EVALUATION AND PROJECTION OF EXTREME TEMPERATURE PERCENTILES BY MEANS OF STATISTICAL AND DYNAMICAL DOWNSCALING METHODS

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ABSTRACT

The study of extreme events has become of great interest in the recent years due to their direct impact on society. Extremes can be evaluated by using either extreme value statistics or extreme indicators, the latter being based in order statistics on the tail of the probability distribution (typically percentiles). In this study we analyze the highest (95p) and the lowest (5p) percentiles in maximum and minimum temperatures, respectively, derived from different downscaling methods (statistical and dynamical) in the Iberian Peninsula. In particular, we analyze the results of the esTcena and ESCENA projects, two strategic actions of Plan Nacional de I+D+i 2008-2011 funded by the Spanish government, which contributed to the new version of the regional climate change scenarios program Escenarios-PNACC 2012 within Plan Nacional de Adaptación al Cambio Climático.

First, the skill of the downscaling methods to reproduce extreme percentiles is tested in present climate conditions, using reanalysis-driven simulations. The comparison among the different methods is performed in terms of the seasonal bias, considering the public gridded dataset Spain02, a new regular (approximately 20km) daily gridded precipitation and temperature dataset covering continental Spain and Balearic Islands.

Secondly, we analyze future projections in different climate change scenarios to check the increments and the uncertainty of the results up to the mid of the century. We also study the effect of nesting the methods to different Global Circulation Models (GCMs), using the 20C3M historical scenario as reference. By analyzing these changes, we are able to extract differences due to the downscaling method and to the driving GCM.

Key words: bias, percentiles, temperature, downscaling.

RESUMEN

El estudio de eventos extremos se ha convertido recientemente en un tema de gran interés debido a su impacto directo en la sociedad. Los extremos pueden ser evaluados por medio de la Teoría de Valores Extremos o mediante indicadores de extremos, estos últimos basados en los estadísticos de la cola de la distribución de probabilidad (típicamente percentiles). En este estudio analizamos uno de los percentiles más altos en temperatura máxima (95) y de los más bajos en la mínima (5) obtenidos a partir de diferentes métodos de regionalización (estadísticos y dinámicos) en la Península Ibérica. En particular, hemos analizado los resultados de los proyectos esTcena y ESCENA, dos acciones estratégicas del Plan Nacional de I+D+i 2008-2011 financiado por el Gobierno de España, que contribuyen a la nueva versión del programa de escenarios regionales de cambio climático Escenarios-PNACC 2012 dentro del Plan Nacional de Adaptación al Cambio Climático.

En primer lugar, se ha probado la habilidad de los métodos de regionalización a la hora de reproducir los percentiles extremos en clima presente, usando simulaciones anidadas a datos de reanálisis. La comparación entre los distintos métodos se ha realizado en términos del bias estacional, considerando la nueva rejilla pública Spain02, una rejilla regular (de aproximadamente 20km) de precipitación y temperatura que cubre España continental y las Islas Baleares.

A continuación, se han analizado proyecciones de futuro en distintos escenarios de cambio climático para conocer los incrementos e incertidumbre de los resultados a mediados del siglo XXI. También se ha estudiado el efecto de anidar los métodos a diferentes Modelos de Circulación General (GCMs), usando el escenario 20C3M como referencia. Analizando esos cambios, somos capaces de atribuir esas diferencias al método de regionalización o al GCM.

Palabras clave: bias, percentiles, temperatura, regionalización.

1. INTRODUCTION

Climate change is one of the topics that have focused the attention of the scientific community in the last decades, particularly at a global scale. More recently, attention has partly shifted to regional scales, aiming at the regionalization (or downscaling) of global climate change scenarios produced by Global Circulation Models (GCMs). Several downscaling techniques have been proposed in the literature for this task. Some of them are dynamical methods, using a GCM-driven Regional Climate Model (RCMs), solving the equations of the atmosphere at a higher resolution; others are based on statistical methods, which generally need a set of observations to build empirical relationships relating large-scale GCM predictors and local variables. Due to the coarse resolution of GCMs, the use of downscaling methods has spread widely to simulate smaller domains with higher resolution, so the climatic characteristics of a specific region are well represented.

