UNIVERSITY OF COPENHAGEN
FACULTY OF SCIENCE

MSc in Climate Change

Regional overestimation of Spain's summer temperatures due to Regional Climate Models deficiencies

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Supervised by Jens Hesselbjerg Christensen

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"*In an interview with Yale Environment 360, Wulf explains what enabled Humboldt to arrive at conclusions that were astonishing for his time. "Most scientists who looked at climate then, looked at weather... But Humboldt very much sees climate as an interconnection of landmass, of altitude, of weather, of oceans. He puts all of this together.*"

Biographer Andrea Wulf about Geographer Alexander von Humboldt (1769-1859)

"*If I have seen further it is by standing on the shoulders of Giants*"

Isaac Newton, Letter to Robert Hooke, 1675

"*Climate change is a threat to global security that can only be dealt with by global cooperation. Through it, we may finally create a stable, healthy world where resources are equally shared and where we thrive in balance with the rest of the natural world*"

David Attenborough, UN climate security session, 2021

Preface

"*I want you to get scientific ideas of this project*", said Jens on our weekly online meeting. At that time, he was in Copenhagen, Denmark, while I was in Majorca, Spain, experiencing 35°C and thinking about all those potential empty beaches that I could go to.

I was always fascinated by climate and weather patterns since I was young. I started to look deep into all atmosphere-land-oceans features that could be the reason for all climate and weather types that we observe every day. Being surrounded by professionals from the Spanish Meteorological Institute to my mentors at the Autonomous University of Madrid and the University of Copenhagen, I find myself doing what I like the most: investigating and sharing how science takes place over a mini-continent called "The Iberian Peninsula". Indeed, we constantly face many difficulties and unexpected code issues during the thesis. Still, with motivation and persistent support from our mentors and friends, it is quite feasible to deal with it. It has been truly an honour to work about my own country and research the climate challenges it is currently facing and expected to do.

Please make yourself comfortable and let me share some scientific ideas I acquired from this master's thesis.

Acknowledgements

I would first like to thank my thesis supervisor Jens Hesselbjerg Christensen of Physics of Ice, Climate and Earth at the University of Copenhagen, whose expertise was invaluable. Thanks for introducing me to your climate research group of PICE and DMI and letting me participate in meetings among other climate experts, as well as for your guidance, knowledge and valuable discussions. I would also like to acknowledge Dominic Matte for his constant assistance from the very beginning, helping me learn how to code on python from scratch. He was always available at the PICE's office or remotely from Canada whenever I ran into a code issue.

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My sincere gratitude goes to my family and friends, for supporting me throughout this 2.5 years experience full of academic and personal lessons.

Abstract

Overestimation of Spain's summer temperatures due to regional climate models non-stationary biases.

The Iberian Peninsula has been experiencing new temperature records in the last few decades, making some parts of this region gradually less habitable, especially during summer. To simulate present-day climate conditions accurately and determine better estimates of extreme temperatures over the southwestern part of Europe, high-resolution regional climate models (RCMs) have been applied. However, it is unknown to which degree state-of-the-art RCMs may tend to overestimate regional amplification of global warming, especially during the warmest months (Christensen *et al.*, 2008; Boberg and Christensen, 2012). Studies have revealed that RCMs have systematic temperature dependence of biases increasing with temperature. The warmer the month is, the stronger this tendency becomes. The project aims to analyse potential non-stationary biases between climate simulations (EURO-CORDEX project) and observational datasets over the Iberian Peninsula (Herrera *et al.*, 2016). However, such an analysis has not been done with the current high-resolution RCMs or relying on a high-resolution observational dataset before. In addition, the analysis will also be extended to address monthly means of daily maximum and minimum temperatures, which has not been addressed before. A bias correction method will be then be proposed to mend some of the model deficiencies.

Keywords: Regional climate models, temperature biases, monthly mean temperatures, observational/reanalysis data, climate change, bias correction, regional warming.

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1 Introduction

The representation of present-day climate conditions by regional climate models (RCMs) remains imperfect. Despite the fact that there has been a remarkable process in climate modelling in the last decades, scientific uncertainty regarding the regional-local scale physical processes is still present (Stocker *et al.*, 2014).

By taking a multi-model ensemble approach, this dissertation provides an analysis of RCMs systematic behaviours and their effects on climate models simulations over Southwestern Europe, in line with previous studies (Christensen *et al.*, 2008; Boberg and Christensen, 2012). Concretely, uncertainties in ensembles of climate reanalysis simulations will be explored.

In particular, it has been demonstrated (Miralles *et al.*, 2014; Hirschi *et al.*, 2011; Santanello Jr *et al.*, 2007) that land-atmosphere processes can affect RCMs simulated temperature, especially in hot and dry climate-areas during the summer season. As a consequence, models tend to share systematic temperature dependence of biases increasing with temperature. However, it is unknown to which degree state-of-the-art RCMs may tend to overestimate regional amplification of global warming, especially during the warmest months (Christensen *et al.*, 2008; Boberg and Christensen, 2012).

This dissertation provides a regional analysis of systematic behaviours for seasonal-diurnal temperature, as well as an interpretation of regional to local climate change signals for Spain.

1.1 Research question

Several studies have revealed that RCMs share systematic temperature dependence of biases, especially during the summer season (Christensen *et al.*, 2008; Boberg and Christensen, 2012). In turn, this present dissertation provides a new analysis of the current high-resolution RCMs relying on a high-resolution observational dataset for the Spanish Iberian Peninsula and the Balearic Islands.

Furthermore, an unprecedented approach will be carried out addressing monthly means of daily maximum and minimum temperatures, looking into this region's warm and cold bias. The case of Spain is relevant to examine as the country is extremely affected by regional amplification of global warming (Stocker *et al.*, 2014), which appear to be overestimated by global and regional climate models (Boberg and Christensen, 2012)

Warm and dry summer conditions directly affect climate simulations' ability to match up with the observed climate. Extreme weather and climate events -heatwaves and droughts-, desertification, severe wildfires, and physical processes such as soil desiccation and atmospheric heat accumulation (Miralles *et al.*, 2014) could explain the underlying temperature-dependent biases of climate simulations, especially during warm seasons.

As the atmospheric and geographic characteristics over Southern Europe are considerably complex, global climate models (GCMs) inadequately account for many regional climate processes as listed before. However, much greater detail and more accurate representation of mean, maximum and minimum temperatures will be provided by regional climate downscaling over such a limited area.

The notion of using state-of-the-art RCMs driven by GCMs to represent better regional scales, as well as the evaluation of its temperature dependence of biases, will be explored to confirm their accuracy and fidelity compared to GCMs.

As such, the research question this dissertation aims at investigating is:

Do the most recent generation of high-resolution RCMs exhibit similar systematic biases behaviour as did older coarser-resolution models?

1.2 Main objectives

This project follows previous climate studies conducted over the Mediterranean by Christensen *et al.*, 2008 and Boberg and Christensen, 2012. The study aimed to confirm that summer temperature projections over this region were overestimated due to model deficiencies. Christensen *et al.*, 2008 and Buser *et al.*, 2009 corroborated the manifestation of systematic temperature-dependent biases on Regional Climate Models (RCMs) compared to observations.

As analysed (Diffenbaugh *et al.*, 2006; Miralles *et al.*, 2014) and stated by (Christensen and Boberg, 2012) particular physical processes between the atmosphere and land surfaces may constrain RCMs climate projections in large parts of Europe, in particular in scorching and dry regions.

For that reason, this project is motivated by the need for RCMs systematic behaviour evaluation over the Iberian Peninsula, characterised by extreme climate conditions. The objective of this present dissertation is to analyse potential non-stationary biases between state-of-the-art RCMs (EURO-CORDEX project) and high resolution observational gridded datasets (Herrera *et al.*, 2016) as a recent scientific approach in the climate modelling area. The analysis will also be extended to address monthly means of daily maximum and minimum temperatures, which has not been addressed before.

As such, we seek to contribute to the existing literature on **(1)** analysing the agreement between climate models and observations regarding temperature-dependent biases and **(2)** their temperature-bias dependency (slopes) given by grid points, therefore with enhanced geographical detail.

(1) It appears that significant limitations for representing not only temperature projections but also present-day climate conditions persist (Christensen *et al.*, 2008; Boberg and Christensen, 2012). Here we assess the uncertainties between current simulations compared to observations on a monthly and annual time scale. Furthermore, particular attention will be paid to overestimated temperature biases for warmer months compared to observations. The high-quality observational gridded dataset determines the analysis of the agreement between individual models and observations. Therefore, we also examine each model's reliability to represent current climate conditions and their implications for projecting future climate.

(2) Limitations in interpreting regional temperature present-day conditions may affect future climate projections accuracy. The slopes of the systematic temperature-dependent biases by grid points are analysed for all models on an annual timescale. Here we aim to investigate if their temperature dependency (slopes) could exacerbate global warming or, conversely, underestimate regional future temperatures for the study area.

1.3 Contributions

In the last decades, model temperature biases have been studied by different authors (Boberg and Christensen, 2012; Christensen *et al.*, 2008; Nahar *et al.*, 2017; Addor *et al.*, 2016), demonstrating its limitations on interpreting current climate conditions and climate change information (Matte *et al.*, 2019)

This study is motivated by analysing potential non-stationary biases between state-of-the-art RCMs and high-resolution observational gridded dataset as a brand new scientific approach in the climate modelling area. To advance in Christensen *et al.*, 2008 and Boberg and Christensen, 2012, we centre our attention onto two approaches:

(1) Monthly mean temperatures averaged for Spain, ranking simulated and observed daily mean (*Tmean*), maximum (*Tmax*) and minimum (*Tmin*) temperatures for 1989-2010.

(2) Monthly mean temperatures per grid points for model temperature biases for 1989-2010, and its annual and seasonal mean representation mapped per grid point with enhanced geographic detail. Concretely, **(2.1)** warm and cold biases are plotted for all models and variables per grid point over Spain. Besides, **(2.2)** temperature slopes are tested per grid point and confront with approach **(1)** showing a clear geographical of enhanced warming for most of the models and variables employed.

The fact that non-stationarity represents an additional source of uncertainty for climate models outputs is introduced and explained with a special focus over the Iberian Peninsula. Several studies have attempted to develop various bias adjustments to compensate for this mismatch (Madani *et al.*, 2020). Here, we introduce a bias correction method that could minimise the temperatures biases between simulations and observations in further investigations.

1.4 Thesis structure

The thesis is structured as follows: First, section 2 provides a background on the key topics related to current climate conditions and climate change signal over Spain with details on climate simulations and their systematic behaviours. Second, the observational dataset and the climate models used in this study are presented along the methods summarized in section 3. Section 4 analyses the EURO-CORDEX evaluation simulations performance against Spain02 observational dataset displaying their systematic behaviours and mapped temperature biases with its slopes and goodness of fit. Finally, section 5 presents the main conclusions and discussions grown from section 4. Lastly, section 6 offers an outlook of the study.

Background

2

2.1 Current climate conditions and climate change in Spain

Spain exhibits a large spatial climate variability (Herrera *et al.*, 2016). Concretely, it is particularly vulnerable to desertification (Miao *et al.*, 2003) and extreme weather events, especially heat waves (Díaz *et al.*, 2006).

The Iberian Peninsula (hereafter IP) and the Balearic Islands are located in the south-western margin of Europe, surrounded by the Atlantic Ocean (West), the Mediterranean Sea (East) and the African continent in the immediate south surroundings (Figure 2.2). This region, situated between 36ºN and 45ºN, embodies a distinct combination of land-atmosphere-ocean feedbacks that determines the well-extended Mediterranean climate (Appendix figure 8.1). This climate is interposed between the temperate maritime (northern Spain) and the arid subtropical desert climate (southeastern areas), showing hot, dry summers and mild, relatively wet winters.

Controlled by the Westerlies in winter and the Azores subtropical anticyclone in summer, the Mediterranean climate can be highly influenced by the configuration of seas and peninsulas, producing a significant regional and local variety weather and climate (Barry, Chorley, *et al.*, 2003). Changes in Jet Stream's variability and high-pressure summer atmospheric patterns are responsible for the significant difference between wet winters and dry summers (Bolle, 2012).

Droughts (Vicente-Serrano *et al.*, 2017), wildfires (Alcasena *et al.*, 2016), heat waves (Fischer and Schär, 2010), severe rainfall (Corada-Fernández *et al.*, 2017), floods (Llasat *et al.*, 2005), low-level inversions (Palarz *et al.*, 2020), and even snowstorms (e.g. "Storm Filomena", 2021) have been widely investigated in terms of severity, duration, intensity and frequency, proving the increase of 1.5ºC average annual temperatures vs pre-industrial times in the region (AA, 2020).

Extreme climate and weather events define this transitional and unique climate area (Strahler, 1980). For instance, in the centre of the IP, Madrid experienced daily mean maximum temperatures of 37ºC for three consecutive weeks in July of 2015 (ÁLVAREZ *et al.*, 2015). On top of that, those extreme temperature conditions were enhanced by the local large-sized urban heat island (UHI), making Spain's capital gradually less habitable, especially during summers night-time (Rasilla *et al.*, 2019).

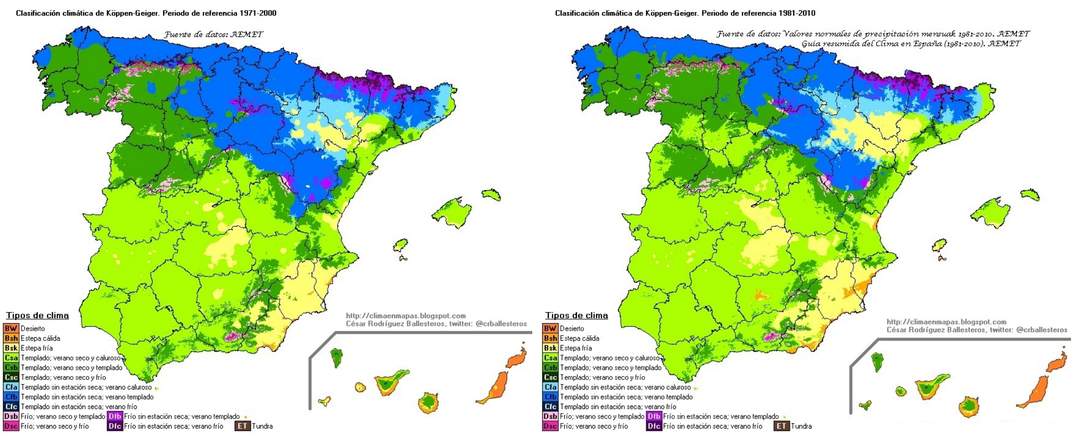


Figure 2.1: Climate conditions in Spain from 1971-2000 (a) to 1981-2010 (b) by using the Koeppen-Geiger System. The spread of light colours from one time scale to another represent a warmer and drier climate. Furthermore, some coastal regions climate is currently shifting from temperate to tropical conditions. (Reproduced from César Rodriguez Ballesteros (2016))

Spain exhibits a complex topography being the second European highest country after Switzerland. Vast plateaus and mountain ranges characterise the IP being less prominent in the Balearic Islands. Topography plays an important role in representing climate variables over Spain, where differences in temperature result from high temperature gradient, coastal and continental air-masses, and regional land-atmosphere feedbacks (Seneviratne *et al.*, 2006, Gobiet *et al.*, 2015, Vicente-Serrano *et al.*, 2017). According to Stocker *et al.*, 2014, there is high confidence that the climate system has been affected by human-induced global warming. The fact that the Mediterranean basin is already entering the 1.5ºC warming era is confirmed by the CORDEX ensemble (Zittis *et al.*, 2019).

Summers will likely warm more than winters. Many extreme weather events are likely to become more frequent and intense, especially heatwaves and high-temperature events (Lionello and Scarascia, 2018). Concretely, Spain is one of the European countries most exposed to extreme heatwaves, in which frequency, intensity and duration are assumed to worsen. Also, future climate projections under all RCP scenarios predict reduced rainfall in the coming decades for this specific region (Saadi *et al.*, 2015). Thus, the same trend is expected for precipitation and droughts events, plus enhanced warming leads to greater soil-temperature feedbacks, especially for those Mediterranean regions with complex topography (e.g. The Iberian Peninsula or Anatolia in Turkey)(Stocker *et al.*, 2014).

Figure 2.2: Satellite image of the southwestern part of Europe and surroundings by Landast 8)

2.2 Regional feedback mechanisms between topography and atmosphere

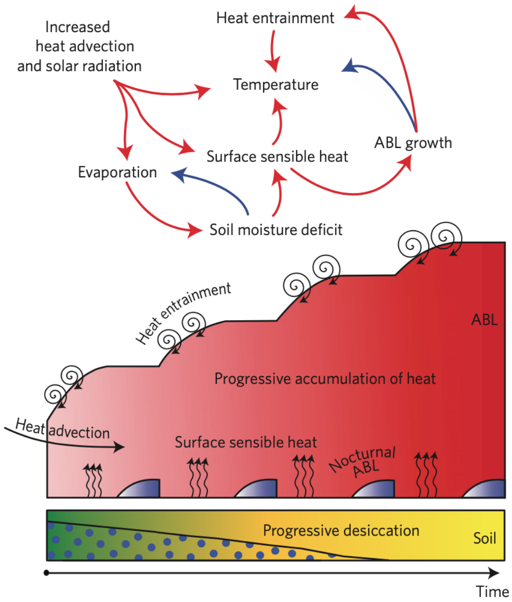


Figure 2.3: Regional physical mechanisms between land and the atmosphere boundary layer. (Reproduced from Miralles et al., 2014))

The stronger the influence of the Azores subtropical high-pressure, the drier the weather over the Iberian Peninsula. Thus, under prolonged atmospheric high-pressure patterns, land-surface is increasingly desiccated, and the depletion of soil moisture leads to a further escalation in air temperatures (Miralles *et al.*, 2014). In other words, successive reduction in evaporative cooling intensifies air temperatures. One of the least known variables in climate modelling is soil moisture (Pan *et al.*, 2001) and thus far. Entin *et al.*, 2000 presented how highly heterogeneous in space soil moisture could be attributed to variability in soil type, landscape and precipitation. According to Pan *et al.*, 2001, soil moisture heterogeneity over land complicates its parameterisation in numerical models. Their principal findings pointed out the need to improve predicting precipitation and representation of biophysical processes to simulate soil moisture correctly.

