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Temperature and precipitation biases in CORDEX RCM simulations over South America: possible origin and impacts on the regional climate change signal

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Abstract
Precipitation and temperature biases from a set of Regional Climate Models from the CORDEX initiative have been analysed to assess the extent to which the biases may impact the climate change signal. The analysis has been performed for the South American CORDEX domain. A large warm bias was found over central Argentina (CARG) for most models, mainly in the summer season. Results indicate that the possible origin of this bias is an overestimation of the incoming shortwave radiation, in agreement with an underestimation of the relative humidity at 850 hPa, a variable that could be used to diagnose cloudiness. Regarding precipitation, the largest biases were found during summertime over northeast of Brazil (NEB), where most models overestimate the precipitation, leading to wet biases over that region. This bias agrees with models' underestimation of both the moisture flux convergence and the relative humidity at lower levels of the atmosphere. This outcome suggests that the generation of more clouds in the models may drive the wet bias over NEB. These systematic errors could affect the climate change signal, considering that these biases may not be stationary. For both CARG and NEB regions, models with higher warm biases project higher warming levels, mainly in the summer season. In addition, it was found that these relationships are statistically significant with a confidence level of 95%, pointing out that biases are linearly linked with the climate change signal. For precipitation, the relationship between the biases and the projected precipitation changes is only statistically significant for the NEB region, where models with the largest wet biases present the greatest positive precipitation changes during the warm season. As in the case of biases, the analysis of the temperature and precipitation projections over some regions of South America suggests that clouds could affect them. The results found in this study point out that the analysis of the bias behaviour could help in a better interpretation of the climate change signal.

Keywords Systematic errors · Climate change signal · South America · RCM CORDEX models

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1 Introduction

Climate models are the main instrument to analyse future climate projections. However, they are imperfect tools because they use approximations to represent the processes that occur in the climate system, mainly for those of sub-grid scale. The errors in climate models have different sources: the equations' discretization, the parameterizations, the initial conditions, the boundary conditions (in the case of Regional Climate Models, RCM), among other factors. These errors could be systematic or random (Menard 2010). Random errors have their origin in the models' internal variability, which is the dominant source of uncertainty in short timescales, from seasonal to decadal (Hawkins and Sutton 2011; Teutschbein and Seibert 2013). On the contrary, systematic errors, also called biases, can originate due to

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misrepresenting some parameters or model structures that are unable to describe physical processes (Allen et al. 2006). These types of errors dominate the uncertainty in longer time scales, from decadal to multidecadal (Hawkins and Sutton 2011; Teutschbein and Seibert 2013). Many studies have assessed the systematic errors of climate models in different regions of the world, using both global and regional models (Cheruy et al. 2014; Kerkhoff et al. 2014; Lin et al. 2017; Zhang et al. 2018; Gnitou et al. 2021, among others). In South America (SA), there are many studies assessing the performance of climate models in reproducing the present climate (Solman et al. 2013; Blázquez and Nuñez 2013; Chou et al. 2014; Llopart et al. 2017; among others), but only a few studies are about biases implications and impacts on the climate change signal. Solman (2016) analysed temperature and precipitation biases for a group of RCMs driven by both ERA-interim reanalysis and Global Climate Models belonging to the Coupled Model Intercomparison Project phase 3 (CMIP3) and found that the systematic errors depend on the RCMs rather than on the driving global models. She also found that errors were not stationary and may affect future climate projections. Other authors described this finding in different regions of the world (Christensen et al. 2008; Maraun et al. 2012; Velázquez et al. 2015). In the same way, Ivanov et al. (2018) found that the model's biases may depend on the climate state, which may indicate that in the future, the systematic errors could be different and do not cancel out when differences between future and present climate are computed. Furthermore, Boberg and Christensen (2012) found that errors are intensity-dependent and that models with larger biases show larger climate change signals. This finding suggests, for example, that in regions with warm biases, climate models could overestimate the future warming. As indicated above, biases in climate models could have different sources, depending on the region and the type of model. Therefore, understanding the possible causes of models' errors would help to improve the simulations and make future projections more reliable.

In the last years, many authors have analysed the possible origin of the biases in climate models, mainly for temperature and precipitation. Lin et al. (2017) studied the causes of the warm and dry bias over central United States using CMIP5 global models. They found that the precipitation deficit due to failures in the models to represent the large precipitation events and wrong representation of land–atmosphere interactions may induce the warm biases. Over central equatorial Africa, Tamoffo et al. (2022) examined the systematic errors of precipitation in two Coordinated Regional Climate Downscaling Experiment (CORDEX) RCMs and found a wet bias at the west and a dry bias at the east of the mentioned region. The authors found that the possible origin is that models misrepresent the Congo basin cell, which produce less water vapour transported to the east of the region, resulting in a higher moisture availability over the western regions. Zhang et al. (2018) used simulations from CMIP5 models to analyse the warm bias over the southern Great Plains in the United States. They found that a possible factor is an overestimation of the absorbed solar radiation at the surface, which is, in turn, affected by the misrepresentation of cloudiness. Over SA, there is a lack of studies that analyse in depth the possible origin of the systematic errors in climate models. Thus, one of this work aims is to understand potential sources of the biases of RCMs over SA, focused on temperature and precipitation. In addition, the projections of future climate conditions are also analysed, considering to what extent the climate change signals may be affected by non-stationary model biases.

This work is organized as follows: Sect. 2 describes the data and methodology used in this study, results are presented in Sect. 3, and the study's conclusions are discussed in Sect. 4.

2 Data and methodology

2.1 Data

Regional climate models from the CORDEX initiative were used in this work (Giorgi and Gutowski 2015). These models were downloaded from one of the CORDEX repositories (https://esg-dn1.nsc.liu.se/search/cordex/). Table 1 lists the models used in this study, some of them belonging to the CORDEX-CORE experiments, with a higher horizontal resolution. All the simulated data were interpolated to a common grid of 0.5°. The present climate is represented by the historical simulation during 1979–2005. For the future climate, the RCP8.5 scenario was used for the period 2071–2100.

To analyse the biases in the climate models, observational gridded data and reanalysis were used for the period 1979–2005. Daily precipitation data was obtained from the Climate Prediction Center (CPC) Unified Gauge-Based Analysis (Xie et al. 2007). The daily mean temperature was obtained by taking the average between the maximum and the minimum daily temperature from the CPC dataset. Both temperature and precipitation data have a horizontal resolution of 0.5°. The specific humidity, temperature and zonal and meridional components of the wind at 850 hPa were obtained from the European Centre for Medium-Range Weather Forecast (ECWMF). The ERA-Interim reanalysis dataset (Dee et al. 2011) for the period 1975–2005 was used, which was previously interpolated from its original 0.7° grid to a 0.5° grid, in agreement with climate models and the CPC dataset. The sensible and latent heat fluxes were obtained from the Global Land Data Assimilation System (GLDAS) with 0.5° of grid spacing. The shortwave and

Table 1 Description of regional models used in the study

Model name	Institution (country)	Resolution (°lat x °lon)
RegCM4-HadGEM2	International Centre for Theoretical Physics, (Italy)	0.44×0.44
SMHI-RCA4-ICHEC	Swedish Meteorological and Hydrological Institute, Rossby Centre (Sweden)	0.44×0.44
SMHI-RCA4-MPI	Swedish Meteorological and Hydrological Institute, Rossby Centre (Sweden)	0.44×0.44
REMO2009-MPI	Helmholtz-Zentrum Geesthacht, Climate Service Center, Max Planck Institute for Meteorology (Germany)	0.44×0.44
REMO2015-HadGEM2	Helmholtz-Zentrum Geesthacht, Climate Service Center (Germany)	0.22×0.22
REMO2015-MPI	Helmholtz-Zentrum Geesthacht, Climate Service Center (Germany)	0.22×0.22
REMO2015-NorESM2	Helmholtz-Zentrum Geesthacht, Climate Service Center (Germany)	0.22×0.22
RegCM4-7-HadGEM2	International Centre for Theoretical Physics, (Italy)	0.22×0.22
RegCM4-7-MPI	International Centre for Theoretical Physics, (Italy)	0.22×0.22
RegCM4-7-NorESM2	International Centre for Theoretical Physics, (Italy)	0.22×0.22

longwave radiation variables were acquired from the Global Energy and Water Exchanges Program (GEWEX-SRB) with 1° of horizontal resolution, also interpolated to the common grid of 0.5°. In this case, the period covers from 1984 to 2005 because of the lack of data availability before 1984.

