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1 **Pan-European climate at convection-permitting scale:**  
2 **a model intercomparison study**

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9 **Abstract** We investigate the effect of using convection-permitting models (CPMs)  
10 spanning a pan-European domain on the representation of precipitation distribu-  
11 tion at a climatic scale. In particular we compare two 2.2km models with two  
12 12km models run by ETH Zürich (ETH-12km and ETH-2.2km) and the Met-  
13 Office (UKMO-12km and UKMO-2.2km).

14 The two CPMs yield qualitatively similar differences to the precipitation cli-  
15 matology compared to the 12 km models, despite using different dynamical cores  
16 and different parameterization packages. A quantitative analysis confirms that the  
17 CPMs give the largest differences compared to 12 km models in the hourly pre-  
18 cipitation distribution in regions and seasons where convection is a key process:  
19 in summer across the whole of Europe and in autumn over the Mediterranean  
20 Sea and coasts. Mean precipitation is increased over high orography, with an in-  
21 creased amplitude of the diurnal cycle. We highlight that both CPMs show an

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increased number of moderate to intense short-lasting events and a decreased number of longer-lasting low-intensity events everywhere, correcting (and often over-correcting) biases in the 12 km models. The overall hourly distribution and the intensity of the most intense events is improved in Switzerland and to a lesser extent in the UK but deteriorates in Germany. The timing of the peak in the diurnal cycle of precipitation is improved. At the daily time-scale, differences in the precipitation distribution are less clear but the greater Alpine region stands out with the largest differences. Also, Mediterranean autumnal intense events are better represented at the daily time-scale in both 2.2 km models, due to improved representation of mesoscale processes.

**Keywords** convection-permitting models · Europe · Mediterranean · diurnal cycle · convection

## 1 Introduction

Global climate models (GCMs) are our primary tool for understanding how climate may change in the future with increasing greenhouse gases. These typically have coarse resolutions with grid spacings of 60-300 km (Taylor et al 2012). To provide regional detail, higher resolution regional climate models (RCMs; 12-50 km grid spacing) are often used, which only span a limited area (Jacob et al 2014). These give a better representation of mountains and coastlines and fine-scale (order 10-100km) physical and dynamical processes. In general, RCMs are able to capture the average statistics of daily precipitation on scales of a few grid boxes, with greatest agreement for moderate intensities and model biases increasing for heavier events (Boberg et al 2009; Kjellström et al 2010).

Both GCMs and RCMs with typical grid spacings ( $>10$ km) rely on a convection parameterisation scheme to represent the average effects of convection. This simplification is a known source of model errors and leads to deficiencies in the diurnal cycle of convection (Brockhaus et al 2008) and the inability by design to produce hourly precipitation extremes (Hanel and Buishand 2010; Gregersen et al 2013). Very high resolution models (order 1 km grid spacing), can represent deep convection explicitly without the need for such parameterisation schemes (Kendon et al 2012; Hohenegger et al 2008). Such models are termed ‘convection-permitting’ (or for simplicity sometimes ‘convection-resolving’ but this is not strictly true): larger storms and mesoscale convective organisation are permitted (largely resolved) but most turbulent kinetic motions are not represented (Wyngaard 2004). More specifically, while there is some evidence that km-scale resolution represents convection in some bulk sense (Langhans et al 2013), resolving convective updrafts requires about ten times higher resolutions (Dauhut et al 2015).

Convection-permitting models (CPMs) are commonly used in short-range weather forecasting, where they have been shown to give a much more realistic representation of convection and can be used to forecast the possibility of localised high-impact rainfall not captured at coarser resolutions (Done et al 2004; Richard et al 2007; Lean et al 2008; Weisman et al 2008; Weusthoff et al 2010; Schwartz 2014). However, due to their high computational cost, they have not commonly been applied at climate-time scales. Studies to date show that convection-permitting models do not necessarily better represent daily mean precipitation (Chan et al

2013), but have significantly better sub-daily rainfall characteristics with improved representation of the diurnal cycle of convection (Ban et al 2014), the spatial structure of rainfall and its duration-intensity characteristics (Kendon et al 2012), the intensity of hourly precipitation extremes (Chan et al 2014; Ban et al 2014; Fosser et al 2015), orographic precipitation and snowpack (Liu et al 2016), which are typically poorly represented in climate models.

Convection-permitting models provide a step change in our ability to represent convection, but there are still remaining issues. Smaller showers are not properly resolved, which results in a tendency for heavy rain to be too intense and for cell sizes to be too large. CPMs are also sensitive to sub-grid scale process representation (turbulence, microphysics), associated with many unknowns. The use of ever higher resolution does not necessarily result in convergence in terms of the representation of convection. For example, showers tend to become smaller (more speckly) with finer resolution rather than upscale on to the correct meteorological scale (Hanley et al 2015) and improvement with resolution can depend on use of appropriate parameterisation (Bryan and Morrison 2012).

Although convection-permitting simulations have been used at climate-scales on small domains in several regions of Europe and North America (see Prein et al (2015) for a review), Mediterranean intense precipitation events occurring in autumn have not yet been studied with such high-resolution on long time-scales. These events have been widely studied mainly on single cases with convection-permitting models within the the Mesoscale Alpine Programme (MAP, Richard et al (2007) and the HyMeX project (Drobinski et al 2014) and climatologically with convection-parameterised models within Med-CORDEX framework (Berthou et al 2016; Cavicchia et al 2016; Vaithinada Ayar et al 2016; Ruti et al 2016). Khodayar et al (2016) compared various convection-permitting models and convection-parameterised models on a single case study and showed that the former better represent the short-intense convective events whereas the convection-parametrized models tend to produce a large number of weak and long-lasting events. Although convection-parameterised models at scales of 10-40 km are able to capture the role of orography, blocking and convergence lines in shaping heavy-precipitation events, organised convection only represented at convection-permitting scales and interaction of this convection with the orography can be important in the triggering, propagation and life-time of some heavy precipitation in the Mediterranean (Ducrocq et al 2008a; Bresson et al 2012; Manzato et al 2015; Meredith et al 2015; Barthlott and Davolio 2016).

Following the work of Leutwyler et al (2017), who provided an analysis of the performance of the 10-year long ETH-2.2 km simulation in comparison with the driving 12 km simulation, we compare 9 years of simulations for a pan-european domain from the UKMO and the ETH 2.2 km models with 12 km models and with observations. The main added value of the article is to provide the first model-intercomparison study of convection-permitting climate simulations across the wide variety of European climates and to objectively assess in which regions and seasons they differ most with coarser resolution models in terms of precipitation.

After presenting the models and datasets in Sect. 2 and the methods in Sect. 3, we identify regions and seasons where the 2.2 km models differ most from the 12 km models in terms of distribution shape and mean of hourly precipitation in Sect. 4 and evaluate if this is an improvement against observations. We then gain more

country/region	name	reference	native resolution	years
France	SAFRAN	Quintana-Segui et al (2008)	8 km	1999-2007
Germany	HYRAS	Rauthe et al (2013)	5 km	1998-2006
Spain	Spain02	Herrera et al (2012)	12 km	1999-2007
United Kingdom	UKCPOBS	Perry et al (2009)	5 km	1999-2007
Alps	APGD-EURO4M	Isotta et al (2014)	5 km	1999-2007
Switzerland	RdisaggH	Perry et al (2009)	1 km	2003-2010
Germany	GERMANY	Paulat et al (2008)	7 km	2001-2008
United Kingdom	NIMROD	Golding (1998)	5 km	2003-2011

**Table 1** Datasets used in this study: daily datasets in the top part of the table, hourly datasets in the bottom part of the table. Years indicate the years of the datasets used in this study. Most datasets span a longer period.

116 insight as to how the distribution changes in summer in Sect. 5. Finally, we focus  
 117 on the representation of Mediterranean heavy precipitation in Sect. 6 with the use  
 118 of high percentiles and an illustrative case study. We provide conclusions and a  
 119 discussion in Sect. 7.

## 120 2 Datasets and simulations

### 121 2.1 Datasets

#### 122 2.1.1 Daily precipitation

123 For the analysis of daily precipitation we use the regional gridded datasets pre-  
 124 sented in the top section of Table 1 covering the UK, France, Germany, the Nether-  
 125 lands, the Alps and Spain. Regional datasets were chosen for the comparison, as  
 126 advised by Prein and Gobiet (2017): their native resolution are higher than the  
 127 european-wide EOBS dataset (Haylock et al 2008) and include higher densities of  
 128 raingauges (up to 44 times more). Furthermore, EOBS is not advised to be used for  
 129 coastal areas and mountainous regions of Southern Europe (Flaounas et al 2012)  
 130 and can be biased over regions with a low density of stations, especially regarding  
 131 the extremes (Hofstra et al 2010; Lenderink 2010; Prein and Gobiet 2017). Fur-  
 132 ther information about how each dataset was computed can be found in Sect. 8.1.  
 133 CMORPH (NOAA Climate Prediction Center morphing method) was also used  
 134 to evaluate the representation of heavy precipitation events in the Mediterranean  
 135 in autumn in Sect. 6. It was not included in the rest of the analysis as it is not  
 136 representative of the whole precipitation spectrum in northern Europe (Kidd et al  
 137 2012).

#### 138 2.1.2 Hourly precipitation datasets

139 For the analysis of hourly precipitation we use the datasets presented in the bottom  
 140 section of Table 1 covering the UK, Germany and Switzerland, which were all the  
 141 gridded hourly datasets available to the authors. 8 or 9 years were used to compare  
 142 with the models, they are not necessarily the same as the model years due to data  
 143 availability (see Table 1). However, we are interested in the multi-year climatology  
 144 of hourly precipitation, and this is not expected to depend strongly on the exact  
 145 choice of years providing a sufficient number of years are chosen.

146 The percentage of missing values for the hourly datasets for 2003-2008 in sum-  
147 mer are shown as a map in Figure 1b. The German dataset shows between 10 and  
148 20% of days with missing data all over Germany, the Swiss dataset about 10% of  
149 missing data in the southeast of the country and the UK dataset does not cover  
150 some regions in the southeast and northeast of England, and has variable coverage  
151 in Scotland with about 40% of missing data. For this dataset, only grid-points  
152 with less than 30% of missing data are used and the same points are used in the  
153 models to avoid inconsistencies.

154 It should be kept in mind that possible uncertainties in the datasets arise from  
155 rain-gauge undercatch, gridding procedures (Frei et al 2003), and weather radar  
156 measurements (Wuest et al 2010). The rain-gauge undercatch implies that rainfall  
157 intensities may well be underestimated with an amplitude that is difficult to assess.  
158 Prein and Gobiet (2017) mention that it can reach up to 80% in mountainous  
159 region for snowfall at exposed locations.

160 All the datasets were conservatively regridded to the 12 km UKMO grid with  
161 the Python interface to the Earth System Modeling Framework (ESMF) regrid-  
162 ding utility interface before the calculation of indices. The first-order conservative  
163 regridding is a variant of a constant method which compares the proportions of  
164 overlapping source and destination cells to determine appropriate weights.

## 165 2.2 Models

166 Both CPMs use the same pan-european domain as shown in Fig. 1a defined on  
167 a 2.2 km regular grid with a rotated pole located at (43N, 190E). The grid has  
168 1536x1536 points and 70 vertical levels for the UKMO model and 60 for the ETH  
169 model. Both models are forced at their boundaries with 6-hourly ERA-interim  
170 reanalyses. ETH-2.2 km uses a 12 km-simulation as an intermediate step for the  
171 downscaling (dashed domain in Fig. 1a), whereas the UKMO-2.2 km is directly  
172 forced by ERA-interim. This large resolution jump (factor 34) for the UKMO  
173 configuration implies that the spin-up zone for small-scale transient eddies to de-  
174 velop is larger than for the ETH model. In fact, Matte et al (2017) suggest that  
175 spin-up effects for small-scale transient eddies in the vorticity field are present on  
176 a  $3xL$  zone, where  $L$  is the e-folding distance on which the asymptotic value is  
177 reached. According to their findings, we get a spin-up zone of  $3x2x75\text{km}/2.2\text{km} \simeq$   
178 205 grid points. Comparing maps of mean precipitation between the UKMO-12km  
179 and UKMO-2.2km (not shown), we removed 220 points from the domain on each  
180 side for our analysis (zone depicted in Fig. 1) to prevent contamination from the  
181 downscaling method.

182 The simulations are starting in March 1998 for UKMO-2.2 km and in November  
183 1998 for ETH-2.2 km. The soil moisture initial conditions in UKMO comes from  
184 ERA-interim from the start of the run. The ETH-2.2 km initialisation is based on  
185 the soil moisture fields of ETH-12 km after 5 years of simulation initialised with  
186 the CCLM EURO-CORDEX simulation (Kotlarski et al 2014). The UKMO-12 km  
187 simulation was set on a wider domain (in yellow in Fig. 1a) and started in January  
188 1998. The article is based on 9 years of simulation from January 1999 to December  
189 2007.

190 *2.2.1 UKMO 12km and 2.2km*

191 The Met Office Unified Model (UM) can be run in climate mode (Walters et al  
192 2016), seasonal forecasting mode (Scaife et al 2014) or at convection-permitting  
193 scales for numerical weather prediction (NWP) (Clark et al 2016). The UKMO  
194 2.2 km (UM version 10.1) model is based on the UKV Met Office regional model  
195 which has been in use for operational numerical weather prediction since 2012  
196 (Clark et al 2016). The UKMO 12 km (UM version 10.3) is based on the climate  
197 version (Williams et al in rev.).

198 The UM is a non-hydrostatic model with a deep-atmosphere formulation based  
199 on a semi-implicit semi-Lagrangian dynamical core: ENDGame (Even Newer Dy-  
200 namics for General atmospheric modelling of the environment) (Wood et al 2014).  
201 The prognostic fields are discretised horizontally onto a rotated-pole grid with  
202 Arakawa C-grid staggering (Arakawa and Lamb 1977) whilst vertical decompo-  
203 sition is done via CharneyPhillips staggering (Charney and Phillips 1953) using  
204 terrain-following hybrid height coordinates on 70 levels for the 2.2 km model and  
205 63 levels for the 12 km model. Both models have a 40km top, but different spacing  
206 of levels in the lower troposphere. The lowest grid level is 2.5 m above the ground  
207 and the grid spacing increases quadratically with height. The model time-step is  
208 1 mn at 2.2 km and 4 mn at 12 km.

209 The 2.2 km model does not include any convection parametrization and relies  
210 on the model dynamics to explicitly represent convective clouds. Although it is  
211 acknowledged that not all types of convection are represented with such grid-  
212 spacing, this choice was made in the current absence of a scale-aware convection  
213 scheme which correctly parametrizes sub-grid convective motion and hands over  
214 to the model dynamics for clouds larger than the model filter scale. The UKMO  
215 12 km model uses a mass flux convection scheme based on Gregory and Rowntree  
216 (1990) with various extensions which include downdrafts (Gregory and Allen 1991)  
217 and convective momentum transport.

218 The UKMO 12 km model uses a prognostic cloud fraction and prognostic con-  
219 densate scheme (PC2; Wilson et al (2008)) whereas the UKMO 2.2 km model, like  
220 other convection-permitting UM formulations, uses the diagnostic Smith (1990)  
221 scheme.

222 Both models use the radiative transfer scheme of Edwards and Slingo (1996)  
223 with a similar configuration as described by Walters et al (2011), with several  
224 upgrades (more details in Stratton et al (in rev.)). Aerosol absorption and scatter-  
225 ing assumes climatological aerosol properties. Full radiation calculations are made  
226 every 15 minutes, with sub-stepped corrections due to cloud evolution performed  
227 every 5 minutes. The treatment of cloud microphysical processes is based on Wil-  
228 son and Ballard (1999), with extensive modifications described in Williams et al  
229 (in rev.). The UKMO 2.2 km model includes graupel as a prognostic variable in  
230 addition to the moist variables of water vapour, cloud liquid, cloud ice and rain  
231 used by the 12 km model. This allows the inclusion of a lightning flash rate pre-  
232 diction scheme (McCaul et al 2009). The UKMO 2.2 km model uses the blended  
233 boundary-layer parametrization (Boutle et al 2014). This scheme transitions from  
234 the one-dimensional vertical scheme of Lock et al (2000), used for lower resolution  
235 simulations such as UKMO 12 km, to a three-dimensional turbulent mixing scheme  
236 based on Smagorinsky (1963) and is suitable for high-resolution simulations, with  
237 a weighting which is a function of the ratio of the grid-length to a turbulent length

238 scale. The UM uses the JULES (Best et al 2011; Clark et al 2011) land surface  
239 scheme with the default four soil layers with thicknesses of 0.1, 0.25, 0.65 and 1.0 m,  
240 giving a total depth of 3 m. The tiles share a common soil water reservoir, with  
241 the van Genuchten et al (1991) relationship describing soil hydraulic conductivity  
242 and soil moisture. Note, however, it has recently been discovered that there may  
243 be an inconsistency between the Van-Genuchten hydrology and the soil properties  
244 provided in the ancillary, such that soil moisture infiltration rates may be too low.  
245 Initial tests using Brooks-Corey hydraulic equations, which are consistent with  
246 the soil properties, show that this impacts the soil moisture content but appears  
247 to have only limited impact on surface temperature and precipitation. The 12km  
248 and 2.2km models also have a different set up in the treatment of saturated soil  
249 layers: in the 2.2km model excess water moves upward, whilst in the 12km model  
250 it moves downward. The sensitivity of the results to this setting are discussed in  
251 Sect. 7 (see supplementary material for more detail).

252 The sub-grid hydrology model is also different: the UKMO 2.2 km configura-  
253 tions use the Probability Distributed Model (PDM Moore (1985)) and the 12 km  
254 follows the climate configuration of the TOPMODEL (Beven and Kirkby 1979).

255 More details can be found in Walters et al (2016), Williams et al (in rev.) and  
256 Stratton et al (in rev.). The latter article provides a more detailed description of  
257 a similar model set-up over Africa.

258 Note that unlike flux formulated schemes, semi Lagrangian advection schemes  
259 are typically not designed to locally conserve the advected quantities. Correctors  
260 are applied in the global UM, but in regional configurations the issue is complicated  
261 by the need to account for fluxes through the lateral boundaries in the calculation  
262 of the error and no correction scheme is implemented in these versions of the  
263 model. Stratton et al (in rev.) showed that it is likely causing enhanced mean  
264 precipitation (by  $\simeq 20\%$  in Africa), especially due to increased intense rainfall  
265 events.

