Multi-year simulations using a regional-climate model over the Iberian Peninsula: Current climate and doubled CO₂ scenario

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SUMMARY

In order to analyse the regional climate sensitivity in the Iberian Peninsula and surrounding areas to the global change related to an increase of CO₂, two simulations (current climate and scenario) are performed using a regional-climate model (RCM) one-way nested in a global circulation model (GCM). Both simulations cover a ten-year period. The results of the control simulation (current climate) are compared to a climatological database. RCM and GCM representations of the climate are realistic, but the RCM shows more detailed results. Following this, a statistical analysis of the differences between current climate and double CO₂ scenario simulations is carried out considering both 2 m temperature and precipitation. The analysis shows a significant warming in seasonal averages and important differences in the 2 m temperature interannual variability. Especially important is the strong increase in interannual variability of precipitation found in winter and autumn. Relationships between anomalies of general circulation (500 hPa geopotential field) and surface temperature, precipitation and cloudiness are also analysed, showing an important effect of cloud cover anomalies over the 2 m temperature interannual variability.

KEYWORDS: Climate change  Greenhouse effect  Iberian Peninsula climate  Regional-climate model

1. INTRODUCTION

The generation of possible climate scenarios is needed to assess the impact of the greenhouse effect on human activities (agriculture, planning of water reserves, etc.). Currently the atmosphere–ocean coupled global circulation models (GCMs) are the most powerful tool able to generate such scenarios but, in general, they do not have enough spatial resolution to supply input data to the impact assessment models (Robinson and Finkelstein 1991). Therefore, additional methods to increase the spatial resolution of the GCM's output are necessary. One possibility is the variable resolution GCMs (Dequé and Piedelieuvre 1995). This method allows simulations to be carried out with high resolution over a particular region of the earth, though it implies a very low resolution in the zone antipodal to the region of interest. The most used procedure is known as regionalization or downscaling and it can be of statistical, dynamic or hybrid (dynamical–statistical) type.

The statistical downscaling methods are based on recent registers, past climate data (palaeoclimate) and output of GCMs. Essentially, they consist of establishing statistical or empirical links between local climatic variables in a certain region and large-scale atmospheric variables (Webb and Wigley 1985; Budyko and Sedunov 1990; Cohen 1990; Storch et al. 1993; Noguer 1994). The dynamic methods rely on applying models based on the fundamental equations of atmospheric dynamics, but due to their special characteristics or the way they are used they can have a higher spatial resolution than the conventional GCMs (Dequé et al. 1994; Cubash et al. 1995).

Finally, in the hybrid or dynamical–statistical downscaling (Frey-Buness et al. 1994), it is assumed that the current regional climate can be characterized by the frequency of some given synoptic situations in the GCM simulations. Based on this

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assumption, a very high-resolution limited area model nested in the GCM is applied in all these synoptic situations, comparing the set of results with the regional or local climatology. If a GCM experiment is done with a higher concentration of greenhouse gases, the frequencies of such synoptic situations will change, therefore the high-resolution field’s weight in the perturbed climate reconstruction will also vary.

The most used dynamic downscaling method is based on regional-climate models (RCMs), which can achieve a very high spatial resolution. These models are conceptually like the atmospheric GCMs. However, the RCMs are not applied to the whole globe but to a limited region. Thus, the RCM needs lateral boundary values, which are supplied by a GCM using a one-way nesting method. The first attempts at applying this method were carried out by Dickinson et al. (1989) and Giorgi and Bates (1989), since when its use has progressively increased throughout the last decade.

A comprehensive description of this method, including an analysis of the pioneering simulations, can be found in Giorgi (1990), Marinucci and Giorgi (1992), and McGregor and Walsh (1993). In these first experiments the RCMs were nested in analysis fields deduced from observations (perfect boundary-conditions runs). Their time spans were either a few consecutive months, or one month which was simulated several times with slightly different conditions to allow statistical analyses. The horizontal resolution ranged from 60 km (Giorgi 1990) to 125 km (McGregor and Walsh 1994); although there are some studies with a higher resolution (Marinucci et al. 1995; Aebischer and Schär 1998) but limited to smaller domains. More recently, increasing computing power has enabled longer and higher-resolution simulations by nesting RCMs in GCMs. For instance, Giorgi and Marinucci (1996) applied a RCM over the United States with a resolution of 50 km in five-year long simulations. Jones et al. (1995) ran a ten-year long simulation in a domain centred in Europe with a resolution of 50 km, and McGregor et al. (1995) used a resolution of 125 km over Australia and Asia in a ten-year long simulation. In general, the RCM simulations with the highest resolution yielded more realistic results than the GCM simulations. The encouraging results of these experiments have encouraged the use of this method in many further studies; for example Christensen et al. (1997), Giorgi et al. (1997), Jones et al. (1997), Walsh and McGregor (1997), Renwick et al. (1998), Murphy (1999), and Leung and Ghan (1999a,b).

In the study presented here the RCM called PROMES is used. This RCM has been entirely developed in the Meteorology and Geophysics Department of the Complutense University of Madrid (Spain). PROMES has been nested in the Hadley Centre for Climate Prediction and Research (the Met Office, Bracknell, UK) GCM, also known as HadCM2. The chosen domain is centred on the Iberian Peninsula (IP hereafter). This region, in south-western Europe, is specially interesting because of its complex orography, its varied land cover and its critical geographic situation, located in the transition zone between middle and subtropical latitudes. The climate in this zone is very sensitive to any variation in the latitudinal configuration of the atmospheric general circulation (Castro et al. 1995).

