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Highlights:

- Weather-conditioned energy demand (degree-days) for indoor cooling in Spain has shown a significant increase in recent decades.
- The North Atlantic Oscillation and the Southern Oscillation also influence the Spanish heating and cooling degree-days.
- Projections for the future from a set of coupled regional simulations are that towards the middle of the 21st century the summer demands for cooling in Spain will be increased by 50 % .

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ABSTRACT

Heating and cooling degree-days estimate the influence of meteorological variability on the domestic energy demand. Heating and cooling degree-day indices are obtained from daily mean temperatures that are weighted by the ratio of the local population that is experiencing such weather, to the total population of the region under study. In this paper we investigate the evolution of heating and cooling degree-days in the case of Spain, under present (1958-2005) and future atmospheric composition. The observed variability is obtained from temperature records at 31 stations through Spain and from the available census data. The evolution presents a trend and an interannual variability that are both found statistically significant. The North Atlantic Oscillation influences winter heating and autumn cooling needs. The influence of the Southern Oscillation is detectable only in the spring cooling degree-days. The observed winter and summer degree-day indices are used to validate the corresponding variability in Spain found in four simulations of the Mediterranean Region performed with high resolution Coupled Regional Climate Models, in the historical period, from 1950 to 2000. The future evolution of degree-days is estimated with four simulations performed with the same models under scenario A1B conditions, for the period 2001-2050. Both, trends found in the simulated and in the observed winter heating degree-days present a similar lack of significance. However, the observed and simulated trends in the case of the summer cooling degree-days are statistically significant. In the historical period, these trends are similar to the observed ones, roughly 5%/decade. Under the scenario conditions the cooling degree-days are increased by 50% with respect to their values in the historical period.

1 Introduction.

According to the 2007 IPCC report (Sims et al. 2007), recent North American studies generally confirm earlier work showing a small net change (increase or decrease, depending on methods, scenarios and location) in the net demand for energy in buildings but a significant increase in the demand for electricity for space cooling, with further increases caused by additional market penetration of air conditioning (high confidence) (Sailor and Muñoz 1997). Residential energy demand depends on economic, socioeconomic and meteorological factors. Usually, for a town or a region, the part of the residential energy demand explained by climate variations is obtained as an average of heating degree-days (hereinafter HDD) and of cooling degree-days (or CDD) for a given period (Heims et al. 2003).

Daily temperature is the key variable in controlling households conditioning (heating or cooling) needs, while other meteorological variables, related to the weather, play a lesser part (Quayle and Díaz 1979; Engle et al (1992)). This relationship can be explained in part by the dependence of these variables, such as humidity, wind or insolation, on the temperature. These issues were discussed in Valor et al. (2001), where the first estimation of the HDD and CDD indices for Spain was presented. For this estimation, observations at four meteorological stations, representing the climatological diversity of Spain, for the years 1983-1999 and weights obtained from an average of the population data through this period were used. In the selected years, there was a daily monitoring of households energy consumption by the Spanish Electricity Network (REE) for the needs of the Spanish Electric Market Operator (OMEL). Notwithstanding the limited temporal coverage, the HDD and CDD data from Valor et al (2001) present traits of interannual variability.

Both, the North Atlantic Oscillation (the main mode of climate variability in the region, hereinafter, NAO), and the El Niño-Southern Oscillation (the main interannual signal at a global scale, hereinafter, ENSO), are known to influence the anomalous variability of the Spanish temperatures. The NAO has been defined as a large scale meridional oscillation in the intensities of the subtropical high near the Azores and the subpolar low close to Iceland (van Loon and Rogers 1978). The NAO influence on the Iberian climate is more important in winter, and more visible on variables like precipitation or sea level pressure anomalies. However, for a number of relevant observatories in Spain, the winter NAO influence on monthly mean temperatures is barely significant (Castro-Díaz et al. 2002). The NAO influence on the daily mean temperatures (T_{mean}) is weaker than in the case that minimum and maximum temperatures (T_{max} and T_{min} , respectively) are considered separately (Trigo et al. 2002). The NAO has also an impact on the daily autumn and spring temperatures, although its effect, which is weaker than in winter, is less well studied (Hurrell and Deser, 2009). This influence is more controversial, regarding summer temperatures (Portis et al. 2001).

The influence of ENSO on the North Atlantic is first detected in late winter, following the peak of the ENSO signal (Kiladis and Díaz 1989; Fraedrich and Mueller 1992) and its effects on precipitation are delayed until spring and autumn, when the NAO signal is less noticeable (van Oldenborgh et al. 1999). Significant positive correlations between the SOI and precipitation anomalies are found in south-eastern Spain. In winter, the influence of La Niña on negative air temperature anomalies in southern Iberia is statistically significant. After an El Niño event, drier, warmer conditions are often observed in central and southern Spain, although this relationship is not statistically significant.

At this point, it seems useful to have projections for the HDD/CDD evolution in different parts of the world. Some of the available studies use only observations, such as Kadioglu et al. (2001) for

Turkey, or Jiang et al. (2009) for the Xingjiang province in Northwest China. Others, like Christenson et al. (2006) in his study of Switzerland, combine the analysis of a few observed HDD and CDD at some representative locations with the analysis of HDD and CDD derived from an ensemble of regional climate change simulations (that were 41 in that case, with boundary conditions taken from 8 global climate models with forcing according to the IPCC scenarios A1F and B2). Moreover, Semmler et al. (2010) investigate the influence of climate change on HDD and CDD for Ireland, using exclusively a small ensemble of simulations with Regional Climate Models (RCM), some of them driven by reanalysis data and some by a global climate model assuming three different greenhouse gas emission scenarios.

A common feature in all of the observational studies is the existence of decreasing trends in HDD and increasing trends in CDD. However, in the case of Turkey, there were also increasing trends at some stations, and at a significant number of them, the decreasing trend in CDD was not found to be statistically significant. In the case of Switzerland, the HDD trends estimated for the whole period of the observations (1901-2003) are between 11% to 18%, increased by a factor of four if the period is limited to 1983-2003. For the scenario simulations, the HDD trends range from 13% to 87%. When considering the increase between 50 and 170 % estimated for the CDD in the historical period, one has to keep in mind that the initial CDD values in Switzerland were almost negligible.

Of special relevance to the present study are the results of Giannakopoulos et al. (2009). Daily output data from six RCM for the Mediterranean domain, developed within the framework of the European Union ENSEMBLES project, were used to estimate changes in HDDs and CDDs. They compared the simulated degree-days obtained for the period 2021-2050 (30 years of scenario conditions) with those of the control simulation (1961-1990) and found negative changes in HDDs, specially for winter and spring, with differences from the HDD scenario to the HDD control of up to 200°C. Changes in CDDs specially affect northern Africa and central and southern Spain. The

relative changes in summer are ten times those found in autumn.