Recent climate modelling studies have postulated a connection between soil moisture deficit and drought on hot extremes (Hirschi *et al.*, 2011; Miralles *et al.*, 2014). Hirschi *et al.*, 2011 found a relationship between soil moisture deficit and hot summer extremes in southeastern Europe. Essentially, soil moisture controls partitioning between sensible and latent heat flux at the land surface, modifying the atmospheric boundary layer (ABL) dynamics. As stated by Seneviratne *et al.*, 2010, soil moisture temperature feedbacks can significantly impact land-surface climates and are key to trigger extreme hot temperatures and heat waves (Miralles *et al.*, 2014, Fischer *et al.*, 2007, Seneviratne *et al.*, 2006).

2.3 Climate model simulations and their uncertainties

Climate models have improved over time allowing for more details to be explored (Flato *et al.*, 2014). From observational initial conditions to small-scale physical processes, the realism of a model simulation can be severely affected. Climate models facilitate the physical understanding of the Earth climate system and climate changes over the past, current and future times. They aim to simulate the physics, chemistry and biology of the atmosphere, oceans and land in great detail. Even though the model performance of historical and future conditions has been constantly updated, the agreement among different ensembles of global climate models (GCMs) and regional climate models (RCMs) still differs.

Herrera *et al.*, 2016; Herrera *et al.*, 2019 confirm that the EURO-CORDEX RCMs are able to express the variability and the spatial pattern observed over the IP. Furthermore, a higher agreement can be seen between simulated and observed temperature than precipitation; furthermore, failing in reproducing extremes (Herrera *et al.*, 2019).

As documented by (Stott *et al.*, 2003; Matte *et al.*, 2019; Zittis *et al.*, 2019) it is worth noting the robustness that a large ensemble of climate models provide for climate change signals and, also, systematic behaviours for temperature projections (Boberg and Christensen, 2012). As carried out in Boberg and Christensen, 2012, coordinated experiments facilitate a better knowledge of climate models strengths and deficiencies. Despite the progress made, scientific uncertainty from small-scale physical processes persists (Flato *et al.*, 2014), limiting the interpretation of climate variables (e.g. temperature). To better represent regional and local scales and deepen our understanding of enhanced geographic detail, a coordinated experiment has been employed driven by the reanalysis GCM ECMWF-ERAINT.

The EURO-CORDEX RCMs ensemble adds higher spatial resolution than coarser models, apart from new physical processes and biochemical cycles. Therefore, RCMs play a significant role by giving climate simulations and projections with much greater detail and a more precise representation of localised extreme events.

2.4 Regional climate models

Regional climate models (RCMs) downscale climate fields over a limited domain produced by coarse resolution global climate models (GCMs). Also, RCMs are forced at the lateral domain boundaries by values from GCMs (Maraun and Widmann, 2018). To simulate present-day climate conditions at high resolution, regional models can also be forced with boundary conditions from reanalysis data. For this study, the European Centre Medium-Range Weather Forecasts (ECMWF) reanalysis provide the possibility for comparing and analysing against observed temperatures. To better simulate the Mediterranean climate (Somot *et al.*, 2018), coupled ocean-atmosphere RCMs have been used. In particular, state-of-the-art EURO-CORDEX RCMs have a horizontal resolution of about 12 to 25 km. Even though most GCMs still share a coarse resolution, this study's reanalysis model looks at $\sim$12.5km over the European domain (EUR-11).

As noted by Flato *et al.*, 2014, regional and local climate over regions with complex topography, such as mountain ranges or coastal areas, are not well represented. Furthermore, RCMs may add considerable value when looking at the grid-scale for regional processes such as land-atmosphere feedbacks, thermodynamical and microphysical processes. PRUDENCE (Christensen *et al.*, 2007), ENSEMBLES and EURO-CORDEX projects have applied RCMs to downscale GCMs simulations for Europe. Christensen *et al.*, 2018 confirmed stronger robustness of state-of-the-art climate change information for Europe along with the development of the projects (from PRUDENCE to CORDEX-11).

2.5 Non-linear behaviour

Model imperfections or biases can be noticed by comparing climate model simulations against real-world observations (Methods 3.3). A vast literature source (Matte *et al.*, 2019; Boberg and Christensen, 2012; Jacob *et al.*, 2014; Cardoso *et al.*, 2019) has proved that model imperfections can be evaluated by assessing the credibility of simulated future trends (Maraun and Widmann, 2018).

Some research studies on climate change impact assessment assume that the bias between simulated and observed climate is constant or stationary across the series (Karlsson *et al.*, 2016; Minville *et al.*, 2010; Teutschbein and Seibert, 2012). However, several authors (Christensen *et al.*, 2008; Buser *et al.*, 2009; Boberg and Christensen, 2012) have suggested that biases may be state-dependent, in other words, time-variant in a changing climate. Maraun, 2012 state that temperatures and general properties of the air masses are likely to influence biases. Although, under regional warming conditions, the air masses' properties and temperatures are likely to fluctuate. Future biases will depend on the actual values and, in particular, on the state of the climate system (Maraun and Widmann, 2018). Furthermore, future biases associated with extreme temperature values will differ from those in the current climate.

Currently, the sixth phase of CMIP (The Coupled Model Intercomparison Project) is underway, and it will be released along with the IPCC's Sixth Assessment Report (AR6) in 2021. Stouffer *et al.*, 2017 has contributed to the climate science research community by identifying and extensively filling some scientific gaps from previous CMIP phases. Particularly by facilitating the identification and interpretation of systematic model biases. These remain to date as significant climate modelling challenges.

3 Data and Methods

3.1 Data processing

3.1.1 Spain02 Observational gridded dataset

The updated version of the Spain02 observational gridded dataset is the primary source of data for this study. It was built from a dense network of over 250 temperature stations from the Spanish Meteorological Institute (AEMET) and is based on 3000 precipitation stations (Herrera *et al.*, 2016).

The first procedure was to compare this high-resolution observational dataset with state-of-the-art regional climate models from the EURO-CORDEX project (table 3.2). Such proceeding could be performed since the Spain02 observational dataset is built on the same standard grids as the EURO-CORDEX and ENSEMBLES projects. Concretely, it is defined on the same 0.11º, 0.22º and 0.44º resolution grids, conducting the study on the fine 12.5 km grid. As is stated by Herrera *et al.*, 2016, the spatial distribution of the station density and the temporal evolution of the average number of stations per grid-box is relatively homogeneous and steady, respectively.

Dataset	Variables	Institution	Covered period	Frequency	Resolution
Spain02_v5	*Tmean, Tmax, Tmin*	CSIC - University of Cantabria (Herrera *et al.*, 2016)	1950-2015*	Monthly, daily*	0.11º(∼12.5km)

Table 3.1: Details of the observational gridded dataset. (*) The covered period is constrained to 22 years (1989-2010), adjusted to the simulated series.(*) In this study, the temperature variables analysed are: monthly mean daily mean temperature, monthly mean daily maximum temperature, and monthly mean daily minimum temperature.

3.1.2 EURO-CORDEX Regional Climate Models

This study selected from the framework EURO-CORDEX initiative an ensemble of 9 RCM simulations forced by the driving global climate model ECMWF-ERAINT. Precisely, a European-wide reanalysis of high-resolution regional climate simulations on a 0.11º

(~12.5km) over the European domain (EUR-11) combining models with observations covering both the Iberian Peninsula and the Balearic Islands. A total of 264 grid-cell monthly mean temperature biases for 1989-2010 were computed using reanalysis simulations and compared against the Spanish observational dataset Spain02. The EURO-CORDEX project's performance was considered to evaluate the model quality in present-day climate simulations and compare monthly-to-monthly consistency among the datasets at hand. Thus, to simulate present climate at high-resolution, RCMs driven by reanalysis data were used.

The availability of the nine RCMs constrains the time period covering this study. Therefore, it was decided to adopt 22 years as a standard reference for all models and observations. Concretely, temperature reanalysis data was extracted from the Earth System Grid Federation (ESGF archive, https://esgf-data.dkrz.de/search/cordex-dkrz/) for the EUR-11 domain of the CORDEX experiment. Details of the RCMs used are displayed in Table 3.2.

Model ID	Regional Climate Model	Acronym	Institution	Timeseries
RCM1	MOHC-HadREM3-GA7-05	MOHC	Met Office Hadley Centre	1982-2012
RCM2	DMI-HIRHAM5	DMI	Danish Meteorological Institute	1989-2011
RCM3	KNMI-RACMO22E	KNMI	Royal Netherlands Meteorological Institute	1979-2012
RCM4	CNRM-ALADIN63	CNRM	Centre National de Recherches Météorologiques	1979-2018
RCM5	GERICS-REMO2015	GERICS	Climate Service Center Germany	1979-2012
RCM6	ICTP-RegCM4-6	ICTP	International Centre for Theoretical Physics	1980-2016
RCM7	CLMcom-ETH-COSMO-crCLIM	ETH	Climate Limited-area Modelling Community Zurich	1979-2010
RCM8	SMHI-RCA4	SMHI	Swedish Meteorological and Hydrological Institute	1980-2010
RCM9	RMIB-UGent-ALARO-0	RMIB	Royal Meteorological Institute of Belgium and Ghent University	1980-2010

Table 3.2: ERA-Interim-Driven EURO-CORDEX (EUR-11) Regional Climate Models considered.

Climate reanalysis combines models and observations (Bengtsson *et al.*, 2007). It gives a numerical description of the recent climate containing air temperature estimates, wind, soil-moisture content, rainfall and pressure. Table 3.2 shows each RCMs time-series length where they span from around 29 years, roughly. However, as mentioned before, to include all 9 RCMs ensemble (e.g. RCM2 and RCM8), the period was shortened to 22 years from 1989 to 2010. A 29-year series with just 8 RCMs were examined to test any systematic temperature bias variability. It turned out that the non-linear biases showed insignificant changes.

3.2 Linear regressions

Simple linear regressions were applied for all RCMs ensemble. This statistical method allowed us to study the relationships between two continuous variables, concretely, observed and simulated monthly data (Mudelsee, 2019).

Christensen *et al.*, 2008 used a polynomial fit while Boberg and Christensen, 2012 applied a linear regression to the 50 percent warmest months for their analysis. Here, we are analyzing the full bias temperature dependence slightly different by using a linear regression to all data points.

Therefore, simple linear regressions were conducted in two different ways to all monthly means. On the one hand, subtraction of observed and simulated spatial averaged points and their bests fits were performed (figure 4.1). On the other hand, subtraction of observed and simulated grid-cells monthly data was fitted using linear functions. In other words, an adjustment was made with a regression line to simplify and facilitate the understanding of the monthly mean temperatures (points, Figure 4.4). The $\hat{Y}_i$ is defined us:

$$\hat{Y}_i = \hat{\beta}_0 + \hat{\beta}_1 X_i \tag{3.1}$$

$$\hat{\epsilon}_i = \hat{Y}_i - Y_i \tag{3.2}$$

where $\hat{\beta}_0$ is the constant associated with a structural bias and $\hat{\beta}_1$ is the slope of the climate model. X_i represents the independent value (observations), and $\hat{\epsilon}_i$ constitutes the error between the $\hat{Y}_i$ and the climate model value. Moreover, a goodness of fit was carried out to see if the simple linear regression is statistically significant and representative (Methods 3.4)

3.3 Temperature biases

Observed and simulated regional climate constitute two multivariate probability distributions with temporal, spatial, marginal and multi-variable aspects (Maraun and Widmann, 2018). According to the World Meteorological Organization (WMO), a bias is the correspondence between a mean forecast and mean observation averaged over a certain domain and time. The $Bias_\theta(t)$ is defined as:

$$Bias_\theta(t) = \theta_m(t) - \theta_o(t) \tag{3.3}$$

Therefore, if the simulated ($\theta_m(t)$) and real-world ($\theta_o(t)$) distributions differ, the model is biased (Maraun and Widmann, 2018). Linear and non-linear monthly data behaviours are detected when summer and winter data is divided. Non-linear patterns appear when summer and winter temperature biases show notable disagreement (figures 4.7 and 4.9). However, if biases remain with no significant changes between seasons, the behaviour would be linear. Therefore, no tendency is observed (Background 2.5)

As such, biases in RCMs simulations can be reduced by performing a bias-adjustment function that adjusts the model evaluation data to a set of observational data (Methods 3.5).

3.4 Goodness-of-fit and R-squared

Linear regression analysis is a statistical analysis that may have some error depending on the data distribution. Therefore, a study of its goodness of fit was required to verify that the results are statistically significant. R-squared was used among other methods since it provides sufficient information about the goodness of fit of linear regressions (Valbuena *et al.*, 2019).

An R-squared method is a straightforward approach in which values perform between 0 and 1. If the R-squared value is close to 0, it indicates that the model explains none of the response data's variability around its mean. On the contrary, if R-squared is close to 1, then the model explains all the response data's variability around its mean. The higher is the R-squared, the better the linear regression slope fits. In particular, all models' temperature bias slope tend to show the "goodness" of fit around 0.9 to 1. In this study, the value 0.80 was considered as an arbitrary threshold from which the regression line fit is not statistically significant, where residuals increase considerably.

3.5 Other methods

3.5.1 Bilinear interpolation

Bilinear interpolation was carried out for both the input data and the target grid. This re-sampling method uses the nearest pixel values' distance-weighted average to estimate a new pixel value. Concretely, we used bilinear interpolation of the RCMs output to the observations grid. This method ensured that the model outputs were interpolated over the same grid as the observational dataset for all time-steps originally in the EURO-CORDEX project. Only grid points covering the Spanish mainland and the Balearic Islands were considered for the results, including reanalysis and observational data.

3.5.2 Standard deviation

The standard deviation is a useful measure of spread for normal distributions. Seasonal standard deviation (SD) is presented for all 9 RMCs in Table 4.1. for *Tmean*, *Tmax* and *Tmin* and for its cold and warm seasons. The SD calculates the distance between monthly data and their means (equation 3.4). In this case, it tells the dispersion of monthly temperatures distribution for each temperature variable.

$$s = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(x_i - \bar{x})^2} \tag{3.4}$$

Thus, a high standard deviation indicates that monthly mean values are far from their mean (linear fits). On the contrary, if monthly data are gathered around their linear fits, the SD remains low.

3.5.3 Bias adjustment: Quantile mapping

A bias-adjustment function was carried out to adjust the current climate evaluation data to a set of observational data to minimise temperature biases. Precisely, the development of bias-correction or bias-adjustment techniques has been quite significant (e.g. Piani *et al.*, 2010; Dosio *et al.*, 2012; Gobiet *et al.*, 2015) to post-process climate model simulations to match the observed climate. The cumulative distribution function (CDF) from the RCMs is mapped onto the observations' distribution (Figure 4.11), thus showing the agreement from both climate data. It has been demonstrated (Gobiet *et al.*, 2015, Boberg and Christensen, 2012) that the value-dependent correction function would not vary for climate change projections.

4 Results

This study is motivated by analysing potential non-stationary biases between state-of-the-art RCMs and high-resolution observational gridded dataset Spain02. To advance in Boberg and Christensen, 2012 and Christensen *et al.*, 2008 research, we centre our results section onto two approaches:

(4.1) Monthly mean temperatures averaged for Spain, ranking simulated and observed daily mean (*Tmean*), maximum (*Tmax*) and minimum (*Tmin*) temperatures for 1989-2010. Model temperature biases can be seen between the model's best fits (slopes; Methods 3.2) and their distance with respect to the diagonal $T_m = T_o$. As presented throughout this section and discussed in the following, limitations are found using this approach for interpreting and analysing systematic temperature-dependent biases in this complex and extreme Mediterranean region.

(4.2) Monthly mean temperatures per grid points for model temperature biases for 1989-2010, and its annual and seasonal mean representation mapped per grid point with enhanced geographic detail. Concretely, **(2.1)** warm and cold biases are plotted for all models and variables per grid point over Spain. Besides, **(4.3, 4.4, 4.5)** temperature slopes are tested per grid point and confront with approach **(4.1)** showing a clear geographical of enhanced warming for most of the models and variables employed. It is worth mentioning that this approach demonstrates great representation and accuracy of non-stationarity patterns over each sub-region of Spain. Furthermore, the overestimation of regional amplification of global warming is captured by the majority of the multi-model ensemble in most of Spain's sub-regions.

Procedures 4.1 and 4.2 take an ensemble approach providing a more robust interpretation of all temperatures variables considered in this dissertation.