Before describing the method and results, we wish to point out that the main goal of this study is to verify the ability of this RCM to generate future climate scenarios, and to assess the sensitivity of the regional climate in the IP to an increased concentration of greenhouse gases. Precise results should be treated with caution because, as Jones et al. (1997) indicate, current RCMs still need improvement in order to predict future climate conditions with enough reliability.

This paper is organized as follows. In the second section the main features of the models used and their parametrizations are described. The third section is a short description of the experiment, and the fourth section contains the analysis of the results
of both current climate (control) and RCM (scenario) simulations, including a statistical study of the significance of the differences between control and scenario results. The main conclusions are summarized in the fifth section.

2. BRIEF DESCRIPTION OF MODELS

The experiments described in this paper have been performed using the RCM known as PROMES, which was driven by a GCM output using the one-way nesting method. The GCM used is the Hadley Centre GCM, which is one of the components of the UK Met Office Unified Forecast/Climate Model.

(a) PROMES model

This RCM is the climatic version of the PROMES limited area model, which was initially developed by our group to perform mesoscale atmospheric numerical simulations over the IP (Gaertner et al. 1993; Fernández et al. 1995; Portela and Castro 1996). PROMES is a hydrostatic, fully compressible, primitive-equation model with pressure-based sigma vertical coordinates and a Lambert conformal projection for Cartesian horizontal coordinates. Prognostic variables are potential temperature, surface pressure, horizontal wind components and water content (vapour, cloud and rain). These variables are supplied from the GCM output through the lateral boundaries of the domain. A Davies-type relaxation scheme has been used (Davies 1976), with a five-point relaxation zone.

The exchanges between soil-vegetation and atmosphere are parametrized by the land surface scheme called SECHIBA (Ducoudré et al. 1993). Soil temperatures over seven layers are used to determine the vertical diffusion of heat by an extended force-restore method (Jacobsen and Heise 1982). The soil heat fluxes depend on some parameters which are a function of the soil water content. The land surface scheme calculates the soil water content in two layers and the bare-soil evaporation. It also computes transpiration and interception loss for each of the seven types of canopies which may be present at a grid point.

Turbulent vertical exchanges for the prognostic variables in the planetary boundary layer (PBL) are modelled considering four turbulent regimes: stable, mechanical turbulence, forced convection and free convection. For the first three regimes a local \( K \)-theory parametrization is used (Blackadar 1976; McNider and Pielke 1981). In the case of free convection (the most unstable case), a non-local scheme following Estoque (1968), Blackadar (1978), and Zhang and Anthes (1982) is used. Outside the PBL the vertical diffusion is also computed using \( K \)-theory.

Cloud absorption and scattering of short-wave radiation are parametrized according to the method of Anthes et al. (1987). The long-wave parametrization follows Stephens (1978a,b) and Garand (1983). Grid-scale clouds and precipitation are modelled according to Hsie et al. (1984). Subgrid-scale convective processes are parametrized using a scheme based on Fritsch and Chappell (1980).

The PROMES model uses a split-explicit integration scheme, based on Gadd (1978). Different terms of the equations are integrated using different time steps, depending on their typical time-scale: ‘adjustment’ terms (basically those related to gravity waves) are integrated with a shorter time step of 100 s, whereas ‘advection’ terms are integrated with a larger time step (300 s). A 600 s time step is applied to integration of physical processes.
(b) The Hadley Centre GCM

Although the Hadley Centre atmosphere–ocean coupled global model is well-known (Murphy 1995a,b; Murphy and Mitchell 1995; Johns et al. 1997), the most relevant features of the version used are briefly described here. Both atmospheric and oceanic components have a horizontal resolution of 2.5° latitude by 3.75° longitude, which is about 300 km in middle latitudes. There are 19 vertical levels in the atmosphere, and 20 in the oceans.

The atmospheric model is hydrostatic and solves a set of primitive equations using horizontal polar coordinates and a hybrid vertical coordinate (Slingo and Pearson 1987). The radiation scheme is based on Slingo et al. (1988). Layered clouds are parametrized by the explicit scheme of Smith (1990), and the subgrid-scale cloud processes follow the implicit scheme created by Gregory and Rowntree (1990).

Surface fluxes of heat, moisture and momentum are calculated by a bulk-type scheme in both land grids (Slingo 1985) and sea grids (Gordon 1989). Evaporation at land points is regulated by vegetation and bare-soil water content (Warrilow et al. 1986). Required soil and vegetation parameters (surface albedo, roughness length, thermal conductivity, surface resistance to evaporation, etc.) are specified depending on the spatial location (Warrilow and Buckley 1989). The model time step is 30 min for physics and dynamics (10 min for the adjustment phase), except for the radiation scheme which has a 3 h time step.