One of the purposes of the present study is to determine if the observed trends in the HDDs and CDDs in Spain and the dependence of the degree-days in the two relevant modes of interannual variability in this region, ENSO and NAO, are statistically significant. Additionally, we intend to estimate the future evolution of those trends, by comparing their values in the scenario simulations with those determined in the historical period, that are previously validated with the observations. Data and data treatment, together with the methodology used throughout this work are detailed in section 2. The results are presented and discussed in section 3, and we finish in section 4 with some concluding remarks.

2 Data.

We use a field of observed daily mean temperatures at 31 meteorological stations through Spain (whose basic statistics are represented in Figure 1a), to build the heating or cooling climate indices required for the HDD and CDD indices. Each of these stations contributes the estimated mean daily temperature of one of the counties in the Spanish census (provincias) where it is located. These stations provide daily temperature coverage with less than 5% of missing data for the period 1958-2005. The data have been quality controlled and homogenized according to the recommendations in Aguilar et al. (2004), and missing contiguous data in numbers exceeding four days have been estimated using both in situ (for the climatological monthly mean value) and regional information for the monthly interannual amplitude and the daily anomalies with respect to the monthly mean value (Schneider 2001). Estimation for the population of the Spanish counties with modern methods are available only after 1970. Additional census were performed for the years 1981, 1991 and 2001. Between these years intercensal estimations were performed by the Spanish National Institute for Statistics (INE) for the intervening period 1970-1981, 1981-1991 and for the historical data of the population in 1996. The basic statistics of the population data field are presented in Figure 1b.

The population at each station was estimated by averaging over all the population data at this location. The spatial coverage provided by the meteorological stations (represented in Figure 1a) is satisfactory in terms of the population represented, although some regions, in the western central and northern part of Spain are undersampled because few meteorological records there meet the quality requirements. However, an extended dataset that includes some additional stations (marked with empty circles in Figure 1) has been build for some complementary studies. This extended dataset includes the mean daily temperature records of 36 meteorological stations but only for the period 1972-2005. The population represented by the extended dataset amount roughly to a 80% of the total population of Spain. Due to the reduced temporal sampling, this dataset is used only for the estimation of the mean values of HDDs and CDDs, and not for the statistical tests of the interannual variability.

The interannual variability is monitored through the Southern Oscillation Index (SOI) and the North Atlantic Oscillation (NAO) Index. The Southern Oscillation Index was obtained as the normalized difference between monthly sea level pressure anomalies at Tahiti and those at Darwin (Ropelewski and Jones, 1987). These data are available at <http://www.cru.uea.ac.uk/cru/data> The NAO Index, defined as the normalized difference between monthly sea level pressure anomalies recorded at Southwest Iceland (Reykjavik) and those observed at Gibraltar (Jones, 1997), is available at the same address.

The future degree-days for Spain were estimated from a small ensemble of coupled simulations of the Mediterranean variability, for the periods 1950-2000 and 2001-2050, with the latter period using the scenario conditions A1B. These simulations were performed with four different high-resolution RCM and were developed for the European Union Research project 'Climate Research and Impact Factors: the Mediterranean Environment' (CIRCE, <http://www.circeproject.eu>). Hereinafter we will

refer to the simulations by the names of the institutions where they were performed: the Istituto Nazionale de Geofisica e Vulcanologia (INGV, Bologna), the Institut Pierre Simon Laplace (IPSL, Paris), the Max Planck Institut fuer Meteorology (MPIM, Hamburg) and MeteoFrance (Toulouse). Further details about the models and the simulations set up can be found in Dubois et al. (2011). Details of the simulations for the historical and the scenario periods can be found in Gualdi et al. (2012). Of relevance for the present study is a cold bias in the SST simulations of more than 2°C in the historical period. Furthermore changes in mean SST in the scenario simulation compared with the historical period go from +0.8°C to 1.8°C. A shift in the start of the transition seasons (delay in the spring and autumn start), characteristics of coupled models, is also present in the historical period of some of the CIRCE simulations.

3. Methods.

For a given station j and a given year i , we have the heating index H_{ij} ,

$$H_{ij} = \sum_k (T_c - T_{kij}) * S(T_c - T_{kij}) \quad (1)$$

where T_{kij} is the daily mean for the day k of year i at the meteorological station j , and T_c is a comfort temperature that corresponds to a null energy demand. Following Valor et al (2001), the comfort temperature is assumed here to be $T_c = 18$ °C. $S(s)$ is the step filter, with $S(s) = 1$ for $s > 0$, and $S(s) = 0$ for $s < 0$. The \sum_k adds the (positive) contributions of all the days of the months between the 1st of July of the year $(i-1)$ and 30th June of the year i . In the seasonal version of this index, \sum_k extends to all days of the corresponding season (e. g., winter (DJF), spring (MAM) ..) of year i .

In the same way, we can compute a cooling index

$$C_{ij} = \sum_k (T_{kij} - T_c) * S(T_{kij} - T_c) \quad (2)$$

but now the \sum_k adds to all days of the months of year i .

When discussing a particular station, these heating indices are also called degree-days.

To estimate the heating or cooling needs of a certain region, we define certain regional indices, the HDD or CDD degree-day indices, which are obtained by a weighted mean of the heating or cooling indices. The weights used take into account the fraction of the population w_{ij} that experiences the weather represented by this meteorological station.

$$w_{ij} = p_{ij}/P_t \quad (3)$$

where p_{ij} is the population of the county j in year i , and P_t is the total population considered. For each of the j years, $\sum_i w_{ij} = 1$.

In this way, the HDD index is given by

$$HDD_i = \sum_j H_{ij} w_{ij} \quad (4)$$

For the cooling degree-days we have

$$CDD_i = \sum_j C_{ij} w_{ij} \quad (5)$$

For the threshold temperature, a daily mean value of $T=18^\circ\text{C}$ was assumed in the case of the observations, as it corresponds to the minimum in the covariance matrix between domestic energy consumption (from the OMEL dataset) and the daily temperatures (Valor et al. 2001; Pardo et al. 2002). Let us remark at this point that the OMEL dataset is not longer available and further analysis are not possible. Although this threshold temperature is quite common in the literature, other studies

use different values. For instance, in the case of Athens, Giannakopoulos and Psiloglou (2006) find the minimum of the covariance matrix at $T=22^{\circ}\text{C}$, and this is therefore the comfort temperature used in their studies. From a practical point of view, the threshold temperature of 18°C was found to be optimal for the analysis of the simulations, because of the cold bias present in some them. Moreover, in the case of simulations, the population weights used in the observations are interpolated to the models grid points.