### 266 *2.2.2 ETH 12km and 2.2km*

267 The simulation setup has been introduced in Leutwyler et al (2016) and verification  
268 was performed in Leutwyler et al (2017). Therefore we here only briefly summarize  
269 the most important aspects.

270 The 12 km and 2.2 km ETH simulations have been performed with version 4.19  
271 of the Consortium for Small-scale Modeling weather and climate model (COSMO)  
272 (Böhm et al 2006; Rockel et al 2008). COSMO is a non-hydrostatic limited-area  
273 model solving the fully compressible governing equations with finite-difference  
274 methods in a rotated coordinate system, projected on a regular structured grid  
275 (Steppeler et al 2003; Förstner and Doms 2004). To integrate the prognostic  
276 variables forward in time, a split-explicit 3-stage Runge-Kutta integrator is used  
277 (Wicker and Skamarock 2002). For horizontal advection a fifth-order upwind scheme  
278 and in the vertical an implicit Crank-Nicholson scheme are used (Baldauf et al  
279 2011). Multi-dimensional advection of scalar fields is implemented using the one-  
280 dimensional Bott scheme (Bott 1989; Schneider and Bott 2014). The model time-  
281 step is 90 s for the 12 km model and 20 s for the 2.2 km model, considerably shorter  
282 than for the UKMO equivalent model.

283 Depending upon resolution, sub-grid convection is parameterized using an  
284 adapted version of the Tiedtke mass-flux scheme with moisture-convergence clo-



285 sure (Tiedtke 1989). Cloud-microphysics are parameterized with a single-moment  
286 bulk scheme using five species (cloud water, cloud ice, rain, snow, and graupel)  
287 (Reinhardt and Seifert 2005), radiative transfer is based on the  $\delta$ -two-stream ap-  
288 proach (Ritter and Geleyn 1992), and a turbulent-kinetic-energy-based parametriza-  
289 tion is used in the planetary boundary layer (PBL) as well as for surface trans-  
290 fer (Mellor and Yamada 1982; Raschendorfer 2001). The ten-layer soil model  
291 TERRA\_ML has a total soil depth of 15.24 m (Heise et al 2006) and the aerosol  
292 climatology has been changed from the default climatology (Tanré et al 1984) to  
293 the AeroCom climatology (Kinne et al 2006).

294 The model configuration follows a two-step one-way nesting approach with the  
295 outer nest consisting of a simulation with parameterized convection (ETH 12km)  
296 and the inner nest of a simulation with the parameterization of deep-convection  
297 switched off (ETH2km, Fig. 1a). It should be noted that the parameterization of  
298 shallow convection remains active in the ETH 2.2km model, which is an impor-  
299 tant difference compared to the UKMO configuration (which has no convective  
300 parameterization). The outer nest has a grid spacing of 12 km and the inner nest  
301 follows the same setup as the UKMO 2.2 km simulation. In both ETH simulations,  
302 the vertical direction is discretized using 60 stretched model levels, ranging from  
303 the first model level at 20 m to the model top at 23.5 km. To provide adequately  
304 spun-up soil moisture fields, the soil layers in ETH 12 km have been initialized  
305 on 1 November 1993 based on the soil-moisture fields from the CCLM EURO-  
306 CORDEX simulation (Kotlarski et al 2014), and thereafter integrated for 5 years.  
307 Subsequently ETH 2.2 km was initialized on 1 November 1998 with the soil mois-  
308 ture fields of ETH 12 km, leaving two months of integration for soil spinup.

309 The simulations have been performed with a version of COSMO capable of  
310 using GPU accelerators (Fuhrer et al 2014). The new COSMO version enables  
311 execution of the time stepping algorithm entirely on accelerators, which is essen-  
312 tial to minimize expensive data movements between the CPU and the GPU. To  
313 this end the dynamical core has been rewritten in C++, using the domain-specific  
314 Stencil Loop Language (STELLA) (Gysi et al 2015; Osuna et al 2015), and the  
315 physical parametrization have been ported using OpenACC (2011) compiler direc-  
316 tives (Lapillonne and Fuhrer 2014). Data exchange at the sub-domain boundaries  
317 (i.e. halo exchange) is handled using a re-usable communication framework. On  
318 144 compute nodes of a hybrid Cray XC30 system, the time-to-solution for a 10-  
319 year-long integration is about 1.7 months (Leutwyler et al 2016).

### 320 3 Methods

321 All the models and datasets are regridded to the UKMO 12 km grid before the  
322 computation of all diagnostics in order to show a fair comparison between models.  
323 Therefore, scales smaller than 12 km are not evaluated. However, most of the  
324 regional datasets are also not necessarily accurate enough to evaluate scales smaller  
325 than 12 km. It should be stressed that this approach is not entirely fair for the  
326 12 km models, as they are not supposed to represent the 12 km scale properly, but  
327 rather a 25 km scale or larger (Skamarock 2004).

328 We use the average of values above the 99<sup>th</sup> percentile of all days to evaluate the  
329 representation of moderate to intense events (*p99avg*) to compare fairly the model

330 extremes, independently from the wet-day/wet-hour frequency, as recommended  
 331 by Schär et al (2016).

332 To gain insight into the distribution of precipitation, we use the ASoP method  
 333 (“Analyzing Scales of Precipitation”, version 1.0 ASoP1) presented in Klingaman  
 334 et al (2017), which gives a spectrum of the precipitation intensities contributing to  
 335 the mean precipitation rate. This allows a comparison of the contribution of differ-  
 336 ent intensities to the mean across different time-scales and grid-point by grid-point  
 337 to better understand the underlying model physics. It provides a view of differ-  
 338 ences in the distribution in its entirety and also allows differences coming from a  
 339 pure shift to higher/lower intensities to be distinguished from an increase/decrease  
 340 of precipitation in all the bins.

Fig. 2 shows the steps of calculation for the ASoP method and illustrates the  
 differences with a probability density function. The example uses the distribution  
 of daily precipitation in the southern UK from the UKCPOBS dataset and the  
 UKMO-12 km model for 1999-2007. The bins used to calculate precipitation fre-  
 quency in the ASoP method are designed such that the number of events per bin  
 is rather similar across bins (except in the largest bins so that their signal is not  
 lost in one single bin). This is illustrated in panel b compared to panel a, where  
 the vertical bars representing each bin are spaced differently. The function defining  
 the bins is given by Eq. (1).

$$b_n = e^{\left(\ln(0.005) + \left[ n \frac{(\ln(120) - \ln(0.005))^2}{59} \right]^{\frac{1}{2}}\right)} \quad (1)$$

341 The frequency of events  $f_i$  in each  $i^{th}$  bin is multiplied by the mean precipita-  
 342 tion rate of the bin  $p_i$ :  $C_i = f_i p_i$ . This provides the actual contribution  $C_i$  of the  
 343 bin to the mean precipitation rate. The sum across all bins (area under the curve)  
 344 gives the mean precipitation rate. The resulting spectrum is shown in Figure 2c.  
 345 It provides information about the relative contribution of each bin to the mean.

Further dividing each bin’s actual contribution by the mean precipitation rate  
 (sum across all bins of the actual contribution spectrum), as shown in Eq. (2) gives  
 a spectrum which area under the curve is unity (fractional contribution, panel d),  
 providing information mostly about the shape of the distribution, independently  
 from the mean precipitation.

$$FC_i = \frac{C_i}{\sum C_i} = \frac{C_i}{mean} \quad (2)$$

346 This method provides a quantitative visualisation of model differences or bi-  
 347 ases against observations in all parts of the precipitation distribution, and not only  
 348 in the head or tail of the distribution like more traditional approaches (probabil-  
 349 ity distribution function, cumulative distribution function). As an example, two  
 350 spectrums are plotted: a reference spectrum and a model spectrum for the actual  
 351 contribution (Fig. 2e) and the fractional contribution (Fig. 2f). Their difference  
 352 is plotted in panels g and h, respectively. These figures illustrate two facts: first  
 353 of all, the model shows a dry bias compared to the reference: the area under the  
 354 red curve in panel e is smaller than the area under the blue curve, which is more  
 355 easily seen in panel g, where the negative area between the curve and the zero  
 356 line is larger than the positive area. More importantly, it illustrates which bins  
 357 contribute to the mean bias: the model shows mainly too much precipitation from

the intensities below 8 mm/day but a stronger underestimation of the contribution from events between 8 and 100 mm/day. This latter contribution has the largest effect on the mean as the sum of all bins is negative. Panels e and g therefore mix the information between the mean bias and the shape of the distribution.

Looking at the fractional contributions in panels f and h, they mainly illustrate the differences in the shape of the distribution between the model and the data. By construction, the integral of the difference between the two curves is zero: the positive and negative grey areas in panel h compensate each other. These figures mainly show that the lower intensity bins contribute too much to the mean compared to the higher intensity means. It loses the information about the differences in the means of the models. In this case, actual contribution and fractional contributions are not very different, but it is easy to think about a model which would have the right shape of fractional distribution but too much precipitation coming from all the bins: the actual contributions would be larger and the mean bias positive, but the fractional contribution would be similar as in the observations. These contributions are calculated at each grid-point and can then be averaged over a given region or maps can be shown by aggregating the contributions over several bin categories.

On top of this method, we build indices to summarize information about the shape of the distribution and the mean precipitation differences between datasets to serve two purposes:

- identify the regions, seasons and timescales where the mean precipitation and the shape of the precipitation distribution are most different between the 12 km and the 2.2 km
- in these cases, identify whether the 2.2 km models provide an overall better or worse representation of the contributions of different intensities to mean precipitation where observations are available.

The first index gives information about how much the fractional contributions differ between a model (*mod*) and a reference dataset (*ref*): the index FC (Fractional Contribution Index) is given in Eq. (3).

$$FC(mod, ref) = \sum_i |FC_i^{mod} - FC_i^{ref}| \quad (3)$$

FC represents how different the shapes of the two distributions are independently from the differences in the means. It has no units either but is the area between the two fractional contribution spectrums (in grey in (Figure 2f and h)). Its minimum and best value is zero while the maximum is two and means no overlap between the distributions.

The second index assesses which model (between *m1* and *m2*) performs best in terms of fractional contributions to the mean (Eq. (4)).

$$FC_{best}(m1, m2) = \frac{FC(m1, obs) - FC(m2, obs)}{FC(m2, obs)} \times 100 \quad (4)$$

This index measures the percentage of improvement or worsening of the fractional spectrum of model *m1* over model *m2* with regards to the observations. If *m2* agrees better with the observations, the index is positive (the area between *m1*

398 and *obs* is larger than the area between *m2* and *obs*) and the index is negative if  
399 *m1* agrees better. The index gives some credit to a model which has a better frac-  
400 tional contribution but a worse bias, meaning that it would potentially reproduce  
401 well the underlying physical processes but just do too much of all of them.

402 The indices are calculated at each grid-point and then averaged over regions  
403 or presented as maps. With these score we require the models not only to capture  
404 the area mean, but also each grid point accurately.

## 405 4 Regions and seasons of largest difference across resolution

### 406 4.1 Comparing 2.2 km with 12 km models

407 In this section, we identify where and for which season the 2.2 km hourly precipi-  
408 tation statistics differ most from the 12 km ones. We use a combination of the ab-  
409 solute mean difference ratio:  $AMD = (|\text{mean}(2.2 \text{ km}) - \text{mean}(12 \text{ km})|) / \text{mean}(12 \text{ km})$   
410 and the fractional contribution index (FC) presented in Sect. 3, calculated between  
411 the 2.2 km and the 12 km models. Calculated at each grid point, these measures are  
412 then averaged over the different domains presented in Fig. 1a. Only points with av-  
413 erage precipitation above  $0.03 \text{ mm h}^{-1}$  for hourly precipitation and  $0.5 \text{ mm day}^{-1}$  for  
414 daily precipitation are taken into account, to avoid regions with too little precipi-  
415 tation which do not have a robust precipitation spectrum. The results are not very  
416 sensitive to these chosen thresholds (not shown).

417 Each domain can be quite vast but this region definition is chosen as a first  
418 order description of the variability of climates using a limited number of regions,  
419 inspired by the Köppen-Geiger map of climates (Peel et al 2007). Figure 3 shows  
420 a plot of FC(2.2 km, 12 km) as a function of AMD for hourly precipitation. The  
421 higher the value of FC, the larger the differences in shape of the distribution  
422 between the 2.2 km and 12 km models and the larger the AMD, the larger the  
423 difference in means of the two models.

424 For both model sets and for each individual region, the 2.2 km models differ  
425 most from the 12 km models in summer in terms of precipitation distribution (FC).  
426 In terms of differences in the mean (AMD), it is largest over high orography in  
427 all seasons ( $>1500 \text{ m}$ ), and it is high in the Mediterranean in summer too. Note  
428 however that the ‘Med Sea’ and ‘Med coast’ points for summer are not as reliable  
429 since they are based on a limited number of points because mean precipitation is  
430 very low.

431 A second conclusion which can be drawn is that the UKMO is overall more  
432 sensitive to the changes in resolution than the ETH model for most regions and  
433 seasons, comparing the right and left panels. This may partly be due to the fact  
434 that the UKMO 12 km model and 2.2 km model do not have exactly the same  
435 model physics.

436 Another point is that in all seasons, the largest differences between resolutions  
437 in terms of shape of the distribution (FC) are found over the Mediterranean sea or  
438 coasts, these points especially stand out compared to the other regions in autumn  
439 and summer.

440 In most seasons and models, the smallest sensitivity to resolution is found in  
441 flat lands in Northern Europe and Central Europe except in summer in the UKMO  
442 where these regions show large differences in the shape of the distribution. Most

443 of the differences occur in the shape of the distribution and not in the mean state  
 444 except in summer in the UKMO. In the ETH model, CEurM (orography between  
 445 500 m and 1500 m in Central Europe) shows more sensitivity to resolution than  
 446 flat lands in all seasons in both the mean and shape of the distribution.

447 Guided by these findings, we will mainly focus the rest of the study on the  
 448 summer season in all regions and the Mediterranean coasts and sea in autumn,  
 449 where the differences between models are largest.

#### 450 4.2 Model performances against available observations

451 We show the mean bias compared to observations and a comparison of the frac-  
 452 tional distribution differences (FC best (2.2 km, 12 km)) at each grid-point on a  
 453 map for daily (Fig. 4)) and hourly precipitation (Fig. 5).

454 Regarding daily precipitation differences, Fig. 4 first highlights that the Alpine  
 455 region stands out as a region of large increase in the mean precipitation in the two  
 456 models, as highlighted in the previous part. The bias increases with height above  
 457 800 m in both of the 2.2 km models (Fig. 5 of the supplementary materials) and  
 458 areas above 1500 m in this region show a wet bias of around 30-70%. Although this  
 459 region tends to be more biased in the 2.2 km mean, it shows a better performance  
 460 for the distribution in the western part of the mountain range and worse in the  
 461 northeastern part (panels c and f). The wet bias partly comes from an overestima-  
 462 tion of wet days for all intensities, which was quantified as an increase by 10-30%  
 463 of the wet-day frequency (not shown). It should be stressed that the observations  
 464 over high ground may underestimate precipitation by at least 10% as discussed in  
 465 Sect. 8.1.

466 A second point which can be made is the overall improvement in the shape  
 467 of the fractional contribution to the mean in both 2.2 km models south of the  
 468 Alps and to a lesser extent north of the range. The improvement is about 30-50%  
 469 compared to the 12 km performances. This is associated with a smaller mean bias  
 470 in the ETH 2.2 km in this region. The UKMO is however dominated by a dry bias  
 471 in this region, although there are improvements in the mean bias in Liguria.

472 Northern Germany, the Netherland and the UK coasts are also regions of im-  
 473 provement in both 2.2 km models. The other regions do not show any clear im-  
 474 provement in the distribution between the 2.2 km and the 12 km models.

475 The mean bias is not very different across resolutions in the ETH model, and is  
 476 worse in the UKMO 2.2 km model with an overall dry bias of 20-50% in northern  
 477 Italy, northern Spain, France and western Germany. The fact that there is not  
 478 much of a resolution-dependence in the model skill in capturing the shape of the  
 479 distribution, but a large dependence in the mean indicates that the dry bias in the  
 480 UKMO 2.2 km mostly comes from a reduction in the overall wet day frequency,  
 481 which was quantified as being around 20%.

482 Regarding the mean and shape of the distribution for hourly precipitation,  
 483 Fig. 5 shows similar mean biases as for daily precipitation, which is reassuring  
 484 given that the reference datasets are different and the time-period of comparison  
 485 is not the same (Table 1). The signal in  $FC_{best}$ , showing which model shows the  
 486 best overlap with the observation in terms of fractional contributions is now much  
 487 stronger than for daily data. There is a clear improvement by the 2.2 km models in  
 488 terms of which intensities contribute to the mean for Switzerland in both models,

489 especially at higher altitudes for the UKMO. In Germany, the overall tendency  
490 is to a worsening of the distribution in the 2.2 km models, especially strong on a  
491 southwest-northeast diagonal. A common improvement is however found in north  
492 and northwestern Germany. In the UK, the model performance is very spatially  
493 dependent and there is mostly a tendency of improvement along the coasts of the  
494 Irish Sea and of a deterioration inland.

495 Overall, the 2.2 km models improve the daily and hourly distribution shape  
496 over the western Alps but show a tendency of having too many wet-days in the  
497 high-grounds, although the raingauge under-catch is hard to evaluate in this region.  
498 They seem to deteriorate the hourly distribution on flat land away from the coasts  
499 in the UK and Germany. The UKMO has also an overall dry bias linked with too  
500 few wet hours and days in France, Spain and northern Italy.

## 501 **5 Shift to shorter and more intense wet-spell intensities in 2.2 km** 502 **models**

### 503 5.1 Shift to larger contributions from moderate and intense precipitation

504 We now look further into the distributions to evaluate which parts are most affected  
505 by the changes in resolution. We focus on hourly distributions, since the differences  
506 are clearer at this scale.