The ocean model is based on that developed by Cox (1984) and has 20 unequally spaced vertical levels with high resolution near the surface. It is a hydrostatic model and its set of equations predicts currents, potential temperature and salinity. A time step of 30 min is used. The ocean model includes a parametrization of the subgrid-scale turbulent diffusion, and a mixed layer submodel (Kraus and Turner 1967) to compute the effect of the wind in the mixing of the uppermost ocean layers. The prediction of sea ice is based on the 'zero-layer' thermodynamic approach of Semtner (1976).

The ocean–atmosphere coupling is carried out for every day of the simulation. During one day the atmospheric component is run separately using fixed sea surface temperatures (SSTs) and sea ice extents. Averaged surface fluxes of this period are used to run the ocean and sea ice models, so that SST values and sea ice extents can be updated.

3. EXPERIMENTS

Two simulations have been accomplished (control and scenario) using the PROMES RCM one-way nested into HadCM2. Firstly, we give a short description of the GCM simulations; see Johns et al. (1997) for a fuller description.

The Climatic Change experiment includes two different integrations of the GCM: current climate (control run) and double CO₂ (scenario run). Both simulations start in 1860 and finish in 2100. There is a spin-up of 510 years that finishes in 1850, which is used to balance the oceanic and atmospheric conditions. During the spin-up the greenhouse gases' (CO₂, N₂O, CFCs) concentrations are constant and equal to those of 1990 (Johns et al. 1997). After this initial run the two above mentioned simulations are carried out. During the control integration the greenhouse gases' concentration is constant and equal to the 1990 concentration (473 ppmv effective CO₂). The perturbed simulation also starts in 1860 but the initial effective CO₂ concentration is 341 ppmv (corresponding to that in 1860). Until 1990 the increase of greenhouse gases follows observations (Shine et al. 1990), and from 1990 to 2100 the increment is 1% per year (compound). This increase corresponds to the 'IPCC scenario IS92a' (Mitchell
and Gregory 1992) and uses the Kattenberg et al. (1996) conversion from emissions to concentrations. The sulphate aerosol effect was not considered in these GCM runs.

The RCM PROMES experiments consist of two 10-year simulations: control and scenario. The time slice chosen goes from 2040 to 2049. The reason for choosing these years is that in this decade the effective CO$_2$ concentration reaches double the average effective CO$_2$ concentration between 1961 and 1990 (approximately 430 ppmv).

The domain used in these simulations is a 2250 by 1950 km region centred on the IP (Fig. 1) with boundaries far enough from the area of interest. Although this domain is smaller than some in previously published papers about regional-climate modelling, there are several other experiments using similar domain sizes ( McGregor and Walsh 1994; Kidson and Thompson 1998; Rotach et al. 1997; Renwick et al. 1998). In other studies of the PROMES model with a similar domain, internal variability has been analysed ( Gaertner et al. 2001; Bossing et al. 2001) showing that PROMES was capable of reproducing relevant mesoscale circulations.

The PROMES model uses cartesian coordinates and a Lambert conformal projection. The horizontal resolution is 50 km, enough to resolve the most relevant orographic features; 25 unequally spaced layers are considered in the vertical, with the top model level at 100 hPa (boundary conditions at this level were obtained from the GCM output).
The topographic heights have been obtained from the National Geophysical Data Center NOAA database (with 5' resolution in latitude and longitude).

Initial and boundary conditions for the RCM are calculated using horizontal and vertical interpolations from the GCM daily output at 00, 06, 12 and 18 (UTC). A linear time interpolation was applied to obtain boundary values at each RCM time step. Vertical interpolation is performed using a procedure that efficiently conserves the geopotential and static stability features of driving fields (Gaertner and Castro 1996).

Initial soil water contents in RCM grids have been deduced from the Mintz and Serafini (1992) climatological database, which is compatible with soil model implementation (Gaertner et al. 2001). The RCM runs started at the end of the summer (1 October) when, due to the scarce rains in this season, most of the IP soils are extremely dry. Thus, any error in initial soil water content is minimized; furthermore, a three-month spin-up period was considered. The RCM also reproduces accurately the climatological soil moisture annual cycle.

The vegetation distribution is taken from Olson et al. (1983). Albedo, roughness, emissivity and LAI (leaf area index) follow a temporal evolution similar to that proposed in Dickinson et al. (1986), changing every 15 days through two transitional periods (spring and autumn) from their winter values to the summer ones and vice versa. Summer and winter parameters are based on Benjamin and Carlson (1986) and Ducoudré et al. (1993). Initial temperature values in the seven RCM ground layers have been interpolated from the GCM output.

4. Results

(a) Control simulation

This control simulation is used to check how well both models reproduce current climate in IP. Surface climatology data supplied by the University of East Anglia's Climate Research Unit (CRU hereafter) were considered. It consists of monthly averages (1961–90) of 2 m temperature (screen temperature) and precipitation based on a 0.5° latitude by 0.5° longitude grid (New et al. 2000). Besides these surface data, monthly average 500 hPa geopotential height (hereafter z500) fields from the European Centre for Medium-Range Weather Forecasts (ECMWF) 1979–94 Re-Analysis (ERA; Gibson et al. 1997) were also used.

Tables 1(a) and 2(a) summarize seasonally averaged values of simulated and observed 2 m temperature and precipitation. We have only considered land points within the IP. For comparing CRU data to RCM results (bias and spatial correlation) the first have been bilinearly interpolated to the RCM mesh discarding sea grids; while in the case of the GCM, CRU data have been averaged on GCM land grids. A similar averaging is done for the GCM–RCM comparison.

