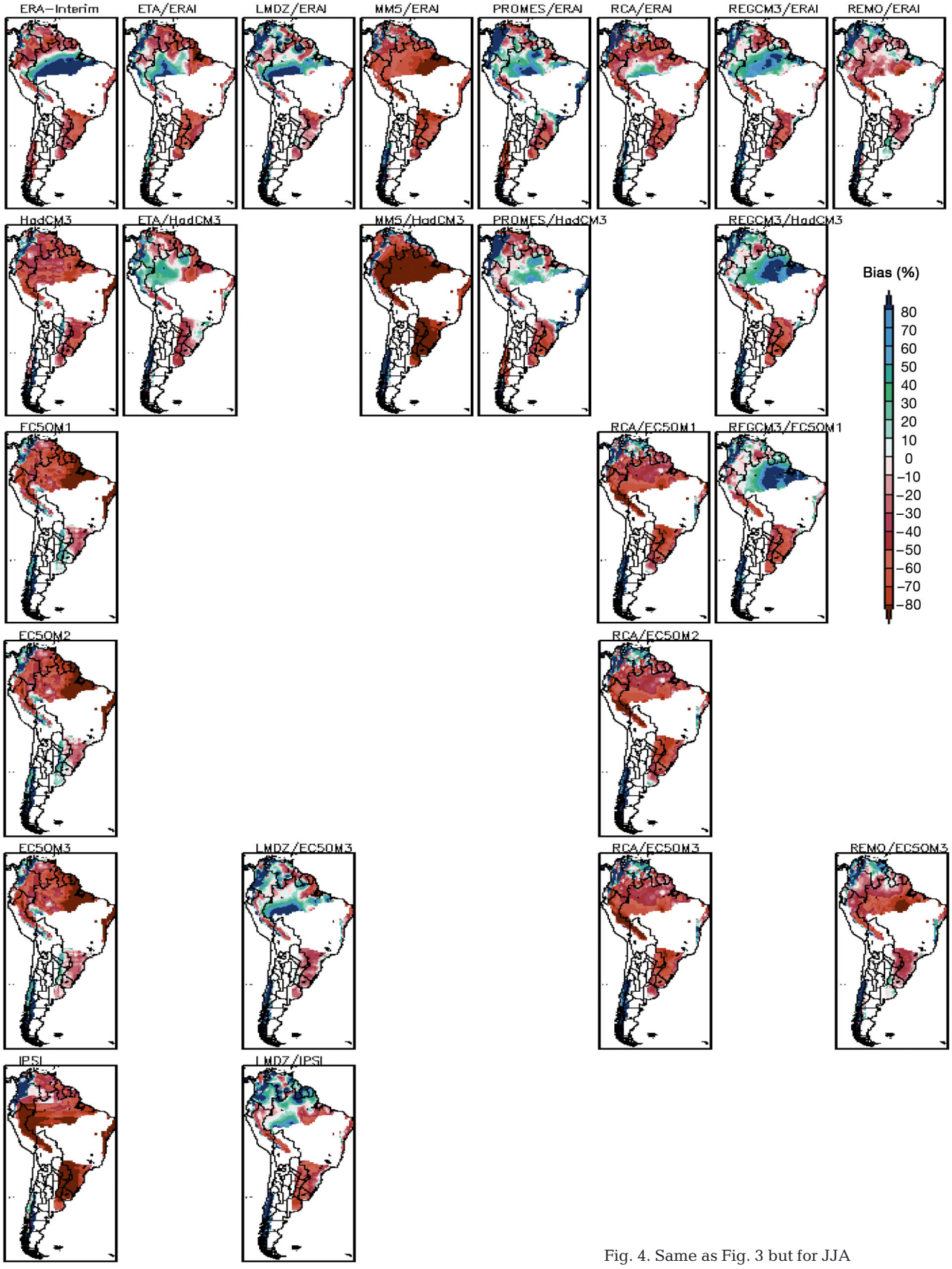

Fig. 4. Same as Fig. 3 but for JJA

than on the model providing the lateral boundary conditions. The GCM-driven simulations are characterized by larger biases, compared with those from the ERA-Interim driven ones. This pattern is particularly evident over the LPB region, where rainfall is systematically underestimated by every RCM, except for the LMDZ/IPSL model. As for modelling exercises over other regions of the world, the quality of the GCM-driven RCM simulations is generally poorer compared with that of the reanalysis-driven simulations (Jacob et al. 2007).

During the austral winter, large amounts of rainfall occur over the northern part of the SA continent (associated with the intertropical convergence zone [ICTZ]); dry conditions are apparent over most of the Amazon basin, and a secondary maximum is apparent over LPB. As for summer, most of the driving models, including the ERA-Interim reanalysis, fail in reproducing the observed rainfall pattern, with a strong underestimation of rainfall over the rainy areas (northern SA and LPB), though ERA-Interim seems to display a southward shift in the ICTZ. The reanalysis-driven simulations display a variety of biases over the northern part of SA but a systematic dry bias over the LPB region, as noted in So13. For the GCM-driven set of simulations, the dry bias over the LPB region is one of the most prominent features in every RCM, as already mentioned in Sa15, even when the driving model depicts the opposite behaviour (as for the EC5OM GCM). Note that even during wintertime, when forcing due to the large-scale circulation exerts a larger control on the regional climate compared with the regional-scale forcing, the errors introduced by imperfect RCM formulations still have a dominant role.

Though understanding the source of model errors is out of the scope of this study, the errors in reproducing the observed climate may be associated with errors in the land-surface interaction, particularly over LPB, where a strong land-atmosphere coupling during the summer months suggests that biases in temperature may be associated with biases in soil moisture, as found by Sorensson & Berbery (2015) and Ruscica et al. (2014). Underestimated rainfall may lead to dryer soils, which may amplify warm temperature biases in a positive feedback mechanism. Biases over complex topography regions may be affected by several sources, including the model's orography, the quality of the CRU data set and the interpolation procedure.

The analysis above allowed identification of the LPB region as one of the regions of the SA continent where models share similar biases, being warmer and dryer than observed.

It is also apparent that the warm and dry biases are generally larger during the summer season. The next step is to evaluate the behaviour of the biases, particularly over the LPB region, to assess the dependence of model biases on the climate regime.