507 Both the differences in fractional and actual contributions against observations  
508 are shown in Figure 6. They illustrate the very different behaviour of the 2.2 km  
509 models compared to the 12 km models on the hourly time-scales. The 12 km models  
510 tend to show a too large contribution to total precipitation from low-intensity  
511 events (below 2-3 mm/h) by 5 to 40% depending on countries, which is can be  
512 over-corrected in the 2.2 km, which tend to have too much rainfall contributed  
513 by moderate and intense (3-30 mm/h) events by 10 to 40%. There is a significant  
514 improvement in Switzerland and to a lesser extend in the UK in terms of fractional  
515 contributions but the 2.2 km ETH model overestimates precipitation in all bins in  
516 terms of actual contributions. In Germany, the 12 km models already have too large  
517 a contribution from intense events (>8 mm/h) by around 40% and the 2.2 km  
518 models have even larger contributions from events above 2 mm/h, resulting in  
519 a 40% increase in contributions from intensities above 2 mm/h. It increases the  
520 distribution biases against observations in this country. In both models, this is  
521 due both to a decrease in the actual contribution of low-intensity events and an  
522 increase in the moderate events. The decrease in actual contribution from low-  
523 intensity events is larger in the UKMO than in ETH and results in biases of -8 to  
524 -34% in the UKMO 2.2 km model to -12 to -15% in ETH (in the UK and Germany  
525 only) for this range of intensities.

526 Although the number of hourly datasets available is limited, the 12 km and  
527 2.2 km model contributions to total rainfall can be compared on the whole domain  
528 by plotting maps of the fractional contribution to total rainfall from low intensity  
529 events (<2 mm/h), moderate events (2-8 mm/h) and intense events (>8 mm/h), as  
530 shown in Figure 7. These maps show that the shift in contribution of precipitation  
531 from low to moderate and intense precipitation in both 2.2 km models is present  
532 everywhere on land and is much larger than differences between the 12 km models.

533 This leads to improvement in Switzerland and to a lesser extend in the UK but to  
534 larger biases in Germany.

## 535 5.2 Analysis of wet-spell durations and intensities

536 Figure 8 presents the distribution of hourly wet-spell frequencies by duration (in  
537 hours) and mean intensity over the wet-spell for the available observation datasets  
538 and the four models. A wet spell is defined as consecutive hours with precipitation  
539 rates larger than 0.1 mm/h at a single grid-point. For the observations, the wet  
540 spell frequency is shown and for the models we show the difference in the number  
541 of wet spells per year in each intensity/duration bin between the model and the  
542 observations normalised by the number of wet spells per year in the observations.  
543 This way, a positive difference between model and observations in a given bin  
544 reflects an overestimation of wet spells in this bin, not just a larger share of this  
545 bin in the wet-spell distribution. We also show percentage differences in the number  
546 of wet-spells against the observations in each panel title.

547 In all three countries, the 2.2 km models increase the frequency of short-lasting  
548 (<10 h) moderate to intense (average intensity of 1-20 mm/h) events and decrease  
549 the share of long-lasting (>5 h) low-intensity (<1 mm/h) wet spells compared to  
550 12 km models. The latter effect is especially strong in the UKMO 2.2 km model.  
551 As a result, the 2.2 km tend to underestimate the long-lasting weak wet-spells  
552 contrary to the 12 km models which overestimate them: the 2.2 km models yield  
553 better results for these events in all countries for the ETH2.2 km and only in  
554 Switzerland and to a lesser extent the UK for the UKMO2.2 km. The total number  
555 of wet-spells generally decreases from 12 to 2.2 km, the effect is more pronounced in  
556 the UKMO 2.2 km due to the former point. The short-lasting moderate to intense  
557 wet-spells tend to be underestimated in the 12 km models and overestimated by  
558 the 2.2 km models (except in the UK). Improvement for these high-impact events  
559 occur for the UK and Switzerland (only for the ETH model).

560 The ETH 2.2 km model also decreases the occurrence of short-lasting wet-spells  
561 whereas the UKMO 2.2 km increases these occurrences compared to the 12 km  
562 model: in this model, low-intensity wet spells become shorter.

563 Note that the UKMO 12 km model shows intense and very short-lasting ( $\leq 3$  h)  
564 wet spells, in disagreement with the German and Swiss datasets but not the British  
565 one, this is probably due to grid-point storms.

## 566 5.3 Changes in the tail of the precipitation distribution

567 Looking at the representation of intense events, Figure 7 shows a larger contribu-  
568 tion from intense events (>8 mm/h) to total precipitation in the 2.2 km models,  
569 especially in the ETH 2.2 km where these events can represent up to 20% of the  
570 mean, as also shown in Figure 6. The average top 1% of all hours shown in Figure 9  
571 shows that the increase in contribution from the moderate and intense events in  
572 the 2.2 km models is partly due to more intense hourly rainfall in both models and  
573 not only linked with a decrease in number of low-intensity hours. This is again an  
574 improvement for Switzerland and the UK and a deterioration for Germany, where  
575 this index is overestimated by 10-30% in the UKMO2.2 km and 10-50% in the

576 ETH 2.2 km. This is not the case for daily precipitation on flat land where this  
577 diagnostic does not show a large intensification (not shown).

#### 578 5.4 Diurnal cycle in summer

579 Finally, Figure 10 and Figure 11 respectively show the amplitude and the phase  
580 (hour of the maximum precipitation in local time) of the mean diurnal cycle at each  
581 grid-point. They show stronger amplitudes in the 2.2 km models over high orog-  
582 raphy (>1500m) compared to the 12 km models, especially in the Swiss, Austrian  
583 and north-italian Alps. According to the Swiss and German datasets over the Alps,  
584 this is an improvement, although the amplitude may tend to be too strong in the  
585 convection-permitting models. Both models also generally show larger amplitudes  
586 of the diurnal cycle on lower level topography (Massif Central, Appenines, Dinaric  
587 Alps), where MCSs are often triggered (Morel and Senesi 2002). The UKMO and  
588 to a lesser extent the ETH 2.2 km models also reproduce the larger amplitude of  
589 the diurnal cycle in southern Germany along the Alpine foothills, where MCSs are  
590 observed (Hagen and Finke 1999; Kaltenböck 2004).

591 Figure 11 shows the better timing of the peak precipitation in the 2.2 km  
592 models, the peak being shifted from late morning-early afternoon in parameterised  
593 models to mid-late afternoon in the convection-permitting models, which is more  
594 realistic, in line with Fosser et al (2015); Ban et al (2014). It is worth noting that  
595 the UKMO-2.2 km still produces precipitation too early in the day in the Swiss  
596 Alps (around 2-4 pm), whereas the ETH-2.2 km model is in better agreement with  
597 the observations with a peak between 4 pm and 8 pm. Nisi et al (2016) observations  
598 are also more in line with the late peak of ETH 2.2 km in the Po valley. Generally,  
599 the UKMO 2.2 km model tends to produce earlier afternoon peaks by about 2 h  
600 than the ETH 2.2 km model, further away from the observations. Both models  
601 reproduce well the spatial gradients of the hour of maximum precipitation in the  
602 UK on the southwestern coasts.

## 603 6 Mediterranean heavy precipitation events

604 In autumn, the heaviest precipitation events in Europe occur on the Mediterranean  
605 coasts, as illustrated by the average of rainfall on the top 1% of all days shown  
606 in Fig. 12e. In this figure, we use daily CMORPH observations (2001-2008) (see  
607 Sect. 8.1) as a complement to the daily precipitation datasets for this metric. This  
608 satellite-derived product is not as reliable as daily observation products and not  
609 as high resolution ( $0.25^\circ$ ), but it provides some estimate of convection over the sea  
610 and in the regions not covered by high resolution datasets, although it was shown  
611 to underestimate coastal heavy precipitation events in this region (Stampoulis et al  
612 2013). This can also probably be seen in the sharp transition between high values  
613 in Italy in the Appenines in the Alpine dataset and lower values in CMORPH.

614 Regions particularly hit by heavy precipitation events are the Valencian coun-  
615 try in Spain, the southern part of the Massif Central (Cévennes) and the Alps  
616 in France, the Ligurian region in Italy, the whole southern edge of the Alps and  
617 the Dinaric Alps. Intense convection also occurs in the Gulf of Lions and the



618 Tyrrhenian Sea. Liguria, most of Italy and the Dinaric Alps were identified as re-  
619 gions with rather large convection-parameterised model biases in the extremes in  
620 convection-parameterised models (Berthou et al 2016; Cavicchia et al 2016; Fantini  
621 et al 2016).

## 622 6.1 Contribution of intense events to mean precipitation in autumn

623 Fig. 12 shows the  $p99_{avg}$  metric for all the models. The two 2.2 km models seem to  
624 actually converge to a solution closer to the observations compared to the 12 km  
625 models which differ from each other. The convection-parameterised models have  
626 very different biases: the UKMO-12 km model shows very intense wet biases on  
627 the upslope side of all mountain ridges and on the coasts, while the ETH 12 km  
628 model underestimates this metric by around 30-50%. The ETH 2.2 km is in better  
629 agreement with the observations and the UKMO 2.2 km mostly shows stronger  
630 intensities in northern Italy. All models show stronger precipitation in the coastal  
631 Pyrenees compared to the observations. The 2.2 km show stronger precipitation in  
632 the Valencian country, in better agreement with the observations.

633 Over the sea, precipitation maximum in CMORPH occurs in the Gulf of Lions  
634 and the Thyrrhenian Sea whereas it is maximum in the Ionian Sea in the UKMO  
635 2.2 km and in the Thyrrhenian Sea in ETH 2.2 km. Precipitation is more intense  
636 over the sea in each 2.2 km model compared to its 12 km counterpart. This suggests  
637 that convection is more easily triggered over the sea away from the influence of  
638 the orography or the coasts in the 2.2 km models.

## 639 6.2 Case study: 8-9 Sept. 2002 in Southern France

640 Having examined the climatological differences between the 12km and the 2.2km  
641 models, we now focus on a single case study to illustrate how processes are rep-  
642 resented differently across resolution. The chosen case is a Mediterranean heavy  
643 precipitation event which occurred on the 8<sup>th</sup> and 9<sup>th</sup> Sept. 2002 in the Gard  
644 region in Southern France. This case was chosen for three main reasons: first, it  
645 is well documented (Delrieu et al 2005; Anquetin et al 2005; Nuissier et al 2008;  
646 Ducrocq et al 2008b). Second, it was strongly forced synoptically (Nuissier et al  
647 2008) so we can expect it to be present in the climate models (which only receive  
648 atmospheric information on the observed state at the lateral boundary) and third,  
649 cold pool interactions with the mesoscale environment played an important role  
650 in setting the location and intensity of the event, so we may expect the 2.2km  
651 models to behave differently from the 12km models (Ducrocq et al 2008b).

652 Over the two days of the event, maximum rainfall of 600-700 mm was recorded  
653 (Fig. 13e). The meteorological environment of the heavy rainfall event was charac-  
654 terized by an upper-level trough centred over Ireland and extending meridionally  
655 to the Iberian peninsula, progressively veering to a northwest, southeast axis. It  
656 generated a south-westerly diffluent flow over south-eastern France. An associated  
657 surface cold front, first located over western France, moved progressively eastward.  
658 Convection first formed well ahead of the front in the warm sector, where a low-  
659 level south-easterly flow prevailed and was later reinforced by embedded convection  
660 in the front. Fig. 13 shows that for both 12km models maximum precipitation falls

661 on the southeast facing slopes of the Cévennes. In both 2.2km models, precipita-  
662 tion occurs both on the slopes of the Cévennes and in the Rhone valley, the latter  
663 being where the maximum in the observations is found. All models underestimate  
664 the precipitation in the Rhone Valley, but the 2.2km models have smaller negative  
665 biases.

666 The UKMO climate models show different time-evolutions of the surface cold  
667 front and first generate precipitation over orography, in association with a strong  
668 temperature gradient, on the afternoon of the 8th (this differs from the real event  
669 which already shows cold pools and precipitation in the valley by the afternoon  
670 of 8<sup>th</sup>, not shown). The 500 hPa synoptic situation is closer to ERA-interim in  
671 the 2.2km model than in the 12km model, probably as a result of domain size  
672 (not shown). The UKMO 12 km model mostly shows orographic precipitation and  
673 convection embedded in the cold front during the whole event. In the UKMO  
674 2.2 km model, following the triggering of precipitation over orography, convection-  
675 induced cold air accumulates in the Rhone valley, leading to the formation of a  
676 mesoscale cold front. By the morning of the 9<sup>th</sup>, convective cells are triggered on  
677 the edge of the cold pool (Fig. 14) which gradually propagates upstream of a 50-60  
678 knot southerly flow, maintaining convective cells in the valley in the 2.2 km model.  
679 There is no hint of interaction of the flow with a cold pool at any stage of the  
680 event in the UKMO 12km model (not shown). The more realistic positioning of  
681 the rainfall maximum, and higher rainfall totals, in the 2.2km models therefore  
682 seems to be related to their ability to represent cold pools and some form of  
683 organised convection. Given this is just a single case study, and we would not  
684 expect the timing or position of rainfall to be exactly captured across models, it is  
685 not possible to make any definite conclusions. However, the results are illustrative  
686 of the potential for improved representation of mesoscale processes and associated  
687 extreme precipitation events at convection-permitting resolution.

## 688 7 Discussion and conclusion

689 This first intercomparison pan-European CPMs confirms and builds on previous  
690 studies on smaller domains or with single models. Quantitatively we find that the  
691 largest precipitation differences between CPMs and 12 km parameterised models  
692 occur at hourly time-scales in summer in most regions. Regions of high topogra-  
693 phy show the largest differences in mean precipitation at the convection-permitting  
694 scales and the Mediterranean coasts and sea are most affected in terms of precip-  
695 itation distribution, especially in summer and autumn.

696 The two pan-european CPMs behave similarly in terms of differences in precip-  
697 itation distribution at the hourly timescale in summer compared to 12 km models.  
698 Mean precipitation comes from an increased contribution of short-lasting moder-  
699 ate and intense events and a decreased contribution of longer lasting low-intensity  
700 events everywhere. This leads to an overall improvement compared with the 12km  
701 models in Switzerland (also found in Ban et al (2014); Lind et al (2016)) and parts  
702 of the UK (also in Kendon et al (2012)) but deteriorates the distribution in most  
703 of Germany with too much moderate and intense precipitation, unlike the find-  
704 ings of Fosser et al (2015) who evaluated their model against hourly raingauges in  
705 Southwestern Germany. The lack of low-intensity events in both models is espe-

706 cially large in the UKMO 2.2 km model and is responsible for a 10-30% dry bias  
707 in France, Spain and Italy in this model.

708 The daily precipitation distribution is mostly affected by resolution changes in  
709 the Alps, in northern Italy and near the coasts (UK/Germany). The Austrian Alps  
710 show a deterioration of the distribution while the southwestern Alps and north-  
711 ern Italy benefit from higher resolution. Mean precipitation is increased over the  
712 Alps and becomes larger than in the observations. This bias increases with height  
713 above 800 m in both 2.2 km models and it is unclear which part is due to obser-  
714 vation uncertainties or model deficiencies ((Lind et al 2016) yield similar results).  
715 Mediterranean intense events in autumn at the daily scale are better represented  
716 by the 2.2 km models, which converge to a solution closer to the observations in  
717 terms of location and intensity than their 12 km counterparts.

718 The phase of the diurnal cycle is better represented in the CPMs but the  
719 UKMO-2.2 km has still too early a peak over orography. This is a well-known  
720 improvement in CPMs due to the fact that convective instability takes more time  
721 to build-up as it is not consumed by parameterised convection which tends to  
722 start convection around midday (Kendon et al 2012; Prein et al 2013; Ban et al  
723 2014; Fossier et al 2015). Both CPMs have an enhanced amplitude over orography  
724 compared to the 12 km models, which is an improvement.

725 Regarding model differences, the UKMO-2.2 km has a much reduced wet-day  
726 frequency compared to the UKMO-12 km, which is a clear bias compared to the  
727 observations; this is not the case in the ETH model. It is not clear whether it comes  
728 directly from resolution changes. One of the model differences that we investigated  
729 is the the way saturated layers of soil are treated. At higher resolution, when  
730 the top layer of soil is saturated, excess water disappears into the surface run-off  
731 whereas it is drained into the second layer in the 12 km. Initial sensitivity tests have  
732 shown that modifying the treatment of saturated layers moistens the lower soil  
733 layers slightly, but has negligible impact on the surface soil moisture (not shown)  
734 and the surface climate (supplementary material). We note that the impact of soil  
735 moisture infiltration rates being too low in the UKMO models, due to the use  
736 of Van-Genuchten hydraulic equations, may impact the 2.2 km model differently  
737 to the 12 km model, given in the former rainfall is more intense and hence the  
738 surface layer is more likely to become saturated. Initial tests, however, suggest the  
739 impact of changing the hydraulic equations on the surface temperature is small,  
740 with warm/dry biases in the UKMO-2.2 km persisting. Thus it is possible that the  
741 intense/intermittent nature of rainfall in the 2.2 km model is responsible for dry  
742 soil conditions and associated warm temperature bias over Eastern Europe but  
743 further work looking at more variables such as the work of Brisson et al (2016) on  
744 clouds is needed. In the ETH model such an effect is less apparent, possibly due  
745 to the use of a shallow convection parameterisation in this model. Other regions  
746 such as the UK are less sensitive, as soil moisture is not close to critical value for  
747 limiting evaporation. It should be noted that Liu et al (2016) using ERA-interim  
748 driven WRF 4 km simulations also show a warm and dry bias in the Central US  
749 in 13-year long simulations over the US.

750 In this study we have shown that two 2.2 km convection-permitting models yield  
751 qualitatively similar differences to the precipitation climatology compared to 12 km  
752 models, despite using different dynamical cores and different parameterization  
753 packages. Its also highlights that both convection-permitting models will need to  
754 address how to better balance the increased number of moderate to intense events

and the decreased number of low-intensity events, which are needed to improve the 12km model hourly distributions but are overcompensated in both models. Work is on-going to introduce a scale-aware convection parameterisation in future model versions of the UKMO, which would enable some sub-grid convection. Work on the boundary layer scheme and its coupling with convection is also on-going.

This intercomparison study would benefit from the availability of new generations of hourly precipitation datasets. Future work will examine whether there are similarly robust signals of future precipitation change across different CPMs, reducing uncertainty in projections of intense events at hourly and km-scales. To this end, the CORDEX-Flagship pilot study on CPMs is a promising initiative, allowing comparison of more CPMs beyond the two available for analysis here.