Finally, z500s from ERA have been interpolated to the GCM grid. Since RCM and GCM z500 monthly average fields are very similar, the ERA–GCM comparison is used for detecting GCM errors eventually incorporated in the RCM, which will help to explain some of the control results.

As Table 1(a) shows, the annual variation of mean 2 m temperature over the IP is satisfactorily simulated, although simulations of both models are slightly colder than climatology. However the RCM temperature bias is slightly smaller than that of GCM. These temperature differences are similar to those shown in Giorgi et al. (1997) and Jones et al. (1995). Nevertheless, the RCM spatial distributions are more realistic and detailed than GCM, when both are compared to CRU fields (see Figs. 2 and 3).
TABLE 1. SEASONAL AVERAGE 2 M TEMPERATURE (°C)

<table>
<thead>
<tr>
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<th>DJF</th>
<th>MAM</th>
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<tbody>
<tr>
<td>Mean OBS</td>
<td>6.8</td>
<td>11.6</td>
<td>20.6</td>
<td>14.4</td>
</tr>
<tr>
<td>Bias RCM</td>
<td>-0.1</td>
<td>-1.4</td>
<td>-1.2</td>
<td>-0.8</td>
</tr>
<tr>
<td>Bias GCM</td>
<td>-1.0</td>
<td>-2.2</td>
<td>-2.5</td>
<td>-1.6</td>
</tr>
<tr>
<td>Bias GCM (LRC)</td>
<td>-1.9</td>
<td>-3.4</td>
<td>-4.0</td>
<td>-2.8</td>
</tr>
<tr>
<td>Diff. GCM-RCM (GCM)</td>
<td>-0.4</td>
<td>-0.1</td>
<td>-0.5</td>
<td>-0.2</td>
</tr>
<tr>
<td>Corr RCM/OBS (RCM)</td>
<td>0.89</td>
<td>0.92</td>
<td>0.85</td>
<td>0.90</td>
</tr>
<tr>
<td>Corr GCM/OBS (LRC)</td>
<td>0.86</td>
<td>0.87</td>
<td>0.78</td>
<td>0.88</td>
</tr>
<tr>
<td>Corr GCM/OBS (GCM)</td>
<td>0.88</td>
<td>0.88</td>
<td>0.81</td>
<td>0.88</td>
</tr>
</tbody>
</table>

Diff. GCM-RCM (GCM) are differences between GCM and RCM on the GCM grid.
Corr RCM/OBS(RCM) are spacial correlation values between RCM and climatology on the RCM grid.
Corr GCM/OBS(GCM) are spacial correlation values between GCM and climatology on the GCM grid.
ISD values are interannual standard deviations.
LRC values include lapse-rate corrections.

TABLE 2. SEASONAL AVERAGE Precipitation (MM DAY⁻¹)

<table>
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<tr>
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<th>DJF</th>
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<tbody>
<tr>
<td>Mean OBS</td>
<td>2.5</td>
<td>2.0</td>
<td>1.0</td>
<td>2.2</td>
</tr>
<tr>
<td>Bias RCM</td>
<td>1.1</td>
<td>0.6</td>
<td>0.5</td>
<td>0.7</td>
</tr>
<tr>
<td>Bias GCM</td>
<td>0.2</td>
<td>0.6</td>
<td>1.0</td>
<td>0.0</td>
</tr>
<tr>
<td>Diff. GCM-RCM (GCM)</td>
<td>-0.9</td>
<td>-0.2</td>
<td>0.2</td>
<td>-0.9</td>
</tr>
<tr>
<td>Corr RCM/OBS (RCM)</td>
<td>0.62</td>
<td>0.73</td>
<td>0.74</td>
<td>0.72</td>
</tr>
<tr>
<td>Corr GCM/OBS (GCM)</td>
<td>0.77</td>
<td>0.84</td>
<td>0.81</td>
<td>0.71</td>
</tr>
</tbody>
</table>

Notes as for Table 1.

The spatial correlations between CRU and both models’ seasonal temperatures are also shown in Table 1(a). The correlation values of the RCM are higher than those of the GCM in all seasons despite the GCM–CRU spatial comparison being less demanding than the RCM–CRU because the former is made over a coarser grid. In summary, the RCM simulates seasonal averaged fields of mean 2 m temperature with better and greater spatial detail than the GCM.

In order to compare the model skill with the distinct orographic signal removed, a new seasonal temperature comparison was made. For this, GCM data were first horizontally interpolated to the RCM mesh and, afterwards, a lapse-rate correction considering differences between GCM and RCM orographies was applied. Both bias and correlation of GCM temperature are still worse than those of the RCM simulation (see Table 1(a)). This clearly showed that, although the orography is an important factor in accurately representing 2 m temperature, the influence of other mesoscale
Factors captured by the RCM is not negligible, especially in summer. For example, the PROMES RCM represents better the higher summer temperature in central-southern IP, which is related to a typical mesoscale circulation pattern (the Iberian thermal low), and not well-resolved by the GCM.

