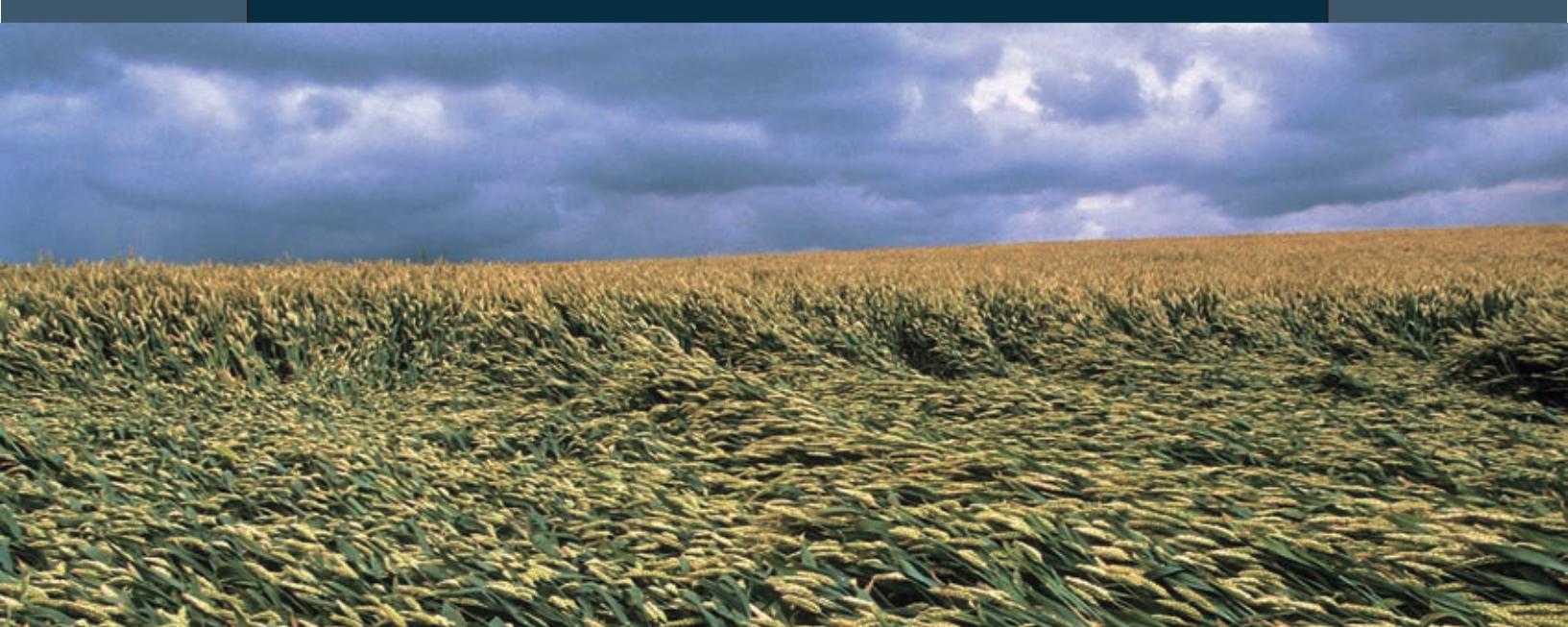




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Statistical Downscaling of Climate Scenarios over Peru



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Meteorología e Hidrología
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Statistical Downscaling of Climate Scenarios over Peru

Author: SENAMHI

National Service of Meteorology and Hydrology of Peru – SENAMHI
Meteorology General Division

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Jr. Cahuide 721 - 785 Jesús María

Telephone: (51 - 1) 6141414 (central) y 2658798 (DGM)

<http://www.senamhi.gob.pe>

Food and Agriculture Organization of the United Nations - FAO

Calle Manuel Almenara 328, Miraflores
Telephone (51-1) 4472641
<http://www.fao.org/peru>

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National Service of Meteorology and Hydrology of Peru- SENAMHI

Executive President of SENAMHI
Amelia Díaz Pablo

Scientific Director
Esequiel Villegas Paredes

General Directorate of Meteorology
Luis Alfaro Lozano

Food and Agriculture Organization of the United Nations - FAO

National Coordinator of AMICAF Project
Julio Postigo

Technical Team of SENAMHI

Clara Oria
Gustavo de la Cruz

Predictia Intelligent Data Solutions and Cantabria University Team

José Manuel Gutiérrez
Rodrigo Manzanas
Daniel San Martín

Graphic Design

Rosa E. Bermúdez Talavera

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Acronym

AMICAF - Assessment of the impacts of climate change and vulnerability mapping food insecurity under climate change to strengthen household food security approach to adapting livelihoods

CMIP5 - Coupled Model Inter Comparison Project Phase 5

FAO - Food and Agriculture Organization of the United Nations

GEI - Greenhouse gases

IPCC - Intergovernmental Panel on Climate Change

GCM - General Circulation Model

RCP - Representative Concentration Pathways

SENAMHI - National Service of Meteorology and Hydrology of Perú

WMO - World Meteorological Organization

1 | Introduction

The Project “Assessment of climate change impacts and mapping of vulnerability to food insecurity under climate change strengthen household food security with livelihood’s adaption approaches AMICAF, (English acronym)”, which is implemented by FAO through a special fund of the Government of Japan, aims at assisting developing countries to address the assessment and adaptation to climate change and thus, contribute to improve food security. Its conceptual framework reconciles the assessment of climate change impacts, the analysis of vulnerability to food insecurity and approaches to adapting livelihoods. Peru has become the first country in Latin America to implement and carry out this project, in which two (2) components will be developed: I) Assessment of climate change impacts and II) Analysis of vulnerability to food insecurity.

General Circulation Models (GCMs) are the main tool for climate research in the coming decades; they simulate flows of energy, mass and momentum between the points of a three-dimensional network that spans across the atmosphere, oceans and upper layers of the lithosphere and cryosphere. However, the spatial resolution of these models is still limited (~ 200 km), for this reason global scenarios do not allow to analyze the magnitude of possible local impacts, so the task of regionalization of global climate change scenarios is important to be able to be performed in the best way to study the impact and adaptation, taking into account regional and local variability of the study area.

There is uncertainty about the magnitudes of these changes at regional scales, but this uncertainty is diminishing. In recent years, researchers specialized in simulation of future climate have succeeded in developing methodologies to perform simulations of the future climate at local level. These simulations, called local climate scenarios, have considerable uncertainty (there are several sources of uncertainty: the future development of society, population, wealth distribution and GHG emissions, the modeling used, regionalization techniques, etc.) but are robust enough to be used in planning and policy making concerning any human activity that is projected for over a decade in the future (forest management, water planning, urban development, agriculture, tourism, etc.) (Brunet et al., 2008.)

Considering the experience gained in the development of regionalization of climate change scenarios, the National Meteorology and Hydrology Service of Peru, SENAMHI (www.senamhi.gob.pe) was appointed to carry out this activity, which considers obtaining local climate projections at national level for rainfall, maximum and minimum temperatures variables towards the period 2050. For this study, it was used the Website Statistical Downscaling (www.meteo.unican.es/downscaling/intro.html) tool developed and supported by Predictia Intelligent Data Solutions (www.predictia.es/en/home) and the Meteorology Group of the University of Cantabria (www.meteo.unican.es/in/main). After obtaining the projections, these will be used by the crop and hydrological modeling groups, using the portal and integrating all components designed for this project, called MOSAICC (Modelling System for Agricultural Impacts of Climate Change).

2 | Data

2.1 Observational Data

SENAMHI provided daily precipitation/maximum/minimum temperature data for an initial set of 366/171/171 stations over Peru (black dots in Fig. 1). However, only 265/105/102 of these stations (red points) were found to have less than 20% of missing data for 1981-2010 and 1971-2000, which are the periods considered for the calibration of the different statistical techniques (Sec. 4) and the assessment of performance of the different ESMs considered (Sec. 5), respectively. In order to obtain robust results, only the latter stations were considered hereafter. Figs. 2 and 3 show their mean (1981-2010) climatology and standard deviation, seasons (in columns).