## 8 Appendix

### 8.1 Daily datasets

**FRANCE: SAFRAN** (8km) Systeme d'Analyse Fournissant des Renseignements Atmospheriques á la Neige (SAFRAN) is a precipitation analysis for continental France that uses an optimal interpolation method. One of the main features of SAFRAN is that the analyses are performed over climatically homogeneous zones, which are areas of irregular shape covering a surface usually smaller than 1000 km and where the horizontal climatic gradients (especially for precipitation) are weak. SAFRAN estimates one value of each parameter for each zone at several altitude levels. Within the zone, analyzed parameters depend only on elevation and aspect. First, SAFRAN performs a quality control of the observations. This is an iterative procedure based on the comparison between observed and analyzed quantities at the observation location. There were 3675 measurement stations for 2004/2005. The precipitation analysis is performed daily at 0600 UTC, to include in the analysis the numerous rain-gauges that measure precipitation on a daily basis (in particular in the climatological and snow networks). The first guess is a very simple and constant field. An hourly separation is then performed, but in this study we use the daily precipitation amount. Further description can be found in Quintana-Segui et al (2008).

**ALPS: APGD\_EURO4M** (5km) The Alpine rain-gauge dataset typically comprises 5500 observations on any day of the period 1971 - 2008. The analysis is based on a first guess for a day that is the long-term mean precipitation (period 1971 - 1990) of the relevant calendar month. The precipitation-elevation relationship is calculated locally and taken into account in this first guess. Then an anomaly is computed for every grid point using the stations located within a radius that depends on the station density. It can be up to 60 km from the grid point. The dataset has a 5km resolution, but its effective resolution is closer to 10-15km. The dataset is provided by the Federal Office of Meteorology and Climatology MeteoSwiss. The dataset incorporates local precipitation topography relationships at the climatological time-scale, which aims at reducing the risk of systematic underestimates at high elevations but does not correct for any gauge undercatch, which is comparatively larger during episodes with strong wind and during weather with low rainfall intensity or with snowfall. Sevruck and Zahlavova (1994) and Richter (1995) estimated measurement errors ranging from 7% (5%)

800 over the flatland regions in winter (summer) to 30% (10%) above 1500m in winter  
801 (summer). Further description can be found in Isotta et al (2014).

802 **SPAIN: Spain02** (0.11°) Daily precipitation gridded dataset developed for  
803 peninsular Spain and the Balearic Islands using 2756 quality-controlled stations  
804 over the time period from 1971 - 2010 (Herrera et al 2012). The grid was produced  
805 by applying the kriging method in a two-step process. First, the occurrence was  
806 interpolated using a binary kriging and, in a second step, the amounts were inter-  
807 polated by applying ordinary kriging to the occurrence outcomes. The elevation  
808 is not explicitly included in the development of the dataset because the available  
809 dense gauge network represents the orography corresponding to the 0.11° grid ap-  
810 propriately. Explicit comparison of Spain02 with the E-OBS dataset shows better  
811 performance of Spain02 to represent extreme events of daily precipitation in the  
812 region of Valencia regarding the amount and spatial distribution of precipitation  
813 (Herrera et al 2012).

814 **UK: UKCPOBS** (5km) The National Climate Information Centre daily UK  
815 gridded precipitation dataset (Perry et al 2009) spans the period 1958-present day,  
816 and from 1990 uses approximately 2500-3500 surface gauge observations. Quality  
817 control is performed through computerized and manual comparisons of individual  
818 daily station values against the daily all-station average and daily values from  
819 nearby stations. Any stations that have failed quality control are excluded from the  
820 computation of the gridded values. The gridding of the gauge data to a 5km×5km  
821 grid uses a cubic inverse-distance weighting interpolation using stations within  
822 50km radius of the grid box.

823 **CMORPH 1.0** (0.25°) The CMORPH (NOAA Climate Prediction Center  
824 morphing method, Joyce et al (2004)) algorithm uses the relatively high-resolution  
825 IR information to infer the hydrometeorological position between two consecu-  
826 tive PMW estimates. IR maps are used to derive cloud system advection vectors  
827 (CSAVs) to propagate PMW rainfall estimates. Such propagation is performed for-  
828 ward and backward for each time step using information provided by the CSAVs.  
829 Final values are achieved by averaging forward and backward rainfall analyses  
830 proportionally to step distance.

## 831 8.2 Hourly datasets

832 **Nimrod (UK):** Gridded hourly radar data for the UK at 5km resolution are avail-  
833 able from the Nimrod database (Golding 1998) for the period 2003-present-day.  
834 There are many issues with radar (clutter, anaprop, bright band, beam attenu-  
835 ation), and in particular radar data are known to systematically underestimate  
836 heavy rainfall amounts. The Met Office calibrates radar against rain gauges and  
837 employs algorithms to take account of known issues but some problems cannot be  
838 fully rectified. One of these is that the hourly gauges used in the calibration are  
839 relatively sparse, and thus are not able to fully correct for locally-varying effects  
840 such as attenuation.

841 **Germany:** The hourly precipitation data set assembled by Paulat et al (2008)  
842 is used. It features a horizontal grid spacing of 7 km and an effective horizontal  
843 resolution of 14-28 km. The time period of the dataset is 2001-2008 (8 years). To  
844 assemble this dataset, measurements from rain gauges have been gridded as daily  
845 sums, following the procedure by Frei and Schär (1998). Afterwards, the daily sums

were disaggregated into hourly values using rain rate retrievals from radar (Wuest et al 2010). Beyond uncertainties arising from rain-gauge undercatch, gridding procedures (Frei et al 2003), and weather radar measurements (Wuest et al 2010), possible inconsistencies between gauge observations and radar restricts the data set to 92% of the possible days, at the respective grid points (Paulat et al 2008).

**Switzerland:** RdisaggH is an experimental precipitation data set for Switzerland which provides gridded, radar-disaggregated rain-gauge observations (Wuest et al 2010). In order to obtain hourly data, a gridded daily product was disaggregated into hourly sums, using information from weather radar fields. The resulting dataset has a grid-spacing of  $0.01^\circ \times 0.01^\circ$  covers Switzerland and is available for the time period May 2003-2010.

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## References

- Anquetin S, Yates E, Ducrocq V, Samouillan S, Chancibault K, Davolio S, Accadia C, Casaioli M, Mariani S, Ficca G (2005) The 8 and 9 september 2002 flash flood event in France: a model intercomparison. *Nat Hazards Earth Syst Sci* 5(5):741–754
- Arakawa A, Lamb VR (1977) Computational design of the basic dynamical processes of the UCLA general circulation model. *Methods Comput Phys* 17:173–265
- Baldauf M, Seifert A, Förstner J, Majewski D, Raschendorfer M, Reinhardt T (2011) Operational convective-scale numerical weather prediction with the COSMO model: Description and sensitivities. *Mon Weather Rev* 139(12):3887–3905, DOI 10.1175/MWR-D-10-05013.1
- Ban N, Schmidli J, Schär C (2014) Evaluation of the convection-resolving regional climate modeling approach in decade-long simulations. *J Geophys Res* 119(13):7889–7907, DOI 10.1002/2014JD021478
- Barthlott C, Davolio S (2016) Mechanisms initiating heavy precipitation over italy during hymex special observation period 1: a numerical case study using two mesoscale models. *Q J R Meteorol Soc* 142:238–258, DOI 10.1002/qj.2630
- Berthou S, Mailler S, Drobinski P, Arsouze T, Bastin S, Béranger K, Flaouanas E, Lebeaupin Brossier C, Stéfanon M (2016) Influence of submonthly air-sea coupling on heavy precipitation events in the western mediterranean basin. *Q J R Meteorol Soc* DOI 10.1002/qj.2717
- Best MJ, Pryor M, Clark DB, Rooney GG, Essery RLH, Ménard CB, Edwards JM, Hendry MA, Porson A, Gedney N, Mercado LM, Sitch S, Blyth E, Boucher O, Cox PM, Grimmond CSB, Harding RJ (2011) The joint uk land environment simulator (jules), model description - part 1: Energy and water fluxes. *Geosci Model Devel* 4:677–699, DOI 10.5194/gmd-4-677-2011
- Beven KJ, Kirkby MJ (1979) A physically based, variable contributing area model of basin hydrology. *Hydrol Sci B* 24:43–69
- Boberg F, Berg P, Thejll P, Gutowski WJ, Christensen JH (2009) Improved confidence in climate change projections of precipitation evaluated using daily statistics from the PRUDENCE ensemble. *Clim Dyn* 32:1097–1106
- Böhm U, Kücken M, Ahrens W, Block A, Hauffe D, Keuler K, Rockel B, Will A (2006) Clm—the climate version of lm: brief description and long-term applications. *COSMO Newsl* 6:225–235

- 899 Bott A (1989) A positive definite advection scheme obtained by nonlinear renormaliza-  
900 tion of the advective fluxes. *Mon Weather Rev* 117(5):1006–1015, DOI 10.1175/1520-  
901 0493(1989)117<1006:APDASO>2.0.CO;2
- 902 Boutle IA, Eyre JEJ, Lock AP (2014) Seamless stratocumulus simulation across the turbulent  
903 gray zone. *Mon Weather Rev* 142:1655–1668, DOI 10.1175/MWR-D-13-00229.1
- 904 Bresson E, Ducrocq V, Nuissier O, Ricard D, de Saint-Aubin C (2012) Idealized numerical  
905 simulations of quasi-stationary convective systems over the northwestern Mediterranean  
906 complex terrain. *Q J R Meteorol Soc* 138(668):1751–1763, DOI 10.1002/qj.1911
- 907 Brisson E, Van Weverberg K, Demuzere M, Devis A, Saeed S, Stengel M, van Lipzig NPM  
908 (2016) How well can a convection-permitting climate model reproduce decadal statistics  
909 of precipitation, temperature and cloud characteristics? *Clim Dyn* 47(9):3043–3061, DOI  
910 10.1007/s00382-016-3012-z
- 911 Brockhaus P, Lüthi D, Schär C (2008) Aspects of the diurnal cycle in a regional climate model.  
912 *Meteorol Z* 17:433–443, DOI 10.1127/0941-2948/2008/0316
- 913 Bryan GH, Morrison H (2012) Sensitivity of a simulated squall line to horizontal resolution and  
914 parameterization of microphysics. *Mon Weather Rev* 140(1):202–225, DOI 10.1175/MWR-  
915 D-11-00046.1
- 916 Cavicchia L, Scoccimarro E, Gualdi S, Marson P, Ahrens B, Berthou S, Conte D, Dell’Aquila  
917 A, Drobinski P, Djurdjevic V, Dubois C, Gallardo C, Li L, Oddo P, Sanna A, Torma C  
918 (2016) Mediterranean extreme precipitation: a multi-model assessment. *Clim Dyn* DOI  
919 10.1007/s00382-016-3245-x
- 920 Chan SC, Kendon EJ, Fowler HJ, Blenkinsop S, Ferro CAT, Stephenson DB (2013) Does  
921 increasing the spatial resolution of a regional climate model improve the simulated daily  
922 precipitation? *Clim Dyn* 41(5-6):1475–1495, DOI 10.1007/s00382-012-1568-9
- 923 Chan SC, Kendon EJ, Fowler HJ, Blenkinsop S, Roberts NM, Ferro CAT (2014) The value  
924 of high-resolution Met Office regional climate models in the simulation of multi-hourly  
925 precipitation extremes. *J Clim* 27(16):6155–6174, DOI 10.1175/JCLI-D-13-00723.1
- 926 Charney JG, Phillips NA (1953) Numerical integration of the quasi-geostrophic equations  
927 for barotropic and simple baroclinic flows. *J Meteorol* 10:71–99, DOI 10.1175/1520-  
928 0469(1953)010<0071:NIOTQG>2.0.CO;2
- 929 Clark DB, Mercado LM, Sitch S, Jones CD, Gedney N, Best MJ, Pryor M, Rooney GG, Essery  
930 RLH, Blyth E, Boucher O, Harding RJ, Huntingford C, Cox PM (2011) The joint uk land  
931 environment simulator (jules), model description - part 2: Carbon fluxes and vegetation  
932 dynamics. *Geosci Model Devel* 4:701–722, DOI 10.5194/gmd-4-701-2011
- 933 Clark P, Roberts N, Lean H, Ballard SP, Charlton-Perez C (2016) Convection-permitting mod-  
934 els: a step-change in rainfall forecasting. *Meteorol Appl* 23:165–181, DOI 10.1002/met.1538
- 935 Dauhut T, Chaboureaud JP, Escobar J, Mascart P (2015) Large-eddy simulations of hector  
936 the convective making the stratosphere wetter. *Atmos Sci Lett* 16(2):135–140, DOI  
937 10.1002/asl2.534
- 938 Delrieu G, Nicol J, Yates E, Kirstetter PE, Creutin JD, Anquetin S, Obled C, Saulnier  
939 GM, Ducrocq V, Gaume E, Payrastré O, Andrieu H, Ayrat PA, Bouvier C, Neppel L,  
940 Livet M, Lang M, Du-Châtelet JP, Walpersdorf A, Wobrock W (2005) The catastrophic  
941 flash-flood event of 89 september 2002 in the gard region, france: A first case study  
942 for the cévennesvivaraïs mediterranean hydrometeorological observatory. *J Hydrometeorol*  
943 6(1):34–52, DOI 10.1175/JHM-400.1
- 944 Done J, Davis CA, Weisman ML (2004) The next generation of NWP: explicit forecasts of  
945 convection using the weather research and forecasting (WRF) model. *Atmos Sci Lett*  
946 5:110–117
- 947 Drobinski P, Ducrocq V, Alpert P, Anagnostou E, Béranger K, Borga M, Braud I, Chanzy  
948 A, Davolio S, Delrieu G, Estournel C, Boubrahmi NF, Font J, Grubisic V, Gualdi S,  
949 Homar V, Ivancan-Picek B, Kottmeier C, Kotroni V, Lagouvardos K, Lionello P, Llasat  
950 MC, Ludwig W, Lutoff C, Mariotti A, Richard E, Romero R, Rotunno R, Roussot O,  
951 Ruin I, Somot S, Taupier-Letage I, Tintore J, Uijlenhoet R, Wernli H (2014) HyMeX, a  
952 10-year multidisciplinary program on the Mediterranean water cycle. *Bull Am Meteorol*  
953 *Soc* 95:1063–1082, DOI 10.1175/BAMS-D-12-00242.1
- 954 Ducrocq V, Nuissier O, Ricard D, Lebeaupin C, Thouvenin T (2008a) A numerical study of  
955 three catastrophic precipitating events over southern France. II: mesoscale triggering and  
956 stationarity factors. *Q J R Meteorol Soc* 134(630):131–145, DOI 10.1002/qj.199
- 957 Ducrocq V, Nuissier O, Ricard D, Lebeaupin C, Thouvenin T (2008b) A numerical study of  
958 three catastrophic precipitating events over southern France. II: Mesoscale triggering and

- stationarity factors. *Q J R Meteorol Soc* 134(630):131–145, DOI 10.1002/qj.199
- 959 Edwards JM, Slingo A (1996) Studies with a flexible new radiation code. I: Choosing a con-  
960 figuration for a large-scale model. *Q J R Meteorol Soc* 122:689–720
- 961 Fantini A, Raffaele F, Torma C, Bacer S, Coppola E, Giorgi F, Ahrens B, Dubois C, Sanchez  
962 E, Verdecchia M (2016) Assessment of multiple daily precipitation statistics in era-interim  
963 driven med-cordex and euro-cordex experiments against high resolution observations. *Clim*  
964 *Dyn* pp 1–24, DOI 10.1007/s00382-016-3453-4
- 965 Flaounas E, Drobinski P, Borga M, Calvet JC, Delrieu G, Morin E, Tartari G, Toffolon R (2012)  
966 Assessment of gridded observations used for climate model validation in the Mediterranean  
967 region: the HyMeX and MED-CORDEX framework. *Environ Res Lett* 7(2):24,017, DOI  
968 10.1088/1748-9326/7/2/024017
- 969 Förstner J, Doms G (2004) Runge-Kutta time integration and high-order spatial discretization  
970 of advection - a new dynamical core for the LMK
- 971 Fosser G, Khodayar S, Berg P (2015) Benefit of convection permitting climate model simula-  
972 tions in the representation of convective precipitation. *Clim Dyn* 44(1-2):45–60, DOI  
973 10.1007/s00382-014-2242-1
- 974 Frei C, Schär C (1998) A precipitation climatology of the Alps from high-resolution rain-gauge  
975 observations. *Int J Clim* 18:873–900
- 976 Frei C, Christensen JH, Déqué M, Jacob D, Jones RG, Vidale PL (2003) Daily precipitation  
977 statistics in regional climate models: evaluation and intercomparison for the european alps.  
978 *J Geophys Res* 108(D3):4124, DOI 10.1029/2002JD002287
- 979 Fuhrer O, Osuna C, Lapillonne X, Gysi T, Cumming B, Arteaga A, Schulthess TC (2014) To-  
980 wards a performance portable, architecture agnostic implementation strategy for weather  
981 and climate models. *Supercomp Front Innov* 1(1), DOI 10.14529/jsfi140103
- 982 van Genuchten MT, Leij FJ, Yates SR (1991) The RETC code for quantifying the hydraulic  
983 functions of unsaturated soils. Tech. Rep. EPA/600/2-91/065, U.S. Environmental Pro-  
984 tection Agency
- 985 Golding BW (1998) Nimrod: A system for generating automated very short range forecasts.  
986 *Meteorol Appl* 5:1–16, DOI 10.1017/S1350482798000577
- 987 Gregersen IB, Sorup HJD, Madsen H, Rosbjerg D, Mikkelsen PS, Arnbjerg-Nielsen K (2013)  
988 Assessing future climatic changes of rainfall extremes at small spatio-temporal scales. *Clim*  
989 *Chang* 118(3-4):783–797, DOI 10.1007/s10584-012-0669-0
- 990 Gregory D, Allen S (1991) The effect of convective downdraughts upon nwp and climate  
991 simulations. In: Ninth Conf. Numer. Weather Predict. Denver, Color., pp 122–123
- 992 Gregory D, Rowntree PR (1990) A mass-flux convection scheme with representation of cloud  
993 ensemble characteristics and stability dependent closure. *Mon Weather Rev* 118:1483–1506,  
994 DOI 10.1175/1520-0493(1990)118<1483:AMFCSW>2.0.CO;2
- 995 Gysi T, Osuna C, Fuhrer O, Bianco M, Schulthess TC (2015) Stella: A domain-specific tool  
996 for structured grid methods in weather and climate models. In: Proc. Int. Conf. HPC,  
997 Networking, Storage Anal., SC '15, pp 41:1—41:12, DOI 10.1145/2807591.2807627
- 998 Hagen M, Finke U (1999) Motion characteristics of thunderstorms in southern germany. *Me-  
999 teorol Appl* 6(3):227–239
- 1000 Hanel M, Buishand TA (2010) On the value of hourly precipitation extremes in regional climate  
1001 model simulations. *J Hydrol* 393:265–273, DOI 10.1016/j.jhydrol.2010.08.024
- 1002 Hanley KE, Plant RS, Stein THM, Hogan RJ, Nicol JC, Lean HW, Halliwell C, Clark PA  
1003 (2015) Mixing length controls on high resolution simulations of convective storms. *Q J R*  
1004 *Meteorol Soc* 141(686):272–284, DOI 10.1002/qj.2356
- 1005 Haylock MR, Hofstra N, KleinTank AMG, Klok EJ, Jones PD, New M (2008) A european  
1006 daily high-resolution gridded dataset of surface temperature and precipitation. *J Geophys*  
1007 *Res* 113:D20,119, DOI 10.1029/2008JD10201
- 1008 Heise E, Ritter B, Schrodin R (2006) Operational implementation of the multilayer soil model,  
1009 COSMO tech. rep., no. 9. Tech. Rep. 5, COSMO
- 1010 Herrera S, Gutierrez JM, Ancell R, Pons MR, Frias MD, Fernandez J (2012) Development  
1011 and analysis of a 50 year high-resolution daily gridded precipitation dataset over Spain  
1012 (SPAIN02). *Int J Clim* 32:74–85, DOI 10.1002/joc.2256
- 1013 Hofstra N, New M, McSweeney C (2010) The influence of interpolation and station network  
1014 density on the distributions and trends of climate variables in gridded daily data. *Clim*  
1015 *Dyn* 35(5):841–858, DOI 10.1007/s00382-009-0698-1
- 1016 Hohenegger C, Brockhaus P, Schär C (2008) Towards climate simulations at cloud-resolving  
1017 scales. *Meteorol Z* 17(4):383–394, DOI 10.1127/0941-2948/2008/0303
- 1018