2.2 Methodology

It is well known that elevation has a direct effect on temperature (Dodson and Marks 1997; Peng et al. 2020) and that climate models have problems representing complex topography. The western part of SA is covered by a prominent mountainous chain (the Andes), so simulated near-surface temperature could be misrepresented over that region, due to differences between models' topography and the actual terrain elevation. Therefore, the near-surface temperature in every grid point of the climate models was corrected to account for these elevation differences using the topography of the observational data (CPC) as reference, following the Eq. (1):

$$T_{mc} = T_{ms} + \Gamma \times \Delta h \tag{1}$$

where T_{mc} is the corrected temperature of the model, T_{ms} is the simulated temperature of the model, Γ is the lapse rate and Δh is the difference between the model and the observations height. In this case, a fixed lapse rate was used (6.5° km^{-1}), following Bordoy and Burlando (2013). Small differences were observed over the Andes between near surface temperature with and without correction with height (not shown). For the rest of the domain, no differences were found. Nevertheless, it was decided to use the corrected data to calculate the temperature biases.

This work focuses on estimating temperature and precipitation seasonal errors in climate models and their possible origin. The biases were calculated by computing the difference between simulated and observed data for two seasons: austral summer (December, January, February, DJF) and austral winter (June, July and August, JJA).

To study the potential origin of these errors, the terms of the energy budget at the Earth's surface were analysed following Zhang et al. (2018) since the near surface temperature is mainly affected by the exchange of energy between the surface and atmosphere:

$$(1-\alpha)R_{SW}^{\downarrow} + R_{LW}^{\downarrow} = R_{LW}^{\uparrow} + LH + SH + G \tag{2}$$

where $(1-\alpha)R_{SW}^{\downarrow}$ is the absorbed shortwave radiation (α is the surface albedo), $R_{LW}^{\downarrow}$ is the downwelling longwave radiation, $R_{LW}^{\uparrow}$ is the upwelling longwave radiation, SH is the sensible heat flux, LH is the latent heat flux, G is the ground heat flux. In addition, the first term of the left hand of Eq. 2 can be split in two: the downwelling shortwave radiation $\left(R_{SW}^{\downarrow}\right)$and the upwelling shortwave radiation $\left(\alpha R_{SW}^{\downarrow}\right)$, i.e., the radiation reflected by the Earth's surface. In this work, these two terms were calculated separately. Furthermore, following Zhang et al. (2018), the ground heat flux G was neglected since it is very small compared with the other terms when averaged over long time scales.

The biases in near surface temperature and precipitation could also have their origin in the models' misrepresentation of the subsidence at low levels of the atmosphere since it can be linked with divergence and suppressed convection and cloud generation. Since the CORDEX models do not have available the vertical velocity, it was computed following the continuity equation in pressure coordinates:

$$\frac{\delta u}{\delta x} + \frac{\delta v}{\delta y} + \frac{\delta \omega}{\delta z} = 0 \tag{3}$$

where u and v are the zonal and the meridional components of the wind, respectively, and ω is the vertical velocity in pressure coordinates. In this study, ω was computed at

850 hPa and 500 hPa levels, considering the models' data availability.

The climate change signal was also analysed in this work. Thus, the seasonal differences between the future (2071–2100) and the present climate (1979–2005) were computed.

Scatter plots were computed by spatially averaging over Central Argentina (CARG) and Northeastern Brazil (NEB) regions to study the relationship between models' biases and projected changes.

3 Results

3.1 Biases in climate models

To achieve one of the goals of this work, biases of seasonal mean temperature and precipitation are analysed over SA. Figure 1 shows the temperature bias for DJF. Most models show a positive bias over CARG, which in some of them reaches 5 °C. Other authors have documented this systematic error (Falco et al. 2019; Llopart et al. 2017; Lopez-Franca et al. 2016; Solman 2016; Sánchez et al. 2015). The rest of the continent presents cold biases, with values between – 1 and – 3 °C. For JJA, a warm bias is also observed over CARG in most of the models (Fig. 2), but in some cases more extended to the north, compared with the summer season. Cold biases are mainly located in the northern part of the continent, with values around – 1 °C. Biases of precipitation for DJF are shown in Fig. 3. The highest values of the mean precipitation are located over the monsoon region (panel 1 of Fig. 3), however, the largest positive biases are found over the NEB region, which in some models reach 10 mm/day, which is a relative error of more than a 100% of the observed precipitation. Another region that presents large wet biases is located over Peru, Bolivia, and northwestern Argentina, where most of the models also simulate cold biases (see Fig. 1). This zone is characterized by a complex terrain where in general, models are deficient in representing the interaction between the topography and the low-level flow, which may lead to a misrepresentation of the simulated precipitation. Note that over this region, easterly winds interact with the topography, producing large precipitation biases. This same behaviour is apparent over central and southern Chile, where westerly winds are blocked by the Andes. The wet biases found in both regions agree with Sánchez et al. (2015), Solman (2016), and Gutowski et al. (2016), who used a previous generation of regional climate models. During wintertime (Fig. 4), the largest precipitation biases are located over northern SA, with values between – 2 and – 4 mm/day, representing a dry bias close to 20%. As stated above, most of the models present biases patterns that have also been documented by other authors using different RCMs.

From the analysis above, it is evident that some regions systematically depict the largest biases. To explore the biases over these specific regions, two areas were selected, the first one is CARG (40°–25° S and 66°–57° W), where the largest biases of temperature were found during both summer and winter seasons, and the second one is NEB (15°–4° S and 50°–35° W), where the most prominent precipitation biases were found during the warm season. Both regions are shown in the first map of Fig. 1.

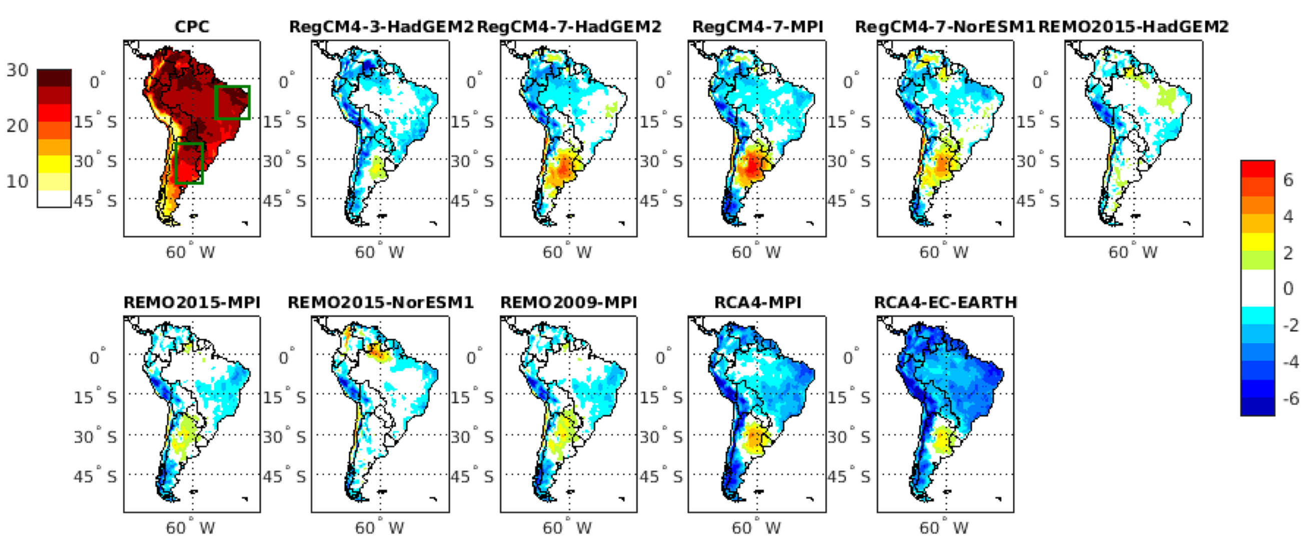

Fig. 1 Observed mean surface temperature (panel 1) and temperature bias for the period 1979–2005 for DJF. Units are °C. Regions CARG and NEB are shown in panel 1

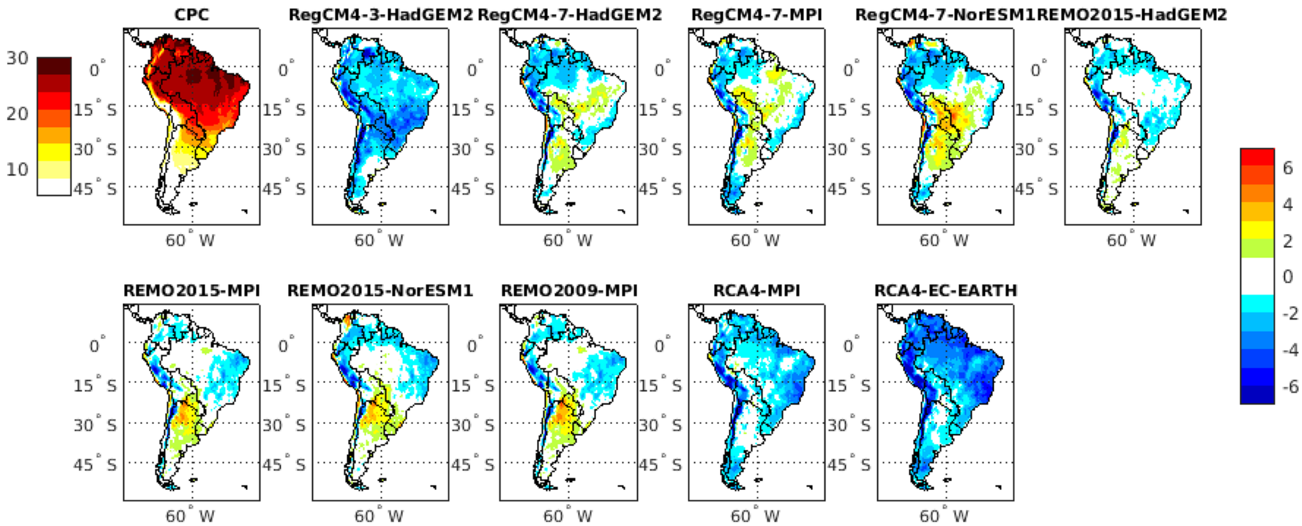

Fig. 2 Same as Fig. 1, but for JJA.

