Multi-model ensemble of statistically downscaled GCMs over southeastern South America: historical evaluation and future projections of daily precipitation with focus on extremes

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Abstract
High-resolution rainfall information is of great value, particularly over southeastern South America (SESA) where the observed and projected climate changes pose a substantial threat to socio-economic activities and the hydrological sector. Consequently, this work focuses on the construction of an unprecedented multi-model ensemble of statistically downscaled (ESD) global climate models (GCMs) for daily precipitation. Different statistical techniques were employed - including analogs, stochastic versions of regression-based models involving neural networks and generalised linear models and linear regressions conditioned by weather types - and a variety of CMIP5 and CMIP6 models. In general, most of the models added value in the representation of the main features of daily precipitation, especially in the spatial and intra-annual variability of extremes. The statistical models were sensible to the driving GCMs, although the ESD family choice also introduced differences among the simulations. The ESD projections depicted increases in mean precipitation associated with a rising frequency of extreme events - mostly during the warm season - following the observed trends over SESA. Change rates were consistent among downscaled models up to mid-21st century, when model spread started to emerge. Furthermore, these projections were compared to the available CORDEX-CORE RCM simulations, evidencing a consistent agreement between statistical and dynamical downscaling procedures in terms of the sign of the changes, presenting the main differences in their intensity. Overall, this study evidences the potential of statistical downscaling in a changing climate and contributes to its ongoing development over SESA.

Keywords Statistical downscaling · Extreme rainfall · Southeastern South America · CMIP5 · CMIP6 · Climate change

1 Introduction
Emerging recognition has lately been seen on precipitation extremes over southeastern South America (SESA, roughly between 50 and 65 °W and 20–40 °S), since SESA stands out as one of the regions where extreme events are becoming more frequent and intense (IPCC, 2021). By being immersed over La Plata basin, the main socio-economic activities in SESA rely on the exploitation of water resources such as rainfed agriculture, hydro-power generation and river transportation. In addition, extreme precipitation events are one of the main contributors to the SESA precipitation annual cycle, triggering the overflow of the main rivers and largely extended floods (Vörösmarty et al. 2013). According to the literature, the positive trends on precipitation and its extremes observed during the recent period are expected to intensify in the late 21st century as global warming conditions enhance the water vapour availability necessary for the development of precipitation systems (Blázquez and Solman, 2020; Li et al. 2020; Diaz et al. 2020; Olmo et al. 2020; Torres et al. 2021; Almazroui et al. 2021).
In a climate change scenario, local adaptation and mitigation policies require the availability of possible evolutions of meteorological variables linked to different climate hazards, such as extreme precipitation. In spite of the significant advances in simulating the Earth’s climate by global climate models (GCMs) - paleoclimatic scenarios, recent and future changes - the uncertainties in future climate projections are still large. This is due to different puzzling aspects of climate modelling, such as the variety of climate models and parametrizations, emission scenarios and natural variability (Lehner et al. 2020). The climate scientific community is devoted to the development and evaluation of different modelling procedures to obtain an optimal representation of the physical mechanisms of the climatic system. In this context, the Coupled Model Intercomparison Projects (CMIPs) provide essential tools for a better understanding of the climate changes that arise from natural variability or in response to changes in radiative forcing. These intercomparison efforts provide long-term historical runs covering much of the industrial period, from 1850 to 2005 in the CMIP experiment 5 (CMIP5) and to 2014 in CMIP6 (Taylor et al., 2012; Eyring et al. 2016). The historical simulations allow us to evaluate model performance during the present climate, which results useful to quantify the possible causes of the spread in the GCMs’ future simulations.

GCMs precipitation outputs typically depict difficulties in reproducing the extreme values - mainly due to not enough spatial resolution and limited representation of sub-grid scale phenomena- pointing out the need for generating regional climate information for mitigation and adaptation strategies. In this context, dynamical and statistical downscaling approaches arise as key procedures to improve the representation of regional and local scale features such as extreme rainfall. Particularly, the Coordinated Regional Climate Downscaling Experiment (CORDEX) initiative is dedicated to the generation of coordinated and consistent downsampling models over different regions of the world (Gutowski et al. 2016). Dynamical downsampling relies on regional climate models (RCMs), that provide high-resolution information by numerically simulating the physical processes of the climatic system (Rummukainen, 2010). However, their high demand of computation resources limits the number of RCM outputs available particularly in domains like South America, where only few modelling institutes can afford to perform these simulations. In this sense, empirical statistical downscaling (ESD) appears as a powerful tool with significantly lower computational cost than other downscaling procedures. Based on the nature of the chosen predictors, different ESD approaches can be considered. The model-output-statistics approach typically establishes statistical relationships between GCM or RCM model outputs and the corresponding local-scale observations. In the perfect-prognosis approach, predictors are typically taken from reanalysis data and are supposed to perfectly represent real synoptic features (Maraun and Widmann, 2018). On this approach, high-resolution information is obtained by identifying relationships between large-scale predictors and the predictand surface variable during the observed climate, which are then applied to GCMs simulations (Maraun et al. 2015). Many studies around the globe have assessed the capability of a variety of ESD techniques in simulating regional and local climate features (i.e., Gutiérrez et al. 2019; Araya-Osses et al. 2020; Sulca et al. 2021; Wang et al. 2021) and in generating future climate projections (i.e., Haylock et al. 2006; Vu et al. 2015; Asong et al. 2016; Baño-Medina et al. 2021). Thus, the design of statistical downscaling strategies becomes of great scientific interest in areas like SESA, where all described above motivates the study of extreme precipitation events, their impact through hydrological modelling and the future changes of heavy rainfall. However, the application of ESD methods over this region is still emerging. Only few studies have evaluated the ESD potential for obtaining regional climate information over SESA (D’onofrio et al. 2010, Menéndez et al. 2010; Bettolli and Penalba, 2018; Bettolli et al. 2021; Solman et al. 2021). Nevertheless, the study of future projections by means of ESD strategies as well as the inspection of the added value of the downscaled simulations are still open lines of research in the region.