Fig. 1

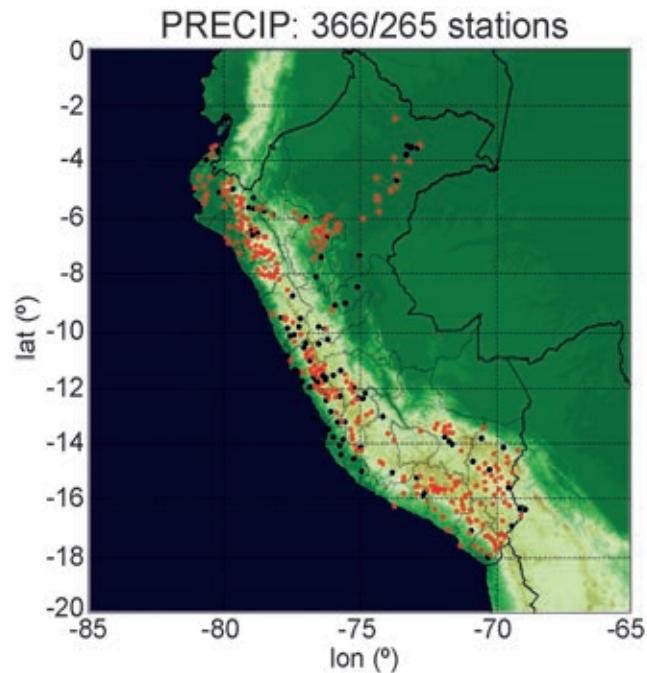


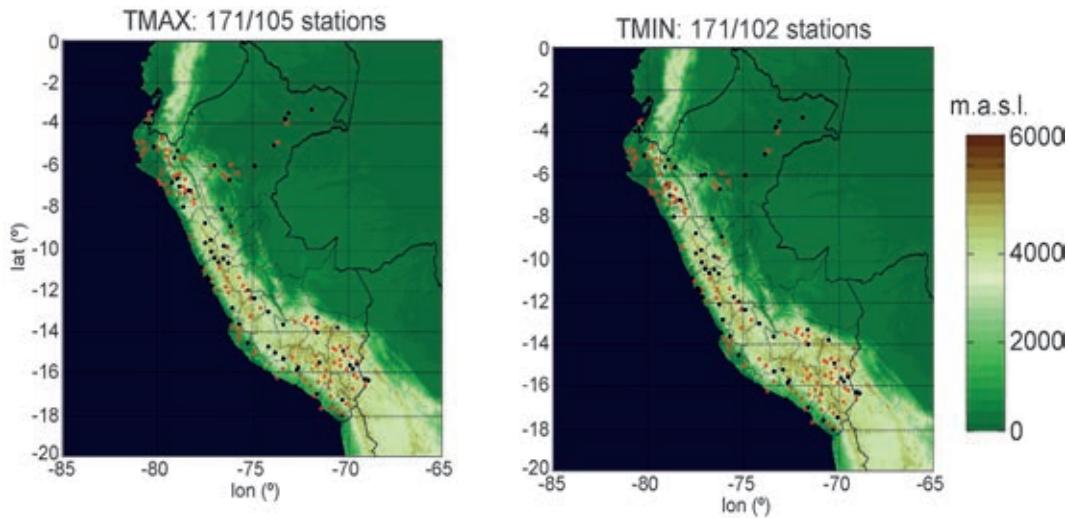
Fig. 1


Fig. 1 Black (red) dots indicate the location of the 366/171/171 (265/105/102) stations of precipitation/maximum/minimum temperature initially provided by SENAMHI (finally considered for the project).

2.2 Predictor Data

On the one hand, the ERA-Interim (Dee et al, 2011) re- analysis - which provides atmospheric fields on a $0.75^\circ \times 0.75^\circ$ resolution from 1979 to present - was considered for the calibration of the different statistical techniques in perfect prog conditions (Sec. 4).

On the other hand, the new generation of General Circulation Models (GCMs) that has become available for the Coupled Model Comparison Project Phase 5 (CMIP5) was considered for the generation of the climate projections (Secs. 5 and 6). In comparison to the former GCMs, these Earth System Models (ESMs) incorporate additional components describing the atmosphere's interaction with land-use and vegetation, as well as explicitly taking into account atmospheric chemistry, aerosols and the carbon cycle (Taylor et al, 2011). This new model generation is driven by newly defined atmospheric composition forcing, the 'historical forcing' for present climate conditions and the Representative Concentration Pathways (RCPs) (Moss et al, 2010) for future scenarios. In particular, there are four different RCPs: RCP2.6, RCP4.5, RCP6.0 and RCP8.5 (from lower to higher 2100 radiative forcing). As the dataset resulting from these global simulations will be the mainstay of future climate change studies and is the baseline of the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (AR5), six different ESMs (see Table 1) and two RCPs (RCP4.5 and RCP8.5; in addition to the historical one) were included in the SDP for this project. The RCP4.5 (Thomson et al, 2011) is a stabilization scenario where total radiative forcing is stabilized before 2100 by employment of a range of technologies and strategies for reducing greenhouse gas emissions. The RCP8.5 (Riahi et al, 2011) -which is based on the A2r scenario (Riahi et al, 2007), is characterized by increasing greenhouse gas emissions over time.

Due to the distinct native horizontal resolution of ERA-Interim and the different ESMs, all of them were re-gridded to a common $2^\circ \times 2^\circ$ grid.

3 | Downscaling Methods

Different Statistical Downscaling Methods (SDMs) commonly used in the literature to downscale climate change scenarios of precipitation and temperatures (Tables 3 and 4, respectively) were considered for this project. In particular, most of these methods have been used in Gutiérrez et al (2012) and Manzanas et al (Preparing submission) to downscale precipitation and temperatures in Spain, respectively.

The first family of methods (AN) is common to precipitation and temperatures, and includes three different versions of the analogue technique (Lorenz, 1963, 1969), which is based on the assumption that similar local occurrences are expected for similar atmospheric configurations - similarity is measured here in terms of the Euclidean distance (Matulla et al, 2008). – an1 only considers the nearest neighbor, whereas an5mean and an15rnd take into account the 5 and 15 nearest neighbors, respectively. an5mean uses the mean of the corresponding observed values as prediction and an15rnd randomly selects one of them. Analog-based methods have been widely used in the literature to downscale climate scenarios of both precipitation and temperatures (Wetterhall et al, 2005; Brands et al, 2011; Cubasch et al, 1996; Timbal et al, 2003; Moron et al, 2008; Timbal and Jones, 2008; Teutschbein et al, 2011; Brandsma and Buishand, 1998; Beersma and Buishand, 2003).

However, the GLM (REG) family is specific for precipitation (temperatures) and includes three different versions of Generalized Linear Models (multiple linear REGression), which only differ in the spatial character of the predictors considered. In particular, glm 15pc (reg 15pc) uses the fifteen leading principal components (PCs) (Preisendorfer, 1988), whereas glm 4nn (reg 4nn) considers - for each gauge - the standardized anomalies at the four nearest grid points. Finally, glm 15pc 4nn (reg 15pc 4nn) combines the fifteen leading PCs with the standardized anomalies at the four nearest grid points, in order to account for both synoptic and local effects. GLM- (see, e.g., Nelder and Wedderburn, 1972, for an introduction) and REG-based methods have been also used in many previous studies to downscale climate change scenarios of precipitation and temperatures, respectively (Brandsma and Buishand, 1997; Fealy and Sweeney, 2007; Hertig et al, 2013; Benestad, 2002, 2005; Huth, 2002, 2004).

Fig. 2

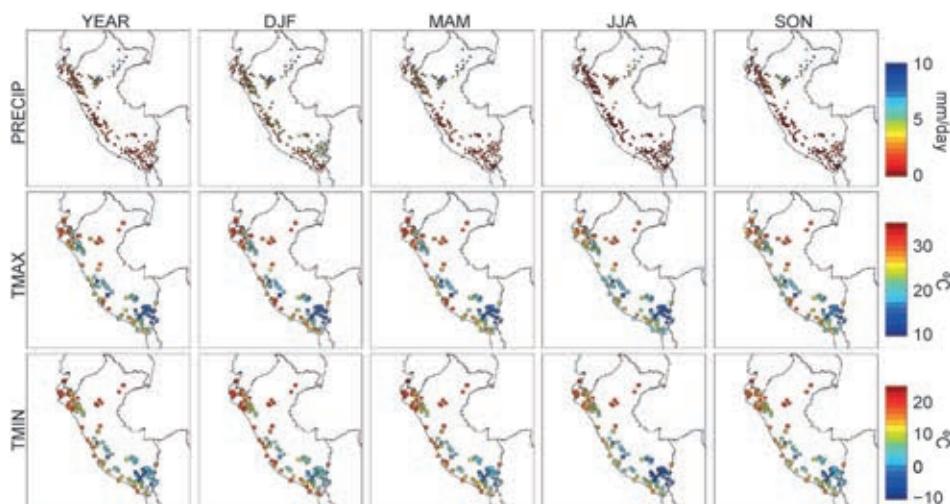


Fig. 2 Mean climatology of the 265/105/102 stations considered for precipitation/maximum/minimum temperature for the period 1981-2010.

