

1 **Assessment of the spatio-temporal variability of the added value on precipitation of convection-permitting**  
2 **simulation over the Iberian Peninsula using the RegIPSL regional earth system model**

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## Abstract

In this study, we have assessed the added value on the spatio-temporal distribution of the precipitation of convection-permitting simulation (3km) compared to the parent coarser-scale parameterized convection simulation (20km) with the high-resolution observational datasets i.e. SPREAD (5km) and IBERIA01 (10km) over the Iberian Peninsula in all four seasons during 2000-2009. Both simulations are evaluation runs based on ERA-Interim reanalysis and performed with the RegIPSL regional earth system model in the frame of the European Climate Prediction system (EUCP) H2020 project and COordinated Regional climate Downscaling Experiment (CORDEX). We have not found significant improvement in the convection-permitting simulation compared to the parent coarser-scale simulation for the seasonal mean precipitation of the Iberian Peninsula except the spatial variation over mountainous peaks. The kilometer-scale simulation significantly underestimates the observed seasonal mean precipitation over the western parts of the Iberian Peninsula compared to the coarser-scale simulation, which may be attributed to a change of local dynamics in the kilometer-scale simulation with a weakening and southward shifts of the westerly winds and also an enhancement of warm and dry southerly winds over the Iberian Peninsula. However, the added value of kilometer-scale simulation over the driving coarser-scale simulation is obtained for various indices; in the representation of the spatio-temporal distribution of the wet-day precipitation frequency and intensity, and the extreme/heavy precipitation events for each season at both resolutions i.e. downscaled and upscaled. It has also been noted that the spatio-temporal distribution of precipitation for all metrics used varies between the two observational datasets for all seasons.

**Keywords:** Added value, Dynamical downscaling, RegIPSL model, Convection-permitting simulation, Precipitation events

## 59 **1 Introduction**

60 Regional climate models (RCMs) have proven to be a powerful/useful tool for dynamically downscaling the  
61 coarse-scale information/datasets at the regional-to-local scale (Prein et al. 2015). The coarse-scale information is handed  
62 over to an RCM via the lateral boundaries, and the information is usually provided from either general circulation models  
63 (GCMs), reanalysis, or large-scale regional models. In the last two-three decades, the RCMs have been used for improving  
64 our understanding of regional climate processes of different parts of the world, and also used for impact assessment studies.  
65 Also, considerable efforts have been/are being made to further advance and improve the RCMs by increasing their  
66 complexity and resolution. Recent advances in supercomputer computing power/resources have allowed limited-area RCMs  
67 to be run at kilometer-scale grid spacing (also known as convection-permitting/resolving/allowing). Increasing the spatial  
68 resolution towards convection-permitting scales ( $\leq 4\text{km}$ ; Weisman et al. 1997) can resolve deep convection explicitly on  
69 the model grid without the need for a convective parametrization scheme (Hohenegger et al. 2008; Kendon et al. 2012;  
70 Prein et al. 2015; Kendon et al. 2017). As several studies have shown that the parameterizations of sub-grid scale convection  
71 are a key source of errors and uncertainties in the climate model simulations (Bechtold et al. 2004; Randall et al. 2007;  
72 Déqué et al. 2007; Hohenegger et al. 2008; Brockhaus et al. 2008). Also, increasing resolution leads to a better  
73 representation of orography and land surface fields which are crucial for the initiation of convection in complex terrain  
74 (Hohenegger et al. 2008), and also provides a step-change in our capability for understanding future climate change at local  
75 to regional scale and for and high-impact extreme weather events that greatest impact society (Rasmussen et al. 2020;  
76 Helsen et al. 2020; Kendon et al. 2019, 2021).

77 Over the last decade, several studies have demonstrated the clear benefits and added value of the convection-  
78 permitting models in the simulation of precipitation characteristics with much greater realism, including the diurnal cycles,  
79 spatial distribution of precipitation, intensity and frequency distribution, and extremes compared to the coarse-scale model  
80 (Prein et al. 2015; Meredith et al. 2015; Fosser et al. 2015; Lind et al. 2016; Brisson et al. 2016; Liu et al. 2017; Leutwyler  
81 et al. 2017; Zittis et al. 2017; Karki et al. 2017; Berthou et al. 2018; Fumière et al. 2019; Broucke et al. 2019; Li et al. 2019;  
82 Chang et al. 2020; Lind et al. 2020; Knist et al. 2020; Kouadio et al. 2020; Coppola et al. 2020; Zhou et al. 2021; Li et al.  
83 2021; Ban et al. 2021).

84 Some recent coordinated efforts towards a better understanding of the regional climate modelling at kilometer  
85 resolutions are undergoing like; the dedicated Coordinated Regional Downscaling Experiment Flagship Pilot Studies  
86 (CORDEX-FPS; <https://cordex.org/experiment-guidelines/flagship-pilot-studies/>) on Convective phenomena at high-  
87 resolution over Europe and the Mediterranean and also within the European Climate Prediction System (EUCP;

88 <https://www.eucp-project.eu/>). Within these projects, several regional modelling groups across Europe are conducting  
89 climate simulations in a common greater Alpine domain with horizontal resolutions around 3 km, with the aim to  
90 generate/build multi-model ensembles of simulations at the convective-permitting scales over a decade-long period to  
91 explore the capabilities and uncertainties of the convective-permitting model simulations in a systematic manner for present  
92 and future climates (Coppola et al 2020; Ban et al. 2021). The ensemble of ERA-Interim driven present-day convection-  
93 permitting climate simulations have shown superior performance in simulating the precipitation characteristics compared to  
94 coarse-resolution climate simulations, although differences between the kilometer-scale simulations and observations still  
95 exist (Coppola et al 2020; Ban et al. 2021). Panosetti et al. (2019) have shown that the kilometer-scale simulations are  
96 climatologically more robust in case of strong orographic forcing (domain over the European Alps) and less robust in  
97 central German.

98         Keeping in mind the usage and added value of convection-permitting model simulations in the above literature,  
99 here we evaluate the added value of the convection-permitting/resolving simulation (3 km resolution) compared to the  
100 coarser-resolution parameterized convection simulation (20 km resolution) in the representation of the spatio-temporal  
101 pattern of the observed mean and extreme precipitation over the Iberian Peninsula for all four seasons [i.e. December-  
102 January-February (DJF; Winter), March-April-May (MAM; Spring), June-July-August (JJA; Summer), and September-  
103 October-November (SON; Autumn)] for the period of 2000-2009. Both simulations are based on the ERA-Interim  
104 reanalysis (Dee et al. 2011) and have been performed using a recently developed regional climate model called RegIPSL by  
105 the Institut Pierre Simon Laplace (IPSL, <https://gitlab.in2p3.fr/ipsl/lmd/intro/regipsl/regipsl/-/wikis/home>) group in the  
106 frame of the European Climate Prediction system (EUCP) H2020 project and COordinated Regional climate Downscaling  
107 Experiment (CORDEX), and details about this model and simulations are given in the next section. The simulated  
108 precipitation is evaluated with the available high-resolution observational gridded datasets i.e. SPREAD (5 km) and  
109 IBERIA01 (10 km). In the comparison of the model-simulated results with observations, the uncertainty associated with the  
110 observational datasets especially over mountainous regions due to the sparseness of rain gauge stations at high elevations  
111 must be taken into account (Sevruk 1985; Frei et al. 2003). Recent studies actually report that total annual precipitation can  
112 be better represented by well-configured high-resolution atmospheric models in mountainous terrain, than with spatial  
113 estimates derived from observational products (Lundquist et al. 2020).

114         The research paper is mainly structured into three sections. In section 2, we have presented a detailed description of  
115 the model configuration for the two simulations, as well as observational datasets used for validation and methodology used.

116 A detailed analysis of the added value of the fine-scale simulation over the driving coarse-scale simulation against the  
117 observations is presented in section 3, and finally, the summary and conclusions are given in section 4.

## 118 **2 Model simulations, Data, and Methodology**

### 119 **2.1 Model simulations and data**

120 In the frame of the EUCP H2020 project and CORDEX, we have performed the ERA-Interim driven regional  
121 climate simulations with the coupled atmosphere-land RegIPSL model over the European domain at 20 km horizontal  
122 resolution (EUR20; with parameterized convection) and also over the European South-West domain at 3 km (SWE3;  
123 convection-permitting/resolving) horizontal grid spacing for the period of 1999-2009 (the first year period has been used as  
124 a model spin-up). The European South-West domain (i.e. Iberian Peninsula) is an area with a rich diversity of climates that  
125 is affected by several high-impact extreme events such as droughts and flash floods, for which the coupling processes  
126 between the land surface and the atmosphere play an important/key role. The experiment is performed as a chain of  
127 simulations while the EUR20 simulation is forced by the 6-hourly ERA-Interim initial and lateral boundary conditions (IC-  
128 LBCs) and the SWE3 simulation is forced by the 3-hourly EUR20 simulated IC-LBCs. The model domain with terrain  
129 height in the meters for the EUR20 and SWE3 simulations is shown in Figs. 1a and 1b, respectively.

130 The RegIPSL is a newly developed regional earth system model and is maintained at the Institut Pierre Simon  
131 Laplace (IPSL). The atmospheric component of the RegIPSL model is WRF (Weather Research and Forecasting;  
132 Skamarock et al. 2008; Fita et al. 2019) model, which is coupled to the ORCHIDEE (Organising Carbon and Hydrology In  
133 Dynamic Ecosystems; Krinner et al. 2005) land-surface model and NEMO (Nucleus for European Modelling of the Ocean;  
134 Madec et al. 1998) ocean model. We have used the OASIS coupler (<https://portal.enes.org/oasis>) for coupling, and XIOS (or  
135 XML I/O Server, <http://forge.ipsl.jussieu.fr/ioserver>) libraries are used for the management of the input/output. The details  
136 of the model configuration and the WRF physical schemes are given in Table 1.