In this way, the present study is based on a recent statistical downsampling experiment for daily precipitation over SESA (Olmo and Bettolli, 2021b), in which an evaluation of multiple ESD methods - including novel methodologies for the region like artificial neural networks and circulation-conditioned generalised linear models - was performed. The authors exhaustively validated the ESD models considering a set of years with the largest frequency of extreme rainfall events to assess model capability in simulating a wetter climate. Here, we propose to apply some of those ESD techniques to a set of GCMs during their historical and future periods. Thereby, the main objectives of the present work are to generate a multi-model ensemble of statistically downscaled GCMs outputs of daily precipitation over SESA and to assess model performance and uncertainty in the historical and future periods, with special focus on extreme precipitation.

2 Data and methodology

2.1 Observational data:

Daily precipitation records from 86 meteorological stations over SESA were considered during the period 1979–2017.
Multi-model ensemble of statistically downscaled GCMs over southeastern South America: historical work following the perfect-prognosis approach, which considers reanalysis predictors as quasi-observations to train the statistical models (Maraun et al. 2015). ESD models were trained during the observational period 1979–2017 using ERA-Interim daily mean fields (Dee et al. 2011) of the following variables interpolated at 2° grid resolution over 50–67°W and 20–40°S (blue box in Fig. 1a): geopotential height at 500 and 1000 hPa (Z500 and Z1000, respectively); meridional wind at 850 hPa (V850); specific humidity at 700 and 850 hPa (Q700 and Q850, respectively) and air temperature at 700 and 850 hPa (T700 and T850, respectively). The choice of predictors was proposed considering previous downscaling experiments and the evaluation of the synoptic environment associated with extreme precipitation over SESA (Rasmussen and Houze 2016; Bettolli and

2.2 ESD

a. Data

Based on the evaluation of multiple cross-validated ESD models performed by Olmo and Bettolli (2021b), the present experiment selected specific models from this previous work following the perfect-prognosis approach, which considers reanalysis predictors as quasi-observations to train the statistical models (Maraun et al. 2015). ESD models were trained during the observational period 1979–2017 using ERA-Interim daily mean fields (Dee et al. 2011) of the following variables interpolated at 2° grid resolution over 50–67°W and 20–40°S (blue box in Fig. 1a): geopotential height at 500 and 1000 hPa (Z500 and Z1000, respectively); meridional wind at 850 hPa (V850); specific humidity at 700 and 850 hPa (Q700 and Q850, respectively) and air temperature at 700 and 850 hPa (T700 and T850, respectively). The choice of predictors was proposed considering previous downscaling experiments and the evaluation of the synoptic environment associated with extreme precipitation over SESA (Rasmussen and Houze 2016; Bettolli and
Penalba 2018; Olmo and Bettolli 2021a). Thus, the predictor sets used in this work involved different configurations with pointwise predictors - using the values from the four and sixteen nearest grid points to the target station point - and spatial-wide predictors information by using the principal components (PCs) - explaining 95% of the total variance (Table 1). The first approach was considered to address local influences, whereas the last one was used to retain the large-scale atmospheric structures. Although a detailed description of the application of the ESD models will be given in the following lines, the reader is referred to Olmo and Bettolli (2021b) for a comprehensive evaluation of the calibrated models selected for the present work.

Simulations from 12 GCMs from the CMIP5 and CMIP6 experiments (Taylor et al. 2012; Eyring et al. 2016) were used in the application of the ESD models. These sets of models were selected since they have full availability for the different predictor variables and levels, including the Andes mountain range. Historical outputs of the predictor variables mentioned above during the period 1979–2005 (1979–2014) were considered for the CMIP5 (CMIP6) models. Furthermore, in order to obtain downscaled climate projections for the 21st century, future model outputs covering the period 2006–2100 (2015–2100) from the RCP8.5 (SSP585) simulations were employed. Although these two future scenarios are not strictly comparable, both imply the worst-case scenario in each CMIP experiment. GCMs predictor variables were interpolated to a common grid of 2°. Additionally, raw precipitation outputs from the GCMs in their native grid resolution - selecting the closest model grid cell to each station point - were included in the different analyses for comparative purposes. A complete description of the GCMs used in this study is presented in Table 2.

b. Methods

Despite the significant advances in the statistical downscaling field, in South America - and particularly over SESA - the different approaches and techniques have not been explored as exhaustively as in other regions of the world. Hence, in order to produce a large multi-model ensemble of statistically downscaled GCMs, a selected set of ESD models based on the perfect prognosis approach, that were assessed in a previous study (Olmo and Bettolli, 2021), were considered in the present work:

| Table 1 | Predictor combinations employed for the ESD models configurations. Each model will be referred to as method_label (for instance: AN_PC corresponds to the analog method when using the PC configuration) |
|-------|---------------------------------------------------------------|
| Label | Predictors configuration | AN  | GLM_ST | GLM_WT | NN_ST |
| L16   | Z500, Q700, T700, U850, V850, Q850, Z1000: 16 nearest grid-points | x   | x     |       | x     |
| L4    | Z500, Q700, T700, U850, V850, Q850, Z1000: 4 nearest grid-points |       | x     | x     |       |
| L5    | Z500, V850, Z1000: Principal components (95% explained variance) |       |       |       | x     |
| L6    | Q700, T700, Q850, T850: 4 nearest grid-points |       |       |       |       |
| PC    | Z500, Q700, T700, U850, V850, Q850, Z1000: Principal components (95% explained variance) | x   | x     | x     | x     |