Finally, the WT-GLM (WT-REG) family consists of the same methods used for precipitation (temperatures) in the GLM (REG) family, with the only particularity that they are applied to a number (10 here) of predefined weather types (WTs) instead of being applied to the entire predictor data space. WTs are obtained by means of the k-means clustering.

The different configurations (number of analogues, PCs, nearest neighbors, WTs) considered for the above methods were chosen accordingly to the sensitivity analysis performed in Gutierrez et al (2012) and roughly reflect the different methodological approaches that guarantee robust results.

4 | Downscaling in Perfect Prog

Statistical Downscaling (SD) is based on the use of the empirical relationships which link predictands (local observations of a target variable, such as precipitation) to a set of suitable predictors (large-scale variables determining the state of the atmosphere, such as geopotential height or wind speed). Under the perfect prog approach, these relationships (models) are obtained by considering quasi-observed predictors from reanalysis. Afterwards, the fitted/calibrated models (coefficients) are applied to predictors from ESMs in order to translate their global coarse simulations to the local scale required by climate change impact and adaptation applications. The typical predictors used in SD are circulation –sea level pressure (SLP), geopotential height (Z), zonal/meridional wind components (U/V) – and thermodynamic –temperature (T), specific humidity (Q) – variables at different pressure levels, from surface or near surface (e.g. 1000 hPa) to mid/upper troposphere (500/250 hPa). The former variables are robust predictors for climate change studies, whereas the latter carry the climate change signal and, therefore, should be considered for climate change studies. Table 2 shows the variables that were considered as potential predictors for this project. All of them were available for both the ERA-Interim reanalysis and the six ESMs included in the SDP (Table 1).

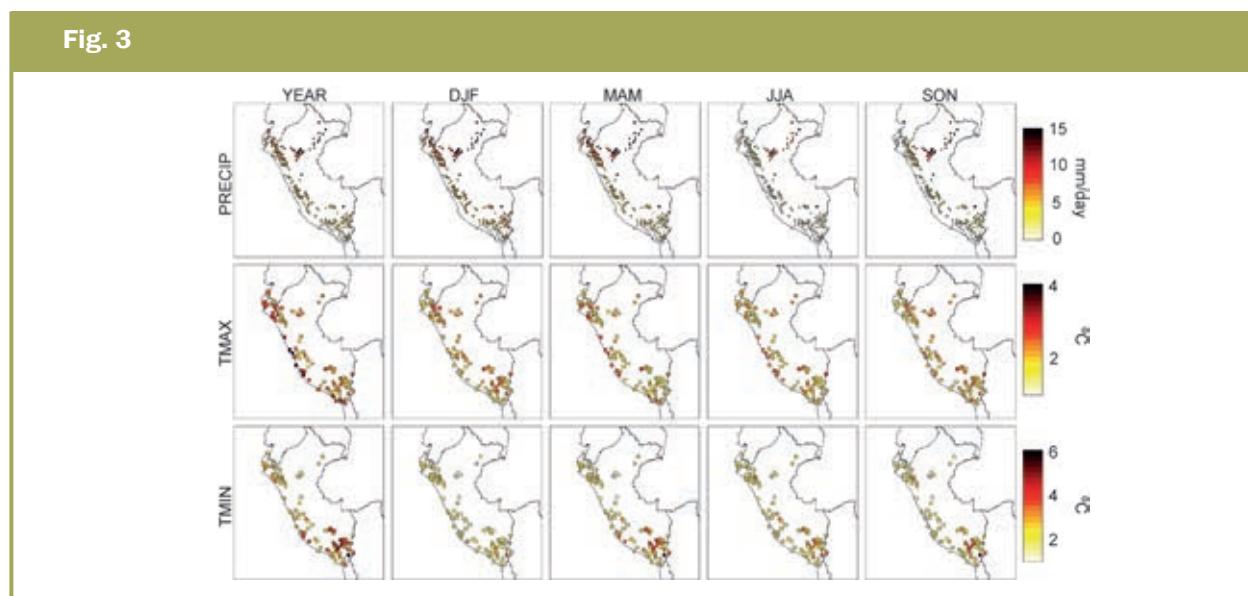


Fig. 3 Standard deviation of the 265/105/102 stations considered for precipitation/maximum/minimum temperature for the period 1981-2010.

Table 1 Six CMIP5 ESMs included in the SDP.

ESM name	Institution acronym	Resolution Reference	
CanESM2	CCCMA	2.8° × 2.8°	Chylek et al (2011)
CNRM-CM5	CNRM-CERFACS	1.4° × 1.4°	Voldoire et al (2011)
GFDL-ESM2M	NOAA GFDL	2.5° × 2°	Dunne et al (2012)
IPSL-CM5A-MR	IPSL	1.5° × 1.27°	Dufresne et al (submitted)
MIROC-ESM	MIROC	2.8° × 2.8°	Watanabe et al (2011)
MPI-ESM-MR	MPI	1.8° × 1.8°	Raddatz et al (2007); Jungclaus et al (2010)

Table 2 Potential predictors (daily mean values) available for ERA-Interim and the six CMIP5 ESMs included in the SDP. 2T stands for 2-meter temperature.

Predictor variable Level	
2T, SLP	Surface
Z, T, Q, U, V	1000, 850, 700, 500, 250 (hPa)

In order to find the optimum SD configuration for each of three target variables (precipitation and maximum/minimum temperatures), a number of suitable predictors and geographical domains (regions where predictors are defined) were identified during the ‘Training Programme on Regional Projection of Climate Change Scenarios for the AMICAF Project in Peru’, held in Lima (17–22 February 2014). However, further analysis was undertaken in order to complete this screening. In particular, we carefully took into account the choice of reanalysis used for calibration. In principle, similar (quasi-observed) time-series should be obtained from different reanalysis. However, significant discrepancies appear for certain variables in the tropics (Brands et al, 2012; Manzanas et al, under review). Fig. 4 shows the correlation between two typical state-of-the-art reanalysis (ERA-Interim and JRA-25) for all the variables in Table 2. The low correlations obtained for temperature and humidity at lower levels illustrates the potential problems which may compromise the use of SD in this region –strictly speaking, SD is not applicable in regions where reanalysis uncertainty is large, since the calibration of the different SDMs requires the use of predictors which reflect the ‘real’ atmospheric processes (Maraun et al, 2010).— In order to cope with this problem, the two aforementioned reanalysis were considered for calibration, finding that ERA-Interim provided better results in most of the cases. Consequently, this was the only reanalysis considered for this project. Moreover, we focused initially on circulation predictors less affected by reanalysis uncertainty. Then, thermodynamic variables were added until no further improvement was attained.

Table 3 Downscaling methods considered for precipitation (see the text for details).

Code	Family	Description
an1	AN	Nearest neighbor
an5mean	AN	Mean of the five nearest neighbors
an15rnd	AN	One out of 15 neighbors (random selection)
glm 15pc	GLM	GLM with 15 PCs
glm 4nn	GLM	GLM with standardized anomalies at the four nearest gridboxes
glm 15pc 4nn	GLM	GLM with 15 PCs + standardized anomalies at the four nearest gridboxes
10wt glm 15pc	WT-GLM	glm 15pc conditioned on 10 weather types (k-means algorithm)
10wt glm 4nn	WT-GLM	glm 4nn conditioned on 10 weather types (k-means algorithm)
10wt glm 15pc 4nn	WT-GLM	glm 15pc 4nn conditioned on 10 weather types (k-means algorithm)

Table 4 Downscaling methods considered for maximum and minimum temperatures (see the text for details).

Code	Family	Description
an1	AN	Nearest neighbor
an5mean	AN	Mean of the five nearest neighbors
an15rnd	AN	One out of 15 neighbors (random selection)
reg 15pc	REG	REG with 15 PCs
reg 4nn	REG	REG with standardized anomalies at the four nearest gridboxes
reg 15pc 4nn	REG	REG with 15 PCs + standardized anomalies at the four nearest gridboxes
10wt reg 15pc	WT-REG	reg 15pc conditioned on 10 weather types (k-means algorithm)
10wt reg 4nn	WT-REG	reg 4nn conditioned on 10 weather types (k-means algorithm)
10wt reg 15pc 4nn	WT-REG	reg 15pc 4nn conditioned on 10 weather types (k-means algorithm)

Additionally, we tested the suitability of daily mean and instantaneous (at different times) predictors, obtaining very similar results in all cases. Thus, we considered daily mean predictors for the sake of compatibility with the CMIP5 ESMs included in the SDP. After an exhaustive screening —testing the performance of multiple predictor combinations (variables in Table 2),— we found the best results for the two predictor sets shown in Table 5, which were the only ones considered for this project. Note that both include two-meter temperature (2T) and some humidity in order to capture the climate change signal when applied to ESM scenario runs.