137 The high-resolution SPREAD ( $0.05^\circ \times 0.05^\circ$ ; Serrano Notivoli et al. 2017) and IBERIA01 ( $0.1^\circ \times 0.1^\circ$ ; Herrera et  
138 al. 2019) daily gridded mean precipitation observational datasets have been used as reference datasets for the validation of  
139 the model simulated precipitation. The SPREAD dataset is based on the 12858 observatories and is available at land points  
140 of Spain, while the IBERIA0 is based on a total of 3761 rain gauge stations and covers the landmass of Spain as well as  
141 Portugal. A detailed description of these datasets can be found from the references given above.

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Table 1. Description of model configurations.

Description	Selection	
	EUR20 simulation	SWE3 simulation
WRF version	3.7.1	3.7.1
Dynamic solver	ARW	ARW
Horizontal grid spacing	20 km	3 km
Grid dimensions	301 × 193	581 × 651
Vertical levels	46 (top 50 hPa)	46 (top 70 hPa)
Integration time	90s	10s
Radiation (Shortwave and Longwave)	RRTMG Scheme (Integration timestep = 30 min)	RRTMG Scheme (Integration timestep = 5 min)
Microphysics	WRF Single-Moment (WSM) 5-class scheme	Thompson Scheme
Atmospheric surface layer	MYNN surface layer	MYNN surface layer
Land surface	ORCHIDEE	ORCHIDEE
Planetary Boundary Layer (PBL)	MYNN 2.5 level TKE scheme	MYNN 2.5 level TKE scheme
Cumulus	Kain-Fritsch scheme	no cumulus scheme is used

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147 **2.2 Methodology**

148 First, we evaluate the added value of the SWE3 in the spatio-temporal distribution of seasonal mean precipitation  
149 and also focus on the altitudinal variations of mean precipitation. We also examine the atmospheric conditions to explain the  
150 differences observed in seasonal mean precipitation between the two simulations (Detailed discussion related to this is given  
151 in section 3.2). In the second step, we examine the added value of SWE3 in the spatial/altitudinal distribution of the wet-day  
152 precipitation frequency and intensity of daily mean precipitation. A wet day is a day with precipitation  $\geq 1$ mm. We also use  
153 the probability density function (PDF) to showcase the overall distribution of daily precipitation intensity, and Kolmogorov-  
154 Smirnov (K-S) goodness-of-fit test is used to measure the dissimilarity/distance between the two samples i.e. model and  
155 observed precipitation (Chakravarti et al. 1967; Torma et al. 2015; Shahi et al. 2021). The KS distance is defined as the  
156 maximum vertical absolute difference between two empirical cumulative distribution functions (ECDFs). The K-S distance  
157 varies between zero (perfect overlap between the two distributions) and one (no overlap between the two distributions). It is  
158 calculated from the formula:

$$159 \quad d_{KS}(F, G) = \sup_{t \in \mathbb{R}} |F(G) - G(t)|$$

160 where  $F$  and  $G$  are the two ECDFs and  $supr$  represents the supremum function (Chakravarti et al. 1967; Torma et  
161 al. 2015).

162 In the final evaluation step, we focus on the representation (spatial/altitudinal) of heavy/extreme precipitation.  
163 Basically, we used two climate extreme indices i.e. R95p and Rx1day (Karl et al. 1999; Peterson 2005). The R95p is the  
164 99th percentile of the precipitation, and Rx1day is the highest one-day precipitation amount.

165 We use the Taylor diagram (Taylor 2001) to assess the performance of both simulations in representing the spatial  
166 distribution of precipitation (for all cases/indices). We constructed the Taylor diagram with the results of the spatial Index of  
167 Agreement (instead of the spatial correlation coefficient) and normalized standard deviation. Willmott (1982) stated that the  
168 correlation coefficient is often a misleading measure of accuracy, and proposed a new skill metric i.e. Index of Agreement  
169 (IOA). The IOA is calculated as follows:

$$170 \quad IOA = 1 - \frac{\sum_{i=1}^n (M_i - O_i)^2}{\sum_{i=1}^n (|M_i - \bar{O}| + |O_i - \bar{O}|)^2}$$

171 where  $M$  and  $O$  represent the model and observation, respectively.  $\bar{O}$  represents the observed mean value and  
172  $n$  is the number of total data/grid points. The IOA is bounded between 0 and 1, where a value close to 1 indicates more  
173 efficient forecasting skills.

## 174 **3 Results and discussion**

### 175 **3.1 Spatio-temporal distribution of seasonal mean precipitation**

176 In this section, we evaluate the spatial distribution of the simulated 10-year seasonal (DJF, MAM, JJA, and SON)  
177 mean precipitation over the Iberian Peninsula (IP). The seasonal mean precipitation of the SWE3 and EUR20 simulations  
178 for each season is shown in Figs. 2(a1-a4) and 2(b1-b4), respectively, and the relative bias in seasonal mean precipitation of  
179 the SWE3 and EUR20 is estimated against the IBERIA01 [SPREAD] datasets and shown in the Figs. 2(c1-c4) [2(e1-e4)]  
180 and 2(d1-d4) [2(f1-f4)], respectively. The difference in seasonal mean precipitation between SPREAD and IBERIA01 at the  
181 3 km resolution grid is also shown in Figs. 2g1-g4 for each season.

182 The climatological seasonal mean pattern shows that the highest precipitation occurs over the northwestern and  
183 northern regions of the IP in all seasons (Fig. 2). As can be seen from figure 2, the regional to local scales precipitation  
184 pattern with maximum precipitation in the mountainous peaks of the study domain has been produced by kilometeric-scale  
185 simulation (SWE3; a1-a4) compared to the coarser-scale simulation (EUR20; b1-b4) for all four seasons; however, the  
186 SWE3 simulation exhibits less precipitation in almost all areas of the IP (including the surrounding oceans) except for hilly

187 peaks compared to the EUR20 simulation, and perhaps it may be related to improper lateral boundary conditions (LBCs  
188 from EUR20), as it is possible that the LBCs (large-scale forcing fields) used for the SWE3 simulation may already have  
189 biases that can propagate in the SWE3 simulation domain. Several studies have shown that the biases existing in the LBCs  
190 affect the entire limited-area regional climate models (RCMs) domain (Warner et al. 1997; Rinke and Dethloff 2000; Wu et  
191 al. 2005; Diaconescu et al. 2007; Køltzow et al. 2008; Diaconescu & Laprise 2013; Brisson et al. 2015; Panosetti et al.  
192 2019; Rocheta et al. 2014, 2020; Ahrens & Leps 2021). In the next section, we have tried to understand all these and  
193 provided some dynamical factors. On the other hand, a better representation of the topography of mountainous regions in  
194 the SWE3 simulation allows the realistic local mountain-valley circulation and other local-scale processes that lead to a  
195 better representation of the precipitation in these areas (Karki et al. 2017).

196 As can be seen from figure 2, the bias patterns derived from the simulations against/using both observations are  
197 more or less similar to each other in terms of variability with slight differences in magnitude at some locations for all  
198 seasons. On the other hand, we have also noted that the intensity of precipitation varies slightly between the two  
199 observations for all seasons which explains the above-noticed differences, as the SPREAD shows slightly higher  
200 precipitation than the IBERIA01 in almost all regions of the IP (Figs. 2g1-g4), and this may be due to the different  
201 resolutions of both observed datasets. However, the noticeable differences between the two observations have been  
202 observed in the eastern and southern parts of the IP for the DJF and JJA seasons; respectively (Figs. 2g1 & 2g3).

203 The SWE3 simulation shows a dry bias of up to 60% (80% for the JJA) in observed seasonal mean precipitation  
204 especially in the western regions of the IP for all the seasons (Figs. 2c1-c4 & 2e1-e4), while the EUR20 simulation exhibits  
205 relatively low wet precipitation bias over the maximum areas of the western regions of the IP for the MAM and JJA seasons  
206 (Figs. 2d2-d3 & 2f2-f3), and the mixture of dry and wet precipitation biases are observed in these areas for SON and DJF  
207 seasons (Figs. 2d4-d1 & 2f4-2f1). On the other hand, the SWE3 simulation slightly overestimates the observed seasonal  
208 mean precipitation in some parts of the mountainous ranges of the IP for the MAM and SON seasons, whereas in the DJF  
209 season, overestimation of precipitation is noted only in the peaks of the mountains ranges. For the JJA season, the SWE3  
210 substantially underestimates the observed mean precipitation over eastern parts of the IP and overestimates the precipitation  
211 over the south-central parts of the IP and also in some parts of the central and northern plateau mountainous regions of the  
212 IP. Due to the sparse station density in the mountainous regions, there is a larger uncertainty in the observational dataset in  
213 these regions, which may explain the bias of mountainous regions in the simulations. The bias pattern of SWE3 is quite  
214 similar to the bias pattern of EUR20 in the central parts of the IP for all seasons and it is most likely that it inherited from  
215 the driving EUR20 simulation. From the above discussion, It can be concluded that the SWE3 simulated more dry bias in



216 more areas of the IP compared to the EUR20, and severely underestimated the observed mean precipitation especially over  
217 the western parts of the IP.