Other formulations of the degree-days, where the averages extend to time slices other than the year, were derived for convenience from the yearly original one. Among these are the seasonal or the monthly degree-days that are routinely provided by NCDC (<http://www.ncdc.noaa.gov/oa>). Seasonal degree-days are frequently used when projections for the future obtained from scenario simulations are used (Giannakopoulos, 2009). Furthermore, it has been found appropriate for our analysis to define nighttime and daytime HDD and CDD. The nighttime HDD and CDD use the minimum instead of the mean temperature and take as threshold temperature 16°C . This is the minimum comfort temperature for sleep found by physiological studies (Muzet et al., 1984). The daytime HDD and CDD use the maximum temperature instead of the mean temperature and assume as threshold temperature 20°C . This temperature is determined by the mean threshold temperature of 18°C , and by the mean nighttime threshold temperature of 16°C .

Two statistical tests are used throughout this study. At each station, a nonparametric Mann-Kendall test (hereinafter Test 1) proof the existence of a trend in the HDD (CDD) time series, at the 95% confidence level. A second test (Test 2) is used to establish the dependence of the HDD and the CDD defined from daily mean temperature (that we will call also HDDmean and CDDmean) on the NAO and ENSO state. The interannual variability is monitored through two climatic indices, the NAO Index and the SOI. Given one of these indices, months where the index value exceeds the values of one standard deviation are labeled as HIGH, while those with values below minus one

standard deviation are considered LOW. At each station, the detrended values of the degree-days anomalies corresponding to HIGH or to LOW index values are segregated into two samples. The significance of the median differences between the HIGH and LOW samples is assessed with a Wilcoxon nonparametric test (Gibbons and Chakraborti, 2011). The dependence of the daytime and nighttime version of the seasonal HDD (CDD) on the NAO and ENSO state, is assessed using the same methodology.

Additionally, trend coefficients for winter HDD and summer CDD are determined by conventional linear regression. The regression coefficients S are translated to percent using the y_i provided by the linear regression fitting $y_i = ai + b$, where i is the numeral of the year (from 1 to 48).

$$S_{10} = 100 * a(10-1)/y_i \quad (6)$$

We also use the linear regression theory to determine the confidence intervals Δa at the 95 % significance level (Pollard, 1977).

$$\Delta a = \frac{(t_{n-2} / \sqrt{(n-2)}) \sqrt{\sum_i (dd_i - y_i)^2}}{\sqrt{\left(\sum_i x_i^2 - (1/n) \left(\sum_i x_i \right)^2 \right)}} \quad (7)$$

where t_{n-2} is Student's t-distribution with $(n-2)$ degrees of freedom, dd_i is the value of the dd for the year i , y_i the value obtained by regression for the x_i observation and n the number of observations (in this case year/season) included in the analysis. The Δa are translated to percent with help of the same expression used in the case of the regression coefficient a .

Alternatively, projections for the changes on degree-days in the future are obtained following Gualdi et al. (2012). Mean values of HDD and CDD (dd_{ms}) for a 30 years base period in the

scenario simulations (2021-2050) are compared with the mean values (dd_{mh}) obtained from a 30 years base period in the historical simulation (1961-1990)

$$S_t = \frac{100(dd_{ms} - dd_{mh})}{dd_{mh}} \quad (8)$$

4. Results and discussion

The locations of the 31 selected meteorological stations are represented in Figure 1a, where the first label denotes the value of the mean temperature at each station and the second (in parentheses) denotes the standard deviation of the daily data with respect to this mean at the same location, in °C. Differences in the mean annual temperature between the northern and the southern coasts are of the order of 4°C. Higher differences are found between these southern stations and the inner Northern Plateau (Meseta Norte). The standard deviations at stations located near the Spanish coasts are typically below 6°C, while higher values are obtained in the Spanish southern interior.

The 31 selected census counties are represented by the location of their respective capital cities in Figure 1b. The first label indicates, as in the case of the temperatures, the value of the population mean (in millions) and the second (in parentheses) indicates the standard deviation value (also in million). Spain's two largest cities can be easily spotted in this figure: in the Central Plateau (Madrid) and in the Mediterranean Coast (Barcelona). Most of the counties with population mean exceeding 1 million are to be found along the coasts. The same is true for values of the standard deviation exceeding 0.1 million.

The results of the trend assessment with the Mann-Kendall test are depicted in Figure 2a, for the observed (yearly) HDDs, and in Figure 2b for the observed (yearly) CDDs. Decreasing trends at confidence levels over 90% are represented by down-tipped triangles and increasing trends by up-

tipped triangles. When the trend is significant at the 95% confidence level, the triangles are filled. Such is the case for the HDDs computed from observations at 22 out of the 31 Spanish stations used (Figure 2a). This result can be related to the decreasing trends found at 23 out of 31 CDD time series (Figure 2b). Stations where the trends are not found to be significant are located in the southwest. Although this result was suggested by the HDD evolution in Valor et al. (2001), this is the first time that its statistical significance could be tested, because the time series length here is 48 years rather than the 17 used in Valor et al. (2001).

The labels in the Figures 2a and 2b give the trend at each station (in percent/decade) estimated through linear regression. For the (yearly) HDDs the regression coefficients range from -2.3%/decade to -6%/decade. In the case of the (yearly) CDD, the coefficients vary from 6%/decade to 9.5%/decade in southern Spain and along the Mediterranean coast, while in the northern part of the peninsula they can exceed 20%/decade. These high percent values can be explained by the reduced CDD magnitude at these locations (less than 150°C).

The influence of the value selected for the threshold temperature on the above results was tested with some complementary analysis. Following Psiloglou et al.(2009), in the case of some stations at southerly locations, the threshold temperature used in the CDD determination is assumed to be 20°C, instead of the 18°C used for the other stations. The special stations were identified as those with mean minimum temperature in summer equal or above 18°C. Only at three out of the seven stations satisfying those requirements, the HDD (CDD) trend has been found significant by the Mann-Kendall test. The use of two different threshold temperatures, 20°C for the seven stations in the south and 18°C for all the other, do not change the results of the Mann-Kendall tests. Likewise, with those new threshold temperatures, the correction introduced in the trend of the index that represents the observed CDD evolution amount roughly to a 5% of its former value.

In Figure 3a we depict the observed winter (DJF) HDD index for all of Spain (that is the population weighted heating indices): each seasonal value is represented by a bar, and a regression line is superimposed. The corresponding summer (JJA) CDD index values (obtained in the same way as the HDD, but using cooling instead of heating indices) and the regression line fitted are shown in Figure 3b. The mean yearly HDD and CDD values obtained from the observed field agree well with those of Valor et al. (2001) when averaged over the overlapping period. The mean winter HDD and mean summer CDD for the period represented in figure 3 are 690°C and 300°C respectively. These values are also in good agreement with those obtained in a similar analysis performed on the extended dataset (daily mean temperature values at 36 stations from 1972 to 2005), which is described in section 2.