4.1 Ranked simulated and observed temperatures

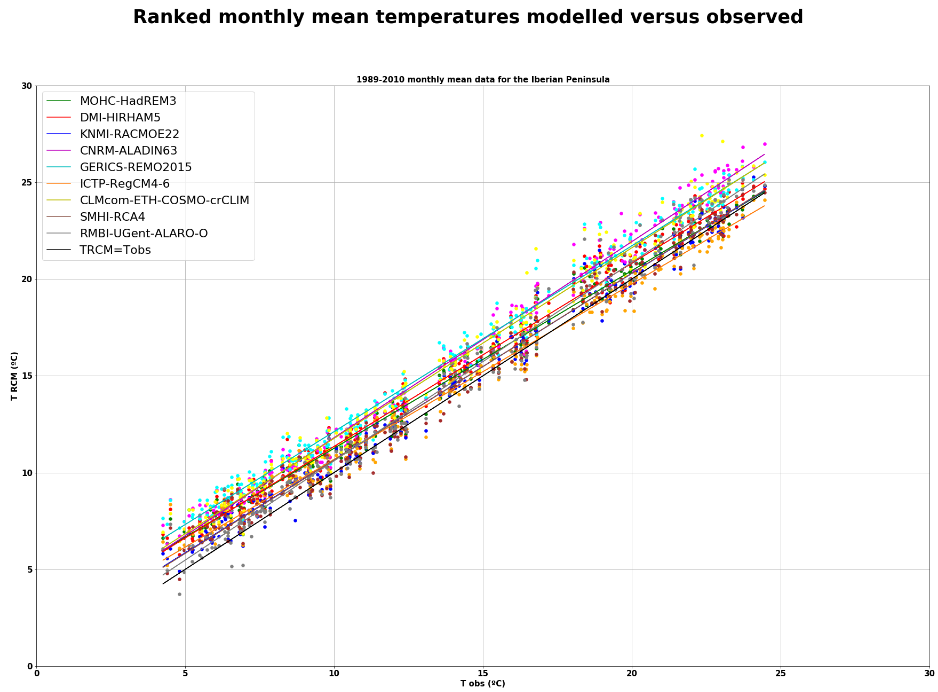


Figure 4.1: Ranked monthly mean temperatures modelled versus observed for Spain covering the period 1989-2010. Points represent monthly EURO-CORDEX RCMs values with respect to the Spain02 observational dataset and lines are best fits based on these points.

Figure 4.1 ranks all monthly mean daily mean temperatures area-averaged for Spain for 1989-2010. From 4ºC to 24ºC, dots represent the monthly means using Spain02 for 9 EURO-CORDEX RCM simulations and lines the best fits for those points with respect to the diagonal $T_m = T_o$. Points and their simple linear regressions are being represented in ascending order.

This figure facilitates the comparison between the simulated present-day conditions and observed climate for Spain. Using area-averaged monthly data, all models tend to exacerbate current mean temperature at both the lowest and highest temperatures of the series compared to observations. However, different upward behaviours are found. Boberg and Christensen, 2012 confirm that both GCMs and RCMs share the same deficiencies in overestimating warming (64 GCM from CMIP3 and 13 RCM forced by ERA-40).

The different behaviours of this sorted data are used for all temperature variables (*Tmean, Tmax, Tmin*) and classified as follows:

(A). Overall overshooting of temperatures. The ensemble of 9 RCMs tends to exacerbate warming for the whole area-averaged values with respect to the diagonal. Figure 4.1 clearly shows the majority of monthly mean data placed on the warm side in reference to the diagonal as well as their own best fits. However, some individual models register different patterns throughout the ascending representation of ranked mean data.

(B). Overestimation of the lowest mean temperatures. Daily mean temperatures corresponding to the winter season are well-affected by a high temperature-dependent bias from all 9 RCMs. Therefore, simulated temperatures generally overshoot the winter values with respect to the observed data.

(C). Warmer months with greater temperature biases. Area-averaged monthly mean summer temperature manifests a particular warm bias using two RCMs: models 4 (CNRM) and 9 (RMIB) (table 4.2 shows the slope's values of the 9 RCMs). Based on their linear fits, summer temperature biases get warmer increasing with temperature. Furthermore, suppose we were to extrapolate these values to a warmer end. In that case, we could expect models 4 and 9 to exacerbate future regional temperature warming since their slopes values are higher than 1°C (table 4.2).

(D). Overshooting is reduced in the warmer months. Models slopes 1 (MOHC), 3 (KNMI), and (8) SMHI tend to be closer to the diagonal, increasing with temperatures. The warmer are the temperatures, the more agreement lies between simulated and observed data, reducing the overshoot during the warmest months.

(E). Underestimation of warmer months. As an exception, model 6 (ICTP) shows a different temperature behaviour. Summer monthly data appears to be underestimated in comparison with the observed data. In particular, this model's behaviour insinuates a potential underestimation of warming if monthly mean temperatures were extrapolated to a warmer end. As such, model 6 is the only individual simulation that suffers from non-stationarity underestimating the warmer months, showing a significant downsloping.

Ranked monthly maximum temperatures modelled versus observed

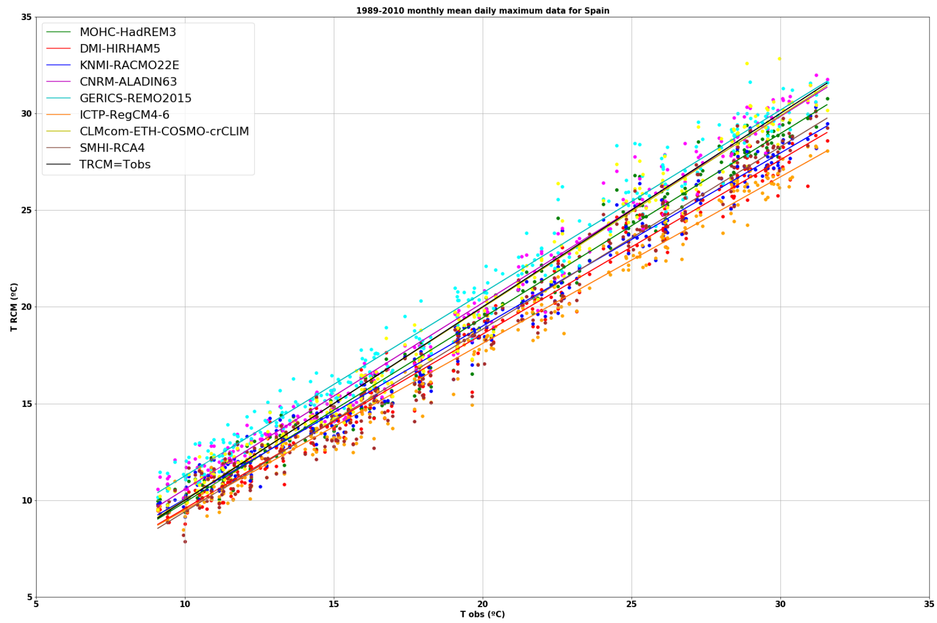


Figure 4.2: Ranked monthly mean daily maximum temperatures modelled versus observed for Spain covering the period 1989-2010. Points represent monthly EURO-CORDEX RCMs values with respect to the Spain02 observational dataset and lines are best fits based on these points.

Figure 4.2 ranks all monthly mean daily maximum temperatures area-averaged for Spain for 1989-2010. From 8ºC to 32ºC, dots represent the monthly means using Spain02 for 9 EURO-CORDEX RCM simulations and lines the best fits for those points with respect to the diagonal $T_m = T_o$.

Maximum simulated and observed temperatures manifest a new tendency to increase with temperatures. The higher the observed maximum temperature, the more underestimated is the simulated temperature **(E)**. Collectively, the ensemble of RCMs shows a more significant agreement for the lowest maximum temperatures (winters) with respect to the highest values (summers). Models 4 (CNRM), 5 (GERICS), and 7 (CLM-ETH) share the same tendency of ranked temperatures increasing their variability for warmer monthly mean maximum temperatures **(D)**. Warmer months show agreement with respect to the observed climate. Furthermore, summer extreme temperatures and positive anomalies might cause the widespread of the monthly data. However, models 1 (MOHC), 2 (DMI), 3 (KNMI), 6 (ICTP), and 8 (SMHI) will likely underestimate the amplification of regional warming using this spatial-area averaged approach for maximum temperatures over the Iberian Peninsula and the Balearic Islands.

Here we also calculate the values of the linear fits (slopes) with respect to the diagonal $T_m = T_o$. Unanimously, RCMs slopes mean values remain below 1, reaffirming the potential underestimation of projected summer maximum temperatures (table 4.3).

Ranked monthly minimum temperatures modelled versus observed

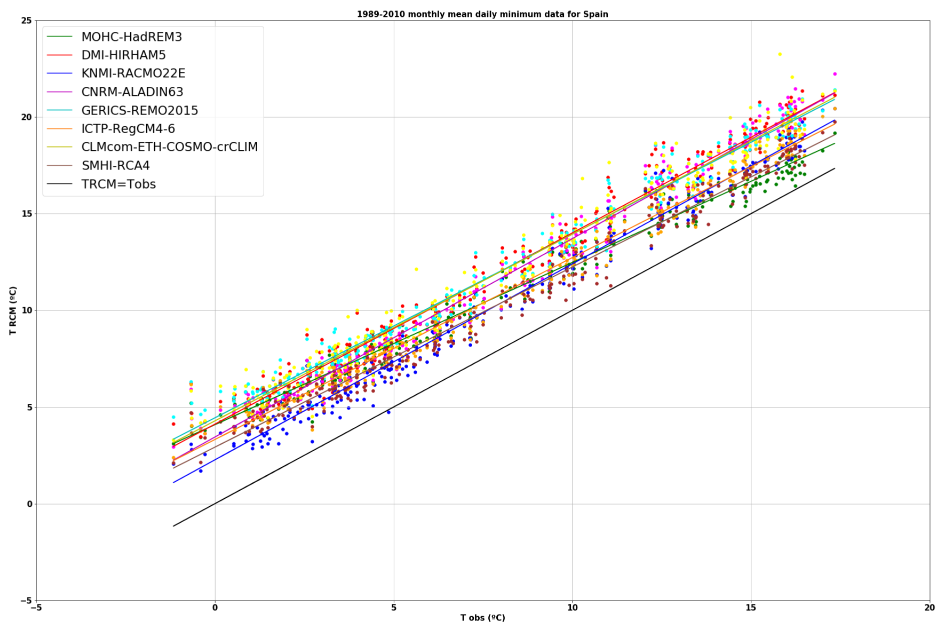


Figure 4.3: Ranked monthly mean daily minimum temperatures modelled versus observed for Spain covering the period 1989-2010. Points represent monthly EURO-CORDEX RCMs values with respect to the Spain02 observational dataset and lines are best fits based on these points.

Figure 4.3 ranks all monthly mean daily minimum temperatures area-averaged for Spain for 1989-2010. From -2ºC to 17ºC, dots represent the monthly means using Spain02 for 9 EURO-CORDEX RCM simulations and lines the best fits for those points with respect to the diagonal $T_m = T_o$. Points and their simple linear regressions are being represented in ascending order. For this night-time temperature variable, the ensemble of 8 RCMs highly exacerbates warming for the whole area-averaged values with respect to the diagonal. Figure 4.3 clearly shows all monthly mean data placed on the warm side in reference to the diagonal as well as their own best fits. However, one individual model registers different patterns throughout the ascending representation of ranked mean data. Concretely, model 1 (MOHC) temperatures tend to be closer to the diagonal, increasing with temperatures **(D)**. Nevertheless, this representation of ranked minimum temperatures reveals a high level of uncertainties from both simulated and observed climate.

4.2 Models temperature biases characteristics

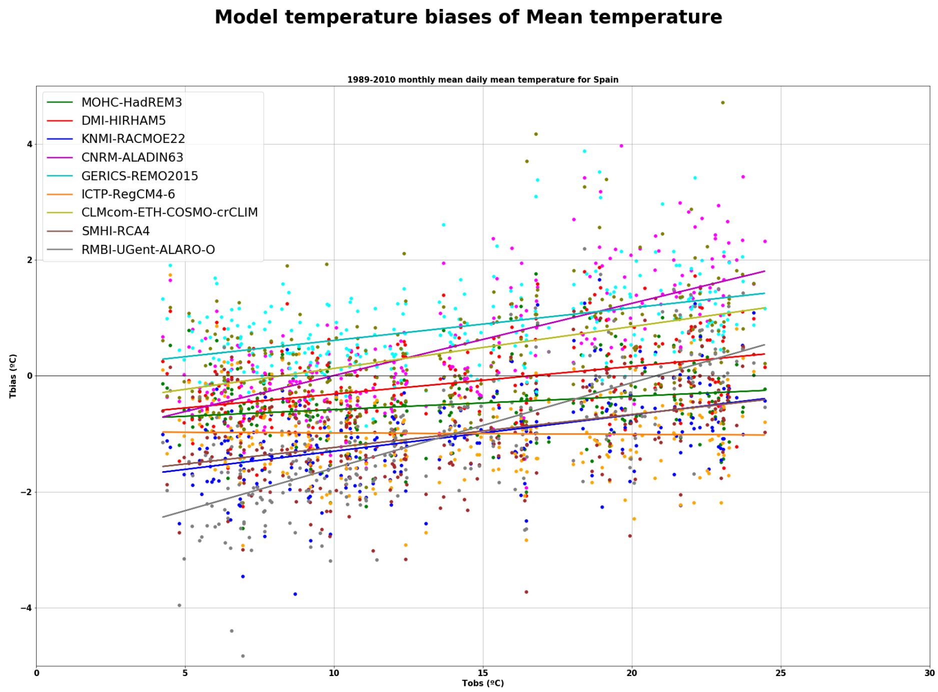


Figure 4.4: Monthly mean model temperature biases versus observed monthly mean temperature for Spain covering the period of 1989-2010. Points manifest monthly EURO-CORDEX RCMs values and lines their simple linear regressions.

The 9 EURO-CORDEX models show different magnitude biases in simulating present-day climate conditions over the Iberian Peninsula and the Balearic Islands. What is primarily remarkable is that 8 out of 9 models exhibit a more significant bias for warmer periods. The warmer the bias is, the stronger the tendency is.

In the GERICS (5), KNMI (3), and CLM-ETH model (7), the coldest months' bias has a stable behaviour, while as temperatures rise, the bias tends to increase. Boberg and Christensen, 2012 research also found this specific pattern, where they operated with KNMI RACMO RCM. This pattern should be kept in mind if climate change projections are interpreted. Not as pronounced as those mentioned above, models 1 (MOHC), 2 (DMI), and 8 (SMHI) also detect a warmer temperature-dependent bias for warmer months. Another noteworthy interpretation can be highlighted from the graph: the colder the month is, the stronger the tendency is. This is the case for two models that manifest a stronger tendency to increase and decrease with temperature. Both models 4 (CNRM) and 9 (RMIB) follow this hypothesis; the higher the temperature bias, the coldest the month is, in absolute terms. Figure 5.1 plots cold and extraordinarily cold monthly mean temperature biases for the winter season using these two francophone climate models.

On the contrary, model 6 (ICTP) does not suffer from this systematic behaviour. In other words, the well-spread non-stationary bias for all simulations appears not to influence the ICTP model. In short, this finding suggests that not all the state-of-the-art regional models show a systematic temperature-dependent bias increasing with warmer or colder temperatures. However, the underestimation of temperature remains unaltered for the entire series, displayed by regions over Spain for the summer, winter and annual season (Figure 5.1). The agreement among the model's systematic behaviour is unquestionable. Nevertheless, it is important to stress that monthly mean points manifest a clear concentration and spread concerning their best fits. For a more profound analysis, a standard deviation is carried out in the next section (table 4.1).

Model temperature biases of Maximum temperature

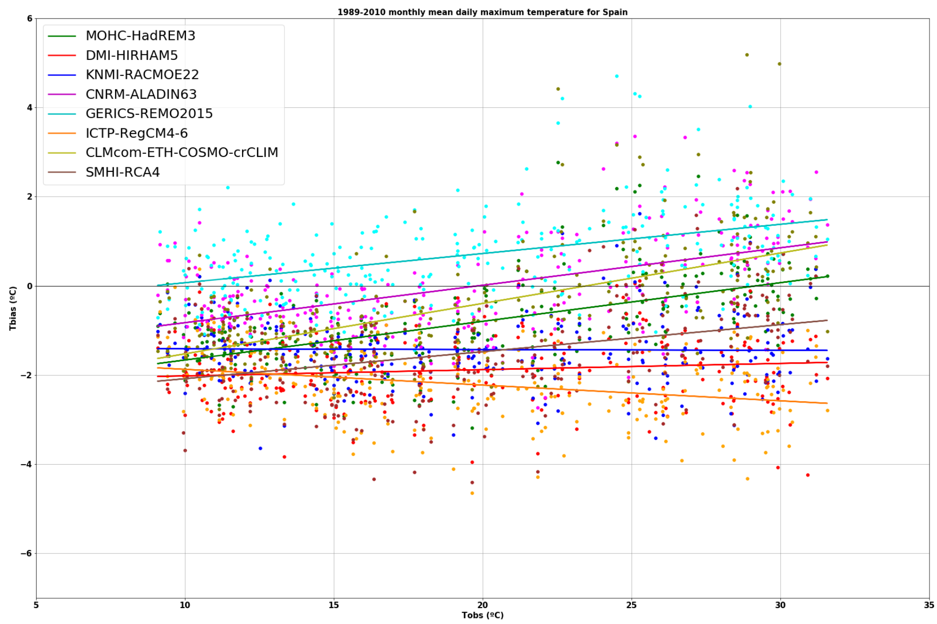


Figure 4.5: Monthly maximum mean model temperature biases versus observed monthly maximum mean temperature for Spain covering the period of 1989-2010. Points manifest monthly EURO-CORDEX RCMs values and lines simple linear regressions.

