Climate change prediction over complex areas: spatial variability of uncertainties and predictions over the Pyrenees from a set of regional climate models

LÓPEZ-MORENO, J. I., GOYETTE, Stéphane, BENISTON, Martin

Abstract

We used a set of six regional climate models (RCMs) from PRUDENCE project to analyse the uncertainties and direction and magnitude of the expected changes on precipitation and temperature (B2 and A2 scenarios) for the end of the 21st century in the Pyrenees, south of Europe. There have been few studies of climate change effects on this mountain range, though there can be noticeable impacts on the economy and ecology of the region and the surrounding lowlands. The analysis of the accuracy of the RCMs and the impacts of climate change over the region are addressed considering the mean values for the whole region, their spatial distribution patterns and the inter-model variability. Previously, the creation of distributed layers of temperature and precipitation from data provided by weather observatories was necessary to assess the ability of RCMs to reproduce the observed climate. Results show that mean biases between observed climate and control runs (1960–1990) are around 20% for precipitation and 1 °C for temperature. At annual basis, a mean decrease of 10.7 and 14.8% in precipitation, and an increase of 2.8 and 4 °C [...]

Reference

LÓPEZ-MORENO, J. I., GOYETTE, Stéphane, BENISTON, Martin. Climate change prediction over complex areas: spatial variability of uncertainties and predictions over the Pyrenees from a set of regional climate models. International Journal of Climatology, 2008, vol. 28, no. 11, p. 1535-1550

DOI : 10.1002/joc.1645

Available at:
http://archive-ouverte.unige.ch/unige:18444

Disclaimer: layout of this document may differ from the published version.
Climate change prediction over complex areas: spatial variability of uncertainties and predictions over the Pyrenees from a set of regional climate models

J. I. López-Moreno,⁎ S. Goyette and M. Beniston

⁎ Correspondence to: J. I. López-Moreno, Climatic Change and Climate Impacts Group, University of Geneva 7, Chemin de Drize, CH-1227, Carouge (Geneve), Switzerland

ABSTRACT: We used a set of six regional climate models (RCMs) from PRUDENCE project to analyse the uncertainties and direction and magnitude of the expected changes on precipitation and temperature (B2 and A2 scenarios) for the end of the 21st century in the Pyrenees, south of Europe. There have been few studies of climate change effects on this mountain range, though there can be noticeable impacts on the economy and ecology of the region and the surrounding lowlands. The analysis of the accuracy of the RCMs and the impacts of climate change over the region are addressed considering the mean values for the whole region, their spatial distribution patterns and the inter-model variability. Previously, the creation of distributed layers of temperature and precipitation from data provided by weather observatories was necessary to assess the ability of RCMs to reproduce the observed climate. Results show that mean biases between observed climate and control runs (1960–1990) are around 20% for precipitation and 1°C for temperature. At annual basis, a mean decrease of 10.7 and 14.8% in precipitation, and an increase of 2.8 and 4°C is expected in the next century in the area for A2 and B2 scenarios respectively. Effects of climate change will be more pronounced in the southern slopes of the range (Spanish Pyrenees), and lower in the coastland areas. Moreover, results on accuracy and expected changes are subject to a large spatial and seasonal variability as well, as the six RCMs present noticeable differences on accuracy and sensitivity to climate change forcings. Copyright © 2007 Royal Meteorological Society

KEY WORDS: climate change; regional climate models (RCMs); inter-model variability mountain areas; Pyrenees

1. Introduction

Over the past few decades, climatic change has become one of the main concerns for the research community, politicians and society. Although future projections still contain large uncertainties (Giorgi, 2005), the best available information predicts a generalized worldwide warming trend, with regionally contrasting changes in climatic variables such as precipitation, cloudiness, radiative fluxes, relative humidity and so on. These changes are likely to have global impacts on numerous aspects of human activities such as agriculture (Mearns et al., 1997; Attri and Rhatore, 2003), tourism (Lise and Tol, 2002; Beniston, 2003), energy production and consumption (Frederick, 1997); the habitability of coastland areas; water resource availability and supply (Arnell, 1999; Barnett et al., 2005); human health (Patz et al., 2005); and the phenology of plants and animals (Theurillat and Guisan, 2001). Thus, it is important to plan different adaptation and mitigation policies that could be used in response to the expected changes.

In this context, it is necessary to acquire robust information on climate change that may be reliably used for different management scales, and to properly assess the spatial distribution of the main uncertainties across areas of interest. Since the 1960s, General Circulation Models (GCMs) provide the most appropriate simulations of climate change for coarse spatial resolutions (Smagorinsky, 1963; Manabe, 1971). Nowadays, the GCM continue as a useful tool for assessing climate change impacts at coarse scales; but the need to increase the spatial resolution of the projections, in order to obtain more detailed regional information suitable for management purposes, led to the application of different downscaling techniques, such as statistical downscaling (Trigo and Palutikof, 2001; Prudhomme et al., 2002; Diaz-Nieto and Wilby, 2005), or dynamical downscaling by means of Regional Climate Models (RCMs) (Giorgi and Mearns, 1991). The latter are the result of relatively recent advances in our understanding of the relationships between different climatic elements and their feedbacks, and the inclusion of fine-scale parameters (e.g. topography, coastlines, different land features, etc.) (Giorgi, 2005). For the European continent, the PRUDENCE project (5th EU Framework Programme) provided a number of high-resolution climate change scenarios for the years 2070 through 2100.
these constitute an outstanding tool for quantifying the accuracies and uncertainties, and offer a good overview of the expected climatic change and their impacts.

Several studies have focussed on assessing the accuracy of the different RCMs for a control period (1960/1961–1990) with regard to the observed climatology (Dequé et al., 2005), as well as the spatial distribution of climate change impacts on different climatic parameters (Mearns et al., 2003). The results from these studies have identified large contrasts between modelled and observed climatologies in the magnitudes and even the directions of the differences, as well as in the expected impacts of the climate change. In addition, researchers have detected an important degree of inter-model variability (Nogués-Bravo et al., in press). These findings, referred to as large areas and based on global datasets, stress the importance of detailed studies into the uncertainty and projected changes for different geographical environments, which will help us understand the nature and causes of spatial variability in failed RCMs, as well as the varying climate change simulated over a given territory. Such analyses have been performed for several areas of Europe, including the Alps (Beniston et al., 2003; Beniston, 2005), the United Kingdom (Hulme and Jenkins, 1998; Jones and Reid, 2001) and Scandinavia (Gottschalk and Krasovskaia, 1997; Christensen et al., 2001). However, numerous geographic sectors of Europe still remain poorly studied. Analyses of such regions should help to improve our understanding of the ability of RCMs to reproduce observed climates, and lead to the identification of sectors where climate changes could affect large populations or very sensitive ecosystems. Such is the case in the Mediterranean mountain areas.