| Table 2 | Global climate models (GCMs) used in this study |
|-------|-----------------------------------------------|
| N°    | Model name                      | Experiments | Resolution | Institute                                | Reference          |
| 1     | CanESM2                         | CMIP5 historical (1979–2005) | 2.8° x 2.8° | Canadian Centre for Climate Modelling and Analysis, Canada | Kirchmeier-Young et al. 2017 |
| 2     | CMCC-CMS                        | and RCP8.5 (2006–2100) | 1.9° x 1.9° | Centro Euro-Mediterraneo per I Cambiamenti Climatici, Italy | Fogli et al. 2009 |
| 3     | CNRM-CM5                        | r1i1p1r1 run | 1.4° x 1.4° | Centre National de Recherches Meteoreologiques/ Centre European de Recherches et de Formation Avancée en Calcul Scientifique, France | Voldoire et al. 2013 |
| 4     | MPI-ESM-LR                      |                          | 1.9° x 1.9° | Max Plank Institute for Meteorology, Germany | Giorgetta et al. 2013 |
| 5     | MPI-ESM-MR                      |                          | 1.9° x 1.9° | Max Plank Institute for Meteorology, Germany | Giorgetta et al. 2013 |
| 6     | NorESM1-M                       |                          | 1.9° x 2.5° | Norwegian Climate Centre, Norway | Bentsen et al. 2013 |
| 1     | CanESM5                         | CMIP6 historical (1979–2014) | 2.8° x 2.8° | Canadian Centre for Climate Modelling and Analysis, Canada | Swart et al. 2019 |
| 2     | INM-CM5-0                       |                          | 1.5° x 2.0° | Russian Institute for Numerical Mathematics, Russia | Volodin et al. (2017) |
| 3     | MPI-ESM2-1-HR                  | and SSP585 (2015–2100) | 0.9° x 0.9° | Max Plank Institute for Meteorology, Germany | Mueller et al. (2018) |
| 4     | MPI-ESM2-1-LR                  | (r1i1p1f1 run) | 1.9° x 1.9° | Max Plank Institute for Meteorology, Germany | Mueller et al. (2018) |
| 5     | NorESM2-LM                     |                          | 1.9° x 2.5° | Norwegian Climate Centre, Norway | Bentsen et al. 2013 |
| 6     | NorESM2-MM                     |                          | 0.9° x 1.2° | Norwegian Climate Centre, Norway | Bentsen et al. 2013 |
• Analogs

The analog method (AN, Zorita and von Storch 1999) consists of finding, for each daily GCM record, the most similar large-scale atmospheric configuration in ERA-Interim (the nearest neighbour) in the period 1979–2017 to obtain the local prediction according to a similarity metric (in this case, the Euclidean distance). The ANs have been widely applied in different regions due to its simplicity and ability to account for the non-linearity of the predictor-predictand relationships (Timbal et al. 2009; Bettolli and Penalba 2018; Gutiérrez et al. 2019). The main drawback of this technique is that the catalogue of analog days is constrained to the observed period and therefore it cannot predict values outside the observed range. This makes the ANs sensible to possible nonstationarities in a climate change scenario, which should be cautiously considered (Benestad, 2010).

• Generalised Linear Models

The generalised linear models (GLMs) are an extension of linear regression in which the predictand variable can belong to a non-gaussian distribution. Given that in this work special attention is taken in extreme precipitation, stochastic versions of GLMs were adopted, considering a random sample from the predicted distribution at each time step (GLM_STs). As performed by Olmo and Bettolli (2021b), these models consisted in a two-stage implementation, with a Bernoulli distribution and a logit link for precipitation occurrence, and a Gamma distribution and log link for precipitation amounts (San Martín et al. 2017; Bedia et al. 2020). Hence, two simulated time-series were produced at each station point so that the final rainfall time-series was calculated by multiplying these two series (see Bedia et al. (2020) for further details).

• Generalised Linear Models + Weather Types

This family of ESD models is made up of circulation-conditioned GLMs (GLM_WTs) (San Martín et al. 2017; Olmo and Bettolli 2021a). The classification of 16 weather types (WT), found in Olmo and Bettolli (2021a) based on Z500 anomalies over southern South America, was used to calibrate the GLM individually for each WT. Note that these are deterministic GLMs, thus, precipitation occurrence is obtained by transforming the simulated probability values into binary ones considering the climatological probability of rain as threshold, whereas precipitation amounts are the expected values modelled by optimising the conditional mean. For this method, the Z500 daily anomalies of the GCMs were projected into the ERA-Interim weather types according to the Euclidean distance.

• Neural Networks

The artificial neural networks (NNs) are non-linear regression-based models made of a chain of neurons organised in layers of feed-forward networks. Model structure relies on these neurons being connected between consecutive layers from the input layer - daily predictors fields - through a set of hidden layers in the network, to the output layer. These connections are characterised by different weights - that the network optimist from the input data - and activation functions, which are non-linear functions applied in each neuron (Cavazos, 1999; Haylock et al., 2006; Vu et al. 2015; Baño-Medina et al., 2020; Baño-Medina et al., 2021). Following the model construction employed in Olmo and Bettolli (2021b), a two-layers NN configuration with 25 and 15 neurons, respectively, was selected. The learning rate parameter was set to 0.01 and the activation function in the hidden layers was the sigmoid function. Similarly to the GLMs, a stochastic set-up of NNs (NN_STs) was included in this study, which was implemented in two stages: one for precipitation occurrence - for which the output layer performed a linear function - and one for precipitation amounts, for which the output layer performed the sigmoid function. Following the recommendations by Baño-Medina et al. (2020), the NN optimises the negative log-likelihood of a Bernoulli-Gamma distribution. Specifically, it estimates rain probability from the Bernoulli distribution and the shape and scale parameters of the Gamma distribution to obtain rain occurrences and amounts, respectively.

Note that deterministic GLM and NN simulations of daily precipitation were previously analysed, resulting in systematic underestimations of precipitation amounts - particularly in extremes - and generally presented poorer performances than their stochastic versions or other ESD families. Hence, this work will be centred on the application of the ESD techniques that best represented the main features of daily precipitation as shown by Olmo and Bettolli (2021b). For each ESD model family (AN, GLM_ST, GLM WT and NN_ST), two models with different predictors configuration were chosen based on their performance in the cross-validation procedure (Olmo and Bettolli 2021b). In this way, in the present study 8 ESD models - outlined in Table 1 - were applied to the GCMs outputs for their historical and future periods. The ESD methods were implemented using the R-based climate4R open framework (Bedia et al. 2020).

c. Evaluation framework

The perfect prognosis approach assumes that GCMs are able to adequately reproduce the predictors as depicted by the reanalysis dataset. For this reason, the distributional similarity between the representation of predictor variables by the
GCMs and ERA-Interim was addressed here by performing a two-sample Kolmogorov-Smirnov (KS) test, which is a non-parametric test for checking the null hypothesis that two datasets come from the same distribution. The KS statistic presents values from 0 to 1, where the lowest values indicate greater distributional similarity. Following the methodology suggested by Bedia et al. (2020), standardised anomalies of the predictor variables were compared using an effective sample size due to the strong serial correlation on the daily time-series, at the 99% level of confidence.