218 We have also calculated the annual cycle of area-averaged monthly mean precipitation over the Spain landmass  
219 (over the area of SPREAD) and shown in Fig. 3. It can be clearly seen from figure 3 that the SWE3 simulation  
220 underestimates the observed mean precipitation of each month, while the EUR20 simulation is in agreement with the  
221 observed monthly mean precipitation, except in the fall (Fig. 3). The SWE3 simulation underestimates the precipitation by  
222 about 0.7 mm/day in October-March, whereas EUR20 simulated precipitation is much closer to the observations in January-  
223 March and underestimates the precipitation by about 0.3 mm/day in October-December (Fig. 3). It is also noted that the  
224 SWE3 (EUR20) underestimates (overestimates) the precipitation in April-September (Fig. 3). The impact of resolution on  
225 seasonal mean precipitation has also been observed as the SPREAD shows slightly less and high precipitation in January-  
226 September and October-December as compared to the IBERIA01, respectively (Fig. 3), and therefore we can say that the  
227 amount of seasonal mean precipitation can vary with resolution.

228 For the quantitative analysis, the Taylor diagram (Taylor 2001) is constructed using the spatial Index of Agreement  
229 (IOA) and normalized standard deviation (NSD) ratio between observed (i.e. SPREAD and IBERIA01) and simulated  
230 seasonal mean precipitation for each season and shown in supplementary Figs. S1a and S1b. Compared to the observed  
231 NSD value, the EUR20 shows slightly better performance than the SWE3 in the simulation of the spatial variability of  
232 seasonal mean precipitation for each season (Figs. S1a & S1b). The high IOA value ( $\geq 0.79$ ) between the simulated and  
233 observed seasonal mean precipitation for each season indicates good quality of the simulation, although the IOA value is  
234 higher for the EUR20 than for the SW3 (Figs. S1a & S1b). Broadly, it can be inferred that EUR20 performed better in  
235 simulating seasonal mean precipitation for each season than the SWE3.

236 From the above discussion, it is clear that SWE3 simulated less seasonal mean precipitation than EUR20 in almost  
237 all areas of IP. In the light of the results, which show a noticeable sensitivity of precipitation associated with the mountain  
238 ranges, we perform a detailed evaluation focused on the elevation. To do so, the altitudinal variation (with elevation class of  
239 200 m) of simulated and observed seasonal mean precipitation for each season is calculated over the Spain subcontinent at  
240 both resolutions i.e. downscaled (3 km) and upscaled (20 km) using the topography of the SWE3 and EUR20 simulations,  
241 respectively and shown in Fig. 4. The percentage of the total grid points covered by each class in the Spain landmass is also  
242 calculated at 3 km and 20 km resolutions and shown in the Figs. 4d1 & 4d2, respectively. The actual number of rain gauge  
243 stations presented in the IBERIA01 dataset for each class is also shown in Fig. 4a1. A topographic map with rain gauge  
244 stations is not available for the SPREAD data. At the 3km grid, the SWE3 simulation shows less and more mean

245 precipitation than the EUR20 for all seasons (except JJA where the SWE3 shows less mean precipitation in all areas) in  
 246 areas with elevations below and above 1600 m which covers about 97% and 3% of the total grid points of the Spain  
 247 landmass, respectively (Figs. 4a1-d1). At the 20km grid, the SWE3 exhibits less mean precipitation than the EUR20 for the  
 248 MAM and JJA seasons in all the areas, and in DJF and SON seasons, a slight improvement in mean precipitation is seen in  
 249 areas with elevations above 1600 m (Figs. 4a2-d2). It is also noted that both observations show almost the same pattern with  
 250 slight differences in precipitation magnitude and this difference may be due to different resolutions of both observations  
 251 (Fig. 4). Compared with observations, the EUR20 shows better results in the lowlands areas, while SWE3 is comparable in  
 252 the higher elevation classes. In the JJA season, the EUR20 is better in all elevation classes. Overall, we have not found  
 253 added value in the simulation of mean precipitation by the SWE3 in comparison to the parent EUR20 simulation, although,  
 254 in the high-elevation classes, slight differences in the mean precipitation of both simulations have been observed. However,  
 255 due to inaccuracies (due to sparse station density) in observational datasets over the mountainous regions, it is difficult to  
 256 decide which one is accurate. Torma et al. (2015) concluded that in general, the amounts of simulated mean precipitation  
 257 increase with the resolution, i.e., going from the coarser to finer scale simulations, while we have found the opposite results.  
 258 Therefore we can say that this can only be true for complex terrain regions like the Alps (Torma et al. 2015), Himalayas  
 259 (Karki et al. 2017), and also depends on many factors such as the quality of initial- and lateral-BCs, and also on the domain  
 260 size of the RCM simulations (Warner et al. 1997; Rinke and Dethloff 2000; Wu et al. 2005; Diaconescu et al. 2007; Körtzow  
 261 et al. 2008; Diaconescu & Laprise 2013; Brisson et al. 2015; Panosetti et al. 2019; Rocheta et al. 2014, 2020; Ahrens &  
 262 Leps 2021).

### 263 3.2 Spatial distribution of mean moisture transport and its convergence

264 As we observed in the previous section, the SWE3 simulated less seasonal mean precipitation than EUR20 in  
 265 almost all regions of the IP, so in this section, we tried to understand the possible dynamical factors responsible for this. In  
 266 order to understand this, basically, we have calculated the vertically integrated moisture transport (VIMT) and vertically  
 267 integrated moisture flux convergence (VIMFC). The VIMT and VIMFC have been computed using the moisture budget  
 268 equation between surface and 300 hPa, since most water vapour exists below 300 hPa. The mathematical form of these  
 269 equations can be written as:

$$270 \quad VIMFC = -\nabla \cdot \frac{1}{g} \int_{P_{top}}^{P_{sfc}} qVdp = P - E + \frac{\partial w}{\partial t}$$

$$271 \quad w = \frac{1}{g} \int_{P_{top}}^{P_{sfc}} qdp$$

272 
$$VIMT = \frac{1}{g} \int_{P_{top}}^{P_{sfc}} qVdp$$

273 where  $\nabla \cdot ()$  is the horizontal divergence in pressure coordinates,  $g$  is the gravity acceleration,  $q$  is the  
 274 specific humidity,  $p$  and  $P_{sfc}$  are the surface air pressure,  $P_{top}$  is the surface air pressure at the top of the  
 275 atmosphere (300 hPa in our case),  $V = (u, v)$  is the horizontal wind vector,  $P$  is the precipitation rate,  $E$  is the  
 276 evaporation rate, and  $w$  is the total precipitable water and it can be referred to as the storage term. For negligible storage  
 277 or annual time scales, the term  $\partial w / \partial t$  can be neglected (Cullather et al. 2000).

278 The seasonal mean VIMT pattern for the SWE3 (interpolated on the 20 km grid) and EUR20 simulations for each  
 279 season is shown in Figs. 5a1-a4 and 5b1-b4; respectively. Similarly, the seasonal mean VIMFC pattern for the SWE3 and  
 280 EUR20 simulations is shown in the Figs. 6a1-a4 and 6b1-b4; respectively. The spatial pattern of the VIMT and VIMFC  
 281 clearly highlights the seasonal difference between SWE3 and EUR20 simulations in terms of the magnitude and spatial  
 282 extent of the large-scale transport of moisture over the IP for all seasons (Figs. 5 and 6). The Atlantic Ocean (with the  
 283 westerly circulation flow) has been found to be one of the major source of moisture for precipitation over the IP (Gimeno et  
 284 al. 2010; Gimeno et al. 2012; Şahin et al. 2015). This transport of moisture-laden westerly movement of winds (west-east)  
 285 from the Atlantic Ocean towards the IP which contributes to the convergence over the IP, can be clearly seen in the EUR20  
 286 simulation, and also this pattern is quite persistent for all seasons. However, the slight west-southeast shift in the west-east  
 287 winds over the Atlantic Ocean has been noted for all seasons except the DJF season, although this signal is more dominant  
 288 in the JJA season, and this can be associated with the formation of a thermal low-pressure system over the Iberian Peninsula  
 289 that slightly deviates the westerly flow to the southeast direction (Font 1983; Martín et al. 2001; Hoinka and Castro 2003).  
 290 The thermal low over the IP is more frequent in summer, but it also occurs in spring and autumn (Font 1983). In summer,  
 291 the tropical circulation patterns are well known to be associated with southerly and southeasterly warmer wind flows, which  
 292 dominate over most of the Mediterranean basin, especially in the eastern Mediterranean region (Şahin et al. 2015), and  
 293 consequently, the southerly blow of winds coming from the southern region towards the northeast direction and its turn to  
 294 the southeastern direction around the eastern Mediterranean have also been observed, and this resulting pattern is mainly  
 295 from the northward motion of the inter-tropical convergence zone (ITCZ) and the thermally originated south-Asian  
 296 monsoon low (Rodwell and Hoskins 1996; Türkeş and Erlat 2006; Şahin et al. 2015), which controls specific humidity over  
 297 the Mediterranean basin and the land areas around it.