3.2. Behaviour of model biases

To explore the behaviour of the model biases, the monthly mean temperature and precipitation biases averaged over the LPB region from the ERA-Interim driven simulations are analysed. Fig. 5 displays the monthly mean temperature bias plotted against the observed temperatures for the period 1990 to 2008 for the ERA-Interim reanalysis and for the individual RCMs. As noted in the previous analysis, the ERA-Interim reanalysis depicts a good agreement with the observations, with the temperature bias close to zero for the whole range of observed temperatures. However, for most of the RCMs, except for the RCA and REMO RCMs, the temperature bias is not invariant but increases as the observed temperature increases, suggesting that the warm bias is amplified for warmer months. Moreover, most RCMs tend to depict negative biases for colder conditions and positive biases for warmer conditions. Note that the dependency between the bias and the observed temperature is model-dependent. This behaviour is similar to that found by Christensen et al. (2008) over Europe for the Mediterranean region.

A similar analysis for precipitation (Fig. 6) suggests that the systematic underestimation of rainfall is exacerbated for wetter months for both the driving reanalysis and the RCMs, except for the REMO RCM. Overall, for the ERA-Interim driven RCM simulations, most of the RCMs depict temperature-dependent temperature biases (larger warm bias for warmer conditions) and precipitation-dependent precipitation biases, (larger dry bias for wetter conditions), suggesting that the biases are certainly not invariant but have a dependency on the mean climate conditions.

Though results from Figs. 1 to 4 suggest that the bias for any given RCM does not depend strongly on which model provides the boundary conditions, it is expected that imperfect boundary conditions have an impact on the quality of RCM results. Accordingly, to compare the bias behaviour from the ERA-Interim and GCM-driven simulations, the modelled and observed temperatures are compared from the 2 sets of present climate simulations. Fig. 7 displays the ranked modelled versus ranked observed tem-

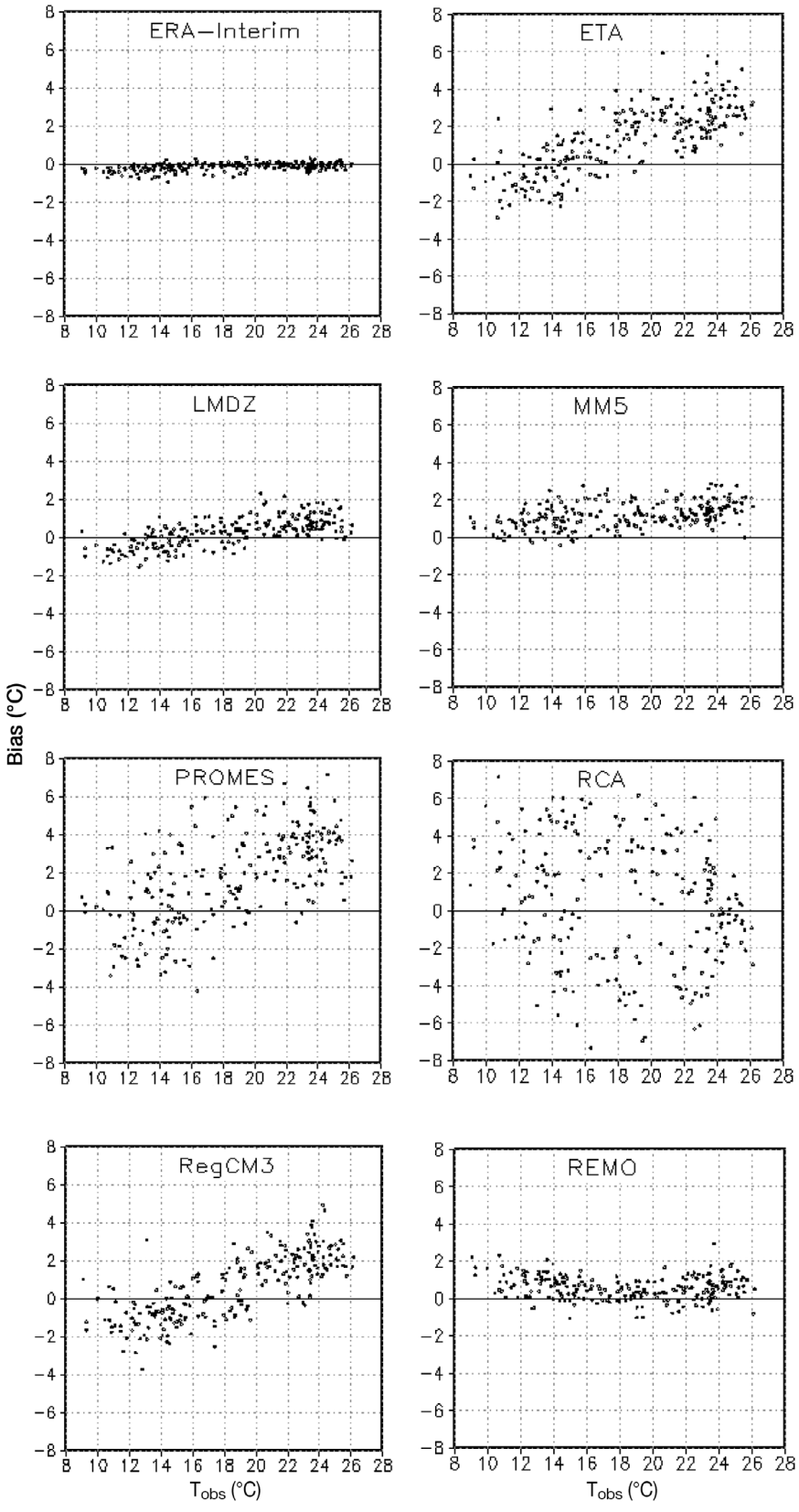

Fig. 5. Monthly mean model temperature bias versus monthly mean observed temperature for the ERA-Interim driven RCM simulations for the La Plata Basin region