Regarding the geographical domain, we considered a national- and a regional- approach. In the former case, one unique domain covering the whole country was tested. In the latter, three different domains —defined according to the main areas of influence of the synoptic phenomena affecting the climate of Peru— were considered. Similar results were found in both cases. Therefore, for simplicity, only the national domain was used for this project.

To assess and compare the performance of the different methods of Sec. 3, a cross-validation approach —needed to avoid model overfitting— was considered. The most popular and simple of these approaches is data splitting, which considers independent data for training and validation/test. In particular, in the SDP, the 75% of the available data is used for training and remaining 25% for test. Accuracy and distributional similarity scores were considered.

Fig. 4

ERA-Interim vs. JRA25 (daily means)
rhoD: 1979-2009

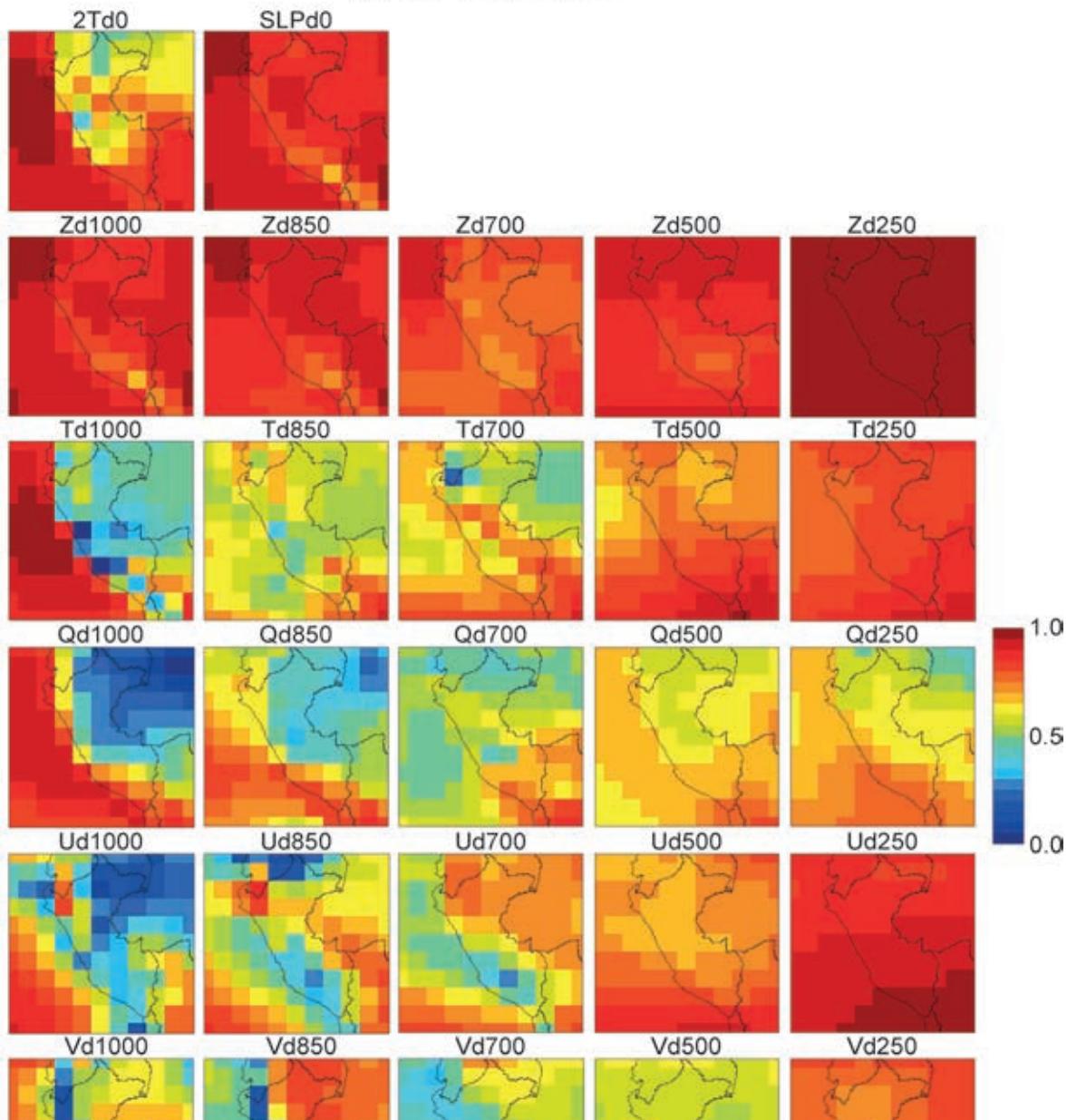


Fig. 4 Daily correlation between ERA-Interim and JRA-25 predictor variables (see Table 2) for the period 1981-2010.

Table 5. Optimum predictor sets found in Perfect Prog conditions

Predictand	Predictor variables
Precipitation	2T, Z250, Q500, U250
Maximum/mínimum temperature	2T, T700, T500, Q700, Q500

On the one hand, accuracy measures the temporal correspondence of the observed and downscaled time-series, which is the basis of SD in perfect prog. We used the Spearman rank (Pearson) correlation coefficient for precipitation (temperatures). On the other hand, distributional similarity evaluates the capability to reproduce the distribution of the target variable –any SDM should properly reproduce the observed distributions in order to avoid the post-hoc correction of the downscaled time-series, which would require the additional assumption of the error being constant under climate change conditions.– The most popular of the scores used to this aim is the bias (mean difference). However, here we considered the PDF-score (Perkins et al, 2007; Maxino et al, 2008), which measures the overlapping area between the observed and downscaled distributions (0=no overlap at all, 1=perfect overlap), accounting therefore both for differences in the mean (bias) but also in higher order moments. Left/middle/right panel of Fig. 5 shows the results obtained for precipitation/maximum/minimum temperature when applying the optimum downscaling configurations (predictor sets of Table 5 over the national domain) in terms of correlations and PDF-score (left and right column, respectively). Each boxplot correspond to each of the nine SDMs considered for each target variable (see Tables 3 and 4). For precipitation, similar correlations are obtained from analog- and GLM- based methods, whereas, for temperatures, REGs lead to higher correlations than analogs. Moreover, for precipitation, WT-conditioned GLMs yield worse distributional similarity than their corresponding unconditioned version, whereas for temperatures, WT-conditioned REGs methods do not provide a significant added value (neither for correlations nor for distributional consistency). Therefore, methods from families WT-GLM and WT-REG were not considered hereafter.

In order to assess the spatial distribution of these results, maps in Figs. 6/7/8 shows the correlations and the PDF-score (top and bottom row, respectively) for the 265/105/102 stations of precipitation/maximum/minimum temperature when applying the optimum predictor sets (see Table 5) to one illustrative SDM, the an1 (see Fig. 5).

Finally, Fig. 9 shows the inter-annual observed and downscaled time-series (black and red lines, respectively) for one selected station for precipitation/maximum/minimum temperature (top/middle/bottom), when applying the optimum predictor set (see Table 5) to the glm 15pc/reg 15pc/reg 15p method, which yields better correlations than an1.

5

Downscaling from Earth System Models in Historical Mode

Once the optimum predictor sets (Table 5) were found in perfect prog (Sec. 4), they were applied to predictor data from ESM in historical mode (the first run r1i1p1 was considered). We detected that some of the ESMs included in the SDP presented problems for some of the variables in Table 5. In particular, GFDL-ESM2M and IPSL-CM5A-MR (MIROC-ESM) were found to contain orographic-driven missing data for all the predictor variables at 850 and 700 hPa (700 hPa) levels over the region of study (see Fig. 10), and consequently, are not suitable for downscaling of temperatures (precipitation).