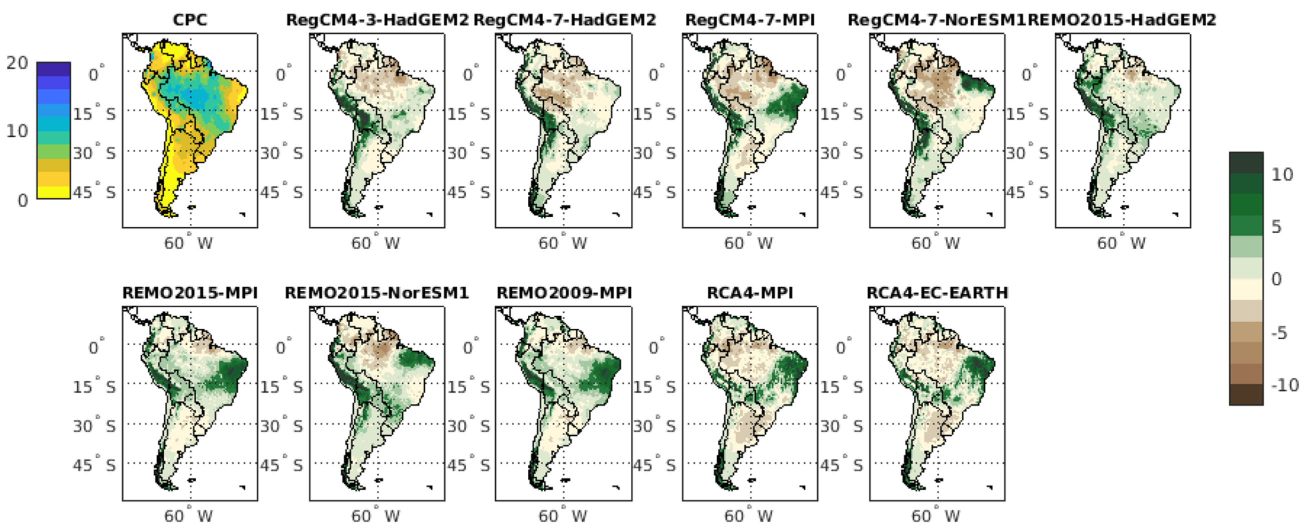

Fig. 3 Observed mean precipitation (panel 1) and precipitation bias for the period 1979–2005 for DJF. Units are mm/day

To analyse the possible origin of the temperature bias over the CARG region, the terms of the surface energy budget were examined (see Eq. 2, Sect. 2.2). In addition, the mid-levels of the atmosphere were also explored to study the effect of the air subsidence and cloudiness over the near surface temperature (see Eq. 3, Sect. 2.2). Figure 5 displays the downwelling shortwave radiation at the surface for DJF. Those models with the largest warm biases (RegCM4-7-HadGEM2, RegCM4-7-MPI, RegCM4-7-NorESM2, RCA4-MPI) show the largest incoming shortwave radiation. The shortwave radiation absroved at the surface shows the same behaviour (not shown). More incoming solar radiation at the surface may be associated with less cloudiness. Due to the total cloud fraction is not available for all the models used in this study, the relative humidity at 850 hPa was analysed instead as a proxy of cloudiness (Walcek 1994; Quaas 2012; Giorgio 2017). It is well known that the parameterizations of clouds use a relative humidity threshold as a parameter of air saturation and cloud formation, so it is a good indicator to diagnose cloud cover in climate simulations (Jakob and Miller 2003). At this point, it is important to clarify that only one level was analysed (850 hPa) because of the lack of availability of models' data in other levels of the atmosphere. Figure 6 shows that models with high warm biases have large negative biases of relative humidity at 850 hPa. This result suggests that models may underestimate cloudiness

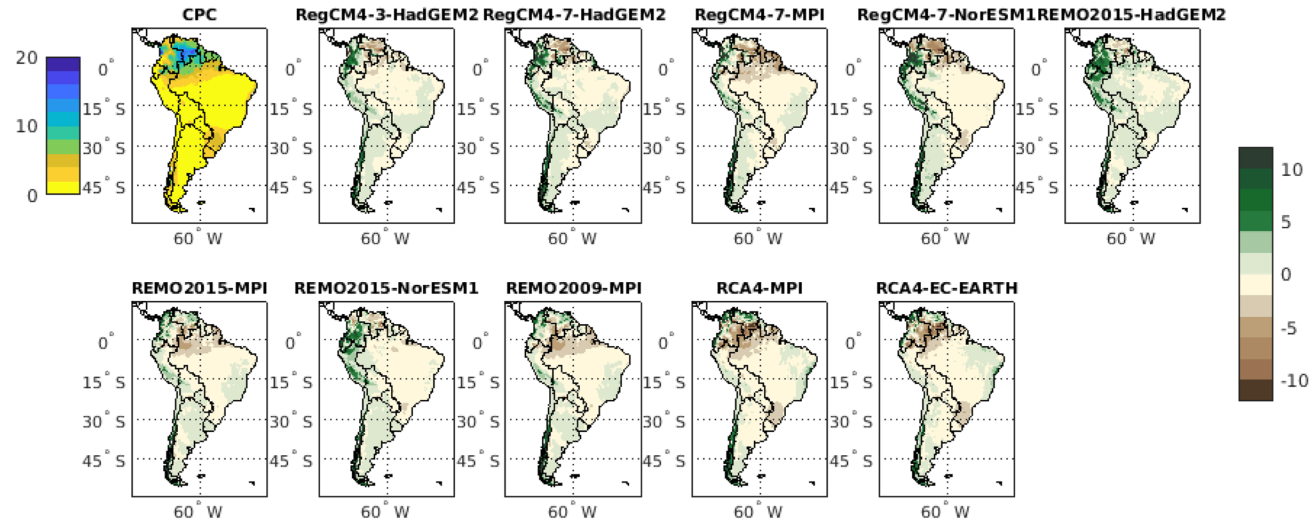

Fig. 4 Same as Fig. 3, but for JJA.

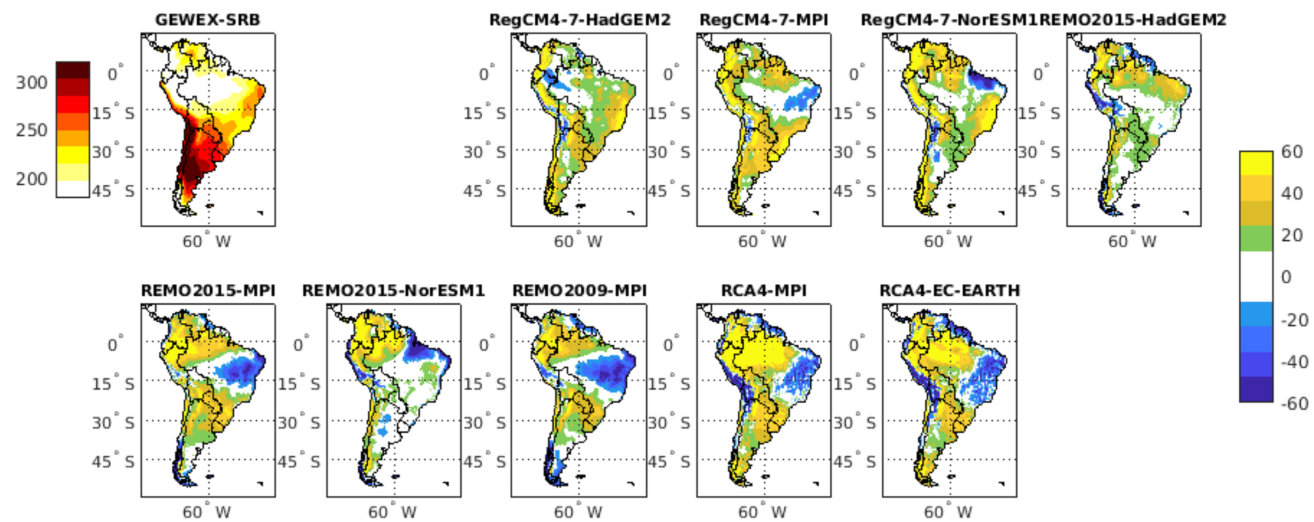

Fig. 5 Same as Fig. 1, but for surface downwelling shortwave radiation. Units are W/m^2

favouring the incoming of solar radiation, which may induce warmer near-surface temperatures. The relationship between warm biases and positive biases of incoming solar radiation at the surface and cloudiness was also found by Zhang et al. (2018), but for the Great Plains in the United States of North America. The downwelling longwave radiation at the surface was also analysed, but no significant biases were found (not shown). Sensible and latent heat fluxes were also examined for summertime (Figures S1 and S2). As expected, the models with large warm biases also present positive biases of sensible heat flux and negative biases of latent heat flux. The results above suggest that underestimating cloudiness could induce warm biases in climate models. In addition, the underestimation of latent heat flux leads to positive feedback since it reduces the moisture transport between the surface and the atmosphere, so the deficit of humidity could cause less cloud generation.