Statistically downscaled GCMs precipitation was analysed for each CMIP experiment, separately (Table 1). Model historical evaluation was carried out considering the 1979–2005 and 1979–2014 periods for CMIP5 and CMIP6 models, respectively. The meteorological station points over SESA were used as reference. On one hand, multiple validation indices adapted from the VALUE intercomparison experiment (Maraun et al. 2015) were estimated during the historical period, encompassing the main features of daily precipitation. The indices are the relative bias (Bias Rel.), the frequency of rainy days (R01), precipitation intensity (as depicted by the simple precipitation intensity index, SDII), the intensity and frequency of days with precipitation above 20 mm (R20 and R20p, respectively) and the 98th percentile of the daily precipitation distribution in wet days (P98). In all cases (observations and models), the threshold for a rainy day was set at 1 mm per day. On the other hand, the spatio-temporal variability of precipitation extremes was assessed by analysing their spatial behaviour, intensity and intra-annual variability. To this end, extreme rainfall was defined at each station point as the precipitation values in those days when the accumulated precipitation exceeded the 95th percentile (P95) of the empirical distribution of rainy days. This daily percentile was calculated in the base period 1986–2005, considering a 29-days moving window centred on each calendar day. In addition, Taylor diagrams (Taylor, 2001) were illustrated for summarising the representation of the spatial patterns of precipitation over SESA. These diagrams quantify the degree of statistical similarity between the stations reference dataset and the models, reporting the Pearson correlation coefficient, the standard deviation and the centred root mean squared error.

For the analysis of the downscaled projections, anomalies from the 1986–2005 base period were estimated in each model output and time-series of specific precipitation indices were constructed using both historical and future simulations. The indices used here were chosen to study changes in both the intensity and frequency of rainy days (PPmean and PPfrequency, respectively) and precipitation extremes based on the estimation of the P95 as described above (R95 and R95p for extremes intensity and frequency, respectively). Moreover, agreement maps showing the coincidence among the multi-model ensemble in the projected changes were plotted over SESA.

2.3 RCMs

In order to inter-compare the statistically downscaled projections obtained here with other dynamical downscaling models, the regional climate models RegCM4v7 and REMO2015 from the CORDEX-CORE initiative (Gutowski et al. 2016) were considered, with a spatial resolution of 0.22°. Particularly, daily RCMs precipitation from the historical (1979–2005) and RCP8.5 (2006–2100) experiments driven by three CMIP5 GCMs were employed (MPI-ESM-LR, MPI-ESM-MR and NorESM1-M). Note that these three GCMs were also used for the ESD simulations in the present work (Table 1). In this way, 4 simulations were compared with the different statistical downscaling outputs of the common GCMs: MPI-ESM-MR_RegCM4v7, NorESM1-M_RegCM4v7, MPI-ESM-LR_REMO2015 and NorESM1-M_REMO2015. A more detailed description of the RCMs simulations is displayed in Table 3. Even though the validation of these RCMs is beyond the scope of this study, they have already been evaluated and used over the region in the literature and their skills and shortcomings were identified (Olmo and Bettolli 2021a; Teichmann et al. 2020). Thereby, the focus of this analysis will be on the comparison of the variety of downscaled projections in terms of model agreement and spread in the intensity of changes over SESA.

3 Results

3.1 Historical evaluation

For the perfect prognosis assessment, KS score maps for V850 and Q850 in three of the GCMs listed in Table 1 are illustrated in Fig. 1b (results of the rest of the GCMs and
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ratios near zero. The GLM_STs and GLM_WTs tended to overestimate the index, more pronounced in GLM_WT_PC. This behaviour of the different ESD models was coincident in all the GCMs from both CMIP experiments (Fig. 2a and b).

Regarding the indices related to heavy precipitation, the ESD models were able to reproduce R20 and R20p when applied to most of the GCMs. The GLM_WTs presented the largest differences, but no general behaviour could be summarised as their performance often varied among GCMs. As mentioned above, ESD performance in NorESM1-M was weaker than in other GCMs, as all ESD models tended to underestimate the indices, although this was less intense than in the raw GCM (Fig. 2a). The analysis of extreme precipitation as depicted by the P98 index exhibited the predictor variables are available in Figure S1 as supplementary material. Distributional similarity varied among GCMs, although the larger discrepancies in the representation of Q850 and Q700 were consistent in many of the models. The differences between ERA-Interim and some GCMs distributions were significant over the centre and northeastern parts of the domain for Q850 and Q700, respectively, thus limiting at some point the validation of the perfect prognosis hypothesis in some areas. For instance, the NorESM1-M model seemed to present significant differences more spatially extended than the rest of the GCMs. It is interesting to highlight that, in the case of Q850, the different MPI models tended to show more agreement with ERA-Interim than the rest of the models. Despite this regular performance of the GCMs in appropriately representing specific humidity, moisture-related variables are crucial predictors when simulating precipitation, which is the reason why it was included in the different predictor sets. The rest of the predictor variables were generally well represented by the GCMs, while V850 exhibited more differences in the grid cells near the Andes mountain range, but were not significant (Fig. 1b and Figure S1 of the supplementary material). These outcomes become useful information for the interpretation of the downscaled results and exhibit the difficulty of some GCMs in representing specific humidity over SESA.