The aim of this paper is to identify spatial patterns in the accuracy of a set of RCMs and the predicted climate changes themselves in an important Mediterranean mountain range, namely, the Pyrenees. A detailed analysis of different RCM outputs for this unstudied area is necessary for several reasons:

- The topography and geographical location of the Pyrenees makes it difficult to adequately reproduce the observed climate. The Pyrenees mountains have a wide range of altitude, and are located between the Atlantic Ocean (a relatively cool water mass) and the Mediterranean Sea (a relatively warm water mass). Moreover, the main divide of the range is located perpendicular to several predominant air masses circulation, forming a clear boundary for several different climatic processes. These characteristics lead to great climatic heterogeneity over short distances, making it difficult for RCMs to accurately reproduce the observed climatology. Thus, this is a good site to test the ability of RCMs to reproduce the climate over complex areas.
- The Pyrenees, especially the southern slopes, form the main source of water resources for the surrounding semi-arid lowlands. The Pyrenees comprise less than 12% of the Ebro River Basin, but it supplies more than 45% of the annual run-off. In the basin, flows from the Pyrenean mountains are used to cultivate 42% of the irrigated crops and produce more than the 60% of the hydropower energy. Moreover, the rivers in the area are highly influenced by the snow (López-Moreno and García-Ruiz, 2004). Numerous studies have suggested that the impact of climate changes on hydrology will be especially pronounced in snow-fed basins (Singh and Bengtsson, 2003; Barnett et al., 2005), such as the headwaters located in the Pyrenees.
- The Pyrenees are a valuable ecological site, characterized by richness of the species and the existence of numerous endemic plants and animals. The location of the Pyrenees in the south of Europe at the boundary between the Atlantic and Mediterranean climatic conditions, along with the great complexity of its terrain, has led to a high degree of biodiversity that could be strongly affected by climate changes and subsequent habitat alterations.

In this paper, we analyse the expected climate changes (temperature and precipitation) predicted for the Pyrenees by several RCMs developed in the frame of the PRUDENCE project. We particularly focus on: (1) assessing the possible uncertainties in the predictions, quantified by the ability of RCMs to reproduce the observed climate during the control period (1961–1990) (2) analysing the spatial patterns of expected climate change and (3) evaluating the inter-model variability in terms of model accuracy and expected climatic change.

For this purpose, the next steps have been implemented: (1) creating high-quality maps of reference climatologies (precipitation and temperature) from local observations for the period 1960–1990 (2) comparing control runs of a set of RCMs with reference climatologies in terms of precipitation and maximum, mean and minimum temperatures (Tmax, Tavg and Tmin, respectively) on a seasonal and annual basis, focusing on mean errors and inter-model variability and (3) comparing control runs with expected precipitation and temperature for the end of the 21st century (2070–2100) under two different emission scenarios. It will enable us to assess the intensity of the predicted climate change (IPCC), its spatial variability and the inter-model consistency of the expected changes throughout the target area.

2. Study area

The study area includes both sides of the Pyrenees (French and Spanish), and is limited by the Atlantic Ocean to the west and by the Mediterranean Sea to the east (Figure 1). Altitudes range from 300 to more than 3000 m above sea level (a.s.l.), with a highly contrasting relief (Del Barrio et al., 1990). The climate in this region is subject to Atlantic and Mediterranean influences and the effect of macro-relief on precipitation and temperature. In the Central Ebro Depression, the average annual precipitation is approximately 300 mm,
and the average annual temperature ranges from 13 to 15°C. In the mountains, annual precipitation exceeds 600 mm and sometimes reaches 2000 mm at the highest divides. The Foehn effect is frequently observed in the area, increasing the differences in precipitation between the north and south slopes, as well as yielding higher temperatures in the latter. Most of the annual precipitation falls during the cold season in the Atlantic areas, and during spring and autumn in the Mediterranean regions. Summers are relatively dry in the Pyrenees in general, and are very dry in the Ebro Depression. The annual 0°C isotherm is located at 2726 m a.s.l. (Del Barrio et al., 1990), and above 1600 m a.s.l., most of the annual precipitation falls as snow during the cold season (November–May).

3. Data and methods

3.1. PRUDENCE data

Information on predicted climate change is obtained from the outputs on precipitation and temperature (\(T_{\text{max}}\), \(T_{\text{min}}\) and \(T_{\text{avg}}\)) of several RCMs developed by different institutions collaborating in the PRUDENCE project. This study used data from the HIRHAM: Danish Meteorological Institute (DMI), HIRHAM: Norwegian Meteorological Institute (METNO), HADRM3: Hadley Center (HC), RCAO: Swedish Meteorological and Hydrological Institute (SMHI), REGCM: International Center for Theoretical Physics (ICTP) and PROMES: University Complutense of Madrid (UCM) models, all of which were driven by the GCM HadAM3H for the European continent. These models were selected on the basis of the availability of experiments run for control conditions (1960/1961–1990) and two (A2, B2) possible future emission scenarios. The A2 and B2 scenarios, which were developed by the IPCC (Intergovernmental Panel on Climate Change), reflect two contrasting greenhouse gas emission futures based on different hypothesis of economy and population trends in the future. A2 is characterized by higher emissions of greenhouse gases than B2 (Nakicenovic et al., 1998; IPCC, 2001). The resolution of these RCMs was close to 50 km (grid spacing of 0.44–0.5 degrees resolution). Related information and used datasets can be freely downloaded from the web site of the PRUDENCE project- http://prudence.dmi.dk.

The outputs of the ICTP and UCM RCMs were given in a Lambert projection, whereas the longitudes and latitudes of the other outputs were given in different rotated coordinate systems. Thus, as the projections were different, the outputs of the different models could not be compared directly. In order to make the available information comparable, we interpolated the seasonal and annual climatic variables using a local method of splines with tension (Mitsova and Mitas, 1993). This method was selected based on error estimators obtained by means of a cross-validation procedure. The regular distribution of the observations over the territory guaranteed an appropriate interpolation of the data (Burrough and McDonnell, 1998). Climatic layers were interpolated within a Lambert projection of 5 km cell size. Obviously, the spatial disaggregation (Hulme and Jenkins, 1998) used from layers at \(\approx50\) km to the new ones at 5 km were not considered to increase the resolution of the information. Instead, it allowed better visualization of the spatial patterns of the climatologies predicted by the RCMs in their original grid sizes (Prudhome et al., 2002).

3.2. Mapping observed temperature and precipitation

Validation of RCMs based on observations is a complex task, since the resolution of the RCM outputs (\(\approx50\) km) is still too far from local observations to be compared directly, especially in mountain areas with complex topography (Daly et al., 1994; Agnew and Palutikof, 2000). Available layers of distributed climatic data (e.g. Reanalysis, National Centers for Environmental Prediction–National Center for Atmospheric Research (NCEP-NCAR), etc.) may be useful for analysis on a larger scale,
but they lack the level of precision required for medium-scale analysis. To overcome these problems, we produced reliable distributed climatic layers from local observations, and used them as a reference for the observed climate (1960–1990) in comparisons with control runs of the various RCMs. For this purpose, predictor variables derived from a Digital Elevation Model (DEM) were related to the spatial variability shown by the 20 tested climatic variables (precipitation and $T_{\text{max}}$, $T_{\text{min}}$ and $T_{\text{avg}}$) on annual and seasonal bases obtained from different observers during the control period (1960–1990).

We obtained seasonal and annual totals of precipitation ($P$) from 57 observatories and average temperatures ($T$) from 46 observatories. The weather stations are located in French and Spanish territories close to the Pyrenees (Figure 1), and are managed by the Instituto Nacional de Meteorología and Meteo France. Climatic data have been subjected to quality control (González-Rouco et al., 2001) and homogenization testing, and the Standard Normal Homogeneity Test (SNHT) had been employed to identify and correct inhomogeneities (Alexandersson, 1986) using the ANCLIM program (Štěpánek, 2004).