The warm biases over CARG could also be due to the overestimation of the large scale subsidence in climate models (Zhang et al. 2018). Therefore, the vertical velocity was analysed at the 850 and 500 hPa levels. Most models present negative values (not shown), suggesting more upward motion in models compared with observations. Thus, the hypothesis that the warm biases in climate models could be related to large scale subsidence was discarded.

The mechanism that could explain the warm biases over CARG during wintertime is not as clear as in the summer season. A weak relationship among the incoming shortwave

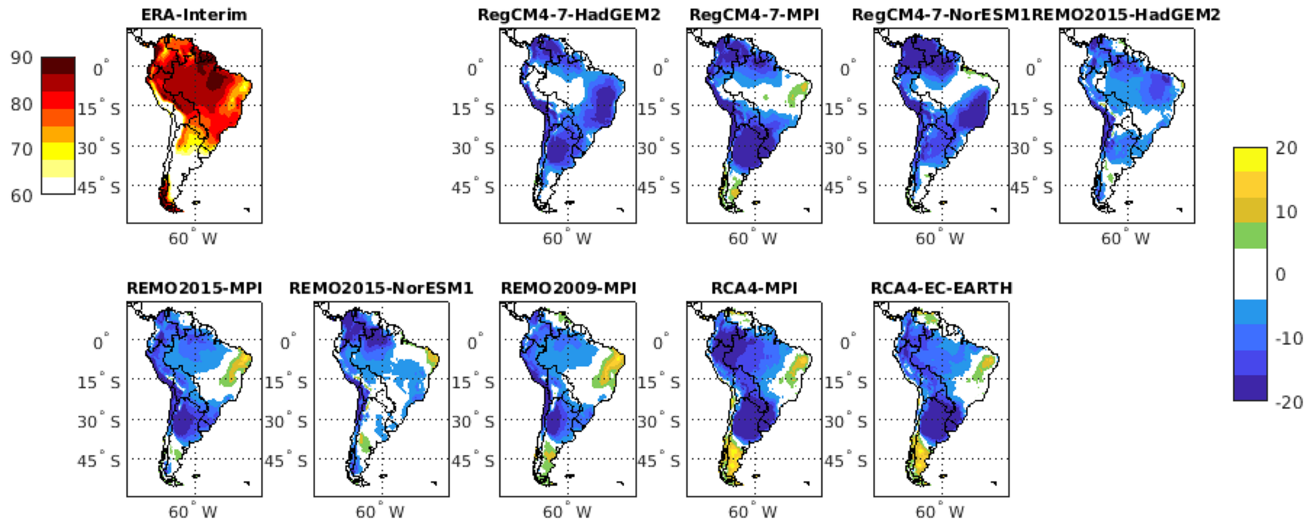

Fig. 6 Same as Fig. 1, but for 850 hPa relative humidity. Units are %

radiation at the surface, the 850 hPa relative humidity, and the near surface temperature was found (not shown).

The attention is turned to the systematic overestimation of precipitation over NEB during summertime. Given that the presence of clouds is closely linked to precipitation, the 850 hPa relative humidity during DJF was explored (Fig. 6). It can be shown in Fig. 3 that models with the largest positive biases of precipitation over NEB (REMO2015-MPI, REMO2009-MPI, RCA4-MPI, RCA4-ICHEC) also present positive biases of relative humidity (Fig. 6), and negative biases of downwelling shortwave radiation (Fig. 5) and temperature (Fig. 1). This result suggests that the overestimation of cloudiness in climate models may generate more precipitation and, in turn, produce less solar radiation reaching the surface and causing an underestimation of near surface temperature over NEB. Leyba (2020) found that more than 60% of the humidity during summer season comes from the subtropical Atlantic Ocean for the NEB region. Hence, the horizontal moisture flux divergence was examined at 850 hPa (Fig. 7). It is apparent from this figure that those models with wet bias over NEB present negative biases of moisture flux divergence (i.e. positive bias of moisture flux convergence), suggesting that models may produce more precipitation than observations due to the misrepresentation of the low level circulation (Figure S3) and the availability of moisture over that region. The wet and dry biases found

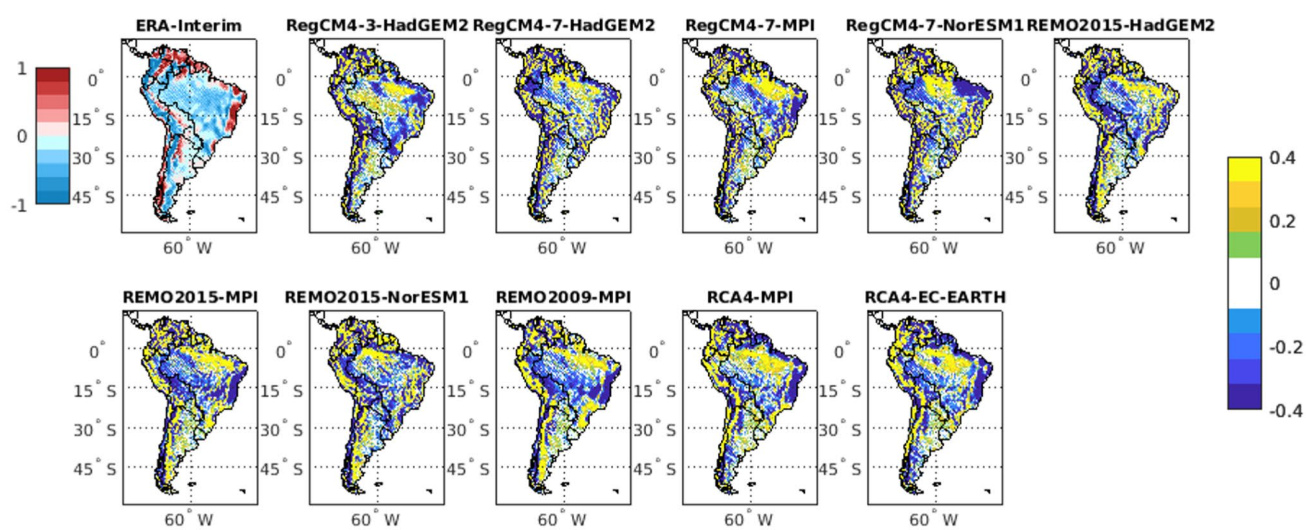

Fig. 7 Same as Fig. 1 but for the horizontal moisture flux convergence. Units are $(\text{seg}^{-1})*1\text{e}^{-7}$

over NEB could also be related to the latent and sensible fluxes at the surface. Those models with positive biases of precipitation and negative biases of temperature also present positive biases of latent heat flux (Figure S1) and negative biases of sensible heat flux (Figure S2), as expected.

Summarizing, in both regions, the exploration of biases of temperature and precipitation suggests that they are related to cloudiness, mainly during the warm season. Over CARG, the lack of simulated clouds may allow for more incoming solar radiation, larger sensible heat flux and, in turn, higher values of temperature in the models compared with the observations. On the other hand, for NEB, the formation of more clouds due to the simulation of more moisture flux convergence could be linked with the generation of more precipitation in climate models, in comparison with observations.

Eum et al. (2015) have posed that confidence in climate projections depends on many factors, among them the reliability of the climate models' simulations. Therefore, it is fair to question if these biases could affect the climate change signal over SA. Figure 8 displays the relationship between the models' biases and the models' projected changes for temperature and precipitation during DJF over CARG and NEB. For both regions, the models present a positive relationship between the bias and the warming level (Fig. 8a, b). This result implies that models with higher warm biases (lower cold biases) present a larger (weaker) warming signal over CARG (NEB). In addition, Table 2 shows that these relationships are statistically significant, with a confidence level of 95%, pointing out that the models' biases are linearly linked with the climate change signal.