Table 1(b) shows the interannual variability of seasonally averaged temperature expressed in terms of interannual standard deviation values (ISD hereafter). These ISD values are mostly similar for both models. Apparently the RCM interannual variability is basically controlled by the GCM, although in summer the RCM ISD is slightly larger.
Figure 3. Observed climatology of New et al. (1998). Seasonally averaged surface air temperature (°C) and precipitation (mm day⁻¹) over land. Seasons as Fig. 2.

A similar result was found by Giorgi et al. (1998) in a simulation over the USA with the same horizontal resolution as in this experiment. The ISD values from both models are somewhat larger than those from CRU data, though we must realize that the statistical populations are dissimilar (30 years for CRU against 10 years for models). In order to check the models ISD accuracy, values from three different decades (1961–70, 1971–80 and 1981–90) of the CRU data were calculated (values not shown); these 10-year period ISD values were not greatly different to those of the 30-year period. So, we conclude that both models have a larger interannual variability than observations.
TABLE 3. AVERAGED 500 hPa GEOPOTENTIAL HEIGHT (M) FOR A REGION CENTRED ON THE IBERIAN PENINSULA

<table>
<thead>
<tr>
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<th>DJF</th>
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<tbody>
<tr>
<td>Bias z500</td>
<td>−40</td>
<td>−57</td>
<td>−77</td>
<td>−22</td>
</tr>
<tr>
<td>MEAN 1×CO₂</td>
<td>5613.00</td>
<td>5606.90</td>
<td>5759.05</td>
<td>5727.93</td>
</tr>
<tr>
<td>MEAN 2×CO₂</td>
<td>5680.98</td>
<td>5665.90</td>
<td>5826.26</td>
<td>5813.48</td>
</tr>
<tr>
<td>ISD OBS</td>
<td>28.30</td>
<td>29.50</td>
<td>17.30</td>
<td>21.50</td>
</tr>
<tr>
<td>ISD 1×CO₂</td>
<td>32.20</td>
<td>32.60</td>
<td>18.61</td>
<td>20.00</td>
</tr>
<tr>
<td>ISD 2×CO₂</td>
<td>(11.7%) 35.97</td>
<td>(−28.2%) 23.40</td>
<td>(27.1%) 23.65</td>
<td>(19.0%) 23.80</td>
</tr>
</tbody>
</table>

Results significant at the 99% level appear in bold. Z500: GCM 500 hPa geopotential height. ISD: interannual standard deviations. OBS: observed climatology of New et al. (1988). Also see Fig. 1.

The seasonally averaged z500 geopotential fields from the GCM have been compared with ERA data (the RCM z500 values are not considered because they are very similar to those of the GCM). As Table 3 shows, the GCM z500 values are lower than ERA throughout the year. This seems to indicate a displacement of storm tracks toward lower latitudes in the GCM simulation (see Fig. 4), as Jones et al. (1995) pointed out. When GCM z500 and temperature biases are analysed together (Table 3 and Table 1(a)) it is clearly observed that negative z500 biases correspond to negative 2 m temperature biases. Therefore, the colder seasonal surface temperatures simulated by the GCM appear to be related to these z500 biases, which are transmitted to the RCM.

Before analysing precipitation values it is advisable to comment briefly on the main characteristics of seasonal precipitation over the IP. The most rainy season is winter (2.5 mm day⁻¹), followed by autumn and spring (2.2 and 2.0 mm day⁻¹ respectively). But, whereas winter and autumn precipitation is mostly related to synoptic-scale dynamical processes, spring precipitation is originated both by synoptic and by local convective processes. The season of minimum precipitation is summer (1.0 mm day⁻¹) when rainfall is mainly related to local convective activity (Font-Tullot 1983).

Seasonal precipitation biases for both models are all positive (Table 2(a)). The maximum GCM bias corresponds to summer (1.0 mm day⁻¹), and the minimum bias to autumn (0.0 mm day⁻¹), which approximately coincides with the seasonal behaviour of the GCM z500 bias (Table 3). The highest RCM precipitation bias appears in winter (1.1 mm day⁻¹), the most rainy season, whereas the lowest bias is in summer (0.5 mm day⁻¹), the driest season, due to the much better simulation of the extreme dryness observed in the southern half of the IP (see Figs. 3 and 5). RCM precipitation is more intense than that of the GCM in winter and autumn (0.9 mm day⁻¹), which are the seasons with more synoptic precipitation. In spring, a transition season, the RCM precipitation is larger (0.2 mm day⁻¹) than the GCM, while in summer, when precipitation is mostly convective, the RCM values are smaller than the GCM. Soil moisture, z500 bias and the different representations of orographic and physical processes in both models will be analysed as possible causes for these differences.

Soil moisture and evaporation play an important role in precipitation regimes, especially in summer when precipitation is mostly convective. But, as shown in Table 5, there are no significant differences between ERA and RCM evaporation values in this season, therefore, this is not likely to be the main factor in the summer precipitation bias.

Positive biases in precipitation could mostly be related to the southward displacement of average z500 fields of the GCM when compared with ERA data (Fig. 4), though these will undoubtedly be modulated by biases from the model physics. In fact, in summer, when the synoptic-scale has less influence, as confirmed by the smallest correlation
values between z500 and precipitation anomalies in this season (Table 4(a)), the RCM is closer to observations than the GCM. A previous experiment with RCM PROMES using perfect boundary conditions (Gaertner et al. 2001) did not show such positive bias in the autumn/winter period, which supports the above hypothesis.