Fig. 5

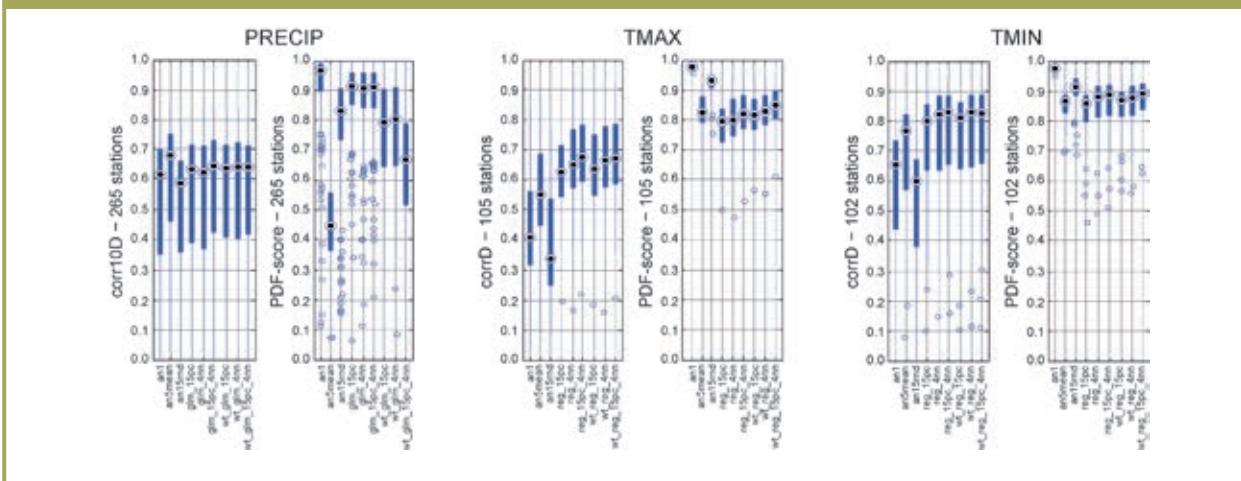


Fig. 5 Performance of the nine SDMs considered (see Tables 3 and 4) for the 265/105/102 stations of precipitation/maximum/minimum temperature, in terms of correlations and PDF-score (left and right column) for the period 1981-2010

Fig. 6

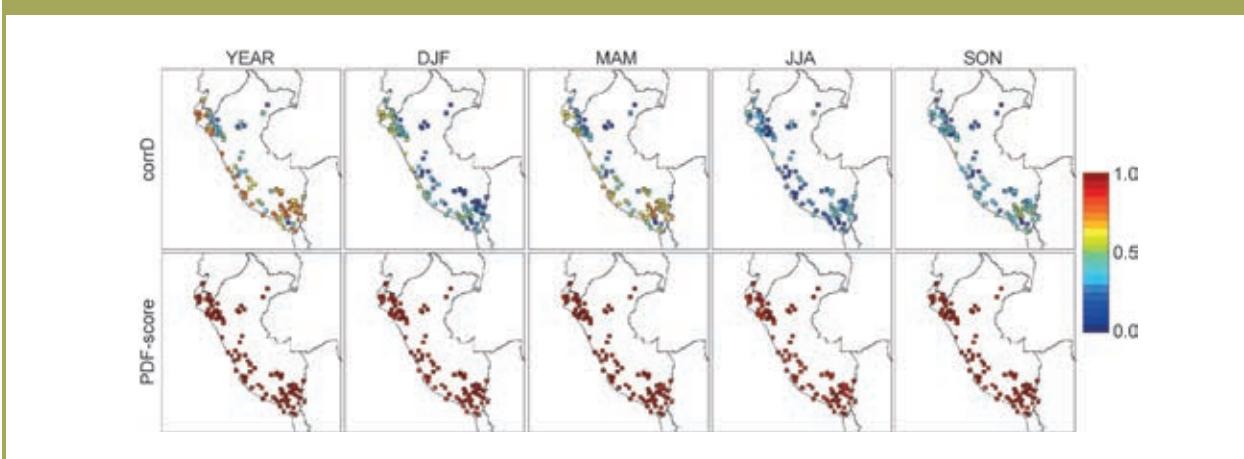


Fig. 6 Ten-day correlation and PDF-score (top and bottom row, respectively) for the 265 stations of precipitation when applying the optimum predictor set (see Table 5) to the an1 method over the period 1981-2010.

Therefore, for coherence, only CanESM2, CNRM-CM5 and MPI-ESM-MR were considered for the three target variables. Methods from the AN and GLM (AN and REG) families (recall that methods conditioned to WTs were discarded in Sec. 4) were applied to the latter models in order to make a selection of the best performing ESM/SDM combinations, which will be later considered for the projections of precipitation (temperatures). To evaluate the suitability of the different ESM/SDM combinations we computed the PDF- score for the thirty-year reference period 1971-2000 — note that low correlations are expected for downscaling from ESMs and performance should be measured in terms of their ability to reproduce the observed distributions.— Left/middle/right panel in Fig. 11 shows the results obtained for precipitation/maximum/minimum temperature. Different colors correspond to distinct ESMs (see the legend). For a particular ESM, each boxplot corresponds to a different SDM (see the labels at the bottom of each panel).

As can be seen, *an1* is the most suitable method among the analog-based ones —yielding the best distributional similarity (especially for precipitation), — whereas there are not significant differences among the three versions of GLMs (REGs). Therefore, since the use of PCs is preferable to the use of anomalies at nearby grid points for climate change studies (the former are less affected by reanalysis uncertainty), *an1* and *glm 15pc* (*an1* and *reg 15pc*) were considered for projecting precipitation (temperatures). Note the appropriateness of considering at least one analog and one GLM- (REG-) based method for precipitation (temperatures) —analog techniques can not predict values out of the historical observed range, whereas GLMs (REGs) do have extrapolation capabilities, and, in principle, might behave differently in climate change scenario conditions.—

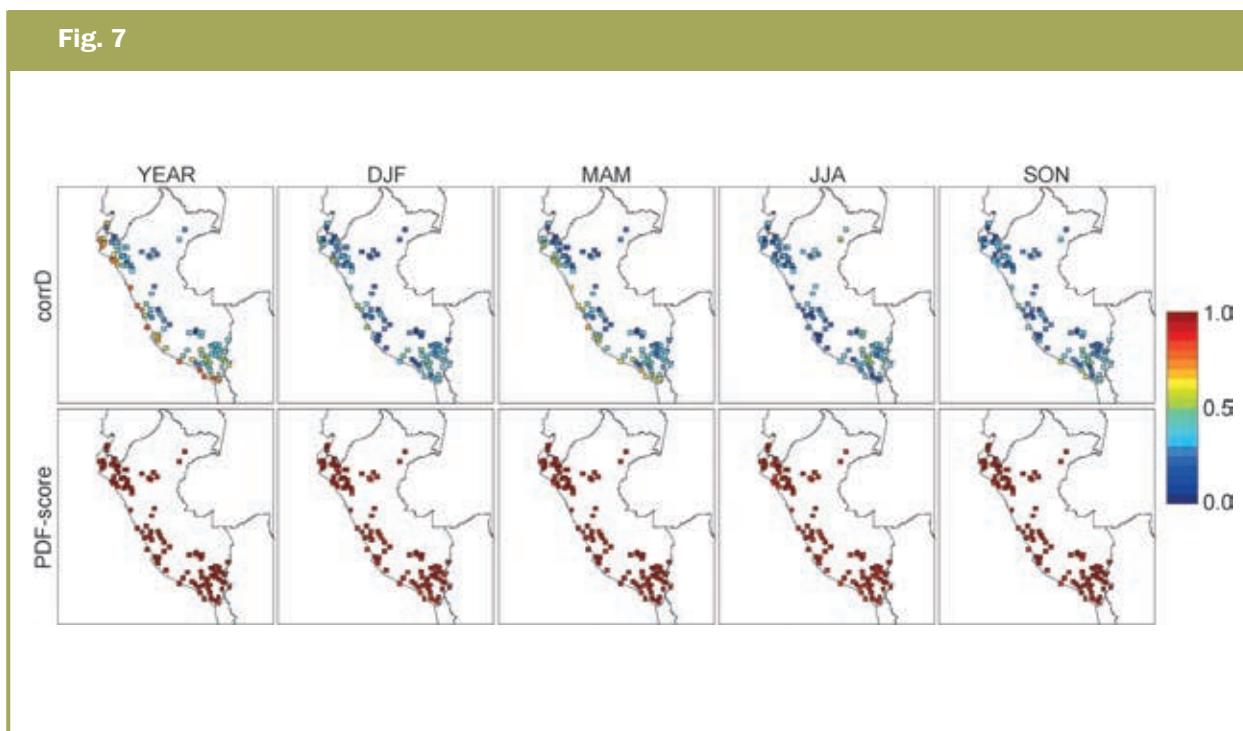


Fig. 7 Daily correlation and PDF-score (top and bottom row, respectively) for the 105 stations of maximum temperature when applying the optimum predictor set (see Table 5) to the *an1* method over the period 1981-2010.