Figure 4.5 shows monthly mean daily maximum temperature biases for 1989-2010, spatially averaged over land for Spain with the bias along the y-axis and the observed temperature along the x-axis. As mentioned before, this approach has never been applied for daily mean maximum and minimum temperatures.

Overall, in simulating maximum temperatures, it can be noticed that models tend to overestimate warm summers (GERICS (5); CNRM (4); CLM-ETH (7); MOHC (1)), respectively. For these simulations, the coldest months' bias has a stable behaviour, while as temperatures rise, the bias tends to increase. Generally, showing a similar systematic bias as the ones used for mean temperatures. Regarding models 3 (KNMI) and 2 (DMI), no systematic temperature-dependence has been found, and if any, it is not significant. As an exception, model 6 (ICTP) exhibits a shift of systematic behaviour, decreasing temperature biases during the warmest months. This model points out a new negative systematic pattern rare but greatly accentuated over the south of Spain for the summer season (Figure 6.2, model ICTP).

Concerning the type of bias, most of the monthly mean data tend to be located below the 0ºC x-axis, clearly underestimating the simulated maximum temperature compared to observations. However, models (5,4,7,1) show a clear positive bias increasing with temperature, in the same line as Boberg and Christensen, 2012 results for mean temperature and for *Tmean* of this study. By representing averaged grid point monthly data, it can be displayed the exact bias that remains between both temperatures. In this case, biases extend from -5ºC to 5ºC, therefore showing a big range for maximum temperature among different EURO-CORDEX RCMs.

For monthly mean daily maximum temperature biases, systematic behaviours remain for more than half of the models. However, in general the non-linear pattern it is attenuated, especially if we were to compare with the previous temperature variable (Figure 4.4).

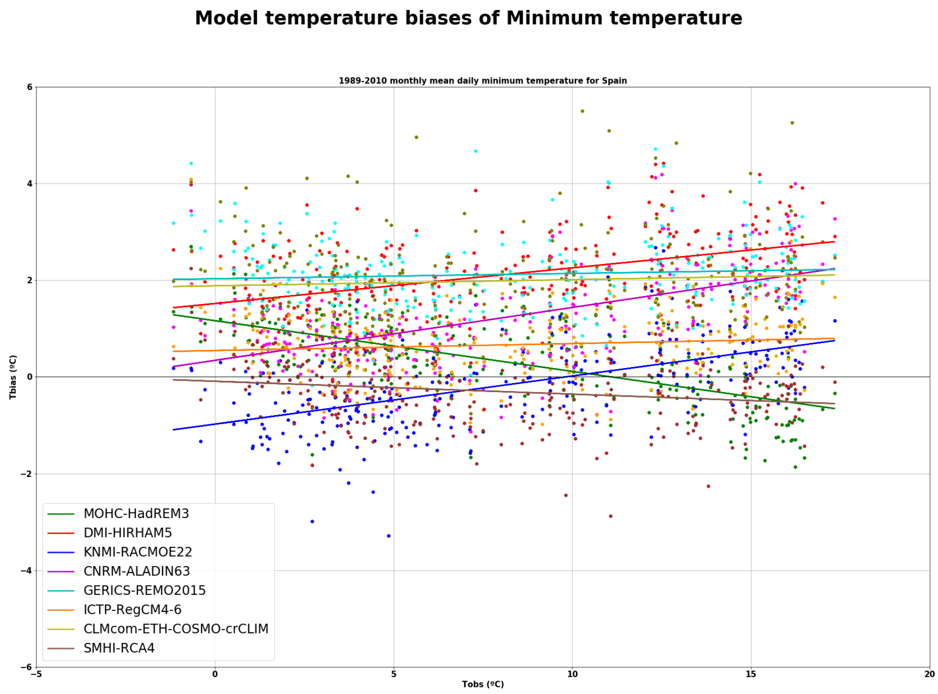


Figure 4.6: Monthly minimum mean model temperature biases versus observed monthly minimum mean temperature for Spain covering the period of 1989-2010. Points manifest monthly EURO-CORDEX RCMs values and lines simple linear regressions.

Figure 4.6 shows monthly mean daily minimum temperature biases for 1989-2010, spatially averaged over land for Spain with the bias along the y-axis and the observed temperature along the x-axis. Overall, as a difference with the mean and maximum graphs, minimum temperature biases evidence higher intrinsic heterogeneity among simulations.

Winter minimum temperatures (from -2ºC to 7ºC) and summer minimum temperatures (13ºC - 18ºC) show substantial positive biases increasing with temperature for some models (e.g. DMI (2); CNRM (4); and 3 (KNMI)). These simulations clearly manifest an increase of temperature biases for summer minimum temperatures. Furthermore, it could be expected an exacerbation of warming for future projections under these models. However, no remarkable variability during colder months is showed. The majority of the models suffer from high biases (0ºC to 5ºC), being less notorious the presence of monthly data underestimated by simulations. However, Models 1 (MOHC) and 8 (SMHI) manifest a shift of the general non-linear behaviour, decreasing temperature biases during the warmest months. Also, non-linear or time-variant biases not always influence the realism of the models. RCMs 5 (GERICS), 6 (ICTP) and 7 (CLM-ETH) slightly suffer from the well-spread systematic behaviour

(Figure 4.6). Nevertheless, results support the argument that models undoubtedly overshoot minimum temperatures for all seasons, with some exceptions (MOHC (1) and KNMI (3)).

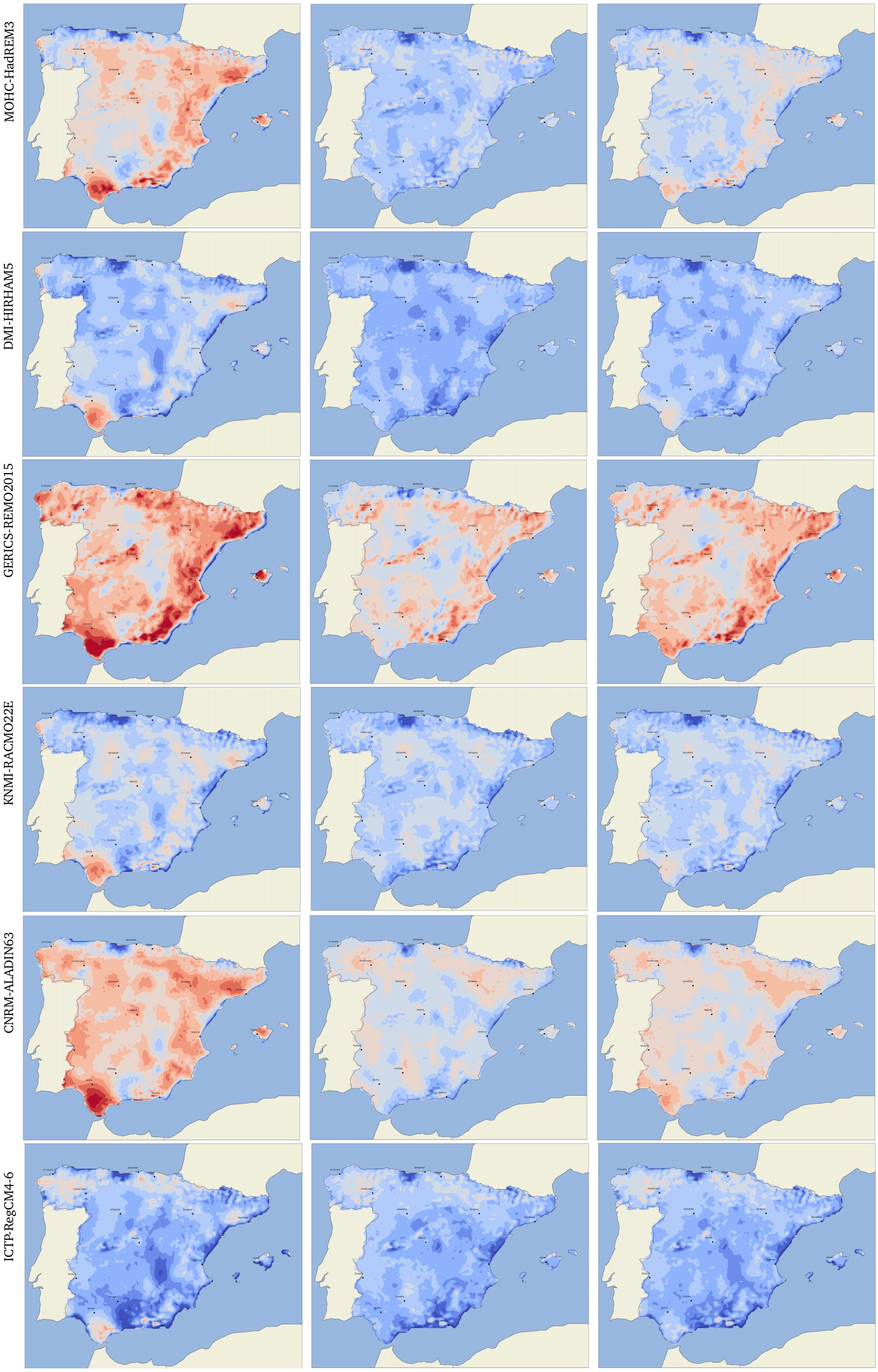
Predominantly, discrepancies among different models for mean, maximum and minimum temperature are substantial. Ultimately, the three temperature variables are analysed by an ensemble of 8 to 9 RCMs, which allow a robust interpretation on temperature biases systematic behaviours. Furthermore, models collectively register similar non-linear patterns suggesting potential regional climate processes on a small scale that affect the models' interpretation of Spain's climate.

4.3 Mapped summer and winter maximum temperature biases

In this section, annual monthly mean temperature biases values are plotted by each model and each grid point over the Spanish mainland and the Balearic Islands. Concretely, temperature biases of maximum temperatures are divided into three columns: summer biases (left), winter biases (center) and annual biases (right) covering the period 1989-2010. In the following enhanced geographical detail maps, we explore the value of the bias ($\theta_m(t)$ - $\theta_o(t)$) of individual models that belong to EURO-CORDEX multimodel ensemble (figure 4.7). Taking an ensemble approach provides a more robust interpretation, enhancing the understanding of models' general aspects (Boberg and Christensen, 2012).

Overall, summer and winter seasons manifest differences among their temperature bias values, as it is presented in Figure 4.5. In the case of annual temperature biases, they tend to have a smoother behaviour. Models 1 (MOHC), 3 (GERICS), 5 (CNRM), 7 (CLM-ETH), and 8 (SMHI), have more geographically varying bias between summer and winter, apart from showing a strong warm bias (exceeding 4ºC) in some southern and eastern mainland regions. However, models 2 (DMI) and 4 (KNMI) exhibit same negative biases for both seasons, indicating that these two models actually show no systematic behaviour, that is, no changes in biases values between seasons. As an exception, model 6 (ICTP) has a systematic behaviour increasing with minimum temperatures. Underestimation of monthly temperatures is enhanced for the warmer season (Figure 4.7).

Model temperature biases are displayed over Spain's grid points with an enhanced geographic detail. Systematic spatial variations widely extend throughout the country and most abrupt changes are mainly imposed by topography and missing physical processes on regional and local scales (Lundquist and Cayan, 2007, Maraun and Widmann, 2018).



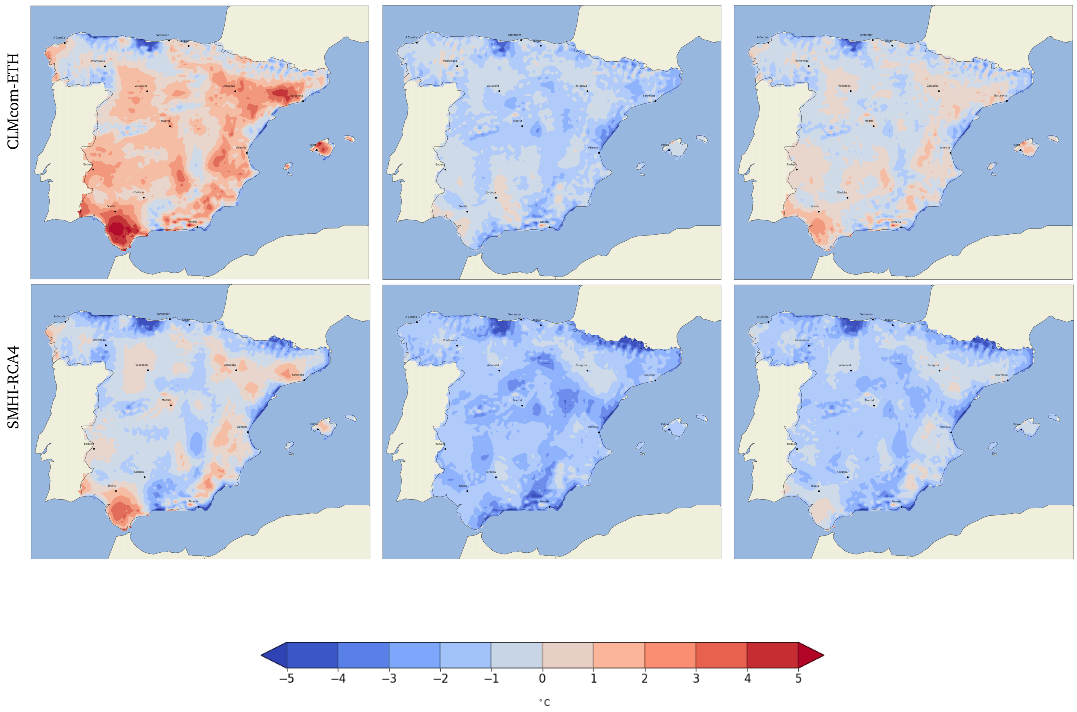


Figure 4.7: Summer (left), winter (center) and annual (right) temperature biases per grid points covering the series 1989-2010 for *Tmax*. The cold period covers December to April (DJFM) and the warm period June to September (JJAS).

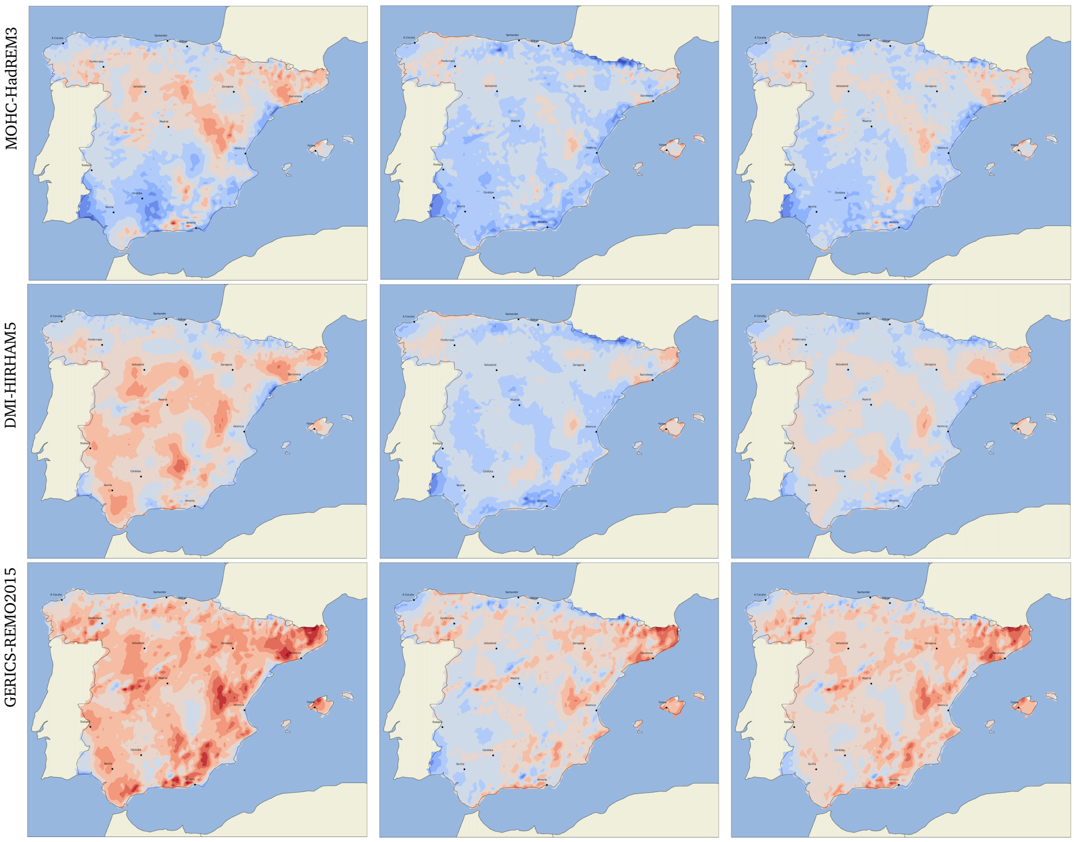
The representation of temperature in complex terrain likely show systematic variations with topography (Maraun and Widmann, 2018). Figure 4.7 depicts well-defined narrow alpine valleys in the Pyrenees mountain range and in northern downsloping areas (Cantabrian range, Appendix Figure 8.4). Local air flows, the topography shading, the presence of snow or the phenomenon "cold-air pooling" could explain the underestimation of temperatures in these complex terrain regions (Pagès *et al.*, 2017, Lundquist and Cayan, 2007).