Both, Figure 3a and 3b, suggest the existence of an interannual variability that is present in both the HDD and CDD. According to the methodology described in section 2, we test the dependence of the HDD (CDD) variability on the two main climatic signals with influence in the region, the NAO and the ENSO. To establish these dependences, we consider at each location the heating (cooling) index used to calculate the HDD (CDD), built from the daily mean temperature as described in Section 2. The heating (cooling) index is segregated according to the season, and the trends of the seasonal time series are estimated using linear regression. Then we proceed to apply Test 2 on the detrended time series as described in the methodology section. Furthermore, at each location and for each season, a daytime (computed from the maximum temperature) and a nighttime (computed from minimum temperature) heating (cooling) index is determined. The methodology previously applied to the HDDmean (or CDDmean) is used on the detrended seasonal daytime and nighttime HDD (or CDD). In the case of the dependence on the NAO state, Figure 4 shows the results obtained for the seasonal HDD and Figure 5 for the seasonal CDD. In the case of HDD, the NAO seems to be the only significant influence, and only in the winter season the HDD corresponding to a HIGH NAO are higher than those corresponding to a LOW NAO (Figure 4a).

Figure 4b, that represents the dependence of the winter nighttime HDD on the NAO state, indicates that this dependence is basically conveyed by the effects of the NAO on nighttime temperatures. However the NAO influence on the CDDs is conveyed through its control of the autumn daytime temperatures, as evidenced from Figures 5a and 5b. The SO, in turns, influences only the nighttime CDD in spring, as appears from Figure 6a and its comparison with Figure 6b (nighttime CDDs). A negative SO (El Niño) implies drier conditions, but daytime temperatures are milder. However, the radiation effect prevails during the night, that is therefore cooler.

The Figure 7 presents the winter HDD indices for Spain estimated from the historical period of the INGV (Figure 7a), IPSL (Figure 7b), MPIM (Figure 7c), and METEOFRACTANCE (Figure 7d). In general, the observed HDD magnitude are not well captured in the simulations, due to the cooling bias that has been mentioned before. The straight line superimposed on the first period of all these plots represents the trends in the historical period, and that superimposed on the last period represents the trends in the scenario conditions. The trends and the confidence limits, computed according to the methodology, are specified in %/decade in the left column of Table 1 (in the case of the historical period) and in the right column of the same Table (in the case of the scenario simulations). In general the observations and the simulations in the historical period show a similar lack of statistical significance. Except for the case of METEOFRACTANCE (where they overlap), the trends estimated for the historical period are different of those estimated for the scenario period. For the HDD trends in the scenario period, trends are significant in three out of the four simulations.

The evolution of the simulated summer CDD indices is shown in Figure 8, with the same distribution as for the HDDs. The CDD values in the historical period (Figure 8) are relatively well captured in the INGV and MPIM simulations. The estimated trends derived from the regression

coefficients can be found in Table 2. Estimation for the historical period appear in the left column and for the scenario simulations in the right column of this table. In the case of the simulated historical period these trends agree in sign (positive), and roughly in absolute value with those of the observations (from 0.76%/decade to 9% /decade). The CDD trend obtained by averaging over the historical simulations is 6.83%/decade \pm 2.72%/decade. For the future conditions, the trends increase, and range from roughly 10%/decade to 27% /decade. The CDD trend obtained by averaging over the scenario simulations is 14.0%/decade \pm 5.3%/decade.

Alternatively, as in Giannakopoulos et al. (2009) or Gualdi et al. (2012), the projected changes can be estimated by the ratio of the mean CDD value of the scenario base period (2021-2050) to the mean CDD value of the historical base period (1961-1990). Results are detailed in Table 3. For the sake of comparison we have estimated the changes from the mid base scenario year period (2035) to the mid base historical period (1975) using the trends. In this way we obtain, with 2.5 decades in the historical period (2000-1975), and 3.5 decades in the scenario (2035-2000), and the corresponding mean trends, a new $S'_t = 65\%$. Likewise, from the confidence intervals of the trends, using the statistical theory, we obtain a confidence interval of 25% for S'_t .

5. Conclusions

Heating and cooling degree-day indices are accepted as good proxies of the part of the energy demand conditioned by meteorological variability. In the present study we estimate trends and interannual variability in the evolution of degree-days in Spain from observations at 31 stations for an extended period 1958-2005. HDD and a CDD indices characterize the evolution of degree-days for Spain. These indices are estimated by weighting the climate (heating or cooling) indices by the population ratios, usually assumed to be constant, and equal to their average value during the time interval considered.

For the HDDs and CDDs derived from observations, there is a trend that is found to be statistically significant at roughly 2/3 of the Spanish stations used in this work. The regression coefficients of the population averaged degree-day index point to a modest decrease (roughly -1.8%/decade) of winter HDDs and a significant increase (+5%/decade) of summer CDDs. These trends are similar to those obtained from observations in other parts of Europe. However, in the case of Spain they have been never estimated before. The trends seem to be quite insensitive to the election of a higher temperature threshold for the stations at southerly locations, as shown by some complementary analysis.

Another novel result of this study is the statistically significant influence of NAO conditions not only in winter nighttime HDDs but also in autumn daytime CDDs. Additionally, the spring conditions in LOW SO (after an El Niño event in the Pacific) are found to be significantly cooler (less CDD required) than those with HIGH SO.

It is commonly accepted that the mean seasonal cycle in coupled RCM simulations for the historical period presents important improvements compared with the seasonal cycle produced with forced RCM for the same period (Dell'Aquila et al. 2012). However coupled regional simulations for present day still show important bias specially in the transition seasons (Jacob et al. 2007). Therefore, when dealing with projections, the present study focuses on the extreme seasons: winter and summer. Values for the trends with the corresponding confidence interval are computed for each period of the simulations. Those of the historical period are validated against the degree-days indices obtained from the observations. The CIRCE simulations analyzed here do not capture well the winter HDD magnitude, a feature that can be explained by the cold bias common to all of them. In the case of the winter HDD evolution, there is agreement between the lack of the significance of the trends in the simulations analyzed here and the small value of the trend derived from observations. The summer CDD magnitudes are better captured, at least in the case of two of

the simulations. In general the CDD trends found in the historical period agree with the observed ones. The mean cumulative summer CDD change can be estimated from those trends, by adding the changes produced by the mean trend in the historical period, averaged over all the simulations, to those due to the mean trend in the scenario period computed similarly. The value found in this way, +65% with a confidence interval of $\pm 25\%$, is in quite good agreement with the cumulative summer CDD change of 50%, obtained from the changes in the base period CDD mean value (represented in Table 3). This sizable increase, however moderate compared with other CDD changes reported in the introduction, agrees also with the moderate temperature increase found in the CIRCE simulations (Gualdi et al., 2012).