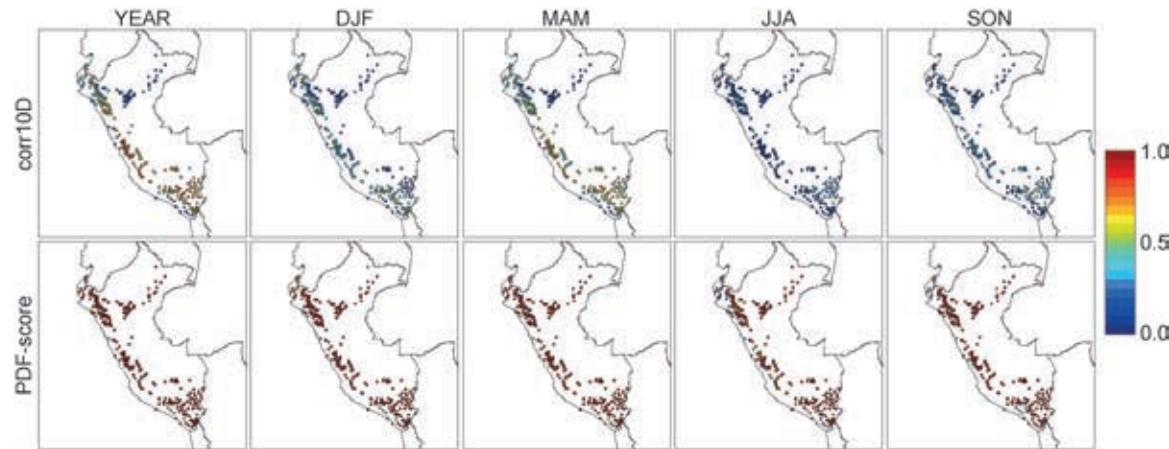
Fig. 8

Fig. 8 Daily correlation and PDF-score (top and bottom row, respectively) for the 102 stations of minimum temperature when applying the optimum predictor set (see Table 5) to the an1 method over the period 1981-2010.

6

Downscaling from Earth System Models in Scenario Mode: Projections of Future Climate

Finally, the statistical models calibrated with ERA- Interim (Sec. 4) were applied to predictor data from ESM in scenario mode (the first run r1i1p1of the RCP4.5 and RCP8.5 scenarios was considered) in order to obtain the projections (up to 2065) of precipitation/maximum/minimum temperature for the 265/105/102 stations of Fig. 1. According to Secs. 4 and 5, three ESMs (CanESM2, CNRM-CM5 and MPI-ESM-MR) and two SDMs were considered for each target variable. However, precipitation (temperatures) projected by the glm 15pc (an1) method were found to be not ‘realistic’ since they clearly overestimated (underestimated) the climate change patterns provided by the global models within the CMIP5 over the region of study (see http://www.climatechange2013.org/images/report/WG1AR5_AISM4.5_FINAL.pdf and http://www.climatechange2013.org/images/report/WG1AR5_AISM8.5_FINAL.pdf). For precipitation, the problems found for the glm 15pc method might be probably related to reanalysis uncertainty or to the propagation of numerical instabilities due to collinearity in the ESM predictor data. In the case of temperatures, previous studies have shown that analog-based methods are particularly sensitive to non-stationarities arising in climate change, being inclined to underestimate the strong warming signal (Benestad, 2010; Gutiérrez et al, 2012).