298 In the SWE3 simulation, the direction of the wind pattern is significantly different from the EUR20 simulation  
299 (Figs. 5 and 6). The first difference is that the westerly circulation pattern is shifted southward in all seasons, although this  
300 shift is observed below 40°N in the DJF season. The shift in the wind patterns leads to a decrease in the transport of  
301 moisture towards the IP from the Atlantic Ocean, leading to a decrease in precipitation over the IP, particularly in the  
302 western region of the IP, and this is also clear from the VIMFC pattern. Apart from the southward shift, a decline in wind  
303 strength has also been observed, especially in the western parts of the domain, although the wind strength is slightly higher  
304 over the southwestern boundary/border in all seasons except DJF season (wind strength is slightly lower in DJF) and this  
305 may be due to the adverse effects of boundary conditions. On the other hand, there is an enhancement of southerly winds  
306 (with slightly shifted towards the north) over the Mediterranean basin, and eastern and central regions of the IP has also  
307 been observed, which further effectively affects the humidity of these regions as these winds are warm and dry, leading to a  
308 decrease in precipitation, and this is also evident from the VIMFC pattern. However, this signal is more prominent in  
309 summer and weaker in winter. In the northern region, the northeasterly movement (north-northeast) of winds has been  
310 observed instead of the westerly flow (west-east), which explains the decrease in precipitation in these regions. We observed  
311 similar results on a 3 km grid (figures not shown).

312 Overall, the large-scale transport of moisture patterns obtained from both simulations explains the differences in  
313 precipitation of both simulations. The circulation patterns acquired from the EUR20 simulation are consistent with previous  
314 studies. On the other hand, the circulation patterns obtained from the SWE3 simulation is quite different from the EUR20  
315 simulation in terms of intensity as well as the direction of the winds, and we also noticed that the differences in circulation  
316 patterns start at the boundary of the SWE3 domain for all seasons, therefore, here it appears that the large scale forcing  
317 fields and its lateral boundary conditions (LBC)-associated errors are also playing a role in the modulation of winds, as the  
318 impact of LBC errors represents an important issue in the RCM simulations (Warner et al. 1997; Rinke and Dethloff 2000;  
319 Wu et al. 2005; Diaconescu et al. 2007; Køltzow et al. 2008; Diaconescu & Laprise 2013; Brisson et al. 2015; Panosetti et  
320 al. 2019; Rocheta et al. 2014, 2020; Ahrens & Leps 2021). Diaconescu & Laprise (2013) suggested that the RCMs can  
321 bring some reduction of errors in large scales when very large domains are used. Additional modeling experiments are  
322 needed for a better understanding of these aspects.

### 323 **3.3 Spatio-temporal distribution of wet-day precipitation frequency and Intensity**

324 The spatial distribution of the frequency and intensity of daily mean precipitation (days where the precipitation  $\geq$   
325 1mm) is calculated for each season during 2000-2009 for both simulations and observations and shown in Fig. 7. Figures  
326 7a1-a4 (7e1-e4), 7b1-b4 (7f1-f4), 7c1-c4 (7g1-g4), and 7d1-d4 (7h1-h4) show the spatial distribution of the precipitation

327 frequency (intensity) obtained from the EUR20, SWE3, IBERIA01, and SPREAD, respectively. We have also calculated the  
328 altitudinal variation (similar to Fig. 4) of the frequency and intensity of the wet-day precipitation for each season at both  
329 resolutions for quantitative assessment and shown in Figs. 8 and 9, respectively. We have taken only the Spain subcontinent  
330 (area of SPREAD) in the altitudinal variation calculation.

331 We find that the SWE3 simulation significantly reduced the frequency of the wet-day precipitation not only over  
332 the land points of the IP but also over the surrounding oceans for all the seasons compared to EUR20 simulation (Figs. 7a1-  
333 a4 and 7b1-b4), while it produces more intense wet-day precipitation over the IP subcontinent (Figs. 7e1-e4 and 7f1-f4). In  
334 general, convection-permitting models tend to produce less frequent but more intense precipitation intensities compared to  
335 coarse resolution models (Berthou et al. 2018; Chan et al. 2020; Ban et al. 2021). Moreover, significant differences have  
336 also been observed in the magnitude of frequency and intensity of the wet-day precipitation obtained from both  
337 observations, as the SPREAD shows less frequent but more intense precipitation than the IBERIA01, and therefore we can  
338 say that the frequency and intensity of precipitation vary with resolution (Fig. 7). The above results are also evident from  
339 Figs. 8 and 9. On the other hand, the spatial structure of the frequency and intensity of wet-day precipitation derived from  
340 the SWE3 (EUR20) shows comparable similarities with respect to the SPREAD (IBERIA01) with slight variations in the  
341 magnitude of the frequency and intensity of the wet-day precipitation at some locations for all seasons, respectively and it  
342 may be because of the finer and coarser resolutions of the observed products (Fig. 7). A detailed comparison of the obtained  
343 simulation results with the observed one is discussed below.

344 The SWE3 simulation substantially underestimates the observed wet-day frequency obtained from the SPREAD  
345 over the northwest corner of the IP, and slightly underestimation is noted in most of the other parts of IP for all seasons  
346 (Figs. 7b1-b4 and 7d1-d4), and these results are more pronounced with altitudinal variation (Fig. 8). The altitudinal  
347 variation of the wet-day frequency obtained from the SWE3 reflects a slight overestimation of frequency compared to  
348 SPREAD for the DJF and MAM seasons in the higher elevation classes, and slightly underestimates the observed frequency  
349 of the rest areas for all seasons (Fig. 8). In the JJA season, the model correctly simulated the observed frequency in areas of  
350 the lowlands. The EUR20 simulation shows almost the same amount of the wet-day frequency compared to the IBERIA01  
351 for the DJF and SON seasons (Figs. 7a1,a4 and 7c1,c4) with slight overestimation of the frequency in the higher elevation  
352 classes (Fig. 8), and notably overestimates the wet-day frequency in the northern parts of the IP for the MAM and JJA  
353 seasons (Figs. 7a2,a3 and 7c2,c3) and consequently overestimation of the observed wet-day frequency by the EUR20 is  
354 noted in all elevation classes (Fig. 8). Compared with the SPREAD, we find the added value in the simulation of wet-day

355 frequency by SWE3 over the parent EUR20, while the performance of the SWE3 deteriorates when compared with  
356 IBERIA01.

357 It can be clearly seen that the finer-scale spatial variability with peaks in the mountainous regions of the observed  
358 wet-day intensity is relatively well captured by the SWE3 (Fig. 7). The EUR20 simulation significantly underestimates the  
359 wet-day intensity in almost all regions of the IP as compared to both observations for all seasons, although the maximum  
360 difference in wet-day intensity has been observed with the SPREAD (Fig. 7) and can also be seen clearly from the Fig. 9.  
361 The SWE3 simulates more intense wet-day precipitation than the EUR20 in almost all regions of the IP for all seasons (Fig.  
362 7) however, we have not observed much difference in the precipitation of lowlands areas (in areas below 600 m for JJA  
363 season and 200 m for the rest of the season) between the two simulations for all seasons (Fig. 9). Compared to the  
364 IBERIA01, the SWE3 simulation overestimates the wet-day precipitation in most areas of the IP, except that it shows an  
365 underestimation of precipitation in some areas in the northwest corner and Mediterranean coasts of southwest and eastern  
366 Spain for all the seasons (Figs. 7f1-f4 and 7g1-g4). It is also clear from figure 9 that the SWE3 simulation slightly  
367 underestimates the observed (IBERIA01) wet-day precipitation of lowland areas (in areas below 600 m for DJF season and  
368 400 m for the rest of the season) and overestimates the observed precipitation in the rest of areas for all the seasons. While  
369 compared to the SPREAD, the SWE3 simulation underestimates the wet-day precipitation in almost all regions of the IP for  
370 all the seasons, although some overestimation of precipitation is noted in the northern and southern plateau regions of the IP  
371 for the MAM season and western parts of the Pyrenees for the DJF season (Figs. 7f1-f4 and 7h1-h4). It can also be seen  
372 from figure 9 that the SWE3 simulation underestimates the observed (SPREAD) wet-day precipitation of all altitude classes  
373 for JJA and SON seasons and slightly overestimates the observed precipitation of mountainous regions for the DJF and  
374 MAM seasons, and also we have not seen much difference in wet-day precipitation between the SWE3 and SPREAD for  
375 the MAM season in areas with elevations of more than 400 m (Fig. 9). Overall, the added value in the SWE3 simulation is  
376 found in the reproduction of wet-day intensity as compared to the EUR20 for all seasons.

377 For the quantitative assessment of simulation performance, the Taylor diagram is produced using the spatial IOA  
378 and NSD ratio between observed and simulated frequency and intensity of the wet-day precipitation for each season and  
379 shown in supplementary Fig. S2. It is clear from the IOA value that the spatial pattern of the wet-day frequency and  
380 intensity of the SPREAD (IBERIA01) are better represented by SWE3 (EUR20) than the EUR20 (SWE3) except for the  
381 case of the wet-day intensity of the IBERIA01 for the DJF season where the SWE3 exhibits a higher IOA value than the  
382 EUR20 (Fig. S2). It is also noted that the EUR20 overestimates the spatial variability (NSD) of the observed wet-day  
383 frequency for all seasons, while the SWE3 underestimates it (Figs. S2a and S2c). The spatial variability of the wet-day

384 frequency of the SPREAD (IBERIA01) is captured quite well by the EUR20 than the SWE3 for the DJF season (DJF-MAM  
385 seasons), and the SWE3 shows better skill in simulating the observed spatial variability compared to the EUR20 for the rest  
386 of the season (Fig. S2a and S2c). The SWE3 shows better skill in predicting the observed spatial variability of the wet-day  
387 intensity than the EUR20 for all the seasons (Figs. S2b and S2d), although SWE3 notably underestimates the observed  
388 (SPREAD) spatial variability of the wet-day intensity (Fig. S2b).