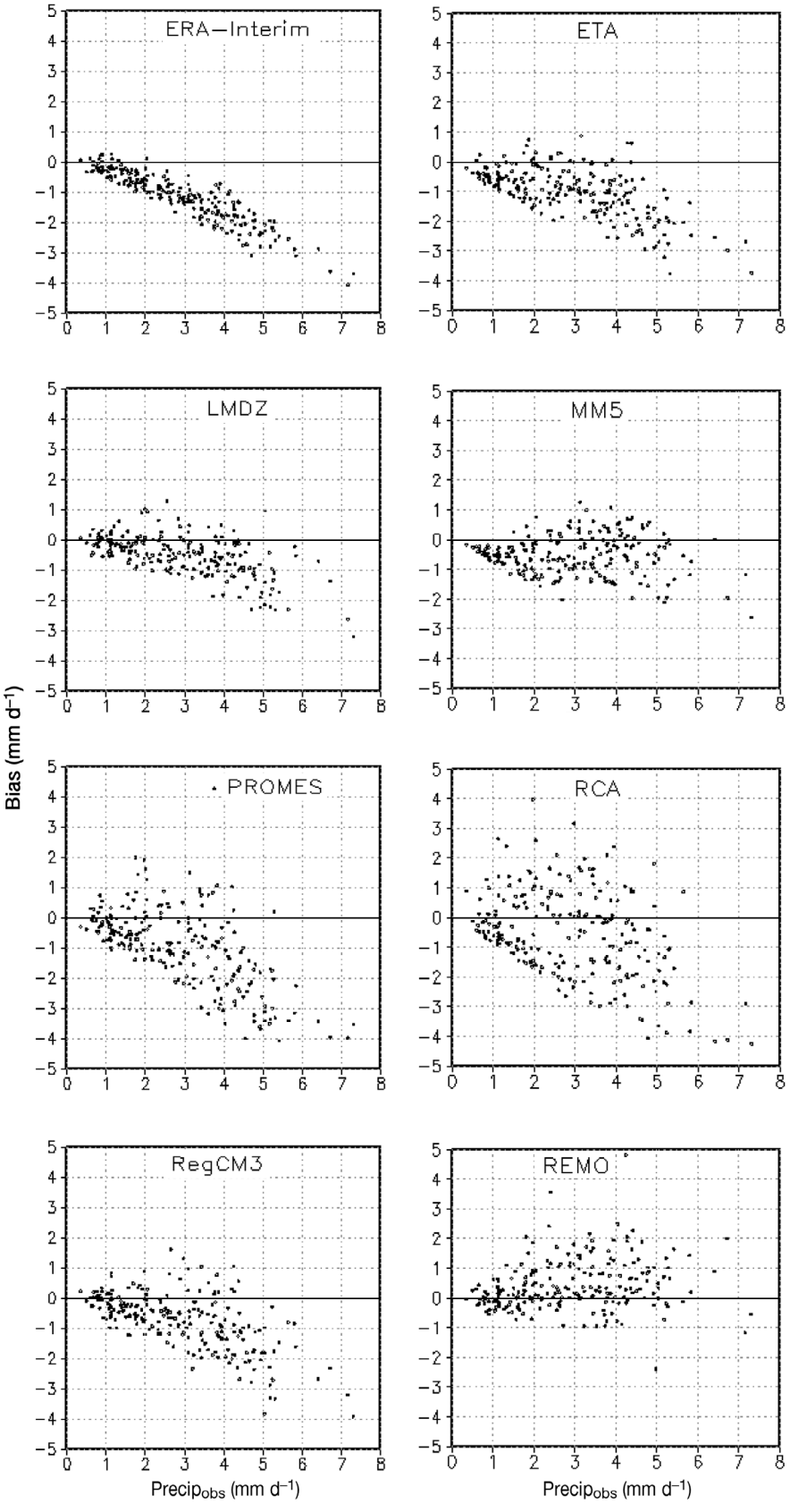

Fig. 6. Same as Fig. 5 but for precipitation

peratures averaged over the LPB region for each individual RCM from both the ERA-Interim and the GCM-driven simulations. As discussed above, for the ERA-Interim driven simulations, the warm bias increases with increasng observed temperature for almost every RCM, except for the LMDZ and REMO models, indicating that larger biases occur during warmer months. For the GCM-driven simulations, the temperature bias also increases with increasing temperature. Note that the bias is also generally larger for the GCM-driven compared with the ERA-Interim driven simulations, as expected.

To quantify the bias dependence on the mean climate conditions, a simple linear fit based on minimum least squares between the modelled and observed ranked temperatures was computed. For a perfect model, the slope of the linear fit should be equal to 1 and should intercept the *y*-axis at zero. A slope > 1 indicates that the warm bias is amplified for higher temperatures. The intercept indicates a con-