Table 2 Pearson correlation coefficient between the biases and the changes for the climate models listed in Table 1. Bold font indicates that the values are statistically significant with a confidence level of 95% following a T-test

Region	Temperature DJF	Temperature JJA	Precipitation DJF	Precipitation JJA
CARG	**0.33**	**−0.63**	−0.29	0.26
NEB	**0.43**	**0.43**	**0.25**	−0.02

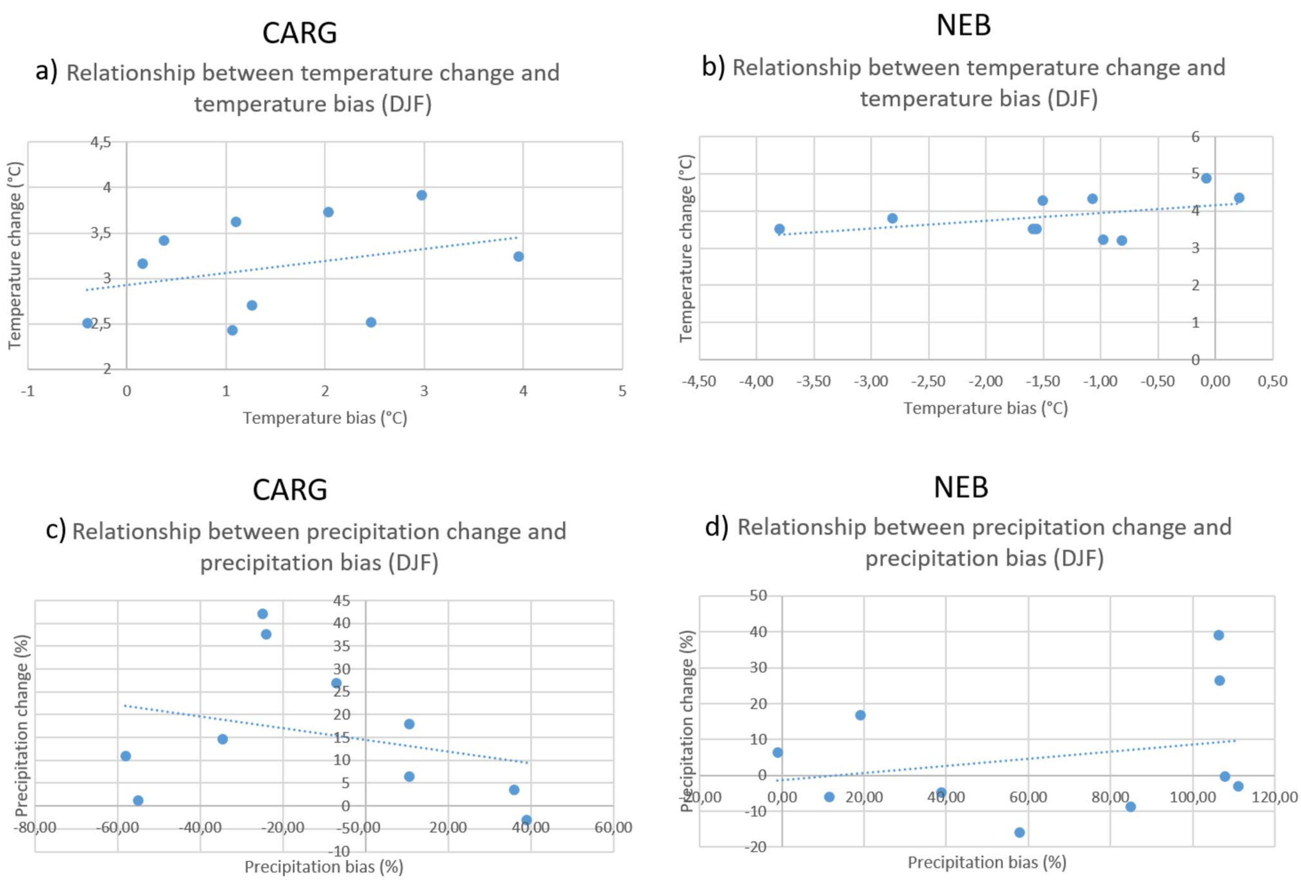

Fig. 8 Scatter plot of mean change (y-axis) versus bias (x-axis) for the 10 models used in this study for DJF. (**a**) Temperature for CARG, (**b**) temperature for NEB, (**c**) precipitation for CARG, (**d**) precipitation for NEB. All the values were spatially averaged over the CARG and NEB regions

During JJA, the relationship between models' biases and projected changes of temperature presents the same behaviour as in DJF for the NEB region (not shown), with a significant correlation coefficient (see Table 2). On the contrary, the CARG region presents the opposite behaviour during the cold season: models with the higher positive biases of temperature present lower values of projected changes (not shown); in this case, the correlation coefficient is also statistically significant (Table 2).

Christensen and Boberg (2012) evaluated the relationship between the temperature bias and the climate change signal over several regions of the world and found that most of the CMIP5 models with positive temperature biases tend to have larger temperature projected changes. Furthermore, Boberg and Christensen (2012) explored RCMs temperature biases over the Mediterranean region and found the same result. Besides, they found that the models' systematic errors may be temperature dependent and do not cancel out in a climate change experiment. This implies that future warming may be overestimated over regions with warm biases. From the results above, it may be expected that warming levels projected at the end of the 21st century under the RCP8.5 scenario over NEB and CARG are overestimated by this set of RCMs during the warm season.

Regarding precipitation, the relationship between the biases and the projected changes are only statistically significant for summertime over the NEB region (Fig. 8d), where models with the highest bias present the largest projected changes. This result suggests that projections of precipitation over NEB could be affected by climate biases during DJF. Therefore, lower values of precipitation change could be expected over NEB. In addition, it can be pointed out that the relationship between the biases and the changes for precipitation are not as strong as was for temperature. This result was also found by Eum et al. (2015) in a southern Canadian region.

3.2 The climate change signal

Figure 9 shows temperature changes for DJF between the future (2071–2100) and the present climate (1979–2005). As was found by other authors (Torres and Marengo 2013; Blázquez and Nuñez 2013; Reboita et al. 2014; Sanchez et al. 2015; López-Franca et al. 2016; among others), all the models simulate positive changes over the entire continent. However, the warming level depends on the models and the regions analysed. For some models, the largest warming is projected over the north of the continent and over the Andes chain, reaching values of more than 6 °C. The amplification of the warming over complex terrain regions has also been reported in several studies (Wang et al. 2014; Pepin et al. 2015; Gao et al. 2021). Regarding CARG and NEB regions, warming levels between 1° and 5 °C are found. For wintertime, higher temperatures are also projected for the end of the 21st century overall the continent (not shown), but the highest values are located over central Brazil, reaching more than 4 °C for most of the models. On the other hand, central

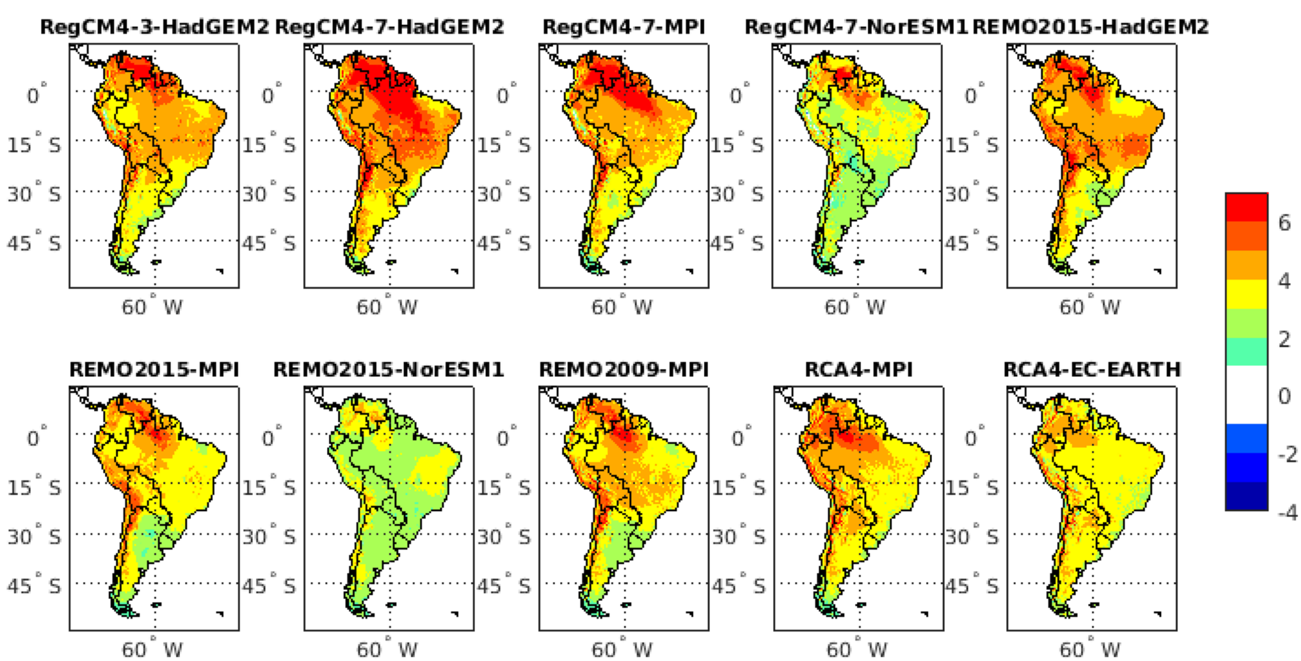

Fig. 9 Mean surface temperature change between future climate (2071–2100) and present climate (1979–2005) for DJF. Units are °C

Argentina presents the lowest values of warming (around 2 °C).