The first step when using downscaling methods is to validate them in present climate conditions, in order to analyze how well they fit the observations. To this aim, simulations driven by reanalysis in a control period ("perfect" GCM output) are also produced, so the error due to the GCM can be taken out. For instance, Christensen *et al.* (1997) compare different dynamical downscaling methods (RCMs) with observations in terms of bias and Gutierrez *et al.* (2012) compare different statistical downscaling methods. Over Europe, several studies were carried out with PRUDENCE Project RCMs (for example in Fowler and Ekstrom, 2009), but nowadays, the state-of-the-art simulations for Europe are the ENSEMBLES Project RCMs (van der Linden and Mitchell, 2009).

Most of the validation studies reported so far focus on the mean climate (Kjellström *et al*, 2010). However, recent studies have pointed out the important changes that are expected to occur in the extremes. According to the last IPCC technical report (2011), it is very likely that there has been an overall decrease in the number of cold days and nights, and an overall increase in the number of warm days and nights, at the global scale. At a regional scale, Rodriguez-Puebla *et al.* (2010) found significant trends of more warm days and fewer cold nights over the Iberian Peninsula in the last decades. Some of these extreme indicators used to quantify extreme events are based on the tail of the probability distribution function. For this reason, in this work we focus on the study of the lowest/highest percentiles of minimum/maximum temperature.

In this study we focus on Spain, and compare the results of two national projects: esTcena (Gutierrez *et al.,* 2012) and ESCENA (Jimenez-Guerrero *et al*., 2012, Dominguez *et al.*, 2012), two strategic actions of Plan Nacional de I+D+i 2008-2011 funded by the Spanish government devoted to statistical and dynamical downscaling, respectively. The aim of this study is to find the most important differences in statistical and dynamical downscaling methods when simulating the tails (extreme percentiles) of the probability distribution functions. According to this, in the first part of the study we compare all the methods (statistical and dynamical) in terms of the seasonal bias of the reanalysis-driven simulations ("perfect" conditions) in the period 1989-2000. Secondly, we obtain the increments in temperature percentiles in a future period (2021-2050) from the A1B scenario, taking 1971-2000 from the 20C3M experiment as a control.

The manuscript is structured as follows. Section 2 describes the data and Section 3 the downscaling methods used in the study. The applied methodology is presented in Section 4. Finally, the main results and conclusions are given in Sections 5 and 6, respectively.

2. DATA

2.1. Observations

We consider the observational dataset Spain02 (Herrera *et al.*, 2012) as a reference to compare different downscaling methods. This data set consists on a new, public, regular 0.2º resolution (approximately 20km) daily gridded precipitation and maximum and minimum temperature covering continental Spain and Balearic Islands. It has been obtained from quality-controlled surface stations from the Agencia Estatal de Meteorología (AEMET), during the period 1950-2008. In this study we use daily maximum and minimum temperature data.

2.2. Reanalysis

ERA-40 (Uppala *et al.*, 2005) is a global reanalysis of meteorological observations for the last decades derived by the European Centre for Medium-Range Weather Forecasts (ECMWF) in collaboration with many institutions. The observations used in ERA-40 were accumulated from many sources. From the 1970s, the observing system changed considerably with assimilable data provided by a succession of satellite-borne instruments, supplemented by increasing numbers of observations from aircraft, ocean-buoys and other surface platforms, but with a declining number of radiosonde ascents since the late 1980s. It has a resolution of 1.125º and it was used as control simulations in esTcena project.

ERA-Interim (Dee *et al.*, 2011) is the latest global atmospheric reanalysis produced by the European Centre for Medium-Range Weather (ECMWF) and has several differences to ERA-40, such as improvements in model physics, new humidity analysis and corrections in the satellite radiance data. All models from ESCENA Project have used the boundary and initial conditions from ERA-Interim every six hours with a spatial resolution of 0.7º.

3. DOWNSCALING METHODS

As mentioned before, we used the statistical downscaling methods from esTcena Project and the dynamical methods from ESCENA Project. In the first part of the study, statistical methods use ERA-40 reanalysis as large scale input data and dynamical methods use ERA-Interim as perfect boundary conditions. Secondly, the methods are nested into several GCMs: ECHAM5, ARPEGE, HADCM3Q0, HADCM3Q3 and HADCM3Q16.