Fig. 9

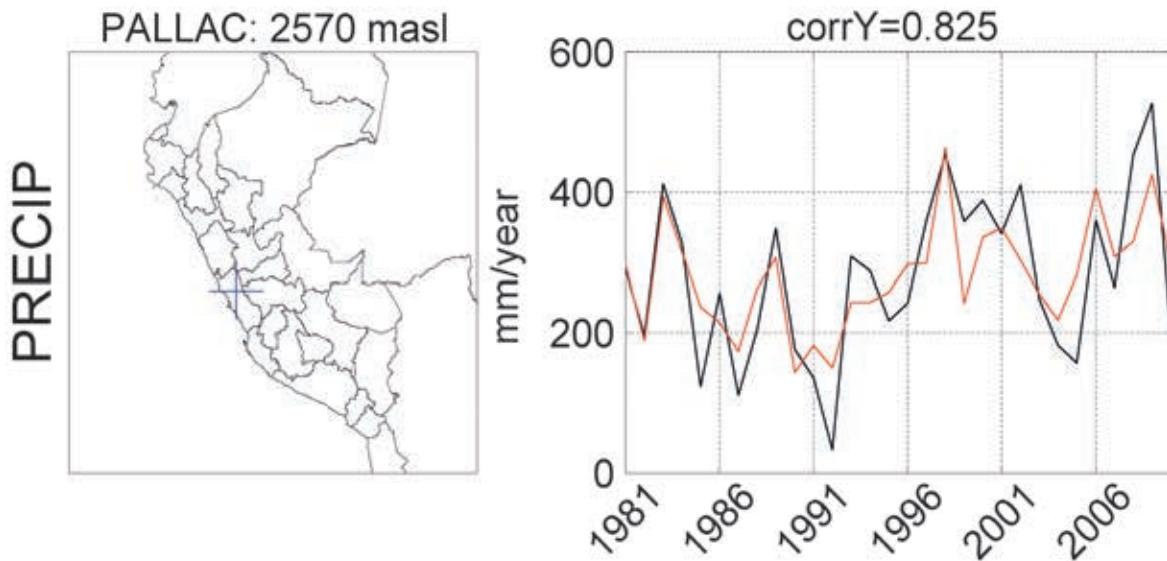


Fig. 9

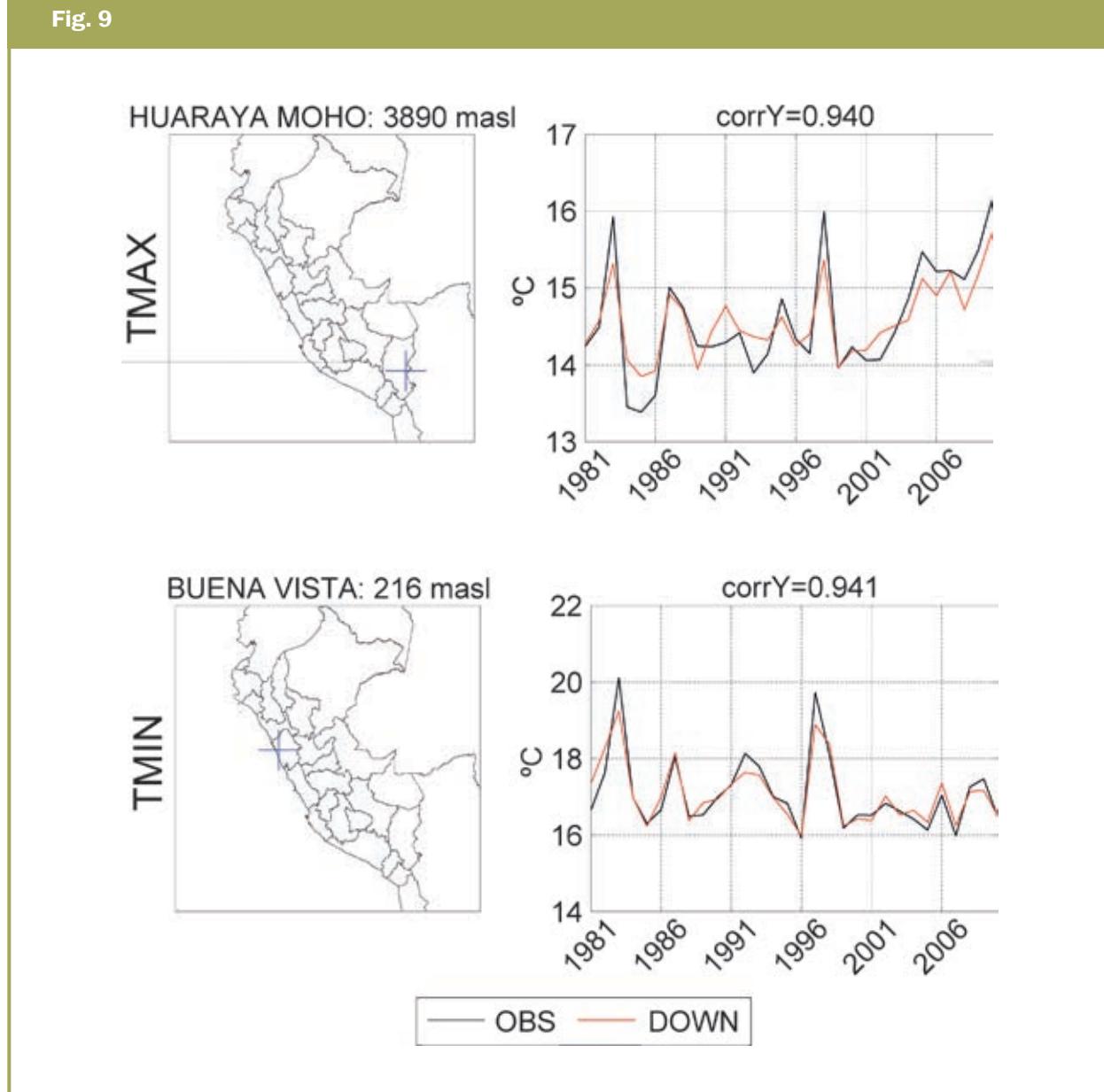


Fig. 9 Inter-annual observed and downscaled time-series (black and red lines, respectively) for one selected station for precipitation/maximum/minimum temperature (top/middle/bottom), obtained by applying the optimum predictor set (see Table 5) to the `glm 15pc/reg 15pc/reg 15pc` method, which yields better correlations than `an1`

Nevertheless, the `an1` (`reg 15pc`) were found to properly reproduce the expected climate change signals—yielding results in good agreement with the aforementioned- CMIP5 global models—and were, thus, the only methods considered for the projections of precipitation (temperatures). Therefore, a final ensemble of six ‘plausible’ projections (3 ESMs \times 2 RCPs) was obtained for each target variable, what allows for the proper characterization of uncertainties. Note that many-fold uncertainties (from the choice of ESM to the choice of RCP) arise in climate change studies and projections should not be considered as ‘forecasts’ by policy makers.

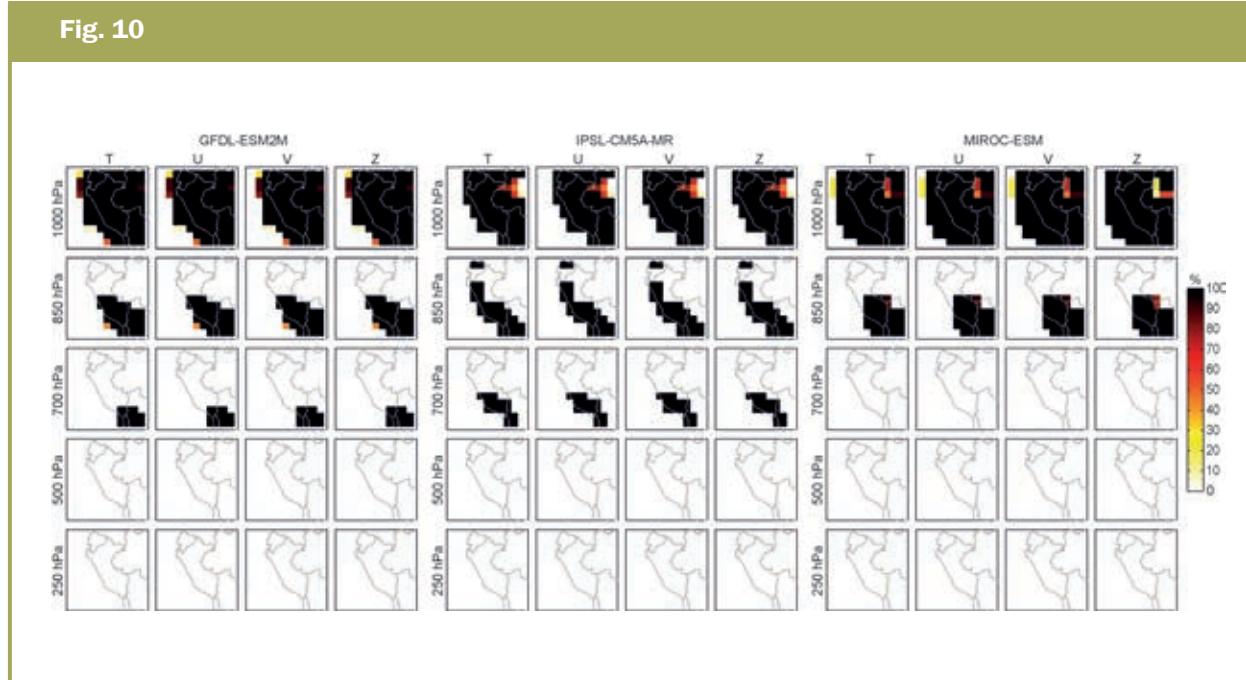
Fig. 10


Fig. 10 Percentage of missing data for all the predictor variables and pressure levels listed in Table 2, for GFDL-ESM2M, IPSL-CM5A-MR and MIROC-ESM models over the thirty-year reference period 1971-2000 (the first historical run r1i1p1 was considered)

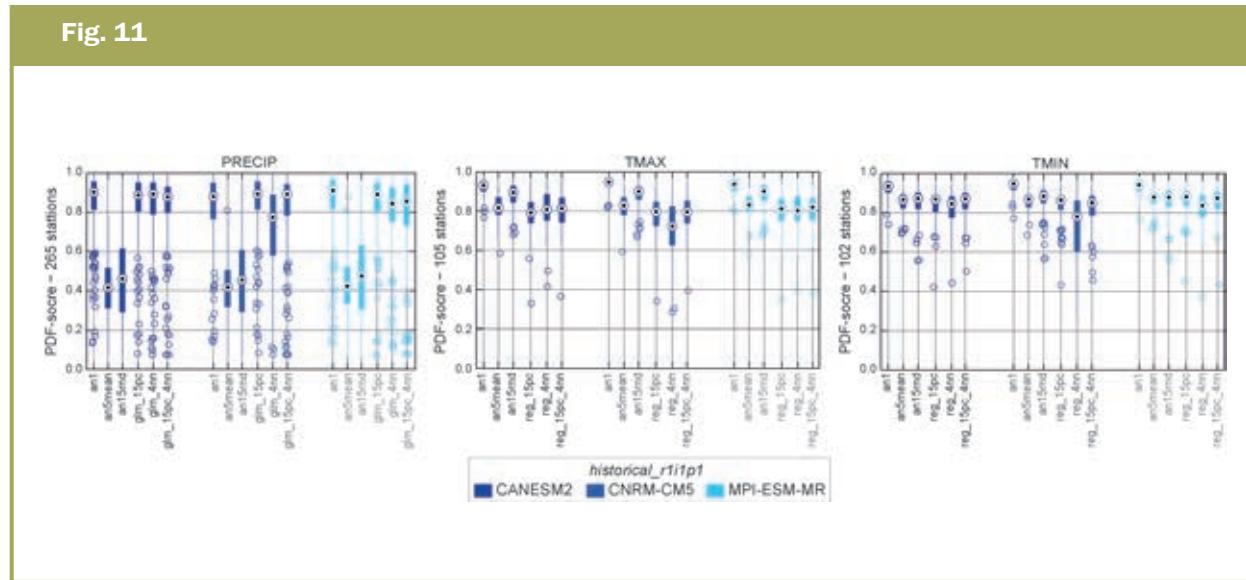
Fig. 11


Fig. 11 Performance of different ESM/SDM combinations for the reference period 1971-2000 (the first historical run r1i1p1 was considered), in terms of distributional similarity (PDF-score). Different colors correspond to distinct ESMs (see the legend). For each ESM, boxplots correspond to different SDMs (see the labels at the bottom of each panel).