As an attempt to verify the influence of orography on precipitation bias, differences between both models were analysed considering averages over all the domain and also over land only. In the first case (sea and land points), very small differences between models were obtained (not shown). When only land points are considered, these differences increase in winter and autumn and, to a smaller extent, in spring. In other
words, the RCM generally simulates more precipitation than the GCM over land points and less over sea points (Fig. 5) in those seasons when synoptic precipitation prevails. A reasonable conclusion is that land precipitation differences between models are related to their different orographic representation. However, vertical resolutions used in both models should not be discarded as being co-responsible for such differences.

Precipitation ISD values from the RCM are higher than observed (Table 2(b)), similarly as for temperature. Nevertheless, the ISD values for precipitation are quite different for both models: those of the RCM are larger than GCM ones, which are closer
TABLE 4. Correlation values between anomalies of different variables \( X_t - X_{\text{med}} \)

<table>
<thead>
<tr>
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<th>DJF</th>
<th>MAM</th>
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<tbody>
<tr>
<td>( 500 \text{-T2} )</td>
<td>0.52</td>
<td>0.85</td>
<td>0.90</td>
<td>0.90</td>
</tr>
<tr>
<td>( 500 \text{-NB} )</td>
<td>-0.71</td>
<td>-0.95</td>
<td>-0.52</td>
<td>-0.80</td>
</tr>
<tr>
<td>( 500 \text{-PR} )</td>
<td>-0.64</td>
<td>-0.84</td>
<td>-0.11</td>
<td>-0.89</td>
</tr>
</tbody>
</table>

(b) Scenario 2×CO₂

<table>
<thead>
<tr>
<th></th>
<th>DJF</th>
<th>MAM</th>
<th>JJA</th>
<th>SON</th>
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</thead>
<tbody>
<tr>
<td>( 500 \text{-T2} )</td>
<td>0.15</td>
<td>0.50</td>
<td>0.90</td>
<td>0.84</td>
</tr>
<tr>
<td>( 500 \text{-NB} )</td>
<td>-0.84</td>
<td>-0.47</td>
<td>-0.79</td>
<td>-0.74</td>
</tr>
<tr>
<td>( 500 \text{-PR} )</td>
<td>-0.97</td>
<td>-0.78</td>
<td>-0.76</td>
<td>-0.66</td>
</tr>
</tbody>
</table>

\( 500 \): GCM 500 hPa geopotential height anomalies.
T2: RCM surface air temperature anomalies.
NB: RCM cloud cover anomalies.
PR: RCM precipitation anomalies.

TABLE 5. Evaporation values (mm day\(^{-1}\)) for control simulation

<table>
<thead>
<tr>
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</thead>
<tbody>
<tr>
<td>EVAP (ERA)</td>
<td>0.52</td>
<td>1.22</td>
<td>1.31</td>
<td>0.74</td>
</tr>
<tr>
<td>EVAP (RCM)</td>
<td>0.37</td>
<td>0.85</td>
<td>1.33</td>
<td>0.66</td>
</tr>
</tbody>
</table>

ERA: observed climatology. RCM: simulated values.

The spatial correlation values between RCM and CRU precipitation are quite satisfactory (around 0.7 throughout the year), but not as good as those obtained for seasonal temperatures. Values of RCM spatial correlation are slightly lower than those of the GCM but, as indicated previously for temperature, the GCM–CRU comparison is less demanding due to its coarser horizontal resolution.

(b) Response to scenario concentration changes

The analysis of differences between control and scenario is focused on the RCM results, since those of the GCM are already commented on in Mitchell and Johns (1997). However some references to GCM results will be included here where convenient. For this control–scenario comparison, two aspects will be addressed: differences of precipitation and temperature (averages and ISD values), and differences of regional spatial distribution of those variables. To analyse the statistical significance of control–scenario changes, a Student’s \( t \)-test is applied.

Table 6 summarizes the most important changes between control and scenario runs (temperature and precipitation averaged over the IP land points). There is an appreciable temperature increase throughout the year, greater in autumn and summer than in winter and spring. This behaviour is found in both RCM and GCM experiments. The averaged surface temperature increase is statistically significant in all seasons over the entire IP (not shown).

The 2 m temperature increase in winter and spring is basically because of the significant increment of incoming long-wave radiation (Table 7), which is related to the enhancement of greenhouse effect due to the CO₂ increase. During the warm months this factor is accompanied by a significant decrease of cloud cover fraction, inducing an increase of net solar radiation (only significant in summer).
In Fig. 6 the spatial distribution of temperature changes for both models can be observed. A higher heating is found in the scenario run during autumn and summer over land points, with increments of about 4 degC. The RCM shows a spatially more detailed structure in all seasons. Regions with more intense heating are more extensive in GCM than in RCM runs. In summer, both models reproduce a larger heating over the south of the IP, but the GCM extends this effect to the north of Spain. For the RCM the highest increment is located in the southern inner half of the IP, which may be related to its better simulation of summer mesoscale circulations. Northern IP and coastal zones show less heating than inland zones, due to the ventilation effects of sea breezes associated with the Iberian thermal low (Gaertner et al. 1993). This effect is also observed in autumn, albeit less intense.