To map the climate variables, we employed multiple regression analysis (Burrough and McDonnell, 1998). Regression techniques account for the variability in a given parameter (in this case seasonal and annual $P$, $T_{\text{max}}$, $T_{\text{avg}}$ or $T_{\text{min}}$) by using external characteristics of the sampling points (the location of the meteorological stations), which are called predictor variables (Burrough and McDonnell, 1998; Agnew and Palutikof, 2000; Ninyerola et al., 2000). The majority of the auxiliary variables were extracted from the DEM on the basis of the close relationship between climate and topography (e.g. Basist et al., 1994; Daly et al., 1994). The spatial resolution of the utilized DEM was 1 km in cell size. Topographic variables stress the impact of altitude and slope aspect in explaining the spatial distribution of climatic variables. The north–south and east–west orientations of the slopes were quantified through the sines and cosines of the aspects, in a procedure that converted the linear units of different functions fitted to the independent variables in order to predict the responses ($Y$-values). Data are fitted with respect to the partial residuals, which are the residuals that remain after removing the effect of all predictor variables. The interpretation of the relationships between response and predictor variables is shown in graphs that relate the magnitude of the response variables against the partial residuals. Partial residuals are obtained after removing the effect of all other predictor variables. A detailed description of how GAMs are fit to the data in relation to the utilized algorithms can be found in Hastie and Tibshirani (1987).

Following the method of Ninyerola et al. (2000) and Agnew and Palutikof (2000), we interpolated the residuals (the differences between the predicted and observed values at station locations) and subtracted the predictions in unsampled areas to obtain more accurate predictions. The residuals were then interpolated using a local method of splines with tension (Mitrosova and Mitas, 1993). Once we obtained the definitive climatic layers, we used a low-pass filter to equalize the spatial resolution of the observed climate with regard to the RCM. Thus, the average value within each $50 \times 50$ km$^2$ was determined for each point. Finally, the rasters of the created climatic layers from observations were degraded from 1 to 5 km of cell size, the same as the interpolated layers of the RCM outputs.

### 3.3. Accuracy estimators and climate change estimations

To assess the accuracy of the created layers of $T$ and $P$ from local observations (Section 3.2), cross-validation was used to compare the estimated and observed values. Cross-validation is an appropriate technique for evaluating models when a relatively low number of cases are being used, meaning that it is not feasible to build independent datasets for calibration and validation (Guisan and Zimmermann, 2000). In cross-validation, one of the cases is omitted from the analysis, the model is fitted to the remainder, and the obtained equation is used to predict the omitted case. This procedure is repeated for each case in the dataset. The values predicted from cross-validation were used to calculate distinct error estimators (Willmott, 1982; Willmott and Matsuura, 2005), such as the Mean Bias Error (MBE), the Mean Absolute Error...
(MAE) and Willmott’s D (D), using the following equations:

$$MBE = N^{-1} \sum_{i=1}^{N} (P_i - O_i)$$

$$MAE = N^{-1} \sum_{i=1}^{N} |P_i - O_i|$$

$$D = 1 - \frac{\sum_{i=1}^{N} (P_i - O_i)^2}{\sum_{i=1}^{N} (|P'_i| + |O'_i|)^2}$$

where $N$ is the number of observations, $O_i$ is the observed value, $P$ is predicted value, $i$ is the counter for individual observed and predicted values, $P'_i = P_i - \overline{O}$, $O'_i = O_i - \overline{O}$ and $\overline{O}$ is the mean of the observed values.

The differences between the observed climate and the results from control runs of the six RCMs were calculated for each cell. Differences in precipitation were divided by the observed precipitation in order to make the magnitudes of the RCM errors comparable among sectors of contrasting precipitation. The errors of the six RCMs, obtained via MBE and MAE, were provided for each cell, and also the averaged errors for the corresponding area of the Pyrenean mountain range (ellipse of Figures 1 and 3).

Climate change estimations were obtained by subtracting the layers of the control runs (1960/1961–1990) from the predicted future climate (2070–2100). We then calculated the coefficients of variation of the differences between observed climate and control runs, and the climatic changes predicted by the six different RCMs. These statistics represent the inter-model variability in model accuracy and predicted changes.

Finally, GAMs (Section 3.2) were used to relate the mean errors and the mean expected changes (average of the six RCMs) in $P$ and $T$ to altitude and the distances to the main divide, the Atlantic Ocean and the Mediterranean Sea. This analysis allowed us to quantify

Figure 2. Response curves to partial residuals of the considered predictors (altitude; distances to the main divide, Atlantic Ocean and Mediterranean Sea; sine and cosine of the aspect at 3000 m) to annual mean temperature and precipitation. Dashed lines are the intervals of confidence at 95%.
the amount of variance explained by each of the tested geographical variables, along with their relative roles, deepening our understanding of the spatial patterns of RCM uncertainties and the impacts of climatic changes across the target region.

4. Results

4.1. Spatial modelling of observed precipitation and temperature

According to the levels of significance, we used altitude, distance to the main divide and distance to the Mediterranean Sea and Atlantic Ocean as predictors for modelling the seasonal and annual temperature layers. The response of each predictor to the partial residuals for the mean annual temperature and precipitation can be seen in Figure 2. Figure 3(A) and(C) show the mean annual temperature and precipitation modelled from observations over the period from 1960 to 1990. As could be expected, temperature decreases as altitude increases, and as the distance to the main divide (central Pyrenees) decreases. Proximity to the main sea water masses (Atlantic to the west and Mediterranean to the east) buffers the trend imposed by the other variables (altitude and distance to the main divide), yielding warmer winters and milder summers in regions closer to the coasts. This buffering effect disappears over a very short distance inland. Precipitation also increases with altitude and proximity to the main divide; this effect is noticeably stronger at the northern slopes of the mountain range due to the barrier effect. In addition, the models indicate that precipitation levels are higher near the Atlantic Ocean and Mediterranean Sea, likely due to exposure to humid air masses. Not surprisingly, the information provided by the distance to the Mediterranean Sea and to the Atlantic Ocean is very similar, but GAMs include both as significant predictors in order to adequately describe the coastal effects. Moreover, variables representing the west-east and north-south orientations of the slopes (the sine and cosine of the aspect, respectively) are also included as significant predictors. The response curves suggest slight increases of precipitation in north and west facing slopes in the area, and significance levels imply that average sine and cosine of the aspect within an area of 3 km (Section 3.3) has the best predictor capacities compared to other low-pass filters or the omission of spatial smoothers. This result indicates that precipitation in a cell is better explained by the general exposure of the slope at a relatively wide spatial resolution (3 × 3 km) than the particular orientation of the target cell at a resolution of 1 × 1 km.

Table I shows the error estimators obtained by cross-validation of the climatic layers modelled from observations. The results of this analysis indicate that the GAMs accurately map climatic variables from terrain characteristics and reliably generated climatic layers. The errors are always below 14 mm day\(^{-1}\) for precipitation, and 0.83 °C for temperature. Willmott’s D exceeds 0.9 for all the modelled climatic variables, indicating very good agreement between the observed and modelled values. In general, slightly higher errors are found for precipitation, particularly in summer. Temperature provided a very good estimator overall, with maximum temperature showing the lowest error. Minimum temperature, especially during winter, accounts for the highest error rate among the temperature parameters, but Willmott’s D remained above 0.95 in this case, supporting the validity of our results.