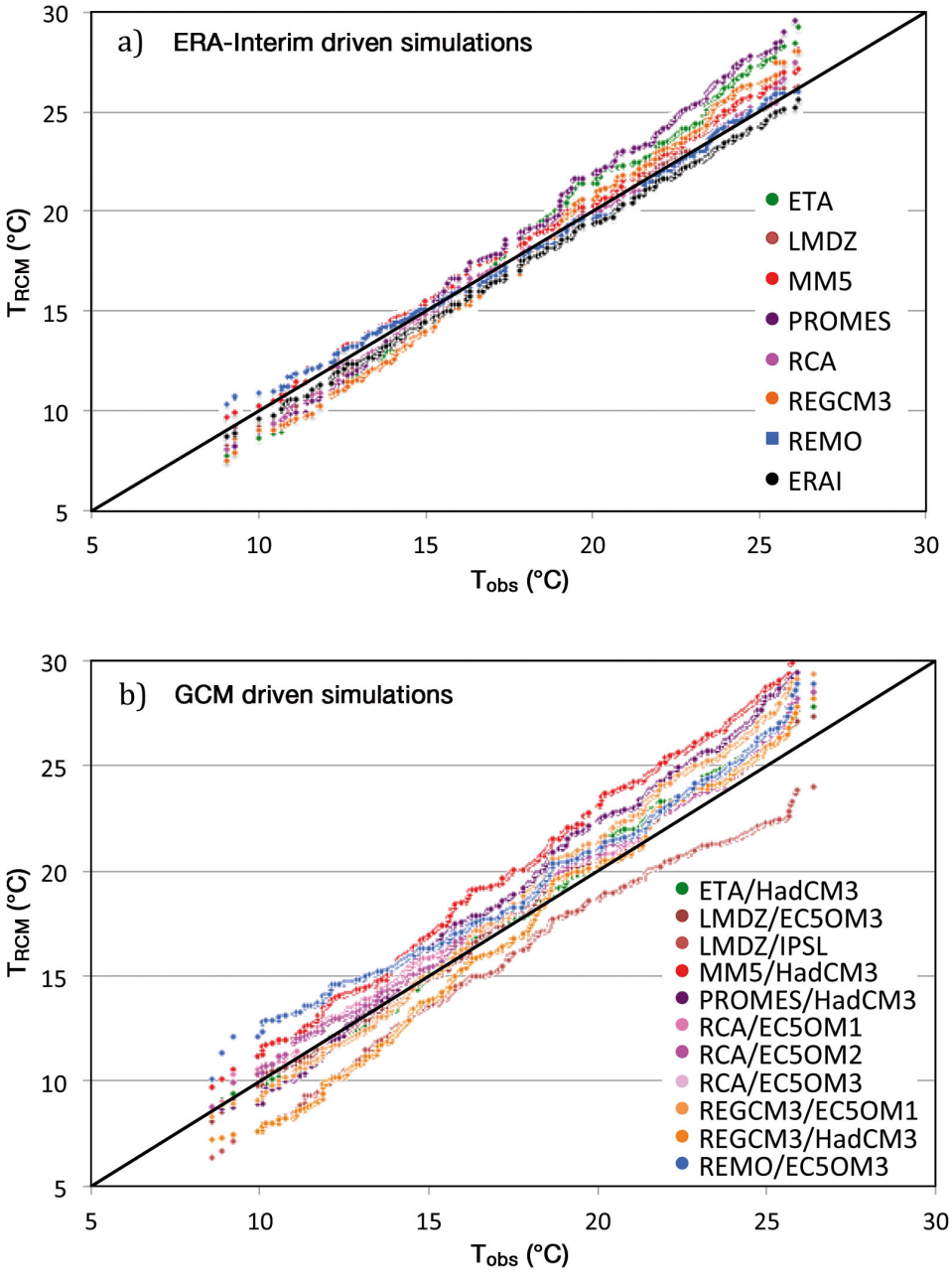

Fig. 7. Ranked monthly mean simulated temperatures versus ranked observed temperatures averaged over the La Plata Basin. (a) RCMs driven by the ERA-Interim reanalysis for the period 1990–2008. (b) RCMs driven by GCMs for the period 1961–1990

stant bias. Table 2 depicts the slope, the intercept and the goodness of fit, measured as the correlation coefficient between the linear fit and the modelled temperatures for the GCM-driven RCM simulations as well as for the GCM results.

For every model, except the LMDZ/IPSL and REMO/EC5OM3 RCMs, the slope is >1 (Table 2), indicating that the warm bias is amplified for higher temperatures, and hence, a temperature-dependent bias is apparent. Note that a similar behaviour is also found for the driving GCMs.

These results suggest that RCMs and GCMs share similar deficiencies, with most of the models depicting larger warm biases during warmer months. Considering these results, the question is whether the temperature bias behaviour identified may affect the projected warming under future climate conditions. Boberg & Christensen (2012) and Christensen & Boberg (2012) demonstrated that temperature-dependent temperature bias is a common behaviour for several regions of the world and may amplify the regional warming signal under future climate conditions. Before exploring the possible implications of this temperature-dependent temperature bias on the future climate projections over the LPB region, the precipitation biases are discussed.

The behaviour of precipitation biases is depicted in Fig. 8, where ranked modelled precipitation is plotted against ranked observed precipitation. For the ERA-Interim driven simulations, the underestimation of rainfall is apparent. Furthermore, the negative precipitation bias is larger for the wetter months, except for the REMO RCM. Recall that the larger rainfall amounts over the LPB region occur during the warm season. For the GCM-driven simulations, the behaviour of model precipitation biases agrees with that from the ERA-Interim driven simulations; however, the biases are generally larger. A summary of the linear fits between the ranked modelled and observed precipitation over the LPB region is displayed in Table 3.

Table 2. Linear fit based on least squares between modelled and observed ranked temperatures averaged over the LPB region. The columns indicate the model, the slope, the intercept and the correlation coefficient, respectively

Model	Slope	Intercept	R
ETA/HadCM3	1.154	−2.397	0.998
LMDZ/EC5OM3	1.084	−1.223	0.998
LMDZ/IPSL	0.958	−1.062	0.988
MM5/HadCM3	1.165	−0.517	0.998
PROMES/HadCM3	1.238	−2.844	0.995
RCA/EC5OM1	1.018	0.493	0.997
RCA/EC5OM2	1.035	0.121	0.997
RCA/EC5OM3	1.236	−3.413	0.998
REGCM3/EC5OM1	1.035	0.121	0.997
REGCM3/HadCM3	1.251	−5.056	0.995
REMO/EC5OM3	0.943	2.400	0.992
HadCM3	1.276	−5.730	0.997
EC5OM1	1.078	−0.018	0.994
EC5OM2	1.086	−0.213	0.994
EC5OM3	1.094	−0.098	0.994
IPSL	1.241	−5.291	0.995

Note that for all the models, except for the LMDZ/IPSL model, the slopes of the linear fit are <1, indicating that the underestimation of rainfall is larger for wetter months. The driving GCMs also depict a similar behaviour. In summary, all the models underestimate rainfall over the LPB region, with the dry bias exacerbated for wetter months.

Overall, inspection of the behaviour of the temperature and precipitation biases over the LPB region suggests that RCMs are affected by temperature-dependent temperature biases (warmer biases for warmer months) and precipitation-dependent precipitation biases (dryer biases for wetter months). The bias slopes computed above quantify the amplification of the warm and dry biases, respectively. Though the behaviour of model biases is similar from the 2 sets of simulations evaluated here, the ERA-Interim driven and the GCM-driven simulations, it is important to note that the magnitude of the biases is generally larger for the latter. Consequently, identifying biases in a perfect boundary conditions approach may help in exploring possible paths for model improvements. However, biases in GCM-driven simulations for the present climate conditions are largely affected by both errors in the RCMs and the driving models.

As discussed in Sa15, the CLARIS-LPB ensemble projects warmer and wetter conditions over the LPB region at the end of the 21st century, particularly for the summer season. The projected temperature and precipitation changes are largely controlled by the forcing GCM and the RCM that modulates the regional climate change signal, but also by the intrinsic systematic bias from the RCM/GCM model. It is then expected that the bias behaviour identified may have implications for interpreting the regional climate change projections. Boberg & Christensen (2012) demonstrated that the projected warming during summer over central and Mediterranean Europe was overestimated due to a temperature-dependent warm bias. With this in mind, the next section is devoted to assessing the impact of the biases on the projected climate change signal over the LPB region, particularly during the summer months. The key question is how the biases identified may affect future climate projections.