389 In summary, SWE3 simulated less frequent but more intense wet-day precipitation intensities compared to EUR20  
390 and it is consistent with previous studies (Chan et al. 2020; Ban et al. 2021). We have also found a large difference in the  
391 intensity and frequency of wet-day precipitation between the two observations, as the SPREAD showed less frequent but  
392 more intense precipitation compared with the IBERIA01, and the SWE3 (EUR20) simulation showed a good similarity with  
393 the observed SPREAD (IBERIA01), and it highlights the importance of having high-resolution good quality observed  
394 datasets for regional-to-local scale assessments. One thing is clear (with the observational evidence) from the above  
395 discussion that the higher resolution datasets have less frequent but more intense wet-day precipitation intensities compared  
396 to the coarser resolution datasets, and also point towards the need of the high-resolution good quality of observational  
397 datasets for good estimation.

### 398 **3.4 Probability distribution of daily mean precipitation**

399 So far we have noted that the SWE3 simulated less seasonal mean precipitation as compared to the EUR20 as well  
400 as the observations. It has also been noted the significant differences in the wet-day frequency and intensity of both  
401 simulations as well as in the observations. However, differences in precipitation amounts and comparative results have been  
402 observed for the lowlands and mountainous regions. So for a better view and for the better comparison of the magnitude of  
403 the precipitation of lowlands and mountainous regions at each grid cell, we have classified the total area of the Spain  
404 landmass into two elevation classes, which is low (area between the altitudes of  $\geq 0$  and  $\leq 1000$  m; which covers about  
405 82% of the total grid points) and high (area above the altitudes of 1000 m; which covers about 18% of the total grid points)  
406 and we computed the PDFs of the daily mean precipitation for each category for all seasons at 3km [20km] resolution grids  
407 and shown in the Figs. 10(a-d) [supplementary: S3(a-d)] and 11(a-d) [supplementary: S4(a-d)], respectively. The PDFs of  
408 daily mean precipitation for the lowlands and mountainous regions at both grids clearly reveal the added value of the fine-  
409 scale simulation over the coarse-scale simulation for all seasons. The significant differences in the PDFs tails of both  
410 observations are also observed for all seasons, and it may be due to the different resolution of both datasets as we earlier  
411 discussed.

412 In the lowlands regions at fine-scale grid (3 km), the SWE3 simulated PDF tail is more in line with the tail of the  
413 IBERIA01 than the SPREAD with slightly underestimations of the low- to moderate-intensity tails of the IBERIA01 for the  
414 DJF season (Fig. 10a). For the MAM and SON seasons, the tail of the SWE3 is in between the tails of the two observations  
415 with slightly underestimations of the low and high intensity tails of the IBERIA01 and SPREAD; respectively and notably  
416 underestimations and overestimations of the low- to moderate-intensity and moderate- to high- intensity tails of the  
417 SPREAD and IBERIA01; respectively (Figs. 10b & 10d). For the JJA season, the SWE3 run slightly overestimates and  
418 underestimates the low intensity events ( $\leq 35$ mm/day) of the IBERIA01 and SPREAD; respectively and significantly and  
419 slightly overestimates the occurrence of medium- to high-intensity events of the IBERIA01 and SPREAD; respectively  
420 (Fig. 10c). It is also noted that the SWE3 underestimates the frequency of occurrence of the intense extreme events of the  
421 SPREAD for all the seasons except for the JJA season, where the SWE3 shows an overestimation (Fig. 10). In the  
422 mountainous region at 3 km grid (Fig. 11), the SWE3 tail is in between the two observations and more in line with the tail of  
423 the SPREAD than the IBERIA01 for all the seasons except for the low intensity tail ( $\leq 20$ mm/day) of the JJA season,  
424 where the SWE3 shows underestimation of precipitation intensity with both observations (Fig. 11). The SWE3  
425 underestimates the tail of the SPREAD for all the seasons except for the MAM season where the SWE3 tail corresponds to  
426 the tail of the SPREAD, although the underestimation is larger for the DJF season (Fig. 11). We have also noted that the  
427 SWE3 underestimates the frequency of occurrence of the high-intensity events of the SPREAD for all seasons except for the  
428 MAM season (Fig. 11). In the mountainous region at 3 km grid, we have noted maximum differences not only in the  
429 moderate- to high- intensity tails of both observations but also in the moderate- to high- intensity tails of both simulations  
430 for all seasons (Fig. 11). However, since the observational rain gauge network stations are very sparse over the higher  
431 mountainous areas (e.g. Pyrenees, Baetic, Cantabrian mountains, etc. of the IP) thereby having considerable uncertainties in  
432 measurements/estimation of excessive rainfall as well, particularly for studying extreme events, so it is difficult to determine  
433 which estimation (observation or model) is correct for the higher mountainous regions. It is clear from the above discussion  
434 that the maximum added value of the fine-scale simulation over the driving coarse-scale simulation is found in the  
435 mountainous region.

436 The PDFs of the upscaled daily mean precipitation for the lowlands and mountainous regions at the coarser  
437 resolution grid (20 km) clearly illustrate the added value of the SWE3 over the EUR20 in the occurrence of the moderate- to  
438 high- intensity events and the tail of SWE3 is closer to the tail of the observations than to the EUR20, while it worsens the  
439 results in the case of the low-intensity events as compared to observations for all the seasons (Figs. S3 & S4). In the  
440 lowlands regions at 20km grid, the moderate- to high- intensity tails of the SWE3 lies between the tails of both observations



441 for the JJA season, and the SWE3 underestimates the observed tails for the rest of the season, however, this underestimation  
442 is very less with the IBERIA01 than with the SPREAD (Fig. S3). In the mountainous region at the upscaled grid, the  
443 moderate- to high-intensity tails of the SWE3 lies between the tail of the IBERIA01 and the SPREAD for all seasons,  
444 although the SWE3 slightly underestimates and overestimates the occurrence of the high-intensity events of the IBERIA01  
445 and the SPREAD; respectively (Fig. S4).

446 In summary, we have found that the significant added value in the simulation of moderate- to high- intensity events  
447 of the daily precipitation by the SWE3 compared to the driving EUR20, not only at the downscaled finer-scale grids but also  
448 when the datasets are upscaled at the coarser-scale grids. However, the maximum added value is seen in the mountainous  
449 region at both grids. We have also observed notable differences in the tails of the distribution of both observations, and the  
450 simulated PDFs are comparable with the observed PDFs.

451 For more quantitative analysis, we have also computed the point-wise K-S distance between the simulated and  
452 observed empirical cumulative distribution functions (ECDFs) of the daily precipitation for each season during 2000-2009  
453 at both resolution grids i.e. 3 km and 20 km and shown in the Figs. 12 and S5 (supplementary), respectively. Figures 12a1-  
454 a4 (12c1-c4) and 12b1-b4 (12d1-d4) show the statistics obtained from the SWE3 and EUR20 using IBERIA01 (SPREAD)  
455 observation for each season at the 3 km resolution, respectively. Similarly, supplementary figure S5 shows the statistics  
456 obtained at the 20 km resolution grid. With the IBERIA01, the KS distance is higher for the SWE3 than the EUR20, while  
457 with the SPREAD, the distance is lower for the SWE3 than the EUR20 in almost all over the study domain for each season  
458 at both resolution grids (Figs. 12 & S5), and it points towards the importance of observed resolution datasets in the  
459 comparison of the model simulated outputs. In other words, the added value of SWE3 over the driving EUR20 is obtained  
460 with the SPREAD in the representation of KS distance, while with the IBERIA01, SWE3 performance is worse than  
461 EUR20 and it may be due to the coarser resolution of the IBERIA01 datasets (Figs. 12 & S5). From the above discussion, it  
462 is clear that the KS distance of both simulations varies with the observed resolution, for example, the SWE3 produces the  
463 lower value of the KS distance with the SPREAD than IBERIA01 and the opposite is true in the case of the EUR20, and it  
464 is likely due to the fact that the tail of the distribution varies with resolution and that can be clearly seen from the PDFs  
465 plots. It can also be suggested from the above discussion that the model simulated datasets must be compared with the same  
466 or nearly identical resolution observational datasets for better estimation, and also interpolating the dataset has no effect on  
467 the actual conclusion.

### 468 **3.5 Spatio-temporal distribution of heavy/extreme precipitation**

469 To examine the added value of the fine-scale simulation over the driving coarser-scale simulation in the simulation  
470 of heavy/extreme precipitation, we have computed the 99th percentile (R95p) of the daily mean precipitation and highest  
471 one-day precipitation amount (Rx1day) in this section, and the obtained results are shown in figure 13. Figures a1-a4 (e1-  
472 e4), b1-b4 (f1-f4), c1-c4 (g1-g4), and d1-d4 (h1-h4) show the spatial distribution of the Rx1day (R95p) for the EUR20,  
473 SWE3, IBERIA01, and SPREAD, respectively. The regional to local scales precipitation pattern with clear added value in  
474 the SWE3 simulation is observed in the representation of extreme precipitation as compared to the EUR20 for both metrics  
475 for all seasons (Fig. 13). It has also been observed that both observations show almost similar precipitation patterns in terms  
476 of spatial variability, although some differences in precipitation magnitudes have been noted (Fig. 13). It can be also seen  
477 from Fig. 13 that the SWE3 simulation captures the observed precipitation pattern to a great extent, however, there are some  
478 biases in the precipitation magnitude at some places, particularly in the southwestern and northwestern regions of Spain and  
479 the Mediterranean coasts, but here, we must also take into account the observational uncertainties in the  
480 estimation/representation of extreme precipitation events.