4.2. Comparison between control data sets and observations

Figure 3 shows the mean annual temperature and precipitation mapped from observations over the control period (1960–1990) and the model average from six RCMs considered over the same period. Visual comparison suggests high agreement between climatologies obtained from observations and those predicted by RCMs. The RCMs
are able to reproduce the contrast between the warm/dry Ebro Depression Valley and the cold/humid central Pyrenees, especially in the northern slopes. The increase of precipitation with altitude and proximity to the Atlantic Ocean is captured by the RCMs, but accumulated rainfall in the Bay of Biscay is somewhat underestimated in these models.

Figure 4 shows the mean error of each RCM, which is quantified as the difference between reference climatic layers created from observations (annual and seasonal precipitation and temperatures) and those modelled by RCMs (the average of the six RCMs). The variability of error among the six models is also shown in Figure 4 through the coefficients of variation. Our results show that although the main spatial patterns of precipitation and temperature were accurately modelled, there are noticeable deviations in magnitude.

The response curves to partial residuals of each topographic and geographic variable versus the RCM errors in reproducing the observed climatologies (Figure 5) were used to understand and establish the spatial patterns of deviations between observations and RCMs. In terms of annual precipitation, the RCM-modelled predictions for some areas show noticeable deviations, which vary between less than –30% to greater than 30% from the observed climatologies. The distribution of error over the analysed territory follows marked spatial patterns, allowing us to model the four considered predictor variables with high accuracy (total explained variance = 73%) (Figure 5). The maximum underestimations of the RCMs appeared over the coastland areas (the Bay of Biscay and Spanish Mediterranean areas) and over the eastern central Pyrenees. Thus, the partial contribution to the modelled error distribution increases from the Atlantic and the lowest altitude areas (Figure 5(A) and (C)) to the highest inland areas. RCM predictions overestimate the annual precipitation for the French Mediterranean coast and central Ebro Depression. The contrasting behaviour of the Spanish (underestimated) and French (overestimated) Mediterranean sectors yield partial contribution values around 0 near this coast (Figure 5(D)). The RCMs accurately predict the annual precipitation for large areas of the central and western Pyrenees, and most of the Spanish and French foothills. Thus, the partial contribution over the altitudinal range 400–800 m a.s.l. (Figure 5(A)) is close to 0. As shown in Figure 5(B), the errors were generally low close to the main divide, and increased (due to overestimations) toward the northernmost and southernmost extremes. The explained variance is reduced by 20 and 24%, respectively, when altitude and distance to the main divide are removed from the model, indicating that these variables largely explain the spatial distribution of error in precipitation. The role of Atlantic and Mediterranean water bodies in explaining the spatial patterns of error distribution is much lower as indicated by the fall of 8 and 5% respectively of explained variance when they are removed from the model.

The pattern of error in annual precipitation is approximately the same for spring, summer and autumn. During these seasons, the RCMs underestimate precipitation for the Atlantic and Spanish Mediterranean coasts, while overestimating that for the French Mediterranean coastland and some areas of the Ebro Depression. In contrast, the RCMs generally underestimate winter precipitation across the entire region, with lower errors seen for the Spanish foothills and some eastern areas.

The temperatures modelled by the RCMs generally show good agreement with those modelled from observations, with these values rarely deviating more than ±1 °C. Errors in annual temperature followed roughly parallel bands comprising the main divide (the Axial Pyrenees; where temperature is overestimated), the foothills on either side (underestimated), and the northernmost and southernmost sectors (overestimated). Response curves reveal that the errors in mean annual temperature increase sharply with altitude (Figure 5(A)), and overestimations increase following a northward trend (Figure 5(B)), and also in areas closer to the Mediterranean sea and the Atlantic Ocean (Figure 5(C) and (D)). Geographical variables explain 59% of the spatial distribution of the error. Although this value is lower than that for error in precipitation, it is still relatively high, demonstrating the existence of marked spatial patterns. Similar to our findings for precipitation, our analysis reveals that altitude and distance to the main divide are the variables governing most of the explained variance, which decreased by 19% when we dropped either of these variables from the model. Explained variance decreases 4 and 9% when distance to the Mediterranean and Atlantic Ocean is removed.

Similar spatial distributions of errors in annual temperature are found across all four seasons, but the magnitude of the differences in temperature in the axial Pyrenees and
Figure 4. Differences between reference climate (annual and seasonal precipitation and temperatures) and control runs (average of the six RCMs). Isolines reflect the coefficient of variation of the error among the 6 RCMs. P: precipitation, T: temperature. 1:DJF, 2: MAM, 3: JJA, 4:SON.

foothills differ by season. For example, very steep gradients are observed in the spring and fall, while smaller differences are found in winter and summer. During the latter two seasons, we observe marked asymmetry between the regions on either side of the main divides, with more moderate errors found in the northern slopes (French territory).

The coefficient of variation (CV) for the errors of the six RCMs (Figure 4) for precipitation exceeds 1 in some areas, suggesting that the accuracy of RCMs for reproducing the observed climatologies during the control period is very different from one model to other. The figure further shows spatial differences in the degree of dispersion of accuracy for each RCM. The isolines indicate that the inter-model variability is very high on a diagonal following a NE–SW direction; high inter-model variation is seen for the Mediterranean slopes of the French Pyrenees and the western part of the Ebro Depression, whereas a narrower range of errors is seen for the Mediterranean regions and the Bay of Biscay. On a seasonal basis, the spatial patterns of spring, summer and fall variability resemble the pattern of annual variability, while the winter pattern reveals systematic underestimation of precipitation by most of the RCMs,
with the latter consistency reflected in a relatively low CV (generally between 0.4 and 0.6).

Interestingly, the spatial inter-model variability in accuracy for temperature contrasts noticeably with that for precipitation (Figure 5). For annual mean temperature, the maximum inter-model variability is observed in the western Pyrenees and some parts of the eastern Spanish foothills, while lower inter-model variability was seen for the Mediterranean coast and the northernmost sectors of the study area. This annual pattern was consistent with those observed for summer and fall, while inter-model variability is larger during winter and spring for the French Pyrenees, the foothills, and the western part of the Spanish territory.

Table II provides the mean error (MBE and MAE) corresponding to the Pyrenean mountain range (within the ellipse drawn in Figures 1 and 2) of each RCM. In general, the large differences between the MBE and MAE values could be explained by the existence of steep north–south and west–east gradients in the sign and magnitude of errors in the modelled precipitation. The existence of overestimations and underestimations within the considered area explain the relatively high frequency of MBE values close to 0, as for annual precipitation calculated using the HC and SMHI models. However, when error is considered in absolute units (MAE), it always exceeds 10% of the reference precipitation. Better estimations of annual precipitation for the whole area were provided by the DMI, SMHI and UCM methods, which had MAE values below 20%. The average MAE across all RCMs was 21%, with a slight trend towards underestimation, as suggested by an MBE value of −7%. We did not observe large differences between seasons, though winter and summer tended to show higher MBE and MAE errors.

As shown in Figure 3, RCMs reproduce temperature more accurately than precipitation. Consistent with this, the mean MAE of mean annual temperature was 1.33 °C across all RCMs. Models generated using DMI, HC and UCM were the most accurate in terms of temperature, with absolute errors below 1.2 °C. Annual temperatures were more accurately reproduced in spring and autumn (MAE ≈ 1.4 °C), with slightly larger errors observed for winter and summer (MAE ≈ 1.5 °C). The largest errors were found for minimum temperature, which was overestimated mainly in winter. Models generated using UCM and HC were the best for reproducing minimum temperature. Overall, the RCMs reproduced maximum temperatures noticeably better than minimum temperatures (mean MAE = 1.08 °C), with HC and METNO providing the best estimations for maximum, both showing errors below 1 °C. UCM, DMI and METNO tended to underestimate the layers modelled from observations, whereas HC, ICTP and SMHI overestimated the same layers.