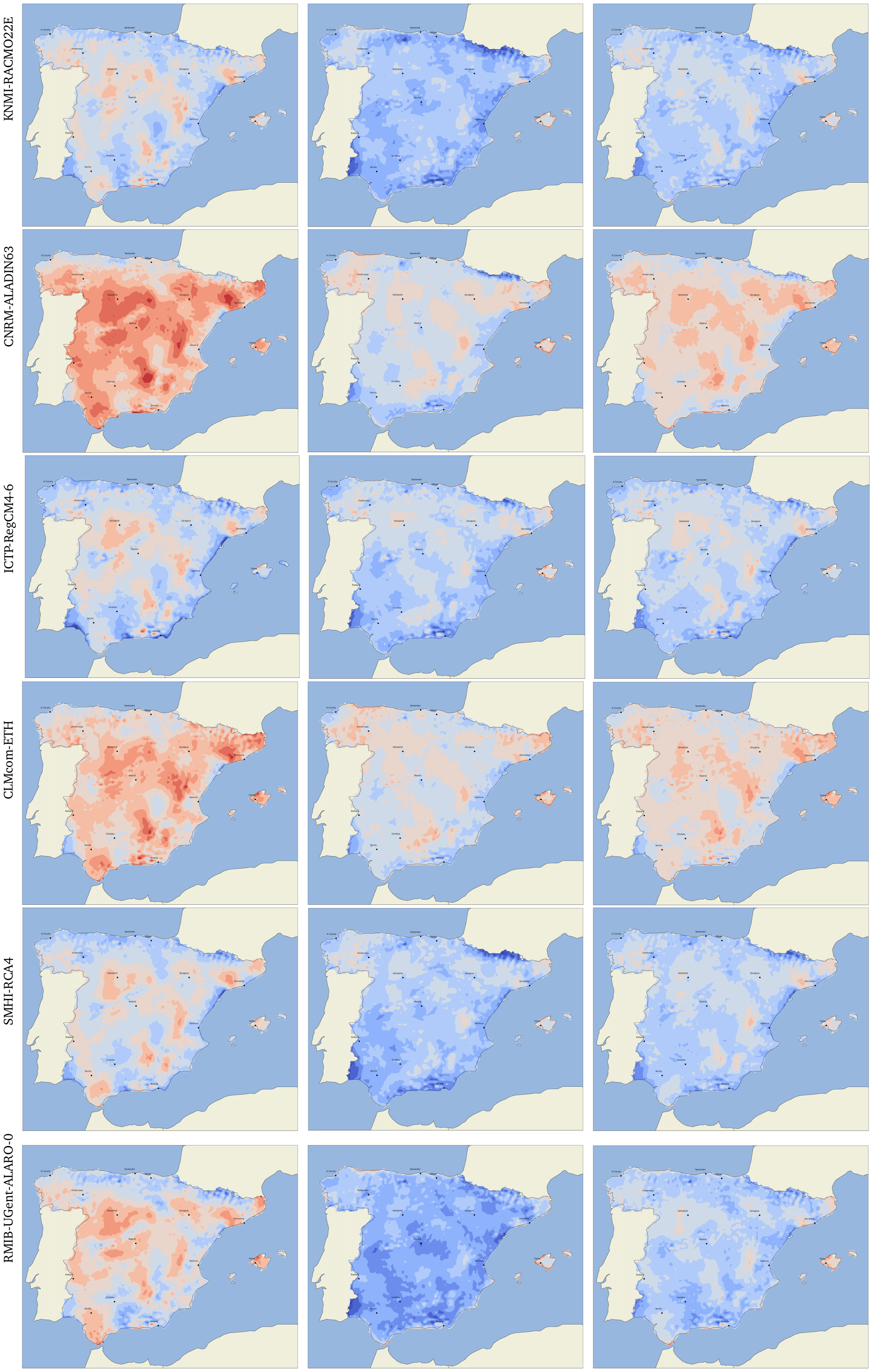
Moreover, models 1 (MOHC), 3 (GERICS), 5 (CNRM), and 7 (CLM-ETH) display a non-linear warm summer bias that aligns with the prominent Ebro Depression (northeastern, see Appendix Figure 8.4). As widely investigated in dry and hot climates (Seneviratne *et al.*, 2006, Fischer *et al.*, 2007, Jaeger and Seneviratne, 2011), large precipitation deficit in Spain's central and eastern regions often contributes to rapid loss of soil moisture, therefore lack of evaporation to cool down the land surface. Collectively, high-resolution maximum temperature biases greatly describes the isolated warm summer bias which overestimates maximum temperatures in uplands areas of Sierra Nevada (southeastern).

4.4 Mapped summer and winter mean temperature biases

Temperature biases of mean temperatures are divided into three columns: summer biases (left), winter biases (center) and annual biases (right) covering the period 1989-2010. Again, here we explore the value of the bias ($\theta_m(t)$ - $\theta_o(t)$) of individual models that belong to EURO-CORDEX multimodel ensemble (Figure 4.8). Overall, summer and winter seasons manifest vast differences among their temperature bias values, as it is presented in Figure 4.4.

Models 5 (CNRM) and 9 (RMIB) evidence distinguished non-linear patterns between warm and cold seasons. Simulations 3 (GERICS), 5 (CNRM), 7 (CLM-ETH), and 8 (SMHI) also show substantial geographically varying bias between summer and winter, apart from showing a robust and warm bias (exceeding 3-4ºC) in some central and eastern mainland regions. Another remarkable interpretation is that mapping non-stationary biases per grid points allows to test models slopes credibility (see Figure 4.4). Apparently, model 6 (ICTP) slope do not exhibit any systematic temperature-dependent biases. However, summer mean temperature biases with respect to the winter ones clearly exacerbate warming in certain central areas of Spain (North-Subplateau).




KNMI-RACMO22E
CNRM-ALADIN63
ICTP-RegCM4-6
CLMcom-ETH
SMHI-RCA4
RMIB-UGent-ALARO-0

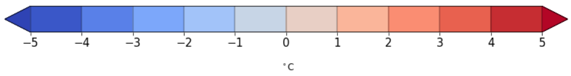


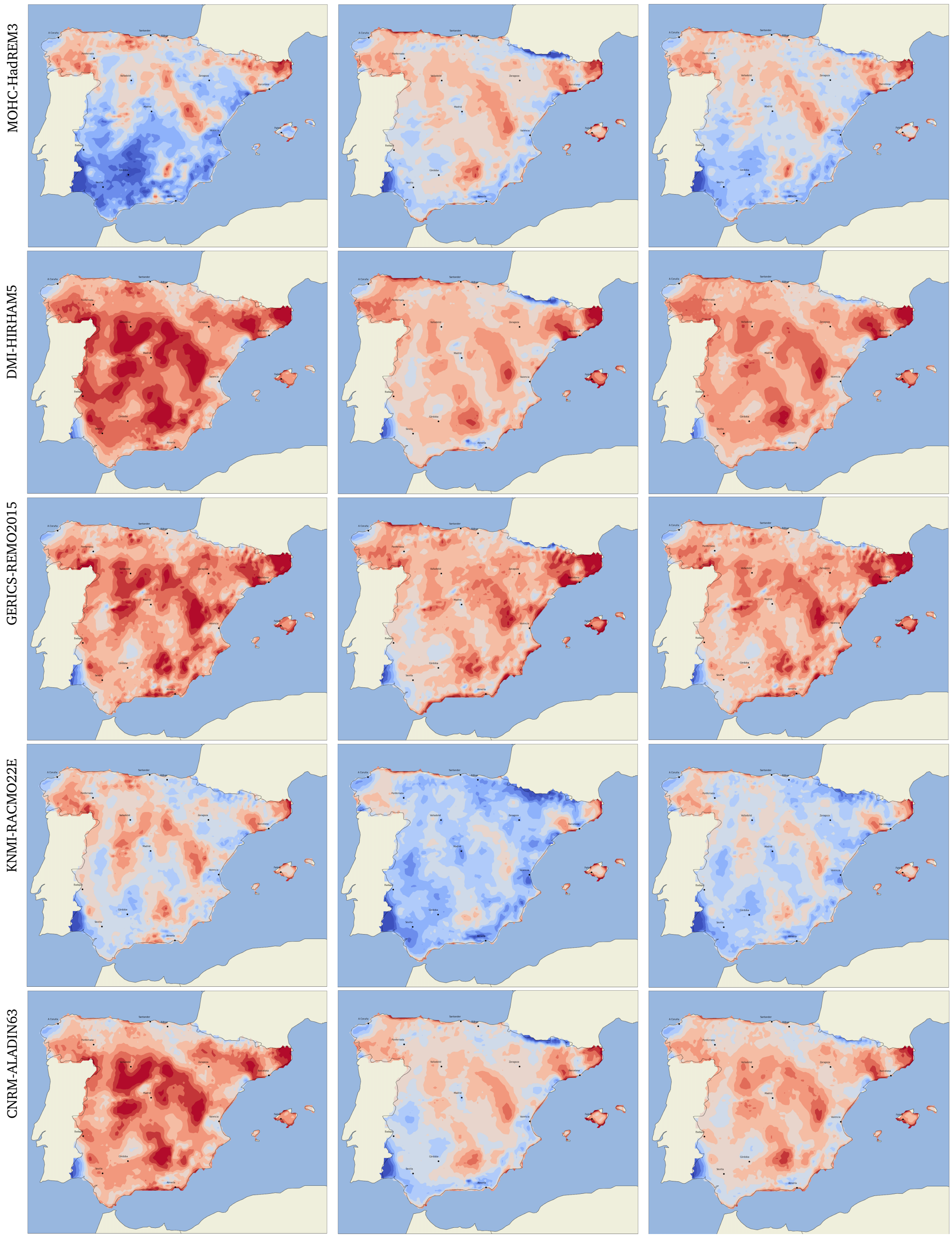
Figure 4.8: Summer (left), winter (center) and annual(right) temperature biases per grid points covering the series 1989-2010 for *Tmean*. The cold period covers December to April (DJFM) and the warm period June to September (JJAS).

The ensemble of RCMs tends to underestimate winter mean temperatures with respect to observed temperatures throughout Spain, especially in northern and southern areas. On the contrary, the exacerbation of warming mainly occurs during summers for central and eastern regions (Models 2, 3, 5, 6, 8). Limestone and clay soils regions share a hot bias in contrast with siliceous areas in the west and north of mainland Spain. Furthermore, lack of evapotranspiration and soil moisture-temperature feedbacks could provoke the overshooting of mean temperatures in inland regions (Jaeger and Seneviratne, 2011, Miralles *et al.*, 2014).

4.5 Mapped summer and winter minimum temperature biases

In this section, monthly minimum temperature biases are plotted by each model and each grid point over the Spanish mainland and the Balearic Islands. Concretely, temperature biases are divided into three columns: summer biases (left), winter biases (center) and annual biases (right) covering the period 1989-2010.

Overall, summer and winter seasons manifest differences among their temperature bias values, as it is presented in Figure 4.9. In the case of annual temperature biases, they tend to have a smoother behaviour. Models DMI (2), GERICS (3), CNRM (5), ICTP (6) and CLM-ETH (7) display a significant warm summer bias exceeding 4ºC in vast areas of central Spain. It seems that these simulations struggle capturing important regional feedbacks and dealing with a complex terrain. Seneviratne *et al.*, 2006 emphasised the role of soil moisture-temperature feedbacks in influencing summer climate variability in Central and Eastern Europe. In the case of Spain's summers, strong positive radiative anomalies and a large precipitation deficit often contributes to rapid loss of soil moisture, therefore lack of evaporation to cool down the land surface. However, northern coastal areas influenced by a temperate climate (Cfb) are dominated by a colder bias with respect to Mediterranean climate areas (Csa). The presence of soil moisture and lower influence of high-pressure systems could determine a moderated systematic bias. Also, the ensemble of RCMs for *Tmin* show the highest heterogeneity among all temperatures. That being said, if the model struggles capturing land-atmosphere feedbacks, then the resulting climate change signal might not be plausible (Maraun and Widmann, 2018). Also, we stress the non-stationary conditions between warm and cold seasons, were biases clearly increase with temperatures. Accumulated heat and lack of soil moisture in the majority of the region in the summer, might be the reason of this systematic temperature-dependent biases.



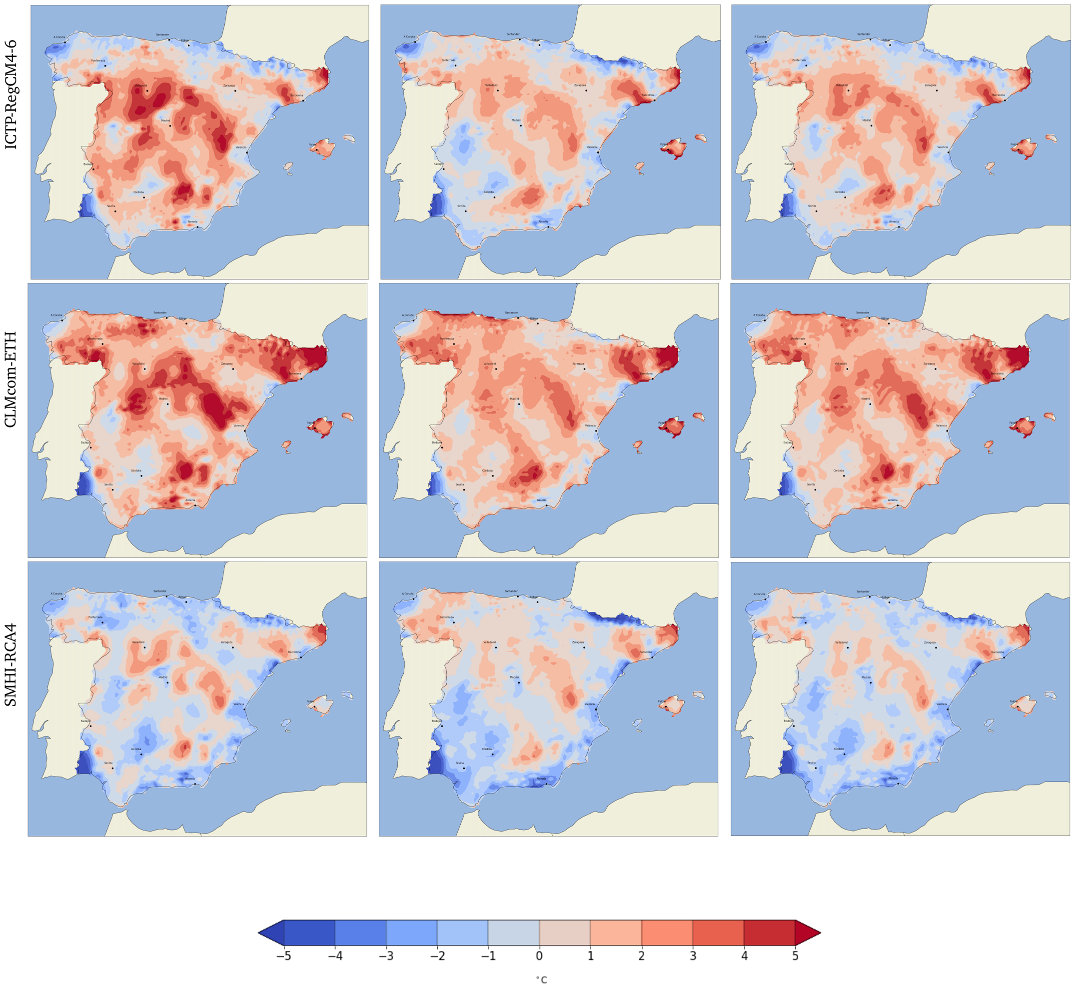


Figure 4.9: Summer(left), winter(center) and annual(right) temperature biases per grid points covering the series 1989-2010 for *Tmin*. The cold period covers December to April (DJFM) and the warm period June to September (JJAS).

On balance, an explicit non-linear behaviour appears comparing mean seasonal temperature biases of all individual models. Also, the use of *Tmean, Tmax, and Tmin* variables confirms that, in general, some models tend to overestimate or underestimate the temperature variable. In particular, simulated minimum temperature shows an inherent warm summer bias significantly intensified in central-northern plateaus and mountainous regions. Furthermore, mapping gridded temperature dependence of biases indicates limitations in interpreting regional present-day climate conditions, especially minimum temperatures. Lastly, systematic spatial variations in certain northern abrupt mountains and southern areas around the Strait of Gibraltar could come from uncertainties in the Spain02 observational dataset.