Fig. 12 shows the projections obtained for precipitation/maximum/minimum temperature, averaged over the 265/105/102 stations of Fig. 1. Different colors correspond to distinct ESMs (see the legend). For each ESM, the solid (dashed) line corresponds to the RCP4.5 (RCP8.5) scenario—a 11-year moving average was applied to smooth the series.—For precipitation (temperatures), absolute and relative—with respect to the historical run for 1971-2000—(absolute) time-series are plotted. As can be seen all ESM/RCP project increasing precipitation and temperatures. For precipitation, CanESM2 and MPI-ESM-MR provide similar results—with mean increments for 2036-2065 in between 10% and 20% (depending on the ESM and RCP),—whereas CNRM-CM5 provides lower changes. Moreover, the two RCPs lead to similar projections up to 2040 (differences start growing this moment onward). For temperatures, the CNRM-CM5 (CanESM2) systematically projects the weakest (strongest) increments, whereas the MPI-ESM-MR provides moderate results. The mean increments for 2036-2065 are in between 2° C and 3° (4° C and 6° C) for maximum (minimum) temperature—depending on the ESM and RCP.—

In order to assess the spatial distribution of these results, ‘delta’ (Raisanen, 2007) maps are shown in Fig. 13—deltas are calculated by subtracting the mean of the historical reference period (1971-2000) from the mean of the target scenario period (2036-2065)—for one illustrative ESM, the MPI-ESM-MR. For precipitation (temperatures), absolute and relative (absolute) changes are shown for the RCP4.5 and RCP8.5 scenarios (left and right columns). For precipitation, the delta patterns obtained exhibit a high spatial variability—with increasing/decreasing changes for nearby stations— except for the northwestern part of the country, where the wetting signal is clear. However, positive deltas are obtained throughout the whole country for temperatures, finding the highest increments over the Altiplano region. Moreover, the projected warming signal is higher for minimum than for maximum temperature. Finally, the two RCPs considered lead to similar delta patterns (although intensified for the RCP8.5) for the three target variables.

Fig. 12

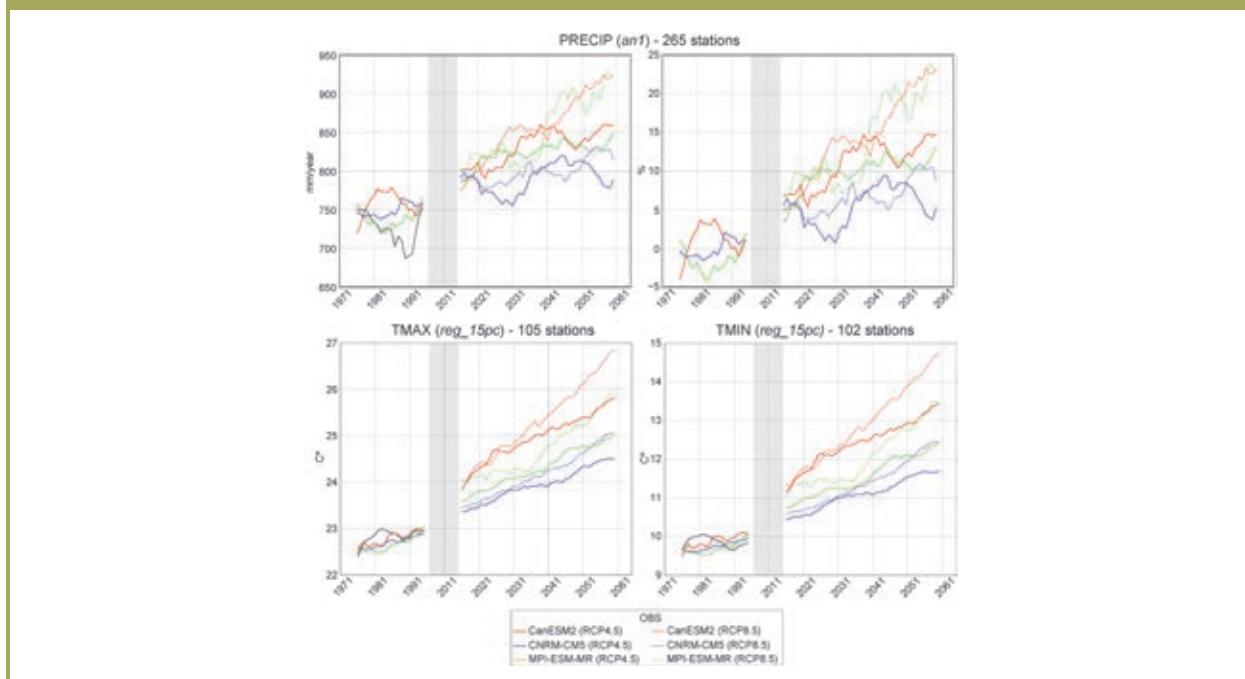


Fig. 12 Absolute and relative—with respect to the historical run for 1971-2000—(absolute) projections for precipitation (maximum/minimum temperature), averaged over the 265 (105/102) stations of Fig.1. For each ESM (colors), the solid (dashed) line corresponds to the RCP4.5 (RCP8.5) scenario. An 11-year moving average was applied to smooth the series. Gray shadows mark the period between the end of the historical simulations and the start of the scenario ones.

Fig. 13

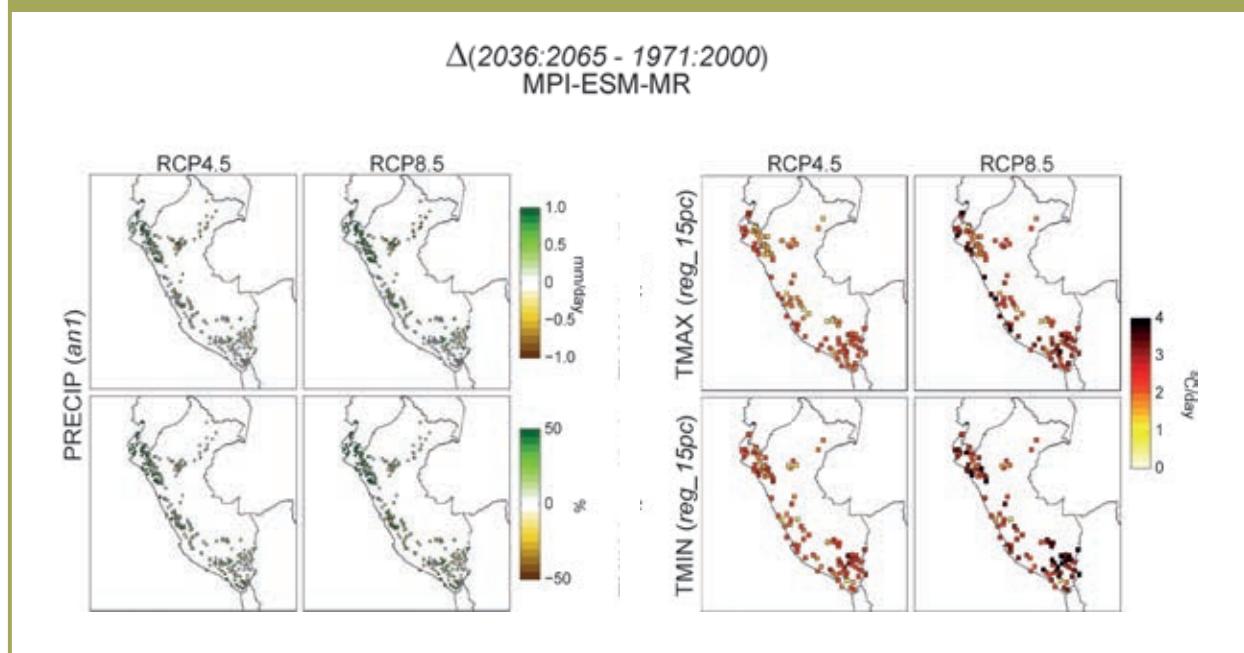


Fig. 13 Delta changes for the period 2036-2065 (with respect to 1971-2000), as projected by the MPI-ESM-MR. For precipitation (temperatures), absolute and relative (absolute) values are shown for the RCP4.5 and RCP8.5 scenarios (left and right column, respectively).

7 | Conclusions

The Component I of AMICAF Peru provides projections of precipitation/maximum/minimum temperature for 256/105/102 stations over Peru up to 2050 (averaged centered to period 2036-2065), by means of statistical downscaling. An ensemble of six ‘plausible’ projections (3 ESMs \times 2 RCPs) is considered for each target variable, which allows for a proper assessment of the uncertainties involved in this type of study. For the period 2036-2065, results show a mean (for the entire country) increment (with respect to 1971-2000) in between 2° C and 3° C (4° C and 6° C) for maximum (minimum) temperature. For precipitation, it is in between 10% and 20%.

In relation to spatial distribution with ‘delta’ maps for precipitation, the delta patterns obtained exhibit a high spatial variability—with increasing/decreasing changes for nearby stations— except for the northwestern part of the country, where the wetting signal is clear. However, positive deltas are obtained throughout the whole country for temperatures, finding the highest increments over the Altiplano region. Moreover, the projected warming signal is higher for minimum than for maximum temperature. Finally, the two RCPs considered lead to similar delta patterns (although intensified for the RCP8.5) for the three target variables.

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