4.3. Predicted climate change for the study area

Figure 6 shows the expected average change from RCMs average quantities (over all six RCMs) in precipitation (%) and mean temperature (°C) according to the difference between scenario A2 (2070–2100) and control runs.
(1960/1961–1990). The inter-model variability was calculated by means of the CV. Figure 7 shows the relative contribution of each predictor variable (altitude and geographical location) for explaining the spatial distribution of the expected changes in annual precipitation and temperature.

According to the RCMs, a general decrease in annual precipitation can be expected for the end of the 21st century. In general, negative values between −20 and −5% were found across the region. The foothills are predicted to be most strongly affected by precipitation decreases; the response curve to partial residuals of the altitude (Figure 7(A)) shows lower values between 500 and 800 m a.s.l., a common altitudinal range found in the foothills. Low errors were found for modelling this sector (Section 4.2), along with low inter-model variability, indicating that this prediction is robust. Negligible to low increases were predicted for the eastern axial Pyrenees, and some decreases were predicted for the western axial zone. The explained variance of change distribution decreased by 25% when altitude is removed from the model.

In Figure 6, PAannual shows the existence of a marked dissymmetry between regions on opposite sides of the
Figure 7. Spatial patterns of the climatic change (mean annual temperature and precipitation) expected for the period 2070–2100. Solid lines are the response to partial residuals of each variable. Dashed lines are the intervals of confidence at 95%. The four variables explain 76% of the variance of the distribution of precipitation and 90% of the change in temperature.

Table II. Mean Bias Error (MBE) and Mean Absolute Error (MAE) of the six selected RCMs obtained in the Pyrenees (within the ellipses of the Figures 1 and 2) when observed and modelled climatologies are compared for the control period.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Period</th>
<th>DMI MBE</th>
<th>HC MBE</th>
<th>ICTP MBE</th>
<th>METNO MBE</th>
<th>SMHI MBE</th>
<th>UCM MBE</th>
<th>Average MBE</th>
<th>DMI MAE</th>
<th>HC MAE</th>
<th>ICTP MAE</th>
<th>METNO MAE</th>
<th>SMHI MAE</th>
<th>UCM MAE</th>
<th>Average MAE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Precipitation</td>
<td>Winter</td>
<td>-0.3</td>
<td>-0.10</td>
<td>0.28</td>
<td>-0.22</td>
<td>0.27</td>
<td>-0.09</td>
<td>-0.14</td>
<td>0.14</td>
<td>0.24</td>
<td>0.31</td>
<td>-0.19</td>
<td>0.26</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Spring</td>
<td>-0.05</td>
<td>0.17</td>
<td>0.34</td>
<td>0.06</td>
<td>0.20</td>
<td>-0.02</td>
<td>0.20</td>
<td>0.11</td>
<td>0.00</td>
<td>0.17</td>
<td>0.03</td>
<td>0.21</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Summer</td>
<td>0.23</td>
<td>-0.02</td>
<td>0.28</td>
<td>0.20</td>
<td>0.32</td>
<td>0.03</td>
<td>-0.06</td>
<td>0.24</td>
<td>0.10</td>
<td>0.21</td>
<td>0.08</td>
<td>0.26</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Autumn</td>
<td>-0.21</td>
<td>-0.06</td>
<td>0.24</td>
<td>-0.04</td>
<td>0.26</td>
<td>-0.08</td>
<td>0.26</td>
<td>0.06</td>
<td>0.17</td>
<td>-0.15</td>
<td>0.08</td>
<td>0.23</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Tmax</td>
<td>Winter</td>
<td>-0.57</td>
<td>0.69</td>
<td>0.83</td>
<td>1.03</td>
<td>1.22</td>
<td>0.56</td>
<td>0.97</td>
<td>1.90</td>
<td>1.93</td>
<td>-0.21</td>
<td>0.82</td>
<td>0.50</td>
<td>1.08</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Spring</td>
<td>-0.49</td>
<td>-0.05</td>
<td>0.86</td>
<td>-0.27</td>
<td>1.48</td>
<td>-0.51</td>
<td>1.19</td>
<td>1.60</td>
<td>1.68</td>
<td>-1.80</td>
<td>1.82</td>
<td>0.25</td>
<td>1.30</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Summer</td>
<td>0.14</td>
<td>0.54</td>
<td>1.57</td>
<td>1.55</td>
<td>1.72</td>
<td>-0.84</td>
<td>1.19</td>
<td>1.71</td>
<td>1.78</td>
<td>-1.34</td>
<td>1.49</td>
<td>0.42</td>
<td>1.38</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Autumn</td>
<td>-0.08</td>
<td>0.58</td>
<td>0.29</td>
<td>0.24</td>
<td>1.13</td>
<td>-0.09</td>
<td>0.89</td>
<td>1.08</td>
<td>1.25</td>
<td>-1.45</td>
<td>1.49</td>
<td>0.00</td>
<td>1.03</td>
<td></td>
</tr>
<tr>
<td>Tmin</td>
<td>Winter</td>
<td>1.68</td>
<td>1.75</td>
<td>0.71</td>
<td>2.50</td>
<td>2.50</td>
<td>0.00</td>
<td>2.20</td>
<td>3.77</td>
<td>3.70</td>
<td>1.93</td>
<td>1.95</td>
<td>1.77</td>
<td>2.21</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Spring</td>
<td>0.96</td>
<td>1.12</td>
<td>0.73</td>
<td>1.00</td>
<td>1.42</td>
<td>1.62</td>
<td>1.19</td>
<td>1.39</td>
<td>2.47</td>
<td>2.63</td>
<td>0.26</td>
<td>0.72</td>
<td>1.17</td>
<td>1.41</td>
</tr>
<tr>
<td></td>
<td>Summer</td>
<td>1.46</td>
<td>1.48</td>
<td>1.70</td>
<td>2.61</td>
<td>2.63</td>
<td>1.23</td>
<td>1.38</td>
<td>2.32</td>
<td>2.41</td>
<td>0.61</td>
<td>0.97</td>
<td>1.66</td>
<td>1.78</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Autumn</td>
<td>1.38</td>
<td>1.42</td>
<td>1.09</td>
<td>2.17</td>
<td>2.17</td>
<td>1.61</td>
<td>1.64</td>
<td>2.21</td>
<td>2.54</td>
<td>0.95</td>
<td>1.14</td>
<td>1.57</td>
<td>1.70</td>
<td></td>
</tr>
<tr>
<td>Tmax</td>
<td>Annual</td>
<td>0.02</td>
<td>0.59</td>
<td>0.43</td>
<td>0.93</td>
<td>0.50</td>
<td>1.18</td>
<td>-0.03</td>
<td>0.94</td>
<td>1.32</td>
<td>1.60</td>
<td>-1.21</td>
<td>1.27</td>
<td>1.08</td>
<td></td>
</tr>
<tr>
<td>Tmam</td>
<td>Winter</td>
<td>1.68</td>
<td>1.75</td>
<td>0.71</td>
<td>2.50</td>
<td>2.50</td>
<td>0.00</td>
<td>2.20</td>
<td>3.77</td>
<td>3.70</td>
<td>1.93</td>
<td>1.95</td>
<td>1.77</td>
<td>2.21</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Spring</td>
<td>0.96</td>
<td>1.12</td>
<td>0.73</td>
<td>1.00</td>
<td>1.42</td>
<td>1.62</td>
<td>1.19</td>
<td>1.39</td>
<td>2.47</td>
<td>2.63</td>
<td>0.26</td>
<td>0.72</td>
<td>1.17</td>
<td>1.41</td>
</tr>
<tr>
<td></td>
<td>Summer</td>
<td>1.46</td>
<td>1.48</td>
<td>1.70</td>
<td>2.61</td>
<td>2.63</td>
<td>1.23</td>
<td>1.38</td>
<td>2.32</td>
<td>2.41</td>
<td>0.61</td>
<td>0.97</td>
<td>1.66</td>
<td>1.78</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Autumn</td>
<td>1.38</td>
<td>1.42</td>
<td>1.09</td>
<td>2.17</td>
<td>2.17</td>
<td>1.61</td>
<td>1.64</td>
<td>2.21</td>
<td>2.54</td>
<td>0.95</td>
<td>1.14</td>
<td>1.57</td>
<td>1.70</td>
<td></td>
</tr>
<tr>
<td>Tmam</td>
<td>Annual</td>
<td>1.38</td>
<td>1.43</td>
<td>1.08</td>
<td>2.19</td>
<td>2.19</td>
<td>1.55</td>
<td>1.62</td>
<td>1.90</td>
<td>2.64</td>
<td>0.95</td>
<td>1.09</td>
<td>1.51</td>
<td>1.70</td>
<td></td>
</tr>
<tr>
<td>Tavv</td>
<td>Winter</td>
<td>0.56</td>
<td>1.22</td>
<td>0.49</td>
<td>1.00</td>
<td>1.77</td>
<td>1.86</td>
<td>1.35</td>
<td>0.49</td>
<td>2.84</td>
<td>2.82</td>
<td>0.86</td>
<td>1.38</td>
<td>1.31</td>
<td>1.46</td>
</tr>
<tr>
<td></td>
<td>Spring</td>
<td>0.24</td>
<td>0.94</td>
<td>0.34</td>
<td>0.93</td>
<td>0.58</td>
<td>1.55</td>
<td>0.34</td>
<td>1.29</td>
<td>2.12</td>
<td>2.16</td>
<td>-0.77</td>
<td>1.27</td>
<td>0.47</td>
<td>1.36</td>
</tr>
<tr>
<td></td>
<td>Summer</td>
<td>0.80</td>
<td>1.01</td>
<td>1.49</td>
<td>1.69</td>
<td>2.09</td>
<td>2.17</td>
<td>0.20</td>
<td>1.29</td>
<td>2.06</td>
<td>2.11</td>
<td>-0.37</td>
<td>1.23</td>
<td>1.05</td>
<td>1.58</td>
</tr>
<tr>
<td></td>
<td>Autumn</td>
<td>0.65</td>
<td>1.00</td>
<td>0.69</td>
<td>1.07</td>
<td>1.21</td>
<td>1.65</td>
<td>0.76</td>
<td>1.26</td>
<td>1.81</td>
<td>2.05</td>
<td>-0.25</td>
<td>1.31</td>
<td>0.81</td>
<td>1.39</td>
</tr>
<tr>
<td>Tavv</td>
<td>Annual</td>
<td>0.70</td>
<td>1.01</td>
<td>0.76</td>
<td>1.09</td>
<td>1.35</td>
<td>1.68</td>
<td>0.76</td>
<td>1.28</td>
<td>1.70</td>
<td>-0.13</td>
<td>1.18</td>
<td>0.94</td>
<td>1.33</td>
<td></td>
</tr>
</tbody>
</table>