4.6 Temperature Models Biases Standard Deviation

	Mean temperature			Maximum temperature			Minimum temperature		
Regional Climate Models	Summer	Winter	Annual	Summer	Winter	Annual	Summer	Winter	Annual
MOHC-HadREM3-GA7-05	**0.68**	0.59	0.64	**0.87**	0.62	0.80	**0.82**	0.63	0.72
DMI-HIRHAM5	**0.76**	0.62	0.74	**0.91**	0.66	0.78	**0.76**	0.77	0.86
KNMI-RACMOE22	**0.77**	0.61	0.77	**0.98**	0.67	0.77	**0.77**	0.69	0.92
CNRM-ALADIN63	**0.92**	0.52	1.06	**1.10**	0.65	1.08	**0.81**	0.66	0.99
GERICS-REMO2015	**0.78**	0.54	0.75	**1.09**	0.68	0.99	**0.72**	0.70	0.72
ICTP-RegCM4-6	**0.65**	0.77	0.66	**0.75**	0.92	0.99	**0.69**	0.78	0.84
CLMcom-ETH-COSMO-crCLIM	**1.10**	0.64	0.96	**1.34**	0.62	1.26	**1.13**	0.88	1.00
SMHI-RCA4	**0.76**	0.77	0.82	**1.00**	0.97	1.06	**0.65**	0.75	0.71
RMBI-UGent-ALARO-O	**0.84**	0.83	1.16	-	-	-	-	-	-

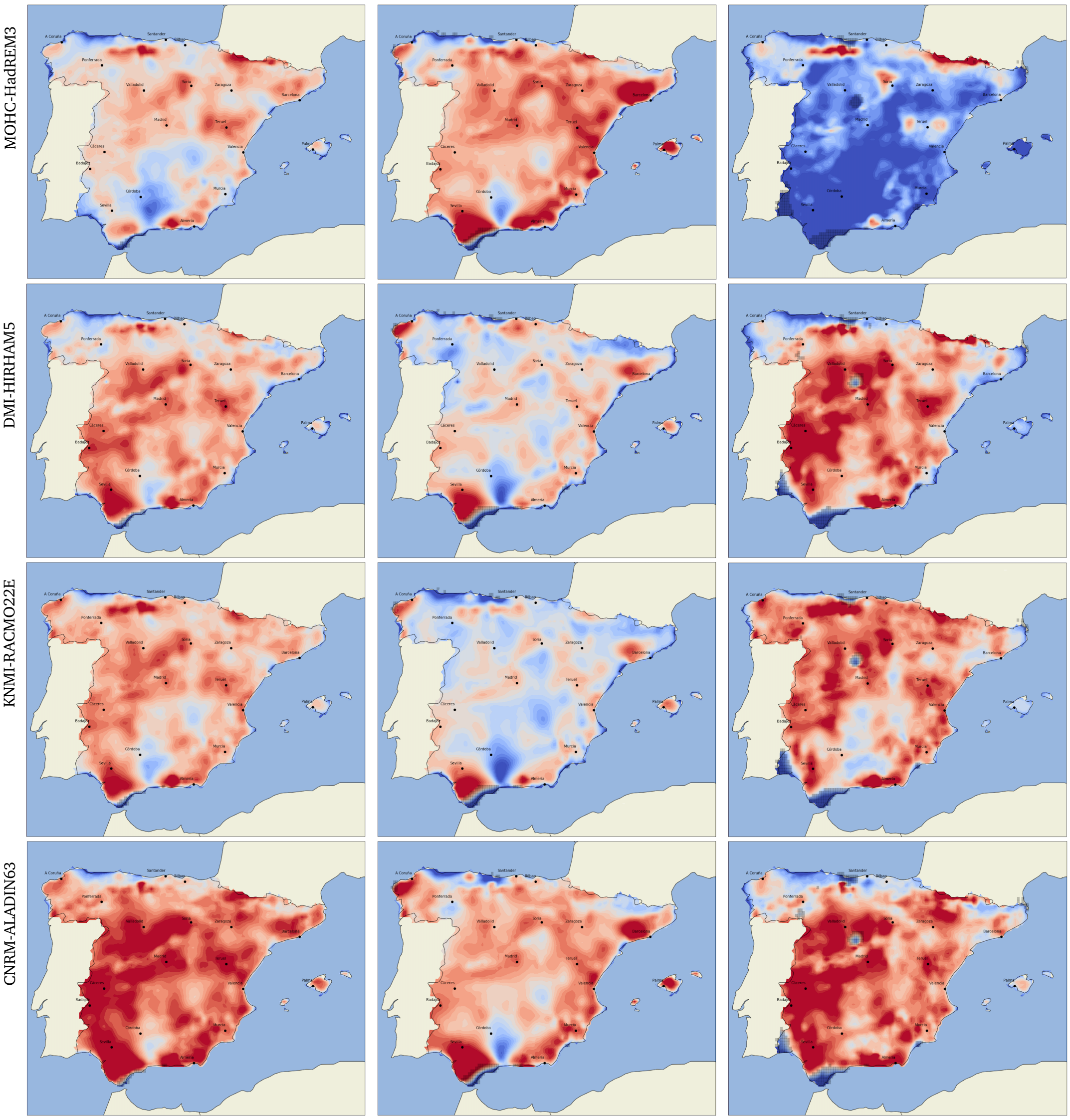
Table 4.1: Seasonal and annual standard deviation for each model and its mean, maximum and minimum variable for 1989-2010. Highlighted summers standard deviation in bold

Temperature model biases for each season exhibit a particular behaviour, being summer biases the most enhanced (figure 4.9). This warm pattern is primarily present in all summer temperatures. However, the winter season tends to suffer from a moderate bias temperature, which regional values indicate low bias, except for the minimum temperatures (Figure 4.9). Table 4.1 shows the seasonal and annual standard deviation for each temperature variable. A Standard Deviation (SD) has been carried out to evaluate the distance between monthly data and their means (Methods 3.5.2). The central idea behind SD is to test state-dependent biases between cold and warm seasons. *Tmean, Tmax and Tmin* variables show higher SD model values for the warm season than the cold season. The higher is the value, the more distant the monthly means lie from their best fits (Figure 4.4). It can be proved that warmer temperatures tend to significantly spread on their values with respect to winter monthly means, which remains more congregated. Extreme temperature values that mainly occur in the summer season may be the cause of such high SD variability. However, the agreement on lower SD values may suggest that monthly mean winter temperatures show less spatial climate variability due to Mediterranean wet and mild winter conditions (Background 2.1). Christensen *et al.*, 2008; Boberg and Christensen, 2012; have demonstrated that biases may not be time-invariant (Maraun, 2012). Significant differences in summer and winter SD temperature biases corroborate systematic behaviours for most RCMs, especially for the maximum temperature. Furthermore, time-variant or state-dependent biases may be linked to processes at all spatial scales and credibility issues (Maraun and Widmann, 2018).

4.7 Climate change signal by regions

It is likely that climate models overshoot regional amplification of global warming due to systematic biases in warm and dry climates (Boberg and Christensen, 2012). This section covers our second approach (Results 4.2) which consist on testing if the temperature slopes per grid points are representative or not. That being said, a goodness of fit was carried out (Methods 3.4) and confirmed that all models' temperature slopes values tend to show a "goodness" of fit around 0.9 to 1, that is, statistically significant.

Figure 4.10 represents slopes for *Tmax* (left), *Tmean* (center) and *Tmin* (right) over each Spanish grid point. The "cool-warm" colour scale indicates the value of the slope which is defined as $\frac{T_m(t)}{T_o(t)}$ where $T_m(t)$ is the simulated temperature and $T_o(t)$ the observed temperature.



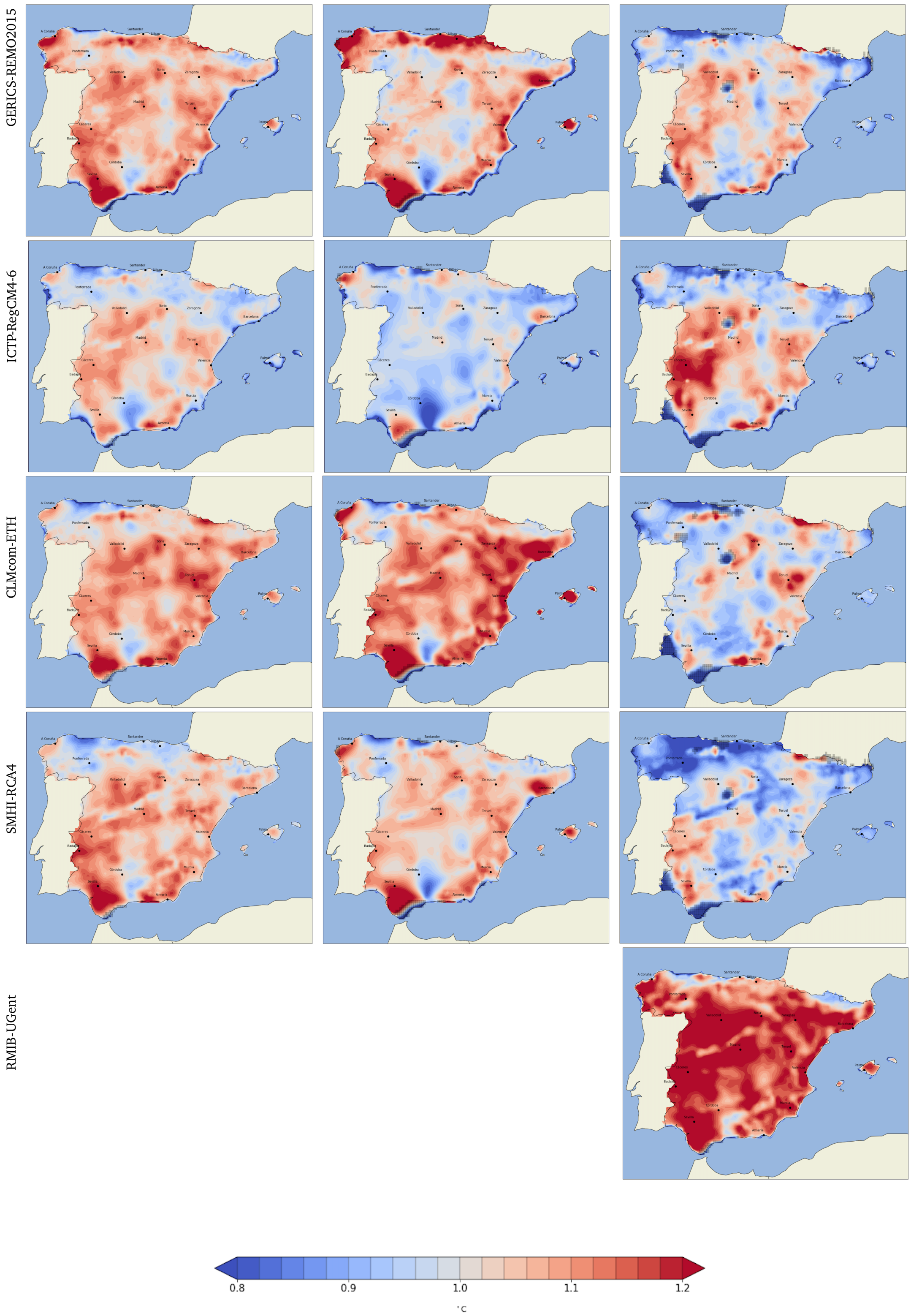

GERICS-REMO2015
ICTP-RegCM4-6
CLMcom-ETH
SMHI-RCA4
RMIB-UGent
0.8
0.9
1.0
1.1
1.2
°C

Figure 4.10: Slopes per grid points of the 9 EURO-CORDEX RCMs showing exacerbation of warming by region. First column (left) represents slopes of maximum temperature; second (center) slopes of mean temperature; and third (right) slopes of minimum temperature. Hatching indicates areas with r2-score < 0.8. The temperature slope is here defined as the slope Tmodel/Tobs covering the period 1989-2010 for Spain.

The following equations explain the three different slopes (A,B,C) that come out from the slopes maps:

$$\text{(A) if } \frac{T_m(t)}{T_o(t)} > 1 \tag{4.1}$$

$$\text{(B) if } \frac{T_m(t)}{T_o(t)} = 1 \tag{4.2}$$

$$\text{(C) if } \frac{T_m(t)}{T_o(t)} < 1 \tag{4.3}$$

Equation 4.1 indicates the exacerbation of warming. If this is the prominent case, the simulated temperature is set to increase more than the observed temperature, thus exaggerating warming. Equation 4.2 shows agreement between models and observations slopes. Simulated temperatures show no signals of cooling or warming. Equation 4.3 reflects a cooling of temperatures. For some areas and, notably affecting minimum temperatures, simulated temperature increases less than the observed temperature. Averaged grid-cells slopes for the study area can be found in table 4.3 for each variable and model.

It is likely that RCMs that overshoot regional warming amplification will exacerbate warming patterns for future projections, as demonstrated in Boberg and Christensen, 2012. From a climate change signal approach, state-of-the-art RCMs will likely project warm and very hot temperatures during the day and night for Spain, especially in mainland areas. Concretely, the majority of the simulations show an exacerbation of warming up to 0.6 degrees for central and southern areas such as the North Subplateau and Guadalquivir Depression (Appendix Figure 8.4). Boberg and Christensen, 2012 found on average a substantial exacerbated warming of 0.8 to 1 degree for the Mediterranean region. It is therefore worth noting the relevance of representing the values of the slope per grid points over Spain. Grid-cell slopes markedly give regional warming and cooling patterns over mainland Spain and the Balearic Islands. Complex topography and noise coming from different unknown sources are well identified using the applied arbitrary threshold (see Methods 3.4), especially for monthly mean minimum temperatures.

Uncertainties that lie on the observational dataset are mostly found in the minimum temperature observed climate for areas of Andalusia in the south, and central and northern uplands areas, influenced by a complex topography. To mend the uncertainties related to complex terrain, Herrera *et al.*, 2016 has suggested employing an interpolation approach AA-3D for temperature.

Models	Slope (ºC) tas TRCM=Tobs	Slope (ºC) tasmax TRCM=Tobs	Slope (ºC) tasmin TRCM=Tobs	Slope of tas_bias value	Slope of tasmax_bias	Slope of tasmin_bias
MOHC-HadREM3	0.917	0.953	0.838	0.022	0.086	-0.104
DMI-HIRHAM5	0.946	0.901	0.988	0.047	0.013	0.073
KNMI-RACMO22E	0.962	0.894	**1.013**	0.062	-0.001	0.099
CNRM-ALADIN63	**1.012**	0.963	**1.026**	**0.124**	0.083	**0.109**
GERICS-REMO2015	0.959	0.945	0.949	0.056	0.065	0.011
ICTP-RegCM4-6	0.906	0.860	0.940	-0.002	-0.035	0.014
CLMcom-ETH-COSMO-crCLIM	0.984	0.992	0.965	0.072	**0.113**	0.012
SMHI-RCA4	0.965	0.943	0.931	0.056	0.060	-0.026
RMBI-UGent-ALARO-O	**1.025**	-		**0.147**		

Table 4.2: Values of the slope from the simulated and observed spatial average temperatures (first 3 columns) and the annual biases slopes of each model with respect to the observations for mean, maximum and minimum temperatures

Regional Climate Models	Mean temperature	Maximum temperature	Minimum temperature
MOHC-HadREM3-GA7-05	1.01	1.07	**0.85**
DMI-HIRHAM5	1.06	1.00	1.07
KNMI-RACMOE22	1.06	0.98	1.08
CNRM-ALADIN63	**1.13**	1.06	1.09
GERICS-REMO2015	1.05	1.04	0.99
ICTP-RegCM4-6	1.00	0.95	1.00
CLMcom-ETH-COSMO-crCLIM	1.06	1.09	0.98
SMHI-RCA4	1.05	1.04	0.94
RMBI-UGent-ALARO-O	**1.15**	-	-

Table 4.3: Slope mean values per grid points computing the ensemble of RCMs considered.

Slopes mean values of approaches **(4.1)** and **(4.2)** are displayed in tables 4.2 and 4.3, respectively. The first three columns of table 4.2 represent the value of the slope (best fits) of each model for simulated and observed spatial-area averaged temperatures with respect to the diagonal $T_m = T_o$. Table 4.3 also displays the mean slope values but per grid points over Spain.

(1) Overall, spatial averaged temperatures experience difficulties in identifying systematic temperature-dependent biases increasing with temperatures. While mean slope values per grid points manifest a clear non-stationary behaviour increasing with temperature, spatial averaged slope values underestimate all RCMs' exacerbation of warming in summers. Following the previous section's equations (climate change signal), if the mean value of the slope is below 1, then the model will likely undervalue regional amplification of global warming. This is the prominent scenario for all spatial averaged slope mean values except for some models that will likely overshoot present-day and projected climate conditions.

(2) However, widespread warming with regional hot spots throughout Spain has been found for most RCMs due to slope values per grid points. Mapped temperatures slopes per grid points show the best performance of current regional warming over Spain. Furthermore, most non-stationary behaviours are well represented by the slope value per grid point since it includes all temperatures over Spain rather than a spatial averaged value. The use of approach 4.2 has provided temperature information at the actual grid point level ($\sim$12.5km).

4.8 Quantile mapping

This study applies a quantile mapping approach since both observations, and state-of-the-art RCMs show similar resolution (∼12.5km grid-cells size). To reduce regional climate models' systematic biases, several techniques and methods are built to compensate for this inconsistency (Mehrotra *et al.*, 2018; Teutschbein and Seibert, 2012). To assess the performance of each temperature variable, a simple empirical quantile mapping has been applied. Namely, a non-parametric estimator called empirical cumulative distribution function (CDF). Figures 4.11, 4.12, and 4.13 show monthly mean temperatures sorted from smallest to largest in value. This is done by assigning a probability of 1/n to each monthly data and calculating the sum of the assigned probabilities up to and including all monthly mean data. Observed mean temperatures (black) manifest "how fast" the CDF increases to 1 (y-axis, likelihood of occurrence). For monthly mean and minimum temperatures, the likelihood of occurrence of simulated warm temperatures is considerably higher than for the observed warm temperatures, being Tmin the most affected (Figure 4.13). However, CDF's for simulated maximum temperature show better agreement with the observed likelihood of occurrence. In short, these three plots compare simulated and observed CDF's representing the gap or bias that lies in between at each monthly mean temperature value. Boberg and Christensen, 2012 also used a bias correction method. Concretely, model biases deficiencies were reduced up to 1 degree.