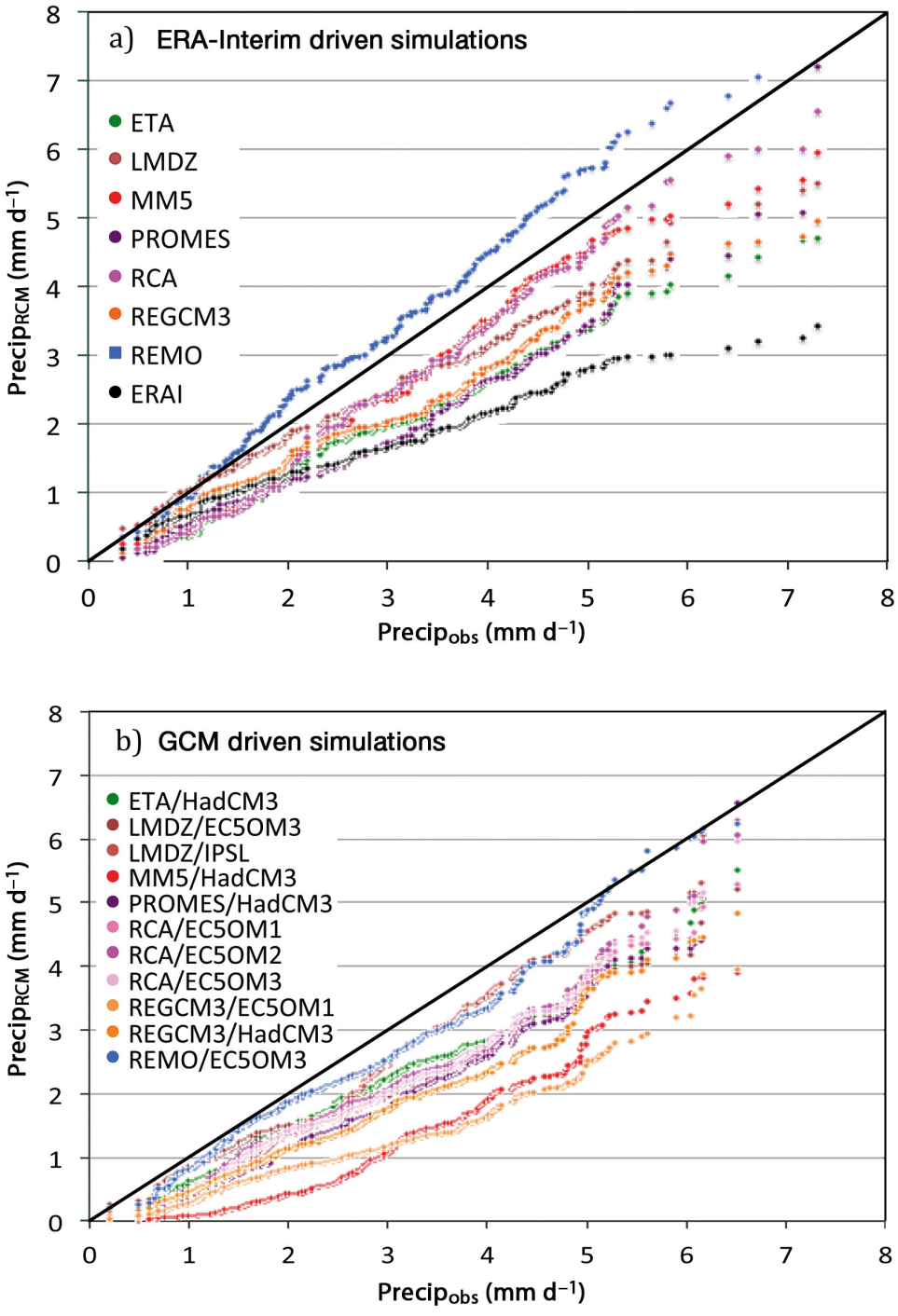

Fig. 8. Same as Fig. 7 but for precipitation

3.3. Climate change projections over the LPB region

First, it is worth exploring the relationship between the bias behaviour identified for the present climate simulations and the projected change for both temperature and precipitation. It is not expected *a priori* that the models with the largest warm bias will project the largest temperature increase, mainly because the regional climate change signal is not only affected by the model errors but also by the driving model climate sensitivity. However, it is expected that the models with larger warm bias amplification may overestimate the projected temperature increase. Similarly, it is also expected that the models with the

Table 3. Same as Table 2 but for precipitation

Model	Slope	Intercept	R
ETA/HadCM3	0.752	−0.081	0.993
LMDZ/EC5OM3	0.646	0.155	0.981
LMDZ/IPSL	1.041	−0.678	0.995
MM5/HadCM3	0.675	−0.820	0.964
PROMES/HadCM3	0.776	−0.433	0.992
RCA/EC5OM1	0.779	−0.265	0.993
RCA/EC5OM2	0.791	−0.257	0.985
RCA/EC5OM3	0.799	−0.315	0.990
REGCM3/EC5OM1	0.491	−0.209	0.972
REGCM3/HadCM3	0.702	−0.307	0.978
REMO/ EC5OM3	0.910	−0.065	0.982
HadCM3	0.784	0.162	0.995
EC5OM1	0.672	0.366	0.986
EC5OM2	0.729	0.282	0.991
EC5OM3	0.697	0.204	0.989
IPSL	0.363	−0.308	0.962

largest dry bias amplification may underestimate the projected rainfall increase. To verify this hypothesis; the bias slope versus the projected change for each individual model has been plotted in Fig. 9 for both temperature and precipitation. The projected changes are evaluated for 2 periods: 2011–2040 and 2071–2100, relative to the 1961–1990 period. The analysis is focused on the summer season, for which almost every RCM project increased rainfall over the LPB region. Moreover, summer is the season for which the warm bias amplification becomes more relevant. Note that the LMDZ/IPSL RCM has been excluded in the analysis for temperature. This RCM is considered an outlier in terms of the projected temperature change over LPB (>5°C), compared with the rest of the models, either RCMs or GCMs, for which the projected change lies between 2 and 3°C, as noted in Sa15 (their Fig. 13). For temperature, Fig. 9 suggests that the larger the temperature bias slope,