In winter, the largest heating in the RCM takes place over the highest mountain range in the IP (Pyrenees), which is related to the simulated snow cover reduction over this zone (not shown) in the scenario simulation and, as a consequence, the decrease of surface albedo (Giorgi et al. 1997).

Comparing control and scenario experiments, the RCM surface temperature ISD (Table 1(b)) increases in summer and decreases through the rest of the year. With the exception of autumn, RCM ISD changes are considerable (45% and 25% smaller in winter and spring, respectively, and about 15% larger in summer). Therefore, a decrease in winter and spring interannual variability would be expected. A similar signal is observed for the GCM.

With the exception of winter, seasonal changes of surface temperature ISD values appear to be related to those of z500 ISD (Table 3). The decrease of temperature ISD

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### Table 6. Seasonally Averaged Differences Between Scenario and Control Run of Surface Temperature and Precipitation for Land Points within the Iberian Peninsula

<table>
<thead>
<tr>
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<th>DJF</th>
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</thead>
<tbody>
<tr>
<td>Bias PRE RCM 2CO₂–1CO₂ (mm day⁻¹)</td>
<td>0.7</td>
<td>0.3</td>
<td>−0.4</td>
<td>−0.3</td>
</tr>
<tr>
<td>Bias PRE GCM 2CO₂–1CO₂ (mm day⁻¹)</td>
<td>0.5</td>
<td>0.0</td>
<td>−0.6</td>
<td>−0.3</td>
</tr>
<tr>
<td>Bias TMP RCM 2CO₂–1CO₂ (degC)</td>
<td>3.3</td>
<td>2.8</td>
<td>3.8</td>
<td>3.9</td>
</tr>
<tr>
<td>Bias TMP GCM 2CO₂–1CO₂ (degC)</td>
<td>3.7</td>
<td>2.8</td>
<td>4.2</td>
<td>4.3</td>
</tr>
</tbody>
</table>

Values in bold are significant at the 0.99% level PRE is precipitation, and TMP 2 m temperature values.

### Table 7. Scenario – Control Differences

<table>
<thead>
<tr>
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<th>DJF</th>
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</thead>
<tbody>
<tr>
<td>ISR</td>
<td>0.14</td>
<td>6.97</td>
<td>24.32</td>
<td>14.70</td>
</tr>
<tr>
<td>ILWR</td>
<td>18.17</td>
<td>14.58</td>
<td>19.96</td>
<td>18.77</td>
</tr>
<tr>
<td>OLWR</td>
<td>15.54</td>
<td>14.10</td>
<td>22.52</td>
<td>21.00</td>
</tr>
<tr>
<td>LH</td>
<td>1.48</td>
<td>3.55</td>
<td>3.16</td>
<td>0.16</td>
</tr>
<tr>
<td>SH</td>
<td>0.25</td>
<td>3.65</td>
<td>16.25</td>
<td>9.43</td>
</tr>
<tr>
<td>CLFR</td>
<td>0.027</td>
<td>−0.008</td>
<td>−0.114</td>
<td>−0.077</td>
</tr>
<tr>
<td>SOIL MOIST</td>
<td>−12.93</td>
<td>−5.33</td>
<td>−19.53</td>
<td>−37.59</td>
</tr>
</tbody>
</table>

Values in bold are significant at the 0.99% level.

ISR: net short-wave radiation flux (W m⁻²).
ILWR (OLWR): incoming (outgoing) long-wave radiation flux (W m⁻²).
LH (SH): latent(sensible)-heat flux (W m⁻²).
CLFR: cloud cover fraction.
SOIL MOIST: soil water content (mm).
in winter corresponds to a relatively small increase of z500 ISD. An explanation for this could be that cloud cover has a stronger influence on winter 2 m temperature than z500. This is supported by the results shown in Tables 4(a) and (b). There we can see that winter is the only season where there is not a significant relationship between z500 and surface temperature anomalies in the control simulation. Furthermore, correlation between z500 and cloud cover anomalies in the scenario simulation becomes larger than in the control run, and significant for this season. This would mean that those winters with a positive z500 anomaly will present a larger negative cloud cover anomaly in
the scenario simulation than in current climate, and vice versa. Similar results were obtained by Mearns et al. (1995). Therefore, in less cloudy winters radiative night-time cooling increases, which modulates the average heating. This is supported by the longer night-time than daytime in midlatitude winters. Thus, a higher interannual variability of z500 in the scenario climate than in the control is compatible with a lower variability of surface temperature in the scenario wintertime. For other seasons, surface temperature and z500 ISD changes are in greater correspondence.

This explanation is consistent with the results obtained when observed seasonal surface temperature and precipitation anomalies averaged over the entire IP are correlated. By using 1971–90 CRU data we obtained a positive correlation (+0.32) in winter but negative in spring (−0.58), summer (−0.58) and autumn (−0.19), although only the spring and summer values are statistically significant with a 0.99 level of confidence. This would imply that, as shown above, anomalous rainy winters (and consequently more cloudy) tend to be warmer, whereas anomalous rainy springs, summers or autumns tend to be colder than normal in the IP.

As expected for regional temperature ISD variation, both models simulate a similar response over land but RCM values are higher. Important ISD temperature changes are observed in the RCM scenario experiment, especially in winter when temperature ISD decreases strongly (more than 50%) over extensive zones in the IP. Regional precipitation ISD changes are very strong over some zones of the IP in winter and autumn; in fact ISD values increase more than 100% over many areas of the southeastern quadrant (not shown).