Quantile mapping (QM). Empirical simulated CDF mapped onto empirical observed CDF

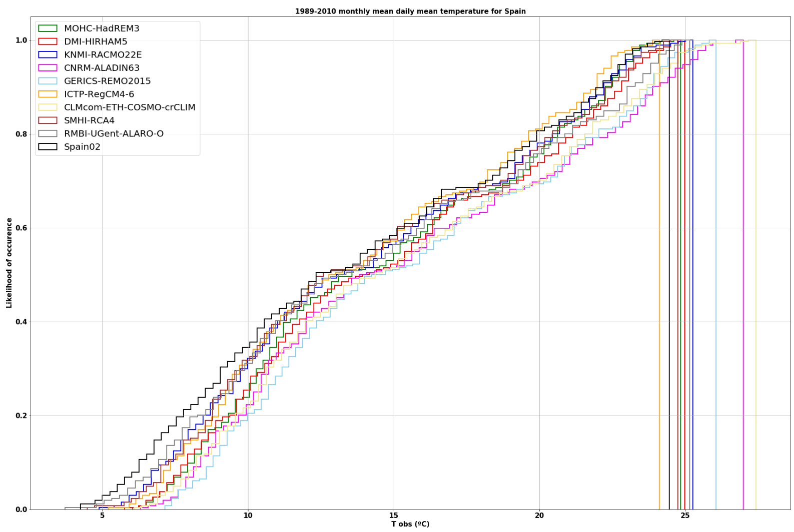


Figure 4.11: Empirical quantile mapping for mean temperature. Simulated cumulative distribution function (RCMs) is mapped onto the observed cumulative distribution function (observations). X-axis shows the temperature and y-axis the likelihood of occurrence.

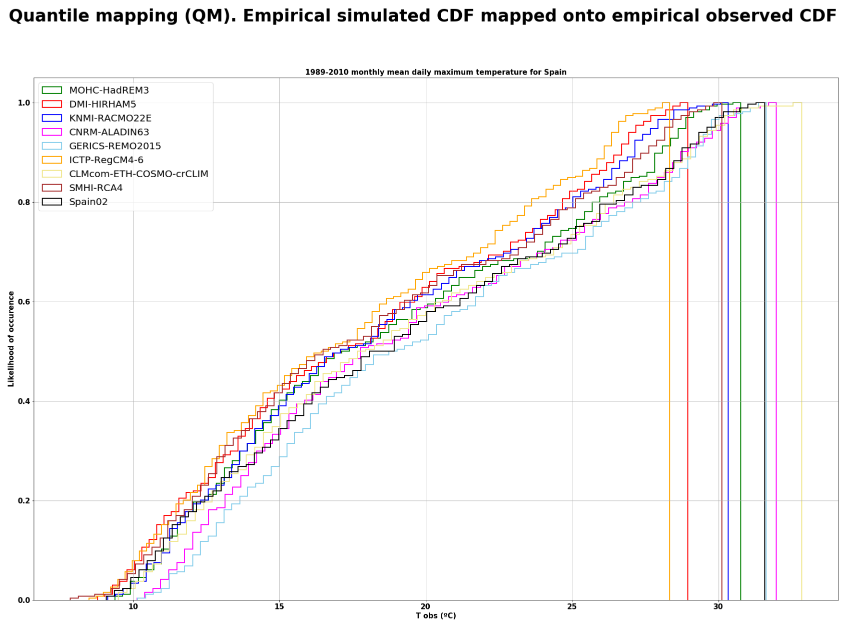


Figure 4.12: Empirical quantile mapping for maximum temperature. Simulated cumulative distribution function (RCMs) is mapped onto the observed cumulative distribution function (observations).

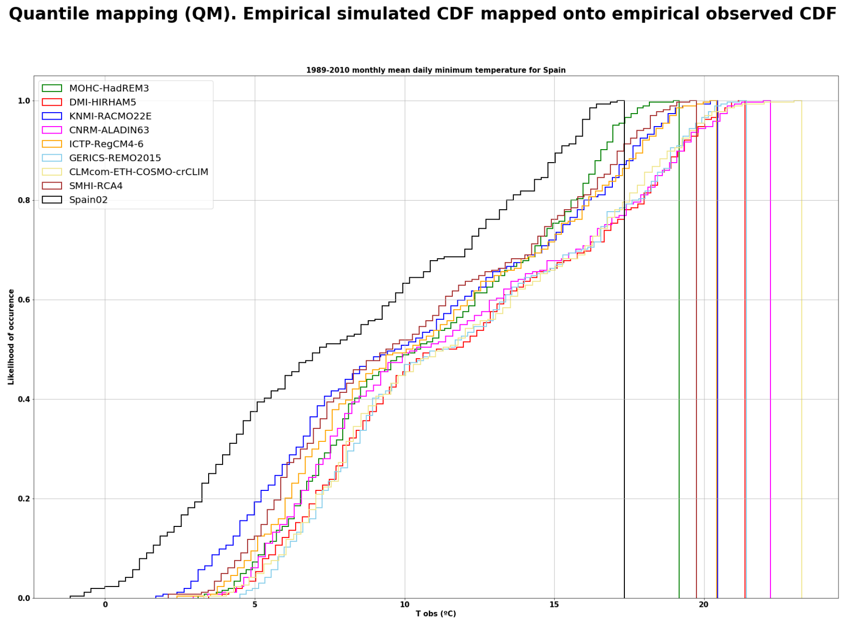


Figure 4.13: Empirical quantile mapping for minimum temperature. Simulated cumulative distribution function (RCMs) is mapped onto the observed cumulative distribution function (observations).

5 Discussion and Conclusions

This dissertation has investigated the temperature biases between state-of-the-art regional climate models (RCMs) and the new gridded observational dataset called Spain02 for the Iberian Peninsula and the Balearic Islands. Furthermore, this study has examined how present-day climate simulations show a significant systematic behaviour affecting their ability to represent Spain's climate, especially summers.

5.1 Systematic temperature-dependent biases present in RCMs

Regional climate models share systematic temperature-dependent biases for present-day climate conditions over Spain. State-dependent biases are higher, increasing with temperature. There is a robust, increasing temperature trend under dry and hot weather and climate conditions (Christensen *et al.*, 2008; Boberg and Christensen, 2012; Christensen and Boberg, 2012). Previous research demonstrated non-linear behaviours in high-resolution climate models using monthly mean temperatures. In addition, this dissertation has also detected non-linear biases adding two more temperature variables: minimum and maximum temperatures. We have used a high-resolution ensemble of RCMs for the Iberian Peninsula by taking a different and straightforward approach, accounting for mean, maximum and minimum temperature biases.

Taking an ensemble approach (Boberg and Christensen, 2012) has provided a more robust interpretation, enhancing the understanding of models' general aspects. As stated by Giorgi *et al.*, 2009, in order to better sample and explore all relevant uncertainty dimensions -in this case, non-linear patterns-, we aim to analyse the larger ensemble of reanalysis models available. Employing up to 9 different EURO-CORDEX RCMs simulations has provided a vast range of non-stationary behaviours for the entire series (1989-2010). Even though the time series has been shortened from 29 to 22 years due to models availability, non-stationary behaviours show no changes with less monthly data points. However, we presume that it could have a warmer temperature bias trend if hot and dry summer monthly means from 2010-2015 were also covered. Furthermore, the use of both high-resolution observational datasets and model simulations ($\sim$12.5km grid-cells size) establishes an accurate representation of the origins and consequences of potential biases.

Ultimately, in the same line as Christensen *et al.*, 2008 and Boberg and Christensen 2012, this dissertation has uncovered that state-of-the-art RCMs seem to have limitations to simulate accurately present-day climate conditions over the Iberian Peninsula and the Balearic Islands. Non-linear patterns indicate to which degree climate models simulations disagree with the observed climate and, more importantly, point out potential climate processes that might not have received the required attention to understand the non-linear behaviours' origins (Stouffer *et al.*, 2017).

5.2 Overestimation of summer temperatures

The majority of the EURO-CORDEX multi-model ensemble overshoot summer temperatures, minimum temperatures being the most affected. As demonstrated by Christensen *et al.*, 2008; Boberg and Christensen, 2012, climate models tend to overestimate regional amplification of global warming in dry and warm areas. In the same line, this dissertation has also confirmed an overestimation of present-day climate conditions in Spain, characterised by warm and dry summers. Spain's summer simulated temperatures manifest an apparent overestimation when compared to wet and cold winters. Collectively, regional climate models simulate warmer diurnal and night-time temperatures, enhancing significant warming in Spain's central and eastern regions. As postulated by Gonzalez-Hidalgo *et al.*, 2016, regional amplification of warming over Spain appears to be more dependent on night-time temperatures than day-time.

This dissertation has corroborated the significant spread of warm biases over main river basins and plateaus for summer minimum temperatures. From a climate change signal approach, we presume that RCMs will likely project warm and scorching summer temperatures, especially night-time conditions in Spain's central areas. The results section displays two different approaches for the purpose of analysing and evaluating model temperature biases. It can be concluded that grid point temperatures represent better the overshooting and underestimation of simulated climate since extreme temperatures grid-cells are better assimilated. As well, a more robust climate change signal can be interpreted from grid-cell slopes over the study area, where most areas are likely to suffer from projected warmer temperatures. Concretely, some mainland central and southern regions could experience up to 0.6 degrees of exacerbated warming, affecting future climate projections accuracy. Boberg and

Christensen, 2012 findings detected up to 1 degree of intensifying warming for the Mediterranean region, especially main river basins and North Africa.

Therefore, it is worth asking whether the next generation of climate models will collectively continue overestimating present-day climate conditions over Mediterranean areas. Conversely, mechanisms underlying climate variability and other misrepresentations will be significantly accounted for by climate models.

5.3 Physical processes conditioning climate models quality

Non-linear temperature biases are likely linked to soil moisture-temperature feedbacks. Namely, systematic summer temperature-dependent biases may appear due to regional climate processes that current climate models do not account for properly.

Indeed, RCMs temperature biases and temperature biases slopes seem to be highly affected by soil desiccation and heat accumulation in many central areas marked by dry and hot summer conditions (Miralles *et al.*, 2014). In general, models exacerbate current present-day warming in areas dominated by a Mediterranean-like climate with an enhanced dry and extreme summer season. Jaeger and Seneviratne, 2011, Miralles *et al.*, 2014, Fischer *et al.*, 2007 demonstrated that land-atmospheric interactions have a strong impact on the European summer climate, especially during extreme weather events. Accordingly, the results have found out that state-of-the-art RCMs will likely project warm and scorching temperatures during the day and night for Spain, especially in mainland areas such as North Subplateau and Guadalquivir and Tajo Depression.

There is a robust, increasing uncertainty concerning small-scale physical processes (IPCC, 2014), limiting the interpretation of climate temperature variables in some dry and hot areas of Spain highly affected by soil moisture-temperature feedbacks (Miralles *et al.*, 2014, Miao *et al.*, 2003, Hirschi *et al.*, 2011). Thus, we highly encourage exploring in great detail potential links behind warm temperature biases over the Iberian Peninsula and soil moisture-temperature feedbacks that mainly take place in the summer season. This suggests the need to revisit the climate models inputs regarding soil moisture-temperature feedbacks during hot and dry climate conditions. Concretely, complex and irregular regions that could be influenced by multiple physical processes.

5.4 The significance of analysing grid point by grid point

Non-linear behaviours or time-variant biases are significantly better represented by model temperature biases per grid points than ranked spatial area-averaged temperatures for Spain. Unlike other European regions, the Iberian Peninsula exhibits a large spatial climate variability that interacts with a very complex terrain leading to extreme temperature values, among other weather phenomena. Therefore, simulated Mediterranean climate displayed by grid points could be comprehensibly used for further bias adjustments or corrections.

Mapped model temperature biases over Spain's grid points show an enhanced geographical detail for the country. Seasonal model biases for each model and temperature variables have confirmed a non-linear behaviour between seasons, which is intensified in certain dry and hot Spain's areas by 4 to 5 degrees. Therefore, regional patterns can be seen throughout the Iberian Peninsula, where topography factors and physical processes become widely evident all over the country. Analysing grid point by grid point, the effect of the temperature-dependent bias could follow an exacerbation of the projected warming, in line with earlier studies (Boberg and Christensen, 2012). Here we confirm that a remarkably warming signal comes out from mapped grid points slopes. If the climate model overestimates current present-day conditions, the resulting climate change signal would likely be overshot (Christensen *et al.*, 2008; Boberg and Christensen, 2012). Collectively, RCMs tend to overshoot warming in areas where summers are mainly dry and hot, which slope is higher than 1.2 degrees. Underestimated climate change signal significantly appears for some models when slopes per grid points are analysed. Even though a few models tend to underestimate simulated and projected climate, it could not be interpreted using the ranking temperatures approach. Also, mapping non-stationary biases per grid points has allowed testing whether models temperature biases slopes are representative or not. While some models' slopes seem not to suffer from non-linear patterns, gridded temperature biases results have confirmed the systematic exacerbation of warming in some central regions of the Iberian Peninsula.

Another significant pattern is that warming signals are less significant in northern areas of Spain compared to central and southern regions. One explanation could be that non-Mediterranean like climates might not suffer to a high degree models non-linear biases since soil moisture is available due to coastal and moderate climate conditions. However, the exacerbation of warming is not always well represented on the grid points. One reason could be the lack of consistency of some observations influenced by Spain's complex terrain, among other factors. Mountain ranges and the

Strait of Gibraltar are highly affected by the complex topography, resulting in a limited representation of temperatures. Moreover, isolated central and northern upland areas seem also to suffer from the observations' uncertainties.

Limitations are found using spatial area-averaged temperatures for interpreting and analysing systematic temperature-dependent biases in this complex and extreme Mediterranean region. Thus, extreme temperature values tend to be smoothed when a spatial area-averaged of the simulated data is carried out. All monthly mean temperatures tend to be overestimated when ranking the spatial area-averaged data from the lowest to highest mean temperature values. However, temperature slopes per grid points and its means clearly manifest an exacerbation of warming, leading to a warmer projected climate. These values are considerably more representative than those coming out from Spain's spatial average temperatures, which tend to be smoothed. This fact is fundamental since positive or negative monthly anomalies can be account for when representing the temperatures slopes per grid points and way less by making the spatial averaged of Spain's temperatures. Furthermore, this method demonstrates higher credibility since extreme maximum, and minimum temperatures are significantly incorporated.

5.5 Scalability considerations

This study could be narrowed down to daily maximum, minimum and mean temperature, contributing to a more detailed analysis of local-scale psychical processes. The Mediterranean region is currently and expected to suffer most from climate change consequences, projecting new extremes above present-day conditions (Stocker *et al.*, 2014). There is a great need to scale down the project to daily data and test RCMs behaviour against local atmospheric-land feedbacks, mainly during summer conditions. For the correct representation of physical processes, RCMs will need to be constrained by high-resolution observational data to reproduce present-day climate conditions accurately. This approach could also lead to investigate in greater detail certain weather phenomena taking place over vast Mediterranean alpine regions. Furthermore, extreme weather events from mega-heatwaves to prolonged droughts are likely to increase over the next decades (Stocker *et al.*, 2014). As discussed by Miralles *et al.*, 2014, persistent synoptic patterns can lead to clear skies and advection of dry continental tropical air, resulting in strong surface sensible heat flux.

5.6 The need for bias adjustment

Boberg and Christensen, 2012 demonstrated that regional simulated warming can be lowered when correcting from systematic temperature-dependent biases. Suggested by Boberg and Christensen, 2012 and Gobiet *et al.*, 2015, a quantile mapping technique could be utilized if the simulated climate change signal is unlikely to happen. Therefore, a bias correction assuming time-variant biases (Maraun and Widmann, 2018). In this dissertation, we have carried out a quantile mapping bias-adjustment technique that might be suitable to mend part of the systematic behaviours. However, it would be highly appropriate to carry out this technique using different global climate models instead, confronting cold, warm months as done by Boberg and Christensen, 2012.

5.7 The need to extrapolate the analysis to other extreme-climate areas

The Iberian Peninsula and the Balearic Islands might not be the only Mediterranean regions that suffer from models deficiencies. The potential for analysing climate model's systematic behaviours for Mediterranean-like climates areas show promise. Boberg and Christensen, 2012 demonstrated a clear geographical pattern for most Mediterranean countries of enhanced warming during summer months, especially in North Africa and main river basins of European Mediterranean countries. Moberg and Jones, 2004 also concluded that warm biases during warmer months for southeastern Europe were often associated with dry soils. Also, non-linear behaviours have been detected in this dissertation, particularly in inland areas that are likely to be influenced by typical physical processes of dry and hot climates. Therefore, this study could guide complex climate and terrain areas to investigate soil moisture temperature feedbacks and appeals for the analysis of other weather patterns (e.g. thermal lows or temperature inversions) that might be behind some models' deficiencies. Furthermore, new extremes and enhanced dry and hot conditions in the last years over non-Mediterranean-like climates (e.g. Central or Eastern Europe) could potentially alter models ability to capture new weather and climate conditions.

6 Outlook

Non-linear climate simulated time-series produces unreliable and overshoot present-day simulations during the summer season in Mediterranean regions. Accordingly, there are reasons to believe that future climate conditions could also be exacerbated in most Spain's regions.

Over the Iberian Peninsula and the Balearic Islands, no study has addressed before the analysis of potential non-stationary biases between state-of-the-art RCMs simulations and high-resolution observational datasets for all monthly mean daily temperature variables. In particular, systematic model biases require increasing attention to better understand their origins and consequences. Land-atmosphere feedbacks induced by Mediterranean-like weather and climate patterns may be the key to mend most of RCMs deficiencies. Because hot and dry conditions are severely intensified by global warming, non-common and extreme physical processes could also affect other temperate climate areas, sharing similar non-linear behaviours currently present in the Iberian Peninsula.

Despite the complexity underlying the climate system and its forcings -altered by the amplification of global warming- current high-resolution climate models proffer an adequate representation of the real world growing the range of regional climate investigations and improving the knowledge of the mechanisms underlying internal climate variability. However, the climate modelling community needs to continue addressing some scientific gaps concerning the origins of non-linear temperature biases.