481 For more quantitative assessment, we computed the altitudinal variation (similar to Fig. 4) of the R95p and Rx1day  
482 for each season at both resolutions and shown in supplementary Figs. S6 and S7, respectively. It can be seen from the figure  
483 that the km-scale simulation shows a clear improvement over the coarse-resolution simulation in the representation of  
484 extreme precipitation in almost all the altitudinal classes for all seasons at both grids. However, in the case of R95p, the  
485 SWE3 simulated slightly less precipitation than the EUR20 in areas  $\leq 200$  m for MAM & SON seasons, areas  $\leq 400$  m  
486 for JJA, and areas  $\leq 600$  m for DJF. On the other hand, differences in the precipitation magnitude of both observations  
487 have also been observed in both cases (R95p and Rx1day), although this difference is larger for higher elevation classes  
488 (Figs. S6 & S7). Furthermore, we noted that the SWE3 simulation underestimates the observed R95p precipitation in  
489 lowlands areas and shows a good agreement with observations for the higher elevation classes with slight variation in the  
490 magnitude of the precipitation (Fig. S6). In the case of Rx1day, the SWE3 is in agreement with the observed precipitation  
491 for all elevation classes with slight variation in the precipitation magnitude (Fig. S7). Overall, these results demonstrate a  
492 clear advantage of km-scale simulations in the representation of high-impact precipitation events.

493 In quantitative terms (Taylor diagram), it is clear from the high IOA value between simulation and observation that  
494 the predictive skill of the simulation is greater in the representation of observed extreme precipitation patterns  
495 (supplementary Fig. S8). It has also been noted that the IOA value is higher for the R95p than the Rx1day. The SWE3  
496 shows better results than the EUR20 in the representation of the observed (SPREAD) spatial variability of both extreme  
497 indices for all seasons, although we have not seen much difference in the IOA value obtained from both simulations for all

498 seasons except JJA, where the EUR20 reflects higher IOA value than the SWE3 (Figs. S8a & S8b). On the other hand, the  
499 EUR20 shows a higher IOA value than the SWE3 for the MAM and JJA seasons with the IBERIA01, and we have not seen  
500 much difference in the IOA value for the remaining two seasons (Figs. S8c & S8d). In the case of R95p, the SWE3  
501 simulated NSD value is closer to the observed one (IBERIA01) for all seasons except JJA, while in the case of Rx1day, the  
502 SWE3 (EUR20) simulated NSD value is closer to the observed one for DJF-SON (MAM-JJA) seasons (Figs. S8c & S8d).

#### 503 **4. Summary and Conclusions**

504 The aim of this study is to evaluate the added value of the convection-permitting simulation (3 km, SWE3)  
505 compared to the driving coarser-resolution parameterized convection simulation (20 km, EUR20) in the representation of  
506 the spatio-temporal pattern of the observed mean and extreme precipitation over the Iberian Peninsula (IP) for all four  
507 seasons (i.e. Winter, Spring, Summer, and Autumn) during 2000-2009. Both simulations are performed with the recently  
508 developed RegIPSL regional earth system model in the frame of the EUCP H2020 project and CORDEX. The coarser-scale  
509 simulation (20 km grid) is forced by the 6-hourly ERA-Interim (0.75° resolution) initial and lateral boundary conditions  
510 (IC-LBCs), while the finer-scale simulation (3km grid) is driven by the 3-hourly coarser-scale simulated IC-LBCs. The  
511 model results are evaluated against two available high-resolution daily gridded observational datasets i.e. SPREAD (5 km  
512 grid) and IBERIA01 (10 km grid), and we have also compared the results obtained from the two observations.

513 No clear benefit/added-value of the convection-permitting simulation has been found in the reproduction of  
514 observed seasonal mean precipitation of the Iberian Peninsula except the spatial variation over hilly peaks compared to  
515 coarse-scale simulation for all seasons. The observed spatio-temporal pattern and variability of the seasonal mean  
516 precipitation are quantitatively better represented by the EUR20 than the SWE3 simulation. The km-scale simulation  
517 substantially underestimates the observed seasonal mean precipitation especially over the western parts of the IP compared  
518 to the EUR20 simulation which explains that on average over the whole IP. The SWE3 simulation shows a southward shift  
519 of the westerly winds at the western side of the Iberian peninsula compared to the EUR20 simulation, reflecting/indicating a  
520 decrease in moisture transport from the Atlantic Ocean towards the IP leading to a decrease in the precipitation.  
521 Additionally, the escalation of southerly winds over the IP has also been observed, bringing warm and dry air which further  
522 affects moisture transport effectively, leading to a decrease in precipitation. We speculate that the changes in the behavior of  
523 circulation patterns in the SWE3 simulation probably attribute to either poor representation of lateral boundary conditions  
524 (LBCs) or poor selection of domain or poor land-surface initialization. Several hypothesis-driven modeling experiments are  
525 needed to better understand these results. It would be interesting to first see the behavior of the convection-permitting  
526 simulation by running the model with a larger domain size but that would require significant computational resources/costs.

527           The clear improvement of kilometric-scale simulation over the driving coarser-scale simulation has been found in  
528 the representation of the spatio-temporal distribution of the Kolmogorov-Smirnov (K-S) distance, wet-day precipitation  
529 frequency and intensity, and also in the reproduction of the heavy precipitation events for each season at both resolutions i.e.  
530 downscaled and upscaled. On the other hand, it has also been noted that the spatio-temporal distribution of precipitation for  
531 all metrics used varies between the two observational datasets for all seasons, although differences are weaker in the case of  
532 the seasonal mean precipitation and larger/notable for the wet-day precipitation frequency and intensity and also for the case  
533 of the extreme precipitation events. In quantitative terms, the SPREAD shows less frequent but more intense wet-day  
534 precipitation and more intense extreme precipitation amounts than the IBERIA01, and this variation may be due to the  
535 different resolutions of the observational datasets, and it also highlights the importance of having high-resolution good-  
536 quality observed datasets for regional-to-local scale assessments. Also, we have observed that the km-scale simulated results  
537 are more comparable and closer to the SPREAD than the IBERIA01 and the opposite is true in the case of coarser-scale  
538 simulation, which emphasizes the fact that the model simulated precipitation should be compared with similar or nearly  
539 identical resolution observational datasets for better evaluation/estimation. It is likely true that we should use the SWE3  
540 simulation to study high-impact weather events because of the intensity of the events. On the other hand, in the  
541 mountainous/hilly regions, it is difficult to determine which estimate is correct because observational rain gauge network  
542 stations in these areas are very sparse, leading to considerable uncertainty in the measurement of the precipitation.

543           These results demonstrate a clear advantage of using a RegIPSL model at the kilometric-scale over the Iberian  
544 Peninsula in the simulation for high-impact weather events, consistently with previous studies over other areas, and also  
545 point towards the need of the very high-resolution good-quality of observational datasets for the accurate evaluation of  
546 model-simulated results.

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559 **Conflicts of interest/Competing interests:** The authors declare that they have no conflict of interest.

560 **Availability of data and material:** The datasets used in this work are available on request from the corresponding author.

561 **Code availability:** The analysis codes are available on request from the corresponding author.

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585 **References**

- 586 Ahrens B, Leps N (2021) Sensitivity of Convection Permitting Simulations to Lateral Boundary Conditions in Idealised  
587 Experiments. *Earth and Space Science Open Archive ESSOAr*. <https://doi.org/10.1002/essoar.10506295.1>
- 588 Ban N, Caillaud C, Coppola E et al (2021) The first multi-model ensemble of regional climate simulations at kilometer-  
589 scale resolution, part I: evaluation of precipitation. *Clim Dyn*. <https://doi.org/10.1007/s00382-021-05708-w>
- 590 Bechtold P, Chaboureau J-P, Beljaars A, Betts AK, Kohler M, Miller M, Redelsperger J-L (2004) The simulation of the  
591 diurnal cycle of convective precipitation over land in a global model. *Q J R Meteorol Soc* 130:3119-3137.  
592 <https://doi.org/10.1256/qj.03.103>
- 593 Berthou S, Kendon E, Chan S, Ban N, Leutwyler D, Schar C, Fosser G (2018) Pan-European climate at convection-  
594 permitting scale: a model intercomparison study. *Clim Dyn* 55:35-59. <https://doi.org/10.1007/s00382-018-4114-6>
- 595 Brisson E, Demuzere M, van Lipzig NP (2015) Modelling strategies for performing convection-permitting climate  
596 simulations. *Meteorol Z* 25(2):149-163. <https://doi.org/10.1127/metz/2015/0598>
- 597 Brisson E, Van Weverberg K, Demuzere M, Devis A, Saeed S, Stengel M, van Lipzig NP (2016) How well can a  
598 convection-permitting climate model reproduce decadal statistics of precipitation, temperature and cloud characteristics?  
599 *Clim Dyn* 47(9-10):3043-3061. <https://doi.org/10.1007/s00382-016-3012-z>
- 600 Brockhaus P, Lüthi D, Schär C (2008) Aspects of the diurnal cycle in a regional climate model. *Meteorol Z* 17:433-443.  
601 <https://doi.org/10.1127/0941-2948/2008/0316>
- 602 Broucke SV, Wouters H, Demuzere M, van Lipzig NP (2019) The influence of convection-permitting regional climate  
603 modeling on future projections of extreme precipitation: dependency on topography and timescale. *Clim Dyn* 52(9):5303-  
604 5324. <https://doi.org/10.1007/s00382-018-4454-2>
- 605 Chakravarty IM, Laha RG, Roy J (1967) *Handbook of methods of applied statistics, Volume I*. John Wiley and Sons,  
606 Hoboken, NJ, pp 392-394
- 607 Chan SC, Kendon EJ, Berthou S, Fosser G, Lewis E, Fowler HJ (2020) Europe-wide precipitation projections at convection  
608 permitting scale with the Unified Model. *Clim Dyn* 55:409-428. <https://doi.org/10.1007/s00382-020-05192-8>
- 609 Chang W, Wang J, Marohnic J, Kotamarthi VR, Moyer EJ (2020) Diagnosing added value of convection-permitting regional  
610 models using precipitation event identification and tracking. *Clim Dyn* 55(1):175-192. <https://doi.org/10.1007/s00382-018->  
611 4294-0