3.1. Statistical downscaled data

For the statistical downscaling methods we use those determined by Gutierrez *et al*. (2012), where the suitability of different statistical downscaling methods for climate change studies is widely analyzed. The selected domain is the Iberian Peninsula (IP) and different sets of predictors have been taken into account. The statistical downscaling methods and predictors used in this study are described in Table 1. Each method is named as the acronym in brackets.

Label	Downscaling Method	Predictor Variables
S1	Nearest neighbor (1 analogue) (AM)	2Td and SLP
S2	Linear regression with 30 PCs (LR)	2Td and SLP
S3	Linear regression with 15 PCs + Nearest grid box (LR)	2Td and SLP
S4	S3 conditioned on 10 Weather Types (k-means with SLP) (LR-WT)	2Td
S5	Weather Generator from gaussian distribution on 100 Weather Types (k-means) (WG-WT)	2Td and SLP

Table 1: *Statistical downscaling methods and predictors.*

3.2. RCM data

A set of high resolution RCMs has been simulated in different institutions. The models used are: PROMES, two versions of WRF, MM5 and REMO. Each model solves the integration of the equations of the atmosphere in a different way. WRF versions consist on different Planetary Boundary Layer (PBL) parameterizations. Table 2 shows their institutions and the labels used below.

Label	Model	Institution	Acronym
D1	WRF-A	University of Cantabria	UC
D2	WRF-B	University of Cantabria	UC
D3	MM5	University of Murcia	UMU
D4	REMO	University of Alcalá de Henares	UAHE
D5	PROMES	University of Castilla La Mancha	UCLM

Table 2: *Dynamical downscaling methods.*

4. METHODOLOGY

In order to evaluate the strengths and weaknesses in all the downscaling methods (statistical and dynamical) with regard to percentiles, we derived the seasonal bias for each individual model. For this task, we compare the seasonal 95^{th} percentile of maximum temperature and the 5^{th} percentile of minimum temperature (nested into the corresponding reanalysis) with Spain02 observations for the period 1989-2000. For the RCMs, we use the nearest neighbor interpolation to work with the same grid as the observations.

Once the biases in the percentiles are obtained, we try to assign them to deficiencies in the mean and variability of their probability distribution functions. For this reason, we calculate two kinds of corrections: seasonal mean correction (Eq.1) and seasonal standard deviation correction (Eq.2). First, we apply these corrections to the maximum and minimum temperature downscaled data. Secondly, we derive again the percentiles from these corrected distributions and, finally, we obtained the seasonal biases in the percentiles with respect to Spain02.

Eq.1 $$x_{\mathbf{i}}^{m} = (x_{\mathbf{i}}^{m} - \mu_{\mathbf{s(i)}}^{m}) + \mu_{\mathbf{s(i)}}^{o}$$

Where $x_{\mathbf{i}}^{m}$ is the first order corrected daily data and $x_{\mathbf{i}}^{m}$ is the daily simulation. $\mu_{\mathbf{s(i)}}^{m}$ and $\mu_{\mathbf{s(i)}}^{o}$ are the seasonal means for the simulation and observation, respectively, depending on the day i.

Eq.2 $$x_{\mathbf{i}}^{m} = (x_{\mathbf{i}}^{m} - \mu_{\mathbf{s(i)}}^{m})\, \sigma_{\mathbf{s(i)}}^{o} / \sigma_{\mathbf{s(i)}}^{m} + \mu_{\mathbf{s(i)}}^{o}$$

Where $x_{\mathbf{i}}^{m}$ is the second order corrected data and $\sigma_{\mathbf{s(i)}}$ is the seasonal standard deviation for a specific day i, for the model (superscript m) or the observations (superscript o).

We complete the study with the analysis of projections by means of the "delta method". Percentiles are derived seasonally considering the period 1971-2000 from 20C3M as a control period and 2021-2050 in A1B scenario. The difference between both percentiles gives the expected increment in the future period. The GCMs considered are ECHAM5 (for the comparison of statistical and dynamical), HADCM3Q0 (for statistical methods) and ARPEGE, HADCM3Q3 and HADCM3Q16 (only for PROMES).