- 1019 Isotta F, Frei C, Weigluni V, Percec Tadi M, Lasssegues P, Rudolf B, Pavan V, Cacciamani C,  
1020 Antolini G, Ratto SM, Munari M, Micheletti S, Bonati V, Lussana C, Ronchi C, Panettieri  
1021 E, Marigo G, Vertani G (2014) The climate of daily precipitation in the Alps: Development  
1022 and analysis of a high-resolution grid dataset from pan-Alpine rain-gauge data. *Int J Clim*  
1023 34:1657–1675, DOI 10.1002/joc.3794
- 1024 Jacob D, Petersen J, Eggert B, Alias A, Christensen OB, Bouwer LM, Braun A, Colette  
1025 A, Déqué M, Georgievski G, Georgopoulou E, Gobiet A, Menut L, Nikulin G, Haensler  
1026 A, Hempelmann N, Jones C, Keuler K, Kovats S, Kröner N, Kotlarski S, Kriegsmann  
1027 A, Martin E, van Meijgaard E, Moseley C, Pfeifer S, Preuschmann S, Radermacher C,  
1028 Radtke K, Rechid D, Rounsevell M, Samuelsson P, Somot S, Soussana JF, Teichmann C,  
1029 Valentini R, Vautard R, Weber B, Yiou P (2014) Euro-cordex: new high-resolution climate  
1030 change projections for european impact research. *Reg Environ Chang* 14(2):563–578, DOI  
1031 10.1007/s10113-013-0499-2
- 1032 Joyce RJ, Janowiak JE, Arkin PA, Xie P (2004) Cmorph: A method that produces  
1033 global precipitation estimates from passive microwave and infrared data at high  
1034 spatial and temporal resolution. *J Hydrometeorol* 5(3):487–503, DOI 10.1175/1525-  
1035 7541(2004)005<0487:CAMTPG>2.0.CO;2
- 1036 Kaltenböck R (2004) The outbreak of severe storms along convergence lines northeast of the  
1037 alps. case study of the 3 august 2001 mesoscale convective system with a pronounced bow  
1038 echo. *Atmos Res* 70(1):55–75, DOI <https://doi.org/10.1016/j.atmosres.2003.11.003>
- 1039 Kendon EJ, Roberts NM, Senior CA, Roberts MJ (2012) Realism of rainfall in a very high-  
1040 resolution regional climate model. *J Clim* 25(17):5791–5806, DOI 10.1175/JCLI-D-11-  
1041 00562.1
- 1042 Khodayar S, Fosser G, Berthou S, Davolio S, Drobinski P, Ducrocq V, Ferretti R, Nuret M,  
1043 Pichelli E, Richard E, Bock O (2016) A seamless weatherclimate multi-model intercompar-  
1044 ison on the representation of a high impact weather event in the western mediterranean:  
1045 Hymex iop12. *Q J R Meteorol Soc* 142, DOI 10.1002/qj.2700
- 1046 Kidd C, Bauer P, Turk J, Huffman GJ, Joyce R, Hsu KL, Braithwaite D (2012) Intercomparison  
1047 of high-resolution precipitation products over northwest europe. *J Hydrometeorol* 13(1):67–  
1048 83, DOI 10.1175/JHM-D-11-042.1
- 1049 Kinne S, Schulz M, Textor C, Guibert S, Balkanski Y, Bauer SE, Berntsen T, Berglen TF,  
1050 Boucher O, Chin M, Collins W, Dentener F, Diehl T, Easter R, Feichter J, Fillmore D,  
1051 Ghan S, Ginoux P, Gong S, Grini A, Hendricks J, Herzog M, Horowitz L, Isaksen I, Iversen  
1052 T, Kirkevåg A, Kloster S, Koch D, Kristjansson JE, Krol M, Lauer A, Lamarque JF, Lesins  
1053 G, Liu X, Lohmann U, Montanaro V, Myhre G, Penner J, Pitari G, Reddy S, Seland O,  
1054 Stier P, Takemura T, Tie X (2006) An AeroCom initial assessment optical properties in  
1055 aerosol component modules of global models. *Atmos Chem Phys* 6(7):1815–1834, DOI  
1056 10.5194/acp-6-1815-2006
- 1057 Kjellström E, Boberg F, Castro M, Christensen JH, Nikulin G, Sánchez E (2010) Daily and  
1058 monthly temperature and precipitation statistics as performance indicators for regional  
1059 climate models. *Clim Res* 44:135–150, DOI 10.3354/cr00932
- 1060 Klingaman NP, Martin GM, Moise A (2017) Asop (v1.0): a set of methods for analyzing  
1061 scales of precipitation in general circulation models. *Geosci Model Dev* 10(1):57–83, DOI  
1062 10.5194/gmd-10-57-2017
- 1063 Kotlarski S, Keuler K, Christensen OB, Colette A, Déqué M, Gobiet A, Goergen K, Jacob D,  
1064 Lüthi D, van Meijgaard E, Nikulin G, Schär C, Teichmann C, Vautard R, Warrach-Sagi  
1065 K, Wulfmeyer V (2014) Regional climate modeling on european scales: a joint standard  
1066 evaluation of the euro-cordex rcm ensemble. *Geosci Model Dev* 7(4):1297–1333, DOI  
1067 10.5194/gmd-7-1297-2014
- 1068 Langhans W, Schmidli J, Fuhrer O, Bieri S, Schär C (2013) Long-term simulations of thermally  
1069 driven flows and orographic convection at convection-parameterizing and cloud-resolving  
1070 resolutions. *J Appl Meteorol Clim* 52:1490–1510, DOI 10.1175/JAMC-D-12-0167.1
- 1071 Lapillonne X, Fuhrer O (2014) Using compiler directives to port large scientific applications  
1072 to GPUs: An example from atmospheric science. *Parallel Process Lett* 24(1):1450,003 (18  
1073 pp.), DOI 10.1142/S0129626414500030
- 1074 Lean HW, Clark PA, Dixon M, Roberts NM, Fitch A, Forbes R, Halliwell C (2008)  
1075 Characteristics of high-resolution versions of the Met Office Unified Model for fore-  
1076 casting convection over the United Kingdom. *Mon Weather Rev* 136:3408–3424, DOI  
1077 10.1175/2008MWR2332.1

- 1078 Lenderink G (2010) Exploring metrics of extreme daily precipitation in a large ensemble of  
1079 regional climate model simulations. *Clim Res* 44(2-3):151–166, DOI 10.3354/cr00946
- 1080 Leutwyler D, Fuhrer O, Lapillonne X, Lüthi D, Schär C (2016) Towards european-scale  
1081 convection-resolving climate simulations. *Geosci Model Devel* DOI 10.5194/gmd-2016-119
- 1082 Leutwyler D, Lüthi D, Ban N, Fuhrer O, Schär C (2017) Evaluation of the convection-resolving  
1083 climate modeling approach on continental scales. *J Geophys Res Atmos* pp n/a—n/a,  
1084 DOI 10.1002/2016JD026013
- 1085 Lind P, Lindstedt D, Kjellström E, Jones C (2016) Spatial and temporal characteristics of  
1086 summer precipitation over central europe in a suite of high-resolution climate models. *J*  
1087 *Clim* 29(10):3501–3518, DOI 10.1175/JCLI-D-15-0463.1
- 1088 Liu C, Ikeda K, Rasmussen R, Barlage M, Newman AJ, Prein AF, Chen F, Chen L, Clark  
1089 M, Dai A, Dudhia J, Eidhammer T, Gochis D, Gutmann E, Kurkute S, Li Y, Thompson  
1090 G, Yates D (2016) Continental-scale convection-permitting modeling of the current and  
1091 future climate of north america. *Clim Dyn* pp 1–25, DOI 10.1007/s00382-016-3327-9
- 1092 Lock AP, Brown AR, Bush MR, Martin GM, Smith RNB (2000) A new boundary layer mixing  
1093 scheme. Part I: Scheme description and single-column model tests. *Mon Weather Rev*  
1094 128(9):3187–3199
- 1095 Manzato A, Davolio S, Miglietta MM, Pucillo A, Setvák M (2015) 12 september  
1096 2012: A supercell outbreak in NE italy? *Atmos Res* 153:98–118, DOI  
1097 <http://doi.org/10.1016/j.atmosres.2014.07.019>
- 1098 Matte D, Laprise R, Thériault JM, Lucas-Picher P (2017) Spatial spin-up of fine scales in  
1099 a regional climate model simulation driven by low-resolution boundary conditions. *Clim*  
1100 *Dyn* 49(1):563–574, DOI 10.1007/s00382-016-3358-2
- 1101 McCaul EW, Goodman SJ, LaCasse KM, Cecil DJ (2009) Forecasting lightning  
1102 threat using cloud-resolving model simulations. *Weather Forecast* 24:709–729, DOI  
1103 10.1175/2008WAF2222152.1
- 1104 Mellor G, Yamada T (1982) Development of a turbulence closure model for geophysical fluid  
1105 problems. *Rev Geophys* 20(4):851–875, DOI 10.1029/RG020i004p00851
- 1106 Meredith EP, Maraun D, Semenov VA, Park W (2015) Evidence for added value of convection-  
1107 permitting models for studying changes in extreme precipitation. *J Geophys Res Atmos*  
1108 120(24):12,500–12,513, DOI 10.1002/2015JD024238
- 1109 Moore RJ (1985) The probability distributed principle and runoff production at point and  
1110 basin scales. *Hydrol Sci J* 30:273–297
- 1111 Morel C, Senesi S (2002) A climatology of mesoscale convective systems over europe using  
1112 satellite infrared imagery. ii: Characteristics of european mesoscale convective systems. *Q*  
1113 *J R Meteorol Soc* 128(584):1973–1995, DOI 10.1256/003590002320603494
- 1114 Nisi L, Martius O, Hering A, Kunz M, Germann U (2016) Spatial and temporal distribution  
1115 of hailstorms in the alpine region: a long-term, high resolution, radar-based analysis. *Q J*  
1116 *R Meteorol Soc* pp n/a—n/a, DOI 10.1002/qj.2771
- 1117 Nuissier O, Ducrocq V, Ricard D, Lebeaupin C, Anquetin S (2008) A numerical study of  
1118 three catastrophic precipitating events over southern France. i: Numerical framework and  
1119 synoptic ingredients. *Q J R Meteorol Soc* 134(630):111–130, DOI 10.1002/qj.200
- 1120 OpenACC (2011) The OpenACC application programming interface, 2011. URL  
1121 <https://www.openacc.org>
- 1122 Osuna C, Fuhrer C, Gysi T, Schulthess TC (2015) Porting the COSMO dynamical core to  
1123 heterogeneous platforms using STELLA library. In: *Parallel Comput. Road to Exascale,*  
1124 *Proc. Int. Conf. Parallel Comput. ParCo 2015, 1-4 Sept. 2015, Edinburgh, Scotland, UK,*  
1125 pp 637–646, DOI 10.3233/978-1-61499-621-7-637
- 1126 Paulat M, Frei C, Hagen M, Wernli H (2008) A gridded dataset of hourly precipitation in  
1127 Germany: Its construction, climatology and application. *Meteorol Z* 17(6):719–732, DOI  
1128 10.1127/0941-2948/2008/0332
- 1129 Peel MC, Finlayson BL, McMahon TA (2007) Updated world map of the köppen-geiger climate  
1130 classification. *Hydrol earth Syst Sci Discuss* 4(2):439–473
- 1131 Perry M, Hollis D, Elms M (2009) The generation of daily gridded datasets of temperature  
1132 and rainfall for the uk
- 1133 Prein AF, Gobiet A (2017) Impacts of uncertainties in european gridded precipitation obser-  
1134 vations on regional climate analysis. *Int J Climatol* 37(1):305–327, DOI 10.1002/joc.4706
- 1135 Prein AF, Gobiet A, Suklitsch M, Truhetz H, Awan NK, Keuler K, Georgievski G (2013)  
1136 Added value of convection permitting seasonal simulations. *Clim Dyn* 41:2655–2677, DOI  
1137 10.1007/s00382-013-1744-6

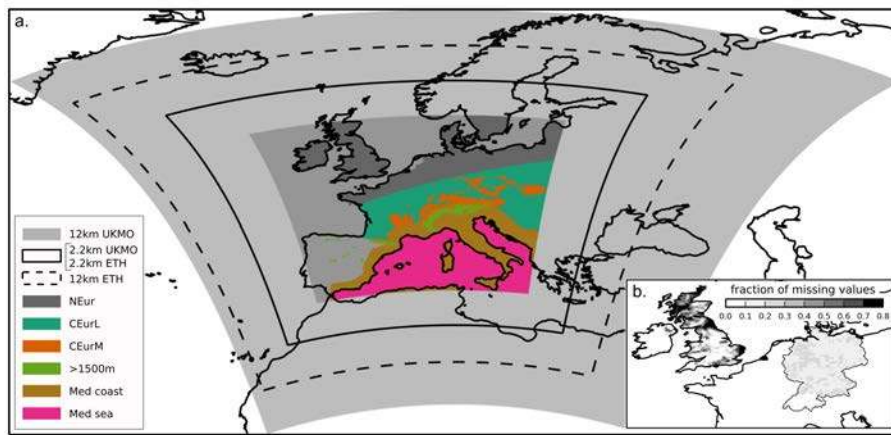
- 1138 Prein AF, Langhans W, Fossier G, Ferrone A, Ban N, Goergen K, Keller M, Tölle M, Gutjahr O,  
 1139 Feser F, Brisson E, Kollet S, Schmidli J, van Lipzig NPM, Leung R (2015) A review on re-  
 1140 gional convection-permitting climate modeling: demonstrations, prospects, and challenges:  
 1141 Convection-permitting climate modeling. *Rev Geophys* DOI 10.1002/2014RG000475
- 1142 Quintana-Segui P, Le Moigne P, Durand Y, Martin E, Habets F, Baillon M, Canellas  
 1143 C, Franchisteguy L, Morel S (2008) Analysis of near-surface atmospheric variables:  
 1144 Validation of the SAFRAN analysis over France. *J Appl Meteorol* 47:92–107, DOI  
 1145 10.1175/2007JAMC1636.1
- 1146 Raschendorfer M (2001) The new turbulence parameterization of LM
- 1147 Rauthe M, Steiner H, Riediger U, Mazurkiewicz A, Gratzki A (2013) A central european pre-  
 1148 cipitation climatology - part i: Generation and validation of a high-resolution gridded daily  
 1149 data set (hyras). *Meteorol Zeitschrift* 22(3):235–256, DOI 10.1127/0941-2948/2013/0436
- 1150 Reinhardt T, Seifert A (2005) A three-category ice-scheme for LMK
- 1151 Richard E, Buzzi A, Zängl G (2007) Quantitative precipitation forecasting in the alps: The  
 1152 advances achieved by the mesoscale alpine programme. *Q J R Meteorol Soc* 133(625):831–  
 1153 846, DOI 10.1002/qj.65
- 1154 Richter D (1995) Ergebnisse methodischer Untersuchungen zur Korrektur des systematischen  
 1155 Messfehlers des Hellmann-Niederschlagsmessers. Selbstverl. des Dt. Wetterdienstes Offen-  
 1156 bach aM
- 1157 Ritter B, Geleyn JF (1992) A comprehensive radiation scheme for numerical weather prediction  
 1158 models with potential applications in climate simulations. *Mon Weather Rev* 120(2):303–  
 1159 325
- 1160 Rockel B, Will A, Hense A (2008) Special issue: Regional climate modelling with cosmo-clm  
 1161 (cclm). *Meteorol Z* 17:477–485
- 1162 Ruti PM, Somot S, Giorgi F, Dubois C, Flaounas E, Obermann A, Dell'Aquila A, Pisacane  
 1163 G, Harzallah A, Lombardi E, Ahrens B, Akhtar N, Alias A, Arsouze T, Aznar R, Bastin  
 1164 S, Bartholy J, B??ranger K, Beuvier J, Bouffies-Cloch?? S, Brauch J, Cabos W, Cal-  
 1165 manti S, Calvet JC, Carillo A, Conte D, Coppola E, Djurdjevic V, Drobinski P, Elizalde-  
 1166 Arellano A, Gaertner M, Gal??n P, Gallardo C, Gualdi S, Goncalves M, Jorba O, Jord??  
 1167 G, L'Heveder B, Lebeaupin-Brossier C, Li L, Liguori G, Lionello P, Maci??s D, Nabat P,  
 1168 ??nol B, Raikovic B, Ramage K, Sevault F, Sannino G, Struglia MV, Sanna A, Torma  
 1169 C, Vervatis V (2016) Med-cordex initiative for mediterranean climate studies. *Bull Am*  
 1170 *Meteorol Soc* 97(7):1187–1208, DOI 10.1175/BAMS-D-14-00176.1
- 1171 Scaife AA, Arribas A, Blockley E, Brookshaw A, Clark RT, Dunstone N, Eade R, Fereday D,  
 1172 Folland CK, Gordon M, Hermanson L, Knight JR, Lea DJ, MacLachlan C, Maidens A,  
 1173 Martin M, Peterson AK, Smith D, Vellinga M, Wallace E, Waters J, Williams A (2014)  
 1174 Skillful long-range prediction of european and north american winters. *Geophys Res Lett*  
 1175 41:2514–2519, DOI 10.1002/2014GL059637
- 1176 Schär C, Ban N, Fischer EM, Rajczak J, Schmidli J, Frei C, Giorgi F, Karl TR, Kendon EJ,  
 1177 Tank AMGK, OGorman PA, Sillmann J, Zhang X, Zwiers FW (2016) Percentile indices  
 1178 for assessing changes in heavy precipitation events. *Clim Chang* 137(1-2):201–216, DOI  
 1179 10.1007/s10584-016-1669-2
- 1180 Schneider W, Bott A (2014) On the time-splitting errors of one-dimensional advection schemes  
 1181 in numerical weather prediction models; a comparative study. *Q J Roy Meteor Soc*  
 1182 140(684):2321–2329, DOI 10.1002/qj.2301
- 1183 Schwartz CS (2014) Reproducing the September 2013 record-breaking rainfall over the Col-  
 1184 orado Front Range with high-resolution WRF forecasts. *Wea Forecast* 29:393–402, DOI  
 1185 <http://dx.doi.org/10.1175/WAF-D-13-00136.1>
- 1186 Sevruk B, Zahlavova L (1994) Classification system of precipitation gauge site exposure: Eval-  
 1187 uation and application. *Int J Climatol* 14(6):681–689, DOI 10.1002/joc.3370140607
- 1188 Skamarock WC (2004) Evaluating mesoscale nwp models using kinetic energy spectra. *Mon*  
 1189 *Weather Rev* 132(12):3019–3032, DOI 10.1175/MWR2830.1
- 1190 Smagorinsky J (1963) General circulation experiments with the primitive equations, Part 1:  
 1191 The basic experiments. *Mon Weather Rev* 91:99–164
- 1192 Smith RNB (1990) A scheme for predicting layer clouds and their water content in a general  
 1193 circulation model. *Q J R Meteorol Soc* 116:435–460
- 1194 Stampoulis D, Anagnostou EN, Nikolopoulos EI (2013) Assessment of high-resolution satellite-  
 1195 based rainfall estimates over the mediterranean during heavy precipitation events. *J Hy-  
 1196 drometeorol* 14(5):1500–1514, DOI 10.1175/JHM-D-12-0167.1