An initial inspection of the statistically downscaled GCMs was carried out by analysing the performance in the indices described in Sect. 2.2. Boxplots in Fig. 2 present, for each GCM, the estimated indices at every station point over SESA, and the first box presents the comparison with the raw GCM precipitation data (CMIP5 and CMIP6 models are displayed in Fig. 2a and b, respectively). In terms of model biases, the different ESD families satisfactorily reduced model biases. The exception were the GLM_WTs, especially the GLM_WT_PC configuration, which often presented wet biases (for instance, in the CanESM2 and CMCC-CMS CMIP5 models and in the CanESM5 and MPI-ESM2-1-HR CMIP6 model). Most of the ESD models showed added value to the raw GCM precipitation, as depicted by the boxes nearer to the zero reference line. This was consistent when applied to almost all the GCMs, although the CMIP5 NorESM1-M model (Fig. 2a) presented dry biases in all ESD models like the raw GCM values. When analysing the frequency of rainy days (R01), all ESD models reduced the magnitude of the differences found in the raw GCM precipitation and exhibited smaller spatial spread as reflected by smaller boxes. GCMs generally overestimate rain frequency, especially at low values (Bador et al. 2020), which was alleviated by the statistical downscaling procedure. In the case of precipitation intensity (SDII), the ESD models again outperformed the raw GCM data, particularly the ANs and NN_STs, which presented SDII

Fig. 2 Results of the indices outlined in Sect. 2.2, estimated for each GCM at every station point over SESA for all ESD models and for the raw GCM precipitation (the nearest grid cell to each station was selected) considering the meteorological stations as reference. All indices but the relative bias are expressed as a ratio between the predicted and the observed index, with the one and zero lines being the references, respectively. Boxplots indicate the 25th, 50th and 75th percentiles in their boxes and the 5th and 95th percentiles in their whiskers. Colours indicate the different ESD model families and the raw GCMs (grey colour): (a) CMIP5 models; (b) CMIP6 models

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of ESD models used in this work exhibited a clear added value in P98. The ANs presented a reduced spatial spread and were always positioned on the reference line, while the stochastic models (GLM_STs and NN_STs) also exhibited a good performance but little overestimating heavy precipitation intensities. The GLM_WTs tended to underestimate the index, especially GLM_WT_L4, which performed similarly

Fig. 3 Taylor diagrams of the spatial pattern of mean and extreme precipitation (PPmean and P95, respectively), considering the meteorological stations as reference. Colours indicate the different ESD model families and the raw GCMs (grey colour). Numbers indicate the different GCMs as described in Table 1, while the coloured squares represent the ensemble mean of all the downscalced GCMs in each ESD family. The diagrams were plotted separately for the CMIP5 and CMIP6 models and for the warm and cold austral seasons (from October to March and from April to September, respectively)
to the raw GCM data. This GLM_WT only considers local predictors, which may be misrepresented by the GCMs (Fig. 1b). Furthermore, the circulation-conditioned GLMs are deterministic models and therefore they are constructed to reproduce the conditional mean, which may cause the models to underestimate heavy precipitation.

In this context, results from the statistically downscaled GCMs are in line with previous findings for these ESD models when considering a cross-validation procedure (Olmo and Bettolli, 2021b), indicating that the models could extrapolate the predictor-predictand relationships learnt from the reanalysis to the GCM predictors data and thereby were able to improve their reproduction of daily precipitation during the historical period, particularly in extremes.

In a following analysis, the spatial patterns of mean and extreme precipitation over SESA were studied through Taylor diagrams (Fig. 3), considering the stations as reference. The diagrams were plotted separately for each CMIP and for the warm and cold austral seasons (from October to March and from April to September, respectively). The different ESD families were illustrated with different colours and the raw GCM precipitation was included for comparative purposes (considering the nearest model grid cell to each station point). A first insight into these diagrams pointed out that the ESD models presented larger spatial variability - in terms of the standard deviation - than raw GCM data, closer to the observations. Note that this is expected at some point since raw GCMs are employed using the nearest model grid cells, which may cause some raw values to be repeated and therefore leading to an underestimation of the spatial variability. Notwithstanding, the ESD techniques produce regional-to-local scale information with higher spatial resolution. The ANs and GLM_STs were the most accurate ESD families in representing the spatial patterns of PPmean and P95, indicated by high correlations and standard deviations generally near one. Furthermore, the configurations with spatial predictors - by considering the principal components of the predictors set - exhibited the best performances (AN_PC and GLM_ST_PC), which is in agreement with results from Olmo and Bettolli (2021b) when driven by ERA-Interim reanalysis. These features were observed for both seasons, CMIP and mean fields (PPmean and P95). The NN_STs tended to overestimate the spatial variability of these patterns particularly during the warm season (standard deviation above one in most of the cases), although they presented small dispersion among predictor configurations and GCMs. The GLM_WTs usually exhibited a larger cloud of points, however, the performance of the GLM_WTs ensembles (indicated with squares) was like the other ESD families in mean precipitation.

When comparing both seasons of the year, the warm season was typically more problematic to be simulated by the different models exhibiting a larger model spread for P95, which seemed to be reduced in each ESD family for the CMIP6 models compared to the CMIP5 models. The warm season presents a marked SW-NE gradient with large amounts of precipitation, and extreme rainfall events during this season are the main contributors to the total annual accumulated precipitation (Cavalcanti et al. 2015). Thus, this is a challenging spatial structure for the downscaled GCMs, as reflected by the lower spatial correlations and larger differences in the standard deviations in P95 than in PPmean. Nonetheless, they adequately simulated this feature of precipitation extremes in most of the cases, better than the raw GCMs. It is worth mentioning that results from NorESM1-M (numbered 6 in the CMIP5 panels of Fig. 3) are usually distinguished from each ESD family cloud, with lower correlations and/or larger overestimations of the standard deviation. This is in line with the model performance and shortcomings in the indices described above (Fig. 2a) and could be related to the misrepresentation of specific humidity identified in the perfect prognosis assessment (Fig. 1b).