main divide, with larger areas affected by pronounced decreases on the south side of the range. Thus, the response curve to partial residuals of distance to the main divide (Figure 7(B)) increases from negative values in the southernmost areas to positive values in the northernmost areas. When this variable (distance from the divide) is removed from the model, the total explained variance decreases by 13%. Although distance to the Atlantic and Mediterranean contributes relatively little to the model (the variance is reduced by only ~5% after each
was removed), their response curves to partial residuals (Figure 7(C) and (D)) predict more intense precipitation decreases for inland regions versus coastal sectors.

Spatial patterns in the distribution of predicted precipitation changes exhibit marked differences on a seasonal basis. For winter, the RCMs predicted relatively large increases in precipitation over the west, decreasing toward the east, whereas the opposite pattern is predicted for autumn. The forecast changes for precipitation in spring showed a clear north-south pattern, with the Spanish side experiencing significant decreases in precipitation. For summer, the models suggest a generalized and intense decrease in precipitation (−30% or more).

The coefficients of variation indicate the existence of higher inter-model variability in areas predicted to experience lower decreases or slight increases in precipitation. In these sectors, the CV sometimes exceeds 1, whereas the CVs in areas predicted to experience marked decreases are around 0.6–0.4, and even lower in some cases.

The changes in average temperature predicted by the RCMs are always positive, and show high magnitudes and marked spatial patterns, with the predictor variables accounting for 90% of the explained variance. The mean changes in annual temperature (Figure 6(T Annual)) tended to be >3°C, and were even >4°C across large areas. As shown in Figure 6(T Annual) and the response curves of the thermal change with respect to altitude and distance to the main divide (Figure 7(A) and (B)) the RCMs predict that climate warming should have more severe effects on the high altitude sector (Central Axial Pyrenees) and the southern slopes (Spanish side). Large decreases in the total explained variance (41 and 44%) occur when altitude and distance to the main divide are removed from the model, indicating that both variables largely help explain the spatial variability of the expected changes. Figures 6(T Annual), 7(A) and (B) also show that the two sea masses buffer the coastal regions, which show less intense predicted temperature changes than inland areas by around 2–2.5°C. However, this effect occurs over a relatively short distance and disappears quickly from the coastline. The latter observation explains why the total variance decreased only slightly when the distances to the Mediterranean and the Atlantic are removed from the model (4 and 6%, respectively).

The inter-model variability in the magnitude of temperature warming is much lower than that for precipitation. We did not observe clear spatial patterns for inter-model variability, although there appears to be a slight trend towards higher inter-model variability along the Atlantic coast.