5. RESULTS

The aim of this study is to provide broader knowledge of the tail of the distribution of different downscaling methods (statistical and dynamical). The starting point is to calculate the highest/lowest percentiles in maximum/minimum temperature. In Fig. 1 we show that the highest values of maximum temperature in summer are found in the south of IP and in winter in the Guadalquivir basin and in the eastern part. Regarding minimum temperature, the lowest values are found in the central part and the Iberian mountain chain in both seasons. As results are similar for the 95th and 90th percentiles of maximum and for the 5th and 10th for minimum temperature, from now we will focus on the 95th percentile of maximum and the 5th percentile of minimum temperature, both in winter and summer.

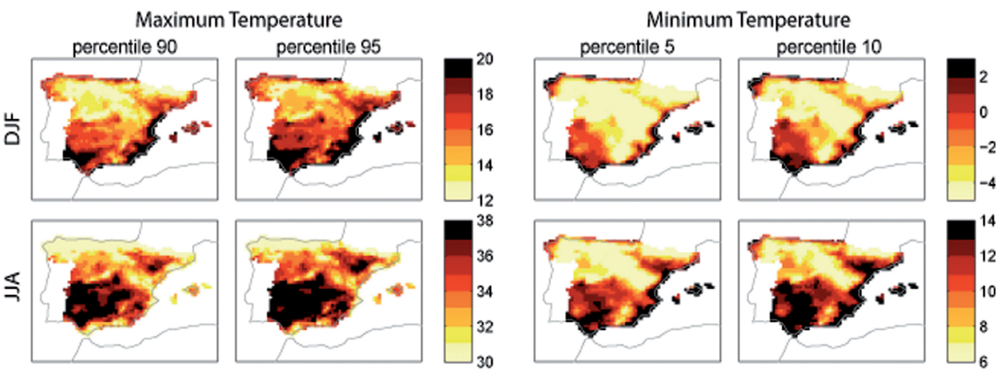

FIG.1: *Observed percentiles for maximum (90th and 95th) and minimum (5th and 10th) temperature in winter (DJF) and summer (JJA) for the period 1971-2000.*

5.1. Present climate

In this section we present the biases in the percentiles for all the downscaling methods with respect to Spain02. Fig. 2 shows the bias for the 5th percentile of minimum temperature in winter. The first column corresponds to the bias of the original model data and the second and third represent the biases when the seasonal mean and the seasonal standard deviation are removed, respectively. The statistical methods have smaller biases than the dynamical models before doing the corrections. S2 (LR), S3 (LR) and S4 (LR-WT) present warm biases while S1 (AM) and S5 (WG-WT) exhibit colder biases. Regarding dynamical methods, all of them present a similar pattern except D4 (REMO), which has a very warm bias, even after doing the correction. For all the methods biases reduce with the first order correction and this reduction is even larger for the RCMs.

Fig. 3 represents the same information as Fig. 2, but for the 95th percentile of maximum temperature in summer. Again S2, S3 and S4 present similar patterns, with a cold bias over a big part of the IP. S1 has a very small bias and S5 is the warmest statistical method. Regarding the RCMs, D1, D2 and D3 (two versions of WRF and MM5) present very cold biases but reduce and even change the sign with the seasonal mean correction. REMO and PROMES present similar patterns, but after the correction REMO has a small warm bias and PROMES a small cold one.

To summarize this information, Fig.4 shows the biases in summer and winter for the 5th percentile of minimum temperature (left) and the 95th percentile of maximum temperature (right) for all the methods. The starting points of the lines (where they are labeled) are the biases in winter (X axis) and summer (Y axis) when the data is not corrected. The ending points of the lines represent the biases when the seasonal mean is corrected. As a meaningful outcome of the study, all the methods reduce strongly their biases when the mean is corrected, mainly the RCMs. Statistical methods have smaller biases before the correction and when it is done results do not improve, since these methods are based on observations from the past and the observational dataset used was Spain02 (Gutierrez *et al*. 2012). The crosses indicate the rescaled standard deviation averaged over the IP in winter (X axis) and summer (Y axis). For all the methods, this spread of the bias reduces with the seasonal mean correction.