In order to evaluate the intra-annual variability of extreme precipitation over SESA, the regional averaged annual cycles of P95 were displayed in Fig. 4. It was notable the clear improvement in the representation of P95 not only in its intensity but also in the shape of the annual cycle when comparing the statistically downscaled GCMs with raw GCM data (grey lines). This added value was congruent in almost all ESD models, except for GLM_WT_L4 that - even though it managed to capture the shape of the cycle systematically underestimated extreme intensities throughout the year, especially during the warm season. Note that GLM_WT_PC exhibited different performances depending on the driving GCM, as reflected by the poor representation of the annual cycle when using MPI-ESM2-1-HR and the overestimation of its amplitude in NorESM2-MM. The rest of the ESD models satisfactorily represented the cycle, with the ANs presenting the best performances and the stochastic models often overestimating extreme intensities. This overestimation varied among GCMs as it was detected during the austral summer, for instance, in the CanESM2 and CanESM5, whereas more clear overestimations were found during winter in some GCMs like MPI-ESM2-1-HR and NorESM2-MM. Nevertheless, the statistically downscaled GCMs outperformed the raw GCMs, which failed in reproducing the intensity and the intra-annual variation of extreme rainfall over SESA, pointing out again the necessity of a downsampling procedure to perform climate studies of spatio-temporal variability of extreme precipitation.
3.2 Future statistically downscaled projections

A general outcome of the evaluation of the statistically downscaled GCMs during the historical period (Sect. 3.1) is that most of the ESD models presented added value in most of the metrics and assessments performed here. The strengths and limitations of the different statistical models were identified, allowing us to continue the analysis of the future projections in a subset of ESD models that were the most accurate during the present climate. Based on these results, in the following analyses one model configuration for each ESD family will be considered. The models AN_PC, GLM_ST_PC, GLM_WT_PC and NN_ST_L16 will be used hereafter in the construction of a multi-model ensemble of downscaled projections.

Figure 5a displays the time-series for mean precipitation changes in terms of the intensity and frequency of rainy days. Changes from the 1986–2005 reference period were calculated for each model and the different ESD families’ ensembles were illustrated together with the raw GCMs ensemble for both CMIP5 and CMIP6, separately. The ensembles were constructed by applying equal weights to each model, however, in order to also analyse the plausibility of the simulations as depicted by each method, the individual results were presented in a supplementary material (Figure S2). In this way, the individual contribution to the ensemble mean can be taken into consideration. In mean precipitation (PPmean, considering rainy days only), greater increases were generally detected in the warm season than in the cold season. The ESD projections showed intensified positive changes compared to the raw GCM outputs, although their intensity and model spread notably varied among ESD families. The NNs exhibited a reduced spread in the ensemble and showed positive changes like the raw GCMs. Greater intensifications in mean precipitation were detected by the ANs and GLM_STs, with the latter presenting a larger spread especially by the end of the 21st century. The largest uncertainty was observed in the GLM_WT_PC projections, as these models depicted the greatest changes and differences among the ensemble, particularly during the warm season. When comparing CMIP5 and CMIP6 downscaled simulations, greater anomalies were reached in the latter set of models, although this was associated with a larger model spread in the GLMs.

In the case of the frequency of rainy days (PPfrequency) (Fig. 5a, right panels), no clear sign of change was found as most of the simulations (ESD and raw GCMs) exhibited fluctuations on the zero anomalies line, particularly in the cold season. Note that raw CMIP5 and CMIP6 changes presented opposite signs at the end of the century during
the warm season. Among the ESD simulations, the ANs differed from the rest of the statistical models as they started
to present larger increases in PPfrequency around 2040, with more discrepancies among the ensemble.

In fact, the performance of the different ESD methods varied among GCMS as displayed in Figure S2 (see supplementary material), where the individual downscaled and raw GCM time-series were illustrated. This analysis exposed that the spread and intensification of PPmean changes in the GLM_ST_PC and GLM_WT_PC ensembles was related with specific GCMS, like CanESM2 and CanESM5, whereas in other GCMS the behaviour of these ESD families was in better agreement with the other statistical models. In addition, the increasing PPfrequency simulated by the ANs was more intense, for instance, in the CanESM2, MPI-ESM-LR, CanESM5 and MPI-ESM2-1-LR models. Therefore, the sensibility of the ESD methods to the driving GCM should be cautiously considered in the evaluation of plausible climate change scenarios over SESA.

Figure 5b presents the agreement among ESD simulations in the changes during the 2071–2100 period in terms of the percentage of ESD models that coincided in the sign of the changes (colours) and the percentage of ESD models that surpassed the observed variance of the time-series (symbols). Most of the models agreed in the general positive sign of PPmean changes (left panels), with percentages between 80 and 100% in the centre of SESA. Model agreement in PPfrequency changes (right panels) was lower especially in the cold season - up to 40% in all the stations - that presented general negative changes in the centre of SESA, whereas the agreement was stronger during the warm season, with mostly positive changes in central SESA. Note, however, that these changes were not larger than the observed variance of this index in most of the ESD simulations, which was consistent with the analysis of the time-series in Fig. 5a.

When analysing the projections in extremes (Fig. 6), general increases in their intensity (R95) and frequency (R95p) were detected in the different simulations. Nevertheless, in coincidence with mean precipitation results as described above, the rates of change varied among them. Raw GCMS exhibited increases in the intensity of extreme rainfall during both seasons from the mid-21st century in CMIP5 and CMIP6 datasets. This was similarly reproduced by the ANs and NN_STs in the cold season, whereas in the warm season they were near zero throughout the 21st century (Fig. 6a). The GLM_STs presented greater changes, although with larger spread in the ensemble. In the case of the GLM_WTs, they exhibited large uncertainty as they differed in the intensity of the changes projected by the end of the century with the rest of the simulations and presented important discrepancies among the ensemble.

The positive changes in the frequency of extreme precipitation events (R95p, right panels in Fig. 6a) were coincident in the different model outputs and more pronounced during the warm season. The ANs and GLM_STs performed similarly, although a larger spread was found in the latter. The NN_STs exhibited the smallest changes and their ensemble mean showed changes even lower than the raw GCMS. Again, the rates of change were the greatest in the GLM_WTs, with large uncertainty in their ensemble. As observed for PPmean (Fig. 5a), model spread during the warm season was larger in CMIP6 than in CMIP5 downscaled models.

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the observed variance of both indices over southern SESA (squares and triangles), indicating larger confidence in the changes over these areas.