- 1197 Steppeler J, Doms G, Schattler U, Bitzer HW, Gassmann A, Damrath U, Gregoric G (2003)  
1198 Meso-gamma scale forecasts using the nonhydrostatic model LM. *Meteorol Atmos Phys*  
1199 82:75–96, DOI 10.1007/s00703-001-0592-9
- 1200 Stratton RA, Senior CA, Vosper SB, Folwell SS, Boutle IA, Earnshaw D, Kendon E, Lock AP,  
1201 Malcolm A, Manners J, Morcrette J, Short C, Stirling AJ, Taylor CM, Tucker S, Webster  
1202 S, Wilkinson JM (in rev.) A pan-africa convection-permitting regional climate simulation  
1203 with the met office unified model : Cp4-africa. *J Clim* pp n–a
- 1204 Tanré D, Geleyn J, Slingo J (1984) *Aerosols and Their Climatic Effects*, A. Deepak, Hampton,  
1205 Va, chap First resu, pp 133–177
- 1206 Taylor KE, Stouffer RJ, Meehl GA (2012) An overview of CMIP5 and the experiment design.  
1207 *Bull Am Meteorol Soc* 93:485–498, DOI 10.1175/BAMS-D-11-00094.1
- 1208 Tiedtke M (1989) A comprehensive mass flux scheme for cumulus parametrization in large-scale  
1209 models. *Mon Weather Rev* 117:1779–1800
- 1210 Vaithinada Ayar P, Vrac M, Bastin S, Carreau J, Déqué M, Gallardo C (2016) Intercomparison  
1211 of statistical and dynamical downscaling models under the euro- and med-cordex initiative  
1212 framework: present climate evaluations. *Clim Dyn* 46(3):1301–1329, DOI 10.1007/s00382-  
1213 015-2647-5
- 1214 Walters D, Brooks M, Boutle I, Melvin T, Stratton R, Vosper S, Wells H, Williams K, Wood  
1215 N, Allen T, Bushell A, Copsey D, Earnshaw P, Edwards J, Gross M, Hardiman S, Harris  
1216 C, Heming J, Klingaman N, Levine R, Manners J, Martin G, Milton S, Mittermaier M,  
1217 Morcrette C, Riddick T, Roberts M, Sanchez C, Selwood P, Stirling A, Smith C, Suri  
1218 D, Tennant W, Vidale PL, Wilkinson J, Willett M, Woolnough S, Xavier P (2016) The  
1219 Met Office Unified Model Global Atmosphere 6.0/6.1 and JULES Global Land 6.0/6.1  
1220 configurations. *Geosci Model Devel* DOI 10.5194/gmd-2016-194
- 1221 Walters DN, Best MJ, Bushell AC, Copsey D, Edwards JM, Falloon PD, Harris CM, Lock AP,  
1222 Manners JC, Morcrette CJ, Roberts MJ, Stratton RA, Webster S, Wilkinson JM, Willett  
1223 MR, Boutle IA, Earnshaw PD, Hill PG, MacLachlan C, Martin GM, Moufouma-Okia  
1224 W, Palmer MD, Petch JC, Rooney GG, Scaife AA, Williams KD (2011) The Met Office  
1225 Unified Model global atmosphere 3.0/3.1 and JULES global land 3.0/3.1 configurations.  
1226 *Geosci Model Devel* 4:919–941, DOI 10.5194/gmd-4-919-2011
- 1227 Weisman ML, Davis C, Wang W, Manning KW, Klemp JB (2008) Experiences with 0-36-h  
1228 explicit convective forecasts with the WRF-ARW model. *Weather Forecast* 23(3):407–437
- 1229 Weusthoff T, Ament F, Arpagaus M, Rotach MW (2010) Assessing the benefits of convection-  
1230 permitting models by neighbourhood verification: Examples from MAP D-PHASE. *Mon*  
1231 *Weather Rev* 138:3418–3433
- 1232 Wicker L, Skamarock W (2002) Time-splitting methods for elastic models using forward time  
1233 schemes. *Mon Weather Rev* 130(8):2088–2097
- 1234 Williams KD, Copsey D, Blockley EW, Calvert D, Comer R, Davis P, Graham T, Hewitt HT,  
1235 Hill R, Hyder P, Ineson S, Johns TC, Keen A, Lee RW, Megann A, Milton SF, Rae JGL,  
1236 Roberts MJ, Scaife AA, Schiemann R, Storkey D, Thorpe L, Watterson IG, Walters DN,  
1237 West A, Wood R, Woollings T, Xavier PK (in rev.) The met office global coupled model  
1238 3.0 and 3.1 (gc3 & gc3.1) configuration. *J Adv Model Earth Syst* 1(0)
- 1239 Wilson DR, Ballard SP (1999) A microphysically based precipitation scheme for the  
1240 UK Meteorological Office Unified Model. *Q J R Meteorol Soc* 125:1607–1636, DOI  
1241 10.1002/qj.49712555707
- 1242 Wilson DR, Bushell AC, Kerr-Munslow AM, Price JD, Morcrette CJ (2008) PC2: A prognos-  
1243 tic cloud fraction and condensation scheme. I: Scheme description. *Q J R Meteorol Soc*  
1244 134:2093–2107, DOI 10.1002/qj.333
- 1245 Wood N, Staniforth A, White A, Allen T, Diamantakis M, Gross M, Melvin T, Smith C,  
1246 Vosper S, Zerroukat M, Thuburn J (2014) An inherently mass-conserving semi-implicit  
1247 semi-Lagrangian discretisation of the deep-atmosphere global nonhydrostatic equations. *Q*  
1248 *J R Meteorol Soc* 140:1505–1520, DOI 10.1002/qj.2235
- 1249 Wuest M, Frei C, Altenhoff A, Hagen M, Litschi M, Schär C (2010) A gridded hourly precip-  
1250 itation dataset for Switzerland using rain-gauge analysis and radar-based disaggregation.  
1251 *Int J Clim* 30:1764–1775
- 1252 Wyngaard JC (2004) Toward numerical modeling in the terra incognita. *J Atmos Sci* 61:1816–  
1253 1826, DOI 10.1175/1520-0469

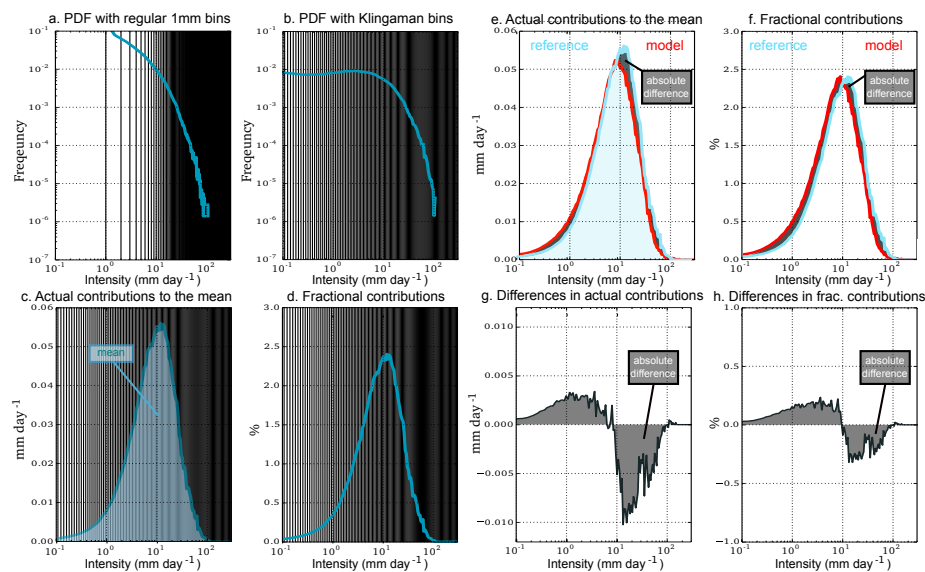
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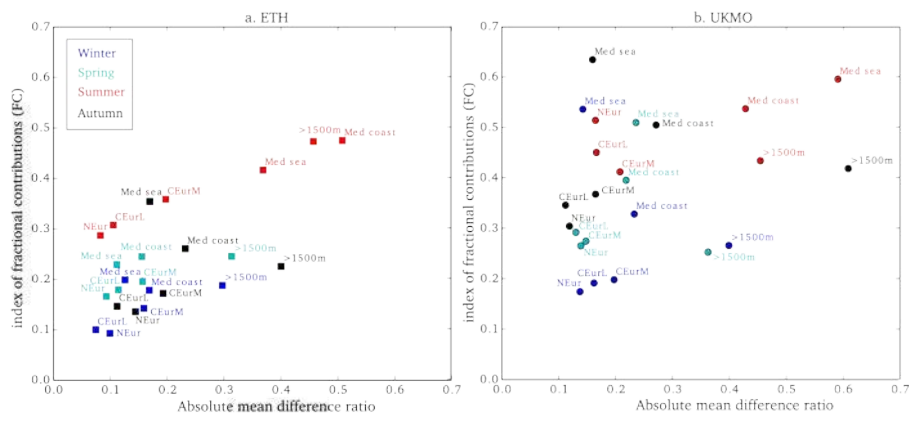


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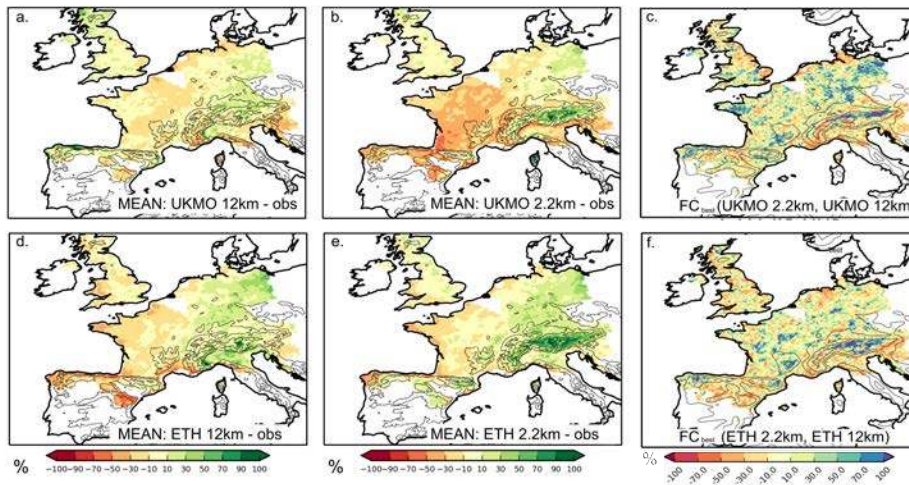


**Fig. 2** Explanation of the ASoP spectral method. a: Probability density function with regular 1 mm bins (frequency of events as a function of event intensity), vertical lines represent the bin widths; b: Probability density function with the ASoP spectral bins defined in Eq. (1); c: Actual contributions to mean precipitation (mm day<sup>-1</sup>) as a function of event intensity (from b to c, each frequency was multiplied by the average intensity of the bin), the area under the curve is the mean precipitation; d: Fractional contributions (percentage of the mean that each bin represents): from c to d, each bin was divided by the mean precipitation. The area under the curve is 1; e: Actual contributions for a reference (blue) and a model (red), the grey area is the mean absolute difference (mm day<sup>-1</sup>); f: Fractional contributions for a reference (blue) and a model (red), the grey area is the absolute difference (%); g: Difference in actual contributions between the model (red in panel e) and the reference (blue in panel e); h: Same as g for the fractional contributions: difference between the red and blue curves of panel f.





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**Fig. 4** Mean daily precipitation bias in percentage of the observation values for the (top) UKMO and (bottom) ETH models in summer at (a, d) 12km and (b, e) 2.2km resolution. The best daily fractional index between the 2.2km and the 12km for (c) UKMO and (f) ETH model (as described by Eq. (4)). Blue means the 12 km model is closest to the observations, red means the 2.2 km is closest. Values indicate percentage of improvement compare to FC(12 km, obs). Regions with means smaller than  $0.5\text{mm day}^{-1}$  in the observations are masked out.

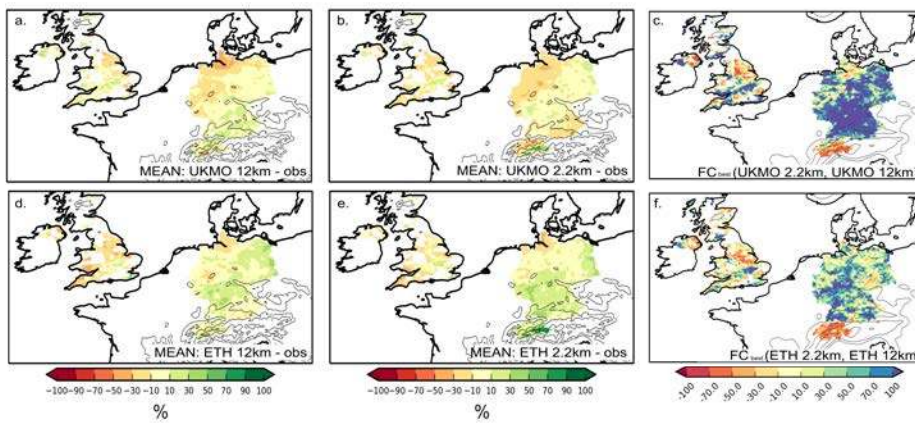
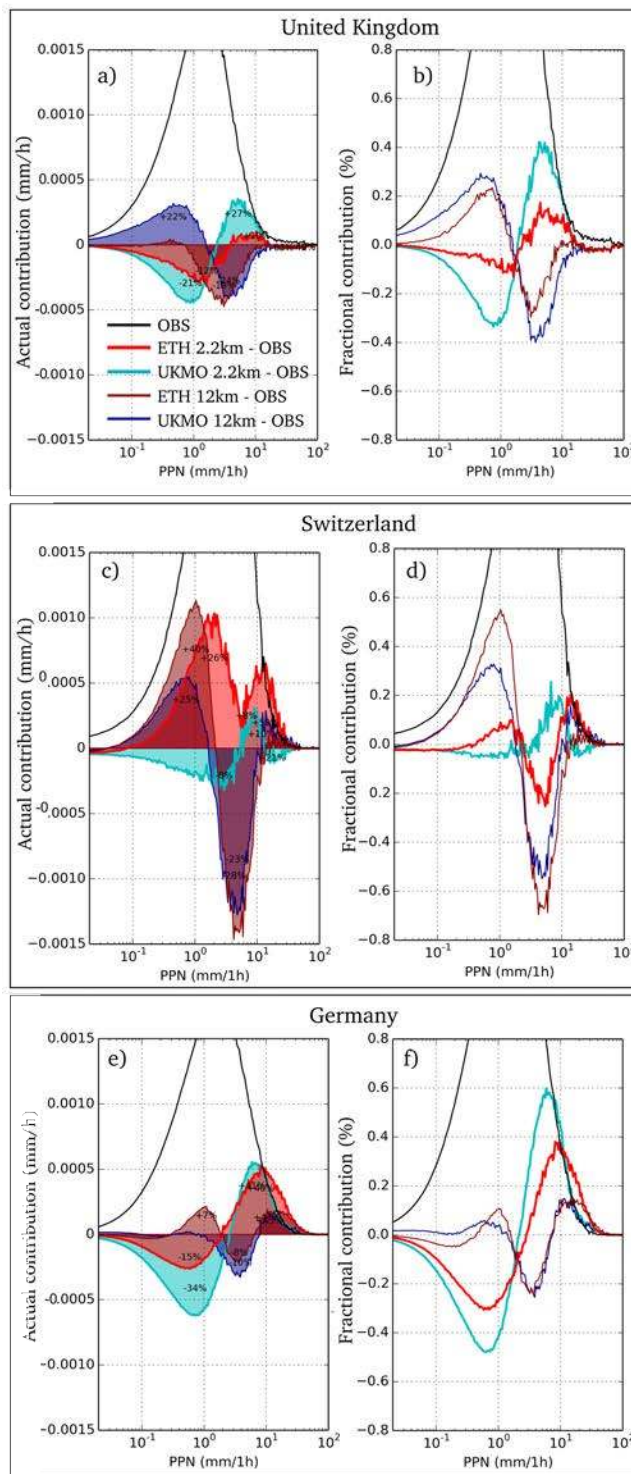
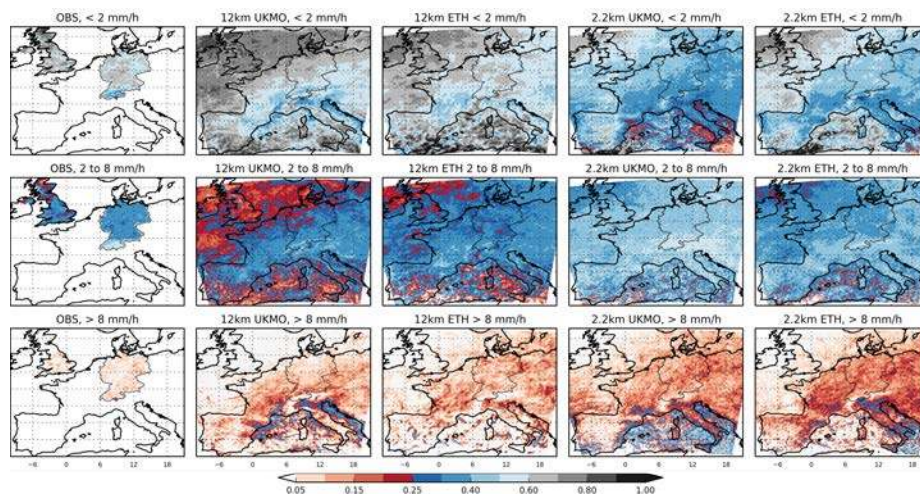