Precipitation changes were also evaluated for DJF (Fig. 10). All the models show negative changes over northern SA and Chile, reaching values of around − 45%, compared with the baseline period (1979–2005). This result agrees with other authors' findings (Bambach et al. 2022; Blázquez and Solman 2020; Llopart et al. 2020; Cavalcanti and Silveira 2016; Gutiérrez et al. 2021). On the contrary, over CARG and Uruguay, positive changes of precipitation (around 45%) are projected in some models, while over NEB, the agreement among models is very poor. The same result was found by Sánchez et al. (2015) with a previous models' generation. Wintertime is the dry season for most of the regions of SA, including CARG and NEB. The zones of maximum precipitation in the historical period are southeastern SA, central Chile, and northern SA (see the first panel of Fig. 4). Most of the models project a decrease of precipitation over northern SA and central Chile, while over southeastern SA, positive changes are projected (not shown). CARG presents positive changes, while over NEB, most models project negative values (not shown).

As was posed above, there are different projections of warming levels and patterns of precipitation changes among models at the end of the 21st century. Thus, it is worth assessing to what extent these differences could be due to the biases identified in the previous subsection. Since cloudiness could be one of the causes of temperature and precipitation biases, and, as was mentioned previously, the relative humidity cloud be related to cloudiness, the changes in relative humidity at the 850 hPa level for DJF (Fig. 11) are examined. Over CARG, those models with positive changes of relative humidity (REMO2015-HadGEM2, REMO2015-MPI, and REMO2009-MPI) agree with positive projected precipitation changes (Fig. 10) and lower warming levels (Fig. 9). This result suggests that clouds not only could be associated with the projected precipitation signal, but also could modulate the radiation that reaches the surface and then reduce the warming signal. In addition, this group of models also presents over CARG positive changes of latent heat flux (Figure S4) and negative changes of sensible heat flux (Figure S5), reinforcing the consistency among the changes in temperature and precipitation. Another region that presents a high consistency among projected changes is northern SA, where, as was mentioned previously, most of the models (RegCM4-7-HadGEM2, RegCM4-7-MPI, RegCM4-7-NorESM2, REMO2015-HadGEM2, REMO2015-MPI, REMO2009-MPI, RCA4-MPI) project negative changes of precipitation (Fig. 10). In addition, these models present negative projections of relative humidity (Fig. 11), negative changes of latent heat flux (Figure S4), positive changes of sensible heat flux (Figure S5), and higher warming levels (Fig. 9). Therefore, these results suggest that cloudiness may modulate the intensity of the projected changes over this region.

During wintertime, there is also a consistency among projected changes in some regions, but not as clear as in the warm season (not shown).

Summarizing, cloudiness may be the variable that affects not only the temperature and precipitation projections but

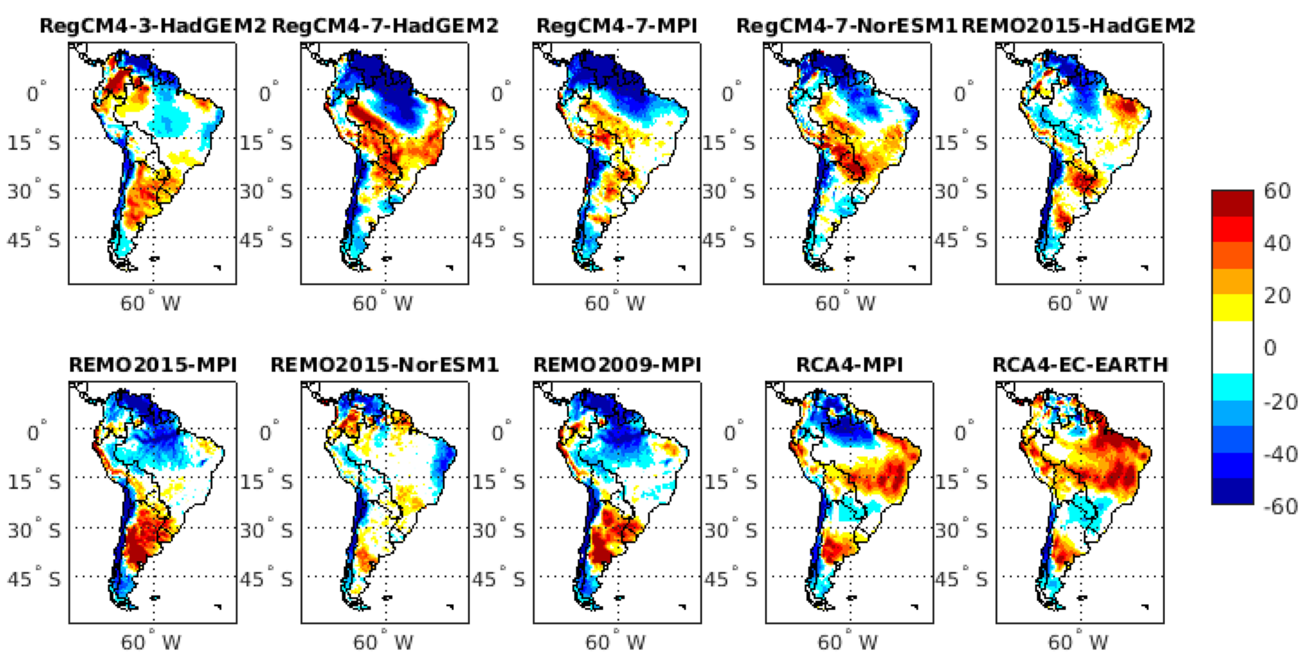

Fig. 10 Same as Fig. 9 but for changes in precipitation compared to the baseline period (1979–2005). Units are %

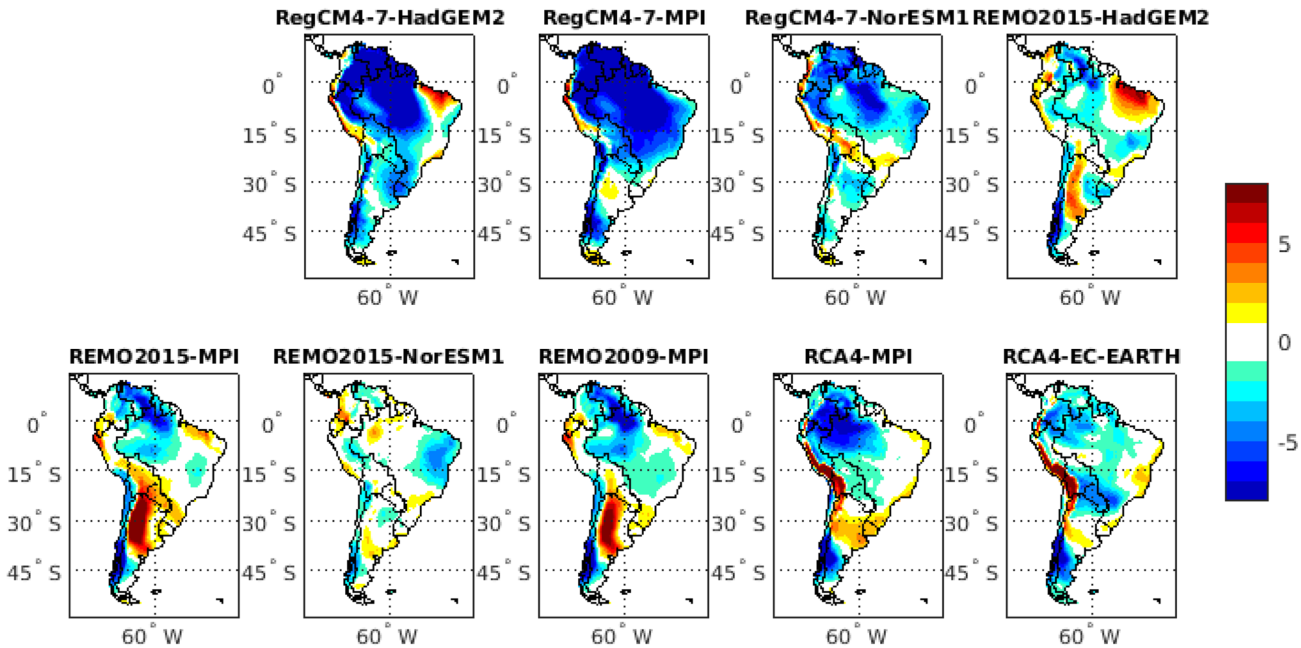

Fig. 11 Same as Fig. 9, but for 850 hPa relative humidity. Units are %

also the models' biases, especially during the warm season, where the convective precipitation is more usual. Convection is generally parameterized in most models, so this result suggests that an improvement of the parameters included in the convective schemes may drive to better results and more reliable projections.