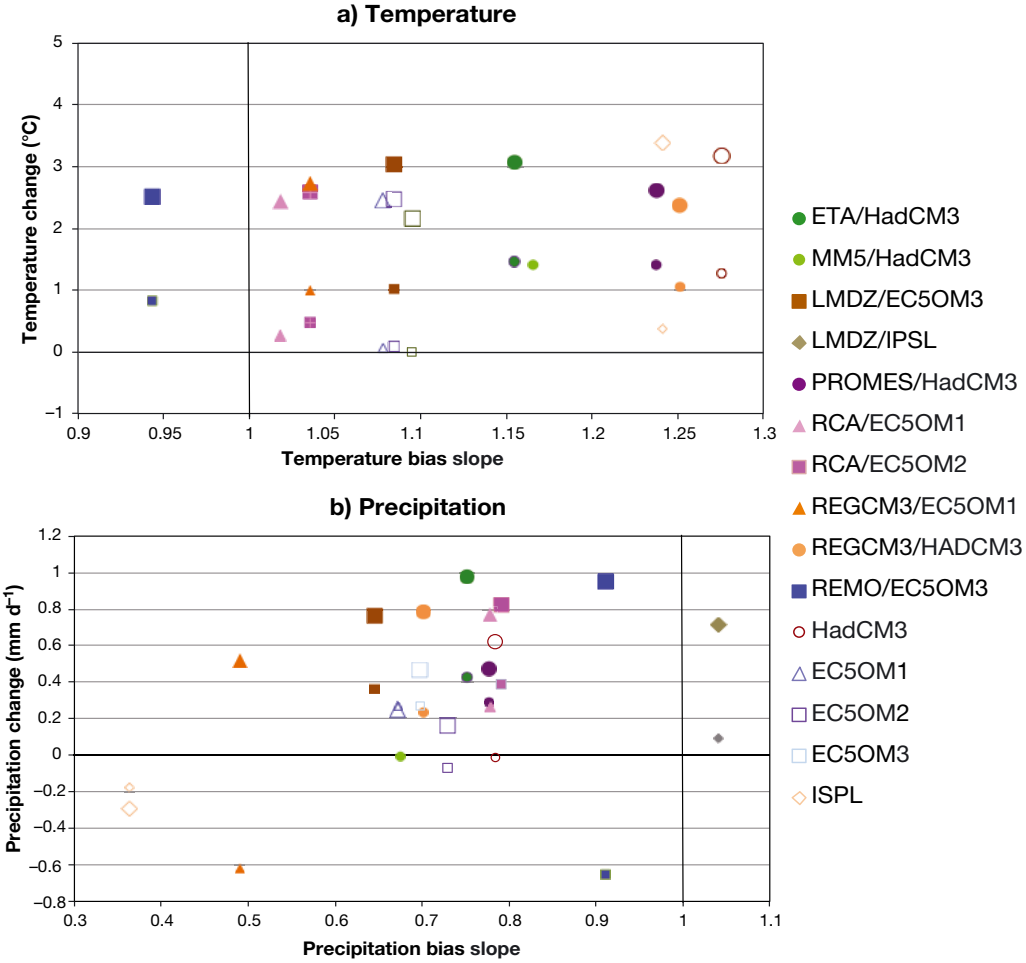

Fig. 9. (a) Projected temperature change for DJF over LPB for the period 2011–2040 (small symbols) and 2071–2100 (large symbols) as a function of the temperature bias slope (unitless) obtained from the linear fit of the ranked simulated versus observed temperatures from the set of GCM-driven RCM simulations. Results from the driving GCMs are also included for reference. Symbols denote the forcing GCM. The vertical solid line indicates the slope equal to 1. (b) Same as (a) but for precipitation

the larger the projected temperature change for the 2 future periods evaluated, indicating that the temperature-dependent temperature bias amplifies the projected temperature change under future warmer conditions.

From Fig. 9, it is also apparent that the projected precipitation increase over the LPB during summer months for the far future horizon (2071–2100) is smaller for those models with smaller precipitation bias slope, indicating that the larger the dry bias amplification, the smaller the projected precipitation increase. Therefore, the precipitation-dependent precipitation bias reduces the projected precipitation increase under future wetter conditions. For the near future horizon (2011–2040), the relationship between the bias slope and the projected change is not clear, probably because the signal is not large enough to emerge from the natural variability.

Linear fits based on the data displayed in Fig. 9 were computed for both temperature and precipitation for the near and far future, respectively. The slope for the far future is statistically significant at a 90% level, so the relationship between the projected changes and the bias slope is robust for the far future projections.

It is clear from the analysis above that the bias behaviour affects the projected changes of both temperature and precipitation. Moreover, under the light of this evidence, a need for a bias correction methodology accounting for the bias dependence on the climate regime is apparent. Boberg & Christensen (2012) proposed a temperature-dependent bias correction method to correct future temperature projections over the Mediterranean region from a suite of RCMs and found that the warming was reduced by up to 1°C. In the present study, a bias correction methodology based on the quantile-based mapping approach (Wood et al. 2002, Saurral et al. 2013) was applied to a sub set of individual RCMs. The bias correction method is based on fitting the modelled empirical frequency distribution of the present climate onto the observed empirical frequency distribution for both monthly temperature and precipitation at every grid point. For each percentile, correction factors are derived as the difference between the corresponding monthly value from the model and observations for temperature and as the ratio between the corresponding monthly value from the model and observations for precipitation. Then, the correction factors are added to the modelled temperature for each percentile and multiplied by the modelled precipitation for each percentile for both present and future conditions. The bias correction method was calibrated using the 1961–1975 period and then verified for the 1976–1990 period. The correction factors in this strategy are dependent on the percentiles; consequently, they account for the range of model biases depending on the temperature and precipitation values, respectively. The spirit of the method aims to keep the modelled distribution close to the observed one. One major shortcoming is that it does not allow for a change in distribution under future climate conditions.

To illustrate the bias correction methodology, the empirical frequency distribution of monthly temperature and precipitation over the LPB region has been computed based on both the raw and the corrected RCM data. For each individual RCM, a single monthly time series was built by concatenating the monthly time series of every grid-point lying within the LPB region. The normalized distribution was computed for both temperature and precipitation using 50 bins defined considering a single maximum and minimum value for all the models. The same procedure has been carried out using the CRU observational dataset. The empirical frequency distribution from the models was computed for both the present and the future climate (2071–2100).

Figs. 10 & 11 summarize these results for temperature and precipitation, respectively. It is clear from Fig. 10 that the mean bias in most of the RCMs is associated with overestimating the frequencies in the upper tail of the distribution. The bias correction method fits the modelled distribution onto the observed (black and dashed blue lines, respectively). For precipitation, most of the models overestimate the frequency of light precipitation and underestimate the frequency of moderate to heavy precipitation, as noted in So13 and Sa15. As for temperature, the bias corrected frequency distribution is closer to the observed, though some errors still remain.

Fig. 12 summarizes the projected climate change for the LPB region at the end of the twenty-first century under the SRESA1B scenario during the summer months from the sub-set of RCMs using both raw model outputs and corrected model outputs. Uncorrected RCMs project increasing temperatures ranging from 1.9 to 2.8°C. However, the projected temperature changes are systematically reduced after applying the bias correction method. The future warming reduction ranges from 0.4 to 0.7°C depending on the model, i.e. depending on the bias behaviour of each individual model. From Fig. 10, it is apparent that the temperature change is mostly associated with a shift of the distribution toward warmer conditions, as noted in Sa15. The empirical frequency