In a world where energy demand is increasing rapidly due to the emerging countries, the prospects for increased energy demands in summer represent a considerable risk on his own. In fact, in a recent report of the British Department for Environment, Food and Rural Affairs, 'Climate Change Risk Assessment 2012' (<http://randd.defra.gov.uk>) the overheating of buildings and other infrastructure in the urban environment appears in the fourth place on a list of six risks that require urgent action. However the problem is more complex, the energy supply in summer being also affected by other risks associated to climate change. Among these are those related to water scarcity and snow reduction (less hydroelectric production in summer), or to water management (need to prevent more floods as a consequence of increased extreme precipitation events), or the reduced cooling potential of river and sea water, due to the increased temperatures, that could affect conventional and nuclear power generation (Greis et al. 2008). Moreover other risks associated to conventional electricity production, like pollution, are higher in summer. All these risks are important in the case of Spain. Their interaction should also be considered by improved Integrated Assessment studies.

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List of Figures

Fig. 1a. Meteorological stations whose data were used to compute the degree-days. The first label indicates the value of the mean of the temperature time series in °C. The second label (in parentheses) is the value of the standard deviation in the same units. Figure 1b. The location of the capital cities of the Spanish census counties selected for this study. The first label indicates the

mean value of the population time series in millions of inhabitants . The second label (in parentheses) is the value of the standard deviation in the same units. The stations marked with an empty circle were those added to the previous ones to build an extended dataset for the period 1972-2005, .

Fig. 2a. Results of the nonparametric (Mann-Kendall) test used for the trend detection in yearly heating degree-days (HDDs) for the period 1970-2005. Fig. 2b. Results of the trend detection in yearly cooling degree-days (CDD) for the period 1970-2005 with the same nonparametric test. Decreasing trends at confidence levels over 90% are represented by down-tipped triangles and increasing trends by up-tipped triangles. When the trend is significant at the 95% confidence level, the triangles are filled. A cross marks the location of a station where no significant trend was found.

Fig. 3a. Evolution of the winter heating degree-days for the period 1970-2005. Fig. 3b. Evolution of the summer cooling degree-days for the period 1970-2005. In both figures, the straight line represents the regression fit to the histograms.

Fig. 4 Results of the nonparametric (Wilcoxon) test that assess the NAO influence on the HDDmean (Figure 4a) and on the nighttime HDD (Figure 4b). The dependence of the seasonal HDD on the NAO state is represented with triangles. The down-tipped vertical triangle represents winter, and the other, clockwise, represent spring, summer (up-tipped) and autumn. Black triangles indicate significance at the 95% confidence level. Grey triangles (with an arrow) denote significance at the 90% confidence level.

Fig. 5. Results of the nonparametric (Wilcoxon) test that assess the NAO influence on the CDDmean (figure 5a) and on the daytime CDD. The dependence of the seasonal CDD on the NAO state is represented with triangles. Starting from the down-tipped vertical one (winter), the

clockwise results are for spring, summer (up-tipped) and autumn. Black triangles indicate statistical significance at the 95% confidence level. Grey triangles (with an arrow) indicate statistical significance only at the 90% confidence level.

Fig. 6 Assessment of the SO influence on the CDD mean (Figure 6a) and the nighttime CDD (Figure 6b) with the same nonparametric test. The dependence of the seasonal CDDs on the SO state is represented with triangles, with the same setting as in the previous figures.

Fig. 7 The histograms show the evolution of the simulated HDD for the INGV (Figure 7a), the IPSL (Figure 7b), the MPIM (Figure 7c) and the MeteoFrance (Figure 7d) simulations. The fitted regression lines for the first (historical) and second (scenario) period are superimposed. Units are °C.

Fig. 8. The histograms show the evolution of the simulated CDD for the INGV (Figure 8a), the IPSL (Figure 8b), the MPIM (Figure 8c) and the MeteoFrance (Figure 8d) simulations. The fitted regression lines for the first and second period are superimposed. Units are °C.