5.2. Future projections

In order to quantify the percentile changes in future projections, we calculate the increment of the percentiles subtracting the 20C3M experiment (period 1971-2000) from the A1B scenario (period 2021-2050). Fig.5 shows these increments (called deltas) for the minimum (left) and maximum (right) temperatures averaged over the IP (starting points of the lines). The increments (A1B minus 20C3M) for the percentiles (5th in minimum and 95th in maximum) averaged over the IP are shown in the ending point of the lines (where each line is labeled). The crosses represent the standard deviation over the IP, in order to have an idea of the spread of these increments over the IP. Although averaging over the IP we are losing information of the spatial variability, the aim of this figure is to compare the behavior of the percentiles with respect to the mean minimum and maximum temperatures in the different downscaling methods, rather than quantifying their spatial distribution. We are also trying to find if these changes depend more on the downscaling method or the GCM.

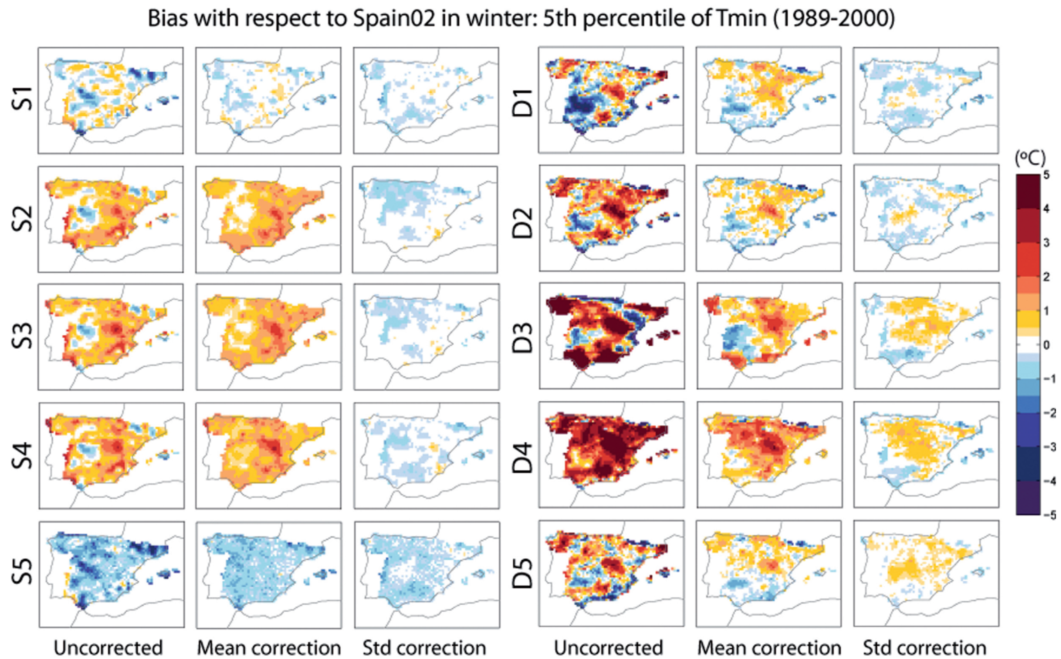

FIG. 2: *Spatial bias (in ºC) for the 5th percentile of minimum temperature for the original data (first column), for the seasonal mean corrected data (second column) and for the seasonal standard deviation corrected data (third column) in winter for all the methods. Bias is calculated with respect to Spain02 dataset. Statistical methods use ERA-40 and dynamical ERA-Interim reanalysis.*