4 Conclusion

This work assesses the biases of precipitation and temperature over SA, focusing in two regions: CARG and NEB. Furthermore, the possible origin of these systematic errors and the impacts on the climate change signal were also analysed. For this study, a set of CORDEX RCM simulations for the South American domain were used, some of them belonging to the CORDEX-CORE experiments. The biases were assessed for the period 1979–2005 and the climate change signal was evaluated at the end of the 21st century (for the period 2071–2100), using the RCP85 scenario.

The largest biases of temperature were found over CARG during summertime, where most models overestimate the observations. The positive biases of the incoming shortwave solar radiation reaching the surface could be one of the factors that explain the warm bias over CARG. This excess in the incoming shortwave radiation at the surface is consistent with negative values of relative humidity at 850 hPa, which may indicate less cloudiness simulated by climate models compared with observations. Biases in latent and sensible heat fluxes are consistent with the warm biases found over CARG, positive (negative) biases of sensible (latent) heat flux were found in the models with largest positive temperature biases.

Regarding precipitation, the largest positive bias was found over NEB during the warm season. This wet bias agree with the positive bias of relative humidity at 850 hPa, possibly connecting with more clouds' generation by climate models, compared with the observations. Results suggest that this overestimation of cloudiness by climate models may be related to the overestimation of the moisture flux convergence over NEB. The latent and sensible fluxes were also consistent with the wet bias in NEB: overestimation of latent heat flux and underestimation of sensible heat flux in models with largest positive values of precipitation bias.

The biases that this group of climate models has shown may not remain constant in the future. In fact, some studies have found that the errors in models are intensity-dependent (Boberg and Christensen 2012; Christensen and Boberg 2012; Solman 2016), which suggest that, for example, models with strong warm biases may project an amplified warming signal in future climate conditions. Thus, to analyse the impact of these biases on the future climate, the correlation coefficient between present biases and the climate change signal for each model was calculated. A statistically significant relationship between the warm bias and the temperature change over CARG and NEB for both summer and winter was identified. This result points out that the systematic errors of RCMs could affect the climate change signal over these regions, overestimating the warming, especially in the summertime, where the correlation coefficient between biases and projected changes is positive. However, for precipitation, that correlation only resulted statistically significant for DJF over NEB, with a positive coefficient between the biases and the changes, suggesting an overestimation of the wet changes during the warm season.

The spatial distribution for the future projections were examined over SA. In spite of all the models projecting positive changes of temperature over the continent for both summer and winter, different warming levels were found. For precipitation, results have shown different projected changes patterns, but most models agree on the projection of negative (positive) changes over northern SA and Chile (CARG and Uruguay) during summertime. For JJA, most of the models project a decrease of precipitation over northern SA, central Chile, and NEB, whereas over CARG and southeastern SA wetter conditions are projected by the end of the 21st century.

Regions with negative (positive) changes of precipitation agree with regions of negative (positive) projections of relative humidity (a variable that could be used to estimate clouds) and latent heat flux, positive (negative) changes of sensible flux and higher (lower) levels of warming. These results suggest that cloudiness may modulate the future projections of both precipitation and temperature.

To summarize, the results found in this study suggest that cloudiness may be the variable that affects both biases and the climate change signal for both temperature and precipitation. It is known that clouds are parameterized in climate models, so a revision of the parameters that drive the air saturation and cloud formation in the microphysics and convections schemes is needed. Furthermore, it is important to highlight that biases in climate models could affect the climate change projections because they should not be considered stationary and when changes between future and present climate are calculated the errors may not cancel out.

In-depth studies of how biases influence climate change signal should continue over SA, where few works approach this issue.

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Data availability The CORDEX regional climate models are available at: https://cordex.org/data-access/.

The CPC dataset is available at: https://psl.noaa.gov/data/gridded/data.cpc.globaltemp.html and https://psl.noaa.gov/data/gridded/data.cpc.globalprecip.html.

The ERA-interim reanalysis are available at: https://www.ecmwf.int/en/forecasts/datasets/reanalysis-datasets/era-interim.

The GLDAS data is available at: https://ldas.gsfc.nasa.gov/data.

The GEWEX-SRB dataset is available at: https://asdc.larc.nasa.gov/project/SRB.

Declarations

Competing interests The authors declare no competing interests.

Ethical approval Not applicable.

References

Allen M, Frame D, Kettleborough J, Stainforth D (2006) Modelerror in weather and climate forecasting. In: Palmer T, Hagedorn R (eds) Predictability of weather and climate. Cambridge University Press, Cambridge, pp 391–427

Bambach NE, Rhoades AM, Hatchett BJ, Jones AD, Ullrich PA, Zarzycki CM (2022) Projecting climate change in South America using variable-resolution community earth system model: an application to chile. Int J Climatol 42:2514–2542. https://doi.org/10.1002/joc.7379

Blázquez J, Nuñez MN (2013) Performance of a high resolution global model over southern South America. Int J Climatol 33:904–919. https://doi.org/10.1002/joc.3478

Blázquez J, Solman SA (2020) Multiscale precipitation variability and extremes over South America: analysis of future changes from a set of CORDEX regional climate model simulations. Clim Dyn 55:2089–2106. https://doi.org/10.1007/s00382-020-05370-8

Boberg F, Christensen JH (2012) Overestimation of Mediterranean summer summer temperature projections due to model deficiencies. Nat Clim Change 2:433–436. https://doi.org/10.1038/nclimate1454

Bordoy R, Burlando P (2013) Bias correction of regional climate model simulations in a region of complex orography. J Appl Meteorol Climatol 52(1):82–101. https://doi.org/10.1175/JAMC-D-11-0149.1

Cavalcanti IFA, Silveira VP (2016) Changes in precipitation over the La Plata Basin, projected by CLARIS-LPB regional models. Clim Res 68:169–182. https://doi.org/10.3354/cr01392

Cheruy F, Campoy A, Dupont JC, Ducharne A, Hourdin F, Haeffelin M, Chiriaco M, Idelkadi A (2013) Combined influence of atmospheric physics and soil hydrology on the simulated meteorology at the SIRTA atmospheric observatory. Clim Dyn 40:2251–2269. https://doi.org/10.1007/s00382-012-1469-y

Chou S, Lyra A, Mourão C, Dereczynski C, Pilotto I, Gomes J, Bustamante J, Tavares P, Silva A, Rodrigues D, Campos D, Chagas D, Sueiro G, Siqueira G, Nobre P, Marengo J (2014) Evaluation of the eta simulations nested in three global climate models. Am J Clim Change 3:438–454. https://doi.org/10.4236/ajcc.2014.35039

Christensen JH, Boberg F (2012) Temperature dependent climate projection deficiencies in CMIP5 models. Geophys Res Lett 39:L24705. https://doi.org/10.1029/2012GL053650

Christensen JH, Boberg F, Christensen OB, Lucas-Picher P (2008) On the need for bias correction of regional climate change projections of temperature and precipitation. Geophys Res Lett 35:L20709. https://doi.org/10.1029/2008GL035694

Dee DP et al (2011) The ERA-interim reanalysis: configuration and performance of the data assimilation system. Q JR Meteorol Soc 137:553–597. https://doi.org/10.1002/qj.828

Dodson R, Marks D (1997) Daily air temperature interpolated at high spatial resolution over a large mountainous region. Clim Res 8:1–20

Falco M, Carril AF, Menéndez CG, Zaninelli PG, Li LZ (2019) Assessment of CORDEX simulations over South America: added value on seasonal climatology and resolution considerations. Clim Dyn 52:4771–4786. https://doi.org/10.1007/s00382-018-4412-z

Gao L, Deng H, Lei L, Wei J, Chen Y, Li Z, Ma M, Chen X, Chen Y, Liu M, Gao J (2021) Evidence of elevation-dependent warming from the chinese Tian Shan. The Cryosphere 15:5765–5783. https://doi.org/10.5194/tc-15-5765-2021