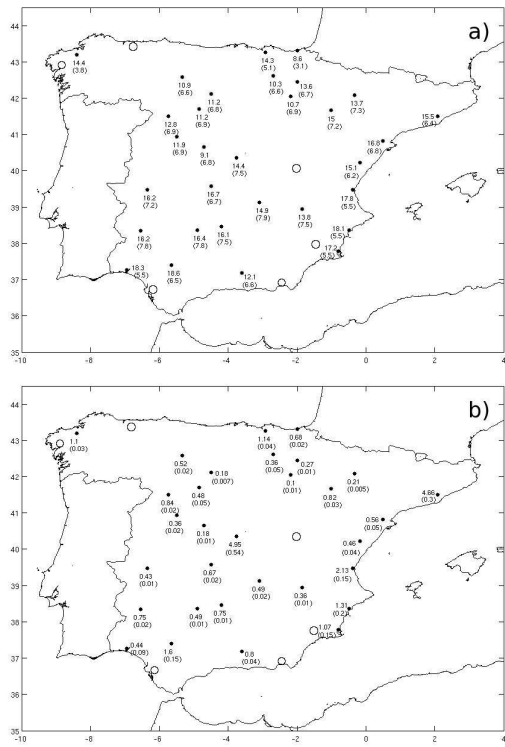


Fig. 1

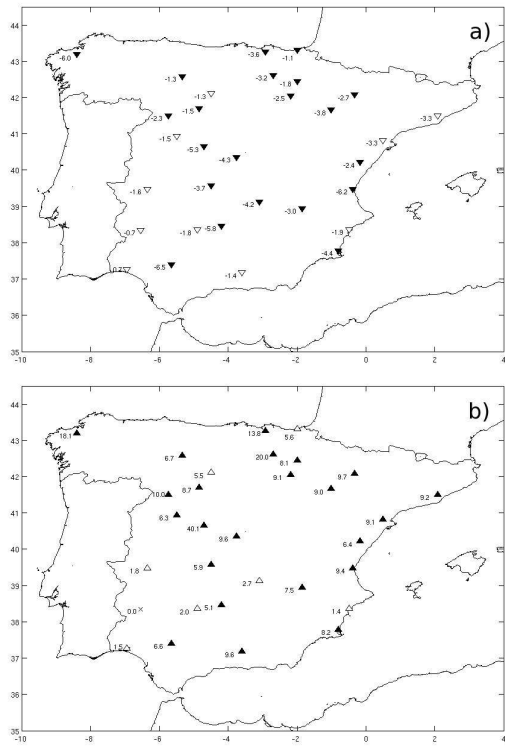


Fig. 2

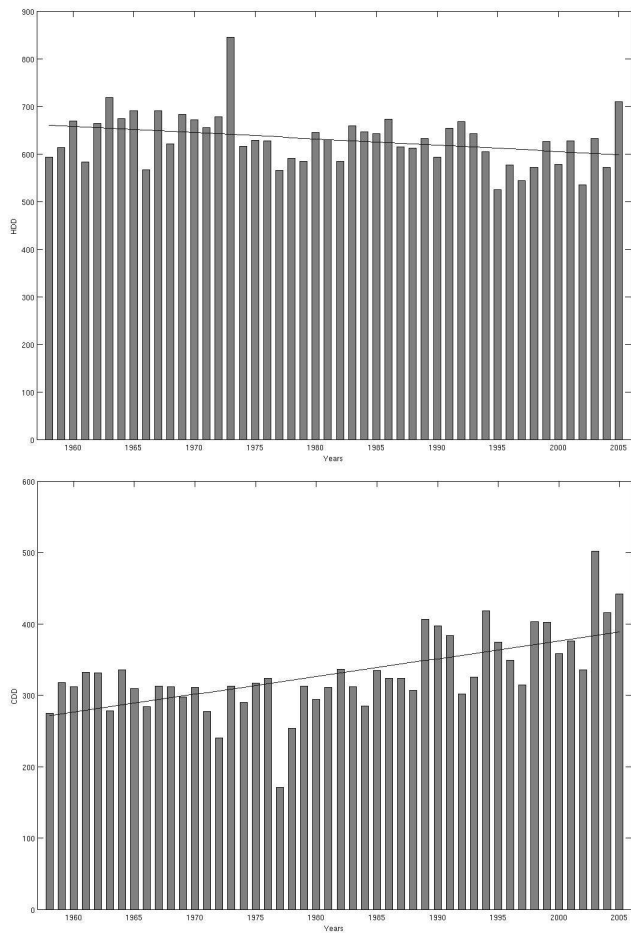


Fig. 3

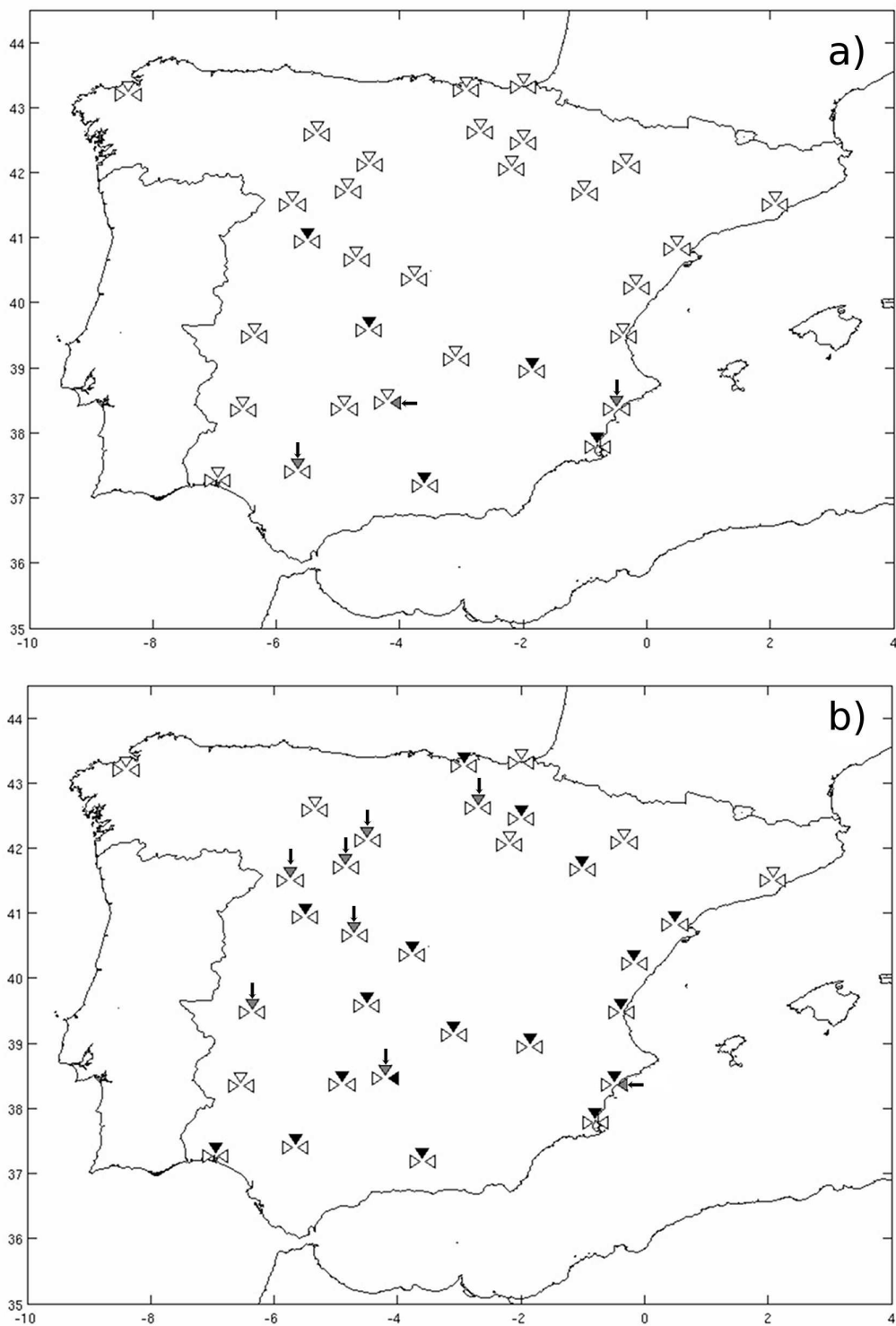


Fig. 4

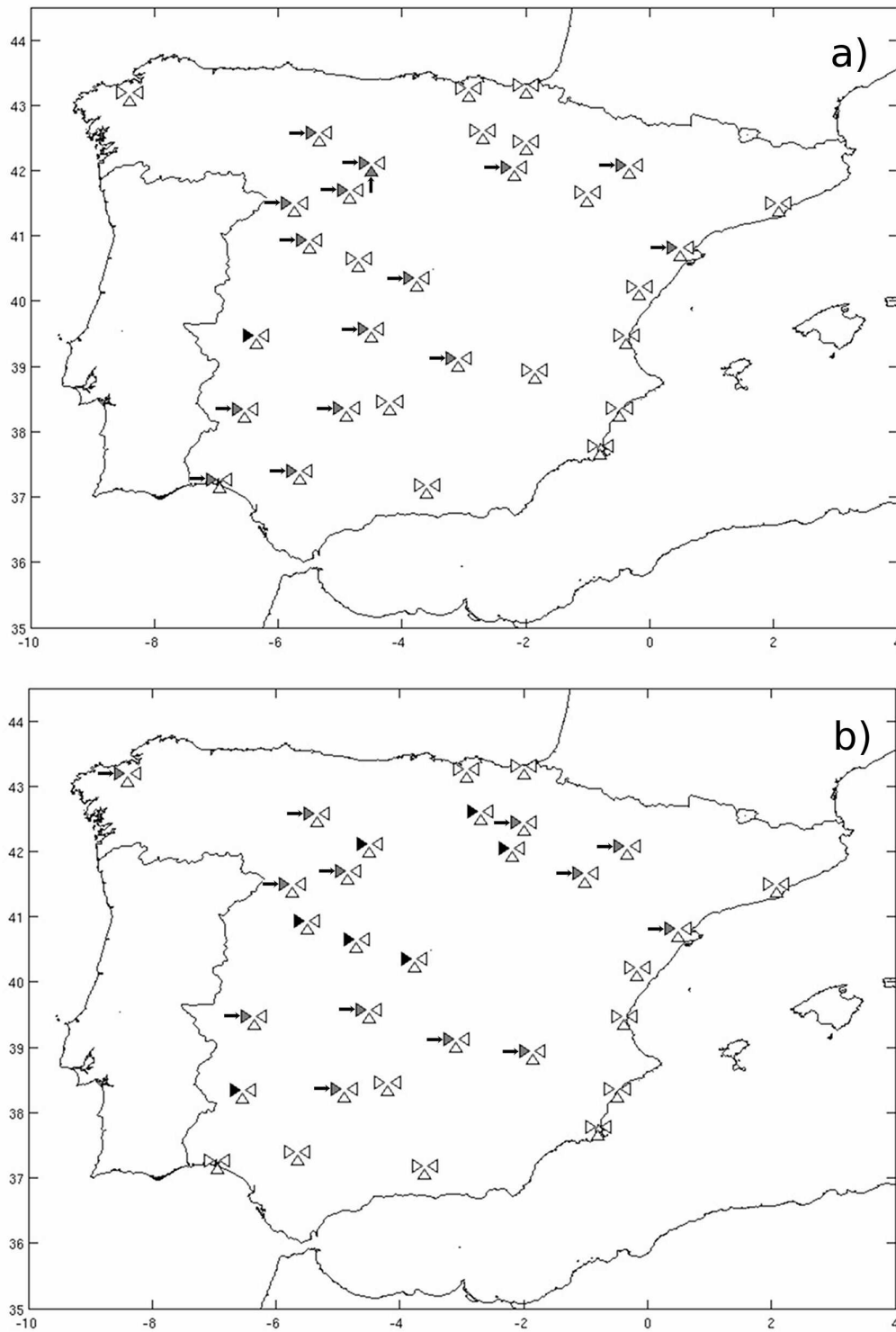


Fig. 5

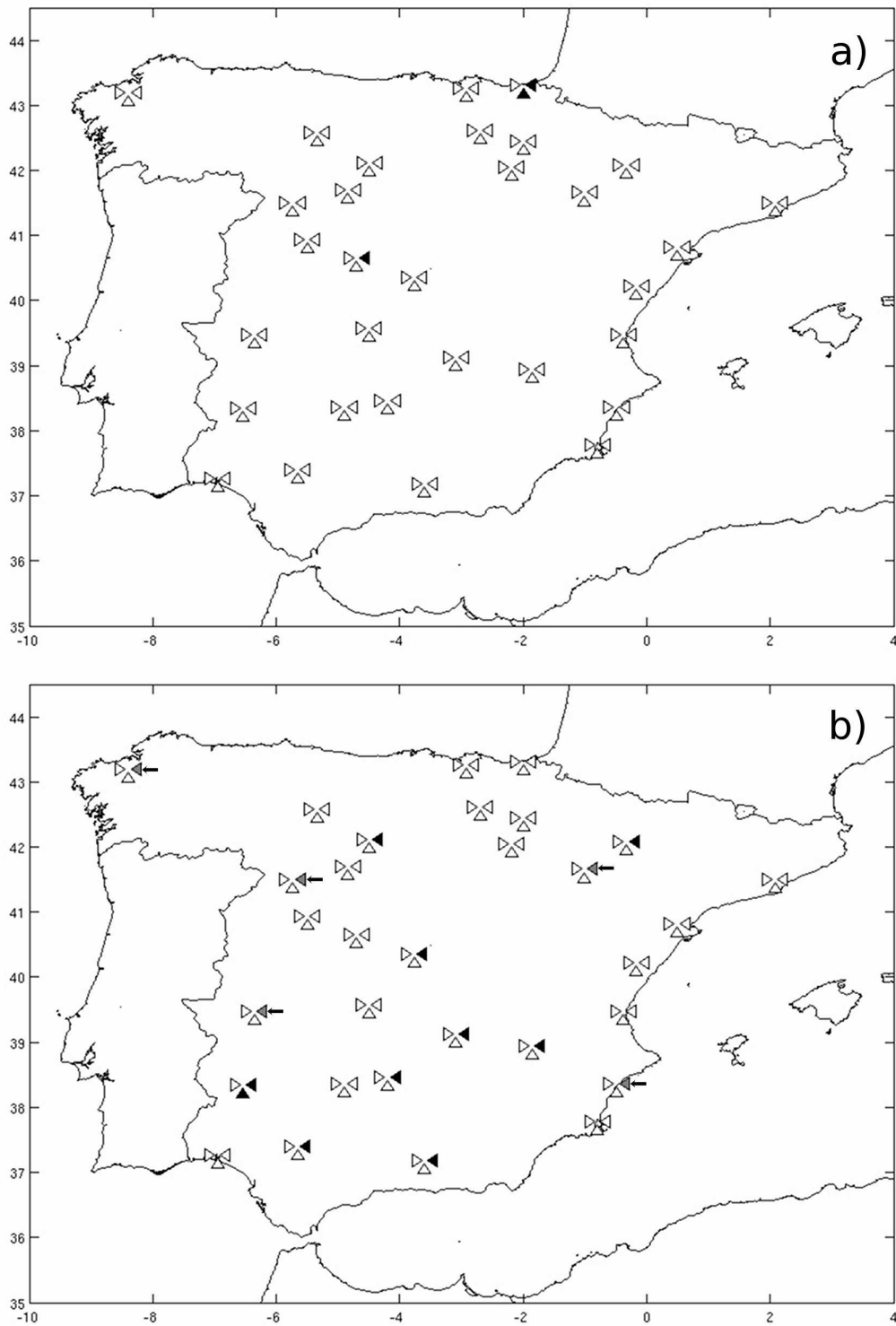


Fig. 6

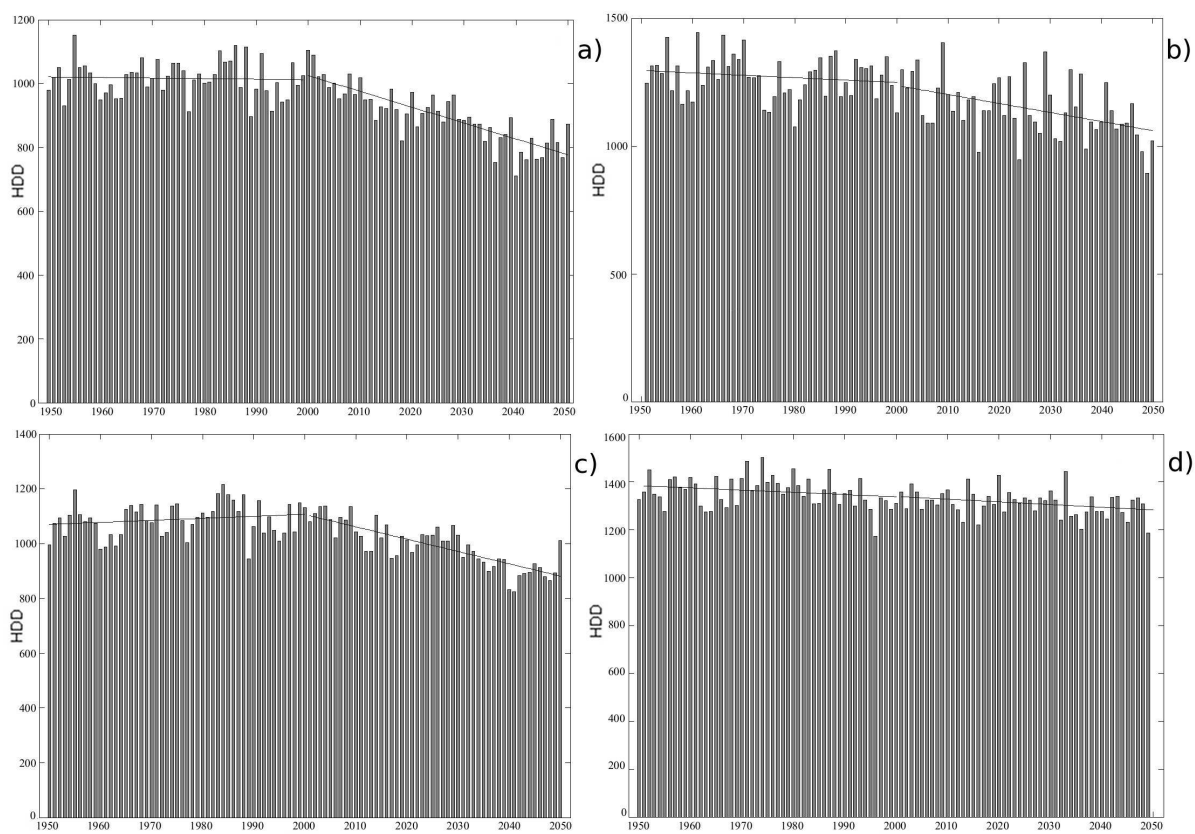


Fig. 7