Table III shows the mean temperature and precipitation changes predicted for the Pyrenees mountain range (within the ellipse of Figures 1 and 2) by each RCM for scenarios A2 and B2. Annual precipitation decreases by ∼15 and 11% under scenarios A2 and B2, respectively, but a large variability is observed among the models (i.e. the decreases for A2 ranged from 10 to 20%). HC and METNO models predict the highest decreases in this region, whereas DMI and ICTP predict the lowest changes. The differences in the changes of precipitation for scenario A2 versus scenario B2 are also highly variable among the models. For example, the decrease of precipitation estimated by METNO for B2 is roughly

<table>
<thead>
<tr>
<th>Variable</th>
<th>Period</th>
<th>DMI A2</th>
<th>HC A2</th>
<th>ICTP A2</th>
<th>METNO A2</th>
<th>SMHI A2</th>
<th>UCM A2</th>
<th>Average</th>
</tr>
</thead>
<tbody>
<tr>
<td>Precipitation</td>
<td>Winter</td>
<td>9.5</td>
<td>6.7</td>
<td>13.7</td>
<td>2.4</td>
<td>3.2</td>
<td>4.1</td>
<td>0.9</td>
</tr>
<tr>
<td></td>
<td>Spring</td>
<td>−13.1</td>
<td>−0.3</td>
<td>−22.6</td>
<td>−23.2</td>
<td>−13.1</td>
<td>−0.3</td>
<td>−20.5</td>
</tr>
<tr>
<td></td>
<td>Summer</td>
<td>−39.3</td>
<td>−31.4</td>
<td>−39.0</td>
<td>−42.7</td>
<td>−38.1</td>
<td>−48.4</td>
<td>−40.1</td>
</tr>
<tr>
<td></td>
<td>Autumn</td>
<td>−5.8</td>
<td>4.6</td>
<td>10.0</td>
<td>−3.9</td>
<td>−21.7</td>
<td>−27.4</td>
<td>−15.5</td>
</tr>
<tr>
<td>Precipitation</td>
<td>Annual</td>
<td>−10.0</td>
<td>−3.2</td>
<td>−20.1</td>
<td>−16.0</td>
<td>−10.9</td>
<td>−6.8</td>
<td>−19.0</td>
</tr>
<tr>
<td>Tmax</td>
<td>Winter</td>
<td>3.3</td>
<td>1.7</td>
<td>3.5</td>
<td>2.8</td>
<td>2.0</td>
<td>0.6</td>
<td>3.4</td>
</tr>
<tr>
<td></td>
<td>Spring</td>
<td>3.1</td>
<td>1.4</td>
<td>3.4</td>
<td>3.0</td>
<td>3.1</td>
<td>2.0</td>
<td>3.1</td>
</tr>
<tr>
<td></td>
<td>Summer</td>
<td>5.6</td>
<td>4.3</td>
<td>6.2</td>
<td>5.0</td>
<td>5.4</td>
<td>4.1</td>
<td>6.3</td>
</tr>
<tr>
<td></td>
<td>Autumn</td>
<td>4.4</td>
<td>2.7</td>
<td>4.8</td>
<td>3.5</td>
<td>4.2</td>
<td>2.3</td>
<td>4.8</td>
</tr>
<tr>
<td>Tmax</td>
<td>Annual</td>
<td>4.1</td>
<td>2.5</td>
<td>4.5</td>
<td>3.6</td>
<td>3.8</td>
<td>2.3</td>
<td>4.4</td>
</tr>
<tr>
<td>Tmin</td>
<td>Winter</td>
<td>3.5</td>
<td>1.7</td>
<td>3.4</td>
<td>2.6</td>
<td>2.5</td>
<td>1.0</td>
<td>3.4</td>
</tr>
<tr>
<td></td>
<td>Spring</td>
<td>2.8</td>
<td>1.4</td>
<td>3.1</td>
<td>2.6</td>
<td>2.5</td>
<td>1.1</td>
<td>2.9</td>
</tr>
<tr>
<td></td>
<td>Summer</td>
<td>4.9</td>
<td>3.6</td>
<td>5.4</td>
<td>4.1</td>
<td>4.3</td>
<td>3.0</td>
<td>5.5</td>
</tr>
<tr>
<td></td>
<td>Autumn</td>
<td>4.2</td>
<td>2.7</td>
<td>4.5</td>
<td>3.2</td>
<td>4.1</td>
<td>2.2</td>
<td>4.5</td>
</tr>
<tr>
<td>Tmin</td>
<td>Annual</td>
<td>3.9</td>
<td>2.4</td>
<td>4.1</td>
<td>3.2</td>
<td>3.4</td>
<td>1.9</td>
<td>4.1</td>
</tr>
<tr>
<td>Tavg</td>
<td>Winter</td>
<td>3.4</td>
<td>1.7</td>
<td>3.5</td>
<td>2.7</td>
<td>2.3</td>
<td>0.8</td>
<td>3.4</td>
</tr>
<tr>
<td></td>
<td>Spring</td>
<td>3.0</td>
<td>1.4</td>
<td>3.2</td>
<td>2.8</td>
<td>2.8</td>
<td>1.5</td>
<td>3.0</td>
</tr>
<tr>
<td></td>
<td>Summer</td>
<td>5.2</td>
<td>4.0</td>
<td>5.8</td>
<td>4.5</td>
<td>4.9</td>
<td>3.6</td>
<td>5.9</td>
</tr>
<tr>
<td></td>
<td>Autumn</td>
<td>4.3</td>
<td>2.7</td>
<td>4.6</td>
<td>3.4</td>
<td>4.1</td>
<td>2.3</td>
<td>4.7</td>
</tr>
<tr>
<td>Tavg</td>
<td>Annual</td>
<td>4.0</td>
<td>2.4</td>
<td>4.3</td>
<td>3.4</td>
<td>3.6</td>
<td>2.1</td>
<td>4.3</td>
</tr>
</tbody>
</table>
half that predicted for scenario A2 (−11.6% and −19% respectively), whereas HC predicts lower differences. As shown in Figure 5, the maximum decrease of precipitation occurs in summer (−44 and −38% for scenarios A2 and B2, respectively), and this prediction shows very low inter-model variability. The mean change in winter precipitation is close to zero, but the inter-model variability is high, and the predicted changes range from increases of 9.5 and 6.7% (DMI model) to decreases of 6.4 and 17.7 (HC) for scenarios A2 and B2, respectively.

In contrast, the CVs show that the expected increases of temperature in the Pyrenees mountain range are very similar across all six RCMs. The mean increases in temperature are predicted to be 4 and 2.8 °C under scenarios A2 and B2, respectively. In summer, the temperatures increase by 5.5 and 4.4 °C, respectively; in winter and spring warming is slightly more moderate, but still remains above 3 °C for scenario A2, and around 2 °C for scenario B2. The RCMs model shows more intense warming for maximum than minimum temperatures across this area. However, in both cases, the seasonal pattern of mean temperatures is maintained, showing a very intense warming during the summer, and more moderate, but still intense, warmings in winter and spring.

5. Discussion and conclusions

Our confidence in the climate change predicted for a given sector will increase if we believe that our climatic observations are reliable and suitable to the resolution of the utilized RCMs, if we see good agreement and low inter-model variability exit when observations and control runs are compared, and if the changes predicted by most of the utilized models coincide in sign and magnitude. Here, we have addressed each of these factors while analysing predicted changes in precipitation and temperature for the Pyrenees. The main findings of this work are the following:

1. Generalized Additive Models (GAMs) are very useful for creating distributed reference climatologies from observations. GAM has been previously used in several fields of science, but relatively few studies have applied this method to climatology. Consistent with a previous study (López- Moreno and Nogués-Bravo, 2005), our present results highlight this method as a promising tool for interpolating different climatic elements. The nonlinear nature of this regression-based technique (Hastie and Tibshirani, 1987) helped coping with the terrain complexity, yielding very good levels of accuracy in our cross-validation procedure. The obtained error estimators for the mapped climatic layers were very low, but there were some aspects where the maps deviated from reality. The highest errors were found for winter temperatures and summer precipitation. Modelling these two variables was a complex task, due to thermal inversion and convective rainfall, respectively (Tabony, 1985). Moreover, in areas with fewer (less dense) observations, it is normal to expect lower accuracy. Thus, although we believe that we have optimized the accuracy of the reference climatologies to the best of our abilities (including a subsequent interpolation of the residuals), the complexity of the modelled area and the low density of climatic observatories in some parts must be considered as a source of uncertainty for evaluating the possible impacts of climate change in mountain areas.