612 Coppola E, Sobolowski S, Pichelli E, Raffaele F, Ahrens B, Anders I, Ban N, Bastin S, Belda M, Belusic D et al (2020) A  
613 first-of-its-kind multi-model convection permitting ensemble for investigating convective phenomena over Europe and the  
614 Mediterranean. *Clim Dyn* 55:3-34. <https://doi.org/10.1007/s00382-018-4521-8>

615 Cullather RI, Bromwich DH, Serreze MC (2000) The atmospheric hydrologic cycle over the Arctic basin from reanalysis.  
616 Part I: comparison with observation and previous studies. *J Clim* 13:923:937. <https://doi.org/10.1175/1520->  
617 [0442\(2000\)013%3C0923:TAHCOT%3E2.0.CO;2](https://doi.org/10.1175/1520-0442(2000)013%3C0923:TAHCOT%3E2.0.CO;2)

618 Dee DP, Uppala SM, Simmons AJ et al (2011) The ERA-Interim reanalysis: configuration and performance of the data  
619 assimilation system. *Q J R Meteorol Soc* 137:535-597. <https://doi.org/10.1002/qj.828>

620 Déqué M, Rowell MP, Lüthi D, Giorgi F, Christensen JH, Rockel B, Jacob D, Kjellström E, de Castro M, van den Hurk B  
621 (2007) An intercomparison of regional climate simulations for Europe: assessing uncertainties in model projections. *Clim*  
622 *Change* 81:53-70. <https://doi.org/10.1007/s10584-006-9228-x>

623 Diaconescu EP, Laprise R (2013) Can added value be expected in RCM-simulated large scales? *Clim Dyn* 41(7):1769-1800.  
624 <https://doi.org/10.1007/s00382-012-1649-9>

625 Diaconescu EP, Laprise R, Sushama L (2007) The impact of lateral boundary data errors on the simulated climate of a  
626 nested regional climate model. *Clim Dyn* 28(4):333-350. <https://doi.org/10.1007/s00382-006-0189-6>

627 Fita L, Polcher J, Giannaros TM, Lorenz T, Milovac J, Sofiadis G, Katragkou E, Bastin S (2019) CORDEX-WRF v1.3:  
628 development of a module for the Weather Research and Forecasting (WRF) model to support the CORDEX community.  
629 *Geosci Model Dev* 12(3):1029-1066. <https://doi.org/10.5194/gmd-12-1029-2019>

630 Font I (1983) *Climatología de España y Portugal (Climate of Spain and Portugal)*. Inst Nacional de Meteorología.  
631 Ministerio de Transportes y Comunicaciones de Madrid, pp 296

632 Fosser G, Khodayar S, Berg P (2015) Benefit of convection permitting climate model simulations in the representation of  
633 convective precipitation. *Clim Dyn* 44:45-60. <https://doi.org/10.1007/s00382-014-2242-1>

634 Frei C, Christensen JH, Dèquè M, Jacob D, Jones RG, Vidale PL (2003) Daily precipitation statistics in regional climate  
635 models: evaluation and intercomparison for the European Alps. *J Geophys Res Atmos* 108:4124.  
636 <https://doi.org/10.1029/2002JD002287>

637 Fumière Q, Déqué M, Nuissier O, Somot S, Alias A, Caillaud C, Laurantin O, Seity Y (2019) Extreme rainfall in  
638 Mediterranean France during the fall: added-value of the CNRM-AROME Convection-Permitting Regional Climate Model.  
639 *Clim Dyn* 55:77-91. <https://doi.org/10.1007/s00382-019-04898-8>

640 Gimeno L, Nieto R, Trigo RM, Vicente-Serrano SM, López-Moreno JI (2010) Where does the Iberian Peninsula moisture  
641 come from? An answer based on a Lagrangian approach. *J Hydrometeorol* 11:421-436.  
642 <https://doi.org/10.1175/2009JHM1182.1>

643 Gimeno L, Stohl A, Trigo RM, Dominguez F, Yoshimura K, Yu L, Drumond A, Durán-Quesada AM, Nieto R (2012)  
644 Oceanic and terrestrial sources of continental precipitation. *Rev Geophys* 50(4):RG4003.  
645 <https://doi.org/10.1029/2012RG000389>

646 Helsen S, van Lipzig NP, Demuzere M, Broucke SV, Caluwaerts S, De Cruz L, De Troch R, Hamdi R, Termonia P, Van  
647 Schaeybroeck B, Wouters H (2020) Consistent scale-dependency of future increases in hourly extreme precipitation in two  
648 convection-permitting climate models. *Clim Dyn* 54(3):1267-1280. <https://doi.org/10.1007/s00382-019-05056-w>

649 Herrera S, Cardoso RM, Soares PM, Espírito-Santo F, Viterbo P, Gutiérrez JM (2019) Iberia01: a new gridded dataset of  
650 daily precipitation and temperatures over Iberia. *Earth Syst Sci Data* 11:1947-1956. [https://doi.org/10.5194/essd-11-1947-](https://doi.org/10.5194/essd-11-1947-2019)  
651 2019

652 Hohenegger C, Brockhaus P, Schär C (2008) Towards climate simulations at cloud-resolving scales. *Meteorol Z* 17(4):383-  
653 394. <https://doi.org/10.1127/0941-2948/2008/0303>

654 Hoinka KP, Castro MD (2003) The Iberian peninsula thermal low. *Quarterly Journal of the Royal Meteorological Society: Q*  
655 *J R Meteorol Soc* 129(590):1491-1511. <https://doi.org/10.1256/qj.01.189>

656 Karki R, Gerlitz L, Schickhoff U, Scholten T, Böhner J (2017) Quantifying the added value of convection-permitting  
657 climate simulations in complex terrain: a systematic evaluation of WRF over the Himalayas. *Earth Syst Dynam* 8:507-528.  
658 <https://doi.org/10.5194/esd-8-507-2017>

659 Karl TR, Nicholls N, Ghazi A (1999) CLIVAR/GCOS/WMO workshop on indices and indicators for climate extremes. *Clim*  
660 *Change* 42:3-7. <https://doi.org/10.1023/A:1005491526870>

661 Kendon EJ, Ban N, Roberts NM, Fowler HJ, Roberts MJ, Chan SC, Evans JP, Fosser G, Wilkinson JM (2017) Do  
662 convection-permitting regional climate models improve projections of future precipitation change? *Bull Am Meteor Soc*  
663 98(1):79-93. <https://doi.org/10.1175/BAMS-D-15-0004.1>

664 Kendon EJ, Prein AF, Senior CA, Stirling A (2021) Challenges and outlook for convection-permitting climate modelling.  
665 *Phil Trans R Soc A* 379:20190547. <https://doi.org/10.1098/rsta.2019.0547>

666 Kendon EJ, Roberts NM, Senior CA, Roberts MJ (2012) Realism of rainfall in a very high-resolution regional climate  
667 model. *J Clim* 25(17):5791-5806. <https://doi.org/10.1175/JCLI-D-11-00562.1>



668 Kendon EJ, Stratton RA, Tucker S, Marsham JH, Berthou S, Rowell DP, Senior CA (2019) enhanced future changes in wet  
669 and dry extremes over Africa at convection-permitting scale. *Nat Commun* 10:1794. [https://doi.org/10.1038/s41467-019-](https://doi.org/10.1038/s41467-019-09776-9)  
670 09776-9

671 Knist S, Goergen K, Simmer C (2020) Evaluation and projected changes of precipitation statistics in convection-permitting  
672 WRF climate simulations over Central Europe. *Clim Dyn* 55:325-341. <https://doi.org/10.1007/s00382-018-4147-x>

673 Køltzow M, Iversen T, Haugen JE (2008) Extended Big-Brother experiments: the role of lateral boundary data quality and  
674 size of integration domain in regional climate modelling. *Tellus A* 60(3):398-410. [https://doi.org/10.1111/j.1600-](https://doi.org/10.1111/j.1600-0870.2007.00309.x)  
675 0870.2007.00309.x

676 Kouadio K, Bastin S, Konare A, Ajayi VO (2020) Does convection-permitting simulate better rainfall distribution and  
677 extreme over Guinean coast and surroundings?. *Clim Dyn* 55(1):153-174. <https://doi.org/10.1007/s00382-018-4308-y>

678 Krinner G, Viovy N, de Noblet-Ducoudré N, Ogée J, Polcher J, Friedlingstein P, Ciais P, Sitch S, Prentice IC (2005) A  
679 dynamic global vegetation model for studies of the coupled atmosphere-biosphere system. *Global Biogeochem Cycles*  
680 19(1):GB1015. <https://doi.org/10.1029/2003GB002199>

681 Leutwyler D, Lüthi D, Ban N, Fuhrer O, Schär C (2017) Evaluation of the convection-resolving climate modeling approach  
682 on continental scales. *J Geophys Res Atmos* 122(10):5237-5258. <https://doi.org/10.1002/2016JD026013>

683 Li P, Furtado K, Zhou T, Chen H, Li J (2021) Convection-permitting modelling improves simulated precipitation over the  
684 central and eastern Tibetan Plateau. *Q J R Meteorol Soc* 147(734):341-362. <https://doi.org/10.1002/qj.3921>