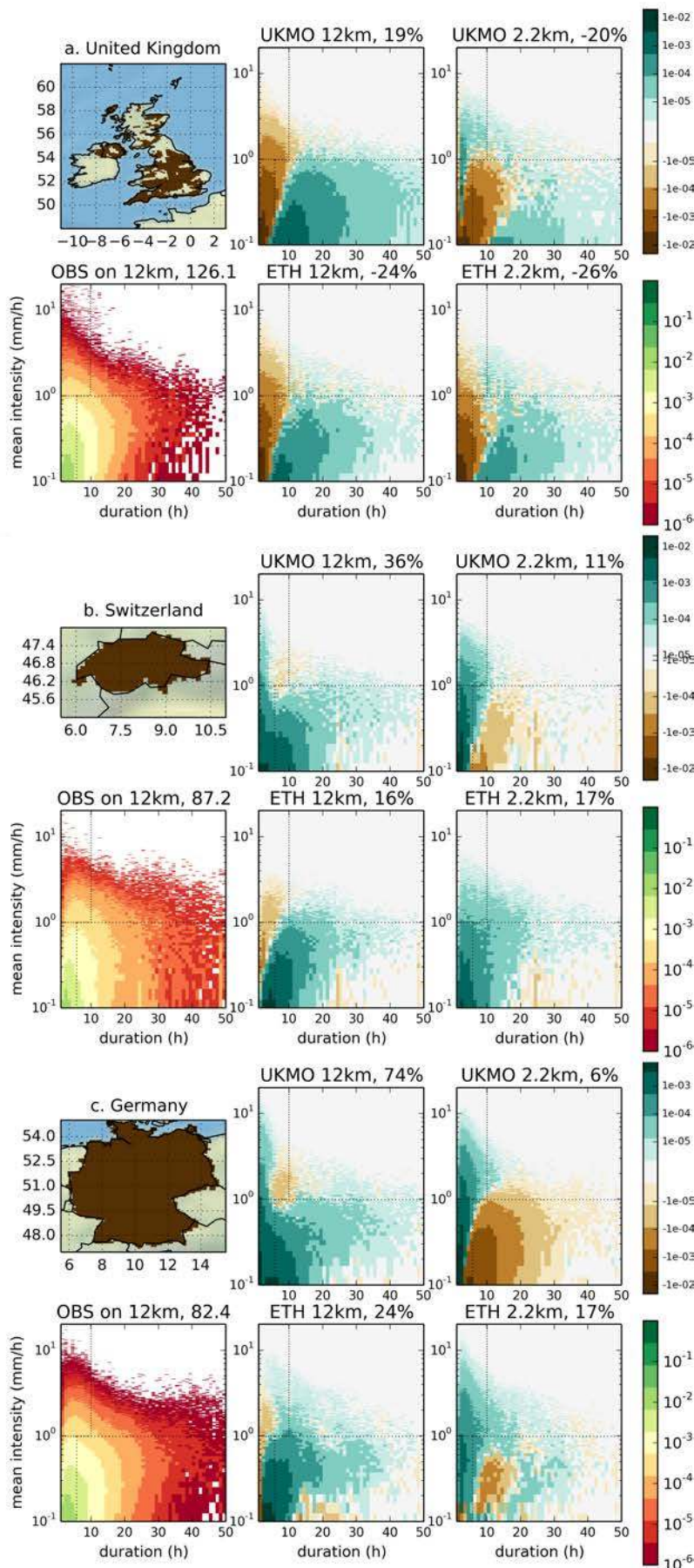
Fig. 5 Same as Fig. 4 for hourly precipitation.



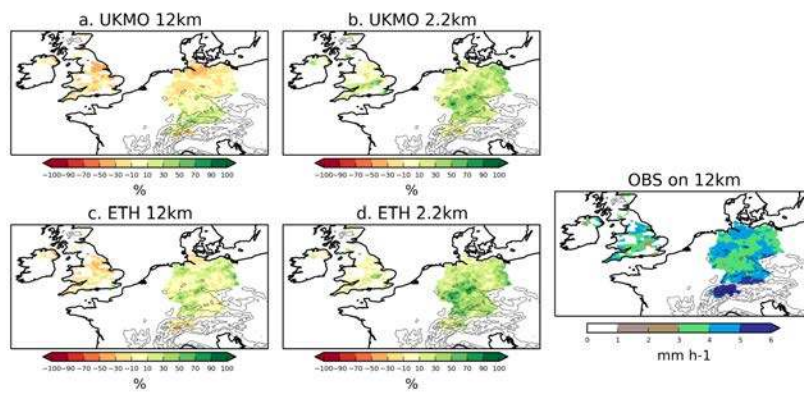
**Fig. 6** Differences in the fractional and actual contribution of hourly precipitation between models and the observations (JJA) for different countries (left: actual contribution, right: fractional contribution). See Sect. 3 and Figure 2 for details about the method. a. Germany, b. Switzerland, c. United Kingdom (only points where less than 30% of data is missing in the observations are taken into account).



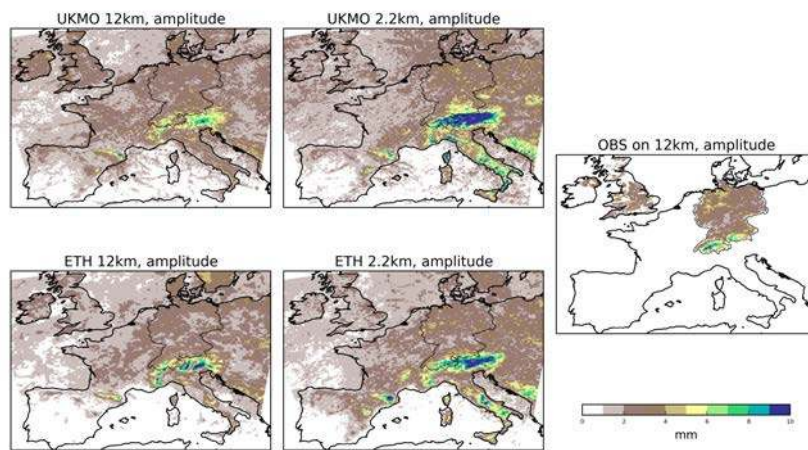
**Fig. 7** Fractional contribution (ratio of actual contribution on total precipitation) of three bin categories in summer: top (<2mm/h), middle (from 2 to 8 mm/h), bottom: above 8 mm/h. From left to right: observations, UKMO-12 km, ETH-12 km, UKMO-2.2 km, ETH-2.2 km.



**Fig. 8** Frequency of wet spells in summer in different duration and intensity bins for the a. UK, b. Switzerland c. Germany. In each panel, observational datasets are shown as reference and model differences with the observations are shown as indicated in the panel titles (see Sect. 5.2 for details). The number written above the observation plots is the average number of wet spells per grid point per season and the percentage indicated above each model panel is the percentage difference in number of wet spells between models and observations.

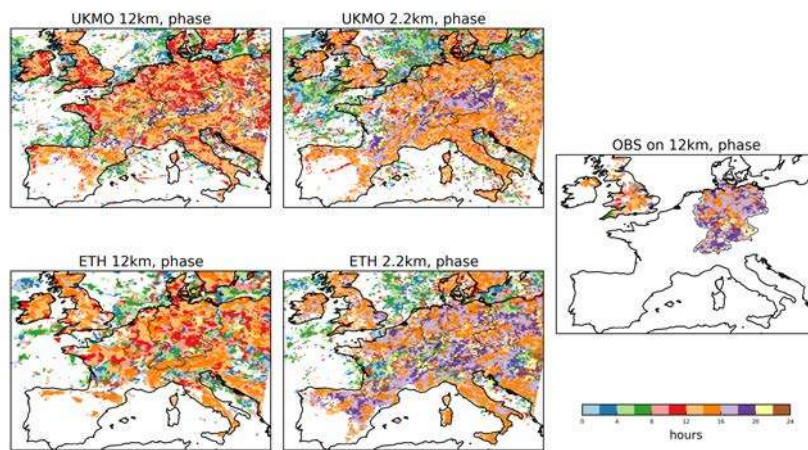


**Fig. 9** Average of values above the 99<sup>th</sup> percentile of all hours in summer. Top row: UKMO 12 km (left) and 2.2 km (right) models (percentage difference with the observations), bottom row: ETH 12 km (left) and 2.2 km (right) models (percentage difference with the observations); right column: observations ( $\text{mm day}^{-1}$ ).

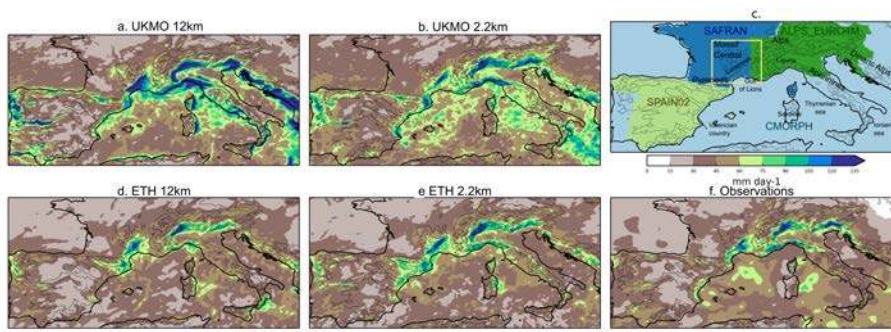


**Fig. 10** Amplitude of mean diurnal cycle in summer (maximum - minimum) (mm). Top row: UKMO 12 km (left) and 2.2 km (right) models, bottom row: ETH 12 km (left) and 2.2 km (right) models; right column: observations.

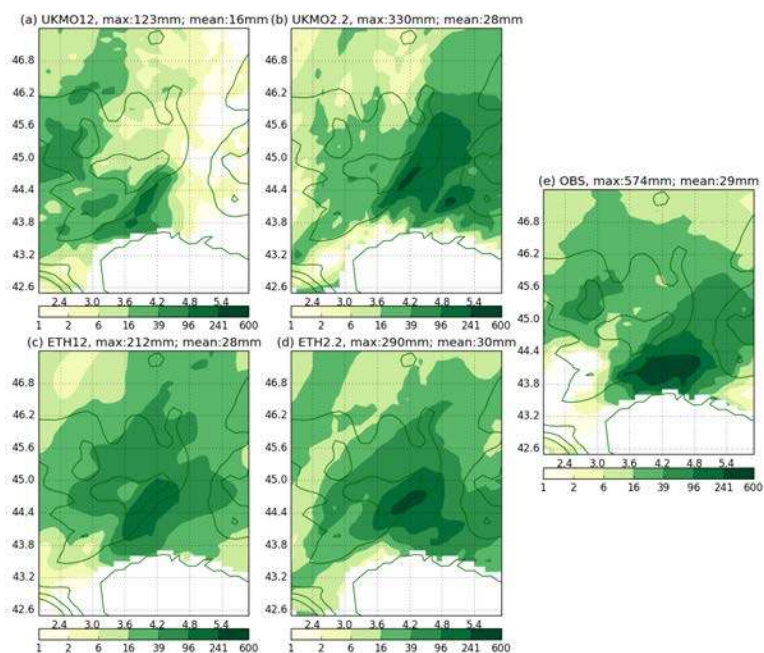




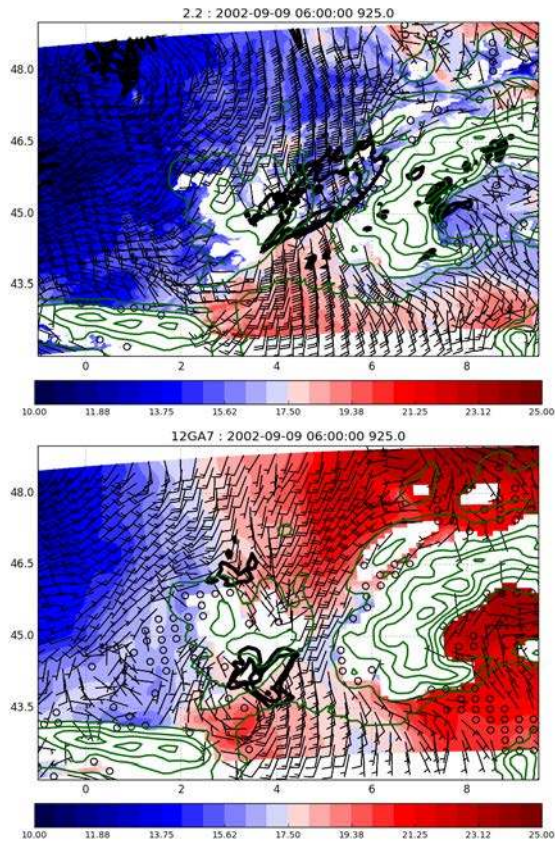
**Fig. 11** Hour of maximum precipitation of the mean diurnal cycle in summer (local time). Top row: UKMO 12 km (left) and 2.2 km (right) models, bottom row: ETH 12 km (left) and 2.2 km (right) models; right column: observations.



**Fig. 12** Average of values above the 99th percentile of all days in autumn (SON). a. UKMO 12 km, b. UKMO 2.2 km, d. ETH 12 km, e. ETH 2.2 km; f. available observations (composite of CMORPH and gridded regional products, as shown in panel c). Yellow area in panel c shows the domain of the case study in Fig. 13 and Fig. 14 (mm/day).



**Fig. 13** 2-day total precipitation between 08/09/2002 and 09/09/2002. The 12 km models, 2.2 km models and SAFRAN observations are respectively on the left, centre and right. Upper and lower row are for UKMO and ETH simulations. Green lines outline surface height above 500 and 1000 m for the UKMO 12-km simulation on which all models and observations are regridded. Maximum and spatial mean are also given. The domain corresponds to the box in Fig. 12.



**Fig. 14** UKMO 2.2 km (upper panel) and 12 km (lower panel) and model-simulated snapshots of 3h-accumulated precipitation (thick black lines; 10, 20, 50 mm/3h), 925 hPa wind (barbs; knots) and virtual temperature (colour shading). White space mask when 925 hPa isobar is below ground.

# Model sensitivity to run-off and soil hydraulic physics – Supplementary Information

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## Land surface physics sensitivity study

The Joint UK land environmental simulation [JULES; Best et al, 2011] is the the standard land surface model (LSM) for the Met Office UM modelling system. Within JULES, soil characteristics are parametrised with either the Van Genuchten [van Genuchten, 1980] or Brooks-Corey [Brooks and Corey, 1964] scheme. The 2.2km and 12km Met Office UM simulations here use Van Genuchten hydraulics, however, this leads to soil infiltration rates being too low as there is an incompatibility with the soil properties defined in the models. Recent internal Met Office work suggests that the Brooks-Corey hydraulics may give improved results, and hence this is tested here. In addition, the 12 km and 2.2km Met Office UM models have a different set-up in the treatment of the saturated layers of soil: in the 2.2km model, if a layer is saturated, the excess of water is transferred to the layer above. If it is the surface layer, then it disappears in the surface run-off term and is not available any more. This is the standard set-up of the operational forecast model. In the 12km model, if a layer is saturated, the excess of water is transferred to the layer below. If it is the bottom layer, then the rainfall disappears in the sub-surface run-off term and is not available any more. This is the standard climate set-up. Here we test the effect changing the treatment of saturated layers in the 2.2km model, from transfer up (giving excess water run-off at the surface) to down (giving excess water run-off at the sub-surface).

The configuration of the sensitivity simulations conducted here are given in Table 1. All simulations are driven by the ERA-Interim reanalysis [Dee et al, 2011]; hence, lateral boundary inter-annual and intra-seasonal variability of all simulations are the same.

The magnitude of the precipitation differences between the simulations for the first model summer (Fig. 1) increases from west to east (note the sharper colours). However, the differences are generally noisy without clear regional patterns. Opposite signed differences often occur in spatial scales less than

100 km; this suggests the difference are caused by uncertainties in movement of precipitation systems. Such uncertainties increase eastward downstream as LBC influence weakens.

The 2.2km simulations have warm summer surface temperature in Central Europe and the Balkans [Kendon et al, 2017]. Shown in Fig. 2a-c are summer surface air temperatures for the first completed model summer. The use of sub-surface runoff cools surface temperature across continental Europe by less than  $0.5^{\circ}\text{C}$ , but larger cooling ( $1 - 1.5^{\circ}\text{C}$ ) are seen in the Balkans. The use of Brooks-Corey soil characteristics [Brooks and Corey, 1964] has the opposite effect; northern continental Europe is warmed by about  $0.5^{\circ}\text{C}$ .