In the RCM scenario run, averaged annual precipitation over the IP increases (+0.3 mm day\(^{-1}\)), but not uniformly through the year (Table 6); there is an increase in winter and spring, but a reduction in summer and autumn. The GCM simulates a precipitation increase only in winter. In summary, both models agree in simulating a winter precipitation increase and a summer and autumn decrease. Only in spring is there a disagreement between these models. Statistical significance of these changes will be explained later.

If control to scenario changes in precipitation, soil moisture and latent heat are analysed together a clear relationship between them can be observed (Tables 6 and 7). Despite the significant decrease in soil moisture content in all seasons, this is smaller in those with an increase in precipitation (winter and spring), reaching its minimum in spring. Latent-heat flux also reach its maximum increase in spring. Apparently, the reduction in precipitation in summer and autumn, combined with the increase in latent-heat flux in summer, leads to a great reduction in soil moisture content.

Apart from these spatially averaged differences, there are also some differences in the regional distribution of precipitation changes (Fig. 7). The largest differences in the RCM are found in winter, when the most important changes are located over the north-west region of the IP; meanwhile, in the GCM simulation they appear over the Atlantic ocean. The RCM simulates an intense decrease of precipitation (3 mm day\(^{-1}\)) over the west zone of the Pyrenees Range. The RCM also simulates a slight increase in spring precipitation in the north of the IP (up to 2 mm day\(^{-1}\)). In summer and autumn the spatial distribution of differences is more similar in both models, but the RCM shows a precipitation decrease in the north-east of the IP during summer.

The RCM precipitation ISD changes follows those of z500 ISD (Tables 2(b) and 3): they increase in winter and autumn (around 50% and 30%, respectively), and decrease in spring. The only exception is summer, when precipitation is mainly convective. These results coincide with those from the GCM, although this does simulate a slight increase of precipitation ISD during summer. The importance of precipitation ISD changes in
winter and autumn can be easily understood since they are the seasons contributing most to the annual precipitation over most of the IP.

Relationships between z500 and precipitation anomalies are not as clear as they are between z500 and 2 m temperature. In the control simulation only spring and autumn show a significant anticorrelation (Table 4(a)), whereas in the scenario run all seasons except autumn present a significant anticorrelation. Especially interesting is the change in summer correlation values (−0.11 in control and −0.76 in scenario) which indicates a larger influence of z500 variability on summer precipitation in a scenario climate.
Precipitation changes are not statistically significant when averaged over the IP (Table 6), although some significant results are found in winter and summer in certain subregions (Fig. 8). Precipitation changes have some significance in the northern half of the IP in the winter season. On the other hand, a zone in the north-east shows a significant change in summer which approximately coincides with the only area in the IP having a summer precipitation maximum. The lowest significance for precipitation changes from the RCM is found in autumn and spring.
5. SUMMARY AND CONCLUSIONS

The RCM shows more detailed fields and reproduces quite accurately the thermal annual wave with a small and negative bias, which is coherent with the lower z500 fields prescribed from the GCM. The interannual variability of temperature is approximately similar for both models, although larger than climatological observed values.

Both models simulate excessive precipitation, the RCM excesses are larger in winter and autumn, and smaller in summer. A possible explanation for this could be the different orographic representation and physics parametrizations of both models, which explains the capacity of the RCM to improve the GCM results in certain situations (especially in summer). The spatial correlation coefficients are quite high for both models.

Two-metre temperature increases significantly in the scenario experiment through all seasons, as expected because of the larger incoming long-wave radiation flux due to the CO₂ increase. Temperature ISD changes considerably in winter, spring and summer but with different sign (there is a decrease of 45% and 25% in winter and spring, respectively, and an increase of 15% in summer). The greatest temperature increase occurs during summer and autumn in some regions (southern inner regions of the IP). The larger temperature increase in summer is related to cloud cover reduction. Cloud cover plays an important role in the decrease of temperature interannual variability (ISD) in winter and autumn (to a smaller extent). The reason is thought to be related to the higher anticorrelation between cloud cover and z500 anomalies in the scenario simulation. As a result of this, in those winters with negative z500 anomaly cloud cover will increase and also the net long-wave surface radiation, giving rise to higher minimum temperatures. Through the rest of the year 2 m temperature interannual variability will be dominated by the z500 variations.

The RCM simulates changes of seasonal precipitation over the IP (increase in winter and spring and decrease in summer and autumn), although they are not significant. There are some regional differences between the RCM and GCM simulations, especially over the north-west (in winter) and the north-eastern areas (in summer). The interannual variability of precipitation increases (near 50% in average, and more than 100% over several parts of the south-eastern quadrant) in winter and autumn, the most rainy seasons in the control simulation over the domain.

Analysing precipitation and 2 m temperature together, there are some changes in the cold (winter and spring) and warm (summer and autumn) seasons between control and scenario simulations. The most important are: the greatest heating during the warm seasons; and a precipitation increase in the northern half of IP during winter and a decrease in the north-east of IP during summer. These changes combined could cause an important effect over the IP vegetation cover since it would produce an increase in the already quite large vegetation stress.

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