It is worth noting that the climate change signal is quite consistent between both GCM generations in all indices and both seasons. Moreover, due to how ESD models were built (except for the AN_PC that by construction preserves the

Fig. 7 Comparison between the ESD and the CORDEX-CORE regional time-series of: (a) mean precipitation intensity during rainy days and frequency of rainy days (PPmean and PPfrequency, respectively); (b) extreme precipitation intensity and frequency (R95 and R95p, respectively). Areal averages were calculated over SESA during the period 1979–2100 for the warm and cold seasons, separately (from October to March and from April to September, respectively). Only 3 CMIP5 GCMs that nested the RCMs were included in the ESD ensemble (MPI-ESM-LR, MPI-ESM-MR and NorESM1-M)
showed a decline in the frequency of rainy days, which was reproduced by the CORDEX ensemble. In contrast, the ESD models presented no clear changes until around 2060, when positive anomalies started to emerge. This was particularly due to the analog models (see Figure S2). During the cold season, the ESD ensemble behaved similarly to the raw GCMs in both ensemble mean and spread, presenting some differences by the end of the century. The CORDEX ensemble exhibited more differences from the raw GCMs and showed positive anomalies in its mean. Despite these particularities, both downscaled sets of simulations showed no clear changes for PPfrequency during the cold season.

In the case of extreme indices (Fig. 7b), the spread in both downscaled sets was larger in R95 than in R95p, particularly in the ESD ensemble. However, the ensemble means were congruent in both seasons, expecting an increase in extreme rainfall intensities by the end of the century. The frequency of extreme events is projected to increase according to both statistical and dynamical downscaling models, which was in good agreement with the climate change signal from raw GCMs. The ESD models closely followed the GCMs ensemble until around 2070, when more intense changes predominated in the ensemble. As observed in Figure S3, this was due to GLM_WT_PC, that amplifies the climate change signal when applied to MPI-ESM-LR and MPI-ESM-MR, whereas the simulations for NorESM1-M were in accordance with the other downscaled simulations.

4 Discussion and conclusions

The present study is centred over southeastern South America (SESA), a region that stands out in terms of the frequency and intensity of extreme precipitation events, which have strong impacts on the socio-economic activities of the region. Thus, high-resolution climate information is required for impact studies such as hydrological modelling and for the evaluation of possible future scenarios in a context of global warming, being rainfall one of the most important and challenging variables needed in such assessments. Thereby, the focus of this work is on the construction of a multi-model ensemble of statistically downscaled GCMs, considering different empirical statistical downscaling (ESD) techniques and a variety of CMIP5 and CMIP6 models. The ESD models were calibrated using ERA-Interim predictors and daily precipitation records from a meteorological stations network over SESA during 1979–2017 and then applied to the sets of GCMs. These models included analogs (ANs), generalised linear models in stochastic and circulation-conditioned versions (GLM_STs and GLM_WTs, respectively) and stochastic neural networks.

3.3 Intercomparison with RCMs

As discussed in the literature, extreme precipitation events over SESA are strongly controlled by regional forcings, which are generally better captured by RCMs than by GCMs (Blázquez and Solman, 2020; Falco et al. 2019). Hence, it is likely that the climate change signal is not always consistent between them, so the downscaled projections become more reliable in terms of the changes in extreme precipitation. As described in Sect. 3.2, the statistical models can also modify the GCM signal of change, although this result clearly depends on the ESD method and the choice of GCM. In this sense, it becomes interesting to evaluate if the ESD models depict climate projections congruent with the RCMs and to inspect their differences in the multiple precipitation indices analysed in Sect. 3.2.

Regional time-series of the mean and extreme precipitation indices previously assessed are displayed for the ESD and CORDEX ensembles in Fig. 7 (a and b, respectively). For each ensemble, only the simulations with the 3 CMIP5 GCMs in common between the ESD and CORDEX-CORE RCM models were considered (Table 3). Raw GCMs ensemble was also illustrated in grey tones. Note that, for this comparison, the ESD ensemble presents a greater number of members than the CORDEX ensemble (12 versus 4 simulations).

In terms of mean precipitation intensities during rainy days (PPmean, left panels in Fig. 7a), the ESD ensemble presented larger spread and more intense positive changes by the end of the century than the CORDEX ensemble - especially during the warm season - which was mainly due to the inclusion of the GLM_WTs. On the other hand, PPfrequency showed different behaviours in both seasons of the year. Raw GCMs projections for the warm season
networks (NN_STs), following the experiment by Olmo and Bettolli (2021b).

The downscaled models showed added value for most of the GCMs in several aspects such as the relative bias and intensity and frequency of rain, but particularly in heavy and extreme intensities, where raw GCMs exhibited strong underestimations (Fig. 2). In terms of spatial variability, the evaluation of the mean and extreme precipitation spatial patterns through Taylor diagrams allowed us to distinguish the performance of the different ESD families, being the ANs and GLM_STs the most accurate, especially in configurations with spatial predictors by considering the principal components (Fig. 3). ESD model performance was better in mean than in extreme precipitation (defined by the 95th percentile, P95), especially during the warm season, when extreme events highly contribute to the total precipitation amounts (Olmo and Bettolli, 2021a). When studying the intra-annual variability of extreme rainfall - in terms of the annual cycle of P95 in Fig. 4 - the added value of most ESD models was clear and consistent in all GCMs. Some GLM_WT models exhibited more difficulties in reproducing the shape of the annual cycle and tended to underestimate extreme intensities, although their performance was usually better than the raw GCMs, which were not able to capture neither the intensities nor the shape of the cycle, pointing out the necessity of performing a downscaling procedure.

Future projections of mean and extreme precipitation from the multi-model ensemble of statistically downscaled GCMs were summarised in regional averaged time-series and model agreement maps (Figs. 5 and 6). ESD projections showed intensified positive changes in mean precipitation compared to raw GCMs - like in the case of the ANs and GLM_STs - even though the intensity of these changes and model spread notably varied between ESD families (Fig. 5a). The circulation-conditioned GLMs (GLM_WTs) presented large uncertainty as depicted by distinguished change rates and ensemble spread, particularly during the warm season. The frequency of rainy days did not evidence a clear sign of change, although ESD simulations presented an increment during the warm season - more pronounced in the ANs - in agreement with CMIP6 raw models but contrary to the CMIP5 set. In the case of extreme precipitation (Fig. 6a), increases in the intensity (R95) and frequency (R95p) were generally detected, even though the change rates varied among simulations. Model agreement was greater for R95p as depicted by the percentage of models that agreed in the sign of the changes, which generally surpassed the observed variance of the index, indicating larger confidence over southern SESA (Fig. 6b). As for mean precipitation, the GLM_WTs exhibited notably larger spread and intensification than other ESD families, while the NN_STs tended to present changes similarly to raw GCMs.