2. RCMs were able to accurately reproduce the main patterns of observed temperatures, and fairly accurately reproduce those of precipitation. However, large mean deviations or noticeable divergences between models were observed in some areas, suggesting that some of the changes predicted by the RCMs should be considered with caution. RCMs showed a generally good ability to reproduce the observed climate in the target area. However, some sectors offered certain difficulties in modelling. This caused some deviations with respect to the reference climatologies, particularly in the case of precipitation (>30% in some cases). The mean magnitude of these deviations for the whole area (generally less than 1 °C for temperature and within 10–20% for precipitation) are in line with the biases found for Europe in previous quality assessment of RCMs over Europe (Giorgi and Pal, 2004; Dequé et al., 2005).

3. The spatial distribution of RCM errors followed marked patterns over the territory. Altitude and distance to the main divide explained most of the variance of error distribution in precipitation and temperature. In this context, the use of regressions (GAMs) between observed errors and predictor variables (altitude and geographical variables) was useful for detecting the main spatial patterns in model accuracy, and for quantifying the contribution of each predictor. It is difficult to identify physical reasons for higher error levels in one particular area versus another across most of the RCMs. It is possible that the resolution level of 50 km² could have led to incorrect representation of the barrier effect, which significantly modifies the distribution of precipitation. In addition, systematic errors could have been introduced by the difficulty of properly reproducing the complex meteorological processes that occur at the interface between land and ocean. Both these explanations could account for the marked underestimation of precipitation near the Atlantic Ocean and the Mediterranean Sea, where contiguous reliefs noticeably increase the precipitation rates. These explanations also account for the general underestimation of winter precipitation, which is mainly caused by advections from the west and northwest, which are largely modulated by the relief (Vicente-Serrano and López-Moreno, 2006).

4. Spatial distribution of error magnitude as well as inter-model variability in accuracy are largely subject to seasonality. The largest differences between reference climatologies and control runs were seen in winter.
5. The comparison of control runs and predicted scenarios forecasts noticeable changes in precipitation and temperature under a greenhouse climate in the Pyrenees. RCMs for the Pyrenees predict a moderate decrease in precipitation and a marked increase in temperature. In general, the robustness of changes in temperature is higher than that for precipitation. Some of the predicted changes were very consistent across certain areas, with good agreement between the reference climate and the RCMs (which agree in the sign and magnitude of changes), and low inter-model variability of accuracy. In other areas, the uncertainties are equal or exceed the expected changes. However, the predicted changes have deep implications even in the most uncertain areas, strongly suggesting that we should take these forecasts into account when planning mitigation and adaptation policies aimed at dealing with future climatic conditions.

6. Predicted changes in climate at the end of the 21st century will have unequal effects on the study area. Altitude and distance to the main divide are the best elements that explain the spatial variability of the predicted impacts of climate change. In general, lower precipitation and warmer temperatures are expected for the southern (Spanish) side of the Pyrenees, which is already more severely affected by water deficit than the northern slopes. The predicted changes in precipitation are more moderate near the coast compared to further inland. In the case of temperature, the Atlantic and Mediterranean have a high capacity to absorb energy and to reduce the warming rates of the coastal areas. However, this coastal buffer effect has a limited spatial repercussion and disappears within a very short distance inland. Consistent with previous predictions in other studies (Giorgi et al., 1994; Beniston and Rebetez, 1996; Fyfe and Flato, 1999), the highest mountainous areas are expected to experience the most intense increases in temperature. If this is true, the impact of climate warming could be enhanced due to the area's high dependence on the water resources and ecological richness of the mountain regions (Beniston, 2003); this could be particularly important in the basins, where snow and glaciers play a major hydrological role (Barnett et al., 2005). However, it should be noted that some other studies have failed to confirm altitude-based differences in warming from long-term observations (Pepin and Seidel, 2005), and the differential behaviour of climate in mountains and lowlands under warming scenarios remains complex and controversial.

7. The magnitude, spatial patterns of change and convergence among models vary noticeably by season. This fact has large implications for evaluating the effect of climate change over a sector, since the impacts on hydrological cycle, agriculture, tourism, electric consumption, etc., will differ depending on the timing of the change (Kulme et al., 1999). Because the fluvial regimes rely on snow accumulation, the relatively moderate and highly uncertain expected decreases in precipitation during winter (especially westward) and increases in temperature (1.8 and 3°C for scenarios B2 and A2, respectively) are likely to have a greater impact than some of the more severe changes during other seasons. However, lower uncertainty was seen in the very marked decreases in precipitation and increases in temperature predicted for summer.  

8. Comparison of the changes predicted under the two considered emission scenarios reveals a large variability in the RCM-modelled responses of the climatic system to the intensity of greenhouse gas forcing. Comparison of the two IPCC scenarios indicates that B2 is forecast to enhance temperatures by 20–40% less than A2, with more variability associated with B2 than A2. Differences between the expected changes under both scenarios are enough to generate contrasted situations of water availability, and could have large effects on ecology and society in the region. 

9. The error estimators as well as the different sensitivity to climate change forcings of each RCM suggests that there may not be a 'best' model for analysing the climate change for a given area. Instead, the use of RCM ensembles appears to be the best approach for obtaining mean changes within intervals of confidence from a large number of simulations. In the present work, we did not identify any one model that significantly outperformed the others with regard to accuracy for reproducing the reference climate over the control period. Frequently, models that fit well with observed temperatures failed to accurately model precipitation, or vice versa. The accuracy of the models for the different variables also varied depending on the season. Moreover, the magnitude (and even the sign) of the climatic changes varied significantly among the RCMs. Thus, it does not seem wise to use a single RCM experiment to define the possible impacts of climate change. Instead, an ensemble of models driven by several GCMs and run for different emissions scenarios should be used to provide a more robust estimation of future conditions, the range
of variability of the predictions, and a better understanding of the uncertainties affecting the climatic change assessment. An appropriate management of uncertainty will increase the credibility of these analyses regarding the impacts of climatic change, which is necessary to convince politicians and society of the need to accelerate the adoption of measures designed to address future climatic change.

Acknowledgements

This study has been supported by the following projects: PROBASE CGL2006-11619 ‘Hydrological and sedimentological processes and budgets at different spatial scales in Mediterranean environments: Effects of climate fluctuations and land use changes’, CANOA CGL 2004-04919-c02-01 ‘Characterisation and modelling of hydrological processes in gauged basins for the prediction of ungauged basins’ both financed by the Spanish Commission of Science and Technology and FEDER. Authors’ thanks to the PRUDENCE project for the free access to the collection of climate model outputs. Research of the first author is supported by post-doctoral fellowships from the Spanish Ministry of Education, Culture and Sports, Spain.

References

Ninyerola M, Pons X, Roure JM. 2000. A methodological approach to climate change assessment. An appropriate management of uncertainties affecting the climatic predictions, and a better understanding of climate variability of the predictions, and a better understanding of the uncertainties affecting the climatic change assessment. An appropriate management of uncertainty will increase the credibility of these analyses regarding the impacts of climatic change, which is necessary to convince politicians and society of the need to accelerate the adoption of measures designed to address future climatic change.
J. I. López-Moreno ET AL.