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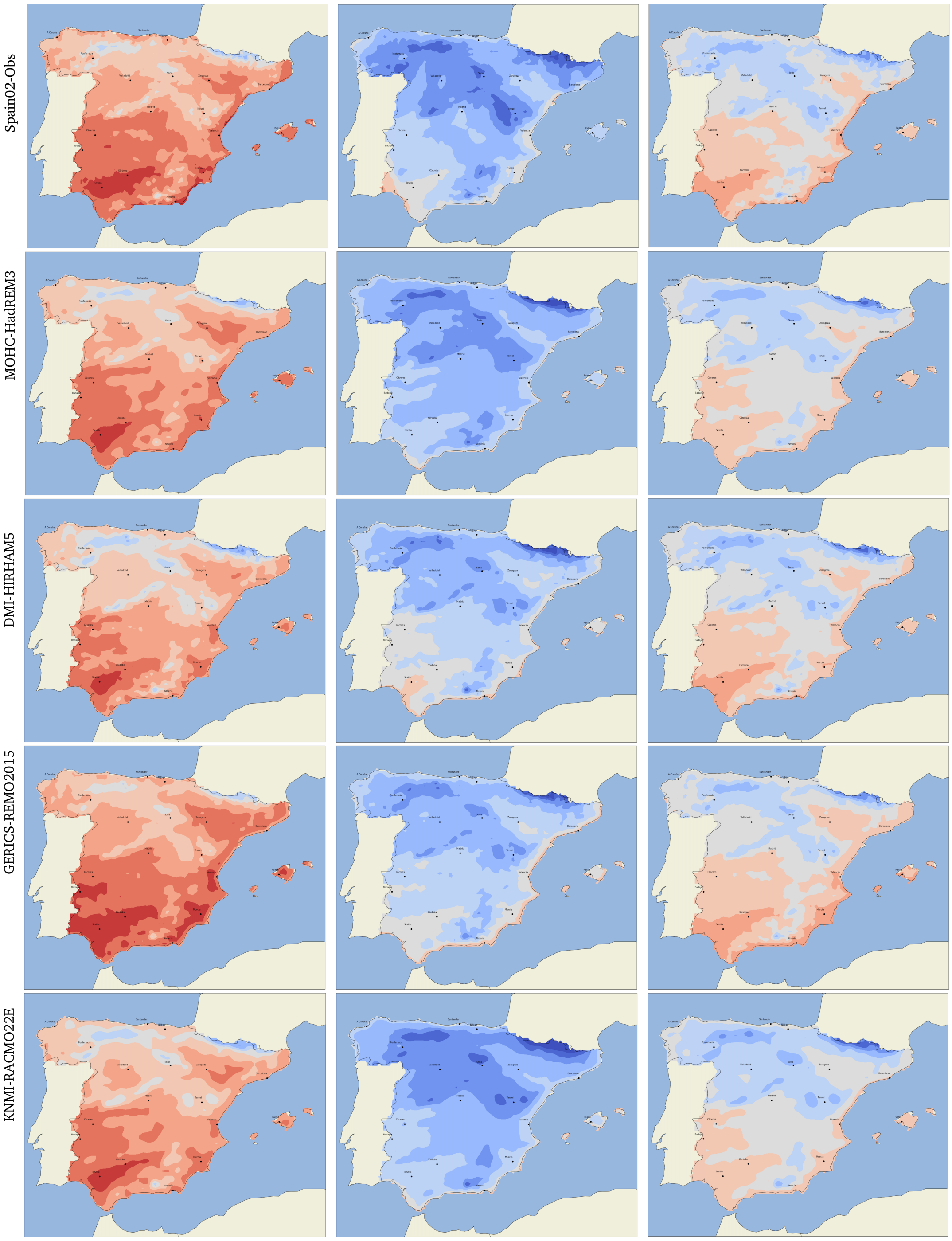
8

Appendix


Spain02-Obs
MOHC-HadREM3
DMI-HIRHAM5
GERICS-REMO2015
KNMI-RACMO22E

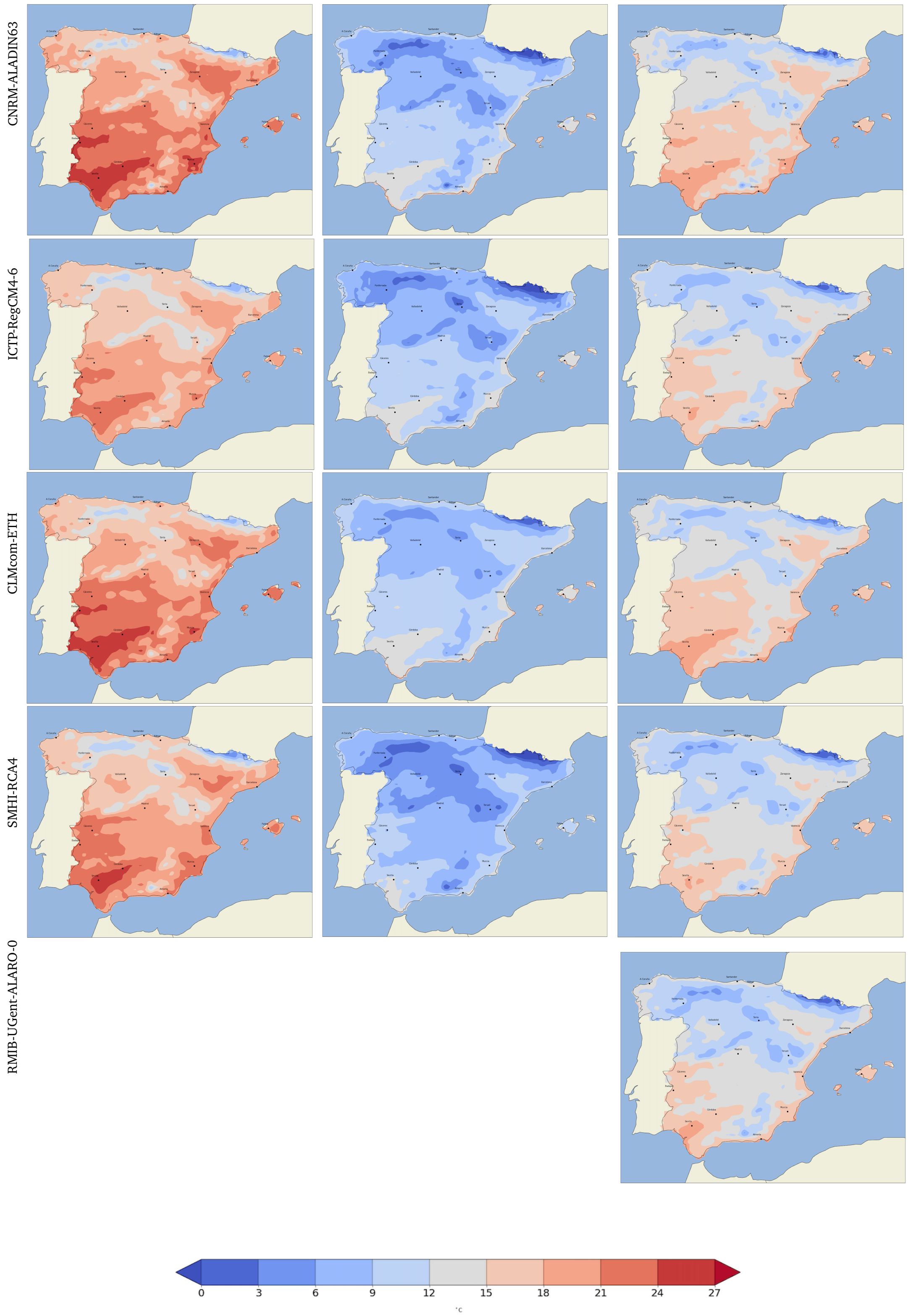


Figure 8.1: Annual mean temperature using individual models from EURO-CORDEX for maximum(left), minimum(center), and mean(right) temperatures covering the period 1989-2010 for the Iberian Peninsula and the Balearic Islands.

Figure 9.1 displays observations and all RCMs annual means of monthly maximum, minimum and mean temperature from the left to the right. The observed climate is represented in the first line which is used as a baseline to compared with EURO-CORDEX simulated climate.

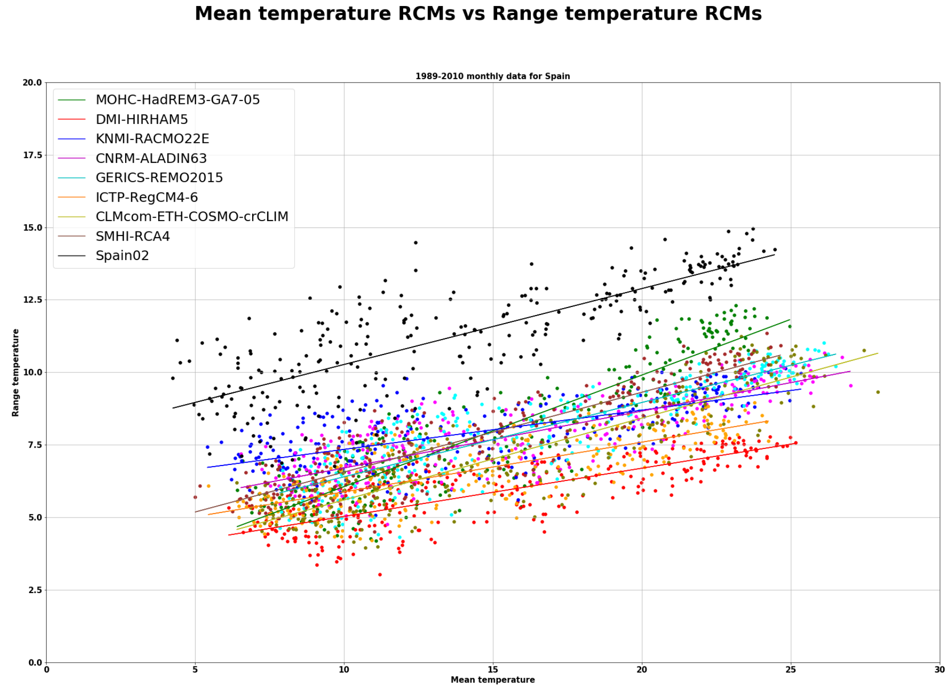


Figure 8.2: Range of temperatures against mean temperatures. Dots represent monthly mean temperatures and lines their best fits. Observations (black) and EURO-CORDEX RCMs in different colours.

Model ID	Regional Climate Model	timeseries	tas	tasmin	tasmax
RCM1	MOHC-HadREM3	1982-2012	X	X	X
RCM2	DMI-HIRHAM5	1989-2011	X	X	X
RCM3	KNMI-RACMOE22	1979-2012	X	X	X
RCM4	CNRM-ALADIN63	1979-2018	X	X	X
RCM5	GERICS-REMO2015	1979-2012	X	X	X
RCM6	ICTP-RegCM4-6	1980-2016	X	X	X
RCM7	CLMcom-ETH-COSMO-crCLIM	1979-2010	X	X	X
RCM8	SMHI-RCA4	1980-2010	X	X	X
RCM9	RMBI-UGent-ALARO-O	1980-2010	X	-	-
Total	Baseline	1989-2010	9	8	8

Table 8.1: ERA-Interim-Driven EURO-CORDEX (EUR-11) Regional Climate Models considered. RCM RMBI-UGent-ALARO-O only includes monthly mean daily mean temperatures.

Figure 9.12 shows observed and simulated ranked range temperatures increasing in the warmer months. Spain's climate and weather variability between winter and summer seasons is greatly represented by the spread of monthly mean simulated and observed temperatures. On the one hand, low-pressure and atmospheric blocking systems regulate winter temperatures. On the other hand, persistent high-pressure atmospheric conditions motivate subsidence and, thus the presence of clear skies.

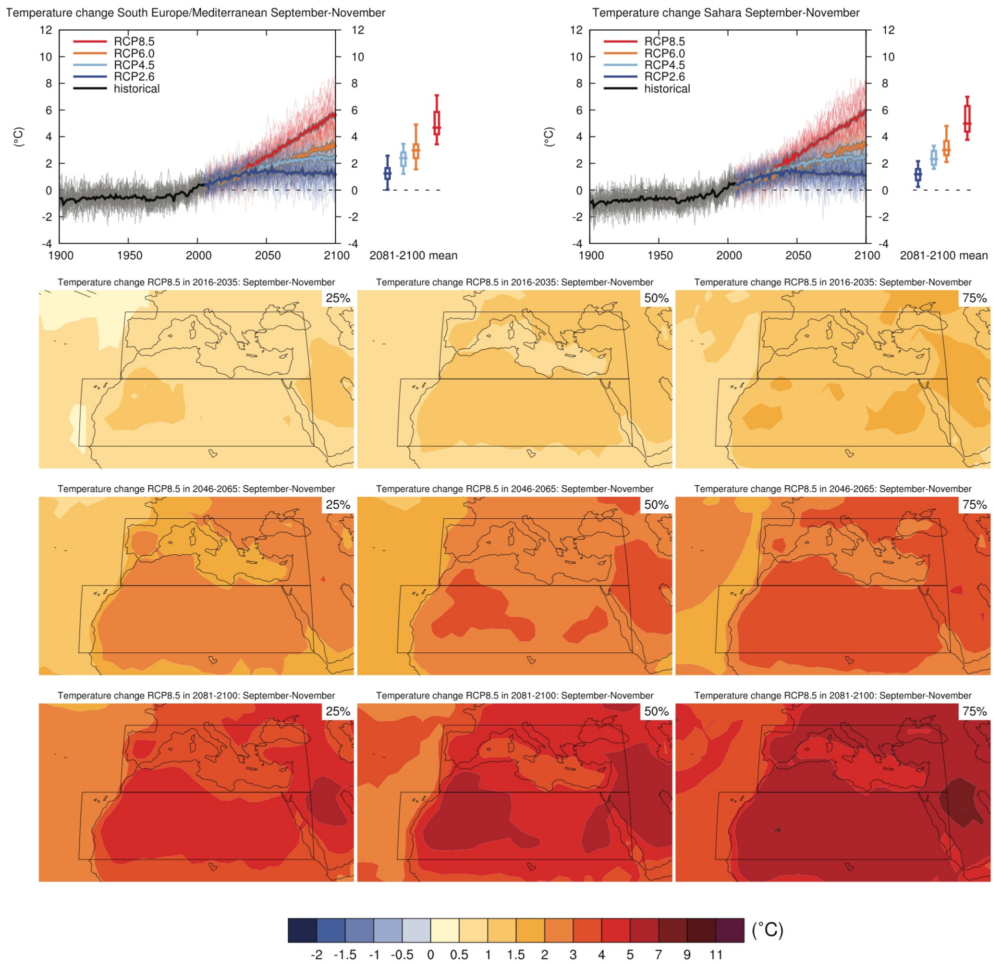


Figure 8.3: Temperature change of South Europe/Mediterranean region and Sahara for 2016-2035; 2046-2065 and 2081-2100 under scenario RCP8.5 (Reproduced from the IPCC, 2014)

Figure 8.4: The physical geography of Spain with prominent upland areas all over the country. Main geographical features are displayed from river basins to mountainous areas and its highest peaks (Reproduced from ANAYA)

Figure 8.5: Spanish physical features represented in Spanish and with a cross-section from northern to southern latitudes. Reproduced from ANAYA. The cross-section and the below first topographic profile goes together.

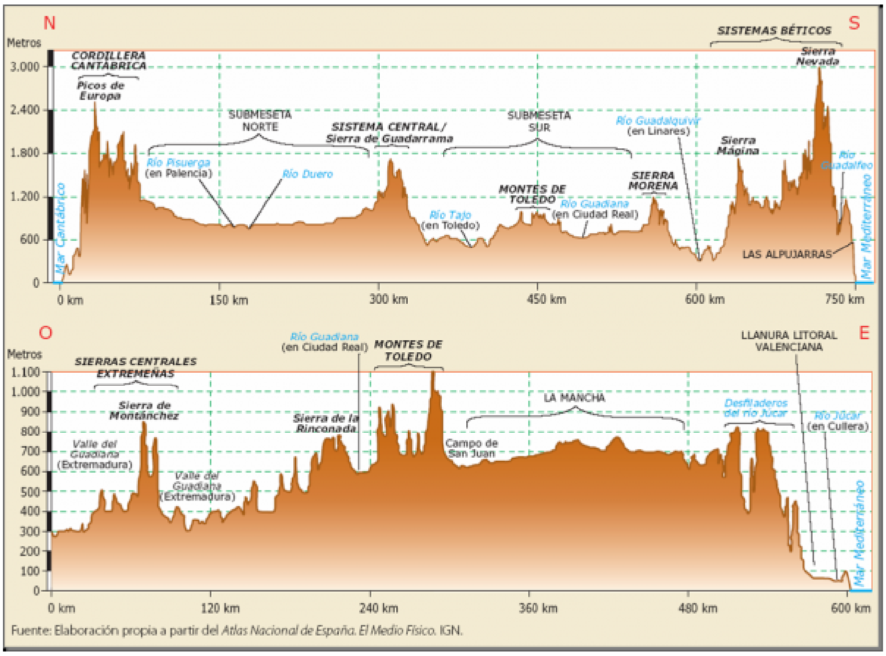


Figure 8.6: Two Topographic profiles from north to south crossing the complex and vast Iberian Peninsula. Reproduced from IGN (Instituto Geográfico Nacional).