It is important to highlight that the behaviour of the different ESD methods varied among GCMs, as seen in the individual time-series (see Figure S2 and S3 in a supplementary material). In addition, even though an optimal outcome from any downscaling procedure would be the reduction of model spread and uncertainty compared to the raw GCM outputs, the intensity of precipitation changes - and particularly in extreme events - expected during the 21st century presented dispersion among the multi-model ensemble of ESD simulations. This was often larger than the one detected in the raw GCM data, although most of them agreed on the sign of the changes. Note, however, that multiple ESD techniques and different GCMs were employed in the generation of the downscaled projections, which may introduce large differences among simulations, intensifying the ensemble spread. Notwithstanding, all ESD models seemed to be coincident until the mid-21st century, when a clear dispersion started to emerge among the ensembles. In this way, the larger spread and/or intensification of changes in some precipitation indices was often related to specific GCMs but affecting the ESD ensemble anyway. This was mainly due to the inclusion of GLM_WT. The reasons behind this behaviour could be different representations of the circulation patterns by the GCMs, their changing frequency and the within-type variability, related to the stationarity assumption on the relationship between WTs and the surface variable (Cahynová and Huth, 2016). The analysis of the weather types evolution and representation by the GCMs is beyond the scope of this work, however, it implies an essential task to understand the GLM_WTs behaviour and sensibility, particularly from the middle and late 21st century. This topic will be addressed in future studies.

Finally, given that extreme precipitation events are strongly controlled by regional forcings, it is expected that the climate change signal presents discrepancies between raw GCMs and downscaled models, as the latter simulations better reproduce the main features of heavy rainfall. In this sense, to compare the statistically downscaled projections with other downscaled simulations available for the region, the CORDEX-CORE RCM simulations for the South American domain were analysed. The ESD ensemble presented larger spread and more intense positive changes in mean precipitation than the CORDEX ensemble, especially during the warm season (Fig. 7a). For extreme indices, both downscaled sets of models agreed on the increase signal for extreme intensities by the end of the century. These ensembles projected increments in R95p in congruence with raw GCMs, while the ESD ensemble started to present more differences only by the end of the century.

As explained before, the ESD ensemble exhibited a larger spread than the CORDEX RCMs ensemble, although this spread was intensified due to the GLM_WTs. In
coincidence, San Martin et al. (2017) evaluated future precipitation projections over Europe by statistical and dynamical downscaling ensembles and found a larger spread in the ESD simulations, while ESD models’ dispersion was dominated by the choice of GCM rather than by the choice of ESD model family. This last result was also found in the evaluation of the future ESD projections over SESA (Sect. 3.2), which evidences the complexity of performing a downscaling procedure and the assessment of possible future expectations, particularly when it comes to intense rainfall, which should be cautiously considered in the evaluation of plausible climate change scenarios over SESA.

It is worthwhile mentioning that NorESM1-M downscaled simulations typically showed lower scores in the different metrics and evaluations during the historical period compared to the rest of the GCMs, such as in extreme intensities indices in Fig. 2 and in the spatial patterns as depicted by Taylor diagrams. These shortcomings could be associated with its limitations in the representation of predictor variables, in particular, specific humidity at 850 hPa (Fig. 1), thus limiting the compliance of the perfect prognosis assumption in the ESD experiment. However, this GCM was included in the analyses since it is one of the few GCMs used to nest the CORDEX-CORE RCMs in the South American domain. Note that the evaluation of the GCM predictors performed here was univariate (for each individual predictor variable), however, multivariate misrepresentations - which other GCMs may have - could have implications in the ESD performance.

Furthermore, although in this study an unprecedented number of GCMs was employed in the statistical downscaling procedure over SESA (6 CMIP5 and 6 CMIP6 models), this is still not enough to present robust conclusions on the performance and comparison of each CMIP experiment. Nonetheless, no particular behaviour was identified in each set of GCMs. Only a more reduced model spread could be found in CMIP6 in the evaluation of the spatial patterns of mean and extreme precipitation over SESA, while the spread in the projections was associated with the choice of ESD family and often on specific GCMs.

Finally, it is relevant to mention that, even though SESA has been identified as a region with remarkable rainfall changes (IPCC 2021), strong discrepancies in GCMs precipitation trends and projections have been found over SESA. This was associated with GCMs internal variability and misrepresentation of different forcings, including the tropical Atlantic multi-decadal variability, the stratospheric ozone depletion and the increase in greenhouse gases concentrations (Diaz et al. 2020; Varulo-Clarke et al. 2021). This poses an additional challenge for model construction and validation (ESD or RCM) as well as to ascertain our confidence in future precipitation changes over SESA.

Overall, this is a novel work that moves forward on the application of statistical downscaling methods to assess climate changes over SESA in a global warming scenario, detecting the strengths and shortcomings of different techniques, particularly in extreme precipitation. Further research needs to be done in order to assess whether statistical downscaling can generate plausible climate change scenarios and to reduce model uncertainty in order to be applied in impact studies. However, a general clear message was found among downscaled projections in terms of their agreement in increased mean precipitation and frequency of extreme events over the region. This agreement was consistent until the mid-21st century, when model spread started to increase. Particularly, a more comprehensive evaluation of the perfect predictors and the stationarity assumptions in the statistical downscaling of future GCM simulations needs to be performed (Vrac et al. 2007), which will be the focus of a follow-up study. In this sense, these results should be cautiously interpreted, although this work reveals that the developed statistical models are able to bridge the gap between coarse-resolution GCM data and regional-to-local scale features and are promising for studying precipitation extremes in a changing climate.

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