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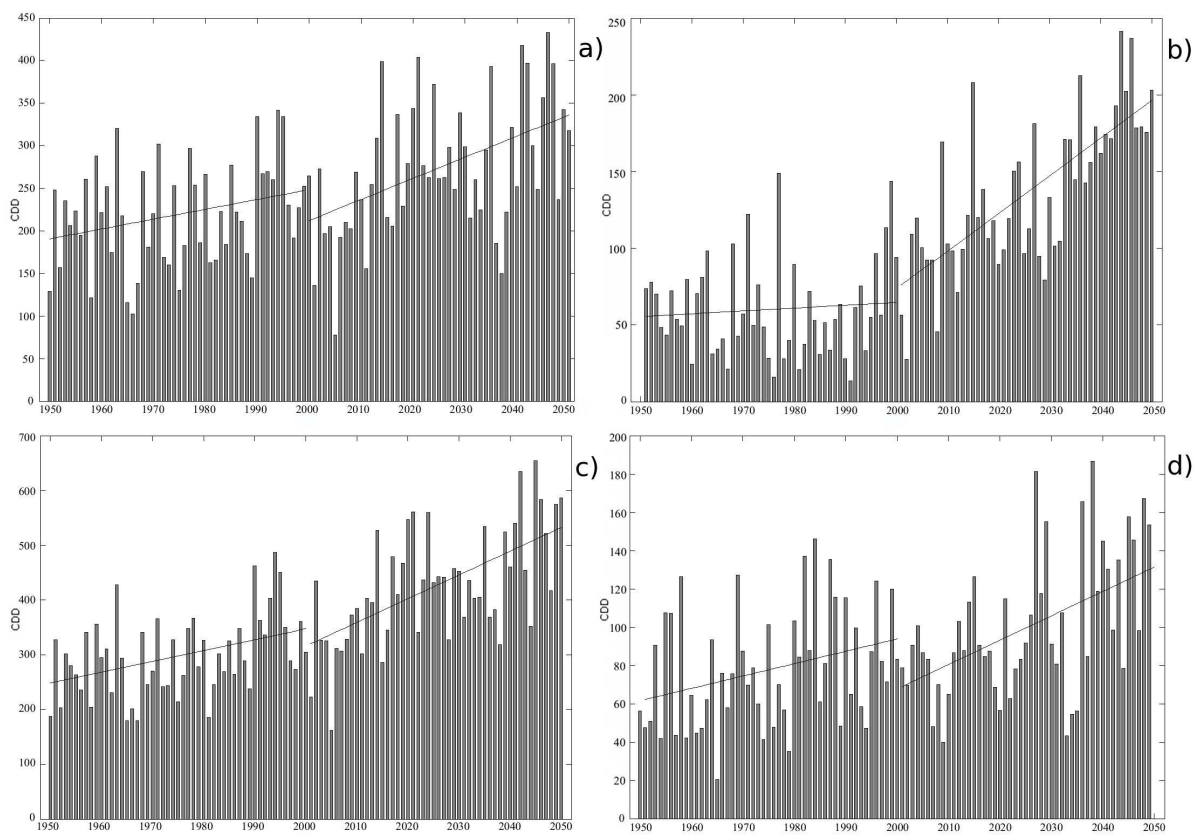


Fig. 8

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Table 1. Winter HDD trends in (% /decade)

Model	(1950 - 1989)	(2010 - 2049)
INGV	(-0.15 % ± 0.8 %)	(-4.57 % ± 0.7 %)
IPSL	(-0.94 % ± 0.9 %)	(-2.56 % ± 1.3 %)
MPIM	(0.55 % ± 0.8 %)	(-2.97 % ± 0.6 %)
METEOFRACTANCE	(-0.67 % ± 0.7 %)	(-0.65 % ± 0.6 %)
Observed	(-1.78 % ± 1.7 %)	

Table 2. Summer CDD trends in (% /decade)

Model	(1950 – 1989)	(2010-2049)
INGV	(5.49 % ± 3.2 %)	(10.61 % ± 4.9 %)
IPSL	(1.07 % ± 8.1 %)	(27.68 % ± 6.4 %)
MPIM	(7.25 % ± 7.2 %)	(12.07 % ± 4.0 %)
METEOFRACTANCE	(9.42 % ± 7.2 %)	(16.47 % ± 6.7 %)
Observed	(4.92 % ± 2.9 %)	

Table 3. Summer CDD: Changes in the scenario/historical base period

Model	
INGV	30 %
IPSL	156 %
MPIM	48 %
METEOFRACTANCE	32 %
Averaged value	50 %