Giorgi F, Gutowski W (2015) Regional dynamical downscaling and the cordex initiative. Annu Rev Environ Resour 40:467–490. https://doi.org/10.1146/annurev-environ-102014-021217

Giorgio N (2017) Relation between cloud cover and relative humidity. Bachelor Thesis. University of Utrecht. Available: https://studenttheses.uu.nl/bitstream/handle/20.500.12932/25986/Paper%20Relative%20Humidity.pdf?sequence=2

Gnitou GT, Tan G, Niu R, Nooni IK (2021) Assessing Past Climate Biases and the added value of CORDEX-CORE Precipitation Simulations over Africa. Remote Sens 13(11):2058. https://doi.org/10.3390/rs13112058

Gutiérrez JM, Jones RG, Narisma GT, Alves LM, Amjad M, Gorodetskaya IV, Grose M, Klutse NAB, Krakovska S, Li J, Martínez-Castro D, Mearns LO, Mernild SH, Ngo-Duc T, van den Hurk B, Yoon J-H (2021) Atlas. In: Zhai VP, Pirani A, Connors SL, Péan C, Berger S, Caud N, Chen Y, Goldfarb L, Gomis MI, Huang M, Leitzell K, Lonnoy E, Matthews JBR, Maycock TK, Waterfield T, Yelekçi O, Yu R, Zhou B (eds) Climate Change 2021: the physical science basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [Masson-Delmotte. Cambridge University Press, Cambridge, pp 1927–2058. https://doi.org/10.1017/9781009157896.021

Gutowski WJ, Giorgi F, Timbal B, Frigon A, Jacob D, Kang H-S, Raghavan K, Lee B, Lennard C, Nikulin G, O'Rourke E, Rixen M, Solman S, Stephenson T, Tangang F (2016) WCRP coordinated regional downscaling experiment (CORDEX): a diagnostic MIP for CMIP6. Geosci Model Dev 9:4087–4095. https://doi.org/10.5194/gmd-9-4087-2016

Hawkins E, Sutton R (2011) The potential to narrow uncertainty in projections of regional precipitation change. Clim Dyn 37:407–418. https://doi.org/10.1007/s00382-010-0810-6

Ivanov MA, Luterbacher J, Kotlarski S (2018) Climate model biases and modification of the climate change signal by intensity-dependent bias correction. J Clim 31:6591–6610. https://doi.org/10.1175/JCLI-D-17-0765.1

Jakob C, Miller M (2003) Parameterization of physical processes. Clouds. In: Holton JR (ed) Encyclopedia of atmospheric sciences. Academic Press, New York, pp 1692–1698

Künsch C, Schär HR (2003) Assesment of bias assumptions for climate models. J Clim 27:6799–6818. https://doi.org/10.1175/JCLI-D-17-0765.1

Lin Y, Dong W, Zhang M, Xie Y, Xue W, Huang J, Luo Y (2017) Causes of model dry and warm bias over central U.S. and impact on climate projections. Nat Commun 8:881. https://doi.org/10.1038/s41467-017-01040-2

Leyba IM (2020) Estudio de la interacción océano-atmósfera en el Atlántico Sur y su rol en la precipitación en el sur de Sudamérica. Ph.D Thesis. University of Buenos Aires. Available at: https://bibliotecadigital.exactas.uba.ar/download/tesis/tesis_n6769_Leyba.pdf

Llopart M, Reboita MS, da Rocha RP (2020) Assessment of multimodel climate projections of water resources over South America CORDEX domain. Clim Dyn 54:99–116. https://doi.org/10.1007/s00382-019-04990-z

Llopart M, da Rocha RP, Reboita M, Cuadra S (2017) Sensitivity of simulated South America climate to the land surface schemes in RegCM4. Clim Dyn 49:3975–3987. https://doi.org/10.1007/s00382-017-3557-5

López-Franca N, Zaninelli PG, Carril AF, Menéndez CG, Sánchez E (2016) Changes in temperature extremes for 21st century scenarios over South America derived from a multi-model ensemble of regional climate models. Clim Res 68:151–167. https://doi.org/10.3354/cr01393

Maraun D (2012) Nonstationarities of regional climate model biases in european seasonal mean temperature and precipitation sums. Geophys Res Lett 39:L06706. https://doi.org/10.1029/2012GL051210

Ménard R (2010) Bias estimation. In: Lahoz W, Khattatov B, Menard R (eds) Data Assimilation. Springer, Berlin, pp 113–135. https://doi.org/10.1007/978-3-540-74703-1_6

Peng X, Wu W, Zheng Y, Sun J, Hu T, Wang P (2020) Correlation analysis of land surface temperature and topographic elements in Hangzhou, China. Sci Rep 10:10451. https://doi.org/10.1038/s41598-020-67423-6

Pepin N, Bradley RS, Diaz HF, Baraer M, Caceres EB, Forsythe N, Fowler H, Greenwood G, Hashmi MZ, Liu XD, Miller JR, Ning L, Ohmura A, Palazzi E, Rangwala I, Schöner W, Severskiy I, Shahgedanova M, Wang MB, Williamson SN, Yang DQ (2015) Elevation-dependent warming in mountain regions of the world. Nat Clim Change 5:424–430. https://doi.org/10.1038/nclimate2563

Quaas J (2012) Evaluating the "critical relative humidity" as a measure of subgrid-scale variability of humidity in general circulation model cloud cover parameterizations using satellite data. J Geophys Res 117:D09208. https://doi.org/10.1029/2012JD017495

Reboita MS, da Rocha RP, Dias CG, Ynoue RY (2014) Climate projections for South America: RegCM3 driven by HadCM3 and ECHAM5. Adv Meteorol. https://doi.org/10.1155/2014/376738

Sánchez E, Solman S, Remedio ARC, Berbery H, Samuelsson P, da Rocha RP, Mourão C, Li L, Marengo J, de Castro M, Jacob D (2015) Regional climate modelling in CLARIS-LPB: a concerted approach towards twenty first century projections of regional temperature and precipitation over South America. Clim Dyn 45:2193–2212. https://doi.org/10.1007/s00382-014-2466-0

Shakespeare CJ, Roderick ML (2021) The clear-sky downwelling longwave radiation at the surface in current and future climates. Q J R Meteorol Soc 147:4251–4268. https://doi.org/10.1002/qj.4176

Simmons A, Uppala S, Dee D, Kobayashi S (2007) ERA-interim: new ECMWF reanalysis products from 1989 onwards. ECMWF Newsl 110:25–35

Solman SA (2016) Systematic temperature and precipitation biases in the CLARIS-LPB ensemble simulations over South America and possible implications for climate projections. Clim Res 68:117–136. https://doi.org/10.3354/cr01362

Solman SA, Sanchez E, Samuelsson P, da Rocha R (2013) Evaluation of an ensemble of regional climate model simulations over South America driven by the ERA-Interim reanalysis: models' performance and uncertainties. Clim Dyn 41:1139–1157. https://doi.org/10.1007/s00382-013-1667-2

Tamoffo AT, Amekudzi LK, Weber T, Vondou DA, Yamba EI, Jacob D (2022) Mechanisms of rainfall biases in two CORDEX-CORE regional climate models at rainfall peaks over central equatorial Africa. J Clim 35:639–668. https://doi.org/10.1175/JCLI-D-21-0487.1

Teutschbein C, Seibert J (2013) Is bias correction of regional climate model (RCM) simulations possible for non-stationary conditions?

Hydrol Earth Syst Sci 17:5061–5077. https://doi.org/10.5194/hess-17-5061-2013
Torres RR, Marengo JA (2013) Uncertainty assessments of climate change projections over South America. Theor Appl Climatol 112:253–272. https://doi.org/10.1007/s00704-012-0718-7
Velázquez JA, Troin M, Caya D, Brissette F (2015) Evaluating the time-invariance hypothesis of Climate Model Bias correction: implications for hydrological impact studies. J Hydrometeorol 16:2013–2026. https://doi.org/10.1175/JHM-D-14-0159.1
Walcek CJ (1994) Cloud cover and its relationship to relative humidity during a springtime midlatitude cyclone. Monthly Weather Rev 122(6):1021–1035
Wang Q, Fan X, Wang M (2014) Recent warming amplification over high elevation regions across the globe. Clim Dyn 43:87–101. https://doi.org/10.1007/s00382-013-1889-3
Xie P, Yatagai A, Chen M, Hayasaka T, Fukushima Y, Liu C, Yang S (2007) A gauge-based analysis of daily precipitation over East Asia. J Hydrometeorol 8:607–626. https://doi.org/10.1175/JHM583.1
Zhang C, Xie S, Klein SA, Ma H-y, Tang S, Van Weverberg K, Morcrette CJ, Petch J (2018) CAUSES: diagnosis of the summertime warm bias in CMIP5 climatemodels at the ARM Southern Great Plains site. J Geophys Res Atmos 123:2968–2992. https://doi.org/10.1002/2017JD027200