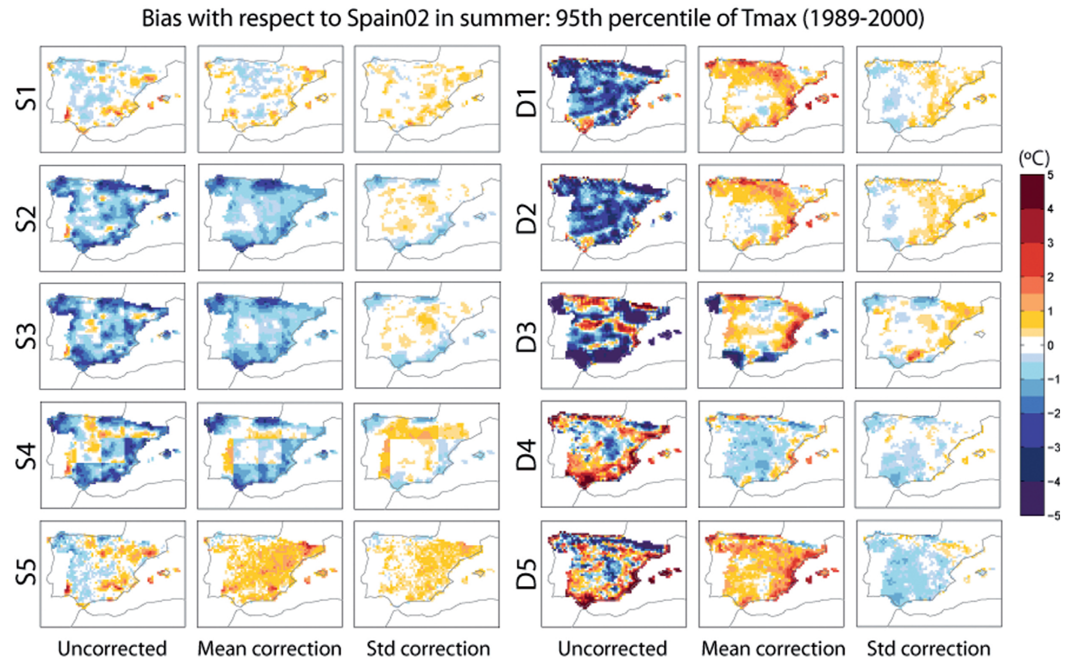

FIG. 3: *The same as Fig.2 for the 95th percentile of maximum temperature in summer.*

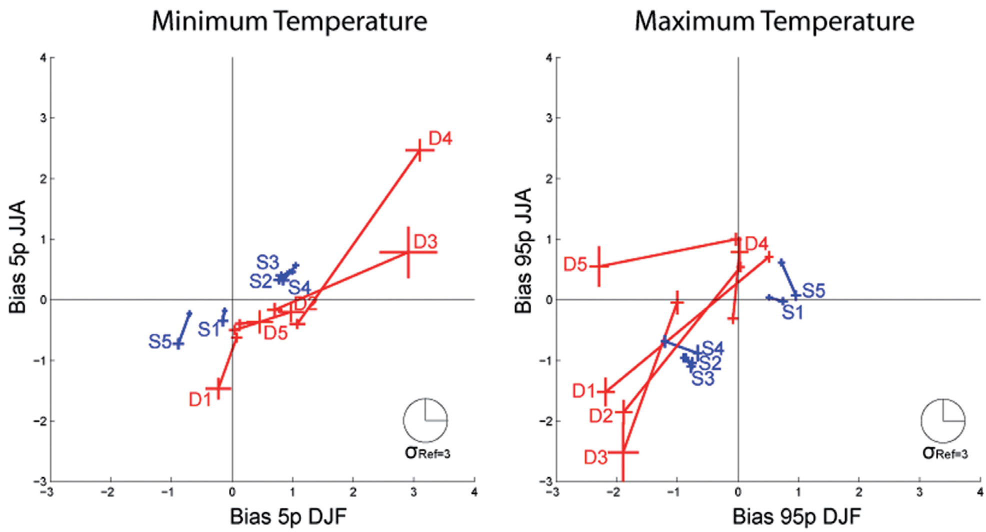

FIG. 4: *Spatially averaged bias (in ºC) of 5th percentile of minimum (left) and 95th percentile of maximum temperature (right) with respect to Spain02. The lines origins (where the lines are labeled) represent the biases without doing any correction in the predictions in winter (X axis) and summer (Y axis). The end of each line represents the bias when the correction in the seasonal mean is done. Each method is labeled as in Tables 1 and 2, red lines for dynamical and blue lines for statistical methods. Crosses indicate the standard deviation of the biases through the IP in winter (X axis) and summer (Y axis). σ are rescaled between 0 and 0.5, and the value* σ_{Ref}*=3 ºC is indicated in the legend as a reference.*