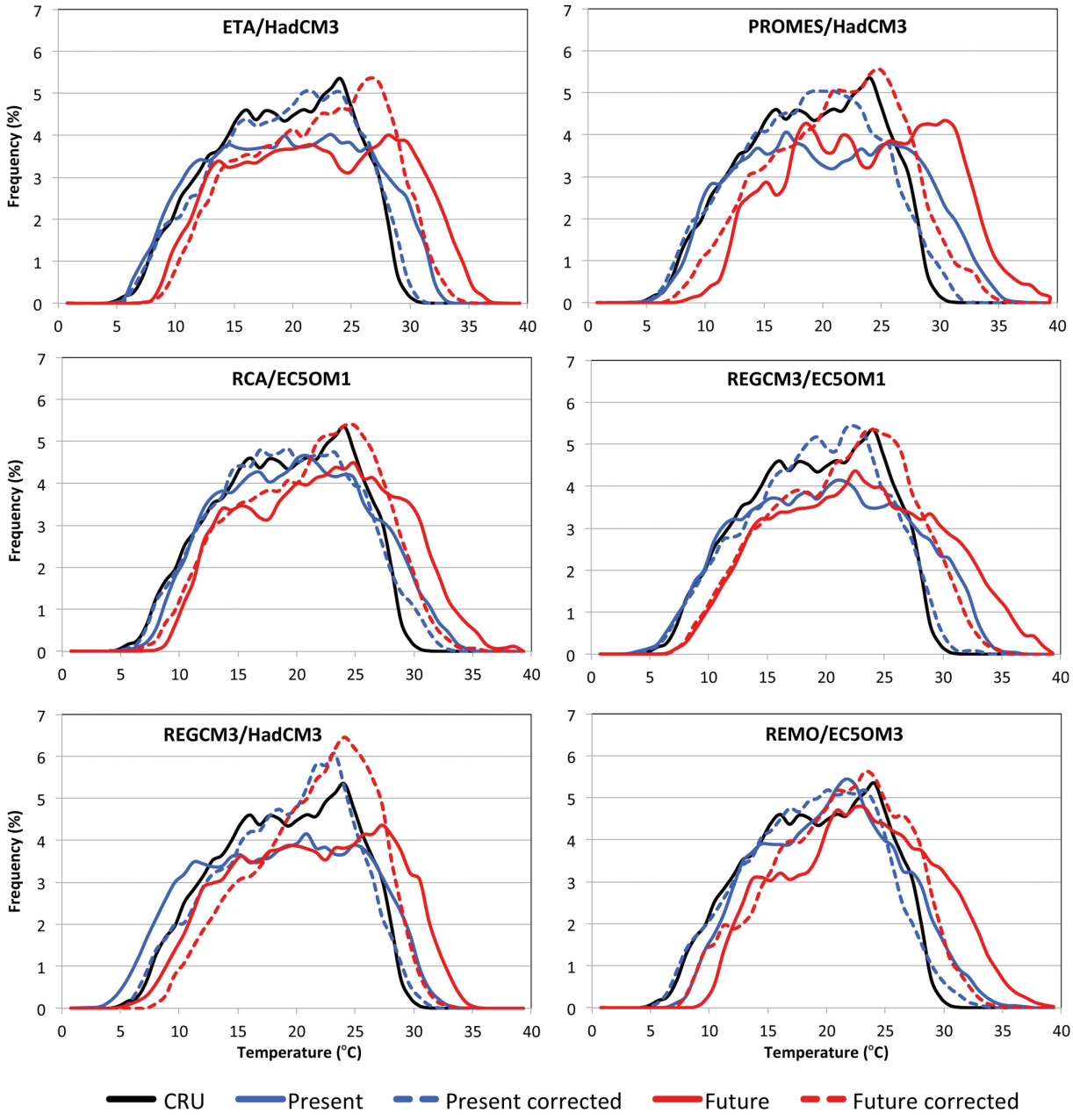

Fig. 10. Empirical frequency distribution of monthly mean temperature for grid points within the LPB region for CRU (black line) and for 6 individual RCMs. Solid lines for raw data; dashed lines for corrected data. Blue and red lines correspond to present climate (verification period 1976–1990) and future climate (2071–2100), respectively

distributions for the future climate based on both the raw and corrected model outputs displayed in Fig. 10 (solid and dashed red lines, respectively) illustrate how the bias correction method reduces the frequency in the upper tail, reducing the overall mean warming. For precipitation, the projected changes range from 0.4 to 1 mm for uncorrected RCMs. The precipitation increase is systematically amplified after bias correction, ranging from 0.6 to 1.6 mm, in agreement with the bias behaviour identified previously. Fig. 11 shows that the projected precipitation change for most of the RCMs is characterized by an increase in the frequency of moderate to heavy precipitation and a decrease in the frequency of light precipitation, in agreement with Sa15. The bias correction method enhances the increase in the frequency of moderate to heavy precipitation, increasing the overall wetting.