The differences with E-OBS [Haylock et al, 2008] temperature for the same summer is illustrated in Fig. 2d. Differences with E-OBS are much larger than the differences between model simulations. In central and south east Europe, there are very large warm biases up to  $5 - 6^{\circ}\text{C}$ . However, the different JULES physics can make notable differences to those temperature biases. Cooling due to switching to downward movement of excess water and sub-surface run-off reduces the warm biases in Central Europe and the Balkans by about  $20 - 25\%$ . This may be explained by less moisture being lost as surface run-off, leading to more moisture being available for evapotranspiration, which in turn cools the surface. Switching to Brooks-Corey soil hydraulics exacerbates existing warm temperature biases in central Europe, but has little impact on the warmest biases in the Balkans. In this case, infiltration rates are increased, but it appears not enough to prevent the loss of moisture as surface run-off, especially given the intense and intermittent nature of rainfall in the 2.2km convection-permitting model.

To illustrate the above further, surface air temperatures within the Central Europe Pannonian Basin for the first full model year are shown in Fig. 3. This region is chosen due to its positive surface air temperature bias, low-lying continental location. Inter-model differences are much smaller than the differences with E-OBS. The seasonal cycle and intra-seasonal variability are generally well-captured by all model simulations. Around late spring, warm biases relative to E-OBS begin to develop for all simulations. The biases are somewhat less severe in SubSfcRunOff simulation, but they are slightly more severe in the BrooksCoreySoil simulation. Despite of the warm biases, model summer intra-seasonal temperature variabilities remain well captured. In pre-summer period, temperature biases are less clear, but individual model days can have large temperature biases (exceeding  $3^{\circ}\text{C}$ ).

Similar temperature changes are seen in regions where summer temperature biases are smaller. Daily temperature changes in France are shown in Fig. 4. Similar to the Pannonian Basin, the seasonal and intra-seasonal variability are well captured by all model simulations for the full model year. However, there is a clear shift from a pre-spring cold temperature bias to a summer warm bias.

The similar trends in both regions suggest that the origin of the temperature biases are unrelated to models developing its internal variability, and the model summer is well constrained by the lateral boundary conditions. The onset of warm bias in both regions are abrupt between May and June 1999.

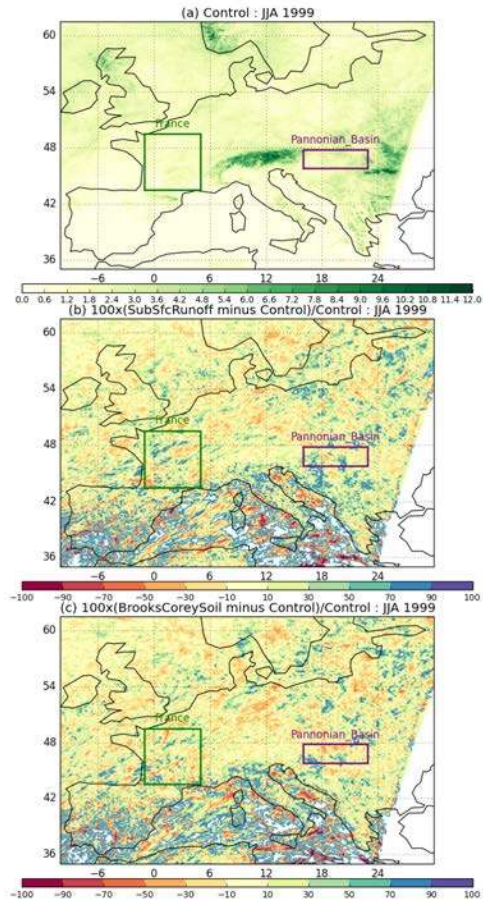
Overall, these sensitivity experiments with the 2.2 km model suggest that removing the inconsistency between the soil hydraulics and soil properties in the Met Office UM model (by using Brooks-Corey equations) has little impact on the warm temperature bias seen over central Europe and the Balkans in summer. Switching the treatment of saturated layers from upward to downward transfer (with sub-surface excess water run-off) reduces the bias, but does not remove it completely. Thus it appears, it is the intense/intermittent nature of rainfall in the 2.2 km model which is mostly responsible for the dry soil conditions and associated warm temperature bias in this region. Other regions such as the UK are less sensitive, as soil moisture is not close to the critical value for limiting evaporation.

It should be noted that these results correspond to a single summer, and further years of simulation are required to draw robust conclusions. In particular, the deepest soil layers are still spinning up in the first few years of simulation, which may impact the results.

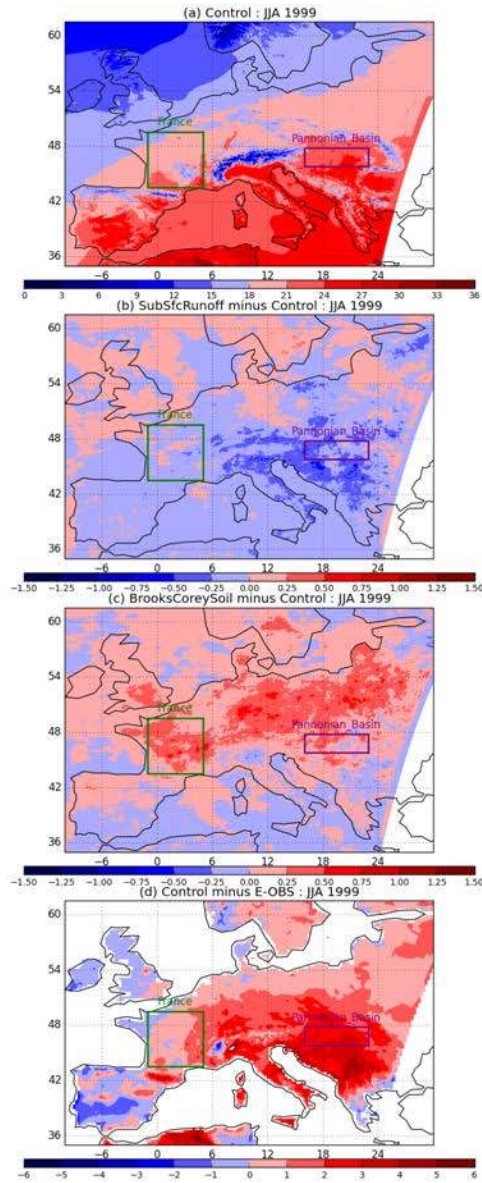
Table 1: The configurations of LSM sensitivity simulation

Simulation	Soil hydraulics	Excess water run-off
Control	Van Genuchten [van Genuchten, 1980]	Surface
SubSfcRunOff	Van Genuchten [van Genuchten, 1980]	Sub-surface
BrooksCoreySoil	Brooks-Corey [Brooks and Corey, 1964]	Surface



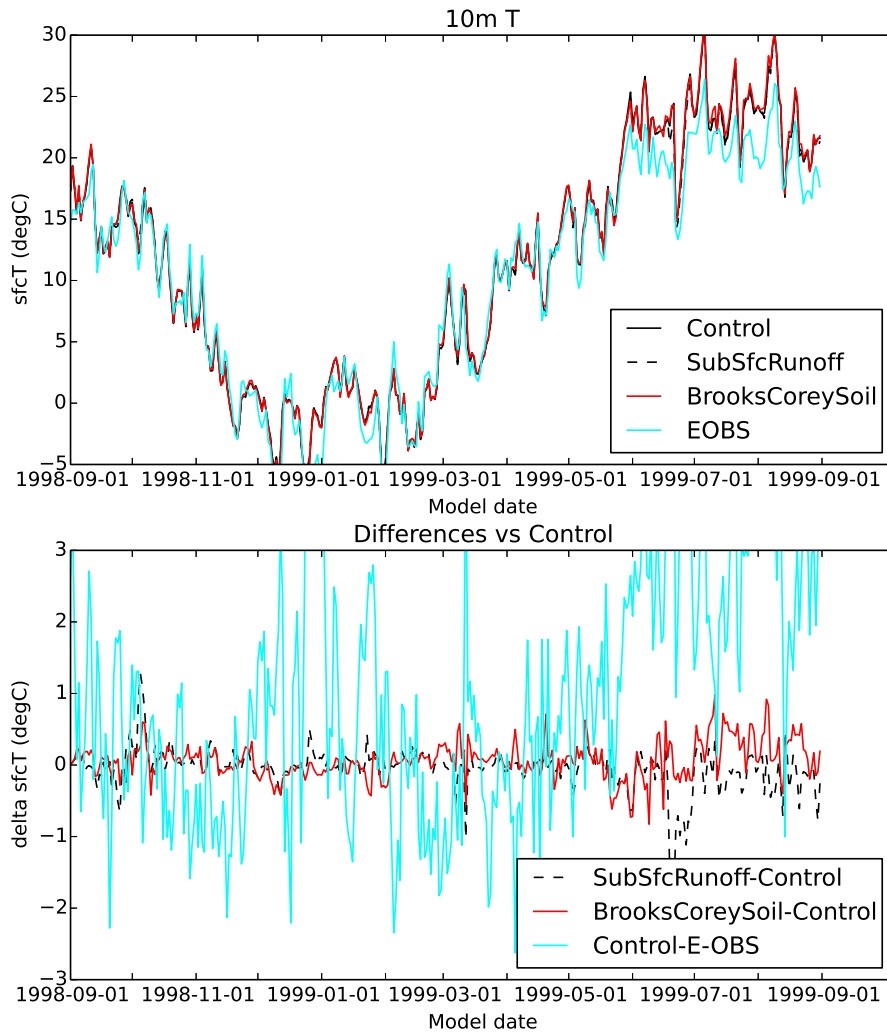


Supplementary Figure 1: Precipitation differences between the control and sensitivity simulations for the first model summer (June-July-August, 1999). Panel a shows the daily-averaged precipitation for the control simulation, and panels b and c show the percentage differences between SubSfcRunOff/Brooks-Corey simulations and the control simulation.

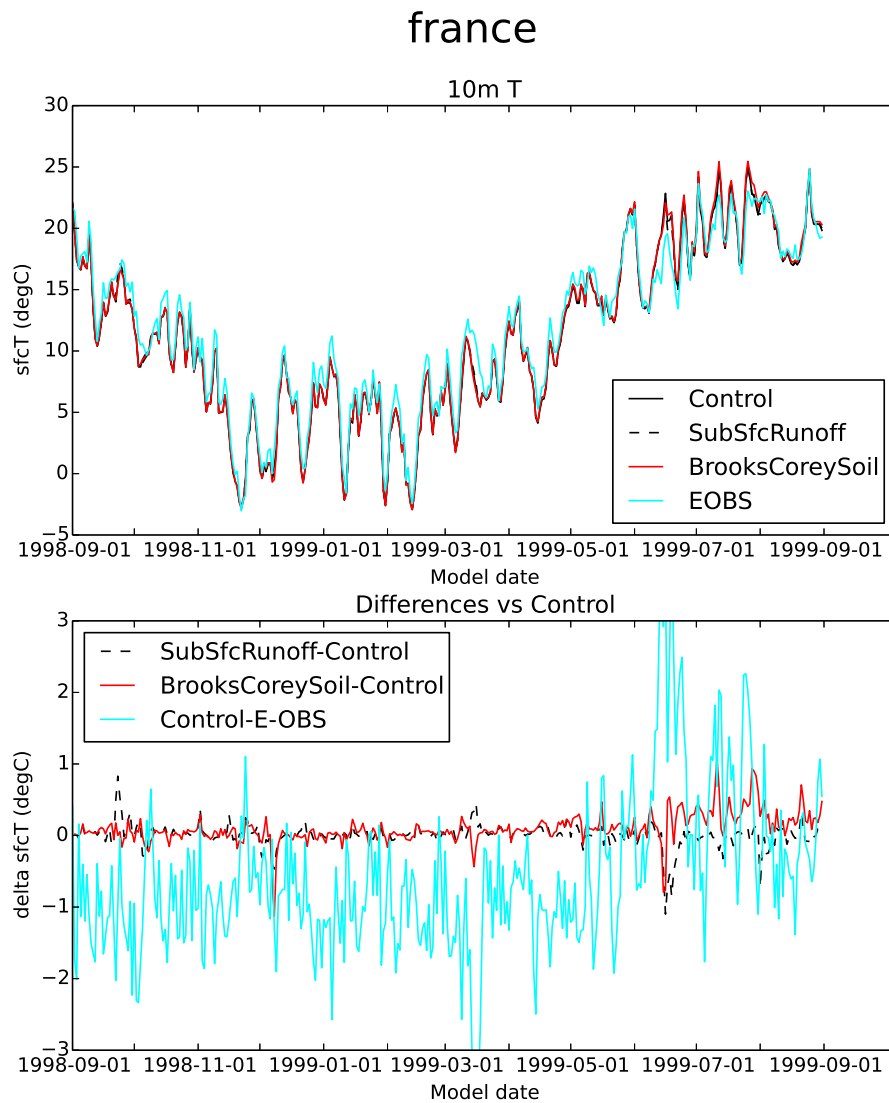


Supplementary Figure 2: Same as in Fig. 1, but for 1.5m temperature. Unlike Fig. 1, °C differences are shown instead. In addition, we also show the biases of the control simulation relative to gridded E-OBS air temperature observations [Haylock et al, 2008] in the bottom panel. The purple and green boxes indicate regions where the spatial averages of 1.5 m temperatures are taken – Fig. 3 for Pannonian Basin and Fig. 4 for France.

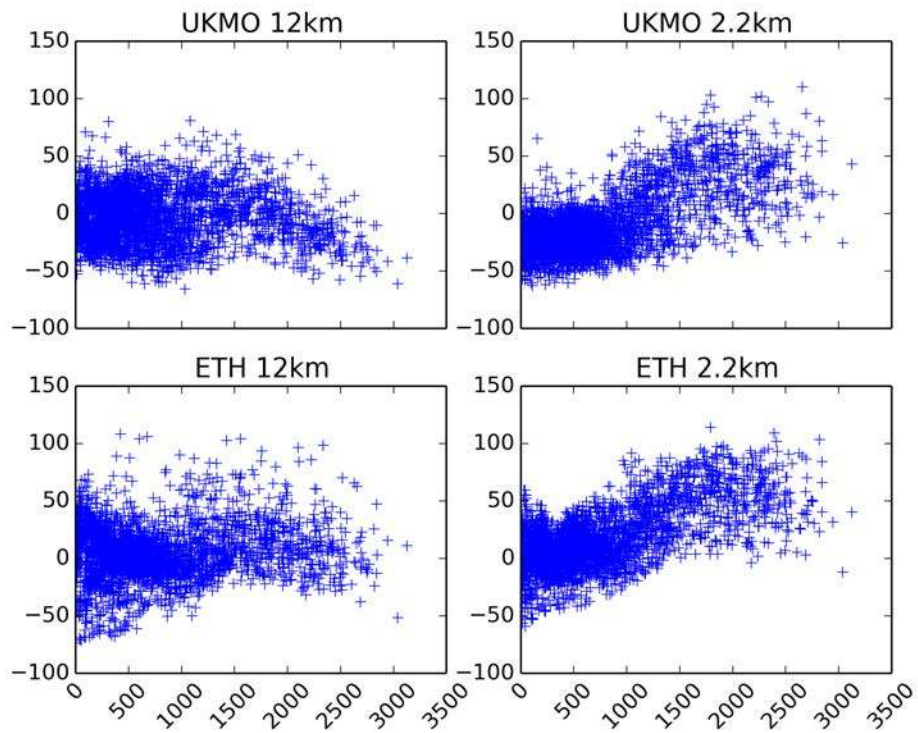
# pannonian\_basin



Supplementary Figure 3: Model-simulated and E-OBS area-averaged 1.5-m air temperatures in the Pannonian Basin region (see Fig. 2). The actual temperatures are shown in the upper panel, and the differences relative to the control simulation are shown in the lower panel. Note the differences between E-OBS and control simulation are control minus E-OBS (i.e. biases relative E-OBS).



Supplementary Figure 4: Same as in Fig. 3, but for France.



Supplementary Figure 5: Mean bias (%) against height (m) in summer for the ALPS\_EURO4M domain (regridded on the UKMO 12km grid) for the UKMO 12km, UKMO2.2km, ETH 12km and ETH2.2km models.

## References

- Best MJ, Pryor M, Clark DB, Rooney GG, Essery RLH, Mnard CB, Edwards JM, Hendry MA, Porson A, Gedney N, Mercado LM, Sitch S, Blyth E, Boucher O, Cox PM, Grimmond CSB, Harding RJ (2011) The joint uk land environment simulator (jules), model description - part 1: Energy and water fluxes. *Geosci Model Devel* 4():677–699, DOI 10.5194/gmd-4-677-2011
- Brooks RJ, Corey AT (1964) Hydraulic properties of porous media. Colorado State University, Fort Collins, Colorado, United States, hydrological Papers 3
- Dee DP, Uppala SM, Simmons AJ, Berrisford P, Poli P, Kobayashi S, Andrae U, Balsameda MA, Balsamo G, Bauer P, Bechtold P, Beljaars ACM, van de Berg L, Bidlot J, Bormann N, Delsol C, Dragani R, Fuentes M, Geer AJ, Haimberger L, Healy SB, Hersbach H, Hölm EV, Isaksen L, Kallberg P, Köhler M, Matricardi M, McNally AP, Monge-Sanz BM, Morcrette JJ, Park PK, Peubey C, de Rosnay P, Tavolato C, Thépaut JN, Vitart F (2011) The ERA-Interim reanalysis: configuration and performance of the data assimilation system. *Q J R Meteorol Soc* 137(656):553–597, DOI 10.1002/qj.828
- van Genuchten MT (1980) A closed-form equation for predicting the hydraulic conductivity of unsaturated soils. *Soil Sci Soc Am* 44:892–898, DOI 10.2136/sssaj1980.03615995004400050002x
- Haylock MR, Hofstra N, Klein Tank AMG, Klok EJ, Jones PD, New M (2008) A european daily high-resolution gridded dataset of surface temperature and precipitation. *J Geophys Res* 113:D20,119, DOI 10.1029/2008JD010201
- Kendon EJ, Chan SC, Berthou S, Fossier G, Roberts MJ, Fowler HJ (2017) Introducing the met office 2.2-km europe-wide convection-permitting regional climate simulations. In: European Geophysical Union General Assembly 2017, Vienna, Austria