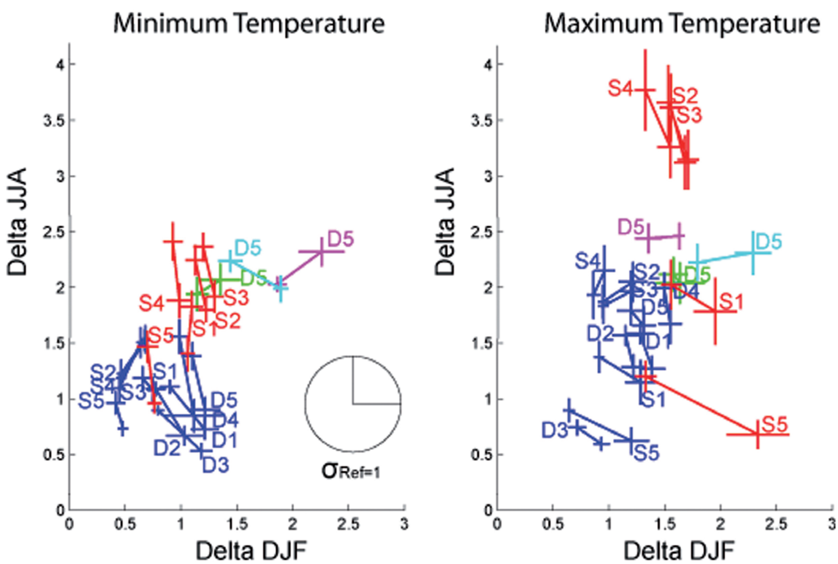

FIG. 5: *Delta values (in ºC) averaged over the IP for the period 2021-2050 of A1B scenario with respect to 1971-2000 of 20C3M. The lines origins are the deltas calculated for the mean variables in winter (DJF, X axis) and summer (JJA, Y axis). The ending points of the lines (labeled points) are the deltas for the 5th percentile (left) and the 95th percentile (right). Methods nested into ECHAM5 are colored in dark blue, HADCM3Q0 in red, HADCM3Q3 in pink, HADCM3Q16 in light blue and ARPEGE in green. Crosses indicate the standard deviation averaged over the IP for winter (X axis) and summer (Y axis). σ are rescaled between 0 and 0.5, and the value* σ_{Ref}*= 1 ºC is indicated in the legend as a reference.*

In Fig. 5 we observe that for some methods the increment is larger for the percentiles. For minimum temperature (left) the increments have similar values in winter and summer. Nevertheless, for maximum temperature (right), the increments are larger in summer than in winter. We have all the methods nested into ECHAM5 (blue lines). For this GCM, dynamical methods have larger deltas than the statistical ones in winter minimum temperature, but smaller in summer maximum temperature. Statistical methods were also nested into HADCM3Q0 (red lines). It seems that this GCM produces larger deltas than ECHAM5, so the increments depend more on the GCM than in the downscaling method. As before in present time, S2, S3 and S4 constitute a cluster apart from S1 and S5. With regard to dynamical methods, PROMES (D5) was nested into four GCMs. The largest increments are found with HADCM3Q3 and HADCM3Q16.

6. CONCLUSIONS

This study tries to clarify the behavior of different downscaling methods (statistical and dynamical) in the tail of the probability distribution function of minimum and maximum temperature. Each method presents strengths and weaknesses and, for this reason, different outcomes have been obtained. Statistical methods depend strongly on observations. This is probably the reason why the biases of high/low percentiles in maximum/minimum temperature were so small. On the other hand, the RCMs present very big biases in the tails of the distributions. These biases reduce nearly to zero only by correcting the seasonal mean with the observations. Also the spread (in terms of standard deviation) over the IP reduces with the correction for all the methods.

For future projections, all the methods agree that there will be a warmer climate and this increase will be more noticeable in summer than in winter up to the mid of the 21st century. All the methods were nested into ECHAM5, giving larger deltas for dynamical than for statistical methods in winter minimum temperature but smaller in summer maximum temperature. We obtained different results using different GCMs and, also, more similar results among the statistical methods for a given GCM. For this reason, we can conclude that the effect of the driving GCM usually dominates the effect of different downscaling methods. Depending on the method used, the increments for the mid of the 21st century are bigger for mean temperatures or for percentiles.

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