685 Li P, Guo Z, Furtado K, Chen H, Li J, Milton S, Field PR, Zhou T (2019) Prediction of heavy precipitation in the eastern  
686 China flooding events of 2016: Added value of convection-permitting simulations. *Q J R Meteorol Soc* 145(724):3300-  
687 3319. <https://doi.org/10.1002/qj.3621>

688 Lind P, Belušić D, Christensen OB, Dobler A, Kjellström E, Landgren O, Lindstedt D, Matte D, Pedersen RA, Toivonen E,  
689 Wang F (2020) Benefits and added value of convection-permitting climate modeling over fenno-scandinavia. *Clim Dyn*  
690 55(7):1893-1912. <https://doi.org/10.1007/s00382-020-05359-3>

691 Lind P, Lindstedt D, Kjellström E, Jones C (2016) Spatial and temporal characteristics of summer precipitation over central  
692 Europe in a suite of high-resolution climate models. *J Clim* 29(10):3501-3518. <https://doi.org/10.1007/s00382-018-4114-6>

693 Liu C, Ikeda K, Rasmussen R, Barlage M, Newman AJ, Prein AF, Chen F, Chen L, Clark M, Dai A, Dudhia J, Eidhammer  
694 T, Gochis D, Gutmann E, Kurkute S, Li Y, Thompson G, Yates D (2017) Continental-scale convection-permitting modeling  
695 of the current and future climate of North America. *Clim Dyn* 49(1):71-95. <https://doi.org/10.1007/s00382-016-3327-9>

696 Lundquist J, Hughes M, Gutmann E, Kapnick S (2020) Our skill in modeling mountain rain and snow is bypassing the skill  
697 of our observational networks. *Bull Am Meteorol Soc* 100(12):2473-2490. <https://doi.org/10.1175/BAMS-D-19-0001.1>

698 Madec G, Delecluse P, Imbard M, Levy C (1998) Opa 8 ocean general circulation model - reference manual. Tech rep  
699 LODYC/IPSL Note 11.

700 Martín F, Crespi SN, Palacios M (2001) Simulations of mesoscale circulations in the center of the Iberian Peninsula for  
701 thermal low pressure conditions. Part I: Evaluation of the topography vorticity-mode mesoscale model. *J Appl Meteorol*  
702 40(5):880-904. [https://doi.org/10.1175/1520-0450\(2001\)040%3C0880:SOMCIT%3E2.0.CO;2](https://doi.org/10.1175/1520-0450(2001)040%3C0880:SOMCIT%3E2.0.CO;2)

703 Meredith E, Maraun D, Semenov V, Park W (2015) Evidence for added value of convection permitting models for studying  
704 changes in extreme precipitation. *J Geophys Res Atmos* 120:12500-12513. <https://doi.org/10.1002/2015JD024238>

705 Panosetti D, Schlemmer L, Schär C (2019) Bulk and structural convergence at convection-resolving scales in real-case  
706 simulations of summertime moist convection over land. *Q J R Meteorol Soc* 145(721):1427-1443.  
707 <https://doi.org/10.1002/qj.3502>

708 Peterson TC (2005) Climate change indices. *WMO Bull* 54(2):83-86

709 Prein AF, Langhans W, Fosser G, Ferrone A, Ban N, Goergen K, Keller M, Tölle M, Gutjahr O, Feser F, Brisson E, Kollet S,  
710 Schmidli J, van Lipzig NPM, Leung R (2015) A review on regional convection-permitting climate modeling:  
711 demonstrations, prospects, and challenges. *Rev Geophys* 53(2):323-361. <https://doi.org/10.1002/2014RG000475>

712 Randall DA, Wood RA, Bony S, Colman R, Fichetef T, Fyfe J, Kattsov J, Pitman A, Shukla J, Srinivasan J, Stouffer RJ,  
713 Sumi A, Taylor KE (2007) Climate models and their evaluation. In: Solomon S, Qin D, Manning M, Chen Z, Marquis M,  
714 Averyt KB, Tignor M, Miller HL (eds) *Climate change 2007: the physical science basis Contribution of working group I to*  
715 *the fourth assessment report of the intergovernmental panel on climate change*. Cambridge University Press, Cambridge

716 Rasmussen KL, Prein AF, Rasmussen RM, Ikeda K, Liu C (2020) Changes in the convective population and thermodynamic  
717 environments in convection-permitting regional climate simulations over the United States. *Clim Dyn* 55(1):383-408.  
718 <https://doi.org/10.1007/s00382-017-4000-7>

719 Rinke A, Dethloff K (2000) On the sensitivity of a regional Arctic climate model to initial and boundary conditions. *Clim*  
720 *Res* 14:101-113. <https://doi.org/10.3354/cr014101>

721 Rocheta E, Evans JP, Sharma A (2014) Assessing atmospheric bias correction for dynamical consistency using potential  
722 vorticity. *Environ Res Lett* 9(12):124010. <https://doi.org/10.1088/1748-9326/9/12/124010>

723 Rocheta E, Evans JP, Sharma A (2020) Correcting lateral boundary biases in regional climate modeling-the effect of the  
724 relaxation zone. *Clim Dyn* 55(9):2511-2521. <https://doi.org/10.1007/s00382-020-05393-1>

725 Rodwell MJ, Hoskins B (1996) Monsoons and the dynamics of deserts. *Q J R Meteorol Soc* 122:1385-1404.  
726 <https://doi.org/10.1002/qj.49712253408>

727 Şahin S, Türkeş M, Wang SH, Hannah D, Eastwood W (2015) Large scale moisture flux characteristics of the  
728 Mediterranean basin and their relationships with drier and wetter climate conditions. *Clim Dyn* 45:3381-3401.  
729 <https://doi.org/10.1007/s00382-015-2545-x>

730 Serrano-Notivoli R, Beguería S, Saz MA, Longares LA, de Luis M (2017) SPREAD: a high-resolution daily gridded  
731 precipitation dataset for Spain-an extreme events frequency and intensity overview. *Earth Syst Sci Data* 9(2):721-738.  
732 <https://doi.org/10.5194/essd-9-721-2017>

733 Sevruk B (1985) Correction of precipitation measurements. *Proc workshop on the correction of precipitation measurements.*  
734 *WMO/IAHS/ETH, Zürich*, pp 13-13

735 Shahi NK, Das S, Ghosh S, Maharana P, Rai S (2021) Projected changes in the mean and intra-seasonal variability of the  
736 Indian summer monsoon in the RegCM CORDEX-CORE simulations under higher warming conditions. *Clim Dyn* 1-18.  
737 <https://doi.org/10.1007/s00382-021-05771-3>

738 Skamarock WC, Klemp JB, Dudhia J, Gill DO, Barker DM, Duda MG, Huang X-Y, Wang W, Powers JG (2008) A  
739 description of the advanced research WRF Version 3. *NCAR Technical Notes NCAR/TN-475+STR.*  
740 <https://doi.org/10.5065/D68S4MVH>

741 Taylor KE (2001) Summarizing multiple aspects of model performance in single diagram. *J Geophys Res Atmos*  
742 106(D7):7183-7192. <https://doi.org/10.1029/2000JD900719>

743 Torma C, Giorgi F, Coppola E (2015) Added value of regional climate modeling over areas characterized by complex  
744 terrain-Precipitation over the Alps. *J Geophys Res Atmos* 120:3957-3972. <https://doi.org/10.1002/2014JD022781>

745 Türkeş M, Erlat E (2006) Influences of the North Atlantic Oscillation on precipitation variability and changes in Turkey.  
746 *Geophys Space Phys* 29:117-135. <https://doi.org/10.1393/ncc/i2005-10228-8>

747 Warner TT, Peterson RA, Treadon RE (1997) A tutorial on lateral boundary conditions as a basic and potentially serious  
748 limitation to regional numerical weather prediction. *Bull Am Meteor Soc* 78(11):2599-2618. [https://doi.org/10.1175/1520-0477\(1997\)078%3C2599:ATOLBC%3E2.0.CO;2](https://doi.org/10.1175/1520-0477(1997)078%3C2599:ATOLBC%3E2.0.CO;2)

749

750 Weisman ML, Skamarock WC, Klemp JB (1997) The resolution dependence of explicitly modeled convective systems.  
751 *Mon Weather Rev* 125(4):527-548. [https://doi.org/10.1175/1520-0493\(1997\)125%3C0527:TRDOEM%3E2.0.CO;2](https://doi.org/10.1175/1520-0493(1997)125%3C0527:TRDOEM%3E2.0.CO;2)

752 Willmott CJ (1982) Some comments on the evaluation of model performance. *Bull Am Meteorol Soc* 63:1309-1313

753 Wu W, Lynch AH, Rivers A (2005) Estimating the uncertainty in a regional climate model related to initial and lateral  
754 boundary conditions. *J Clim* 18(7):917-933. <https://doi.org/10.1175/JCLI-3293.1>

755 Zhou X, Yang K, Ouyang L, Wang Y, Jiang Y, Li X, Chen D, Prein A (2021) Added value of kilometer-scale modeling over  
756 the third pole region: a CORDEX-CPTP pilot study. *Clim Dyn* 1-15. <https://doi.org/10.1007/s00382-021-05653-8>

757 Zittis G, Bruggeman A, Camera C, Hadjinicolaou P, Lelieveld J (2017) The added value of convection permitting  
758 simulations of extreme precipitation events over the eastern mediterranean. *Atmos Res* 191:20-33.  
759 <https://doi.org/10.1016/j.atmosres.2017.03.002>