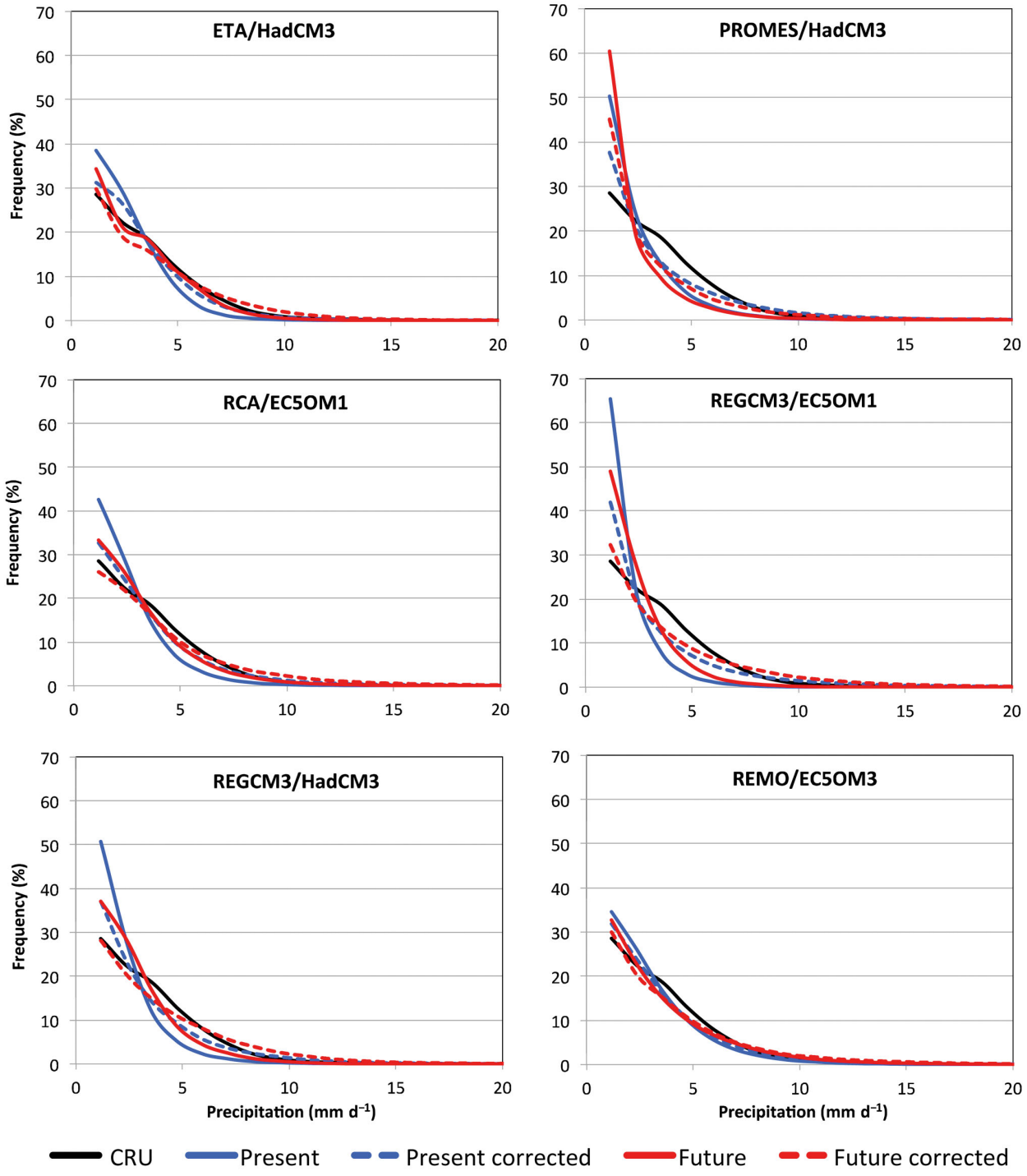

Fig. 11. Same as Fig. 10 but for precipitation

Though applying bias correction methodologies to projected climate conditions is controversial, because they add an additional source of uncertainty to the projected climate change estimates, this study demonstrates that bias correction methodologies should be considered in order to better interpret climate change signals. For this particular region of South America, it has been demonstrated that the behaviour of model biases has an impact on the future climate projected by the models, and a close inspection of model biases is needed in order to make a better interpretation of the climate change signal.

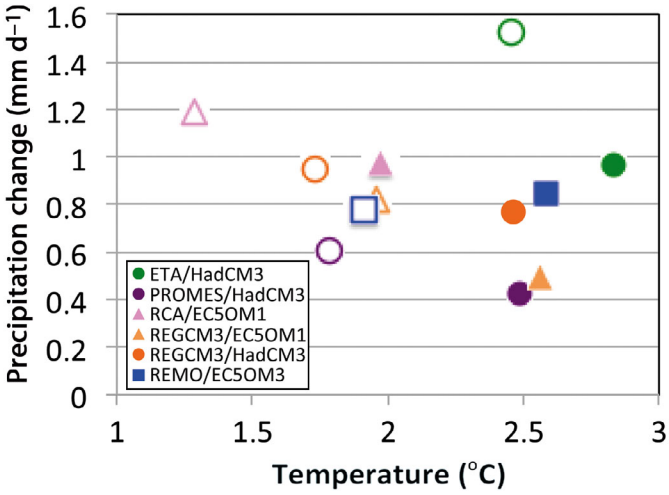

Fig. 12. Precipitation change versus temperature change for DJF over LPB projected for the period 2071 to 2100 from a sub-set of RCMs. Filled symbols are raw RCM data; empty symbols are bias corrected RCM data

4. SUMMARY AND CONCLUSIONS

The present work is focused on evaluating the systematic biases in the simulated monthly mean temperature and precipitation over South America from 2 sets of RCM ensembles performed under the CLARIS-LPB project. The present climate simulations performed by 7 RCMs driven by a set of 3 CMIP3 GCMs together with the ERA-Interim driven simulations are compared against the CRU data set. The validation exercise allows identification of the main shortcomings in RCMs for simulating the South American climate, which will certainly lead to possible paths for further model improvement. Moreover, it has also been shown that identifying the behaviour of model biases may have serious implications for the interpretation of future climate change projections.

The spatial structure of the seasonal biases for both temperature and precipitation suggests that the bias is largely dominated by RCM imperfections rather than the driving GCM, in agreement with Sa15. Moreover, as for other modelling exercises around the world, the biases in the GCM-driven RCM simulations are generally larger compared with those driven by reanalysis (Jacob et al. 2007). The analysis also showed that the models suffer from common biases, particularly over the La Plata basin region, that are to some extent shared by every RCM, suggesting common shortcomings in the models. These systematic biases for the LPB region were already identified in previous modelling exercises over South America (So13, Sa15; Solman 2013 and references therein). Overall, the models simulate warmer and dryer climate conditions compared with observations. Possible causes for such systematic model errors may be due to model deficiencies in representing land-surface processes, which have a strong coupling with near-surface climate, mainly during the warm season (Sorensson & Berbery 2015). Dryer conditions may lead to overestimation in the near-surface temperature, which in turn may amplify the negative precipitation bias due to positive feedback mechanisms. These results highlight the need for RCM improvement to attain a better representation of the observed climate over the South American continent.

In addition to identifying the main biases, one of the key findings in this study is that both temperature and precipitation biases over the LPB region are not invariant but are amplified under warmer and wetter climate conditions. Accordingly, almost every model depicts a temperature-dependent temperature bias and a precipitation-dependent precipitation bias, with the warm bias exacerbated particularly during the warm season and the dry bias amplified for wetter months. Additionally, the bias behaviour identified has an influence on the projected climate. The models with the largest temperature bias amplification depict the largest warming levels projected for the future under the SRESA1B emission scenario. This result indicates that the amplification of the warm bias may overestimate the future warming. Furthermore, for the LPB region, most of the models project wetter conditions for the future, particularly during the summer months. The models with the largest dry bias amplification project the smallest precipitation increase for the future. The bias behaviour results in an underestimation of the projected precipitation increase.

The results summarized above indicate that understanding the bias behaviour may help in the interpretation of the projected changes under future climate conditions. Moreover, these results are also useful to develop bias correction methodologies. In this sense, a bias correction strategy was applied to the models using a quantile-quantile mapping methodology for both monthly mean temperature and precipitation. In this method, the bias removed depends on the range of the variable, taking into account the dependence of model biases on the range of values of each individual variable. After bias correcting the models, the projected temperature change was reduced, and the projected precipitation change was increased, as expected.

Similar results by Christensen et al. (2008) and Christensen & Boberg (2012) identified temperature-

dependent model biases influencing the projected warming over some regions of the world. Consequently, it is clear that understanding the behaviour of model biases is key in order to build criteria to assess reliability of the future climate projections from RCMs.

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